Universitat Autònoma de Barcelona

Expanding the role of environmental, material and bio-economic factors in energy transition decision making

Nicholas Martin

Expanding the role of environmental, material and bio-economic factors in energy transition decision making

Nicholas Martin

Doctoral thesis

Co-supervisors: Laura Talens Peiró
Cristina Madrid López

Academic tutor: Gara Villalba Méndez

A thesis submitted in fulfillment of the requirements for the doctoral degree in Environmental Sciences and Technology

Sostenipra Research Group

Institut de Ciència i Tecnologia Ambientals (ICTA)

Universitat Autònoma de Barcelona (UAB)

Bellaterra (Cerdanyola del Vallès), December 2022

Expanding the role of environmental, material and bio-economic factors in energy transition decision making

Nicholas Martin

A thesis submitted in fulfilment of the requirements for the PhD degree in Environmental Sciences and Technology

December 2022

This doctoral thesis has been developed as part of the SENTINEL project under the European Union's Horizon 2020 research and innovation program (Grant Agreement No. 837089)

This thesis, entitled “Expanding the role of environmental, material and bio-economic factors in energy transition decision making”, was undertaken at the Institut de Ciència i Tecnologia Ambientals (ICTA) within the Universitat Autònoma de Barcelona (UAB) by

Nicholas Martin

under the supervision of Dr. Cristina Madrid López from ICTA, Dr. Laura Talens Peiró from ICTA and Dr. Gara Villalba Méndez from ICTA and the Department of Chemical, Biological and Environmental Engineering at UAB.

Cristina Madrid López Laura Talens Peiró Gara Villalba Méndez

Bellaterra (Cerdanyola del Vallès), December 2022

Summary

The ongoing threat of climate change has forced policymakers at all levels to seek new ways of lowering the production of harmful greenhouse gas (GHG) emissions. One of the key pathways identified for achieving such a reduction involves the widespread implementation of energy technologies that rely on the use of renewable resources. As many such technologies are used primarily to produce electricity, it is widely accepted that many processes–particularly within the transport and heating sectors–should also be transformed to use electrical power as quickly as possible. This switch towards renewable energy sources and “electrification” of certain processes form integral parts of the “energy transition” process.

A range of different technologies are now vying to be a part of the rapidly expanding renewable energy market as government and industry decisionmakers attempt to identify the most efficient and practical pathways towards rapid emission reductions. At the same time, a variety of models are being developed to predict the outcomes of the energy transition, providing forecasts of future energy system configurations and emergence patterns for individual technologies. In doing so, they also provide much needed feedback that informs important energy and climate policy decisions. As such, these models represent a critical tool to decisionmakers as they endeavour to streamline overall transition processes.

However, while most of these models offer detailed considerations of energy systems and, at times, their interactions with the biosphere that contains them, most fail to consider the breadth of factors that are likely to constrain and influence energy transition processes as they occur. Indeed, most models remain focussed on technical or economic outcomes and offer few considerations of environmental or resource-related parameters beyond relatively simple estimations of GHG emissions and land use.

To bridge this gap, the thesis firstly includes an overview of the key factors that could constrain and influence energy transition processes and the possible consequences of neglecting such factors in models. A list of 11 general factors is then identified that, together, represents a range of political, economic and physical considerations. A selection of particularly overlooked factors is then also provided alongside several potential disconnects within the context of the current European energy system.

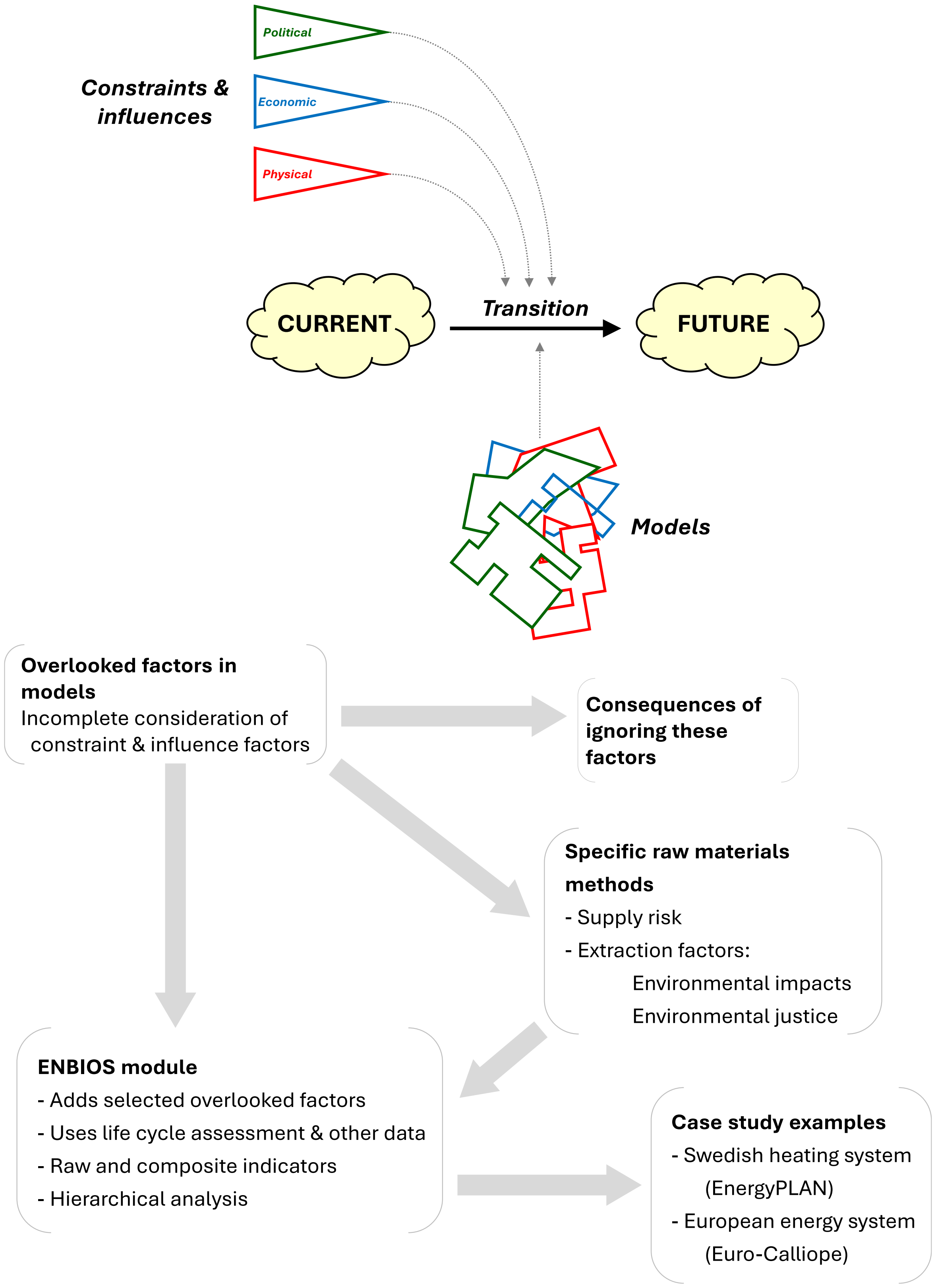
To improve the representation of these factors in the models being used to guide policy, a number of new approaches are then introduced, primarily involving life cycle assessment (LCA) information in conjunction with other existing data sources. Firstly, the wider use of direct LCA data would enable more accurate estimations of environmental impacts and resource requirements to be implemented as this data considers the full life cycles of energy-related processes. Secondly, new methodologies are proposed that allow indicators to be derived for various raw material issues using material

inventory data from LCA sources alongside other available data. This includes quantifications of overall material supply risk and the environmental damages and justice implications that relate to localised extraction and processing operations. Thirdly, the use of labour requirement data allows the hours of labour required to provide a unit of energy at different locations within a system to be calculated. Lastly, combinations of all of these indicators enable additional socio-metabolic and other customised indicators to be derived.

These new approaches are then operationalised and demonstrated using the ENBIOS workflow developed as part of the SENTINEL project that provided the foundation for the doctoral program. ENBIOS can take multiple different energy configurations and return a detailed set of indicators within and across the hierarchical levels in an energy system. This allows the characteristics and relationships that exist within energy systems at different levels to be determined. Although ENBIOS was designed to be highly customisable, the pilot version defined and used in the thesis is focussed upon the previously identified group of especially overlooked environmental and resource-based factors.

Two case studies are included that highlight the effectiveness of ENBIOS. One of these analyses current and future district heating systems in Sweden based on outputs from the EnergyPLAN model. A second case study analyses 441 possible future configurations of the European energy system provided by the Euro-Calliope model. In both instances, findings suggests that a number of important trade-offs are likely to be involved, highlighting the need to consider a range of additional constraint and influence factors.

Graphical abstract



Acknowledgements

Firstly, a huge set of thank-yous goes to my two supervisors, Laura and Cristina, for being with me on the journey. Equally, thank-you to Gara for always being there to pull everything together.

Within the SENTINEL project I would like to thank Diana, Hannes and Johan, Bryn and Stefan, Vassilis, Andrzej and Amanda, Jakob, Laura and Tony, Iain and Gabrielle, Mark, Miguel and Jakob, and everyone else that helped along the way.

Also, to my other friends and co-conspirators within the greater world of ICTA, particularly Jeroen, Isabelle, Helen, Ita and James.

A very special mention goes to Austin for being the biggest rock among rocks.

To all of my other friends and family in Barcelona, Australia, London and elsewhere. Somehow, I managed to keep it all together thanks to you all.

Lastly, above all, I thank Sandra.

Contents

Figures

Tables

Units

Energy	
J	joule
MJ	megajoule (x10^6 joules)
GJ	gigajoule (x10^9 joules)
TJ	terajoule (x10^{12} joules)
EJ	exajoule (x10^{18} joules)
Wh	watt-hour
kWh	kilowatt-hour (x10^3 watt-hours)
MWh	megawatt-hour (x10^6 watt-hours)
GWh	gigawatt-hour (x10^9 watt-hours)
TWh	terawatt-hour (x10^{12} watt-hours)
Power capacity	
W	watt or joule per second
MW	megawatt (x10^6 watts)
GW	gigawatt (x10^9 watts)
Time	
s	second
h	hour
Gh	gigahour (x10^9 hours)
yr	year
Mass	
kg	kilogram
Area	
m^2	square metre
km^2	square kilometre
Volume	
L	litre
TL	teralitre (x10^{12} litres or 10^9 cubic metres)
GHG emissions	
g CO_2-eq	gram of carbon dioxide equivalent
kgCO_2-eq	kilogram of carbon dioxide equivalent
PgCO_2-eq	petagram of carbon dioxide equivalent (x10^{12} kgCO_2-eq)
Other	
kg oil-eq	kilograms of oil equivalent, a measure of fossil depletion
kg Fe-eq	kilograms of iron equivalent, a measure of metal depletion
kg P-eq	kilograms of phosphorous equivalent, a measure of freshwater eutrophication
kg N-eq	kilograms of nitrogen equivalent, a measure of marine eutrophication
kg 1,4-DC	kilograms of 1,4 dichlorobenzene equivalent, a measure of human toxicity

Abbreviations

AAU	Aalborg University
ABMs	agent-based models
ADP	abiotic depletion potential
ALOP	agricultural land occupation (LCIA method)
AP	acidification potential
a-Si	amorphous silicon
ATOM	Agent-based Technology adOption Model
AWARE	Available WAter REmaining
BFE	Bundesamt für Energie
CAES	compressed air energy storage
CaTiO3	calcium titanate
CCGT	combined cycle gas turbine
CdTe	cadmium telluride
CED	cumulative energy demand
CEENE	cumulative exergy extraction from the natural environment
CExD	cumulative exergy demand
CH_4	methane
CHP	combined heat and power
CIGS	copper indium gallium diselenide
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalent
COP	coefficient of performance
CRM	critical raw material
C-Si	crystalline silicon
CSP	concentrated solar power
CV	calorific value
CZTS	copper zinc tin sulphide solar
DC	direct current
DD	direct-drive
DFIG	double-fed induction generator
DSSC	dye-sensitized solar cell (or Grätzel cell)
E3 model	energy-environment-economy model
EC	European Commission
EDGAR	Emissions Database for Global Atmospheric Research
EESG	electrically excited synchronous generator
EF	emission factor
EI	environmental impact
EJ	environmental justice
EMR	energy metabolic rate
ENBIOS	ENvironmental and BIOeconomic System assessment
ENTSO-E	European Network of Transmission System Operators for Electricity
EoLRIR	end-of-life recycling input rate
EROI	energy return on investment
ESM	energy system model
ETHZ	Swiss Federal Institute of Technology in Zürich
EU	European Union
EU-28	European Union-28 countries (includes United Kingdom)

EV	electric vehicle
FCV	fuel cell vehicle
FF	fate factor
GB	gearbox
GD	government directed
GHG	greenhouse gas
GHGMR	greenhouse gas metabolic rate
GLAM	Global Life Cycle Assessment Method
GTP	global temperature potentials
GWEC	Global Wind Energy Council
GWP	global warming potential
GWP100	global warming potential (100-year time horizon) (LCIA method)
HA	human activity
HAWT	horizontal-axis wind turbine
HDS	high-demand scenario
HFB	hybrid flow battery
HHI	Herfindahl-Hirschman Index
HRE	heavy rare earth
IAM	integrated assessment model
IAMC	Integrated Assessment Modeling Consortium
IASS	Institute for Advanced Sustainability Studies
ICEV	internal combustion engine vehicles
IEA	International Energy Agency
IEDC	Industrial Ecology Data Commons
iF	intake fraction
ILO	International Labour Organization
IMAGE	Integrated Model to Assess the Global Environment
INDC	intended nationally determined contribution
IPCC	Intergovernmental Panel on Climate Change
IR	import reliance
IRENA	International Renewable Energy Agency
ISIC	International Standard Industrial Classification
JGCRI	Joint Global Change Research Institute
LCA	life cycle assessment
LCI	life cycle inventory
LCIA	life cycle impact assessment
LDS	low-demand scenario
LFR	linear Fresnel reflectors
LRE	light rare earth
MCFC	molten carbonate fuel cell
MD	market driven
MDS	medium-demand scenario
MFA	material flow analysis
MGA	modelling to generate alternatives
MLP	Multi-Level Perspective
MuSIASEM	Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism
N_2O	dinitrogen monoxide
NGO	non-governmental organisation
OSC	organic solar cell
P2G	power-to-gas

P2L	power-to-liquids
P2X	power-to-liquids and power-to-gas
PAFC	phosphoric acid fuel cell
PEMFC	proton-exchange membrane fuel cell
PGM	platinum group metal
pLCA	prospective life cycle assessment
PMFP	particulate matter formation potentials
PMSG	permanent magnet synchronous generator
PP	people powered
PSC	perovskite solar cell
PTES	pumped thermal electricity storage
PV	photovoltaic
QDSSC	quantum-dot sensitized solar cell
QTDIAN	Quantification of Technological DIffusion and sociAl constraiNts
R2	R-squared
RES	renewable energy sources
RFB	redox flow battery
RoW	rest of the world
rpm	revolutions per minute
RQ	research question
SDS	Sustainable Development Scenario
SENTINEL	Sustainable Energy Transitions Laboratory
SIEC	Standard International Energy Product Classification
sLCA	social life cycle assessment
SOP	surplus ore potential
SPORES	spatially explicit practically optimal results
SPS	Stated Policies Scenario
SR	supply risk
TSG	tidal stream generator
TYNPD	Ten-Year Network Development Plan
ULOP	urban land occupation (LCIA method)
UNEP	United Nations Environment Programme
US	United States
V2G	vehicle-to-grid
WDP	water depletion (LCIA method)
WEM	World Energy Model
WGI	Worldwide Governance Indicators
WMR	water metabolic rate
ZEBRA	zero emissions batteries research activity (or sodium-nickel-chloride)

Dissemination and training

Peer reviewed articles

The thesis is based on five published peer reviewed articles:

- "Overlooked factors in predicting the transition to clean electricity", Nick Martin, Cristina Madrid-López, Gara Villalba-Méndez, Laura Talens-Peiró, *Environmental Research: Infrastructure and Sustainability*, 15 June 2022, *https://doi.org/10.1088/2634-4505/ac70f7*

- "Why energy models should integrate social and environmental factors: Assessing user needs, omission impacts, and real-world accuracy in the European Union", Diana Süsser, Nick Martin, Vassilis Stavrakas, Hannes Gaschnig, Laura Talens-Peiró, Alexandros Flamos, Cristina Madrid-López, Johan Lilliestam, *Energy Research & Social Science*, 20 September 2022, *https://doi.org/10.1016/j.erss.2022.102775*

- "Integration of raw materials indicators of energy technologies into energy system models", Laura Talens-Peiró, Nick Martin, Gara Villalba-Méndez, Cristina Madrid-López, *Applied Energy*, 1 February 2022, *https://doi.org/10.1016/j.apenergy.2021.118150*

- "New techniques for assessing critical raw material aspects in energy and other technologies", Nick Martin, Cristina Madrid-López, Gara Villalba-Méndez, Laura Talens-Peiró, *Environmental Science & Technology*, 24 November 2022, *https://doi.org/10.1021/acs.est.2c05308*

- "An energy future beyond climate neutrality: Comprehensive evaluations of transition pathways", Nick Martin, Laura Talens-Peiró, Gara Villalba-Méndez, Rafael Nebot-Medina, Cristina Madrid-López, *Applied Energy*, 14 November 2022, *https://doi.org/10.1016/j.apenergy.2022.120366*

Project involvement

Funding for the doctoral program was received via the institute's involvement in the SENTINEL project (SENTINEL n.d.), a European Union Horizon 2020 research and innovation program (GA 837089), and much of the research undertaken in completing the thesis was directly related to the project.

Aside from the research articles listed above, collaborations within the project yielded two key project deliverables:

- "Observed trends and modelling paradigms on the social and environmental aspects of the energy transition. Deliverable 2.1. Sustainable Energy Transitions Laboratory (SENTINEL) project", Nick Martin, Cristina Madrid-López, Laura Talens-Peiró, Diana Süsser, Hannes Gaschnig, Johan Lilliestam, 30 May 2020, *https://doi.org/10.5281/zenodo.4917183*

- "Model development to match ENVIRO[1], QTDIAN and ATOM to user needs. Deliverable 2.4. Sustainable Energy Transitions Laboratory (SENTINEL) project", Cristina Madrid-López, Diana

[1] ENVIRO was an early name for the workflow and in-development software package later renamed ENBIOS.

Süsser, Vassilis Stavrakas, Johan Lilliestam, Alexandros Flamos, Laura Talens-Peiró, Nick Martin, 11 March 2021, *https://doi.org/10.5281/zenodo.4912687*

Furthermore, the project involved organisation and participation in several workshops and other activities:

- "Models for the European energy transition: Your questions, your needs!", SENTINEL user needs workshop, online, 1 October 2020
- "Circularity and use of raw materials", focus group session, Energy Modelling Platform for Europe (EMP-E) Conference 2020: "Modelling Climate Neutrality for the European Green Deal", online, 6 October 2020
- SENTINEL Nordic case study workshop, online, 4 November 2020
- "Environmental assessment for energy modelling and policy", parallel session, Energy Modelling Platform for Europe (EMP-E) Conference 2021: "Re-Energising Sustainable Transitions in Europe. Energy System Modelling, Methods & Results to Support the European Green Deal", Brussels and online, 28 October 2021

Conference presentations

Presentations and posters were presented at various conferences throughout the doctoral program:

Presentations

- "Challenges in modelling energy system material requirements: The ENVIRO perspective", Cristina Madrid-López, Laura Talens-Peiró, Nick Martin, *Energy Modelling Platform for Europe (EMP-E) Conference 2020: "Modelling Climate Neutrality for the European Green Deal"*, online, 6 October 2020
- "How clean is your "clean" energy? The ENVIRO module for energy system models", Nick Martin, Laura Talens-Peiró, Bryn Pickering, Cristina Madrid-López, *European Geosciences Union (EGU) General Assembly 2021. Session ERE2.2: "Spatial and temporal modelling of renewable energy systems"*, online, 30 April 2021
- "Identifying roadblocks on the pathway to a cleaner future. Raw material supply factors in the modelling and planning of sustainable energy systems", Nick Martin, Laura Talens-Peiró, Cristina Madrid-López, *20th European Round Table on Sustainable Consumption and Production (ERSCP21). Biennial international Workshop, "Beyond energy scarcity. Empowering Communities"*, Graz and online, 9 September 2021
- "How sustainable is your new energy pathway? Exploring environmental impacts of EU energy scenarios with ENBIOS", Cristina Madrid-López, Nick Martin, Laura Talens-Peiró, *20th European Round Table on Sustainable Consumption and Production (ERSCP21). Biennial international Workshop, "Beyond energy scarcity. Empowering Communities"*, Graz and online, 9 September 2021

- "Towards the integration of environmental and bio-economic indicators in energy systems modelling", Nick Martin, Laura Talens-Peiró, Gara Villalba-Méndez, Cristina Madrid-López, *13th International Conference on Applied Energy (ICAE2021)*, Bangkok and online, 4 December 2021, *https://doi.org/10.46855/energy-proceedings-9354*

Posters

- "ENVIRO: An in-development module to assess sustainable energy transition scenarios", Laura Talens-Peiró, Cristina Madrid-López, Nick Martin, *Open Energy Modelling Workshop 2020*, Berlin, 16 January 2020

- "How sustainable is your clean energy pathway?", Cristina Madrid-López, Nick Martin, Rafael Nebot-Medina, Laura Talens-Peiró, Gara Villalba-Méndez, *Gordon Research Conference, Industrial Ecology (GRS), "Advancing the Circular Economy for Human and Planetary Wellbeing"*, Newry, Maine, 16 June 2022

- "The many faces of district heating transitions. Deeper understandings of future systems in Sweden and beyond", Nick Martin, Marie Cloarec, Laura Talens-Peiró, Cristina Madrid-López, *European Climate and Energy Modelling Platform (ECEMP) Conference 2022: "Acting on the ambitions to a net-zero EU: roadblocks, challenges, and opportunities"*, Brussels and online, 7 October 2022

Other collaborations

Several collaborations with other colleagues within the Institut de Ciència i Tecnologia Ambientals (ICTA) produced additional outcomes:

Articles

- "Green gentrification in European and North American cities", Isabelle Anguelovski, James J. T. Connolly, Helen Cole, Melissa Garcia-Lamarca, Margarita Triguero-Mas, Francesc Baró, Nicholas Martin, David Conesa, Galia Shokry, Carmen Pérez del Pulgar, Lucia Argüelles Ramos, Austin Matheney, Elsa Gallez, Emilia Oscilowicz, Jesúa López Máñez, Blanca Sarzo, Miguel Angel Beltrán, Joaquin Martinez Minaya, *Nature Communications*, 2 July 2022, *https://doi.org/10.1038/s41467-022-31572-1*

- "Exploring green gentrification in 28 Global North cities: The role of urban parks and other types of greenspaces", Margarita Triguero-Mas, Isabelle Anguelovski, James J.T. Connolly, Nick Martin, Austin Matheney, Helen V.S. Cole, Carmen Pérez-del-Pulgar, Melissa García-Lamarca, Galia Shokry, Lucía Argüelles, David Conesa, Elsa Gallez, Blanca Sarzo, Miguel Angel Beltrán, Jesúa López Máñez, Joaquín Martínez-Minaya, Emilia Oscilowicz, Mariana C. Arcaya, Francesc Baró, *Environmental Research Letters*, 4 October 2022, *http://doi.org/10.1088/1748-9326/ac9325*

Presentations

- "Mental health and greenspace in Barcelona: Are gentrification and social class effect modifiers?", Montserrat Zayas-Costa, Helen Cole, James Connolly, Isabelle Anguelovski, Nick

Martin, Margarita Triguero-Mas, *APHA's 2020 VIRTUAL Annual Meeting and Expo*, online, 26 October 2020

- "A universal quantitative methodology for assessing green gentrification", Nick Martin, Barcelona Lab for Urban Environmental Justice and Sustainability (BCNUEJ) seminar series: "Green planning for the just and inclusive city", online, 4 March 2021

Training activities

- "Becoming a Scientific Writer: Putting Why? Before How?", *ICTA Unit of Excellence/Maria de Maeztu training sessions*, Gavin Lucas, ThePaperMill Group, 13-15 October 2021

Supervision

Assistance was provided to two students completing their final master's thesis within the Interdisciplinary Studies in Environmental, Economic and Social Sustainability (SAES) master's degree at the university during the 2020/2021 academic year:

- "Environmental performance of future integrated DH system: A case study for Sweden", Marie Cloarec
- "The material dependency of photovoltaics in the EU Energy Roadmap 2050", Friedrich Brämer

Article reviews

Several peer reviews were completed for scientific journals during completion of the doctoral program, resulting in a "Trusted Reviewer" certificate from IOP Publishing:

- "Near term carbon tax policy in the us economy: Limits to deep decarbonization", Michael Buchdahl Roth, Peter J. Adams, Paulina Jaramillo, Nicholas Z. Muller, *Environmental Research Communications*, 5 May 2020, *https://dx.doi.org/10.1088/2515-7620/ab8616*
- "An assessment of the potential of using carbon tax revenue to tackle poverty", Shinichiro Fujimori, Tomoko Hasegawa, Ken Oshiro, *Environmental Research Letters*, 11 November 2020, *https://doi.org/10.1088/1748-9326/abb55d*
- "Can climate clubs be legitimate?", unknown, Humanities and Social Sciences Communications, February 2022, rejected by editors
- "Is the problem or the solution riskier? Predictors of carbon tax policy support", Valon Hasanaj, Isabelle Stadelmann-Steffen, *Environmental Research Communications*, 6 October 2022, *https://dx.doi.org/10.1088/2515-7620/ac9516*

A INTRODUCTION

A.1 Foundations

A.1.1 Background and general introduction

The first World Climate Conference took place in Geneva in 1979 and eventually led to the formation of the Intergovernmental Panel on Climate Change (IPCC) in 1988. Yet, despite the fact that scientists and politicians have been aware of the threat of climate change for over 40 years, the ongoing use of fossil fuels in global energy systems has resulted in the ever-increasing production of greenhouse gases (GHGs). This, in turn, has resulted in unabated rises in atmospheric GHG concentration and subsequent changes to global climate patterns, leading to what is now being called a global "climate emergency" (Ripple et al 2019).

The rapid integration of renewable and sustainable energy sources is widely seen as a pathway to reducing global GHG emissions (Chu and Majumdar 2012) and mitigating the impacts of climate change. Furthermore, as many of these "greener" renewable energy technologies are related explicitly to the generation of electricity, a push is also being made to switch as many societal processes as possible to using electrical power to take advantage of the reduced impacts that these technologies offer. While many industrial activities and air and sea transportation are likely to remain locked-in to their use of fossil fuels for now, many activities within the residential and transport sectors could be electrified within relatively short timespans. In fact, coupling a growth in renewable energy generation to the so-called "electrification" of heating and mobility functions is seen as a critical pathway towards rapidly raising the overall use of renewable sources of energy (Bellocchi et al 2020, IEA 2021c).

Collectively, this realignment of global energy systems towards more sustainable energy production and consumption practices is being termed the "energy transition" (Smil 2010). Yet, in order to streamline the implementation of this transition and to optimise the reductions in GHG emissions that it is aiming to achieve, policymakers–within both the governmental and private sectors–must balance a variety of *political*, *economic* and *physical* considerations when planning and negotiating their way through the energy transition as it occurs. Computer-based models in various forms have been used for many years to guide energy decision making and are still seen as a vital tool in this regard (Süsser et al 2021a). However, more detailed models, capable of integrating a wider range of the *constraints* and *influences* that affect the implementation of different energy systems, could vastly improve the effectiveness of energy planning processes going forward.

A.1.2 Current energy statistics

Global energy use data (IEA 2020)–for the year 2019 and shown in **Figure A.1**–suggests that oil products remain the dominant primary energy supply (31.4%). Solid fossil fuel in the form of coal is the second most popular source (26.2%), followed by natural gas (23.2%). Global renewable energy use remains low (14.1%), while nuclear energy is far less common (5.0%). Note that 2019 data is used here as it represents energy use prior to the COVID-19 pandemic and is, thus, more representative of energy use under "standard" conditions.

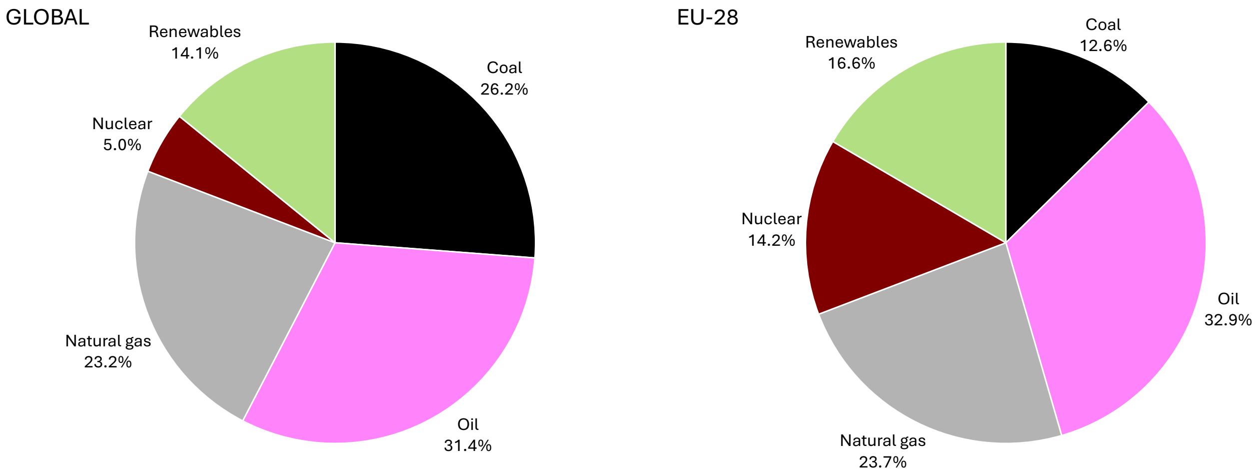


Figure A.1. Split of global and EU-28 primary energy supply by energy source in 2019. Data source: IEA (2020)

Similar data is also available for the 28 EU states, also shown in **Figure A.1**. The data suggests that the total energy supply is again dominated by oil products (32.9%) and natural gas (23.7%). However, coal use is far lower in the EU (12.6%), renewable energy being the third highest category (16.6%). It is notable that nuclear power is significantly higher in the EU (14.2%).

Figure A.2 demonstrates trends at the energy demand end. Transport, buildings and industry are shown to represent similar shares at the global level, consuming shares of 29.1%, 30.7% and 29.1%, respectively. All other sectors are grouped together and occupy the remaining 11.1% of demand. Comparable distributions are observed in the EU. Values for transport (28.4%) and other (11.2%) are very similar to those observed at the global level. However, when compared with global energy use, the EU consumes more of its energy in buildings (36.2%) and less in industrial applications (24.2%).

The current mix of renewable energy use within the EU is determined using higher resolution data from Eurostat (2022), as summarised in **Figure A.3**. The data suggests that renewable energy supply is currently dominated by biological energy ("bioenergy") sources, which account for some 60.1% of the total renewable energy supply. This is mostly comprised of primary solid biofuels (43.0%), but also includes liquid biofuels such as biogasoline and biodiesels (9.0%). The bioenergy total also includes two significant energy types derived from waste-to-energy technologies in the form of biogas production (4.3%) and the incineration of renewable municipal waste (2.8%). Renewable energy is also derived from wind energy (17.7%), hydropower (14.5%), solar sources–comprising solar photovoltaic or "solar PV" (5.5%) and solar thermal consisting of small-scale collectors and concentrated solar plants or "CSPs" (1.4%)–and geothermal (0.7%) sources.

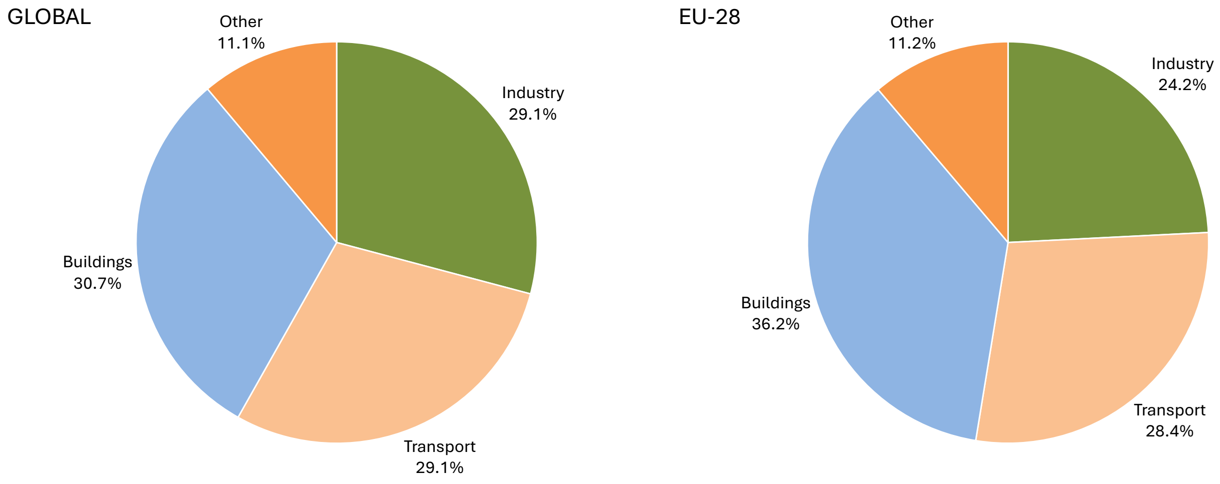


Figure A.2. Split of global and EU-28 supply by consumption sector in 2019. Data source: IEA (2020)

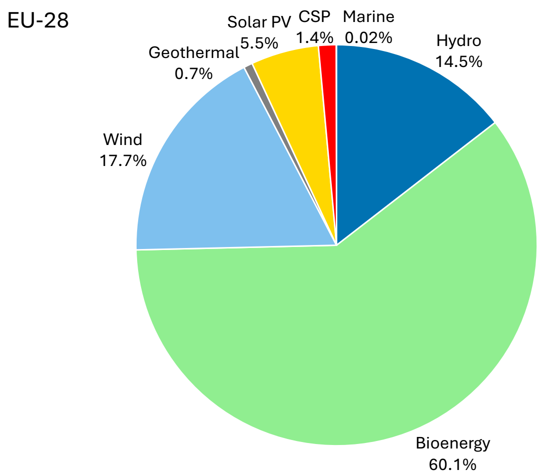


Figure A.3. Split of total renewable energy supply by energy source for EU-28 countries in 2019. Data source: Eurostat (2022)

This data is more or less in line with the observed global statistics for total renewable energy use. Available data (IEA 2020) confirms that bioenergy is again the dominant type of renewable energy (66.4%), higher than EU levels largely because of the increased use of traditional biomass sources in developing countries (REN21 2019). Hydropower is the next highest category (18.2%)–also above EU levels–while wind and solar energy dominate the remaining 15.4% (BP 2019).

The rapidly increasing focus on the further electrification of energy systems, particularly in heating and mobility processes, highlights the specific importance of analysing renewable energy sources within electricity generation processes. With this in mind, the current mix of renewable energy sources used in the generation of global electricity supplies in 2019 is shown in **Figure A.4**. Note that these sources account for 26.6% of total electricity supply.

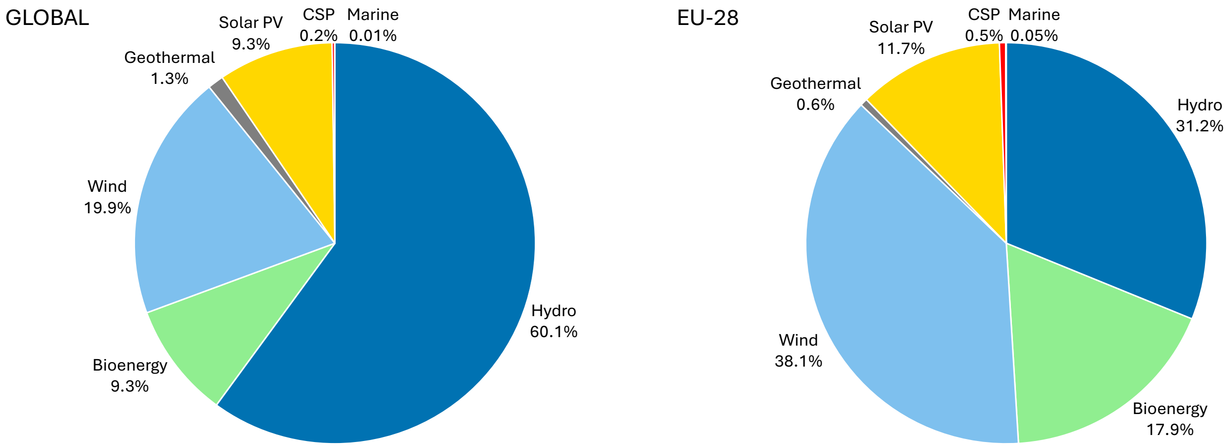


Figure A.4. Split of global and EU-28 electricity supply derived from renewable energy sources by energy source category in 2019. These sources provide 26.6% and 35.1% of the total electricity supply globally and of the EU-28 countries, respectively. Data sources: IEA (2019b), Eurostat (2022)

Data for renewable energy sources used to generate electricity within the EU is also shown in **Figure A.4**. Combined, these renewable sources provide 35.1% of the total electricity supply. It is noted that the use of hydropower is much less common in the EU–31.2% compared to 60.1% globally. In its place, the use of wind is significantly higher–38.1% compared to 19.9%. Solar PV and bioenergy sources are also notably higher within the EU. Furthermore, comparison with **Figure A.4** confirms that wind, hydropower and solar PV are almost exclusively used in electricity generation while–with the exception of CSP plants–solar thermal and geothermal sources are more typically used in heating operations. The greatly reduced proportion of bioenergy in the spectrum of electricity generation confirms that bioenergy is also used extensively to provide heat and fuel energy.

A.1.3 Broad future predictions

Renewable energy sources are being heavily promoted as the key to addressing climate change and their use is expected to increase significantly in the coming decades. In an effort to quantify these increases, the International Energy Agency (IEA) published several projected energy use scenarios as part of its World Energy Outlook 2020 report (IEA 2020). The first of these scenarios–the so-called Stated Policies Scenario–considers all existing government policy frameworks as well as expected future actions in accordance with announced policy positions. The second–known simply as the Sustainable Development Scenario–attempts to imagine a major transformation in the global energy system in response to the potential consequences of climate change.

The projected percentage shares of renewable energy use in accordance with these scenarios, at the global and EU scales, are visualised as extensions to recorded historical shares in **Figure A.5**. The key observation is that renewable energy use is expected to escalate while coal and oil use are expected to fall under both scenarios and across both scales. Comparing the two figures also suggests that the transition to renewable sources is likely to be more pronounced within the EU; even under the Stated Policies Scenario, levels are predicted to rise from 16.6% in 2019 to 35.2% in 2040 compared to a change of 14.1% to 21.8% at the global scale.

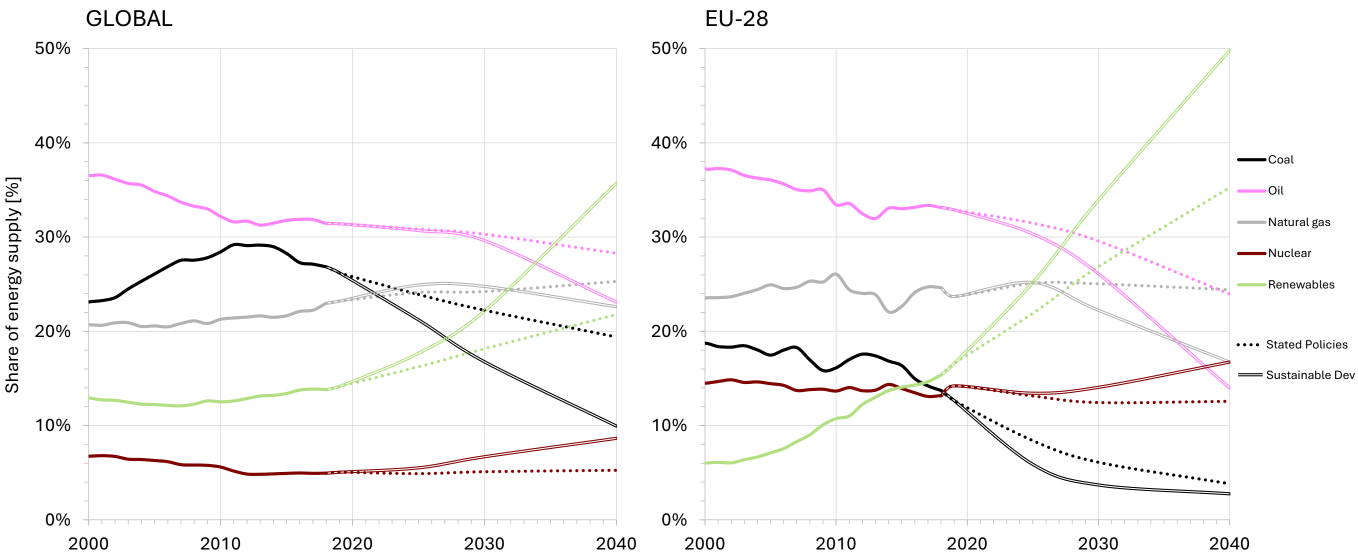


Figure A.5. Observed distribution of global and EU-28 energy supply by source for the period 2000 to 2018. Projected future distributions for the period 2018 to 2040 also shown, in accordance with IEA Stated Policies Scenario and Sustainable Development Scenario. Data sources: IEA (2020b, 2019a), Eurostat (2022)

It is also worth noting that the use of natural gas and nuclear sources are generally not predicted to lower significantly under these scenarios. In fact, both are expected to increase slightly at the global scale to offset the short-term reductions in coal and oil, although the use of natural gas is expected to eventually lower. Within the EU, energy derived from natural gas and nuclear sources are expected to remain at similar levels within the Stated Policies Scenario although, again, natural gas is likely to reduce in time. Meanwhile, much like the global predictions, the use of nuclear energy is expected to rise slightly under the Sustainable Development Scenario to offset reductions in all three fossil fuel categories.

The same data sources can also be used to provide insights into past and predicted electricity use at both the global and EU-28 scales, as shown in **Figure A.6**. The data confirms that total levels of electricity use have been steadily increasing since 2000 at the global level. However, these levels stagnated somewhat between 2008 and 2014 within the EU-28 countries before slowly rising once again. Regardless of these differences, levels of electricity use are predicted to increase in all scenarios and scales. Within these totals, the use of renewable energy technologies in providing this electricity is predicted to rise dramatically across the board.

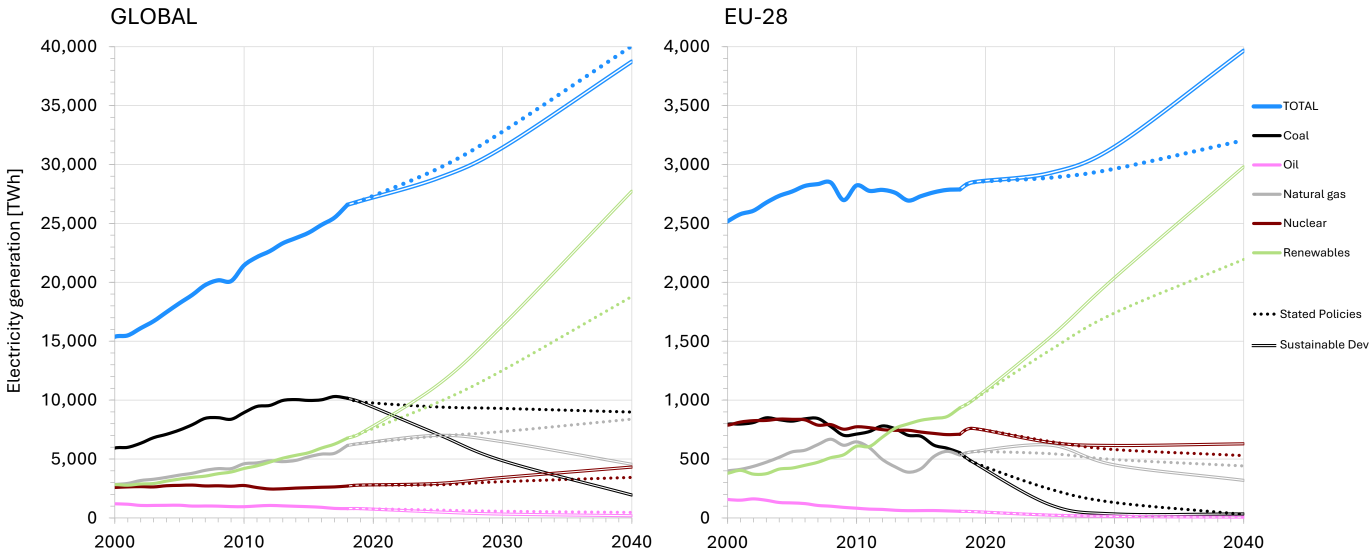


Figure A.6. Observed generation of global and EU-28 electricity supply by source for the period 2000 to 2018. Total electricity supply also shown. Projected future distributions for the period 2018 to 2040 also shown, in accordance with IEA Stated Policies Scenario and Sustainable Development Scenario. Data sources: IEA (2020b, 2019a), Eurostat (2022)

A.1.4 Predicting the energy transition

Studying recent energy statistics and broad future predictions of this kind offers a suitable outline of the general trends occurring within the energy field. Furthermore, a thorough overview of the status quo and latest developments in renewable energy generation and storage technologies, also completed within the doctoral program, is provided in sections **J.1.1** and **J.1.2**. Nevertheless, despite the existence of this information, the precise manner in which the energy transition will actually unfold remains unclear and an array of different eventualities are, of course, possible.

What is certain, however, is that the progress of the transition and the composition of future energy systems will depend on a complex and ever-changing set of vectors relating to the various *constraints* and *influences* that will operate within and around the energy sector during the transition process. This includes a variety of dynamics that affect the policy decisions of individual governments, economic considerations within the energy industry, global geo-political forces, issues of public support, various physical limitations and, undoubtedly, a number of other factors.

A.1.4.1 The Multi-Level Perspective

One of the most well-established frameworks for understanding, describing and analysing complex socio-technical transition processes like the ongoing energy transition is that of the Multi-Level Perspective (MLP) (Rip and Kemp 1998, Geels 2002, Smith and Stirling 2010). The MLP describes many types of transition–including potential energy transition processes–by framing them as a dynamic system whereby activities interact across three distinct levels (see **Figure A.7**).

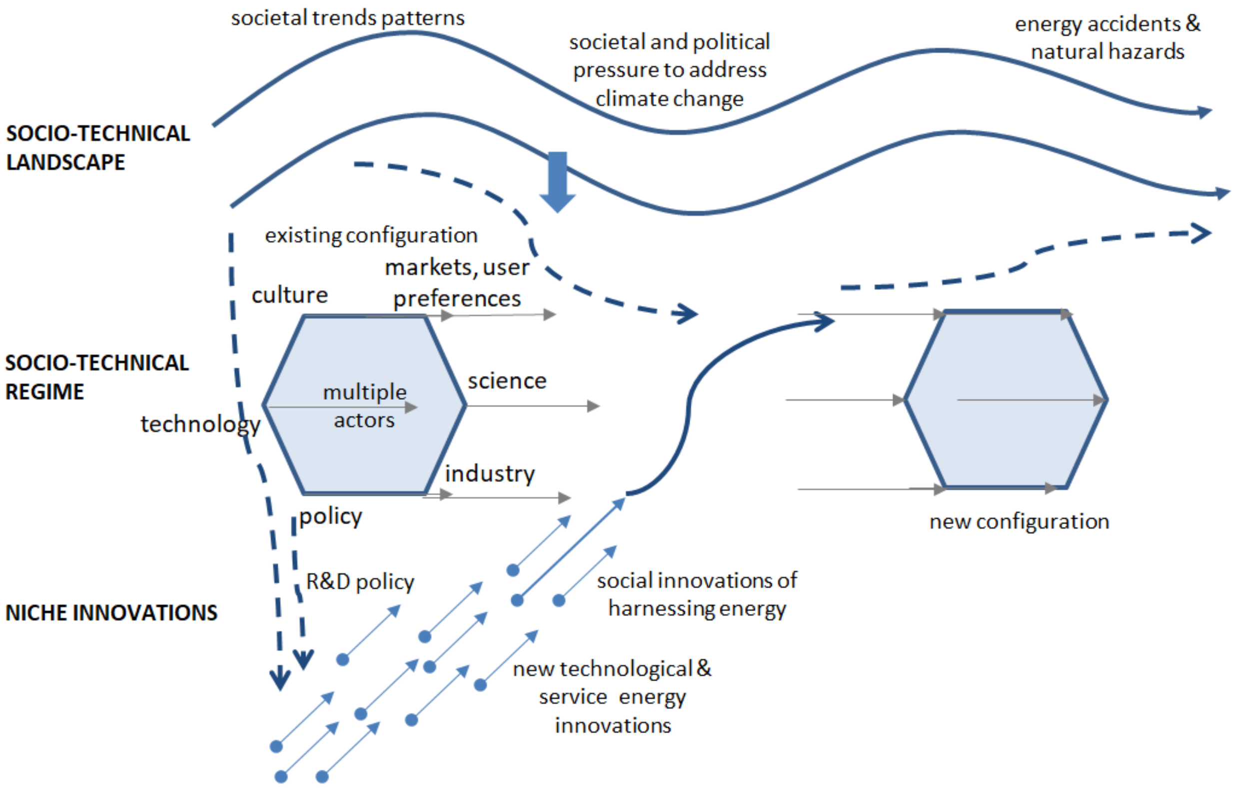


Figure A.7. Energy transition processes within the framework of the Multi-Level Perspective. These transitions can be thought of as a change from the existing configuration towards a new configuration with greater inclusion of renewable energy sources. While some renewable energy technologies are well developed and in use, increasing the use of these and other renewable energy sources are considered to represent niche-innovation pathways within this framework. Source: Martin et al (2020), adapted from Geels and Schot (2007)

The *socio-technical regime* occupies the meso-level at the centre of the framework and represents the current practices and institutions–in the fields of technology, science, markets, industry, policy and culture–within a society. In an energy context, this is the level in which energy systems, and all associated activities, exist. Changes within this level are what fundamentally constitute a "transition", and an energy transition can be thought of as a change from the current energy profile to another different profile in the future. Such transitions occur as a result of interactions with developments at the other two levels within the framework, at the micro- and macro-levels.

The *socio-technical landscape* occupies the macro-level of the framework and represents the general, ever-changing contextual developments within the global society. Operating above the regime, activities at this level represent the broader and deep-seated patterns in cultural behaviour, macro-economics and macro-politics. Examples could include societal consumer trends and exogenous shocks. Exogenous shocks are conceived as abrupt events of any kind–such as industrial accidents and natural hazards–that introduce radical system changes and lead to an altered or changed path (Süsser et al 2019, Victor et al 2019).

Geels and Schot (2007) defined five general types of change that can occur at the landscape level according to the frequency, amplitude, speed and scope of these changes. Of these five types–regular, hyperturbulence, specific shock, disruptive and avalanche–climate change was identified as being a disruptive type of change. In fact, the impact of these disruptions can already be observed at the present-day landscape level. Global systems are already experiencing the physical impacts of climate change (e.g., global warming, extreme weather events, sea-level rise or landscape morphology), increased levels of public awareness and concern for these and future impacts, and changes in the global macro-policies with respect to climate change. As such, climate change is already creating disruption at the macro-level, placing pressure on the levels below to address the physical impacts and social pressure resulting from climate change.

Lastly, *niche-innovations* occupy the micro-level of the framework and represent new and/or underutilised technologies or social practices that seek to become part of the regime via processes of emergence (Süsser et al 2019). While the term is more often used to describe physically tangible examples of technological advancements in science or engineering, it can also refer to developments in the less tangible aspects of society. For example, new socio-political ideologies, management practices or social norms could also be considered types of niche-innovations in certain contexts. Niche-innovations are further classified as being either competitive where they aim to replace an existing technology or practice, or symbiotic where they can be adopted into or enhance an existing technology or practice. In the current context, the most obvious examples of these innovations are renewable energy technologies attempting to gain further presence within the energy system.

A.1.4.2 Modelling approaches

The MLP offers a robust and tangible method for conceptualising and understanding transition processes. Indeed, it has been used extensively to analyse energy-related transition processes within the EU, including the wind energy industry in Germany (Jacobsson and Lauber 2006), the German transition to renewable electricity in general (Geels et al 2017b), district heating in Sweden (Dzebo and Nykvist 2017) and bioenergy in the Netherlands (Raven and Verbong 2009). However, in order to gain specific insights and quantify the potential pathways and outcomes of transition processes, the use of computer-based models is now commonplace in the energy industry and among energy policymakers.

Various forms of models are currently being employed for different transition-related tasks. Perhaps the most visible of these are the large-scale integrated assessment models (IAMs) used to test and explore climate and energy policy options, typically at the global scale. Meanwhile, a range of other energy system models (ESMs) are used to simulate individual energy systems at local, national or regional scales. IAMs and other ESMs both operate at the *socio-technical regime* level of the MLP framework, simulating the operations and changes that occur when transitioning from one system configuration to another; in some cases, IAMs may also simulate a small number of dynamics at the higher *socio-technical landscape* level, particularly in relation to economic shocks or crises (Geels et al 2017a, 2017b). Conversely, a third group of agent-based models (ABMs) operate in an entirely different space as they are used to capture specific emergence and transition processes via the simulation of different behavioural and decision-making processes. Therefore, although they are used to analyse potential changes at the *socio-technical regime* level, they are particularly well suited to analysing emergence at the *niche innovations* level of the MLP (Hansen et al 2019). A matrix summarising the three modelling methods in relation to the three levels of the MLP is provided as **Table A.1**. Each of the three general approaches to modelling are discussed in the sections that follow.

Table A.1. Modelling methods used to predict energy transition processes and their applicability to different levels of the Multi-Level Perspective

MLP level	Description	IAM	Other ESM	ABM
Socio-technical landscape	Broad and deep-seated patterns within cultural, macro-economic and macro-political aspects of the global society	●		
Socio-technical regime	Current practices and institutions in technology, science, markets, industry, policy and culture. Current energy systems exist at this level, changes of which constitute a "transition"	●	●	●
Niche-innovations	New and/or underutilised technologies or social practices seeking to become part of the regime			●

A.1.4.2.1 Integrated assessment models

An integrated assessment model (IAM) is modelling package that incorporates knowledge–usually in the form of pre-existing models–from multiple domains into a single, new modelling framework (Nordhaus 2013). IAMs attempt to integrate geophysical stocks and flows with economic flows such that the key features of a system and its economy are assessed in conjunction with its interactions with the environment (Wang et al 2017); GHG emissions and their impacts on temperature and climate are a key focus, particularly in terms of their economic implications (Weyant 2017). Although they have been used in some instances to model other social processes, IAMs are predominantly used in the field of climate change policy (Capellán-Pérez et al 2020), predominantly for testing different policy options. And, while their original intention was to aid global policy decision making in this manner, they are also sometimes used to assess mitigation scenarios at regional and national scales.

Process IAMs have become highly influential in informing energy and climate policy debate in recent years (Krey et al 2019). Indeed, the Intergovernmental Panel on Climate Change (IPCC) have used IAMs to assess mitigation scenarios for over 30 years (Parson and Fisher-Vanden 1997) and continue to do so (Farmer et al 2015). More recently, many national and regional governments have begun to use IAMs to provide data for formulating their intended nationally determined contributions (INDCs) under the 2015 Paris Agreement. It is expected that IAMs will continue to be favoured for undertaking large-scale assessments of this kind in the coming years.

Although many process IAMs have been developed–e.g., see Nikas et al (2019)–a set of seven well-established models tend to be preferred for governmental policymaking; in fact, with exception of the POLES model, these are the set of models utilised by the IPCC in their own assessments (Rogelj et al 2018, IPCC 2019). The models are summarised in **Table A.2**, which contains quantifications of the levels of representation of various factors within each model. This was done by assessing the composition of each model with respect to each factor using data from the Joint Global Change Research Institute (JGCRI) for GCAM (JGCRI n.d.) and the Integrated Assessment Modeling Consortium (IAMC) (IAMC n.d.) for all other models. A level of low, medium or high was assigned based on the percentage of the parameters included in relation to the total possible number of identified parameters. The findings demonstrate the wide variety of strengths and weaknesses within each of these models, and that no one model can model all aspects of these systems at an optimum spatial and temporal resolution.

Another notable IAM is the MEDEAS-World model, recently developed within the EU H2020 MEDEAS project (Capellán-Pérez et al 2020). The model is structured into seven submodules: economy, energy, infrastructures, materials, land use, climate change and social and environmental impacts indicators, each of which can be expanded, simplified or replaced within the overall model configuration. From an environmental modelling perspective, the MEDEAS-World model is more complete than the larger IAMs discussed in **Table A.2** as it includes a far more detailed approach to land use and emissions modelling, and contains a material module that accounts for the materials and energy required for energy infrastructure manufacturing. Accordingly, MEDEAS assesses the implications that mineral depletion may exert on transitions in energy use in relation to potential mineral supply constraints and mineral demand can be compared with current levels of geological availability (reserves and resources) for qualitative detection of risks of material supply.

Table A.2. Summary of key examples of process integrated assessment models (IAMs). Data sources: IAMC (n.d.), JGCRI (n.d.), Kriegler et al (2015)

	IMAGE	MESSAGE-GLOBIUM	AIM-CGE	GCAM	REMIND	WITCH	POLES
Country of origin	Netherlands	Austria	Japan	US	Germany	Italy	Belgium
Start year	1970	2030	2005	2015	2005	2005	2015
End year	2100	2110	2100	2100	2100	2150	2100
Timestep *[yr]*	1-5	5-10	1	5	5	5	1
Spatial regions	26	11	17	32	12	17	66
Levels of representation							
Socio-economic drivers	Medium	Medium	Medium	Low	Medium	Medium	Low
Macro economy	Medium	Medium	Medium	Low	Low	Low	Low
Economic sectors	High	Medium	High	Medium	Low	Low	Medium
Resource use	High	Medium	Medium	Medium	Medium	Medium	Medium
Technological changes	High	Medium	High	Low	Low	Medium	Medium
Technology substitution	High	High	Medium	High	Low	High	Medium
Land use	Yes	-	-	Yes	-	-	Yes
Land-use definition	High	-	High	High	High	Low	Medium
Energy types	High	High	Low	High	Medium	Low	High
Renewables	High	High	Medium	High	Medium	High	High
Grid and infrastructure	High	Medium	Low	Medium	Medium	Low	High
Energy end-users	High	Low	Low	Medium	Low	Low	Medium
Emissions and impacts	High	High	High	Medium	High	High	Medium
Inequality	Yes	-	-	-	-	-	-

A.1.4.2.2 Other energy system models

While IAMs are widely used in a variety of policy-based applications, they are simply one of the many types of energy system models (ESMs) currently in use. Indeed, the group of common ESMs includes a range of different scopes and model types, from the simple, purely technical models used to simulate energy functions within a local energy system to the largest models that replicate the complex interactions between energy, environmental and economic factors at national and global scales. In fact, IAMs themselves are simply a combination of one or more smaller ESMs–alongside various other models for simulating other sectors–aggregated to create a larger ESM.

Nevertheless, despite the broad range of available ESMs, most can be classified according to five general categorisations. Firstly, models are delineated according to their *analytical approach*. Here, “top-down” models are those that are predominantly driven by the macro-economic relationships between their components (Despré et al 2015); these relationships then determine the interactions that occur at the technical level. Such models are likely to be more appropriate for studying system responses to changes in policy and other drivers (Song et al 2022). Conversely, models adopting a "bottom-up" approach are driven by a multitude of technical information about the system. As they are highly technology-specific they provide far wider scope for testing different technical possibilities but frequently also include environmental and economic parameters. As a consequence, top-down models tend to provide better examinations of economic factors such as consumer preferences and different cost factors, while bottom-up models offer far better consideration of energy and technology issues and, potentially, interactions with the environment (Hall and Buckley 2016). Nonetheless, individual models can operate as either type, depending on the way they are applied, and "hybrid" models–that combine aspects of both model types–are becoming more common.

The second common categorisation relates to the fundamental *methodology* applied. Here, top-down models usually employ macro-economic approaches to solve for the system. This includes input-output analysis, econometric statistical techniques and, most notably, equilibrium models, where the model attempts to locate the economic equilibrium point for the system, considering the interactions between sectors. Equilibrium models can be further classified as being either general equilibrium models (which solve for all sectors) or partial equilibrium models (where equilibrium is only reached in a certain sector, such as the energy sector). Meanwhile, bottom-up models are generally classified as applying either an optimisation or a simulation approach; models can be run with the aim of finding an optimal solution for a given objective function for a given set of inputs or by merely simulating interactions and changing parameters as they occur throughout a given time period.

Other categorisations are for *geographical scope* (global, regional, national, local or single project), typical simulation *timing* (hourly, daily or yearly timesteps over a timeframe of days, weeks or years) and, finally, *sectoral coverage* (a single sector, multiple sectors or all sectors) (Song et al 2022). Such issues of scoping represent an important distinction between many of the models currently in use and various trade-offs exist between the different approaches. For example, models that simulate particular sectors or provide analysis at higher resolutions are capable of more detailed and more robust examinations within their limited scope. On the other hand, larger energy-environment-economy (E3) models–including IAMs–that consider a wider number of complex interactions within a wider scope are far more holistic but are forced to make concessions in terms of their resolution (Pickering et al 2022). A summary of the five categorisations is shown in **Table A.3**.

In any case, a wide variety of different ESM options are currently in use that satisfy a range of different user needs. Again, while many of these are utilised in isolation for specific applications, some are also incorporated into larger scale IAMs and other E3 models. Indeed, the European Commission (EC) use their own combination of sub-models–including the PRIMES energy model (Capros et al 2018)–when producing energy system forecasts for the EU as part of their "Reference Scenario" reports (European Commission 2021b). Furthermore, the International Renewable Energy Agency (IRENA) use an ESM known as PLEXOS (Energy-Exemplar n.d.) alongside the E3ME macroeconomic model (Cambridge Econometrics n.d.) when making global energy systems projections (IRENA

2020), and the International Energy Agency (IEA) use their own World Energy Model (WEM) (IEA 2021) when predicting and assessing future energy scenarios; in fact, the values for the IEA projections shown in **Figure A.5** and **Figure A.6** were derived using this model.

Table A.3. Five general categorisations of energy system models. Sources: Despré et al (2015), Hall and Buckley (2016), Song et al (2022)

Categorisation	Description
Analytical approach	"Top down" Driven by macro-economic relationships "Bottom up" Driven by technical aspects Hybrid models also exist
Methodology	For "top down" - input-output analysis - econometric statistical techniques - (general or partial) equilibrium models - others For "bottom up" - optimisation *(Calliope)* - simulation *(EnergyPLAN)*
Geographical scope	Area represented in model e.g., global, regional, national, local, single project or plant
Timing	Timestep e.g., hourly, daily, yearly Time frame e.g., days, weeks, years
Sectoral coverage	Single sector e.g., economic or energy sector only Multiple or all sectors e.g., E3 models such as IAMs

The range of available ESMs is too numerous to discuss in further detail here, although several thorough reviews offer useful overviews of some of the more popular ESMs (Hall and Buckley 2016, Song et al 2022). However, two of the more commonly used models are particularly relevant to the current thesis as they were used to provide input data to processes described in later sections. Indeed, as the creators of these ESMs were part of the Sustainable Energy Transitions Laboratory (SENTINEL) (SENTINEL n.d.) project that formed the basis of the doctoral program, a significant amount of collaboration was undertaken in relation to these two models.

A.1.4.2.2.1 Calliope

Calliope is a bottom-up optimisation application developed at the Swiss Federal Institute of Technology in Zürich (ETHZ) in Switzerland (Pfenninger and Pickering 2018). Created as an open-source Python application, its key benefits are high flexibility levels, an ability to operate at high spatial and temporal resolution and a well-defined separation between the framework and model input and output data. Calliope is especially well-suited to executions based upon a common base model, allowing for the streamlined exploration of different policy options.

Systems are first defined using a "web" of nodes to represent the locations within a network (see **Figure A.8**). Various demand, supply and storage processes can then be defined at each of these locations and transmission processes can occur between locations via linkages. To date, eight major applications of Calliope have been created at the city (Bangalore and Cambridge), national (Kenya, South Africa, China, Italy and the United Kingdom) and regional (Europe) levels.

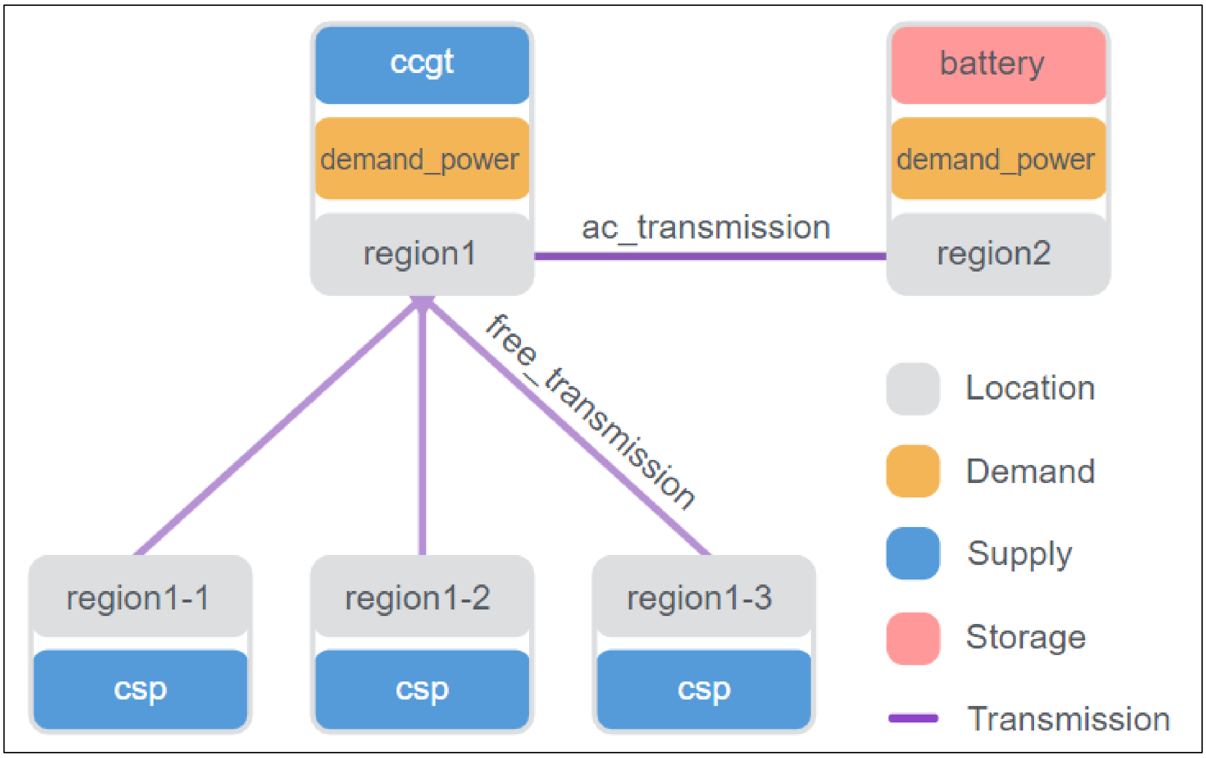


Figure A.8. Simplified representation of Calliope network configuration. In this example, the "CCGT" supply element represents a combined cycle gas turbine, capable of generating both electricity and heat from natural gas combustion, while the "CSP" supply elements represent concentrated solar power plants generating electricity from solar heat. Source: Pfenninger and Pickering (n.d.)

The version of Calliope created for the European energy system–known as "Euro-Calliope"(Tröndle n.d., Tröndle et al 2020)–was used within the SENTINEL project. It includes 35 countries within the European energy system, including all EU member states (except Malta), Albania, Bosnia and

Herzegovina, North Macedonia, Montenegro, Serbia, Switzerland, the United Kingdom, Iceland and Norway; a total of 98 regions are defined within the 35 countries. An illustration of the regions within each country and connections between each of these regions is provided in **Figure A.9**.

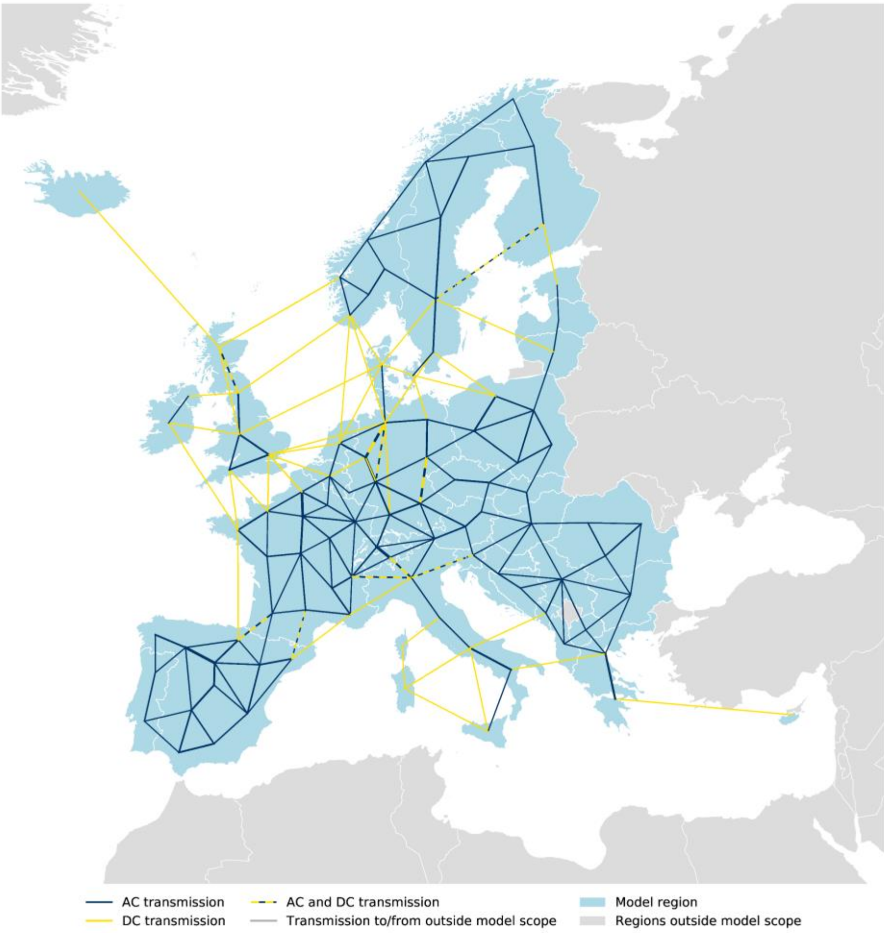


Figure A.9. Extent and structural composition of Euro-Calliope model. Source: Pickering et al (2022)

A total of 13 energy carriers–electricity, hydrogen, GHG emissions as carbon dioxide (CO_2), hydrocarbons (kerosene, methanol, diesel, and methane), solids (biofuel and municipal waste), low-temperature heating (space heating/hot water and cooking heat), and vehicle distance (heavy and light road vehicles)–are included in Euro-Calliope calculations (Pickering et al 2022). It is noted that the consideration of GHG emissions in Calliope is based on simplified calculations using combustion coefficients. The final outputs of Calliope are a series of comma-separated value (.csv) files that specify the input and output flows of each carrier within the different functional processes and across different regions in the modelled system; values of power capacity are also provided, where applicable.

A.1.4.2.2.2 EnergyPLAN

EnergyPLAN is a bottom-up application capable of performing simulation operations on both the technical aspects of the system and the market economy (Lund and Thellufsen 2020); optimisation calculations can also be performed for specific system functions, but not on the system itself. The model has been developed at Aalborg University (AAU) in Denmark and can be modified and run via a Windows GUI interface. Development of the model began in 1999. Since then, it has risen to become a commonly used tool for guiding the design and implementation of local, national and regional energy systems and is particularly well-suited to those with high renewable energy use (Lund et al 2021). To date, it has been provided the basis for over 300 published articles (Østergaard et al 2022).

The model is capable of incorporating all aspects of an energy system, including fuels, electricity and district heating and its representation of renewable energy technologies is especially well detailed. It also incorporates hydrogen production and use from electrolysis, transport demand, industrial heat, cooling systems and water use. As with Calliope, it contains simplified calculations of GHG emissions as equivalent CO_2 emissions. However, unlike Calliope, EnergyPLAN is not designed to replicate network flows and balances between different spatial locations. Rather, although the different functions within the system are modelled in great detail, the system itself is a singular entity and simulations are run for individual systems as a whole.

The architecture of system components used in EnergyPLAN is shown in **Figure A.10**. The final outputs of EnergyPLAN consist of tables of results that represent a "snapshot" of the final system configuration. The tabular results can be either viewed onscreen, printed or copied to a clipboard in an Excel-friendly format.

A.1.4.2.3 Agent-based modelling

Detailed simulations of specific aspects of transition processes–particularly those involving the emergence of new technologies–requires the modelling of so-called "complex systems". Here, the most common general approach to modelling such systems is the use of agent-based models (ABMs). An ABM models a system as a collection of autonomous decision-making "agents"–for example, individual consumers, households or businesses–whose behaviour is defined by a series of simple rules (Bonabeau 2002). The system as a whole then evolves as the model simulation progresses according to the ongoing decisions–for example, level of consumption or whether to invest in a certain technology–and interactions between the agents within it, allowing predicted outcomes and emergent patterns within groups of individuals to be determined (Goldstone and Janssen 2005).

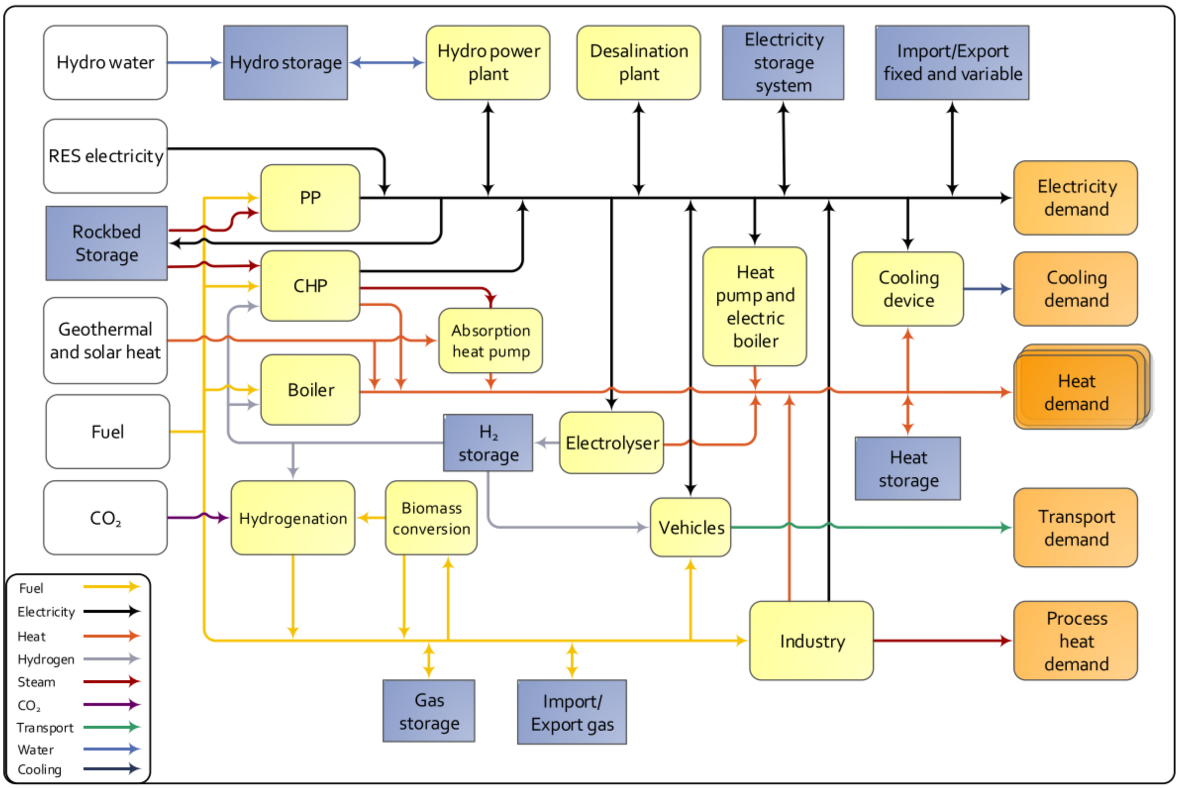


Figure A.10. Architecture of EnergyPLAN model components. Source: Lund and Thellufsen (2020)

The key advantage of using ABMs–and what sets them apart from the broader approach adopted within IAMs and other ESMs–is their ability to deal with heterogeneity within systems (Lamperti et al 2019). As Sachs et al (2019) point out, consumer decisions such as energy-related investment tend to be highly variable according to budget, value systems and perceptions about technology, even when individuals are faced with identical decision tasks. This highlights the importance of including heterogeneity within energy transition models rather than assuming that all consumers will make the same rational decision at all times.

Including a diversity of well-defined agent types within a system also provides a better representation of the complexities of social interaction and enables important behavioural phenomena such as conformism, status seeking and imitation to be considered (Castro et al 2020). As such, ABMs allow for the bounded rationality of agents and provide a link between technical analysis and elements of behavioural economics.

The other key element of ABMs in relation to transition modelling is their ability to capture emergence processes. So, an ABM could be used to determine emergent phenomena in spatial or temporal patterns within, say, a market sector or a community of consumers. Accordingly, they are thought to be highly suitable for analysing the emergence of niche innovations within the MLP framework and, hence, for studying renewable energy technologies within energy transition pathways (Hansen et al 2019).

Another great advantage of ABMs lies in their flexibility. Theoretically, they are capable of representing any system at any level of detail and, hence, are capable of encompassing any of the features of a transition (Köhler et al 2018). However, while the architectures of ABM software make the coding of decision rules relatively simple in theory (Zhang and Nuttall 2011), the construction of a truly representative and detailed ABM is still likely to be a difficult process and models that attempt to include high levels of detail can soon become unmanageable (Sun et al 2016). Similarly, as the systems they attempt to simulate are complex by definition, ABMs are often difficult to calibrate or validate (Ringler et al 2016), and less-tangible social or psychological parameters can be difficult to define quantitatively.

Nevertheless, the open-ended nature and flexibility of ABMs means that they can be applied to any number of situations and have been used to model transportation systems, land use, markets and transaction costs, technology diffusion and environmental policy in recent years (Rai and Robinson 2015). ABMs have been highlighted as being particularly applicable to climate and energy policy (Farmer and Lafond 2016) and especially to energy demand modelling applications (Rai and Henry 2016). Such models typically include consumers and energy suppliers as agents operating under certain market structures but are also likely to include a mixture of other elements such as demand side networks and other infrastructure, new technology types, innovation markets and social networks within their calculations (Holtz 2011).

To date, the use of ABMs within the energy field has largely been focused on electricity markets. Nonetheless, a growing number of models and studies are addressing other energy-related elements, principally those relating to energy system transition dynamics. Hansen et al (2019) offer a literature review involving 62 articles assigned to the categories of electricity market, transitions, consumption dynamics/consumer behaviour, policy and planning, new technologies/innovation and energy system. Likewise, Castro et al (2020) reviewed a set of 61 climate and energy policy-related ABM studies within the categories of emissions reduction, product and technology diffusion and energy conservation alongside 23 sub-categories. Ringler et al (2016) summarise 18 smart grid-related ABMs, while Moglia et al (2017) provide a review of the potential employment of ABM in studying the diffusion of more efficient residential energy demand technologies.

Lastly, it is noted that some are now also proposing that hybrid models combining the benefits of both IAMs and ABMs could provide the next evolution in modelling transitions. Farmer et al (2015) suggest that the added detail that ABMs provide could result in more robust IAM outputs, particularly in the area of technological transitions, while accepting the challenges associated with the creation of detailed ABMs. Similarly, both Lamperti et al (2018, 2019) and Safarzyska and van den Bergh (2022), among others, have proposed hybrids of ABMs and IAMs in order to address the shortcomings of the individual approaches.

A.1.5 Status of determining factors in current modelling

While the previous sections discuss the wide range of models available for guiding energy policy options and predicting energy transition processes, many of these are criticised for their inability to consider all of the relevant factors in sufficient detail. In this regard, the main criticisms levelled at current models relate to the fact that many social and other qualitative elements are either absent or oversimplified within their calculations (Köhler et al 2018, Turnheim et al 2015). Past studies have highlighted the general omission of important institutional, social and behavioural factors (van Sluisveld et al 2020, Koppelaar et al 2016, Trutnevyte et al 2019, Geels et al 2017) or a lack of flexibility in modelling changes in technical aspects of energy systems (Edelenbosch et al 2020, Savvidis et al 2019). However, it remains that a range of the factors that will genuinely *constrain* and *influence* ongoing transition processes are not sufficiently included in most models. This is especially true of the IAMs and other ESMs currently used as the key quantitative inputs to many important energy and climate policy decisions.

To help analyse this situation, **Figure A.11** provides a general conceptualisation of the links between energy model use, public and private policymakers and energy transition outcomes. The figure demonstrates, again, that the results of modelling studies are used to inform policy decisions (Süsser et al 2021) *and* that the details of current or proposed policy are themselves often used to define model functionalities. It should be noted here that "policy" in this context is assumed to be the totality of both governmental (public) and market-based (private) decision making. For example, a government may choose to adopt a policy preference for a certain technology for one reason while members of the energy sector may adopt their own policy preferences based on other–presumably mostly economical–reasons. The collective mix of all such "policy" decisions then ultimately determine the ongoing characteristics of the energy transition.

A set of possible *constraints* and *influences*–in three distinct categories–is then also shown to act upon models and policy processes. Here, the three categories–political, economic and physical–all form links with both stages. However, links to the modelling stage are in the form of information inputs, while links to the policy stage are more tangible, real-world influences on policy decision makers. So, for example, a political influence like industry lobbying could influence policy decisions indirectly via its inclusion in modelling simulations or via direct pressure on a government or industry body.

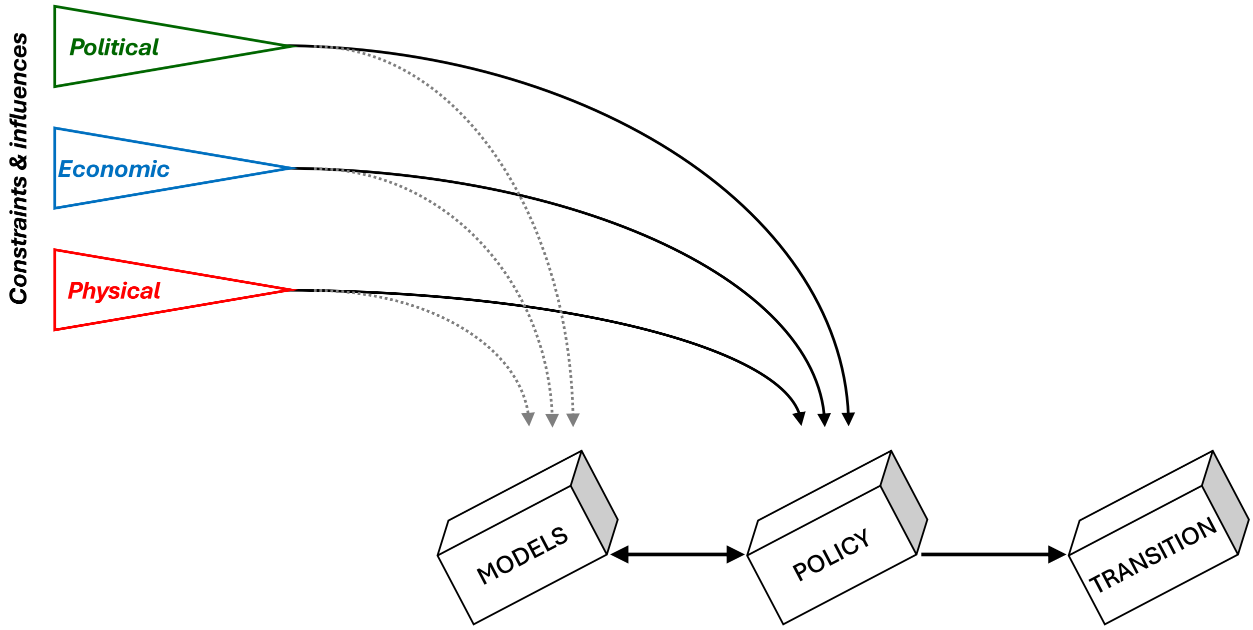


Figure A.11. Constraints and influences on emergence and transition processes in energy systems. Groups of political, economic and physical factors are shown in relation to models, policy decisions and, ultimately, energy transition outcomes. Dotted lines denote inputs to model calculations while solid lines denote direct influences on policy decision makers. Source: own elaboration

A set of 11 broad factors within these categories were then selected as the key constraints and influences on future energy transition processes, as detailed below:

- <u>Public acceptance and support</u>
  A general term that includes all aspects relating to public preferences and opinions that can influence the emergence of one technology or approach over another. This includes a wide variety of aspects from resistance from local residents to broader changes in political trends
- <u>Lobbying</u>
  Despite the support of the public, lobbying from powerful stakeholders can also have a significant influence over policy decisions. In the energy field, the obvious example of this is lobbying from the fossil fuel industry for governments and other industries to resist switching to renewable energy
- <u>Environmental justice issues</u>
  Many energy-related activities require key process inputs sourced from locations where environmental justice issues are a major concern, particularly in the Global South. Such issues generally relate to the extraction of fuels and raw materials for infrastructure. A growing public awareness of these issues means that pressure on policymakers looks likely to increase in this regard

- Labour requirements

  This represents the number of hours of human labour required to implement, operate and decommission different types of energy infrastructure
- Market forces

  A very general category encompassing the myriad market and economic forces that affect all aspects of the energy industry.
- Learning rates

  A subset of the market forces category, learning rates define the rate at which the cost of a technology drops over time. They are now a common metric for gauging technological progress and market attractiveness and are frequently used in existing IAMs and other models.
- Energy return on investment

  Similarly, energy return on investment (EROI) is used to define the attractiveness of a technology by comparing the energy provided by a given technology with the energy used to build, operate and dismantle it over its lifetime. As such, approaches with higher EROI values are less energy-intensive and, theoretically, more economically and environmentally desirable.
- GHG emissions

  Reducing GHG emissions is perhaps the single most important issue when considering the energy transition. However, there is a growing call to consider these emissions in further detail, to include the totality of emissions that occur during the life cycle of an energy process and not merely the emissions created during the final energy generation stage. For example, although wind or solar farms produce no direct emissions, to report their "true" emissions, one must consider all of the emissions that occur within the full life cycles of these processes.
- Other environmental impacts

  Likewise, a raft of other forms of pollution and environmental degradation can result from different technological approaches and many of these occur before or after the actual energy generation stage of the process. Accordingly, a full life cycle perspective should once again be taken when assessing potential impacts.
- Resource limits

  Physical limitations on the resources required to realise different technological approaches could provide serious constraints to their implementation. This is particularly true in relation to the requirements, and availability, relating to land and water resources. The availability and supply of critical raw materials also applies here, although the many issues that surround this topic are covered in a separate factor (see below).
- Material supply risk

  Many forms of renewable energy infrastructure depend on significant amounts of critical raw materials (CRMs)–as defined by the EC (European Commission 2020c)–that are in short supply or are only available from a limited number of locations, many of which are deemed to be politically unstable. Accordingly, future supply chains relating to some technologies could be disturbed in the future and this could genuinely affect the feasibility of certain policies.

A matrix showing the relationship of each of these factors to the three general categories is given in **Table A.4**. Although some of these factors are very general in their definition, it is believed that the 11 factors represent most, if not all, of the most important dynamics; all are (theoretically) capable of being integrated into models *and* affecting policy decisions.

Table A.4. Matrix of the 11 constraint and influence factors in relation to the three general categories

	Political	Economic	Physical
Public acceptance and support	•		
Lobbying	•		
Environmental justice issues	•		
Labour requirements	•	•	
Market forces		•	
Learning rates		•	
Energy return on investment		•	•
GHG emissions		•	•
Other environmental impacts			•
Resource limits			•
Material supply risk	•	•	•

In order to determine key aspects that are underrepresented in current modelling applications, **Table A.5** summarises the degree of representation of each of the 11 *constraint* and *influence* factors within current IAMs, ESMs and ABMs. The findings here are not absolute and some examples may exist for combinations that are not marked in the table. However, it is thought that they provide an accurate indication of general findings. The observations suggest that the complex dynamics of public acceptance and support and industrial lobbying are included in ABMs but that another political factor–environmental justice–is not included in any current models. Labour considerations are often included within the socio-economic drivers in IAMs (see **Table A.2**) and have been modelled within ABMs. It can have implications for both political and economic dynamics as it provides an indication of higher employment potential; it can also indicate a lower efficiency in providing energy per hour of human activity.

Table A.5. Representation of the 11 constraint and influence factors in three general modelling approaches

	IAMs	Other ESMs	ABMs
Public acceptance and support			●
Lobbying			●
Environmental justice issues			
Labour requirements	●		●
Market forces	●	●	●
Learning rates	●	●	●
Energy return on investment			●
GHG emissions	●	●	●
Other environmental impacts	●	●	●
Resource limits	●	●	●
Material supply risk			

Not surprisingly, both purely economic factors–market forces and learning rates–are routinely included in all model types. Nonetheless, as a subset of market forces, it is important to note that learning rates are far less common than many other market force parameters. Despite having important economic and physical implications, EROI is not generally included in energy models, but has been used is a small number of ABMs.

GHG emissions is a key indicator in all IAMs and is included in many other ESMs and ABMs. Nevertheless, it is again noted that the emissions within these models are almost always calculated using simple combustion emission coefficients that relate to the final energy generation stage; this is similar in concept to the “Scope 1” emissions used to account for corporate emissions (WRI and WBCSD 2004), where upstream and downstream emissions are not considered. In reality, thorough investigations of life cycle GHG emissions are very rarely included in models. Similarly, while environmental impacts and resource limits have been included in many models in some form or other, these inclusions have also tended to use simple relationships that rarely if ever involve detailed considerations of impacts or requirements over full life cycles. Lastly, as with environmental justice aspects, aside from a few basic attempts in a small number of models, the serious implications relating to critical material supply risk have been almost entirely ignored by modelling applications to date.

This simple analysis yields several conclusions. Firstly, it appears that political factors are highly underrepresented in most models, especially in IAMs and other ESMs. However, the complexity of public acceptance and support issues and the influence of outside lobbying suggest that these factors may be more suited to ABMs which could potentially be integrated into IAMs. Although they are already relatively commonplace in current models, labour considerations have great potential to be used more for investigating socio-metabolic relationships within systems. Conversely, quantifying environmental justice issues in relation to material extraction sources appears to be highly underrepresented in modelling, although it appears to be far more computationally feasible. Likewise, material supply issues remain largely absent from the energy modelling field; the availability of suitable data and a growing awareness of the potential consequences of these issues suggest that this is a fertile area for further research. Economic factors are well-represented across all modelling approaches and are of least concern, although EROI remains an underrepresented indicator overall. Lastly, although GHG emissions, other environmental impacts and resource limits are all relatively well represented, the use of life cycle approaches appears to offer a pathway to including more robust consideration of many environmental and resource-related aspects in energy models.

A.1.6 Life cycle assessment in models

Knowing the importance of the various physical factors involved in the evolution of the energy transition, it is imperative that more rigorous methods be investigated for the evaluation of resource inputs and environmental impacts in the models that guide policy. Ideally, this would include approaches that take the full life cycle of a process into account. In this sense, life cycle assessment (LCA) is a very well-established technique for calculating the environmental and other impacts associated with the full value chain of products and processes (Finkbeiner et al 2006, ISO 2007). The extent of such assessments depends on the system boundary defined for a given process. However, an assessment can include any number of stages, from the initial material extraction and processing, the production, transportation and installation of infrastructure and fuel supplies, ongoing use and maintenance processes, all the way through to the end-of-life disposal, reuse and/or recycling stages. A generalised representation of the stages that make up the life cycle of a physical product–e.g., a wind turbine, automobile or television–is given in **Figure A.12** which also shows the locations of common markers used when defining system boundaries.

It is noted that most processes defined within an LCA are, in fact, made up of combinations of many individual sub-processes. So, for example, the individual processes of extraction, processing, and so on, are themselves defined by their own data listings; data for each sub-process is then combined to define full processes like the one represented in **Figure A.12**. Furthermore, within each process, the "foreground system" represents the steps and infrastructure specifically related to the product in focus, while the "background system" is made up of the processes that supply the required raw materials and energy to the foreground system. Lastly, it should also be noted that the definitions of stages will differ when considering the life cycles of a less tangible "products" like electricity or heat, where the sub-processes within the "manufacturing" stage will be energy generation processes and the boundary would typically end at the "gate", where the product is supplied to a grid for final consumption.

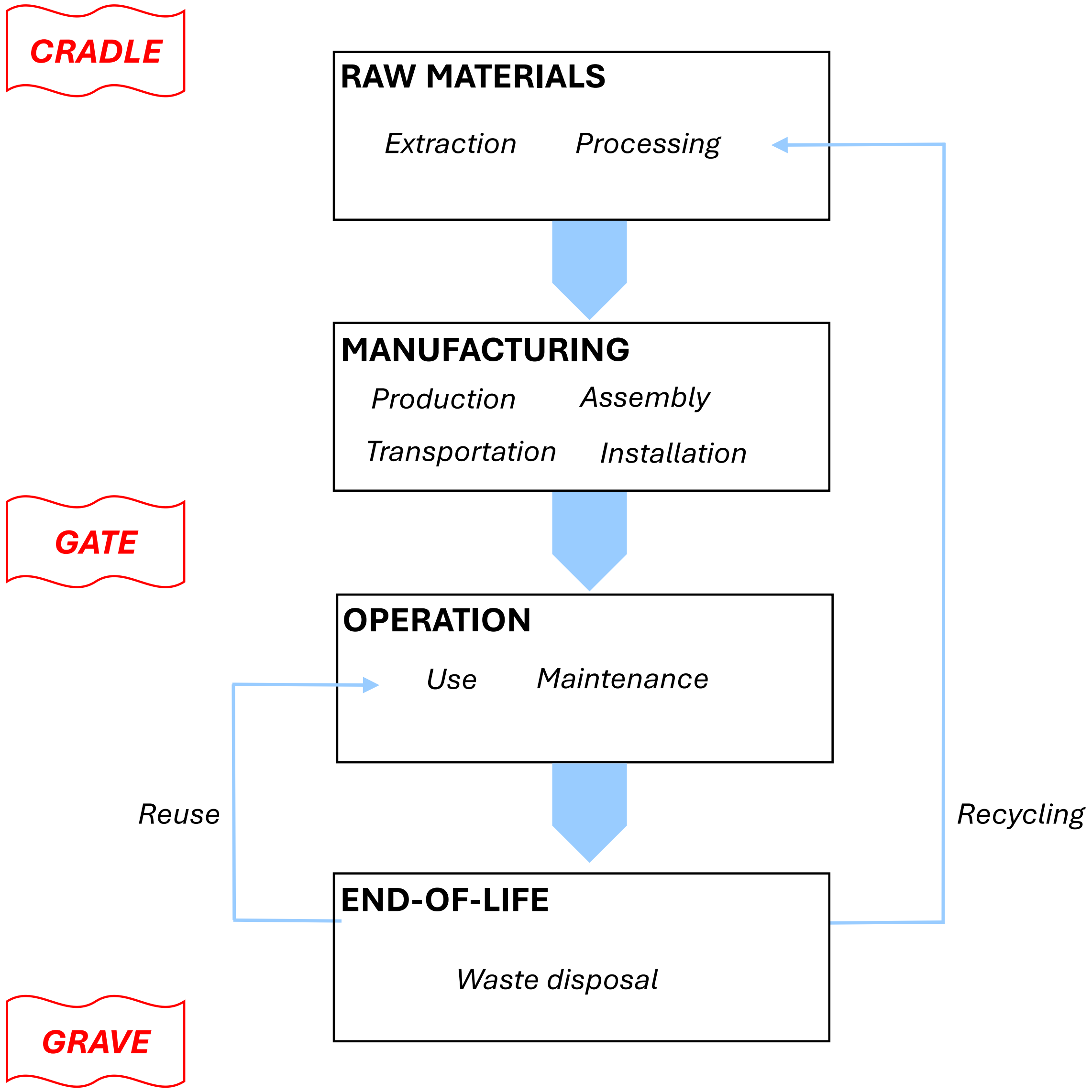


Figure A.12. Representation of stages potentially included in life cycle assessment. Actual stages included in inventory depends on definition of system boundary. Common markers used in system boundary definitions are shown on the left. Source: EPA (2006)

When conducting an LCA, the first step is to define the goal and scope of the investigation. Following this, the second step is to complete a thorough life cycle inventory (LCI) for the process at hand. This involves collating a list of all the raw material, water use, land occupation and land transformation inputs and individual outputs involved in the production of one final output unit. Detailed LCI data of this kind is available for many energy-related processes within the two most common sources; the latest versions of the GaBi (Kupfer et al 2021, Sphera 2021) and Ecoinvent (Ecoinvent 2021, Wernet et al 2016) databases contain over 2,300 and 2,000 listings, respectively, for processes that are applicable to Europe.

Collected inventory data can then be summed according to the life cycle stream and used to calculate a final set of indicator values within a life cycle impact assessment (LCIA). Here, the accumulated values obtained from the LCI are converted into final estimates of environmental impact categories according to a set of "characterisation factors" and calculation rules contained within a defined LCIA "method". Many LCIA methods exist (Rosenbaum 2018, Jungbluth 2021), each of which includes a battery of available indicators. Applying characterisation factors to LCI data in LCIA calculations then provides "midpoint" indicators for very specific characteristics (e.g., GHG emissions or land use requirements). A selection of common LCIA midpoint indicators that are to be used in the remainder of the thesis are described in **Table A.6**. Midpoint indicators can then also be aggregated in a variety of predefined ways to create less tangible "endpoint" indicators (e.g., ecosystem quality or damage to human health).

Table A.6. Description of midpoint indicators used in the thesis. All indicators use the "ReCiPe Midpoint (H)" method (Goedkoop et al 2013, Huijbregts et al 2017) and are calculated using data from the Ecoinvent database (Ecoinvent 2021)

Indicator name	Description	Units
Climate change	A measure of infrared radiative forcing increase, reported as the total level of GHG emissions. Also known as Global Warming Potential (GWP)	kg CO_2-eq
Land occupation	A measure of land occupation and time-integrated land transformation. Final value is comprised of both agricultural and urban components	m^2
Water depletion	A measure of the total volume of water consumed or required	m^3
Fossil depletion	A measure of all fossil fuel use (i.e., those containing hydrocarbons). This includes liquid, gaseous and solid fuels	kg oil-eq
Metal depletion	A measure of the total mass of metals taken from natural deposits	kg Fe-eq
Freshwater eutrophication	A measure of potential water pollution resulting from nutrient enrichment of freshwater aquatic environments. Nutrient level increases lead to "eutrophication", where water bodies become polluted by uncontrolled biomass growth (e.g., algal blooms)	kg P-eq
Marine eutrophication	A measure of potential water pollution resulting from nutrient enrichment of marine aquatic environments	kg N-eq
Human toxicity	A measure of contributions to cancer and non-cancer toxicity for humans	kg 1,4-DC

LCA methodologies have been used extensively within the energy field to provide comprehensive assessments of the environmental aspects that relate to individual technologies or processes (e.g., Asdrubali et al 2015, Mahmud et al 2020). This is in stark contrast to IAMs and other ESMs which provide low granularity results for a narrower selection of environmental indicators but are capable of simulating system behaviours over far wider extents. The scoping and conceptual differences between the two approaches are illustrated in **Figure A.13**.

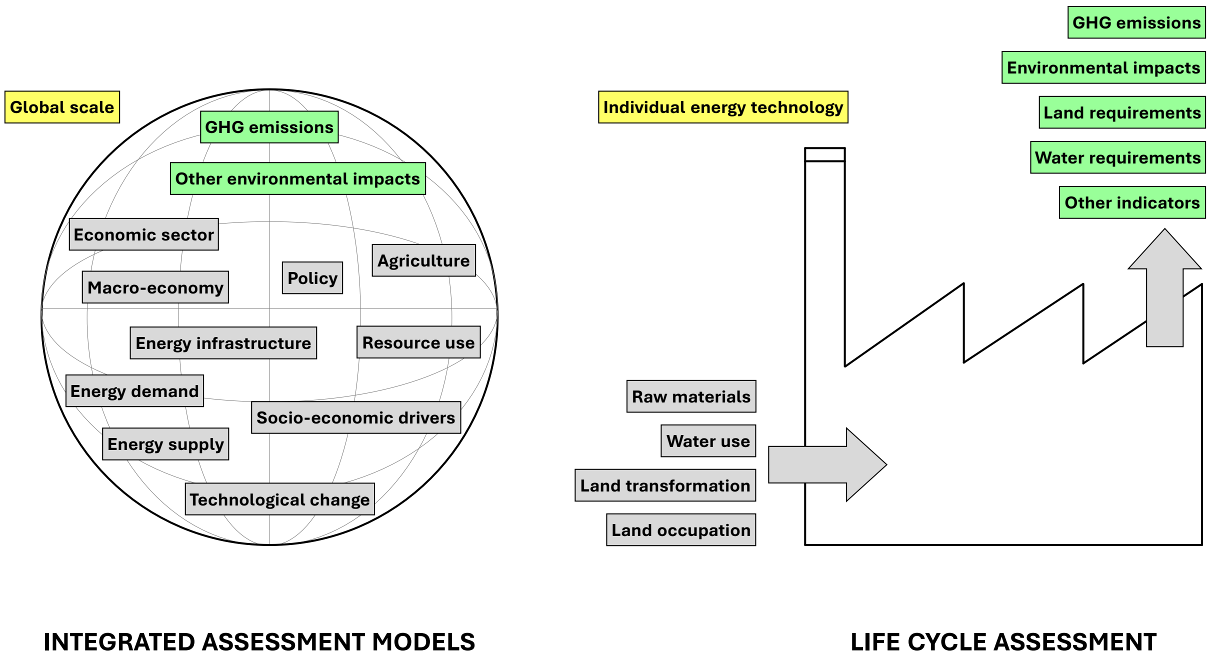


Figure A.13. Simplified representation of the scoping and conceptual differences between IAM and LCA approaches. Source: own elaboration

The need to upgrade the consideration of environmental parameters in energy models via the integration of LCA data has been gathering momentum over the last decade. Indeed, Pauliuk et al (2017) proposed a general framework for implementing LCA functionality into IAMs, adding that IAMs could lose their relevance as policy guidance tools without the added detail that LCA integration can bring. The first efforts to bridge this gap endeavoured to use life cycle data for individual energy sources to provide aggregated assessments for complete energy systems, typically at the local or national level. However, to date these have tended to focus on specific technologies or applications or have been limited to single cities or regions (Laurent et al 2018).

More importantly, a number of attempts have now been made to integrate IAM and LCA functionality directly. Early studies in this area used economic input-output data to provide mix data for different types of energy within a system (Daly et al 2015, Scott et al 2016). Subsequently, the concept of the prospective life cycle assessment (pLCA) (van der Giesen et al 2020, Arvidsson et al 2018) was able to provide a far more direct link between the two formats. Using this approach, selected outputs from IAMs have been used to inform the composition of background systems (e.g., changing heat sources or electricity mixes) and other aspects (e.g., higher efficiencies or carbon capture) within LCA processes in future scenarios.

Although an earlier study experimented with altering background systems via the post-processing of LCA outputs for different technologies (Hertwich et al 2015), the introduction of the THEMIS model in 2015 represented a major step forward by automating the links between IAMs and changes in background and foreground systems (Gibon et al 2015). As a consequence, THEMIS is capable of providing a framework for altering LCA parameters in conjunction with projected climate mitigation scenario data in order to adjust the impacts derived from different technologies under assumed future conditions. A further study used projected energy mix data from the REMIND IAM alongside LCA-based coefficients from THEMIS to calculate emissions and other data for future energy scenarios, although the two models were not linked (Pehl et al 2017). Conversely, later studies used a methodology that allows THEMIS LCA coefficients to be used directly within the IAM simulations themselves (Luderer et al 2019, Arvesen et al 2018). In any case, no hard links were formed between LCA and IAM environments in these studies.

More recently, the pLCA concept has been expanded by allowing life cycle data to be manipulated within Python environments, enabling outputs from IAMs to be automated with LCA calculations directly. For example, a methodology has been proposed that uses a dedicated application known as Wurst (Mutel and Cox n.d.) to import different background electricity mixes and other parameters from the IMAGE model into future LCA processes to account for changes in renewable energy use (Mendoza Beltran et al 2020). The PREMISE model (Sacchi et al 2022), meanwhile, expands upon these principles but adds greater compatibility with different IAMs and can analyse industries beyond electricity production. The IAM developed during the recent REFLEX project (REFLEX n.d.) produced energy system layouts that were then further analysed using traditional environmental LCA and social LCA (sLCA) approaches alongside human health and air pollution assessments (Brown et al 2019, Möst et al 2021). A detailed analysis of the German energy system also used LCA data from a wide range of sources to produce indicators for scenarios provided by the MESAP/PlaNet model (Junne et al 2020). So, while the idea of integrating LCA data and concepts into energy modelling tools remains in its infancy, progress is certainly being made an increasing number of projects are investigating options for improving model accuracy and relevance via this route.

Lastly, it is worth noting that the usefulness of LCA data in modelling need not be limited to the final impact indicators derived from LCIA calculations. Again, LCI information provides a thorough list of all of the individual inputs–and outputs–to a process. This includes all raw materials and other required resources on a per-unit basis. As such, this data can be used to derive a variety of other indicators, particularly in regard to the raw material factors that relate to energy-related processes.

A.2 Thesis development

A.2.1 Motivations

In the broadest sense, the motivation for the thesis is to contribute to the process of mitigating the impacts of climate change. More specifically, it was hoped that the work undertaken could help to facilitate a faster and more efficient transition towards more sustainable energy systems. This was to be achieved, primarily, by helping to optimise the accuracy and effectiveness of the models that guide energy policy–and, hence, the transition itself–by contributing to the growing movement of technicians seeking to create more detailed and robust modelling platforms. In this regard, the particular aim was to further enhance the use of life cycle assessment (LCA) concepts in energy modelling environments, to highlight the importance of various raw material supply aspects and to introduce new approaches for analysing socio-metabolic and other relationships within energy systems.

Perhaps the most obvious and valuable way to use LCA databases in energy modelling applications is to use them to produce more accurate estimations of GHG emissions. Indeed, this has tended to be the focus of many attempts to integrate LCA functionality into energy models to date (Pehl et al 2017, Arvesen et al 2018, Sacchi et al 2022). In this way, outputs from LCIA calculations can be used to quantify emissions for individual components or to aggregate results to create estimates for different system configurations. However, estimates can also be derived for other environmental impacts, such as resource depletion, particulate matter to air or toxicity to humans (Luderer et al 2019). It follows that LCA functionality could theoretically be used to add greater resolution to a variety of environmentally based considerations in future energy models. It can also be used to provide estimates of land and water use which can provide information about related resource constraints in these areas.

Although they are beginning to receive increased attention in recent years (European Commission 2020), the implications of raw material factors in energy systems and the energy transition are notably underrepresented in climate and energy policy discourse, particularly in energy system modelling. Implementing the energy transition will require a significant number of new infrastructure items to be built and installed. This will necessitate the sourcing of large amounts of raw materials, many of which have relatively uncertain futures in terms of available reserves and the geo-political aspects of maintaining supply lines. As a result, the requirement volumes of many of these materials could introduce very real constraints on the implementation of certain projected configurations. This is especially true for wind turbines and solar photovoltaic cells, both of which rely heavily on certain critical materials (Bobba et al 2020).

Aside from the risks associated with the overall supply of critical raw materials, localised environmental damages and environmental justice issues relating to the extraction and processing of these materials is rarely discussed in the context of the energy transition (Lèbre et al 2020).

Moreover, these considerations appear to be missing entirely in current energy modelling applications. As both aspects could potentially have serious political and economic implications on the transition as it progresses, particularly where large surges in required extraction rates could occur, it was also viewed as a key research gap and motivation during the program.

To enable these new approaches to be facilitated in way that could potentially be used by fellow energy modellers–and also potentially directly by policymakers–a computer-based application was required. The resulting software, firstly, needed to be capable of calculating a range of LCA and other indicators for all individual processes within a defined energy system. Furthermore, in order to understand how these indicators are distributed, and how they could potentially introduce constraints into the system, the workflow also needed to incorporate a social metabolism approach. To that end, it was designed to be capable of combining indicator outputs–from LCA and other methodologies–with the systemic upscaling capabilities of the Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM). As such, the resulting approach–known as ENBIOS–can return a range of customisable, composite indicators at different levels within the system hierarchy.

Lastly, ENBIOS was developed as part of the Sustainable Energy Transitions Laboratory (SENTINEL) modelling platform and needed to be capable of linking with modelled results for the European energy system from the Calliope and EnergyPLAN models. Accordingly, it was used to test and report results for several case studies connected to the project, helping to identify constraints and influences that could hinder certain proposed configurations and help to identify preferred technologies and pathways. This demonstrated the functionality of the ENBIOS concept as a tool capable of being used alongside a variety of ESMs–or standalone system configuration data–to provide a range of important new indicators that are generally not available to modellers and policymakers.

A.2.2 Research questions

Above all, the aim of the thesis is to highlight the need to improve the models used to guide important energy policy decisions by integrating several underrepresented factors. To address this aim, and the established research gaps, four research questions are offered, as follows.

Research question #1

“What factors are likely to constrain and influence the energy transition and are these factors adequately considered in energy policy decision-making processes?”

Research question #2

“What are the potential consequences of failing to adequately consider all of these factors in the models used to guide energy policy?”

Research question #3

"How can life cycle inventories and other data sources be used to improve the integration of these factors in energy models?"

Research question #4

"What insights can the proposed techniques offer about specific energy technologies and projected energy system configurations in Europe?"

A.2.3 Thesis Structure

To respond to the given research questions, eight specific objectives were established. The first of these has been addressed in the introductory section, while the remaining seven are to be addressed in separate sections throughout the remainder of the thesis. A summary of these objectives and the relationship of each objective to the four research questions is provided in **Table A.7**; the section that relates to each objective is also listed.

To complement the listings in **Table A.7**, a summary of the thesis workflow is illustrated in **Figure A.14**; chapter numbers corresponding to each element are also shown.

Table A.7. Eight objectives of the thesis alongside their relationship to each research question (RQ) and the sections in which they are addressed

	Objective	RQ	Section
1	To identify a set of important factors for forecasting the energy transition and determine which of these are underrepresented in energy models	1	**A**
2	To perform a preliminary assessment of five overlooked factors to determine which renewable energy technologies are more or less likely to face constraints as the transition continues	2	**B**
3	To investigate which factors are most relevant to stakeholders, discuss how these are addressed in current models and explain the consequences of not improving the coverage of these factors in future models	2	**C**
4	To investigate the possibility of including detailed assessments of raw material factors in energy models and to demonstrate this potential using findings for key renewable energy technologies	3	**D**
5	To develop detailed methodologies for assessing specific raw material factors and to use them within a case study for current and projected electricity supply in the EU	3	**E**
6	To develop a workflow for assessing the constraints and limitations on energy systems using life cycle assessment, the proposed raw material methodologies and other data sources	3	**F**
7	To use the developed workflow to perform a national case study analysis on historical and projected scenarios for the Swedish heating system	4	**G**
8	To use the developed workflow to perform a regional case study analysis on historical scenarios and multiple possible projections for the European energy system as a whole	4	**H**

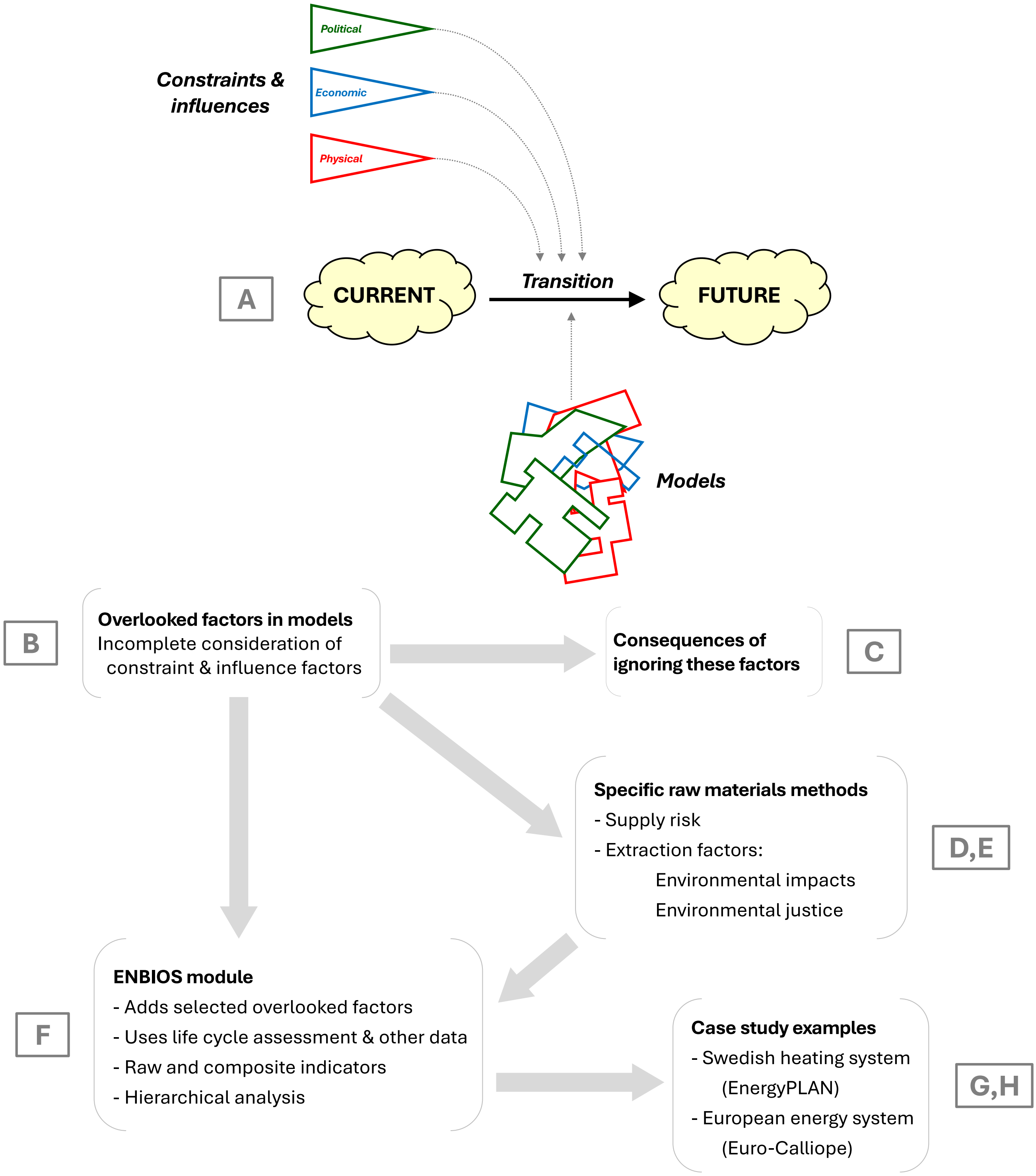


Figure A.14. Summary of thesis workflow. Chapters that correspond to each element of the workflow are shown in grey boxes

B FIRST ARTICLE

Overlooked factors in predicting the transition to clean electricity

Nick Martin, Cristina Madrid-López, Gara Villalba-Méndez, Laura Talens-Peiró

Environmental Research: Infrastructure and Sustainability, 15 June 2022, https://doi.org/10.1088/2634-4505/ac70f7

Abstract

The transition to clean energy will require significant increases in electricity sourced from renewable energy technologies. While wind and solar photovoltaic sources are generally expected to overtake hydropower to dominate the renewable electricity supply market, numerous other technologies vie for a share in this rapidly evolving arena. To date, predicting the emergence of different technologies has relied on large-scale energy models that employ simplified optimisations of economic and emissions reductions outcomes. This is problematic as many additional factors, largely underrepresented in current models, are likely to co-determine technological emergence storylines in the real world. Here, a summary of the best available information is presented for five key factors as they apply to the seven most common renewable electricity technology categories. The findings suggest that wind and solar photovoltaic technologies remain the most likely to dominate the market going forward but could face considerable raw material supply risk issues. Other potentially more desirable alternatives exist but face their own geographic and environmental limitations. Ultimately, this section demonstrates the potential and importance of expanding the use of other relevant factors in the forecasting of energy transition pathways and in the field of energy modelling as a whole.

B.1 Introduction

It is now widely agreed that a rapid transition towards renewable sources of energy is required in order to reduce greenhouse gas (GHG) emissions and the dangers of climate change. As part of the global response to the issue, the "electrification" of energy systems and increased use of renewable energy sources (RES) in supplying electricity are seen as key pathways for achieving the necessary reductions in emissions (IRENA 2020).

Electricity currently accounts for 19.2% of global energy consumption and 20.9% within the European Union (EU-28) (IEA 2019). These shares are expected to rise to between 23.1% and 30.5% globally and 25.5% and 37.2% across EU-28 countries by 2040. RES technologies currently provide 25.5% of global electricity and 33.4% at the EU-28 scale, but these shares are expected to more than double by 2040 (IEA 2019, IRENA 2020). Historical and projected shares of the renewable electricity market for seven key renewable electricity supply technologies at both scales are displayed in **Figure B.1**. The data suggests that the deployment of wind and solar PV will continue to rise in the short to medium term. The decline of hydropower looks likely to continue, while bioenergy use is predicted to decline slightly. The remaining three categories–geothermal, marine energy and concentrated solar power (CSP)–are all expected to rise, albeit at a much lower scale than the four dominant technologies.

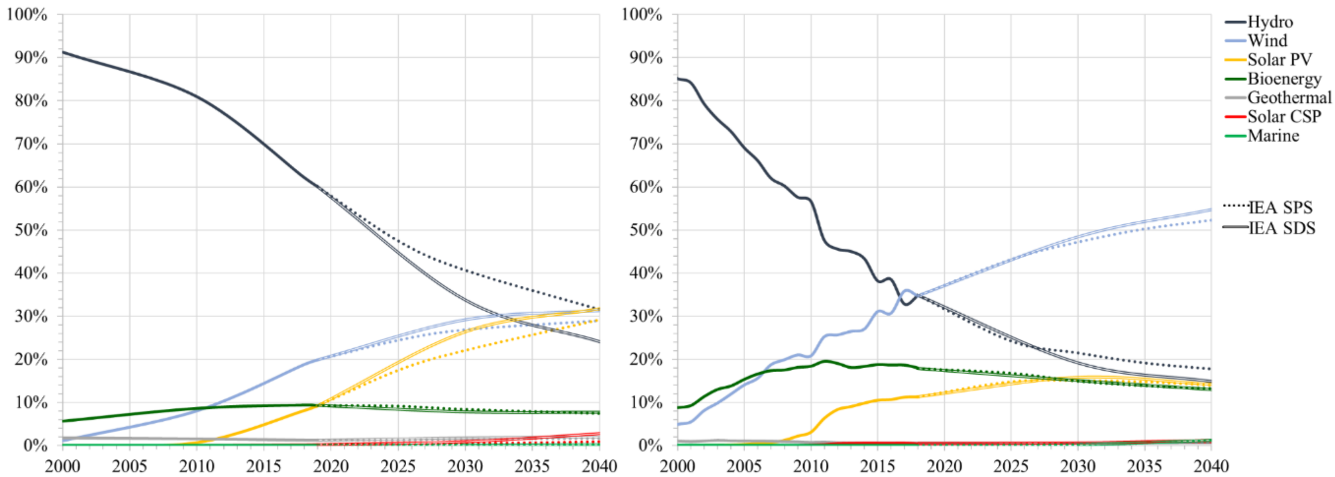


Figure B.1. Existing predictions for future use of renewable electricity supply technologies. Historical distribution of global (left) and EU-28 (right) electricity supply derived from renewable energy sources by energy source shown for the period 2000 to 2018 (Eurostat 2022, IEA 2019). Projected future distributions also shown for IEA Stated Policies (SPS) and Sustainable Development (SDS) scenarios for 2018 to 2040 (IEA 2020, 2019)

While such projections provide useful insights into current market and policy directions, it is notable that forecasts of this type almost always rely on large-scale energy models–particularly integrated assessment models (IAMs)–that include simplified policy assumptions and calculations focused on the optimisation of economic or emissions reductions outcomes. Deeper insights into the desirability or feasibility of implementing individual electricity supply technologies can be provided by more detailed considerations of emissions, materials supply and other techno-economic and socio-political aspects, but these are rarely integrated into existing models (Capellán-Pérez et al 2020, van Sluisveld et al 2020, Krumm et al 2022, Köhler et al 2018). As such, while current predictions provide adequate general overviews of likely trends going forward, the robustness of current forecasting methods could be greatly improved via the further integration of additional technical determinants and potential sources of constraint.

A thorough review of current technologies, transition modelling methodologies and the frameworks used to conceptualise and forecast future transitions was undertaken (Martin et al 2020) as part of the ongoing SENTINEL project (SENTINEL n.d.). In this section, the findings of this review are used to identify five additional factors that are currently underrepresented in the IAMs and other models used to guide energy policy. Three technical determinants–life cycle greenhouse gas emissions, energy return on investment and learning rate–and two potential sources of constraint–critical raw material requirements and socio-political acceptance–are identified. The best available data for these factors is then presented for seven key renewable electricity supply technologies. Collectively, the findings yield an updated summary of the outlook for each technology that includes the key insights and potential issues generated by the five additional factors. These observations are then discussed, mirroring the growing movement to obtain more detailed, reliable and realistic simulations of future energy system configurations.

B.2 Additional technological emergence factors

The five most critical drivers of technological emergence acknowledged as being inadequately represented within current energy models are listed in **Table B.1** alongside their relevance in energy system forecasting activities. The first three of these are technical determinants that provide further insights into emission reduction potential and future market potential in terms of technical and economic attractiveness. These elements are then juxtaposed by considering two additional factors that reflect potential constraints to wider implementation. Note that, while an array of electrical transmission and storage technologies will also need to be implemented as part of the transition to more renewable electrical networks, the scope of the paper is limited to electrical supply technologies. Furthermore, it is recognised that all of the factors under consideration have received some prior attention within the literature in relation to renewable technologies, the energy transition and, to some extent, to energy modelling itself, and that learning rates are already included in many IAMs, albeit in simplified forms. In any case, these factors are thought to represent those that could best improve forecasting methods via further integration.

Table B.1. Five additional factors identified for assessing emergence potentials

	Factor	Description	Relevance
Technical determinants	Life cycle GHG emissions	GHG emissions during all sub-processes required to produce one final unit of energy	Provides more robust quantification of GHG emissions than solely emissions from final energy production stage
	Energy return on investment	Units of useable energy produced for each unit of energy expended during production process	Provides indication of efficiency of energy production process. This, in turn, may affect economic costs and emission rates
	Learning rate	Percentage drop in unit costs following each doubling of cumulative production	Provides indication of technological maturity and ongoing changes in economic attractiveness and feasibility
Sources of constraint	Critical raw material requirements	Quantification of materials considered critical that are required for the construction of infrastructure	Provides indication of vulnerability to material shortages or other supply risks that could affect infrastructure implementation rates
	Socio-political acceptance	Extent of known issues regarding public acceptance and associated political dynamics, including those affected by siting and land use issues, local environmental impacts and other quality of life issues	Provides indication of vulnerability to opposition and delays that could affect infrastructure implementation rates

Much of the data used within the analysis was collated as part of a previous literature review (Martin et al 2020). The dataset has subsequently been expanded by undertaking a thorough literature search for more recent data and for additional literature reviews that addressed similar requirements. Accordingly, it is believed that the data presented includes most if not all of the best available estimates. Each factor is outlined individually in the sections that follow, and full listings of the datasets are available as supplementary materials.

B.2.1 Life cycle GHG emissions

Reducing GHG emissions from energy production processes is the primary driver in the transition to sustainable energy systems (IRENA 2020) and, logically, processes with lower per-energy-unit emissions should be prioritised. However, the majority of current accounting and modelling methodologies rely on simple calculations based on emissions produced during final combustion processes. These approaches neglect the "hidden" emissions that occur within the overall life cycles of energy production processes (Pehl et al 2017). For example, raw materials are extracted for fuel and infrastructure inputs, infrastructure components undergo individual production, transportation and installation stages, and functioning plants require ongoing operation and maintenance processes. Considering all contributing sub-processes processes is especially relevant when assessing renewable electricity technologies, many of which are considered to be "clean" by virtue of their absence of final emissions. Consequently, there is a growing realisation that renewable technologies should be analysed using a life cycle perspective (Luderer et al 2019, Pehl et al 2017).

Here, in order to estimate life cycle GHG emissions for the identified technologies, a general set of values was first extracted from the Ecoinvent database (Ecoinvent 2021)–using the "ReCiPe Midpoint (H):GWP100" method–that includes all 33 renewable electricity production processes available within the 2021 version. Details of the processes used and GHG emissions derived are listed in **Table J.5** in the appendices. Additional data was also collated from detailed literature reviews of individual technologies undertaken for hydropower (Kadiyala et al 2016), wind (Mendecka and Lombardi 2019, Bhandari et al 2020), solar PV (Kommalapati et al 2017, Ludin et al 2018), bioenergy (Kadiyala et al 2016), geothermal (Tomasini-Montenegro et al 2017) and solar CSP (Kommalapati et al 2017).

The categorised findings, shown in **Figure B.2**, demonstrate that ranges within individual categories are often sizeable, reflecting the extent of different sub-technologies assessed. Hydropower and wind are generally seen to produce lower emissions than other technologies. Moderate mean emission levels are observed for geothermal and solar technologies, although the range of values for solar sub-technologies is also high. Finally, though some lower individual values are observed, most values for bioenergy technologies are within the medium to high emissions range, and the mean observed value is considerably higher than those in other categories.

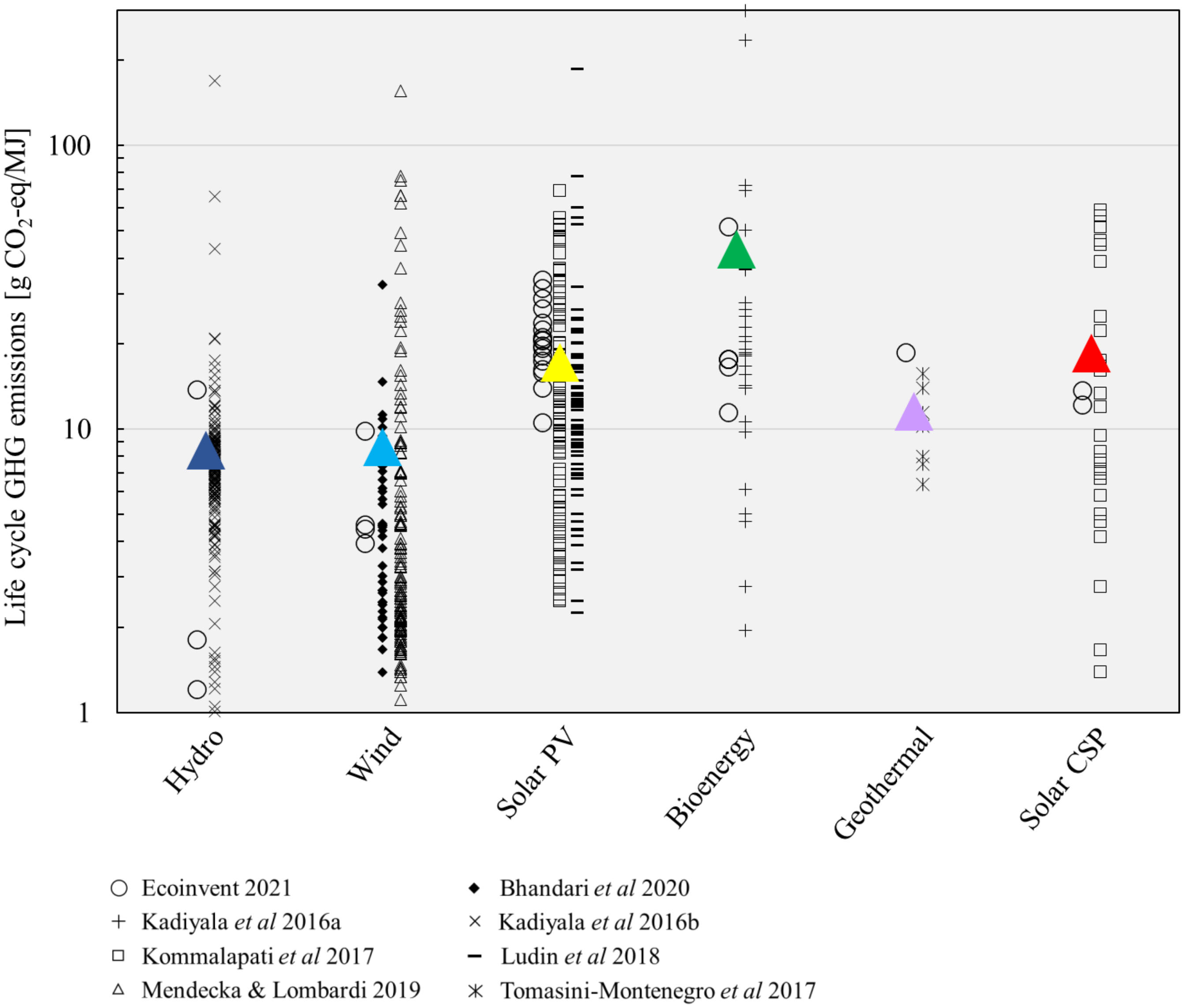


Figure B.2. Life cycle GHG emissions for renewable electricity supply technologies. Values taken directly from the Ecoinvent (Ecoinvent 2021) database (using "ReCiPe Midpoint (H) V1.13:climate change:GWP100" method) are shown alongside additional literature review data for hydropower (Kadiyala et al 2016), wind (Mendecka and Lombardi 2019, Bhandari et al 2020), solar PV (Kommalapati et al 2017, Ludin et al 2018), bioenergy (Kadiyala et al 2016), geothermal (Tomasini-Montenegro et al 2017) and solar CSP (Kommalapati et al 2017). A total of 635 individual point values is shown. Final mean values shown as coloured triangles

B.2.2 Energy return on investment

A similar scope is applied to the energy efficiency aspects of a technology when undertaking energy return on investment (EROI) calculations. EROI is defined as the units of useable energy–or exergy–made available for every unit of exergy used within the process of obtaining it. For RES technologies–where these inputs tend to be largely infrastructure-based–EROI is mostly a measure of the energy provided over the lifetime of the infrastructure divided by the energy used to build, operate and dismantle it (Fabre 2019). Forms of energy with higher EROIs are less energy-intensive to obtain and, therefore, are theoretically more economically and environmentally desirable.

EROI values for certain technologies vary significantly by geographical location. For example, solar panels or wind turbines return far more energy outputs in sunnier or windier locations, respectively. Differing production processes may also result in slight variations and future technological advances are likely to affect EROI values. Furthermore, choice of infrastructure lifetime can create significant differences in EROI values, particularly for hydropower, solar, wind and geothermal energy where infrastructure represents the majority of the lifetime energy inputs–the energy generation itself is mostly taken without energy "costs" from the surrounding environment.

Valero et al (2016) undertook a thorough review of published EROI values for electricity production processes, collating over 160 estimates from a variety of sources. Meanwhile, King and van den Bergh (2018) considered gross energy production–instead of the usual net production–for various renewable electricity technologies to produce EROIs ranging from lower "pessimistic" values to higher "optimistic" values. More recently, de Castro and Capellán-Pérez (2020) calculated EROI ranges for different technologies based on estimations of individual material requirements. The collective results are shown in **Figure B.3**.

The data indicates that hydropower possesses a far higher mean EROI than other technologies. So, despite its diminishing popularity (IRENA 2020), hydropower remains a dependable option in terms of overall energy efficiency. Data for wind, solar and geothermal display significant levels of variation, although all present moderately high returns. The single value for marine energy places it within this group, though this remains uncertain ahead of wider implementation. Among this group, the values for wind tend to be higher on average. Values for all forms of bioenergy are low–particularly biogas and biofuels–at least when producing electricity. Indeed, bioenergy is a notably poor performer in this category.

B.2.3 Learning rate

The concepts of learning and experience curves–where a learning curve describes a single company or product while an experience curve encompasses an entire industry–are rooted in the idea that gaining production experience leads to lower production costs over time and, hence, greater economic feasibility and desirability (Louwen and Lacerda 2020). The curves are now a conventional metric for gauging technological progress, and some consider them to be the single most important driver for defining the cost of energy technologies and the shape of future energy configurations (Berglund and Söderholm 2006). In fact, learning curves have already been used to some degree to provide technology cost inputs within IAM calculations. Nevertheless, the simplified methods used have been questioned alongside other efforts to include technoeconomic data estimates (Ellenbeck and Lilliestam 2019, Shiraki and Sugiyama 2020, Lilliestam et al 2020, Witajewski-Baltvilks et al 2015) and improved integration methods are required.

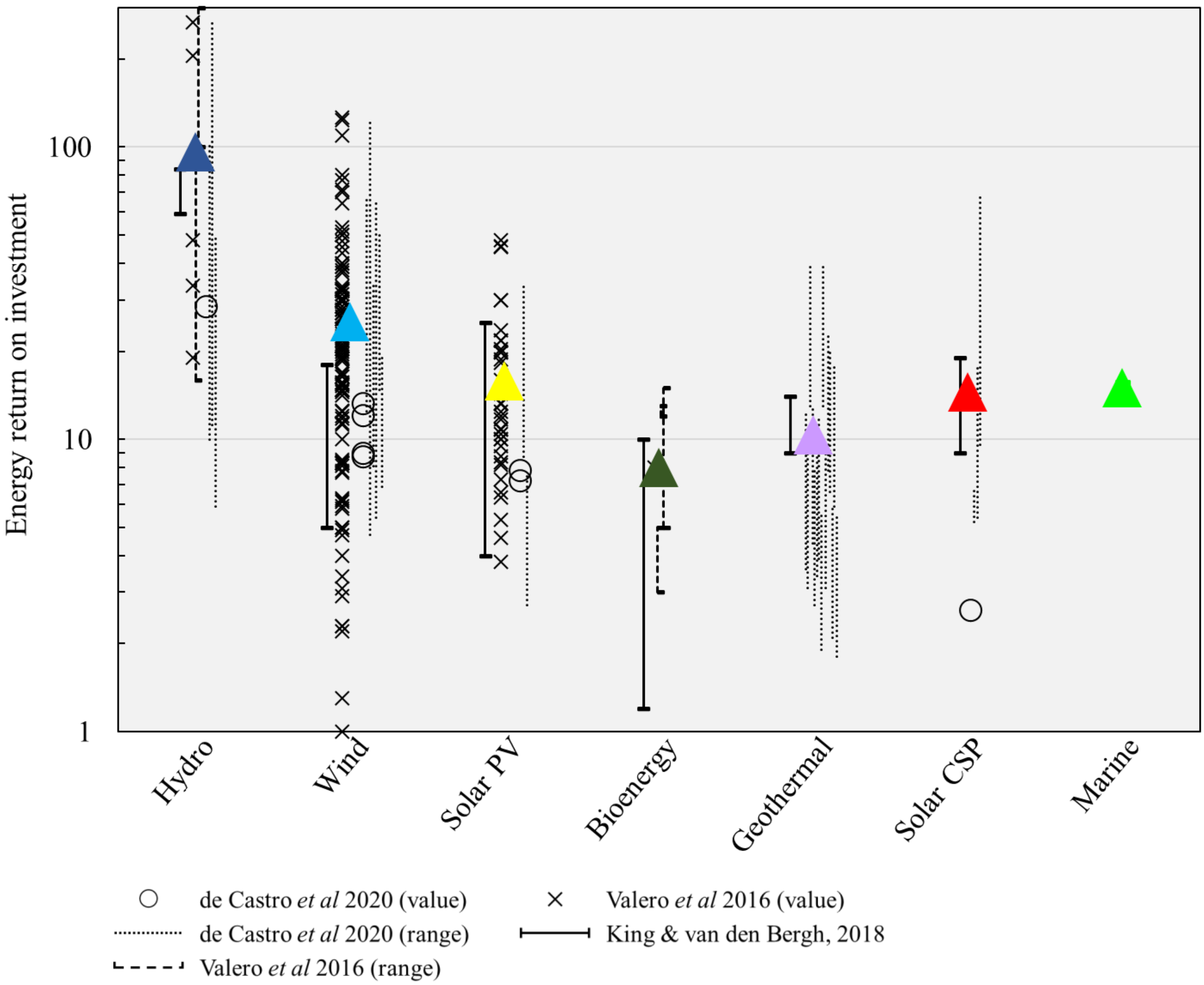


Figure B.3. Energy return on investment values for renewable electricity supply technologies. Values from a thorough literature review (Valero et al 2016) are shown alongside more recent calculations that use specific assumptions to derive ranges of values for various technologies (King and van den Bergh 2018, de Castro and Capellán-Pérez 2020). A total of 204 individual range and point values are shown. Final mean values shown as coloured triangles

The learning rate–the percentage at which costs decline after each doubling of cumulative production–is the commonly used metric for defining the rate of change in product costs derived from learning curves. As "learning" continues the cost is bound to fall, although the exponential nature of the curves means that reductions will slowly level-off over time (Karali et al 2015). More importantly, ongoing learning effects reduce costs and enable a technology to reach broader markets and extend its range of applications.

Many studies have attempted to quantify learning rates for different electricity technologies. Findings from four comprehensive studies (Weiss et al 2010, Rubin et al 2015, Louwen et al 2018, Yao et al 2021) are shown in **Figure B.4**. Data for less common forms of RES are harder to locate, but data for four further studies were also used (Hernández-Moro and Martínez-Duart 2012, Platzer and Dinter 2016, MacGillivray et al 2014, van der Zwaan and Dalla Longa 2019). Results indicate that a great deal of variation exists in the data for hydropower and geothermal technologies, and these are both seen to have low learning rates overall. Meanwhile, wind, solar CSP and marine energy are seen to offer moderate rates, although certain observations for wind turbines are higher. Solar PV and biomass production display the highest learning rates overall as a result of significant ongoing technological advances and efficiency improvements in some sub-technologies.

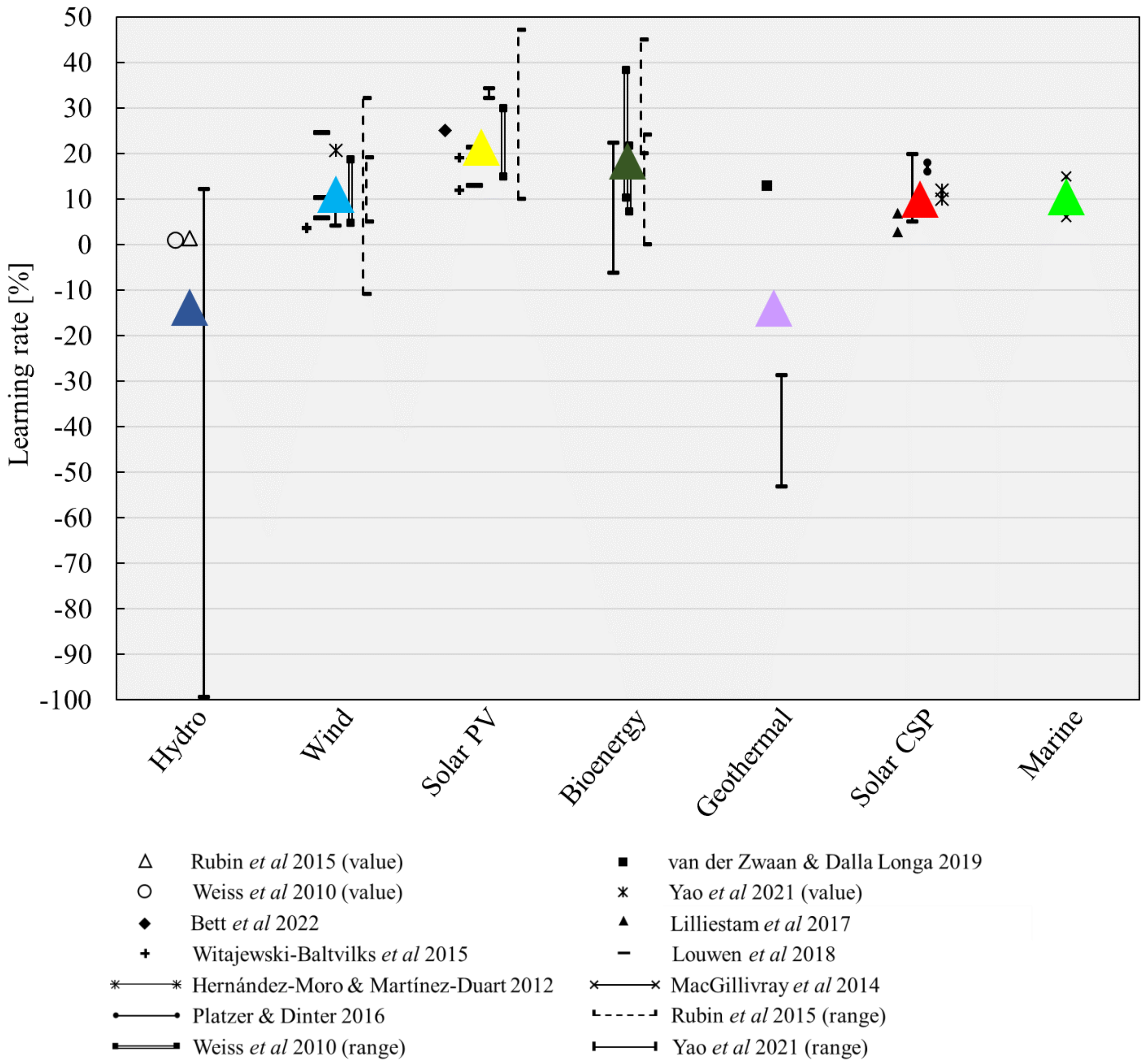


Figure B.4. Learning rates for renewable electricity supply technologies (Weiss et al 2010, Rubin et al 2015, Louwen et al 2018, Hernández-Moro and Martínez-Duart 2012, Platzer and Dinter 2016, MacGillivray et al 2014, van der Zwaan and Dalla Longa 2019, Yao et al 2021, Bett et al 2022, Lilliestam et al 2017, Witajewski-Baltvilks et al 2015). A total of 35 individual range and point values are shown. Final mean values shown as coloured triangles

B.2.4 Critical raw material requirements

Variations and uncertainties within the raw material supply chains required to enable the manufacture of new infrastructure items could strongly impact the feasibility of producing the levels of renewable electricity infrastructure required to implement different transition strategies, particularly in relation to the so-called critical raw materials (CRMs) (European Commission 2020). In order to produce new infrastructure items for different technologies, all supplies of CRMs would need to both exist *and* be free of supply issues in the quantities required. However, the EU, for example, is a net importer of CRMs and is between 75% and 100% reliant on imports for most supplies (European Commission 2020). As many of these materials are only available from a limited number of locations–and often in politically sensitive areas–problems could arise in the future, particularly if sudden shifts in demand were to occur. It follows that technologies with higher dependencies on CRMs with unreliable supply lines are more likely to be exposed to implementation constraints. This is especially true if the opportunities for alleviating such risks via recycling initiatives are less technically feasible for the CRMs involved. At the very least, price fluctuations could affect the economic viability of certain technologies which could also be reflected in investment or consumer confidence barriers.

Several studies have investigated the CRM dependencies of different technologies at both the global (Buchholz and Brandenburg 2018, Dominish et al 2019, Hund et al 2020, Giurco et al 2019, Congressional Research Service 2019, U.S. Geological Survey 2020) and EU scales (Bobba et al 2020, European Commission 2020). The dependencies identified for individual technologies within these studies are summarised in **Table B.2**. In all, the data reports that, although potential raw materials issues exist for all technologies listed, wind and solar PV are considerably more likely to face challenges in this regard. Wind turbines are especially noteworthy in that certain designs are known to have strong reliances on relatively tenuous stocks of rare earth materials that are frequently identified as having potential supply disruption issues (Apergis and Apergis 2017), particularly in relation to Chinese supply chains (Mancheri et al 2019). Conversely, the simpler technological approaches employed in hydropower, geothermal and solar CSP infrastructures suggest far lower vulnerabilities in this respect.

Table B.2. Summary of materials considered critical to production of renewable power supply technologies within the literature. Material requirement estimates of required mass of critical material, in tonnes, for each gigawatt of installed electricity generation capacity are shown, where available (Buchholz and Brandenburg 2018, Bobba et al 2020, Dominish et al 2019, Hund et al 2020, Giurco et al 2019, U.S. Geological Survey 2020, European Commission 2020, The World Bank 2017, U.S. Department of Energy 2010, Carrara et al 2020, Pihl et al 2012). Requirements are assumed to be low in cases where a material is known to be required but estimates are not listed in the literature. Specific estimates for hydropower and geothermal electricity are unavailable. Current EU estimates for end-of-life recycling input rate (EoLRIR) (European Commission 2020) are also shown and provide a proxy measure for the potential to alleviate future material supply risks via recycling. The top section of the table highlights materials identified as being most critical within the EU (European Commission 2020). The count for each technology in the final row shows the sum of occurrences for all listed materials, with those for EU-specific critical materials in brackets

Material	**Material requirements by technology** *[tonnes/installed GW]*					**EoLRIR** *[%]*
	Hydropower	**Wind energy**	**Solar PV**	**Geothermal**	**Solar CSP**	
Borate		0-7	0.0008			1.0
Cobalt		*low*				22.0
Gallium			0-7		*low*	-
Germanium			36-48			2.0
Graphite natural						3.0
Indium			4-45		*low*	-
Lithium						-
Rare earth - light						
Praseodymium		0-35				10.0
Neodymium		12-186				1.3
Yttrium		*low*				31.4
Lanthanum						1.0
Rare earth - heavy						
Terbium		0-7				6.0
Dysprosium		2-25				-
Samarium						1.0
Silicon metal			150-4,000			-
Titanium	*unknown*			*unknown*		19.0
Vanadium						2.0
Aluminium		500-1,600	102-7,500		470-23,000	12.4
Cadmium			1-84			30.0
Chromium	*unknown*	470-902		*unknown*		21.0
Copper	*unknown*	950-5,000	17-4,600	*unknown*	1,400-3,200	17.0
Manganese	*unknown*	32-800		*unknown*		8.0
Molybdenum	*unknown*	99-136	*low*	*unknown*		30.0
Nickel	*unknown*	240-663	*low*	*unknown*		17.0
Niobium		*low*				-
Selenium			15-84			1.0
Silver			5-20		4-16	19.0
Tellurium			5-90		*low*	1.0
TOTAL COUNT	6 (1)	14 (6)	13 (5)	6 (1)	6 (2)	

Exposure to CRM supply risks can be alleviated by improving levels of recycling. As a proxy measure of the potential to recycle specific materials, current EU values for the end-of-life recycling input rate (EoLRIR)–the level of input within the production stream that is sourced from recycled materials (European Commission 2020)–are also listed in **Table B.2**. Here, materials with higher present-day EoLRIR levels indicate that opportunities to offset supply risks do exist, while the negligible values observed elsewhere confirm that technical issues of accessibility and separability can hinder recycling opportunities for certain materials. This remains a complex issue, and it is important to note that recycled materials will not always be produced in generic forms that can be reused in all technologies (Ciacci et al 2015). As such, there is a growing push to integrate ecodesign concepts into renewable energy infrastructure production processes (Babbitt et al 2021, Gallagher et al 2019) to increase product lifespans and to improve the recycling aspects of valuable materials within the technologies themselves (Dodd et al 2020).

B.2.5 Socio-political acceptance

Various social and political factors–particularly those involving public acceptance and opposition–are also likely to have a strong influence on the evolution of electrical networks and the emergence of specific technologies. The least qualitative of the factors analysed here, issues of acceptance operate at the nexus between economic policies and incentives, issues of social preferences and the many elements that influence local and wider-scale public acceptance, all of which affect consumer and business behaviour and political directions (Victor et al 2019).

An analysis of 25 recent European studies (Segreto et al 2020) determined that two of the most significant drivers and barriers to the social acceptance of RES relate to procedural and distributional justice. In other words, support for RES is higher when processes of implementation and sharing of benefits are deemed to be fair and equitable. Increasing interest in the decentralised production and storage of electricity by so-called “prosumers” provides an example of increased public ownership and support for RES initiatives, assuming that adequate attention is given to the potential legal and technical issues that could arise. Solar PV is probably the most applicable supply technology for such initiatives (Parag and Sovacool 2016). Furthermore, as with any market, issues of investor and consumer confidence also appear to be vital in driving the penetration of RES and related technologies, and evidence of reliability, adequate financial support and stable policy frameworks can greatly enhance acceptance levels at all scales (Masini and Menichetti 2013, Eleftheriadis and Anagnostopoulou 2015). Such influences at least partly explain the ongoing support for wind and solar power.

The acceptance and feasibility of individual technologies can also be significantly dampened by localised opposition and political factors, particularly where geographical siting and land use limitations exist, and environmental impacts and other quality of life issues are involved. Wind farms (Caporale et al 2020), biomass plantations (Fytili and Zabaniotou 2017), geothermal plants (Manzella et al 2019) and, especially, hydropower dams (Mayeda and Boyd 2020, Sütterlin and

Siegrist 2017) are the most obvious examples of this. Conversely, utility-scale solar plants typically receive less opposition than other technologies (Sütterlin and Siegrist 2017), although potential limitations have been noted (Roddis et al 2020). And, while relatively few plants exist, opposition to new marine energy facilities are not generally expected (Bailey et al 2011). Changing governments may also have their own preferences, perhaps even driven by resistance from industry-based lobbying (Lockwood et al 2020, Catola and D'Alessandro 2020). In any case, the complexity of these relationships introduces a variety of unknowns, and their absence remains a critical shortcoming of IAMs and other energy models (Krumm et al 2022).

B.3 Assessed potentials for renewable electricity technologies

A survey of existing literature and data sources produced a qualitative summary of the five influencing factors for each of the seven renewable electricity technologies, as summarised in **Table B.3**. Simplified classifications of "low", "medium" and "high" potentials were assigned based on observed ranges. For consistency, the indicators for GHG emissions and raw material requirements have been inverted such that lower emissions and reliances yield higher final potentials. Likewise, a higher classification for socio-political acceptance implies a lower number of barriers in these areas. It is also noted that the final classifications for GHG emissions reductions are relative to the other renewable technologies considered as, again, these processes generally produce significantly less emissions as a group than current fossil fuel-based technologies.

B.3.1 Hydropower

As the most established technology, hydropower experiences very low learning rates offset by low emissions, very high EROI values and no major raw material issues. Nevertheless, the social, environmental and financial costs relating to new large-scale installations are known to be substantial (Ansar et al 2014, Botelho et al 2017). However, smaller-scale applications are likely to remain attractive based on the given indicators and hydropower, overall, appears likely to maintain at least moderate popularity into the future.

Table B.3. Summary of factors influencing technological penetration for renewable electricity supply technologies. Potentials for reduced life cycle greenhouse gas emissions (Ecoinvent 2021), energy return on investment (King and van den Bergh 2018), learning rate (Weiss et al 2010, Rubin et al 2015, Louwen et al 2018, Hernández-Moro and Martínez-Duart 2012, Platzer and Dinter 2016, MacGillivray et al 2014, van der Zwaan and Dalla Longa 2019, Yao et al 2021), critical raw material independence (Buchholz and Brandenburg 2018, Bobba et al 2020, Dominish et al 2019, Hund et al 2020, Giurco et al 2019, U.S. Geological Survey 2020, European Commission 2020, The World Bank 2017, U.S. Department of Energy 2010, Carrara et al 2020, Pihl et al 2012) and social and political acceptance (Segreto et al 2020, Parag and Sovacool 2016, Caporale et al 2020, Fytili and Zabaniotou 2017, Manzella et al 2019, Mayeda and Boyd 2020, Sütterlin and Siegrist 2017, Carlisle et al 2015, Bailey et al 2011) are provided. Cells are shaded according to determined emergence potential, from green ("high" potential), through cream ("medium" potential) to red ("low" potential)

	Reduced life cycle GHG emissions	EROI	Learning rate	CRM independence	Social & political acceptance
Hydropower	High	High	Low	High	Low Social & environmental issues for new plants
Wind	High	Medium	Medium	Low Several potential issues, particularly rare earth materials in permanent magnet generators	Medium Social & environmental issues, particularly for onshore facilities
Solar PV	Medium	Medium	High	Low Several potential issues mainly related to solar panels; these tend to be highly technology dependent. Copper & aluminium for other infrastructure of less concern (Carrara et al 2020)	High Desirable at building level, potential for "prosumer" involvement. Minimal social & environmental issues at utility level
Bioenergy	Low to medium	Low	High (biomass production) Medium (energy production)	High	Medium Social & environmental issues, particularly for biomass production
Geothermal	Medium	Medium	Low to medium	High	Medium Social & environmental issues for new plants
Solar CSP	Medium	Medium	Medium	High Limitations mostly relate to construction metals of less concern (Pihl et al 2012)	High Minimal social & environmental issues
Marine	*(no information)*	Medium	Medium	*(no information)*	High Minimal social & environmental issues

B.3.2 Wind

Wind turbines represent another relatively mature technology, although substantial innovations continue to occur. They offer high emissions reduction potential and moderate EROI values, and larger structures and better efficiencies will offer improvements in all of these regards in coming years. Despite these advantages, social and environmental issues can be considerable, especially for onshore wind farm installations; the current shift towards offshore wind farms may help to mitigate such concerns (Hevia-Koch and Klinge Jacobsen 2019). A key concern remains in relation to raw material requirements, particularly regarding rare earths in permanent magnet turbines (Carrara et al 2020, Bobba et al 2020).

B.3.3 Solar PV

As with wind turbines, raw material issues appear to be a significant potential constraint for solar PV cells and GHG emissions can be fairly high for certain sub-technologies; emissions for first-generation single cell technologies can be three times higher than the best performer, cadmium telluride (CdTe) cells. Nonetheless, their current popularity is likely to continue based on a moderately high EROI and relatively low vulnerability to socio-political barriers. The ongoing ability to produce solar cells easily and cheaply–reflected in high learning rates–is another key element affecting their future prospects and their viability will only increase if less material-reliant technologies, such as organic solar cells, continue to be developed (Carrara et al 2020).

B.3.4 Bioenergy

Learning rates for bioenergy technology are medium to high and they are typically far less reliant on critical raw materials. Yet, low EROI values–particularly for biogas and biofuels–and moderate to high emission rates could restrict the attractiveness of bioenergy as a long-term solution. More importantly, a variety of social and environmental issues relating to the production and processing of raw biomass remain as key obstacles to the widespread adoption of bioenergy in electrical and other energy systems.

B.3.5 Geothermal

Geothermal energy is a mature technology with low learning rates. It offers moderate emissions concerns and EROI levels with few raw material barriers. However, it can be susceptible to social acceptance factors in some locations (Manzella et al 2019). Thus, while its widespread adoption is restricted by the number of suitable geographical locations, electricity from geothermal heat represents an otherwise attractive option in many ways.

B.3.6 Solar CSP

Although learning rates, emissions reduction potential and EROI values are only moderate, no significant constraints are likely for solar CSP plants. Accordingly, it also appears to be a relatively desirable alternative. Nevertheless, large-scale utility installations are better suited to very sunny areas, explaining their rise in popularity in developing countries with increasing energy demands and high levels of solar radiation (Shahsavari and Akbari 2018). Solar CSP could well find greater success in such markets.

B.3.7 Marine

Despite a paucity of reliable EROI data, values for marine energy are unlikely to be high for smaller-scale applications. Larger tidal barrages, meanwhile, are likely to rival hydropower facilities. Notwithstanding this uncertainty, the simple and largely physical nature of the required infrastructure is likely to be reflected in lower material independence and socio-political concerns for most sub-technologies, although potential locations are limited. Future learning rates are predicted to be moderate, but more time and research are required for it to become a serious contender.

B.4 Discussion and conclusions

While most projections suggest that wind and solar PV will replace hydropower as the dominant renewable electricity technologies, various technical, economic, social and policy factors have the potential to influence the speed and degree of penetration of different forms of RES going forward (Selvakkumaran and Ahlgren 2019). This section has presented a timely overview of five overlooked factors that are likely to influence the ongoing penetration of different technologies into global electricity networks.

The current findings confirm that wind and solar PV remain likely to maintain their momentum towards becoming the dominant technologies. Both are rapidly developing with acceptable EROI values, and ongoing efficiency improvements and medium-high learning rates will continue to raise their attractiveness. Overall GHG emissions for wind turbines are on par with those for hydropower and, hence, are significantly lower than other technologies, including values for solar PV which vary significantly between the different technological approaches employed. At any rate, wind and solar PV are both notably vulnerable to raw material supply issues which could become a significant issue in the medium- to long-term and have impacts on the pace and ease of accomplishing the transition process. Bioenergy is revealed to be a relatively poor option due to low EROI values and the myriad social and political acceptance issues that surround it, particularly in relation to biomass production. At the same time, three currently less-dominant technologies–solar CSP, geothermal and marine energy–are comparably attractive and appear less susceptible to raw material issues. However, all three will be limited by their need for specific geographical or environmental conditions.

The current section does not attempt to provide definitive predictions for the future of electrical systems and markets as they develop, nor does it attempt to quantify final scores for each technology by applying weightings that reflect the importance of one category over another. Moreover, it is acknowledged that varying levels of uncertainty can be assigned to each of the factors and that, although clear patterns are often observed, significant levels of variation are often observed within categories. While these differences are primarily based on the different technological approaches contained within each category, uncertainty levels may also be linked to a lack of data or differing assumptions used. Indeed, it was observed that learning rate estimates for well-established technologies like wind and solar appear to be far more consistent than relatively undeveloped technologies like geothermal and marine energy, or than hydropower where old and new approaches produce a wider range of estimates. Furthermore, the section has not addressed the influence of the fossil fuel industry and other interest groups who actively seek to discourage and delay the uptake of renewable energy technologies (Stokes 2020) and acknowledge that these dynamics are likely to continue to play a significant role in determining the speed and shape of the transition as it develops. Rather, an attempt has been made to introduce and summarise the five additional factors in order to present a simple demonstration of the various strengths and weaknesses of each technology and their market penetration potential in the short to medium term.

In the end, it is hoped that the findings highlight important differences between technological approaches and the need to better incorporate a wider range of factors into the consideration of transition pathways. Fortunately, efforts are already being made within the modelling community to address these gaps. For example, new approaches to integrating life cycle aspects–and GHG emissions in particular–into IAMs and other energy models are developing (Pehl et al 2017, Pauliuk et al 2017, Arvesen et al 2018, Sacchi et al 2022), as have methodologies for expanding the consideration of material supply constraints (Capellán-Pérez et al 2020). The ENBIOS workflow, currently being developed within the SENTINEL project (SENTINEL n.d.), is designed to specifically produce indicators relating to these and other factors in conjunction with energy model outputs. A growing field of research is also beginning to explore methods that allow the complex range of socio-political and behavioural aspects of the energy transition to be included in IAMs and other energy models. This is typically achieved using a two-step process whereby quantitative scenarios or "storylines" are created exogenously before being translated into quantitative scenarios that can be included in model simulations (Köhler et al 2018, van Sluisveld et al 2020). A recent application of this approach can be found in a further application–known as QTDIAN (Süsser et al 2021)–also being developed within the SENTINEL project. Ultimately, it is suggested that the further integration and greater inclusion of a broader range of key emergence factors will result in more robust and meaningful modelling processes that, in turn, will enable more informed energy policy decision-making to occur.

C SECOND ARTICLE

Why energy models should integrate social and environmental factors: Assessing user needs, omission impacts, and real-world accuracy in the European Union

Diana Süsser, *Nick Martin*, Vassilis Stavrakas, Hannes Gaschnig, Laura Talens-Peiró, Alexandros Flamos, Cristina Madrid-López, Johan Lilliestam

Energy Research & Social Science, 20 September 2022, *https://doi.org/10.1016/j.erss.2022.102775*

Abstract

Energy models are used to inform and support decisions within the transition to climate neutrality. In recent years, such models have been criticised for being overly techno-centred and ignoring environmental and social factors of the energy transition. Here, the impacts of ignoring such factors are explored and illustrated by comparing model results to model user needs and real-world observations. Concrete user needs for the better representation of environmental and social factors in energy modelling are first identify via interviews, a survey and a workshop. The effects of omitting non-techno-economic factors in modelling are then explored and illustrated by contrasting policy-targeted scenarios with reality in four EU case study examples. It is shown that, by neglecting environmental and social factors, models risk generating overly optimistic and potentially misleading results, for example by suggesting transition speeds far exceeding any speeds observed, or pathways facing hard-to-overcome resource constraints. As such, modelled energy transition pathways that ignore such factors are likely to be neither desirable nor feasible from an environmental and social perspective, and scenarios may be irrelevant in practice. Finally, a sample of recent energy modelling innovations are discussed alongside a call for continued and increased efforts for developing improved approaches that better represent environmental and social factors in energy modelling and increase the relevance of energy models for informing policymaking.

C.1 Introduction

The European Union (EU) has set the goal of transitioning to a modern, resource-efficient, and competitive European economy, with the overarching objective of climate neutrality by 2050 (European Commission 2019). The energy transition is crucial to this plan and is a cross-societal process, including both socio-technical and socio-ecological drivers and constraints that underlie the required system changes (Martin et al 2020). EU energy policy strategies under the “European Green Deal” emphasise the need to develop energy systems that provide secure, affordable and clean energy, reduce environmental impacts, and enable citizens to participate and benefit (European Commission 2015, 2019). Nevertheless, most visions and policy goals concern the technological optimisation and economic costs or benefits of the energy transition and do not fully address multiple dimensions of truly sustainable pathways, including regional environmental impacts, material requirements of energy technologies, diverging normative views or citizen preferences. This imbalance, where energy policy is determined at the expense of factors outside the techno-economic realm, is also reflected in current energy modelling practices.

Most energy models used to inform the energy transition ignore factors other than techno-economic ones, generally seeking cost-optimal futures. They rarely consider environmental factors beyond greenhouse gas (GHG) emissions. For example, integrated assessment models (IAMs) typically only include simplified emission and land-use assumptions (IAMC n.d.). Modellers often entirely ignore social aspects, or only consider them as an exogenous narrative do be discussed “on top” of techno-economic findings, as a lens through which techno-economic scenarios can be discussed (Krumm et al 2022). Nevertheless, there is growing recognition that environmental and social factors must be included in models (Trutnevyte et al 2019, Nikas et al 2020). As with present energy systems, future decarbonised energy systems will face environmental constraints such as raw material or water availability (Moreau et al 2019, Calvo and Valero 2021). Presently, public opposition against energy infrastructure projects is halting transition progress in Europe and across the world (Sovacool et al 2022). Ignoring such factors risks producing mathematically elegant but politically irrelevant scenario results. At the same time, modellers are bound by model and computational capacities (Savvidis et al 2019) and will only include factors that are easily quantifiable or do not challenge the disciplinary barriers of their respective modelling frameworks (Pfenninger et al 2014).

These challenges result in a gap between the information provided by energy models and the information needed by those who use the model results. Scholars have identified gaps related to the modelling of behavioural and lifestyle changes (Chatterjee et al 2022), particular policy challenges (Savvidis et al 2019) and modelling of political or societal paradigm shifts (Koppelaar et al 2016). Neglecting these factors may result in energy policy goals or implementation strategies that conflict with environmental policy (Scott et al 2011), or undermine social goals unknowingly (Sokołowski and Heffron 2022). As a result, oversimplified models could fail to inform policymakers about the multiple dimensions crucial for a sustainable energy transition.

In this section, the concrete needs for better representation of environmental and social factors in energy modelling are outlined and the implications of current model shortcomings are explored. In a recent study (Süsser et al 2022), it was shown that both model users and modellers see a need for improved representation of social and environmental aspects in modelling. Here, the field is expanded by analysing more deeply what concrete environmental and social factors are considered most important for better representation in energy models and, by examining why these factors are important, their importance is highlighted. To do this, a two-fold approach is adopted. Firstly, specific user modelling needs for environmental and social aspects are identified and ranked via a series of interviews, a survey and an online workshop with different model users. Secondly, real world case studies are used to illustrate the magnitude of the problems that could potentially arise if important social and environmental factors re emitted from models. Finally, it is shown that the impact of omitting such factors could prove to be so large as to render results unfeasible and irrelevant, highlighting the necessity of considering non-technoeconomic factors as integral parts of energy models.

C.2 Background on environmental and social factors and energy modelling

A wealth of literature exists that addresses the different environmental and social factors that can drive or hinder energy transitions. Many studies investigate environmental impacts of renewable electricity production (Hollingsworth et al 2020, Li et al 2020), storage (Barnhart and Benson 2013), electric vehicles (EVs) (Mendoza Beltran et al 2020), material dependency (Watari et al 2019), or emissions (Nabernegg et al 2019). Other authors investigate social issues of energy transitions, such as behaviour and lifestyle (Lombardi et al 2019, Boßmann and Staffell 2015, Stavrakas and Flamos 2020), public acceptance (Tröndle et al 2020, Stavrakas et al 2019) and ownership (Perger et al 2021, Nikas et al 2020). Some studies also integrate both perspectives, by addressing environmental justice in energy and climate policy, for example (Hess et al 2022, Avila 2018). In the following, the current state of the literature regarding environmental and social factors in the field of energy modelling, particularly in relation to energy transition processes, are outlined and discussed.

C.2.1 Environmental implications of the energy transition

The reduction of carbon dioxide (CO_2) and other GHG emissions needed for mitigating climate change dominates the debate about environmental impacts in the energy sector (Iacobuta et al 2018), although policy decisions and models generally only depict the direct emissions during the final stages of energy production. Indirect emissions related to other stages of production life cycles–e.g., those related to extraction of raw materials, production, transportation, and installation of components, and the ongoing maintenance and eventual decommissioning of plants–are often not accounted for and remain “hidden” (Pehl et al 2017).

The need for raw materials is another issue that has gained increasing public and political attention as the ongoing production of many sustainable energy technologies–especially wind turbines, solar photovoltaic (PV) cells, and lithium-ion batteries–require supplies of critical raw materials (CRMs) (Carrara et al 2020). For example, Europe is 100 % import reliant on borates, lithium, and graphite for EV batteries, silicon metal for photovoltaic panels, niobium for permanent magnets in wind turbines, and a mix of diverse rare earth elements for EV batteries and permanent magnets (Bobba et al 2020). China remains the dominant provider of processed materials and components (Carrara et al 2020, Bobba et al 2020). Dependency on scarce raw material often leads to geopolitical clashes, "carbon leakage" (Nabernegg et al 2019, Liu et al 2018, Saevarsdottir et al 2020), externalisation of impacts (Lèbre et al 2020) or environmental dumping (Ma and Duan 2009). Greater adoption of material reuse and recycling could help to alleviate such pressures (Gaustad et al 2018) and, therefore, strengthening the circular economy has become a key strategy within the EU (Mayer et al 2019).

Quantifying the impacts of energy infrastructure on land, water, and biodiversity is also gaining attention, particularly within the growing literature surrounding the water-energy-food nexus (Diaz-Maurin et al 2014). For example, impacts relating to land occupation have been identified for wind and solar installations (Voigt et al 2019, Bennun et al 2021), land-use impacts and water overexploitation are often linked to bioenergy (Santangeli et al 2016), and biodiversity issues can be linked to hydropower, marine and geothermal energy (Gasparatos et al 2017). Although some studies have investigated land-use for solar farms (Giamalaki and Tsoutsos 2019), onshore wind turbine siting remains the most prominent example of land-use conflicts regarding renewable energy technologies (Gross 2020, Felber and Stoeglehner 2014). Finally, the water required for different energy production options is gaining attention as southern and more arid countries seek to adopt cleaner technologies and general awareness of water availability issues grows (Huang and Eckelman 2020).

Nevertheless, despite the importance of these aspects, most of the models used to inform energy policy are limited in their consideration of environmental factors. First, most accounting methods only consider direct emissions, and the indirect emissions and other impacts embodied within energy processes. Second, CRMs are generally not considered in any detail, particularly not in the large-scale models being used to inform overarching climate policy. Third, although land availability issues continue to be an issue in energy planning processes (Rinne et al 2018, Shum 2017, Capellán-Pérez et al 2017, Palmer-Wilson et al 2019, McKenna et al 2022), it is generally only modelled as a constraining factor for technical potentials and societal or political preferences for present or future land use are largely ignored.

C.2.2 Social drivers and barriers to the energy transition

While environmental aspects are considered constraining factors to most transition options, social aspects can influence transition processes by both accelerating or impeding them (Sovacool et al

2022). Although the transition to renewable energy enjoys high public approval levels within the EU (European Union 2021), concrete projects often face considerable opposition (Sovacool et al 2022, Cohen et al 2022). Issues typically relate to the increasing number of renewable energy plants and associated transmission infrastructure, conflicts arising from place attachment (Devine-Wright and Batel 2017), planning and siting issues (Quentin 2019), visual and aesthetic impacts (Borch 2018), land-use conflicts (Månsson 2015), biodiversity loss (Voigt et al 2019, Vasilakis et al 2016, Kati et al 2021), and noise, or health concerns (Knopper et al 2014). Accordingly, the social acceptance of strategies and projects is gaining importance as the transition accelerates towards 2030 and 2050 targets. This includes not only acceptance of technologies, but also of new end-use services or practices and lifestyles or cultural meanings of energy (Geels 2019). The effort to increase awareness and acceptance accompanies calls for comprehensive citizen participation and ownership (Cowell et al 2011, Süsser and Kannen 2017, Walker et al 2014) and research continues about the ways that local populations make choices about consumption and investments (Balest et al 2018), and how social acceptance is formed. However, this knowledge is yet to be widely integrated into energy models.

The energy transition has given rise to a new generation of agents who take on the role of active producers, distributors, consumers, and sellers of renewable electricity, the so-called “prosumers.” Citizens may become owners, eventually consuming their own electricity, or become part of community energy projects (European Commission 2015), potentially bringing local benefits, such as employment and increasing project acceptance (Cowell et al 2011). Still, the advantages and mechanisms that allow citizens to participate in transition processes are also generally excluded from energy models.

Furthermore, many researchers have studied how norms, practices and culture shape energy behaviour (Stephenson et al 2015) and how consumer behaviour and lifestyle affect climate change mitigation (Creutzig et al 2018). Despite the high environmental awareness among citizens in industrialised countries, behavioural changes and sufficiency-based lifestyles are still relatively uncommon for reasons such as lack of awareness, comfort, fear of loss, or exclusion (Toulouse et al 2017). In contrast, behavioural change is often seen not as a welfare loss but as a gain in wellbeing and satisfaction (Samadi et al 2017), as beneficial lifestyle innovation (Göllinger 2012), and the “holy grail” of sustainability (Morrissey et al 2016), particularly outside mainstream economics. Nevertheless, energy sufficiency remains a marginal strategy in energy policy documents compared to energy efficiency and renewable energy sources (Zell-Ziegler et al 2021). Many models, however, assume that lifestyle changes are happening, and demand-side measures have gained increasing interest to initiate consumer behaviour.

As behaviour is strongly guided by routines, public policy plays a central role in adapting behaviour, including modifying consumption and investment choices (Tummers 2019) and in municipal renewable energy deployment (Lerman et al 2021). For example, some EU member states, including Germany, Spain and Denmark, implemented feed-in laws in the 1990s, thus supporting the early adoption of renewable energy technologies by individuals and municipalities (Mey and Diesendorf 2018, Süsser et al 2017).

In any case, while current energy models rarely represent these social factors, different model types do offer some capabilities (Krumm et al 2022). For example, more nuanced bottom-up modelling approaches, like agent-based models (ABMs), can address social barriers for solar PV adoption (Nikas et al 2020) or peer-to-peer energy trading in local communities (Perger et al 2021), while demand models can address drivers and patterns of household energy consumption (Stavrakas and Flamos 2020). However, significant modelling gaps exist, especially when dealing with transition dynamics, e.g., speed of transformations and path dependencies (Trutnevyte et al 2019), and socio-technical systems that captures agent heterogeneity, e.g., zero-energy communities (Mittal et al 2019).

C.3 Methods

To highlight the relevance of including social and environmental aspects in energy modelling, a previous, related study (Süsser et al 2022) is used as a starting point. This study found that, in general, environmental and social aspects are relevant to modellers and users of model results, is used. Here, working with the same data, further investigation reveals which environmental and social factors of the energy transition are relevant for inclusion in energy models. These factors are then ranked in order of importance using stakeholder-based information. Several case studies are then investigated that provide instances where models have ignored these central environmental and social factors. Their importance is then illustrated by comparing them to real world conditions and constraints. As **Figure C.1** suggests, both empirical and desk research was conducted. It is noted that the study largely coincided with the COVID-19 pandemic. As such, all stakeholder engagement activities were conducted online, as was common practice in the EU energy research community at the time (Süsser et al 2021).

C.3.1 User needs: identification and ranking

A total of 32 interviews were conducted in five jurisdictions: the EU, Germany, Greece, Poland, and Sweden. This included four different stakeholder groups that participate in modelling-informed energy policymaking in Europe: scientists, non-governmental organisations (NGOs), energy industry experts and policymakers. The interviews were guided by a semi-structured guideline, were conducted in English, or in the national language of the location, and all interviews were transcribed and anonymised after being recorded. More information is provided in the appendix in section **J.3**.

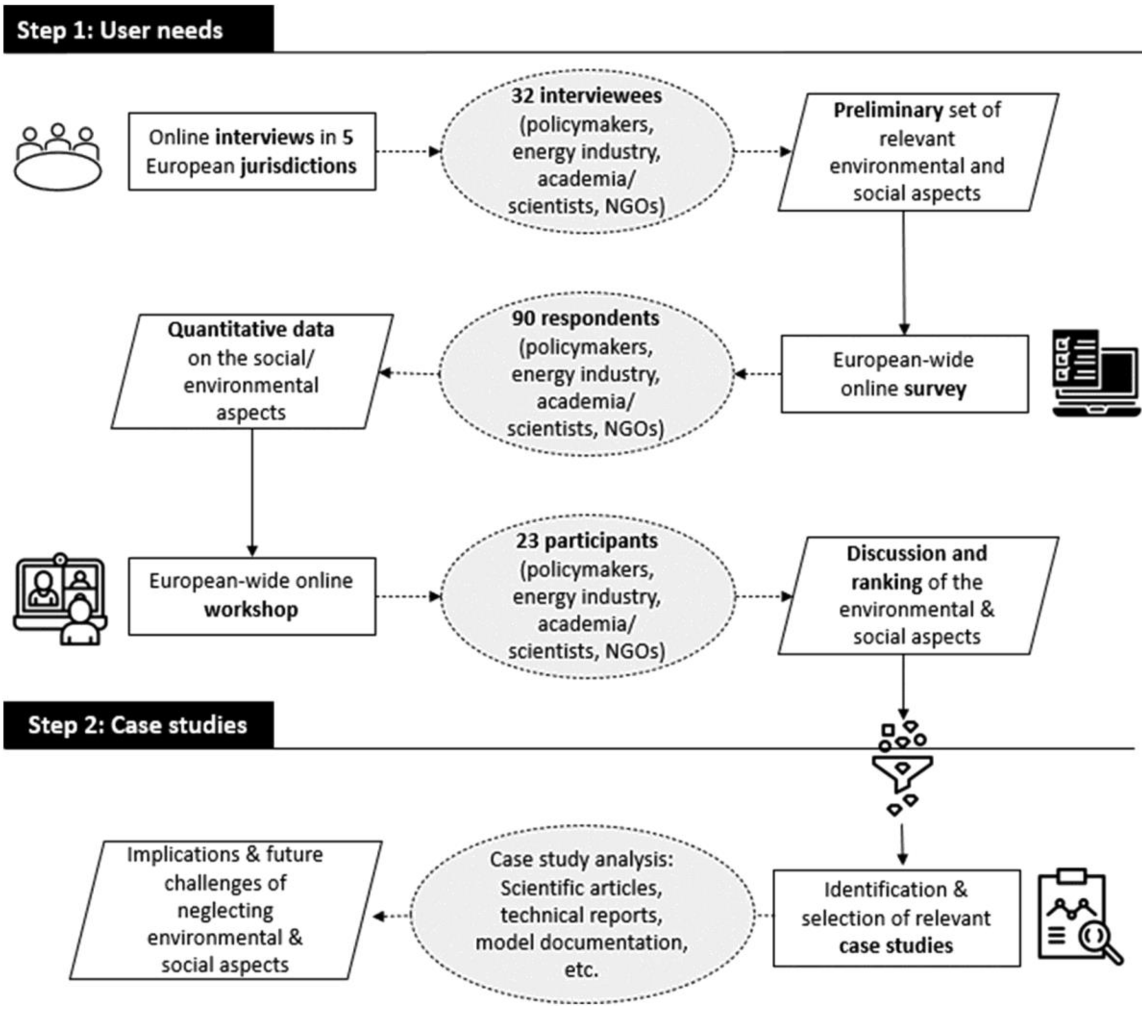


Figure C.1. Two-step approach employed within the study, consisting of empirical and desk research components

Building on the interview findings, a Europe-wide survey was performed to obtain deeper insights about which social and environmental factors are important from a larger stakeholder sample. The survey was designed as a semi-quantitative online questionnaire and contained different question formats, from single and multiple choice to Likert-like scales and free-text boxes, depending on the variables to be addressed. The survey was distributed among national, European and international organisations, to representatives from politics, civil society, business/industry and research, via private and public online channels. Questions were aimed at determining which factors should be better represented by models and asked specific follow-up questions regarding environmental and social aspects. In all, a total of 90 completed questionnaires were received. Further information on the survey can be found in the appendix in section **J.3** and the questionnaire and anonymised aggregated data are available at Zenodo (Gaschnig et al 2021).

Finally, the environmental and social factors identified were discussed and ranked in a workshop with stakeholders from different EU member states. The workshop allowed us to discuss specific user needs in more detail and collect more data on the different aspects. One breakout session on the modelling of environmental aspects was held alongside one on the modelling of social aspects. For the social aspects, the ranking results from two live polls were integrated into two breakout sessions. For environmental aspects, attendants to two breakout sessions discussed and agreed a ranking. Accordingly, only integrated results are shown here. Furthermore, because only 25 stakeholders participated in the workshop, no distinction was made between each stakeholder group. Further information on the workshop also can be found in the appendix in section **J.3**.

C.3.2 Case studies on omitting environmental and social factors in energy modelling

For the top-ranked user needs, specific cases where energy system models have neglected environmental and social factors were identified and selected (see **Figure C.1**). These cases illustrate the type and magnitude of problems on the relevance of model-informed policymaking that may arise when models ignore these factors. Four case studies were then selected, each within a different European context. Each of these demonstrate instances in which model output and observed development are strongly misaligned because a critical social or environmental factor has been ignored within the relevant models. For each case, a thorough document analysis was conducted in relation to modelling applications and these findings were compared with real-world developments and policy targets. The goal was not to demonstrate that models fail to predict the future, as this is not their aim; most models are used to explore possible (simplified) systems and investigate options and sensitivities. Rather, the findings are used to illustrate the importance of environmental and social concerns within models so that deeper and more robust understandings of the mechanisms of transition pathways and more policy-relevant model advice can be obtained in the future.

C.4 Results

C.4.1 User needs on environmental and social aspects of the energy transition

The findings suggest that model users want better integration of different environmental and social factors of the energy transition in models, particularly with respect to raw material demand/availability and natural impacts (environmental) and social acceptance, consumer behaviour and policy dynamics (social). The results show that users prefer the explicit integration of social and environmental aspects over further improvements of techno-economic aspects: The workshop participants ranked “Impact on the environment and natural resources” highest, followed by policy impacts, social impacts and costs (see **Figure A.1**). The high-level results from the survey have been reported elsewhere (Süsser et al 2022, Gaschnig et al 2020). Here, the environmental and social aspects model users see as particularly important are presented in more detail alongside the ways in which the users ranked these aspects and the reasons provided for their relevance.

C.4.1.1 Environmental aspects

The results identify raw material use and material circularity as central model user concerns. More than half of the survey respondents stated that they would like to see raw material demand integrated into energy models, followed by GHG emissions, air pollution, water usage and loss of biodiversity (see **Figure C.2**), although relevance varies strongly by user group. Energy industry and researchers tended to prioritise GHG emissions and air pollution, whereas NGOs and policymakers expressed greater concern about raw materials, water issues and biodiversity. One NGO representative underlined this by saying: "*Also, the whole environmental aspects, like the biodiversity aspect of wind energy... we can't achieve 100% renewables without having hundreds of gigawatts of offshore wind. That is going to be crucial, but you also have to do it in a sustainable way*" (EU_NGO#2). Another interviewee added that "*It is a question of resource efficiency. The resources to reduce climate gases, but also that we need to use the resources we are having as efficient as possible–also if it's waste, we are using*" (Sweden_science#4).

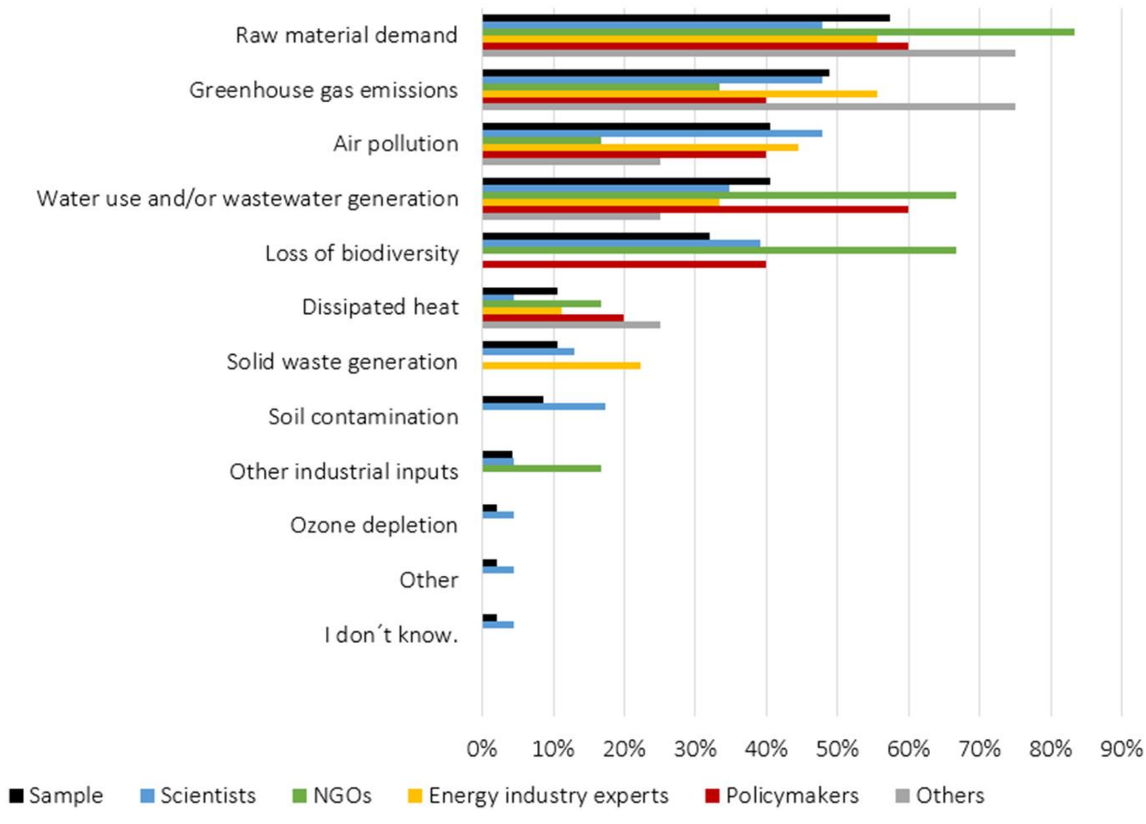


Figure C.2. Key environmental aspects identified by the user needs survey (choice frequency; up to three answers possible, voluntary question). Responses were obtained for the following question: "You stated that environmental, or resource-relevant issues should receive more attention by energy models. What environmental factors would you like to see integrated into energy models more in the future?", N = 47

In the interviews and at the workshop, methods to capture the full life cycle of energy technologies and infrastructures, and not only direct impacts, and the degree of externalisation of impacts that can be observed in the literature, were further central concerns. The relative importance of environmental aspects was also explored within the workshop. When asked to rank factors, participants identified four aspects of particular importance: (E1) Raw materials, (E2) Biodiversity, land use, and water use, (E3) Life-cycle perspective, and (E4) GHG emissions beyond combustion (see **Table C.1**). The inclusion of environmental aspects goes beyond the need to protect our ecosystems and natural resources. Indeed, the main reasons argued for the need of including environmental aspects were: i) to support decision-making processes, ii) to enable links to other models, policies, and strategies, and iii) to facilitate citizen empowerment and stakeholder engagement.

Table C.1. Ranking of environmental factors

Ranking	Factor
1	Raw materials
2	Biodiversity, land use, and water use
3	Life-cycle perspective
4	GHG emissions beyond combustion

C.4.1.2 Social aspects

A high demand was also found for the better representation of social aspects in energy models. When asked to select aspects that require better integration, participants nominated three aspects most often: co-benefits of prosumerism and community energy, social drivers and barriers of innovation diffusion, and dynamics of social acceptance and individual attitudes (see **Figure C.3**). Here again, different stakeholder groups differ in choice frequency. Social acceptance and individual attitudes were more often chosen by NGOs, whereas policymakers raised concern about the impacts of social issues on politics and policies more often than other users. Both NGOs and researchers agreed that benefits of individual and community participation should receive more attention. One interviewee highlighted the interlinkage between these different factors: *"…we have connections to social acceptability, because if we go into a more decentralised approach, we can create more value for the regions, or for all European places, where you have your own creation of energy and you have your own value chains. You have local jobs, local economy, and then, local acceptance*" (EU_NGO#1).

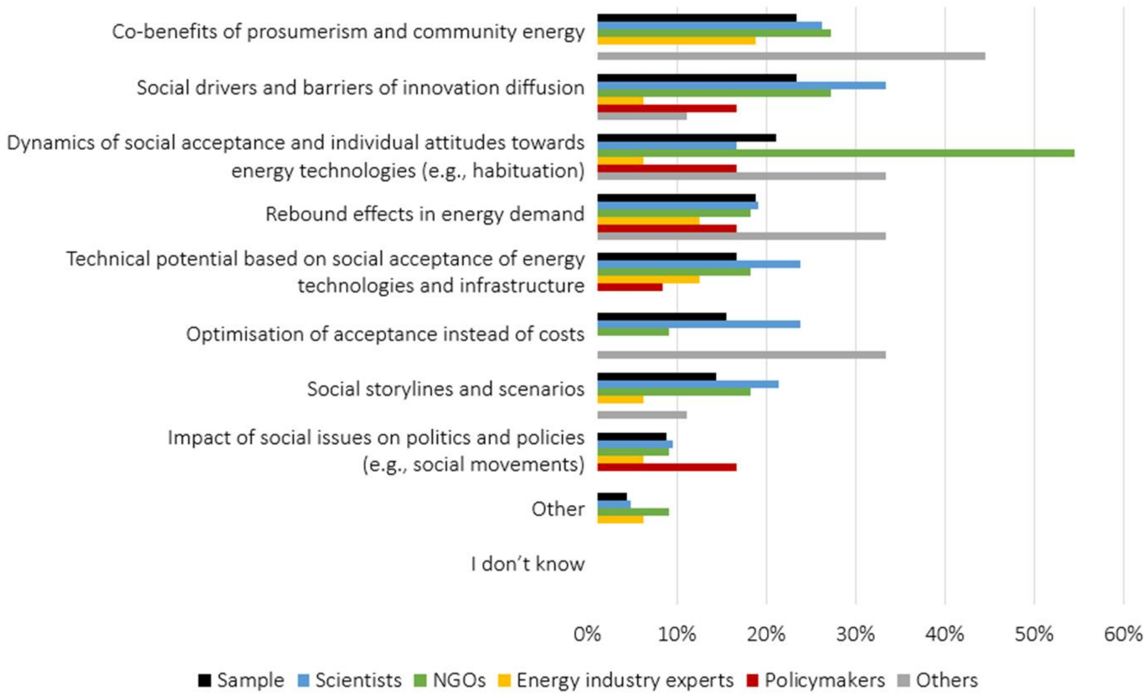


Figure C.3. Key social aspects identified by user needs survey (choice frequency; up to three answers possible, voluntary question). Responses were obtained for the following question: "You stated that social aspects should receive more attention by models. What social aspects would you like to see integrated into energy models more in the future?" (voluntary, multiple choices, up to three answers), N = 49, Explanation of terms: "Social acceptance" refers to the willingness of people to accept the installation of energy-related infrastructure, usually near them. "Optimisation of acceptance" refer to the aim of making resistance to installation as low as possible. "Social storylines and scenarios" refer to scenarios that include qualitative storylines, describing also societal developments and interactions and interdependencies between actors, technologies, and policy interventions in the context of the energy transition

In addition to social aspects, discussions in the stakeholder workshop also revealed the relevance of a better integration of policies in energy modelling, going beyond CO_2 prices as the only policy measure for prioritisation. During the discussion, participants expressed the need to understand the science and to compare it with ongoing policy processes, and to understand how policy changes can trigger behavioural changes. Many stakeholders also raised questions in connection to the choice of policy instruments for reaching targets. One interviewee asked: "*And in the area of policy instruments, how you can move faster with the climate action? What instruments do we need?*" (Sweden_scientist#4).

In the workshop, stakeholders were asked to rank different social aspects in two breakout sessions and two subsequent rounds of live polling, finding the most important aspects to be: (S1) Social acceptance/opposition, (S2) Individual and community participation, (S3) Consumer behaviour and lifestyle, and (S4) Policy dynamics (see **Table C.2**). One interviewee confirmed the limitations of current energy models by stating: "*It can be in terms of social acceptance, it can be in terms of job creation, it can be in terms of socio-economic impacts that are not all factored in the model that is* *being run*" (EU_industry#2). One policymaker added that "*[t]he improved simulation of "real-world" decision-making and behavioural aspects is always welcome and offer robust results in the quantitative analysis*" (Greece_policymaker#1). The main reasons argued for the need of including social aspects were: i) to better understand people's decision-making processes and criteria, and lifestyle choices, ii) to enable citizen and community participation in the energy transition, and iii) to understand the (distributional) effects of different policy measures.

Table C.2. Ranking of social factors

Ranking	Factor
1	Social acceptance/opposition
2	Individual and community participation
3	Consumer behaviour and lifestyle
4	Policy dynamics

C.4.2 Case studies on the importance of environmental and social factors

Four case studies were undertaken to illustrate the potential effects of omitting the top-ranked environmental and social factors from energy modelling. The case studies and the omitted user needs are listed in **Table C.3**. Note that point E3 (life-cycle perspective) is not explicitly illustrated because it is implicit in the materials issue. Likewise, point E4 (GHG emissions beyond CO_2) is not illustrated because reducing emissions is understood to be the key motivation of the energy transition and a key variable in most energy models. For each case, the published model scenarios–or, in some cases, the lack of suitable outputs–are presented alongside real-world situations to highlight mismatches between model results, real-world developments and policy targets.

Table C.3. Identified case studies for demonstrating the importance of integrating environmental and social aspects into energy modelling

Case study	User needs
The EU electricity grid plan without people and nature	(E2) land use
An environmental dilemma for electric vehicles in the EU?	(S1) social acceptance/opposition
Headwind for onshore wind power in Germany	(E1) raw materials
Domestic investment behaviour for small-scale PV in Greece	(S3) consumer behaviour

C.4.2.1 The EU electricity grid plan without people and nature

Transmission grid expansion is a key pathway for integrating fluctuating renewable supplies into power systems. Many modelling studies show that new transmission lines must be built for a least-cost electricity system in the EU. Rodríguez et al (2014) quantified the benefit of power transmission between countries to support almost 100% renewable power, finding a cost-minimum for a grid five times as large as today's. Similarly, Tröndle et al (2020) found that the cheapest, continent-wide, fully renewable electricity supply would require twice the present transmission grid. However, they also show that if the transmission grid is used for the continental-scale balancing of net self-sufficient regional supplies, much less transmission capacity–roughly the size of today's transmission system, but with twice the cross-border capacities–would be required. Most cost-optimised renewable power scenarios critically hinge on the realisation and feasibility of grid expansion.

Beyond grid expansion, such scenarios often envisage large concentrations of generation and transmission at specific locations (Tröndle et al 2020). Therefore, local acceptance is an essential factor; if citizens in these key places do not accept the plans, the scenario becomes irrelevant as the proposed projects may be delayed or not built at all. For example, the main scenario of the German Advisory Council for the Environment projected 42 gigawatts (GW) of interconnection between Germany and Denmark, and 48 GW crossing the Skagerrak to the hydropower stations in Norway; in their *Supergrid* scenario, these interconnectors are 53 GW and 116 GW, respectively (German Advisory Council on the Environment 2011). In 2020, the German-Danish interconnection capacity was 1.7 GW northward, with an ongoing expansion project to 2.5 GW (Energinet 2020). The Danish mainland is just over 50 kilometres wide at its narrowest point, suggesting that, if lines are land-based, these scenarios imply on average 1.0-2.5 GW of transit powerline per cross-section kilometre in Denmark. This casts great doubt on the feasibility–especially the social and political feasibility–of such a plan: Will Denmark accept such enormous capacity lines, especially if they are merely passing their country with no immediate benefit to them? Indeed, opposition from transit countries has been problematic in past projects, including the Desertec plan to import solar power from Morocco to Germany (Lilliestam et al 2016).

Most political visions and plans are model supported. For example, the European Commission (EC) use the EU Reference Scenario as a central basis for their decisions (European Commission 2021b). Furthermore, many models, such as PRIMES, assume that the infrastructure plans within their simulations are completed as intended (European Commission 2021b). ENTSO-E's Ten-Year Network Development Plan (TYNPD) 2020 expects that over 300 transmission projects of some 45,000 kilometres will be commissioned by 2040 (ENTSO-E 2022), with about 50% of projects expected to be operational by 2021–2025 (see Figure C.4). However, if such plans do not materialise, models using this assumption clearly produce less meaningful results.

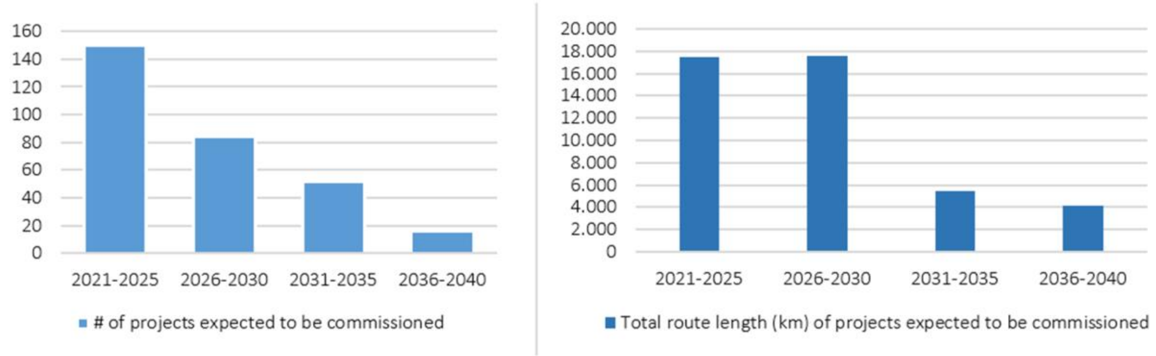


Figure C.4. Transmission project timeline in the 2020 ENTSO-E Ten-Year Network Development Plan. Data source: ENTSO-E (2022b)

In reality, implementation has been slow, with only 40% of projects on or ahead of schedule, and all others delayed or altered in various ways (see **Figure C.5**). In 2020, 65 TYNDP transmission projects (17%) were reported as delayed, and this only includes early projects (2021–2025) as later projects have not yet entered stages in which delays can occur (ENTSO-E 2022). This has not changed significantly over time: in 2012, a third of projects were reported as being delayed due to "social resistance and longer than initially expected permitting procedures" (ENTSO-E 2012). Pall et al (2019) investigated the causes of deployment delays in international power transmission projects and found that local public resistance and political interventions (strikes/blockades) are the main reason, while other research found that public opposition is the most important delay factor in national projects (Perras 2015). Underlying causes could be environmental concerns related to new grid infrastructure, as new expansions in power lines have the potential to harm local environments, and impact biodiversity during both the construction and operation phases (Biasotto and Kindel 2018).

In sum, there is a large gap between what scientific and advice-oriented models project and what is observed on the ground in transmission projects: not only are network plans much smaller than the vast-scale expansion that cost-optimising models find beneficial, but actual progress is typically much slower than models optimise/simulate. This means that system models risk generating meaningless findings, highlighting the problem of ignoring social factors in technical models.

C.4.2.1 An environmental dilemma for electric vehicles in the EU?

The EU aims to reduce CO_2 emissions from cars by 55% (compared to 1990) by 2030 and proposes to ban sales of fossil-fuelled cars by 2035 (European Commission 2019). Electrification of transport plays an important role in reaching net-zero emissions by 2050 (IEA 2021). A variety of energy models have explored future EV penetration rates and project EV use to increase dramatically in coming decades. For example, the International Energy Agency (IEA) Mobility Model projects 16 million electric cars in their Stated policies scenario in the EU by 2030 and 33 million in their *Sustainability* development scenario (IEA 2022). Statharas et al (2019) quantitatively assessed the impacts of factors that drive market penetration of electric cars in the EU, using the PRIMES-TREMOVE model, and project under the most optimistic scenario, that 18% of the total car fleet in the EU will be electric by 2030.

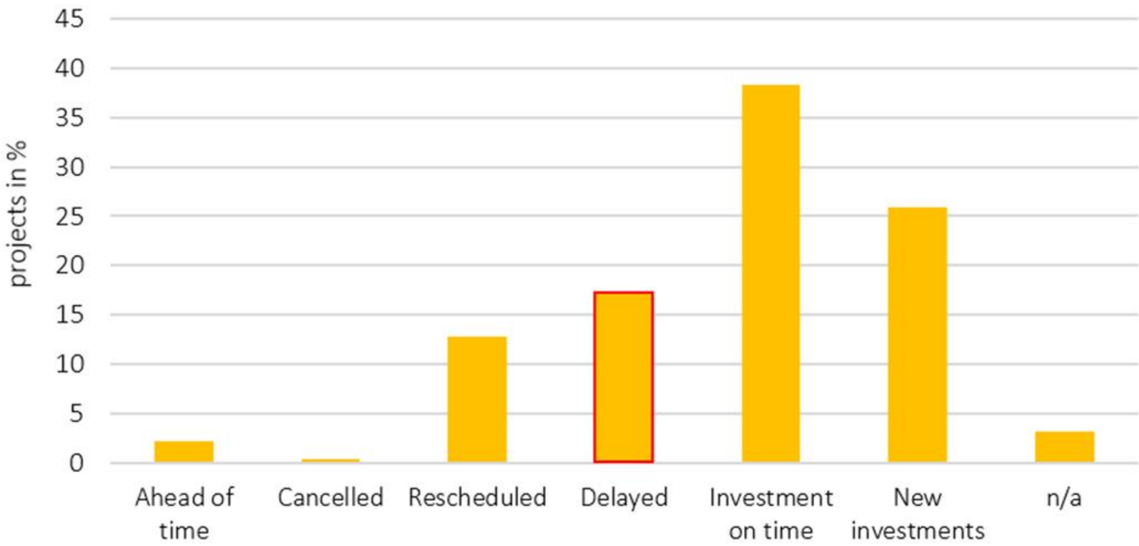


Figure C.5. Progress of all transmission investments since TYNDP 2018, n = 321 projects. “Ahead of time”: expected commissioning date is earlier than anticipated in the previous TYNDP. “Rescheduled”: commissioning has been postponed due to a voluntary decision. “Delayed”: expected commissioning date is later due to delay (unvoluntary). “On time”: no change compared to previous TYNDP. “New investments”: new in the TYNDP 2020 (in comparison to 2018). Data source: ENTSO-E (2022)

Although energy models include detailed analyses of the transport sector and EV numbers, very few consider raw material requirements as a potentially constraining factor in their calculations. Yet, such factors may prove critical. For example, Xu et al (2020) developed a material flow analysis showing that global EV battery demand would increase key minerals consumption by a factor of 20–30 by 2050. While progress has been made to develop methods for assessing material requirements (Boubault et al 2019) and supply risk (see sections **D** and **E**) within energy models, these concepts are yet to be widely implemented, and most IAMs and energy models are yet to include CRM constraints at all.

The EU seeks to increase its EV fleet from about 3.2 million in 2020 (IEA 2021) to at least 30 million by 2030 (European Committee of the Regions 2022). Although electric car registrations in Europe more than doubled in 2020 compared to 2019 (IEA 2021), this target requires a sharp increase in sales, especially as there are large differences across Europe: Norwegian new sales now exceed 75%, whereas many Eastern and Southern European countries remain below 5% (EEA 2021). Adding to concerns about range and charger availability, many consumers and policymakers also question whether the technology is more environmentally friendly (Burkert et al 2021, Continental 2021).

For EV battery production, the materials of most concern in current designs are lithium, cobalt and natural graphite. New, advanced battery designs are under development and may bring increasing demand of silicon, titanium and niobium (Bobba et al 2020), all of which are considered critical by the EC (European Commission 2020). The EU relies almost exclusively on imported raw materials in battery manufacturing, with one-third imported from China and one-fifth from Latin America and Africa, respectively. Processed materials, particularly those used for cathodes and anodes, are also imported, especially from China (52%) and Japan (31%) (European Commission 2020). The EU does not produce any of the finished battery assemblies it uses, importing these mainly (66%) from China. Europe thus faces a two-fold challenge: not only are many needed materials scarce in general, but almost all of them are not produced domestically, making the European EV strategy vulnerable to supply risks.

The European Union (Bobba et al 2020) made material demand projections for lithium-ion battery production for three future e-mobility pathways, showing that even the lowest deployment pathway for batteries alone requires several times the present total EU consumption of lithium, cobalt and graphite (see **Table C.4**). This suggests that serious limitations may occur unless the EU can drastically increase its supplies of the three CRMs considered. Even if the EU imports all its EV batteries (Naumanen et al 2019), global resources and production remain limited, showing that there is a very real threat to the accelerated uptake of EVs, both in Europe and globally (Xu et al 2020). This raises the question of how feasible such projections are if they neglect material constraints, or whether sufficiency strategies for avoiding mobility, or shifting to other modes of transport, do not need to be pushed much more in the social and political debate.

C.4.2.1 Headwind for onshore wind power in Germany

Wind power substantially contributes to the power mix in Germany. In 2020, around 18% of gross electricity production came from onshore and about 5% from offshore plants (Statista 2022). In December 2021, the German onshore wind power capacity was 56 GW (AGEE-Stat 2022) and, as the energy transition progresses, it will likely become the most important electricity source (Fraunhofer ISI et al 2017). The Renewable Energy Act 2021 aims for 71 GW capacity by 2030 (Bundesregierung 2021), while the government’s long-term climate scenarios foresee 80 GW (das Umweltbundesamt 2021). These targets equal an annual average expansion of 1.7–2.7 GW/year.

Table C.4. Current total EU consumption and projected requirements for EV batteries alone for three key materials. Projected electric vehicle numbers are listed in accordance with low-, medium-, high-demand scenarios (LDS, MDS, HDS). Adapted from Bobba et al (2020)

		2020	2030			2050		
			LDS	MDS	HDS	LDS	MDS	HDS
Total EU consumption *[tonnes]*	Cobalt	30,000						
	Lithium	6,000						
	Graphite	250,000						
Projected EV requirements *[tonnes]*	Cobalt		38,000	67,000	120,000	38,000	110,000	290,000
	Lithium		32,000	51,000	90,000	48,000	130,000	260,000
	Graphite		340,000	500,000	820,000	700,000	1,800,000	2,700,000
Projected EV requirements *[times total EU consumption in 2020]*	Cobalt		1.3	2.2	4.0	1.3	3.7	9.7
	Lithium		5.3	8.5	15.0	8.0	21.7	43.3
	Graphite		1.4	2.0	3.3	2.8	7.2	10.8

Many studies are investigating the wind power expansion needs for decarbonising the German power system. For example, Fraunhofer ISE (Brandes et al 2021) analysed options for GHG neutrality by 2045 using the REMod model in which energy system simulation and cost-optimisation are coupled (hybrid optimisation). Modellers developed four scenarios characterised by multiple restrictions. The *Reference, Inertia and Sufficiency* scenarios assume a German onshore wind fleet of up to 230 GW. Meanwhile, in the *Unacceptance* scenario, where it is assumed that expansion struggles from strong public opposition, capacity only reaches up to 80 GW; instead, emissions targets being achieved via a massive expansion of solar PV (660 GW), which may also face strong opposition due to high installation rates. Either way, the more ambitious wind deployment figures roughly correspond to a tripling and quadrupling of current onshore capacity and an average expansion pace of up to 7 GW/year.

The deployment rates required for such climate-neutral system projections depart strongly from the observed development. While Germany seemed almost “on track” with growing annual expansion rates between 3.7 and 5.2 GW onshore wind power during 2014–2017, this pace has since dropped to 1.1–1.9 GW/year (Deutsche WindGuard GmbH 2021). The decline was caused by changes in the policy support (shift from feed-in-tariff to auctions) and, especially, difficulties with installation permits, often originating from local opposition to new wind power projects (Quentin 2020, Witsch 2021). Despite broad support for the energy transition in general, one-fifth of the population rejects or strictly rejects further deployment of onshore wind power (Renn et al 2020), with numerous anti-wind citizen initiatives emerging (Gardt et al 2021). The causes of opposition, indicated by lawsuits and local resistance, are manifold and largely connected to environmental and social factors. Some 20% of all onshore wind power projects are affected by litigation (Quentin 2019), mainly from environmental organisations, but also from citizens and citizen initiatives, often raising concerns about biodiversity (Voigt et al 2019). This situation is similar around Europe (Kati et al 2021, Vasilakis et al 2016). A further key driver of wind power opposition is its land use, owing to the vast amounts of land required for wind farms, potentially triggering direct land-use conflicts, and public opposition due to visual and aesthetic landscape impacts (Deutsche WindGuard GmbH 2021, Quentin 2020). In the long run, wind power land use could be substantial, at least 1–2 % the German land area (Bund-Länder-Kooperationsausschuss 2021, Tröndle 2020).

In summary, large disconnects exist between what models say is necessary for carbon-neutrality and what is feasible given the opposition (see **Figure C.6**). On the one hand, current onshore wind development does not align with prominent scenario results (except, for example, *Unacceptance* scenarios). On the other hand, current policy targets are not ambitious enough to reach the demanded wind fleet. The latter might, however, change as the government plans to update the expansion targets of onshore wind power in the Renewable Energy Act, with a substantial increase in the annual auction volume to 10 GW by 2027 (BMWK 2022). If the law passes the parliament, Germany is on the path to reach more than twice the installed capacity compared to current plans by 2035 and soon even overtake the ambitious *Reference* scenario of the Fraunhofer study. However, if the government does not react to the causes of the “wind market implosion”, especially the growing opposition to wind power plants routed in environmental and social factors, its expansion plans might fail and possibly contribute to further resistance.

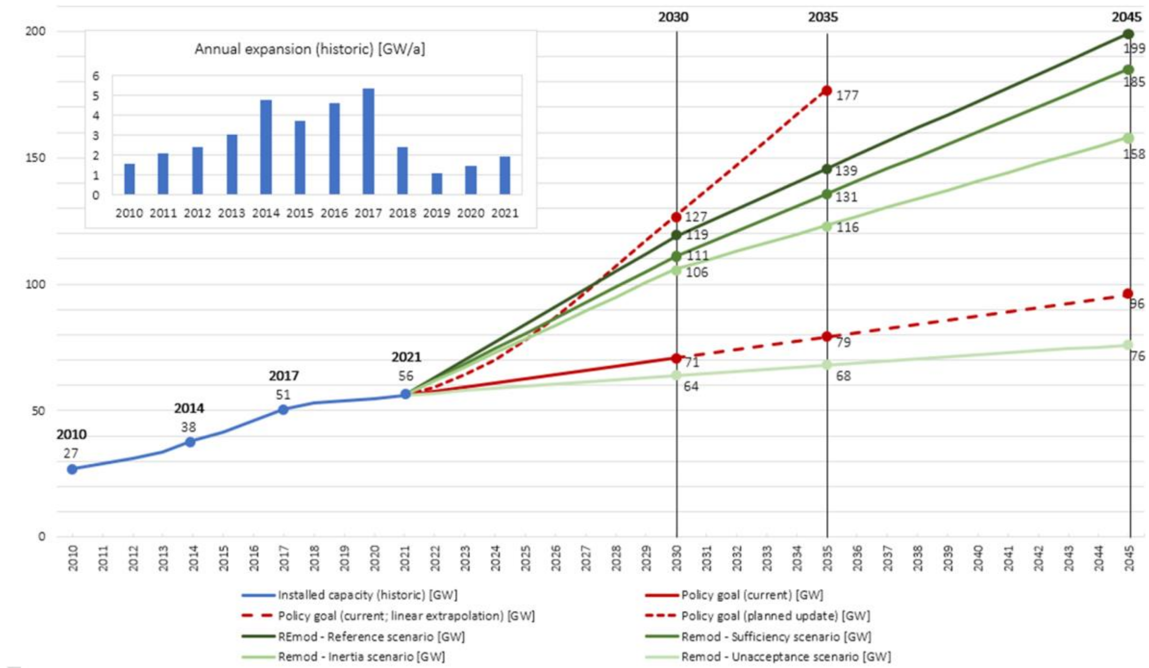


Figure C.6. Installed onshore wind capacity in Germany. Real-world developments, policy goals, and modelled needs in a 100 % renewable future. Data sources: Bundesregierung (2021), Brandes et al (2021), BMWK (2022), Bundesverband Windenergie (2021) and linear interpolation and extrapolation of missing data; rounded values

C.4.2.2 Domestic investment behaviour for small-scale PV in Greece

In June 2009, the Greek government introduced the "Special programme for the deployment of solar photovoltaics (PV) on buildings and roofs", which simplified installation procedures for domestic solar PV installers and provided a generous feed-in-tariff of €550/MWh to attract investments (Anagnostopoulos et al 2017). Later that year, the process for the transposition of the Renewable Energy Directive into the national legislation was initiated. Different energy models were used in this process to evaluate the energy policy scenarios developed, and to perform a sensitivity analysis taking into account different evolution paths of fiscal/regulatory parameters. In particular, the TIMES-MARKAL model (Loulou and Labriet 2008) was used to calculate the specific targets for each type of technology, underneath the overall national renewable target, while the ENPEP model (ANL 2008) was used for the assessment of different policy measures for achieving the targets. Both models used inputs from the models WASP (Santisirisomboon et al 2001) (used for optimum electricity generation planning) and COST (used for the stochastic simulation of the electricity generation system). Based on this modelling work, the government set the 2020 target to 2,200 megawatts (MW) of total PV capacity (Ministry of Environment and Energy 2010), while model results suggested that the feed-in-tariff policy design would drive consumer investments in a linear way to the achievement of the 2020 PV target (see **Figure C.7**).

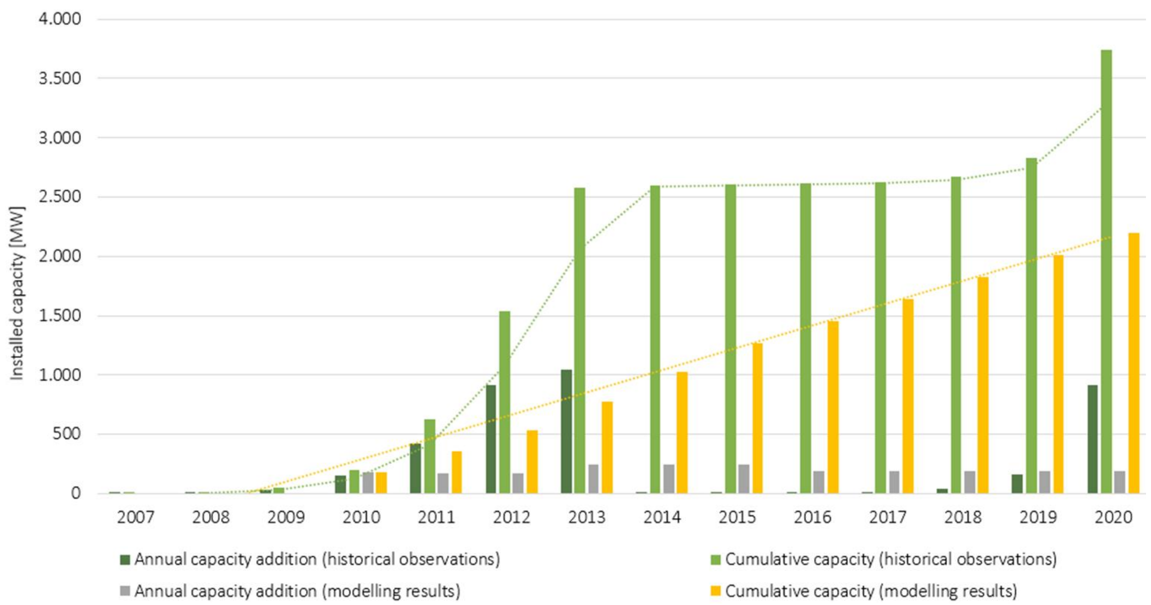


Figure C.7. Total PV capacity installed in Greece during the period 2007–2020: Modelling results vs historical observations. Data sources: Ministry of Environment and Energy (2010), Psomas (2018)

However, the targets defined by the model and set by the government were disconnected from the adoption realities on the ground. Many consumers saw the feed-in tariff as an attractive source of additional revenue during a period of great financial distress for the country, leading to a PV boom between 2009 and 2013. Thus, the model-based target of 2,200 MW of PV capacity by 2020 was met and exceeded in 2013 (Michas et al 2020). Consequently, the government, without consulting any further model-based analyses, imposed an additional tax on consumer incomes from renewable electricity generation, simultaneously with a reduction on tariffs to counterbalance negative fiscal implications (Koumparou et al 2017). This political decision shook the confidence of domestic investors in the stability and credibility of the support system (Papadelis et al 2016, Flamos 2016), leading to a complete shutdown of the domestic PV market (Hess et al 2022).

Here, once again, neither the political reality nor the consumer behaviour was reflected in the energy models used to inform policymaking. Accordingly, model-supported policy expectations and reality diverged: the adoption was first much higher than the energy models anticipated, and then completely collapsed following the policy change. Indeed, the policy change was such a strong shock that subsequent efforts to rekindle the residential uptake of PV expansion through a net-metering scheme (Tselepis 2015) did not work, causing the updated 2020 PV target of 3,300 MW (by the end of 2019) to fail.

This case study demonstrates the problems arising from a non-adaptive model-informed policymaking process, the consequences of not being flexible and allowing for contingency measures in case of a policy failure, and of the necessity for energy models to evaluate consumer response to specific policy incentives, especially when high tariffs are provided. By only using top-down optimisation models for target setting, model-informed policymaking risks being misleading: such models assume a benevolent planner with central control over the system and investments, but investor behaviour may be very different than this centrally planned perspective assumes. If policy measures whose success depends on investor responses are based only on top-down optimisation model results ignoring actual behaviour, there is a risk that the policy will fail, triggering either too much or too little investment.

C.5 Discussion

The results demonstrate that model users request better integration of the environmental and social factors of the energy transition into energy models so that models can provide results that better represent real-world developments, thereby improving their usefulness as policy advice tools. According to users, environmental factors should go beyond GHG emissions and include the demand of raw materials, impacts on biodiversity, land use and water consumption, and other indirect and externalised impacts. Among the social factors, social acceptance, individual and community participation, consumer behaviour and lifestyles, and policy preferences and dynamics were identified as the most relevant. The identified needs largely align with the environmental and social factors that are currently discussed in the scientific literature (see section **C.2**), underlining their relevance.

In the four case studies, it was shown that omitting the environmental and social factors deemed most important to model users could well lead to less relevant–or even misleading–results in several ways:

1) Neglecting social factors can lead to unrealistic model assumptions and misleading findings about the *speed* of the transition: The cases of grid expansion in the EU and onshore wind power in Germany show that public opposition, related to land-use and biodiversity concerns, substantially delays the implementation of the energy transition, often by many years and for single projects over a decade. Similarly, the Greek case study on solar PV illustrates the perils of ignoring investor behaviour and solely basing target-setting on top-down optimisation models assuming a benevolent central planner, in this case resulting in overly rapid deployment.

2) Models may make unrealistic assumptions about the *potential* of renewable energy if they focus only on the technical potential, ignoring societal preferences and their impact on land availability. The example of onshore wind power in Germany shows that wind power expansion can be hindered when wind turbines are not accepted in certain areas. Whether temporary or permanent, such delays can reduce local and, consequently, countrywide wind capacity potentials.

3) Not considering the demand of land and raw materials for renewable energy assets and related infrastructure may generate scenarios that neglect central *impacts* of the energy transition and support *technology options* that cannot materialise or that bring substantial supply risks. The case of EV batteries shows that the availability of raw materials could become both a deployment constraint and a geopolitical or economic risk factor as the transition progresses unless a significant system change is made regarding the recycling of materials. Furthermore, land-use conflicts are an increasing problem for deployment of renewables and infrastructure.

4) Ignoring environmental concerns and societal preferences can lead to problematic or misaligned *design* of future energy and mobility systems. The cases indirectly show that consumers have strong attitudes and opinions towards technologies such as EV and wind turbines and should therefore also have an influence on the siting of renewable energy and planning of solutions more broadly.

Collectively, this demonstrates a large need to integrate social and environmental factors as variables in energy models. Achieving this is difficult because such variables must be based on context-specific empirical observation and because transitions are dynamic processes and change, possibly fundamentally, over time. For example, environmental impacts and resource demands could be reduced during the transition via circularity initiatives or by innovations in new materials. Accordingly, technological change must also be depicted in environmental assessments, including emerging approaches such as prospective life cycle assessment (LCA). Similarly, the drivers of public opposition against wind power may be different in, for example, Germany and Greece, and will likely change between now and 2030. To depict such developments, models may need to endogenize social factors, modelling the underlying drivers such as regional density and size of existing wind farms (Setton 2019) instead of considering them as exogenous variables, as independent factors of a multi-criteria analysis, or ex-post indicators. Furthermore, political realities and regulation–both of which are dynamic–greatly affect transitions, for example, by adding constraints such as wind farm distance rules or alleviating constraints such as recycling requirements to avoid material shortage. These may also "change the sign" of a factor, turning a barrier into a driver, e.g., enabling community renewables can reduce opposition and create a new potential transition driver. Several approaches for including environmental and social factors into energy models are emerging and, although none of them fully integrate all such issues, the seeds for doing so are probably being sown; existing approaches for such integration are discussed in sections **C.5.1** and **C.5.2**.

Adding these additional factors will align energy models more closely to observable realities and will thus make them more policy relevant. However, it will also make models more complex, reducing their transparency and risk increasing the "black-box" nature of models. To avoid overloading models and, indeed, increase their usefulness as advice tools, it is essential to include stakeholders in the modelling process, both to provide data and, critically, context for that data and for the context-sensitive interpretation of model outputs.

C.5.1 Approaches for integrating environmental factors in energy models

Several approaches exist to better represent environmental factors in energy models. One promising approach is the integration of life-cycle perspectives and data sources into energy models, which provides greater access to high-resolution raw material information and other valuable environmental indicators. For example, Pehl et al (2017) and Luderer et al (2019) linked IAMs with LCA information using the THEMIS model (Gibon et al 2015), enabling high-resolution GHG emissions and several other environmental impacts to be included within modelling processes. This concept has recently been expanded by allowing life-cycle data to be manipulated within Python environments, enabling outputs from models to be directly automated with LCA calculations. For example, the PREMISE model (Sacchi et al 2022) enables different background electricity mixes and other parameters from the IMAGE model to inform future LCA processes to account for future changes in renewable energy use while others propose allowances for future technological improvements (Mendoza Beltran et al 2020). In any case, none of these approaches allow for the further analysis of LCA outputs beyond the simple aggregation of values across system components.

Few attempts have been made to include detailed information about raw materials demand and supply within energy models. One notable example is the MEDEAS-World model (Capellán-Pérez et al 2020), which includes a module that accounts for the materials and energy required for energy infrastructure manufacturing. The model quantifies the material requirements for implementing renewable energy infrastructure, including 19 CRMs, and compares these with current global availability estimates to detect potential supply issues. For that reason, it represents a much-needed initial foray into the inclusion of CRM aspects within a detailed IAM suite.

To facilitate greater analysis of raw material aspects and LCA outputs with and across energy system levels, a new application–known as the ENvironmental and BIOeconomic System assessment (ENBIOS) approach (Nebot-Medina et al n.d.)–was developed. ENBIOS takes system specification data ("energy mix" and other information) from models, combines this data with raw material requirement information and calculated environmental and socio-metabolic indicator data to produce extensive outputs such as life cycle impact assessment indicators and bespoke indicators derived from life cycle and other data. ENBIOS also directly integrates raw material supply risks, circularity and local impacts at the point of extraction via a methodology that combines life-cycle inventory data, supply risk and end-of-life recycling input rate data (European Commission 2020), and localised environmental performance data for the countries from which materials are sourced (European Commission 2020, 2020). As such, it brings a more systemic method to the assessment of material use and environmental impacts than previous approaches while offering a first attempt at quantifying these impacts alongside the socio-metabolic aspects that also apply to energy systems. Outputs from ENBIOS can be used to inform the selection of subsequent model scenarios or, for example, guide constraint parameters.

C.5.2 Approaches for integrating social factors in energy models

The need to integrate social factors into energy models has been previously addressed, and several approaches exist. These are typically focused on implementing social factors as constraints, but some have attempted to integrate them as explicit variables within energy models. For example, the Quantification of Technological DIffusion and sociAl constraiNts (QTDIAN) toolbox allows modellers both to include real-world, non-idealised policy constraints (e.g., actual national/regional setback distances for wind power), and to base scenario construction on observed policy objectives beyond GHG elimination, such as decentralisation/centralisation or transmission system preferences (Süsser et al 2021). Seeking to enable model-based assessment of the impact of different policy measures, (Best et al 2022) built a database for energy sufficiency policies, allowing the explicit integration of sufficiency indicators into energy modelling. Presently, there is a strong trend towards integration of social science and humanities in energy system analysis, and several model frameworks are being rebuilt to become more realistic and holistic.

Including public acceptance of renewable energy deployment strategies in new modelling frameworks has become a particular recent focus. One approach is to seek the fair geographical distribution of production and infrastructure assets, thus avoiding overly strong concentration of deployment in single regions (Degel et al 2016). Others seek to generate scenario-based options to identify which parts of a deployment trajectory are necessary, and where more flexibility is available, as a first step towards increasing stakeholder engagement and including public deliberations about the most attractive pathways for a country or region. For example, the spatially explicit practically optimal results (SPORES) approach explores nearly cost-optimal systems. Applying SPORES to Italy, Lombardi et al (2020) found that only photovoltaic and storage technologies are necessary components for a zero-carbon power system by 2050, whereas wind power choices are more flexible, allowing for deliberation-centred planning. Yet others include "resistance factors" for grid expansion, including these in their model to generate delay-minimal expansion pathways instead of purely cost-optimal ones (Degel et al 2016).

Adopting an entirely different approach, McKenna et al (2022) quantified the visual impacts of onshore wind in energy system analyses, basing the analysis on "scenicness" values of onshore wind site. In four scenarios for onshore wind potential, they gradually reduced the technical potential by quartiles of the scenicness distribution, revealing that the windiest locations are generally also the most scenic ones. Hence, including this parameter in models could greatly reduce the wind power potential, while generating more relevant results and exposing conflicts between landscape protection and renewables, facilitating solution-oriented deliberation.

Finally, although energy modelling is still dominated by central planner-based optimisation modelling, alternatives are emerging, including models that describe actor behaviour instead of top-down optimal deployment (Mittal et al 2019, Zhang and Nuttall 2011). Such models, including ABMs, can be used both to inform policy design decisions and to set appropriate targets. For example, Melliger and Lilliestam (2021) explored the effects of exposing renewable electricity technologies to market competition using an ABM fed with investor behaviour data from a conjoint analysis. They show that although policies to increase competition seek to reduce energy system costs, they likely both slow down deployment and increase costs because investors flock to still supported and more expensive technologies. Similarly, addressing the same case in section **C.4.2.2**, the Agent-based Technology adOption Model (ATOM) simulates the diffusion of small-scale PV in Greece under the net-metering scheme currently in operation (Stavrakas et al 2019, Michas et al 2020), based on behavioural profiles of small-scale investors. Indeed, ATOM shows that the existing net-metering policy is unable to achieve the 2025 and 2030 PV targets due to policy shortcomings, a finding that could not be detected using system optimisation models.

C.5.3 Limitations and future research

This section illustrates that energy models should consider environmental and social aspects of the energy transition and indicates the magnitude of the problems arising by ignoring such factors. However, it is acknowledged that it does not necessarily provide generalised findings for user needs as it was not possible to capture needs and differences between EU member states, or for countries beyond the EU. Just as social and environmental barriers and drivers may differ across both time and countries, user needs for model-based information will also be both dynamic and context-sensitive. While it is believed that that the explored barriers–material requirements, opposition, etc.–are relevant to all countries, the relative importance of each factor may differ, depending on political factors, geography and transition progress. Further studies could explore the context-specific needs and reasons for modelling requirements to support the further improvement of modelling tools tailored to specific countries and challenges.

The given examples present illustrative, non-exclusive examples of situations where energy modelling studies have generated problematic or unfeasible policy-advice because they did not sufficiently consider environmental or social factors. However, model results do not (always) directly lead to policy decisions but are–and should be–only one of many possible sources of information (Süsser et al 2021). Further research could investigate how policy and decision-making processes deal with factors that are not considered in energy models and what concrete impact this has on policy decisions.

It is also noted that the levels of granularity within current LCA databases make it difficult to localise the various impacts that occur along the overall supply chains that produce energy and infrastructure. As such, it may be unclear whether the emissions, resource requirements and impacts assigned to a process are occurring locally or in other regions of the world. This is less of an issue for GHG emissions, where impacts are assumed to occur globally, regardless of their origin. However, a shortcoming exists when assessing more localised impacts such as air and water pollution or land use. There are a few initiatives working on the regionalization of life cycle data and methods (Mutel et al 2019) and, while the push to expand these initiatives remains in its infancy, its importance needs to be recognised.

Lastly, further research relating to the integration or linking of environmental and social aspects and modelling–beyond the consideration of these factors as basic "add-ons"–needs to be undertaken. For example, future research could investigate the soft linking of energy models with environmental models to assess wider environmental impacts of transition pathways and energy systems.

C.6 Conclusions

It is concluded that users desire better representation of environmental and social factors in energy models. Furthermore, it has been demonstrated that ignoring these critical aspects of the energy transition can lead to wrong or misleading evidence about the potential of renewable electricity, and the speed, impacts and technological options of the energy transition. While the modelling community is taking steps to better incorporate social and environmental factors into energy models, the current results suggest that many of these key areas are not yet considered in sufficient detail and that existing approaches have not been sufficiently applied. And, although energy models will undoubtedly continue to be used to inform policymaking, the findings provide a call to energy modellers to further advance the representation of these factors in models or to advance the interlinking of different modelling tools. This includes the mainstreaming of social and environmental factors as explicit variables in models, possibly even by endogenizing particularly important parameters, such as social preferences, into the models based on context-sensitive empirical data. Including these factors would vastly improve the robustness of energy system models and, ultimately, would increase the suitability and meaningfulness of models to informing policy decision regarding the complex interplay between energy requirements, societal objectives and environmental considerations as Europe and the world continue advancing towards climate neutrality.

D THIRD ARTICLE

Integration of raw materials indicators of energy technologies into energy system models

Laura Talens-Peiró, *Nick Martin*, Gara Villalba-Méndez, Cristina Madrid-López

Applied Energy, 1 February 2022,
https://doi.org/10.1016/j.apenergy.2021.118150

Abstract

Raw materials and their related environmental impacts will play a key role in the implementation of renewable energy infrastructures for decarbonization. Despite the growing amount of data quantifying raw materials for energy production technologies, few examples of these data sources are being included in current energy system models. Accordingly, this paper introduces possible pathways for integrating material-specific life cycle assessment outputs and material metabolism indicators into energy system models so that raw material requirements, and their associated impacts, can be accounted for. The paper discusses the availability of life cycle inventories, impact assessment methods and important output indicators. The material metabolism indicators most relevant to the current policy debate surrounding the European Green Deal–namely, material supply risk and contribution of recycled materials to total supply–are also discussed alongside the value of adding this information to energy system models. A methodology for using data from both approaches is offered and operationalised using four sub-technologies of both wind turbines and solar photovoltaic panels as case studies. The results show that considerable variation exists between and within the two groups for all indicators. The technologies with the lowest global warming potential, cumulative energy demand and supply risk are turbines with gearbox double-fed induction generators and cadmium telluride photovoltaics. Furthermore, wind turbines exhibit significantly higher recycling rates than photovoltaics. Ultimately, the integration of such methodologies into energy system models could greatly increase the awareness of raw material issues and guide policies that maximise compatibilities between resource availability and cleaner energy systems.

D.1 Introduction

The European Green Deal is the latest response by the European Commission (EC) to climate and other environmental related challenges (European Commission 2019). Its key objective is to decouple economic growth from resource use, and for Europe to become the first carbon neutral economy by 2050. As stated in the plan, around 75% of greenhouse gas (GHG) emissions in the European Union (EU) are generated by the production and use of energy (IEA 2020) and, in order to decarbonise the EU, it is crucial to increase the share of low carbon technologies in the generation and use of this energy.

Emissions relating to energy generation can be systematically assessed by the methodology known as life cycle assessment (LCA). LCA evaluates the environmental burdens stemming from a process by considering the entire life cycle of the process under study using a holistic perspective (de Bruijn et al 2004). Results from an LCA are given as environmental impact categories, among them the global warming potential (GWP) measured in terms of greenhouse gas generation in carbon dioxide equivalent (CO_2-eq) units. Most previous studies that have used LCA in combination with ESM have used ex-post processes to account for the potential environmental impacts of specific technologies, specific sectors or at a global level under different policy scenarios (Blanco et al 2020). These studies have tended to use the environmental impact categories described in the ReCiPe (Igos et al 2015) or Impact 2002+ (García-Gusano et al 2016) assessment methods to account for potential environmental and human health impacts. However, mineral resource depletion is not included in some cases due to data uncertainty on recycling rates and material balances (Volkart et al 2018).

Energy supply is addressed from a holistic perspective in the European Green Deal, thus potential dependencies on resources key to reaching the EU goals also need to be addressed. Indeed, one of the EU's major fears appears to be the shift from a fossil fuel to a materials-dependent economy. To avoid this situation, and to identify materials that may potentially become problematic in coming decades, the EC has produced several reports addressing the use of so-called critical raw materials (CRMs). The EU considers CRMs to be materials with high importance to the union's economy (e.g., lithium for electric mobility) and with a potentially high risk regarding their supply (Nuss and Blengini 2018). Since 2010, the EC has reviewed and updated the list of CRMs for the EU every three years (European Commission 2010, Chapman et al 2013, European Commission 2017, 2020). The methodology relating to CRMs has been also revised and formally presented together with an extensive guideline document (European Commission 2017). The reports published by the EC highlight the material needs for growing technologies, especially for renewables and electric mobility (Bobba et al 2020). In 2020, the EC presented the European Raw Materials Alliance for securing the supply of raw materials within its borders (European Commission 2020). The report listed borates (batteries), lithium (batteries), natural graphite (batteries), niobium (magnets), silicon metal (PV), and a mix of diverse rare earth elements (batteries and magnets) as materials with 100% import reliance.

As the dependencies on raw materials for the development of low carbon energy technologies become more evident, the need to include them as a variable in energy system models is being acknowledged. However, to date, only a small number of energy system models (ESMs) consider environmental impacts. One of the most renowned integrated assessment models (IAMs) used to model energy systems is IMAGE (Stehfest et al 2014, PBL Netherlands Environmental Agency 2021), a large-scale, ecological-environmental model framework that simulates the environmental consequences of human activities worldwide. It addresses some of the most prominent environmental issues and sustainability challenges such as climate change, land-use change, biodiversity loss, modified nutrient cycles and water scarcity. However, in the latest version (IMAGE 3.2), raw material use is yet to be included. Indeed, raw material use is not included in any of the major IAMs currently being used to guide global climate and energy policy decisions (IAMC n.d.)

Raw materials have been addressed in the MEDEAS model created within the framework of the EU H2020 project MEDEAS (Capellán-Pérez et al 2020). The model contains seven submodules including one which models material requirements. This submodule accounts for the materials needed for energy infrastructure and the energy related to its manufacturing, expressed as an energy return on investment (EROI). Using this approach, the model assesses the implications that mineral depletion may exert on energy transitions in relation to potential mineral supply constraints. The demand of minerals is compared with their currently estimated level of geological availability (reserves and resources) for the qualitative detection of risks of material supply from a global perspective. These concepts are now being further developed within another EU H2020 project known as LOCOMOTION (LOCOMOTION n.d.) wherein a materials module based on geological supply is being employed. In any case, neither project is assessing material metabolism factors beyond the physical quantities that exist; geopolitical and other risk factors relating to material supply between countries are not considered.

So, although some efforts have been made to assess raw materials using a holistic perspective, and several new indicators have been defined (European Commission 2020, Bobba et al 2020), their use in ESMs remains limited. This is partially because a systematic process for collecting and providing such information in an ESM-usable format is yet to be developed.

Accordingly, this section follows introduces the concept of using LCA data alongside material metabolism approaches as a way of providing a more complete picture of the raw materials use and associated environmental impacts within ESM processes. The section continues by briefly explaining the LCA methodology and how it could be used to integrate the potential environmental impacts of energy production into ESMs. It also discusses existing LCA data and outlines a simple methodology for creating environmental impact indicators for energy infrastructures per unit of power capacity. Existing material metabolism information and ways that this information can complement LCA results are then investigated. The standard LCA methodology is expanded further to include material supply parameters for supply risk and recycling rates. The section then provides the results of a set of four environmental indicators readily usable in ESM to support the assessment of wind turbines and solar photovoltaic cells. It concludes by confirming the potential of such approaches, the need for further integration of environmental and metabolic data into ESMs and, to aid future policy decision-making, the ongoing need for good quality life cycle and material supply data.

D.2 Potential contribution of LCA methodology to ESM

The LCA methodology is used for evaluating the environmental burden of a process by accounting for the inflow and outflow of materials and energies alongside the wastes released to the environment (de Bruijn et al 2004). Such evaluations are undertaken using a holistic perspective that considers the entire life cycle of the process under study. LCA accounts for the inflows and outflows of the system from “cradle to grave”; that is, from the extraction, manufacturing, consumption and recycling to the final disposal. The methodology can be divided into four steps: goal and scope definition, inventory analysis, life cycle impact assessment (LCIA) and interpretation. Once the objective and functional unit are defined as part of the goal and scope stage, an inventory analysis is done to quantify the raw material and energy inputs, and to account for the atmospheric emissions, waterborne emissions, solid wastes and other releases over the entire life cycle of a product, process or activity.

Each product system inventoried in this stage can be divided into both foreground and background systems (Carrara et al 2020). The foreground system refers to the main process steps and infrastructure related to the focused product or system of the study. Meanwhile, the background system is comprised of the processes needed for the supply of raw materials and energy to the foreground system. This generally includes the more dominant processes outside of the study’s focus and are typically out of the direct control of those undertaking the assessment (Guinée et al 2011). Commonly, the background system’s infrastructure (e.g., the manufacturing of the power plant or the fossil fuels production infrastructure) is included in the secondary data sets used for modelling the background system. The background system deals with almost all material and energy flows going to and coming from the foreground system. Data for the background system is typically taken from existing databases–e.g., Ecoinvent v3.7.1 (Wernet et al 2016) and GaBi (Kupfer et al 2021)–while the foreground system can often be quantified using primary data from case studies, peer-review papers and technical reports.

In the stage that follows, an LCIA procedure establishes a link between the materials and energy compiled by the LCI inventories and their potential environmental impacts. Potential environmental burdens are given in the form of impact categories defined and selected to describe the impacts caused by the emissions and the consumption of natural resources. Impact categories can refer to a single-issue such as the cumulative energy demand, or to multiple issues as in the commonly used ReCiPe method (Huijbregts et al 2017) which includes 21 indicators. In most multiple issue LCIAs, the emissions and consumption of resources are attributable to three main areas of protection (ecosystem quality, human health and natural resources), which are preceded by several impact indicators that express the impact on the environment as midpoint and/or endpoint indicators (Dewulf et al 2015). Midpoint indicators represent the actual environmental phenomena caused by the life cycle system, such as "global warming potential" (CO_2-eq) (IPCC 2013) and "ozone depletion potential" (kg CFC-11-eq) (World Meteorological Organization 1998), whereas endpoint indicators are composites that result from a combination of midpoint indicators that reflect the damage on so-called areas of protection (European Commission 2011). For example, in the ReCiPe method the midpoint indicators for "global warming potential" and "ozone depletion" are combined into the endpoint indicator "damage to human health" (Huijbregts et al 2017).

Figure D.1 provides a simple conceptualisation for a potential integration of LCA and ESMs by illustrating where inputs and outputs to these models are situated in relation to the four stages of the LCA framework. Again, the most relevant stages for ESMs within this framework involve the LCI and LCIA calculations. Assessing the LCI includes the background (green) and the foreground (blue) systems. As always, the background system refers to all processes needed to supply the raw materials and energy to the processes of the foreground system. In the case of ESMs, the foreground system refers to the processes needed to manufacture a specific energy technology. For example, for a solar photovoltaic panel the foreground system would include the processes for manufacturing the cells and the frame and the balance of system (wiring, switches, mounting system, solar inverter, battery bank and charger), transport and assembly of all components, operation and maintenance, use, dismantling and transport and all waste disposal operations.

Figure D.1 also displays the most common multiple issue methods used in LCIAs in dark blue., The most frequently used LCIA methods (Jungbluth 2021) are CML2002 (de Bruijn et al 2004), ILCD2010 (European Commission 2011), ReCiPe 2016 (Huijbregts et al 2017), the EU Product Environmental Footprint 2018 (Sala et al 2019) and ImpactWorld+ (Bulle et al 2019). Each of these methods includes a list of impact categories that differ in scope and procedure for characterisation and weighting. In 2016, the United Nations Environment Programme (UNEP) launched a consultation for the creation of a Global Life Cycle Assessment Method (GLAM) with the objective of identifying scientifically robust and applicable methods (Frischknecht and Jolliet 2017). Discussions within the scope of GLAM have led to a prolific number of papers discussing LCA indicators, especially regarding resource use and availability indicators (Sonderegger et al 2020, Berger et al 2020). Another important aspect highlighted in the figure is the potential contribution of background systems to the overall environmental impacts of renewable energy supply processes (Nuss and Eckelman 2014). For example, the potential environmental impacts of wind generation are largely influenced by the mix of electricity supplied to the production of raw materials, mostly steel, concrete and aluminium, which are highly energy intensive (Garrett and Rønde 2013).

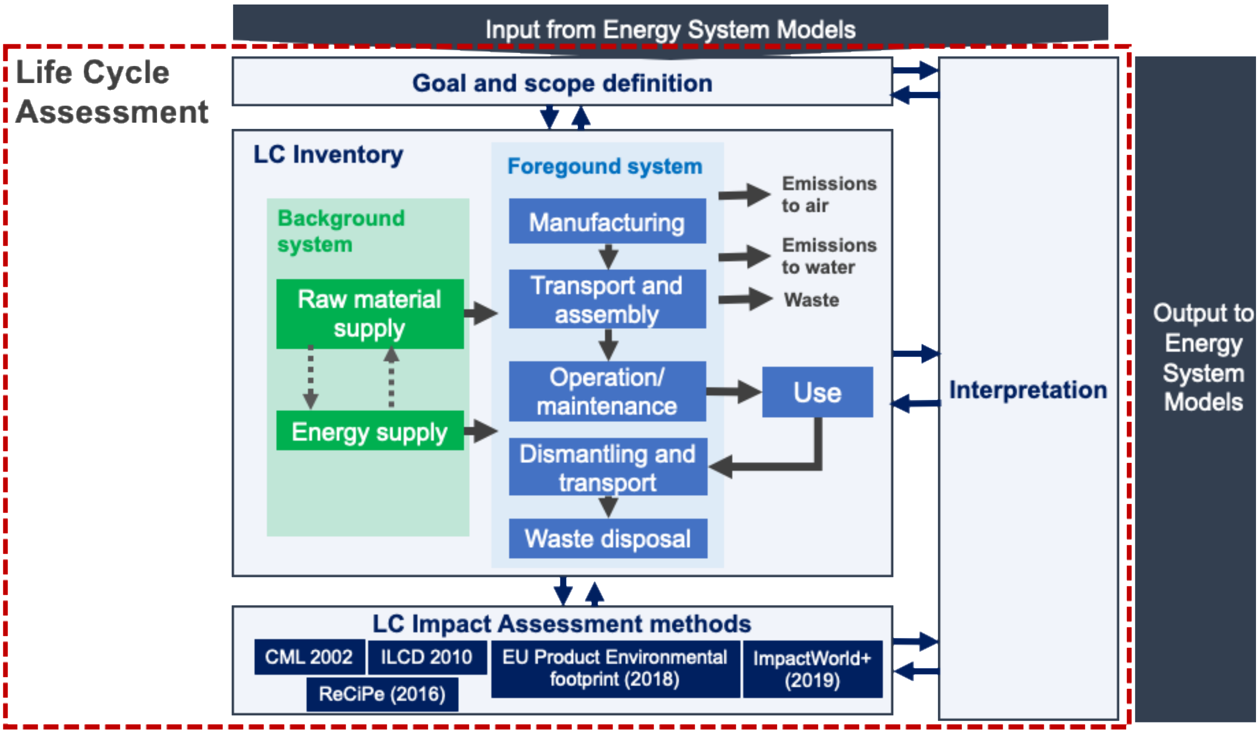


Figure D.1. Possible linkages between energy system models (ESMs) and the life cycle assessment (LCA) framework according to ISO14040 standard. The life cycle inventory (LCI) includes the background system (in green) and foreground system (in light blue). Diverse LCIA methods are represented for illustrative purposes as dark blue rectangles

D.2.1 Inputs from LCI

D.2.1.1 The background system

Two types of inputs are considered for background systems: raw materials and energy. The most common source of data for the assessment of raw materials is the fee-paid Ecoinvent database (Wernet et al 2016); version 3.7.1 of Ecoinvent (Ecoinvent 2020) includes LCIs for the production of about 30 metals, 20 types of industrial minerals and seven forms of primary solid biomass. An extensive list of inventories is available for base metals, especially aluminium, iron and steel, copper, zinc, and nickel, as well as some precious metals like gold, silver and the platinum group metals (platinum, palladium, rhodium), alongside specialty metals such as titanium, tungsten, and uranium. An effort has also been made to include LCIs for other materials that are produced in lower quantities but have high economic importance such as rare earth elements, indium and gallium. Additional inventory data for the extraction and purification of metals is highly scattered in publications and reports, and funding for generating bespoke data inventories for LCA purposes is often not available. As such, LCA practitioners tend to use existing LCI information within databases such as Ecoinvent.

Several previous studies have attempted to compile life cycle data for metals. Nuss and Eckelman (2014) compiled proprietary data from Ecoinvent version 2.2 in conjunction with data from various reports and scientific publications. Meanwhile, van der Voet et al (2019) used Ecoinvent version 2.2 to complete an inventory of the background system and datasets from two previous studies (Verboon 2016, Kuipers 2016) to assess the environmental implications of future demand scenarios of seven major metals: aluminium, copper, iron and steel, lead, nickel, manganese and zinc. The LCIs generated by both studies have not been made available and, therefore, it is not possible to use them directly in future studies. Although some recognised LCI formats do exist (e.g., Ecospold), the general lack of LCI data in formalised formats impedes their use in LCA software tools and restricts their widespread use by LCA practitioners. Furthermore, not disclosing inventory data in published articles and other reports hinders the reproducibility and replicability of the assessment.

Although some initiatives exist for generating fee-free LCIs for raw materials, these tend to only partially cover raw materials and rarely focus specifically on CRMs. The UNEP Global Life Cycle Assessment Data Access network (GLAD), launched in April 2018, aims to address this issue by providing a platform for hosting independent LCA databases–so-called “nodes”–that are made available in various data formats. One of the main functions offered is the conversion of LCI data from the native format to a format that allows their use in common LCA softwares. In GLAD, LCA practitioners can check the availability of datasets from diverse providers such as IDEA, Ecoinvent, USA LCA Digital Commons, SICV Brazil and ELCD (Ciroth et al 2017). Another less ambitious initiative is the updated database of the DoSE-LCADB (Talens Peiró and Gabarrell i Durany 2019, Talens Peiró et al 2019). This includes current LCI data for agriculture (mainly vegetables), bioenergy (biomass from poplar and soybean biofuel), and manufacturing (cement, natural cork, rubber mix and fertiliser). LCIs for individual raw materials are not yet available, although this looks likely to change in coming years as the database becomes more widely known and more nodes begin to be linked with the GLAD database. Lastly, Pauliuk and Hasan (2017) created the Industrial Ecology Data Commons (IEDC) prototype which contains around 180 industrial ecology-related datasets from the literature. Datasets are not limited to LCIs and include stocks, flows, process descriptions, input-output tables, material composition of products and other factors. At present this collection only contains inventories for a small number of unit processes for aluminium and steel.

As with raw materials, the major source of LCI information for energy systems is the Ecoinvent database (Wernet et al 2016). In an LCA context, energy inputs generally refer to electricity consumption and, thus, are assessed based on the so-called electricity production mix, the share of individual electricity sources, generated from a diverse group of technologies, within a local electricity supply. The composition of this mix changes according to the geographical location of the system under study (i.e., region, country and continent). It also varies from year to year due to changing energy policy measures, economic growth, energy intensity, technology changes, meteorological conditions, and so on (Díaz et al 2019). Accordingly, potential environmental impacts can be considered to vary over time and between location.

The number of studies analysing the effects of changing electricity background systems on LCA results is limited. Mendoza Beltrán et al. combined the Integrated Model to Assess the Global Environment (IMAGE) with the Ecoinvent database to perform prospective LCAs for electric vehicles (EV) and internal combustion engine vehicles (ICEV) (Mendoza Beltran et al 2020). Changes were mainly focused on the electricity sector as electricity is the largest potential source of variability in the environmental impact results (Cox et al 2018). The development of electricity scenarios firstly included scenario generation using the IMAGE model; scenarios could then be evaluated using LCIA. The adaptation of inventory parameters within LCA consisted of using and adapting the emission factors of the GHG emissions, mostly from the Emissions Database for Global Atmospheric Research (EDGAR) (European Commission n.d.), and replacing the shares of electricity-producing technologies, both using IMAGE. LCI inventories were adapted to IMAGE by the development of the Wurst software platform (Mutel and Cox n.d.), a Python-based application that enables the systematic importing, filtering and modification of LCI data.

D.2.1.2 The foreground system

Conversely, foreground systems focus on the processes needed to generate a certain amount of energy using a particular energy technology. For example, the LCA for generating one kilowatt-hour (kWh) of electricity from a solar photovoltaic (PV) panel includes all processes from the extraction of raw materials for the manufacturing of the panel to its end-of-life. As many current decarbonisation targets are based on increased electrification of the energy sector by increasing the share of renewable energy technologies, the number of LCIs for these technologies has increased considerably in the past decade. **Table J.7**–in the appendices–includes a list of LCIs available in version v3.7.1 of Ecoinvent and the 2020 edition of GaBi, considering different energy sources and energy carriers. While these values suggest that a significant amount of data is already available, new technologies continue to be developed and data for the newest iterations of energy technologies is often not available in a useable format for several years after its introduction. As such, an increased effort is needed to formalise and incorporate such data into databases in a more timely fashion. As an example, over 90% of the LCI listings for solar PV cells in Ecoinvent v3.7.1 relate to first-generation cell technologies–41% single crystalline silicon (C-Si), 55% multi-crystalline and 4% ribbon–while only 10% refer to second-generation technologies–50% amorphous silicon (a-Si), 25% cadmium telluride (CdTe) and 25% copper indium gallium diselenide (CIGS). In the 2020 edition of GaBi, 60% of these datasets are dedicated to first-generation cells–38% C-Si, 37% multi-crystalline and 25% ribbon–with 20% describing second-generation cells–40% a-Si, 24% CdTe and 36% CIGS. The remaining 22% refer to general datasets.

It is also notable that neither of these databases currently contain LCI data for the third generation of cells such as metal halide perovskite cells which are believed to hold significant economic and efficiency advantages over the currently commercialised first and second-generation variants (Wilson et al 2020). Though not yet in widespread use, these technologies are expected to play a significant role in the emergence of solar PV cells going forward. This highlights the importance of including data relating to burgeoning technologies in prospective energy system assessments and the shortcomings in the current data.

D.2.2 Inputs from LCIA

Using the collected LCI data, an LCIA attempts to form a connection between the product or system and its potential environmental impacts by creating indicator values relating to specific impacts; the results of the assessment are given in the form of environmental impact categories to help evaluate outcomes in various areas (e.g., potential human health and ecological effects). Environmental impact categories can consider one selected environmental aspect, such as the cumulative energy demand, water footprint or carbon footprint, or combine several environmental impacts to become a "method". Each of the most commonly used methods include a list of impact categories; see **Table J.8** in the appendices for an exhaustive list.

As a result of the ongoing discussions surrounding the development of the GLAM (Frischknecht and Jolliet 2017), attention to resource availability indicators has been increasing in recent years and several publications now provide a comprehensive review of indicators. Sonderegger et al (2020) revised the 27 different methods suitable for LCIA for mineral resource use and grouped these methods into four categories: depletion methods, future efforts methods, thermodynamic accounting methods and supply risk methods. The two former methods consider resource depletion from a more "traditional" LCIA perspective, where the availability of mineral resources given a certain stock are considered (depletion method) or the potential increase of extraction and refining costs, surplus energy use and other related aspects are considered under the assumption of ore decline (future effort methods). The two latter methods, however, provide complementary information to LCA outputs regarding the use of cumulative material and energy use for a product (accounted in useful energy or exergy), and the availability of materials based on the supply disruption probability and vulnerability, respectively. Berger et al (2020) built on this analysis to provide recommendations for the application of such methods by formulating seven questions that can be further classified into "inside-out" (i.e., current resource use changing the opportunities for future users to use resources) and "outside-in" (i.e., potential resource availability issues for current resource use). The study concluded that there is a need for methodological enhancement across method categories. Additionally, the authors suggest that future methods increase the number of abiotic resources considered, including secondary resources and anthropogenic stocks, and include the concept of dissipative resources in future developments.

In terms of natural resources, critical raw materials–and metals in particular–have attracted most of the attention in this regard as many of them look set to play a key role in the development of renewable energy technologies (Nuss and Blengini 2018). However, at present there is no consensus on a single method or set of methods for measuring resource availability using LCA methodologies and only a small number of approaches are currently available, as listed in **Table J.9** in the appendices. Nevertheless, a number of studies have published data for individual raw materials. Nuss and Eckelman (2014) performed LCA analyses for 63 metals and reported the results for five main environmental impact categories: the global warming potential (kg CO_2-eq), the cumulative energy demand (CED) (MJ-eq), terrestrial acidification (kg SO_2-eq), freshwater eutrophication (kg P) and human toxicity (CTUh). The investigation yielded several interesting results. The global CED of metal production is estimated to have been 49 PJ in 2008, which represents 9.5% of the global primary energy demand. Iron and steel (74%) and aluminium (17%) dominate the CED impact category; the remaining 60 metals collectively represented only 9% of the total CED. Globally, the largest environmental impacts are found in the purification and refining of these metals. The environmental assessment of the seven major metals by van der Voet et al (2019) referred to the CED (MJ-eq) and GHG emissions (kg CO_2-eq) as defined by the CML2002 impact categories (de Bruijn et al 2004). Their results show that the environmental impacts generated by metal production look set to increase gradually, and designate iron as the metal responsible for most impacts and emissions. Both studies provide valuable information about the potential environmental impacts of metals in energy systems.

The availability of LCIA estimates for these and other materials allows composite values to be calculated for specific energy infrastructures. If a breakdown of the main material components of a piece of infrastructure (kg of each material) with a given power capacity (MW) is available, a series of material intensities (kg/MW) can be calculated. Values of LCIA indicators for a unit mass of each individual material can then be used to calculate a composite score of the indicator per unit of power capacity. This methodology is formalised for GWP and CED in section **J.4** of the appendices. Using these two methodologies as examples allows final values–per MW of installed capacity–to be calculated for GWP (kg CO_2-eq/MW) and CED (MJ-eq/MW). Outputs of this type then allow side-by-side evaluations to be made between different energy technologies as the values of the chosen LCIA output category can be directly compared in terms of installed capacity. Furthermore, using assumptions for infrastructure lifetime and typical energy outputs allows values to be calculated–and compared–for each unit of energy produced. It is noted that using the CED as an input to this methodology would return the total energy requirement per unit of produced energy (MJ-eq/MJ, say) which is essentially the inverse of the EROI, a common indicator used in MEDEAS, LOCOMOTION and many other projects.

In any case, some limitations exist in relation to the indicators used in LCA. Firstly, although LCA uses quantitative material and energy input data to account for the potential environmental impacts, this information is not generally used when quantifying material requirements. Similarly, LCA indicators do not provide feedback on the contribution of recycling to the total supply of raw materials. In the EU, both of these issues are progressively gaining more importance (European Commission 2020). As such, in order to provide more complete environmental assessments in ESM there is a need to develop methodologies that use LCA indicators which capture the potential environmental impacts of energy technologies alongside material specific indicators which give additional information about the raw material supply factors of energy technologies.

D.3 Potential contribution of material metabolism analysis to ESM

The previous section reveals that LCA indicators provide a useful way to assess the environmental performance of the life cycle of an energy system (Mendoza Beltran et al 2020). However, the findings also suggest that other characteristics of energy systems, such as the supply of materials, are poorly captured within LCA methodologies. One of the most overlooked of these is material metabolism. Material metabolism studies offer complementary information about the supply of raw materials as they consider the whole, integrated collection of physical processes that convert raw materials to processed materials, components and finished products (Ayres 1989). Material metabolism studies, including so-called material flow analysis (MFA) approaches, help practitioners attain a better understanding of the flows and stocks associated with materials, the interconnection between mineral ores and materials, recycling aspects, and shed light on potential future constraints for technology development and diffusion. Some of the most relevant issues quantified by MFA are the supply of raw materials from mineral deposits and from recycling, and the interconnection with other raw materials along the value chain.

Mineral deposits are heterogeneously and unequally distributed across the Earth and the availability of resources depends on various factors such as natural occurrence, concentration (if they are sufficiently attractive to be mined) and accessibility. Geological surveys generally provide figures about geological availability as “reserves”, “reserve base” and “resources” (British Geological Survey n.d., U.S. Geological Survey 2020). However, the lifetimes of many reserves and resources have continually been extended over the last 50 years. Thus, the published reserve figures do not adequately reflect the total amount of mineral potentially available in the long term and should not be used in the evaluation of future material availability (European Commission 2010). As a result, MFA processes do not, strictly speaking, focus on resource depletion indicators. Rather, they focus on raw material supply indicators, which can refer to either primary production (mining) or secondary production (recycling). In fact, recycling represents a significant challenge due to the great diversity of applications and end products where materials are embodied, the diversity of products recycled together and the variability of the related processes. Despite such difficulties, a few existing studies supply recycling estimates, which allow meaningful indicators for the secondary supply of raw materials to be defined.

The production of raw materials is highly interconnected, especially those involving metals. Indeed, the topic of by-product dynamics is often discussed (Nuss and Eckelman 2014, Verhoef et al 2004, Talens Peiró et al 2013), although only a few publications propose a methodology for providing quantitative estimates (Graedel et al 2012, Nassar et al 2015, Roelich et al 2014). Based on the literature available, three different types of by-product metals are distinguished: metals derived from ores of major metals (e.g., germanium, indium), metals that occur without a major metal (e.g., platinum group metals) and metals that can be mined when found in high concentrations (e.g., cobalt, gold). The availability of all three types is largely determined by the availability of the main ore as mine production cannot adapt quickly to meet structural changes in demand patterns. As a result, the supply risk of these metals is high when the volume mined does not match with market demand. Talens Peiró et al (2013) offered one of the first figures illustrating the metabolism of scarce materials and provided production shares between them. Nuss and Eckelman (2014) subsequently provided a more complete and detailed illustration of the interlinkages between metals along the supply chain. Obtaining more detailed information about the linkages between raw materials helps identify potential supply restrictions across the value chain that cannot be predicted based on LCA studies. In the EU, the European Commission itself has performed several studies. The first of these identified information and data needs for a complete MFA involving 21 materials and groups of materials in 2012 (RPA 2012). The second, from 2015, provided a detailed methodology for developing MFAs (BIO by Deloitte 2015). The study, referred to as the EC MSA study, illustrated the entire life cycle of materials using a list of parameters which describe physical flows (including import and export flows to each stage of the life cycle) and stocks. The study included a total of 52 parameters divided into three groups: parameters representing physical flows and stocks of materials, parameters relating to policy objectives and criticality, and parameters relating to future supply and demand change. In 2020, the EC also published the latest data relating to raw material supply of critical raw materials (European Commission 2020) and non-critical raw materials factsheets (European Commission 2020). Employing a material metabolism perspective, the EU also proposed a method for estimating the criticality of resources (Blengini et al 2017). This method is considered to be a snapshot of the current situation in the EU and aims to support the development of EU raw materials policy to help monitor supply risk and recycling aspects.

The 2020 CRM assessment sheds further light on the supply of raw materials within the value chain, assuming that raw materials can be supplied in value chains as raw materials, processed materials, components and assemblies (European Commission 2020). Within value chains, many aspects relating to local supply and demand of materials, the location and characteristics of external supplies, substitutability and end-of-life recycling rates were identified as being relevant to the assessment of future supply constraints. Tellingly, calculations performed within the study found that the EU depends on non-domestic production for more than 80% of the raw materials demanded by its economy. Many of these materials are extracted within a small group of countries which increases the probability of supply shortages and affects the strength of the supply chain.

As a way of monitoring this dependency on non-domestic production, the CRM methodology analysed the import dependencies of specific materials in further detail by assuming that local dependence–or import reliance (IR)–can be calculated as the amount of imports divided by the total supply (imports plus domestically-sourced supply). IR can be calculated for diverse stages across the value chain (e.g., as unprocessed material at the extraction stage or as refined material at the processing stage). The results show that 28 of all 80 materials analysed–and 19 of the 30 materials marked as "critical"–have an IR of 100%. Many others have IR values well over 50%. This confirms that the EU is highly dependent on imports for many raw materials which are increasingly affected by growing demand pressure from emerging economies and by an increasing number of national policy measures that disrupt the normal operation of global markets. Moreover, the production of many materials is concentrated in a small number of countries (e.g., more than 90% of rare earths and antimony, and more than 75% of germanium and tungsten, are produced in China, 90% of niobium is from Brazil and 77% of platinum from South Africa).

The supply of secondary materials via recycling represents an opportunity to offset overall supply risks, particularly for materials with high dependencies on non-domestic production. Recycling can occur at each of the stages considered along the life cycle of a material or a product (e.g., materials can be recycled at either the extraction stage or the assembly stage). As such, when defining recycling indicators, it is important to define the system boundaries in detail alongside the material flows included in the calculations. The 2020 CRM assessment (European Commission 2020) considers recycling to be a "risk-reducing factor" and quantifies the supply of secondary materials using the so-called end-of-life recycling input rate (EoLRIR) indicator. EoLRIR reflects the total material input into the production stage that comes from recycling of post-consumer scrap and is regarded as a robust measure of the contribution of recycling to meeting materials demand. The results for EoLRIR suggest that 47 of the 80 materials assessed currently play an insignificant role in the overall EU supply (less than 10% EoLRIR); the results are starker for the group of more "critical" materials, where 26 of the 30 materials have EoLRIR scores less than 10%.

The key parameter presented in the 2020 CRM assessment (European Commission 2020) was a supply risk (SR) factor that used aspects of supply concentration, world governance indicators (WGIs), IR (as above), trade restrictions and agreements, supply chain and bottleneck issues, EoLRIR (as above) and criticality of substitutes to capture a dimensionless composite measure of EU supply risk for each material. Calculations were made for both the mining/extracting and processing/refining stages, and the greater of the two chosen as the final indicator.

The report by Bobba et al (2020) provides data for EU domestic production at the extraction stage (materials in the form of mineral ore) and the processing stage (materials considered refined material). In the EU, most of the materials domestically produced are generated at the processing stage, whereas materials obtained from the extraction stage represent around 20%. In other words, the greatest supply risks are located at the extraction stage of resources. For example, in the wind power supply chain, the risk is reduced along the supply chain from 99% at the extraction stage to 88% at the refining stage, 80% at the component stage to a final 42% at the assembly stage. For solar PV, the supply risk does not vary considerably from the extraction stage (94%) to the assembly stage (99%).

At the larger scale, materials demand can be seen to be driven by technological changes as well as the continual growth of emerging economies. In the EU, raw materials demand is likely to continue to increase as a result of a commitment to becoming a climate neutral economy by 2050. Several studies exist that assess the demand for CRMs coming from several strategic technologies, including wind energy and solar PV technologies. The results are given for low-demand (LDS), medium-demand (MDS) and high-demand (HDS) decarbonisation scenarios (Bobba et al 2020). Information relating to the value chains can also help unravel the potential to decarbonise raw material supplies. As 17 of the 24 key materials used in these technologies are supplied as refined materials to the EU, higher GHG emissions will inevitably be associated with the transport of these materials. Accordingly, less opportunity exists to reduce the overall carbon footprint of these technologies.

Expanding upon the methodology proposed for calculating composite LCIA indicators, further methodologies are proposed here for using the values of EoLRIR and SR for individual raw materials in the EC's 2020 CRM assessment (European Commission 2020) to calculate composite scores for different energy production processes. As with the LCIA indicator values, it is hoped that these new scores can be integrated into ESMs as a way of including material metabolism aspects into the assessment processes relating to a variety of future energy systems. It is believed that this is the first time this has been attempted in such a way.

D.3.1 The circularity of energy technologies in the EU

Eurostat uses the EoLRIR parameter as an indicator for monitoring the EU's progress towards a circular economy on the thematic area of "secondary raw materials". The current paper proposes the use of EoLRIR as a way of monitoring circularity aspects of energy technologies within ESM practices. The EoLRIR for a technology can be calculated by considering the EoLRIR values for individual materials in relation to the overall mass of materials in the item of infrastructure under study, in this case expressed as the material intensity *m*. As rates are expressed as a percentage, the pro-rata EoLRIR values for each material must be divided by the total mass of all materials to provide the final EoLRIR value. Accordingly, the composite EoLRIR for a given technology using inputs from *n* materials is as follows:

$$EOLRIR_{technology} = \frac{\sum_{i=1}^{n} m_i \; EOL-RIR_i}{\sum_{i=1}^{n} m_i}$$

The results indicate the overall percentage of recycled materials that occur within end product and provide a better understanding of the circularity of a technology from a material perspective. To assess the circularity of the technology itself, further analysis that assesses the disassembly along with a more detailed analysis of the material recovery from these technologies would need to be further developed.

D.3.2 The supply risk of energy technologies in the EU

Again, the key output from the 2020 CRM assessment (European Commission 2020) was the SR factor that quantifies the overall supply risk for each material as a dimensionless constant based on a number of physical and geopolitical factors. Initial attempts to define a methodology for creating a composite SR score were based on the same pro-rata approach used for the LCIA outputs. However, in order to capture the importance of materials that exist in much smaller quantities, an additional parameter was required to normalise the amounts of required materials using some measure of overall abundance of supply. Consequently, in the final formula, each material intensity value, m, is normalised by dividing it by the annual consumption level within the EU, c. This provides a more useful measure of the significance of using the given amount in relation to the overall supply. Accordingly, the composite supply risk factor for a given technology using inputs from n materials is as follows:

$$SR_{technology} = \sum_{i=1}^{n} \frac{m_i \, SR_i}{c_i}$$

It is noted that, although the final value of SR is essentially dimensionless, the final units are actually the timeframe of the consumption data divided by the unit that the material intensity is based upon. In this example, the final units are, in fact, the relatively meaningless year per MW. Other measures of material intensity, such as kg of materials per MJ of energy or kg of fuel supplied could also be used–highlighting the flexibility of this methodology to different datasets–but would result in different final units of the composite SR score. However, while many types of units can be used, one cannot directly compare final scores that use different units of material intensity and/or consumption data.

D.4 Case studies: Wind turbines and solar PV panels in the EU

A better understanding of both the typologies and quantities of raw materials used by energy technologies is required to identify technologies that may introduce more significant resource use issues in terms of both environmental impacts and material availability. Inclusion of such factors within ESM projects has the potential to contribute to the current research by allowing for more complete assessments of future energy scenarios to be generated.

Most projected future energy scenarios predict significant increases in the share of renewable energies in the EU energy mix, predominantly via wind turbine and solar PV technologies (European Commission 2020). And, while utilising such technologies results in far lower day-to-day emissions once in operation, the production of the infrastructure required to implement more renewable energy regimes is often overlooked (Amponsah et al 2014). In the section that follows, the methodologies for the two LCIA indicators–GWP and CED, as outlined in **Table J.10** of the appendices–are operationalised alongside the methodologies for EoLRIR and SR outlined in the previous section using material intensity information for the most common wind and solar photovoltaic technologies.

Carrara et al. studied the raw material demands relating to four key infrastructure types for both wind turbine and solar PV technologies (Carrara et al 2020). Data from the study provides inputs to case studies using the current methodology. Firstly, inputs are provided for four types of wind turbine: two direct-drive (DD)–electrically excited synchronous generator (EESG) and permanent magnet synchronous generator (PMSG)–and two gearbox (GB) driven–PMSG and double-fed induction generator (DFIG). Material intensity data is supplied for concrete, glass/carbon composites, cast iron, epoxy resin polymers and steel alongside 12 critical metals. These values are provided alongside the corresponding LCIA indicator data–GWP and CED–and material supply data–EoLRIR, overall annual consumption and SR–for the EU in **Table D.1**. Meanwhile, the study also reports data for installations based on four types of solar PV cell: the first-generation crystalline silicon (C-Si) and three of the newer, second-generation “thin-film” cells–cadmium telluride (CdTe), copper indium gallium diselenide (CIGS) and amorphous silicon (a-Si). Material intensity data is supplied for concrete, glass, plastic, and steel alongside 10 critical metals. Input data values are provided in **Table D.2**. All sources of data used in the analysis are summarised in **Table J.11** and **Table J.12** of the appendices for wind turbines and solar PV, respectively.

Results for both groups are summarised in **Table D.3**. The results for wind turbines indicate that a significant amount of variation exists between the four types analysed. The results for GWP and CED are all dominated by steel, which contributes around half of the total for all turbine types. The higher level of steel in DD-EESG turbines means that it scores considerably higher than other turbines in both of these categories. The four other non-critical materials, alongside zinc, provide most of the remaining contributions to GWP and CED values. Variation is far higher within the supply risk category. For all turbines, this factor is dominated by amounts of the rare earths dysprosium and neodymium and, to a lesser extent, praseodymium and terbium. Accordingly, the final score for the DD-PMSG turbine is substantially higher than the other turbines owing to higher levels of all four of these metals. The lowest levels of variation occur in the results for EoLRIR, which are dominated by amounts of concrete and steel. Overall, the most “desirable” of the four wind turbines analysed is the GB-DFIG turbines which return the lowest scores for GWP, CED and SR and the second highest EoLRIR.

Table D.1. LCIA indicators, EU material supply data and specific material inputs for four wind turbine sub-technology case studies

Material	LCIA indicators[a]		EU material supply data[a]			Case study material inputs[b]			
	GWP	CED	Consumption	SR	EoLRIR	Material intensity			
						DD-EESG	DD-PMSG	GB-PMSG	GB-DFIG
	[kg CO_2-eq/MW]	*[MJ/MW]*	*[kg/yr]*		*[%]*	*[kg/MW]*	*[kg/MW]*	*[kg/MW]*	*[kg/MW]*
Concrete	0.12	0.9			90.0	369,000	243,000	413,000	355,000
Glass/carbon composites	2.45	37.9			19.0	8,100	8,100	8,400	7,700
Cast iron	1.91	20.9			85.0	20,100	20,100	20,800	18,000
Polymers (epoxy resins)	4.70	97.3			1.0	4,600	4,600	4,600	4,600
Steel	1.45	17.3			85.0	132,000	119,500	107,000	113,000
Aluminium (Al)	9.36	107.7	5,252,000,000	0.59	12.4	700	500	1,600	1,400
Boron (B)	1.42	22.4	62,850,000	3.19	1.0		6	1	
Chromium (Cr)	0.04	0.7	1,200,000,000	0.86	21.0	525	525	580	470
Copper (Cu)	1.23	19.6	4,000,000,000	0.32	17.0	5,000	3,000	950	1,400
Dysprosium (Dy)	59.60	1,170.0	14,000	6.20	0.0	6	17	6	2
Manganese (Mn)	2.95	36.9	800,000,000	0.93	8.0	790	790	800	780
Molybdenum (Mo)	16.93	232.1	60,000,000	0.94	30.0	109	109	119	99
Neodymium (Nd)	49.60	733.7	100,000	6.07	1.3	28	180	51	12
Nickel (Ni)	6.50	111.0	460,000,000	0.49	17.0	340	240	440	430
Praseodymium (Pr)	78.43	1,158.4	41,000	5.49	10.0	9	35	4	
Terbium (Tb)	297.00	5,820.0	24,000	5.51	6.0	1	7	1	
Zinc (Zn)	2.76	49.4	4,000,000,000	0.34	31.0	5,500	5,500	5,500	5,500

[a] See **Table J.11** in the appendices for detailed description of data sources, [b] Material intensities sourced from European Commission (2020c)

A significant amount of variation also exists between the four types of PV cells analysed. The results for GWP and CED are again dominated by steel, which contributes between 30 and 40% of the observed levels in both categories. Glass and plastic also influence the final scores in these categories, as does aluminium. Nevertheless, the levels of all materials are assumed to be identical to the material intensities given in the EC study (Carrara et al 2020), so the intensities of the critical metals other than aluminium are ultimately responsible for variations in GWP and CED. Hence, the levels of germanium and silicon in a-Si cells give them the highest scores in these categories.

Table D.2. LCIA indicators, EU material supply data and specific material inputs for four solar photovoltaic sub-technology case studies

Material	LCIA indicators[a]		EU material supply data[a]			Case study material inputs[b]			
	GWP	CED	Consumption	SR	EoLRIR	Material intensity			
						DD-EESG	DD-PMSG	GB-PMSG	GB-DFIG
	[kg CO_2-eq/MW]	*[MJ/MW]*	*[kg/yr]*		*[%]*	*[kg/MW]*	*[kg/MW]*	*[kg/MW]*	*[kg/MW]*
Concrete	0.12	0.9			90.0	60,700	60,700	60,700	60,700
Glass	0.97	12.3			40.0	46,400	46,400	46,400	46,400
Plastic	3.62	90.8			32.5	8,600	8,600	8,600	8,600
Steel	1.45	17.3			85.0	67,900	67,900	67,900	67,900
Aluminium (Al)	9.36	107.7	5,252,000,000	0.59	12.4	7,500	7,500	7,500	7,500
Cadmium (Cd)	5.52	93.4	700,000	0.34	30.0		50		
Copper (Cu)	1.23	19.6	4,000,000,000	0.32	17.0	4,600	4,600	4,622	4,600
Gallium (Ga)	169.31	2,605.6	27,000	1.26	0.0			4	
Germanium (Ge)	170.00	2,890.0	39,000	3.89	2.0				48
Indium (In)	119.37	2,101.3	30,000	1.79	0.0			15	
Selenium (Se)	3.44	60.2	1,000,000	0.41	1.0			35	
Silicon (Si)	49.42	964.9	433,000,000	1.18	0.0	4			150
Silver (Ag)	512.52	7,858.7	3,800,000	0.68	19.0	20			
Tellurium (Te)	6.94	125.4	30,000	0.51	1.0		52		

[a] See **Table J.12** in the appendices for detailed description of data sources, [b] Material intensities sourced from European Commission (2020c)

Table D.3. Final indicator results for wind turbine and solar PV case studies (per MW of installed capacity). Lowest values of GWP, CED and supply risk and highest value of EoLRIR are shaded

		Net GWP	Net CED	Net SR	Net EoLRIR
		[10^3 kg CO_2-eq]	*[GJ]*	*[-]*	*[%]*
Wind turbines	DD-EESG	353	4,382	0.006	85.2
	DD-PMSG	326	4,166	0.025	84.1
	GB-PMSG	329	4,058	0.006	85.9
	GB-DFIG	319	3,960	0.002	85.5
Solar PV	C-Si	268	3,640	0.000	69.2
	CdTe	258	3,490	0.001	69.2
	CIGS	260	3,523	0.001	69.2
	a-Si	273	3,762	0.005	69.1

Variation is again significantly higher in the supply risk category. By far the lowest score here is for the first-generation c-Si cells, with only small contributions from silver, aluminium and copper (silicon itself does not make a significant impact). The final SR factor scores for CdTe and CIGS cells are both moderately high, predominantly because of the presence of tellurium and indium, respectively. However, by far the highest score in this category was returned for a-Si cells, which is over four times higher than the other cell types. This high score is almost exclusively the result of a requirement for germanium. Lastly, the results for EoLRIR are almost identical for all turbine types as they are overwhelmingly dominated by concrete and steel which are assumed to be identical in plants for all four cell types. Selecting the most "desirable" of the four solar PV technologies is less straightforward. CdTe cells return the lowest scores for GWP and CED and the second lowest for SR, making it a strong performer. However, the low SR score for C-Si give it a very strong advantage if this category is prioritised.

It is noted that the scores for GWP, CED and SR are all significantly higher in wind turbines when compared to solar PV facilities on a per MW basis. For GWP and CED, this is explained by the far higher levels of concrete and steel required in wind turbine structures, while the differences for supply risk are predominantly due to the presence of rare earth materials in wind turbine generator systems. Conversely, high levels of recovery and/or recycling for concrete and steel mean that overall EoLRIR rates are higher for wind turbines. Nevertheless, the results strongly indicate that production of a single MW of electricity generation capacity via new wind turbine installations is considerably less desirable than solar PV panels in terms of GWP, CED and SR. Although many other aspects ultimately affect the adoption of different technologies, these simple findings suggest that certain elements of wind turbine designs would need to be improved if they were to become comparable to solar PV panels in the aspects investigated. For example, new wind turbine generators should be designed to include features that facilitate their repairability by allowing access, disassembly and the replacement of specific parts. Extending the service life using these design features would enhance the remanufacturing and reuse of these parts and reduce their dependency on imports. Extending the lifespans of foundations, blades and other components may also improve their desirability in relation to other renewable energy technology options. Collectively, these measures would result in lower SR and higher EoLRIR values.

The given case studies confirm the effectiveness of employing a relatively simple methodology for obtaining useful information regarding emissions, embedded energy, supply risk factors and recycling rates that allow robust comparisons to be made between technologies using readily available data. Furthermore, the exercise demonstrates that including raw materials assessments in ESM can help to visualise the relevance of certain materials in achieving energy targets and, therefore, to urge the development of new resource management measures directed to ensure the supply of key raw materials and/or components for renewable energy technologies.

D.5 Discussion and conclusions

Renewable energy technologies are evolving as a promising way of reducing global warming potential and the effects of climate change. Meanwhile, energy system models represent a powerful tool for forecasting possible low carbon future energy scenarios. Although, from a system perspective, environmental implications aside from greenhouse gas emissions need to be addressed to ensure the implementation of the most sustainable energy systems, most present-day energy system models cannot provide information about the other potential environmental and raw materials implications of the systems they replicate. This paper proposes a methodology that combines indicators based on life cycle assessment and material metabolism studies with the objective of providing complete and valuable new information for exploring potential climate policy pathways for reducing greenhouse gas emissions from a holistic perspective. This includes additional information about the potential reduction of greenhouse gas emissions, total energy demand and, more importantly, a better understanding of the possible limitations on obtaining projected installed capacities based on disruptions of raw material supply. Such information will lead to the identification of renewable energy technologies with lower environmental footprints in terms of greenhouse gas emissions while allowing more sustainable and realistic energy system options to be pinpointed using a range of material supply indicators.

The proposed methodology for calculating composite indicators for energy supply technologies demonstrates that useful and informative information can be calculated relatively simply from material intensity data in conjunction with life cycle impact assessment outputs and material supply data. In that sense, the methodology proposed offers, on one hand, a clear definition of a set of indicators that support a more complete assessment of energy technologies alongside existing life cycle assessment studies. On the other hand, the use of established and reliable data sources (Ecoinvent and official EU data) allows bespoke data in a readily usable format to be easily elaborated by energy system modellers.

Additionally, while the given examples use data inputs for the European Union based on a single megawatt of installed capacity, the methodology could easily be adapted to data sources from other regions, for smaller or larger scales and for net energy units. The simplicity of the approach also means that any number of other life cycle impact assessment or material supply data sources could be adapted and applied. The study has demonstrated that a variety of life cycle assessment and material metabolism data is already available that can be used to assess many forms of fossil-based and renewable energy technologies using the proposed methodology and, ultimately, to include the generated indicators in energy system models or similar investigations. For some technologies, greater effort is needed to improve the availability of life cycle inventory data in a useable and formalised format (e.g., the Ecospold standard), particularly for newer solar, geothermal and fuel cell technologies and the myriad electricity storage options available, to name a few. For biomass-derived products used for energy purposes, the data currently available regarding material metabolism studies is limited. For instance, the 2020 European Commission report (European Commission 2020) included supply risk and end-of-life recycling input rate data for three biomass materials (natural cork, natural teakwood and sapele wood) mainly used for construction material and high-end furniture and, thus, of little relevance for energy system models. With the increasing importance of the circular bioeconomy in the European Union, more material metabolism studies of biomass-derived products are likely to be available shortly. As a consequence, applying the indicator calculation methodologies proposed in this paper will soon become feasible for a range of biomass applications. In that sense, it is thought that the potential of the methodology for comparing competing sub-technologies within a field could be especially useful.

Although this section is limited in its investigation of material metabolism indicators to supply risk and end-of-life recycling input rate, it is thought that import reliance–included in the European Commission's calculations of supply risk scores for individual materials–could also be used to provide critical information as a standalone indicator. While the European Commission leans heavily on the supply risk factor for quantifying the overall criticality of materials, it is recognised that import reliance is more relevant in terms of greenhouse gas emissions as it essentially provides information about the transport requirements for obtaining the raw materials for producing energy infrastructure. As such, it could be considered to be a proxy environmental impact indicator and worthy of further investigation using similar analysis techniques to the current study, particularly as a readily available dataset already exists–at least for the European Union–for the set of most critical raw materials. For now, such approaches could be used in conjunction with the many energy system models and datasets already in existence for European Union and other global and local energy systems to obtain more accurate information regarding materials metabolism. This would enable more informed strategy decisions to be made by climate and resource management policymakers. As wind and solar energy look likely to remain a policy priority in many European countries in coming years, the European Union will need to emphasise the importance of better wind turbine and solar photovoltaic designs, including the implementation of circular economy strategies such as repair and remanufacture, as they strive to meet decarbonisation goals. Demand for such indicators looks set to increase, particularly as new regulations continue to include them as requirements. Consideration of the indicators proposed in this paper represents a vital first step in progressing towards a more complete methodology for the modelling and identification of more sustainable energy systems.

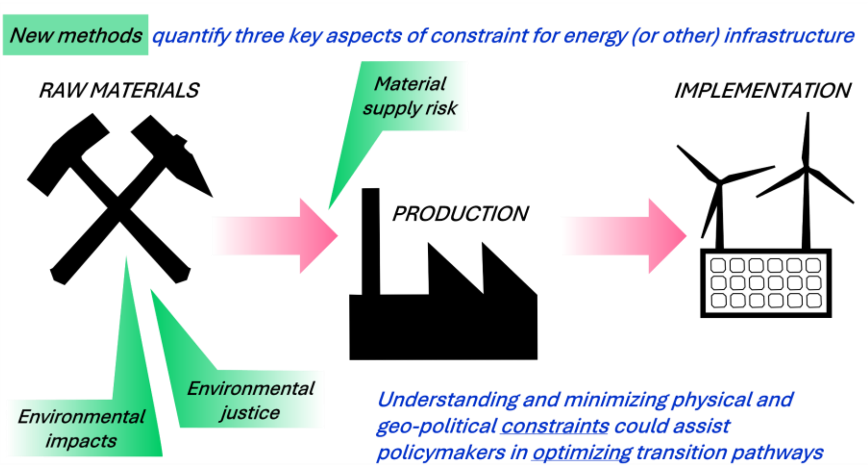
E FOURTH ARTICLE

New techniques for assessing critical raw material aspects in energy and other technologies

Nick Martin, Cristina Madrid-López, Gara Villalba-Méndez, Laura Talens-Peiró

Environmental Science & Technology, 24 November 2022, *https://doi.org/10.1021/acs.est.2c05308*

Abstract



Transitioning to more sustainable energy technologies is a vital step in the move towards reducing global greenhouse gas emissions. However, several physical constraints could hinder the implementation of these technologies and many of the raw materials required to produce new infrastructure are scarce, non-renewable and non-substitutable. Various factors relating to material extraction and processing activities may also affect the security and socio-political aspects of future supply lines. Here, methods are introduced for quantifying three key indicators relating to raw material supplies for specific production processes: (1) overall supply risk; (2) environmental impacts from sourcing raw materials; and (3) environmental justice threats at sourcing locations. The use of the proposed methods is demonstrated via an exploratory case study examining projected electricity production scenarios within the European Union. Results suggest that renewable sources of electricity–particularly wind, solar and geothermal technologies–are more likely to exacerbate supply risks and environmental issues than other technologies. Furthermore, projected expansions of wind and solar technologies mean that all three indicators appear likely to rise significantly systemwide by 2050. Ultimately, the methods represent a much needed first attempt at providing practitioners with simple and robust approaches for integrating factors relating specifically to raw material supply into energy modeling and other applications.

E.1 Introduction

Scientists and policymakers have now widely accepted the need to reduce emissions of greenhouse gases (GHGs) at all scales (Ripple et al 2019). This is reflected in symbolic global initiatives like the Paris Agreement (United Nations 2015) and in the many national, regional and local policies that are being formulated to address the issue. Within the rapidly evolving arena of energy and environmental policy, the need to accelerate the adoption of more "sustainable" sources of energy is viewed as one of the key pathways to reducing emissions and achieving future targets (IRENA 2021).

However, the concept of sustainability in energy systems is evolving beyond the mere reduction of GHG emissions. Among other things, the ongoing sourcing of the raw materials and components required to implement new infrastructure continues to gain policy focus (Bleicher & Pehlken 2020, Bobba et al 2020, Hund et al 2020, Nansai et al 2014, Wellmer et al 2019) and mainstream media attention (Ambrose 2021, Ewing 2021, Glüsing et al 2021, Pattisson & Firdaus 2021, Searcey et al 2021), and several potential "roadblocks" have been identified. The range of issues triggered by the COVID-19 pandemic and war in Ukraine have further highlighted the vulnerability of infrastructure development to supply chain disruptions (European Commission 2022, Hoang et al 2021).

A number of specific concerns have been raised in this regard, mostly surrounding the available stocks of necessary materials (Calvo & Valero 2021, European Commission 2020c, Valero et al 2018), geopolitical and governance issues associated with supplying countries (European Commission 2018b, Lee et al 2020, Vlaskamp 2019) and the issues of social justice and localized environmental damages that surround the increased demand for materials (Fortier et al 2019, McLellan 2020, Sovacool et al 2019). All three aspects are likely to play a role in determining the speed and direction of the energy transition going forward. The European Commission (EC) has begun to quantify supply risk for specific materials (European Commission 2020c) and now includes geographical concentration and governance, import reliance and responsible sourcing aspects as part of its triennial "Raw Materials Scoreboard" assessments (European Commission 2021a). A handful of additional studies have also attempted to measure other aspects of material sourcing, particularly in relation to justice and conflict issues (Church & Crawford 2018, Lèbre et al 2019, 2020). However, these assessments generally only apply to individual materials. As such, despite a relative paucity of suitable data, a clear need for the quantification of raw material-related constraints relating to *individual technologies and processes* is arising, particularly for those wishing to optimize system-wide transition pathways and minimize the exposure of these pathways to risk.

To bridge this gap, a series of methods–developed for assessing energy system characteristics as part of the SENTINEL project (SENTINEL n.d.)–are presented here that use raw material inventory information from life cycle assessment (LCA) databases alongside other data sources to generate three unique indicators specifically related to the supply of raw materials. Firstly, the risk of interruption to raw material supply channels is quantified by incorporating supply risk data published by the EC (European Commission 2020c). Two further indicators attempt to quantify the possibility of localized issues occurring during the extraction and processing of raw materials: the potential to exacerbate local environmental conditions is estimated using ecosystem and human health data relating to individual materials from the Ecoinvent LCA database (Ecoinvent 2021, Huijbregts et al 2017), while the potential to reproduce local environmental justice issues is quantified using data relating to sourcing countries within the Worldwide Governance Indicators (WGI) dataset (Kaufmann et al 2011, The World Bank n.d.). Collectively, it is believed that these three indicators represent the majority of key issues in relation to raw material supply at present.

The methods enable composite values to be derived for individual technology types or, indeed, for any unit process defined within LCA databases; higher scores highlight processes that involve material sourcing from locations with higher inherent risks of supply interruption, with poor environmental impact characteristics or where environmental justice issues are potentially more likely to occur. Values could be integrated into existing energy modeling applications to account for these aspects–e.g., as in-built calculations or soft-linked constraint parameters within integrated assessment models or other energy system models–or be used as standalone indicators for assessing proposed energy system configurations in other applications. Full descriptions of the methods and suggested data inputs for each indicator are provided. The approach is then operationalized via a case study involving current and projected scenarios for the European Union (EU) electricity network. A validation and sensitivity analysis is also provided. Findings from the case study and further aspects of the methods are then discussed alongside a final set of conclusions.

E.2 Methodology

The proposed methods all use material requirement information provided by life cycle inventory (LCI) data as their foundation. An LCI represents one of the four phases within life cycle assessment (LCA) (ISO 2006). During this phase, all of the elementary material and energy flows that occur within a process are determined. This includes all sub-processes that occur during the materials extraction, processing and manufacturing stages–and, if required, the product use and disposal stages–within the entire life cycle of a process. The resulting breakdown includes listings of all inputs and outputs that occur for a range of different materials. Furthermore, it will include specific items for the process in question–the “foreground” system–alongside those for the broader industrial economy–the “background” system. Final material requirements are given as the total mass of a material required to produce one “unit” of a process. Here a small selection of the available LCI data–using the Ecoinvent database (Ecoinvent 2021)–are used to perform a customized set of calculations relating to the supply of a unique set of raw materials to a given process.

The methods use 55 of the raw materials identified as being most important to the EU in accordance with the latest list of so-called critical raw materials (CRMs) published by the EC. The most recent investigation, from 2020 (European Commission 2020c), considers a group of 80 materials as potential CRM candidates, of which 44 were deemed critical using a standardized methodology (European Commission 2017a) based on economic importance and supply risk factors. The list includes the five platinum group metals, 10 heavy rare earth and five light rare earth elements; holmium, thulium, lutetium and ytterbium are grouped as a single heavy rare earth entry.

An attempt to align the 80 candidate materials from the 2020 EC study with the listings in the December 2020 version of the Ecoinvent LCI database (Ecoinvent 2021) found that 30 of the 44 CRMs and 25 of the remaining 36 candidate materials are represented in the database; full documentation is provided in **Table J.16** in the appendices. While it is observed that 25 of the 80 materials were found to have no suitable match in the LCI database, it is noted that 14 of these "missing" materials were categorized as "industrial and construction"–e.g., aggregates, rocks, sand–or "biological and other"–e.g., rubber, cork, wood–many of which are either too generic, not relevant or too complex to quantify in LCI listings.

Material requirement data for a given process–relating to the 55 selected materials–is then used alongside other data for each material to create the three composite indicator values. That is, individual "scores" can be obtained for any process defined by an LCI. The three final scores then enable direct comparisons of raw material indicators to be made for different processes. However, though the approach fundamentally provides scores for unit processes, the obtained scores can also be upscaled to provide composite scores for entire systems of individual processes. For example, in an energy system, each indicator can be applied pro-rata according to the relative contributions of each energy source to obtain composite scores that allow complete system configurations, such as those derived from energy systems modeling, to be compared. In this manner, the raw material characteristics of current and proposed energy systems can be analysed for energy policy and planning purposes. Furthermore, as the methods are generically based on LCI definitions, it can equally be applied to any process defined within existing LCI databases. **Figure E.1** provides a final conceptual overview of the proposed approach prior to the detailed descriptions of each method.

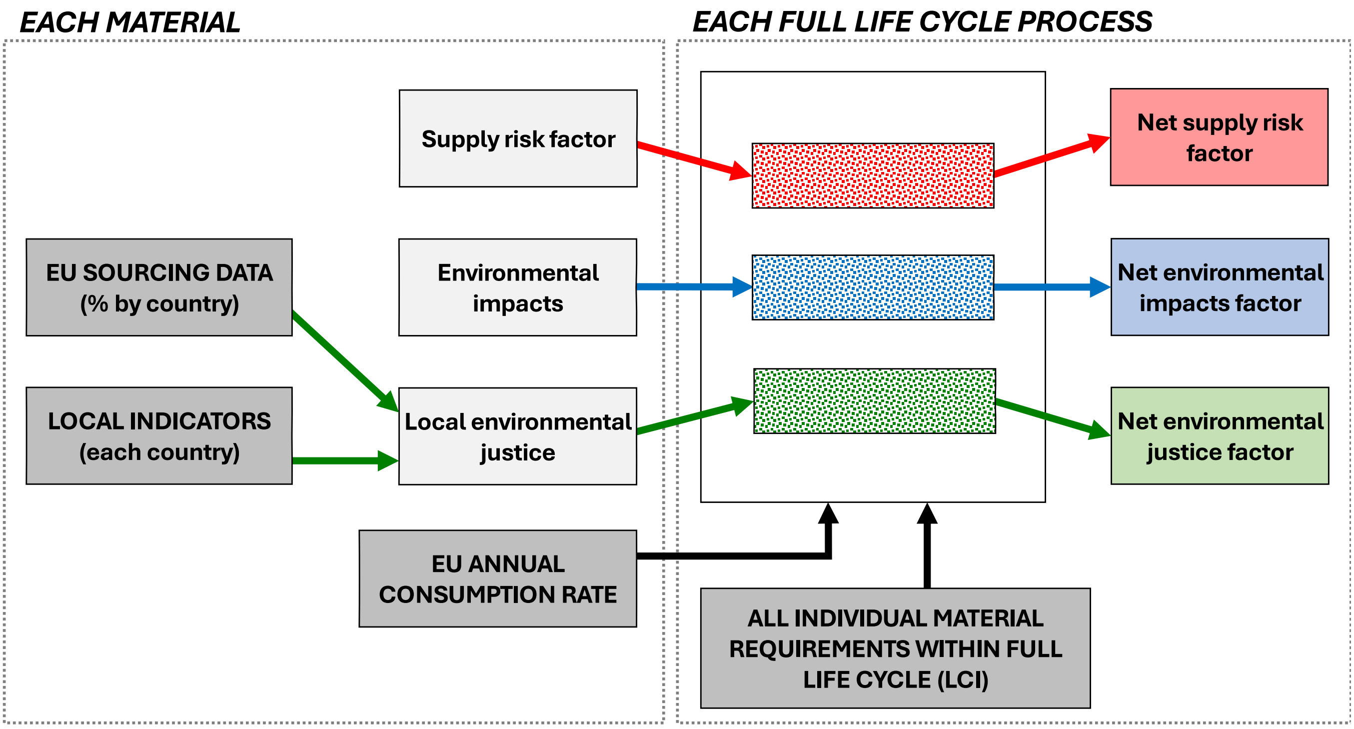


Figure E.1. Conceptual overview of methods used for deriving the three raw material indicators for the extraction and processing of 55 selected materials. It is noted that all three indicators relate solely to the activities involved in deriving and supplying a specific group of raw materials to a process and do not attempt to quantify all supply risk, environmental impacts or environmental justice aspects relating to the entire life cycle of that process

E.2.1 Supply risk

The first method attempts to quantify the level of supply risk inherent to the sourcing of raw materials for a given process. Alongside an indicator for economic importance, the EC uses a derived measure of supply risk (SR) as one of the two key inputs its own assessments of CRM status (European Commission 2017a, 2021a). In essence, the EC's SR factor quantifies the potential risk of a disruption occurring within the supply chain of a material by considering the current sourcing locations of supplies and the governance and trade attributes of those locations. It is produced using the latest (2020) data for overall EU import reliance, a circularity indicator (the end-of-life recycling input rate, EoLRIR), a substitution index, and two versions of the Herfindahl-Hirschman Index (HHI) (Matsumoto et al 2012)–derived using Worldwide Governance Index (WGI) (The World Bank n.d.) data–that reflect locational concentration and governance issues for the countries supplying the material at both EU and global levels. A complete listing of raw SR factor values for the materials examined in the study is provided in **Table J.17** in the appendices.

Here, a composite SR indicator for a particular process is created by summing all SR factor values in proportion to the amount of the corresponding material required (*mass*) to produce one unit of the final “product” defined by the LCI. Initial attempts at deriving the indicator considered only these two inputs. However, it was soon discovered that using “raw” values of material requirement placed a large bias on materials used in larger amounts; this tended to vastly overshadow the significance of scarce materials used in much smaller amounts. For example, although both are considered to be CRMs, the required and available masses of materials such as silicon or titanium can be up to five orders of magnitude higher than those of rare earth materials. To overcome this bias, EU annual consumption levels (Bobba et al 2020, European Commission 2020c, Eurostat 2018) were used as a “scaling” measure to represent the relative magnitudes of the requirements for different materials in the EU. As such, each material requirement value was first normalized by being divided by the corresponding EU consumption rate. Accordingly, the proposed formula for calculating the net SR factor for a given process is as follows:

$$SR_{process} = \sum_{i=1}^{n} \frac{m_i \, SR_i}{c_i}$$

where:
$SR_{process}$ = net supply risk factor for the process under study [yr/MJ]
n = number of selected individual materials in the process under study
m_i = mass of material i required by the process under study [kg/MJ]
SR_i = supply risk factor of material i [dimensionless]
c_i = annual consumption level in EU of material i [kg/yr]

It is noted that, while the final value for the net SR factor is essentially dimensionless, the final units are actually the timeframe of the consumption data divided by the unit that the material intensity is based upon–in this case, the relatively meaningless years per megajoule. Although calculations could also be undertaken using LCI data for processes based on different “functional units”–e.g., megawatts of installed capacity or kilometres of travel–these would naturally return final values in different units. Though this demonstrates the flexibility of the method, it follows that one cannot directly compare final scores based on different functional units or consumption data.

E.2.2 Local environmental impacts

A second method was developed to capture the potential for local environmental damages to occur during the extraction and processing of primary materials for a given process. Here, LCA data from the Ecoinvent database (Ecoinvent 2021) is again used. However, in this instance the methodological guidance of Graedel et al (2012) is followed by using LCIA endpoint indicators for the production processes of individual materials. As in this study, dimensionless indicators are derived for both ecosystem quality and human health for the production of a single kilogram of each material in accordance with the ReCiPe Endpoint (H,A) method (Huijbregts et al 2017).

The *ecosystem quality* indicator aggregates values for terrestrial acidification, terrestrial ecotoxicity, freshwater ecotoxicity, marine ecotoxicity, freshwater eutrophication, agricultural land occupation, urban land occupation, natural land transformation and climate change (on ecosystems). Analysis of the data suggests that this indicator is overwhelmingly influenced by some combination of marine ecotoxicity, natural land transformation and climate change values for all materials examined. Meanwhile, the *human health* indicator aggregates values for human toxicity, photochemical oxidant formation, particulate matter formation, ionizing radiation, ozone depletion and climate change (on human health). In this case, the indicator is overwhelmingly influenced by human toxicity values for all materials. A simple average of the net ecosystem quality and human health indicators was used as the final environmental impact (EI) value for each material. Although it is acknowledged that these impacts could occur anywhere along the supply chain of these raw materials, it is assumed here that a significant amount are directly related to the extraction and processing operations that occur near or close to their source locations. Full listings of the assumed processes and LCIA endpoint indicators used to define EI values for each material are provided in **Table J.18** and **Table J.17**, respectively, in the appendices. It is noted that the values for gold and the three platinum group metals (PGMs)–palladium, platinum and rhodium–are orders of magnitude higher than most of the other materials tested. This can be traced primarily to extremely high impacts encountered specifically during the extraction and refinery operations relating to these metals (Ecoinvent 2021).

The values for individual materials are then used to create a final indicator for a given process as follows:

$$EI_{process} = \sum_{i=1}^{n} \frac{m_i \ EI_i}{c_i}$$

where:
$EI_{process}$ = net local environmental impacts score for the process under study [yr/MJ]
n = number of selected individual materials in the process under study
m_i = mass of material i required by the process under study [kg/MJ]
EI_i = local environmental impacts score for material i [dimensionless]
c_i = annual consumption level in EU of material i [kg/yr]

E.2.3 Local environmental justice

A third method adopts a similar approach, this time attempting to determine how (un)just the sourcing of raw materials is likely be for a given process. Though perhaps less directly tangible than SR and EI, the environmental justice (EJ) indicator seeks to widely embody a set of concepts that includes conflicts relating to the effects of pollution and the distribution of environmental risks (Martinez-Alier 2002). While the energy transition is widely predicted to exacerbate such issues at the global scale (Bainton et al 2021, Marín & Goya 2021), much of the existing discourse on "energy justice" is focused on the siting of new facilities and the extraction and mining of fuels (Carley & Konisky 2020, Levenda et al 2021, McCauley & Heffron 2018, Ottinger 2013, Sovacool et al 2017, Sovacool & Dworkin 2015) or on the embodied impacts caused by outsourcing energy, products and services from other countries (Akizu-Gardoki et al 2021). In addition to this, a small number of previous studies have attempted to broadly address environmental justice issues in relation to the new infrastructure required to implement the energy transition (Church & Crawford 2018, Dominish et al 2019). Meanwhile, a growing number of studies are endeavouring to quantify (Lèbre et al 2019, 2020) or catalogue (Martinez-Alier 2021) justice-related issues specifically in relation to resource extraction and processing. Moreover, the burgeoning field of social life cycle assessment (sLCA) is beginning to address the impacts caused within these stages, including those used in energy production, and in new renewable energy infrastructure in particular (Fortier et al 2019). Nevertheless, to date, no studies have quantified justice elements in relation to specific materials or processes.

Here, information from an established dataset is again used as a proxy indicator within the method. In this case, a composite value has been derived for each material using values taken directly from the Worldwide Governance Indicator (WGI) dataset (Kaufmann et al 2011, The World Bank n.d.), as used within the EC's derivation of supply risk factor (European Commission 2020c). The WGI provides values *by country* across six categories: voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law and control of corruption. All six categories are thought to be generally associated with conditions that enable or reflect the potential for environmental justice issues to occur and, hence, are assumed to provide a suitable proxy for the potential occurrence of such issues. However, as the scores are provided on an arbitrary scale that typically ranges from around -2.5 to +2.5–where negative scores denote less desirable conditions and positive denote more desirable conditions–values for each indicator and each country are first normalized to percentage scores according to the range observed across *all* countries in that category. Accordingly, the proposed formula for calculating normalized composite WGI scores that equally weight each indicator for each country is as follows:

$$WGI_h = \frac{1}{p} \sum_{g=1}^{p} \frac{v_{g,h} - \min_h \{v_{g,h}\}_{h=1}^{z}}{\max_h \{v_{g,h}\}_{h=1}^{z} - \min_h \{v_{g,h}\}_{h=1}^{z}}$$

where:
WGI_h = composite WGI indicator for country h [%]
p = number of individual indicator categories in WGI database
$v_{g,h}$ = value of indicator number g for country h [dimensionless]
z = number of individual countries in WGI database

Composite EJ indicators for each material are calculated by combining the WGI scores for each country and the percentage breakdown of global supply sources for each of the 80 candidate materials. However, as higher WGI scores reflect better environmental health characteristics, the values used are inverted by subtracting them from unity. Accordingly, the proposed formula for calculating the net environmental justice indicator for a given material is as follows:

$$EJ_i = \sum_{h=1}^{n} s_{h,i}\,(1 - WGI_h)$$

where:
EJ_i = local environmental justice score for material i [dimensionless]
n = number of countries included in analysis
$s_{h,i}$ = share of global supply of material *i* sourced from country *h* [%]
WGI_h = composite WGI indicator for country *h* [%]

As with the previous indicators, the composite EJ values for each material–as listed in **Table J.17** of the appendices–can then be used to create a final indicator for a given process, viz.:

$$EJ_{process} = \sum_{i=1}^{n} \frac{m_i\,EJ_i}{c_i}$$

where:
$EJ_{process}$ = local environmental justice score for the process under study [yr/MJ]
n = number of selected individual materials in the process under study
m_i = mass of material i required by the process under study [kg/MJ]
EJ_i = local environmental justice score for material i [dimensionless]
c_i = annual consumption level in EU of material i [kg/yr]

E.2.4 Possible applications

Calculating values of the three indicators for individual life cycle processes allows comparisons of different technologies or sub-technologies to be undertaken. For example, the indicators derived for a unit of heat or electricity from non-renewable sources could be directly compared with various renewable sources. Likewise, results for different sub-technologies could be compared within a technology group such as wind turbines or solar photovoltaic (PV) panels. Moreover, while the present article focuses on energy-related applications of the methods, it could theoretically be applied to any process defined by an LCI.

At a wider scale, scores for entire systems can be generated by tallying the product of the indicator and the total energy generated by each technology to derive final system-wide values. This would enable, for example, the characteristics of current systems to be compared against multiple future alternatives to inform policy decision making. The proposed formula for calculating aggregated scores over entire systems is as follows:

$$I_{system} = \sum_{i=1}^{n} E_i \ I_i$$

where:
I_{system} = aggregated indicator score for the system under study
n = number of selected individual processes in the system under study
E_i = total energy production derived from technology i
I_i = indicator score of process i

E.3 Case study: EU electricity supply

To demonstrate the value and functionality of the proposed methods, they are applied here to an exploratory case study involving existing and projected electricity generation levels for the EU, by technology, according to the EC's latest "reference scenario" (European Commission 2021b). Values are firstly derived for all available individual LCI listings within the Ecoinvent database (Ecoinvent 2021). Using mean values for each technological group defined within the EC data, aggregated system values were then produced using values from the EC scenario datasets to determine predicted changes in the three indicators under these assumptions.

E.3.1 Individual and grouped scores by technology

Using the 11 technological categories defined within the reference scenario as a basis, all 51 regionally applicable electricity production processes within the 2021 version of the Ecoinvent LCI database (Ecoinvent 2021) were collected and grouped. Values of the three indicators were then derived for each individual process on a per-MJ basis as displayed in **Figure E.2**.

The results for the three indicators demonstrate a relatively clear pattern across all three methods. The mean results by category suggest that risks and impacts are considerably lower for lake and river hydropower and nuclear processes, reflecting their relative simplicity and lower reliance on CRMs. Values for the three fossil fuel sources–natural gas, petroleum and solid fossil–are typically moderate, although natural gas scores are generally lower for SR and EJ. Notwithstanding this, major variations are observed for natural gas in the EI category, where three of the 12 processes are significantly higher as a result of their high reliance on platinum and rhodium; all other natural gas processes are far more consistent with scores observed for the other two indicators.

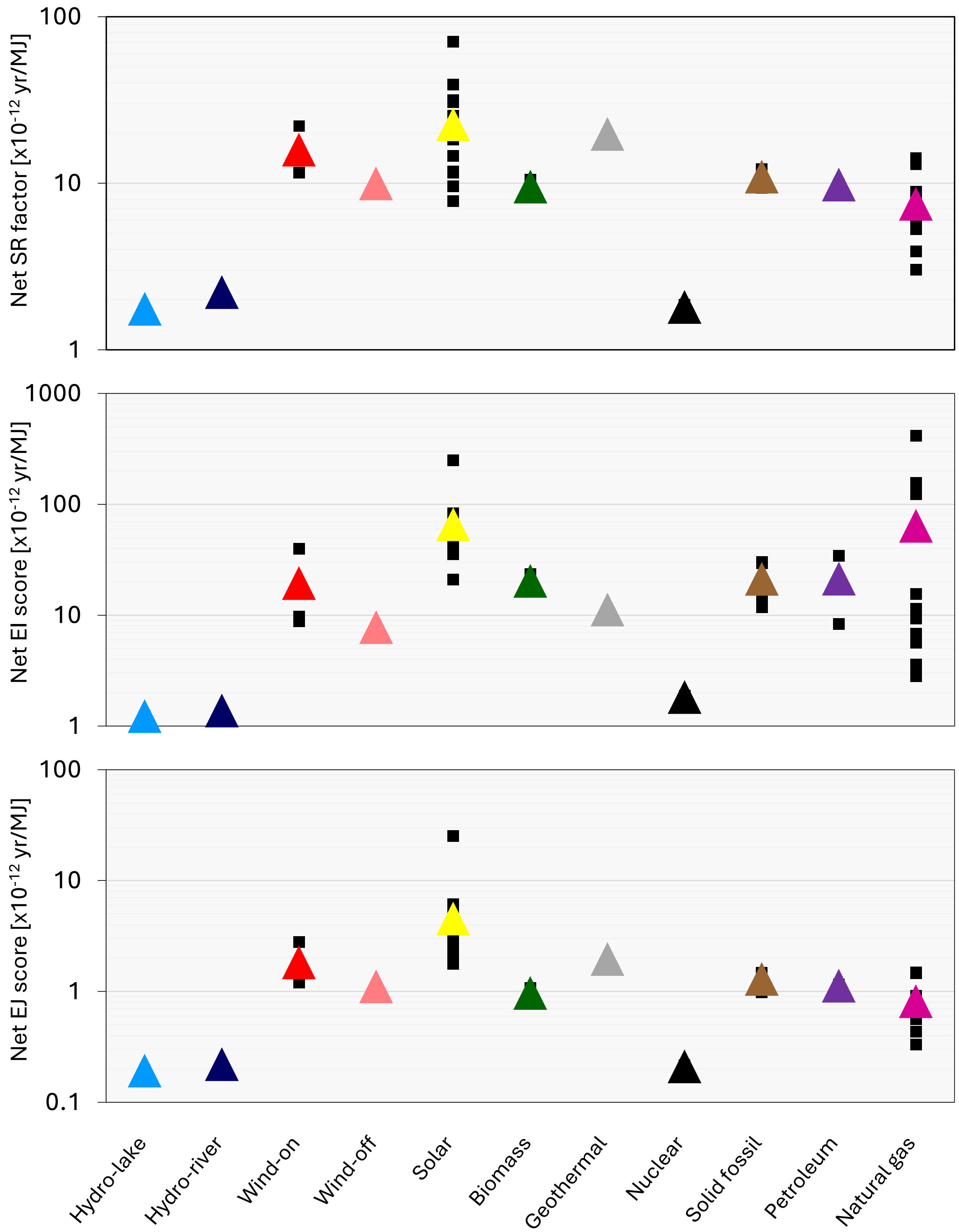


Figure E.2. Results for supply risk factors and environmental impacts and environmental justice scores for all available processes, grouped by category. Mean values shown as coloured triangles

Values for biomass sources also tend to be in this moderate range alongside offshore wind turbines, although the value for offshore wind is somewhat lower in the EI category. Conversely, the scores derived for onshore wind are approximately double these levels as a result of their elevated reliance on rare earth materials, predominantly in the permanent magnets used in certain generator mechanisms (Carrara et al 2020, Rabe et al 2017, Sprecher et al 2015); the offshore turbine assessment within the Ecoinvent dataset assumes the use of hybrid approaches that rely less on rare earth materials. Values for geothermal energy are high in the SR and EJ categories but are noticeably lower for EI and are only considered moderate.

The solar technologies group–which includes both PV panels and concentrated solar power (CSP) plants–is more extensive than other categories, reflecting the many different approaches employed in the field. Values for different solar technologies range from moderate to very high, and more or less cover an entire order of magnitude for each indicator. Copper indium gallium selenide (CIS) cells represent the higher scores in all three indicators, largely based on a strong need for gallium.

The relatively consistent trend observed in the results reflects the influence of using the same masses of material (m_i)–derived from LCI listings–across all three sets of calculations. As such, each indicator can be seen to be, first and foremost, a reflection of the *total* amount of all key materials required–relative to total consumption–per unit of output; a process that uses higher levels of key materials overall will always be more likely to obtain higher scores than those with lower material requirements. In this sense, while the overall trends are clear cut, the three inputs applied for each material–SR_i, EI_i and EJ_i–can be viewed as contributing varying levels of additional "scaling" within each calculation.

Nevertheless, variability in these "scaling" inputs can still be influential and result in significant variations in indicator results, particularly where inputs are not well correlated for a given set of materials. This issue is further investigated via a series of regression analyses, provided in section **J.5.1.1**. Regression analysis on the three indicators at the material and process level revealed that the results appear to be suitably "unique" at the *material* level, particularly for EI values which are significantly different to the findings for SR and EJ. Notably, despite the fact that both include data from the WGI database in their derivation, the "R-squared" (R^2) value comparing SR and EJ at the material level was found to be relatively low (0.15780). In any case, the common material use amounts used in both calculations scale up these factors and provide similarity at the *process* level.

E.3.2 Current and projected scores for EU system

To demonstrate the application of the three indicators to real-world scenarios, they are applied to projected values of gross electricity generation, by source, from the EU reference scenario (European Commission 2021b); observed and projected values for the 11 categories are provided at five-year intervals between 2005 to 2050, as listed and illustrated in **Table J.19** and **Figure J.7** in the appendices, respectively. The raw data demonstrates that wind, solar and biomass are the only technologies to have risen significantly since 2005, although this trend is not expected to continue for biomass. Although geothermal sources are expected to rise slightly after 2035, the utilizations of onshore and offshore wind and solar technologies are projected to *increase* by factors of 2.9, 7.6 and 4.2, respectively, between 2020 and 2050. All other technologies are seen to remain relatively stable going forward. However, in the cases of petroleum and solid fossil fuels, levels are predicted to *decrease* by factors of 30.2 and 9.6, respectively. As such, wind, solar, petroleum and solid fossil fuels are expected to have the biggest influence on overall changes across all three factors.

Values for individual technological categories are first calculated by multiplying the mean values for each indicator–in yr/MJ–by the amount of energy reported for that category–in MJ/yr–in the EU data. Final system values for the three indicators are then calculated by aggregating the scores for all 11 categories. Final values for the three indicators at each interval–normalized to "base" levels in 2005–are shown in **Figure E.3**; a full listing of these results is also provided in **Table J.20** in the appendices.

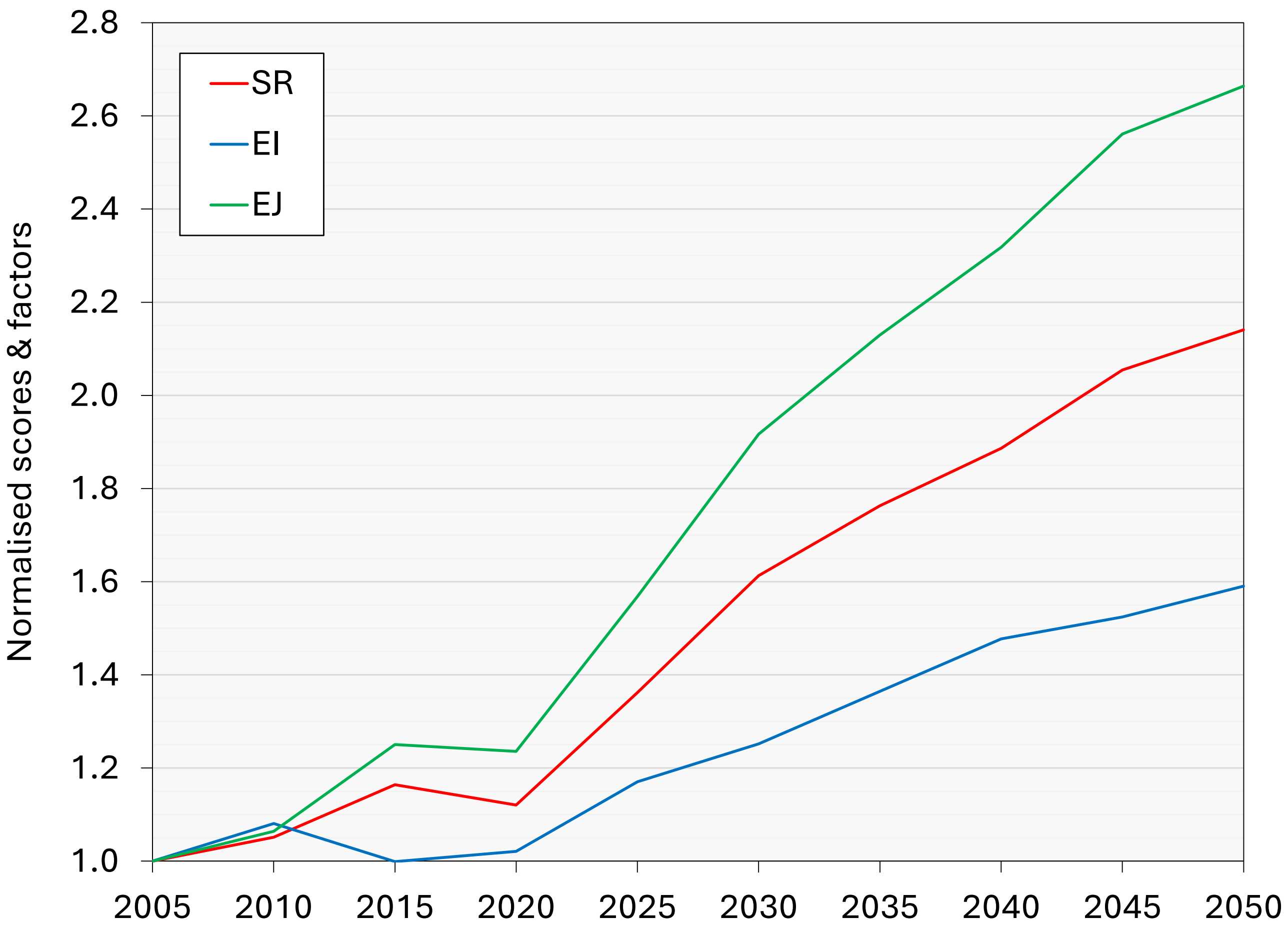


Figure E.3. Normalized values of overall supply risk (SR) factors and environmental impacts (EI) and environmental justice (EJ) scores for the EU electricity system for the period 2005 to 2050 according to technological projections defined by the EU reference scenario. All values are relative to the dimensionless values of SR, EI and EJ for 2005 of 67.8, 219.8 and 7.7, respectively. It is noted that the projections are based on the current values for SR, EI and EJ for each material. As such, they do not purport to predict any future variations in these factors for different materials going forward or to reflect previous values. Rather they are used to broadly illustrate the vulnerability of forecast energy systems in the EU to raw materials supply issues, based on current estimates for each material

The results indicate that the overall values of each indicator are likely to increase dramatically under the forecast scenario. Values of SR and EJ are both predicted to more or less double between 2020 and 2050; the value of EI is expected to rise by around 56%. A small downturn was noted in the SR and EJ observations between 2015 and 2020, largely due to the especially hurried withdrawal of solid fossil fuels and petroleum–which have significantly higher per-MJ values for both SR and EJ than legacy non-renewable technologies like natural gas and nuclear–and the slight reduction in the growth rate of the highest-ranking group, solar. Similarly, a drop in EI values between 2010 and 2020 is predominantly the result of a drop in the use of natural gas, which has the second highest per-MJ value for EI.

It is noted that these calculations do not take future variations in SR, EI and EJ inputs into account. Present day values are assumed when, in reality, these values are likely to fluctuate over time because of geo-political shifts, technical advancements, changes in recycling practices or discoveries of new reserves. Nevertheless, this example provides a simple demonstration of the potential issues that could result from transitioning to renewable technologies which will most likely continue to rely on materials with higher risk factors.

In the end, the key finding here is that the substantial rises in electricity from wind and solar sources that are predicted by 2050 look likely to result in significant increases in the net scores for all three of the examined indicators. Indeed, onshore wind and solar technologies are predicted to generate the highest and third highest amounts of electricity, respectively, by 2050, while also representing the third highest and highest per-MJ scores for each of the indicators.

E.3.3 Sensitivity analysis

While using annual EU consumption values, c_i, appears to be a logical way to normalize scores and avoid issues of disproportionate weighting in the presented methods, it was deemed necessary to test the influence of these values on final scores. To do this, a simple sensitivity analysis was undertaken. To allow for uncertainties in the estimates of c_i, an additional 20% was added to the annual consumption values for a group of 13 key materials, all of which are high influential in determining indicator values while having annual consumption rates of less than 1,000 tonnes. As expected, all three indicators were shown to be sensitive to these changes, with reductions of between 11.7 and 16.6% being observed. However, very low standard deviations–between 1.0% and 2.8%–were observed within the changes, suggesting that the method can maintain consistent delineation between processes when uncertainties in inputs are experienced. Full details of the analysis are contained in section **J.5.1.2** in the appendices.

E.4 Discussion

Raw material supply is an ongoing concern in relation to the transition to renewable energy sources. Although we are limited to present day assumptions about material supply characteristics, applying newly developed methods to EU system projections strongly suggests that the potential for environmental impacts and justice issues to occur during the extraction and processing phases of the identified set of key materials look likely to rise dramatically over the coming decades. Likewise, the overall risks associated with obtaining these materials also looks set to increase sharply based on current projections. Recent disruptive events such as the COVID-19 pandemic and war in Ukraine have highlighted the fragility of global markets to supply chain issues and made the consequences of such disruptions more tangible in the minds of many. Indeed, Russia currently produces 33 of the 44 materials identified as CRMs by the EC (European Commission 2020c); for five of these–palladium (40.0%), scandium (26.0%), titanium (22.0%), platinum (12.9%) and rhodium (12.0%)–Russia supplies over 10% of current global supplies.

Meanwhile, China is a known producer of 39 of these 44 materials and is responsible for over 80% of current global supplies of 16 such materials, including gallium, germanium and all light and heavy rare earths, all of which are important in the manufacture of wind turbines and solar PV panels (Bobba et al 2020). Ongoing tensions between China and the west could have very serious implications in this regard (Rabe et al 2017, Sattich et al 2021, Vakulchuk et al 2020). For certain materials, increased levels of recycling could help to offset strong import reliances, although recycling activities would also need to be undertaken at the local level to avoid further supply-related issues relating to the importation of recycled materials. Either way, circularity principles look likely to become an integral part of future raw material landscapes (Babbitt et al 2021, Gaustad et al 2018). Nevertheless, many CRMs are technically difficult to recover from waste streams (European Commission 2021a) and strong reliances on newly extracted materials look set to continue for the foreseeable future. Collectively, these observations highlight the need to continue to monitor key materials and to assess the indicators that best reflect the status of these materials over time.

In any case, while most discussions in this area concern the locations of global reserves and the importance of maintaining adequate supply lines, localized environmental impacts during the material extraction and processing stages, and aspects of environmental justice that relate to these impacts, are increasingly being considered. The methods introduced here represent a first attempt at addressing this gap. Furthermore, as the three methods are fundamentally based on listings of individual materials required to produce one “unit” of a given process, they could theoretically be applied to any process defined by an LCI listing and could, theoretically, find use in any number of applications inside and outside of the energy sphere.

Results from the case study strongly suggest that renewable technologies within the wind, solar and geothermal categories present higher SR, EI and EJ values than other technologies, while fossil fuel technologies tend to present midrange values. The higher scores for solar and wind energy present a particular cause for concern in this regard, especially when coupled with the fact that both technologies are expected to play key roles in most predicted transition scenarios worldwide (European Commission 2021b, IEA 2021c, IRENA, 2020). While continuing to rely on fossil fuels would result in lower scores in all three indicators, other ramifications relating to these technologies–not least of which far higher GHG emissions–mean that they are generally no longer considered viable future alternatives. Conversely, although hydropower, biomass and nuclear technologies also bring their own constraints and controversies, it is noted that their potential to introduce disturbances are among the lowest in all three metrics considered here. At any rate, it is hoped that the methods and findings presented will further highlight the seriousness of raw material issues in energy transition processes and the need to interrogate and balance these aspects when considering different technological options.

Nonetheless, while these approaches are thought to represent an original and valuable contribution to the field, several limitations are noted. Firstly, they only consider the group of 80 materials identified as potentially critical by the EC (European Commission 2020c). As such, other key materials could potentially be neglected for certain processes, and aspects relating to the extraction and processing of fossil fuels and uranium–particularly in relation to localized environmental impacts and justice issues–are not included. Furthermore, 25 of the 80 identified materials are not currently represented in the LCI databases. Again, though many of the omitted materials are not considered vital, materials such as niobium, germanium and indium are known to be important in a number of key future technologies (Bobba et al 2020, Buchholz & Brandenburg 2018, Dominish et al 2019, Giurco et al 2019, Hund et al 2020). Wider inclusion of materials in future LCI data releases would provide more robust coverage in this respect.

Similarly, many key technologies are poorly represented in current LCI datasets, limiting deeper analyses or comparisons. For example, only one type of geothermal electricity and two types of solar CSP are represented, and listings for key renewable energy technologies such as biofuel production, power-to-gas (P2G), power-to-liquids (P2L), hydrogen electrolysis and most forms of electrical storage are almost entirely absent in the current databases. Wind power, widely predicted to be a dominant player in most future energy scenarios, is only represented by three onshore processes and one offshore process in the latest Ecoinvent database compared to the 19 listings for solar PV technologies. And, although data can sometimes be obtained from secondary sources (Junne et al 2020), more complete listings of key technologies within universal databases such as Ecoinvent (Wernet et al 2016) and GaBi (Kupfer et al 2020) would greatly improve the ability of practitioners to assess future energy systems.

It is also important to address locational issues as they relate to the methods being presented. As the SR factors being used were specifically derived for EU supplies, they can strictly only be used for processes occurring within the EU. Naturally, local SR factors could be vastly different in certain countries, particularly in those that are dominant suppliers of particular materials or use different supply mixes. On the other hand, the calculations for EI and EJ are far more universal as they rely on global supply mix data or LCIA data where only a single global estimate is used. This highlights the fact that the SR method intrinsically assumes that SR is the same whether materials are brought to the EU as raw and processed materials or embedded within intermediate products; this is thought to be an acceptable assumption in lieu of vastly more complex calculations. Likewise, owing to the complex array of components within most products and processes, it is assumed that using global data is suitable when assessing EI and EJ scores.

Nevertheless, higher levels of granularity in LCA datasets, particularly in relation to the locations in which sub-processes occur, would allow more complete assessments of intermediate materials, components and finished assemblies to be undertaken. In this regard, future studies could attempt more-detailed assessments involving sub-processes within overall processes. As many such sub-processes are likely to occur outside of the EU, SR factors would need to be calculated for each material for different regional locations using a similar approach to that used in the EU (European Commission 2020c). For example, SR factors in China would be vastly different for materials they are currently key suppliers of, and a sub-process occurring in China would then need to use these inputs. The same is true for calculating EJ scores in different territories, where unique supply mixes could theoretically be applied, and EI scores could use more specific LCA processes for materials where regional data exists. Such assessments would be large undertakings and are well beyond the boundaries of the current study. However, the concept could provide a basis for future research.

The supply of raw materials looks likely to remain a concern as we attempt to implement greater levels of renewable energy and other strategic technologies going forward. As such, robust methods for quantifying the constraints and other aspects relating to raw material supply are vital to ensuring that decarbonization pathways are optimized at all levels. In this sense, it is hoped that the introduced methods provide a valuable new contribution to the field of raw material supply at large, and a specific starting point for energy modelling and related applications, as we strive to optimize pathways towards more sustainable energy systems.

F FIFTH ARTICLE

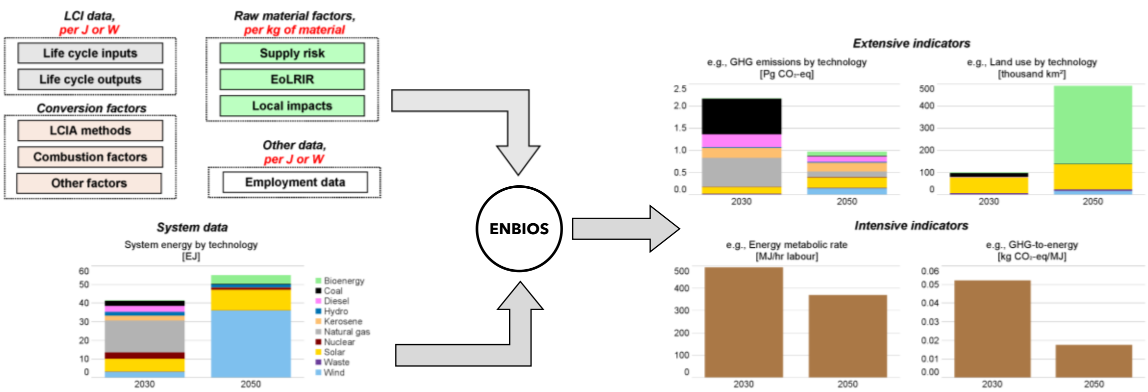
An energy future beyond climate neutrality: Comprehensive evaluations of transition pathways

Nick Martin, Laura Talens-Peiró, Gara Villalba-Méndez, Rafael Nebot-Medina, Cristina Madrid-López

Applied Energy, 14 November 2022, *https://doi.org/10.1016/j.apenergy.2022.120366*

Abstract

ENBIOS enables deeper, multi-scale analysis of future energy systems



Many of the long-term policy decisions surrounding the sustainable energy transition rely on models that fail to consider environmental impacts and constraints beyond direct greenhouse gas emissions and other simplified calculations. Such assessments offer incomplete and potentially misleading information about the true sustainability aspects of transition pathways. Meanwhile, although decision-makers desire greater access to a broader range of environmental, material and socio-economic indicators, few current tools address this gap. Here, we introduce ENBIOS, a framework for integrating a broader range of such indicators into energy modelling and policymaking practices. ENBIOS takes system configuration data from models–or other sources–and produces a series of indicators for each element in the system based on life cycle assessment and other methods. Multi-scale system analyses then enable these indicators to be analysed within and across hierarchical levels. This allows deeper understandings of the sustainability and metabolic aspects of future energy systems to be derived. Its functionality is demonstrated via the analysis of projected scenarios for the European energy system in 2030 and 2050. Although overall emissions will drop significantly, considerable rises in land, labour and critical raw material requirements are likely. These outcomes are further reflected in unfavourable shifts in key metabolic indicators during this period; energy metabolic rate of the system will drop by 25.6%, land requirement-to-energy will quadruple, while the critical raw material supply risk-to-energy ratio will rise by 74.2%. Heat from biomass and electricity from wind and solar are shown to be the dominant future processes across most indicator categories.

F.1 Introduction

Global and local responses to the threat of climate change call for large reductions in the production of greenhouse gases (GHGs) via a rapid transition towards more sustainable energy system configurations. In the European Union (EU), the decarbonization of the economy–where renewable energy technologies replace older fossil fuel-based technologies–acts as one of the five "dimensions" of the energy union strategy (European Commission 2015). However, while "decarbonised" energy systems are generally seen to represent cleaner and more sustainable alternatives, wider understandings of the impacts and constraints that relate to different energy technologies are often overlooked in decision-making. Indeed, the integrated assessment models (IAMs) and other energy system models (ESMs) used to inform energy-related decisions in the EU and elsewhere tend to only include simplified estimates of direct GHG emissions and other environmental factors–such as land and water use and air pollution–as limiting factors in their calculations (IAMC n.d., Pang et al 2014).

Incorporating detailed sets of environmental calculations into such models is cumbersome not only from a computational point of view; it is also complicated by the vastly different semantics employed to define energy and environmental dynamics (Giampietro 2018). Nevertheless, continuing to overlook or simplify certain environmental aspects and constraints could result in suboptimal outcomes in proposed transition pathways (see section **C**). What's more, research suggests that energy decision makers are eager to access more comprehensive information about the range of possible environmental impacts and other limitations that could affect future energy scenarios (Süsser et al 2022a).

The use of life cycle assessment (LCA) (Finkbeiner et al 2006) approaches is one way to address these shortcomings. Within an LCA analysis, the full life cycle of an energy–or any other–process is considered (Arvesen et al 2018). So, rather than basing quantifications solely on the most obvious or visible aspects of a process, LCA-based approaches require the collection of input-output inventories for all contributing operations, from material extraction through to end-of-life disposal or recycling stages. Input flows include aspects like raw material, land, water and energy use, while output flows include emissions to the atmosphere, water bodies and other ecosystems as well as the products and co-products of a technology. Collectively, this life cycle inventory (LCI) data can be converted into more tangible indicator outputs using predefined life cycle impact assessment (LCIA) methods or other calculations.

LCA approaches have been widely adopted in recent years for comparing different existing and emerging technologies, including those within the energy sector (Laurent et al 2018, Valente et al 2021). Furthermore, they are beginning to be used to quantify impacts within complete energy systems by aggregating the impacts of the various technological processes that occur within them (Junne et al 2020). Attempts have also been made to integrate LCA data sources directly into energy models (Arvesen et al 2018, Luderer et al 2019, Reinert et al 2022), and by creating simplified inventories on-the-fly within IAM simulations (Tokimatsu et al 2020). Conversely, within the burgeoning field of prospective life cycle assessment (pLCA) (Arvidsson et al 2018, Gibon et al 2015, Hertwich et al 2015, Pehl et al 2017, Sacchi et al 2022, Dirnaichner et al 2022) information *from* IAMs and other sources regarding future variations in energy system configurations–e.g., energy mixes or efficiencies–are used to incorporate provisions for future changes within LCA calculations.

In any event, no existing approaches allow for the detailed inclusion and analysis of LCA-related inputs or outputs across hierarchical levels within energy systems. In this regard, a number of studies have applied relational analysis principles to assessing the social metabolism aspects of energy systems (di Felice et al 2019, Parra et al 2018). However, such analyses have not attempted to assess environmental impacts or constraints in any detail, nor have they included other socio-metabolic indicators or been able to integrate the resource needs of those systems.

To bridge this gap, we introduce the ENvironmental and BIOeconomic System Assessment (ENBIOS) (Nebot-Medina et al n.d.) framework. ENBIOS has been developed to perform sustainability assessments within the energy modelling platform developed as part of the Sustainable Energy Transitions Laboratory (SENTINEL) project (SENTINEL n.d.). The approach has been designed to connect the functionality of LCA with the multi-level capabilities of the Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM) approach (Giampietro et al 2009, Giampietro and Mayumi 1997, 2000a, 2000b). ENBIOS takes system definition information from ESMs–or any other real or theoretical systems–and combines this with built-in datasets to generate a range of environmental and other indicators at each element in that system. This fundamentally includes the use of LCA-based datasets and methods. However, any number of other user-defined methodologies or datasets can be included in these calculations.

Two broad types of indicators are produced within an ENBIOS simulation. The first of these, *extensive* indicators, are the “primary” indicators produced using the fundamental LCIA and other calculation methods at each system element. For example, energy production, GHG emissions, land requirements or human labour could all be calculated for a given technological process in a system. Combining extensive indicator values for each of these elements then allows a second set of *intensive* indicators to be calculated within the system. Using the previous examples, indicators could be derived to represent the energy produced per hour of labour or GHG emissions per unit of energy, providing useful information about system performance.

The set of extensive and intensive indicators can then be examined within and across hierarchical levels using multi-scale system analysis. This can provide valuable information about the nature of systems at different levels, from individual processes or grouped categories to entire energy systems. For example, visualisations of extensive data could help to identify if higher land requirements are caused by heat or electricity sources in a given scenario, or the relative contributions to labour requirements from different technologies across different scenarios.

Likewise, changes in intensive indicators–e.g., a drop in water use per unit of energy–can be compared and traced according to the changes that occur at different hierarchical levels.

Ultimately, the innovation of the ENBIOS is rooted in its ability to operationalise LCA functionality, and a variety of other methods for deriving extensive and intensive indicators, all within a package designed to evaluate systems from a hierarchical analysis perspective. The flexibility of the workflow to different systems and applications allows simple but powerful observations to be made about the different characteristics that exist at different places within a given hierarchy. This, in turn, provides insights into the potential constraints, "hot spots" and possible trade-offs that exist when analysing current or future systems, energy or otherwise.

The article continues in Section **F.2** with a description of the development of the workflow, including further descriptions of the LCA and MuSIASEM approaches that form its basis and the various inputs and outputs involved in an ENBIOS simulation. A selection of indicators and possible applications are also discussed. A preliminary case study example is then provided in Section **F.3**, based on a projected "climate neutrality" scenario for the European energy system using outputs from the Euro-Calliope model. The article concludes in Section **F.4** with a discussion of key outcomes, potential issues and a roadmap for further development.

F.2 The ENBIOS workflow

While previous efforts have attempted to integrate LCA-based thinking with energy system configurations *and* to consider the socio-metabolic dynamics of energy systems, to the best of our knowledge ENBIOS represents the first attempt to consolidate these two perspectives into a single package. To do this, ENBIOS integrates the high-resolution impact assessment capabilities of LCA with the systemic upscaling capabilities of MuSIASEM. A summary of the ENBIOS workflow is represented in **Figure F.1** and detailed in the following sections.

F.2.1 Preparation

The first step in the development of an ENBIOS simulation is typically to define the system framework within a MuSIASEM environment. To do this one must first define a "dendrogram", a multi-level structure that arranges the system hierarchically into "processor" nodes where the relationships between input and output flows are calculated. Processors can operate in one of two capacities within the "tree" of the dendrogram. "Structural processors" represent the most specific and tangible activities that can easily be located within a spatial-temporal context (e.g., specific technologies like wind turbines or nuclear stations). Meanwhile, "functional processors" represent a less tangible social function (e.g., wind turbines or solar PV panels could exist as "structures" related to the "function" of renewable electricity supply, which is itself related to electricity supply and, ultimately, energy supply). In other words, the lower levels of the dendrogram are typically represented by *structures* that are later related to the *functions* they can provide further “up” the hierarchical structure, respecting their multifunctionality.

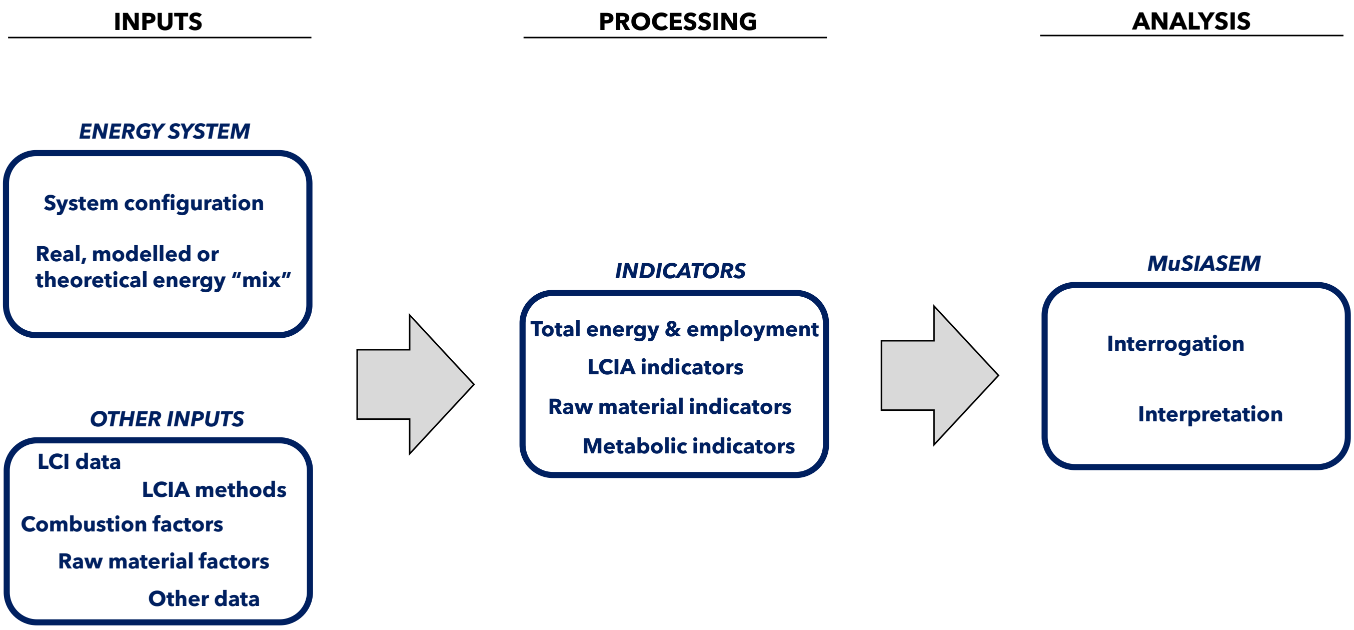


Figure F.1. Overview of general workflow used in the operation of ENBIOS alongside typical inputs and indicators for energy systems

With the hierarchical definition in place, one must relate each structural processor to a specific activity which must be defined by an LCI listing. Several types of additional data are then also required to enable indicators to be calculated at each processor. The “foreground” scaling information is provided by scenario information such as energy mix and installed capacity data, supplied by outputs from ESMs or other system configuration data. By its nature, this data will differ the most between individual scenarios, where different configurations are being tested, for example. Other “background” input data–e.g., employment rates or constants for raw material calculations–are likely to remain relatively constant from scenario to scenario.

The key background inputs are taken from LCA databases. Firstly, an LCI listing provides a detailed set of information relating to the masses of individual materials, volumes of water and areas of land required as inputs to a given process–e.g., the production of one unit of energy using a certain technology or process. Outputs to land, water and soil are also given in relation to radiation, waste and several other aspects. LCI data is assigned at each structural processor in the system dendrogram–one LCI process per processor–and is provided using the ecospold (.spold) format utilised within the Ecoinvent 3.8 database (Ecoinvent 2021).

Meanwhile, an LCIA “method” defines the way that LCI listings for a given process are transformed into useful final indicators–e.g., global warming potential (GWP), total land and water use, and a raft of other resource and environmental impact metrics. Many methods exist for defining a range of such indicators (Jungbluth 2021, Rosenbaum 2018). A number of these are included in the internal library of ENBIOS and the required method must be specified prior to initiating calculations. Furthermore, as LCI processes for fuel production do not consider the combustion of fuels during their final use stage (e.g., the operation of internal combustion engines or home heating using natural gas) the additional GHG emissions for fuels must also be considered. Here, the required emission factors are taken from the Intergovernmental Panel on Climate Change (IPCC) database (IPCC 2021). It is noted that similar estimates would need to be added to account for the additional contributions from combustion processes when other air pollution indicators are being used.

Aside from life-cycle data, any number of additional socio-metabolic indicator data sources can also be included, provided it has been normalised for installed capacity or for each unit of energy produced. For example, employment data typically specifies the labour required to maintain a given capacity of electricity and heat infrastructure or produce a certain amount of fuel (Ram et al 2020, Rutovitz et al 2015). Indicators can also be calculated that use raw materials requirements from LCI data in conjunction with other conversion factors or formulae. Indeed, methods for using LCI data to estimate raw material supply risks, end-of-life recycling input rates (EoLRIR) and local environmental impact and environmental justice threats for individual materials have been hypothesised elsewhere (see sections **D** and **E**). In theory, any number of methodologies and sets of input data could be used to create customised indicators for each process within a defined system, and ENBIOS has been specifically formulated to offer high levels of flexibility to users in this regard. Nevertheless, a summary of typical ENBIOS data inputs for energy systems, as utilised during the development of the approach, is shown in **Figure F.2**.

F.2.2 Simulation

Once the system hierarchy has been defined and input parameters have been specified, indicators can begin to be produced. The first step is to produce a set of *extensive* results; an extensive indicator is one that is provided in units capable of being added and are not dependent on a particular object or system (e.g., mass, area or volume). These initial, extensive indicators are calculated at all structural and functional processors according to the selected LCIA methods and any other formulae used to create customised indicator outputs, as specified in simulation system files. It is important to note here that–unlike most previous attempts to aggregate LCA and other indicators for complete systems–ENBIOS does not perform simple linear aggregations on the *results* for individual processors when upscaling to higher hierarchical levels. Rather, the *input variables* themselves are aggregated at each point within the system hierarchy before the calculations are made. That is, ENBIOS preferentially aggregates data inputs over the indicators themselves. In our previous example, indicators would easily be calculated using the applicable LCI data at the structural processors for wind turbines or solar PV. However, at the functional processor that encompasses these two processors, upscaled LCI data items would need to be summed before the indicator calculations could proceed. While this will not change indicators derived using linear relationships–e.g., GHG emissions generated using characterization factors in LCIA calculations–it is vital for the robustness of the model, and its potential suitability to different applications, that separate calculations are performed in situations where non-linear relationships are involved.

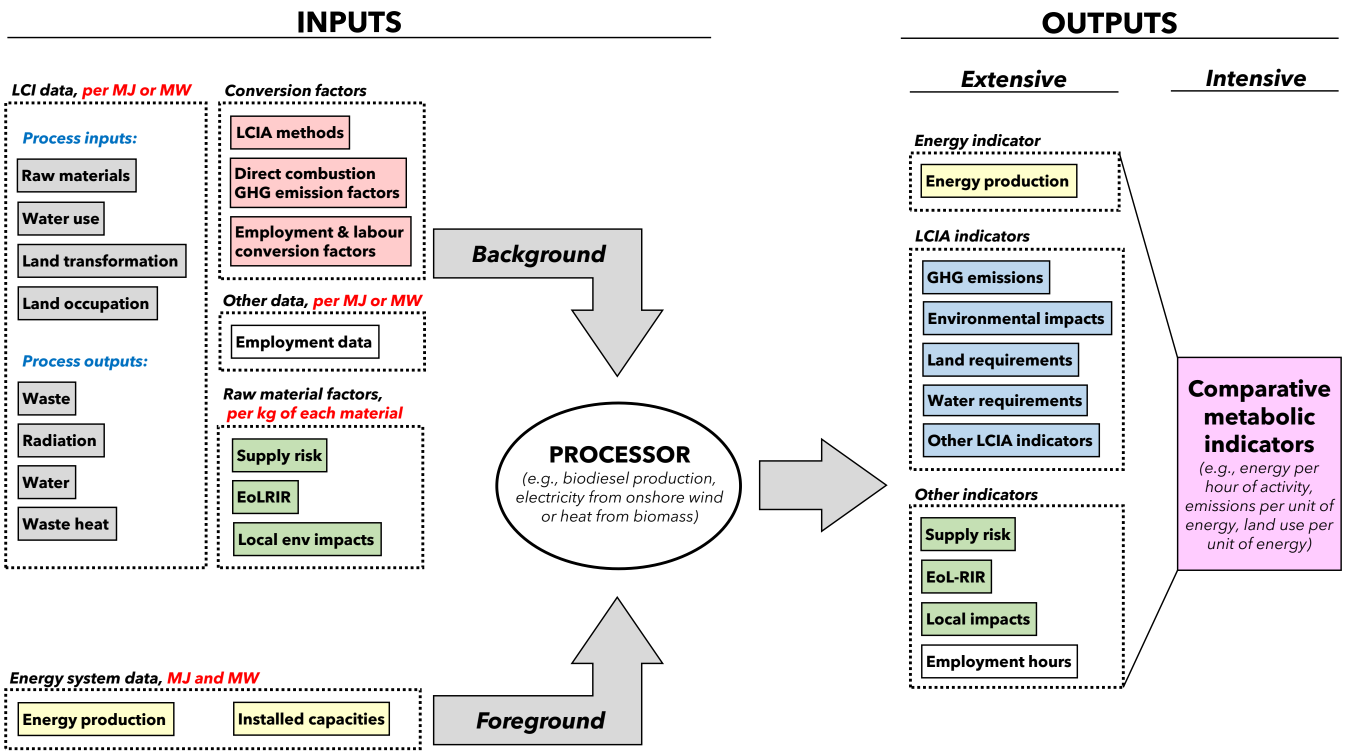


Figure F.2. Overview of typical data and methodological inputs and derived final outputs at each processor in an ENBIOS simulation for a given energy system. LCI data, conversion factors, raw material factors and other such data inputs define the system background and are typically entered at the system definition stage and only updated sporadically. Meanwhile, foreground data inputs for individual energy system configurations change according to each scenario being tested. It is noted that input values are aggregated to previous levels of system hierarchies and that calculations always occur at each processor in a system; indicator outputs themselves are never aggregated directly

A further round of indicators can then be created by relating the initial indicators to additional data about the internal functioning of the system, thus characterizing the metabolic relationships and constraints that exist within the system. This includes–but is not limited to–the derivation of further *intensive* indicators. Unlike their extensive counterparts, intensive indicators cannot be added and are specific to a given system (e.g., rates, ratios or densities). For example, using the approach shown in **Figure F.2**, one could report "metabolic rate" indicators based on labour requirements or per-unit-of-energy indicators based on the total amount of energy produced. Indeed, an array of possible intensive indicators is possible based on the number of extensive indicators available. As with the definition of extensive indicators, ENBIOS offers the user great flexibility to define customised intensive indicators of their choosing within the interface. In this case, we use the most common indicator of system functioning–human activity–using the hours of labour associated with the life cycle of each technology.

Once all extensive and intensive indicators have been calculated on a per-unit-of-energy basis, the MuSIASEM approach is employed to upscale and further analyse these indicators. MuSIASEM allows values to be calculated and examined at different levels within the system based on the defined energy system hierarchy (i.e., the system configuration or "energy mix"). A broad range of indicators can then be examined from individual or grouped energy sub-technologies to entire energy systems, and vice versa.

F.3 Application to European energy scenarios

To demonstrate the functionality of ENBIOS, the workflow was applied to the European energy system using a set of projected scenario results for the years 2030 and 2050 obtained from partners within the SENTINEL project.

F.3.1 System definition

The dendrogram for the case study system was defined to align with outputs obtained from Euro-Calliope (Tröndle et al 2020), a version of the Calliope model (Pfenninger and Pickering 2018) being utilised within the project. The model includes all EU member states (except Malta), together with Albania, Bosnia and Herzegovina, North Macedonia, Montenegro, Serbia, Switzerland, the United Kingdom, Iceland and Norway. Euro-Calliope simulates all regional processes of electricity and heat generation at the centralised utility level alongside the most common forms of fuels used for direct consumption (predominantly those for transport, non-centralised electricity and heat generation and use in industrial applications). A representation of the dendrogram is shown in **Figure F.3**.

Structural processors representing the individual sub-technologies are shown as rounded blocks at the "n-5" level, on the right-hand side of the diagram. Functional processors that represent higher level combinations of these sub-technologies according to energy supply technology type ("n-4"), renewable status ("n-3") and energy carrier type ("n-1") are then shown as square blocks to the left of this column.

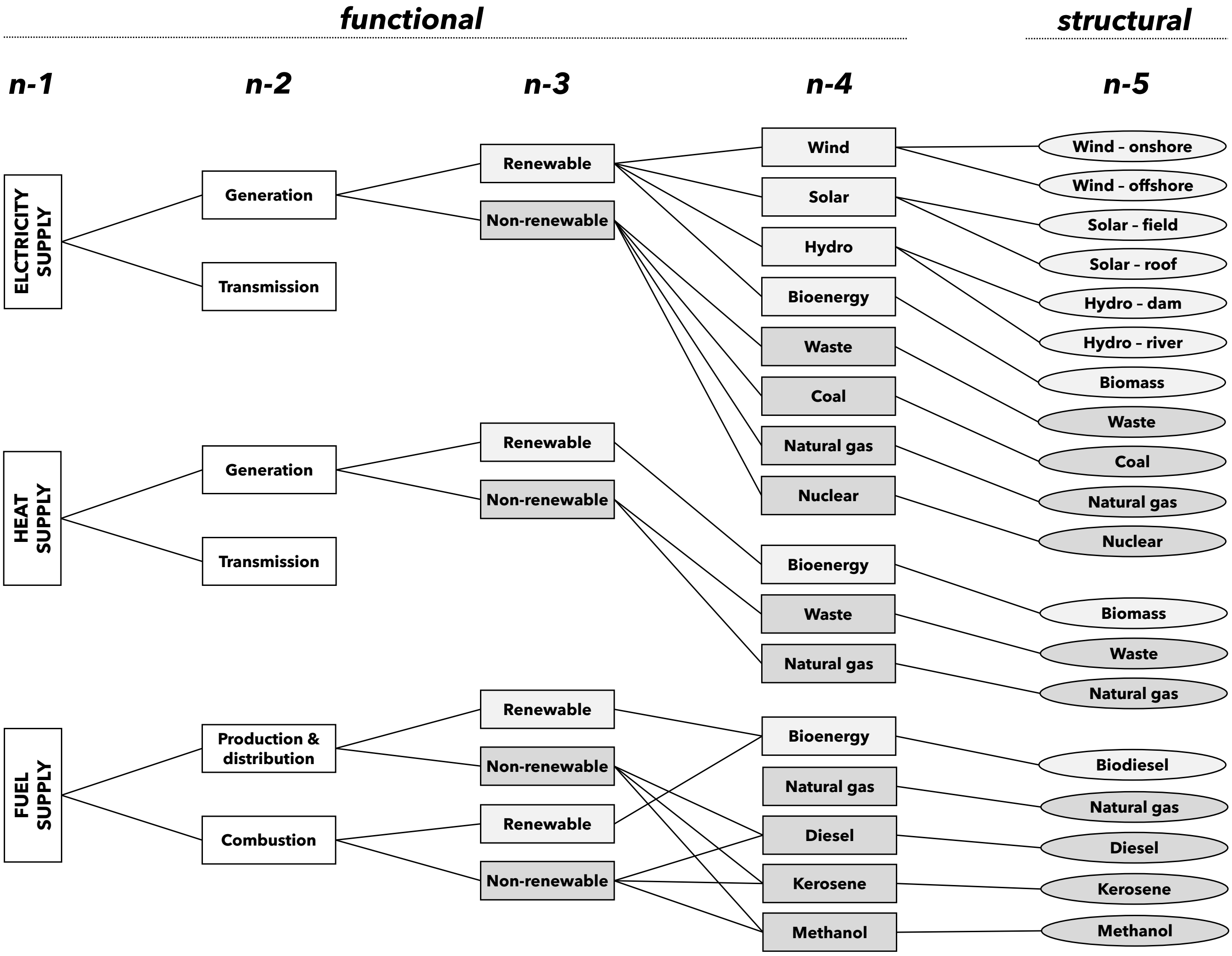


Figure F.3. ENBIOS dendrogram structure for the EU energy system. Structural processors representing specific electricity, heat and fuel supply processes are located on the right side of the figure. Functional processors are shown on the left of the figure

F.3.2 Data inputs

Results obtained from Euro-Calliope that reflect the information for the system under the "climate neutrality" scenario were used here for the years 2030 and 2050 (Pickering et al 2022). This includes energy production data in terawatt-hours (TWh) and installed capacity data in megawatts (MW) for 11 sources of utility-level electricity and three sources of utility-level heat. Total production levels (TWh) were also obtained for five sources of fuel supply. Note that no methanol use was included under this particular scenario. LCI data was assigned at each structural processor from the Ecoinvent 3.8 database (Ecoinvent 2021). All electricity processes are defined per kilowatt-hour (kWh) of energy produced, while heat processes are defined per megajoule (MJ); all inventory items are, thus, initially converted to TWh equivalents according to standard conversions. Fuel production processes are defined per kilogram (kg), which requires the data to be converted to energetic equivalents using known MJ/kg calorific value equivalents (Eurostat 2020). As the case study uses total energy inputs for the European energy system as a whole, generalised LCI process listings for Europe were used, where available. Where these processes are not available, rest of world (RoW) values are used. However, in some cases the RoW values deviate significantly from those of individual European countries, which are often quite similar. In these instances, the European country that represents the highest share for that category in the case study energy mix is used. Lastly, GHG emission factors for combustion of the five fuels–in kg carbon dioxide equivalent (CO_2-eq) per kg fuel–were obtained from the IPCC database (IPCC 2021). A full listing of the input data is provided in **Table J.21** in the appendices.

Three sample LCIA impact categories from the ReCiPe Midpoint (H) group (Huijbregts et al 2017) were chosen in this example: GHG emissions in kg CO_2-eq were derived using the "GWP100" method, total land occupation in m^2 was estimated by summing outputs from the agricultural ("ALOP") and urban ("ULOP") land occupation methods, while water depletion in m^3 used the "WDP" method.

Employment data that estimates of the number of full-time jobs provided by each installed MW of capacity for each electricity and heat generation category (Rutovitz et al 2015) was also obtained for each technology. The data includes employment across the manufacturing, construction and installation periods, as well as the ongoing operation and maintenance tasks occurring within the equipment's lifetime. Decommissioning periods are also included, where appropriate. Consequently, although the lifetimes of energy infrastructure are generally between 20 and 50 years (Ram et al 2020), and capacities fluctuate from year to year as equipment is implemented and retired, a total number of job positions can be calculated for each moment in time based on current capacities. Data for fuel production processes is typically given on a per-unit-of-energy basis. Hence, the total amount of fuel supplied within a given period–in this case, one year–contributes to the maintenance of a certain number of positions within that timeframe. A full listing of the utilised data is provided in **Table J.22** in the appendices.

In order to fully incorporate labour aspects into the metabolic calculations within ENBIOS, raw job data was then converted into hours of human activity (HA) using estimates of annual working hours from relevant sectors. Here, "mean weekly hours actually worked" data was obtained from the International Labour Organization (ILO) for each country represented in the Euro-Calliope model (International Labour Organization 2022); data is available for all sectors identified within the International Standard Industrial Classification (ISIC) level 2 definitions, of which four are directly applicable to the energy sector and assigned to each ENBIOS processor. Composite annual values for the full model extent–one for each sector–were then calculated using the weekly hours worked in individual countries, weighted according to ILO employment rate data. The final data for each sector is listed in **Table J.23** in the appendices.

Lastly, raw material factors that enable calculations to be made for material supply risk (SR) according to established methodologies (see sections **D** and **E**) were also included. Factors were obtained via external sources (Wendling et al 2020, European Commission 2020c) for the 55 substances contained within the LCI database that are considered to be critical raw materials (CRMs) by the European Commission (EC) (European Commission 2020c). It should be noted that, although SR values are essentially dimensionless, years (yr) are used as units in accordance with the adopted formula.

F.3.3 Analysis

Results were firstly derived at each of the 19 structural ("n-5") processors for a group of six extensive indicators: the total energy production (directly from Euro-Calliope results), three LCIA indicators, raw material SR and employment-related human activity. A full listing is provided in **Table J.24** in the appendices. Further calculations were then performed in relation to energy supply technology type ("n-4"), renewable status ("n-3") and energy carrier type ("n-1"). The findings are displayed in **Figure F.4** and listed in **Table J.25** in the appendices. A summary of the overall percentage changes at the system level are shown in **Table F.1** alongside a listing of the technology type ("n-4") that makes the most significant contribution to overall system change.

Table F.1. Summary of changes in extensive indicators between projected 2030 and 2050 scenarios. Overall system changes at the "n" level, in relative percentage, are listed for each indicator. The most significant contributors at the "n-4" level, by change in overall percentage share, are also listed

	Total energy	GHG emissions	Land occupation	Water depletion	Material supply risk	Human activity
Change ("n")	+32.5%	-55.4%	+385.8%	-38.4%	+146.4%	+78.0%
Most significant contributor	Wind	Coal	Bioenergy	Bioenergy	Wind	Wind
Change in share ("n-4")	+58.2% *(7.3% to 65.5%)*	-37.0% *(37.0% to zero)*	+70.6% *(0.8% to 71.4%)*	+38.8% *(zero to 38.8%)*	+45.2% *(11.8% to 57.0%)*	+14.6% *(2.4% to 17.1%)*

The extensive data outputs reveal several key findings. The most immediate trends observed in the energy production data are the overall increase of energy production within the system boundary, the move towards renewable energy and the increased electrification of the system by 2050. The breakdown of technologies also reflects the forecast dominance of electricity from wind (65.5%) and solar (20.4%), heat from biomass (7.6%) and the phasing out of natural gas, which would drop from 40.9% of system share in 2030 to 0.1% by 2050. As expected, net GHG emissions are predicted to drop significantly between 2030 and 2050, reducing by 54.7%; the highest contributor to this drop is coal, which drops from 34.8% of system share in 2030 to zero in 2050.

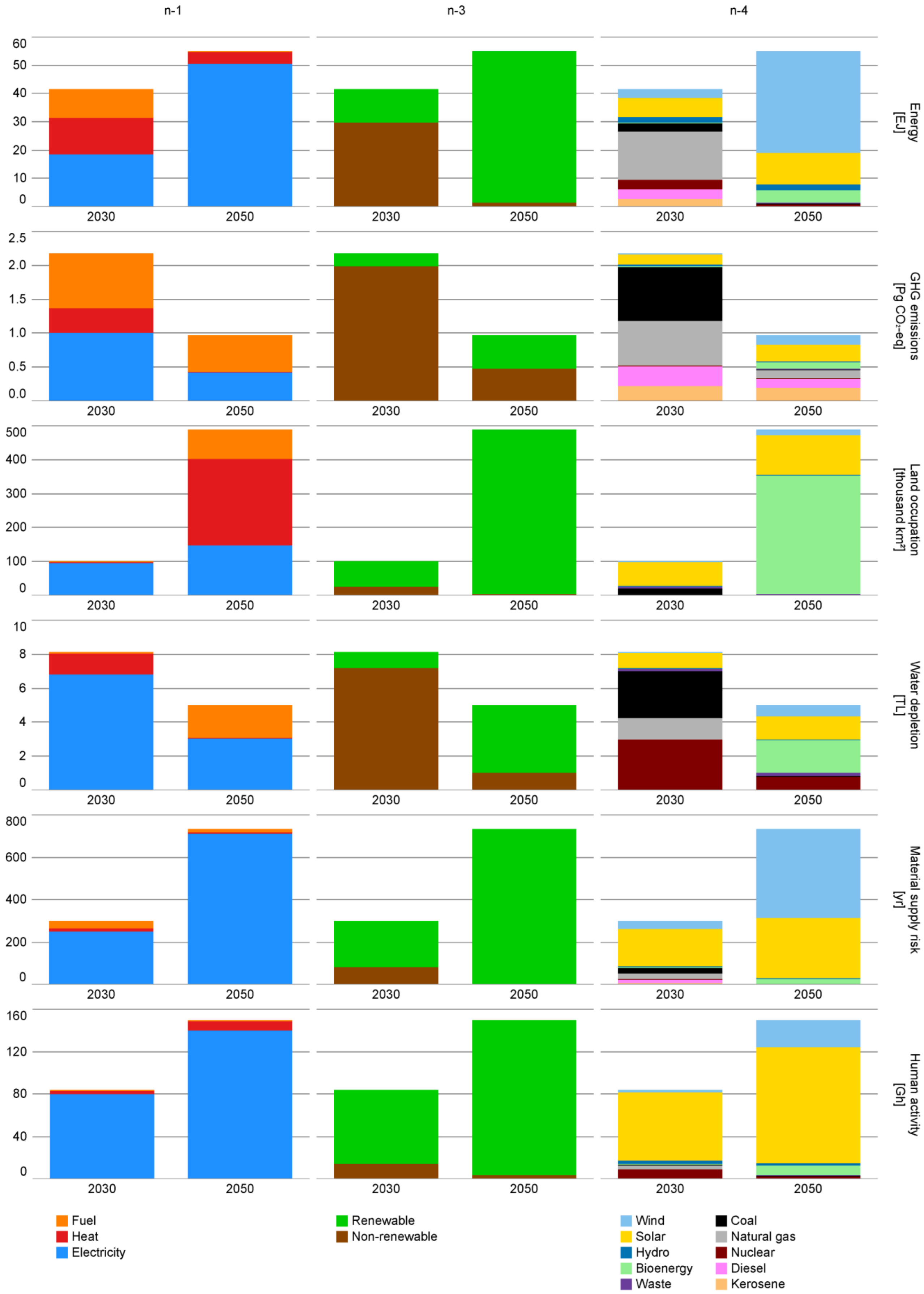


Figure F.4. ENBIOS results showing outputs for extensive indicators. Results shown for six indicators across three hierarchical level groupings for projected 2030 and 2050 energy mix outcomes under the EU "climate neutrality" scenario

The level of emissions produced in 2050 are predominantly linked to electricity production (43.0%) and the combustion of fuels produced via electrolysis and hydrogen-to-fuel processes (55.8%); emissions from centralised heat processes are relatively negligible (1.2%). Solar PV (24.5%), wind (14.8%), natural gas (13.3%) and bioenergy (9. 6%) processes are all significant contributors to overall emissions in 2050, and emissions created by combusting kerosene (20.4%) and diesel (13.8%) formed from electrolysis processes are also significant. These replace the fossil fuel sources–coal (37.0%), natural gas (30.1%), diesel (13.3%) and kerosene (10.4%)–predicted to remain as the dominant emitters in 2030.

Conversely, land occupation increases dramatically, largely driven by renewable energy sources. This rise is heavily influenced by the use of bioenergy sources, which supplies 71.1% of the total required land in 2050, up from 0.8% in 2030. Water depletion is expected drop by 38.4%, the changes largely being linked to the move away from fossil fuel processes with higher water requirements, particularly coal and natural gas. Meanwhile, total SR more than doubles between 2030 and 2050 in this example. This is overwhelmingly the result of electricity from wind and solar sources, which contribute 57.0% and 39.0% of the total score in 2050, respectively. Lastly, the required number of hours of HA from employment increases by 78.0% between 2030 and 2050 under this scenario. This is, again, largely driven by increases in wind and solar installations; wind is the dominant contributor here, rising from a 2.4% share of overall activity in 2030 to a 17.1% share in 2050.

Additional intensive indicators were then derived by comparing extensive indicators across and between MuSIASEM hierarchical levels. **Figure F.5** provides side-by-side comparisons between 2030 and 2050 values for three "metabolic rate" indicators and four indicators that present extensive attributes on a per-MJ basis. Findings are presented for the three previous levels alongside the total system values at level "n". A full listing is provided in **Table J.26** of the supplementary information. A summary of the overall percentage changes at the system level are shown in **Table F.2**.

Table F.2. Summary of changes in intensive indicators between projected 2030 and 2050 scenarios. Overall system changes at the "n" level, in relative percentage, are listed for each indicator

	Energy metabolic rate	GHG metabolic rate	Water metabolic rate	Water use-to-energy	Land use-to-energy	GHG-to-energy	Supply risk-to-energy
Change ("n")	-25.6%	-74.9%	-65.4%	-53.5%	-66.3%	+266.7%	+86.0%

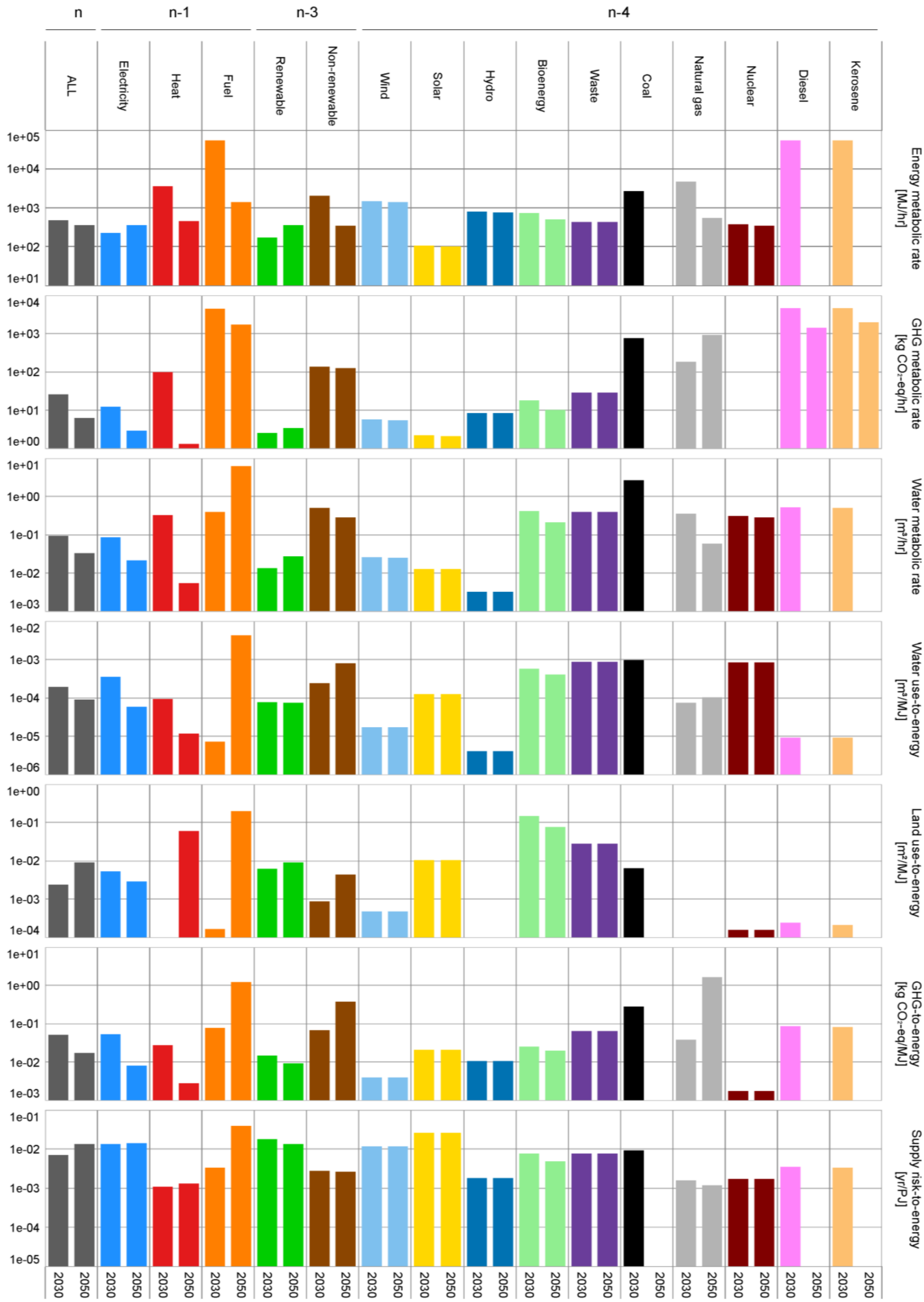


Figure F.5. ENBIOS results showing outputs for intensive indicators. Results shown for seven indicators over complete system and three hierarchical level groupings for projected 2030 and 2050 energy mix outcomes under the EU “climate neutrality” scenario

The first of these analyses suggests that the energy metabolic rate (EMR) of the European energy system would drop by 25.6% between 2030 and 2050 under this scenario. This is predominantly the result of the large swing to electricity–and wind and solar technologies in particular–which rises from 44.6% to 91.5% of system energy supply (fuels created via hydrogen from electrolysis are included in electricity totals). And, though heat and fuels are seen to provide significantly higher levels of energy per unit of activity, their shares of overall energy production decline from 31.2% to 7.7% and 24.2% to 0.8%, respectively, during this period. The rapid phasing out of natural gas assumed in the heating sector by 2050 results in the sharp drop observed in the EMR value for heat in this period and, coincidentally, a rise in the overall value for natural gas as its use as a direct fuel remains relatively high (see **Figure F.4**).

Yet, while more hours of human activity would be required to produce a unit of energy by 2050, findings for the GHG metabolic rate (GHGMR) confirm that significantly less emissions would be produced for each of these labour hours. This reduction is again strongly linked to a substantial change in the share of renewables which, on average, have GHGMR values less than 3% of those for non-renewables. As a result, overall GHGMR values would reduce by 74.6% between 2030 and 2050.

Values for the water metabolic rate (WMR)–which decrease at the system level by 65.4% between 2030 and 2050–are, again, strongly influenced by the dramatic drop in the use of fossil fuels. This is especially true of coal and natural gas, whose extensive water use values represented 34.2% and 15.5% of the total contribution, respectively, in 2030 but are expected to be virtually zero by 2050. A fall in the use of nuclear sources of electricity production, from which also have high per-MJ water requirements, is also a factor. Moreover, an increase of technologies with relatively low water requirements such as wind and solar energy would help to reduce overall water use. Very similar results are observed for the water use-to-energy ratio, where the system-wide result is seen to reduce by 53.5% by 2050.

Meanwhile, the land use-to-energy ratio is predicted to almost quadruple between 2030 and 2050 under this scenario, predominantly due to the dramatic shift towards bioenergy (see **Figure F.4**). Overall land occupation for the system in 2050 was calculated to be around 4.9 times that in 2030, the contribution from bioenergy increasing from 0.8% in 2030 to 71.4% in 2050; 51.8% of this contribution is from heat derived from biomass. This is also reflected in the dramatic rise in the intensive value of heating witnessed at the “n-1” level. In this sense, it is noted that natural gas, nuclear energy, diesel and kerosene require considerably lower areas of land according to this metric.

The net amount of GHG emissions produced per unit of supplied energy is a key system indicator for analysing system performance alongside emissions reduction targets. In this scenario, an overall reduction of 66.3% is observed in this indicator between 2030 and 2050. Again, overall system emissions are likely to remain dominated by non-renewable energy forms in 2030, although by 2050 the dominance of renewables would mean that a relatively large share of emissions would also be provided by renewables (51.0%). Nevertheless, GHG-to-energy ratios for renewables remain predictably lower than non-renewables–around 40 times lower at the “n-3” level in 2050–and wind technologies comfortably provide the best outcomes within the group. However, it is noted that nuclear power is the lowest of the technologies examined and produces less than half of the emissions of wind energy.

Finally, the level of extensive SR in the 2050 system is almost 2.5 times that of the 2030 system, reflecting a substantial rise in potential supply disruptions during this period. Again, these values are rooted predominantly in contributions from wind (57.0%) and solar (39.0%) technologies. Analysis of SR-to-energy ratios confirms that solar and wind are substantially higher than all other categories at the “n-4” level; both are between 1.5 and 21.1 times higher than other technologies. Consequently, a net increase of 86.0% is observed in the level of expected SR per unit of energy for the system as a whole between 2030 and 2050.

F.4 Discussion and conclusions

The development of the ENBIOS workflow brings a new and more systemic approach to the assessment of environmental impacts and constraints within energy systems using a methodology that combines the high resolution of LCA methodologies with the multi-level functionality of the MuSIASEM approach. Furthermore, the workflow offers a first attempt at systematizing the integration of raw material indicators into energy modelling practices. Ultimately, ENBIOS has been designed to enable the relationships between indicators at different hierarchical levels to be analysed and the trade-offs between different energy transition pathways to be compared–with each other and with defined benchmarks–with the aim of informing better energy policy decision making. Full sets of indicators can be produced for multiple energy system scenarios, derived from different system configurations or across different regions and timeframes. Analysis of indicators can provide further information about preferred options, depending on the preferences or perceived limitations of policymakers, and determine whether certain scenarios are more–or less–technically feasible than others in terms of land use, raw material supply issues, employment or other socio-economic factors. The ability to observe indicator data across and between levels also allows problem areas such as constraint hotspots to be more easily identified.

The capabilities of the ENBIOS workflow were demonstrated using inputs from a “climate neutrality” scenario for the European energy system in 2030 and 2050. Extensive outputs revealed that system changes in this period–where a rapid switch is made towards renewables, particularly wind and solar electricity and heat from biomass–would result in a significant reduction in GHG emissions. However, although water requirements are unlikely to present serious issues, land occupation, material SR and labour requirements are all likely to rise dramatically. It is recognised that the derived values of land use can refer to many different types of use. For example, the land required by a nuclear plant is vastly different from land required for a hydropower dam or wind far.

Nevertheless, here, the land use totals are largely related to biomass plantations. Meanwhile, material issues are strongly linked to wind and solar infrastructure, while the higher labour needs for solar contribute far more than wind or biomass operations.

Further analysis of the system, via composite intensive indicators, provided further insights. At the system level, positive outcomes were observed for overall reductions in GHGMR (74.9%), WMR (65.4%), water-to-energy (53.5%) and GHG-to-energy (66.3%) ratios. Even so, an EMR reduction of 25.6% suggests that the system would generate less energy per unit of human activity in 2050, which could have implications on labour markets. Ratios of land use-to-energy and SR-to-energy are both also projected to increase markedly. Indeed, the consequences of different energy transition pathways on both of these issues is increasingly being highlighted and could result in wider ecological, political and environmental justice concerns (Tröndle et al 2020, Lèbre et al 2020, Bobba et al 2020).

Looking specifically to the three key processes at the "n-5" level–electricity from wind and solar, and heat from biomass–reveals their influence on overall system indicators. Again, the high labour requirement for solar infrastructure has a strong influence on lowering all metabolic rate values. Very low water requirements for wind turbines have positive effects on both water-related indicators. Similarly, their low GHG-to-energy ratios tend to dictate wider outcomes for this indicator. Extremely high land use-to-energy ratios for biomass result in their total dominance in this regard. Finally, high SR-to-energy ratios for wind and solar infrastructure are highly influential on the score reductions for this indicator.

The case study provides a simple illustration of the ability of the ENBIOS workflow to perform deeper analyses on the different relationships that exist within current and future energy systems, relationships that quantify constraints and areas of concern across different system levels. While this example provides a broad demonstration of the potential of using this approach to assess European energy system configurations, it is noted that greater detail is possible and that, as the Python-based version of ENBIOS continues to be developed, future studies will aim to utilise system dendrograms that incorporate separate consideration of individual regions or countries, where LCA data exists. For example, outputs from the Euro-Calliope model are provided for 35 individual countries and separate definitions are often available for LCA processes at the national level. What's more, shares of energy within technological groups could be further delineated into sub-technologies where suitable LCA data is available. While a lack of data is observed for certain technologies–such as wind and hydropower–a large selection of different LCA processes is defined for solar and biomass sub-technologies. This would allow far more detailed analyses to be undertaken, subject to computer processing considerations.

In this regard, the validity of the LCIA indicators used in the case study was tested by comparing them against the range of available results for individual European countries. The investigation found that most individual values for GHG emissions, land occupation and water depletion were within 2-

3% of the values used to represent Europe as a whole in the case study. The most significant differences by far were observed for waste incineration, where values could be several *times* higher or lower than others. The process used to represent Europe in the current version of ENBIOS is for Germany, which is the current and projected largest adopter of waste incineration. As such, the best possible representation is being used. However, it is recognised that a considerable amount of uncertainty is inherent within the results for waste incineration as a result of the variability in the regional data. Variations of 10-20% are observed in the values for natural gas, coal, wind turbines and solar PV cells, suggesting that more regionally detailed investigations are also likely to improve the accuracy of results for these technologies.

It is also noted that to date the workflow has only been tested using system configuration data taken *from* energy models. However, it is hoped that information produced by ENBIOS could also be used to provide inputs back *into* such models. For example, extensive indicator values such as GHG emissions, land and water use or raw material requirement data–provided on a per-unit-of-energy basis for individual system components–could be integrated into ESMs relatively simply. Moreover, results for intensive indicators at different system levels or entire systems could be incorporated into the calculations of larger modelling platforms. This, of course, would require ENBIOS to be included within the broader architecture of an integrated model in order to become a truly interactive element of its system optimisation calculations. In this sense, it is also important to note that, while ENBIOS is primarily being formulated to analyse energy systems, it has been designed to be adaptable to any type of hierarchical system and could, theoretically, be used in any number of other applications where multi-level analysis is required. This is especially true if users also require LCA functionalities to be integrated into their analysis.

In any case, despite the potential of ENBIOS in its current form, a number of limitations are noted. Firstly, as with many LCA-related applications, assessments are limited to using static information based on current inventories. That is, the derived outputs for future processes do not contain allowances for future improvements in the background systems that supply energy and material inputs. For example, the mix of electricity inputs used in creating or transporting a wind turbine in 2040 is essentially “locked” in its current configuration. In reality, many of these inputs would, themselves, produce less emissions or include higher amounts of recycled content as greener energy practices and circularity initiatives are implemented. It is hoped that the further integration of pLCA concepts–which enable the modification of background systems in modelled environments of this kind–can be included as the concept continues to be developed. This would allow users to manipulate LCI data assumptions to reflect future developments. Nevertheless, current ENBIOS assessments are capable of providing indications of key bottleneck hotspots in terms of required technological or sourcing improvements, using current conditions as reference benchmarks.

Similarly, it is acknowledged that variations may well occur to many of the input parameters used within the calculations for extensive indicators. For example, in the case study presented here, values of SR for individual materials are likely to change over time as reserve amounts and geopolitical aspects fluctuate. Likewise, improvements in manufacturing or increased levels of automation may result in lower labour requirements, particularly for newer technologies like wind turbines, solar PV cells or biofuel production. Naturally, the extent of these improvements is difficult to predict, although learning curves or other approaches could be applied (see section **B**). However, the architecture of ENBIOS means that it is simple to change input parameters of this kind for investigating multiple future scenarios.

Several issues relating to LCA data availability have also been identified. Although Ecoinvent and other major LCI databases contain several thousand energy-related processes, a lack of good quality data remains for some common processes, especially for newer technologies. For example, newer wind, solar PV and bioenergy technologies are underrepresented and energy storage technologies are not yet represented beyond the production of lithium-ion cells. Accordingly, they have not been included in the current version of ENBIOS. Such infrastructure should be included in future releases in order to truly investigate the requirements of different energy transition scenarios. Moreover, most common LCA data sources are restricted to paying clients, which could seriously restrict the penetration of ENBIOS and similar applications as data remains “trapped” behind paywalls for many potential users.

ENBIOS joins a growing move towards the wider inclusion of LCA concepts in energy modelling processes. The key to further progress in this area would seem to lie in the ability to place LCA-related data and operations into environments that are also compatible with the models themselves. As such, open-source applications such as Wurst (Mendoza Beltran et al 2020), PREMISE (Sacchi et al 2022) and ENBIOS are making it easier to import model output data and manipulate and automate the processing of life cycle data. Again, the ability to return outputs from applications such as ENBIOS back into energy models directly to achieve genuine two-way synthesis would greatly improve the ability of models to integrate the power of LCA and other high resolution environmental data in this manner. This would result in modelling platforms that include far better representations of environmental impacts and constraints as we strive to implement cleaner and more sustainable energy systems as safely, efficiently and rapidly as possible.

G FIRST CASE STUDY

The many faces of heating transitions. Deeper understandings of future systems in Sweden and beyond

Abstract

As with all five Nordic countries, Sweden has a particularly cold climate where heat sources are required for many months of the year. Much of the heat provided to buildings in Sweden is provided by the direct combustion of fuels–predominantly biomass and municipal solid waste–in district heating systems. These systems also receive recycled heat from industry and flue gas condensation and from electrical devices such as boilers and heat pumps. Indeed, the popularity of electrically powered heat pumps continues to rise within and outside of district heating systems while the use of electrical boilers remains stable. An overall summation of newly-generated heat in Sweden–i.e., if the "neutral" contributions of recycled heat sources are discounted–finds that the combustion of fuels in district heating contributes around 53% of total heat while the use of electricity represents around 47% of this total. Meanwhile, optimised projections for the so-called "smart energy" scenario–developed within the SENTINEL project using the EnergyPLAN model–predict a dramatic drop in the direct use of biomass in district heating by 2050, while the use of waste will remain high. However, electricity use will rise in this period to represent around 65% of the heat generated in the country. The technologies used to generate this electricity are also predicted to change significantly, moving strongly towards hydro, wind and solar power, with significantly less reliance on biomass and nuclear sources. Nevertheless, while the predicted changes are broadly predicted to result in lower overall greenhouse gas emissions, current assessment methods do not tend to examine the wide variety of other environmental impacts and material supply aspects involved in such transition processes. Accordingly, the ENBIOS workflow is used here to provide deeper insights into predicted heating scenarios for Sweden by generating outputs for 12 key indicators for two historical baselines–2015 and 2019–alongside the predicted configuration for 2050 provided by the EnergyPLAN model. The results suggest that favourable reductions are likely in five of the indicators, including greenhouse gas emissions, but that these benefits are offset by a number of unfavourable outcomes in other indicators, including all three of the material supply indicators tested. A thorough description of these outcomes and possible implications for policy planning are included. Ultimately, the section provides a novel example of the ways in which tools such as ENBIOS can be used to complement existing modelling techniques and expand the scope of available tools for assisting heating policy decisions.

G.1 Introduction

In order to demonstrate the use of the ENBIOS workflow to a real-world scenario, its application to the Swedish heating system is presented in the following chapter. As a Nordic country, Sweden requires higher than average heat energy inputs to make buildings liveable throughout the year and has an existing system that relies heavily on district heating networks. Furthermore, as in many other European countries, the use of electrically powered heat pumps is growing in Sweden as it is seen to represent a more efficient and potentially more "green" solution to space heating. For these reasons, the heating system of Sweden was thought to represent an interesting subject for the first case study.

The system is first defined in accordance with the available data and includes all heat supplied from the district heating system and the use of electricity at the building level using heat pumps and electric heating devices. Analyses are undertaken for historical configurations from 2015 and 2019 and compared to a projected "Smart Energy" scenario for the system in 2050 using results from the EnergyPLAN model. The sections that follow provide a thorough description of the input data, presentation of the results obtained for a range of indicators and a discussion of the key outcomes.

G.1.1 District heating

District heating is a method for distributing thermal energy–in the form of steam or hot water–throughout a series of insulated pipes to provide heating to multiple buildings within a local network (Sandberg et al 2018). It is mostly used for space heating applications and to provide hot water to residents and businesses. At present, heat used in district heating systems is predominantly derived from the combustion of fuels (Ericsson and Werner 2016). This can be undertaken in heat only boilers and alongside electricity generation processes in combined heat and power (CHP) plants. Heat can also be obtained from various forms of recycled heat; the use of excess heat from industrial processes and the combustion of fuels condensed from flue gases are common examples of this. Thermal energy is sometimes also transferred directly to district heating networks from geothermal and solar sources. Lastly, electricity can be used to generate system heat using electric boilers and heat pumps.

Heat pumps are devices that use electrical energy to produce volumes of warm air or water suitable for heating applications (see section **J.1.1.8**). Within a heat pump system, a compressor is used to circulate a refrigerant within a closed loop in order to amplify temperature differentials, much like an air conditioner in reverse (Johansson 2021). The coefficient of performance (COP) reflects the ratio of heat energy produced to electrical energy used; values of COP depend on the temperature differentials at play but are generally between two and seven for most applications (Fischer and Madani 2017, Pospíšil et al 2018). As such, they offer efficient and attractive pathways for heating spaces using electricity, especially if renewable forms of electricity can be used. Not surprisingly, the use of heat pumps is projected to become an important element of sustainable heating systems and are widely predicted to achieve wider presence in the district heating systems of the future (Magnusson 2016). More importantly, they are also rapidly gaining popularity as a standalone method for vastly improving the efficiency of heating in buildings (Paardekooper et al 2018), particularly in areas where district systems are not available or viable.

G.1.2 Heating in Sweden

As with all Nordic countries, Sweden has a cold climate and heating is required for eight to 10 months of the year in most regions (Johansson 2021) Accordingly, it consumes approximately 50% more heat energy per person, on average, than the EU as a whole. Not surprisingly, the use of district heating in Sweden is high; in 2014 approximately 93% of multi-residence buildings were connected to a district heating network (Werner 2017). However, this has not always been the case.

Figure G.1 displays the market share percentages of the different heating techniques employed to heat buildings in Sweden between 1960 and 2020. The data indicates that the use of individual oil-based heaters dominated the market during the 1960s, but sharply declined in popularity in the wake of the global oil crisis in the 1970s (Gross and Hanna 2019). District heating subsequently rose in popularity and has continued to steadily increase its market share, mostly under municipal ownership. A national program to develop public housing between 1965 and 1974 assisted in the rise in popularity of district heating as most new buildings were designed specifically to include district heating connectivity (Magnusson 2016). Nevertheless, coal was the dominant fuel in these district heating systems until the end of the 1980s when biomass began to dominate the market (di Lucia and Ericsson 2014).

Outside of centralised district heating systems, the deregulation of the electricity market in 1996 led to an increase in the use of individual heat pumps (Magnusson 2016), which have continued to gain acceptance in the last 20 years to become the main competitor to district heating overall (Werner 2017). Indeed, Sweden is now one of the top countries in the world for heat pump ownership per capita (Johansson 2021) and over half of its residential buildings now have at least one heat pump installed. In this sense, small-sized units tend to be installed in one and two dwelling houses and medium-sized units are used in apartment blocks and commercial buildings; much larger units are used in district heating applications. Lastly, many residents–particularly in rural and isolated areas of the country where district heating systems are not present–still rely on the traditional method of heating their homes via the combustion of oil, biomass and other fuels. **Figure G.1** suggests that this method of heating still occupies around 9% of the heating system overall.

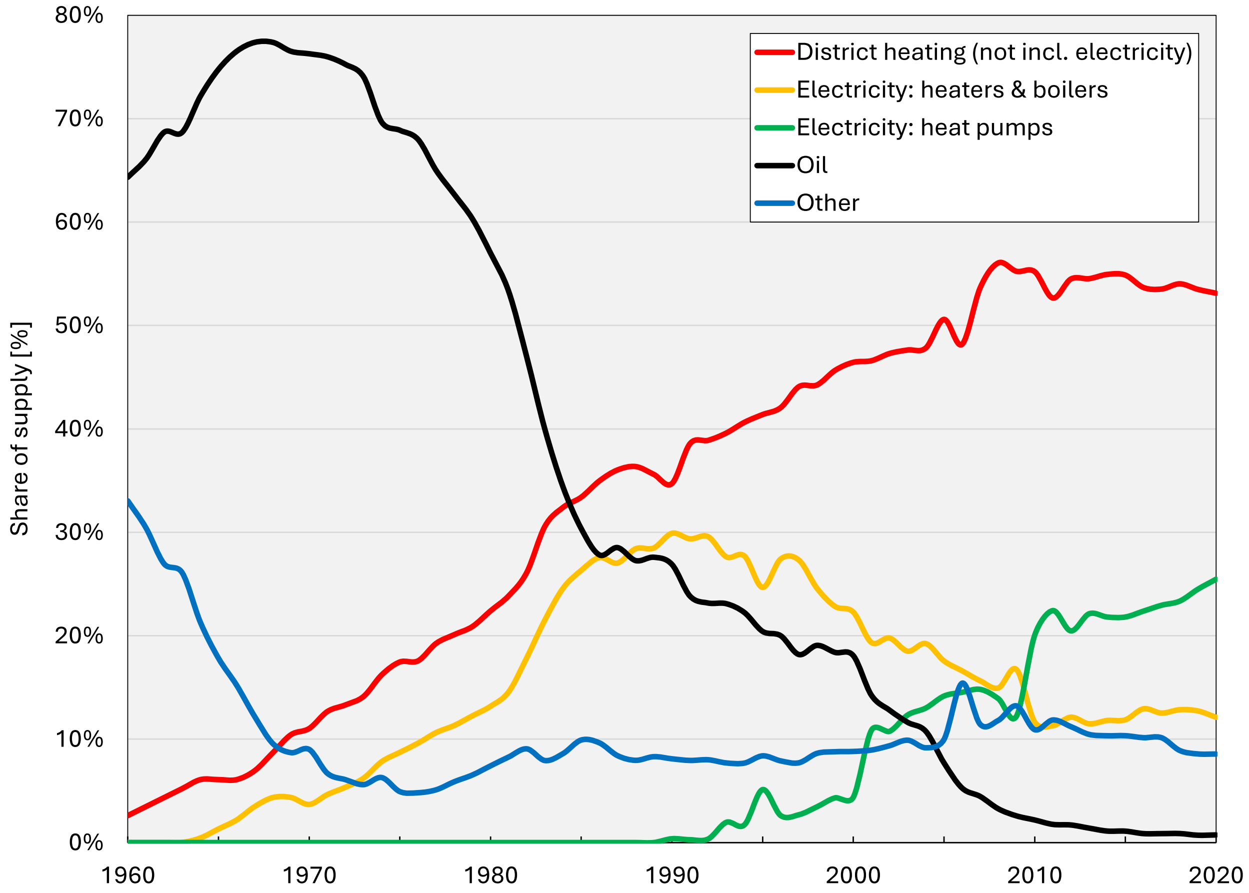


Figure G.1. Generation sources, by percentage of energy share, for heat supply to residential and service sector buildings within the Sweden energy system. Note that all forms of electrical heat generation are grouped together; including those used within district heating networks. As such, district heating totals do not include electrical component. The “Other” category incorporates all other heat sources not related to district heating systems, including–but not limited to–locally combusted firewood, wood pellets and natural gas. Data sources: Werner (2017, 2022)

G.2 Methodology

In order to assess the characteristics of different historical and future configurations of the Swedish heating system, a version of the ENBIOS workflow is defined and implemented, as described in the sections that follow.

G.2.1 System definition

The first stage of an ENBIOS analysis typically involves the definition of a customised hierarchical structure–as a so called “dendrogram”–for the system at hand, governed by the available data and analytical needs of the user. In this case, a dendrogram was created to represent the supply of heat energy within the Swedish energy system, as shown in **Figure G.2**. Here, the hierarchy captured in the dendrogram is defined in accordance with the available categories provided in the historical data (Swedish Energy Agency 2019, 2022) and projected modelling outputs (Lund and Thellufsen 2020) for Sweden. Firstly, it includes the majority of district heating processes within the system. This includes heat derived from the direct combustion of fuels and from utility-scale electrical infrastructure such as heat pumps and boilers. However, amounts of heat from so called "recycled" sources like industrial excess heat and flue gas condensation–which represented approximately 19.1% of total district heating outputs in 2019–are not included here. This is because such processes are assumed to represent beneficial utilisations of existing energy with negligible added environmental externalities. Furthermore, these values are not reported in the modelled projections. Likewise, heating generated by the combustion of oil, biomass and other fuels in individual buildings *outside* of district heating systems are not included in the modelling results and are, thus, omitted from the system considered here. Nevertheless, the use of electricity for generating heat at localised sites–primarily in heat pumps and electrical heaters and boilers at the building level–*are* provided in both the historical data and modelled projections and are, therefore, included in the dendrogram.

In the end, 25 structural processors at the "n-5" level are aggregated into 10 source categories at the "n-4" level: hydro, wind, solar, wood biomass, waste incineration, biogas, natural gas, coal, oil and nuclear. These are further grouped into three renewability classes at the "n-3" level: renewable, non-renewable, and bioenergy and waste. The direct use of fuels and the use of electricity are then delineated at the "n-2" level. Electricity use is applied to both district heating and local generation processes at the "n-1" level; again, the direct use of fuels is only accounted for in district heating systems, meaning that the localised burning of oil, biomass and other fuels at the individual building level is not included in this analysis.

G.2.2 Additional specifications

With the system specified, a selection of additional specification data is required to define the way in which the analysis is undertaken. First of all, individual life cycle inventory (LCI) data is required for each of the structural processors in **Figure G.2**; these are taken from v3.8 of the Ecoinvent LCA database (Wernet et al 2016, Ecoinvent 2021). Where possible, specific processes for Sweden are chosen. Where this is not possible, nearby countries or regional processes for Europe are used; global or "rest of world" values are used when no other appropriate processes are available. A summary of the processes assigned to each processor in the defined system is given in **Table J.27** of the appendices. Where multiple appropriate listings are available, an effort is made to select processes that represent typical or average values in that category to avoid biasing issues resulting from processes that reflect outlier values.

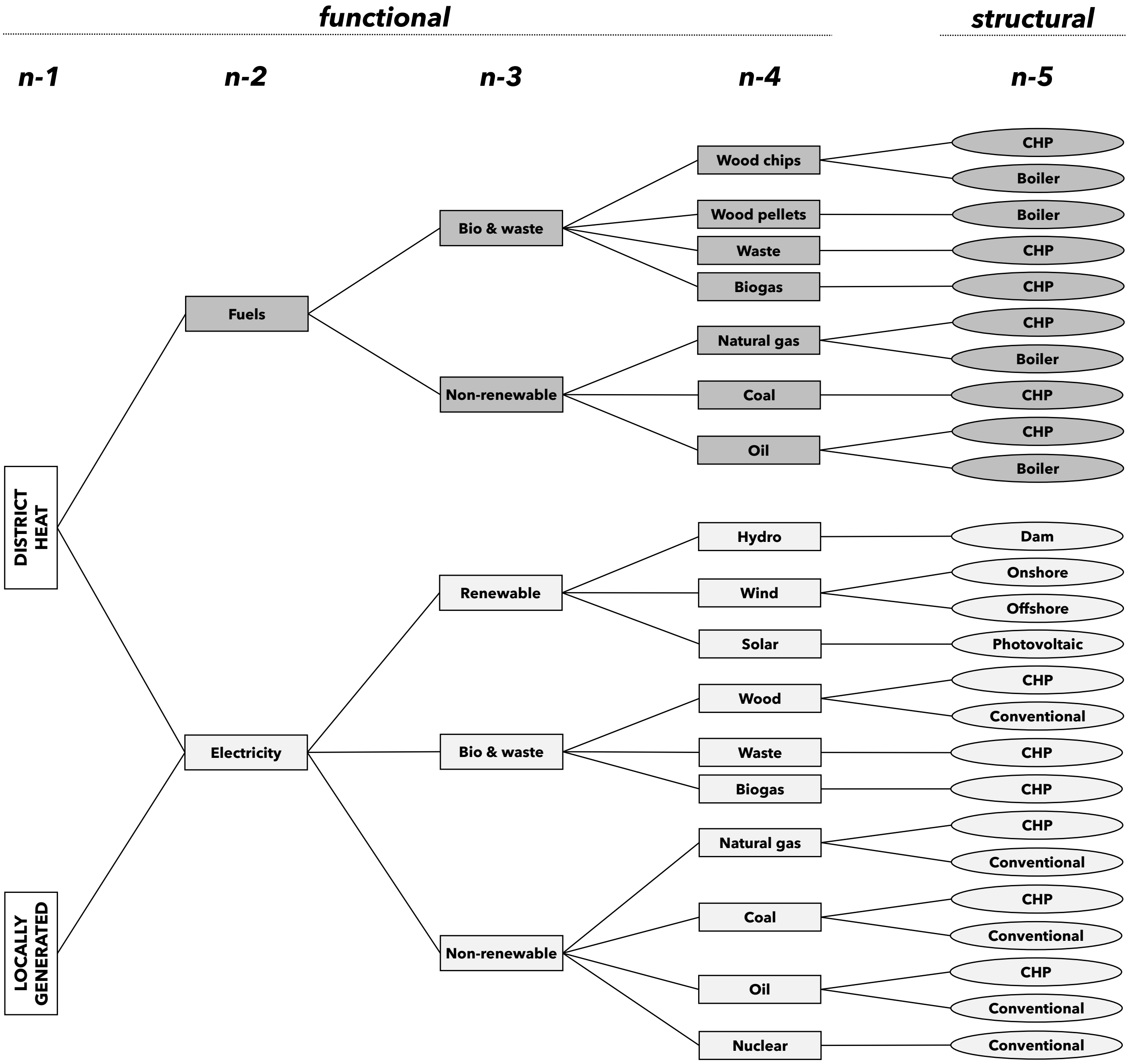


Figure G.2. Representation of Swedish heating system used in the analysis. District heating systems receive inputs from the direct combustion of fuels and heat generated from utility-scale electrical heat pumps and boilers. Locally generated forms of heat using electrical inputs are also included, assumed to be from smaller scale heat pumps, boilers and heaters, typically at the building level. Electrical inputs to both groups are then disaggregated into typical technological categorisations

Final indicator values are then able to be calculated using the standard approach described in section **F**. The majority of the remaining indicators use life cycle impact assessment (LCIA) methods to generate a range of environmental impact and resource use indicators. These methods are again taken from v3.8 of the Ecoinvent LCA database; all selections are part of the "ReCiPe Midpoint (H)" group. Values for three additional raw material indicators are also derived using the material requirement values from LCI listings in conjunction with the methodologies defined in section **E**. A summary of the methods adopted for calculating the final 12 indicators is provided in **Table G.1**.

Table G.1. Listing of methodologies used in deriving final indicators. A full listing is contained in **Table J.27** in the appendices

Group	Indicator	Method	Units
Total energy	Energy generation	Summing heat output values	TWh
LCIA	GHG emissions	climate change, GWP100	Tg CO_2-eq
	Land occupation	agricultural land occupation, ALOP + urban land occupation, ULOP	$x10^3$ km^2
	Water depletion	water depletion, WDP	TL
	Fossil depletion	fossil depletion, FDP	Tg oil-eq
	Metal depletion	metal depletion, MDP	Tg Fe-eq
	Freshwater eutrophication	freshwater eutrophication, FEP	Gg P-eq
	Marine eutrophication	marine eutrophication, MEP	Gg N-eq
	Human toxicity	human toxicity, HTPinf	Tg 1-4-DC
Raw materials	Material supply risk	As per section **E**	yr
	Env impacts relating to material supply	As per section **E**	yr
	Env justice issues relating to material supply	As per section **E**	yr

G.2.3 Historical data

The Swedish Energy Agency (Energimyndigheten) provides detailed annual data for the district heating and electricity supply systems as part of its "Electricity supply, district heating and supply of natural gas" ("El-, gas- och fjärrvärmeförsörjningen") series of reports. For district heating, the reports provide totals for the production of district heating from fuels and the breakdown of which fuel inputs provided these outputs for both CHP plants and heat only boilers. Accordingly, total amounts of energy generated from each fuel and plant type can be derived. Here, ten of the most common fuel/plant combinations are used, as shown in **Table G.2**; where only one plant type is significant, a combination of both is used. Values are also given for industrial excess heat and flue gas condensation but, again, these are not considered in the analysis. Transmission losses are also given. However, as these are not included in the modelled data described in section **G.2.4**, they are removed from the historical heat generation totals to facilitate direct comparisons in the subsequent analysis. Calculated final totals using the 2015 (Swedish Energy Agency 2015) and 2019 (Swedish Energy Agency 2019) versions of the report are also shown in **Table G.2**. Note that values for 2020 are not used as they are significantly different than those in preceding years as a result of drastic changes in energy use resulting from the COVID-19 pandemic.

Table G.2. Summary of historical and projected heat generation from fuel combustion in district heating system. A single plant type is use in instances where one type dominates the observed data or where only one type is represented in the LCI database

Fuel	**Plant type**	**Heat generation**		
		2015	**2019**	**2050**
		[GWh]	*[GWh]*	*[GWh]*
Wood chips	CHP	12,066	12,188	854
	Boiler	5,622	5,671	456
Wood pellets	Boiler	2,637	2,260	182
Waste	CHP	12,019	13,893	14,940
Biogas	CHP	30	116	4,408
Natural gas	CHP	1,221	741	46
	Boiler	85	23	35
Coal	CHP	1,938	1,270	
Oil	CHP	371	348	
	Boiler	397	251	
TOTAL		36,386	36,760	20,920

Electricity inputs into the electric boilers and heat pumps used within district heating systems for these years are also listed in the respective reports and are summarised in **Table J.28** of the appendices. No specific data is available for the use of electricity in heat pumps, heaters and boilers outside of the district heating. However, the *total* amounts of electricity used to generate heat in *all* applications are available elsewhere (Werner 2017, 2022), also based on data from the Swedish Energy Agency. Subtracting district heating input amounts from these totals, therefore, provides the totals used to generate heat from electricity at the local level. The heat totals created in these processes are then calculated assuming no losses for boilers and heaters and a COP of 2.0 for heat pumps, as per Werner (2022); it is noted that COP values for district heating are reported to be between 4.0 to 4.2.

A thorough breakdown of electricity generation is also provided by the Swedish Energy Agency for 2015 (Swedish Energy Agency 2015) and 2019 (Swedish Energy Agency 2019). A summary of the electricity mix, by technology, is shown in **Table G.3**. Note that no distinction between onshore and offshore wind power is provided in the data. Despite this, the Global Wind Energy Council (GWEC) provides breakdowns of installed capacity for Sweden for both years (GWEC 2021) and this data was used to further delineate the single wind power totals. Nevertheless, the totals for offshore wind remain very low.

Table G.3. Summary of historical and projected electricity mix by technology

Technology group	Plant type	Share in electricity mix		
		2015	2019	2050
		[%]	*[%]*	*[%]*
Hydro		46.6	38.8	22.7
Wind	Onshore	10.0	11.8	33.9
	Offshore		0.004	32.2
Solar		0.1	0.4	7.8
Wood	CHP	5.5	6.6	0.3
	Conventional	0.002	0.002	0.4
Waste incineration		1.7	2.1	0.9
Biogas		0.005	0.008	1.9
Natural gas	CHP	0.3	0.2	0.01
	Conventional	0.04		0.02
Coal	CHP	0.6	0.5	
	Conventional	0.2	0.1	
Oil	CHP	0.2	0.2	
	Conventional	0.1	0.04	
Nuclear		34.8	39.3	

G.2.4 Projected data

Predictions for 2050 are provided by modelled outputs from the EnergyPLAN model (Lund and Thellufsen 2020, Østergaard et al 2022). Specific results were provided for Sweden (EnergyPLAN 2022) as a sub-region within a wider simulation of a "Smart Energy" scenario (Connolly et al 2016, Lund et al 2017, 2021) for the European energy system. This scenario seeks to maximise the use of renewable energy technologies while creating a more flexible energy system where interactions between sectors are optimised.

EnergyPLAN outputs provide a thorough inventory of district heating outputs from boilers and CHP units for a range of fuels. A thorough breakdown of methane use is also given, allowing splits between fossil natural gas and biogas derived from waste to be determined. It is noted, however, that EnergyPLAN provides a single total for biomass use and no distinction is made between raw wood chips and processed pellets. Therefore, to maintain this delineation and allow comparison with the historical scenarios, the biomass total is split according to the observed ratio for 2019. A summary of the projected heat generation from fuel combustion in the district heating system for 2050 is provided in **Table G.2**. The data also includes heating produced via electricity inputs to heat pumps and electric boilers within the district heating system; electricity inputs to these devices are back-calculated according to a given COP value, in this case 4.0. Values are also given for electricity inputs to electrolysers that generate hydrogen later used in district heating networks and for heat supplied from solar thermal infrastructure.

As with the historical data described in section **G.2.3**, no specific values are provided for electrical inputs to devices outside of the district heating system. However, total inputs to *all* heat pumps and electric boilers are given, allowing the balances between district heating and the total to be calculated. As in the model itself, a COP for heat pumps was also assumed to be 4.0, enabling final heat outputs from these devices to be calculated. A summary of the projected heat generation from electricity use inside and outside of the district heating system is provided in **Table J.28** in the appendices. It is noted that solar thermal heat is arbitrarily bundled into the electricity total here because no life cycle assessment (LCA) data is available for heat from large-scale solar thermal plants (see section **G.2.2**). For the electricity itself, EnergyPLAN provides a detailed breakdown of all contributing technologies, including the split between CHP and boilers, where appropriate. A summary of the projected electricity mix, by technology, is listed in **Table G.3**. The sum of electrical inputs to heat generation can then be proportioned pro-rata to the different electrical generation processes.

A breakdown of the total inputs to the Swedish heating system–as defined in **Figure G.2**–is provided in **Figure G.3**. It includes historical data for 2019 (Swedish Energy Agency 2019, Werner 2022) and projected values for 2050 (EnergyPLAN 2022). Again, this definition of the system does not include recycled heat sources, assumed to have negligible additional impacts. Furthermore, the private combustion of oil and natural gas in individual buildings is not included in this system. However, although the correct approach to accounting for biomass emissions remains a topic of some debate, emissions from the burning of firewood or wood pellets in home boilers or fireplaces are assumed to have negligible net GHG emissions.

The findings indicate that the share of electricity use is expected to rise from 47% to 65%. Most notably, this projection assumes a drop in wood biomass use from 29% to around 2%. The direct use of waste in incinerators is predicted to increase from 20% to 25% while biogas derived from waste will rise from negligible levels in 2019 to around 7% in 2050. All fossil fuels will be eliminated with the exception of natural gas, which will still be used in very small amounts (0.1%). The breakdown of electricity generation, as illustrated in **Figure G.4**, is also expected to change. Here, the biggest change is the complete elimination of nuclear power, which represented 39% of generation in 2019. Wind power is the biggest mover in replacing nuclear power, rising from 12% to 66%; this move also impacts hydro power, which drops from 39% to 23%. Solar power also makes a noticeable impact in the electricity market, rising from negligible levels in 2019 to attain an 8% share by 2050. Fossil fuels are also eliminated in the electricity sector and the use of wood and waste reduce significantly. Biogas is again predicted to achieve a small penetration in the market, achieving a 7% share by 2050.

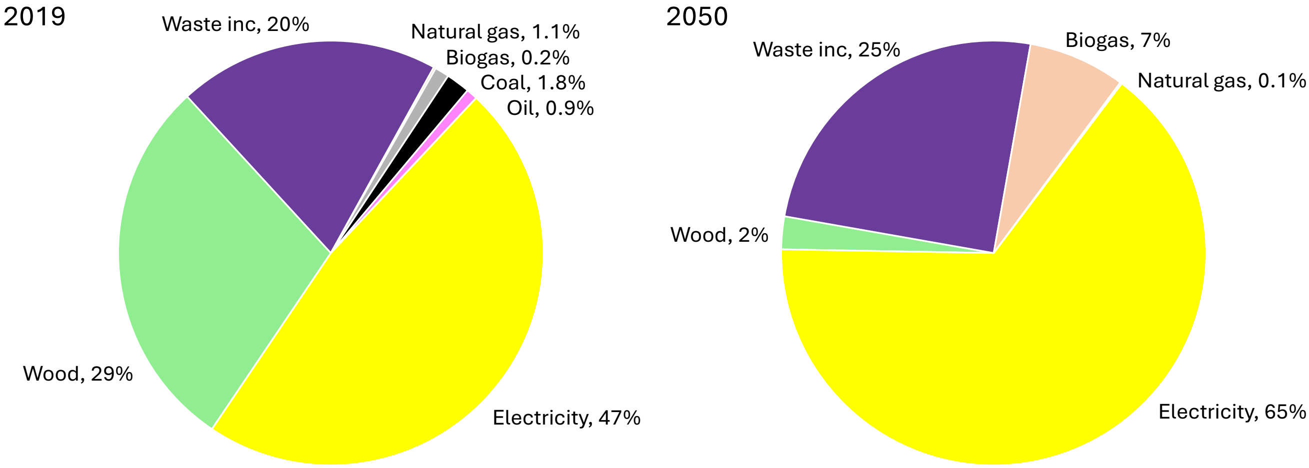


Figure G.3. Historical and projected percentage breakdowns of total heat generation. Further breakdown of electricity component is given in **Figure G.4**. Data sources: Swedish Energy Agency (2019), EnergyPLAN (2022), Werner (2022)

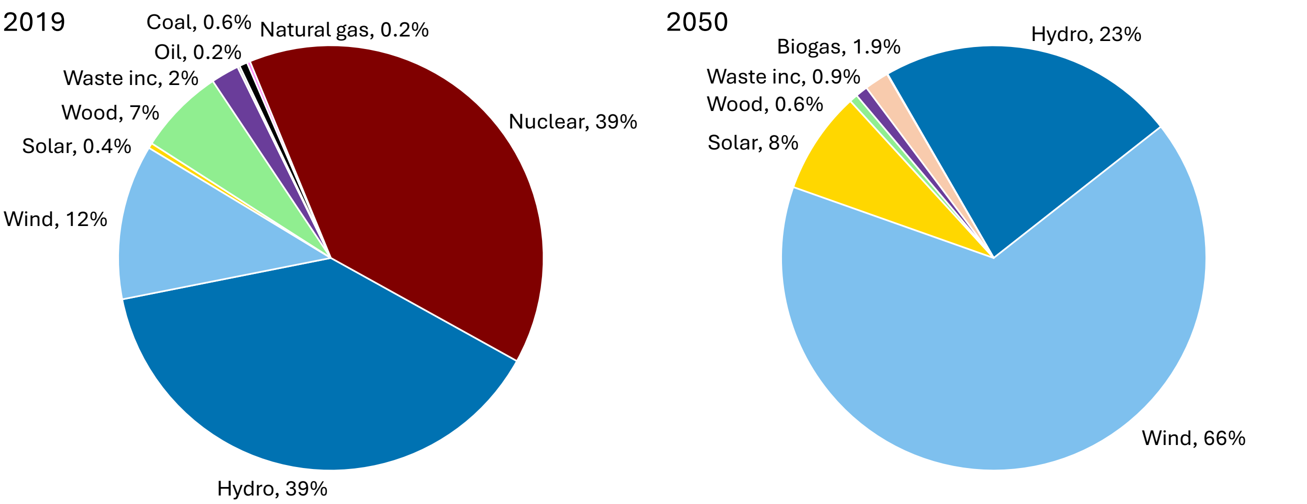


Figure G.4. Historical and projected percentage breakdowns of electricity generation. Data sources: Swedish Energy Agency (2019), EnergyPLAN (2022), Werner (2022)

G.3 Results of analysis

With the system specified and all historical and projected data in place, results are generated at each processor in the ENBIOS dendrogram for each of the indicators listed in **Table G.1**. Scaling of LCI processes is performed using the final amounts of energy that relate to each processor. For heat, the final generation values shown in **Table G.2** are used. For electricity the total amount of energy *input* values from **Table J.28** are used in conjunction with the technological mix data in **Table G.3**.

The only exception here is in the reporting of final energy generation totals which use the electricity *output* values from **Table J.28**.

G.3.1 Summary of overall changes

A summary of the percentage changes forecast to occur between 2019 and 2050 is given in **Table G.4**. The results reveal that adverse changes–where increases are observed–are predicted to occur in six of the 12 indicators. These range from a minor increase in freshwater eutrophication of 16.0% to a rise of 163.1% in relation to the environmental impacts generated from raw material extraction. Beneficial changes are observed in the remaining six indicators. Notably, four of these indicators reduce by at least 50% between 2019 and 2050. The remaining two indicators–energy generation and GHG emissions–reduce by 14.6% and 36.0%, respectively. The phasing out of fossil fuels, wood biomass and nuclear power by 2050 has resulted in many reductions in key indicators. However, replacing these sources with other renewable energy, bioenergy and waste technologies is also shown to have detrimental effects on future outcomes, especially with respect to wind, solar and biogas sources.

Table G.4. Summary of percentage changes observed for 12 indicators between 2019 and 2050. Potentially adverse results are displayed in shaded cells. A summary of the key determinants of the predicted changes is also provided

Group	Indicator	Observed change (2019-2050)	Key determinants
Total energy	Energy generation	-14.6%	Annual variations Contributions of recycled heat in 2050
LCIA	GHG emissions	-36.0%	Phasing out of coal, oil & wood Waste remains
	Land occupation	-66.9%	Phasing out of wood
	Water depletion	+61.7%	Phasing out of nuclear Replaced by biogas
	Fossil depletion	-57.2%	Phasing out of coal, oil, natural gas & wood
	Metal depletion	+51.2%	Wind, solar & biogas
	Freshwater eutrophication	+16.0%	Phasing out of coal & wood Replaced by biogas
	Marine eutrophication	-52.0%	Phasing out of wood
	Human toxicity	-59.5%	Phasing out of wood
Raw materials	Material supply risk	+52.7%	Wind, solar & biogas
	Env impacts relating to material supply	+163.1%	Wind, solar & biogas
	Env justice issues relating to material supply	+80.1%	Wind, solar & biogas

G.3.2 Findings by indicator

Results for each of the 12 indicators are displayed in individual figures in the sections that follow; each row illustrates the totals for a given indicator for the two historical system configurations–2015 and 2019–alongside the projected system for 2050. Representations are shown for three hierarchical levels: "n-2" for fuel combustion and electricity, "n-3" for renewability category, and "n-4" for individual technology categories. Brief discussions are also provided for each indicator.

G.3.2.1 Energy generation

Overall heat energy generation totals are predicted to fall by approximately 14.6% between 2019 and 2050, as shown in **Figure G.5**. However, observing the historical values of this indicator between 2015 and 2019 reveals that changes of between 1% and 8% are commonplace from year to year (Swedish Energy Agency 2015, 2016, 2017, 2018, 2019). This is hardly surprising considering that milder or colder winters can easily affect overall heating requirements. Furthermore, it is unclear what contributions are assumed for recycled heat in the EnergyPLAN results obtained for the analysis. Although not include in any of the totals presented here, this heat has represented 17.7-19.5% of recorded district heating totals between 2015 and 2019. As such, uncertainties in this regard could also provide some explanation for the differences in the historical and predicted values, particularly if higher utilisations of recycled heat are assumed in future EnergyPLAN scenarios. In any case, it is worth keeping in mind that the overall amounts of heat are assumed to be lower in the EnergyPLAN results when comparing the findings for other indicators.

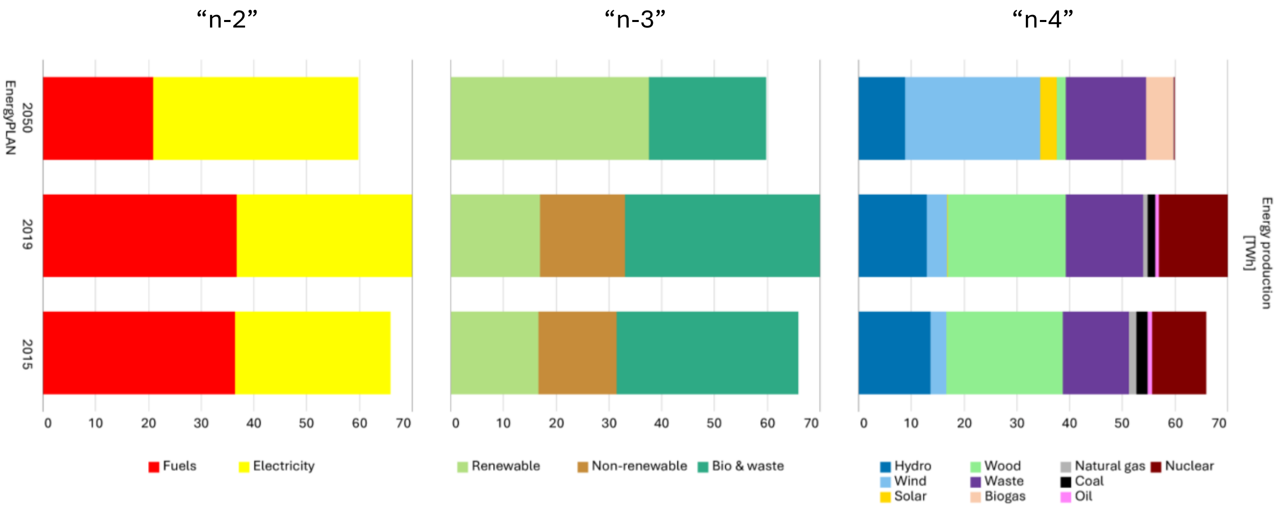


Figure G.5. Comparison of historical and predicted values for total energy generation. Results are shown across three separate hierarchical levels

As previously demonstrated in **Figure G.3**, a clear move towards electrification is observed, as is a dramatic shift towards renewable energy use and away from non-renewables, bioenergy and waste.

And, while solar energy is expected to make inroads into the electricity market, by far the biggest shift at the "n-4" technological level is in the increased use of wind energy.

G.3.2.2 GHG emissions

Following a slight decrease of 4.6% between 2015 and 2019, GHG emissions drop a further 36.0% by 2050, as shown in **Figure G.6**. Results at the "n-3" level reveal that these reductions are largely linked to the non-renewable forms of heat. Further analysis at the "n-4" level reveals the specific connection to natural gas, coal and oil alongside nuclear, all of which are virtually eliminated by 2050 under this scenario; large reductions in wood use are also clearly a factor. Despite the large rises in wind and solar use predicted by 2050, these processes do not contribute significant amounts of GHG emissions. However, the burning of waste continues to produce large amounts of emissions, as does the increasing use of derived biogas.

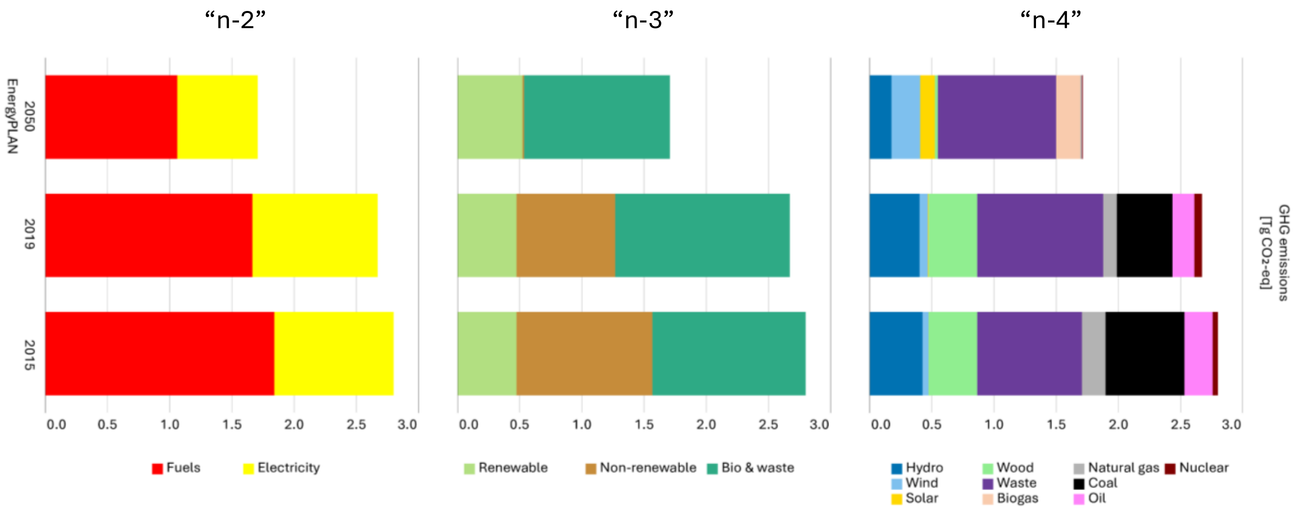


Figure G.6. Comparison of historical and predicted values for GHG emissions. Results are shown across three separate hierarchical levels

Nevertheless, although no specific GHG emissions targets have been specified for heating by the Swedish government, the country's national energy and climate plan (Infrastrukturdepartementet 2020) states that net GHG emissions must be reduced to zero and all electricity must be from renewable sources by 2040. As a result, the projected scenario from EnergyPLAN does not come close to satisfying current policy targets using the assumptions used in this assessment. This, again, highlights the differences between the assumptions made in LCA processes against those made in other policy-based quantifications. It also highlights the importance of changing "background" systems when making assessments for future energy systems. This topic is discussed further in section **I.3** as an important area of future research.

G.3.2.3 Land occupation

The total area of land required to maintain the heating system are predicted to fall dramatically under the examined scenario, as shown in **Figure G.7**. Indeed, the area required in 2050 is less than one third of the amount required in 2019, falling by some 66.9%. Analysis at the three levels clearly demonstrates that these reductions are almost exclusively linked to the use of wood, which contributes a mere 2.5% of total heat by 2050, down from 28.7% in 2019. It is also notable that the majority of the land requirement in 2050–totalling 89.0%–is linked to direct heat production, largely from wood, waste and biogas; renewable energy sources contribute less than 1% of the total requirement.

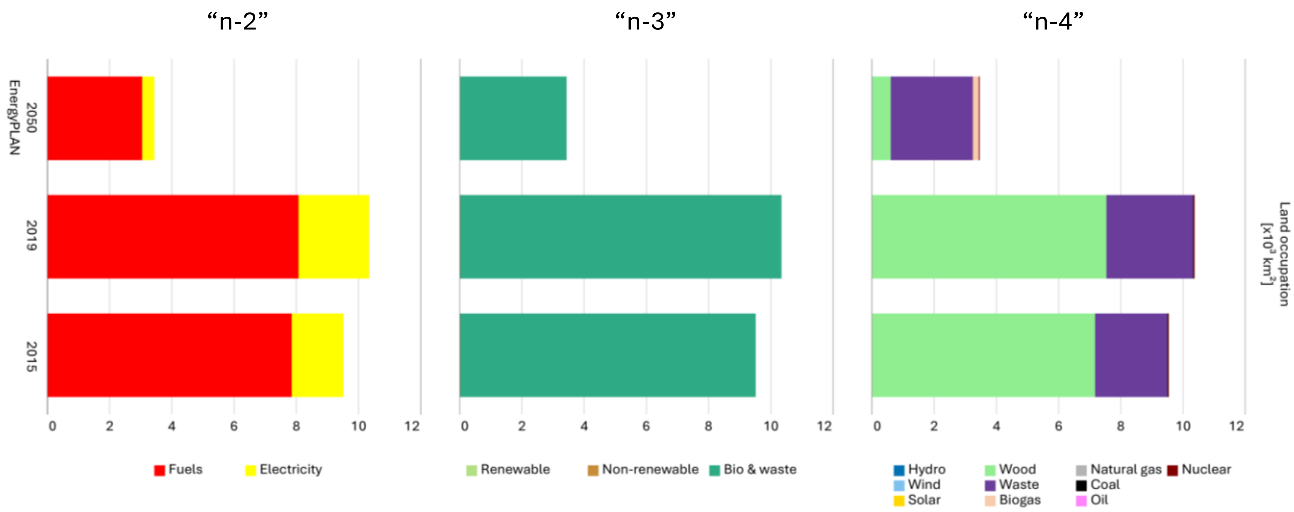


Figure G.7. Comparison of historical and predicted values for land occupation. Results are shown across three separate hierarchical levels

G.3.2.4 Water depletion

Conversely, the required amounts of water are predicted to rise by around 61.7% between 2019 and 2050, as shown in **Figure G.8**. Analysis at the "n-3" level immediately reveals that this rise is strongly linked to bioenergy and waste sources. Subsequent findings at the "n-4" level show that biogas production is by far the dominant source of this requirement, replacing the previous dominance of nuclear power which itself requires particularly large amounts of water inputs to generate electricity in steam turbines (Macknick et al 2012). According to the applied data (Ecoinvent 2021), the use of biogas to generate heat and electricity in CHP plants requires between 16 and 3,300 *times* as much water per unit of heat than all other processes being considered. As such, although the use of biogas is only predicted to rise from 0.2% to 7.4% of total heat energy, its impact on water requirements here is substantial, indicating the significant risk associated with increasing biogas use in this regard. That being said, it must be stated that the LCI data used to define biogas here is the only available listing in Ecoinvent and represents biogas from manure. It is not known if biogas from other sources–e.g., from municipal or agricultural waste or sewage sludge–would return substantially different results.

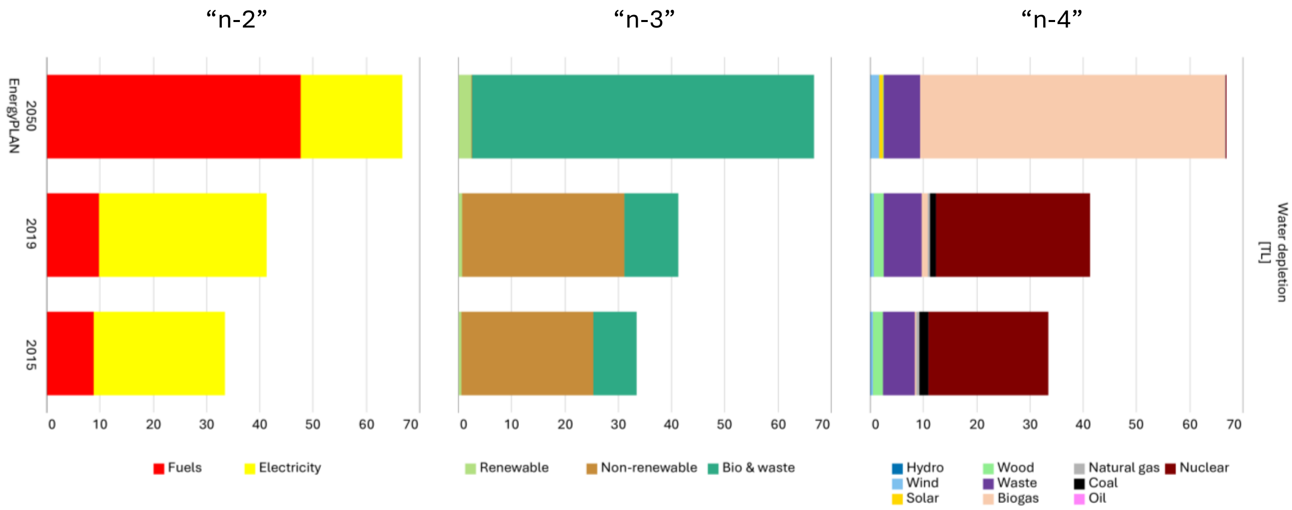


Figure G.8. Comparison of historical and predicted values for water depletion. Results are shown across three separate hierarchical levels

G.3.2.5 Fossil depletion

Not surprisingly, the vast reduction in non-renewable fossil fuel use between 2019 and 2050 results in a significant reduction in fossil depletion, which falls by 57.2%, as shown in **Figure G.9**. Nevertheless, analysis at the "n-4" level reports that the remaining depletion rate in 2050 is made up of larger contributions from wind energy, solar and biogas while, again, levels from waste incineration remain stable.

G.3.2.6 Metal depletion

Meanwhile, levels of metal depletion are set to rise by around 51.2% according to the system forecast for 2050, as shown in **Figure G.10**. Observations at the "n-2" and "n-3" levels suggest that this rise is largely from electricity generation via renewable energy processes. In particular, wind turbines and solar PV cells–both of which require significantly higher levels of rare earth materials and a variety of other metals than other technologies (Bobba et al 2020)–contribute 71.9% and 13.3% of the 2050 depletion totals, respectively.

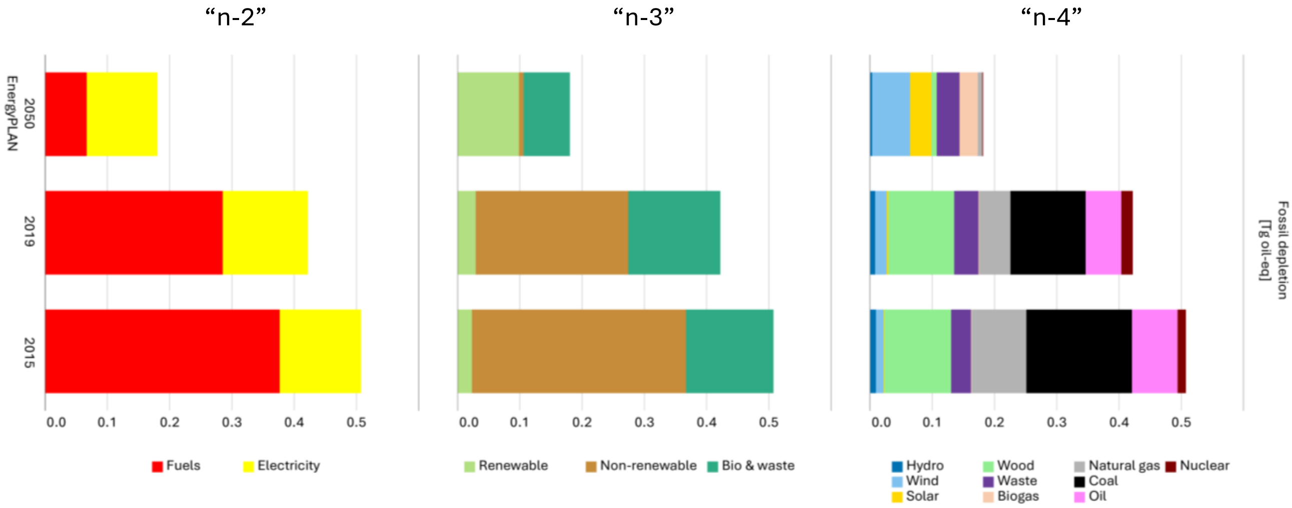


Figure G.9. Comparison of historical and predicted values for fossil depletion. Results are shown across three separate hierarchical levels

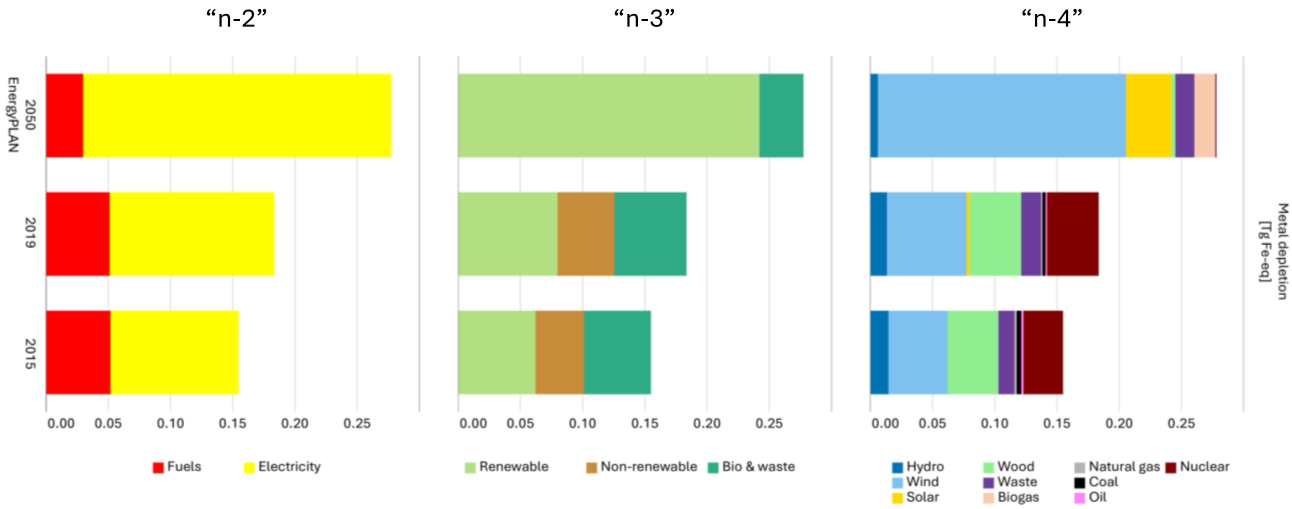


Figure G.10. Comparison of historical and predicted values for metal depletion. Results are shown across three separate hierarchical levels

G.3.2.7 Freshwater eutrophication

Overall levels of freshwater eutrophication are likely to hold relatively steady under the projected scenario for 2050, increasing by 16.0%, as shown in **Figure G.11**. Findings at the "n-2" level confirm that these changes are almost all from increases in electricity use as the value for direct heat remains virtually unchanged between 2019 and 2050. Nevertheless, the sources of change are more nuanced than for other indicators; the breakdown of different technologies at the "n-4" level change considerably between the two historical observations and the modelled scenario for 2050. Here, once again, a significant contribution can be observed for biogas, which represents around 52.6%

of the 2050 total despite the fact that it provides only 7.4% of the heat energy in this scenario. All other changes are more or less in line with the transition away from non-renewable sources and greater adoption of wind and solar.

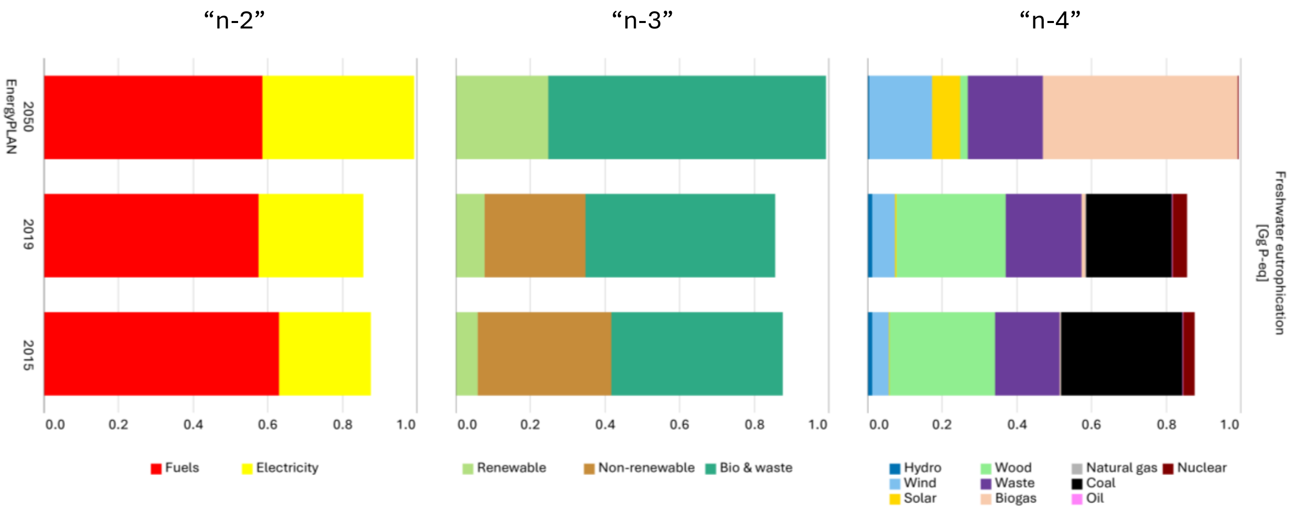


Figure G.11. Comparison of historical and predicted values for freshwater eutrophication. Results are shown across three separate hierarchical levels

G.3.2.8 Marine eutrophication

Eutrophication in marine systems, meanwhile, is predicted to decrease by more than half–52.0%–between 2019 and 2050, as shown in **Figure G.12**. Unlike its freshwater counterpart, marine eutrophication levels are not dramatically affected by biogas production. As such, the phasing out of fossil fuels and, especially, wood biomass result in substantial reductions in this indicator. Furthermore, upturns in wind- and solar-based generation do not cause any significant increases.

G.3.2.9 Human toxicity

Overall levels of human toxicity are also predicted to decline significantly between 2019 and 2050 in the given scenario, reducing by 59.5%, as shown in **Figure G.13**. At the "n-3" level, the replacement of non-renewable fossil fuel sources is more or less directly substituted by renewable sources; bioenergy and waste sources represent the most significant reduction. Analysis at the "n-4" level once again reveals these changes to be largely dominated by the phasing out of wood. In fact, per-unit levels of human toxicity in relation to biomass use for heat and electricity generation are among the highest in the analysis, the only comparable processes being those for coal.

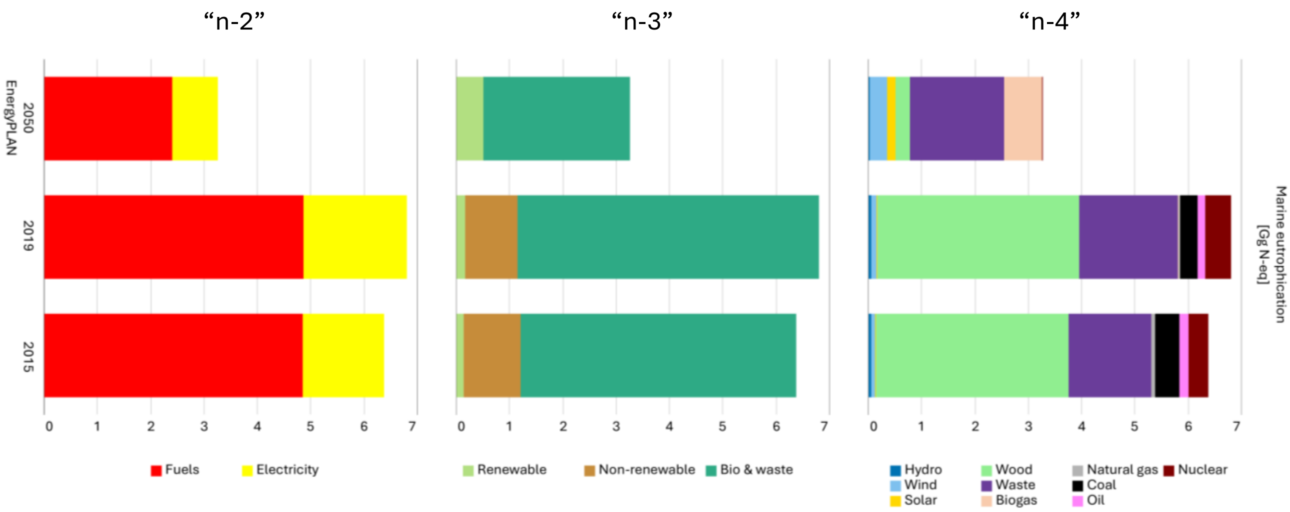


Figure G.12. Comparison of historical and predicted values for marine eutrophication. Results are shown across three separate hierarchical levels

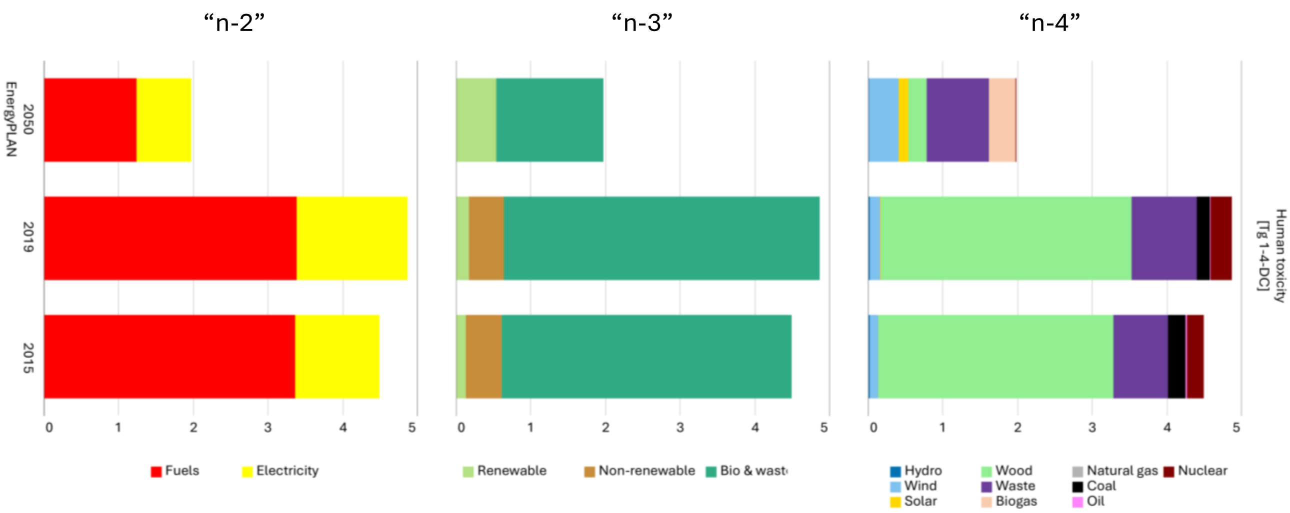


Figure G.13. Comparison of historical and predicted values for human toxicity. Results are shown across three separate hierarchical levels

G.3.2.10 Material supply risk

The overall level of raw material supply risk is forecast to rise by 52.7% between 2019 and 2050 under this scenario, as shown in **Figure G.14**. Observing the results obtained at the “n-2” and “n-3” levels indicate that this growth is strongly linked to electricity generated from renewable energy technologies, although bioenergy and waste continue to be factors. Closer inspection at the “n-4” level confirms that wind, solar and biogas are the key contributors to the increase, representing 58.2%, 14.3% and 14.5% of the total in 2050, respectively. As with most processes, neodymium, praseodymium and samarium all have a significant influence on the three key technological groups; gallium is also a notable material in the score for solar power while phosphorus requirements elevate the overall score for biogas.

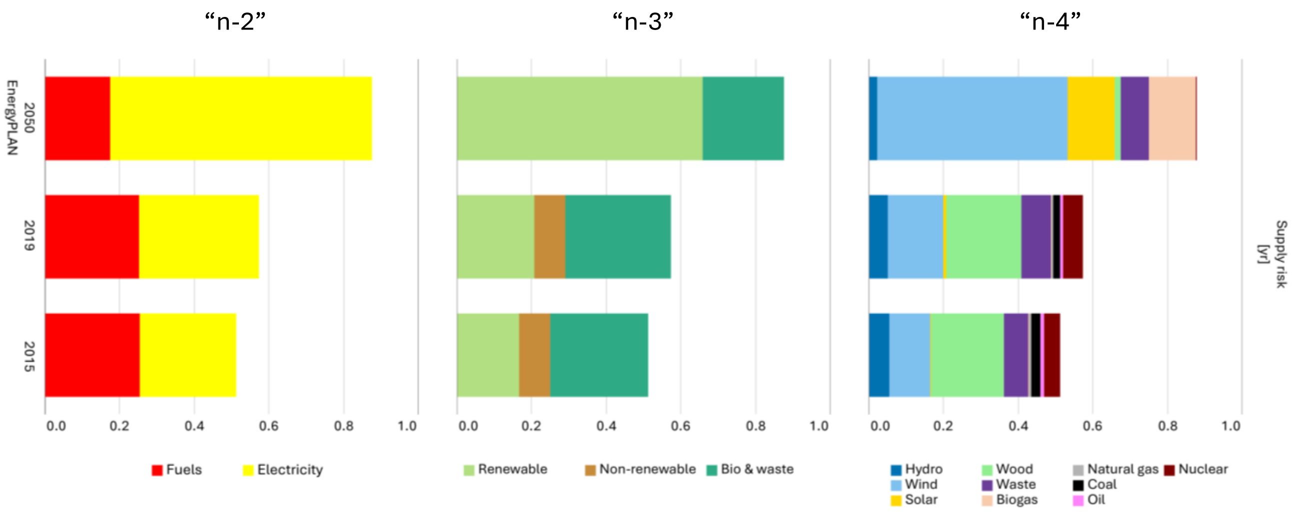


Figure G.14. Comparison of historical and predicted values for material supply risk. Results are shown across three separate hierarchical levels

G.3.2.11 Environmental impacts relating to material supply

A particularly sharp rise is observed in the environmental impacts derived from raw material extraction and processing in the case study, as shown in **Figure G.15**. In fact, overall values are predicted to rise by over 163% by 2050. As with the water depletion indicator, this increase is connected to both direct fuel combustion and electricity generation and is strongly linked to biogas us which provides around 54.4% of the total score in 2050. Indeed, the per-unit score for electricity from biogas is five times higher than all other technologies analysed at the "n-4" level; this is strongly linked to a higher requirement for platinum group metals (PGMs), and rhodium and platinum in particular. Wind and solar power are again seen to be important contributors here, occupying 38.7% of the remaining score between them.

G.3.2.12 Environmental justice issues relating to material supply

Lastly, the level of environmental justice threats relating to the extraction and processing of raw materials are also expected to rise considerably, increasing by a total of 80.1% by between 2019 and 2050, as shown in **Figure G.16**. Here, electricity from renewable sources is once again the clearest influence when analysing results at the "n-2" and "n-3" levels. Biogas remains a considerable factor overall, alongside solar power. However, the most notable technology is wind power, which represents some 52.9% of the total in 2050. Neodymium, praseodymium and samarium are, again, highly influential materials in these calculations, all of which are predominantly sourced from China. Other materials such as tellurium, magnesite and gadolinium also introduce significant potential threats in this regard.

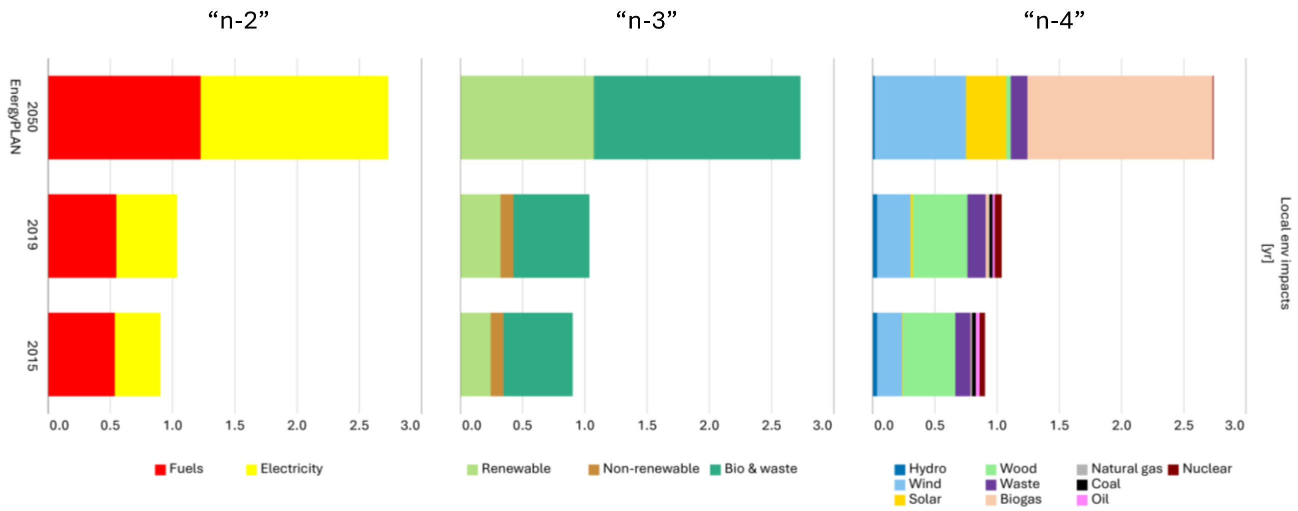


Figure G.15. Comparison of historical and predicted values for environmental impacts relating to material supply. Results are shown across three separate hierarchical levels

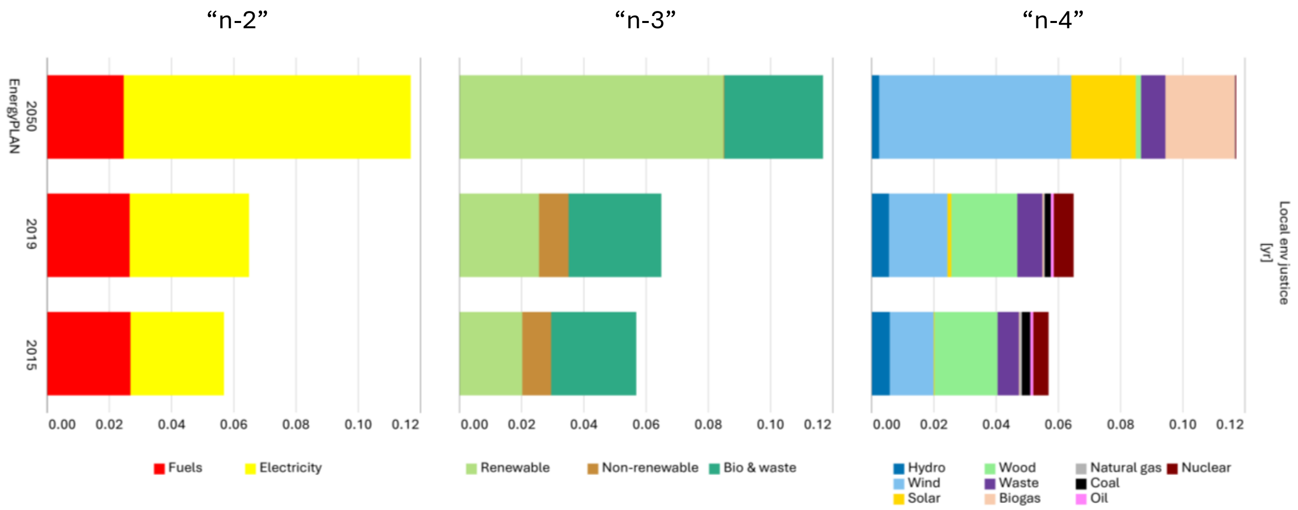


Figure G.16. Comparison of historical and predicted values for environmental justice issues relating to material supply. Results are shown across three separate hierarchical levels

G.4 Discussion and conclusions

Buildings in Sweden require heating for at least eight months in every year. The last 50 years has since a dramatic shift away from obtaining this heat from oil heaters at the individual building level towards centralised district heating approaches and, more recently, towards the use of electric heat pumps. To analyse the ongoing transition in the Swedish heating system, the ENBIOS workflow was used to identify and analyse projected changes in the system for a group of 12 key indicators using system configuration data for 2015 and 2019 as historical baselines, and a predicted configuration for 2050 derived from the EnergyPLAN model.

The results found an even spread in results in that reductions were predicted in six of the indicators examined, while the remaining six indicators were predicted to increase. The phasing out of fossil fuels, wood biomass and nuclear power assumed in the EnergyPLAN scenario for 2050 has resulted in beneficial reductions in the GHG emissions and fossil depletion indicators, which drop by 36.0% and 57.2%, respectively. At the same time, wood biomass alone is largely responsible for beneficial reductions in the land occupation, marine eutrophication and human toxicity indicators, which fell by 66.9%, 52.0% and 59.5%, respectively.

Meanwhile, large overall reductions in water depletion amounts caused by the assumed phasing out of nuclear power were overshadowed by even greater requirements coming from biogas, resulting in an overall increase of 61.7% in this category. Similarly, reductions in marine eutrophication potential relating to coal and biomass use were more than nullified by the influence of emerging technologies, particularly of biogas which also dominated the projected values in this category. The value for this indicator is expected to rise by 16.0% between 2019 and 2050. Again, it is realised that the indicator values for biogas are calculated using the lone LCI listing available for biogas–using manure waste–and it is unclear if other biogas production techniques would yield different results.

For the remaining four indicators–metal depletion and supply risk, environmental impacts and environmental justice threats from raw material supply–any reductions relating to the phasing out of fossil fuels, wood biomass and nuclear power are also predicted to be offset by the detrimental characteristics of the technologies that are predicted to replace them. In fact, for all four of these indicators, the dominant contributions in 2050 are clearly derived from three technologies: solar PV, wind and biogas. The use of wind turbines represents over half of the overall contributions to the fossil depletion, supply risk and environmental justice indicators in 2050, resulting in overall increases of 51.2%, 52.7% and 80.1%, respectively. Elsewhere, biogas is found to be the overwhelming contributor to the environmental impacts from material supply indicator, contributing well over half of the 2050 value to result in an overall increase of 163.1%.

The use of waste incineration as a source of both heat and electricity is predicted to remain more or less at current levels in 2050, meaning that no major changes are expected in the contributions from waste in any of the indicator categories. However, perhaps the most concerning example of this is observed in its impact on system GHG emissions. Here, large emissions reductions are predicted as a result of the phasing out of fossil fuels, wood biomass and nuclear power. And, although the increased use of wind, solar and biogas offset these reductions somewhat, significant emissions resulting from waste incineration–representing 55.5% of the total emissions in 2050–contribute to a somewhat muted overall reduction of only 36.0%. As GHG emissions are generally seen as the most high-profile indicator used in climate policy decision making, the impact of continuing to incinerate waste for energy generation purposes is highlighted as perhaps the key observation in this chapter.

While the results of the investigation provide a selection of useful insights, a number of limitations have been identified. Firstly, it is assumed that the observed differences in overall energy between the historical and modelled results is predominantly due to annual variations and, especially, different heat demand assumptions in the future scenario. In any event, several differences were also evident in the two data sources–historical data from the Swedish government databases and EnergyPLAN data–which required some arbitrary assumptions to be made. For example, although excess industrial heat is considered in EnergyPLAN, it is unclear if this heat is reported in the received datasets. As there is no indication that it *is* included in these results, this heat was removed from the government historical data, and it is assumed that the two datasets have been correctly aligned; it remains unclear if some variation could have been introduced here.

Secondly, neither the historical datasets nor the EnergyPLAN outputs include consideration of heat coming from the "other" heating methods–mostly the burning of biomasses, gases or oils in small-scale stoves or boilers–that still exist within decentralised parts of the Swedish heating system. Indeed, these sources provided around 9% of total system heat in Sweden in 2019, as shown in **Figure G.1**. It seems likely that such practices will be reduced further by 2050 as more sustainable and centralised practices are pursued, but are likely to remain in some places, particularly in remote areas. In any case, such totals are not included in either the historical or projected assessments undertaken here and could introduce some level of uncertainty when comparing the two datasets.

Finally, an issue of uncertainty is also acknowledged in relation to the ratio of electricity inputs to heat outputs–the coefficient of performance (COP)–assumed in the heat pumps within these analyses. In the data for historical systems (Werner 2022) a COP of 2.0 was assumed when calculating the heat outputs from electricity use. However, in the EnergyPLAN modelling, electricity requirements are calculated using a COP of 4.0, implying that large increases in heat pump efficiency are likely to occur by 2050. Both of these assumptions appear to be somewhat arbitrarily selected as no explanation or source are provided. In reality, if either COP assumption is inaccurate, the total electricity requirement values could change, thus affecting the indicator calculations relating to electricity.

The investigation provides a selection of novel and useful insights into some of the lesser-known aspects of heat generation practices. Ultimately, it is recognised that policymakers must continue to juggle a variety of issues when planning the heating systems of the future, particularly in colder climates where reliable and efficient heating systems are vital. In this sense, it is hoped that deeper analyses of this kind can be used to complement existing modelling techniques and expand the scope of available tools for assisting heating policy decisions as we strive to achieve more sustainable energy systems.

H SECOND CASE STUDY

Where to from here? Defining environmental, labour and material supply implications for a spectrum of possible energy system configurations in Europe

Abstract

The European energy system encompasses a wide-ranging network of 35 countries that goes beyond the European Union to include all Balkan nations, Switzerland, the United Kingdom, Iceland and Norway. As with most of the world's energy networks, the system is now attempting to transition away from fossil fuels and embrace more sustainable technologies in an effort to lower greenhouse gas emissions and address the threat of climate change. However, while wind and solar technologies are generally tipped to emerge as the dominant technologies within an increasingly electrified system, a wide spectrum of possible future alternatives–both technologically and spatially–are possible. The following chapter investigates the application of the ENBIOS workflow to various possible future configurations of the European energy system, as defined by two sets of outputs from the Euro-Calliope optimisation model. Here, system definitions are taken from the model that includes installed capacity and annual energy generation data for a range of electricity, district heat and direct fuel use processes to produce a variety of environmental, labour and material supply indicators. The first set of data involves three configurations based on specific real-world constraints–known as "storyline" scenarios–provided to Euro-Calliope by the QTDIAN toolbox. Of these three storylines, the so-called "people powered" scenario is found to generally produce less-desirable outcomes across the chosen set of indicators than the less restricted "market driven" and "government directed" scenarios. A second set of Euro-Calliope data defines 441 solutions used to represent the "decision space" of available options for the European energy system. Applying the ENBIOS approach to each of the 441 possible configurations enables a corresponding "decision space" to be defined for the selected environmental, labour and material supply indicators. The results indicate that greenhouse gas emissions reduce in all 441 of these scenarios while energy generation rises as a response to the losses encountered when increasing the use of electricity storage and creation of fuels via electrolysis. Nevertheless, large increases are observed in human activity and two of the raw materials factors–supply risk and environment justice–for all 441 scenarios. Conversely, a range of increases and decreases are observed across the spectrum of scenarios for all other indicators, suggesting that far greater flexibility is available to policymakers where these aspects are concerned. Comparing the three storyline scenarios with the full cross section of available options reveals that, as more conditions are placed on these scenarios, all three are generally found to exist at the less-desirable end of the spectrum of possibilities.

H.1 Introduction

To further demonstrate the use of the ENBIOS approach on the European energy system–as defined by the Euro-Calliope model–two further applications are explored as examples in the following chapter. Firstly, forecast configurations for 2030 and 2050 were analysed for three scenarios optimised in accordance with constraint parameters defined by socio-economic “storylines” provided by another group within the SENTINEL project (SENTINEL n.d.). Secondly, a set of 441 different technically and economically feasible future configurations were analysed in order to gain information about the range of available approaches for building an energy system in Europe that is both energy independent and devoid of fossil fuel use. It is also notable that both applications use thoroughly researched historical observations for the same system as a baseline.

As both applications use the same fundamental system setup, in conjunction with inputs obtained from the same version of the Euro-Calliope model, the fundamental system definition–and the historical data that relates to that system–is explored in the first section of the chapter. Full explorations of the data used as inputs and results obtained in the two application examples are provided, in turn, in the two sections that follow. The chapter concludes with discussion and conclusions relating to both examples.

H.2 General definitions

H.2.1 System hierarchy

In order to assess the characteristics of historical configurations of the European energy system and the many possible future systems defined by the storyline and SPORES data (Pickering et al 2022), a customised version of the ENBIOS approach was required. As with any such investigation, the hierarchy of the system was first defined by creating a “dendrogram” structure that reflects the available data and requirements of the analysis. In this case, the energy system was initially delineated to represent three main energy carrier groups: (1) electricity, (2) centralised heat generation (i.e., district heat); and (3) fuel for direct utilisation. Indeed, these three categories represent the “n-1” level of the dendrogram in this investigation, as shown in **Figure H.1**; the energy system as a whole represents the overarching “n” level.

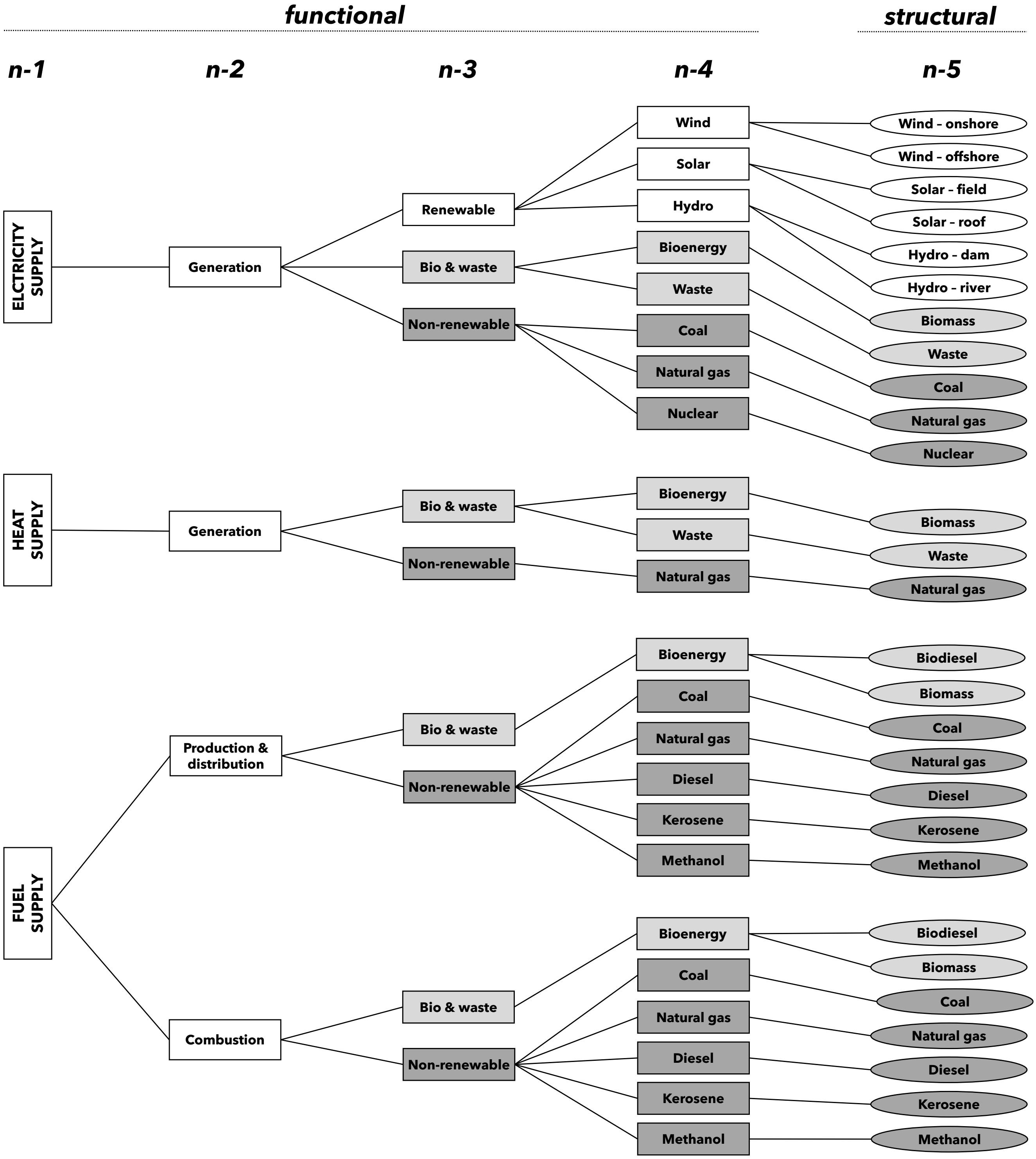


Figure H.1. Hierarchical representation of European energy system used in the analysis

The version of Euro-Calliope defined and used in the SENTINEL project implements 13 energy carriers in total: electricity, hydrogen, GHG emissions as carbon dioxide (CO_2), hydrocarbons (kerosene, methanol, diesel, and natural gas/methane), solids (biofuel and municipal waste), low-temperature heating (space heating/hot water and cooking heat), and vehicle distance (heavy and light road vehicles). A series of result files are then used to specify the various inputs and outputs of these carriers within the different functional processes and across different regions in the modelled system; values of power capacity are also provided, where applicable. GHG emissions are addressed in more detail within ENBIOS itself and, as an “end use” process, vehicle distance is not considered. However, the movement of all other carrier “flows” and power capacities within modelled Euro-Calliope systems can be used to define the ENBIOS system at hand.

Considering these datasets in conjunction with the available LCI data resulted in a total of 24 structural processors at the “n-5” level of the dendrogram, as illustrated in **Figure H.1**. These are then consolidated into 11 general technological categories at the “n-4” level: wind, hydro, solar photovoltaic (PV), bioenergy, waste, coal, natural gas, nuclear, diesel, kerosene and methanol. These groups could then be simplified into three general classes of energy at the “n-3” level: renewable, bioenergy and waste, and non-renewable. It is noted that all electricity and heat processes relate simply to the generation of these carriers and are grouped accordingly at the “n-2” level.

At any rate, as the direct use of fuels requires two very distinct processes to occur–fuel production and final combustion–these processes are delineated into two categories at this level. Here, emissions from combustion are calculated using common emission factors that provide GHG emissions for each unit of energy produced from a given fuel source (IPCC 2021). Nevertheless, as with the LCI data for generating electricity and heat from biomass, no additional carbon dioxide (CO_2) emissions are added for the direct combustion of biomass or biodiesel[2], as it is assumed that these emissions are offset during the plant growing stages (Hanaki and Portugal-Pereira 2018). Emissions from other GHGs–predominantly methane (CH_4) and dinitrogen monoxide (N_2O)–are included for biomass and biodiesel combustion, but these emissions are far lower than those for CO_2. As such, combustion emissions for both are significantly less than for other fuels.

Finally, although Euro-Calliope includes the use of hydrogen derived from electrolysis as a source of storage and for the production of synthetic fuels–namely, diesel, kerosene, methane and methanol–these processes are all accounted in ENBIOS via the electricity used in these processes. However, the GHG emissions resulting from the eventual use of these “artificially” derived fuel products is accounted for at the relevant combustion processors. Additional specifications

With the hierarchy defined, additional information is required to specify the way in which outputs from Euro-Calliope are received and the way in which subsequent analyses are undertaken. The first

[2] In the preliminary version of the ENBIOS workflow presented in section **F**, CO_2 combustion emissions from biodiesel were assumed *not* to be offset and were added to the final GHG emission totals. However, for these case studies, it was decided that the CO_2 portion of the GHG emissions from biodiesel combustion can be assumed to be offset by the growth of the soybeans and rape seeds that the Ecoinvent inventory assumes forms the majority of the oil inputs. Accordingly, the relevant combustion input parameters were changed to reflect this updated approach.

step is to connect each structural processor with the specific source(s) of data coming from the Euro-Calliope model. Again, the model output files contain a wide variety of information about the flows of individual carriers in and out of different technological processes; information about installed "nameplate capacity" and consumption in different sectors is also included. A complete listing of the sources used to define the total energy and, where applicable, installed capacity values at each structural processor are listed in **Table J.29** in the appendices.

Direct alignments between Euro-Calliope and ENBIOS structural processors can generally be made. However, a few exceptions are noted. The first of these involves the direct use of fuels and the fact that production and combustion inputs can differ in places where synthetic versions of combustible gases and liquids are also produced from biomass and via hydrogen from electrolysis in power-to-X (P2X) processes. In such cases, all biodiesels are included within the same LCI process for biodiesel production, regardless of the type of fuel produced. Again, the production of P2X fuels is assumed to be accounted for in the electricity used to make it and is, therefore, not included in the fuel production branch of the dendrogram structure. In any case, combustion calculations are undertaken based on the type of fuel, regardless of the production process used to obtain it.

Another notable exception involves the alignments for natural gas, identified as "methane" in Euro-Calliope to account for both the fossil and synthetic versions of the gas. In this case, the issue is that methane is the only carrier in Euro-Calliope available as a fossil fuel *and* created via auxiliary methods–i.e., biofuel and P2X processes–that is used as a fuel *and* as a feedstock to electricity and heat generation. This introduces a degree of uncertainty in that the information in Euro-Calliope files does not always make a clear distinction between the three sources of methane once it has been created and is being used within the system.

Accordingly, a number of assumptions and workarounds need to be made to match the Euro-Calliope outputs for methane to the system architecture defined in the ENBIOS workflow. Firstly, although the life cycle aspects of creating electricity and heat from synthetic methane in the future will be slightly different than the current, fossil-based method, the calculations here continue to use the available LCI information of these two processes. While not a perfect solution, the contributions of the infrastructure, combustion emissions and general production processes will remain the same regardless of the feedstock used. Secondly, no specific data outputs are available from Euro-Calliope for the direct use of fossil natural gas as a fuel outside of the electricity and heating sectors. Nonetheless, the total amount of methane–from all sources–used for this purpose is obtainable. Therefore, to calculate the fossil-based portion, the total direct use amount–i.e., all methane used in industry and gas hobs–is simply multiplied by the fraction of the fossil supply ("methane_supply") to the total that also includes biofuel and P2X portions ("methane_supply" + "biofuel_to_methane" + "hydrogen_to_methane"). Lastly, to calculate the total amount of methane of all forms combusted in direct uses, all inputs of methane to the electricity and heating sectors ("ccgt" + "chp_methane_extraction" + "methane_boiler") are subtracted from the total amount of methane calculated in the previous operation.

The second step in finalising the system definition is to assign individual life cycle inventory (LCI) processes–from v3.8 of the Ecoinvent LCA database (Wernet et al 2016, Ecoinvent 2021)–to each of the structural processors in **Figure H.1**. Where possible, regional processes for Europe are chosen. However, in several instances only individual countries in Europe or generalised global processes are available. In these cases, countries that tend to have higher shares in the observed Euro-Calliope totals *or* those whose characteristics were similar to most other European countries were selected; this avoided the use of unrepresentative or "outlier" processes. Where no European alternatives were available, global or "rest of world" (RoW) processes are used. A summary of the processes assigned to each processor in the defined system is given in **Table J.30** in the appendices. For fuels, the assumed calorific values (CVs)–used to convert energy amounts to the per-mass values given in LCA datasets–are also listed. Likewise, the emission factors (EFs) used to calculate GHG emissions at the combustion processors, taken from the Intergovernmental Panel on Climate Change (IPCC) database (IPCC 2021) are provided for all fuels. Again, for biomass and biodiesel these EFs do not include CO_2 emissions but do include emissions of all other GHGs.

Table H.1. Listing of methodologies used in deriving final indicators. A full listing is contained in **Table J.30** in the appendices

Group	Indicator	Method	Units
Total energy	Energy generation	Summing heat output values	TWh
LCIA	GHG emissions	climate change, GWP100	Tg CO_2-eq
	Land occupation	agricultural land occupation, ALOP + urban land occupation, ULOP	x10^3 km^2
	Water depletion	water depletion, WDP	TL
	Human toxicity	human toxicity, HTPinf	Tg 1-4-DC
Socio-metabolic	Human activity	Multiplying capacity and energy values by published constants	h
Raw materials	Material supply risk	As per section **E**	yr
	Env impacts relating to material supply	As per section **E**	yr
	Env justice issues relating to material supply	As per section **E**	yr
Intensive	Energy metabolic rate (EMR)	Dividing energy generation by human activity	MWh/h
	GHG metabolic rate (GHGMR)	Dividing GHG emissions by human activity	kg CO_2-eq/h
	GHG-to-energy	Dividing GHG emissions by energy generation	kg CO_2-eq/MWh

Final indicator values are then able to be calculated using the standard approach described in section **F**. Scaling of LCI processes is performed using the final amounts of energy that relate to each processor. The majority of the remaining indicators use life cycle impact assessment (LCIA) methods to generate a range of environmental impact and resource use indicators. Here, these methods are again taken from v3.8 of the Ecoinvent LCA database; all selections are part of the "ReCiPe Midpoint (H)" group. Values for human activity are calculated using hours per unit of capacity values for electricity and heat generation infrastructure and hours per unit of energy values for fuel production (Rutovitz et al 2015). Three additional raw material indicators are also derived using the material requirement values from LCI listings in conjunction with the methodologies defined in section **E**. A summary of the methods adopted for calculating the final indicators is provided in **Table H.1**. Lastly, three intensive indicators are calculated–in the second of the two analyses–using combinations of the energy generation, GHG emissions and human activity indicators.

H.2.2 Historical data

With the system dendrogram in place and other system data sources defined, historical data could be obtained in relation to each of the structural processors at the "n-5" level of the system hierarchy. To do this, two types of data are required: (1) Total annual energy–typically in joules (J) or watt-hours (Wh)–for a given technology and year, used to "scale" the per-energy-unit information obtained from LCA datasets and to calculate labour requirements for fuel production, and (2) Total installed capacity–typically in watts (W)–for a given technology and year, used to calculate labour requirements for electricity and heat generation.

Comprehensive listings of historical energy statistics for 34 European countries are available from the Eurostat database maintained by the European Commission (EC) (Eurostat 2022). A detailed summary of the sources used to define the annual energy totals–and, where applicable, power capacity–at each structural processor are given in **Table J.31** and **Table J.32** of the appendices. Further data was also required for Switzerland–not included in the Eurostat datasets–and obtained via the Bundesamt für Energie (BFE) (BFE 2021, 2022a, 2022b, 2022c). Summaries for these sources are also listed in **Table J.33** and **Table J.34** of the appendices.

Collectively, this data could then be used to define the energy and power capacities of the European energy system as a whole for the years 2000, 2005, 2010, 2015, 2018 and 2019. It should be noted that values for 2020 were also obtained during this process. However, they are not used in the analysis as they differ significantly from those observed in preceding years as a result of the COVID-19 pandemic. Overall energy use in the system analysed dropped by 16.0% between 2019 and 2020. While district heating deliveries only reduced by 4.7% in this period, overall electricity use fell by 12.2% and fuels by 18.2%. The most significant reduction in this period was the 60.2% fall in kerosene use, the dominant fuel in the aviation industry. As such, although it represents the most recent available information, the dataset from 2020 provides a misleading indication of the historical progress of energy use and was deemed inappropriate for representing the "current" energy landscape. Final, calculated energy totals for all other years are listed in **Table J.35** of the appendices; capacity totals for electricity and heat generation are listed in **Table J.36**.

The historical data suggests that, while overall energy generation fluctuates over the years, electricity from wind and solar PV continues to rise as does the use of biomass, bioenergy and waste. Hydro and nuclear power remain steady or drop slightly. Elsewhere, coal use almost halves between 2000 and 2019, particularly since 2015. The use of natural gas has fluctuated greatly but remained steady overall, rising in recent years for electricity generation while falling in direct use. Again, as kerosene is chiefly used in air travel it has remained steady. Conversely, as ground transportation continues to become more and more electrified, the use of diesel appears to be dropping. The final distribution of technologies within the 2019 European energy system is illustrated in **Figure H.2** and acts as a snapshot of the current system for later comparison with projected system configurations.

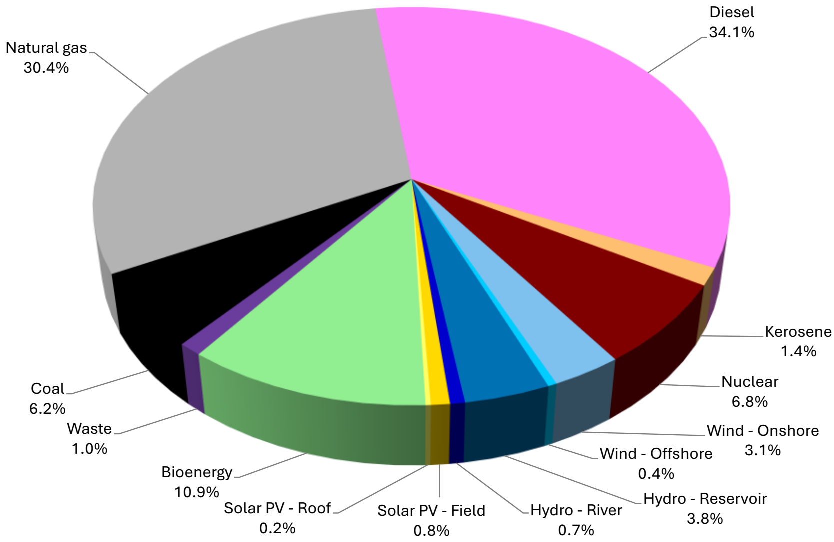


Figure H.2. Current percentage distribution of energy generation in European energy system, by technology category (2019). Data sources: BFE (2021, 2022a, 2022b), Eurostat (2022)

Meanwhile, electricity and heat generation capacity has risen dramatically in the last two decades. As expected, much of this is connected to wind and solar PV infrastructure, whose capacity rose by 33 and 673 times, respectively, between 2000 and 2019. The capacities of biomass and waste incineration plants have also grown in this time, both more or less tripling in capacity. Likewise, the implementation of natural gas infrastructure almost doubled between 2000 and 2019, although it has dropped slightly since 2015 as it loses favour as a source of district heat. Lastly, hydropower, nuclear and coal plant capacities have all remained relatively stable over this period despite their declining contributions to electricity and heat totals.

H.3 Storyline scenarios

H.3.1 System definition inputs

Having defined the system and established "baseline" images for historical configurations of the system, comparisons with possible future configurations can be made. The first such investigation involves the analysis of three projected scenarios defined by another application newly developed during the SENTINEL project, the Quantification of Technological DIffusion and sociAl constraiNts (QTDIAN) toolbox. QTDIAN is an application that can be used to generate qualitative and quantitative descriptions of the socio-technical and political aspects that influence energy transition processes, with a particular focus on the emergence of renewable energy technologies for electricity production (Süsser et al 2021e). These descriptions can then be used as input specifications or constraints within other models.

Within the development of the QTDIAN toolbox in the SENTINEL project, three distinct "storylines" were defined to represent "government directed" (GD), "market driven" (MD) and "people powered" (PP) transition pathways. Each of these storylines represents a unique narrative pathway that links the current system ("where we are") with different targets ("where we want to go"). All three storylines are rooted in the objective of achieving climate neutrality in the European Union (EU) by 2050 (European Commission 2019) and assume that public awareness and interest in the mitigation of climate change. However, each storyline is also based on an individual set of approaches or determinants that influence the technological and institutional changes that occur within each transition scenario. A summary of the three storylines and a selection of their key characteristics is provided in **Table H.2**.

The individual characteristics relating to each of these storylines then needed to be translated into a series of quantitative constraints that could be embedded into three subsequent runs of the Euro-Calliope model (Pickering 2022a). Naturally, the characteristics defined by QTDIAN storylines can only be implemented into Euro-Calliope in places where model input parameters align with factors or concepts reported in the QTDIAN findings. In this case, 10 sources of constraint were identified that could be altered to reflect the conceptual characteristics of each storyline using model parameters (Süsser et al 2021d), as listed in **Table H.3**. Full descriptions of the 10 constraint types, with detailed descriptions and mathematical formulae, are also listed in **Table J.37** of the appendices.

Table H.2. Summary of QTDIAN storyline concepts. Source: Süsser et al (2021e)

	Government directed (GD)	Market driven (MD)	People powered (PP)
Summary	Government directs transition, mainly at national level. Public support generally high but some local opposition occurs. Society less involved in transition. A governmental "energy efficiency first" philosophy decreases energy consumption	Market actors and new technologies drive transition, driven by cost-effectiveness concerns. Continental scope. Society does not play a large role. High local opposition to large-scale projects. System characterised by centralised generation and transmission	People drive transition, seeking individual and collective (co-)ownership of renewables. Transition occurs mainly at regional level. System characterised by decentralised generation and minimal grid expansion. A "renewable energy first" philosophy
Problem definition (today)	Emissions too high because we use wrong technologies and adopt wrong practices	Transition could be too expensive if governments interfere with market	System characterised by fossil-nuclear complex, centralised structures and undemocratic supply
Solution (future)	Reduce emissions by adopting low carbon technologies while maintaining energy security and controlling direction of transition	Governments price externalities and set long-term climate targets but leave it to market to find efficient solution	Break up existing centralised system and rebuild system to benefit citizens, cooperatives and municipalities
Decision "logic"	Security & control	Cost-effectiveness	Local needs and capacities
Geographical focus	National	European	Regional
Philosophy	"Energy efficiency first"	Transition left to market actors and technological breakthroughs	"Renewable energy first"
Ownership of renewables	Many private and public utilities	Strong corporate ownership	Citizen and community ownership
Centralisation	Mostly centralised, larger units	Centralised, larger units	Decentralised, small units
Opposition to projects	High public support, with local opposition	High local opposition	Policies support citizens

Table H.3 also describes the quantitative values of each of these constraints subsequently used to define the three storylines in Euro-Calliope. As expected, the PP scenario is generally seen to be the most aggressive storyline in terms of renewable energy use, electrification of transport and fossil fuel phase-out. However, it is shown to be less motivated to reduce energy intensity or foster better grid and storage infrastructure at the wider level and is less stringent with onshore wind turbine placement. Conversely, the GD and MD storylines tend to prioritise changes in infrastructure at broader scales and higher changes in overall energy intensity while being more permissive with cross border transfers. The MD storyline is certainly the less focussed of the three, generally adopting less ambitious targets but favouring high transfer rates and preferring a more laissez faire, market-based approach overall.

Using these input parameters, Euro-Calliope optimisation runs were undertaken for each storyline, returning projected energy system configurations for 2030 and 2050. A complete listing of the final energy generation and capacity data supplied from Euro-Calliope–in relation to each structural processor and for each storyline and year–is provided in **Table J.38** and **Table J.39** of the appendices.

Table H.3. Summary of model constraints and data applied in individual Euro-Calliope runs for QTDIAN storylines. Source: Süsser et al (2021d)

No.		Government directed (GD)	Market driven (MD)	People powered (PP)
(1)	Limit of CO_2 emissions to 1990 levels	>55% reduction by 2030 Climate neutrality by 2050	>55% reduction by 2030 Climate neutrality by 2050	65% reduction by 2030 Net-zero by 2040
(2)	Minimum renewable technologies in electricity generation	40% by 2030 100% efficiency by 2050	40% by 2030 Increase further by 2050 (nuclear energy possible)	>50% by 2030 100% by 2040
(3)	Reduction in energy intensity	36-39% decrease (compared to projection) by 2030 Increase further by 2050	36-39% decrease (compared to projection) by 2030 Increase further by 2050	25% decrease (compared to projection) by 2030
(4)	Details of fossil fuel phase-out	Coal by 2038 Fossil gas and oil by 2050	No fixed dates, but coal capacity must decrease by 2030	Coal by 2030 Fossil gas by 2035 Fossil oil by 2040
(5)	Limit of cross-border transfer capacity	<15% of hourly exchange by 2030	≥15% of hourly exchange by 2030	<5% of hourly exchange by 2030
(6)	Level of car use reduction	Electric vehicles 25% electric vehicles by 2030 Phase-out fuel-based cars by 2050	Phase-out fuel-based cars by 2035	All private cars electrified by 2040, up to half by 2030 10% increase in passengers/vehicle by 2040
		Transport mode <20% reduction in car use by 2040 25% increase of rail freight between 2015 and 2040 6% shift in car km to bus, train, walk and bicycle	Modes remain the same 0% reduction in car use	>20% reduction in car use by 2040 Doubling of rail freight between 2015 and 2040 12% shift in car km to bus, train, walk and bicycle
(7)	Preferred electricity mix	"Best" balanced mix of technologies	Minimise land use/demand	Maximise roof top solar PV (lower bound of 45% of electricity) Double share for wind
(8)	Level of grid development	As much as needed	Prioritised, European focus	Minimised (no new projects to start)
(9)	Minimum battery storage capacity	26 projects (with 29,000 GWh capacity)	39 projects (with 45,500 GWh capacity)	13 projects (with 14,500 GWh capacity)
(10)	Limit of land developed for onshore wind power	Onshore plants to housing 700m for large turbines 200m for small turbines	1000m	500m for large turbines 200m for small turbines
		Onshore density in municipalities 8% of municipal land area	4% of municipal land area	No restrictions

Historical observations and modelled projections are also shown for all three storylines in terms of energy carrier group ("n-1") and renewable status ("n-3") in **Figure H.3**. The results reveal a clear move away from fuel use towards electrification at the "n-1" level. Heating is predicted to rise substantially by 2030 in the GD and MD storylines, but eventually returns to current levels in both cases. At the "n-3" level, the use of renewable energy increases considerably in al storylines, replacing non-renewables which are more or less phased out by 2050. The use of bioenergy and waste technologies grows slightly in this period, but any changes are minor compared to those observed for renewable energy.

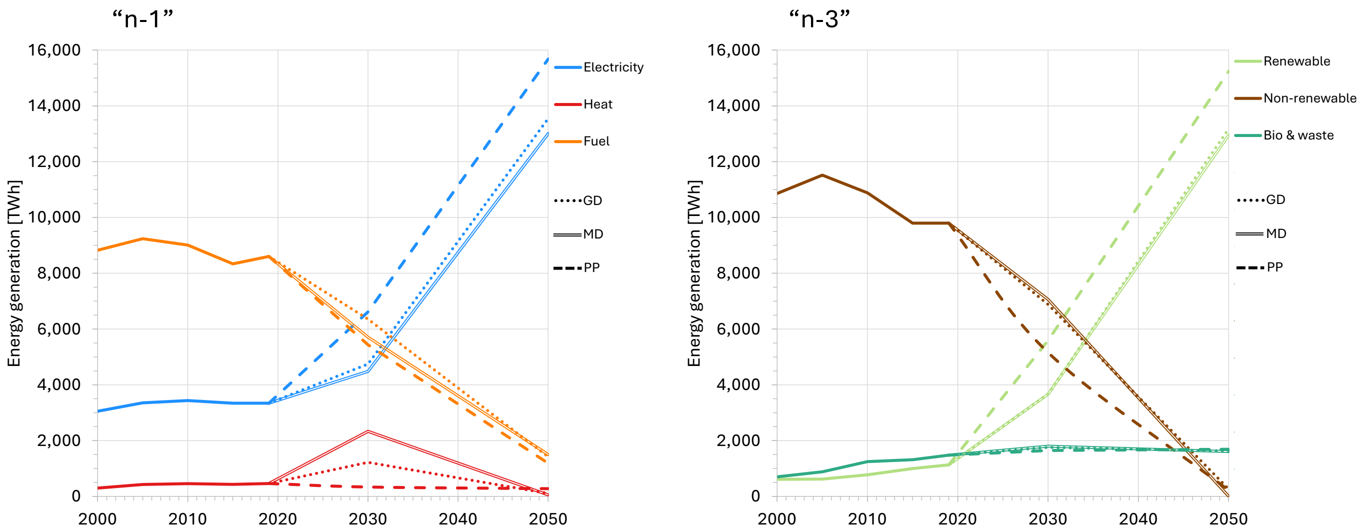


Figure H.3 . Historical and projected "storyline" energy generation totals in European energy system according to the energy carrier group ("n-1") and renewable status ("n-3") levels of the system hierarchy defined in **Figure H.1**. Data sources: BFE (2021, 2022a, 2022b), Eurostat (2022), Pickering (2022a)

The percentage distributions of total energy generation in 2050 are illustrated for each storyline in **Figure H.4** Comparing these findings to the present-day distributions shown in **Figure H.2** clearly demonstrates a dramatic shift away from natural gas, nuclear and diesel sources, all of which are virtually eliminated in the projections for 2050. While hydropower and bioenergy levels have remained fairly constant, levels of wind and solar PV have increased significantly to become the dominant forms of energy in all three storylines. Interestingly, although the combined share of wind and solar PV is between 84% and 86% in all three scenarios, the share of wind energy is notably higher for the MD storyline. The MD also presents a less diverse energy mix in 2050, having no contributions at all from natural gas, nuclear or rooftop solar PV. Conversely, the GD scenario is the most diverse, with trace levels of natural gas and nuclear energy remaining and a considerably higher share of offshore wind than other storylines. Lastly, the PP scenario is the only one to reflect any serious expansion in rooftop solar PV use, suggesting that field-based solar PV farms offer far more desirable outcomes if no restrictions are in place. Note that all projected scenarios assume that no limitations are placed on new infrastructure, hence it is assumed that the large increases in generation from wind and solar are technically feasible in all of these examples.

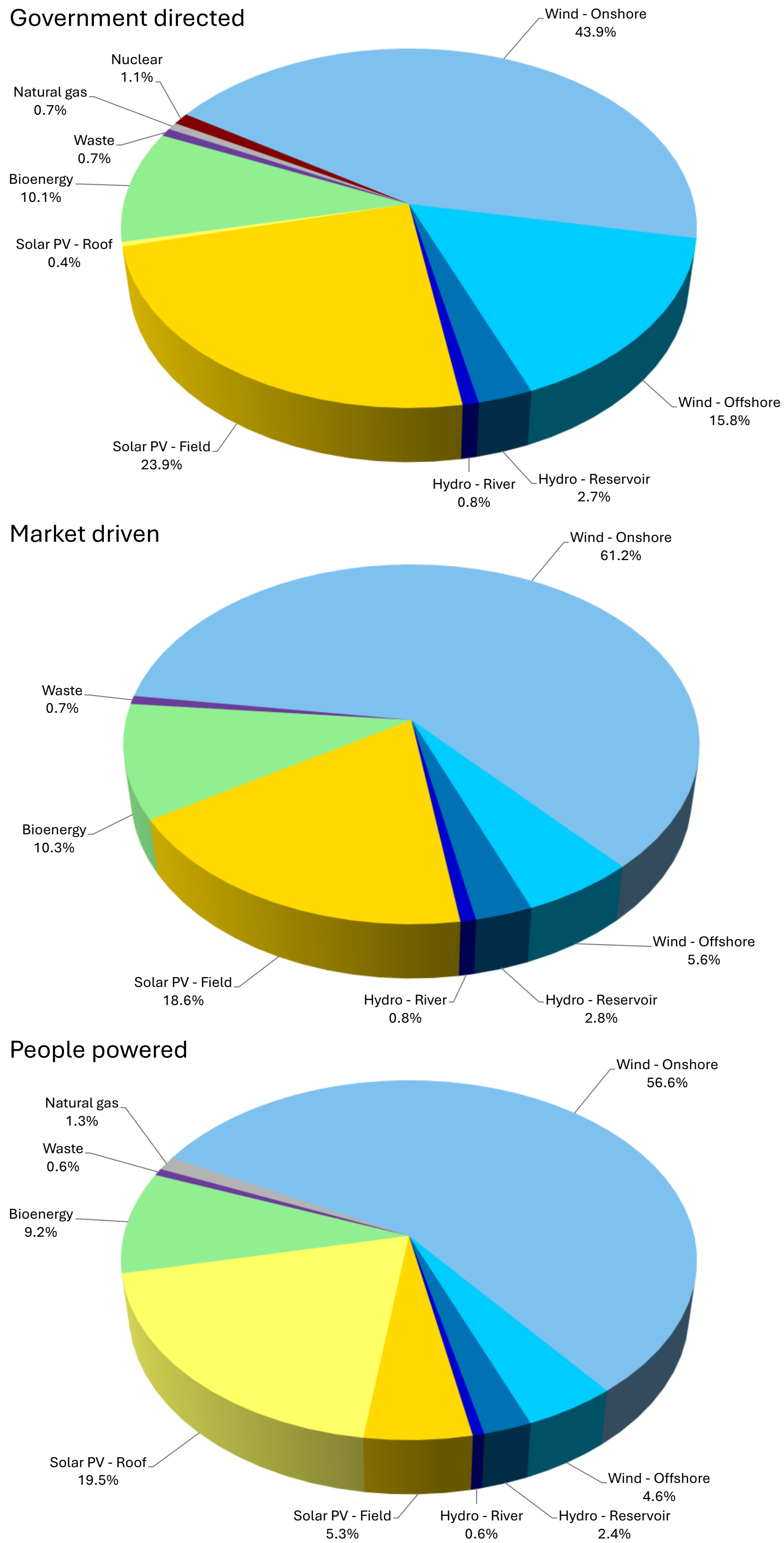


Figure H.4. Projected percentage distributions of energy generation in European energy system, by technology category, for three storyline scenarios (2050). Data source: Pickering (2022a)

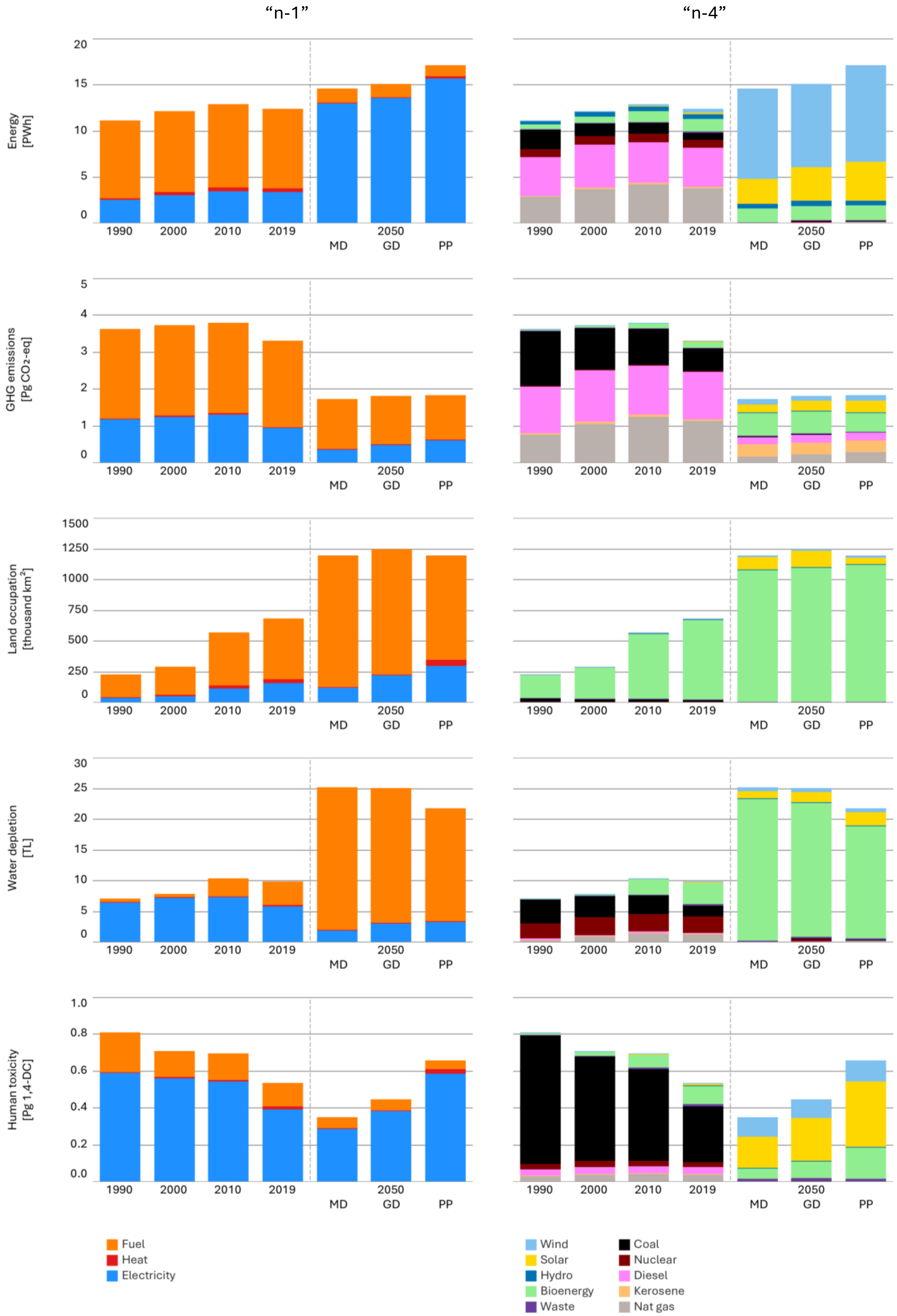
H.3.2 Results of analysis

Historical values for 1990, 2000, 2010 and 2019 and projected values for all storyline scenarios in 2050 are shown for nine extensive indicators in **Figure H.5**; breakdowns are illustrated for all indicators at both the energy carrier group ("n-1") and technology group ("n-4") levels. Full listings of the values and percentage shares for all of the data shown are provided in **Table J.40** of the appendices. The changes, for each storyline and indicator, are also summarised in **Table H.4**, alongside a simple assessment of the key determinants contributing to each result. Though not discussed here, results for a series of intensive indicators are provided for the entire energy system ("n"), energy carrier group ("n-1") and technology group ("n-4") levels in **Figure J.8** and **Figure J.9** in the appendices.

The findings reveal that increases are observed for most indicators and projected storylines. The clear exception is with GHG emissions which, as expected, reduce significantly for all storylines. Meanwhile, human toxicity and environmental impacts from material supply remain relatively steady, and both increases and decreases are observed between the different storylines. Brief summaries are provided for each of the nine indicators in the following sections.

Table H.4. Summary of predicted percentage changes for nine indicators between 2019 and 2050 for the three projected storylines. Potentially adverse results are displayed in shaded cells. A summary of the key determinants of the predicted changes is also provided

Group	Indicator	Predicted changes (2019-2050)			Key determinants
		GD	MD	PP	
		[%]	*[%]*	*[%]*	
Total energy	Energy generation	+21.5	+17.4	+38.2	Electrification of system Storage & hydrolysis losses
LCIA	GHG emissions	-45.1	-47.8	-44.3	Phasing out of coal, natural gas & diesel
	Land occupation	+82.4	+75.2	+75.2	Bioenergy, particularly biodiesel
	Water depletion	+155.1	+156.6	+121.8	Bioenergy, particularly biodiesel
	Human toxicity	-16.6	-34.2	+22.9	Electricity from solar PV & biomass
Socio-metabolic	Human activity	+623.6	+416.0	+854.5	Electricity from solar PV Ongoing capacity increases
Raw materials	Material supply risk	+340.8	+320.9	+370.0	Electricity from wind & solar PV Direct use of biodiesel
	Env impacts relating to material supply	-0.2	-13.0	+23.7	Phasing out of diesel Replacing with electricity from solar PV
	Env justice issues relating to material supply	+390.3	+354.0	+429.4	Electricity from wind & solar PV Direct use of biodiesel



"n-1"
"n-4"
Energy [PWh]
GHG emissions [Pg CO2-eq]
Land occupation [thousand km²]
Water depletion [TL]
Human toxicity [Pg 1,4-DC]
1990
2000
2010
2019
2050
MD
GD
PP
Fuel
Heat
Electricity
Wind
Solar
Hydro
Bioenergy
Waste
Coal
Nuclear
Diesel
Kerosene
Nat gas

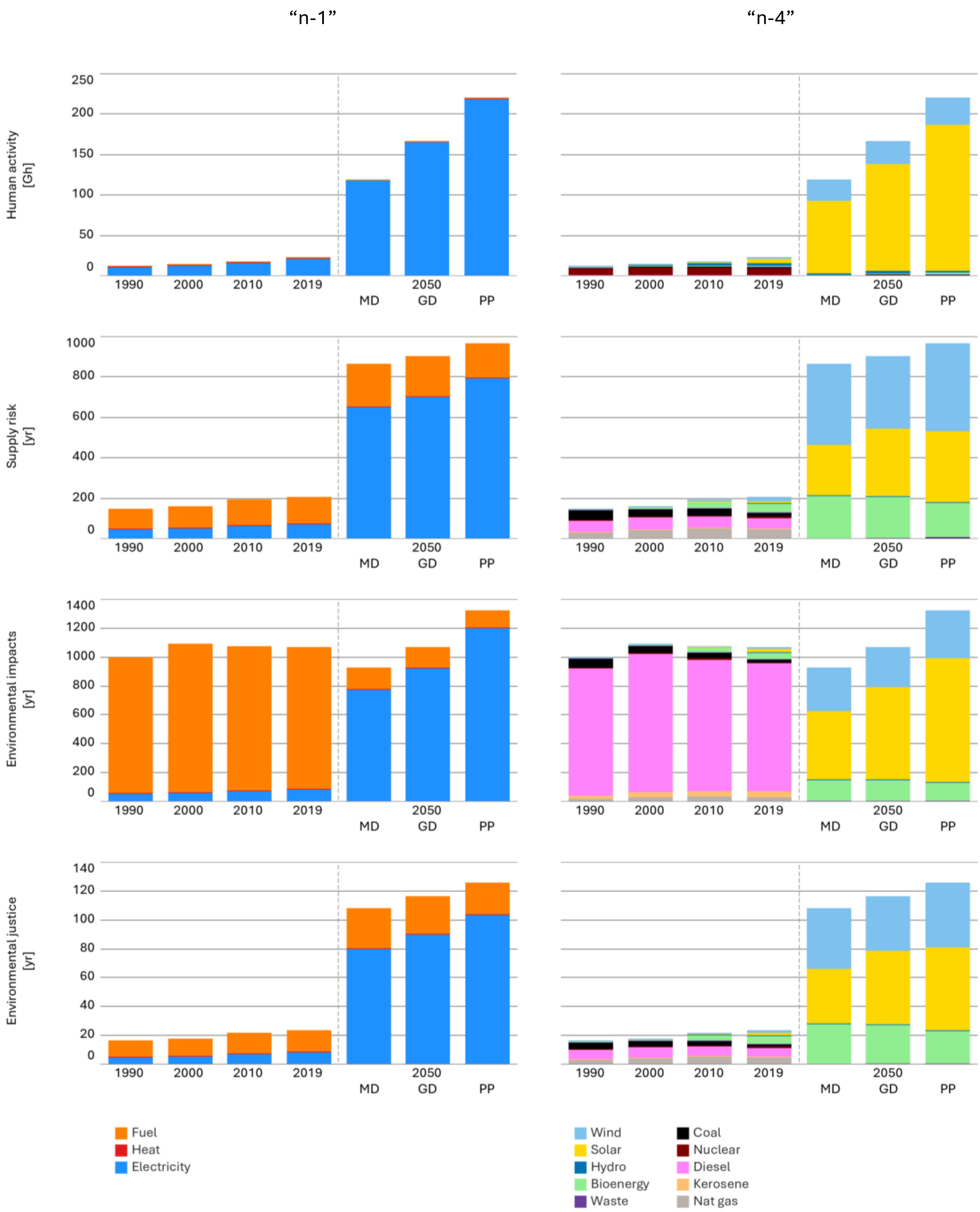


Figure H.5. Results for extensive indicators at the energy carrier group ("n-1") and technology group ("n-4") levels. Analyses are reported for three historical configurations–2000, 2010 and 2019–alongside projected storylines configurations that reflect market driven (MD), government directed (GD) and people powered (PP) scenarios. Note that, unlike elsewhere in the chapter, MD is shown ahead of GD as it returns lower values in most indicators

H.3.2.1 Energy generation

Levels of overall energy generation rise for all storylines; MD by 17.4%, GD by 21.5% and PP by 38.2%. While levels of final energy *consumption* are likely to remain relatively stable between time periods, the observed rises in overall generation in the storyline cases are thought to be the result of two main factors. Firstly, small differences in the system definitions and boundaries between the historical datasets and the Euro-Calliope model are likely to result in some slight differences in final values. The second and most significant aspect relates to the fact that much of the electricity generated in the storyline scenarios is stored in batteries or converted to hydrogen–via electrolysis–for storage purposes of for the later conversion to fuels. As the conversion and reconversion stages within these processes can introduce considerable losses in electricity, additional amounts of electricity are generated within the three future scenarios. Accordingly, the total amounts of energy *generation* will be higher in the future scenarios.

Analysing the changes at the "n-1" level confirms the additional contributions of electricity in the system by 2050; electricity represents around 90% of the total generation in each of the three storylines. As previously demonstrated in **Figure H.2** and **Figure H.4**, wind and solar technologies are expected to replace previously dominant technologies such as coal, nuclear, natural gas and diesel in all scenarios at the "n-4" level.

H.3.2.2 GHG emissions

The three storyline scenarios are rooted in maximising the use of renewable energy technologies at the "n-4" level. Consequently, GHG emission levels are shown to reduce significantly in all scenarios, as expected; reductions of between 44.3% and 47.8% are observed, the highest reduction being predicted within the MD scenario. Results at the "n-1" level suggest that these results are spread fairly evenly between the three carrier types. However, at the "n-4" level it can be seen that the reductions are strongly linked to the emissions of three fossil fuels, namely coal, natural gas and diesel. Nevertheless, although overall emissions reduce substantially by 2050 in these scenarios, the increased use of wind, solar, bioenergy–particularly biodiesel–and the derivation of synthetic forms of diesel, kerosene and natural gas via P2X processes, are shown to introduce GHG emissions of their own, albeit at much lower levels.

Clearly the fact that residual GHG emissions are still existent in all three projected systems means that none of the storyline scenarios are seen to come close to achieving the EU's Paris Agreement target of climate neutrality–i.e., zero net emissions–by 2050 (European Commission 2020e). This is somewhat misleading, though, as many of these emissions are related to the fact that the "background" energy supplies that occur within each of the life cycle processes in the system do not change over time. So, for example, the process of building a wind turbine in 2050 is assumed in the ENBIOS calculations to be using a present-day electricity mix which still contains fossil fuels. That is, the background energy mix in the system does not change as the foreground energy mix does, meaning that GHG emissions are still produced. Other smaller sources of emissions are also likely to persist, meaning that genuine climate neutrality is not likely to be achieved in the strictest sense regardless of this issue. However, the ability to change background systems in future systems is the key contributor to the residual GHG emissions observed in these results. As an acknowledged issue within the field, it is discussed in further detail in several sub-sections within section I.

H.3.2.3 Land occupation

The overall areas of land required to maintain the three storyline energy systems in 2050 are all projected to increase: by 82.4% for the GD storyline and 75.2% for both the MD and PP storylines. In all cases, fuel production is shown to be a significant factor at the "n-1" level. Because much of the additional land requirement is also shown to be linked to bioenergy technologies at the "n-4" level, biodiesel is revealed to be a key contributor to the overall increases observed. Indeed, the production of biodiesel rises to between five and six *times* the 2019 levels by 2050, to represent between 6.9% and 10.3% of the energy generation in the system for the storyline scenarios. Meanwhile, other uses of bioenergy are seen to only rise slightly or, in the case of biomass as a fuel, cut out entirely. Further analysis of the LCA data for land occupation reveals that values for all four sources of bioenergy are considerably higher than all other processes in the system, confirming bioenergy technologies as the key factor in calculations for this indicator.

H.3.2.4 Water depletion

Bioenergy technologies are also strongly linked to the projected increases in water depletion, which rise by 121.8% for the PP storyline and 155.1% and 156.6% for the GD and MD storylines, respectively. But, while values of land occupation are almost entirely dominated by bioenergy for historical and projected scenarios, water depletion can also be strongly influenced by the water requirements of traditional thermal electricity generation plants; coal and nuclear technologies were both significant contributors in historical configurations. As these technologies are largely removed from the storyline systems for 2050, the high projected increases are clearly seen to be linked to bioenergy technologies at the "n-4" level. Deeper analysis of the LCA data again uncovers the strong influence of biodiesel production: although thermal electricity generation is far higher than most technologies, the water requirements for biodiesel production are between four and five *times* higher than these. This, once again, confirms biodiesel production as a key contributor to this indicator and the lower dependence on biodiesel in the PP storyline configuration is directly related to its uncharacteristically low score for this indicator.

H.3.2.5 Human toxicity

Historical levels of human toxicity are seen to have been reducing steadily between 2000 and 2019, with a clear link to electricity production at the "n-1" level and coal at the "n-4" level. However, projected values of human toxicity across the three storyline scenarios are observed to vary significantly compared to most other indicators; overall levels reduce by 34.2% and 16.6% for the MD and GD scenarios, respectively, and increase by 22.9% for the PP scenario. Examining the results at the “n-1” level finds that the contributions of heat and fuel processes are similar across the three storylines, as are the contributions of wind, waste and other technologies at the “n-4” level. Accordingly, electricity from either solar or bioenergy sources are presented as the obvious influences on this indicator. Indeed, the three potential technologies–rooftop and field-based solar PV and biomass–all vary significantly between the three storylines, and all present high per-unit toxicity values in the LCA data, electricity from biomass combined heat and power (CHP) plants being by far the highest.

H.3.2.6 Human activity

The highest relative increases between 2019 and 2050 values are seen in the total hours of human activity (HA) indicator. In this case, the annual number of required hours to reproduce and maintain the system is 5.2 times higher in 2050 for the MD storyline configuration, 7.2 times higher for GD and 9.5 times higher for the PP scenario. These increases are largely related to the fact that Euro-Calliope does not tend to assume the widespread decommissioning of infrastructure as the use of different technologies changes over time; total installed capacities in 2050 for electricity and heat generation are 5.9, 4.6 and 7.8 *times* their values in 2019 for the GD, MD and PP scenarios, respectively. This is roughly in line with historical capacity data (BFE 2021, 2022b, 2022c, EC Joint Research Centre 2019, Eurostat 2022) which demonstrates that overall installed capacities in the European energy system more than doubled–rising by 126%–between 1990 and 2019. As labour is based on installed capacity, it is no surprise that more labour is assumed to be required to keep this infrastructure in service and the ENBIOS calculations assume that full staff numbers will be maintained at all locations, even if older plants do not maintain high levels of actual generation in reality.

Most of the increases in capacity–and resulting increases in labour requirements–are linked to electricity generation at the “n-1” level and wind and solar PV at the “n-4” level. Analysis of the data used to calculate labour requirements finds that wind requires between 1.2 and 4.9 times the hours of labour required to maintain similar capacities in the coal and natural gas power plants they are replacing. Meanwhile, solar PV requires between 5.9 and 16.3 times the values for coal and natural gas. Likewise, the production of one unit of diesel fuel–also being widely replaced by electricity in all storyline scenarios–is known to have very low human activity requirements compared to most other energy sources (Rutovitz et al 2015). Nevertheless, observing that solar PV produces more notable differences than wind at the “n-4” level, it appears that the differences in solar PV use between the three storylines have the greatest influence with this indicator. It is also notable that nuclear power requires the highest levels of labour per watt of capacity of all technologies–requiring over 1.7 times those of solar PV–although its use is only predicted to rise very slightly in the MD scenario, drop significantly in the GD scenario and fall to zero in the PP scenario. As a consequence, nuclear power is not seen as a major contributor to the observed changes here.

Comparing these projections with current employment data for the system represented in the Euro-Calliope model (International Labour Organization 2022) reveals that around 48, 72 and 98 *million* new jobs would need to be created by 2050 for the MD, GD and PP scenarios, respectively. Of course, not all of these jobs would necessarily be located within Europe, staff could be retrained from other sectors and the per-unit values for each technology could well reduce as a result of "learning" (Rubin et al 2015, Yao et al 2021) and automation processes in the future. However, if one considers that only around 246 million jobs existed within the system area in all sectors in 2019–plus 17 million unemployed–the projected increases are certainly significant.

H.3.2.7 Material supply risk

Levels of material supply risk (SR) also rise dramatically for all three storylines, increasing by 320.9%, 340.8% and 370.0% for the MD, GD and PP storylines, respectively. Nevertheless, less differences are observed *between* the three storylines for this indicator. Here, once again, wind and solar PV are seen to be the dominant technologies at the "n-4" level, alongside bioenergy, all of which are greatly expanded in the three storyline scenarios. Inspection of the individual SR values for each technology reveals that the two solar PV processes have per-unit scores more than double all other electricity and heat processes, while the two wind turbine processes represent the next two highest levels of SR. Meanwhile, the SR value for biodiesel production is the highest score of all processes considered. As such, the differences in the mixes of wind, solar PV and biodiesel in the storylines are seen as the key determinants in the large changes observed in this indicator category.

H.3.2.8 Environmental impacts relating to material supply

As with many other indicators, the scores relating to local environmental impacts from material supply (EI) are highest for the PP storyline and lowest for the MD storyline. Yet, for this indicator, historical levels are also found to be high, largely the result of diesel production. Examination of the input data for each technology reveals that electricity from solar PV and the production of diesel and kerosene possess per-unit values that are many times higher than most other technologies. As the historical configurations are essentially "swapping" the high values for diesel in 2019 with the high values for solar PV–and, to a lesser extent, for wind and biodiesel–in 2050, the overall changes in EI values between 2019 and 2050 are not nearly as severe as those observed in most other categories. In fact, although higher levels of rooftop solar result in a higher rise of 23.7% in the PP storyline, reductions of 0.2% and 13.0% are seen in the GD and MD storylines, respectively.

H.3.2.9 Environmental justice issues relating to material supply

Lastly, the findings relating to local environmental justice relating to material supply (EJ) are very similar to those observed for SR, where changes in electricity from solar PV and wind and the production of biodiesel are the key contributors to large rises in scores for all three storylines. In this example, the change for PP was again the highest at around 429.4%, while those for GD (390.3%)

and MD (354.0%) are also high. As with SR, the changes can be traced to high per-unit EI values for each of the three key technologies in conjunction with high increases in implementation between 2019 and 2050. Indeed, the per-unit values for solar PV and biodiesel are again the highest in this indicator category, being between 3.1 and 4.7 *times* higher than wind turbines, the next highest technologies.

H.4 SPORES configurations

H.4.1 System definition inputs

A second investigation also used optimised result data from the Euro-Calliope model as input data. However, while modelled data was once again used to define possible future configurations of the European energy system, a vastly different approach was taken in this example. In the previous example, three sets of constraints were placed into three Euro-Calliope optimisation runs to provide projected system configurations for the years 2030 and 2050. In this example, rather than derive results for such unique scenarios, a wide-ranging group of 441 constraint scenarios was tested in order to assess a much wider *range* of unique infrastructure and siting combinations for the European energy system. What's more, while the models used in the previous example generated optimised results for the system as it evolved to 2030 and 2050, the 441 results obtained here are optimised based on a changing set of constraints and a static set of system demands. As such, the resulting system configurations are not linked to any specific year. Rather, they represent a spectrum of potential technically and economically feasible outcomes relating to a set of different system constraint values.

The study that produced these results (Pickering et al 2022) expands upon the growing concept of modelling to generate alternatives (MGA) (DeCarolis 2011), where multiple optimisation model runs are used to uncover a range of near-optimal solutions that represent the "decision space" of available options. Applying the concept to a Calliope model of the Italian electricity system, Lombardi et al (2020) introduced a method for generating what was termed spatially explicit practically optimal results (SPORES). This idea was then expanded to the full European energy system, also modelled in Euro-Calliope, to provide the 441 configurations used as inputs here (Pickering 2022b).

All 441 of the configurations provided in the study are subject to a variety of unique constraints. For example, as with the previous example, different technological or spatial limitations could be placed on different supply aspects relating to electricity, heat and fuels or on transport modes and transmission and storage components within the system. In doing so, the model was forced to seek a range of unique solutions that were still able to satisfy the two fundamental and universal requirements of the optimisation process, namely: (1) energy self-sufficiency (i.e., no imports of external energy sources), and (2) carbon-neutrality[3]. Furthermore, while theoretically an infinite number of solutions would be possible, each of the final 441 solutions were optimised such that configurations with the highest levels of technology and spatial diversity were favoured while remaining within 10% of the optimal economic cost.

Although the technologies supplying energy carriers within the system were allowed to vary within these optimisations, the overall demands assumed within each region–for things such as building heating and cooling, home appliance use and transportation requirements–rely on a static set of data based on 2018 levels. Moreover, Euro-Calliope takes a conservative approach in terms of future technological development by favouring proven technologies that are currently commercially available. For example, while hydrogen from electrolysis is used extensively as an energy carrier within Euro-Calliope runs, its use is assumed to be limited to the generation of power-to-gas and power-to-liquid fuels and as a form of electrical storage; its use in heating and transport applications is assumed to require a complex system overhaul which the model assumes cannot be implemented for now.

As with the previous example, the first step in the analysis requires the 441 SPORES configurations to be aligned with the defined hierarchy shown in **Figure H.1**. It is noted, again, that the optimised systems represented in the SPORES configurations are assumed to have abolished fossil fuels entirely. Accordingly, all fossil fuel use has been replaced by biodiesel production from biomass and the derivation of methane, diesel, kerosene and methanol via power-to-gas and power-to-liquid (P2X) processes based on hydrogen from electrolysis; methane derived in this manner is used as direct replacement for natural gas.

Figure H.6 presents the observed ranges for all electricity, heat and fuel sources within the ENBIOS hierarchy–i.e., for all structural processors at the "n-5" level–considering all 441 of the available SPORES system configurations. The locations of the three storyline scenarios introduced in section **H.3** are also shown in the figure. To accompany the figure, **Table H.5** provides a summary of the minimum and maximum values produced within each category alongside the average (mean) and standard deviation values.

Collectively, analysis of the SPORES data finds that the use of hydropower is expected to remain relatively high in most scenarios but cannot compete with the overwhelming emergence of wind and solar PV, which are found to be dominant in most configurations. Nevertheless, it is notable that rooftop solar PV underperforms considerably compared to its field-based equivalent. The use of biomass is widely expected to represent a viable option, particularly in heating operations, and electricity from nuclear plants remains a reliable option in all configurations. On the other hand, waste incineration is generally not found to be an overly desirable option for either electricity or heat, although it maintains a steady level of use as a source of electricity. Meanwhile, the use of methane

[3] It is noted that "carbon neutrality" is defined here in a much more general sense than the life cycle approach being employed within the ENBIOS workflow and discussed elsewhere in the thesis. In this context, carbon neutrality is understood to mean that all energy is derived from renewable energy, bioenergy and waste and nuclear technologies.

from P2X–as a replacement for natural gas–is only found to be desirable in a small number of cases. Despite this, the direct use of methane as a fuel is generally high, as are all of the other P2X fuels, finding a variety of uses, particularly in transportation and industry. The use of different forms of biodiesel is also found to be high in most scenarios, presumably due to its use as a substitute fuel in the transport sector.

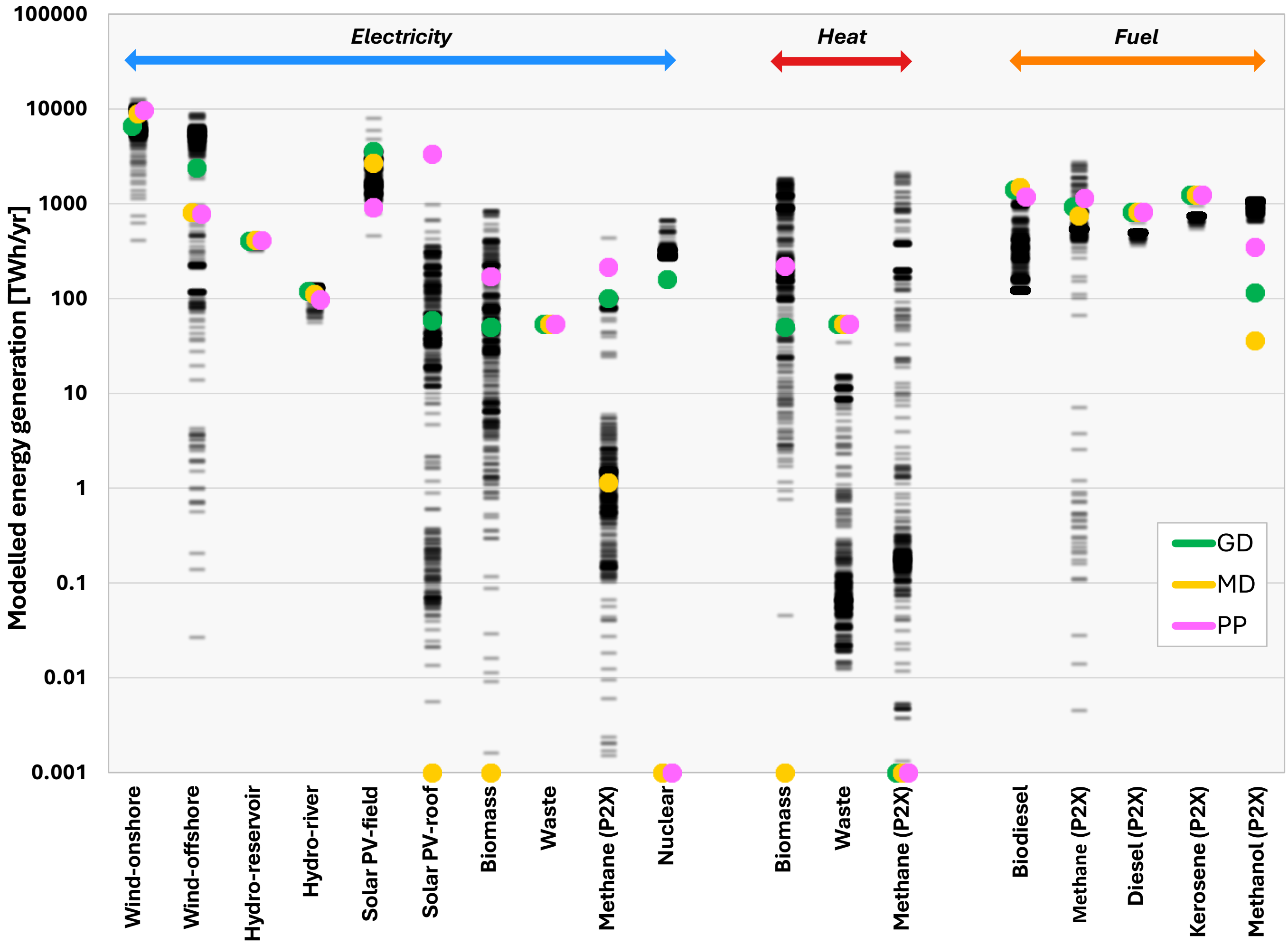


Figure H.6. Range of observed energy generation totals for electricity, heat and fuel sources across all 441 SPORES system configurations, arranged according to structural processor categories. Each black bar represents observations for a single SPORE configuration. Corresponding locations of three storyline scenario configurations are also shown as coloured dots. Data sources: Pickering et al (2022), Pickering (2022b)

It is notable that several technologies–specifically, electricity from hydro, waste and nuclear, and the use of diesel, kerosene and methanol from P2X processes–remain relatively unchanged between the different optimisation scenarios. For electricity this points to the infrastructure constraints or technical disadvantages of the technologies involved. These aspects may also affect the three P2X fuels, although the results for kerosene and methanol are likely also related to their lack of flexibility and restriction to a limited number of applications. The use of all other technologies varies far more between the different SPORES configurations.

Table H.5. Statistical summary of 441 SPORES system configurations, arranged according to structural processor categories. Data sources: Pickering et al (2022), Pickering (2022b)

		Min *[TWh]*	**Max** *[TWh]*	**Std dev** *[TWh]*	**Average** *[TWh]*
Electricity	Wind–onshore	413	12,785	2,238	7,005
	Wind–offshore	0	8,939	2,492	3,751
	Hydro–reservoir	319	413	11	404
	Hydro–river	56	138	13	124
	Solar PV–field	0	7,996	874	2,091
	Solar PV–roof	0	978	110	75
	Biomass	0	842	148	98
	Waste	54	54	0	54
	Methane (P2X)	0	436	39	17
	Nuclear	270	668	59	313
Heat	Biomass	0	1,831	512	495
	Waste	0	35	4.5	2.1
	Methane (P2X)	0	2,129	324	120
Fuel	Biodiesel	0	1,444	274	372
	Methane (P2X)	0	2,787	395	633
	Diesel (P2X)	364	635	18	495
	Kerosene (P2X)	546	953	27	742
	Methanol (P2X)	655	1,096	117	977

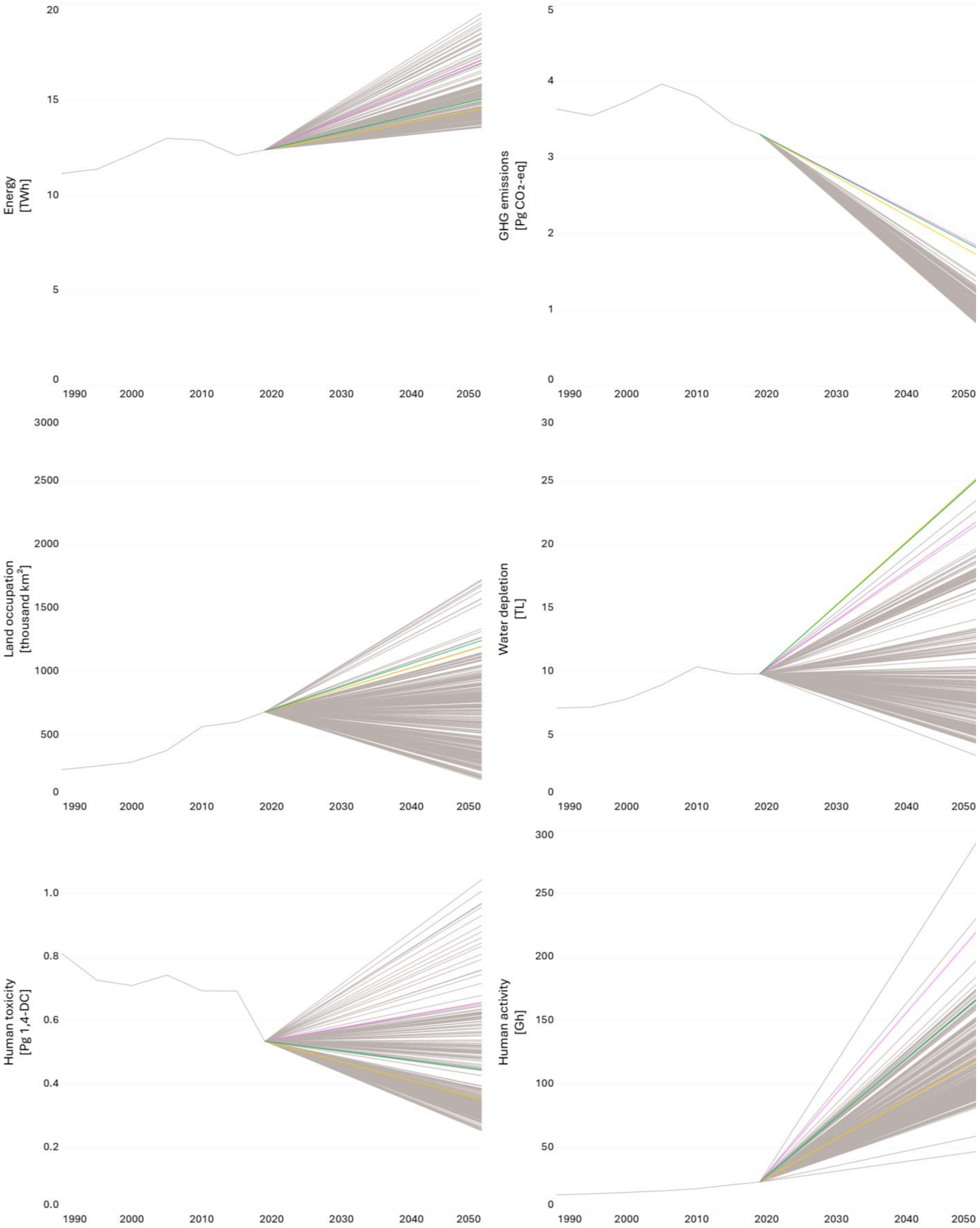
Lastly, the comparison of the three storyline scenarios with the SPORES scenarios–as shown in **Figure H.6**–finds that the projected levels within all three storylines are generally situated within the common ranges in each category. Nevertheless, a few notable exceptions are observed. Firstly, the absence of rooftop solar PV panels in the MD storyline is only observed in a very small number of the SPORES scenarios. The use of biomass for electricity is also notably low in the MD storyline. Conversely, the amount of rooftop solar PV projected for the PP scenario is over three times higher than any of the SPORES configurations. Secondly, although all SPORES configurations include a considerable level of nuclear power, only the GD storyline includes any use of this technology by 2050. Thirdly, heating in the storyline scenarios favours waste incineration higher than all SPORES scenarios while seeming to ignore the possibility of replacing natural gas with methane via P2X; methane is not used for centralised heat generation in any of the storyline configurations for 2050. Similarly, no biomass is used for heat in the MD storyline. Finally, for fuels, levels of biodiesel production are high for all storylines, as is the use of diesel and kerosene from P2X; methane from P2X levels are all within the typical range. However, the use of methanol from P2X is significantly lower than SPORES configurations for all three storylines.

H.4.2 Results of analysis

Values for the nine extensive indicators previously analysed in section **H.3.2** and an additional three intensive indicators–energy metabolic rate (EMR, in MWh per hour of HA), GHG metabolic rate (GHGMR, in MWh per hour of HA) and GHG-to-energy (in $kgCO_2$-eq per MWh energy)–were derived for all 441 SPORES configurations. The scope of the findings for each indicator is shown in **Figure H.7** alongside historical values for the years 2000, 2005, 2010, 2015, 2018 and 2019; projected values for the three storyline scenarios in 2050 are also shown on the figure, to be discussed in the following section. Again, the SPORES configurations were derived to quantify the myriad possibilities for future European energy systems and, as such, they do not represent projected scenarios for any particular year. Nevertheless, in order to visualise the characteristics of the SPORES configurations with historical and storyline configurations, they are assumed in **Figure H.7** to have been implemented by the year 2050. **Table H.6** provides a summary of the range of percentage differences observed for each indicator in comparison with the corresponding value in 2019; the average and standard deviation values for these changes are also listed. Brief summaries are provided for each of the 12 indicators in the following sections.

H.4.2.1 Energy generation

Values for total energy generation all rise, with percentage increases ranging from a low of 9.5% to a high of 57.8%. It is noted that SPORE scenarios where storage or electrolysis are limited in some way tend to result in lower increases in this indicator, confirming the contribution of losses within these processes to increases in overall energy generation. Conversely, scenarios where heat pumps are restricted–hence, limiting the extraction of "free" heat from the environment–result in the highest increases in energy input requirements.


Energy [TWh]
GHG emissions [Pg CO2-eq]
Land occupation [thousand km2]
Water depletion [TL]
Human toxicity [Pg 1,4-DC]
Human activity [Gh]
1990
2000
2010
2020
2030
2040
2050

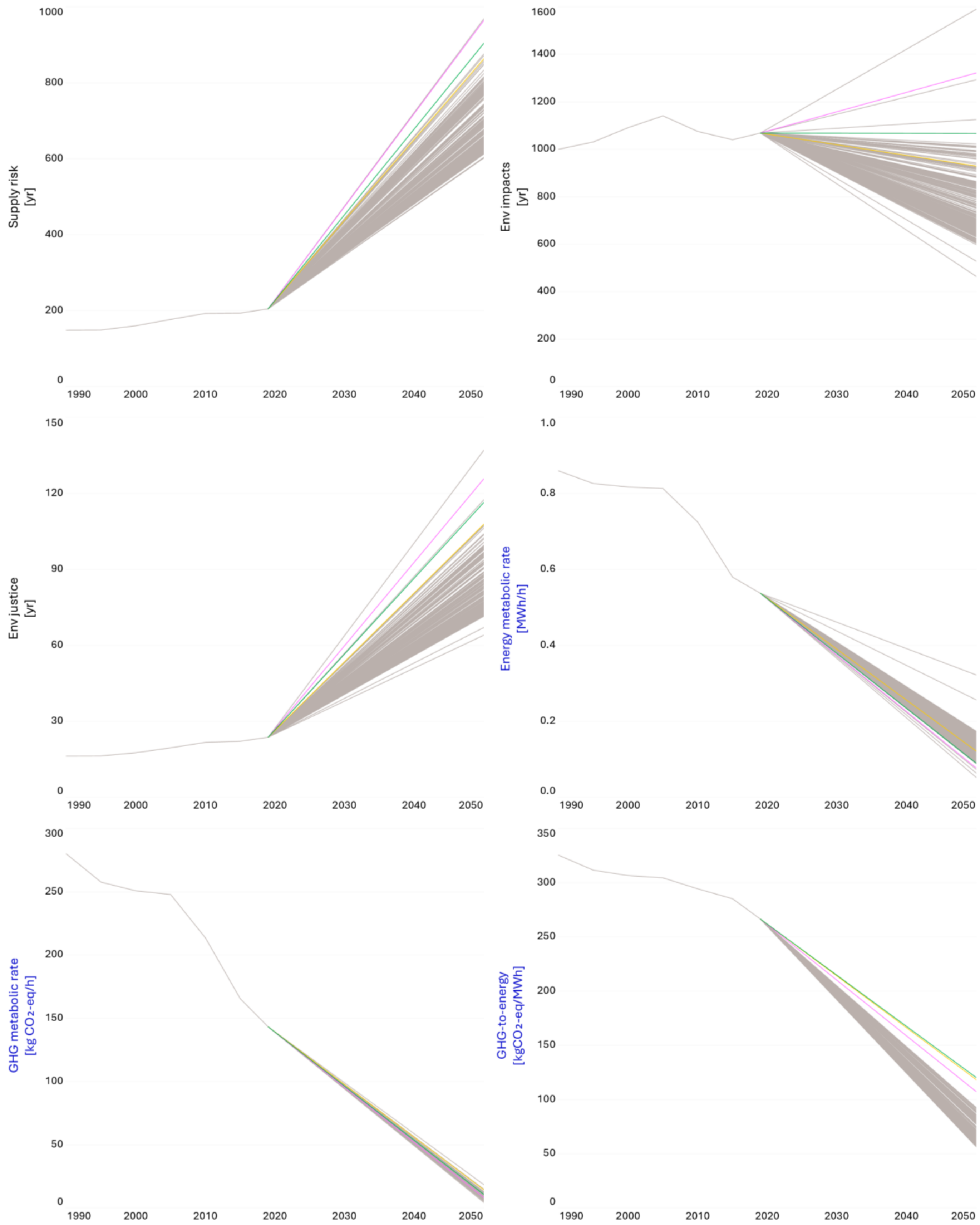


Figure H.7. Results for extensive indicators at the energy carrier group ("n-1") and technology group ("n-4") levels. Analyses are reported for historical configurations–1990, 1995, 2000, 2005, 2010, 2015 and 2019–alongside projected storylines configurations that reflect green government directed (GD), yellow market driven (MD) and pink people powered (PP) scenarios

Table H.6. Summary of range of percentage changes between 2019 values and 441 SPORES configurations for nine extensive indicators and three intensive indicators. Potentially adverse results are displayed in shaded cells. Corresponding values for three storyline scenarios are also listed. Instances where storyline results are outside of the range of SPORES results are shown as bold and underlined text

Group	Indicator	SPORES				Storylines		
		Min *[%]*	Max *[%]*	Range *[%]*	Average *[%]*	GD *[%]*	MD *[%]*	PP *[%]*
Extensive indicators								
Total energy	Energy generation	+9.5	+57.8	48.3	+20.3	+21.5	+17.4	+38.2
LCIA	GHG emissions	-75.0	-56.1	18.9	-69.6	-**<u>45.4</u>**	-**<u>47.8</u>**	-**<u>44.3</u>**
	Land occupation	-78.4	+152.7	231.0	-12.1	+82.4	+75.2	+75.2
	Water depletion	-65.5	+156.0	221.5	-11.4	+155.1	+**<u>156.6</u>**	+121.8
	Human toxicity	-52.7	+95.0	147.7	-23.4	-16.6	-34.2	+22.9
Socio-metabolic	Human activity	+103.9	+1159.7	1055.8	+406.0	+623.6	+416.0	+854.5
Raw materials	Material supply risk	+193.5	+372.2	178.7	+235.9	+340.8	+320.9	+370.0
	Env impacts relating to material supply	-56.5	+48.8	105.3	-28.7	-0.2	-13.0	+23.7
	Env justice issues relating to material supply	+169.7	+476.9	307.2	+252.4	+390.3	+354.0	+429.4
Intensive indicators								
Metabolic rate	Energy metabolic rate	-90.2	-40.0	50.2	-75.1	-83.2	-77.3	-85.5
	GHG metabolic rate	-96.9	-87.0	9.8	-93.7	-92.4	-89.9	-94.2
By unit of energy	GHG-to-energy	-78.7	-65.2	13.6	-74.6	-**<u>54.8</u>**	-**<u>55.5</u>**	-**<u>59.7</u>**

H.4.2.2 GHG emissions

As predicted, GHG emission levels all reduce significantly, ranging from a best-case scenario of a 75.0% drop to a worst-case scenario of a 56.1% drop. However, only 61 of the 441 configurations drop by less than 65%, many of which are scenarios where electric vehicle and other transport-related constraints are in place, forcing the higher per-unit emissions derived from biodiesel use to become an offsetting factor. Meanwhile, 248 of the 441 configurations drop by more than 70%. In any case, significant reductions in GHG emissions are observed for the majority of the scenarios presented. Again, many of the residual GHG emissions observed are related to the inability of LCA database users to change the "background" assumptions in the LCI data, meaning that future processes are still required to use older energy mix inputs in their calculations. A known limitation, this issue is discussed further in detail within the discussion and conclusions to the thesis provided in section I.

H.4.2.3 Land occupation

The values for changes in land requirements is split almost evenly between increases and decreases, the overall spread ranging from a drop of 78.4% to a rise of 152.7%. Nevertheless, it is curious that 56 of the drops predicted are more than 60%, while only 30 scenarios return rises of over 60%. As observed in section **H.3.2.3**, land occupation is often dominated by bioenergy processes, particularly the high requirements assumed for biodiesel production. As a result, many of the biggest reductions in land occupation are observed in SPORES scenarios where biofuel supply is constrained. On the other hand, eight of the nine scenarios where increases of over 100% occur– i.e., a doubling of requirements–involve restrictions that force the system to prioritise heating from biomass in combined heat and power (CHP) plants.

H.4.2.4 Water depletion

Results for water depletion are observed to be very similar to those for land occupation; the spread here ranges from a drop of 65.5% to a rise of 156.0% and the range is once again evenly spread between rises and falls. Remembering from section **H.3.2.4** that biodiesel production has very high water requirements, it is perhaps not surprising that many of the biggest reductions in water depletion are linked to SPORES scenarios where biofuel supply is restricted. Furthermore, only a small number of high increases are predicted to occur; a total of 13 scenarios produce overall increases above 90%. Nonetheless, unlike land occupation, most of these increases relate to scenarios where electric vehicle constraints force the system to use biodiesel as the dominant transport fuel.

H.4.2.5 Human toxicity

Human toxicity results are also found to occupy a range of decrease and increase outcomes, varying from a fall of 52.7% to a rise of 95.0%. However, for this indicator the spread is far from even: 360 of the 441 scenarios analysed are for overall reductions in human toxicity. Here, as with land occupation, almost all of the highest increases–10 of the 11 increases of over 60%–relate to scenarios where restrictions on heating systems force the system to prioritise the use of biomass combined heat and power (CHP) plants. This is consistent with the findings of section **H.3.2.5**, where biomass CHP plants were found to be key determinants in producing high human toxicity values.

H.4.2.6 Human activity

As with the storyline scenarios, values for human activity rise very significantly across all of the SPORES configurations examined. These increases range from 103.9% to 1159.7%, although 433 of the 441 SPORES configurations produce rises of between 250% and 660%. Again, as discussed in section **H.3.2.6**, assumed ongoing increases of infrastructure capacity–and the assumption that very little of this capacity is decommissioned over time–is the most significant contributor to these increases. Indeed, total installed capacities in 2050 for electricity and heat generation are 5.9, 4.6 and 7.8 *times* their values in 2019 for the GD, MD and PP scenarios, respectively

The analysis of the storyline scenarios in section **H.3.2.6** revealed that Euro-Calliope does not tend to assume the widespread decommissioning of infrastructure and that, as a result, installed capacities tend to rise far more than energy generation totals. This explains many of the large differences seen between the 2019 human activity requirements and those calculated for the different SPORES configurations. Nevertheless, solar PV and nuclear infrastructure require more labour per unit of energy than all other technologies. As a result, scenarios with higher shares in solar PV and nuclear would be expected to return higher increases in human activity requirements. Analysis of the SPORES configurations confirms this expectation: the highest increases are found in scenarios where restrictions are placed on wind power, driving the system towards extremely high levels of solar PV. Conversely, the scenarios with the lowest rises in human activity are those where solar PV is restricted.

H.4.2.7 Material supply risk

The risk associated with the supply of raw materials (SR) is another factor that is predicted to rise under all SPORES scenarios. Risk levels are expected to rise by between 193.5% and 372.2%, although only 10 of these are above 300%. The analysis in section **H.3.2.7** found that wind, solar PV and biodiesel all represent key determinants in this indicator category. Accordingly, as most combinations within the SPORES datasets include significant levels of these three technologies in one way or another, all configurations result in high overall rises in SR. As such, connecting supply risk results with the conditions imposed within individual SPORES setups is far less predictable here than for other indicators.

H.4.2.8 Environmental impacts relating to material supply

The environmental impacts derived from the extraction and processing of raw materials (EI) is another indicator category where a wide range of decreases and increases are observed. Here, changes range from a reduction of 56.5% to an increase of 48.8%. However, this range is highly misleading as increases are only predicted to occur in three of the 441 configurations considered. Knowing–from section **E**–that solar PV presents the highest per-unit level of risk among all electricity technologies, one would naturally assume that configurations with elevated levels of solar PV would return higher changes in SR values, and vice versa. This is true, as the three outlier configurations, where rises are calculated, all contain specific restrictions on wind power use, driving the system towards solar PV; many configurations with low reductions also have these restrictions. At the same time, many of the largest reductions involve restrictions on solar PV or other combinations that favour alternative technologies.

H.4.2.9 Environmental justice issues relating to material supply

The final extensive indicator reflects potential environmental justice issues relating to the extraction and processing of raw materials (EJ). Much like the SR indicator, the findings here suggest that significant increases–between 169.7% and 476.9%–are expected in all 441 SPORES scenarios. Nevertheless, once again, most of these are found within a particular range: all but 16 increases are between 200% and 320%. As with all raw materials indicators considered here, the per-unit values for EJ are higher for solar PV and biodiesel production processes than for all other emerging technologies, with wind also providing very high values. It follows that all 14 of the changes above 320% relate to scenarios where conditions are placed on electric vehicles–driving the use of biodiesel–or the use of wind or heating infrastructure, all of which drives the system to use high levels of solar PV. Alternatively, many of the lowest increases involve restrictions on electricity use, and solar PV in particular.

H.4.2.10 Energy metabolic rate

Results for the three intensive indicators find that all are predicted to reduce in all SPORES configurations and that these reductions are generally far more uniform that those observed for the extensive indicators. For the energy metabolic rate (EMR)–the amount of energy produced for each hour of human labour used to produce that energy–reductions range from 40.0% to 90.2%, although all but seven configurations result in reductions of 67% to 83%. Again, as solar PV and nuclear approaches require far more hours of labour than others, they would be expected to be key influences on the results for this indicator, where configurations with higher proportions of these technologies would be expected to produce less energy per hour of labour. This proves to be true in the observed results, where scenarios that restrict wind power–and, hence, prioritise solar PV–represent many of the lowest values, while those that constrain solar PV result in lower overall reductions in EMR.

H.4.2.11 GHG metabolic rate

The GHG metabolic rate (GHGMR) reflects the level of GHG emissions produced by a process for each hour of human labour associated with the process. Accordingly, reductions will be influenced by technologies with low levels of GHG emissions and higher levels of required human activity. As the ratios of these two factors are very similar in wind and solar PV technologies–two of the more dominant technologies in most SPORE configurations–the resulting reductions in GHGMR are much more homogeneous than all other indicators analysed here. All GHGMR rates reduce between 87.0% and 96.9%. Even so, the highest reductions are observed in scenarios where wind power is restricted to some extent and solar PV cells are favoured.

H.4.2.12 GHG-to-energy

Lastly, the GHG-to-energy ratio is a simple reflection of the level of GHG emissions produced per unit of energy generated within an energy system. Significant reductions are again seen in all 441 SPORES configurations, ranging from 65.2% to 78.7%, although 236 of these reductions are higher than 75%. As with the findings for total GHG emissions in section **H.4.2.2**, the use of biodiesel can act to offset emissions reductions as it produces much higher per-unit emissions than all other renewable energy technologies. Indeed, 21 of the 24 configurations with the lowest predicted reductions are those where electric vehicle use is constrained, demonstrating yet again the influence of biodiesel in this regard. In any event, substantial reductions are achieved in all SPORES configurations for this indicator.

H.4.3 Comparison with storyline results

The results derived for the 441 SPORES configurations allow us to visualise the range of possible outcomes that relate to a complete spectrum of feasible future energy systems. To enable these characteristics to be visualised and compared side by side **Figure H.8** presents the results for all nine extensive indicators as percentage changes, relative to 2019 values. The findings confirm the small rises in overall energy generation and considerable increases in material supply risk, environmental justice threats relating to material supply and, especially, human activity requirements. GHG emissions are again shown to decrease considerably for all scenarios. The remaining indicators–human toxicity, land occupation, water depletion and local environmental impacts from material supply–present both increases and decreases as possibilities, although decreases are more prevalent in all four of these indicators. **Figure H.9** presents the findings for the intensive indicators, confirming that significant drops are expected for all three indicators shown.

With a knowledge of the scope of available possibilities for these 12 indicators it becomes possible to recontextualise the results of the three storyline scenarios to determine their relative “positions” within the full spectrum of possible outcomes. To enable these comparisons, **Figure H.8** and **Figure H.9** also present the values that relate to the predicted 2050 configurations for each of the three storyline scenarios. These values are also summarised in **Table H.6** and were previously overlaid onto the SPORES results for individual indicators in **Figure H.7**. The results demonstrate that storyline results are generally contained within the range of possibilities defined by the SPORES configurations, although a small number of outliers exist, as highlighted in **Table H.6**. However, overall, the storyline results tend to exist within the upper ranges of the SPORES results. Of course, trade-offs between attributes in systems are always necessary and large variations exist within the SPORES configurations themselves, as discussed in the original study (Pickering et al 2022); no one configuration will perform well in all indicator categories. Nevertheless, it is notable that the configurations from the storyline scenarios exist towards the less preferable end of the SPORES data spectrum in so many instances.

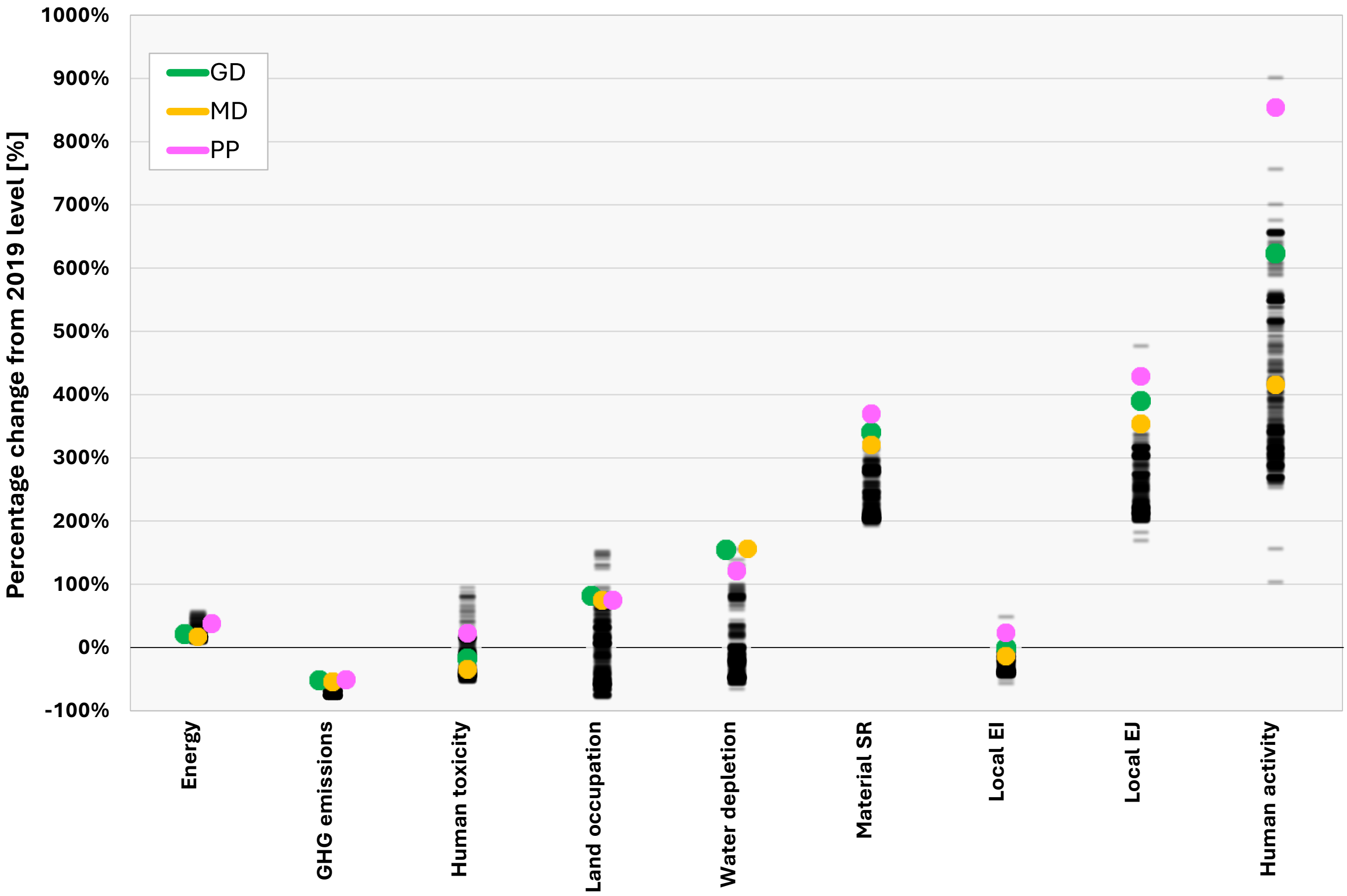


Figure H.8. Percentage changes, relative to 2019 values, for nine extensive indicators for all 441 SPORES system configurations. Each black bar represents results for a single SPORE configuration. Corresponding results for three storyline scenario configurations are also shown as coloured dots. Data sources: Pickering et al (2022), Pickering (2022b)

Deeper comparisons between the storyline and SPORES configurations–as previously illustrated in **Figure H.6**–reveals the key differences in this regard and helps to explain why storyline scenarios are often observed to underperform in comparison to many of the SPORES configurations. Firstly, onshore and offshore wind turbines are the dominant forms of energy production in many of the SPORES scenarios. However, although onshore wind is shown to be leading energy source in all three storyline configurations, the use of offshore wind is very minimal compared to the levels observed in SPORES configurations. Secondly, to substitute for the low levels of offshore wind in storyline scenarios, high levels of field-based solar PV are used in the GD and MD scenarios and rooftop solar PV in the PP scenario. The fact that solar PV presents substantially higher per-unit contributions for all seven of the extensive indicators examined here–see **Table J.41** in the appendices–the storyline scenarios are bound to produce less-desirable outcomes than many of the SPORES configurations where offshore wind is preferred over solar PV options. Lastly, the use of biodiesel is far more prevalent in the storyline scenarios than typical shares derived from the SPORES optimisations. This is largely due to the electric vehicle quotas imposed in the storyline scenarios–listed in **Table H.3**–which leave less room for the full-scale electrification of transport systems obtained in many of the SPORES configurations.

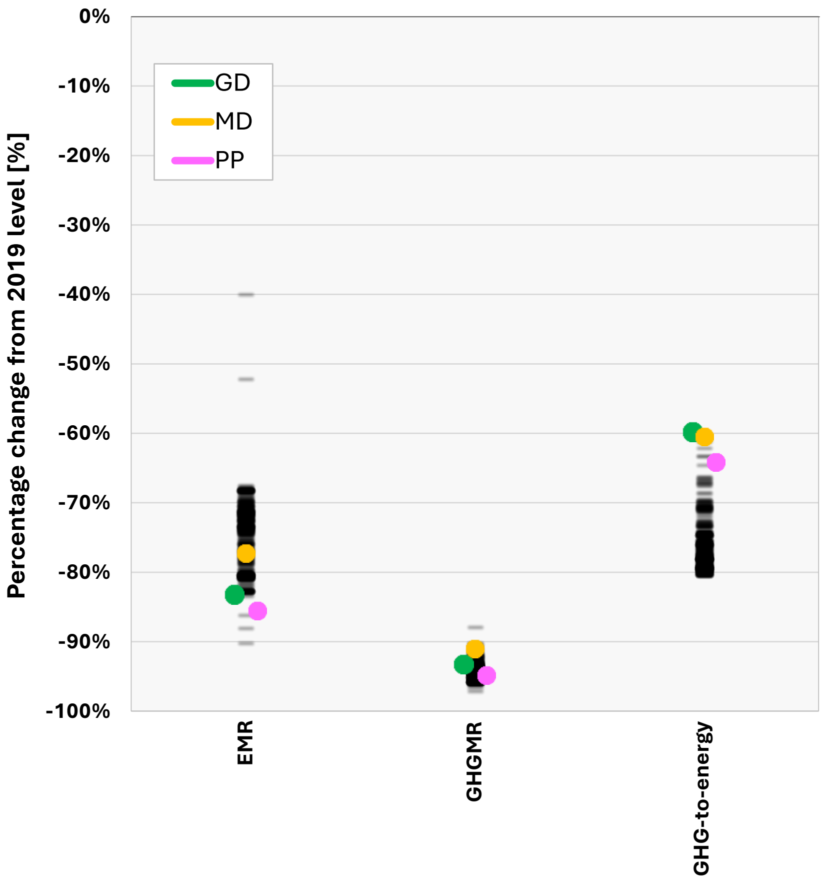


Figure H.9. Percentage changes, relative to 2019 values, for three intensive indicators for all 441 SPORES system configurations. Each black bar represents results for a single SPORE configuration. Corresponding results for three storyline scenario configurations are also shown as coloured dots. Data sources: Pickering et al (2022), Pickering (2022b)

H.5 Discussion and conclusions

A series of detailed assessments were undertaken for the European energy system using historical inputs from government data sources and data for potential future systems from the Euro-Calliope energy model (Tröndle n.d.). The assessments were performed using the ENBIOS workflow which is capable of calculating a variety of environmental, socio-metabolic and raw material indicators using life cycle assessment principles and other methodologies.

A first series of assessments involved the use of three specific sets of conditions–provided by the QTDIAN toolbox (Süsser et al 2021e)–to create three unique “storylines” for the energy system by the year 2050. All three future system configurations were assessed to determine the different trade-offs that exist between each of the three different approaches to transforming the energy system in Europe, as summarised in **Table H.4**. The most notable observation in the results is that the “people powered” (PP) scenario produces higher values in seven of the nine extensive indicators generated. This includes GHG emissions–meaning it creates the lowest overall reduction in emissions–alongside human toxicity, all three raw material factors, the total amount of energy generated and the hours of human labour required.

While all three scenarios are characterised by large switches to wind and solar PV electricity (see **Figure H.4**), the preference for solar PV in the PP scenario is a critical factor in its dominance in so many categories; solar PV technologies have high per-unit values for all of these indicators (see **Table J.41** in the appendices). Conversely, the “market driven” (MD) scenario–which utilises comparable levels of wind but far less solar PV–returns the lowest scores in the same seven indicator categories; the final “government directed” (GD) scenario, of course, claims the middle ground in all seven of these categories.

The remaining two indicators–land occupation and water depletion–are largely determined by the use levels of bioenergy products, and biodiesel production in particular. For this reason, findings for these two indicators tend to deviate from the pattern observed elsewhere. In any case, the results for the three storyline scenarios provide remarkably consistent findings across seven of the nine indicators (see **Figure H.5**), suggesting that an over-reliance on solar PV panels will generally introduce more potential issues than wind turbines or other approaches.

To broaden the scope of assessed system configurations–and to provide context to the three storyline scenarios–a second group of Euro-Calliope scenarios was also analysed. Here, a set of 441 technically and economically feasible outcomes were derived, each relating to a specific set of different system constraint values (see **Figure H.6**). This allowed a “spectrum” of possible values for each of the nine extensive indicators–and an additional three intensive indicators–to be produced (see **Figure H.7**). Percentage changes–compared to 2019 values–are shown for each extensive indicator in **Figure H.8** and for each intensive indicator in **Figure H.9**.

Not surprisingly, GHG emissions are expected to reduce in all 441 of these scenarios and energy generation is required to increase in all scenarios as a result of losses caused by the increased use of electricity storage and creation of P2X fuels via electrolysis. Nevertheless, large increases are observed in human activity and two of the raw materials factors–supply risk and environment justice–for all 441 scenarios. Once again, these increases are linked to the higher per-unit values for these indicators found in renewable energy technologies, particularly for solar PV (see **Table J.41** in the appendices). Luckily, a range of increases and decreases are observed across the spectrum of scenarios for all other indicators, suggesting that far greater flexibility is available to policymakers where these aspects are concerned.

Situating the storyline scenarios within the spectrum of SPORES system options indicates that all three generally perform poorly when compared to the full spectrum of possible options available (see **Figure H.8** and **Figure H.9**). For most indicators, results for the three storylines are situated towards the higher end of the spectrum, and sometimes beyond it (see **Table H.6**). Once again, the source of these observations can be largely traced to the influence of wind, biodiesel and, especially, solar PV. The findings also suggest that the very specific constraints put on the storyline scenarios when optimised in the Euro-Calliope model mean that they are not capable of exploring a wider range of configuration possibilities. As such, they tend to be “locked in” to a limited set of possible outcomes, unlike the SPORES scenarios which are generally able to seek different spatial and technological combinations within the model.

The use of so-called modelling to generate alternatives (MGA) approaches–such as those employed in supplying the SPORES configurations–are proving to be highly useful in allowing researchers and policymakers to understand the broad range of available possibilities. Moreover, the case study detailed in this chapter demonstrates that combining such outputs with a secondary approach such as ENBIOS enables data to be analysed further to obtain an additional range of values that could be used to aid policy decisions.

The analysis also provides further proof of the potential of ENBIOS as a tool for coupling with model outputs to provide information about particular influences and constraints. In this case it also demonstrates the ability of the ENBIOS approach to provide further insights to those seeking to examine the breadth of options and trade-offs that exist within the full spectrum of possible system configurations. For example, further interrogation of the data presented here could be used to identify system configurations that satisfy the best available “balance” of certain indicators, possibly based on weightings or prioritisation methods of researchers or policymakers. Indeed, such investigations could provide a basis for further research at the European or regional level.

In that sense, it is noted that the SPORES data used in this investigation (Pickering 2022b) and the study that produced it (Pickering et al 2022) considered both the technological *and* spatial aspects of different systems. So, while only the final technological mixes for the system were considered here, the many spatial aspects relating to the siting of different capacities across the 35 countries and 98 regions were also optimised within Euro-Calliope in the 441 SPORES runs. Therefore, as with many other examples, it is acknowledged that one of the next possible steps in the evolution of the ENBIOS concept could involve more detailed analyses that account for processes at regionalised spatial locations within energy systems. This would require more complex dendrograms to be defined that include additional structural processors for different countries or regions. Of course, this would be far more computationally demanding, although the possibility of employing this approach remains as a possible avenue for future research.

Lastly, it is noted that neither the Euro-Calliope nor ENBIOS calculations considered here account for specific physical limitations that could affect the implementation of different technologies. As an example, a recent study (Bódis et al 2019) found that the maximum possible amount of electricity that can be produced via rooftop solar PV panels in the EU-28 countries is around 680 TWh. Although this estimate does not include the eight countries in the system that lie outside of the former EU-28, it is significantly lower than the system amount calculated for the PP scenario, which is around 3,337 TWh; a single SPORES scenario returned a value above 680 TWh (978 TWh). Examples like this–alongside other physical limitations, especially those relating to land and water use and labour requirements–provide additional evidence of the very genuine need to harmonise modelling processes with real-world data such that the findings of modelling studies are both useful and sensible in practice. Ultimately, investigations of this kind highlight the need for government and industry decisionmakers to better understand the full range of options available to them–and, indeed, the potential limitations they may encounter–as they seek to identify the most optimal pathways for transitioning towards cleaner and more sustainable energy systems.

I DISCUSSION AND CONCLUSIONS

I.1 Discussion of main contributions

Above all, the thesis provides further contributions towards the *notional* concept of expanding the use of key constraint and influence factors within the tools that guide energy policy decisions. This predominantly involved–but is not necessarily limited to–investigating ways of implementing these factors into the modelling applications used to inform and guide policymakers within both the governmental and private sectors. After defining the ways in which models can affect transition processes, generalised categories of constraint and influence factors were defined. A list of underrepresented factors in existing models was then offered alongside an analysis of the consequences of continuing to neglect such factors.

The key contributions that followed can then be classified into two groups. Firstly, a set of *technical* contributions were made by helping to develop tools that could be used to integrate several overlooked factors into future modelling investigations or, indeed, to act as standalone tools. Secondly, these technical tools were used to investigate current and projected energy system configurations. This produced a set of *empirical* contributions that help to identify key areas of concern that exist within current energy technologies and–by extension–in proposed energy systems. A representation of the three levels of contributions is presented in **Figure I.1** and a simplified summary of these contributions is provided in **Table I.1**. Each of the three levels are discussed, in turn, in the sections that follow.

I.1.1 Expanding the inclusion of key constraints and influences

At the foundational level, the objective of the thesis was to investigate the factors that constrain and influence real-world energy transition processes and to explore new techniques for better implementing these factors into the models and other tools used to guide energy policy decisions. Ultimately, it is hoped that the work documented within the thesis will contribute towards the current discourse on climate change and resource policy by highlighting gaps in the current research and a number of potential issues that could impact the implementation of different proposed policies. In that sense, it is also hoped that the work will provide some amount of progress towards the growing push to create more robust and efficient policy directions that will help to ensure that the most realistic and balanced pathways are pursued as we collectively strive to limit the impacts of climate change.

Although the investigations reported in the thesis were primarily based on energy transition processes within Europe, the universal nature of the proposed theories and techniques means that, in theory, they can be adapted and applied to other locations. This is especially important when one considers locations with less ambitious or progressive climate policies which are likely to face unique and potentially more complex challenges than in Europe. Again, it is hoped that the concepts and methodologies presented in the thesis will join the collective move to provide deeper knowledge of the key issues that affect transition pathways to climate and energy policymakers at all levels and locations.

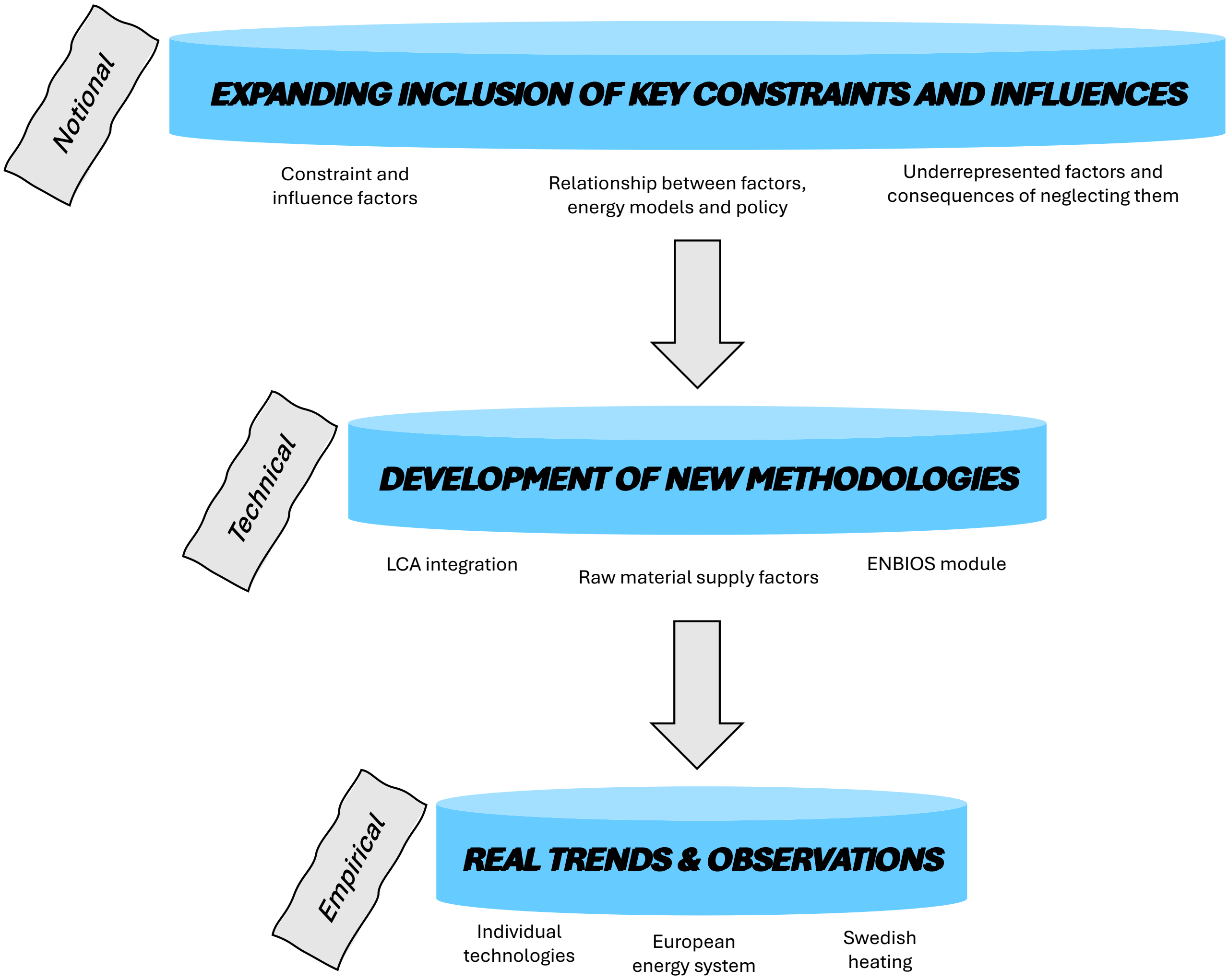


Figure I.1. Conceptual representation of the three levels of contributions made in the thesis. At the highest level, the thesis contributed towards developing the *notional* concept of expanding the inclusion of constraints and influence factors into the tools that guide policy decisions. To assist in this contribution, several new *technical* methodologies were developed. These were then operationalised to produce useful *empirical* contributions in the form of real trends and observations

The general theoretical aspects of this objective are documented towards the end of section **A**. Here, the initial contribution was to define the general conceptualisation of the way that different types of constraint and influence factors can affect policy decision-making processes while also acting as inputs in the models used to guide these policies, as shown in **Figure A.11**. A range of 11 constraint and influence factors were defined, each belonging to one or more of the three broad categorisations: (1) political; (2) economic; and (3) physical. The distribution of the 11 factors among the three categories is displayed in **Table A.4** while the level of inclusion of each factor in current modelling applications was also derived and presented in **Table A.5**.

Table I.1. Summary of main contributions provided within the thesis

Level	Contributions	Section(s)
Notional	Definition of 11 constraint and influence factors Conceptualisation of relationship between these factors, energy models and policy decision-making processes	**A.1.5**
	In-depth discussion of underrepresented factors and consequences of neglecting them in energy models	**B, C**
Technical	Development of methodologies for quantifying raw material supply issues for individual processes	**D, E**
	Assistance in design and development of ENBIOS workflow that combines inventory and impact assessment capabilities of LCA with the systemic upscaling capabilities of MuSIASEM	**F**
	Furthering use of life cycle assessment principles in energy system analysis	**D, E, F**
Empirical	Identification of specific trends and observations: - Individual technologies - Swedish heating system - European energy system as a whole	**F, G, H**

With the 11 constraint and influence factors in mind, section **B** provided further contributions by identifying a list of five overlooked issues that were deemed to be particularly necessary for establishing more robust and effective energy models in the future. The alignments of these five factors and the 11 general sub-categories are shown in **Table I.2** which demonstrates that nine of the 11 factors addressed in some way within the thesis. While public acceptance and support concepts are addressed in the section, the main focus is on a variety of economic and physical factors. As a consequence, political and economic factors like lobbying, environmental justice, labour requirements and market forces are not specifically discussed. As **Table A.5** suggests, labour and market forces are already well represented in a wide range of models and the impact of lobbying is difficult to represent outside of a small number of agent-based approaches. Meanwhile, environmental justice aspects, omitted from this section, are discussed addressed in some detail in the methodologies developed later in the thesis.

Section **C** extended this analysis by confirming the demand for many of these aspects–according to user needs surveys–and provided specific examples of the ways in which current models are poorly equipped to represent some of these factors. The section also detailed the potential consequences of failing to consider these factors now and in the future. It is noted that section **C** also provides much greater depth in its analysis of social factors–particularly in relation to public acceptance and support–thanks to the expertise and contributions of co-authors from the Institute for Advanced Sustainability Studies (IASS) in Potsdam. The scope of investigation is shown to be similar to those addressed in the previous section but does not include two economic factors–learning rates and energy return on investment–as these were deemed to be outside of the specified scope of this section.

Table I.2. Matrix of the 11 identified constraint and influence factors and their subsequent consideration within the articles included as sections in the thesis

	Section B	Section C	Sections D & E	Section F
Public acceptance and support	•	•		
Lobbying				
Environmental justice issues			•	•
Labour requirements				•
Market forces				
Learning rates	•			
Energy return on investment	•			
GHG emissions	•	•		•
Other environmental impacts	•	•	•	•
Resource limits	•	•	•	•
Material supply risk	•	•	•	•

In any case, it is thought that the delineation of the 11 constraint and influence factor categories, and the in-depth discussion of many of the underrepresented factors within these groupings, provides the first of the key contributions of the thesis.

I.1.2 Development of new methodologies

Following the *notional* investigations into the factors that should be better represented in energy policy processes, several *technical* contributions were developed. The contributions are in the form of new methodologies for calculating indicators that could be used as standalone tools or integrated into energy models and, potentially, other policy-related applications. The alignments of the factors addressed in these methodologies with the 11 general sub-categories are again displayed in **Table I.2**.

Two general methodological contributions were made in this regard. Firstly, new methodologies were developed to improve the consideration of issues relating to the supply of raw materials required to implement different energy technologies, as detailed in sections **D** and **E**. Maintaining stable supply sources for so-called critical raw materials (CRMs) is an ongoing concern in the European Union (EU) and abroad (Wellmer et al 2019, Bobba et al 2020, Hund et al 2020) and potential "roadblocks" are beginning to be highlighted. These concerns have only been exacerbated by the COVID-19 pandemic and war in Ukraine, further exposing the vulnerability of infrastructure development to supply chain disruptions (Hoang et al 2021, European Commission 2022).

Nevertheless, although the EC routinely quantifies supply risk (European Commission 2020c) and certain related parameters (European Commission 2021a), and a small number of other studies have addressed justice and conflict issues relating to material sourcing (Church and Crawford 2020, Lèbre et al 2020) all such assessments are limited to the study of individual materials. As such, the new methodologies developed here are thought to represent the first attempts to quantify raw material-related constraints in relation to entire technologies or processes and could well find use–or stimulate further research–in a variety of quantitative applications. Again, the methodologies are not limited to energy systems and could, theoretically, be applied to any process defined by an LCI.

A second methodological contribution was made by playing a major role in the ongoing development of the ENBIOS workflow, as described in section **F**. ENBIOS is the first application to link LCA functionality with the multi-level capabilities of the Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM) approach (Giampietro et al 2009). Taking energy system configuration data from modelled outputs–or any system definition–it then generates a range of environmental and other indicators at each element within the system. This includes "primary" extensive indicators–e.g., energy production, GHG emissions, land requirements or human labour–derived using LCIA and other calculations. However, a set of "secondary" intensive indicators can also be calculated by combining extensive indicator values for each location within a hierarchy.

The multi-scale analysis capabilities of MuSIASEM then allows indicators to be analysed within and across hierarchical levels, providing valuable information about the nature of systems at different levels. Indeed, the fundamental function of ENBIOS is to enable the relationships between indicators at different hierarchical levels to be analysed; the use of the MuSIASEM "dendrogram" is also thought to be a highly effective approach to structuring and presenting system hierarchies. In the end, this approach allows the various trade-offs and hotspots that exist within different energy systems or transition pathways to be assessed with the aim of informing better energy policy decision making.

The key contributions of ENBIOS, therefore, lie in the innovative combination of the high-resolution impact assessment capabilities of LCA with the systemic upscaling capabilities of MuSIASEM. While some previous studies have applied LCA-based thinking with energy system configurations or investigated the socio-metabolic dynamics of energy systems, ENBIOS is believed to represent the first attempt to consolidate these two perspectives. Accordingly, ENBIOS represents a pioneering new approach to assessing the environmental, resource and socio-economic aspects of energy systems in a single package. Furthermore, it can easily be linked to output data sets from a range of energy models and is capable of and producing a wide variety of useful extensive and intensive indicators in different formats.

In both of these methodologies, much of the basic input data is provided from LCI sources (Ecoinvent 2021, Sphera 2021, GreenDelta n.d.). This inventory data is then transformed to final indicator values using life cycle impact assessment (LCIA) methods or, in the case of the newly developed methodologies for raw material indicators, in conjunction with other data sources. Both methodologies represent novel new contributions to the assessment of energy system characteristics in a broad sense. However, they also provide valuable new contributions to the growing movement to improve the accuracy and robustness of energy modelling results by implementing the added resolution provided by LCI data and life cycle assessment (LCA) approaches as a whole.

I.1.3 Specific trends and observations

The newly developed *technical* contributions were also used to provide a set of *empirical* contributions that offer valuable insights into the attributes of individual technologies and for two specific energy systems: the Swedish heating system and the European energy system as a whole. The key findings at each of these scales are discussed in the following sub-sections.

I.1.3.1 Individual technologies

A simple analysis of the per-unit data for common energy generation technologies and for selected indicators is given in **Table I.3**. It provides a simplified overview of the normalised contributions for each of the elements that form the “building blocks” of a typical energy system. In this case, the technologies included, and data listed in the table, are based on those used in the analyses for the European energy system in section **H**, with values for biogas and fuel oil added from the Swedish heating study in section **G**. While the technologies assessed and the exact data used will vary from study to study, the values included here provide good general indications of the typical trends in relation to these technologies, based on current assumptions for background and foreground systems within these processes.

Table I.3. Summary of per-unit values for selected indicators and individual technology types. All listings represent per-TWh values with the exception of human activity for electricity and heat generation, which are given per-TW of installed capacity. “Heat map” formatting in each cell ranges from the maximum (darker red) to minimum (darker green) values in each column

		LCIA				Socio-metabolic		Raw materials		
		GHG emissions [x10^6 kg CO_2-eq/TWh]	Land occupation [x10^6 m^2/TWh]	Water depletion [x10^4 m^3/TWh]	Human toxicity [x10^6 kg 1,4-DC/TWh]	Human activity [x10^9 h/yr.TW]	[x10^4 h/yr. TWh]	Supply risk [x10^{-3}yr/TWh]	Environmental impacts [x10^{-3}yr/TWh]	Environmental justice [x10^{-3}yr/TWh]
Electricity	Wind–onshore	14.3	1.8	6.3	10.8	8.5		41.7	31.9	4.3
	Wind–offshore	16.0	0.9	7.9	12.9	12.2		35.9	28.1	4.0
	Hydro–reservoir	49.3	0.2	1.7	2.1	11.3		6.3	4.2	0.7
	Hydro–river	4.1	0.1	1.0	1.4	36.6		7.9	4.8	0.8
	Solar PV–field	76.0	37.3	44.6	62.7	40.9		91.6	174.0	13.9
	Solar PV–roof	73.6	5.9	51.5	88.5	40.9		79.8	208.4	13.3
	Biomass	51.6	1,288.7	21.7	598.1	20.0.		28.2	50.8	2.9
	Waste	237.7	101.1	324.9	242.1	21.5		28.2	50.8	2.9
	Biogas	185.4	177.9	5,478.5	339.9	21.5		121.4	1,425.0	21.4
	Coal	1,007.4	23.0	348.2	536.5	6.9		33.9	42.7	3.5
	Oil	809.5	2.1	67.7	55.0	2.5		33.3	106.2	3.9
	Natural gas	541.7	1.2	183.3	9.6	2.5		21.2	19.0	2.4
	Nuclear	6.3	0.6	302.8	31.9	70.6		6.3	6.4	0.7
Heat	Biomass	8.8	218.7	3.7	101.5	20.0		4.8	8.6	0.5
	Waste	42.6	12.2	61.4	34.8	21.5		4.8	8.6	0.5
	Biogas	31.5	30.2	929.5	57.7	21.5		20.6	241.8	3.6
	Oil	149.1	0.4	12.5	10.1	21.5		6.1	19.6	0.7
	Natural gas	99.8	0.2	33.8	1.8	2.5		3.9	3.5	0.4
Fuel	Biodiesel	417.6	716.7	1,547.6	39.9		6.1	140.3	98.6	18.6
	Biomass	61.0	369.6	12.6	12.5		21.3	7.3	13.2	0.8
	Coal	387.8	6.1	32.9	125.9		30.0	12.5	15.6	1.4
	Natural gas	256.8	0.1	1.1	12.2		6.7	11.3	6.4	1.1
	Diesel	307.7	0.9	3.4	8.5		6.5	12.6	209.4	1.5
	Kerosene	302.2	0.8	3.3	8.3		6.5	12.3	204.3	1.5

To demonstrate the spread of higher and lower scores for particular technologies, the cells in **Table I.3** have also been coloured to provide a “heat map” that highlights the more influential technologies within each indicator category. In this context, it can immediately be seen that fossil fuels provide high GHG emissions but are generally lower than average for other indicators. The exceptions here are the high environmental impacts from raw material supply from diesel and kerosene and the high human toxicity potential of coal-based electricity. The other obvious observation is that one or more bioenergy and waste technologies perform poorly in almost all indicators. This is especially true for biomass and biogas in electricity generation, and biomass and biodiesel as direct fuels; even when CO_2 emissions are disregarded for biodiesel it produces slightly higher per-unit emissions than any of the four direct fossil fuel sources due to the very high emissions assumed during its production.

Not surprisingly, it can be seen that most of the traditional forms of thermal electricity require large amounts of water, while one of them–nuclear power–also requires very high levels of human activity, alongside solar PV. Indeed, solar PV is found to represent moderate to high per-unit values for all indicators except GHG emissions. Meanwhile, the other form of renewable energy widely tipped to play a major role in future energy systems, wind power, displays low values in most categories but returns moderately high values for all three raw materials indicators.

The issue of GHG emissions appearing in what are generally assumed to be “green” technologies is once again highlighted in **Table I.3**. It is true that parts of these totals can be traced to genuine emissions in some cases (e.g., non-CO_2 GHG emissions or land use changes, particularly in bioenergy processes). However, most of the observed emissions for, say, wind or solar power are related to the energy mix assumed in the “background” system used during the production of infrastructure and, to a lesser extent, in the eventual operation of that infrastructure. For current assessments these estimates are assumed to be more or less accurate as the creation and operation of these devices does, in fact, require inputs from energy systems that still use significant amounts of fossil fuels (see **Figure A.2**). That being said, by 2050 the energy system operating in the background of each of the processes analysed in **Table I.3** will almost certainly be dominated by much “cleaner” technologies, meaning that far lower life cycle emissions will be produced.

In reality, future changes in background systems and other input parameters will affect all of the indicators assessed here to some degree. Certainly, as examples, the limitations regarding future changes in labour and raw materials parameters have been discussed several times in previous sections. For this reason, all future predictions of this kind are, ultimately, merely estimates based on current assumptions. Even so, as the reduction of GHG emissions is unquestionably the most high-profile indicator used in energy and climate policy discussions, it is here that this limitation in the current methodologies is most noticeable. Fortunately, the idea of adapting life cycle methodologies to allow for changes in background systems is becoming a point of focus for a growing number of researchers and is discussed as a topic for further research in section **I.3**.

I.1.3.1 Existing and projected systems

The analyses performed on current and projected configurations of the Swedish heating system and European energy system provided practical illustrations of the impact that the adoption of different technologies could have on different constraint and influence factors in the future. Generally speaking, both investigations confirmed that the increased use of renewable energy sources will reduce GHG emissions significantly, but that supply risk and justice issues relating to raw material supply and required levels of human activity are bound to rise. The findings for all other indicators vary between the different system configurations being considered.

I.1.3.1.1 LCIA indicators

As expected, overall GHG emissions are expected to reduce for all scenarios tested. These reductions are largely influenced by the significant lowering–or complete phasing out–of fossil fuels with high per-unit emissions, particularly coal, natural gas and diesel. In fact, the significant drops in emissions that result from lowering the use of natural gas–and the individual results for natural gas observed in **Table I.3**–highlight the clear danger of implementing natural gas as an interim energy source (Brauers 2022, Kemfert et al 2022). Likewise, the results widely confirm that biodiesel is unlikely to be a suitable long-term solutions to reducing GHG emissions in the transport sector. Furthermore, it is also notable that GHG emissions from wind are around one fourth of those from solar PV, and this is reflected in the lower emissions observed in configurations with higher shares of wind energy.

Unlike the consistent decreases observed for GHG emissions, a range of possible outcomes are predicted for land occupation. For this indicator, bioenergy approaches are clearly the dominant technology types, particularly processes involving biomass and biodiesel, where significant changes, up or down, invariably result in equally significant shifts in overall land requirements. Indeed, the broad scope of possible increases and reductions in land requirements observed in the SPORES results in section **H** largely reflects the range of different levels of biomass and biodiesel implementation in these scenarios.

As with land occupation, water depletion was found to be highly variable and is again strongly linked to bioenergy use, particularly biodiesel production. However, in this case, thermal electricity generation is also highly influential and many of the SPORES scenarios have elevated scores as a result of nuclear energy; most other forms of thermal generation are phased out in these scenarios resulting in decreases that help to offset rises in many scenarios. Additionally, in the investigation into the Swedish heating system in section **G**, it was found that heat and electricity from biogas is even more dominant, having a per-unit water requirement often several orders of magnitude higher than other technologies. At any rate, the findings for water depletion offer a clear demonstration of the potential water-related issues that could occur in some locations if the wider implementation of bioenergy technologies is to be pursued.

Biomass is again seen to be a factor in terms of human toxicity. Nonetheless, considerable offsets are gained by the phasing out of coal and, accordingly, overall values are seen to reduce in most SPORES scenarios. Meanwhile, although per-unit values are not as high as biomass, waste and coal, solar PV was still observed to be a significant contributor to toxicity scores due to its widespread use in future scenarios and higher per-unit values than electricity from wind turbines.

I.1.3.1.2 Socio-metabolic indicator

Large rises in labour requirements are seen in all projected scenarios for several reasons. Firstly, significant increases in overall installed capacity are observed in all scenarios. Most of this added capacity relates to renewable energy technologies, most of which have far higher per-unit requirements than the natural gas, coal and hydro they are replacing. Again, much of the legacy capacity is still assumed to be in service in Euro-Calliope, meaning the growth in overall capacity far exceeds the growth in energy generation and this contributes significantly to the large overall changes in human activity values. This is somewhat consistent with historical observations for the system (BFE 2021, 2022b, 2022c, EC Joint Research Centre 2019, Eurostat 2022) which show that installed capacities more than doubled in the European energy system between 1990 and 2019, although the changes forecast to occur by 2050 are higher still.

Nevertheless, it is noted that some burgeoning renewable technologies–notably wind and biodiesel–do not have overly high labour requirements and that the highest requirement value among all technologies is for nuclear power. Even so, the high human activity requirements and high forecast capacities for solar PV means that all scenarios look set to rise dramatically. Whether the current job requirement estimates for each technology will change over time–e.g., as technologies become more efficient or tasks become more automated–remains unclear, and more detailed analyses in the future could yield more robust estimations in this regard. In any case, it appears that many energy transition scenarios are likely to result in significant increases in labour requirements. Although fulfilling these requirements could present a genuine concern to policymakers as the transition progresses, it is difficult to know if such changes represent a negative or positive impact. On one hand, systems with high labour requirements could be seen as being less efficient. Conversely, higher employment opportunities could be viewed as being more socially or politically preferable, particularly in light of the need to maintain worker livelihoods within a "just transition" (Carley and Konisky 2020, Patrizio et al 2020). In any case, the observed results confirm that labour requirements is an area that warrants more detailed consideration in the policy decisions that surround the transition to renewable energy sources.

I.1.3.1.3 Raw materials indicators

Within the group of raw material-related factors, the supply risk and environmental justice indicators were found to be generally quite similar and significant rises are observed for both indicators and for all scenarios. For both of these indicators, the per-unit values in **Table I.3** confirm the dominant technologies to be solar PV, biodiesel and, where applicable, biogas. Indeed, the results confirm that scenarios with higher shares of solar PV were found to return the highest indicator values. Still, although the per-unit values for wind turbines are generally less than half those of solar panels, high projected penetration levels mean that wind energy use is also quite influential on both of these indicators.

At the same time, the indicator for environmental impacts tends to follow a very different pattern and totals are projected to lower in many scenarios. Here, because per-unit values for solar PV are again high, overall levels for electricity supply are expected to increase significantly in the future, as demonstrated in section **D**. However, impacts for overall systems are offset by the dramatic drop in diesel use which has a similarly high per-unit level of impact. Accordingly, the elevated contributions of solar PV are considerably negated by the phasing out of contributions from diesel in many instances. At any rate, one must be careful not to overlook the fact that different materials–and, hence, different production processes and sources of environmental damage–are involved in system reconfigurations of this kind, even if net scores are negative. For example, in this particular case, the impacts from producing diesel are largely associated with the extraction and processing of three platinum group metals–platinum, palladium and rhodium–whereas the impacts from solar PV are derived from a broader group of materials that prominently includes gallium and gold.

I.1.3.1.1 Intensive indicators

Various intensive indicators from ENBIOS were also presented in the thesis, particularly in section **F**. As these indicators are created by combining two extensive indicators, any changes that occur will ultimately be determined by the relative changes that occur within the two contributing indicators. The intensive indicators analysed in the thesis can all be classified into two general types. Firstly, “metabolic rate” indicators are formed by dividing an extensive indicator value by the corresponding number of annual human activity hours at that processor. As such, it is a measure of the level of a given indicator that corresponds to one hour of labour. Meanwhile, a second type of intensive indicator adopts a similar approach but uses the total amount of energy as the divisor. These “to-energy” indicators provide a useful indication of the amount of a given indicator that corresponds to a single unit of energy being produced.

As one would expect, changes in intensive indicators can be influenced by both of the two extensive indicators being used to produce them. Nevertheless, larger changes in one indicator will naturally tend to dominate the result at the expense of the other indicator. In the cases analysed here, large decreases were observed across the board for all three intensive indicators. For the energy and GHG metabolic rate indicators, these reductions were heavily affected by the significant increases observed for human activity. However, the influences were shared in the GHG metabolic rate (GHGMR) as GHG emissions were also seen to reduce significantly; the relatively minor increases in overall energy generation did not have such a large effect on the energy metabolic rate (EMR). It follows that the GHG-to-energy was mostly affected by the larger changes in GHG emissions compared to overall energy generation.

I.2 Conclusions to research questions

Having discussed the main contributions of the thesis in a general sense, the final responses to each of the four specific research questions can be provided. Individual responses to each question are included in the sections that follow.

I.2.1 Research question #1

"What factors are likely to constrain and influence the energy transition and are these factors adequately considered in energy policy decision-making processes?"

> **Response summary:** A group of 11 constraint and influence factors are likely to play a role in the dynamics of the energy transition as it progresses. Some of these are already included in many of the models and other decision-making processes that will ultimately determine how the energy transition proceeds. However, several of these factors–particularly those relating to raw material supply and political aspects–do not tend to be adequately considered in these processes. Furthermore, it was noted that life cycle approaches provide opportunities for obtaining more robust estimations of many environmental and resource-related aspects.
>
> **Addressed in section A**

In order to address this question, a general conceptual representation was first created to illustrate the ways in which models affect government and industry policy decisions, and vice versa, and that policy decisions, ultimately, determine the outcomes of the transition itself; the representation is shown in **Figure A.11**. A list of 11 unique factors believed to constrain and influence the dynamics within these processes was then defined, each of which can be classified into one or more of three general categories: physical, economic or political. In models, these factors are enacted in the form of input data parameters (e.g., land availability, system efficiency or public support ranking). Elsewhere, the impact of these factors on policy decisions is via more tangible real-world pathways (e.g., global warming, infrastructure costs or public opposition). A full listing of the 11 factors, and the category or categories that each are associated with, is provided in **Table I.4**.

To assess the levels of inclusion of each of these factors in the models currently being used to predict and guide energy transition processes, a thorough investigation of the most applicable current approaches was performed. This included integrated assessment models (IAMs), other energy system models (ESMs) and the relevant set of agent-based models (ABMs). Although some exceptions exist, the level that each of the 11 factors is represented in each of the modelling groups was then, as summarised in **Table I.4**.

Table I.4. Categorisations of each of the 11 constraint and influence factors and their representation in the three general modelling groups

	Category			Representation		
	Political	Economic	Physical	IAMs	Other ESMs	ABMs
Public acceptance and support	●					●
Lobbying	●					●
Environmental justice issues	●					
Labour requirements	●	●		●		●
Market forces		●		●	●	●
Learning rates		●		●	●	●
Energy return on investment		●	●			●
GHG emissions		●	●	●	●	●
Other environmental impacts			●	●	●	●
Resource limits			●	●	●	●
Material supply risk	●	●	●			

The investigation revealed that all factors are not adequately represented in the modelling applications that currently guide energy policy decision-making processes. The key findings can be summarised as follows:

- Economic factors are well-represented across all modelling approaches and are of least concern.
- However, political factors are mostly underrepresented outside of specialised ABMs.
- Although they are considered in some applications, human activity and labour considerations could potentially be used more for investigating more complex socio-metabolic relationships.
- The quantification of environmental justice issues relating to material extraction is highly underrepresented.
- In fact, material supply issues in general are largely absent from energy models.
- Although GHG emissions, other environmental impacts and resource limits are all relatively well represented, the use of life cycle approaches appears to offer a pathway to including more robust estimates of environmental and resource-related aspects.

I.2.2 Research question #2

"What are the potential consequences of failing to adequately consider all of these factors in the models used to guide energy policy?"

Response summary: Neglecting to consider all of the factors that affect energy transition processes could result in policy directions that are more likely to encounter undesirable "roadblocks" during their implementation or that do not produce optimal transition pathways. Ultimately, this could produce outcomes that are undesirable in a variety of ways and that are not adequate solutions to achieving climate change mitigation targets.

Addressed in sections B and C

The analysis undertaken in section **C** concluded that, ultimately, disregarding or underrepresenting important environmental and social factors when planning the energy transition is likely to result in outcomes that are undesirable or, in fact, not feasible. The four case studies introduced in the section also illustrated the importance of improving the representation of environmental and social concerns in models by providing a selection of examples of situations where a disconnect exists between real-world policy directions and known, tangible issues. The examples can be summarised as follows:

- Issues of social acceptance could seriously hinder the vast upgrades in transmission infrastructure that would be required to implement many of the modelled transition scenarios; such proposals would be rendered irrelevant if the necessary upgrades are delayed or later deemed unfeasible.
- Raw material requirements for the lithium-ion batteries used to power electric vehicles could introduce serious bottlenecks to implementing the widespread electrification of the transport sector that is assumed in many forecasting models.
- Similar issues could well affect the proposed increases in onshore and offshore wind energy capacity in Europe as wind turbines also require vast amounts of raw materials with known scarcity and supply issues; onshore turbines are also known to attract different degrees of public opposition and land use/siting restrictions, and these issues are only bound to rise if large increases in capacity are to be implemented in the future.
- Finally, it was demonstrated that a range of political policy and investment and consumer behaviour factors have affected the penetration of wind turbines in the Greek energy system and that these vectors were not adequately considered in the models used to guide local policy.

In a similar vein, the analysis undertaken in section **B** revealed a small selection of constraint and influence factors that included material supply risk (more broadly termed "critical raw material independence"), GHG emissions (using more accurate LCA approaches), a general consideration of social and political acceptance and two techno-economic factors: learning rates and energy return of investment. Knowing that large increases in the use of electricity are predicted, and that renewable technologies are expected to provide far more of this electricity going forward, the characteristics of the seven most common renewable electricity technology categories were quantified for each of the identified factors.

The analysis found that wind and solar PV–as the renewable energy technologies most commonly predicted to emerge in future electricity systems–are both relatively desirable and free of constraints in most categories. However, they are both known to rely heavily on materials with known supply risks. Moreover, wind turbines tend to introduce more social acceptance concerns than solar PV panels and other technologies, while the life cycle GHG emissions for solar PV panels are often considerably higher than wind turbines. As another commonly promoted technology group, bioenergy also performs poorly for some factors, most notably GHG emissions and EROI, and brings with it a considerable number of social acceptance issues. Meanwhile, other technologies like solar CSP and the ever-reliable legacy of hydropower outperform all other technologies in many of the factors considered.

All of these findings highlight the fact that additional factors of this kind have the potential to introduce a variety of constraint and influence dynamics that are currently not adequately included within the modelling packages relied on to guide important energy policy decisions. More importantly, the consequences of neglecting these factors could very easily result in sub-optimal outcomes or, at worst, deeply problematic political, economic or political bottlenecks. Such outcomes could have serious consequences on the need to implement transition strategies at the rates required to meet emissions reduction targets and mitigate the impacts of climate change.

I.2.3 Research question #3

“How can life cycle inventories and other data sources be used to improve the integration of these factors in energy models?”

Response summary: A growing number of studies are investigating methods for integrating underrepresented factors into energy modelling processes. Here, new methodologies were introduced for calculating four indicators relating to raw material supply aspects that use life cycle inventory data alongside several other data sources. Furthermore, a new workflow was developed for analysing life cycle impact assessment outputs and other indicators within and across system levels using a multi-level hierarchical approach. It is hoped that both methodologies could be used alongside or within energy modelling applications in the future to allow better integration of some of the overlooked constraint and influence factors.

Addressed in sections D, E and F

Life cycle inventories (LCIs) provide a range of useful information about individual processes by containing detailed listings of all of the inputs and outputs associated with the life cycle of a given process. Values for individual inputs and outputs can then be transformed into LCIA indicators or be used alongside other data and methodologies to produce additional indicators. In this thesis, two unique methodologies were introduced that use LCI data to derive outputs for a range of indicators, including many of those highlighted as being underrepresented in modelling and in energy policy making generally. Indeed, both methodologies were previously highlighted and described as key contributions in section **I.1.2**.

Firstly, as one of the most underrepresented aspects of energy transition processes, new techniques were developed for a series of indicators relating to the extraction, production and supply of raw materials. The techniques, introduced in section **D** and expanded upon in section **E**, use LCI data for 55 raw materials considered to be important to the European Union alongside other data sources to generate four unique indicators. The indicators, described as follows, can be calculated for any technological process defined by an LCI listing:

1) Risk of required raw material supply channels becoming interrupted.
2) Environmental impacts from extraction and processing of raw materials.
3) Environmental justice threats from extraction and processing of raw materials.
4) Circularity, defined by net end-of-life recycling input rate.

The techniques allow a series of indicator values to be quantified for each "unit" of a process described in an LCI (e.g., 1 MJ of electricity from coal or 1 kg of biodiesel). This enables different processes to be compared in relation to the aspects reflected by the different indicators. For example, the "risk" of obtaining the materials required to produce a single unit of electricity from wind, solar or nuclear could be compared to assess which technology introduces more supply uncertainty; similar comparisons can be undertaken to compare, say, different sub-technologies or spatial locations where suitable LCI data exists.

However, as with any "extensive" indicator, individual per-unit values can also be upscaled to achieve aggregated values for sub-systems or entire energy system configurations. This would allow, for example, overall indicator values to be compared between a number of potential system configurations. In this sense, the techniques are computationally quite simple and could be adapted and integrated into existing modelling packages to enable the integration of materials-related aspects.

The ENBIOS workflow, described in section **F**, provides a second working example of a methodology that uses inventory and other data in the analysis of energy systems. One of the fundamental design aims for ENBIOS is its ability to calculate LCIA indicators from raw LCI inputs, as accomplished in a "standard" life cycle assessment (LCA) analysis. Hence, a wide range of different indicators can be obtained for every process defined within a system under analysis. The workflow is also highly customisable and, thus, can be programmed to calculate any number of unique indicators using LCI and other data according to specified methodologies. In this regard, the prototype versions of ENBIOS, as described in the present thesis, also include the four raw materials methodologies described above alongside an additional methodology for calculating human activity requirements. Furthermore, once values for all "extensive" indicators have been generated, a second round of "intensive" indicators can be derived using combinations of other indicators. For example, if GHG emissions and total energy generation are calculated as extensive indicators at a given element in the system, the GHG emissions *per unit of energy* can also be calculated as a useful intensive indicator.

Using input data at the end of the furthest "branches" of the system hierarchy, indicator results can be obtained at any location back "up" a defined system hierarchy using the multi-level, hierarchical and systemic upscaling capabilities adapted from the MuSIASEM approach. As such, ENBIOS can be used to generate a variety of extensive and intensive indicators at all levels within an entire energy system and, indeed, for the system as a whole. This flexibility–particularly the ability to derive a range of useful intensive indicators within a hierarchy–represents one of the key contributions of ENBIOS.

Ultimately, ENBIOS has been designed to accept energy system information from energy models as its primary "foreground" input. Although not addressed in this thesis, one of the ongoing aims for the next generations of the concept is to develop methods for creating hard links between ENBIOS and energy models to allow ENBIOS outputs to be placed back *into* modelling environments to enable them to be part of integrated optimisation runs. This topic is discussed further in section **I.3** as a likely area for future research. At any rate, the two new methodological approaches introduced in the thesis represent new and innovative procedures for integrating underrepresented factors into the energy models used to guide energy policymaking.

I.2.4 Research question #4

"What insights can the proposed techniques offer about specific energy technologies and projected energy system configurations in Europe?"

> **Response summary:** Analysing the Swedish heating system and a variety of proposed energy systems for Europe as a whole revealed several insights about specific technologies and about projected future systems. The most significant concerns relate to the large increases that could occur in labour requirements and in the supply risk and environmental justice aspects relating to the supply of raw materials. These concerns mostly relate to the requirements for new wind and solar infrastructure, although biodiesel production is also a notable contributor. Several further observations were made in relation to other indicators and technologies.
>
> **Addressed in sections G and H**

In order to derive indicators for individual technological processes within an energy system, the ENBIOS approach–which also incorporates the methodologies for raw materials factors–was operationalised. As the first step in an ENBIOS analysis is to calculate indicator values at the most elemental resolution in the system–at so-called "structural processors"–a first round of results can be obtained that relate to the values for individual technologies. Values at other hierarchical levels and those of the whole system can then also be obtained.

Within the thesis, two case studies for complete energy systems were investigated. The first of these–described in section **G**–investigated the Swedish heating system by examining the characteristics of historical configurations alongside a projected 2050 scenario provided by the EnergyPLAN model. A second utilisation of ENBIOS used historical data and outputs from the Euro-Calliope model to explore a variety of possible futures for the European energy system as a whole. This initially involved three "storylines" for 2050 where Euro-Calliope parameters were defined according to narrative pathways provided by the QTDIAN toolbox. A second set of inputs involved a complete spectrum of 441 possible technically and economically feasible configurations defined by the "SPORES" concept. Collectively, the data for individual technologies and the two case studies were able to provide several consistent insights about (1) the specific energy technologies that act as key determinants in different indicator categories, and (2) general conclusions about the outlooks for these indicators in projected energy system configurations in Europe.

A summary of the observations for each of the key indicators analysed is provided in **Table I.5**. As expected, the findings suggest that reductions in GHG emissions are likely to occur for all future scenarios, although it is acknowledged that these reductions are likely to be even higher than reported because future changes in "background" energy systems are not yet possible in the calculations. These reductions are contrasted by increases in human activity requirements and supply risk and environmental justice aspects relating to certain raw materials. As a result, reductions are also observed in all three of the key intensive indicators considered. Meanwhile, a range of possibilities–i.e., both increases and decreases–were found to exist for all other indicators, depending on the individual shares of technologies in system configurations.

Table I.5. Summary of most influential technologies and general outlook across different indicators. Instances where large increases are predicted are displayed in shaded cells.

Group	Indicator	Key determinants	Outlook
LCIA	GHG emissions	Biodiesel as direct fuel Phasing out of direct fossil fuel use Phasing out of electricity from coal, oil & natural gas	Large reductions
	Land occupation	Bioenergy, especially biodiesel & electricity from biomass	Small increases for all “storylines” However, many reduction scenarios possible if bioenergy minimised
	Water depletion	Bioenergy, especially biodiesel Phasing out of thermal electricity generation	Large increases for all “storylines” Various increase & reduction scenarios possible
	Human toxicity	Electricity from biomass, biogas & waste Phasing out of electricity from coal	Increases & reductions in “storylines” However, many reduction scenarios possible if bioenergy & waste minimised
Socio-metabolic	Human activity	Solar PV & nuclear Ongoing capacity increases	Large increases
Raw materials	Material supply risk	Electricity from wind & solar PV Biodiesel as direct fuel	Large increases
	Env impacts relating to material supply	Electricity from solar PV Phasing out of diesel as direct fuel	Increases & reductions in “storylines” However, most possible scenarios suggest overall decreases
	Env justice issues relating to material supply	Electricity from wind & solar PV Biodiesel as direct fuel	Large increases
Intensive	Energy metabolic rate	Human activity, largely determined by solar & nuclear	Large reductions
	GHG metabolic rate	Co-determined by solar & nuclear for human activity and GHG emissions determinants for individual scenarios	Large reductions
	GHG-to-energy	GHG emissions, see key determinants above	Large reductions

In that sense, several technologies were highlighted as having particularly high potentials to affect the outcomes of different indicators. Perhaps the most obvious concern relates to solar PV devices, widely predicted to play a dominant role in energy transition scenarios. Solar PV was found to be a major contributor to increases in human activity and all three raw material indicators. Interestingly, it was also observed that one of the “storyline” scenarios calculated a requirement for rooftop solar

PV well in excess of the amount thought to be technically feasible in the EU. While this does not directly relate to ENBIOS, it provides another example of the need for models to be equipped with suitable data about a wider range of constraint factors. The other significant concern relates to bioenergy technologies, many of which display a great potential to exacerbate land occupation, water depletion and human toxicity issues; biodiesel production was also found to be a key contributor to increases in the supply risk and environmental justice indicators relating to raw materials.

Lastly, although wind energy is generally not seen to provide as many concerns as solar PV on a per-unit basis, the high levels of wind turbine use assumed in many forecasts means that it was still observed to make strong contributions to the overall scores for many future system configurations. In any case, of the two sources of renewable electricity generation overwhelmingly being touted as future market leaders, wind turbines were clearly demonstrated to be preferable to solar PV cells overall.

I.3 Future research

The thesis has provided an overview of the ways in which modelling tools are used to inform energy policymaking and identified several of the shortcomings in current approaches. Several new methodologies have also been described in detail and applications of these methodologies have been used to derive a series of insights about current and proposed energy systems in Europe. Nevertheless, some limitations in the proposed methodologies have been noted and a number of avenues of further exploration are available that would enable progress to be made in this ever-developing field of research.

Perhaps the most pressing immediate limitation involves availability issues in the LCA data that provides the foundation for many of the calculations in the newly proposed methodologies. While many energy technologies are very well represented in Ecoinvent (Ecoinvent 2021) and the other major LCI databases[4], quality listings are still not available for many of the newer technologies, including many that are predicted to play major roles in the implementation of the transition to more sustainable systems. For example, only a small number of older generation wind turbines are included in the Ecoinvent database, and newer solar PV and bioenergy technologies are largely absent. Similarly, only one type of geothermal electricity generation and two types of solar CSP are included. And, although the development of power-to-gas (P2G), power-to-liquids (P2L) and newer bioenergy technologies remain in their infancy, their availability would greatly improve the robustness of applications like ENBIOS.

Likewise, energy storage technologies–including the lithium-ion batteries that are already is relatively widespread use–are not yet represented in the common LCA databases. As such, the impacts and constraints relating to these technologies were not able to be included in the present analysis. This is unfortunate as large volumes of storage capacity are considered vital to the implementation of most of the scenarios investigated here and elsewhere (Cebulla et al 2018, Zerrahn and Schill 2017), particularly where major increases in intermittent electrical technologies like wind and solar power are involved. Such devices will need to be included before a truly robust assessment of the issues surrounding sustainable energy systems can be completed, particularly in relation to raw material aspects where potential constraint issues have already been noted (Bobba et al 2020, Olivetti et al 2017, Zeng et al 2022).

On a related note, it should be remembered that the proposed methodologies for assessing raw material factors–as detailed in sections **D** and **E**–currently only consider 55 of the group of 80 potentially critical materials. Greater inclusion of these materials–especially important missing materials such as niobium, germanium and indium–would allow the assessments to be expanded and improved. Likewise, improvements in the spatial descriptions of sub-processes within processes would enable more detailed understandings of intermediate materials, components and

[4] A thorough listing of all available LCI data is provided at the openLCA Nexus website (GreenDelta n.d.).

finished assemblies to be undertaken. This would allow practitioners to perform individual, regionally accurate material supply assessments on the different sections of a supply chain, thus improving the overall accuracy of these indicators.

Another possible future development of ENBIOS involves expanding the spatial resolution of analyses to account for multiple countries or regions. The two demonstrations of ENBIOS presented in the thesis use a single system definition to represent a single spatial region, in these cases Sweden and Europe. However, larger system dendrograms could be defined that incorporate multiple regions or countries within the same hierarchical system. For example, one of the models used to demonstrate the use of ENBIOS–the Euro-Calliope model–provides output data for 35 individual countries. So, in theory, greater levels of accuracy could be achieved by including system configuration data for multiple countries or sub-regions as individual branches within a larger dendrogram, particularly in cases where LCI listings are available for individual countries in Europe. Moreover, if greater levels of delineation were required within technological groups, many different technological processes could be applied at additional structural processors to define, for example, a range of solar PV technologies. All of these options are possible as ENBIOS continues to be developed, subject to data availability, although their feasibility may also be subject to computer processing limitations.

One of the issues most often highlighted during the development and subsequent peer-reviews of ENBIOS–and, indeed, in a growing amount of literature in the LCA field–concerns the fact that the LCI information being used to define the components of future energy systems is "locked" into using present-day assumptions about "background" systems. While other indicators will be affected by changing backgrounds, the issue is predominantly a cause for concern in terms of GHG emissions. For example, if one wished to assess the characteristics of an electrical network in 2050 that used only wind and solar technologies, GHG emissions would still be reported as the energy system that *provides* the energy to all of the steps within that process would be assumed to be the *current* one. Naturally, this would still include all of the fossil fuels and other components presently providing this electricity mix, meaning that "low-GHG" technologies like wind and solar would still produce some emissions (see **Table I.3**). Again, this explains why GHG emissions are present in all of the projected scenarios reported throughout the thesis. In reality, just as the configurations of energy systems in 2050 are predicted to change, so will the background systems that sit behind each process. This gives rise to what has been called a "temporal mismatch" between foreground and background systems (Arvidsson et al 2018).

This mismatch is a known issue for assessments of this type and has given rise to the idea of the prospective life cycle assessment (pLCA) (Sacchi et al 2022, Mendoza Beltran et al 2020, van der Giesen et al 2020, Dirnaichner et al 2022). When adopting pLCA concepts into an assessment, the practitioner attempts to make changes to the background systems over time, thus "correcting" the results of LCIA analyses that occur in the future. As the field of pLCA continues to develop, it is hoped that future versions of ENBIOS could contain allowances for users to manipulate LCI data assumptions in order to allow for future developments, which are themselves often provided by outputs from energy models, especially IAMs (Arvidsson et al 2018). Similarly, input values relating to material supply risk and the local impacts and justice implications of material supply are also likely to change over time as reserve amounts and other geo-political aspects fluctuate. In the meantime, by applying current assumptions about background systems and the characteristics of raw material supply, ENBIOS assessments provide information about "worst case scenario" outcomes that enable possible future bottlenecks and "hotspots" to be identified.

One of the more striking hotspots identified in the thesis involves the large increases in labour requirements calculated for many of the projected scenarios analysed in section **H**. Although some of this relates to the higher labour requirements for certain technologies, particularly solar PV, much of it relates to the fact that installed capacities continue to rise, at least in the historical data and projected scenarios. This is most likely misleading as, in reality, full capacity staffing is unlikely to be maintained for older power plants, even if their capacity is theoretically still available. Likewise, the labour requirements that relate to many newer technologies are likely to reduce over time as the influences of "learning" processes (Rubin et al 2015, Yao et al 2021) and further automation are felt. Even so, the magnitude of these increases could well become a concern to policymakers. As such, obtaining more robust estimates for different technologies, with particular focus on the potentially shifting requirements and other factors in future systems, would seem to represent another fertile area for further research.

Of course, although ENBIOS has been presented as a package for analysing underrepresented aspects of energy systems, and its potential as a standalone package has been demonstrated using outputs from two common modelling packages, no attempts have yet been made to return outputs from ENBIOS back *into* energy models. Indeed, the conceptual aspects and potential methodologies for achieving this will likely become the focus of subsequent research. One possible approach would be to integrate ENBIOS functionality directly into an existing energy modelling application or within some type of integrated modelling environment. In this sense, open-source applications such as Wurst (Mutel and Cox n.d.), PREMISE (Sacchi et al 2022) and ENBIOS that can manipulate LCA data within digital environments represent positive steps towards the automation of LCA-related calculations within environments that could theoretically be linked to other modelling applications. In any case, modellers would also need to decide on preferences or priorities with respect to the different indicators produced by ENBIOS, particularly if one or more are being used within optimisation model runs; no attempt was made here to speculate on whether one indicator should carry more "weight" than others in this regard. Like ENBIOS itself, these developments remain in their initial stages and further research will be required before genuine two-way synthesis can be achieved.

Lastly, although not addressed in detail outside of sections **B** and **C**, the issue of public acceptance and support remains as one of the key constraint and influence factors not substantially addressed in energy models (outside of specialist agent-based models used to predict trends in the issue itself).

It is hoped that recent developments in this arena, such as the QTDIAN toolbox (Süsser et al 2021e), can help to spread awareness of the importance of such factors in forecasting and analysing future energy systems and provide food for thought for investigating the issue in more detail. By bridging this gap, and the many other gaps discussed within the thesis and elsewhere, the modelling applications that guide important energy policy decisions will be able to consider a more complete range of the many factors that will ultimately determine the dynamics of energy transition processes.

J APPENDICES

J.1 Introduction

Much of the content of section J is adapted from sections authored for the SENTINEL deliverable "Observed trends and modelling paradigms on the social and environmental aspects of the energy transition. Deliverable 2.1. Sustainable Energy Transitions Laboratory (SENTINEL) project" (*https://doi.org/10.5281/zenodo.4917183*).

J.1.1 Technological directions in energy supply

With large rises in the use of renewable energy predicted, the majority of broad forecasts suggest that wind power, solar PV and, to a lesser extent, bioenergy look the most likely technologies to emerge in the foreseeable future, replacing the formerly dominant hydropower, which looks likely to continue to lose popularity (IRENA 2020). However, a thorough survey reveals that many existing and emerging technologies are actively competing for a place in the ever-growing renewable energy marketplace.

J.1.1.1 Wind turbines

Wind turbines come in many forms and numerous vertical and horizontal approaches have been proposed. Furthermore, they can be situated on land ("onshore" turbines) or within bodies of water ("offshore" turbines). In any case, the most commonly used designs follow the traditional windmill approach of collecting rotational energy along a horizontal axis and, indeed, are known collectively as horizontal-axis wind turbines (HAWTs). By far the most popular of these uses a three-blade design consisting of a high tower anchored to a highly reinforced set of foundations. A nacelle structure atop the tower houses the generator mechanism that converts the rotational energy from the rotors into electricity.

At the utility scale, a typical modern wind turbine can deliver between one and three megawatts (MW) of power. Individual turbines tend to be installed in arrays known as "windfarms" which can be as small as 20 or 30 units or, in the world's largest installations, several thousand units. Turbines are expected to complete hundreds of millions of loading cycles, giving them an expected lifespan of around 25 years (Mishnaevsky et al 2017).

Although wind turbines are now considered to be a mature technology, their design elements continue to evolve, and great scope still exists for further advances. At the broader scale, the main area of evolution is in their size. This includes the diameter of the rotors, the height of tower required to support these rotors and, consequently, the power outputs they are capable of delivering (Serrano-González and Lacal-Arántegui 2016). Again, while it is commonplace for modern turbines to deliver several MW of power, turbines built in the 1980s were only capable of producing around 50kW, less than 3% of current rates (Blaabjerg and Ionel 2015). Likewise, rotor diameters and tower heights have risen from 20 or 30 metres in the 1980s to over 150 metres today.

These evolutions are largely due to advances in materials technology that have enabled larger blades to be manufactured that retain the lightness and high stiffness levels required for safe and efficient operation. At present, the rotor blades used in most utility-scale wind turbines are made of plastics reinforced with glass fibres known as “e-fibres”. However, as blade sizes continue to increase, turbine manufacturers are eager to develop advanced composite materials that are stronger, lighter, more resistant to damage and easier to produce. Carbon fibre materials offer many advantages and have been proposed as a viable option but may prove be too expensive for widespread adoption. Accordingly, the use of e-glass/carbon hybrids is thought to offer a suitable compromise. Other high-strength glasses containing basalt and aramid have also been proposed, as well as the use of nanoengineered polymers and composites (Mishnaevsky et al 2017).

The other highly contested field of research within wind turbine technology involves the generator mechanisms. Traditionally, the relatively slow rotational speeds of rotors have been converted to the faster rates required to produce electricity via a gearbox mechanism. However, so-called direct-drive mechanisms–that can convert the rotation of the rotor directly to electricity at lower rotational speeds via the use of magnets–are now being favoured as they involve fewer moving parts and require less maintenance (Wilburn 2011). This is seen as a key benefit as turbines are frequently situated in isolated locations.

But, while direct-drive generators have become the norm in new wind turbine constructions, two very different varieties of these generators have emerged based on the type of magnet used in the conversion process. The first uses an electromagnet, whereby a magnetic field is created using electrical current through wound copper coils. Meanwhile, the second uses permanent magnets that contain rare earth metals such as neodymium (Nd), praseodymium (Pr), terbium (Tb) and dysprosium (Dy) (Buchholz and Brandenburg 2018). These magnets are generally more efficient than electromagnets but are significantly more expensive.

Moreover, the global supply of the rare earth elements used in permanent magnet generators, and of neodymium and dysprosium in particular, could become an issue in the future. This is especially true as the vast majority of these metals are mined in China where the government has previously employed export quotas. Unsurprisingly, European turbine manufacturers have tended to employ electrically excited generators while Chinese manufacturers strongly favour the use of permanent magnets (Serrano-González and Lacal-Arántegui 2016). In any case, it is worth noting that rare earth supply could become a resource scarcity issue within the wind turbine industry in the future, particularly for producers outside of China.

It is also worth noting that wind turbines–and onshore wind farms, in particular–have attracted some controversy in the past as a result of uncertainties about their potential social and environmental impacts. This has included general discourse regarding the impacts of large-scale wind farms on societal harmony and lifestyles within smaller rural communities (Borch 2018), specific health impacts relating to the electromagnetic fields, shadow flicker and noise generated by wind farms

(Knopper et al 2014, Onakpoya et al 2015), aesthetic impacts (Klæboe and Sundfør 2016, Oosterlaken 2014) and the physical impacts on local species, particularly larger birds (Vasilakis et al 2016). A shortage of suitable land-based locations could also constrain the future propagation of onshore wind farms (Dupont et al 2018, Yamani Douzi Sorkhabi et al 2016).

In 2019, 95.2% of global wind energy capacity was from onshore wind turbine installations (GWEC 2021); the remaining 4.8% was contained in offshore turbines. In the EU–which contained 27.4% of total global capacity in 2019–onshore turbines are less dominant and represent 88.5% of installed capacity against 11.5% for offshore (WindEurope 2020). At both scales, the perceived limitations of onshore wind farms appear to have contributed to a significant increase in the use of offshore wind turbine technology in recent years. At the global scale, 6.5% of new installed capacity in 2020 was from offshore turbines down from 10.3% in 2019 (GWEC 2020). The use of offshore wind turbines is becoming considerably more widespread within the EU, where they represented 27.5% of the new capacity in 2019. Moreover, the capacity share of offshore wind turbines in the EU is expected to rise to almost 40% by 2030 (WindEurope 2017).

Harvesting wind energy in offshore locations is thought to be generally advantageous to using onshore locations for several reasons (Myhr et al 2014). Firstly, coastal and open sea locations generally receive higher winds. The potential environmental damages caused by their installation and operation are generally considered to be lower. Being more “out of sight and out of mind”, levels of political and public resistance also tend to be far lower. Finally, in theory, far more potential sites exist in offshore locations.

Conversely, the key constraints to developing offshore wind turbine facilities have historically been related to higher costs and technical limitations. However, the kilowatt-hour (kWh) price estimates for potential UK offshore developments have dropped by a third since 2017 and two-thirds since 2015 (Vaughan 2019). This considerable decrease is sure to drastically increase the economic viability and attractiveness of future investment in offshore infrastructure.

The vast majority of current offshore wind turbines are installed in shallow water settings; in 2012, the average depth of water was a mere 22 metres (Athanasia and Genachte 2013). This represents the key technical constraint to offshore wind energy in that it greatly restricts the number of suitable sites for future developments. In order to address this limitation, recent research has focused on operationalising turbines in “deep offshore” waters where depths are in excess of 50 metres. But, while initial studies tended to favour the implementation of sturdier bottom-fixed structures (Pérez-Collazo et al 2015), the use of such options does not appear to be practical in deeper waters.

Accordingly, floating wind turbines are now being seen as the superior option for opening large areas of open seas to wind energy generation. Although the turbine structures are allowed to float on the water’s surface, they are fixed to a single location on the ocean floor and are not moveable in nature. While tethering turbines such that they can withstand heavy winds, waves and tidal movements requires relatively complex infrastructure to be assembled, turbines can be placed in depths of several hundred metres. At present, only a small number of floating wind turbine farms exist in Scotland and Japan. However, many large-scale research and development projects are currently in operation in Europe and the United States (US), and the technology is predicted to become cost-competitive by the end of the decade (GWEC 2018).

J.1.1.2 Third-generation photovoltaic cells

The original, first-generation of photovoltaic (PV) cell technology utilises a single layer of crystalline silicon, wafer-based cells. Owing to the fragile nature of these cells, they are generally encased in several millimetres of glass, making them heavy, difficult to manufacture and limited in their scope of applications.

Subsequently, the second-generation of PV technology allowed a so-called “thin-film” of cells to be arranged on substrate surfaces to form far lighter and more flexible sheets. This greatly improved the range of applications that could utilise PV cells although, until recently, such cells could not rival the solar conversion efficiencies offered by the first-generation technology. In any case, the efficiency rates of both of these technologies are, at best, around 25% for first-generation and 20% for second-generation cells (Ananthakumar et al 2019).

Production of PV cells is still dominated by these two technologies. However, while still largely at the research and development stage, the next wave of third-generation photovoltaic cell technologies is emerging, with the aim of improving overall efficiency and reducing costs while maintaining the simplicity and versatility of thin film cells.

Many unique approaches are contained within this third generation of technologies. This includes the dye-sensitized solar cell (DSSC), or “Grätzel cell”, where an organic dye is used to absorb light energy, much like chlorophyll in plants. DSSCs are capable of high efficiency levels but concerns have been raised regarding their stability in extreme temperatures and higher manufacturing costs. Another alternative, the quantum-dot sensitized solar cell (QDSSC), offers higher efficiencies and greater stability than DSSC using “quantum dots”–extremely small semiconductor particles–as the absorbing material. Although QDSSC has shown promising technical characteristics, some concerns remain about potential toxicity and stability issues and further research to address these issues is required (Pan et al 2018). Conversely, copper zinc tin sulphide solar (CZTS) cells were specifically designed to provide a non-toxic product made from cheap and earth-abundant materials, albeit with lower efficiency levels than other technologies (Ito 2015).

However, the third-generation technology receiving the most attention in recent years is the perovskite solar cell (PSC) (Mora-Seró 2018, Yoo et al 2021). Although, strictly speaking, the word perovskite refers to a specific compound–calcium titanate ($CaTiO_3$)–the term is used here in reference to a group of compounds that share a similar crystal structure. These so-called “perovskite structured” compounds act as the light-absorbers in a PSC.

The upswing in the commercial appeal of PSC technology is largely due to the fact that they are relatively inexpensive and simple to produce, and recent research has resulted in dramatic increases in observed efficiencies. In fact, efficiencies of just under 30% have been achieved in recent PSC research (Green et al 2022), and efficiencies of up to 32% are predicted (Hossain et al 2019), confirming that they can be more than competitive with first generation cells in this regard. Add to this chemical stability, potential transparency, the ability to be printed on any number of flexible surfaces and functionality in low-light conditions and PSC technology can be seen to offer an attractive list of benefits (Fakharuddin et al 2017).

The ability to produce solar cells easily and cheaply is a key element in their prospects as a viable future renewable energy technology. In this regard, organic solar cell (OSC) technology is also attracting attention in recent years. OSC is especially attractive because of its low production costs and environmental impacts, high flexibility and the ease of printing OSCs over large areas. Traditionally, the major disadvantage of OSC technology has been far lower solar conversion efficiency; the maximum rate in 2013 was still barely 10% (You et al 2013). However, recent advancements have resulted in far more competitive efficiencies of around 17% (Meng et al 2018). Ultimately, the attractiveness of OSCs still hinges on the balance between cost, printability and efficiency.

J.1.1.3 Concentrated solar power

Concentrated solar power (CSP) is a form of thermal solar energy generation whereby sunlight is focused towards a common location allowing very high levels of heat energy to accumulate at a single point. As with other thermal power stations–e.g., coal, gas, nuclear or geothermal–a heat engine is then used to convert the collected heat to mechanical energy and, finally, electricity.

The most common type of CSP is the parabolic-trough collector. Indeed, parabolic-trough plants dominate the global distribution of CSP plants (Zhang et al 2013). As they name suggests, they are comprised of parabola-shaped mirrored troughs with a receiver tube of flowing fluid travelling along the focal point of the parabola to collect heat (Barlev et al 2011). Higher efficiencies and better energy storage capabilities have seen a sharp rise in the popularity of solar towers, the second most common CSP technology. In fact, they now represent around half of the world's new CSP plant constructions (REN21 2019).

Solar tower operations use a large array of heliostat reflectors, each focusing sunlight towards a single, central collection point within an elevated tower. The third most common CSP type, Linear Fresnel Reflectors (LFRs), are similar to parabolic troughs in that they focus solar heat into a local receiver tube. However, LFRs utilise complex arrays of flat mirrors to direct incoming sunlight. Although LFR use is thought to be more cost-effective, it is generally considered to be a low efficiency technology (Abbas et al 2013). As such, pending further research, interest in LFRs remains low when compared with parabolic-trough and power towers.

At present, all large-scale CSP plants (with capacities above 50 MW) in the EU are located within Spain and use parabolic-trough technology. These plants represent 94% of installed capacity within the EU (National Renewable Energy Laboratory 2019) and approximately 42% of global capacity (REN21 2019). Several smaller towers, representing a further 4.4% of EU capacity, are in operation in Spain, France, Italy, Greece, Germany and Denmark. Three Linear Fresnel Reflector plants operate in France, Italy and Spain and represent the final 1.7% of EU installed capacity.

CSP is seen as a relatively mature technology and many new plants are planned worldwide, particularly outside of Europe. And, although the investment feasibility of CSP projects is generally limited to sunnier regions, the technology is of particular interest to developing countries with increasing energy demands and high levels of solar radiation.

J.1.1.4 Marine energy

The constant movement of vast volumes of ocean water offer a substantial and largely untapped source of renewable energy. Various approaches now exist that seek to harness this potential in the form of tidal and wave energy technologies, although most are yet to make it beyond the conceptual or demonstration stages. Nevertheless, research continues to produce encouraging results, suggesting that this is a field of renewable energy research with considerable potential (Uihlein and Magagna 2016).

The most obvious benefit of utilising tidal energy is that the high reliability of tidal cycles effectively eliminates the intermittency issues inherent in other forms of renewable energy generation such as wind and solar. The most established of these methods is known broadly as tidal range technology and generates energy using the potential energy difference between the high and low levels within a tidal cycle. During the peak, “high tide” period some form of mechanical restriction is applied such that the level is maintained within a given location. The most common of these is to apply a moveable barrage, much like a dam. Then, when outside water levels recede, energy can be generated by driving the higher water levels within the storage space through turbines, much as energy is generated in a hydropower dam. Although this is by no means a new practice–the Rance Tidal Power Station was completed in France in 1966–only a handful of such structures are in operation. However, even if their functionality is more or less limited to areas with large tidal differences, their potential is still recognised in many locations (O’Doherty et al 2018).

The most promising new approach to tidal energy is that of the tidal stream generator (TSG). Here, the tidal energy is accessed directly in open bodies of water using underwater turbines in horizontal or vertical configurations. Unlike tidal range approaches, this method does not require the construction of large infrastructure and is, hence, far cheaper, less resource intensive and less disruptive to local ecosystems. As they are best driven by higher velocity flows, such devices are ideally situated where some form of natural restriction causes incoming and receding tidal flows to be faster than in more open locations. A single tidal stream turbine was in operation in the UK from

2008 to 2019, although no facilities are currently in operation. However, a number of technologies and projects are currently in development.

Although less inherently predictable than tidal energy, wave energy is also increasingly being investigated as a potential marine energy source. Wave energy collectors aim to exploit the kinetic energy of wave motions using a variety of different approaches. In fact, over 1000 patents have been filed for a range of available technologies (Greaves 2018).

Wave energy technologies can be broadly classified according to the methodology employed. Oscillating water columns are partially submerged objects with a volume of air trapped within it. Incoming wave actions generate energy by forcing his air through a turbine. Hinged contour devices involve two or more individual parts which move around each other in some pattern as waves pass by. This relative motion is then used to generate energy. Buoyant moored devices are relatively simple devices where the motion of a floating device bobbing on the surface is converted to energy. Finally, overtopping devices generate energy by forcing water that flows through an open inlet to flow through a turbine beneath.

In both hemispheres, the highest levels of wave energy occur at locations with between 40 and 60 degrees of latitude and these are seen as the most suitable locations for collecting wave energy (López et al 2013). Accordingly, a growing number of "wave farms"–where multiple wave energy devices are installed–have been or are being constructed in and around these zones, particularly in the UK, Portugal, the US and Australia. In any case, wave power remains a niche technology and even the world's largest wave farms are only capable of delivering between 5 and 20 MW of power.

J.1.1.5 Biogas

Biogas is a combustible mixture of gases–primarily methane and carbon dioxide, but often also containing traces of hydrogen sulphide, water and siloxanes–formed by the anaerobic digestion of organic matter. Gases produced at biogas plants are typically converted to electricity, heat or a combination of both using onsite gas-fired engines and it is thought that the split between these two uses is currently more or less even within the EU. Furthermore, carbon dioxide and trace gases can also be removed from biogas to produce biomethane which can be used as a vehicle fuel or be transferred to the local natural gas grid. This is said to represent around 7% of the current biogas production in the EU (Scarlat et al 2018).

The EU is the current world leader in the field of biogas production and produces around half of the global supply. Although the growth rate in overall biogas capacity in the EU appears to have peaked around 2007, the total number of biogas plants in the EU rose from 6,227 in 2009 to 17,783 in 2017. This suggests that the ongoing steady increases in capacity are now driven by smaller plants, many of which are used to digest agricultural plant substrates, the dominant type of biogas facility in the EU (71%) (Banja et al 2019). Other common types are those that digest sewage sludge (16%) and landfill waste (9%).

So, while fuels derived from biological sources still dominate the overall statistics for renewable energy in the EU (see **Figure A.3**) the biggest gains within the group of bioenergy sources in the past ten years has been from biogas. Indeed, while the share of renewable energy attributed to biologically sourced fuels has dropped from 59.2% in 2008 to 50.0% in 2007, the share for biogas has risen from 4.5% to 7.2%. This suggests that, although biogas production is a mature technology with a limited scope for further technical advances, it is the ongoing quiet achiever in the world of bioenergy and may well continue to expand its share in the renewable energy mix.

J.1.1.6 Hydrogen–fuel cells

Originally invented in 1838, the fuel cell is a theoretically simple device that creates electrical energy from a fuel source and an oxidising agent via a pair of redox chemical reactions (O'Hayre et al 2016). The fuel–most commonly hydrogen–is first split into positive ions and electrons at an anode in the presence of a catalyst. The ions then flow from the anode towards a cathode via an electrolyte compound that runs between them. At the cathode, an oxidising agent–most commonly oxygen–reacts with the ions, also in the presence of a catalyst, to form a waste product, in this example water. Most importantly, the electrons released in the initial reaction generate direct current (DC) electrical energy.

Individual fuel cells are not capable of producing large amounts of power. Consequently, in order to produce usable amounts, many smaller units are typically combined in a multi-cell setup. And, while almost all fuel cells use hydrogen and oxygen as the fuel and oxidising agent, respectively, different fuel cell technologies, capable of producing different levels of power, are distinguished by the electrolyte used as well as their typical operating temperatures.

Smaller-scale units tend to operate at lower temperatures. The most common commercially available examples of these technologies include the well-established alkaline fuel cell (AFC) and the proton-exchange membrane fuel cell (PEMFC), both of which typically operate below 80°C, and the phosphoric acid fuel cell (PAFC), which operates at around 200°C (Badwal et al 2014). Working examples of these technologies have produced power outputs as high as 200-500 kW, although typical applications tend to be far smaller.

Conversely, larger-scale "high-temperature" units, operating at temperatures well over 600°C, are able to produce far higher power outputs. The solid oxide fuel cell (SOFC) and molten carbonate fuel cell (MCFC) have both proven capable of delivering up to 2 MW of power, although designers have predicted that units of up to 100 MW are possible (Smithsonian Institution 2017).

At present, the dominant uses of fuel cell technology are localised power supply and transportation. Stationary fuel cells are already used in a variety of industrial, commercial and residential settings as sources both primary and backup power supplies. Owing to the simplicity and reliability they are especially useful in remote locations. Indeed, alkaline fuel cells provided energy and water to the Apollo spacecraft in the 1960s. Installing fuel cells within post-transition renewable energy power grids has also been identified as a potential solution to the intermittency issues that are inherent to wind and solar energy (Ehteshami and Chan 2014, Heilek et al 2014).

Fuel cell vehicles (FCVs), predominantly cars and buses, are already in use. Although their market penetration has been limited to date, Hyundai, Toyota and Honda all have fuel cell-powered models currently in production. Likewise, although only around 100 buses are in use globally, fuel cell buses are capable of far higher fuel economies than either diesel or natural gas-powered equivalents. Fuel cells are theoretically capable of efficiently powering many other vehicle types, from motorcycles, boats and trains, and even jet engines for aviation (Hamacher 2014). Nevertheless, it is noted that the global availability of platinum–the most common catalyst in FCV cells–has been highlighted as a potential future constraint (Stephens et al 2016).

J.1.1.7 Hydrogen–electrolysis

While the operation of a fuel cell itself does not produce harmful emissions–only electricity and water–it does require hydrogen as a fuel. This is problematic as raw hydrogen is predominantly still produced using processes that utilise fossil fuels in the form of natural gas (48%), oil (30%) and coal (18%), all of which produce sizeable volumes of greenhouse gas emissions (Chouhan et al 2016). The remaining 4% of hydrogen is produced using the far cleaner process of electrolysis, where electrical energy is applied to water to produce hydrogen and oxygen. As such, it can be seen as the reverse of the fuel cell process and equally devoid of harmful emissions.

Accordingly, if the electricity used in this process is derived from renewable sources, electrolysis and the use of hydrogen represents a promising gateway to an array of new possibilities in renewable energy storage and use. Aside from the many functions offered by powering fuel cells, cleanly-produced hydrogen–or “green hydrogen”–can be combusted directly for use as a heat source in a variety of industrial applications, particularly those that require very high heat levels (Wilkes et al 2019). Large-scale electrolysis plants are yet to become operational, although several high-profile demonstrations projects are currently in development, particularly in Europe.

J.1.1.8 Heat pumps

Although not directly related to electricity generation processes, heat pumps are another form of energy-capturing technology making recent headway in the renewable energy sector. They take advantage of the often-small amounts of ambient heat that already exist around us in a variety forms and sources and convert them into useable heat. As these pieces of heat are generally not hot enough to be used directly as heat sources, a heat pump uses external electrical energy to amplify the heat differential to a temperature that is useable for space heating applications, particularly in residential and commercial buildings (Urchueguia 2016).

The concept of the heat pump is a very mature technology; Lord Kelvin first proposed the idea in 1852. In fact, many other common devices that use external energy to move heat from one place to another, such as air conditioners and refrigerators, operate in much the same way using what is known as the vapour-compression refrigeration cycle. First, heat is removed from one location–the "source"–by transferring it into a transfer medium or "refrigerant" within a pipe. The refrigerant is then mechanically compressed, raising its heat and pressure. This pressure increase also helps to transfer it to a second location in the pipe network. Here the temperature of the heated refrigerant drops as it transfers its heat to a cooler space that requires heating–the "sink". The cooler, but still pressurised, refrigerant is then allowed to expand and is moved back to the source location to begin the cycle again.

So, while an additional amount of external energy is required for their operation, the net energy gains from a heat pump can be significant. Certainly, heat pumps use less energy to produce a given amount of heat than the direct use of electrical or fossil fuel energy in, for example, electric furnaces or radiant heaters. It is here that the benefits of heat pumps are best demonstrated, and these benefits are even more pronounced when they are powered by electricity from renewable sources (Ruhnau et al 2020).

The sources of heat used in heat pump setups are generally air and water, although any temperature differential could theoretically be used to drive a heat pump cycle, and heat from such things as sewage, industrial waste and flue gas have been used. Large scale heat pump applications tend to operate on geothermal energy whereby heat from the earth–typically within groundwater, but also within heated streams and other bodies of water, or the earth itself–is used to provide heated water to local networks. In fact, it is estimated that around 70% of the world's geothermal energy consumption is via heat pump applications (DiPippo and Renner 2014).

The heat pump market within the EU is currently dominated by small-scale air-based applications for building heating applications and this is likely to remain the case for the foreseeable future in light of increasing legislation on energy efficient heaters and buildings (Urchueguia 2016). While the geothermal share has stagnated at around 10% in recent years, a growing interest in the use of large-scale heat pumps, where geothermal sources are more prevalent, is predicted to bolster future levels of use. This would seem to be largely driven by the attractiveness of using large-scale heat pumps for district heating and industrial applications (Paardekooper et al 2018).

J.1.2 Technological directions in energy storage

Intermittency factors, inherent in most renewable energy sources, have the potential to introduce major reliability issues to current networks. In fact, it has been estimated that even a 20% increase in renewables use could significantly destabilise many existing networks (Gür 2018). Accordingly, any future attempts to decarbonise energy networks must also include methods for regulating supplies such that they are at least as reliable as energy derived using existing methods. The widespread integration of energy storage technology appears to be the best option for achieving these outcomes.

Most modern applications of the concept of energy storage are within electricity networks. Here, excess electrical energy is converted into a secondary form of energy–typically when it is unneeded or inexpensive–such that it can be reconverted back to electricity at a later time when demands are higher. Again, such mechanisms are vital for contending with the intermittent energy supplies derived from renewable sources. However, storage technology can also act to balance energy loads within networks in real time, which is vital to the efficient functioning of smart grids (Wagner 2014). At smaller scales, energy storage devices are often used to store locally generated renewable energy within buildings or microgrids. Outside of electrical networks, thermal energy is also stored as part of efficient heating and cooling systems.

It is generally assumed that a combination of technologies operating at different scales will be required to perform the range of energy storage tasks required to optimise the operation of future smart grids (Javed et al 2020, Zame et al 2018). Accordingly, a wide variety of energy storage technologies exist, each of which offer their own physical and operational characteristics. These can be characterised by the amounts of energy they can store, the rates of power they can deliver, and the timeframes required to convert and discharge electricity. Values of specific energy and specific power–the energy and power characteristics per unit of mass or volume–are also often discussed as they be decisive practical considerations. Other environmental, resource scarcity, geographic and cost aspects determine the advantages and disadvantages inherent in each energy storage option.

The most common current methods fall broadly into one of two categories. The first involves large-scale electromechanical devices that use potential energy to store higher volumes of energy that is accessed in longer timeframes. This includes pumped hydro and compressed air technologies. The second category involves smaller-scale devices that use electrochemical energy (e.g., batteries), electromagnetic energy (e.g., ultracapacitors) and electromechanical energy in the form of kinetic energy (e.g., flywheels) to store and release smaller volumes of energy within shorter timeframes. The use of thermal storage technologies also occurs at multiple scales.

Data for currently operating energy storage infrastructure is available in the Global Energy Storage Database (U.S. Department of Energy n.d.). A summary of this data–in terms of the percentage of total power capacity assigned to each category–is provided in **Table J.1**. Values are shown for all global infrastructure and for infrastructure within EU-28 countries. In order to estimate future directions for each category, percentage breakdowns are also given for in-progress developments. This includes all projects that have been announced, contracted or are currently under construction.

Table J.1. Summary of operational and in-progress energy storage infrastructure (February 2020). Data source: U.S. Department of Energy (n.d.)

Technology	Global		EU-28	
	Operational	In-progress	Operational	In-progress
TOTAL *[MW]*	173,943	16,681	50,998	2,031
Pumped hydro *[%]*	96.6	78.0	94.9	64.2
Compressed air *[%]*	0.4	5.4	0.6	26.4
Secondary batteries *[%]*	1.0	9.8	0.5	8.6
Flow batteries *[%]*	< 0.1	1.4	< 0.1	0.1
Metal air batteries *[%]*	-	0.1	-	-
Ultracapacitors *[%]*	< 0.1	< 0.1	< 0.1	0.1
Flywheels *[%]*	0.5	0.3	1.7	< 0.1
Thermal energy *[%]*	1.4	5.0	2.3	0.5

The data indicates that the implementation of energy storage is currently dominated by pumped hydro infrastructure. However, it also suggests that the use of CAES is on the rise for large-scale storage applications, particularly within Europe. The use of secondary batteries also appears to be increasing dramatically, suggesting that it is the most significant emerging technology at the smaller scale. The use of flow batteries is also rising, particularly in larger-scale applications, but there appear to be no significant improvements in the use of metal air batteries, ultracapacitors and flywheels. The global use of thermal energy storage is rising, although this does not appear to be being mirrored within Europe at present.

J.1.2.1 Pumped hydro

The concept of storing large volumes of water such that it can be used to produce electricity when required is nothing new; hydroelectric dams have been in existence since the 1890s (Koch 2002). Strictly speaking, these dams represent the world's largest man-made sources of available stored energy. However, their importance is in their ability to store large amounts of potential energy for extended periods. Pumped hydro facilities borrow many of the theoretical fundamentals of hydroelectric dams, albeit at smaller geographical scales and with the purpose of converting electricity back and forth at smaller timescales.

Two bodies of water are required to operate such a facility. Firstly, a lower reservoir or open body of water provides a reliable source of water. Electrical energy from a grid is used to pump water from this source to an upper reservoir when energy is cheaper or more available. Electricity can then be recreated when required by allowing water to flow, under gravity, from the upper reservoir back through a turbine generator near the lower reservoir or water source (Díaz-González et al 2016). Conversion and discharge timescales can be as low as a few hours and efficiencies of between 70 and 85% are generally achieved. The world's highest-rated energy storage facility–the Bath County station in Virginia–outputs over 3 GW of power. In fact, the top 140 energy storage facilities are pumped hydro plants, all of which are capable of producing in excess of 400 MW of power. A typical pumped hydro plant layout is shown in **Figure J.1**.

Figure J.1. The Geesthacht pumped hydro storage plant in Germany. Photo credit: Vattenfall AB

Aside from their high power capacities, the main advantage of such plants is their relatively cheap and easy mode of operation, which involves no significant ongoing emissions or resource scarcity issues. Their projected lifespans are very long, and daily operation costs are low. However, their high setup costs and potential geographic or land availability issues may limit their use in some situations (Wagner 2014). Nevertheless, many new projects are in progress (see **Table J.1**), suggesting that pumped hydro will continue to be a dominant energy storage option for larger-scale applications.

J.1.2.2 Compressed air

Much like pumped hydro storage, compressed air energy storage (CAES) relies on a relatively simple electromechanical process to store electrical energy, typically at the utility scale. In this case, excess electricity is used to operate compressors that push high-pressure air into large underground aquifers, caverns and other rock formations, or into tanks or pipes in smaller-scale operations. When required, this air can then be released through turbine generators to produce new electricity.

Unlike pumped hydro, CAES is a relatively undeveloped technology; only one currently operational plant–the Kraftwerk Huntorf in Germany–can release over 300 MW of power. However, this seems likely to change in the coming years as many new installations are planned (see **Table J.1**), including two plants in the US and one in Northern Ireland, all capable of releasing over 300 MW.

As with pumped hydro, the key advantages to CAES lie in their simplicity and low environmental impacts. Furthermore, as large-scale plants make use of naturally occurring geological spaces, installation costs per watt are typically much lower than for other technologies (Gür 2018). Conversely, this requirement greatly reduces the number of possible sites, at least for large-scale operations. Turnaround timescales for CAES operations are also relatively long and are generally measured in hours or days, while expected efficiencies are no higher than 70%. In any case, CAES appears to represent a key technology in the future of energy storage and, according to 2020 data within the Global Energy Storage Database data (U.S. Department of Energy n.d.), more overall capacity is in progress (903 MW) than is already installed (724 MW). This represents the second highest growth rate according to this ratio, only surpassed by flow batteries (discussed later in the section).

J.1.2.3 Secondary batteries

The use of rechargeable or "secondary" batteries is perhaps the most significant of the currently available energy storage options. For many years, the high cost per unit of energy of these batteries was seen as a limiting factor to their widespread implementation. However, in recent years, substantial cost reductions–around 45% between 2012 and 2018–have resulted in dramatic changes in the prospects of secondary battery implementation at both local and utility scales. Indeed, according to the International Energy Agency (IEA 2019) battery use is predicted to be the fastest growing energy storage resource over the next 20 years, rising in capacity by a factor of 40 by 2040. Aside from the ongoing reductions in cost, the widespread availability, modularity and ease of construction of battery setups has made them an increasingly attractive choice in many energy storage applications.

Several secondary battery technologies have been proposed over the years. The distribution of the most common of these within current energy storage projects, and projects that are in development, are shown in **Table J.2**. Again, values are provided for all global infrastructure and for infrastructure solely within EU-28 countries. The data clearly shows that lithium-ion technology is the most commonly implemented type of secondary battery at present and that they are overwhelmingly the most popular choice for projects that are currently in progress. It is also significant that the total power capacity data for in-progress projects–which includes projects that are announced, contracted or are currently under construction–are roughly on par with operational projects. This suggests a very rapid rise in the use of secondary batteries for energy storage operations worldwide.

Table J.2. Summary of operational and in-progress secondary battery infrastructure (February 2020). Data source: U.S. Department of Energy (n.d.)

Technology	Global		EU-28	
	Operational	In-progress	Operational	In-progress
TOTAL *[MW]*	1,661	1,630	262	175
Lithium-ion *[%]*	80.6	98.3	82.0	97.3
Sodium-ion *[%]*	0.1	< 0.1	< 0.1	-
Lead-acid *[%]*	5.3	1.3	0.8	-
Nickel-cadmium *[%]*	1.8	0.1	1.1	-
Sodium-sulphur *[%]*	11.4	-	14.4	-
Sodium-nickel-chloride (ZEBRA) *[%]*	0.9	0.3	1.6	2.7
Other nickel *[%]*	< 0.1	-	-	-
Zinc-manganese-dioxide *[%]*	-	< 0.1	-	-

The emergence of the lithium-ion battery as the battery of choice in energy storage applications is for good reason. They possess excellent energy density and power-to-energy ratios, discharge and recharge within short timeframes, operate simply and reliably at safe temperatures and require relatively little maintenance. While once slightly restrained by the burden of high setup costs, the popularity of lithium-ion technology has been significantly boosted in recent years by rapid reductions in price and by equally impressive improvements in their energy density characteristics (Nayak et al 2018). And, while other second battery types have proven capable of delivering better returns, lithium-ion installations are still capable of delivering more than adequate round-trip efficiencies of between 70 and 80% for most applications (Schimpe et al 2018).

It should also be noted that the dominance observed in the field of energy storage is part of a larger wave of popularity currently being enjoyed by lithium-ion battery technology in general. For several years it has also been the favoured battery type for portable electronic devices and electric vehicles, among other things, further highlighting the momentum and dominance of the technology within a variety of global markets. This has caused many to begin to investigate the potential that dramatic increases in demand for lithium could have on its global supply reserves and, indeed, on future price variations. Cobalt and nickel are also vital to the creation of lithium-ion batteries and have been identified as further potential sources of future production bottlenecks (Delucchi et al 2014).

A lithium-ion battery used within an electrical grid is expected to have a lifespan of between seven and 10 years (Smith et al 2017). As such, suitable replacement and disposal strategies need to be in place when implementing long-term energy storage projects involving lithium-ion components. Here, improvements in recycling processes–known to be undeveloped at present–could provide economically and ecologically beneficial solutions that also address the resource-scarcity issues surrounding lithium, cobalt and nickel. To date, investigations in this area have tended to neglect options for lithium itself in favour of cobalt, nickel and copper, simply because of its lower market value. However, easily accessible lithium could become scarce by 2050 and recycling processes capable of recovering the majority of lithium from batteries is likely to be needed to sustain supplies into the second half of the century (Hanisch et al 2015).

Although the spread of lithium-ion batteries looks set to continue, scarcity issues, potential environmental impacts–predominantly related to copper and aluminium extraction rather than lithium (Notter et al 2010, Stamp et al 2012)–and the possibility of thermal runaway incidents, such as those that affected air travel in recent years (Zubi et al 2018), have also fuelled research into safer alternatives. The most promising immediate replacements involve sodium-ion batteries (Li et al 2018), which are technologically very similar but far less burdened by resource constraints. What's more, life cycle assessment (LCA) findings suggest that sodium-ion cell production is less damaging to the environment (Peters et al 2016). In any case, sodium-ion batteries are still incapable of comparable lifespans, and this restriction would need to be overcome for them to pose any serious threat to the dominance of lithium-ion cells.

Two formerly prominent older technologies–lead-acid and nickel-cadmium batteries–have fallen notably out of favour. Lead-acid batteries, still extremely common in automobile ignition systems and other settings, were never likely to be adopted in the long-term due to their poor energy density, high operation and maintenance costs, temperature sensitivity, relatively poor reliability, long charge times and, perhaps most notably, their reliance on hazardous lead (Zubi et al 2018). Similarly, nickel-cadmium batteries, which rely on another hazardous substance in cadmium, also suffer from energy density limitations and are susceptible to the "memory effect", where voltage drops occur during use as a result of past recharging patterns.

Once popular in larger-scale applications, particularly in Japan, sodium-sulphur batteries also seem to have lost their appeal. However, they may still prove to be a viable solution in certain applications. The key materials in their design, sodium and sulphur, are both inexpensive and readily available (Gür 2018), energy densities are high, and they can deliver high efficiencies–typically around 90%–throughout a high number of life cycles (Ould Amrouche et al 2016). Nevertheless, as they operate at temperatures of approximately 350°C, they are less practical for safe use in household settings.

Another sodium-based technology–sodium-nickel-chloride or Zero Emissions Batteries Research Activity (ZEBRA) batteries–operate at similarly high temperatures. However, they are considered safer and easier to maintain than sodium-sulphur batteries, while still achieving high efficiencies and long life cycle expectancies (Chamberlain et al 2017). ZEBRA batteries are perhaps best suited to larger storage plant scenarios but are also being considered for their potential in electric vehicle applications. Although their use remains low at the utility level, a small number of newer plants are in development.

J.1.2.4 Flow batteries

A very different type of battery–the flow battery–has also been discussed as a suitable energy storage option, particularly for larger-scale applications for electrical utility and industrial users (Wang et al 2013). Unlike conventional secondary batteries, where energy inside a charged battery is stored within the unit's electrodes, energy inside a flow battery is stored within electroactive chemicals dissolved into liquid electrolytes (Salman 2017). Excess electrical energy is used to charge the batteries by generating these chemicals–and, hence, chemical energy–within an electrolyte solution using a pair of electrodes and a second electrolyte solution as part of an electrochemical reactor cell setup. The energy-rich solution is then stored within an external tank until needed, when the same reactor can be used to convert chemical energy back to electricity (Badwal et al 2014).

Two general types of flow battery exist. In a redox flow battery (RFB) both electrolyte solutions are kept within tanks and pumped into the reactor when in operation. **Table J.3** displays the distribution of flow batteries at the global and EU scales and clearly demonstrates that the vanadium-redox version is the most dominant form, accounting for over half of the globally operational flow battery capacity and a high proportion of the projects now in progress. Vanadium redox batteries also account for most existing and in-progress EU capacity, although it is noted that the use of flow batteries is substantially lower within the EU.

The other type of flow battery is the hybrid flow battery (HFB). Here, one solution remains in the reactor at all times and the second solution is pumped through its side of the reactor during operation. The most common type of HFB is the zinc-bromine version which, although used in around 43% of the currently installed flow battery capacity, appears to be losing its popularity to vanadium redox batteries.

While the total capacity of in-progress flow batteries cannot hope to compete with secondary batteries (see **Table J.3**), the rate of growth is substantially higher; over three times as much capacity is in progress compared to current installations. Although flow batteries are more complex than conventional secondary batteries in many ways, they are capable of fast response times and have relatively high efficiencies of between 75 and 85% (Skyllas-Kazacos et al 2011). Furthermore, as the solutions used within them are very stable and do not degrade over time, flow batteries are theoretically capable of achieving very long lifecycles. So, although they tend to have higher upfront costs, they may be a cheaper option in the long run for long-life applications (Ding et al 2013). New developments in organic redox flow battery technologies may also result in cheaper and less environmentally hazardous alternatives, although more research is required (Zhao et al 2020).

Table J.3. Summary of operational and in-progress flow battery infrastructure (February 2020). Data source: U.S. Department of Energy (n.d.)

Technology	Global		EU-28	
	Operational	In-progress	Operational	In-progress
TOTAL *[MW]*	75	241	1	3
Vanadium redox *[%]*	56.5	88.3	93.8	100.0
Zinc-iron redox *[%]*	0.3	1.3	6.3	-
Zinc-bromine hybrid *[%]*	43.0	10.4	-	-
Hydrogen-bromine hybrid *[%]*	0.1	-	-	-
Zinc-nickel-oxide hybrid *[%]*	0.1	-	-	-

Perhaps the biggest advantage of flow batteries is in their flexibility. In a conventional secondary battery, the amount of energy stored and the power that can be delivered are inextricably tied to the volume of the battery and, thus, to each other. So, to increase the power available from a lithium-ion battery you would typically need to build a larger unit capable of carrying more energy. In flow batteries, however, the energy capacity is defined by the volume of the electrolyte storage tanks, while the power output is derived from the surface area of the electrodes used in the reactor unit. This allows engineers to effectively “decouple” the two concepts and design flow battery modules with the electrode and tank configurations that suit the requirements of individual plants (Gür 2018).

This can be advantageous considering the fact that flow batteries tend to have lower energy densities. Lithium-ion batteries, for example, have higher energy densities, but tend to weigh more and are less suited to stacking. Meanwhile, flow batteries can be stored in modular stacks (see **Figure J.2**) capable of delivering the required power outputs while occupying similar footprints to comparable lithium-ion batteries (Skyllas-Kazacos et al 2011). Again, although lithium-ion batteries dominate the present-day battery market, the ratio of in-progress capacity (241 MW) to operational capacity (75 MW) for flow batteries marks it as having the highest growth rate of all categories presented here. This suggests that flow batteries will continue to be an attractive option in many applications.

J.1.2.5 Ultracapacitors

Ultracapacitors–alternatively known as supercapacitors–work in a similar fashion to batteries. However, rather than using chemical energy as a storage agent, they utilise the electrostatic energy that results from the physical charge separation between two electrodes. As no chemicals are involved, the process is highly reversible and is theoretically capable of undertaking an unlimited number of cycles. Energy efficiency is also very high and values of over 90% are generally achieved. The main downside of using ultracapacitors lies in their inability to contain their charge for long periods of time and most devices lose around 10% of their energy per day (Chamberlain et al 2017). As such, they are often used in places where electrical energy is exchanged relatively quickly, and they are particularly common in railway applications. However, it is hoped that they may find more electrical network applications in the future, particularly in conjunction with batteries in hybrid storage systems (Ould Amrouche et al 2016).

Figure J.2. Typical flow battery installation showing three rows of stacked cells. Photo credit: Redflow Limited

J.1.2.6 Flywheels

Like ultracapacitors, flywheels are used in energy storage applications that require fast charge and discharge rates over short or medium periods of time (Gür 2018). In the case of flywheels, the energy is stored as kinetic energy within a large rotating cylinder that is coupled to an electrical conversion device that acts as both a motor and generator (Akinyele and Rayudu 2014). As a motor, incoming electrical energy is used to drive the wheel, increasing its rotational speed. When energy is required, the converter can act as a generator by applying torque to the rotating cylinder, slowing the wheel and producing electricity (Wagner 2014).

The amount of energy stored within a moving flywheel has a linear relationship to its mass and the square of its rotational velocity. Hence, steel is often used in low-speed flywheels, which operate at speeds of up to 10,000 revolutions per minute (rpm), while high-speed flywheels operating at up to 100,000 rpm tend to incorporate lighter and more efficient composite materials. However, the superior performance offered by high-speed versions comes at a price and they can cost up to five times that of a low-speed equivalent (Arani et al 2017).

While flywheels are normally not capable of achieving high levels of energy density, their key characteristics as energy storage devices are in their abilities to charge and discharge energy at very high rates and, hence, to accumulate and deliver very high levels of power over relatively short periods of time. As such, they are ideal as a “rapid-response” form of storage, best suited to grid-level power quality applications relating to power smoothing, frequency regulation and general stability improvement. However, flywheels have also been implemented specifically to support the integration of renewable energy sources.

Flywheels possess several other important advantages over other energy storage technologies, mostly relating to their relatively simple nature. They are generally very predictable, reliable and require very little ongoing maintenance (Mousavi G et al 2017). Likewise, they are designed to have very long life cycles and a well-engineered unit could theoretically continue to operate indefinitely. So, even if the cost of an installed device is high–up to 40% more than an equivalent battery-based installation–this can be compensated over time. The physical nature of their operation also means that net emissions are very low, making them one of the most environmentally friendly of the current energy storage options.

Efficiency levels in flywheel installations also tend to be high, and efficiencies of between 80 and 90% are typical. However, these levels can drop significantly over time as a result of frictional forces during dissipation; losses can lower efficiencies to below 80% after a few hours and down to 50% if outputting power for 24 hours (Ibrahim et al 2008). Similarly, their low energy density characteristics mean that massive flywheels would be required in order to deliver sustained amounts of energy. This reiterates the fact that flywheels are really only viable for use within minutes or, at most, one or two hours. However, while not the most cutting-edge of the available energy storage options, flywheel projects continue to be implemented and the technology is likely to play a role in future electricity networks.

J.1.2.7 Thermal energy storage

Thermal energy storage devices operate by storing a heated or cooled medium within an insulated enclosure such that it can be used for heating, cooling and power generation at a later time. Installations are categorised into three very distinct functional categories. The first two, both already in widespread use, perform utility operations that offer slight variations in the standard pathways of energy storage devices. A third category, still in its infancy, uses thermal energy to regulate electricity flows within networks in much the same way as other energy storage technologies.

The most common type of thermal energy storage currently in use involves the intermediate storage of heat collected in concentrated solar power (CSP) power plants prior to its conversion to electricity (see **Table J.4**). Here, the intermittency of solar energy is addressed more directly by storing the raw heat generated in CSP processes within large tanks at the plant itself. This heat can be converted directly to electricity and provided to the grid as required. Storage periods are usually less than eight or nine hours, but very high efficiencies–up to 98%–are reported (González-Roubaud et al 2017).

Table J.4. Summary of operational and in-progress thermal energy storage infrastructure (February 2020). Data source: U.S. Department of Energy (n.d.)

Technology		**Global**		**EU-28**	
		Operational	**In-progress**	**Operational**	**In-progress**
TOTAL *[MW]*		2,432	831	1,154	10
Heat storage in solar thermal electricity production	Molten salt	84.0	94.5	95.7	-
	Steam	7.3	1.1	3.9	86.5
Time-shifted electrical cooling	Chilled water	5.6	-	< 0.1	-
	Ice	3.0	4.3	0.4	-
Time-shifted electrical heating		0.1	-	-	-
Pumped thermal electricity storage		-	0.2	-	13.5

The most common medium used to store heat in these plants are so-called molten salts–typically mixtures of sodium and potassium nitrates–which offer good thermal properties at low cost. Heat stored in these salts is converted to steam and used in generators when needed. The only other medium in current operation is steam, which is used for storing heat and driving generators without the need for an additional heat transfer process.

The second category includes technologies that act to "time-shift" the electricity used in heating and cooling operations. Motivated by price incentives and a desire for more efficient temperature-control processes, these systems use a thermal storage medium that can be heated or cooled during off-peak periods, when electricity is cheaper and more readily available, only to be used at a later time (Kalaiselvam and Parameshwaran 2014). The most common application is in cooling (see **Table J.4**), where reserves of cold water or ice are created and stored at night then used during the day in building air conditioning systems.

Applications of this kind are conceptually very similar to conventional energy storage technologies that seek to smooth demands on the electricity network while offering the advantages of demand response mechanisms. However, in these cases, the energy used is not intended to be reconverted to electricity. Rather, the changed thermal properties of the storage media are used directly for their intended purpose at the local scale.

Conversely, the final category–pumped thermal electricity storage (PTES)–operates in precisely the same manner as conventional energy storage technologies in that heat is simply used as the storage method for converting and reconverting electrical energy within grid networks. Various technical methodologies have been proposed, all of which involve relatively simple and well-established engineering theory and, potentially, existing equipment (Benato and Stoppato 2018).

PTES is seen as a potential competitor to large-scale options such as pumped hydro, CAES or flow batteries and is seen as being comparable in cost and projected lifespan, but with considerably less geographic, resource or environmental constraints. However, low efficiency levels–expected to be between 40 and 50% using existing methods–remain a key barrier. This could be overcome by advancing research into this technology. Indeed, the only plant of this type currently in development–the Isentropic PTES demonstration plant in the United Kingdom–is endeavouring to address this and other limitations in the hope that PTES could become a viable large-scale option in the future.

While the overall percentage of in-progress projects (831 MW) to operational projects (2,432 MW) is not as high as flow and secondary batteries or CAES, thermal energy storage installations appear likely to remain an active player in the spectrum of energy storage options. However, it is notable that very few projects are in progress within Europe; aside from the Isentropic PTES demonstration plant, only a single 9 MW steam-based storage at a CSP plant in France is planned. This is likely to change if further CSP plants come online or if PTES is further embraced. For now at least, it appears that Europe is tending towards alternative technologies for its general energy storage applications.

J.1.2.8 Vehicle-to-grid

Another novel idea in the ongoing development of the nexus between energy storage and smart grid technologies is the vehicle-to-grid (V2G) concept. Considering the fact that the average electric vehicle is not being driven approximately 95% of the time, it has been proposed that their batteries could be used as grid-connected energy storage devices during these downtime periods (Mwasilu et al 2014). Using smart technology, owners could choose to sell electricity within their vehicles by either returning it outright or throttling their recharge rates during times of elevated network demand (Tan et al 2016).

Although most electric vehicles use lithium-ion batteries–with efficiencies of around 90%–the actual efficiencies obtained using V2G are likely to be much lower. Various losses within the power electronics components undertaking the AC to DC conversion within a vehicle (Apostolaki-Iosifidou et al 2017), and significant decreases related to higher and lower ambient temperatures, mean that expected efficiencies from using V2G are probably more likely to be between 53 and 70% (Apostolaki-Iosifidou et al 2018, Shirazi and Sachs 2018).

Concerns have also been raised that more frequent and somewhat random charging and discharging of lithium-ion batteries could reduce their battery life and, hence, offset the financial and environmental benefits of taking part in V2G programs. However, research found that battery degradation could actually be reduced by participating in smart grid schemes that optimise vehicle battery use as part of its operations (Uddin et al 2017). Although still in its early stages of development, V2G technology could offer another innovative pathway for stabilising electricity networks and allowing greater infiltration of renewable energy sources while offering demand response incentives to energy users.

J.2 First article

Table J.5. Summary of Ecoinvent processes used in analysis and derived GHG emissions according to “ReCiPe Midpoint (H):GWP100” method

Category	Activity name	Location	GWP100 *[g CO_2-eq/MJ]*
Hydro	electricity production, hydro, reservoir, non-alpine region	RoW	13.82
	electricity production, hydro, reservoir, alpine region	RoW	1.82
	electricity production, hydro, run-of-river	RoW	1.21
Wind	electricity production, wind, 1-3MW turbine, onshore	RoW	3.97
	electricity production, wind, <1MW turbine, onshore	RoW	4.61
	electricity production, wind, >3MW turbine, onshore	RoW	9.84
	electricity production, wind, 1-3MW turbine, offshore	RoW	4.44
Solar PV	electricity production, photovoltaic, 570kWp open ground installation, multi-Si	RoW	21.12
	electricity production, photovoltaic, 3kWp facade installation, multi-Si, laminated, integrated	RoW	26.63
	electricity production, photovoltaic, 3kWp facade installation, multi-Si, panel, mounted	RoW	28.86
	electricity production, photovoltaic, 3kWp facade installation, single-Si, laminated, integrated	RoW	31.43
	electricity production, photovoltaic, 3kWp facade installation, single-Si, panel, mounted	RoW	33.53
	electricity production, photovoltaic, 3kWp flat-roof installation, multi-Si	RoW	19.32
	electricity production, photovoltaic, 3kWp flat-roof installation, single-Si	RoW	22.42
	electricity production, photovoltaic, 3kWp slanted-roof installation, a-Si, laminated, integrated	RoW	14.01
	electricity production, photovoltaic, 3kWp slanted-roof installation, a-Si, panel, mounted	RoW	19.62
	electricity production, photovoltaic, 3kWp slanted-roof installation, CdTe, laminated, integrated	RoW	10.56
	electricity production, photovoltaic, 3kWp slanted-roof installation, CIS, panel, mounted	RoW	16.28
	electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, laminated, integrated	RoW	17.36
	electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted	RoW	20.45
	electricity production, photovoltaic, 3kWp slanted-roof installation, ribbon-Si, laminated, integrated	RoW	15.85
	electricity production, photovoltaic, 3kWp slanted-roof installation, ribbon-Si, panel, mounted	RoW	18.09
	electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, laminated, integrated	RoW	20.59
	electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted	RoW	23.72
Bioenergy	heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014	RoW	16.53
	heat and power co-generation, biogas, gas engine	RoW	51.58
	heat and power co-generation, wood chips, 2000 kW	CH	17.63
	electricity production, wood, future	GLO	11.47
	heat and power co-generation, wood chips, 2000 kW, state-of-the-art 2014	CH	17.62
	heat and power co-generation, wood chips, 6667 kW	RoW	17.62
Geothermal	electricity production, deep geothermal	RoW	18.68
Solar CSP	electricity production, solar thermal parabolic trough, 50 MW	RoW	13.65
	electricity production, solar tower power plant, 20 MW	RoW	12.18

J.3 Second article

Table J.6. Stakeholder engagement activities and participants

Method	Questions and content	Engaged model users	Further information
Interviews in five jurisdictions: 1) The EU, 2) Germany, 3) Greece, 4) Poland, 5) Sweden	Interview guidelines included questions to energy modellers: 1) In your opinion, what kind of information should an energy model deliver, now and in the future, to inform decision-making (processes) in energy policy? 2) In your opinion, how should the process of model development be designed to increase the chance of the later model use in policymaking? 3) Which conditions must be given that increase the chance that you would use the models or the results, respectively, in future policymaking/your work? Questions to non-modellers were also included: 1) What are the current and future challenges or aspects of the energy transition that should be integrated into future energy models? 2) In your opinion, what kind of information should an energy model deliver to help make good decisions about energy policy/energy issues? 3) Which conditions must be given that increase the chance that you would use the models or the results, respectively, in future policymaking/your work?	32 interviewees: 11 policymakers, 4 energy industry experts, 5 NGO representatives, 12 researchers	Complete interview guideline (Süsser et al 2021b)
Online survey	Survey was designed around six sections: 1) Personal background, model use, and general demands, 2) Model content, 3) Model design, 4) Modelling process, 5) Modelling outreach, 6) Others and demographic data	90 responders: 12 policymakers, 16 energy industry experts, 11 NGO representatives, 42 researchers	Complete survey (Gaschnig et al 2021)
Workshop on user needs for energy modelling, European Member States	Five breakout sessions: 1) Social and policy aspects in energy models 2) Including environmental aspects in energy system models 3) Modelling energy demand and supply 4) Modelling the economic impacts of the energy transition 5) Designing the model platform of SENTINEL	23 non-SENTINEL participants from different European Member States: 2 policymakers, 11 energy industry experts, 6 NGO representatives, 4 researchers	Full list of participants (Süsser et al 2020)

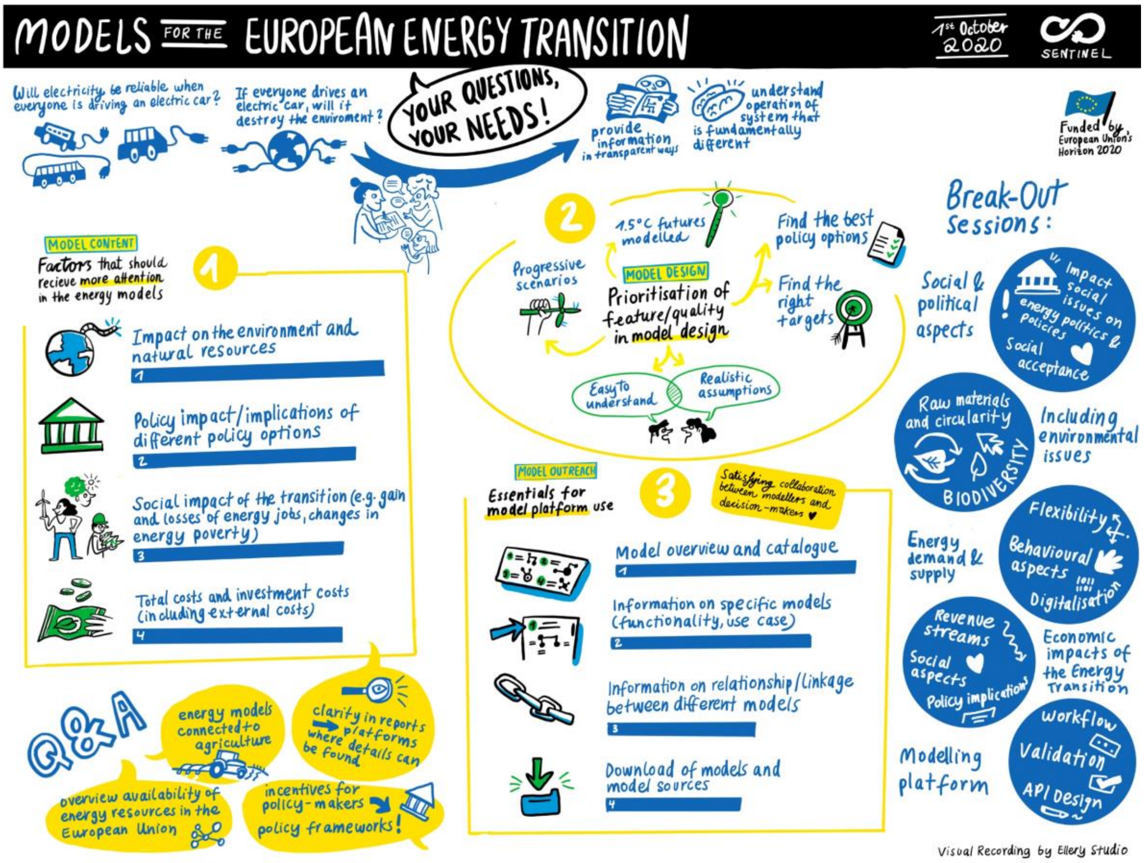


Figure J.3. Graphical recording of the workshop, including a ranking of factors that receive more attention in energy models

J.4 Third article

Table J.7. LCI data for renewable energy supply and infrastructure available in Ecoinvent v3.7.1 and GaBi 2020

Source	Carrier	Ecoinvent v3.7.1		GaBi 2020	
		Energy	Infrastructure	Energy	Infrastructure
Biodiesel	Fuel	39 LCI datasets 8 biodiesel, 31 ethanol Geography: 25 global, 2 EU, 12 specific EU states Time: 29 pre-2010, 10 2010-2015	3 LCI datasets 3 ethanol Geography: 2 global, 1 Swiss Time: 2 pre-2010, 1 2010-2015	11 LCI datasets 2 biodiesel, 9 ethanol Geography: 9 EU, 2 German Time: 2016 or 2019	
	Electricity	1 LCI dataset Geography: 1 Swiss Time: 1 2010-2015			
Biogas	Fuel	39 LCI datasets Geography: 19 global, 20 Swiss Time: 20 pre-2010, 7 2010-2015, 12 2015-2020	12 LCI datasets Geography: 8 global, 4 Swiss Time: 8 pre-2010, 4 2010-2015	39 LCI datasets Geography: 3 EU, 36 specific EU states Time: 2016 or 2019	
	Heat	8 LCI datasets Geography: 3 global, 3 EU, 2 Swiss Time: 3 pre-2010, 3 2010-2015, 2 2015-2020		102 LCI datasets Geography: 2 EU, 100 specific EU states Time: 2016 or 2019	
	Electricity		34 LCI datasets Geography: 2 EU, 32 specific EU states Time: 2016 or 2019		
	Combined	64 LCI datasets Geography: 4 global, 60 specific EU states Time: 64 2015			
Biomass	Heat	87 LCI datasets 12 logs, 4 straw, 4 waste wood, 49 wood chips, 18 wood pellets Geography: 43 global, 6 EU, 38 Swiss Time: 10 pre-2010, 77 2010-2015	3 LCI datasets 3 wood pellets Geography: 2 global, 1 EU Time: 3 2010-2015	185 LCI datasets 27 general, 5 peat, 90 wood chips, 63 wood pellets Geography: 11 EU, 174 specific EU states Time: 2016 or 2019	33 LCI datasets 21 wood chips, 12 wood pellets Geography: 13 EU, 20 German Time: 2016 or 2019
	Electricity	7 LCI datasets 6 peat, 1 wood chips Geography: 2 global, 5 specific EU states Time: 6 2010-2015, 1 2015-2020		47 LCI datasets 41 general, 6 peat Geography: 6 EU, 41 specific EU states Time: 2016 or 2019	
	Combined	88 LCI datasets 84 wood chips, 4 wood pellets Geography: 12 global, 76 specific EU states Time: 4 pre-2010, 84 2010-2015	1 LCI datasets 1 wood pellets Geography: 1 global Time: 1 2010-2015	2 LCI datasets 1 general, 1 wood chips Geography: 1 EU, 1 German Time: 2016 or 2019	
Fuel cells	Electricity		17 LCI datasets Geography: 12 global, 5 Swiss		

			Time: 10 pre-2010, 7 2010-2015		
Geothermal	Electricity	14 LCI datasets Geography: 1 global, 13 specific EU states Time: 7 2010-2015, 7 2015-2020	8 LCI datasets Geography: 6 global, 2 specific EU states Time: 2 pre-2010, 6 2010-2015	6 LCI datasets Geography: 2 EU, 4 specific EU states Time: 2016 or 2019	
Heat pumps	Heat	11 LCI datasets 3 general, 6 electric (3 air, 3 brine), 2 gas Geography: 4 global, 3 EU, 4 Swiss Time: 11 pre-2010	13 LCI datasets 3 general, 6 electric (3 general, 3 brine), 4 gas Geography: 8 global, 2 EU, 3 Swiss Time: 8 pre-2010, 5 2010-2015	284 LCI datasets 168 electric (84 brine, 84 water), 116 gas Geography: 10 EU, 174 specific Time: 2016 or 2019	81 LCI datasets 75 electric (12 air, 42 brine, 21 water), 6 gas Geography: 30 EU, 51 German Time: 2016 or 2019
Hydro	Electricity	55 LCI datasets 33 run-of-river, 22 reservoir Geography: 6 global, 49 specific EU states Time: 53 2010-2015, 2 2015-2020	13 LCI datasets 4 run-of-river, 9 reservoir Geography: 8 global, 3 EU, 2 Swiss Time: 9 pre-2010, 4 2010-2015	34 LCI datasets 34 general Geography: 4 EU, 30 specific EU states Time: 2016 or 2019	
Solar PV	Electricity	99 LCI datasets 91 first gen (37 single, 50 multi, 4 ribbon), 8 second gen (4 a-Si, 2 CdTe, 2 CIS) Geography: 19 global, 80 specific EU states Time: 14 pre-2010, 77 2010-2015, 8 2015-2020	125 LCI datasets 27 general, 73 first gen (28 single, 27 multi, 18 ribbon), 25 second gen (10 a-Si, 6 CdTe, 9 CIS) Geography: 87 global, 17 EU, 21 specific EU states Time: 81 pre-2010, 44 2010-2015	33 LCI datasets 33 general Geography: 1 global, 2 EU, 30 specific EU states Time: 2016 or 2019	
Solar thermal	Heat	8 LCI datasets 6 flat plate, 2 tube Geography: 4 global, 4 Swiss Time: 8 pre-2010	21 LCI datasets 3 general, 12 flat plate, 6 tube Geography: 14 global, 1 EU, 6 specific EU states Time: 14 pre-2010, 7 2010-2015	60 LCI datasets 30 flat plate, 30 tube Geography: 2 EU, 58 specific EU states Time: 2016 or 2019	15 LCI datasets 8 flat plate, 7 tube Geography: 7 EU, 8 German Time: 2016 or 2019
	Electricity	4 LCI datasets 2 parabolic trough, 2 power tower Geography: 2 global, 2 Spanish Time: 4 2015-2020	16 LCI datasets 6 parabolic trough, 10 power tower Geography: 16 global Time: 15 2015-2020	3 LCI datasets 3 Fresnel reflector Geography: 2 EU, 1 Spanish Time: 2016 or 2019	
Wind	Electricity	111 LCI datasets 96 onshore, 15 offshore Geography: 8 global, 103 specific EU states Time: 98 2010-2015, 13 2015-2020	22 LCI datasets 4 general, 14 onshore, 4 offshore Geography: 22 global Time: 14 pre-2010, 8 2010-2015	35 LCI datasets 35 general Geography: 4 EU, 31 specific EU states Time: 2016 or 2019	

Table J.8. Description of the most widely used LCIA methods for each impact category)

Life Cycle Impact Assessment methods						
	Framework	CML2002	ILCD2010	ReCiPe	EU PEF	ImpactWorld+
	Reference	Global	Europe	Global	Europe	Global
	Publication date	2002	2010	2016	2018	2019
	Damage assessment	No	Yes	Yes	No	Partially
	Normalisation	Global	Global	Global	Global	none
	Weighting	No	Yes	Yes	Yes	No
	Reference	(de Bruijn et al 2004)	(European Commission 2010b)	(Huijbregts et al 2017)	(European Commission, 2018a)	(Bulle et al 2019)
Environmental impact categories						
Resources	**Energy, non-renewable**	[MJ] (de Bruijn et al 2004)	[kg Sb-eq] Midpoint indicator for fossil energy resource use	[kg oil] The midpoint indicator for fossil resource use, determined as the Fossil Fuel Potential of fossil resource x (kg oil-eq/unit of resource), is defined as the ratio between the energy content of fossil resource x and the energy content of crude oil (Vieira et al 2017)	[MJ] (de Bruijn et al 2004)	[MJ derived] (Emamgheis 2014)
Resources	**Ore and minerals**	[kg Sb-eq] Within midpoint indicator for "depletion of abiotic resources" (de Bruijn et al 2004)	[kg Sb-eq] Within midpoint indicator for "resource depletion"	[kg Cu-eq] The midpoint characterization factor (CF) for mineral resource scarcity is Surplus Ore Potential (SOP) which expresses the average additional amount of ore to be produced in the future due to the extraction of 1 kg of a mineral resource x, considering all future production (R) of that mineral resource relative to the average extra amount of ore produced in the future due to the extraction of 1 kg of copper (Cu), considering all future production of copper (Vieira et al 2017).	[kg Sb-eq] (de Bruijn et al 2004)	[kg derived] For mineral resource depletion impact, the material competition scarcity index is applied as a midpoint indicator (de Bruille 2014)
Resources	**Water depletion/scarcity**	*None currently, but further research recommended*	[m^3 water eq] Not specifically modelled. But available within midpoint indicator for "resource depletion"	[m^3 water consumed] Midpoint and endpoint CFs for impacts on human health and terrestrial vegetation (ecosystem quality) (Pfister et al 2009, de Schryver et al 2011) and impacts from water consumption on the aquatic ecosystems endpoint (Hanafiah et al 2011)	[m^3 world eq] Available WAter REmaining (AWARE) value (Frischknecht and Jolliet 2017)	[m^3 world eq] Water consumption impacts are modelled using the consensus-based scarcity indicator AWARE as a proxy midpoint, while damages account for competition and adaptation capacity (Boulay et al 2018)

	Land occupation	[units] As "land use – land competition"(Heijungs et al 1992)	[kg C deficit] Midpoint indicator for "land use". Both direct land use and indirect land use under consequential modelling are inventoried and used for emissions calculations	[$m^2 \times$ yr annual cropland] CFs for the impact of land transformation and occupation are based on relative species losses (de Baan et al 2013, Elshout et al 2014). CFs for land relaxation are calculated based on the model (Koellner and Scholz 2007), using applicable recovery times (Curran et al 2016)	[units] Soil quality index based on LANCA (Beck et al 2010, Bos et al 2016)	[m^2 arable land eq yr (biodiversity)] Impacts on ecosystem quality from land occupation empirically characterized at the biome level (Saad et al 2011, de Baan et al 2013, Cao et al 2015)
	Land-transformation	-	-	[units] Included within the midpoint CFs for agricultural land occupation potential (ALOP) and the endpoint damage pathway for land use (de Baan et al 2013, Curran et al 2016)	-	[m^2 arable land eq] Impacts on ecosystem quality from land transformation empirically characterized at the biome level (Saad et al 2011, de Baan et al 2013, Cao et al 2015, Curran et al 2016)
Emissions	**Climate change incl. CO_2**	[kg CO_2-eq] (Heijungs et al 1992)	[kg CO_2-eq] Uses IPCC report (IPCC 2013)	[kg CO_2-eq] The GWPs for 20 and 100 years are directly provided by IPCC report (IPCC 2013)	[kg CO_2-eq] Baseline model for 100 years from IPCC report (IPCC 2013)	[kg CO_2-eq] Complementary to the global warming potential (GWP100), the IPCC Global Temperature Potentials (GTP100) are used as a proxy for climate change long-term impacts at midpoint. At damage level, shorter-term damages (after 100 years from time of emission) are also differentiated from long-term damages (de Schryver et al 2009, Joos et al 2012, Myhre et al 2013, Levasseur et al 2016)
	Ozone depletion	[kg CFC-11-eq] (Heijungs et al 1992)	[kg CFC-11-eq] Midpoint indicator for "ozone depletion"	[kg CFC-11-eq] Ozone Depletion Potentials (Hayashi et al 2006, de Schryver et al 2011, World Meteorological Organization 2010)	[kg CFC-11-eq] Steady-state ODPs (Frischknecht and Jolliet 2017).	[kg CFC-11-eq] (The Royal Society 2008, Struijs et al 2009)
	Human toxicity	[kg 1,4-DB-eq] (Heijungs et al 1992)	[CTUh] Midpoint indicator for "human toxicity"	[kg 1,4-DCB to urban air] The multimedia fate, exposure and effects model USES-LCA, the Uniform System for the Evaluation of Substances adapted for LCA (van Zelm et al 2009, 2013)	[kg 1,4-DCB to urban air] Both cancer and non-cancer according to USEtox model (Rosenbaum et al 2008)	[kg 1,4-DCB to urban air] Human ecotoxicity impacts based on the parameterized version of USEtox for continents. The authors consider indoor emissions and differentiate the impacts of metals and persistent organic pollutants for the first 100 years from longer-term impacts

						(Huijbregts et al 2005a, Hauschild et al 2008a, Rosenbaum et al 2008a, Hellweg et al 2009a, Fantke et al 2011a, Kounina et al 2013a, Fantke and Jolliet 2016a)
	Particulate matter	-	[kg PM2.5-eq] Midpoint indicator for "respiratory inorganics"	[kg PM2.5-eq] For the midpoint characterization factors of damage to human health due to PM2.5, the intake of pollutants is important as the effect and damage are precursor substance independent. The intake fraction (iF) of fine particulate matter due to emissions in region i is determined per precursor x ($iF_{x,i}$). Particulate matter formation potentials (PMFP) are expressed in primary PM2.5-equivalents by dividing $iF_{x,i}$ with the emission-weighted world average iF of PM2.5 (van Zelm et al 2016)	Disease incidence PM method recommended by UNEP (Frischknecht and Jolliet 2017).	[kg PM2.5-eq] Particulate matter formations are modelled using the USEtox regional archetypes to calculate intake fractions and epidemiologically derived exposure response factors (Humbert et al 2011, Gronlund et al 2015, Fantke and Jolliet 2016a)
	Photochemical ozone formation	[kg C_2H_4-eq] (Heijungs et al 1992)	[kg NMVOC-eq] Midpoint indicator for "(ground-level) photochemical ozone formation"	[kg NO_x to air (ecosystem quality)] [kg NOx to air (human health)] ODPs calculated using World Meteorological Organization method (World Meteorological Organization 2010)	[kg NMVOC-eq] LOTOS-EUROS model (Huijbregts et al 2017) as implemented in ReCiPe 2008	[kg NMVOC-eq]
	Ecotoxicity	[kg 1,4-DB-eq] (Heijungs et al 1992) However, not included in baseline impact categories. Rather, within the "study-specific" category	[CTUe(freshwater)] Midpoint indicator for "ecotoxicity" includes freshwater, marine and terrestrial	[kg 1,4- DCB to industrial soil (terrestrial)] [kg 1,4- DCB to fresh water] [kg 1,4- DCB to marine water] Toxicity potential (TP) used as CF at the midpoint level for human toxicity, freshwater aquatic ecotoxicity, marine ecotoxicity and terrestrial ecotoxicity (van Zelm et al 2009, 2013)	[CTUe] Freshwater: USEtox model (Rosenbaum et al 2008a)	[CTUe (freshwater)] Ecotoxicity impact based on parameterized version of USEtox for continents. The authors consider indoor emissions and differentiate impacts of metals and persistent organic pollutants for the first 100 years from longer-term impacts (Hauschild et al 2008b, Rosenbaum et al 2008b, Kounina et al 2013b, Huijbregts et al 2005b, Hellweg et al 2009b, Fantke et al 2011b, Fantke and Jolliet 2016b)

	Acidification	[kg SO_2-eq] (Heijungs et al 1992)	[Mol H^+-eq] Midpoint indicator for “acidification” includes land and water	[kg SO_2 to air (Terrestrial)] Terrestrial: The fate factor (FF) for acidification due to emissions in grid i is determined per precursor x ($FF_{x,i}$). Acidification Potential (AP), expressed in kg SO_2 equivalents, is calculated by dividing $FF_{x,i}$ by emission-weighted world average FF of SO_2 (Roy et al 2014b)	[Mol H^+-eq] Accumulated Exceedance (Seppälä et al 2006, Posch et al 2008)	[kg SO_2-eq] Terrestrial and freshwater acidification impact assessment combines global atmospheric source-deposition relationships with soil and water ecosystems’ sensitivity at a resolution of 2° × 2.5° (latitude × longitude) Terrestrial and freshwater: based on several related studies (Roy et al 2012a, 2012b, 2014a) Marine: based on the same fate model as climate change, combined with the H+ concentration affecting 50% of the exposed species
	Eutrophication	[kg PO_4^{2-}-eq] (Heijungs et al 1992)	[Mol N-eq terrestrial] [kg N-eq marine] [kg P-eq freshwater] Midpoint indicator for “eutrophication” includes land and water	[kg N-eq marine] [kg P-eq freshwater] Freshwater: country and world aggregated fate factors (Helmes et al 2012) based on gridded population estimates which served as proxy for emission intensity of P in a grid. (Helmes et al 2012, Azevedo et al 2013a, 2013b) Marine: emission (E)-weighted combined fate factor and exposure factor, scaled to the world average of N emitted to marine water (Cosme et al 2015, Cosme and Hauschild 2016)	[mol N-eq terrestrial] [kg N-eq marine] [kg P-eq freshwater] Terrestrial: Accumulated Exceedance (Seppälä et al 2006, Posch et al 2008) Freshwater: EUTREND model (Struijs et al 2009) as implemented in ReCiPe	[kg N N-lim-eq marine] [kg PO_4 P-lim-eq freshwater] Marine: (Roy et al 2012) Freshwater: spatially assessed in 0.5° × 0.5° grid based on global hydrological dataset (Tirado-Seco 2005, Helmes et al 2012)
	Ionising radiation	[units] (Heijungs et al 1992) However, not included in baseline impact categories. Rather, included within the “study-specific” category	[CTUe (E interim)] [kBq U-235-eq (HH)] Midpoint indicator for “ionising radiation” in units of kBq (for emitted radioactive isotopes)	[kBq Co-60 to air] Relative to the emission of reference substance cobalt-60 to air, yielding a midpoint factor in Co-60 to air equivalents (Frischknecht et al 2000, de Schryver et al 2011)	[kBq U-235-eq (HH)] Human health effect model (Dreicer et al 1995, Frischknecht et al 2000)	[BqC-14-eq] (Frischknecht et al 2000, Margni et al 2008, Garnier-Laplace et al 2015)

Table J.9. Methodologies that account for resource depletion. Based on Sonderegger et al (2020)

Name	Description	Units
Cumulative Energy Demand (CED)	Accounts for resources which may be used as energy carriers and, hence, neglects resources traditionally considered nonenergetic like water, minerals, and metals.	MJ-eq
Abiotic Depletion Potential (ADP)	Based on the ratio between the annual extraction of mineral resources and the square of a natural stock estimate (Guinée et al 2011). There are several variations: ADP ultimate reserves (crustal content estimates) ADP reserve base (USGS 2010 estimates) ADP economic reserves (USGS 2010 estimates)	kg Sb-eq
ReCiPe 2008–ore grade–surplus cost method	Evaluates the grades and yields of all mines exploiting a particular deposit type in order to estimate marginal ore grade decline and assumes a constant cost to calculate the surplus cost (Huijbregts et al 2017).	kg Cu-eq
Cumulative Exergy Demand (CExD)	Accounts for energy and non-energetic resources (water, minerals, metals) (Dewulf et al 2007).	MJex
Cumulative Exergy Extraction from the Natural Environment (CEENE)	Accounts for evaluates energy carriers, nonenergetic resources, and land occupation (Dewulf et al 2007).	MJex

Table J.10. Additional impact categories for possible use in ESM

Global warming potential (GWP)
GWP information, in kg CO_2-eq produced per kg of material, is provided as a midpoint indicator for all common material inputs within the Ecoinvent database. A net value of GWP can be calculated by summing the product of material intensity–the mass, in kg, of each material required to produce a single MW of installed energy-production capacity–and GWP for all individual materials in an infrastructure device. For m individual material components, the formula is as follows: $$GWP_{technology} = \sum_{i=1}^{n} m_i \, GWP_i$$ where: $GWP_{technology}$ = net GWP of the technology under study [kg CO_2-eq/MW] n = number of individual materials in the technology under study m_i = mass of material i contained in the technology under study [kg/MW] GWP_i = GWP of material i [kg CO_2-eq/MW]
Cumulative energy demand (CED)
Information for CED–the number of MJ of energy required to produce a kg of each material–is also provided as a midpoint indicator in the Ecoinvent database. A net value of the CED requirement for a single MW of installed energy-production capacity is calculated in much the same way as the GWP. The formula is as follows: $$CED_{technology} = \sum_{i=1}^{n} m_i \, CED_i$$ where: $CED_{technology}$ = net CED of the technology under study [MJ/MW] n = number of individual materials in the technology under study m_i = mass of material i contained in the technology under study [kg/MW] CED_i = GWP of material i [MJ/MW]

Table J.11. Sources of LCA and material metabolism data for wind turbine case study

Parameter	Material	Source
GWP[a] and CED[b]	Concrete	Ecoinvent v3.7.1, "market group for concrete, normal, GLO". Converted from m^3 to kg assuming a density of 2400 $kg.m^{-3}$
	Glass/carbon composites	Ecoinvent v3.7.1, "market for glass fibre, GLO"
	Cast iron	Ecoinvent v3.7.1, "market for cast iron, GLO"
	Polymers (epoxy resins)	Ecoinvent v3.7.1, "market for epoxy resin, liquid, RER"
	Steel	Ecoinvent v3.7.1, "market for steel, low-alloyed, GLO"
	Aluminium (Al)	Ecoinvent v3.7.1, "market for aluminium, wrought alloy, GLO" (64%), "market for aluminium scrap, new, RER" (20%), "market for aluminium scrap, post-consumer, GLO" (16%). Splits from Nuss and Eckelman (2014)
	Boron (B)	Ecoinvent v3.7.1, "market for borax, anhydrous, powder, GLO" (81%), "market for boric acid, anhydrous, powder, GLO" (19%). Splits from Nuss and Eckelman (2014)
	Chromium (Cr)	Ecoinvent v3.7.1, "market for chromite ore concentrate, GLO". Splits from Nuss and Eckelman (2014)
	Copper (Cu)	Ecoinvent v3.7.1, "market for copper concentrate, sulfide ore, GLO" (84%), "market for copper scrap, sorted, pressed, GLO" (16%). Splits from Nuss and Eckelman (2014)
	Dysprosium (Dy)	No data available in Ecoinvent 3.7.1. Values taken from Nuss and Eckelman (2014)
	Manganese (Mn)	Ecoinvent v3.7.1, market for ferromanganese, high-coal, 74.5% Mn, GLO" (97%), "market for manganese, GLO" (1%), "market for manganese concentrate, GLO" (1%), "market for manganese(III) oxide, GLO" (1%). Splits from Nuss and Eckelman (2014)
	Molybdenum (Mo)	Ecoinvent v3.7.1, "market for molybdenum, GLO", as per Nuss and Eckelman (2014)
	Neodymium (Nd)	Ecoinvent v3.7.1, "market for neodymium oxide, GLO", as per Nuss and Eckelman (2014)
	Nickel (Ni)	Categories available in Ecoinvent 3.7.1 very different to those in Nuss and Eckelman (2014). So, values taken directly from Nuss and Eckelman (2014)
	Praseodymium (Pr)	Ecoinvent v3.7.1, "market for praseodymium oxide, GLO", as per Nuss and Eckelman (2014)
	Terbium (Tb)	No data available in Ecoinvent 3.7.1. Values taken directly from Nuss and Eckelman (2014)
	Zinc (Zn)	Ecoinvent v3.7.1, "market for zinc, GLO", as per Nuss and Eckelman (2014)
EU consumption	Aluminium (Al)	European Commission (2020)
	Boron (B)	European Commission (2020)
	Chromium (Cr)	Bobba et al (2020)
	Copper (Cu)	Bobba et al (2020)
	Dysprosium (Dy)	European Commission (2020)
	Manganese (Mn)	Bobba et al (2020)
	Molybdenum (Mo)	Bobba et al (2020)
	Neodymium (Nd)	European Commission (2020)

	Nickel (Ni)	Bobba et al (2020)
	Praseodymium (Pr)	European Commission (2020)
	Terbium (Tb)	European Commission (2020)
	Zinc (Zn)	Bobba et al (2020)
EU SR	All elemental metals	European Commission (2020)
EoLRIR	Concrete	Eurostat (2021)
	Glass/carbon composites	Mohamed Sultan and Mativenga (2019) Recycling plus reuse of glass fibres and carbon fibres in the UK assumed to be 18% and 20%, respectively, averaged to 19%
	Cast iron	Data for iron and steel (Graedel et al 2011, USGS 2021) varies between 52% and 98%, depending on its use. Recycling of iron from construction sector tends to be far higher (as high as 98%). Conservatively assume 85% for wind turbines
	Polymers (epoxy resins)	Recycling of epoxies in wind turbines assumed to be very minimal (Wu et al 2019), although recyclable technologies are being developed. Arbitrarily set rate to 1%
	Steel	As for cast iron, above. Assumed to be 85% for wind turbines
	All elemental metals	European Commission (2020)

[a] "IPCC 2013:climate change:GWP 100a" category, [b] Sum of all CED categories

Table J.12. Sources of LCA and material metabolism data for solar PV case study

Parameter	Material	Source
GWP[a] and CED[b]	Concrete	Ecoinvent v3.7.1, "market group for concrete, normal, GLO". Converted from m^3 to kg assuming a density of 2400 kg/m^3
	Glass	Ecoinvent v3.7.1, "market for flat glass, uncoated, RER"
	Plastic	Ecoinvent v3.7.1, "market for polystyrene, expandable, GLO"
	Steel	Ecoinvent v3.7.1, "market for steel, low-alloyed, GLO"
	Aluminium (Al)	Ecoinvent v3.7.1, "market for aluminium, wrought alloy, GLO" (64%), "market for aluminium scrap, new, RER" (20%), "market for aluminium scrap, post-consumer, GLO" (16%). Splits from Nuss and Eckelman (2014)
	Cadmium (Cd)	Ecoinvent v3.7.1, "market for cadmium, GLO" (50%), "market for cadmium, semiconductor-grade, GLO" (50%). Splits from Nuss and Eckelman (2014)
	Copper (Cu)	Ecoinvent v3.7.1, "market for copper concentrate, sulfide ore, GLO" (84%), "market for copper scrap, sorted, pressed, GLO" (16%). Splits from Nuss and Eckelman (2014)
	Gallium (Ga)	Ecoinvent v3.7.1, "market for gallium, semiconductor-grade, GLO", as per Nuss and Eckelman (2014)
	Germanium (Ge)	No data available in Ecoinvent 3.7.1. Values taken directly from Nuss and Eckelman (2014)
	Indium (In)	Ecoinvent v3.7.1, "market for indium, GLO", as per Nuss and Eckelman (2014)
	Selenium (Se)	Ecoinvent v3.7.1, "market for selenium, GLO", as per Nuss and Eckelman (2014)
	Silicon (Si)	Ecoinvent v3.7.1, "market for silicon, solar grade, GLO", as per Nuss and Eckelman (2014)
	Silver (Ag)	Ecoinvent v3.7.1, "market for silver, GLO", as per Nuss and Eckelman (2014)
	Tellurium (Te)	Ecoinvent v3.7.1, "market for tellurium, semiconductor-grade, GLO", as per Nuss and Eckelman (2014)
EU consumption	Aluminium (Al)	European Commission (2020)
	Cadmium (Cd)	Bobba et al (2020)
	Copper (Cu)	Bobba et al (2020)
	Gallium (Ga)	European Commission (2020)
	Germanium (Ge)	European Commission (2020)
	Indium (In)	European Commission (2020)
	Selenium (Se)	Bobba et al (2020)
	Silicon (Si)	European Commission (2020)
	Silver (Ag)	Bobba et al (2020)
	Tellurium (Te)	Bobba et al (2020)
EU SR	All elemental metals	European Commission (2020)
EoLRIR	Concrete	Eurostat (2021) Recovery rate of construction and demolition waste in 2018 for all EU-28 countries given as 90%
	Glass	No specific data found for building or construction glass. Building-related glass is almost never recycled to new glass in current systems (Hestin et al 2016). However, it is often recovered and reused alongside general building waste at a rate of around 40%. So, assume a rate of 40%

	Plastic	No specific data found. However, the overall rate of plastic recycling in Europe is around 30% or 32.5% (PlasticsEurope 2019) and 30% for all developed countries (D’Ambrières 2019). The exact rates for the various plastics–even if assumed to be mostly polystyrene–in solar PV installations are difficult to know. But assume a general rate of 32.5%
	Steel	Data for iron and steel (Graedel et al 2011, USGS 2021) varies between 52% and 98%, depending on its use. Recycling of iron from construction sector tends to be far higher (as high as 98%). Conservatively assume 85% for solar PV at all scales
	All elemental metals	European Commission (2020)

[a] “IPCC 2013:climate change:GWP 100a” category, [b] Sum of all CED categories

J.5 Fourth article

J.5.1 Further analysis

In order to test the uniqueness of the three methods, a series of regression analyses were undertaken to determine the levels of correlation that exist between the data at the different stages of the overall approach. Analyses were performed on the intermediate results for supply risk Two further processes of investigation were undertaken to validate and test the sensitivity of the case study results. Firstly, a regression analysis was undertaken to test the levels of independence in the data at the material and process levels. Secondly, a sensitivity analysis was undertaken to test the effect that changes in one of the input parameters–EU consumption levels, a denominator in the calculations for specific technologies–could have on the final results.

J.5.1.1 Regression analysis

In order to test the uniqueness of the three methods, a series of regression analyses were undertaken to determine the levels of correlation that exist between the data at the different stages of the overall approach. Analyses were performed on the intermediate results for supply risk (SR), environmental impact (EI) and environmental justice (EJ) indicators for the individual *materials* selected and the final SR, EI and EJ indicators for all 51 of the electricity production *processes* examined in the study. A simple least-squares regression analysis was performed on the combinations of indicators at each level. "R-squared" (R^2) values were chosen as the most appropriate indicator for the analysis. The results are displayed in **Table J.13**.

Table J.13. Summary of regression analysis results. Correlations analysed between derived SR, EI and EJ values for individual materials and final SR, EI and EJ values for complete processes

	Variables	R-squared value
For materials	SR, EI	0.00319
	SR, EJ	0.15780
	EI, EJ	0.00114
For processes	SR, EI	0.15857
	SR, EJ	0.83447
	EI, EJ	0.20772

Firstly, the derived values of SR, EI and EJ for individual *materials* were all found to be poorly correlated, particularly when comparing EI with SR and EJ, which returned final R-squared values of 0.00319 and 0.00114, respectively. The value for the relationship between SR and EJ was found to be comparatively high–0.15780–confirming that there is a link between these two indicators, most likely derived from their mutual use of inputs from the World Governance Index (WGI) database (The World Bank n.d.). Nevertheless, all of these connections should ultimately be considered to be low. This highlights the relative "uniqueness" of the three indicators at the material level.

Secondly, when SR, EI and EJ values for individual materials are upscaled for selected *processes*–according to the amounts of each material stated in the life cycle inventory (LCI) listings obtained from the Ecoinvent database (Ecoinvent 2021)–higher levels of correlation are observed. This is to be expected in such cases, when all values are "scaled-up" using the same material use amounts. Here, SR is shown to be well correlated to EJ, with an R^2 value of 0.83447. The findings for EI to SR and EI to EJ–0.15857 and 0.20772, respectively–suggest that some correlation is observed, largely as a result of the common material use amounts used in the calculations for different LCA processes. In all, the regression analysis confirms that the three factors are all suitably "unique" at the *material* level but that the common material use amounts scale up these factors and provide at least some similarity at the *process* level.

J.5.1.2 Sensitivity to changes in annual consumption values

In order to test the validity of the analysis and determine the sensitivity of the results to changes in input parameters a test was performed on the denominator used in each of the final indicator calculations, the existing levels of consumption within the EU. To do this, it was first necessary to assess the relative contributions of individual materials to the final scores for the indicators in order to detect the most "influential" and, hence, suitable, materials for the test. This was achieved by calculating the percentage contributions of each material to the final indicator scores for each of the Ecoinvent processes analysed in the case study for the EU electricity system.

Table J.14 displays the mean and maximum contributions of the 20 most significant materials to each of the indicators. The results show that a group of critical raw materials (CRMs) with relatively low annual consumption rates–including gallium and several light (LRE) and heavy (HRE) rare earth materials–tend to dominate the scores for these indicators. It is interesting to note that gold and the three platinum group metals (PGMs) included here–platinum, rhodium and palladium–were found to make far higher contributions to EI scores on account of the high environmental impacts that relate to their respective extraction activities. The data for maximum contributions also demonstrates the significance of certain materials in specific processes, the best example being gallium and its overwhelming impact on the values for copper indium gallium selenide (CIS or CIGS) solar photovoltaic cells.

Table J.14. Summary of materials with highest contributions to indicator scores for electricity technologies, in order of mean supply risk (SR) factor contribution

				SR factor			EI score			EJ score		
Material	EU CRM?	Rare earth/PGM?	Annual EU consumption	Value	Mean contribution	Max contribution	Value	Mean contribution	Max contribution	Value	Mean contribution	Max contribution
			[tonnes]		*[%]*	*[%]*		*[%]*	*[%]*		*[%]*	*[%]*
Samarium	x	LRE	6	6.12	28.2	33.5	1.13	3.9	10.7	0.51	19.3	28.1
Neodymium	x	LRE	100	6.07	21.3	24.7	2.76	7.1	19.8	0.51	14.6	21.0
Praseodymium	x	LRE	41	5.49	15.3	17.8	3.98	8.2	22.7	0.51	11.6	16.7
Gallium	x		27	1.26	7.8	83.2	4.81	10.9	89.6	0.50	16.0	93.1
Rhodium	x	PGM	7	2.14	0.1	1.0	6,240	21.0	50.7	0.47	0.1	1.9
Gadolinium	x	HRE	11	6.06	7.9	9.2	5.12	4.9	13.6	0.51	5.4	7.8
Platinum	x	PGM	64	1.84	0.0	0.7	5,860	17.3	40.4	0.46	0.1	1.6
Lanthanum	x	LRE	645	6.04	6.9	8.2	2.06	1.7	4.8	0.51	4.8	7.0
Gold			1,425	0.19	0.0	0.0	3,501	11.8	42.3	0.49	0.0	0.1
Tellurium			30	0.51	1.2	7.2	0.59	0.6	1.9	0.43	5.9	22.4
Palladium	x	PGM	59	1.27	0.0	0.4	1,570	6.5	17.2	0.49	0.1	1.2
Magnesite			49,459	0.65	0.7	1.6	0.04	0.0	0.1	0.51	4.3	10.6
Baryte	x		506,410	1.26	0.8	6.7	0.15	0.1	1.0	0.54	3.2	24.5
Magnesium	x		113,000	3.91	1.7	39.7	1.87	0.6	22.5	0.52	1.7	44.0
Tantalum	x		395	1.36	0.9	5.3	1.99	0.4	1.7	0.64	2.1	9.2
Beryllium	x		38	2.29	0.4	8.0	29.62	2.3	38.6	0.34	0.5	9.0
Phosphorus	x		48,300	3.55	1.4	13.6	0.17	0.0	0.2	0.52	1.5	15.0
Dysprosium	x	HRE	14	6.20	1.3	1.6	0.06	0.0	0.0	0.51	0.9	1.4
Tungsten	x		431	1.61	0.4	8.2	4.11	0.5	7.8	0.52	1.0	20.0
Silver			3,800	0.68	0.1	0.5	36.97	1.4	5.4	0.38	0.2	1.2

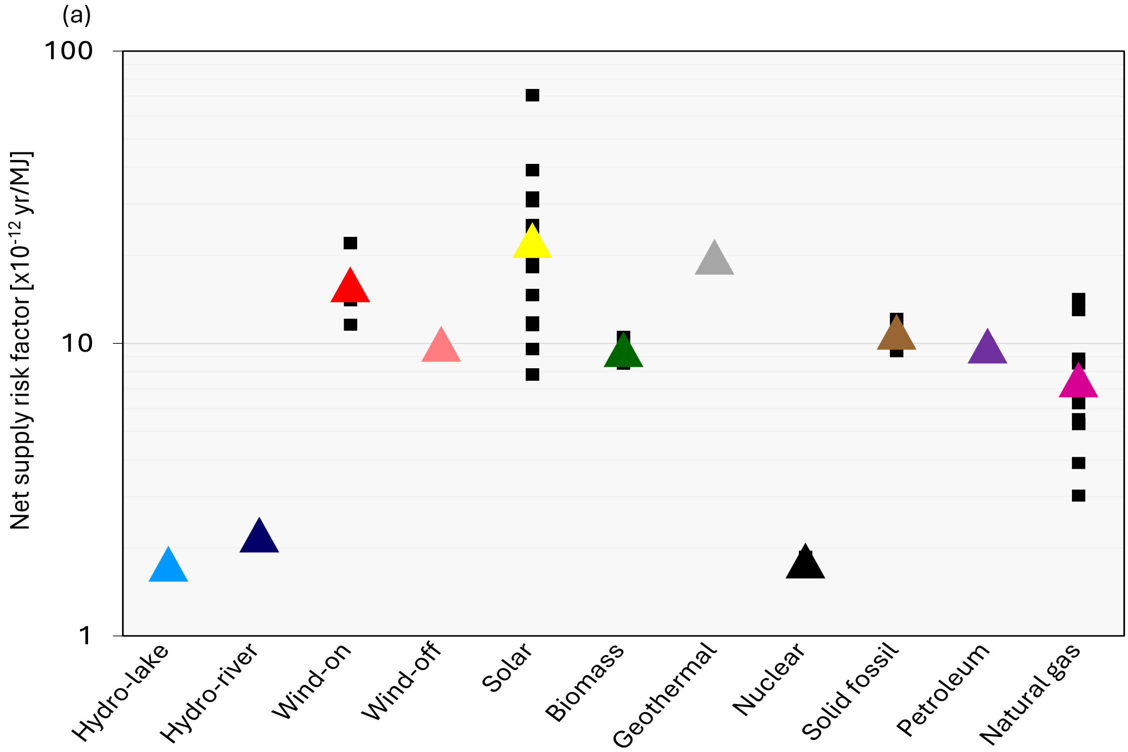
As the calculations for each indicator require individual contributions to be divided by the annual EU consumption amount, indicators are particularly sensitive to changes in these values. This is especially true as most of the influential materials are consumed in low amounts; low denominators, therefore, result in higher contributions. Accordingly, to test the sensitivity of the calculations to uncertainties in the estimated annual EU consumption levels, 20% was added to the levels of all 14 of the 20 identified materials that have current annual consumption estimates under 1,000 tonnes. Updated results for this sensitivity scenario are shown for SR, EI and EJ in **Figure J.4(b)**, **Figure J.5(b)** and **Figure J.6(b)**, respectively. A summary of the percentage changes that occur to the derived SR and EI values under this scenario are shown in **Table J.15**. The figures and tabulated data suggest that, although the changes to the overall values of the two indicators are significant–between 11.7%

and 16.6%–the changes are generally very consistent, with observed standard deviations for all indicators across all processes of between 1.0% and 2.8%.

As such, it is concluded that, while the results are certainly sensitive to changes in values of EU consumption for the most influential materials, the overall findings in the results are not altered in any significant way. These findings also reinforce the idea that, ultimately, the results are heavily influenced by the levels of individual material use in each process and confirms that small changes to the parameters relating to those materials will not drastically alter the rankings for a set of processes.

Table J.15. Summary of sensitivity analysis for electricity technology categories

Category	Mean percentage changes per category *[%]*		
	SR	EI	EJ
Hydro–lake	-15.7	-16.2	-13.9
Hydro–river	-15.9	-16.2	-14.1
Wind–onshore	-15.8	-13.7	-13.9
Wind–offshore	-15.6	-15.4	-13.2
Solar	-15.2	-12.0	-14.9
Biomass	-15.7	-16.2	-13.9
Geothermal	-15.8	-16.1	-14.0
Nuclear	-15.6	-15.7	-13.4
Solid fossil	-14.5	-16.3	-13.4
Petroleum	-14.9	-16.4	-11.7
Natural gas	-15.6	-16.6	-13.7



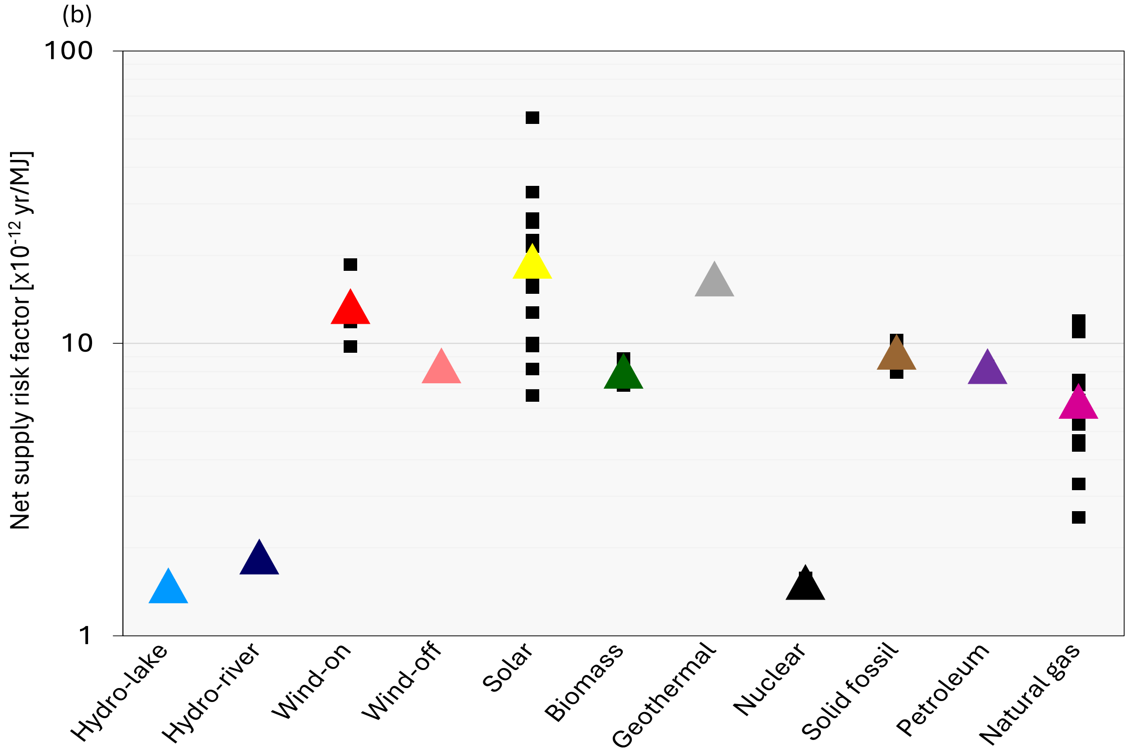


Figure J.4. Results for net supply risk (SR) factors by technological category (a) base results, (b) sensitivity results for increasing consumption values for 13 key materials by 20%

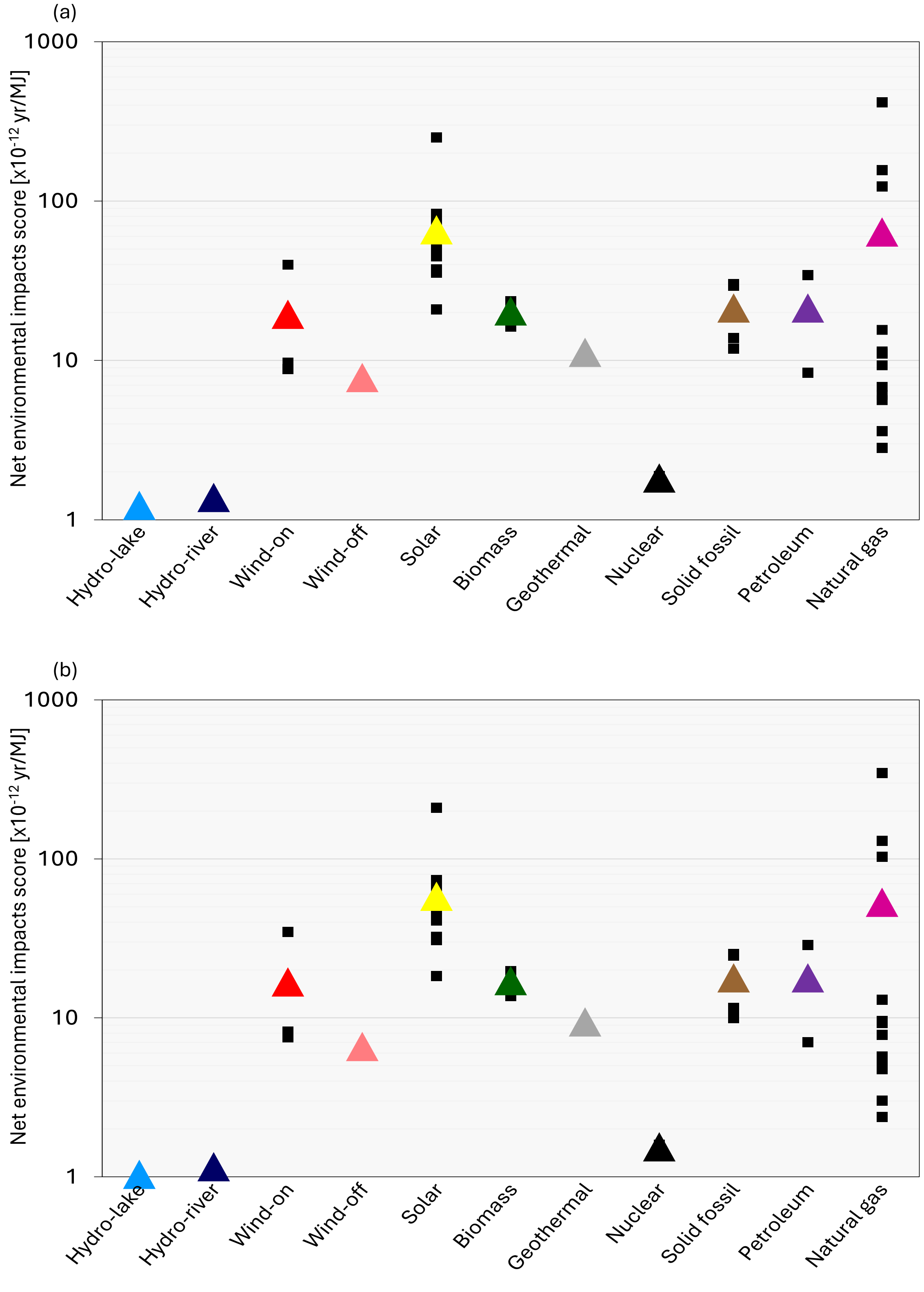


Figure J.5. Results for net local environmental impacts (EI) scores by technological category. (a) base results, (b) sensitivity results for increasing consumption values for 13 key materials by 20%

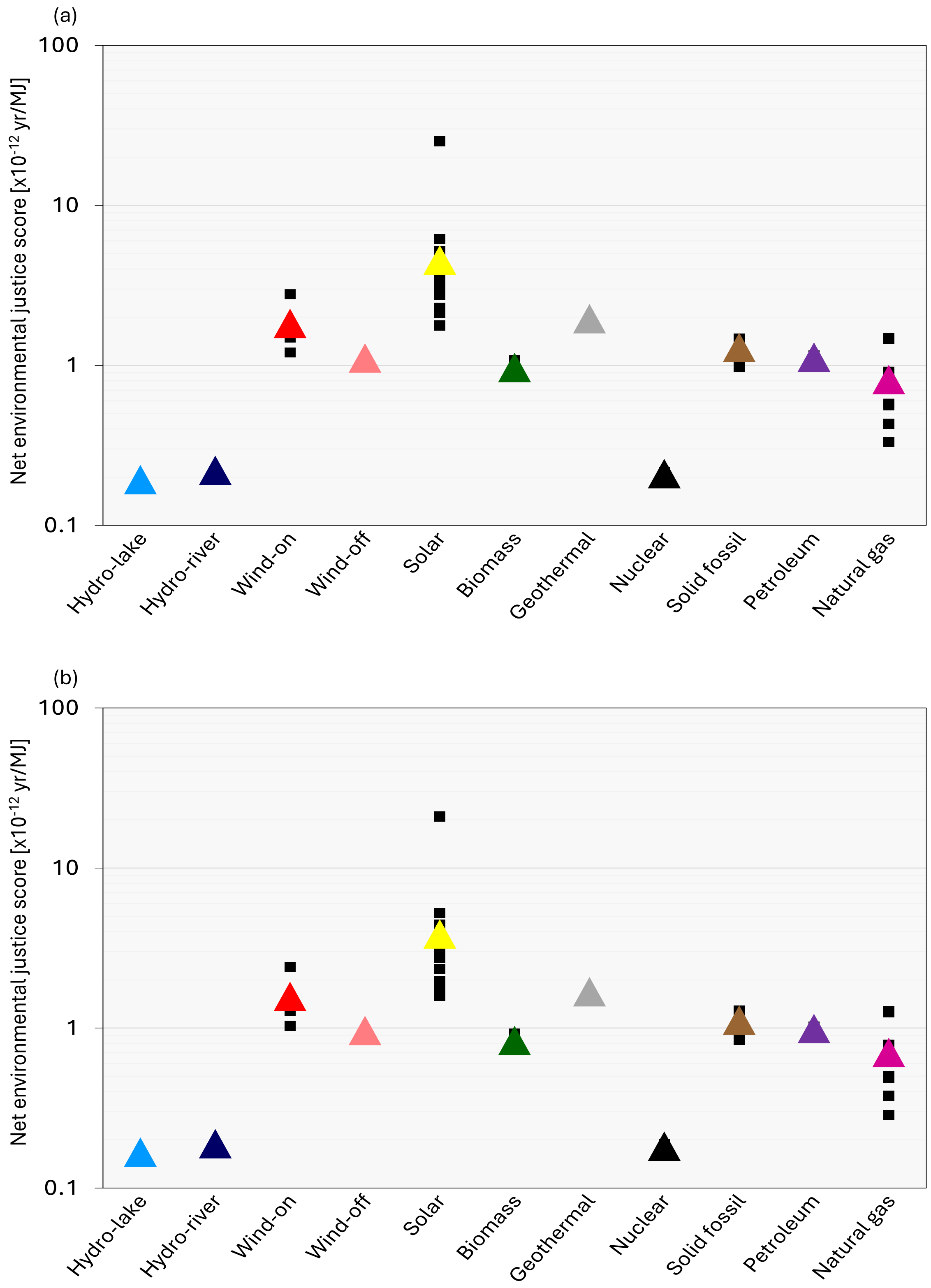


Figure J.6. Results for net local environmental justice (EJ) scores by technological category. (a) base results, (b) sensitivity results for increasing consumption values for 13 key materials by 20%

J.5.2 Data listings

Table J.16. EC critical and other materials with corresponding Ecoinvent LCI categories. Sources: European Commission (2020c), Ecoinvent (2021)

Group	Sub-group	Material	Matched?	Ecoinvent LCI category name
Critical	Platinum group metals	Iridium		
		Palladium	y	Palladium, in ground
		Platinum	y	Platinum, in ground
		Rhodium	y	Rhodium, in ground
		Ruthenium		
	Heavy rare earths	Dysprosium	y	Dysprosium, in ground
		Erbium		
		Europium	y	Europium, in ground
		Gadolinium	y	Gadolinium, in ground
		Terbium	y	Terbium, in ground
		Yttrium	y	Yttrium, in ground
		Ho, Tm, Lu, Yb		
	Light rare earths	Cerium	y	Cerium, in ground
		Lanthanum	y	Lanthanum, in ground
		Neodymium	y	Neodymium, in ground
		Praseodymium	y	Praseodymium, in ground
		Antimony	y	Antimony, in ground
		Baryte	y	Barium, in ground
		Bauxite		
		Beryllium	y	Beryllium, in ground
		Bismuth		
		Borates	y	Borax, in ground
		Cobalt	y	Cobalt, in ground
		Coking coal		
		Fluorspar	y	Fluorspar, in ground
		Gallium	y	Gallium, in ground
		Germanium		
		Hafnium		
		Indium		
		Lithium	y	Lithium, in ground
		Magnesium	y	Magnesium, in ground
		Natural graphite	y	Metamorphous rock, graphite containing, in ground
		Natural rubber		
		Niobium		
		Phosphate rock		
		Phosphorus	y	Phosphorus, in ground
		Samarium	y	Samarium, in ground
		Scandium		
		Silicon metal	y	Silicon, in ground
		Strontium	y	Strontium, in ground

	Tantalum	y	Tantalum, in ground
	Titanium	y	Titanium, in ground
	Tungsten	y	Tungsten, in ground
	Vanadium	y	Vanadium, in ground
Other	Aggregates		
	Aluminium	y	Aluminium, in ground
	Arsenic	y	Arsenic, in ground
	Bentonite		
	Cadmium	y	Cadmium, in ground
	Chromium	y	Chromium, in ground
	Copper	y	Copper, in ground
	Diatomite	y	Diatomite, in ground
	Feldspar		
	Gold	y	Gold, in ground
	Gypsum	y	Gypsum, in ground
	Helium		
	Hydrogen		
	Iron ore	y	Iron, in ground
	Kaolin clay	y	Kaolinite, in ground
	Lead	y	Lead, in ground
	Limestone		
	Magnesite	y	Magnesite, in ground
	Manganese	y	Manganese, in ground
	Molybdenum	y	Molybdenum, in ground
	Natural cork		
	Natural teak wood		
	Nickel	y	Nickel, in ground
	Perlite	y	Perlite, in ground
	Potash		
	Rhenium	y	Rhenium, in ground
	Sapele wood		
	Selenium	y	Selenium, in ground
	Silica sand		
	Silver	y	Silver, in ground
	Sulphur	y	Sulfur, in ground
	Talc	y	Talc, in ground
	Tellurium	y	Tellurium, in ground
	Tin	y	Tin, in ground
	Zinc	y	Zinc, in ground
	Zirconium	y	Zirconium, in ground

Table J.17. Input parameters for chosen materials. Data sources: European Commission (2020), Ecoinvent (2021), The World Bank (n.d.)

Group	Sub-group	Material	Supply risk	Environmental impacts	Environmental justice	EU consumption
			[-]	*[-]*	*[-]*	*[tonnes]*
Critical	Platinum group metals	Palladium	1.27	1,569.67	0.49	59
		Platinum	1.84	5,860.26	0.46	64
		Rhodium	2.14	6,240.38	0.47	7
	Heavy rare earths	Dysprosium	6.20	0.06	0.51	14
		Europium	3.66	0.05	0.51	24
		Gadolinium	6.06	5.12	0.51	11
		Terbium	5.51	0.16	0.51	24
		Yttrium	4.20	1.52	0.51	509
	Light rare earths	Cerium	6.17	0.68	0.51	4,027
		Lanthanum	6.04	2.06	0.51	645
		Neodymium	6.07	2.76	0.51	100
		Praseodymium	5.49	3.98	0.51	41
		Antimony	2.01	4.51	0.46	649
		Baryte	1.26	0.15	0.54	506,410
		Beryllium	2.29	29.62	0.34	38
		Borates	3.19	0.01	0.32	62,850
		Cobalt	2.54	2.42	0.42	31,441
		Fluorspar	1.15	0.01	0.41	755,000
		Gallium	1.26	4.81	0.50	27
		Lithium	1.64	0.29	0.41	3,225
		Magnesium	3.91	1.87	0.52	113,000
		Natural graphite	2.27	0.00	0.53	86,000
		Phosphorus	3.55	0.17	0.52	48,300
		Silicon metal	1.18	0.37	0.46	6
		Samarium	6.12	1.13	0.51	433,000
		Strontium	2.57	0.11	0.54	49,298
		Tantalum	1.36	1.99	0.64	395
		Titanium	1.26	1.64	0.48	1,509,000
		Tungsten	1.61	4.11	0.52	431
		Vanadium	1.69	0.03	0.48	12,717
Other		Aluminium	0.59	0.69	0.46	5,252,000
		Arsenic	1.19	0.12	0.52	354
		Cadmium	0.34	0.23	0.41	700
		Chromium	0.86	0.88	0.49	1,200,000
		Copper	0.32	1.85	0.42	4,000,000
		Diatomite	0.46	0.00	0.37	132,493
		Gold	0.19	3,501.24	0.49	1,425
		Gypsum	0.50	0.00	0.53	4,596,092
		Iron ore	0.46	0.01	0.45	292,000,000
		Kaolin clay	0.40	0.01	0.42	3,100,479
		Lead	0.09	0.13	0.42	1,385,399

	Magnesite	0.65	0.04	0.51	49,459
	Manganese	0.93	0.23	0.49	800,000
	Molybdenum	0.94	2.36	0.44	60,000
	Nickel	0.49	1.56	0.40	460,000
	Perlite	0.42	0.00	0.49	3,677,958
	Rhenium	0.45	2.36	0.30	2,842
	Selenium	0.41	0.55	0.32	1,000
	Silver	0.68	36.97	0.38	3,800
	Sulphur	0.27	0.01	0.41	1,223,738
	Talc	0.40	0.01	0.41	1,114,963
	Tellurium	0.51	0.59	0.43	30
	Tin	0.90	1.49	0.51	63,932
	Zinc	0.34	0.16	0.43	4,000,000
	Zirconium	0.83	0.14	0.34	273,789

Table J.18. Ecoinvent electricity generation processes used in case study. Source: Ecoinvent (2021)

Category	Process name	Region
Hydro–lake	electricity production, hydro, reservoir, non-alpine region	RoW
	electricity production, hydro, reservoir, alpine region	RoW
Hydro–river	electricity production, hydro, run-of-river	RoW
Wind–onshore	electricity production, wind, <1MW turbine, onshore	RoW
	electricity production, wind, 1-3MW turbine, onshore	RoW
	electricity production, wind, >3MW turbine, onshore	RoW
Wind–offshore	electricity production, wind, 1-3MW turbine, offshore	RoW
Solar	electricity production, photovoltaic, 3kWp facade installation, multi-Si, laminated, integrated	RoW
	electricity production, photovoltaic, 3kWp facade installation, multi-Si, panel, mounted	RoW
	electricity production, photovoltaic, 3kWp facade installation, single-Si, laminated, integrated	RoW
	electricity production, photovoltaic, 3kWp facade installation, single-Si, panel, mounted	RoW
	electricity production, photovoltaic, 3kWp flat-roof installation, multi-Si	RoW
	electricity production, photovoltaic, 3kWp flat-roof installation, single-Si	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, a-Si, laminated, integrated	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, a-Si, panel, mounted	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, CdTe, laminated, integrated	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, CIS, panel, mounted	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, laminated, integrated	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, ribbon-Si, laminated, integrated	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, ribbon-Si, panel, mounted	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, laminated, integrated	RoW
	electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted	RoW
	electricity production, photovoltaic, 570kWp open ground installation, multi-Si	RoW
	electricity production, solar tower power plant, 20 MW	RoW
	electricity production, solar thermal parabolic trough, 50 MW	RoW
Biomass	heat and power co-generation, wood chips, 2000 kW	Switzerland
	heat and power co-generation, wood chips, 2000 kW, state-of-the-art 2014	Switzerland
	heat and power co-generation, wood chips, 6667 kW	RoW
	heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014	RoW
Geothermal	electricity production, deep geothermal	RoW
Nuclear	electricity production, nuclear, pressure water reactor	RoW
	electricity production, nuclear, boiling water reactor	RoW
Solid fossil	electricity production, hard coal	RoW
	heat and power co-generation, hard coal	RoW
	electricity production, lignite	RoW
	heat and power co-generation, lignite	RoW
Petroleum	electricity production, oil	RoW
	heat and power co-generation, oil	RoW
Natural gas	heat and power co-generation, natural gas, mini-plant 2KW electrical	Europe without Switzerland
	heat and power co-generation, natural gas, 50kW electrical, lean burn	Europe without Switzerland
	heat and power co-generation, natural gas, 160kW electrical, Jakoberg	RoW
	heat and power co-generation, natural gas, 160kW electrical, lambda=1	Europe without Switzerland

heat and power co-generation, natural gas, 200kW electrical, lean burn	RoW
heat and power co-generation, natural gas, 500kW electrical, lean burn	RoW
heat and power co-generation, natural gas, 1MW electrical, lean burn	Europe without Switzerland
electricity production, natural gas, 10MW	RoW
heat and power co-generation, natural gas, conventional power plant, 100MW electrical	RoW
heat and power co-generation, natural gas, combined cycle power plant, 400MW electrical	RoW
electricity production, natural gas, combined cycle power plant	RoW
electricity production, natural gas, conventional power plant	RoW

Table J.19. Summary of EU reference scenario projections for gross electricity generation. Data source: European Commission (2021)

Category	Gross electricity generation by source										Increase (2020-2050)
	2005	2010	2015	2020	2025	2030	2035	2040	2045	2050	
	[MJ]										*[%]*
Raw											
Hydro–river	5.05×10^{11}	5.94×10^{11}	5.58×10^{11}	5.65×10^{11}	6.03×10^{11}	6.14×10^{11}	6.21×10^{11}	6.24×10^{11}	6.37×10^{11}	6.38×10^{11}	13
Wind–onshore	2.38×10^{11}	4.82×10^{11}	8.84×10^{11}	1.23×10^{12}	1.79×10^{12}	2.42×10^{12}	2.79×10^{12}	3.02×10^{12}	3.40×10^{12}	3.57×10^{12}	190
Wind–offshore	5.48×10^{9}	1.90×10^{10}	6.23×10^{10}	1.70×10^{11}	4.10×10^{11}	7.30×10^{11}	9.42×10^{11}	1.10×10^{12}	1.24×10^{12}	1.30×10^{12}	661
Solar	5.22×10^{9}	8.36×10^{10}	3.64×10^{11}	5.10×10^{11}	8.76×10^{11}	1.26×10^{12}	1.52×10^{12}	1.79×10^{12}	2.09×10^{12}	2.16×10^{12}	324
Biomass	2.74×10^{11}	4.77×10^{11}	6.24×10^{11}	6.34×10^{11}	6.32×10^{11}	6.20×10^{11}	6.31×10^{11}	6.93×10^{11}	6.82×10^{11}	7.46×10^{11}	18
Geothermal	2.12×10^{10}	2.19×10^{10}	2.52×10^{10}	2.55×10^{10}	2.57×10^{10}	2.63×10^{10}	2.63×10^{10}	3.36×10^{10}	5.79×10^{10}	6.00×10^{10}	135
Nuclear	3.30×10^{12}	3.08×10^{12}	2.83×10^{12}	2.43×10^{12}	2.07×10^{12}	1.87×10^{12}	1.72×10^{12}	1.64×10^{12}	1.52×10^{12}	1.45×10^{12}	-40
Solid fossil	2.99×10^{12}	2.60×10^{12}	2.56×10^{12}	1.40×10^{12}	1.19×10^{12}	9.71×10^{11}	5.82×10^{11}	1.38×10^{11}	4.81×10^{10}	4.65×10^{10}	-97
Petroleum	4.95×10^{11}	2.96×10^{11}	2.44×10^{11}	9.96×10^{10}	4.10×10^{10}	2.50×10^{10}	2.23×10^{10}	1.89×10^{10}	1.21×10^{10}	1.04×10^{10}	-90
Natural gas	1.99×10^{12}	2.24×10^{12}	1.53×10^{12}	1.78×10^{12}	1.82×10^{12}	1.56×10^{12}	1.67×10^{12}	1.81×10^{12}	1.57×10^{12}	1.65×10^{12}	-7
Normalised											
Hydro–river	1.0	1.2	1.1	1.1	1.2	1.1	1.1	1.1	1.1	1.1	
Wind–onshore	1.0	1.2	1.1	1.1	1.2	1.2	1.2	1.2	1.3	1.3	
Wind–offshore	1.0	2.0	3.7	5.2	7.5	10.2	11.7	12.7	14.3	15.0	
Solar	1.0	3.5	11.4	31.0	74.8	133.2	171.8	201.0	226.4	236.2	
Biomass	1.0	16.0	69.7	97.6	167.8	240.9	290.8	343.7	400.0	413.6	
Geothermal	1.0	1.7	2.3	2.3	2.3	2.3	2.3	2.5	2.5	2.7	
Nuclear	1.0	1.0	1.2	1.2	1.2	1.2	1.2	1.6	2.7	2.8	
Solid fossil	1.0	0.9	0.9	0.7	0.6	0.6	0.5	0.5	0.5	0.4	
Petroleum	1.0	0.9	0.9	0.5	0.4	0.3	0.2	0.0	0.0	0.0	
Natural gas	1.0	0.6	0.5	0.2	0.1	0.1	0.0	0.0	0.0	0.0	

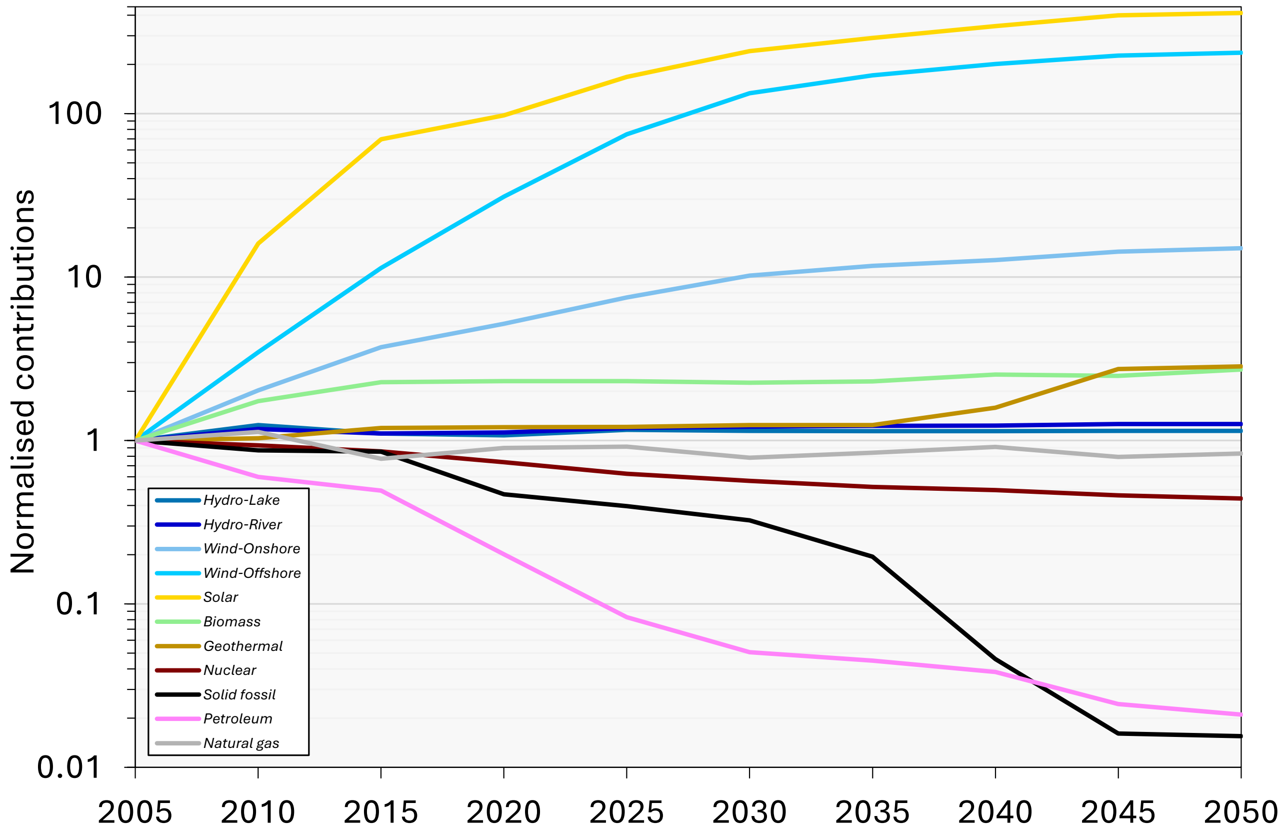


Figure J.7. Illustration of EU reference scenario projections for all electricity generation technologies normalised to 2005 values. Data source: European Commission (2021)

Table J.20. Summary of calculated raw material factors using EU reference scenario projections for gross electricity generation

Indicator	**Net score**										**Increase (2020-2050)**
	2005	**2010**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**	*[%]*
Raw											
SR	67.75	71.22	78.88	75.92	92.29	109.29	119.43	127.80	139.18	145.05	91
EI	219.83	237.55	219.54	224.45	257.33	275.21	299.95	324.71	335.02	349.57	56
EJ	7.74	8.24	9.68	9.56	12.14	14.84	16.48	17.95	19.83	20.62	116
Normalised											
SR	1.00	1.05	1.16	1.12	1.36	1.61	1.76	1.89	2.05	2.14	
EI	1.00	1.08	1.00	1.02	1.17	1.25	1.36	1.48	1.52	1.59	
EJ	1.00	1.06	1.25	1.24	1.57	1.92	2.13	2.32	2.56	2.66	

J.6 Fifth article

Table J.21. Summary of linkages between ENBIOS structural processors, Euro-Calliope outputs and corresponding Ecoinvent processes

ENBIOS structural processor		Euro-Calliope output(s)			Ecoinvent LCI process	
		File	"techs"	"carriers"	Activity name	Region
Electricity	Wind–onshore	flow_out_sum	wind_onshore	electricity	electricity production, wind, 1-3MW turbine, onshore	RoW
	Wind–offshore	flow_out_sum	wind_offshore	electricity	electricity production, wind, 1-3MW turbine, offshore	RoW
	Hydro–reservoir	flow_out_sum	hydro_reservoir	electricity	electricity production, hydro, reservoir, non-alpine region	SE
	Hydro–river	flow_out_sum	hydro_run_of_river	electricity	electricity production, hydro, run-of-river	DE
	Solar PV–field	flow_out_sum	open_field_pv	electricity	electricity production, photovoltaic, 570kWp open ground installation, multi-Si	RoW
	Solar PV–roof	flow_out_sum	roof_mounted_pv	electricity	electricity production, solar thermal parabolic trough, 50 MW	RoW
	Biomass	flow_out_sum	chp_biofuel_extraction	electricity	heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014	FI
	Waste	flow_out_sum	chp_wte_back_pressure	electricity	electricity, from municipal waste incineration to generic market for electricity, medium voltage	DE
	Coal	flow_out_sum	coal_power_plant	electricity	electricity production, hard coal	RoW
	Natural gas	flow_out_sum	ccgt	electricity	heat and power co-generation, natural gas, conventional power plant, 100MW electrical	DE
		flow_out_sum	chp_methane_extraction	electricity		
	Nuclear	flow_out_sum	nuclear	electricity	electricity production, nuclear, pressure water reactor	RoW
Heat	Biomass	flow_out_sum	biofuel_boiler	heat	heat and power co-generation, wood chips, 6667 kW, state of the art, 2014	FI
		flow_out_sum	chp_biofuel_extraction	heat		
	Waste	flow_out_sum	chp_wte_back_pressure	heat	heat, from municipal waste incineration to generic market for heat district or industrial, other than natural gas	DE
	Natural gas	flow_out_sum	chp_methane_extraction	heat	heat and power co-generation, natural gas, conventional power plant, 100MW electrical	DE
		flow_out_sum	methane_boiler	heat		
Fuel	Biodiesel	flow_out_sum	biofuel_to_diesel	diesel	market for fatty acid methyl ester	GLO
		flow_out_sum	biofuel_to_liquids	diesel		
		flow_out_sum	biofuel_to_liquids	kerosene		
		flow_out_sum	biofuel_to_methane	methane		
		flow_out_sum	biofuel_to_methanol	methanol		
		flow_out_sum	biofuel_to_liquids	electricity		
	Natural gas	flow_in_sum	demand_industry_methane	methane	market for natural gas, high pressure	RoW
		flow_in_sum	gas_hob	methane		
	Diesel	flow_out_sum	diesel_supply	diesel	market for diesel	Europe without Switzerland
	Kerosene	flow_out_sum	kerosene_supply	kerosene	market for kerosene	Europe without Switzerland
	Methanol	flow_out_sum	methanol_supply	methanol	market for methanol	GLO

Table J.22. Summary of job requirement data for selected electricity, heat and fuel technologies (Rutovitz et al 2015). Also includes listing of relevant International Standard Industrial Classification (ISIC) level 2 economic activity (International Labour Organization 2022)

		Manufacturing	Construction & installation	Time	Operation and maintenance	Decommissioning	Time	ELECTRICITY & HEAT TOTAL	FUEL TOTAL	ISIC activity
		[job.yr/MW]	*[job.yr/MW]*	*[yr]*	*[job.yr/MW]*	*[job.yr/MW]*	*[yr]*	*[job/MW]*	*[job/MJ]*	
Electricity	Wind–onshore	4.7	3.2	2	0.3			4.3		35
	Wind–offshore	15.6	8.0	4	0.2			6.1		35
	Hydro–reservoir	3.5	7.4	2	0.2			5.7		35
	Hydro–river	10.9	15.8	2	4.9			18.3		35
	Solar PV–field	6.7	13.0	1	0.7			20.4		35
	Solar PV–roof	6.7	13.0	1	0.7			20.4		35
	Biomass	2.9	14.0	2	1.5			10.0		35
	Waste	2.9	14.0	2	2.25			10.7		35
	Coal	5.4	11.2	5	0.14			3.5		35
	Natural gas	0.9	1.3	2	0.14			1.3		35
	Nuclear	1.3	11.8	10	0.6	0.95	35	35.2		35
Heat	Biomass	2.9	14.0	2	1.5			10.0		35
	Waste	2.9	14.0	2	2.25			10.7		35
	Natural gas	0.93	1.3	2	0.14			1.3		35
Fuel	Biodiesel								8.6	02
	Natural gas								8.6	06
	Diesel								8.6	19
	Kerosene								8.6	19

Table J.23. Hours worked by International Standard Industrial Classification (ISIC) level 2 economic activity. Aggregated by respective employment rates for 35 countries represented in Euro-Calliope model (International Labour Organization 2022)

Economic activity (ISIC level 2)	Aggregated mean weekly hours worked *[hr/wk.job]*	Aggregated mean annual hours worked *[hr/yr.job]*
02 - Forestry and logging	37.97	1,981
06 - Extraction of crude petroleum and natural gas	41.38	2,159
19 - Manufacture of coke and refined petroleum products	40.09	2,092
35 - Electricity, gas, steam and air conditioning supply	38.46	2,007

Table J.24. Summary of extensive data outputs at level “n-5” structural processors. Listings for projected 2030 and 2050 energy mixes under the EU “climate neutrality” scenario according to Euro-Calliope model outputs. Percentage contributions of individual technologies to total are also provided. Note that energy totals for fuels created from electrolysis-based hydrogen are included within the electricity used to create them to avoid "double accounting". However, emissions from their eventual combustion are included within the totals for that fuel category. Percentages of total are given below

		CLIMATE NEUTRALITY SCENARIO DATA											
		2030						2050					
		Energy production *[MJ]*	GHG emissions *[kg CO_2-eq]*	Land occupation *[m^2]*	Water depletion *[m^3]*	Material supply risk *[yr]*	Human activity *[hr]*	Energy production *[MJ]*	GHG emissions *[kg CO_2-eq]*	Land occupation *[m^2]*	Water depletion *[m^3]*	Material supply risk *[yr]*	Human activity *[hr]*
Electricity	Wind–onshore	3.02×10^{12}	1.20×10^{10}	1.48×10^{9}	1.20×10^{8}	3.50×10^{1}	2.03×10^{9}	3.60×10^{13}	1.43×10^{11}	1.76×10^{10}	6.35×10^{8}	4.18×10^{2}	2.55×10^{10}
		7.26%	*0.55%*	*1.46%*	*0.51%*	*11.76%*	*2.41%*	*65.45%*	*14.79%*	*3.60%*	*12.70%*	*56.96%*	*17.05%*
	Wind–offshore	7.64×10^{8}	3.39×10^{6}	1.83×10^{5}	4.11×10^{4}	7.61×10^{-3}	8.80×10^{5}	3.39×10^{9}	1.51×10^{7}	8.12×10^{5}	7.48×10^{4}	3.38×10^{-2}	3.68×10^{6}
		0.00%	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.01%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*
	Hydro–reservoir	1.48×10^{12}	2.03×10^{10}	9.68×10^{7}	1.21×10^{10}	2.58	1.1910^{9}	1.46×10^{12}	2.00×10^{10}	9.53×10^{7}	6.74×10^{6}	2.54	1.19×10^{9}
		3.57%	*0.94%*	*0.10%*	*51.66%*	*0.87%*	*1.42%*	*2.66%*	*2.07%*	*0.02%*	*0.13%*	*0.35%*	*0.80%*
	Hydro–river	4.94×10^{11}	5.66×10^{8}	2.05×10^{7}	2.91×10^{6}	1.09	1.27×10^{9}	4.15×10^{11}	4.76×10^{8}	1.73×10^{7}	1.16×10^{6}	9.17×10^{-1}	1.27×10^{9}
		1.19%	*0.03%*	*0.02%*	*0.01%*	*0.37%*	*1.51%*	*0.75%*	*0.05%*	*0.00%*	*0.02%*	*0.12%*	*0.85%*
	Solar PV–field	6.94×10^{12}	1.46×10^{11}	7.19×10^{10}	4.70×10^{9}	1.77×10^{2}	6.50×10^{10}	1.12×10^{13}	2.37×10^{11}	1.16×10^{11}	1.39×10^{9}	2.86×10^{2}	1.09×10^{11}
		16.68%	*6.75%*	*71.35%*	*20.14%*	*59.30%*	*77.51%*	*20.40%*	*24.51%*	*23.79%*	*27.87%*	*38.98%*	*72.77%*
	Solar PV–roof	2.28×10^{8}	4.65×10^{6}	3.74×10^{5}	1.55×10^{5}	5.05×10^{-3}	4.08×10^{6}	5.58×10^{8}	1.14×10^{7}	$9.17\ \times10^{5}$	$7.99\text{xx}10^{4}$	1.24×10^{-2}	1.03×10^{7}
		0.00%	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.01%*
	Biomass	1.32×10^{9}	1.90×10^{7}	4.74×10^{8}	3.99×10^{5}	1.04×10^{-2}	2.48×10^{6}	$2.31\ \times10^{10}$	3.31×10^{8}	8.26×10^{9}	1.39×10^{6}	1.81×10^{-1}	4.57×10^{7}
		0.00%	*0.00%*	*0.47%*	*0.00%*	*0.00%*	*0.00%*	*0.04%*	*0.03%*	*1.69%*	*0.03%*	*0.02%*	*0.03%*
	Waste	1.85×10^{11}	1.22×10^{10}	5.19×10^{9}	1.02×10^{9}	1.45	2.52×10^{8}	1.93×10^{11}	$1.27\ \times10^{10}$	5.41×10^{9}	1.74×10^{8}	1.51	2.63×10^{8}
		0.44%	*0.56%*	*5.15%*	*4.35%*	*0.49%*	*0.30%*	*0.35%*	*1.31%*	*1.11%*	*3.48%*	*0.21%*	*0.18%*
	Coal	2.87×10^{12}	8.03×10^{11}	1.84×10^{10}	1.43×10^{9}	2.70×10^{1}	1.04×10^{9}						
		6.90%	*37.00%*	*18.22%*	*6.13%*	*9.07%*	*1.24%*						
	Natural gas	6.18×10^{10}	9.30×10^{9}	2.00×10^{7}	2.06×10^{7}	3.63×10^{-1}	1.69×10^{7}	1.95×10^{9}	2.94×10^{8}	6.32×10^{5}	9.94×10^{5}	1.15×10^{-2}	3.18×10^{6}
		0.15%	*0.43%*	*0.02%*	*0.09%*	*0.12%*	*0.02%*	*0.00%*	*0.03%*	*0.00%*	*0.02%*	*0.00%*	*0.00%*
	Nuclear	3.49×10^{12}	6.14×10^{9}	5.49×10^{8}	2.95×10^{9}	6.11	9.24×10^{9}	9.97×10^{11}	1.76×10^{9}	1.57×10^{8}	8.39×10^{8}	1.75	2.90×10^{9}
		8.39%	*0.28%*	*0.54%*	*12.64%*	*2.05%*	*11.01%*	*1.81%*	*0.18%*	*0.03%*	*16.79%*	*0.24%*	*1.94%*
Heat	Biomass	3.60×10^{9}	8.76×10^{6}	2.19×10^{8}	1.84×10^{5}	4.78×10^{-3}	5.34×10^{6}	4.18×10^{12}	$1.02\ \times10^{10}$	2.54×10^{11}	4.27×10^{7}	5.54	9.02×10^{9}
		0.01%	*0.00%*	*0.22%*	*0.00%*	*0.00%*	*0.01%*	*7.58%*	*1.05%*	*51.81%*	*0.85%*	*0.76%*	*6.04%*
	Waste	2.51×10^{8}	2.97×10^{6}	8.54×10^{5}	2.19×10^{5}	3.33×10^{-4}	1.66×10^{8}	4.28×10^{8}	5.06×10^{6}	1.46×10^{6}	7.30×10^{4}	5.68×10^{-2}	1.69×10^{8}
		0.00%	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.20%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.00%*	*0.11%*
	Natural gas	1.30×10^{13}	3.59×10^{11}	7.72×10^{8}	7.95×10^{8}	1.40×10^{1}	3.47×10^{9}	7.50×10^{10}	2.08×10^{9}	$4.4\ \times10^{6}$	7.04×10^{6}	8.13×10^{-2}	2.31×10^{7}
		31.17%	*16.56%*	*0.77%*	*3.41%*	*4.71%*	*4.14%*	*0.14%*	*0.21%*	*0.00%*	*0.14%*	*0.01%*	*0.02%*
Fuel	Biodiesel	7.43×10^{8}	1.14×10^{8}	1.48×10^{8}	1.35×10^{6}	2.89×10^{-2}	1.27×10^{4}	4.41×10^{11}	8.21×10^{10}	8.78×10^{10}	1.90×10^{9}	1.72×10^{1}	7.52×10^{6}
		0.00%	*0.01%*	*0.15%*	*0.01%*	*0.01%*	*0.00%*	*0.80%*	*8.49%*	*17.95%*	*37.95%*	*2.34%*	*0.01%*
	Natural gas	4.00×10^{12}	2.85×10^{11}	1.53×10^{8}	2.79×10^{7}	1.25×10^{1}	7.42×10^{7}		1.26×10^{11}				1.12×10^{8}
		9.61%	*13.14%*	*0.15%*	*0.12%*	*4.19%*	*0.09%*		*13.03%*				*0.07%*
	Diesel	3.38×10^{12}	2.89×10^{11}	8.14×10^{8}	1.22×10^{8}	1.18×10^{1}	6.08×10^{7}		1.34×10^{11}				9.32×10^{7}
		8.13%	*13.32%*	*0.81%*	*0.52%*	*3.98%*	*0.07%*		*13.84%*				*0.06%*
	Kerosene	2.70×10^{12}	2.26×10^{11}	5.73×10^{8}	9.49×10^{7}	9.19	4.85×10^{7}		1.97×10^{11}				9.70×10^{7}
		6.49%	*10.44%*	*0.57%*	*0.41%*	*3.09%*	*0.06%*		*20.40%*				*0.06%*

Table J.25. Summary of aggregated extensive data outputs. Listings for projected 2030 and 2050 energy mixes under the EU “climate neutrality” scenario according to Euro-Calliope model outputs. Percentage contributions of individual technologies to total are also provided. Note that energy totals for fuels created from electrolysis-based hydrogen are included within the electricity used to create them to avoid "double accounting". However, emissions from their eventual combustion are included within the totals for that fuel category. Percentages of total are given below

		CLIMATE NEUTRALITY SCENARIO DATA											
		2030						**2050**					
	Level	**Energy production** *[MJ]*	**GHG emissions** *[kg CO_2-eq]*	**Land occupation** *[m^2]*	**Water depletion** *[m^3]*	**Material supply risk** *[yr]*	**Human activity** *[hr]*	**Energy production** *[MJ]*	**GHG emissions** *[kg CO_2-eq]*	**Land occupation** *[m^2]*	**Water depletion** *[m^3]*	**Material supply risk** *[yr]*	**Human activity** *[hr]*
ALL SYSTEM	n	4.16×10^{13}	2.17×10^{12}	1.01×10^{11}	8.11×10^{9}	2.98×10^{2}	8.39×10^{10}	5.51×10^{13}	9.68×10^{11}	4.89×10^{11}	5.00×10^{9}	7.34×10^{2}	1.49×10^{11}
Electricity	n-1	1.85×10^{13}	1.01×10^{12}	9.81×10^{10}	6.83×10^{9}	2.50×10^{2}	8.01×10^{10}	5.04×10^{13}	4.16×10^{11}	1.48×10^{11}	3.05×10^{9}	7.11×10^{2}	1.40×10^{11}
		44.59%	*46.55%*	*97.34%*	*84.13%*	*84.02%*	*95.44%*	*91.48%*	*42.98%*	*30.24%*	*61.05%*	*96.89%*	*93.62%*
Heat	n-1	1.30×10^{13}	3.59×10^{11}	9.92×10^{8}	1.22×10^{9}	1.40×10^{1}	3.65×10^{9}	4.25×10^{12}	1.22×10^{10}	2.54×10^{11}	4.98×10^{7}	5.62	9.21×10^{9}
		31.18%	*16.56%*	*0.98%*	*14.98%*	*4.72%*	*4.35%*	*7.72%*	*1.26%*	*51.82%*	*1.00%*	*0.77%*	*6.17%*
Fuel	n-1	1.01×10^{13}	8.00×10^{11}	1.69×10^{9}	7.23×10^{7}	3.35×10^{1}	1.84×10^{8}	4.41×10^{11}	5.40×10^{11}	8.78×10^{10}	1.90×10^{9}	1.72×10^{1}	3.10×10^{8}
		24.23%	*36.90%*	*1.43%*	*0.89%*	*11.27%*	*0.22%*	*0.80%*	*55.76%*	*17.95%*	*37.95%*	*2.34%*	*0.21%*
Renewable	n-2	1.19×10^{13}	1.80×10^{11}	7.43×10^{10}	9.25×10^{8}	2.15×10^{2}	6.95×10^{10}	5.38×10^{13}	4.94×10^{11}	4.84×10^{11}	3.98×10^{9}	7.30×10^{2}	1.46×10^{11}
		28.72%	*8.28%*	*73.77%*	*11.40%*	*72.30%*	*82.87%*	*97.70%*	*50.99%*	*98.86%*	*79.57%*	*99.54%*	*97.55%*
Non-renewable	n-2	2.96×10^{13}	1.99×10^{12}	2.64×10^{10}	7.19×10^{9}	8.25×10^{1}	1.44×10^{10}	1.27×10^{12}	4.74×10^{11}	5.58×10^{9}	1.02×10^{9}	3.35	3.66×10^{9}
		71.28%	*91.72%*	*26.23%*	*88.60%*	*27.70%*	*17.13%*	*2.30%*	*49.01%*	*1.14%*	*20.43%*	*0.46%*	*2.45%*
Wind	n-4	3.02×10^{12}	1.20×10^{10}	1.48×10^{9}	5.32×10^{7}	3.50×10^{1}	2.03×10^{9}	3.60×10^{13}	1.43×10^{11}	1.76×10^{10}	6.35×10^{8}	4.18×10^{2}	2.55×10^{10}
		7.26%	*0.55%*	*1.46%*	*0.66%*	*11.76%*	*2.41%*	*65.46%*	*14.79%*	*3.60%*	*12.70%*	*56.96%*	*17.05%*
Hydro	n-4	1.98×10^{12}	2.09×10^{10}	1.17×10^{8}	8.23×10^{6}	3.67	2.46×10^{9}	1.88×10^{12}	2.05×10^{10}	1.13×10^{8}	7.91×10^{6}	3.46	2.46×10^{9}
		4.76%	*0.96%*	*0.12%*	*0.10%*	*1.23%*	*2.93%*	*3.41%*	*2.12%*	*0.02%*	*0.16%*	*0.47%*	*1.65%*
Solar	n-4	6.94×10^{12}	1.46×10^{11}	7.19×10^{10}	8.60×10^{8}	1.77×10^{2}	6.50×10^{10}	1.12×10^{13}	2.37×10^{11}	1.16×10^{11}	1.39×10^{9}	2.86×10^{2}	1.09×10^{11}
		16.69%	*6.75%*	*71.35%*	*10.60%*	*59.30%*	*77.52%*	*20.40%*	*24.51%*	*23.79%*	*27.87%*	*38.98%*	*72.77%*
Bioenergy	n-4	5.67×10^{9}	1.42×10^{8}	8.41×10^{8}	3.31×10^{6}	4.41×10^{-2}	7.83×10^{6}	4.64×10^{12}	9.26×10^{10}	3.50×10^{11}	1.94×10^{9}	2.29×10^{1}	9.07×10^{9}
		0.01%	*0.01%*	*0.83%*	*0.04%*	*0.01%*	*0.01%*	*8.43%*	*9.57%*	*71.45%*	*38.84%*	*3.12%*	*6.08%*
Waste	n-4	1.85×10^{11}	1.22×10^{10}	5.19×10^{9}	1.67×10^{8}	1.45	4.18×10^{8}	1.93×10^{11}	1.27×10^{10}	5.42×10^{9}	1.74×10^{8}	1.51	4.32×10^{8}
		0.45%	*0.56%*	*5.15%*	*2.06%*	*0.49%*	*0.50%*	*0.35%*	*1.32%*	*1.11%*	*3.48%*	*0.21%*	*0.29%*
Coal	n-4	2.87×10^{12}	8.03×10^{11}	1.84×10^{10}	2.77×10^{9}	2.70×10^{1}	1.04×10^{9}						
		6.90%	*37.00%*	*18.22%*	*34.19%*	*9.07%*	*1.24%*						
Natural gas	n-4	1.70×10^{13}	6.53×10^{11}	9.45×10^{8}	1.26×10^{9}	2.69×10^{1}	3.57×10^{9}	7.70×10^{10}	1.28×10^{11}	5.11×10^{6}	8.03×10^{6}	9.28×10^{-2}	1.38×10^{8}
		40.93%	*30.12%*	*0.94%*	*15.52%*	*9.03%*	*4.25%*	*0.14%*	*13.27%*	*0.00%*	*0.16%*	*0.01%*	*0.09%*
Nuclear	n-4	3.49×10^{12}	6.14×10^{9}	5.49×10^{8}	2.93×10^{9}	6.11	9.24×10^{9}	9.97×10^{11}	1.76×10^{9}	1.57×10^{8}	8.39×10^{8}	1.75	2.90×10^{9}
		8.39%	*0.28%*	*0.54%*	*36.14%*	*2.05%*	*11.01%*	*1.81%*	*0.18%*	*0.03%*	*16.79%*	*0.24%*	*1.94%*
Diesel	n-4	3.38×10^{12}	2.89×10^{11}	8.14×10^{8}	3.20×10^{7}	1.18×10^{1}	6.08×10^{7}		1.34×10^{11}				9.32×10^{7}
		8.13%	*13.32%*	*0.81%*	*0.39%*	*3.98%*	*0.07%*		*13.84%*				*0.06%*
Kerosene	n-4	2.70×10^{12}	2.26×10^{11}	5.73×10^{8}	2.46×10^{7}	9.19	4.85×10^{7}		1.97×10^{11}				9.70×10^{7}
		6.49%	*10.44%*	*0.57%*	*0.30%*	*3.09%*	*0.06%*		*20.40%*				*0.06%*

Table J.26. Summary of intensive data outputs. Listings for projected 2030 and 2050 energy mixes derived from combinations of aggregated extensive indicators

		CLIMATE NEUTRALITY SCENARIO DATA														
		2030							2050							
	Level	Energy metabolic rate [MJ/hr]	GHG metabolic rate [kg CO_2-eq/hr]	Water metabolic rate [m^3/hr]	Water use-to-energy [m^3/MJ]	GHG-to-energy [kg CO_2-eq/MJ]	Land use-to-energy [m^2/MJ]	Supply risk-to-energy [yr/PJ]	Energy metabolic rate [MJ/hr]	GHG metabolic rate [kg CO_2-eq/hr]	Water metabolic rate [m^3/hr]	Water use-to-energy [m^3/MJ]	GHG-to-energy [kg CO_2-eq/MJ]	Land use-to-energy [m^2/MJ]	Supply risk-to-energy [yr/PJ]
ALL SYSTEM	n	4.96×10^{2}	2.59×10^{1}	9.67×10^{-2}	1.95×10^{-4}	5.22×10^{-2}	2.42×10^{-3}	7.16×10^{-3}	3.69×10^{2}	6.48	3.35×10^{-2}	9.08×10^{-5}	1.76×10^{-2}	8.89×10^{-3}	1.33×10^{-2}
Electricity	n-1	2.32×10^{2}	1.26×10^{1}	8.53×10^{-2}	3.68×10^{-4}	5.45×10^{-2}	5.29×10^{-3}	1.35×10^{-2}	3.60×10^{2}	2.98	2.18×10^{-2}	6.06×10^{-5}	8.26×10^{-3}	2.94×10^{-3}	1.41×10^{-2}
Heat	n-1	3.55×10^{3}	9.85×10^{1}	3.33×10^{-1}	9.38×10^{-5}	2.77×10^{-2}	7.66×10^{-5}	1.08×10^{-3}	4.61×10^{2}	1.33	5.41×10^{-3}	1.17×10^{-5}	2.88×10^{-3}	5.97×10^{-2}	1.32×10^{-3}
Fuel	n-1	5.49×10^{4}	4.36×10^{3}	3.94×10^{-1}	7.18×10^{-6}	7.95×10^{-2}	1.68×10^{-4}	3.33×10^{-3}	1.43×10^{3}	1.74×10^{3}	6.13	4.30×10^{-3}	1.22	1.99×10^{-1}	3.90×10^{-2}
Renewable	n-2	1.72×10^{2}	2.58	1.33×10^{-2}	7.74×10^{-5}	1.50×10^{-2}	6.23×10^{-3}	1.80×10^{-2}	3.69×10^{2}	3.39	2.73×10^{-2}	7.39×10^{-5}	9.17×10^{-3}	9.00×10^{-3}	1.36×10^{-2}
Non-renewable	n-2	2.06×10^{3}	1.38×10^{2}	5.00×10^{-1}	2.43×10^{-4}	6.72×10^{-2}	8.92×10^{-4}	2.78×10^{-3}	3.46×10^{2}	1.30×10^{2}	2.79×10^{-1}	8.06×10^{-4}	3.74×10^{-1}	4.40×10^{-3}	2.64×10^{-3}
Wind	n-4	1.49×10^{3}	5.92	2.63×10^{-2}	1.76×10^{-5}	3.97×10^{-3}	4.89×10^{-4}	1.16×10^{-2}	1.42×10^{3}	5.62	2.49×10^{-2}	1.76×10^{-5}	3.97×10^{-3}	4.89×10^{-4}	1.16×10^{-2}
Hydro	n-4	8.05×10^{2}	8.51	3.35×10^{-3}	4.16×10^{-6}	1.06×10^{-2}	5.93×10^{-5}	1.86×10^{-3}	7.64×10^{2}	8.35	3.22×10^{-3}	4.21×10^{-6}	1.09×10^{-2}	6.00×10^{-5}	1.84×10^{-3}
Solar	n-4	1.07×10^{2}	2.25	1.32×10^{-2}	1.24×10^{-4}	2.11×10^{-2}	1.04×10^{-2}	2.55×10^{-2}	1.03×10^{2}	2.18	1.28×10^{-2}	1.24×10^{-4}	2.11×10^{-2}	1.04×10^{-2}	2.55×10^{-2}
Bioenergy	n-4	7.24×10^{2}	1.81×10^{1}	4.23×10^{-1}	5.84×10^{-4}	2.50×10^{-2}	1.48×10^{-1}	7.77×10^{-3}	5.11×10^{2}	1.02×10^{1}	2.14×10^{-1}	4.18×10^{-4}	2.00×10^{-2}	7.54×10^{-2}	4.94×10^{-3}
Waste	n-4	4.43×10^{2}	2.92×10^{1}	3.99×10^{-1}	9.01×10^{-4}	6.60×10^{-2}	2.81×10^{-2}	7.81×10^{-3}	4.47×10^{2}	2.95×10^{1}	4.03×10^{-1}	9.01×10^{-4}	6.59×10^{-2}	2.80×10^{-2}	7.81×10^{-3}
Coal	n-4	2.75×10^{3}	7.71×10^{2}	2.66	9.67×10^{-4}	2.80×10^{-1}	6.40×10^{-3}	9.41×10^{-3}							
Natural gas	n-4	4.77×10^{3}	1.83×10^{2}	3.53×10^{-1}	7.40×10^{-5}	3.84×10^{-2}	5.55×10^{-5}	1.58×10^{-3}	5.57×10^{2}	9.30×10^{2}	5.81×10^{-2}	1.04×10^{-4}	1.67	6.63×10^{-5}	1.21×10^{-3}
Nuclear	n-4	3.77×10^{2}	6.65×10^{-1}	3.18×10^{-1}	8.41×10^{-4}	1.76×10^{-3}	1.57×10^{-4}	1.75×10^{-3}	3.44×10^{2}	6.05×10^{-1}	2.89×10^{-1}	8.41×10^{-4}	1.76×10^{-3}	1.57×10^{-4}	1.75×10^{-3}
Diesel	n-4	5.56×10^{4}	4.75×10^{3}	5.25×10^{-1}	9.45×10^{-6}	8.55×10^{-2}	2.41×10^{-4}	3.50×10^{-3}		1.44×10^{3}					
Kerosene	n-4	5.56×10^{4}	4.67×10^{3}	5.07×10^{-1}	9.12×10^{-6}	8.40×10^{-2}	2.13×10^{-4}	3.41×10^{-3}		2.03×10^{3}					

J.7 First case study

Table J.27. Listing of LCI processes from the Ecoinvent v3.8 database assigned to each structural processor in the defined heating system

Carrier	Processor	Activity name	Geography
Heat	Wood chips, CHP	heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014, heat	Sweden
	Wood chips, boiler	heat production, softwood chips from forest, at furnace 1000kW, state-of-the-art 2014	Switzerland
	Wood pellets, boiler	heat production, wood pellet, at furnace 300kW, state-of-the-art 2014	Rest of world
	Waste, CHP	heat, from municipal waste incineration to generic market for heat district or industrial, other than natural gas	Sweden
	Biogas, CHP	heat and power co-generation, biogas, gas engine, heat	Sweden
	Natural gas, CHP	heat and power co-generation, natural gas, conventional power plant, 100MW electrical, heat	Sweden
	Natural gas, boiler	heat production, natural gas, at boiler condensing modulating >100kW	Europe without Switzerland
	Coal, CHP	heat and power co-generation, hard coal, heat	Sweden
	Oil, CHP	heat and power co-generation, oil, heat	Sweden
	Oil, boiler	heat production, heavy fuel oil, at industrial furnace 1MW	Europe without Switzerland
Electricity	Hydro	electricity production, hydro, reservoir, non-alpine region	Sweden
	Wind, onshore	electricity production, wind, >3MW turbine, onshore	Sweden
	Wind, offshore	electricity production, wind, 1-3MW turbine, offshore	Sweden
	Solar	electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted	Sweden
	Wood, CHP	heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014, electricity	Sweden
	Wood, conventional	electricity production, wood, future	Global
	Waste, CHP	electricity, from municipal waste incineration to generic market for electricity, medium voltage	Sweden
	Biogas, CHP	heat and power co-generation, biogas, gas engine, electricity	Sweden
	Natural gas, CHP	heat and power co-generation, natural gas, conventional power plant, 100MW electrical, electricity	Sweden
	Natural gas, conventional	electricity production, natural gas, conventional power plant	Norway
	Coal, CHP	heat and power co-generation, hard coal, electricity	Sweden
	Coal, conventional	electricity production, hard coal	Rest of world
	Oil, CHP	heat and power co-generation, oil, electricity	Sweden
	Oil, conventional	electricity production, oil	Sweden
	Nuclear	electricity production, nuclear, boiling water reactor	Sweden

Table J.28. Summary of historical and projected heat generation from electricity use in district heating system and in localised generation at building level. Values of electricity inputs and derived heat are both provided

Scale	Device type	Inputs			Derived heat		
		2015	2019	2050	2015	2019	2050
		[TWh]	*[TWh]*	*[TWh]*	*[TWh]*	*[TWh]*	*[TWh]*
District heating	Boilers	222	178	1,830	173	173	1,830
	Heat pumps	1,074	896	2,355	4,330	3,726	9,420
	Solar thermal			920			920
	Electrolysers			3,120			3,120
	TOTAL	1,296	1,074	8,225	4,504	3,899	15,290
Locally generated	Heaters & boilers	9,418	10,522	2,520	9,418	10,522	2,520
	Heat pumps	7,786	9,404	5,255	15,571	18,807	21,020
	TOTAL	17,204	19,926	7,775	24,989	29,329	23,540
TOTAL		18,500	21,000	16,000	29,493	33,228	38,830

J.8 Second case study

Table J.29. Summary of linkages between structural processors and Euro-Calliope outputs

Structural processor		File	"techs"	"carriers"
Electricity	Wind–onshore	flow_out_sum	wind_onshore	electricity
	Wind–offshore	flow_out_sum	wind_offshore	electricity
	Hydro–reservoir	flow_out_sum	hydro_reservoir	electricity
	Hydro–river	flow_out_sum	hydro_run_of_river	electricity
	Solar PV–field	flow_out_sum	open_field_pv	electricity
	Solar PV–roof	flow_out_sum	roof_mounted_pv	electricity
	Biomass	flow_out_sum	chp_biofuel_extraction	electricity
	Waste	flow_out_sum	chp_wte_back_pressure	electricity
	Coal	flow_out_sum	coal_power_plant	electricity
	Natural gas/methane	flow_out_sum	ccgt	electricity
		flow_out_sum	chp_methane_extraction	electricity
	Nuclear	flow_out_sum	nuclear	electricity
Heat	Biomass	flow_out_sum	biofuel_boiler	heat
		flow_out_sum	chp_biofuel_extraction	heat
	Waste	flow_out_sum	chp_wte_back_pressure	heat
	Natural gas/methane	flow_out_sum	chp_methane_extraction	heat
		flow_out_sum	methane_boiler	heat
Fuel (production)	Biodiesel	flow_out_sum	biofuel_to_diesel	diesel
		flow_out_sum	biofuel_to_liquids	diesel
		flow_out_sum	biofuel_to_liquids	kerosene
		flow_out_sum	biofuel_to_methane	methane
		flow_out_sum	biofuel_to_liquids	electricity
		flow_out_sum	biofuel_to_methanol	methanol
	Biomass	final_consumption	Industry	biofuel
	Coal	final_consumption	Industry	coal
	Natural gas/methane	flow_in_sum	demand_industry_methane	methane
		flow_in_sum	gas_hob	methane
		flow_out_sum	biofuel_to_methane	methane
		flow_out_sum	hydrogen_to_methane	methane
		flow_out_sum	methane_supply	methane
	Diesel	flow_out_sum	diesel_supply	diesel
	Kerosene	flow_out_sum	kerosene_supply	kerosene
	Methanol	flow_out_sum	methanol_supply	methanol
Fuel (combustion)	Biodiesel	flow_out_sum	biofuel_to_diesel	diesel
	Biomass	(as per production)		
	Coal	(as per production)		
	Natural gas	flow_out_sum	biofuel_to_methane	methane
		flow_out_sum	hydrogen_to_methane	methane
		flow_out_sum	methane_supply	methane
		flow_in_sum	ccgt	methane
		flow_in_sum	chp_methane_extraction	methane

	flow_in_sum	methane_boiler	methane
Diesel	flow_out_sum	biofuel_to_liquids	diesel
	flow_out_sum	diesel_supply	diesel
	flow_out_sum	hydrogen_to_liquids	diesel
Kerosene	flow_out_sum	biofuel_to_liquids	kerosene
	flow_out_sum	kerosene_supply	kerosene
	flow_out_sum	hydrogen_to_liquids	kerosene
Methanol	Methanol currently only used in chemical industry and does not undergo combustion. Future versions may include methanol for transport		

Table J.30. Listing of LCI processes from the Ecoinvent v3.8 database assigned to each structural processor in the defined heating system. Fuel calorific values and combustion factors are also provided. Data sources: Eurostat (2020), IPCC (2021)

Carrier	LCI processes			Fuel variables	
	Processor	Activity name	Geography	Net CV *[TWh/kg]*	EF *[kg/TWh]*
Electricity	Wind–onshore	electricity production, wind, 1-3MW turbine, onshore	RoW		
	Wind–offshore	electricity production, wind, 1-3MW turbine, offshore	RoW		
	Hydro–reservoir	electricity production, hydro, reservoir, non-alpine region	SE		
	Hydro–river	electricity production, hydro, run-of-river	DE		
	Solar PV–field	electricity production, photovoltaic, 570kWp open ground installation, multi-Si	RoW		
	Solar PV–roof	electricity production, solar thermal parabolic trough, 50 MW	RoW		
	Biomass	heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014	FI		
	Waste	electricity, from municipal waste incineration to generic market for electricity, medium voltage	DE		
	Coal	electricity production, hard coal	RoW		
	Natural gas	heat and power co-generation, natural gas, conventional power plant, 100MW electrical	DE		
	Nuclear	electricity production, nuclear, pressure water reactor	RoW		
Heat	Biomass	heat and power co-generation, wood chips, 6667 kW, state of the art, 2014	FI		
	Waste	heat, from municipal waste incineration to generic market for heat district or industrial, other than natural gas	DE		
	Natural gas	heat and power co-generation, natural gas, conventional power plant, 100MW electrical	DE		
Fuel	Biodiesel	market for fatty acid methyl ester	RoW	7.50×10^{-9}	1.54×10^{6}
	Biomass	market for wood pellet, measured as dry mass	RoW	4.33×10^{-9}	2.81×10^{7}
	Coal	market for hard coal	Europe, without Russia and Turkey	7.17×10^{-9}	3.43×10^{8}
	Natural gas	market for natural gas, high pressure	RoW	1.23×10^{-8}	2.33×10^{8}
	Diesel	market for diesel	Europe without Switzerland	1.19×10^{-8}	2.68×10^{8}
	Kerosene	market for kerosene	Europe without Switzerland	1.23×10^{-8}	2.64×10^{8}
	Methanol	market for methanol	GLO	6.31×10^{-9}	-

Table J.31. Summary of data sources used to define historical electricity, heat and fuel generation in European energy system for all countries except Switzerland. All data sourced from Eurostat (2022). Definitions from the Standard International Energy Product Classification (SIEC) (United Nations Statistical Division 2017), as used in Eurostat listings, are also given

		Database	"Energy balance"	SIEC classification	Notes
Electricity	Wind–onshore	NRG_BAL_PEH	Gross electricity production	Wind	Split according to onshore/offshore capacity ratio in NRG_INF_EPCRW
	Wind–offshore	NRG_BAL_PEH	Gross electricity production	Wind	
	Hydro–reservoir	NRG_BAL_PEH	Gross electricity production	Hydro	Split according to reservoir/river capacity ratio in NRG_INF_EPCRW
	Hydro–river	NRG_BAL_PEH	Gross electricity production	Hydro	
	Solar PV–field	NRG_BAL_PEH	Gross electricity production	Solar photovoltaic	Split according to field/roof capacity ratio in NRG_INF_EPC
	Solar PV–roof	NRG_BAL_PEH	Gross electricity production	Solar photovoltaic	
	Biomass	NRG_BAL_PEH	Gross electricity production	Primary solid biofuels	
	Waste	NRG_BAL_PEH	Gross electricity production	Renewable municipal waste + Non-renewable waste	
	Coal	NRG_BAL_PEH	Gross electricity production	Solid fossil fuels	
	Natural gas	NRG_BAL_PEH	Gross electricity production	Natural gas	
	Nuclear	NRG_BAL_PEH	Gross electricity production	Nuclear heat	
Heat	Biomass	NRG_BAL_PEH	Gross heat production	Primary solid biofuels	
	Waste	NRG_BAL_PEH	Gross heat production	Renewable municipal waste + Non-renewable waste	
	Natural gas	NRG_BAL_PEH	Gross heat production	Natural gas	
Fuel	Biodiesel	NRG_BAL_C	Final consumption - energy use	Pure biogasoline + Blended biogasoline + Pure biodiesels + Blended biodiesels + Pure bio jet kerosene + Blended bio jet kerosene + Other liquid biofuels	
	Biomass	NRG_BAL_C	Final consumption - energy use	Primary solid biofuels	
	Coal	NRG_BAL_C	Final consumption - energy use	Solid fossil fuels	
	Natural gas	NRG_BAL_C	Final consumption - energy use	Natural gas	
	Diesel	NRG_BAL_C	Final consumption - energy use	Motor gasoline (excluding biofuel portion) + Gas oil and diesel oil (excluding biofuel portion)	
	Kerosene	NRG_BAL_C	Final consumption - energy use	Kerosene	
	Methanol	Assumed zero			

Table J.32. Summary of data sources used to define historical electricity and heat generation capacity in European energy system for all countries except Switzerland. All data sourced from Eurostat (2022) except listings for coal and natural gas which use data from the Open Power Plants Database (EC Joint Research Centre 2019). Definitions from the Standard International Energy Product Classification (SIEC) (United Nations Statistical Division 2017), as used in Eurostat listings, are also given

		Database	“Energy balance”	SIEC classification	Notes
Electricity	Wind–onshore	NRG_INF_EPCRW	Wind on shore	Net maximum electrical capacity	
	Wind–offshore	NRG_INF_EPCRW	Wind off shore	Net maximum electrical capacity	
	Hydro–reservoir	NRG_INF_EPCRW	Pure hydro power + Mixed hydro power	Net maximum electrical capacity	
	Hydro–river	NRG_INF_EPCRW	Run-of-river hydro power	Net maximum electrical capacity	
	Solar PV–field	NRG_INF_EPC	Solar photovoltaic	Main activity producers	
	Solar PV–roof	NRG_INF_EPC	Solar photovoltaic	Autoproducers	
	Biomass	NRG_INF_EPCRW	Solid biofuels	Net maximum electrical capacity	
	Waste	NRG_INF_EPCRW	Waste	Net maximum electrical capacity	
	Coal	JRC-PPDB-OPEN	Fossil Brown coal/Lignite, Fossil Coal-derived gas, Fossil Hard coal	-	Total for all 31 countries in database except Switzerland, plus estimated totals for Cyprus, Luxembourg & Iceland based on ratio of capacities for “ALL producers” in Eurostat NRG_INF_EPC data
	Natural gas	JRC-PPDB-OPEN	Fossil Gas	-	Total for all 31 countries in database except Switzerland, plus estimated totals for Cyprus, Luxembourg & Iceland based on ratio of capacities for “ALL producers” in Eurostat NRG_INF_EPC data
	Nuclear	NRG_INF_EPC	Nuclear fuels and other fuels n.e.c.	Main activity producers	
Heat	Biomass	Ratio of heat to electricity production (see **Table 10.26**) times electrical capacity			
	Waste	Ratio of heat to electricity production (see **Table 10.26**) times electrical capacity			
	Natural gas	Ratio of heat to electricity production (see **Table 10.26**) times electrical capacity			

Table J.33. Summary of data sources used to define historical electricity, heat and fuel generation in Switzerland. Data sources: BFE (2021, 2022a, 2022b)

		Root source	Table or file	Column	Notes
Electricity	Wind–onshore	Schweizerische gesamtenergiestatistik	Table 31	Elektrizitätsproduktion	
	Wind–offshore	Assume no offshore wind in landlocked country			
	Hydro–reservoir	Elektrizitätsstatistik	Zeitreihe Elektrizitätsproduktion Wasserkraft nach Kraftwerkstyp		
	Hydro–river	Elektrizitätsstatistik	Zeitreihe Elektrizitätsproduktion Wasserkraft nach Kraftwerkstyp		
	Solar PV–field	Schweizerische gesamtenergiestatistik	Table 32	Netzgekoppelt	
	Solar PV–roof	Schweizerische gesamtenergiestatistik	Table 32	Inselanlagen	
	Biomass	Schweizerische gesamtenergiestatistik	Table 24	Feuerungen mit Holz und Holzanteilen	
	Waste	Schweizerische gesamtenergiestatistik	Table 27	Elektrizität	
	Coal	Schweizerische gesamtenergiestatistik	Table 24	Konventionell-thermische Kraft- und Fernheizkraftwerke	Split of coal & natural gas according to ratio of “Kohle” & “Gas” in Table 14
	Natural gas	Schweizerische gesamtenergiestatistik	Table 24	Konventionell-thermische Kraft- und Fernheizkraftwerke	Split of coal & natural gas according to ratio of “Kohle” & “Gas” in Table 14
	Nuclear	Elektrizitätsstatistik	Zeitreihe Kernkraftwerke der Schweiz		
Heat	Biomass	Schweizerische gesamtenergiestatistik	Table 26	Fernwärme	Split of biomass, waste & natural gas according to ratio of “Holz”, “Müll” & “Gas”
	Waste	Schweizerische gesamtenergiestatistik	Table 26	Fernwärme	Split of biomass, waste & natural gas according to ratio of “Holz”, “Müll” & “Gas”
	Natural gas	Schweizerische gesamtenergiestatistik	Table 26	Fernwärme	Split of biomass, waste & natural gas according to ratio of “Holz”, “Müll” & “Gas”
Fuel	Biodiesel	Schweizerische gesamtenergiestatistik	Table 14	Biogene Treibstoffe	
	Biomass	Schweizerische gesamtenergiestatistik	Table 14	Holzenergie	
	Coal	Schweizerische gesamtenergiestatistik	Table 14	Kohle	
	Natural gas	Schweizerische gesamtenergiestatistik	Table 14	Gas	
	Diesel	Schweizerische gesamtenergiestatistik	Table 14	Treibstoffe	Split of gasoline/diesel & kerosene according to ratio of “davon Benzin”, “davon Diesel” & “davon Flugtreibstoffe” in Table 17e
	Kerosene	Schweizerische gesamtenergiestatistik	Table 14	Treibstoffe	Split of gasoline/diesel & kerosene according to ratio of “davon Benzin”, “davon Diesel” & “davon Flugtreibstoffe” in Table 17e
	Methanol	Assumed zero			

Table J.34. Summary of data sources used to define historical electricity and heat generation capacity in Switzerland. Data sources: BFE (2021, 2022b, 2022c)

		Root source	Table or file	Column	Notes
Electricity	Wind–onshore	Schweizerische gesamtenergiestatistik	Table 31	Installierte Leistung	
	Wind–offshore	Assume no offshore wind in landlocked country			
	Hydro–reservoir	Wasserkraft	Statistik der Wasserkraftanlagen der Schweiz	Netzgekoppelt	
	Hydro–river	Wasserkraft	Statistik der Wasserkraftanlagen der Schweiz	Inselanlagen	
	Solar PV–field	Schweizerische gesamtenergiestatistik	Table 32		
	Solar PV–roof	Schweizerische gesamtenergiestatistik	Table 32		
	Biomass	Schweizerische gesamtenergiestatistik	Table 36		Split of biomass, coal & natural gas according to generation ratio (see Table J.33)
	Waste	Schweizerische gesamtenergiestatistik	Table 27	Installierte elektrische Nennleistung	
	Coal	Schweizerische gesamtenergiestatistik	Table 36		Split of biomass, coal & natural gas according to generation ratio (see Table J.33)
	Natural gas	Schweizerische gesamtenergiestatistik	Table 36		Split of biomass, coal & natural gas according to generation ratio (see Table J.33)
	Nuclear	Elektrizitätsstatistik	Zeitreihe Kernkraftwerke der Schweiz		
Heat	Biomass	Ratio of heat to electricity generation (see **Table J.33**) times electrical capacity			
	Waste	Ratio of heat to electricity generation (see **Table J.33**) times electrical capacity			
	Natural gas	Ratio of heat to electricity generation (see **Table J.33**) times electrical capacity			

Table J.35. Summary of historical energy generation in the European energy system. Data sources: BFE (2021, 2022a, 2022b), Eurostat (2022)

"n-1"	**"n-5"**	**Historical energy generation**				
		2000	**2005**	**2010**	**2015**	**2019**
		[TWh]	*[TWh]*	*[TWh]*	*[TWh]*	*[TWh]*
Electricity	Wind–onshore	22	71	145	282	389
	Wind–offshore	0.2	0.8	6	24	50
	Hydro–reservoir	542	475	522	510	476
	Hydro–river	48	71	78	79	82
	Solar PV–field	0.1	1.4	21	86	105
	Solar PV–roof	0.03	0.1	1.6	18	28
	Biomass	21	44	70	92	107
	Waste	20	27	37	46	52
	Coal	947	974	840	824	500
	Natural gas	482	670	773	501	705
	Nuclear	970	1,020	942	879	847
Heat	Biomass	38	57	89	113	136
	Waste	32	41	54	70	78
	Natural gas	228	327	316	248	248
Fuel	Biodiesel	8	39	160	169	222
	Biomass	582	674	839	825	885
	Coal	461	384	364	319	265
	Natural gas	3,022	3,215	3,120	2,722	2,823
	Diesel	4,585	4,759	4,359	4,145	4,233
	Kerosene	168	169	171	159	176
TOTAL		12,176	13,018	12,907	12,112	12,406

Table J.36. Summary of historical electricity and heat generation capacities in the European energy system. Data sources: BFE (2021, 2022b, 2022c), EC Joint Research Centre (2019), Eurostat (2022)

"n-1"	**"n-5"**	**Historical energy capacities**				
		2000	**2005**	**2010**	**2015**	**2019**
		[MW]	*[MW]*	*[MW]*	*[MW]*	*[MW]*
Electricity	Wind–onshore	5,857	37,696	75,157	127,674	172,873
	Wind–offshore	50	444	2,879	10,936	22,015
	Hydro–reservoir	155,980	160,817	167,146	174,052	181,651
	Hydro–river	11,628	22,050	23,455	25,107	28,482
	Solar PV–field	157	2,188	27,948	79,414	105,254
	Solar PV–roof	42	126	2,154	16,914	28,534
	Biomass	5,329	9,799	13,370	17,044	20,505
	Waste	3,919	6,596	8,580	10,201	11,563
	Coal	157,919	160,934	164,733	172,308	163,944
	Natural gas	87,569	126,311	171,224	189,787	189,898
	Nuclear	140,537	138,214	134,984	125,290	122,548
Heat	Biomass	9,929	12,706	16,952	21,025	26,067
	Waste	6,356	10,024	12,438	15,751	17,529
	Natural gas	41,333	61,592	69,971	94,113	66,910
TOTAL		626,606	749,499	890,991	1,079,615	1,157,773

Table J.37. Full list of Euro-Calliope model constraints used to implement QTDIAN storyline components. Source: Süsser et al (2021d)

No.	Constraint	Approximate mathematical equation
(1)	Maximum limit on total annual CO_2 emissions compared to 1990 levels. Only applies to 2030 model as 2050 model is assumed to be fully decarbonised	sum(emissions[carrier, region, hour] for all carrier in fossil_fuel_energy_carriers, region in model_regions, hour in year) <= energy_sector_emissions[1990] * emissions_reduction_target
(2)	Minimum contribution from renewable technologies to total consumption of electricity. As with (1), this predominantly impacts 2030 as Euro-Calliope does not represent carbon capture and storage. However, nuclear power is available	sum(electricity_production[tech, region, hour] for all tech in [onshore wind, offshore wind, PV, hydropower, biofuel], region in model_regions, hour in year) / sum(electricity_consumption[region, hour] for all region in model_regions, hour in year) >= renewables_contribution_target
(3)	Energy intensity reduction. Used to scale input end-use demands across all sectors. This implies that reduction in energy intensity does not change the profile of demand within a year	
(4)	Fossil fuel phase-out. As with (1) and (2) this only applies to 2030 model as 2050 model is assumed to be fully decarbonised. Coal plants will not be available in by 2030 in PP storyline, will be capped based on expected total phase-out by 2038 in GD storyline, and will be capped based on current capacity in MD storyline	
(5)	Limit of cross-border international net transfer capacity. Based on hourly absolute net import/export in each country compared to total electricity production in that country	abs(electricity_import[region, hour] - electricity_export[region, hour]) <= sum(electricity_production[tech, region, hour] for all tech in electricity_production_techs) * percentage_NTC_limit for all region in model_regions, hour in year
(6)	Level of car use reduction. Applied to total demand for passenger vehicle travel. The percentage of electric vehicles in vehicle fleet in 2030/2050 will be applied as fixed percentage of total vehicle travel requirement (i.e., from internal combustion and electric vehicles)	sum(mobility_production [EV, region, hour] for all hour in year) == sum(mobility_production[tech, region, hour] for all tech in [EV, ICE], hour in year) * share_of_EVs_in_fleet for all region in model_regions
(7)	Preferred electricity mix. Imposed by set shares of specific renewables in electricity mix and as strict limits on total capacity of certain renewables. In PP storyline technologies which allow a high share of citizen participation (i.e., rooftop solar PV and onshore wind) are prioritised. So, all available rooftop space and all available space for onshore wind will be used. Open-field PV and offshore wind will only be added in situations when other technologies are insufficient to meet demand. In GD storyline a balanced mix of renewables is desired and is enforced by fixed, even shares of each renewable technology. In MD storyline, technologies with the lowest costs will be prioritised	sum(electricity_production[specific_tech, region, hour] for all region in model_regions, hour in year) <= Sum(electricity_production[tech, region, hour] for all tech in [onshore wind, offshore wind, PV, hydropower, biofuel], region in model_regions, hour in year) * renewables_contribution_target [specific_tech] for all specific_tech in [onshore wind, offshore wind, open field PV, rooftop PV]
(8)	Level of grid development. Based on ENTSO-E's TYNDP2020 scenario reference and expanded grids. Assumed that expanded grid is only relevant for GD storyline and as a reference for PP storyline. The MD storyline will use grid transfer capacities according to Euro-Calliope's internal dataset as a lower bound, with the ability to pay for increased capacity	
(9)	Minimum storage capacity of batteries in Europe. No differentiation is made between grid-scale and home batteries in Euro-Calliope. However, the cost of batteries will change in each storyline to reflect dominant battery choice in each storyline: PP - home batteries, GD - average of grid scale and home, MD - cheapest	sum(battery_storage_capacity[region] for all region in model_regions) >=expected_projects_storage_capacity
(10)	Limit of onshore wind power. Cannot be imposed by distance to housing as available datasets describing urban settlements not of sufficient quality. However, can employ a limit on land that can be developed for onshore wind	wind_land_use [region] <= maximum_land_use_percentage * land_area[region] for all region in model_regions

Table J.38. Summary of energy generation in the European energy system in 2030 and 2050 according to all three storyline scenarios. Data source: Pickering (2022a)

"n-1"	"n-5"	Government directed		Market driven		People powered	
		2030	**2050**	**2030**	**2050**	**2030**	**2050**
		[TWh]	*[TWh]*	*[TWh]*	*[TWh]*	*[TWh]*	*[TWh]*
Electricity	Wind–onshore	2,033	6,611	1,865	8,911	2,730	9,698
	Wind–offshore	488	2,388	292	814	327	783
	Hydro–reservoir	325	409	414	414	407	412
	Hydro–river	94	120	133	112	98	98
	Solar PV–field	726	3,596	956	2,702	80	914
	Solar PV–roof	12	59	-	0.1	1,942	3,337
	Biomass	272	50	113	-	222	171
	Waste	52	54	52	54	52	54
	Coal	4	0	18	-	-	-
	Natural gas	138	101	26	1.1	184	215
	Nuclear	599	159	615	0.1	574	-
Heat	Biomass	609	50	940	0.4	277	221
	Waste	52	54	52	54	52	54
	Natural gas	559	-	1,342	0.1	7	0.5
Fuel	Biodiesel	416	1,418	284	1,498	686	1,186
	Biomass	358	-	358	-	358	-
	Coal	216	-	216	-	216	-
	Natural gas	1,120	-	1,179	-	604	-
	Diesel	3,311	-	2,732	-	2,642	-
	Kerosene	935	-	935	-	928	-
TOTAL		12,319	15,071	12,521	14,561	12,386	17,145

Table J.39. Summary of energy generation capacities in the European energy system in 2030 and 2050 according to all three storyline scenarios. Data source: Pickering (2022a)

"n-1"	"n-5"	Government directed		Market driven		People powered	
		2030	2050	2030	2050	2030	2050
		[MW]	*[MW]*	*[MW]*	*[MW]*	*[MW]*	*[MW]*
Electricity	Wind–onshore	815,211	2,550,824	615,225	2,741,248	1,100,337	3,625,462
	Wind–offshore	117,897	542,047	70,657	206,962	100,267	226,078
	Hydro–reservoir	104,814	104,814	104,814	104,814	104,814	104,814
	Hydro–river	34,652	34,652	34,652	34,652	34,652	34,652
	Solar PV–field	645,001	3,174,665	786,789	2,194,150	78,920	836,249
	Solar PV–roof	12,402	63,342	35	32	2,228,647	3,562,914
	Biomass	67,931	12,495	26,507	9	63,278	44,229
	Waste	11,860	13,374	11,820	14,030	11,946	13,072
	Coal	17,376	0	103,231	0	0	0
	Natural gas	206,982	244,181	50,670	37,295	358,141	482,387
	Nuclear	90,930	24,154	87,147	9	87,147	0
Heat	Biomass	174,074	11,033	295,400	101	73,063	56,419
	Waste	5,931	6,687	5,911	7,018	5,975	6,538
	Natural gas	212,402	0	503,436	48	2,927	156
TOTAL		2,517,463	6,782,269	2,696,294	5,340,369	4,250,115	8,992,971

Table J.40. Complete listing of extensive data outputs for storyline scenarios. For each indicator, the system total is given followed by the percentage contributions of different carrier types ("n-1") and technology groups ("n-4"). Results are given for historical configurations for the years 1990, 2000, 2010 and 2019 alongside projected "storyline" scenarios for 2050 according to market driven (MD), government directed (GD) and people powered (PP) specifications

	1990	2000	2010	2019	2050		
					MD	GD	PP
Energy							
TOTAL *[PWh]*	11.17	12.18	12.91	12.41	14.56	15.07	17.14
Electricity *[%]*	22.8	25.1	26.6	26.9	89.3	89.9	91.5
Heat *[%]*	1.7	2.4	3.6	3.7	0.4	0.7	1.6
Fuel *[%]*	75.6	72.5	69.8	69.4	10.3	9.4	6.9
Wind *[%]*	0.0	0.2	1.2	3.5	66.8	59.7	61.1
Solar *[%]*	0.0	0.0	0.2	1.1	18.6	24.3	24.8
Hydro *[%]*	4.3	4.8	4.7	4.5	3.6	3.5	3.0
Bioenergy *[%]*	4.5	5.3	9.0	10.9	10.3	10.1	9.2
Waste *[%]*	0.3	0.4	0.7	1.0	0.7	0.7	0.6
Coal *[%]*	19.5	11.6	9.3	6.2	0.0	0.0	0.0
Natural gas *[%]*	25.5	30.7	32.6	30.4	0.0	0.7	1.3
Nuclear *[%]*	7.3	8.0	7.3	6.8	0.0	1.1	0.0
Diesel *[%]*	37.7	37.7	33.8	34.1	0.0	0.0	0.0
Kerosene *[%]*	1.0	1.4	1.3	1.4	0.0	0.0	0.0
GHG							
TOTAL *[Pg CO_2-eq]*	3.635	3.736	3.841	3.364	1.727	1.816	1.844
Electricity *[%]*	32.3	33.6	34.2	28.2	22.0	27.7	33.9
Heat *[%]*	0.4	0.7	0.9	0.9	0.1	0.2	0.2
Fuel *[%]*	67.2	65.8	64.9	70.9	77.9	72.2	65.9
Wind *[%]*	0.0	0.0	0.1	0.2	8.1	7.3	8.2
Solar *[%]*	0.0	0.0	0.0	0.3	11.9	15.3	17.1
Hydro *[%]*	0.6	0.7	0.7	0.7	1.2	1.1	1.1
Bioenergy *[%]*	0.8	1.1	4.2	6.2	36.1	32.7	27.3
Waste *[%]*	0.1	0.2	0.3	0.5	0.9	0.8	0.8
Coal *[%]*	40.8	30.3	25.7	18.0	0.0	0.0	0.0
Natural gas *[%]*	21.0	28.4	32.6	33.6	10.0	12.5	15.7
Nuclear *[%]*	0.1	0.2	0.2	0.2	0.0	0.1	0.0
Diesel *[%]*	35.6	37.8	34.9	38.7	12.8	12.2	12.0
Kerosene *[%]*	0.9	1.4	1.3	1.6	18.9	18.0	17.7
Land occupation							
TOTAL *[thousand km^2]*	230.1	288.7	567.2	683.4	1,197	1,247	1,197
Electricity *[%]*	17.3	17.9	20.5	23.5	10.3	17.5	24.9
Heat *[%]*	1.1	3.1	3.6	4.5	0.1	0.9	4.1
Fuel *[%]*	81.6	79.1	76.0	72.0	89.7	81.5	71.0
Wind *[%]*	0.0	0.0	0.0	0.1	1.4	1.1	1.5
Solar *[%]*	0.0	0.0	0.1	0.6	8.4	10.8	4.5
Hydro *[%]*	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Bioenergy *[%]*	84.0	88.6	94.2	95.6	89.7	87.6	93.5
Waste *[%]*	0.5	0.8	0.8	0.9	0.5	0.5	0.5
Coal *[%]*	13.4	8.5	3.8	1.9	0.0	0.0	0.0
Natural gas *[%]*	0.3	0.4	0.2	0.2	0.0	0.0	0.0
Nuclear *[%]*	0.2	0.2	0.1	0.1	0.0	0.0	0.0
Diesel *[%]*	1.6	1.4	0.7	0.5	0.0	0.0	0.0
Kerosene *[%]*	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Water depletion							
TOTAL *[TL]*	7.143	7.848	10.39	9.836	25.24	25.09	21.81
Electricity *[%]*	90.5	91.8	70.8	59.8	8.0	12.4	15.7

Heat *[%]*	0.9	1.2	1.4	1.4	0.1	0.1	0.2
Fuel *[%]*	8.6	7.0	27.8	38.8	91.9	87.5	84.1
Wind *[%]*	0.0	0.0	0.1	0.3	2.5	2.4	3.1
Solar *[%]*	0.0	0.0	0.1	0.6	4.8	6.5	9.8
Hydro *[%]*	0.1	0.1	0.1	0.1	0.0	0.0	0.0
Bioenergy *[%]*	0.9	2.6	25.0	36.3	91.9	87.5	84.3
Waste *[%]*	0.6	1.1	1.5	2.2	0.8	0.8	1.0
Coal *[%]*	55.6	44.0	29.3	18.6	0.0	0.0	0.0
Natural gas *[%]*	6.1	12.7	15.0	14.3	0.0	0.7	1.8
Nuclear *[%]*	34.6	37.4	27.4	26.1	0.0	1.9	0.0
Diesel *[%]*	2.0	2.0	1.4	1.5	0.0	0.0	0.0
Kerosene *[%]*	0.1	0.1	0.1	0.1	0.0	0.0	0.0
Human toxicity							
TOTAL *[Pg 1,4-DC]*	0.8111	0.7106	0.6941	0.5354	0.3522	0.4467	0.6580
Electricity *[%]*	72.9	79.1	78.3	73.4	82.5	85.8	89.1
Heat *[%]*	0.3	0.8	1.6	3.2	0.5	1.6	3.7
Fuel *[%]*	26.8	20.1	20.1	23.4	17.0	12.7	7.2
Wind *[%]*	0.0	0.0	0.2	0.9	30.4	22.9	17.5
Solar *[%]*	0.0	0.0	0.2	1.7	48.1	51.6	53.6
Hydro *[%]*	0.1	0.2	0.2	0.2	0.3	0.2	0.2
Bioenergy *[%]*	1.7	3.3	9.8	18.2	17.0	20.5	26.2
Waste *[%]*	0.4	0.9	1.6	2.9	4.3	3.4	2.3
Coal *[%]*	86.1	79.7	71.5	56.3	0.0	0.0	0.0
Natural gas *[%]*	4.0	5.9	6.6	7.8	0.0	0.2	0.3
Nuclear *[%]*	3.2	4.4	4.3	5.0	0.0	1.1	0.0
Diesel *[%]*	4.4	5.5	5.3	6.7	0.0	0.0	0.0
Kerosene *[%]*	0.1	0.2	0.2	0.3	0.0	0.0	0.0
Human activity							
TOTAL *[Gh]*	12.98	14.89	17.79	23.06	119.0	166.9	220.1
Electricity *[%]*	91.1	91.9	91.1	92.1	99.6	99.6	99.3
Heat *[%]*	2.1	2.9	4.4	4.6	0.1	0.2	0.6
Fuel *[%]*	6.9	5.2	4.5	3.3	0.2	0.2	0.1
Wind *[%]*	0.0	0.3	3.8	7.6	21.8	17.0	15.3
Solar *[%]*	0.0	0.1	6.9	23.7	75.5	79.4	81.8
Hydro *[%]*	14.3	14.7	15.5	13.5	2.1	1.5	1.1
Bioenergy *[%]*	1.7	2.9	4.5	4.9	0.1	0.3	0.9
Waste *[%]*	1.1	1.5	2.5	2.7	0.4	0.3	0.2
Coal *[%]*	10.2	8.3	7.0	5.3	0.0	0.0	0.0
Natural gas *[%]*	3.2	3.5	4.6	3.6	0.1	0.4	0.6
Nuclear *[%]*	67.4	66.6	53.5	37.5	0.0	1.0	0.0
Diesel *[%]*	2.1	2.0	1.6	1.2	0.0	0.0	0.0
Kerosene *[%]*	0.1	0.1	0.1	0.0	0.1	0.0	0.0
Material supply risk							
TOTAL *[yr]*	149.0	160.5	193.1	205.3	864.1	904.9	965.0
Electricity *[%]*	32.1	33.8	34.2	36.6	75.7	78.0	82.6
Heat *[%]*	0.5	0.8	1.0	1.0	0.0	0.1	0.1
Fuel *[%]*	67.4	65.4	64.8	62.4	24.3	22.0	17.2
Wind *[%]*	0.0	0.6	3.2	8.8	46.4	40.0	44.9
Solar *[%]*	0.0	0.0	1.1	5.8	28.7	36.9	36.3
Hydro *[%]*	2.0	2.3	2.0	1.8	0.4	0.4	0.3
Bioenergy *[%]*	2.6	3.8	16.0	20.1	24.3	22.2	17.8
Waste *[%]*	0.2	0.5	0.7	0.9	0.2	0.2	0.2
Coal *[%]*	33.1	23.6	17.1	9.9	0.0	0.0	0.0
Natural gas *[%]*	22.1	28.1	27.3	23.2	0.0	0.2	0.5

Nuclear *[%]*	3.5	3.8	3.1	2.6	0.0	0.1	0.0
Diesel *[%]*	35.6	36.0	28.5	26.0	0.0	0.0	0.0
Kerosene *[%]*	0.9	1.3	1.1	1.1	0.0	0.0	0.0
Environmental impacts from material supply							
TOTAL *[yr]*	1,001	1,092	1,076	1,069	930.2	1,067	1,322
Electricity *[%]*	5.6	5.6	6.8	8.3	84.1	86.8	91.0
Heat *[%]*	0.1	0.1	0.2	0.3	0.1	0.1	0.2
Fuel *[%]*	94.3	94.3	93.0	91.5	15.9	13.1	8.8
Wind *[%]*	0.0	0.1	0.4	1.3	33.0	26.0	25.0
Solar *[%]*	0.0	0.0	0.4	2.3	50.5	59.8	64.6
Hydro *[%]*	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Bioenergy *[%]*	0.7	0.9	2.9	3.8	15.9	13.4	9.6
Waste *[%]*	0.1	0.1	0.2	0.3	0.3	0.3	0.2
Coal *[%]*	6.2	4.4	3.9	2.4	0.0	0.0	0.0
Natural gas *[%]*	2.0	2.7	3.3	3.0	0.0	0.2	0.3
Nuclear *[%]*	0.5	0.6	0.6	0.5	0.0	0.1	0.0
Diesel *[%]*	88.0	87.9	84.8	82.9	0.0	0.0	0.0
Kerosene *[%]*	2.3	3.1	3.2	3.4	0.0	0.0	0.0
Environmental justice relating to material supply							
TOTAL *[yr]*	16.36	17.68	21.79	23.79	108.0	116.6	125.9
Electricity *[%]*	31.2	33.0	33.1	36.3	74.2	77.3	82.4
Heat *[%]*	0.5	0.8	1.0	0.9	0.0	0.0	0.1
Fuel *[%]*	68.3	66.2	66.0	62.8	25.8	22.6	17.5
Wind *[%]*	0.0	0.5	3.0	7.9	38.8	32.8	35.9
Solar *[%]*	0.0	0.0	1.4	7.7	34.9	43.7	45.3
Hydro *[%]*	2.0	2.3	1.9	1.6	0.3	0.3	0.3
Bioenergy *[%]*	2.7	4.1	18.0	22.1	25.8	22.8	18.0
Waste *[%]*	0.2	0.4	0.6	0.8	0.2	0.2	0.1
Coal *[%]*	31.8	22.5	15.9	8.9	0.0	0.0	0.0
Natural gas *[%]*	19.9	25.8	24.7	20.5	0.0	0.2	0.4
Nuclear *[%]*	3.7	4.0	3.2	2.6	0.0	0.1	0.0
Diesel *[%]*	38.6	39.0	30.1	26.7	0.0	0.0	0.0
Kerosene *[%]*	1.0	1.4	1.1	1.1	0.0	0.0	0.0

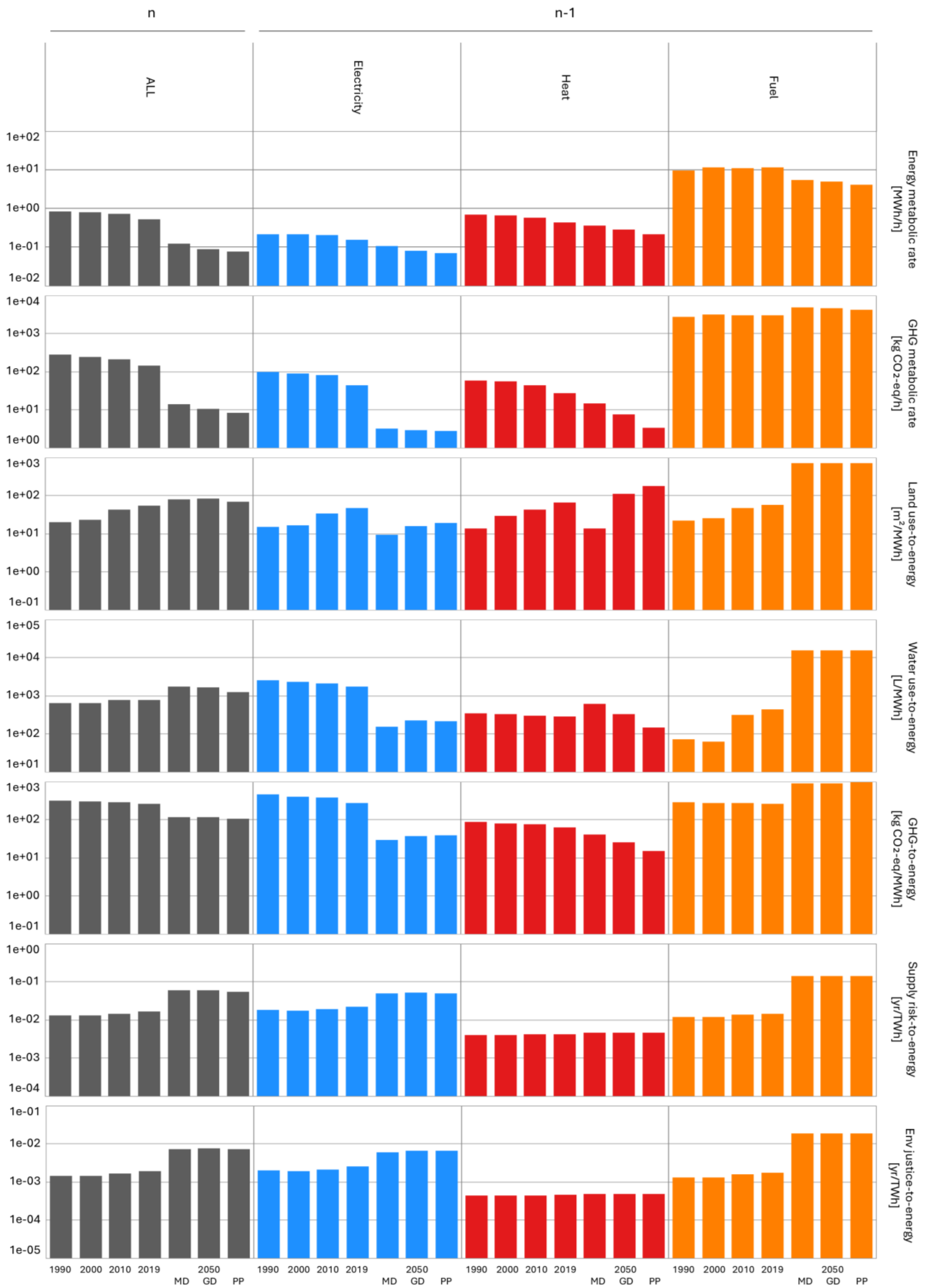


Figure J.8. Results for intensive indicators for entire system ("n") and energy carrier group ("n-1") levels. Results are given for historical configurations for the years 2000, 2010 and 2019 alongside projected "storyline" scenarios for 2050 according to market driven (MD), government directed (GD) and people powered (PP) specifications

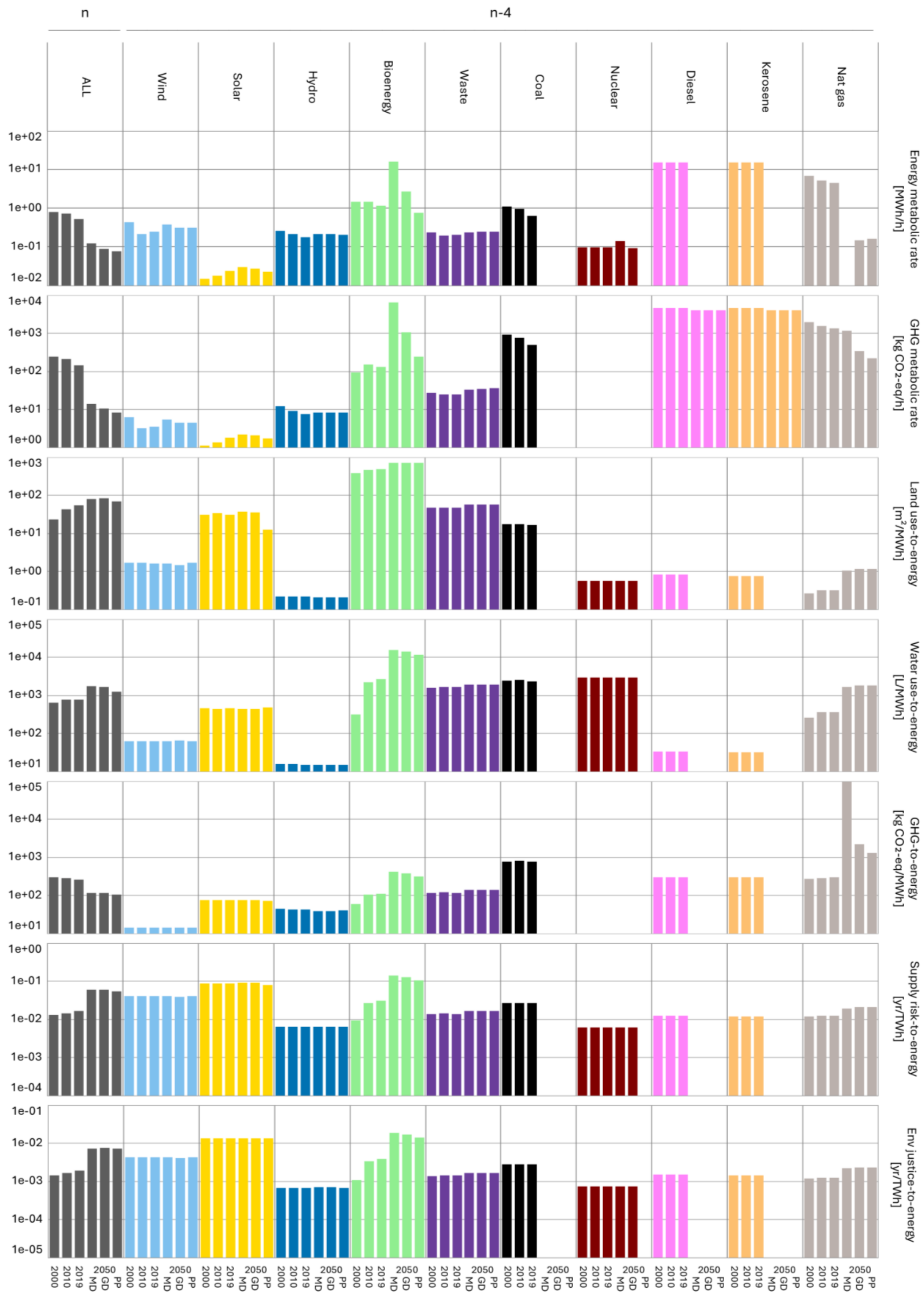


Figure J.9. Results for intensive indicators for entire system ("n") and technology group ("n-4") levels. Results are given for historical configurations for the years 2000, 2010 and 2019 alongside projected "storyline" scenarios for 2050 according to market driven (MD), government directed (GD) and people powered (PP) specifications

Table J.41. Summary of per-unit values for all eight indicators at each structural processor. All values are given per-TWh, except human activity for electricity and heat generation, which are given per-TW of installed capacity. GHG emissions values for fuels include production and combustion, although no combustion emissions are assumed for biomass while methanol is assumed not to be used for combustive purposes

		LCIA				Socio-metabolic		Raw materials		
		GHG emissions	Land occupation	Water depletion	Human toxicity	Human activity		Supply risk	Environmental impacts	Environmental justice
		[kg CO_2-eq/TWh]	*[m^2/TWh]*	*[m^3/TWh]*	*[kg 1,4-DC/TWh]*	*[hr/yr.TW]*	*[hr/yr.TWh]*	*[yr/TWh]*	*[yr/TWh]*	*[yr/TWh]*
Electricity	Wind–onshore	1.43×10^{7}	1.08×10^{7}	1.76×10^{6}	6.34×10^{4}	8.53×10^{9}		4.17×10^{-2}	3.19×10^{-2}	4.34×10^{-3}
	Wind–offshore	1.60×10^{7}	1.29×10^{7}	8.62×10^{5}	7.94×10^{4}	1.22×10^{10}		3.59×10^{-2}	2.81×10^{-2}	4.00×10^{-3}
	Hydro–reservoir	4.93×10^{7}	2.07×10^{6}	2.35×10^{5}	1.66×10^{4}	1.13×10^{10}		6.26×10^{-3}	4.25×10^{-3}	6.80×10^{-4}
	Hydro–river	4.12×10^{6}	1.42×10^{6}	1.50×10^{5}	1.01×10^{4}	3.66×10^{10}		7.94×10^{-3}	4.84×10^{-3}	7.83×10^{-4}
	Solar PV–field	7.60×10^{7}	6.27×10^{7}	3.73×10^{7}	4.46×10^{5}	4.09×10^{10}		9.16×10^{-2}	1.74×10^{-1}	1.39×10^{-2}
	Solar PV–roof	7.36×10^{7}	8.85×10^{7}	5.91×10^{6}	5.15×10^{5}	4.09×10^{10}		7.98×10^{-2}	2.08×10^{-1}	1.33×10^{-2}
	Biomass	5.16×10^{7}	5.98×10^{8}	1.29×10^{9}	2.17×10^{5}	2.00×10^{10}		2.82×10^{-2}	5.08×10^{-2}	2.89×10^{-3}
	Waste	2.38×10^{8}	2.42×10^{8}	1.01×10^{8}	3.25×10^{6}	2.15×10^{10}		2.82×10^{-2}	5.08×10^{-2}	2.89×10^{-3}
	Coal	1.01×10^{9}	5.36×10^{8}	2.30×10^{7}	3.48×10^{6}	6.94×10^{9}		3.39×10^{-2}	4.27×10^{-2}	3.54×10^{-3}
	Natural gas	5.42×10^{8}	9.57×10^{6}	1.17×10^{6}	1.83×10^{6}	2.52×10^{9}		2.12×10^{-2}	1.90×10^{-2}	2.39×10^{-3}
	Nuclear	6.34×10^{6}	3.19×10^{7}	5.67×10^{5}	3.03×10^{6}	7.06×10^{10}		6.31×10^{-3}	6.39×10^{-3}	7.37×10^{-4}
Heat	Biomass	8.75×10^{6}	1.01×10^{8}	2.19×10^{8}	3.68×10^{4}	2.00×10^{10}		4.78×10^{-3}	8.62×10^{-3}	4.90×10^{-4}
	Waste	4.26×10^{7}	3.48×10^{7}	1.22×10^{7}	6.14×10^{5}	2.15×10^{10}		4.78×10^{-3}	8.62×10^{-3}	4.90×10^{-4}
	Natural gas	9.98×10^{7}	1.76×10^{6}	2.15×10^{5}	3.38×10^{5}	2.52×10^{9}		3.90×10^{-3}	3.49×10^{-3}	4.40×10^{-4}
Fuel	Biodiesel	4.18×10^{8}	3.99×10^{7}	7.17×10^{8}	1.55×10^{7}		6.13×10^{4}	1.40×10^{-1}	9.86×10^{-2}	1.86×10^{-2}
	Biomass	6.10×10^{7}	1.25×10^{7}	3.70×10^{8}	1.26×10^{5}		2.13×10^{5}	7.27×10^{-3}	1.32×10^{-2}	8.38×10^{-4}
	Coal	3.88×10^{8}	1.26×10^{8}	6.10×10^{6}	3.29×10^{5}		3.00×10^{5}	1.25×10^{-2}	1.56×10^{-2}	1.36×10^{-3}
	Natural gas	2.57×10^{8}	1.22×10^{7}	1.38×10^{5}	1.14×10^{4}		6.69×10^{4}	1.13×10^{-2}	6.42×10^{-3}	1.09×10^{-3}
	Diesel	3.08×10^{8}	8.49×10^{6}	8.67×10^{5}	3.40×10^{4}		6.48×10^{4}	1.26×10^{-2}	2.09×10^{-1}	1.50×10^{-3}
	Kerosene	3.02×10^{8}	8.27×10^{6}	7.65×10^{5}	3.28×10^{4}		6.48×10^{4}	1.23×10^{-2}	2.04×10^{-1}	1.46×10^{-3}
	Methanol	1.00×10^{8}	1.72×10^{7}	1.16×10^{6}	2.78×10^{5}		6.48×10^{4}	1.29×10^{-2}	4.24×10^{-2}	1.55×10^{-3}

K References

Abbas R, Muñoz-Antón J, Valdés M and Martínez-Val J M 2013 High concentration linear Fresnel reflectors *Energy Convers Manag* **72** 60–8 Online: http://dx.doi.org/10.1016/j.enconman.2013.01.039

AGEE-Stat 2022 *Monatsbericht zur Entwicklung der erneuerbaren Stromerzeugung und Leistung in Deutschland* (Dessau-Roßlau: Arbeitsgruppe Erneuerbare Energien-Statistik)

Akinyele D O and Rayudu R K 2014 Review of energy storage technologies for sustainable power networks *Sustainable Energy Technologies and Assessments* **8** 74–91 Online: http://dx.doi.org/10.1016/j.seta.2014.07.004

Akizu-Gardoki O, Wakiyama T, Wiedmann T, Bueno G, Lenzen M and Lopez-Guede J M 2021 Hidden Energy Flow indicator to reflect the outsourced energy requirements of countries *J Clean Prod* **278** 123827 Online: http://dx.doi.org/10.1016/j.jclepro.2020.123827

Ambrose J 2021 Record metals boom may threaten transition to green energy *The Observer*

Amponsah N Y, Troldborg M, Kington B, Aalders I and Hough R L 2014 Greenhouse gas emissions from renewable energy sources: A review of lifecycle considerations *Renewable and Sustainable Energy Reviews* **39** 461–75 Online: http://dx.doi.org/10.1016/j.rser.2014.07.087

Anagnostopoulos P, Spyridaki N A and Flamos A 2017 A "new-deal" for the development of photovoltaic investments in Greece? A parametric techno-economic assessment *Energies (Basel)* **10** 1173 Online: https://dx.doi.org/10.3390/en10081173

Ananthakumar S, Kumar J R and Babu S M 2019 Third-generation solar cells: Concept, materials and performance - An overview *Emerging nanostructured materials for energy and environmental science. Environmental chemistry for a sustainable world, Volume 23* ed S Rajendran, Mu Naushad, K Raju and R Boukherroub (Cham: Springer Nature) pp 305–39 Online: https://doi.org/10.1007/978-3-030-04474-9_7

ANL 2008 *Energy and power evaluation program (ENPEP-BALANCE): Brief model overview - Version 2.25* (Lemont, IL: Argonne National Laboratory)

Ansar A, Flyvbjerg B, Budzier A and Lunn D 2014 Should we build more large dams? The actual costs of hydropower megaproject development *Energy Policy* **69** 43–56 Online: http://dx.doi.org/10.1016/j.enpol.2013.10.069

Apergis E and Apergis N 2017 The role of rare earth prices in renewable energy consumption: The actual driver for a renewable energy world *Energy Econ* **62** 33–42 Online: http://dx.doi.org/10.1016/j.eneco.2016.12.015

Apostolaki-Iosifidou E, Codani P and Kempton W 2017 Measurement of power loss during electric vehicle charging and discharging *Energy* **127** 730–42 Online: https://dx.doi.org/10.1016/j.energy.2017.03.015

Apostolaki-Iosifidou E, Kempton W and Codani P 2018 Reply to Shirazi and Sachs comments on "Measurement of power loss during electric vehicle charging and discharging" *Energy* **142** 1142–3 Online: http://dx.doi.org/10.1016/j.energy.2017.10.080

Arani A A K, Karami H, Gharehpetian G B and Hejazi M S A 2017 Review of Flywheel Energy Storage Systems structures and applications in power systems and microgrids *Renewable and Sustainable Energy Reviews* **69** 9–18 Online: http://dx.doi.org/10.1016/j.rser.2016.11.166

Arvesen A, Luderer G, Pehl M, Bodirsky B L and Hertwich E G 2018 Deriving life cycle assessment coefficients for application in integrated assessment modelling *Environmental Modelling and Software* **99** 111–25 Online: https://dx.doi.org/10.1016/j.envsoft.2017.09.010

Arvidsson R, Tillman A M, Sandén B A, Janssen M, Nordelöf A, Kushnir D and Molander S 2018 Environmental assessment of emerging technologies: Recommendations for prospective LCA *J Ind Ecol* **22** 1286–94 Online: https://dx.doi.org/10.1111/jiec.12690

Asdrubali F, Baldinelli G, D'Alessandro F and Scrucca F 2015 Life cycle assessment of electricity production from renewable energies: Review and results harmonization *Renewable and Sustainable Energy Reviews* **42** 1113–22 Online: http://dx.doi.org/10.1016/j.rser.2014.10.082

Athanasia A and Genachte A B 2013 Deep offshore and new foundation concepts *Energy Procedia* **35** 198–209 Online: http://dx.doi.org/10.1016/j.egypro.2013.07.173

Avila S 2018 Environmental justice and the expanding geography of wind power conflicts *Sustain Sci* **13** 599–616 Online: http://dx.doi.org/10.1007/s11625-018-0547-4

Ayres R U 1989 Industrial metabolism *Technology and environment* ed J H Ausubel and H E Sladovich (Washington, DC: National Academy Press) pp 23–49 Online: https://dx.doi.org/10.17226/1407

Azevedo L B, Henderson A D, van Zelm R, Jolliet O and Huijbregts M A J 2013a Assessing the importance of spatial variability versus model choices in life cycle impact assessment: The case of freshwater eutrophication in Europe *Environ Sci Technol* **47** 13565–70 Online: https://dx.doi.org/10.1021/es403422a

Azevedo L B, van Zelm R, Hendriks A J, Bobbink R and Huijbregts M A J 2013b Global assessment of the effects of terrestrial acidification on plant species richness *Environmental Pollution* **174** 10–5 Online: http://dx.doi.org/10.1016/j.envpol.2012.11.001

de Baan L, Alkemade R and Koellner T 2013 Land use impacts on biodiversity in LCA: A global approach *International Journal of Life Cycle Assessment* **18** 1216–30 Online: https://dx.doi.org/10.1007/s11367-012-0412-0

Babbitt C W, Althaf S, Cruz Rios F, Bilec M M and Graedel T E 2021 The role of design in circular economy solutions for critical materials *One Earth* **4** 353–62 Online: https://dx.doi.org/10.1016/j.oneear.2021.02.014

Badwal S P S, Giddey S S, Munnings C, Bhatt A I and Hollenkamp A F 2014 Emerging electrochemical energy conversion and storage technologies *Front Chem* **2** 1–28 Online: http://dx.doi.org/10.3389/fchem.2014.00079

Bailey I, West J and Whitehead I 2011 Out of sight but not out of mind? Public perceptions of wave energy *Journal of Environmental Policy & Planning* **13** 139–57 Online: https://dx.doi.org/10.1080/1523908X.2011.573632

Bainton N, Kemp D, Lèbre E, Owen J R and Marston G 2021 The energy-extractives nexus and the just transition *Sustainable Development* **29** 624–34 Online: https://dx.doi.org/10.1002/sd.2163

Balest J, Pisani E, Vettorato D and Secco L 2018 Local reflections on low-carbon energy systems: A systematic review of actors, processes, and networks of local societies *Energy Res Soc Sci* **42** 170–81 Online: https://dx.doi.org/10.1016/j.erss.2018.03.006

Banja M, Jégard M, Motola V and Sikkema R 2019 Support for biogas in the EU electricity sector - A comparative analysis *Biomass Bioenergy* **128** 105313 Online: https://dx.doi.org/10.1016/j.biombioe.2019.105313

Barlev D, Vidu R and Stroeve P 2011 Innovation in concentrated solar power *Solar Energy Materials and Solar Cells* **95** 2703–25 Online: http://dx.doi.org/10.1016/j.solmat.2011.05.020

Barnhart C J and Benson S M 2013 On the importance of reducing the energetic and material demands of electrical energy storage *Energy Environ Sci* **6** 1083–92 Online: https://dx.doi.org/10.1039/c3ee24040a

Beck T, Bos U, Wittstock B, Baitz M, Fischer M and Sedlbauer K 2010 *LANCA® Land use indicator value calculation in life cycle assessment - Method report* (Stuttgart: Fraunhofer Verlag)

Bellocchi S, Manno M, Noussan M and Prina M G 2020 Electrification of transport and residential heating sectors in support of renewable penetration: Scenarios for the Italian energy system *Energy* **196** 117062 Online: https://dx.doi.org/10.1016/j.energy.2020.117062

Benato A and Stoppato A 2018 Pumped thermal electricity storage: A technology overview *Thermal Science and Engineering Progress* **6** 301–15 Online: https://dx.doi.org/10.1016/j.tsep.2018.01.017

Bennun L, van Bochove J, Ng C, Fletcher C, Wilson D, Phair N and Carbone G 2021 *Mitigating biodiversity impacts associated with solar and wind energy development. Guidelines for project developers* (Gland: IUCN) Online: https://dx.doi.org/10.2305/IUCN.CH.2021.04.en

Berger M, Sonderegger T, Alvarenga R, Bach V, Cimprich A, Dewulf J, Frischknecht R, Guinée J, Helbig C, Huppertz T, Jolliet O, Motoshita M, Northey S, Peña C A, Rugani B, Sahnoune A, Schrijvers D, Schulze R, Sonnemann G, Valero A, Weidema B P and Young S B 2020 Mineral resources in life cycle impact assessment: Part II - Recommendations on application-dependent use of existing methods and on future method development needs *International Journal of Life Cycle Assessment* **25** 798–813 Online: https://dx.doi.org/10.1007/s11367-020-01737-5

Berglund C and Söderholm P 2006 Modeling technical change in energy system analysis: Analyzing the introduction of learning-by-doing in bottom-up energy models *Energy Policy* **34** 1344–56 Online: http://dx.doi.org/10.1016/j.enpol.2004.09.002

Best B, Thema J, Zell-Ziegler C, Wiese F, Barth J, Breidenbach S, Nascimento L and Wilke H 2022 Building a database for energy sufficiency policies *F1000Res* **11** 229 Online: https://dx.doi.org/10.12688/f1000research.108822.1

Bett A, Burger B, Friedrich L, Kost C, Nold S, Peper D, Philipps S, Preu R, Rentsch J, Stryi-Hipp G, Wirth H and Warmuth W 2022 *Photovoltaics report* (Freiburg: Fraunhofer ISE)

BFE 2022a 9605-Zeitreihe_Elektrizitätsproduktion_Wasserkraft_nach_Kraftwerkstyp Online: https://www.bfe.admin.ch/ogd62

BFE 2022b 9606-Zeitreihe_Kernkraftwerke_der_Schweiz Online: https://www.bfe.admin.ch/ogd62

BFE 2022c 10894-Statistik der Wasserkraftanlagen der Schweiz Stand 1.1.2022 Online: https://www.bfe.admin.ch/bfe/en/home/supply/renewable-energy/hydropower.html

BFE 2021 *Schweizerische gesamtenergiestatistik 2021* (Ittigen: Bundesamt für Energie)

Bhandari R, Kumar B and Mayer F 2020 Life cycle greenhouse gas emission from wind farms in reference to turbine sizes and capacity factors *J Clean Prod* **277** 123385 Online: https://dx.doi.org/10.1016/j.jclepro.2020.123385

Biasotto L D and Kindel A 2018 Power lines and impacts on biodiversity: A systematic review *Environ Impact Assess Rev* **71** 110–9 Online: https://dx.doi.org/10.1016/j.eiar.2018.04.010

BIO by Deloitte 2015 *Study on data for a raw material system analysis: Roadmap and test of the fully operational MSA for raw materials. Prepared for the European Commission, DG GROW*

Blaabjerg F and Ionel D M 2015 Renewable energy devices and systems - State-of-the-art technology, research and development, challenges and future trends *Electric Power Components and Systems* **43** 1319–28 Online: https://dx.doi.org/10.1080/15325008.2015.1062819

Blanco H, Codina V, Laurent A, Nijs W, Maréchal F and Faaij A 2020 Life cycle assessment integration into energy system models: An application for power-to-methane in the EU *Appl Energy* **259** 114160 Online: https://dx.doi.org/10.1016/j.apenergy.2019.114160

Bleicher A and Pehlken A 2020 *The material basis of energy transitions* (London: Academic Press) Online: https://dx.doi.org/10.1016/C2018-0-05595-4

Blengini G A, Nuss P, Dewulf J, Nita V, Talens Peiró L, Vidal-Legaz B, Latunussa C, Mancini L, Blagoeva D, Pennington D, Pellegrini M, van Maercke A, Solar S, Grohol M and Ciupagea C 2017 EU methodology for critical raw materials assessment: Policy needs and proposed solutions for incremental improvements *Resources Policy* **53** 12–9 Online: http://dx.doi.org/10.1016/j.resourpol.2017.05.008

BMWK 2022 *Kerninhalte der Referentenentwürfe des BMWK zur Novelle des Novelle des Wind-auf-See-Gesetzes und zum EEG-Entlastungsgesetz* (Berlin)

Bobba S, Carrara S, Huisman J, Mathieux F and Pavel C 2020 *Critical raw materials for strategic technologies and sectors in the EU: A foresight study* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2873/865242

Bódis K, Kougias I, Jäger-Waldau A, Taylor N and Szabó S 2019 A high-resolution geospatial assessment of the rooftop solar photovoltaic potential in the European Union *Renewable and Sustainable Energy Reviews* **114** 109309 Online: https://dx.doi.org/10.1016/j.rser.2019.109309

Bonabeau E 2002 Agent-based modeling: Methods and techniques for simulating human systems *Proc Natl Acad Sci U S A* **99** 7280–7 Online: http://dx.doi.org/10.1073/pnas.082080899

Borch K 2018 Mapping value perspectives on wind power projects: The case of the Danish test centre for large wind turbines *Energy Policy* **123** 251–8 Online: https://dx.doi.org/10.1016/j.enpol.2018.08.056

Bos U, Horn R, Beck T, Lindner J P and Fischer M 2016 *LANCA® - Characterisation factors for life cycle impact assessment. Version 2.0* (Stuttgart)

Boßmann T and Staffell I 2015 The shape of future electricity demand: Exploring load curves in 2050s Germany and Britain *Energy* **90** 1317–33 Online: http://dx.doi.org/10.1016/j.energy.2015.06.082

Botelho A, Ferreira P, Lima F, Pinto L M C and Sousa S 2017 Assessment of the environmental impacts associated with hydropower *Renewable and Sustainable Energy Reviews* **70** 896–904 Online: http://dx.doi.org/10.1016/j.rser.2016.11.271

Boubault A, Kang S and Maïzi N 2019 Closing the TIMES Integrated Assessment Model (TIAM-FR) raw materials gap with life cycle inventories *J Ind Ecol* **23** 587–600 Online: https://dx.doi.org/10.1111/jiec.12780

Boulay A-M, Bare J, Benini L, Berger M, Lathuillière M J, Manzardo A, Margni M, Motoshita M, Núñez M, Pastor A V, Ridoutt B, Oki T, Worbe S and Pfister S 2018 The WULCA consensus characterization model for water scarcity footprints: Assessing impacts of water consumption based on available water remaining (AWARE) *Int J Life Cycle Assess* **23** 368–78 Online: https://dx.doi.org/10.1007/s11367-017-1333-8

BP 2019 *BP statistical review of world energy 2019* (London)

Brandes J, Haun M, Wrede D, Jürgens P, Kost C and Henning H-M 2021 *Wege zu einem klimaneutralen Energiesystem: Update Klimaneutralität 2045* (Freiburg) Online: https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/Fraunhofer-ISE-Studie-Wege-zu-einem-klimaneutralen-Energiesystem-Update-Klimaneutralitaet-2045.pdf

Brauers H 2022 Natural gas as a barrier to sustainability transitions? A systematic mapping of the risks and challenges *Energy Res Soc Sci* **89** 102538 Online: https://dx.doi.org/10.1016/j.erss.2022.102538

British Geological Survey What is the difference between resources and reserves? Online: https://www2.bgs.ac.uk/mineralsuk/mineralsYou/resourcesReserves.html

Brown N, Lindén D, Fuss M, Xu L and Wyrwa A 2019 Report for the REFLEX Project: D6.3 Social, environmental and external cost assessment of future energy technologies and future energy systems

de Bruijn H, van Duin R, Huijbregts M A J, Guinée J B, Gorree M, Heijungs R, Huppes G, Kleijn R, Koning A de, van Oers L, Wegener Sleeswijk A, Suh S and de Haes H A U 2004 *Handbook on life cycle assessment: Operational guide to the ISO standards* (Dordrecht: Springer) Online: https://dx.doi.org/10.1007/0-306-48055-7

de Bruille V 2014 *Impact de l'utilisation des ressources minérales et métalliques dans un contexte cycle de vie: Une approche fonctionnelle* (Polytechnique Montréal)

Buchholz P and Brandenburg T 2018 Demand, supply, and price trends for mineral raw materials relevant to the renewable energy transition: Wind energy, solar photovoltaic energy, and energy storage *Chem Ing Tech* **90** 141–53 Online: http://dx.doi.org/10.1002/cite.201700098

Bulle C, Margni M, Patouillard L, Boulay A M, Bourgault G, de Bruille V, Cao V, Hauschild M, Henderson A, Humbert S, Kashef-Haghighi S, Kounina A, Laurent A, Levasseur A, Liard G, Rosenbaum R K, Roy P O, Shaked S, Fantke P and Jolliet O 2019 IMPACT World+: A globally regionalized life cycle impact assessment method *International Journal of Life Cycle Assessment* **24** 1653–74 Online: http://dx.doi.org/10.1007/s11367-019-01583-0

Bundesregierung 2021 *Gesetz für den Ausbau erneuerbarer Energien (ErneuerbareEnergien-Gesetz - EEG 2021)*

Bundesverband Windenergie 2021 Windenergie in Deutschland - Zahlen und Fakten Online: https://www.wind-energie.de/themen/zahlen-und-fakten/deutschland/

Bund-Länder-Kooperationsausschuss 2021 *Bericht des Bund-Länder-Kooperationsausschusses zum Stand des Ausbaus der erneuerbaren Energien sowie zu Flächen, Planungen und Genehmigungen für die Windenergienutzung an Land*

Burkert A, Fechtner H and Schmuelling B 2021 Interdisciplinary analysis of social acceptance regarding electric vehicles with a focus on charging infrastructure and driving range in Germany *World Electric Vehicle Journal* **12** 25 Online: https://dx.doi.org/10.3390/wevj12010025

Calvo G and Valero A 2021 Strategic mineral resources: Availability and future estimations for the renewable energy sector *Environ Dev* 100640 Online: https://dx.doi.org/10.1016/j.envdev.2021.100640

Cambridge Econometrics E3ME macro-econometric model Online: https://www.e3me.com/

Cao V, Margni M, Favis B D and Deschênes L 2015 Aggregated indicator to assess land use impacts in life cycle assessment (LCA) based on the economic value of ecosystem services *J Clean Prod* **94** 56–66 Online: https://dx.doi.org/10.1016/j.jclepro.2015.01.041

Capellán-Pérez I, de Blas I, Nieto J, de Castro C, Miguel L J, Carpintero Ó, Mediavilla M, Lobejón L F, Ferreras-Alonso N, Rodrigo P, Frechoso F and Álvarez-Antelo D 2020 MEDEAS: A new modeling framework integrating global biophysical and socioeconomic constraints *Energy Environ Sci* **13** 986–1017 Online: https://dx.doi.org/10.1039/c9ee02627d

Capellán-Pérez I, de Castro C and Arto I 2017 Assessing vulnerabilities and limits in the transition to renewable energies: Land requirements under 100% solar energy scenarios *Renewable and Sustainable Energy Reviews* **77** 760–82 Online: http://dx.doi.org/10.1016/j.rser.2017.03.137

Caporale D, Sangiorgio V, Amodio A and de Lucia C 2020 Multi-criteria and focus group analysis for social acceptance of wind energy *Energy Policy* **140** 111387 Online: https://dx.doi.org/10.1016/j.enpol.2020.111387

Capros P, Kannavou M, Evangelopoulou S, Petropoulos A, Siskos P, Tasios N, Zazias G and DeVita A 2018 Outlook of the EU energy system up to 2050: The case of scenarios prepared for European Commission's "clean energy for all Europeans" package using the PRIMES model *Energy Strategy Reviews* **22** 255–63 Online: https://doi.org/10.1016/j.esr.2018.06.009

Carley S and Konisky D M 2020 The justice and equity implications of the clean energy transition *Nat Energy* **5** 569–77 Online: http://dx.doi.org/10.1038/s41560-020-0641-6

Carlisle J E, Kane S L, Solan D, Bowman M and Joe J C 2015 Public attitudes regarding large-scale solar energy development in the U.S. *Renewable and Sustainable Energy Reviews* **48** 835–47 Online: http://dx.doi.org/10.1016/j.rser.2015.04.047

Carrara S, Alves Dias P, Plazzotta B and Pavel C 2020 *Raw materials demand for wind and solar PV technologies in the transition towards a decarbonised energy system, EUR 30095 EN* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2760/160859

de Castro C and Capellán-Pérez I 2020 Standard, point of use, and extended energy return on energy invested (EROI) from comprehensive material requirements of present global wind, solar, and hydro power technologies *Energies (Basel)* **13** 3036 Online: http://dx.doi.org/10.3390/en13123036

Castro J, Drews S, Exadaktylos F, Foramitti J, Klein F, Konc T, Savin I and van den Bergh J 2020 A review of agent-based modeling of climate-energy policy *Wiley Interdiscip Rev Clim Change* **11** e647 Online: http://dx.doi.org/10.1002/wcc.647

Catola M and D'Alessandro S 2020 Market competition, lobbying influence and environmental externalities *Eur J Polit Econ* **63** 101886 Online: https://dx.doi.org/10.1016/j.ejpoleco.2020.101886

Cebulla F, Haas J, Eichman J, Nowak W and Mancarella P 2018 How much electrical energy storage do we need? A synthesis for the U.S., Europe, and Germany *J Clean Prod* **181** 449–59 Online: https://dx.doi.org/10.1016/j.jclepro.2018.01.144

Chamberlain J P, Hammerschlag R and Schaber C P 2017 Energy storage technologies *Energy management and conservation handbook* ed F Kreith and D Y Goswami (Boca Raton, FL: CRC Press) Online: https://dx.doi.org/10.1201/9781315374178

Chapman A, Arendorf J, Castella T, Thompson P, Willis P, Tercero Espinoza L, Klug S and Wichmann E 2013 *Study on critical raw materials at EU level: Final report* (Oakdene Hollins and Fraunhofer ISI)

Chatterjee S, Stavrakas V, Oreggioni G, Süsser D, Staffell I, Lilliestam J, Molnar G, Flamos A and Ürge-Vorsatz D 2022 Existing tools, user needs and required model adjustments for energy demand modelling of a carbon-neutral Europe *Energy Res Soc Sci* **90** 102662 Online: https://dx.doi.org/10.1016/j.erss.2022.102662

Chouhan N, Meena R K and Liu R-S 2016 Hydrogen: An alternative fuel *Solar energy conversion and storage: Photochemical modes* ed S C Ameta and R Ameta (Boca Raton, FL: CRC Press) pp 139–72 Online: http://dx.doi.org/10.1201/b19148

Chu S and Majumdar A 2012 Opportunities and challenges for a sustainable energy future *Nature* **488** 294–303 Online: http://dx.doi.org/10.1038/nature11475

Church C and Crawford A 2018 *Conflict minerals: The fuels of conflict in the transition to a low-carbon economy* (Winnipeg: International Institute for Sustainable Development)

Church C and Crawford A 2020 Minerals and the metals for the energy transition: Exploring the conflict implications for mineral-rich, fragile states *The geopolitics of the global energy transition* ed M Hafner and S Tagliapietra (Cham: Springer) pp 279–304 Online: https://dx.doi.org/10.1007/978-3-030-39066-2_12

Ciacci L, Reck B K, Nassar N T and Graedel T E 2015 Lost by design *Environ Sci Technol* **49** 9443–51 Online: http://dx.doi.org/10.1021/es505515z

Ciroth A, Arbuckle P, Cherubi E, Ugaya C and Edelen A 2017 *Task 3: Core meta-data descriptors and guidance on populating descriptors*

Cohen J, Moeltner K, Reichl J and Schmidthaler M 2022 An empirical analysis of local opposition to new transmission lines across the EU-27 *The Energy Journal* **37** 59–82 Online: http://dx.doi.org/10.5547/01956574.37.3.jcoh

Congressional Research Service 2019 Projected demand for critical minerals used in solar and wind energy systems and battery storage technology. Memorandum of September 10, 2019

Connolly D, Lund H and Mathiesen B v. 2016 Smart Energy Europe: The technical and economic impact of one potential 100% renewable energy scenario for the European Union *Renewable and Sustainable Energy Reviews* **60** 1634–53 Online: http://dx.doi.org/10.1016/j.rser.2016.02.025

Continental 2021 Many people still doubtful about electric cars' environmental friendliness press release

Cosme N and Hauschild M Z 2016 Effect Factors for marine eutrophication in LCIA based on species sensitivity to hypoxia *Ecol Indic* **69** 453–62 Online: https://dx.doi.org/10.1016/j.ecolind.2016.04.006

Cosme N, Koski M and Hauschild M Z 2015 Exposure factors for marine eutrophication impacts assessment based on a mechanistic biological model *Ecol Modell* **317** 50–63 Online: https://dx.doi.org/10.1016/j.ecolmodel.2015.09.005

Cowell R, Bristow G and Munday M 2011 Acceptance, acceptability and environmental justice: The role of community benefits in wind energy development *Journal of Environmental Planning and Management* **54** 539–57 Online: https://dx.doi.org/10.1080/09640568.2010.521047

Cox B, Mutel C L, Bauer C, Mendoza Beltran A and van Vuuren D P 2018 Uncertain environmental footprint of current and future battery electric vehicles *Environ Sci Technol* **52** 4989–95 Online: https://dx.doi.org/10.1021/acs.est.8b00261

Creutzig F, Roy J, Lamb W F, Azevedo I M L, Bruine De Bruin W, Dalkmann H, Edelenbosch O Y, Geels F W, Grubler A, Hepburn C, Hertwich E G, Khosla R, Mattauch L, Minx J C, Ramakrishnan A, Rao N D, Steinberger J K, Tavoni M, Ürge-Vorsatz D and Weber E U 2018 Towards demand-side solutions for mitigating climate change *Nat Clim Chang* **8** 268–71 Online: http://dx.doi.org/10.1038/s41558-018-0121-1

Curran M, de Souza D M, Antón A, Teixeira R F M, Michelsen O, Vidal-Legaz B, Sala S and Milà I Canals L 2016 How well does LCA model land use impacts on biodiversity? - A comparison with approaches from ecology and conservation *Environ Sci Technol* **50** 2782–95 Online: http://dx.doi.org/10.1021/acs.est.5b04681

Daly H E, Scott K, Strachan N and Barrett J 2015 Indirect CO_2 emission implications of energy system pathways: Linking IO and TIMES models for the UK *Environ Sci Technol* **49** 10701–9 Online: https://dx.doi.org/10.1021/acs.est.5b01020

D'Ambrières W 2019 Plastics recycling worldwide: Current overview and desirable changes *Field Actions Sci Rep* 12–21

DeCarolis J F 2011 Using modeling to generate alternatives (MGA) to expand our thinking on energy futures *Energy Econ* **33** 145–52 Online: http://dx.doi.org/10.1016/j.eneco.2010.05.002

Degel M, Christ M, Becker L and Grünert J 2016 *Sozial-ökologische und technisch-ökonomische Modellierung von Entwicklungspfaden der Energiewende* (Berlin)

Delucchi M A, Yang C, Burke A F, Ogden J M, Kurani K, Kessler J and Sperling D 2014 An assessment of electric vehicles: Technology, infrastructure requirements, greenhouse-gas emissions, petroleum use, material use, lifetime cost, consumer acceptance and policy initiatives *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* **372** 20120325 Online: http://dx.doi.org/10.1098/rsta.2012.0325

Despré J, Hadjsaid N, Criqui P and Noirot I 2015 Modelling the impacts of variable renewable sources on the power sector: Reconsidering the typology of energy modelling tools *Energy* **80** 486–95 Online: https://dx.doi.org/10.1016/j.energy.2014.12.005

Deutsche WindGuard GmbH 2021 *Status des Windenergiezubaus an Land in Deutschland: Halbjahr 2021* (Varel)

Devine-Wright P and Batel S 2017 My neighbourhood, my country or my planet? The influence of multiple place attachments and climate change concern on social acceptance of energy infrastructure *Global Environmental Change* **47** 110–20 Online: https://dx.doi.org/10.1016/j.gloenvcha.2017.08.003

Dewulf J, Benini L, Mancini L, Sala S, Blengini G A, Ardente F, Recchioni M, Maes J, Pant R and Pennington D 2015 Rethinking the area of protection “natural resources” in life cycle assessment *Environ Sci Technol* **49** 5310–7 Online: https://dx.doi.org/10.1021/acs.est.5b00734

Dewulf J, Bösch M E, de Meester B, van der Vorst G, van Langenhove H, Hellweg S and Huijbregts M A J 2007 Cumulative exergy extraction from the natural environment (CEENE): A comprehensive life cycle impact assessment method for resource accounting *Environ Sci Technol* **41** 8477–83 Online: https://dx.doi.org/10.1021/es0711415

Díaz A, Marrero G A, Puch L A and Rodríguez J 2019 Economic growth, energy intensity and the energy mix *Energy Econ* **81** 1056–77 Online: https://dx.doi.org/10.1016/j.eneco.2019.05.022

Díaz-González F, Sumper A and Gomis-Bellmunt O 2016 Energy storage technologies *Energy storage in power systems* ed F Díaz-González, A Sumper and O Gomis-Bellmunt (Chichester: John Wiley & Sons) pp 93–141 Online: https://dx.doi.org/10.1002/9781118971291.ch4

Diaz-Maurin F, Cadillo-Benalcazar J J, Kovacic Z, Madrid-López C, Serrano-Tovar T, Giampietro M, Aspinall R J, Ramos-Martin J and Bukkens S G F 2014 The Republic of South Africa *Resource accounting for sustainability: The nexus between energy, food, water and land use* ed M Giampietro, R J Aspinall, J Ramos-Martin and S G F Bukkens (Abingdon: Routledge) pp 194–213 Online: https://dx.doi.org/10.4324/9781315866895

Ding C, Zhang H, Li X, Liu T and Xing F 2013 Vanadium flow battery for energy storage: Prospects and challenges *Journal of Physical Chemistry Letters* **4** 1281–94 Online: http://dx.doi.org/10.1021/jz4001032

DiPippo R and Renner J L 2014 Geothermal energy *Future energy: Improved, sustainable and clean options for our planet* ed T M Letcher (London: Elsevier) pp 471–92 Online: http://dx.doi.org/10.1016/B978-0-08-099424-6.00022-3

Dirnaichner A, Rottoli M, Sacchi R, Rauner S, Cox B, Mutel C, Bauer C and Luderer G 2022 Life-cycle impacts from different decarbonization pathways for the European car fleet *Environmental Research Letters* **17** 044009 Online: https://dx.doi.org/10.1088/1748-9326/ac4fdb

Dodd N, Espinosa Martinez M D L N, van Tichelen P, Peeters K and Soares A 2020 *Preparatory study for solar photovoltaic modules, inverters and systems, EUR 30468 EN* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2760/852637

Dominish E, Teske S and Florin N 2019 *Responsible minerals sourcing for renewable energy. Report prepared for Earthworks by the Institute for Sustainable Futures* (Sydney: University of Technology Sydney)

Dreicer M, Tort V and Manen P 1995 *ExternE: Externalities of energy Vol. 5: Nuclear* (Luxembourg)

Dupont E, Koppelaar R and Jeanmart H 2018 Global available wind energy with physical and energy return on investment constraints *Appl Energy* **209** 322–38 Online: http://dx.doi.org/10.1016/j.apenergy.2017.09.085

Dzebo A and Nykvist B 2017 A new regime and then what? Cracks and tensions in the socio-technical regime of the Swedish heat energy system *Energy Res Soc Sci* **29** 113–22 Online: http://dx.doi.org/10.1016/j.erss.2017.05.018

EC Joint Research Centre 2019 JRC open power plants database (JRC-PPDB-OPEN) Online: http://data.europa.eu/89h/9810feeb-f062-49cd-8e76-8d8cfd488a05

Ecoinvent 2020 Ecoinvent version 3.7.1 (December 2020) database Online: https://v371.ecoquery.ecoinvent.org/Home/Index

Ecoinvent 2021 Ecoinvent version 3.8 (2021) database Online: https://v38.ecoquery.ecoinvent.org/Home/Index

Edelenbosch O Y, van Vuuren D P, Blok K, Calvin K and Fujimori S 2020 Mitigating energy demand sector emissions: The integrated modelling perspective *Appl Energy* **261** 114347 Online: https://dx.doi.org/10.1016/j.apenergy.2019.114347

EEA 2021 New registrations of electric vehicles in Europe Online: https://www.eea.europa.eu/ims/new-registrations-of-electric-vehicles

Ehteshami S M M and Chan S H 2014 The role of hydrogen and fuel cells to store renewable energy in the future energy network - potentials and challenges *Energy Policy* **73** 103–9 Online: http://dx.doi.org/10.1016/j.enpol.2014.04.046

Eleftheriadis I M and Anagnostopoulou E G 2015 Identifying barriers in the diffusion of renewable energy sources *Energy Policy* **80** 153–64 Online: http://dx.doi.org/10.1016/j.enpol.2015.01.039

Ellenbeck S and Lilliestam J 2019 How modelers construct energy costs: Discursive elements in Energy System and Integrated Assessment Models *Energy Res Soc Sci* **47** 69–77 Online: https://dx.doi.org/10.1016/j.erss.2018.08.021

Elshout P M F, van Zelm R, Karuppiah R, Laurenzi I J and Huijbregts M A J 2014 A spatially explicit data-driven approach to assess the effect of agricultural land occupation on species groups *Int J Life Cycle Assess* **19** 758–69 Online: https://dx.doi.org/10.1007/s11367-014-0701-x

Emamgheis F F 2014 *A novel methodology for the assessment of the direct and indirect impacts associated with the depletion of fossil resources in life cycle assessment* (Polytechnique Montréal)

Energinet 2020 Kassø-Frøslev: New electricity interconnector to Germany Online: https://en.energinet.dk/Infrastructure-Projects/Projektliste/UdvidelseAfElforbindelseTilTyskland

Energy-Exemplar PLEXOS integrated energy model Online: https://www.energyexemplar.com/plexos

EnergyPLAN 2022 EnergyPLAN model 16.1 results: Smart energy scenario (SE - Sweden)

ENTSO-E 2012 *10-Year Network Development Plan 2012* (Brussels: European Network of Transmission System Operators for Electricity)

ENTSO-E 2022a *Ten-Year Network Development Plan (TYNDP) 2022: High-level report* (Brussels: European Network of Transmission System Operators for Electricity)

ENTSO-E 2022b Ten-Year Network Development Plan (TYNDP) 2022: Maps and data Online: https://tyndp.entsoe.eu/maps-data/

EPA 2006 *Life cycle assessment: Principles and practices (EPA/600/R-06/060)* (Washington, DC: U.S. Environmental Protection Agency)

Ericsson K and Werner S 2016 The introduction and expansion of biomass use in Swedish district heating systems *Biomass Bioenergy* **94** 57–65 Online: http://dx.doi.org/10.1016/j.biombioe.2016.08.011

European Commission 2021a *3rd raw materials scoreboard: European innovation partnership on raw materials* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2873/680176

European Commission 2019a *Clean energy for all Europeans* (Luxembourg: Publications Office of the European Union) Online: http://dx.doi.org/10.2833/9937

European Commission 2015 *COM(2015) 80 final: Energy union package - Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee of the Regions and European Investment bank. A framework strategy for a resilient energy union* (Brussels: European Commission)

European Commission 2020a *COM(2020) 474 final: Critical raw materials resilience: Charting a path towards greater security and sustainability* (Brussels: European Commission)

European Commission 2019b *Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions: The European Green Deal - COM/2019/640 final* (Brussels: European Commission)

European Commission 2010a *Critical raw materials for the EU: Report of the ad-hoc working group on defining critical raw materials* (Brussels: European Commission)

European Commission EDGAR - Emissions Database for Global Atmospheric Research Online: https://edgar.jrc.ec.europa.eu/

European Commission 2021b *EU reference scenario 2020: Energy, transport and GHG emissions - Trends to 2050* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2833/35750

European Commission 2018a *Guidance for product environmental footprint category rules (PEFCRs)* Online: https://ec.europa.eu/environment/eussd/smgp/pdf/PEFCR_guidance_v6.3.pdf

European Commission 2010b *Institute for environment and sustainability: International reference life cycle data system (ILCD) handbook - General guide for life cycle assessment - Detailed guidance (EUR 24708 EN)* (Luxembourg: Publications Office of the European Union) Online: http://dx.doi.org/10.2788/38479

European Commission 2011 *International reference life cycle data system (ILCD) handbook - Recommendations for life cycle impact assessment in the European context* (Luxembourg: Publications Office of the European Union) Online: https://doi.org/10.2788/33030

European Commission 2022 *Joint research centre (JRC), EC's raw materials information system (RMIS) - RMIS Newsletter special edition: focus on the Ukraine-Russia crisis*

European Commission 2017a *Methodology for establishing the EU list of critical raw materials* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2873/040300

European Commission 2018b *Raw materials scoreboard 2018: European innovation partnership on raw materials* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2873/13314

European Commission 2020b *Study on the EU's list of critical raw materials (2020) - Critical raw materials factsheets* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2873/631546

European Commission 2020c *Study on the EU's list of critical raw materials (2020) - Final report* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2873/11619

European Commission 2020d *Study on the EU's list of critical raw materials (2020) - Non-critical raw materials factsheets* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2873/867993

European Commission 2017b *Study on the review of the list of critical raw materials: Final report* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2873/876644

European Commission 2020e Update of the NDC of the European Union and its member states

European Committee of the Regions 2022 EU must support every region, city and village to deliver zero transport emissions by 2050 Online: https://cor.europa.eu/en/news/Pages/zero-transport-emissions.aspx

European Union 2021 *Climate change. Special Eurobarometer 513* (Brussels) Online: http://dx.doi.org/10.2834/437

Eurostat 2022 Complete energy balances Online: https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_bal_c&lang=en

Eurostat 2020 *Energy data: 2020 edition* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2785/68334

Eurostat 2018 EU trade since 1988 by HS2,4,6 and CN8 [DS-645593], Extra-EU28, IMPORT, QUANTITY_IN_100KG Online: https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=DS-645593&lang=en

Eurostat 2021 Recovery rate of construction and demolition waste: % of construction and demolition mineral waste recycled [cei_wm040]

Ewing J 2021 The world wants Greenland's minerals, but Greenlanders are wary *The New York Times*

Fabre A 2019 Evolution of EROIs of electricity until 2050: Estimation and implications on prices *Ecological Economics* **164** 106351 Online: https://dx.doi.org/10.1016/j.ecolecon.2019.06.006

Fakharuddin A, Schmidt-Mende L, Garcia-Belmonte G, Jose R and Mora-Seró I 2017 Interfaces in perovskite solar cells *Adv Energy Mater* **7** Online: https://dx.doi.org/10.1002/aenm.201700623

Fantke P, Charles R, Alencastro L F de, Friedrich R and Jolliet O 2011a Plant uptake of pesticides and human health: Dynamic modeling of residues in wheat and ingestion intake *Chemosphere* **85** 1639–47 Online: https://dx.doi.org/10.1016/j.chemosphere.2011.08.030

Fantke P, Charles R, Alencastro L F de, Friedrich R and Jolliet O 2011b Plant uptake of pesticides and human health: Dynamic modeling of residues in wheat and ingestion intake *Chemosphere* **85** 1639–47

Fantke P and Jolliet O 2016a Life cycle human health impacts of 875 pesticides *Int J Life Cycle Assess* **21** 722–33 Online: https://dx.doi.org/10.1007/s11367-015-0910-y

Fantke P and Jolliet O 2016b Life cycle human health impacts of 875 pesticides *Int J Life Cycle Assess* **21** 722–33

Farmer J D, Hepburn C, Mealy P and Teytelboym A 2015 A third wave in the economics of climate change *Environ Resour Econ (Dordr)* **62** 329–57 Online: http://dx.doi.org/10.1007/s10640-015-9965-2

Farmer J D and Lafond F 2016 How predictable is technological progress? *Res Policy* **45** 647–65 Online: http://dx.doi.org/10.1016/j.respol.2015.11.001

Felber G and Stoeglehner G 2014 Onshore wind energy use in spatial planning—a proposal for resolving conflicts with a dynamic safety distance approach *Energy Sustain Soc* **4** 22 Online: https://dx.doi.org/10.1186/s13705-014-0022-8

di Felice L J, Ripa M and Giampietro M 2019 An alternative to market-oriented energy models: Nexus patterns across hierarchical levels *Energy Policy* **126** 431–43 Online: https://dx.doi.org/10.1016/j.enpol.2018.11.002

Finkbeiner M, Inaba A, Tan R B H, Christiansen K and Klüppel H-J 2006 The new international standards for life cycle assessment: ISO 14040 and ISO 14044 *Int J Life Cycle Assess* **11** 80–5 Online: http://dx.doi.org/10.1065/lca2006.02.002

Fischer D and Madani H 2017 On heat pumps in smart grids: A review *Renewable and Sustainable Energy Reviews* **70** 342–57 Online: https://dx.doi.org/10.1016/j.rser.2016.11.182

Flamos A 2016 A sectoral micro-economic approach to scenario selection and development: The case of the Greek power sector *Energies (Basel)* **9** 77 Online: https://dx.doi.org/10.3390/en9020077

Fortier M O P, Teron L, Reames T G, Munardy D T and Sullivan B M 2019 Introduction to evaluating energy justice across the life cycle: A social life cycle assessment approach *Appl Energy* **236** 211–9 Online: https://dx.doi.org/10.1016/j.apenergy.2018.11.022

Fraunhofer ISI, Consentec and Ifeu 2017 *Langfristszenarien für die Transformation des Energiesystems in Deutschland. Modul 0: Zentrale Ergebnisse und Schlussfolgerungen Studie im Auftrag des Bundesministeriums für Wirtschaft und Energie*

Frischknecht R, Arthur B, Hofstetter P and Suter P 2000 Human health damages due to ionising radiation in life cycle impact assessment *Environ Impact Assess Rev* **20** 159–89 Online: https://dx.doi.org/10.1016/S0195-9255(99)00042-6

Frischknecht R and Jolliet O 2017 *Global guidance for life cycle impact assessment indicators: Volume 1* (Paris: UNEP DTIE)

Fytili D and Zabaniotou A 2017 Social acceptance of bioenergy in the context of climate change and sustainability - A review *Curr Opin Green Sustain Chem* **8** 5–9 Online: https://dx.doi.org/10.1016/j.cogsc.2017.07.006

Gallagher J, Basu B, Browne M, Kenna A, McCormack S, Pilla F and Styles D 2019 Adapting stand-alone renewable energy technologies for the circular economy through eco-design and recycling *J Ind Ecol* **23** 133–40 Online: https://dx.doi.org/10.1111/jiec.12703

García-Gusano D, Iribarren D, Martín-Gamboa M, Dufour J, Espegren K and Lind A 2016 Integration of life-cycle indicators into energy optimisation models: The case study of power generation in Norway *J Clean Prod* **112** 2693–6 Online: http://dx.doi.org/10.1016/j.jclepro.2015.10.075

Gardt A, Broekel T and Gareis P 2021 *Blowing against the winds of change? The relationship between anti-wind initiatives and wind turbines in Germany: Papers in Evolutionary Economic Geography (PEEG)* vol 2119 (Utrecht: Utrecht University)

Garnier-Laplace J, Alonzo F and Adam-Guillermin C 2015 Establishing relationships between environmental exposures to radionuclides and the consequences for wildlife: Inferences and weight of evidence *Ann ICRP* **44** 295–303 Online: http://dx.doi.org/10.1177/0146645315572311

Garrett P and Rønde K 2013 Life cycle assessment of wind power: Comprehensive results from a state-of-the-art approach *International Journal of Life Cycle Assessment* **18** 37–48 Online: https://dx.doi.org/10.1007/s11367-012-0445-4

Gaschnig H, Süsser D, Ceglarz A, Stavrakas V, Flamos A and Lilliestam J 2021 Survey questionnaire and results on user needs for energy models for the European energy transition, related to Süsser et al. (2021) Online: https://dx.doi.org/10.5281/zenodo.5040378

Gaschnig H, Süsser D, Ceglarz A, Stavrakas V, Giannakidis G, Flamos A, Sander A and Lilliestam J 2020 *User needs for an energy system modeling platform for the European energy transition. Deliverable 1.2. Sustainable Energy Transitions Laboratory (SENTINEL) project* (Potsdam: Institute for Advanced Sustainability Studies (IASS)) Online: https://dx.doi.org/10.48481/iass.2020.059

Gasparatos A, Doll C N H, Esteban M, Ahmed A and Olang T A 2017 Renewable energy and biodiversity: Implications for transitioning to a Green Economy *Renewable and Sustainable Energy Reviews* **70** 161–84 Online: http://dx.doi.org/10.1016/j.rser.2016.08.030

Gaustad G, Krystofik M, Bustamante M and Badami K 2018 Circular economy strategies for mitigating critical material supply issues *Resour Conserv Recycl* **135** 24–33 Online: https://dx.doi.org/10.1016/j.resconrec.2017.08.002

Geels F W 2019 Socio-technical transitions to sustainability: A review of criticisms and elaborations of the Multi-Level Perspective *Curr Opin Environ Sustain* **39** 187–201 Online: https://dx.doi.org/10.1016/j.cosust.2019.06.009

Geels F W 2002 Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study *Res Policy* **31** 1257–74 Online: http://dx.doi.org/10.1016/S0048-7333(02)00062-8

Geels F W and Schot J 2007 Typology of sociotechnical transition pathways *Res Policy* **36** 399–417 Online: http://dx.doi.org/10.1016/j.respol.2007.01.003

Geels F W, Sovacool B K, Schwanen T and Sorrell S 2017a The socio-technical dynamics of low-carbon transitions *Joule* **1** 463–79 Online: https://dx.doi.org/10.1016/j.joule.2017.09.018

Geels F W, Sovacool B, Schwanen T and Sorrell S 2017b Sociotechnical transitions for deep decarbonization: Accelerating innovation is as important as climate policy *Science (1979)* **357** 1242–4 Online: http://dx.doi.org/10.1126/science.aao3760

German Advisory Council on the Environment 2011 *Pathways towards a 100% renewable electricity system: Special report* (Berlin: German Advisory Council on the Environment)

Giamalaki M and Tsoutsos T 2019 Sustainable siting of solar power installations in Mediterranean using a GIS/AHP approach *Renew Energy* **141** 64–75 Online: https://dx.doi.org/10.1016/j.renene.2019.03.100

Giampietro M 2018 Perception and representation of the resource nexus at the interface between society and the natural environment *Sustainability (Switzerland)* **10** 2545 Online: https://dx.doi.org/10.3390/su10072545

Giampietro M and Mayumi K 1997 A dynamic model of socioeconomic systems based on hierarchy theory and its application to sustainability *Structural Change and Economic Dynamics* **8** 453–69 Online: https://dx.doi.org/10.1016/S0954-349X(97)00017-9

Giampietro M and Mayumi K 2000a Multiple-scale integrated assessment of societal metabolism: Integrating biophysical and economic representations across scales *Popul Environ* **22** 155–210 Online: https://dx.doi.org/10.1023/A:1026643707370

Giampietro M and Mayumi K 2000b Multiple-scale integrated assessment of societal metabolism: Introducing the approach *Popul Environ* **22** 109–53 Online: https://dx.doi.org/10.1023/A:1026691623300

Giampietro M, Mayumi K and Ramos-Martin J 2009 Multi-scale integrated analysis of societal and ecosystem metabolism (MuSIASEM): Theoretical concepts and basic rationale *Energy* **34** 313–22 Online: http://dx.doi.org/10.1016/j.energy.2008.07.020

Gibon T, Wood R, Arvesen A, Bergesen J D, Suh S and Hertwich E G 2015 A methodology for integrated, multiregional life cycle assessment scenarios under large-scale technological change *Environ Sci Technol* **49** 11218–26 Online: https://dx.doi.org/10.1021/acs.est.5b01558

van der Giesen C, Cucurachi S, Guinée J, Kramer G J and Tukker A 2020 A critical view on the current application of LCA for new technologies and recommendations for improved practice *J Clean Prod* **259** 120904 Online: https://dx.doi.org/10.1016/j.jclepro.2020.120904

Giurco D, Dominish E, Florin N, Watari T and McLellan B 2019 Requirements for minerals and metals for 100% renewable scenarios *Achieving the Paris Climate Agreement goals: Global and regional 100% renewable energy scenarios with non-energy GHG pathways for +1.5°C and +2°C* ed S Teske (Cham: Springer Open) pp 437–57 Online: https://dx.doi.org/10.1007/978-3-030-05843-2_11

Glüsing J, Hage S, Jung A, Klawitter N and Schultz S 2021 Mining the planet to death: The dirty truth about clean technologies *Der Spiegel*

Goedkoop M, Heijungs R, Huijbregts M, de Schryver A, Struijs J and van Zelm R 2013 *ReCiPe 2008: A life cycle assessment method which comprises harmonised category indicators at the midpoint and the endpoint level. First edition (version 1.08). Report I: Characterisation* (Amsterdam: Ministry of Housing, Spatial Planning and Environment (VROM))

Goldstone R L and Janssen M A 2005 Computational models of collective behavior *Trends Cogn Sci* **9** 424–30 Online: http://dx.doi.org/10.1016/j.tics.2005.07.009

Göllinger T 2012 *Systemisches Innovations- und Nachhaltigkeitsmanagement* (Marburg: Metropolis-Verlag)

González-Roubaud E, Pérez-Osorio D and Prieto C 2017 Review of commercial thermal energy storage in concentrated solar power plants: Steam vs. molten salts *Renewable and Sustainable Energy Reviews* **80** 133–48 Online: http://dx.doi.org/10.1016/j.rser.2017.05.084

Graedel T E, Allwood J, Birat J-P, Buchert M, Hagelüken C, Reck B K, Sibley S F and Sonnemann G 2011 *Recycling rates of metals - A status report: A report of the working group on the global metal flows to the International Resource Panel* (Paris: United Nations Environment Programme (UNEP))

Graedel T E, Barr R, Chandler C, Chase T, Choi J, Christoffersen L, Friedlander E, Henly C, Jun C, Nassar N T, Schechner D, Warren S, Yang M and Zhu C 2012 Methodology of metal criticality determination *Environ Sci Technol* **46** 1063–70 Online: https://dx.doi.org/10.1021/es203534z

Greaves D 2018 Wave energy technology *Wave and tidal energy* ed D Greaves and G Iglesias (Hoboken, NJ: John Wiley & Sons) pp 52–104 Online: https://dx.doi.org/10.1002/9781119014492.ch3

Green M A, Dunlop E D, Hohl-Ebinger J, Yoshita M, Kopidakis N, Bothe K, Hinken D, Rauer M and Hao X 2022 Solar cell efficiency tables (Version 60) *Progress in Photovoltaics: Research and Applications* **30** 687–701 Online: http://dx.doi.org/10.1002/pip.3595

GreenDelta openLCA Nexus Online: https://nexus.openlca.org/databases

Gronlund C J, Humbert S, Shaked S, O'Neill M S and Jolliet O 2015 Characterizing the burden of disease of particulate matter for life cycle impact assessment *Air Qual Atmos Health* **8** 29–46 Online: https://dx.doi.org/10.1007/s11869-014-0283-6

Gross R and Hanna R 2019 Path dependency in provision of domestic heating *Nat Energy* **4** 358–64 Online: http://dx.doi.org/10.1038/s41560-019-0383-5

Gross S 2020 *Renewables, land use, and local opposition in the United States* (Washington, DC: Brookings)

Guinée J B, Heijungs R, Huppes G, Zamagni A, Masoni P, Buonamici R, Ekvall T and Rydberg T 2011 Life cycle assessment: Past, present, and future *Environ Sci Technol* **45** 90–6 Online: https://dx.doi.org/10.1021/es101316v

Gür T M 2018 Review of electrical energy storage technologies, materials and systems: Challenges and prospects for large-scale grid storage *Energy Environ Sci* **11** 2696–767 Online: http://dx.doi.org/10.1039/c8ee01419a

GWEC 2018 *Global wind report 2017* (Brussels: Global Wind Energy Council)

GWEC 2020 *Global wind report 2019* (Brussels: Global Wind Energy Council)

GWEC 2021 *Global wind report 2021* (Brussels: Global Wind Energy Council)

Hall L M H and Buckley A R 2016 A review of energy systems models in the UK: Prevalent usage and categorisation *Appl Energy* **169** 607–28 Online: http://dx.doi.org/10.1016/j.apenergy.2016.02.044

Hamacher T 2014 Hydrogen as a strategic secondary energy carrier *Hydrogen and fuel cell: Technologies and market perspectives* ed J Töpler and J Lehmann (Heidelberg: Springer-Verlag) pp 1–20 Online: http://dx.doi.org/10.1007/978-3-662-44972-1

Hanafiah M M, Xenopoulos M A, Pfister S, Leuven R S E W and Huijbregts M A J 2011 Characterization factors for water consumption and greenhouse gas emissions based on freshwater fish species extinction *Environ Sci Technol* **45** 5272–8 Online: https://dx.doi.org/10.1021/es1039634

Hanaki K and Portugal-Pereira J 2018 The effect of biofuel production on greenhouse gas emission reductions *Biofuels and sustainability: Holistic perspectives for policy-making* ed K Takeuchi, H Shiroyama, O Saito and M Matsuura (Tokyo: Springer) pp 53–71 Online: https://dx.doi.org/10.1007/978-4-431-54895-9_6

Hanisch C, Diekmann J, Stieger A, Haselrieder W and Kwade A 2015 Recycling of lithium-ion batteries *Handbook of Clean Energy Systems* 1–24 Online: https://dx.doi.org/10.1002/9781118991978.hces221

Hansen P, Liu X and Morrison G M 2019 Agent-based modelling and socio-technical energy transitions: A systematic literature review *Energy Res Soc Sci* **49** 41–52 Online: https://dx.doi.org/10.1016/j.erss.2018.10.021

Hauschild M Z, Huijbregts M, Jolliet O, Macleod M, Margni M, van de Meent D, Rosenbaum R K and McKone T E 2008a Building a model based on scientific consensus for life cycle impact assessment of chemicals: The search for harmony and parsimony *Environ Sci Technol* **42** 7032–7 Online: https://dx.doi.org/10.1021/es703145t

Hauschild M Z, Huijbregts M, Jolliet O, Macleod M, Margni M, van de Meent D, Rosenbaum R K and McKone T E 2008b Building a Model Based on Scientific Consensus for Life Cycle Impact Assessment of Chemicals: The Search for Harmony and Parsimony *Environ Sci Technol* **42** 7032–7

Hayashi K, Nakagawa A, Itsubo N and Inaba A 2006 Expanded damage function of stratospheric ozone depletion to cover major endpoints regarding life cycle impact assessment *International Journal of Life Cycle Assessment* **11** 150–61 Online: https://dx.doi.org/10.1065/lca2004.11.189

Heijungs R, Guinée J B, Huppes G, Lankreijer R M, Udo de Haes H A, Wegener Sleeswijk A, Ansems A M M, Eggels P G, Duin R van and Goede H P de 1992 *Environmental life cycle assessment of products: Guide - October 1992*

Heilek C, Kuhn P and Kühne M 2014 The role of large-scale hydrogen storage in the power system *Hydrogen and fuel cell: Technologies and market perspectives* ed J Töpler and J Lehmann (Heidelberg: Springer-Verlag) pp 21–38 Online: http://dx.doi.org/10.1007/978-3-662-44972-1

Hellweg S, Demou E, Bruzzi R, Meijer A, Rosenbaum R K, Huijbregts M A J and Mckone T E 2009a Integrating human indoor air pollutant exposure within life cycle impact assessment *Environ Sci Technol* **43** 1670–9 Online: https://dx.doi.org/10.1021/es8018176

Hellweg S, Demou E, Bruzzi R, Meijer A, Rosenbaum R K, Huijbregts M A J and McKone T E 2009b Integrating Human Indoor Air Pollutant Exposure within Life Cycle Impact Assessment *Environ Sci Technol* **43** 1670–9

Helmes R J K, Huijbregts M A J, Henderson A D and Jolliet O 2012 Spatially explicit fate factors of phosphorous emissions to freshwater at the global scale *Int J Life Cycle Assess* **17** 646–54 Online: https://dx.doi.org/10.1007/s11367-012-0382-2

Hernández-Moro J and Martínez-Duart J M 2012 CSP electricity cost evolution and grid parities based on the IEA roadmaps *Energy Policy* **41** 184–92 Online: https://dx.doi.org/10.1016/j.enpol.2011.10.032

Hertwich E G, Gibon T, Bouman E A, Arvesen A, Suh S, Heath G A, Bergesen J D, Ramirez A, Vega M I and Shi L 2015 Integrated life-cycle assessment of electricity-supply scenarios confirms global environmental benefit of low-carbon technologies *Proc Natl Acad Sci U S A* **112** 6277–82 Online: https://dx.doi.org/10.1073/pnas.1312753111

Hess D J, McKane R G and Pietzryk C 2022 End of the line: environmental justice, energy justice, and opposition to power lines *Env Polit* **31** 663–83 Online: https://dx.doi.org/10.1080/09644016.2021.1952799

Hestin M, de Veron S and Burgos S 2016 *Economic study on recycling of building glass in Europe* (Deloitte Sustainability)

Hevia-Koch P and Klinge Jacobsen H 2019 Comparing offshore and onshore wind development considering acceptance costs *Energy Policy* **125** 9–19 Online: https://dx.doi.org/10.1016/j.enpol.2018.10.019

Hoang A T, Sandro Nižetić, Olcer A I, Ong H C, Chen W H, Chong C T, Thomas S, Bandh S A and Nguyen X P 2021 Impacts of COVID-19 pandemic on the global energy system and the shift progress to renewable energy: Opportunities, challenges, and policy implications *Energy Policy* **154** 112322 Online: https://dx.doi.org/10.1016/j.enpol.2021.112322

Hollingsworth J A, Ravishankar E, O'Connor B, Johnson J X and DeCarolis J F 2020 Environmental and economic impacts of solar-powered integrated greenhouses *J Ind Ecol* **24** 234–47 Online: http://dx.doi.org/10.1111/jiec.12934

Holtz G 2011 Modelling transitions: An appraisal of experiences and suggestions for research *Environ Innov Soc Transit* **1** 167–86 Online: http://dx.doi.org/10.1016/j.eist.2011.08.003

Hossain M I, Qarony W, Ma S, Zeng L, Knipp D and Tsang Y H 2019 Perovskite/silicon tandem solar cells: From detailed balance limit calculations to photon management *Nanomicro Lett* **11** 1–24 Online: https://dx.doi.org/10.1007/s40820-019-0287-8

Huang K and Eckelman M J 2020 Appending material flows to the National Energy Modeling System (NEMS) for projecting the physical economy of the United States *J Ind Ecol* Online: https://dx.doi.org/10.1111/jiec.13053

Huijbregts M A J, Rombouts L J A, Ragas A M J and van de Meent D 2005a Human-toxicological effect and damage factors of carcinogenic and noncarcinogenic chemicals for life cycle impact assessment *Integr Environ Assess Manag* **1** 181–244 Online: https://dx.doi.org/10.1897/2004-007R.1

Huijbregts M A J, Rombouts L J A, Ragas A M J and van de Meent D 2005b Human-toxicological effect and damage factors of carcinogenic and noncarcinogenic chemicals for life cycle impact assessment *Integr Environ Assess Manag* **1** 181–244

Huijbregts M A J, Steinmann Z J N, Elshout P M F, Stam G, Verones F, Vieira M, Zijp M, Hollander A and van Zelm R 2017 ReCiPe2016: A harmonised life cycle impact assessment method at midpoint and endpoint level *International Journal of Life Cycle Assessment* **22** 138–47 Online: http://dx.doi.org/10.1007/s11367-016-1246-y

Humbert S, Marshall J D, Shaked S, Spadaro J v, Nishioka Y, Preiss P, McKone T E, Horvath A and Jolliet O 2011 Intake fraction for particulate matter: Recommendations for life cycle impact assessment *Environ Sci Technol* **45** 4808–16 Online: http://dx.doi.org/10.1021/es103563z

Hund K, la Porta D, Fabregas T P, Laing T and Drexhage J 2020 *Minerals for climate action: The mineral intensity of the clean energy transition* (Washington, DC: Climate Smart Mining Initiative, World Bank Group)

Iacobuta G, Dubash N K, Upadhyaya P, Deribe M and Höhne N 2018 National climate change mitigation legislation, strategy and targets: A global update *Climate Policy* **18** 1114–32 Online: https://dx.doi.org/10.1080/14693062.2018.1489772

IAMC Integrated Assessment Modeling Consortium wiki Online: https://www.iamcdocumentation.eu/index.php/IAMC_wiki

Ibrahim H, Ilinca A and Perron J 2008 Energy storage systems - Characteristics and comparisons *Renewable and Sustainable Energy Reviews* **12** 1221–50 Online: http://dx.doi.org/10.1016/j.rser.2007.01.023

IEA 2020a *European Union 2020: Energy policy review* (Paris: International Energy Agency)

IEA 2022 Global EV data explorer Online: https://www.iea.org/articles/global-ev-data-explorer

IEA 2021a *Global EV outlook 2021* (Paris: International Energy Agency)

IEA 2019a Headline global energy data (2019 edition)

IEA 2021b *World energy model documentation* (Paris: International Energy Agency)

IEA 2019b *World energy outlook 2019* (Paris: International Energy Agency) Online: https://dx.doi.org/10.1787/caf32f3b-en

IEA 2020b *World energy outlook 2020* (Paris: International Energy Agency) Online: https://dx.doi.org/10.1787/557a761b-en

IEA 2021c *World energy outlook 2021* (Paris: International Energy Agency) Online: https://dx.doi.org/10.1787/20725302

Igos E, Rugani B, Rege S, Benetto E, Drouet L and Zachary D S 2015 Combination of equilibrium models and hybrid life cycle-input-output analysis to predict the environmental impacts of energy policy scenarios *Appl Energy* **145** 234–45 Online: http://dx.doi.org/10.1016/j.apenergy.2015.02.007

Infrastrukturdepartementet 2020 Sweden’s integrated national energy and climate plan reporting

International Labour Organization 2022 ILOSTAT data catalogue Online: https://ilostat.ilo.org/data/

IPCC 2013 *Climate change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* ed T F Stocker, D Qin, G-K Plattner, M Tignor, S K Allen, J Boschung, A Nauels, Y Xia, V Bex and P M Midgley (Cambridge: Cambridge University Press)

IPCC 2021 Emission factor database Online: https://www.ipcc-nggip.iges.or.jp/EFDB/main.php

IPCC 2019 *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,* ed V Masson-Delmotte, P Zhai, H-O Pörtner, D Roberts, J Skea, P R Shukla, A Pirani, W Moufouma-Okia, C Péan, R Pidcock, S Connors, J B R Matthews, Y Chen, X Zhou, M I Gomis, E Lonnoy, T Maycock, M Tignor and T Waterfield (Cambridge: Cambridge University Press)

IRENA 2020 *Global renewables outlook: Energy transformation 2050* (Abu Dhabi: International Renewable Energy Agency)

IRENA 2021 *World energy transitions outlook: 1.5°C pathway* (Abu Dhabi: International Renewable Energy Agency)

ISO 2006 ISO 14044:2006 Environmental management - Life cycle assessment - Requirements and guidelines

Ito K 2015 An overview of CZTS-based thin-film solar cells *Copper zinc tin sulfide-based thin-film solar cells* ed K Ito (Chichester: John Wiley & Sons) pp 3–41 Online: https://dx.doi.org/10.1002/9781118437865

Jacobsson S and Lauber V 2006 The politics and policy of energy system transformation - Explaining the German diffusion of renewable energy technology *Energy Policy* **34** 256–76 Online: https://dx.doi.org/10.1016/j.enpol.2004.08.029

Javed M S, Ma T, Jurasz J and Amin M Y 2020 Solar and wind power generation systems with pumped hydro storage: Review and future perspectives *Renew Energy* **148** 176–92 Online: https://dx.doi.org/10.1016/j.renene.2019.11.157

JGCRI Joint Global Change Research Institute: Global Change Assessment Model (GCAM) v5.2 Documentation Online: http://jgcri.github.io/gcam-doc/index.html

Johansson P 2021 Heat pumps in Sweden – A historical review *Energy* **229** 120683 Online: https://dx.doi.org/10.1016/j.energy.2021.120683

Joos F, Roth R, Fuglestvedt J S, Peters G P, Enting I G, von Bloh W, Brovkin V, Burke E J, Eby M, Edwards N R, Friedrich T, Frölicher T L, Halloran P R, Holden P B, Jones C, Kleinen T, Mackenzie F, Matsumoto K, Meinshausen M, Plattner G-K, Reisinger A, Segschneider J, Shaffer G, Steinacher M, Strassmann K, Tanaka K, Timmermann A and Weaver A J 2012 Carbon dioxide and climate impulse response functions for the computation of greenhouse gas metrics: A multi-model analysis *Atmospheric Chemistry and Physics Discussions* **12** 19799–869 Online: https://dx.doi.org/10.5194/acpd-12-19799-2012

Jungbluth N 2021 *Description of life cycle impact assessment methods: Supplementary information for tenders* (Schaffhausen: ESU-services Ltd.)

Junne T, Simon S, Buchgeister J, Saiger M, Baumann M, Haase M, Wulf C and Naegler T 2020 Environmental sustainability assessment of multi-sectoral energy transformation pathways: Methodological approach and case study for Germany *Sustainability (Switzerland)* **12** 1–28 Online: https://dx.doi.org/10.3390/su12198225

Kadiyala A, Kommalapati R and Huque Z 2016a Evaluation of the life cycle greenhouse gas emissions from different biomass feedstock electricity generation systems *Sustainability (Switzerland)* **8** 1181 Online: http://dx.doi.org/10.3390/su8111181

Kadiyala A, Kommalapati R and Huque Z 2016b Evaluation of the life cycle greenhouse gas emissions from hydroelectricity generation systems *Sustainability (Switzerland)* **8** 539 Online: https://dx.doi.org/10.3390/su8060539

Kalaiselvam S and Parameshwaran R 2014 Thermal energy storage technologies *Thermal energy storage technologies for sustainability: Systems design, assessment and applications* (London: Academic Press) pp 57–64 Online: https://dx.doi.org/10.1016/C2013-0-09744-7

Karali N, Park W Y and McNeil M A 2015 *Using learning curves on energy-efficient technologies to estimate future energy savings and emission reduction potentials in the U.S. iron and steel industry* (Berkeley, CA) Online: https://dx.doi.org/10.2172/1372638

Kati V, Kassara C, Vrontisi Z and Moustakas A 2021 The biodiversity-wind energy-land use nexus in a global biodiversity hotspot *Science of the Total Environment* **768** 144471 Online: https://dx.doi.org/10.1016/j.scitotenv.2020.144471

Kaufmann D, Kraay A and Mastruzzi M 2011 The worldwide governance indicators: Methodology and analytical issues *Hague Journal on the Rule of Law* **3** 220–46 Online: https://dx.doi.org/10.1017/S1876404511200046

Kemfert C, Präger F, Braunger I, Hoffart F M and Brauers H 2022 The expansion of natural gas infrastructure puts energy transitions at risk *Nat Energy* **7** 582–7 Online: https://dx.doi.org/10.1038/s41560-022-01060-3

King L C and van den Bergh J C J M 2018 Implications of net energy-return-on-investment for a low-carbon energy transition *Nat Energy* **3** 334–40 Online: http://dx.doi.org/10.1038/s41560-018-0116-1

Klæboe R and Sundfør H B 2016 Windmill noise annoyance, visual aesthetics, and attitudes towards renewable energy sources *Int J Environ Res Public Health* **13** 1–19 Online: http://dx.doi.org/10.3390/ijerph13080746

Knopper L D, Ollson C A, McCallum L C, Aslund M L W, Berger R G, Souweine K and McDaniel M 2014 Wind turbines and human health *Front Public Health* **2** 1–20 Online: http://dx.doi.org/10.3389/fpubh.2014.00063

Koch F H 2002 Hydropower - The politics of water and energy: Introduction and overview *Energy Policy* **30** 1207–13 Online: https://dx.doi.org/10.1016/S0301-4215(02)00081-2

Koellner T and Scholz R W 2007 Assessment of land use impacts on the natural environment. Part 1: An analytical framework for pure land occupation and land use change *Int J Life Cycle Assess* **12** 16–23 Online: http://dx.doi.org/10.1065/lca2006.12.292.1

Köhler J, de Haan F, Holtz G, Kubeczko K, Moallemi E, Papachristos G and Chappin E 2018 Modelling sustainability transitions: An assessment of approaches and challenges *Journal of Artificial Societies and Social Simulation* **21** 8 Online: http://dx.doi.org/10.18564/jasss.3629

Kommalapati R, Kadiyala A, Shahriar M T and Huque Z 2017 Review of the life cycle greenhouse gas emissions from different photovoltaic and concentrating solar power electricity generation systems *Energies (Basel)* **10** 1–18 Online: http://dx.doi.org/10.3390/en10030350

Koppelaar R H E M, Keirstead J, Shah N and Woods J 2016 A review of policy analysis purpose and capabilities of electricity system models *Renewable and Sustainable Energy Reviews* **59** 1531–44 Online: https://dx.doi.org/10.1016/j.rser.2016.01.090

Koumparou I, Christoforidis G C, Efthymiou V, Papagiannis G K and Georghiou G E 2017 Configuring residential PV net-metering policies – A focus on the Mediterranean region *Renew Energy* **113** 795–812 Online: https://dx.doi.org/10.1016/j.renene.2017.06.051

Kounina A, Margni M, Bayart J-B, Boulay A-M, Berger M, Bulle C, Frischknecht R, Koehler A, Milà i Canals L, Motoshita M, Núñez M, Peters G, Pfister S, Ridoutt B, van Zelm R, Verones F and Humbert S 2013a Review of methods addressing freshwater use in life cycle inventory and impact assessment *Int J Life Cycle Assess* **18** 707–21 Online: https://dx.doi.org/10.1007/s11367-012-0519-3

Kounina A, Margni M, Bayart J-B, Boulay A-M, Berger M, Bulle C, Frischknecht R, Koehler A, Milà i Canals L, Motoshita M, Núñez M, Peters G, Pfister S, Ridoutt B, van Zelm R, Verones F and Humbert S 2013b Review of methods addressing freshwater use in life cycle inventory and impact assessment *Int J Life Cycle Assess* **18** 707–21

Krey V, Guo F, Kolp P, Zhou W, Schaeffer R, Awasthy A, Bertram C, de Boer H S, Fragkos P, Fujimori S, He C, Iyer G, Keramidas K, Köberle A C, Oshiro K, Reis L A, Shoai-Tehrani B, Vishwanathan S, Capros P, Drouet L, Edmonds J E, Garg A, Gernaat D E H J, Jiang K, Kannavou M, Kitous A, Kriegler E, Luderer G, Mathur R, Muratori M, Sano F and van Vuuren D P 2019 Looking under the hood: A comparison of techno-economic assumptions across national and global integrated assessment models *Energy* **172** 1254–67 Online: https://dx.doi.org/10.1016/j.energy.2018.12.131

Kriegler E, Petermann N, Krey V, Schwanitz V J, Luderer G, Ashina S, Bosetti V, Eom J, Kitous A, Méjean A, Paroussos L, Sano F, Turton H, Wilson C and van Vuuren D P 2015 Diagnostic indicators for integrated assessment models of climate policy *Technol Forecast Soc Change* **90** 45–61 Online: http://dx.doi.org/10.1016/j.techfore.2013.09.020

Krumm A, Süsser D and Blechinger P 2022 Modelling social aspects of the energy transition: What is the current representation of social factors in energy models? *Energy* **239** 121706 Online: https://dx.doi.org/10.1016/j.energy.2021.121706

Kuipers K 2016 *Environmental implications of alternative global copper supply scenarios and the supply criticality of selected copper by-product metals* (Leiden University & Delft University of Technology)

Kupfer T, Baitz M, Colodel C M, Kokborg M, Schöll S, Rudolf M, Bos U, Bosch F, Gonzalez M, Schuller O, Hengstler J, Stoffregen A and Thylmann D 2020 *GaBi databases & modeling principles 2020* (Sphera)

Kupfer T, Baitz M, Colodel C M, Kokborg M, Schöll S, Rudolf M, Bos U, Bosch F, Gonzalez M, Schuller O, Hengstler J, Stoffregen A, Thylmann D and Koffler C 2021 *GaBi databases & modelling principles* (Sphera)

Lamperti F, Dosi G, Napoletano M, Roventini A and Sapio A 2018 Faraway, so close: Coupled climate and economic dynamics in an agent-based integrated assessment model *Ecological Economics* **150** 315–39 Online: https://dx.doi.org/10.1016/j.ecolecon.2018.03.023

Lamperti F, Mandel A, Napoletano M, Sapio A, Roventini A, Balint T and Khorenzhenko I 2019 Towards agent-based integrated assessment models: Examples, challenges, and future developments *Reg Environ Change* **19** 747–62 Online: http://dx.doi.org/10.1007/s10113-018-1287-9

Laurent A, Espinosa N and Hauschild M Z 2018 LCA of energy systems *Life cycle assessment: Theory and practice* ed M Z Hauschild, R K Rosenbaum and S I Olsen (Cham: Springer) pp 633–68 Online: https://dx.doi.org/10.1007/978-3-319-56475-3_26

Lèbre É, Owen J R, Corder G D, Kemp D, Stringer M and Valenta R K 2019 Source risks as constraints to future metal supply *Environ Sci Technol* **53** 10571–9 Online: http://dx.doi.org/10.1021/acs.est.9b02808

Lèbre É, Stringer M, Svobodova K, Owen J R, Kemp D, Côte C, Arratia-Solar A and Valenta R K 2020 The social and environmental complexities of extracting energy transition metals *Nat Commun* **11** 1–8 Online: http://dx.doi.org/10.1038/s41467-020-18661-9

Lee J, Bazilian M, Sovacool B, Hund K, Jowitt S M, Nguyen T P, Månberger A, Kah M, Greene S, Galeazzi C, Awuah-Offei K, Moats M, Tilton J and Kukoda S 2020 Reviewing the material and metal security of low-carbon energy transitions *Renewable and Sustainable Energy Reviews* **124** 109789 Online: https://dx.doi.org/10.1016/j.rser.2020.109789

Lerman L V, Gerstlberger W, Ferreira Lima M and Frank A G 2021 How governments, universities, and companies contribute to renewable energy development? A municipal innovation policy perspective of the triple helix *Energy Res Soc Sci* **71** 101854 Online: https://dx.doi.org/10.1016/j.erss.2020.101854

Levasseur A, Cavalett O, Fuglestvedt J S, Gasser T, Johansson D J A, Jørgensen S v, Raugei M, Reisinger A, Schivley G, Strømman A, Tanaka K and Cherubini F 2016 Enhancing life cycle impact assessment from climate science: Review of recent findings and recommendations for application to LCA *Ecol Indic* **71** 163–74 Online: https://dx.doi.org/10.1016/j.ecolind.2016.06.049

Levenda A M, Behrsin I and Disano F 2021 Renewable energy for whom? A global systematic review of the environmental justice implications of renewable energy technologies *Energy Res Soc Sci* **71** 101837 Online: https://dx.doi.org/10.1016/j.erss.2020.101837

Li J, Li S and Wu F 2020 Research on carbon emission reduction benefit of wind power project based on life cycle assessment theory *Renew Energy* **155** 456–68 Online: https://dx.doi.org/10.1016/j.renene.2020.03.133

Li M, Lu J, Chen Z and Amine K 2018 30 years of lithium-ion batteries *Advanced Materials* **30** 1–24 Online: https://dx.doi.org/10.1002/adma.201800561

Lilliestam J, Ellenbeck S, Karakosta C and Caldés N 2016 Understanding the absence of renewable electricity imports to the European Union *International Journal of Energy Sector Management* **10** 291–311 Online: https://dx.doi.org/10.1108/IJESM-10-2014-0002

Lilliestam J, Labordena M, Patt A and Pfenninger S 2017 Empirically observed learning rates for concentrating solar power and their responses to regime change *Nat Energy* **2** 17094 Online: http://dx.doi.org/10.1038/nenergy.2017.94

Lilliestam J, Melliger M, Ollier L, Schmidt T S and Steffen B 2020 Understanding and accounting for the effect of exchange rate fluctuations on global learning rates *Nat Energy* **5** 71–8 Online: https://dx.doi.org/10.1038/s41560-019-0531-y

Liu L, Huang G, Baetz B and Zhang K 2018 Environmentally-extended input-output simulation for analyzing production-based and consumption-based industrial greenhouse gas mitigation policies *Appl Energy* **232** 69–78 Online: https://dx.doi.org/10.1016/j.apenergy.2018.09.192

Lockwood M, Mitchell C and Hoggett R 2020 Incumbent lobbying as a barrier to forward-looking regulation: The case of demand-side response in the GB capacity market for electricity *Energy Policy* **140** 111426 Online: https://dx.doi.org/10.1016/j.enpol.2020.111426

LOCOMOTION Low-carbon society: An enhanced modelling tool for the transition to sustainability Online: https://www.locomotion-h2020.eu/

Lombardi F, Pickering B, Colombo E and Pfenninger S 2020 Policy decision support for renewables deployment through spatially explicit practically optimal alternatives *Joule* **4** 2185–207 Online: https://dx.doi.org/10.1016/j.joule.2020.08.002

Lombardi F, Rocco M V and Colombo E 2019 A multi-layer energy modelling methodology to assess the impact of heat-electricity integration strategies: The case of the residential cooking sector in Italy *Energy* **170** 1249–60 Online: https://linkinghub.elsevier.com/retrieve/pii/S0360544219300040

López I, Andreu J, Ceballos S, Martínez De Alegría I and Kortabarria I 2013 Review of wave energy technologies and the necessary power-equipment *Renewable and Sustainable Energy Reviews* **27** 413–34 Online: http://dx.doi.org/10.1016/j.rser.2013.07.009

Loulou R and Labriet M 2008 ETSAP-TIAM: The TIMES integrated assessment model Part I: Model structure *Computational Management Science* **5** 7–40 Online: https://dx.doi.org/10.1007/s10287-007-0046-z

Louwen A, Krishnan S, Derks M and Junginger H M 2018 *REFLEX project deliverable 3.2: Comprehensive report on experience curves*

Louwen A and Lacerda S J 2020 The experience curve: Concept, history, methods, and issues *Technological learning in the transition to a low-carbon energy system* ed M Junginger and A Louwen (London: Academic Press) pp 9–31 Online: https://dx.doi.org/10.1016/B978-0-12-818762-3.00002-9

di Lucia L and Ericsson K 2014 Low-carbon district heating in Sweden - Examining a successful energy transition *Energy Res Soc Sci* **4** 10–20 Online: http://dx.doi.org/10.1016/j.erss.2014.08.005

Luderer G, Pehl M, Arvesen A, Gibon T, Bodirsky B L, de Boer H S, Fricko O, Hejazi M, Humpenöder F, Iyer G, Mima S, Mouratiadou I, Pietzcker R C, Popp A, van den Berg M, van Vuuren D and Hertwich E G 2019 Environmental co-benefits and adverse side-effects of alternative power sector decarbonization strategies *Nat Commun* **10** 1–13 Online: http://dx.doi.org/10.1038/s41467-019-13067-8

Ludin N A, Mustafa N I, Hanafiah M M, Ibrahim M A, Asri Mat Teridi M, Sepeai S, Zaharim A and Sopian K 2018 Prospects of life cycle assessment of renewable energy from solar photovoltaic technologies: A review *Renewable and Sustainable Energy Reviews* **96** 11–28 Online: https://dx.doi.org/10.1016/j.rser.2018.07.048

Lund H, Østergaard P A, Connolly D and Mathiesen B V 2017 Smart energy and smart energy systems *Energy* **137** 556–65 Online: https://dx.doi.org/10.1016/j.energy.2017.05.123

Lund H and Thellufsen J Z 2020 EnergyPLAN - Advanced energy systems analysis computer model (Version 15.1) Online: http://dx.doi.org/10.5281/zenodo.4017214

Lund H, Thellufsen J Z, Østergaard P A, Sorknæs P, Skov I R and Mathiesen B V 2021 EnergyPLAN - Advanced analysis of smart energy systems *Smart Energy* **1** 100007 Online: https://dx.doi.org/10.1016/j.segy.2021.100007

Ma J and Duan Q 2009 Environmental dumping and international unionized oligopolies *SSRN Electronic Journal* Online: http://dx.doi.org/10.2139/ssrn.1494877

MacGillivray A, Jeffrey H, Winskel M and Bryden I 2014 Innovation and cost reduction for marine renewable energy: A learning investment sensitivity analysis *Technol Forecast Soc Change* **87** 108–24 Online: http://dx.doi.org/10.1016/j.techfore.2013.11.005

Macknick J, Newmark R, Heath G and Hallett K C 2012 Operational water consumption and withdrawal factors for electricity generating technologies: A review of existing literature *Environmental Research Letters* **7** 045802 Online: http://dx.doi.org/10.1088/1748-9326/7/4/045802

Magnusson D 2016 Who brings the heat? - From municipal to diversified ownership in the Swedish district heating market post-liberalization *Energy Res Soc Sci* **22** 198–209 Online: http://dx.doi.org/10.1016/j.erss.2016.10.004

Mahmud M A P, Huda N, Farjana S H and Lang C 2020 Life-cycle impact assessment of renewable electricity generation systems in the United States *Renew Energy* **151** 1028–45 Online: https://dx.doi.org/10.1016/j.renene.2019.11.090

Mancheri N A, Sprecher B, Bailey G, Ge J and Tukker A 2019 Effect of Chinese policies on rare earth supply chain resilience *Resour Conserv Recycl* **142** 101–12 Online: https://dx.doi.org/10.1016/j.resconrec.2018.11.017

Månsson A 2015 A resource curse for renewables? Conflict and cooperation in the renewable energy sector *Energy Res Soc Sci* **10** 1–9 Online: http://dx.doi.org/10.1016/j.erss.2015.06.008

Manzella A, Allansdottir A and Pellizzone A 2019 *Geothermal energy and society* (Cham: Springer) Online: https://dx.doi.org/10.1007/978-3-319-78286-7

Margni M, Gloria T, Bare J, Seppälä J, Steen B, Struijs J, Toffoletto L and Jolliet O 2008 *Guidance on how to move from current practice to recommended practice in Life Cycle Impact Assessment* (UNEP-SETAC Life Cycle Initiative)

Marín A and Goya D 2021 Mining - The dark side of the energy transition *Environ Innov Soc Transit* **41** 86–8 Online: https://dx.doi.org/10.1016/j.eist.2021.09.011

Martin N, Madrid-López C, Talens-Peiró L, Süsser D, Gaschnig H and Lilliestam J 2020 *Observed trends and modelling paradigms on the social and environmental aspects of the energy transition. Deliverable 2.1. Sustainable Energy Transitions Laboratory (SENTINEL) project* Online: https://dx.doi.org/10.5281/zenodo.4917183

Martinez-Alier J 2021 Mapping ecological distribution conflicts: The EJAtlas *Extr Ind Soc* **8** 100883 Online: https://dx.doi.org/10.1016/j.exis.2021.02.003

Martinez-Alier J 2002 *The environmentalism of the poor: A study of ecological conflicts and valuation* (Cheltenham: Edward Elgar)

Masini A and Menichetti E 2013 Investment decisions in the renewable energy sector: An analysis of non-financial drivers *Technol Forecast Soc Change* **80** 510–24 Online: http://dx.doi.org/10.1016/j.techfore.2012.08.003

Matsumoto A, Merlone U and Szidarovszky F 2012 Some notes on applying the Herfindahl-Hirschman Index *Appl Econ Lett* **19** 181–4 Online: https://dx.doi.org/10.1080/13504851.2011.570705

Mayeda A M and Boyd A D 2020 Factors influencing public perceptions of hydropower projects: A systematic literature review *Renewable and Sustainable Energy Reviews* **121** 109713 Online: https://dx.doi.org/10.1016/j.rser.2020.109713

Mayer A, Haas W, Wiedenhofer D, Krausmann F, Nuss P and Blengini G A 2019 Measuring progress towards a circular economy: A monitoring framework for economy-wide material loop closing in the EU28 *J Ind Ecol* **23** 62–76 Online: https://dx.doi.org/10.1111/jiec.12809

McCauley D and Heffron R 2018 Just transition: Integrating climate, energy and environmental justice *Energy Policy* **119** 1–7 Online: http://dx.doi.org/10.1016/j.enpol.2018.04.014

McKenna R, Mulalic I, Soutar I, Weinand J M, Price J, Petrović S and Mainzer K 2022 Exploring trade-offs between landscape impact, land use and resource quality for onshore variable renewable energy: an application to Great Britain *Energy* **250** 123754 Online: https://dx.doi.org/10.1016/j.energy.2022.123754

McLellan B C 2020 Environmental impacts of mineral sourcing and their impacts on criticality *The material basis of energy transitions* ed A Bleicher and A Pehlken (London: Academic Press) pp 109–20 Online: https://dx.doi.org/10.1016/B978-0-12-819534-5.00007-6

Melliger M and Lilliestam J 2021 Effects of coordinating support policy changes on renewable power investor choices in Europe *Energy Policy* **148** 111993 Online: https://dx.doi.org/10.1016/j.enpol.2020.111993

Mendecka B and Lombardi L 2019 Life cycle environmental impacts of wind energy technologies: A review of simplified models and harmonization of the results *Renewable and Sustainable Energy Reviews* **111** 462–80 Online: https://dx.doi.org/10.1016/j.rser.2019.05.019

Mendoza Beltran A, Cox B, Mutel C, van Vuuren D P, Font Vivanco D, Deetman S, Edelenbosch O Y, Guinée J and Tukker A 2020 When the background matters: Using scenarios from integrated assessment models in prospective life cycle assessment *J Ind Ecol* **24** 64–79 Online: https://dx.doi.org/10.1111/jiec.12825

Meng L, Zhang Y, Wan X, Li C, Zhang X, Wang Y, Ke X, Xiao Z, Ding L, Xia R, Yip H L, Cao Y and Chen Y 2018 Organic and solution-processed tandem solar cells with 17.3% efficiency *Science (1979)* **361** 1094–8 Online: http://dx.doi.org/10.1126/science.aat2612

Mey F and Diesendorf M 2018 Who owns an energy transition? Strategic action fields and community wind energy in Denmark *Energy Res Soc Sci* **35** 108–17 Online: https://dx.doi.org/10.1016/j.erss.2017.10.044

Michas S, Stavrakas V, Papadelis S and Flamos A 2020 A transdisciplinary modeling framework for the participatory design of dynamic adaptive policy pathways *Energy Policy* **139** 111350 Online: https://dx.doi.org/10.1016/j.enpol.2020.111350

Ministry of Environment and Energy 2010 *1st National Renewable Energy Action Plan (NREAP)* (Athens)

Mishnaevsky L, Branner K, Petersen H N, Beauson J, McGugan M and Sørensen B F 2017 Materials for wind turbine blades: An overview *Materials* **10** 1–24 Online: https://dx.doi.org/10.3390/ma10111285

Mittal A, Krejci C C, Dorneich M C and Fickes D 2019 An agent-based approach to modeling zero energy communities *Solar Energy* **191** 193–204 Online: https://dx.doi.org/10.1016/j.solener.2019.08.040

Moglia M, Cook S and McGregor J 2017 A review of Agent-Based Modelling of technology diffusion with special reference to residential energy efficiency *Sustain Cities Soc* **31** 173–82 Online: http://dx.doi.org/10.1016/j.scs.2017.03.006

Mohamed Sultan A A and Mativenga P T 2019 Sustainable Location Identification Decision Protocol (SuLIDeP) for determining the location of recycling centres in a circular economy *J Clean Prod* **223** 508–21 Online: https://dx.doi.org/10.1016/j.jclepro.2019.03.104

Mora-Seró I 2018 How do perovskite solar cells work? *Joule* **2** 585–7 Online: https://dx.doi.org/10.1016/j.joule.2018.03.020

Moreau V, dos Reis P C and Vuille F 2019 Enough metals? Resource constraints to supply a fully renewable energy system *Resources* **8** 29 Online: https://dx.doi.org/10.3390/resources8010029

Morrissey J E, Axon S, Aiesha R, Hillman J, Revez A, Lennon B, Dunphy N P, Salel M and Boo E 2016 *Identification and characterisation of energy behaviour change initiatives: Deliverable D4.4 of ENTRUST project* Online: https://dx.doi.org/10.5281/ZENODO.3479377

Möst D, Schreiber S, Herbst A, Jakob M, Martino A and Poganietz W-R 2021 *The future European energy system: Renewable energy, flexibility options and technological progress* (Cham: Springer) Online: https://dx.doi.org/10.1007/978-3-030-60914-6

Mousavi G S M, Faraji F, Majazi A and Al-Haddad K 2017 A comprehensive review of Flywheel Energy Storage System technology *Renewable and Sustainable Energy Reviews* **67** 477–90 Online: http://dx.doi.org/10.1016/j.rser.2016.09.060

Mutel C and Cox B Wurst Online: https://github.com/polca/wurst

Mutel C, Liao X, Patouillard L, Bare J, Fantke P, Frischknecht R, Hauschild M, Jolliet O, Maia de Souza D, Laurent A, Pfister S and Verones F 2019 Overview and recommendations for regionalized life cycle impact assessment *Int J Life Cycle Assess* **24** 856–65 Online: https://dx.doi.org/10.1007/s11367-018-1539-4

Mwasilu F, Justo J J, Kim E K, Do T D and Jung J W 2014 Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration *Renewable and Sustainable Energy Reviews* **34** 501–16 Online: http://dx.doi.org/10.1016/j.rser.2014.03.031

Myhr A, Bjerkseter C, Ågotnes A and Nygaard T A 2014 Levelised cost of energy for offshore floating wind turbines in a lifecycle perspective *Renew Energy* **66** 714–28 Online: http://dx.doi.org/10.1016/j.renene.2014.01.017

Myhre G, Samset B H, Schulz M, Balkanski Y, Bauer S, Berntsen T K, Bian H, Bellouin N, Chin M, Diehl T, Easter R C, Feichter J, Ghan S J, Hauglustaine D, Iversen T, Kinne S, Kirkeväg A, Lamarque J F, Lin G, Liu X, Lund M T, Luo G, Ma X, van Noije T, Penner J E, Rasch P J, Ruiz A, Seland, Skeie R B, Stier P, Takemura T, Tsigaridis K, Wang P, Wang Z, Xu L, Yu H, Yu F, Yoon J H, Zhang K, Zhang H and Zhou C 2013 Radiative forcing of the direct aerosol effect from AeroCom Phase II simulations *Atmos Chem Phys* **13** 1853–77 Online: https://dx.doi.org/10.5194/acp-13-1853-2013

Nabernegg S, Bednar-Friedl B, Muñoz P, Titz M and Vogel J 2019 National policies for global emission reductions: Effectiveness of carbon emission reductions in international supply chains *Ecological Economics* **158** 146–57 Online: https://dx.doi.org/10.1016/j.ecolecon.2018.12.006

Nansai K, Nakajima K, Kagawa S, Kondo Y, Suh S, Shigetomi Y and Oshita Y 2014 Global flows of critical metals necessary for low-carbon technologies: The case of neodymium, cobalt, and platinum *Environ Sci Technol* **48** 1391–400 Online: https://dx.doi.org/10.1021/es4033452

Nassar N T, Graedel T E and Harper E M 2015 By-product metals are technologically essential but have problematic supply *Sci Adv* **1** e1400180 Online: http://dx.doi.org/10.1126/sciadv.1400180

National Renewable Energy Laboratory 2019 Concentrating solar power projects by country Online: https://solarpaces.nrel.gov/

Naumanen M, Uusitalo T, Huttunen-Saarivirta E and van der Have R 2019 Development strategies for heavy duty electric battery vehicles: Comparison between China, EU, Japan and USA *Resour Conserv Recycl* **151** 104413 Online: https://dx.doi.org/10.1016/j.resconrec.2019.104413

Nayak P K, Yang L, Brehm W and Adelhelm P 2018 From lithium-ion to sodium-ion batteries: Advantages, challenges, and surprises *Angewandte Chemie - International Edition* **57** 102–20 Online: https://dx.doi.org/10.1002/anie.201703772

Nebot-Medina R, Madrid-López C, Martin N and Talens-Peiró L The ENvironmental and BIOeconomic System Assessment (ENBIOS) module Online: https://github.com/ENVIRO-Module/enbios

Nikas A, Doukas H and Papandreou A 2019 A detailed overview and consistent classification of climate-economy models *Understanding risks and uncertainties in energy and climate policy: Multidisciplinary methods and tools for a low carbon society* ed H Doukas, A Flamos and J Lieu (Cham: Springer) pp 1–54 Online: http://dx.doi.org/10.1007/978-3-030-03152-7

Nikas A, Lieu J, Sorman A, Gambhir A, Turhan E, Baptista B V and Doukas H 2020a The desirability of transitions in demand: Incorporating behavioural and societal transformations into energy modelling *Energy Res Soc Sci* **70** 101780 Online: https://dx.doi.org/10.1016/j.erss.2020.101780

Nikas A, Stavrakas V, Arsenopoulos A, Doukas H, Antosiewicz M, Witajewski-Baltvilks J and Flamos A 2020b Barriers to and consequences of a solar-based energy transition in Greece *Environ Innov Soc Transit* **35** 383–99 Online: https://dx.doi.org/10.1016/j.eist.2018.12.004

Nordhaus W 2013 Integrated economic and climate modeling *Handbook of computable general equilibrium modeling* vol 1A, ed P B Dixon and D W Jorgenson (Oxford: Elsevier) pp 1069–131 Online: http://dx.doi.org/10.1016/B978-0-444-59568-3.00016-X

Notter D A, Gauch M, Widmer R, Wäger P, Stamp A, Zah R and Althaus H J 2010 Contribution of Li-ion batteries to the environmental impact of electric vehicles *Environ Sci Technol* **44** 6550–6 Online: http://dx.doi.org/10.1021/es903729a

Nuss P and Blengini G A 2018 Towards better monitoring of technology critical elements in Europe: Coupling of natural and anthropogenic cycles *Science of the Total Environment* **613–614** 569–78 Online: https://dx.doi.org/10.1016/j.scitotenv.2017.09.117

Nuss P and Eckelman M J 2014a Life cycle assessment of metals: A scientific synthesis *PLoS One* **9** e101298 Online: https://dx.doi.org/10.1371/journal.pone.0101298

Nuss P and Eckelman M J 2014b Life cycle assessment of metals: A scientific synthesis - Supporting information *PLoS One* **9** Online: https://dx.doi.org/10.1371/journal.pone.0101298.s001

O'Doherty T, O'Doherty D M and Mason-Jones A 2018 Tidal energy technology *Wave and tidal energy* ed D Greaves and G Iglesias (Hoboken, NJ: John Wiley & Sons) pp 104–50 Online: https://dx.doi.org/10.1002/9781119014492.ch4

O'Hayre R, Cha S, Colella W G and Prinz F B 2016 *Fuel cell fundamentals* (Hoboken, NJ: John Wiley & Sons) Online: http://dx.doi.org/10.1002/9781119191766

Olivetti E A, Ceder G, Gaustad G G and Fu X 2017 Lithium-Ion battery supply chain considerations: Analysis of potential bottlenecks in critical metals *Joule* **1** 229–43 Online: https://dx.doi.org/10.1016/j.joule.2017.08.019

Onakpoya I J, O'Sullivan J, Thompson M J and Heneghan C J 2015 The effect of wind turbine noise on sleep and quality of life: A systematic review and meta-analysis of observational studies *Environ Int* **82** 1–9 Online: http://dx.doi.org/10.1016/j.envint.2015.04.014

Oosterlaken I 2014 Applying value sensitive design (VSD) to wind turbines and wind parks: An exploration *Sci Eng Ethics* **21** 359–79 Online: http://dx.doi.org/10.1007/s11948-014-9536-x

Østergaard P A, Lund H, Thellufsen J Z, Sorknæs P and Mathiesen B v. 2022 Review and validation of EnergyPLAN *Renewable and Sustainable Energy Reviews* **168** 112724 Online: http://dx.doi.org/10.1016/j.rser.2022.112724

Ottinger G 2013 The winds of change: Environmental justice in energy transitions *Sci Cult (Lond)* **22** 222–9 Online: http://dx.doi.org/10.1080/09505431.2013.786996

Ould Amrouche S, Rekioua D, Rekioua T and Bacha S 2016 Overview of energy storage in renewable energy systems *Int J Hydrogen Energy* **41** 20914–27 Online: http://dx.doi.org/10.1016/j.ijhydene.2016.06.243

Paardekooper S, Lund R S, Mathiesen B V, Chang M, Petersen U R, Grundahl L, David A, Dahlbæk J, Kapetanakis I A, Lund H, Bertelsen N, Hansen K, Drysdale D W and Persson U 2018 *Heat roadmap Europe 4: Quantifying the impact of low-carbon heating and cooling roadmaps* (Aalborg: Aalborg Universitetsforlag) Online: https://vbn.aau.dk/en/publications/heat-roadmap-europe-4-quantifying-the-impact-of-low-carbon-heatin

Pall G K, Bridge A J, Gray J and Skitmore M 2019 Causes of delay in power transmission projects: An empirical study *Energies (Basel)* **13** 17 Online: https://dx.doi.org/10.3390/en13010017

Palmer-Wilson K, Donald J, Robertson B, Lyseng B, Keller V, Fowler M, Wade C, Scholtysik S, Wild P and Rowe A 2019 Impact of land requirements on electricity system decarbonisation pathways *Energy Policy* **129** 193–205 Online: https://dx.doi.org/10.1016/j.enpol.2019.01.071

Pan Z, Rao H, Mora-Seró I, Bisquert J and Zhong X 2018 Quantum dot-sensitized solar cells *Chem Soc Rev* **47** 7659–702 Online: http://dx.doi.org/10.1039/c8cs00431e

Pang X, Mörtberg U and Brown N 2014 Energy models from a strategic environmental assessment perspective in an EU context - What is missing concerning renewables? *Renewable and Sustainable Energy Reviews* **33** 353–62 Online: http://dx.doi.org/10.1016/j.rser.2014.02.005

Papadelis S, Stavrakas V and Flamos A 2016 What do capacity deployment rates tell us about the efficiency of electricity generation from renewable energy sources support measures in Greece? *Energies (Basel)* **9** 38 Online: https://dx.doi.org/10.3390/en9010038

Parag Y and Sovacool B K 2016 Electricity market design for the prosumer era *Nat Energy* **1** 16032 Online: http://dx.doi.org/10.1038/nenergy.2016.32

Parra R, di Felice L J, Giampietro M and Ramos-Martin J 2018 The metabolism of oil extraction: A bottom-up approach applied to the case of Ecuador *Energy Policy* **122** 63–74 Online: https://dx.doi.org/10.1016/j.enpol.2018.07.017

Parson E A and Fisher-Vanden K 1997 Integrated assessment models of global climate change *Annual Review of Energy and the Environment* **22** 589–628 Online: https://dx.doi.org/10.1146/annurev.energy.22.1.589

Patrizio P, Pratama Y W and MacDowell N 2020 Socially equitable energy system transitions *Joule* **4** 1700–13 Online: https://dx.doi.org/10.1016/j.joule.2020.07.010

Pattisson P and Firdaus F 2021 “Battery arms race”: How China has monopolised the electric vehicle industry *The Guardian*

Pauliuk S, Arvesen A, Stadler K and Hertwich E G 2017 Industrial ecology in integrated assessment models *Nat Clim Chang* **7** 13–20 Online: http://dx.doi.org/10.1038/nclimate3148

Pauliuk S and Hasan M 2017 Industrial ecology data commons prototype Online: https://www.database.industrialecology.uni-freiburg.de/

PBL Netherlands Environmental Agency 2021 IMAGE 3.2 Documentation Online: https://models.pbl.nl/image/index.php/Welcome_to_IMAGE_3.2_Documentation

Pehl M, Arvesen A, Humpenöder F, Popp A, Hertwich E G and Luderer G 2017 Understanding future emissions from low-carbon power systems by integration of life-cycle assessment and integrated energy modelling *Nat Energy* **2** 939–45 Online: http://dx.doi.org/10.1038/s41560-017-0032-9

Pérez-Collazo C, Greaves D and Iglesias G 2015 A review of combined wave and offshore wind energy *Renewable and Sustainable Energy Reviews* **42** 141–53 Online: http://dx.doi.org/10.1016/j.rser.2014.09.032

Perger T, Wachter L, Fleischhacker A and Auer H 2021 PV sharing in local communities: Peer-to-peer trading under consideration of the prosumers’ willingness-to-pay *Sustain Cities Soc* **66** 102634 Online: https://dx.doi.org/10.1016/j.scs.2020.102634

Perras S 2015 *Electricity transmission line planning: Success factors for transmission system operators to reduce public opposition* (Dresden: Technischen Universität Dresden)

Peters J, Buchholz D, Passerini S and Weil M 2016 Life cycle assessment of sodium-ion batteries *Energy Environ Sci* **9** 1744–51 Online: https://dx.doi.org/10.1039/c6ee00640j

Pfenninger S, Hawkes A and Keirstead J 2014 Energy systems modeling for twenty-first century energy challenges *Renewable and Sustainable Energy Reviews* **33** 74–86 Online: http://dx.doi.org/10.1016/j.rser.2014.02.003

Pfenninger S and Pickering B 2018 Calliope: A multi-scale energy systems modelling framework *J Open Source Softw* **3** 825 Online: http://dx.doi.org/10.21105/joss.00825

Pfenninger S and Pickering B Calliope v0.6.8: Tutorials Online: https://calliope.readthedocs.io/en/stable/user/tutorials.html

Pfister S, Koehler A and Hellweg S 2009 Assessing the environmental impacts of freshwater consumption in LCA *Environ Sci Technol* **43** 4098–104 Online: https://dx.doi.org/10.1021/es802423e

Pickering B 2022a Auxiliary Euro-Calliope datasets: QTDIAN storyline-specific spatial data to represent a European energy system model at several spatial resolutions (2022-06-01) Online: https://doi.org/10.5281/zenodo.6603146

Pickering B 2022b Diversity of options to eliminate fossil fuels and reach carbon-neutrality across the entire European energy system (2022-05-13) [Data set] Online: https://dx.doi.org/10.5281/zenodo.6546817

Pickering B, Lombardi F and Pfenninger S 2022 Diversity of options to reach carbon-neutrality across the entire European energy system *Joule* **6** 1253–1276 Online: https://dx.doi.org/10.1016/j.joule.2022.05.009

Pihl E, Kushnir D, Sandén B and Johnsson F 2012 Material constraints for concentrating solar thermal power *Energy* **44** 944–54 Online: http://dx.doi.org/10.1016/j.energy.2012.04.057

PlasticsEurope 2019 *Plastics - The Facts 2019: An analysis of European plastics production, demand and waste data* (Brussels: PlasticsEurope AISBL)

Platzer W J and Dinter F 2016 A learning curve for solar thermal power *AIP Conf Proc* **1734** 160013 Online: http://dx.doi.org/10.1063/1.4949254

Posch M, Seppälä J, Hettelingh J-P, Johansson M, Margni M and Jolliet O 2008 The role of atmospheric dispersion models and ecosystem sensitivity in the determination of characterisation factors for acidifying and eutrophying emissions in LCIA *Int J Life Cycle Assess* **13** 477 Online: https://dx.doi.org/10.1007/s11367-008-0025-9

Pospíšil J, Špiláček M and Kudela L 2018 Potential of predictive control for improvement of seasonal coefficient of performance of air source heat pump in Central European climate zone *Energy* **154** 415–23 Online: https://dx.doi.org/10.1016/j.energy.2018.04.131

Psomas S 2018 *Status and outlook of the Greek PV Market* (Athens)

Quentin J 2020 *Ausbausituation der Windenergie an Land im Jahr 2020: Auswertung windenergiespezifischer Daten im Marktstammdatenregister für den Zeitraum Januar bis Dezember 2020* (Berlin)

Quentin J 2019 *Hemmnisse beim Ausbau der Windenergie in Deutschland. Ergebnisse einer Branchenumfrage zu Klagen gegen Windenergieanlagen sowie zu Genehmigungshemmnissen durch Drehfunkfeuer und militärische Belange der Luftraumnutzung* (Berlin)

Rabe W, Kostka G and Smith Stegen K 2017 China's supply of critical raw materials: Risks for Europe's solar and wind industries? *Energy Policy* **101** 692–9 Online: http://dx.doi.org/10.1016/j.enpol.2016.09.019

Rai V and Henry A D 2016 Agent-based modelling of consumer energy choices *Nat Clim Chang* **6** 556–62 Online: http://dx.doi.org/10.1038/nclimate2967

Rai V and Robinson S A 2015 Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors *Environmental Modelling and Software* **70** 163–77 Online: http://dx.doi.org/10.1016/j.envsoft.2015.04.014

Ram M, Aghahosseini A and Breyer C 2020 Job creation during the global energy transition towards 100% renewable power system by 2050 *Technol Forecast Soc Change* **151** 119682 Online: https://dx.doi.org/10.1016/j.techfore.2019.06.008

Raven R P J M and Verbong G P J 2009 Boundary crossing innovations: Case studies from the energy domain *Technol Soc* **31** 85–93 Online: https://dx.doi.org/10.1016/j.techsoc.2008.10.006

REFLEX REFLEX - Analysis of the European energy system under the aspects of flexibility and technological progress Online: https://reflex-project.eu/

Reinert C, Schellhas L, Mannhardt J, Shu D Y, Kämper A, Baumgärtner N, Deutz S and Bardow A 2022 SecMOD: An open-source Modular framework combining multi-sector system optimization and life-cycle assessment *Front Energy Res* **10** 884525 Online: https://dx.doi.org/10.3389/fenrg.2022.884525

REN21 2019 *Renewables 2019: Global status report* (Paris: REN21 Secretariat)

Renn O, Wolf I and Setton D 2020 Soziales Nachhaltigkeitsbarometer der Energiewende Online: https://dx.doi.org/10.7802/2120

Ringler P, Keles D and Fichtner W 2016 Agent-based modelling and simulation of smart electricity grids and markets - A literature review *Renewable and Sustainable Energy Reviews* **57** 205–15 Online: http://dx.doi.org/10.1016/j.rser.2015.12.169

Rinne E, Holttinen H, Kiviluoma J and Rissanen S 2018 Effects of turbine technology and land use on wind power resource potential *Nat Energy* **3** 494–500 Online: http://dx.doi.org/10.1038/s41560-018-0137-9

Rip A and Kemp R 1998 Technological change *Human choice and climate change. Vol. II, Resources and technology* ed S Rayner and E L Malone (Columbus, OH: Battelle Press) pp 327–99

Ripple W J, Wolf C, Newsome T M, Barnard P and Moomaw W R 2019 World scientists' warning of a climate emergency *Bioscience* **70** 8–12 Online: https://dx.doi.org/10.1093/biosci/biz088

Roddis P, Roelich K, Tran K, Carver S, Dallimer M and Ziv G 2020 What shapes community acceptance of large-scale solar farms? A case study of the UK's first "nationally significant" solar farm *Solar Energy* **209** 235–44 Online: https://dx.doi.org/10.1016/j.solener.2020.08.065

Rodríguez R A, Becker S, Andresen G B, Heide D and Greiner M 2014 Transmission needs across a fully renewable European power system *Renew Energy* **63** 467–76 Online: https://dx.doi.org/10.1016/j.renene.2013.10.005

Roelich K, Dawson D A, Purnell P, Knoeri C, Revell R, Busch J and Steinberger J K 2014 Assessing the dynamic material criticality of infrastructure transitions: A case of low carbon electricity *Appl Energy* **123** 378–86 Online: http://dx.doi.org/10.1016/j.apenergy.2014.01.052

Rogelj J, Popp A, Calvin K v, Luderer G, Emmerling J, Gernaat D, Fujimori S, Strefler J, Hasegawa T, Marangoni G, Krey V, Kriegler E, Riahi K, Vuuren D P van, Doelman J, Drouet L, Edmonds J, Fricko O, Harmsen M, Havlík P, Humpenöder F, Stehfest E and Tavoni M 2018 Scenarios towards limiting global mean temperature increase below 1.5 °C *Nat Clim Chang* **8** 325–332 Online: http://dx.doi.org/10.1038/s41558-018-0091-3

Rosenbaum R K 2018 Overview of existing LCIA methods - Annex to Chapter 10 *Life cycle assessment: Theory and practice* ed M Z Hauschild, R K Rosenbaum and S I Olsen (Cham: Springer) pp 1147–83 Online: https://dx.doi.org/10.1007/978-3-319-56475-3_40

Rosenbaum R K, Bachmann T M, Gold L S, Huijbregts M A J, Jolliet O, Juraske R, Koehler A, Larsen H F, MacLeod M, Margni M, McKone T E, Payet J, Schuhmacher M, van de Meent D and Hauschild M Z 2008a USEtox - The UNEP-SETAC toxicity model: Recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment *Int J Life Cycle Assess* **13** 532 Online: https://dx.doi.org/10.1007/s11367-008-0038-4

Rosenbaum R K, Bachmann T M, Gold L S, Huijbregts M A J, Jolliet O, Juraske R, Koehler A, Larsen H F, MacLeod M, Margni M, McKone T E, Payet J, Schuhmacher M, van de Meent D and Hauschild M Z 2008b USEtox—the UNEP-SETAC toxicity model: recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment *Int J Life Cycle Assess* **13** 532

Roy P O, Azevedo L B, Margni M, van Zelm R, Deschênes L and Huijbregts M A J 2014a Characterization factors for terrestrial acidification at the global scale: A systematic analysis of spatial variability and uncertainty *Science of the Total Environment* **500–501** 270–6 Online: http://dx.doi.org/10.1016/j.scitotenv.2014.08.099

Roy P O, Deschênes L and Margni M 2012a Life cycle impact assessment of terrestrial acidification: Modeling spatially explicit soil sensitivity at the global scale *Environ Sci Technol* **46** 8270–8 Online: http://dx.doi.org/10.1021/es3013563

Roy P-O, Azevedo L B, Margni M, van Zelm R, Deschênes L and Huijbregts M A J 2014b Characterization factors for terrestrial acidification at the global scale: A systematic analysis of spatial variability and uncertainty *Science of The Total Environment* **500–501** 270–6

Roy P-O, Huijbregts M, Deschênes L and Margni M 2012b Spatially-differentiated atmospheric source-receptor relationships for nitrogen oxides, sulfur oxides and ammonia emissions at the global scale for life cycle impact assessment *Atmos Environ* **62** 74–81 Online: https://dx.doi.org/10.1016/j.atmosenv.2012.07.069

RPA 2012 *Data needs for a full raw materials flow analysis* (Norfolk: Risk & Policy Analysts Limited)

Rubin E S, Azevedo I M L, Jaramillo P and Yeh S 2015 A review of learning rates for electricity supply technologies *Energy Policy* **86** 198–218 Online: http://dx.doi.org/10.1016/j.enpol.2015.06.011

Ruhnau O, Hirth L and Praktiknjo A 2020 Heating with wind: Economics of heat pumps and variable renewables *Energy Econ* **92** 104967 Online: https://dx.doi.org/10.1016/j.eneco.2020.104967

Rutovitz J, Dominish E and Downes J 2015 *Calculating global energy sector jobs: 2015 methodology update* (Sydney: Institute for Sustainable Futures, University of Technology Sydney)

Saad R, Margni M, Koellner T, Wittstock B and Deschênes L 2011 Assessment of land use impacts on soil ecological functions: Development of spatially differentiated characterization factors within a Canadian context *Int J Life Cycle Assess* **16** 198–211 Online: https://dx.doi.org/10.1007/s11367-011-0258-x

Sacchi R, Terlouw T, Siala K, Bauer C, Cox B, Daioglou V and Luderer G 2022 PRospective EnvironMental Impact asSEment (premise): A streamlined approach to producing databases for prospective life cycle assessment using integrated assessment models *Renewable and Sustainable Energy Reviews* **160** 112311 Online: https://dx.doi.org/10.1016/j.rser.2022.112311

Sachs J, Meng Y, Giarola S and Hawkes A 2019 An agent-based model for energy investment decisions in the residential sector *Energy* **172** 752–68 Online: https://dx.doi.org/10.1016/j.energy.2019.01.161

Saevarsdottir G, Kvande H and Welch B J 2020 Aluminum production in the times of climate change: The global challenge to reduce the carbon footprint and prevent carbon leakage *JOM* **72** 296–308 Online: https://dx.doi.org/10.1007/s11837-019-03918-6

Safarzyska K and van den Bergh J C J M 2022 ABM-IAM: Optimal climate policy under bounded rationality and multiple inequalities *Environmental Research Letters* **17** 094022 Online: https://dx.doi.org/10.1088/1748-9326/ac8b25

Sala S, Benini L, Castellani C, Vidal Legaz B, de Laurentiis V and Pant R 2019 *Suggestions for the update of the Environmental Footprint Life Cycle Impact Assessment. Impacts due to resource use, water use, land use, and particulate matter* (Luxembourg: Publications Office of the European Union) Online: https://dx.doi.org/10.2760/356756

Salman S K 2017 Smart grid and energy storage systems *Introduction to the smart grid: Concepts, technologies and evolution* (London: The Institution of Engineering and Technology) pp 193–221 Online: https://dx.doi.org/10.1049/PBPO094E_ch10

Samadi S, Gröne M C, Schneidewind U, Luhmann H J, Venjakob J and Best B 2017 Sufficiency in energy scenario studies: Taking the potential benefits of lifestyle changes into account *Technol Forecast Soc Change* **124** 126–34 Online: http://dx.doi.org/10.1016/j.techfore.2016.09.013

Sandberg E, Sneum D M and Trømborg E 2018 Framework conditions for Nordic district heating - Similarities and differences, and why Norway sticks out *Energy* **149** 105–19 Online: https://dx.doi.org/10.1016/j.energy.2018.01.148

Santangeli A, Toivonen T, Pouzols F M, Pogson M, Hastings A, Smith P and Moilanen A 2016 Global change synergies and trade-offs between renewable energy and biodiversity *GCB Bioenergy* **8** 941–51 Online: http://dx.doi.org/10.1111/gcbb.12299

Santisirisomboon J, Limmeechokchai B and Chungpaibulpatana S 2001 Impacts of biomass power generation and CO_2 taxation on electricity generation expansion planning and environmental emissions *Energy Policy* **29** 975–85 Online: https://dx.doi.org/10.1016/S0301-4215(01)00028-3

Sattich T, Freeman D, Scholten D and Yan S 2021 Renewable energy in EU-China relations: Policy interdependence and its geopolitical implications *Energy Policy* **156** 112456 Online: https://dx.doi.org/10.1016/j.enpol.2021.112456

Savvidis G, Siala K, Weissbart C, Schmidt L, Borggrefe F, Kumar S, Pittel K, Madlener R and Hufendiek K 2019 The gap between energy policy challenges and model capabilities *Energy Policy* **125** 503–20 Online: https://dx.doi.org/10.1016/j.enpol.2018.10.033

Scarlat N, Dallemand J F and Fahl F 2018 Biogas: Developments and perspectives in Europe *Renew Energy* **129** 457–72 Online: https://dx.doi.org/10.1016/j.renene.2018.03.006

Schimpe M, Naumann M, Truong N, Hesse H C, Santhanagopalan S, Saxon A and Jossen A 2018 Energy efficiency evaluation of a stationary lithium-ion battery container storage system via electro-thermal modeling and detailed component analysis *Appl Energy* **210** 211–29 Online: https://dx.doi.org/10.1016/j.apenergy.2017.10.129

de Schryver A M, Brakkee K W, Goedkoop M J and Huijbregts M A J 2009 Characterization factors for global warming in life cycle assessment based on damages to humans and ecosystems *Environ Sci Technol* **43** 1689–95 Online: https://dx.doi.org/10.1021/es800456m

de Schryver A M, van Zelm R, Humbert S, Pfister S, McKone T E and Huijbregts M A J 2011 Value choices in life cycle impact assessment of stressors causing human health damage *J Ind Ecol* **15** 796–815 Online: https://dx.doi.org/10.1111/j.1530-9290.2011.00371.x

Scott C A, Pierce S A, Pasqualetti M J, Jones A L, Montz B E and Hoover J H 2011 Policy and institutional dimensions of the water-energy nexus *Energy Policy* **39** 6622–30 Online: https://dx.doi.org/10.1016/j.enpol.2011.08.013

Scott K, Daly H, Barrett J and Strachan N 2016 National climate policy implications of mitigating embodied energy system emissions *Clim Change* **136** 325–38 Online: http://dx.doi.org/10.1007/s10584-016-1618-0

Searcey D, Forsythe M and Lipton E 2021 A power struggle over cobalt rattles the clean energy revolution *The New York Times*

Segreto M, Principe L, Desormeaux A, Torre M, Tomassetti L, Tratzi P, Paolini V and Petracchini F 2020 Trends in social acceptance of renewable energy across Europe - A literature review *Int J Environ Res Public Health* **17** 1–19 Online: http://dx.doi.org/10.3390/ijerph17249161

Selvakkumaran S and Ahlgren E O 2019 Determining the factors of household energy transitions: A multi-domain study *Technol Soc* **57** 54–75 Online: https://dx.doi.org/10.1016/j.techsoc.2018.12.003

SENTINEL Sustainable Energy Transitions Laboratory (SENTINEL) Online: https://sentinel.energy/

Seppälä J, Posch M, Johansson M and Hettelingh J-P 2006 Country-dependent characterisation factors for acidification and terrestrial eutrophication based on accumulated exceedance as an impact category indicator *Int J Life Cycle Assess* **11** 403–16 Online: https://dx.doi.org/10.1065/lca2005.06.215

Serrano-González J and Lacal-Arántegui R 2016 Technological evolution of onshore wind turbines - A market-based analysis *Wind Energy* **19** 2171–87 Online: https://dx.doi.org/10.1002/we.1974

Setton D 2019 *Soziales Nachhaltigkeitsbarometer der Energiewende 2018* (Potsdam) Online: http://dx.doi.org/10.2312/iass.2019.002

Shahsavari A and Akbari M 2018 Potential of solar energy in developing countries for reducing energy-related emissions *Renewable and Sustainable Energy Reviews* **90** 275–91 Online: https://dx.doi.org/10.1016/j.rser.2018.03.065

Shiraki H and Sugiyama M 2020 Back to the basic: Toward improvement of technoeconomic representation in integrated assessment models *Clim Change* **162** 13–24 Online: https://dx.doi.org/10.1007/s10584-020-02731-4

Shirazi Y A and Sachs D L 2018 Comments on “Measurement of power loss during electric vehicle charging and discharging” - Notable findings for V2G economics *Energy* **142** 1139–41 Online: https://dx.doi.org/10.1016/j.energy.2017.10.081

Shum R Y 2017 A comparison of land-use requirements in solar-based decarbonization scenarios *Energy Policy* **109** 460–2 Online: http://dx.doi.org/10.1016/j.enpol.2017.07.014

Skyllas-Kazacos M, Chakrabarti M H, Hajimolana S A, Mjalli F S and Saleem M 2011 Progress in flow battery research and development *J Electrochem Soc* **158** R55 Online: http://dx.doi.org/10.1149/1.3599565

van Sluisveld M A E, Hof A F, Carrara S, Geels F W, Nilsson M, Rogge K, Turnheim B and van Vuuren D P 2020 Aligning integrated assessment modelling with socio-technical transition insights: An application to low-carbon energy scenario analysis in Europe *Technol Forecast Soc Change* **151** 119177 Online: https://dx.doi.org/10.1016/j.techfore.2017.10.024

Smil V 2010 *Energy transitions: History, requirements, prospects* (Santa Barbara, CA: Praeger)

Smith A and Stirling A 2010 The politics of social-ecological resilience and sustainable socio-technical transitions *Ecology and Society* **15** 11 Online: https://dx.doi.org/10.5751/ES-03218-150111

Smith K, Saxon A, Keyser M, Lundstrom B, Cao Z and Roc A 2017 Life prediction model for grid-connected Li-ion battery energy storage system *Proceedings of the American Control Conference* 4062–8 Online: https://dx.doi.org/10.23919/ACC.2017.7963578

Smithsonian Institution 2017 Fuel cell history project Online: https://americanhistory.si.edu/fuelcells/index.htm

Sokołowski M M and Heffron R J 2022 Defining and conceptualising energy policy failure: The when, where, why, and how *Energy Policy* **161** 112745 Online: https://dx.doi.org/10.1016/j.enpol.2021.

Sonderegger T, Berger M, Alvarenga R, Bach V, Cimprich A, Dewulf J, Frischknecht R, Guinée J, Helbig C, Huppertz T, Jolliet O, Motoshita M, Northey S, Rugani B, Schrijvers D, Schulze R, Sonnemann G, Valero A, Weidema B P and Young S B 2020 Mineral resources in life cycle impact assessment: Part I - A critical review of existing methods *International Journal of Life Cycle Assessment* **25** 784–97 Online: https://dx.doi.org/10.1007/s11367-020-01736-6

Song D, Meng W, Dong M, Yang J, Wang J, Chen X and Huang L 2022 A critical survey of integrated energy system: Summaries, methodologies and analysis *Energy Convers Manag* **266** 115863 Online: https://dx.doi.org/10.1016/j.enconman.2022.115863

Sovacool B K, Burke M, Baker L, Kotikalapudi C K and Wlokas H 2017 New frontiers and conceptual frameworks for energy justice *Energy Policy* **105** 677–91 Online: http://dx.doi.org/10.1016/j.enpol.2017.03.005

Sovacool B K and Dworkin M H 2015 Energy justice: Conceptual insights and practical applications *Appl Energy* **142** 435–44 Online: http://dx.doi.org/10.1016/j.apenergy.2015.01.002

Sovacool B K, Hess D J, Cantoni R, Lee D, Claire Brisbois M, Jakob Walnum H, Freng Dale R, Johnsen Rygg B, Korsnes M, Goswami A, Kedia S and Goel S 2022 Conflicted transitions: Exploring the actors, tactics, and outcomes of social opposition against energy infrastructure *Global Environmental Change* **73** 102473 Online: https://dx.doi.org/10.1016/j.gloenvcha.2022.102473

Sovacool B K, Martiskainen M, Hook A and Baker L 2019 Decarbonization and its discontents: a critical energy justice perspective on four low-carbon transitions *Clim Change* **155** 581–619 Online: https://dx.doi.org/10.1007/s10584-019-02521-7

Sphera 2021 GaBi LCA databases Online: https://gabi.sphera.com/databases/gabi-databases/

Sprecher B, Daigo I, Murakami S, Kleijn R, Vos M and Kramer G J 2015 Framework for resilience in material supply chains, with a case study from the 2010 rare earth crisis *Environ Sci Technol* **49** 6740–50 Online: https://dx.doi.org/10.1021/acs.est.5b00206

Stamp A, Lang D J and Wäger P A 2012 Environmental impacts of a transition toward e-mobility: The present and future role of lithium carbonate production *J Clean Prod* **23** 104–12 Online: http://dx.doi.org/10.1016/j.jclepro.2011.10.026

Statharas S, Moysoglou Y, Siskos P, Zazias G and Capros P 2019 Factors influencing electric vehicle penetration in the E.U. by 2030: A model-based policy assessment *Energies (Basel)* **12** 2739 Online: https://dx.doi.org/10.3390/en12142739

Statista 2022 Share of renewable energy sources in gross electricity generation in Germany in 2020 and 2021 Online: https://de.statista.com/statistik/daten/studie/171368/umfrage/struktur-der-bruttostromerzeugung-durch-erneuerbare-energien-in-deutschland/

Stavrakas V and Flamos A 2020 A modular high-resolution demand-side management model to quantify benefits of demand-flexibility in the residential sector *Energy Convers Manag* **205** 112339 Online: https://dx.doi.org/10.1016/j.enconman.2019.112339

Stavrakas V, Papadelis S and Flamos A 2019 An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers *Appl Energy* **255** 113795 Online: https://dx.doi.org/10.1016/j.apenergy.2019.113795

Stehfest E, van Vuuren D, Kram T, Bouwman L, Alkemade R, Bakkenes M, Biemans H, Bouwman A, den Elzen M, Janse J, Lucas P, van Minnen J, Müller C and Prins A G 2014 *Integrated Assessment of Global*

Environmental Change with IMAGE 3.0: Model description and policy applications (The Hague: PBL Netherlands Environmental Assessment Agency)

Stephens I E L, Rossmeisl J and Chorkendorff I 2016 Toward sustainable fuel cells *Science (1979)* **354** 1378–9 Online: http://dx.doi.org/10.1126/science.aal3303

Stephenson J, Barton B, Carrington G, Doering A, Ford R, Hopkins D, Lawson R, McCarthy A, Rees D, Scott M, Thorsnes P, Walton S, Williams J and Wooliscroft B 2015 The energy cultures framework: Exploring the role of norms, practices and material culture in shaping energy behaviour in New Zealand *Energy Res Soc Sci* **7** 117–23 Online: http://dx.doi.org/10.1016/j.erss.2015.03.005

Stokes L C 2020 *Short circuiting policy: Interest groups and the battle over clean energy and climate policy in the American states* (Oxford: Oxford University Press) Online: https://dx.doi.org/10.1093/oso/9780190074258.001.0001

Struijs J, van Wijnen H J, van Dijk A and Huijbregts M A J 2009 Ozone depletion *ReCiPe 2008. A life cycle impact assessment method which comprises harmonised category indicators at the midpoint and the endpoint level. First edition. Report I: Characterisation* ed M Goedkoop, R Heijungs, M A J Huijbregts, A de Schryver, J Struijs and R van Zelm pp 37–53

Sun Z, Lorscheid I, Millington J D, Lauf S, Magliocca N R, Groeneveld J, Balbi S, Nolzen H, Müller B, Schulze J and Buchmann C M 2016 Simple or complicated agent-based models? A complicated issue *Environmental Modelling and Software* **86** 56–67 Online: http://dx.doi.org/10.1016/j.envsoft.2016.09.006

Süsser D, Ceglarz A, Gaschnig H, Stavrakas V, Flamos A, Giannakidis G and Lilliestam J 2021a Model-based policymaking or policy-based modelling? How energy models and energy policy interact *Energy Res Soc Sci* **75** 101984 Online: https://dx.doi.org/10.1016/j.erss.2021.101984

Süsser D, Ceglarz A, Gaschnig H, Stavrakas V, Giannakidis G, Flamos A, Sander A and Lilliestam J 2021b *The use of energy modelling results for policymaking in the EU. Deliverable 1.1. Sustainable Energy Transitions Laboratory (SENTINEL) project* (Potsdam: Institute for Advanced Sustainability Studies (IASS)) Online: https://dx.doi.org/10.48481/iass.2020.058

Süsser D, Ceglarz A, Stavrakas V and Lilliestam J 2021c COVID-19 vs. stakeholder engagement: The impact of coronavirus containment measures on stakeholder involvement in European energy research projects *Open Research Europe* **1** 57 Online: https://dx.doi.org/10.12688/openreseurope.13683.3

Süsser D, Döring M and Ratter B M W 2017 Harvesting energy: Place and local entrepreneurship in community-based renewable energy transition *Energy Policy* **101** 332–41 Online: https://dx.doi.org/10.1016/j.enpol.2016.10.018

Süsser D, Gaschnig H, Ceglarz A, Stavrakas V, Flamos A and Lilliestam J 2022 Better suited or just more complex? On the fit between user needs and modeller-driven improvements of energy system models *Energy* **239** 121909 Online: https://dx.doi.org/10.1016/j.energy.2021.121909

Süsser D, Gaschnig H, Ceglarz A, Stavrakas V, Giannakidis G, Flamos A, Sander A and Lilliestam J 2020 *Models for the European energy transition: Your questions, your needs!: Workshop synthesis report*

Süsser D and Kannen A 2017 'Renewables? Yes, please!': Perceptions and assessment of community transition induced by renewable-energy projects in North Frisia *Sustain Sci* **12** 563–78 Online: http://dx.doi.org/10.1007/s11625-017-0433-5

Süsser D, Pickering B, Chatterjee S, Oreggioni G, Stavrakas V and Lilliestam J 2021d *Integration of socio-technological transition constraints into energy demand and systems models. Deliverable 2.5. Sustainable Energy Transitions Laboratory (SENTINEL) project* (Potsdam: Institute for Advanced Sustainability Studies (IASS)) Online: https://dx.doi.org/10.48481/iass.2021.030

Süsser D, al Rakouki H and Lilliestam J 2021e *The QTDIAN modelling toolbox - Quantification of social drivers and constraints of the diffusion of energy technologies. Deliverable 2.3. Sustainable Energy Transitions Laboratory (SENTINEL) project* (Potsdam) Online: https://dx.doi.org/10.48481/iass.2021.015

Süsser D, Weig B, Döring M and Ratter B M W 2019 Entrepreneurs for renewables: Emergence of innovation and entrepreneurship in complex social systems *Entrepreneurial complexity: Methods and applications* ed M Dehmer, F Emmert-Streib and H Jodlbauer (Boca Raton, FL: CRC Press) pp 1–47 Online: https://dx.doi.org/10.1201/9781351250849

Sütterlin B and Siegrist M 2017 Public acceptance of renewable energy technologies from an abstract versus concrete perspective and the positive imagery of solar power *Energy Policy* **106** 356–66 Online: http://dx.doi.org/10.1016/j.enpol.2017.03.061

Swedish Energy Agency 2015 *Electricity supply, district heating and supply of natural gas 2015. Final statistics* (Eskilstuna)

Swedish Energy Agency 2016 *Electricity supply, district heating and supply of natural gas 2016. Final statistics* (Eskilstuna)

Swedish Energy Agency 2017 *Electricity supply, district heating and supply of natural gas 2017. Final statistics* (Eskilstuna)

Swedish Energy Agency 2018 *Electricity supply, district heating and supply of natural gas 2018. Final statistics* (Eskilstuna)

Swedish Energy Agency 2019 *Electricity supply, district heating and supply of natural gas 2019. Final statistics*

Swedish Energy Agency 2022 Energy in Sweden facts and figures 2022 Online: https://www.energimyndigheten.se/495a34/globalassets/statistik/energilaget/energy-in-sweden-facts-and-figures_220329.xlsx

Talens Peiró L and Gabarrell i Durany X 2019 DoSE database (i-depot: 120009)

Talens Peiró L, Gabarrell i Durany X, Martinez Gasol C and Rieradevall Pons J 2019 LCADB database (i-depot 120008)

Talens Peiró L, Villalba Méndez G and Ayres R U 2013 Material flow analysis of scarce metals: Sources, functions, end-uses and aspects for future supply *Environ Sci Technol* **47** 2939–47 Online: http://dx.doi.org/10.1021/es301519c

Tan K M, Ramachandaramurthy V K and Yong J Y 2016 Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques *Renewable and Sustainable Energy Reviews* **53** 720–32 Online: http://dx.doi.org/10.1016/j.rser.2015.09.012

The Royal Society 2008 *Ground-level ozone in the 21st century: Future trends, impacts and policy implications* (London: The Royal Society)

The World Bank 2017 *The growing role of minerals and metals for a low carbon future* (Washington, DC: The World Bank) Online: https://dx.doi.org/10.1596/28312

The World Bank Worldwide governance indicators: World Bank data catalog Online: http://info.worldbank.org/governance/wgi/

Tirado-Seco P 2005 *Development of damage functions for aquatic eutrophication in life cycle assessment* (Université de Genève)

Tokimatsu K, Tang L, Yasuoka R, Ii R, Itsubo N and Nishio M 2020 Toward more comprehensive environmental impact assessments: Interlinked global models of LCIA and IAM applicable to this century *International Journal of Life Cycle Assessment* **25** 1710–36 Online: https://dx.doi.org/10.1007/s11367-020-01750-8

Tomasini-Montenegro C, Santoyo-Castelazo E, Gujba H, Romero R J and Santoyo E 2017 Life cycle assessment of geothermal power generation technologies: An updated review *Appl Therm Eng* **114** 1119–36 Online: http://dx.doi.org/10.1016/j.applthermaleng.2016.10.074

Toulouse E, Gorge H, le Dû M and Semal L 2017 Stimulating energy sufficiency: Barriers and opportunities *ECEEE Summer Study Proceedings* 59–68

Tröndle T Euro-Calliope Online: https://github.com/calliope-project/euro-calliope

Tröndle T 2020 Supply-side options to reduce land requirements of fully renewable electricity in Europe *PLoS One* **15** e0236958 Online: https://dx.doi.org/10.1371/journal.pone.0236958

Tröndle T, Lilliestam J, Marelli S and Pfenninger S 2020 Trade-offs between geographic scale, cost, and infrastructure requirements for fully renewable electricity in Europe *Joule* **4** 1929–48 Online: http://dx.doi.org/10.1016/j.joule.2020.07.018

Trutnevyte E, Hirt L F, Bauer N, Cherp A, Hawkes A, Edelenbosch O Y, Pedde S and van Vuuren D P 2019 Societal transformations in models for energy and climate policy: The ambitious next step *One Earth* **1** 423–33 Online: https://dx.doi.org/10.1016/j.oneear.2019.12.002

Tselepis S 2015 The PV market developments in Greece, net-metering study cases *31st EUPVSEC Conference, Hamburg*

Tummers L 2019 Public policy and behavior change *Public Adm Rev* **79** 925–30 Online: https://dx.doi.org/10.1111/puar.13109

Turnheim B, Berkhout F, Geels F, Hof A, McMeekin A, Nykvist B and van Vuuren D 2015 Evaluating sustainability transitions pathways: Bridging analytical approaches to address governance challenges *Global Environmental Change* **35** 239–53 Online: http://dx.doi.org/10.1016/j.gloenvcha.2015.08.010

Uddin K, Jackson T, Widanage W D, Chouchelamane G, Jennings P A and Marco J 2017 On the possibility of extending the lifetime of lithium-ion batteries through optimal V2G facilitated by an integrated vehicle and smart-grid system *Energy* **133** 710–22 Online: http://dx.doi.org/10.1016/j.energy.2017.04.116

Uihlein A and Magagna D 2016 Wave and tidal current energy - A review of the current state of research beyond technology *Renewable and Sustainable Energy Reviews* **58** 1070–81 Online: http://dx.doi.org/10.1016/j.rser.2015.12.284

das Umweltbundesamt 2021 Windenergie an Land Online: https://www.umweltbundesamt.de/themen/klima-energie/erneuerbare-energien/windenergie-an-land#flaeche

United Nations 2015 *C.N.63.2016.TREATIES-XXVII.7.d Paris Agreement* (New York) Online: https://treaties.un.org/pages/ViewDetails.aspx?src=TREATY&mtdsg_no=XXVII-7-d&chapter=27&clang=_en

United Nations Statistical Division 2017 *International recommendations for energy statistics (IRES)* (New York, NY: United Nations)

Urchueguia J F 2016 Shallow geothermal and ambient heat technologies for renewable heating *Renewable heating and cooling: Technologies and applications* ed G Stryi-Hipp (Cambridge: Woodhead Publishing) pp 89–118 Online: https://dx.doi.org/10.1016/B978-1-78242-213-6.00005-9

U.S. Department of Energy 2010 *Critical materials strategy* (Washington DC: U.S. Department of Energy)

U.S. Department of Energy Global energy storage database Online: https://www.sandia.gov/ess-ssl/download/4440/

U.S. Geological Survey 2020 *Mineral commodity summaries 2020* (Reston, VA: U.S. Geological Survey) Online: https://dx.doi.org/10.3133/mcs2020

USGS 2021 *Mineral commodity summaries, January 2021 - Iron and steel scrap* (Reston, VA: U.S. Geological Survey)

Vakulchuk R, Overland I and Scholten D 2020 Renewable energy and geopolitics: A review *Renewable and Sustainable Energy Reviews* **122** 109547 Online: https://dx.doi.org/10.1016/j.rser.2019.109547

Valente A, Iribarren D and Dufour J 2021 Comparative life cycle sustainability assessment of renewable and conventional hydrogen *Science of the Total Environment* **756** 144132 Online: https://dx.doi.org/10.1016/j.scitotenv.2020.144132

Valero A, Ortego A, Calvo G, Valero A, Círez F, Kimmich C, Černý M, Kerschner C, Černík M, Theofilidi M, Bardi U, Perissi I and Falsini S 2016 *Guiding European policy toward a low-carbon economy. Modelling sustainable energy system development under environmental and socioeconomic constraints: MEDEAS project deliverable D2.1*

Valero A, Valero A, Calvo G, Ortego A, Ascaso S and Palacios J L 2018 Global material requirements for the energy transition. An exergy flow analysis of decarbonisation pathways *Energy* **159** 1175–84 Online: https://dx.doi.org/10.1016/j.energy.2018.06.149

Vasilakis D P, Whitfield D P, Schindler S, Poirazidis K S and Kati V 2016 Reconciling endangered species conservation with wind farm development: Cinereous vultures (Aegypius monachus) in south-eastern Europe *Biol Conserv* **196** 10–7 Online: https://dx.doi.org/10.1016/j.biocon.2016.01.014

Vaughan A 2019 The cost of subsidising UK wind farms has dropped to an all-time low *New Sci (1956)* Online: https://www.newscientist.com/article/2217235-the-cost-of-subsidising-uk-wind-farms-has-dropped-to-an-all-time-low/

Verboon M 2016 *Environmental impacts of nickel production, 2010-2050. An assessment of the environmental impacts of metal demand and supply scenarios using life cycle assessment* (Leiden University & Delft University of Technology)

Verhoef E v., Dijkema G P J and Reuter M A 2004 Process knowledge, system dynamics, and metal ecology *J Ind Ecol* **8** 23–43 Online: https://dx.doi.org/10.1162/1088198041269382

Victor D G, Geels F W and Sharpe S 2019 *Accelerating the low carbon transition: The case for stronger, more targeted and coordinated international action* (Washington, D.C.: Brookings) Online: https://www.brookings.edu/wp-content/uploads/2019/12/Coordinatedactionreport.pdf

Vieira M D M, Ponsioen T C, Goedkoop M J and Huijbregts M A J 2017 Surplus ore potential as a scarcity indicator for resource extraction *J Ind Ecol* **21** 381–90 Online: https://dx.doi.org/10.1111/jiec.12444

Vlaskamp M C 2019 The European Union and natural resources that fund armed conflicts: Explaining the EU's policy choice for supply chain due-diligence requirements *Coop Confl* **54** 407–25 Online: https://dx.doi.org/10.1177/0010836718808314

van der Voet E, van Oers L, Verboon M and Kuipers K 2019 Environmental implications of future demand scenarios for metals: Methodology and application to the case of seven major metals *J Ind Ecol* **23** 141–55 Online: https://dx.doi.org/10.1111/jiec.12722

Voigt C C, Straka T M and Fritze M 2019 Producing wind energy at the cost of biodiversity: A stakeholder view on a green-green dilemma *Journal of Renewable and Sustainable Energy* **11** 063303 Online: http://dx.doi.org/10.1063/1.5118784

Volkart K, Mutel C L and Panos E 2018 Integrating life cycle assessment and energy system modelling: Methodology and application to the world energy scenarios *Sustain Prod Consum* **16** 121–33 Online: https://dx.doi.org/10.1016/j.spc.2018.07.001

Wagner L 2014 Overview of energy storage technologies *Future energy: Improved, sustainable and clean options for our planet* ed T M Letcher (London: Elsevier) pp 613–31 Online: http://dx.doi.org/10.1016/B978-0-08-099424-6.00027-2

Walker B J A, Wiersma B and Bailey E 2014 Community benefits, framing and the social acceptance of offshore wind farms: An experimental study in England *Energy Res Soc Sci* **3** 46–54 Online: http://dx.doi.org/10.1016/j.erss.2014.07.003

Wang W, Luo Q, Li B, Wei X, Li L and Yang Z 2013 Recent progress in redox flow battery research and development *Adv Funct Mater* **23** 970–86 Online: http://dx.doi.org/10.1002/adfm.201200694

Wang Z, Wu J, Liu C and Gu G 2017 *Integrated assessment models of climate change economics* (Singapore: Springer Nature) Online: http://dx.doi.org/10.1007/978-981-10-3945-4

Watari T, McLellan B C, Giurco D, Dominish E, Yamasue E and Nansai K 2019 Total material requirement for the global energy transition to 2050: A focus on transport and electricity *Resour Conserv Recycl* **148** 91–103 Online: https://dx.doi.org/10.1016/j.resconrec.2019.05.015

Weiss M, Junginger M, Patel M K and Blok K 2010 A review of experience curve analyses for energy demand technologies *Technol Forecast Soc Change* **77** 411–28 Online: http://dx.doi.org/10.1016/j.techfore.2009.10.009

Wellmer F W, Buchholz P, Gutzmer J, Hagelüken C, Herzig P, Littke R and Thauer R K 2019 *Raw materials for future energy supply* (Cham: Springer) Online: https://dx.doi.org/10.1007/978-3-319-91229-5

Wendling Z A, Emerson J W, de Sherbinin A and Esty D C 2020 *Environmental performance index 2020 - Global metrics for the environment: Ranking country performance on sustainability issues* (New Haven, CT: Yale Center for Environmental Law & Policy)

Werner S 2017 District heating and cooling in Sweden *Energy* **126** 419–29 Online: http://dx.doi.org/10.1016/j.energy.2017.03.052

Werner S 2022 Personal correspondence

Wernet G, Bauer C, Steubing B, Reinhard J, Moreno-Ruiz E and Weidema B 2016 The ecoinvent database version 3 (part I): Overview and methodology *International Journal of Life Cycle Assessment* **21** 1218–30 Online: http://dx.doi.org/10.1007/s11367-016-1087-8

Weyant J 2017 Some contributions of integrated assessment models of global climate change *Rev Environ Econ Policy* **11** 115–37 Online: http://dx.doi.org/10.1093/reep/rew018

Wilburn D R 2011 *Wind energy in the United States and materials required for the land-based wind turbine industry from 2010 through 2030. U.S. Geological Survey Scientific Investigations Report 2011-5036* (Reston, VA: U.S. Geological Survey)

Wilkes W, Dezem V and Shiryaevskaya A 2019 How "green hydrogen" could make "green steel" real *Bloomberg* Online: https://www.bloomberg.com/news/articles/2019-11-23/how-green-hydrogen-could-make-green-steel-real-quicktake

Wilson G M, Al-Jassim M, Metzger W K, Glunz S W, Verlinden P, Xiong G, Mansfield L M, Stanbery B J, Zhu K, Yan Y, Berry J J, Ptak A J, Dimroth F, Kayes B M, Tamboli A C, Peibst R, Catchpole K, Reese M O, Klinga C S, Denholm P, Morjaria M, Deceglie M G, Freeman J M, Mikofski M A, Jordan D C, Tamizhmani G and Sulas-Kern D B 2020 The 2020 photovoltaic technologies roadmap *J Phys D Appl Phys* **53** 493001 Online: https://dx.doi.org/10.1088/1361-6463/ab9c6a

WindEurope 2020 *Wind energy in Europe in 2019: Trends and statistics* (Brussels: WindEurope)

WindEurope 2017 *Wind energy in Europe: Scenarios for 2030* (Brussels: WindEurope) Online: https://windeurope.org/wp-content/uploads/files/about-wind/reports/Wind-energy-in-Europe-Scenarios-for-2030.pdf

Witajewski-Baltvilks J, Verdolini E and Tavoni M 2015 Bending the learning curve *Energy Econ* **52** S86–99 Online: http://dx.doi.org/10.1016/j.eneco.2015.09.007

Witsch K 2021 Trotz Milliardeninvestments und grüner Finanzprodukte: Ausbau der Windkraft stockt *Handelsblatt* Online: r-finanzprodukte-ausbau-der-windkraft-stockt/26853040.html

World Meteorological Organization 1998 *Scientific assessment of ozone depletion: 1998, WMO Global Ozone Research and Monitoring Project - Report No. 44* (Geneva: World Meteorological Organization)

World Meteorological Organization 2010 *Scientific assessment of ozone depletion: 2010* (Geneva: World Meteorological Organization)

WRI and WBCSD 2004 *The Greenhouse Gas Protocol: A corporate accounting and reporting standard - Revised edition* (Washington, DC: The Greenhouse Gas Protocol)

Wu M S, Jin B C, Li X and Nutt S 2019 A recyclable epoxy for composite wind turbine blades *Advanced Manufacturing: Polymer and Composites Science* **5** 114–27 Online: https://dx.doi.org/10.1080/20550340.2019.1639967

Xu C, Dai Q, Gaines L, Hu M, Tukker A and Steubing B 2020a Future material demand for automotive lithium-based batteries *Commun Mater* **1** 99 Online: http://dx.doi.org/10.1038/s43246-020-00095-x

Xu L, Fuss M, Poganietz W R, Jochem P, Schreiber S, Zoephel C and Brown N 2020b An Environmental Assessment Framework for Energy System Analysis (EAFESA): The method and its application to the European energy system transformation *J Clean Prod* **243** 118614 Online: https://dx.doi.org/10.1016/j.jclepro.2019.118614

Yamani Douzi Sorkhabi S, Romero D A, Yan G K, Gu M D, Moran J, Morgenroth M and Amon C H 2016 The impact of land use constraints in multi-objective energy-noise wind farm layout optimization *Renew Energy* **85** 359–70 Online: http://dx.doi.org/10.1016/j.renene.2015.06.026

Yao Y, Xu J-H and Sun D-Q 2021 Untangling global levelised cost of electricity based on multi-factor learning curve for renewable energy: Wind, solar, geothermal, hydropower and bioenergy *J Clean Prod* **285** 124827 Online: https://dx.doi.org/10.1016/j.jclepro.2020.124827

Yoo J J, Seo G, Chua M R, Park T G, Lu Y, Rotermund F, Kim Y K, Moon C S, Jeon N J, Correa-Baena J P, Bulović V, Shin S S, Bawendi M G and Seo J 2021 Efficient perovskite solar cells via improved carrier management *Nature* **590** 587–93 Online: http://dx.doi.org/10.1038/s41586-021-03285-w

You J, Dou L, Yoshimura K, Kato T, Ohya K, Moriarty T, Emery K, Chen C C, Gao J, Li G and Yang Y 2013 A polymer tandem solar cell with 10.6% power conversion efficiency *Nat Commun* **4** 1446 Online: https://dx.doi.org/10.1038/ncomms2411

Zame K K, Brehm C A, Nitica A T, Richard C L and Schweitzer G D 2018 Smart grid and energy storage: Policy recommendations *Renewable and Sustainable Energy Reviews* **82** 1646–54 Online: http://dx.doi.org/10.1016/j.rser.2017.07.011

Zell-Ziegler C, Thema J, Best B, Wiese F, Lage J, Schmidt A, Toulouse E and Stagl S 2021 Enough? The role of sufficiency in European energy and climate plans *Energy Policy* **157** 112483 Online: https://dx.doi.org/10.1016/j.enpol.2021.112483

van Zelm R, Huijbregts M A J and van de Meent D 2009 USES-LCA 2.0 - A global nested multi-media fate, exposure, and effects model *International Journal of Life Cycle Assessment* **14** 282–4 Online: https://dx.doi.org/10.1007/s11367-009-0066-8

van Zelm R, Preiss P, van Goethem T, van Dingenen R and Huijbregts M 2016 Regionalized life cycle impact assessment of air pollution on the global scale: Damage to human health and vegetation *Atmos Environ* **134** 129–37 Online: http://dx.doi.org/10.1016/j.atmosenv.2016.03.044

van Zelm R, Stam G, Huijbregts M A J and van de Meent D 2013 Making fate and exposure models for freshwater ecotoxicity in life cycle assessment suitable for organic acids and bases *Chemosphere* **90** 312–7 Online: http://dx.doi.org/10.1016/j.chemosphere.2012.07.014

Zeng A, Chen W, Rasmussen K D, Zhu X, Lundhaug M, Müller D B, Tan J, Keiding J K, Liu L, Dai T, Wang A and Liu G 2022 Battery technology and recycling alone will not save the electric mobility transition from future cobalt shortages *Nat Commun* **13** 1341 Online: https://dx.doi.org/10.1038/s41467-022-29022-z

Zerrahn A and Schill W P 2017 Long-run power storage requirements for high shares of renewables: Review and a new model *Renewable and Sustainable Energy Reviews* **79** 1518–34 Online: http://dx.doi.org/10.1016/j.rser.2016.11.098

Zhang H L, Baeyens J, Degrève J and Cacères G 2013 Concentrated solar power plants: Review and design methodology *Renewable and Sustainable Energy Reviews* **22** 466–81 Online: http://dx.doi.org/10.1016/j.rser.2013.01.032

Zhang T and Nuttall W J 2011 Evaluating government's policies on promoting smart metering diffusion in retail electricity markets via agent-based simulation *Journal of Product Innovation Management* **28** 169–86 Online: http://dx.doi.org/10.1111/j.1540-5885.2011.00790.x

Zhao E W, Liu T, Jónsson E, Lee J, Temprano I, Jethwa R B, Wang A, Smith H, Carretero-González J, Song Q and Grey C P 2020 In situ NMR metrology reveals reaction mechanisms in redox flow batteries *Nature* **579** 224–8 Online: http://dx.doi.org/10.1038/s41586-020-2081-7

Zubi G, Dufo-López R, Carvalho M and Pasaoglu G 2018 The lithium-ion battery: State of the art and future perspectives *Renewable and Sustainable Energy Reviews* **89** 292–308 Online: https://dx.doi.org/10.1016/j.rser.2018.03.002

van der Zwaan B and Dalla Longa F 2019 Integrated assessment projections for global geothermal energy use *Geothermics* **82** 203–11 Online: https://dx.doi.org/10.1016/j.geothermics.2019.06.008