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Advanced Energy Management/Control Strategies for Smart Manufacturing Systems

Jenny Lorena Diaz Castañeda

Director: Prof. Carlos Ocampo-Martinez

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To my parents,

to my brother.

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ABSTRACT

This thesis is devoted to the study of optimisation-based control techniques for the design of management strategies that contribute to improving the energy efficiency of smart manufacturing systems. Currently, the manufacturing industry is suffering a transformation towards smart, flexible, and energy-efficient manufacturing systems promoted by the advances in sensing technologies, data management techniques, and communication and connectivity tools. This transformation requires the manufacturing systems will be modularised and made reconfigurable to be able of adapting to changes in productions programs, demand of pieces, and in the design of them while keeping an energy-efficient and sustainable operation. Therefore, to achieve a smarter manufacturing industry, suitable control systems should be designed to satisfy the requirements of this transformation, as well as to contribute to minimising the energy consumption and maximise the plant profit. In this regard, optimisation-based controllers and non-centralised control architectures could be suitable for the design of control systems that allow minimising the total energy consumption of such systems while remaining their productivity and taking into account the operational conditions and the factors that affect such systems. Thus, using these advanced control techniques, the control systems can be suitably updated to include the new information about the changes in the operation of manufacturing systems as well as the energy-market information to minimise the total energy cost during the plant operation.

First, this dissertation presents and discusses the strategies currently implemented by the manufacturing industry to improve its energy efficiency. Based on this review, the research gaps in this field are identified, and it is discussed how optimisation-based control techniques can contribute to facing the challenges of the new era of the manufacturing industry (Industry 4.0). Thus, according to the literature review, the manufacturing industry is classified by levels, i.e., machine, process line, and plant levels, for the design of optimisation-based controllers. Moreover, with the aim to design control strategies that do not affect plant productivity, i.e., the number of processed pieces in a fixed period, the constitutive elements of manufacturing systems

are also classified in machining and peripheral devices according to the operations performed. The elements of the former class are directly related to the machining operations, while the latter class refers to those devices that provide the resources required for the machining devices. Then, based on the latter classification, control strategies are proposed to minimise either the total energy consumption of manufacturing systems or the energy costs related to the operation of such systems.

At both machine and process line levels, control strategies are designed based on model predictive control approach to minimise the total energy consumption of manufacturing systems. The underlying idea behind the proposed control strategies consists in independently managing the peripheral devices (or systems) to avoid affecting the time to process a piece while keeping the same operation for the machining devices. In this regard, energy consumption models are required to predict the total energy consumption profile of manufacturing systems and, based on this prediction, to select the activation/deactivation instants for the manipulated devices that minimise the energy consumption and guarantee the proper operation of such systems. Furthermore, a control strategy based on two control modes is proposed to reduce the computational burden when the size and complexity of manufacturing systems increase, e.g., at both the process line and plant levels. Thus, because the manufacturing systems exhibit periodic behaviour, an algorithm to detect the periodicity of such systems is proposed in order to switch from a control mode based on online optimisation to an autonomous control mode without solving in real time an optimisation problem.

Besides, due to the need for flexible and reconfigurable manufacturing systems, non-centralised control strategies are proposed at higher industrial levels to minimise their energy consumption. In this regard, both cooperative and non-cooperative local controllers are designed considering a fixed system partitioning and using alternative direction methods of multipliers to solve the optimisations problems in a distributed fashion. Besides, due to the nature of the proposed control objective, which is focused on minimising the energy consumption of manufacturing systems, a way to define the consensus stage among the local controllers with coupled dynamics is proposed. Then, the proposed algorithms are extended to the plant level using economic cost functions, and the closed-loop performance and the computational burden for both centralised and non-centralised control architectures are compared.

Finally, at the plant level, control strategies are designed based on the economic model predictive control approach and oriented to maximise the plant profit and minimise the operational costs related to the plant operation. Thus, at this level, control objectives are focused on

determining the economic-optimal production programming of the plant that the control strategies at lower levels should follow. In this regard, the production programming of the plant is determined taking into account the pieces demand, the energy consumption of manufacturing systems, and the current energy market and their fluctuations. All control strategies proposed in this thesis are tested in simulation considering different scenarios that were based on the real operation of a manufacturing plant designed for automotive parts production.

Keywords: model predictive control (MPC), economic model predictive control (EMPC), non-centralised MPC, cooperative control, non-cooperative control, subspace identification, smart manufacturing systems (SMS), energy consumption reduction, plant profit maximisation, energy efficiency

RESUMEN

Esta tesis concierne principalmente al estudio de las técnicas de control basadas en optimización para el diseño de estrategias que contribuyan a mejorar la eficiencia energética de los sistemas de manufactura inteligentes. Actualmente, la industria manufacturera está atravesando una transformación hacia sistemas de manufactura inteligentes, flexibles y eficientes energéticamente, impulsada por los avances en dispositivos de medición, gestión de datos y herramientas de comunicación y conectividad. Esta transformación requiere que los sistemas de manufactura sean modulares y reconfigurables para poder responder a los cambios en la programación de la producción, demanda de las piezas, y en el diseño de estas mientras continúan operando de manera eficiente y sostenible. Por lo tanto, para alcanzar una industria de manufactura más inteligente, se deben diseñar sistemas de control adecuados que permitan cumplir los requerimientos de dicha transformación, así como también minimizar el consumo de energía y maximizar la rentabilidad de la planta. En este sentido, los controladores basados en optimización y las arquitecturas de control no centralizado podrían ser adecuados para el diseño de sistemas de control que contribuyan a minimizar el consumo de energía total de dichos sistemas mientras mantienen su productividad y tienen en cuenta las restricciones operativas y los factores externos que afectan dichos sistemas. Por lo tanto, mediante el uso de estrategias de control avanzado, los sistemas de control pueden ser debidamente actualizados para incluir la información sobre los cambios en la operación de los sistemas de manufactura, así como también la variación del mercado energético para minimizar los costos de energía durante la operación de la planta.

Primero, en esta tesis, se presentan y discuten las estrategias actualmente implementadas en la industria manufacturera para mejorar su eficiencia energética. En base a esta revisión, se identifican las principales brechas de investigación en este campo y se discute como las técnicas de control basadas en optimización pueden contribuir a hacer frente a los desafíos impuestos por la nueva era de la industria manufacturera (Industry 4.0). Con base en la revisión de la literatura, se propone clasificar la industria manufacturera por niveles, considerando el nivel de

máquina, línea de proceso, y planta, para el diseño de controladores basados en optimización. Además, con el fin de diseñar estrategias de control que no afecten la productividad de la planta, es decir, el número de piezas procesadas por unidad de tiempo, los elementos constitutivos de los sistemas de manufactura también se clasifican como dispositivos de mecanizado y periféricos en función de las operaciones realizadas. Los elementos de la primera clase corresponden a aquellos que están directamente involucrados en las operaciones de mecanizado, mientras que los de la segunda clase son aquellos que se encargan de proveer los recursos requeridos por los dispositivos de mecanizado. Luego, con base en dicha clasificación, se proponen estrategias de control en cada nivel para minimizar su consumo de energía o los costos asociados a dicho consumo.

Para los niveles de máquina y línea de proceso, se diseñan estrategias de control para minimizar el consumo de energía de los sistemas de manufactura con base en el enfoque de control predictivo basado en modelo. Las estrategias propuestas se basan en la idea de gestionar de forma independiente los dispositivos (o sistemas) periféricos con el fin de no afectar el tiempo de procesamiento de las maquinas manteniendo la operación de los dispositivos de mecanizado. Por lo tanto, se requiere determinar modelos de consumo de energía para predecir el perfil del consumo de energía de los sistemas de manufactura y, con base en esta predicción, seleccionar los instantes de activación/desactivación para los dispositivos manipulados a partir de los cuales se minimice el consumo de energía total y se pueda garantizar el funcionamiento correcto de dichos sistemas. Por otro lado, dado que al nivel de línea de proceso el tamaño y la complejidad de los sistemas de manufactura aumenta, se propone una estrategia de control basada en dos modos de control con el fin de reducir la carga computacional y diseñar controladores que puedan ser implementados en tiempo real. En este sentido, teniendo en cuenta que los sistemas de manufactura presentan un comportamiento periódico, se propone un algoritmo para detectar la periodicidad de dichos sistemas y, luego, conmutar a un modo de control autónomo que no requiere de resolver un problema de optimización en línea.

Por otro lado, dada la necesidad de sistemas de manufactura flexibles y reconfigurables, se proponen estrategias de control no centralizadas para minimizar el consumo de energía de los sistemas de fabricación a los niveles más altos. Para este fin, los sistemas de manufactura se dividen en subsistemas, y se diseñan controladores locales de tipo cooperativo y no cooperativo usando métodos alternativos de dirección de multiplicadores para resolver los problemas de optimización de manera distribuida. Además, debido a la naturaleza del objetivo de control propuesto, el cual está enfocado en minimizar el consumo de energía de los sistemas de manufactura, se propone una forma de establecer el consenso entre los controladores locales con dinámicas acopladas. Luego, las estrategias de control propuestas son extrapoladas al nivel de planta usando objetivos de tipo económico, y se comparan las arquitecturas de control centralizado y no centralizado con respecto a su desempeño en lazo cerrado y la carga computacional requerida para encontrar una solución.

Finalmente, a nivel de planta, se diseñan estrategias de control con base en el enfoque control predictivo basado en modelo económico con el fin de maximizar la rentabilidad de la planta y minimizar los costos asociados a su operación. Por lo tanto, a este nivel, los objetivos de control se centran en determinar la programación de la producción óptima para la planta que deberán seguir las estrategias de control diseñadas a los niveles más bajos. En este sentido, la programación de la producción de la planta es determinada teniendo en cuenta la demanda actual de piezas, el consumo de energía de los sistemas de manufactura, y el mercado energético con sus fluctuaciones. Todas las estrategias de control propuestas en esta tesis fueron probadas en simulación considerando diferentes escenarios basados en la operación real de una planta de fabricación de piezas automotrices.

Palabras clave: control predictivo, control predictivo no centralizado, control cooperativo, control no cooperativo, identificación por subespacios, sistemas de manufactura inteligente, reducción del consumo de energía, maximización de la rentabilidad de una planta, eficiencia energética

RESUM

Aquesta tesi es centra principalment en l'estudi de les tècniques de control basades en optimització per al disseny d'estratègies que contribueixin a millorar l'eficiència energètica dels sistemes de manufactura intel·ligents. Actualment, la indústria manufacturera està experimentant una transformació cap a sistemes de manufactura intel·ligents, flexibles i eficients energèticament, impulsada pels avenços en dispositius de mesura, gestió de dades i eines de comunicació i connectivitat. Aquesta transformació requereix que els sistemes de manufactura siguin modulars i reconfigurables per poder respondre als canvis en la programació de la producció i de la demanda i disseny de les peces mentre continuen operant de manera eficient i sostenible. Per tant, per tal d'assolir una indústria de manufactura més intel·ligent, s'han de dissenyar sistemes de control adequats que permetin complir els requeriments d'aquesta transformació, així com també minimitzar el consum d'energia i maximitzar la rendibilitat de la planta. En aquest sentit, els controladors basats en optimització i les arquitectures de control no centralitzat podrien ser adequats per al disseny de sistemes de control que contribueixin a minimitzar el consum d'energia total d'aquests sistemes mentre mantenen la seva productivitat i tenen en compte les restriccions operatives i els factors externs que afecten aquests sistemes. Per tant, mitjançant l'ús d'estratègies de control avançat, els sistemes de control poden ser degudament actualitzats per incloure la informació sobre els canvis en l'operació dels sistemes de manufactura, així com també la variació del mercat energètic per minimitzar els costos d'energia durant l'operació de la planta.

Primer, en aquesta tesi, es presenten i discuteixen les estratègies actualment implementades en la indústria manufacturera per millorar la seva eficiència energètica. En base a aquesta revisió, s'identifiquen les principals bretxes de recerca en aquest camp i es discuteix com les tècniques de control basades en optimització poden contribuir a fer front als desafiaments imposats per la nova era de la indústria manufacturera (Industry 4.0). Recolzant-se en la revisió de la literatura, es proposa classificar la indústria manufacturera per nivells, considerant el nivell

de màquina, línia de procés i planta, per al disseny de controladors basats en optimització. A més, per tal de dissenyar estratègies de control que no afectin la productivitat de la planta, és a dir, el nombre de peces processades per unitat de temps, els elements constitutius dels sistemes de manufactura també es classifiquen en dispositius de mecanitzat i perifèrics en funció de les operacions realitzades. Els elements de la primera classe corresponen a aquells que estan directament involucrats en les operacions de mecanitzat, mentre que els de la segona classe són aquells que s'encarreguen de proveir els recursos requerits pels dispositius de mecanitzat. Després, en base a aquesta classificació, es proposen estratègies de control en cada nivell per minimitzar el seu consum d'energia o els costos associats a aquest consum.

Per als nivells de màquina i línia de procés, es dissenyen estratègies de control per minimitzar el consum d'energia dels sistemes de manufactura en base a l'enfocament de control predictiu basat en model. Les estratègies proposades es basen en la idea de gestionar de manera independent els dispositius (o sistemes) perifèrics per tal de no afectar el temps de processament de les màquines tot mantenint l'operació dels dispositius de mecanitzat. Per tant, calen models de consum d'energia per a predir el perfil de consum d'energia dels sistemes de manufactura i, en base a aquesta predicció, seleccionar els instants d'activació / desactivació per als dispositius manipulats a partir dels quals es minimitzi el consum d'energia total i es pugui garantir el correcte funcionament d'aquests sistemes. D'altra banda, atès que al nivell de línia de procés la mida i la complexitat dels sistemes de manufactura augmenta, es proposa una estratègia de control basada en dos modes de control per tal de reduir la càrrega computacional i dissenyar controladors que puguin ser implementats en temps real. En aquest sentit, tenint en compte que els sistemes de manufactura presenten un comportament diari, es proposa un algoritme per detectar la periodicitat d'aquests sistemes i, després, commutar a un mode de control autònom que no requereixi resoldre un problema d'optimització en línia.

D'altra banda, donada la necessitat de sistemes de manufactura flexibles i reconfigurables, es proposen estratègies de control no centralitzades per minimitzar el consum d'energia dels sistemes de fabricació als nivells més alts. Amb aquesta finalitat, els sistemes de manufactura es divideixen en subsistemes, i es dissenyen controladors locals de tipus cooperatiu i no cooperatiu utilitzant mètodes alternatius de direcció de multiplicadors per resoldre els problemes d'optimització de manera distribuïda. A més, a causa de la naturalesa de l'objectiu de control proposat, el qual està enfocat en minimitzar el consum d'energia dels sistemes de manufactura, es proposa una forma d'establir el consens entre els controladors locals amb dinàmiques acoblades. Després, les estratègies de control proposades són extrapolades al nivell de planta usant objectius de tipus econòmic, i es comparen les arquitectures de control centralitzat i no centralitzat pel que fa al seu acompliment en llaç tancat i la càrrega computacional requerida per trobar una solució.

Finalment, a nivell de planta, es dissenyen estratègies de control en base a l'enfocament de control predictiu basat en model econòmic per tal de maximitzar la rendibilitat de la planta i minimitzar els costos associats a la seva operació. Per tant, a aquest nivell, els objectius de control se centren a determinar la programació de la producció òptima de la planta que hauran de seguir les estratègies de control dissenyades als nivells més baixos. En aquest sentit, la programació de la producció de la planta és determinada tenint en compte la demanda actual de peces, el consum d'energia dels sistemes de manufactura i el mercat energètic amb les seves fluctuacions. Totes les estratègies de control proposades en aquesta tesi es proven en simulació considerant diferents escenaris basats en l'operació real d'una planta de fabricació de peces automotrius.

Paraules clau: control predictiu, control predictiu no centralitzat, control cooperatiu, control no cooperatiu, identificació per subespais, sistemes de manufactura intel·ligent, reducció del consum d'energia, maximització de la rendibilitat d'una planta, eficiència energètica

NOTATION

Symbol	Description
$\{\cdots\}$	Set
$\emptyset$	Empty set
$\mathbb{R}$	Set of real numbers
$\mathbb{R}^n$	Space of n-dimensional column vectors with real entries
$\mathbb{R}_{\geq 0}$	Set of positive real numbers
$\mathbb{Z}$	Set of integer numbers
$\mathbb{Z}_{\geq 0}$	Set of positive integer numbers
$\lvert \cdot \rvert$	Cardinality operator
$\lVert \cdot \rVert_2$	Euclidean norm
$\lVert \cdot \rVert_2$	Euclidean norm
$\sum$	Summation operator

Acronyms

Acronym	Description
ABS	Agent Based Simulation
ADMM	Alternative Direction Method of Multipliers
APS	Advanced Planning and Scheduling
CDMPC	Cooperative Distributed Model Predictive Control
CEMPC	Centralised Economic Model Predictive Control
CEP	Complex-Event-Processing
CNC	Computer Numerical Control
CPMS	Cyber-Physical Manufacturing Systems

CPS	Cyber-Physical Systems
CVA	Canonical Variate Analysis
DCS	Distributed Control Systems
DES	Discrete Event Simulation
DEMPC	Distributed Economic Model Predictive Control
DMPC	Distributed Model Predictive Control
DSS	Dynamic Systems Simulation
EAS	Energy-Aware Scheduling
ECE	Energy Conversion Efficiency
EDA	Event-Driven Architecture
EEC	Energy efficiency control
EER	Energy Efficiency Ratio
EI	Energy Intensity
EMPC	Economic Model Predictive Control
EPI	Energy Performance Index
EU	European Union
HMOBSA	Hybrid Multi-Objective Backtracking Search Algorithm
ICT	Information and Communications Technologies
IoT	Internet of Things
KPI	Key Performance Indicator
LAM	Laser-Assisted Machining
LTI	Linear Time-Invariant
MC	Markov Chains
MCS	Monte Carlo Simulation
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MIP	Mixed Integer Programming
MOESP	Multi-variable Output Error State Space
MPC	Model Predictive Control
MRR	Material Removal Rate
N4SID	Numerical algorithm For Subspace Identification
NCDMPC	Non-Cooperative Distributed Model Predictive Control
NIST	National Institute of Standards and Technology
NLPP	Non-linear Process Planning
OBC	Optimisation-Based Control

PLC	Programmable Logic Controllers
PN	Petri Nets
RBC	Rule-Based Control
ROI	Return of Investment
SCADA	Supervisory Control and Data Acquisition
SDS	System Dynamic Simulation
SEC	Specific Energy Consumption
SI	Subspace Identification
SM	Smart Manufacturing
SMS	Smart Manufacturing Systems
SVD	Singular Value Decomposition
TBS	Technical Building Services
UPS	Uninterruptible Power Supply

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Part I

Preliminaries

CHAPTER 1

INTRODUCTION

1.1 Motivation

Manufacturing industry consumes a significant amount of energy and resources to provide products to the society. As a consequence, many industries around the world have started their transform towards more efficient and sustainable production processes to reduce their wastes, to use better resources and energy, and to minimise their operational costs. In addition to these factors, recent advances in sensing technology, connectivity, computer science, and data management have also motivated the transformation of manufacturing industry towards smart, efficient, and flexible manufacturing systems. This transformation is known as Industry 4.0. Into the context of Industry 4.0 and smart factories, the manufacturing industry has been addressed as Cyber-Physical Systems (CPS), which refer to the new generation of systems that integrate computational and physical capabilities while offering interoperability and resilience [BG11, LKBK16]. Moreover, flexibility refers to the ability to respond quickly and efficiently to changing products design, production requirements, and market demands [EAAE12].

Although there is an increasing interest in transforming manufacturing systems towards Smart Manufacturing Systems (SMS), most of the effort performed so far are focused on the sensing technology, and data processing and management, as well as on the designing of new devices, machines, and machining technologies. However, few research works have addressed the problem of integration of these technological advances with the management of the manufacturing systems in real time, to face the challenges of energy efficiency and flexibility of Smart

Manufacturing (SM). For instance, regarding the energy efficiency in the manufacturing industry, the research has focused on the development of new processes for obtaining products using less energy, producing less waste, and new designs or modifications in both the existing machines tools and machining processes. Besides, since machine tools are the fundamental units of the discrete manufacturing industry, several proposals have been reported in the literature to improve their energy efficiency by optimising the processing times and process parameters [Zei12, SB13, YKK+15, ZLH+17].

Regarding flexibility, researches have focused on improving the modelling procedures to achieve more modularised plant structures, the optimisation of plant distribution, and programming, planning, and controlling tools of production that ensure the effectiveness of fulfilling the due dates and the optimal use of resources [EAAE12]. Although strategies for flexible manufacturing have been developed, energy consumption has not been generally considered as a critical factor for the processes planning and scheduling. Indeed, the policies that include energy consumption are limited to an initial optimisation regarding the production programming of the existing devices in the plant [SBR16, KR16]. That is, these strategies are not able to manage/control manufacturing systems in real time, taking into account the time-varying constraints and uncertainty in both the process and the working environment. It should be noted that most of the proposed strategies (including or not energy as a critical objective) do not consider the working environment, the interactions among machines and other elements, the temporal variation of operational conditions, and neither the information about the energy market. Indeed, most of these strategies consider the system analysed as isolated entities from which improvements in energy efficiency can be achieved. Still, in a real context, such systems are affected by the interactions with other manufacturing devices and machines, and they can show unexpected behaviour that do not contribute to improving the energy efficiency reducing energy consumption or minimising energy costs.

Thus, there exists a clear need to develop tools and management strategies that not only contribute to improving the energy efficiency of manufacturing systems but also to confer greater flexibility and adaptation of the manufacturing processes. The latter fact is motivated by the temporal variation of the operational conditions imposed by the working environment and constant changes in the product demand. Thereby, due to the nature, the size (large scale), and the complexity of the current manufacturing industry, the design of management/control strategies is a complex task that can be addressed based on Optimisation-Based Control (OBC) techniques [WCS+16, BHMA17, ZCAX17, UDOMA17]. From these techniques, the control problem can be expressed as an optimisation problem, in which the cost function defined as the total energy consumption can be penalised. At the same time, the system limitations and its environment can be included as the set of constraints of such an optimisation problem. Besides, the integration of the advances in sensing technology could help the optimisation-based controllers in transforming the acquired information into a predictive behaviour to reduce the total energy consumption as well as smoothing load profiles, avoiding peak-load penalties. Thus, the motivation in this doctoral thesis is to propose a framework to address manufacturing systems for the design of optimisation-based controllers that allow improving the energy efficiency of such systems while taking advantage of the fundamental concepts of Industry 4.0 for the implementation of the proposed control strategies.

This doctoral dissertation firstly introduces a division of manufacturing industry by levels according to their processing units and their interactions to simplify and make more treatable the large-scale manufacturing systems. Furthermore, a classification of their constitutive elements is also proposed towards the design of control strategies that improve energy efficiency without affecting their productivity. Then, based on these classifications, centralised control strategies are proposed to minimise both the total energy consumption and the energy costs during the operation of such systems. Besides, to design control strategies that can be suitably implemented in real time and confer more flexibility to manufacturing systems, a dual-mode control strategy and non-centralised control architectures are proposed. In this regard, a way to achieve consensus among the local controllers with coupled dynamics in non-centralised control architectures is proposed to explicitly consider the total energy consumption into the consensus stage. The proposed methodologies are implemented in simulation considering real case studies to compare their closed-loop performance, their effectiveness, and the computational burden with control strategies that are generally used in this industry.

1.2 Research Questions

This dissertation is devoted to identify energy-saving opportunities and to design OBC strategies for improving the energy efficiency of manufacturing systems. The following key research questions motivate the main research goal of this thesis:

(Q1) What is the current context of energy efficiency in the manufacturing industry, and what are the main research gaps regarding their energy efficiency?

(Q2) How optimisation-based control techniques can contribute to improving the energy efficiency of manufacturing systems?

(Q3) How the energy efficiency of manufacturing systems could be improved and which control techniques could be useful to this end?

(Q4) How can manufacturing systems be addressed for the design of control strategies?

(Q5) How to model the energy consumption of manufacturing systems for the design of control strategies that can be suitable for being implemented in real time?

(Q6) How to design and implement an energy management/control strategy for manufacturing systems without affecting their productivity?

(Q7) How to reduce the computational burden of centralised control architectures when large-scale manufacturing systems are studied?

(Q8) May the non-centralised control approaches help to confer more flexibility to manufacturing systems while improving heir energy efficiency?

(Q9) Can the energy costs be minimised taking advantage of the energy-price fluctuations?

The research questions mentioned above have been addressed throughout this thesis. Questions *(Q1)* and *(Q2)* are oriented to the identification of the research gaps related to control strategies for energy efficiency of manufacturing systems. Based on the identified research opportunities, answers to questions *(Q3)*-*(Q9)* are presented in Chapters 3 to 8, which become the contributions of this thesis.

1.3 Thesis Outline

This dissertation is divided into three parts, and the connections among the chapters are presented in Figure 1.1. It should be noted that each chapter is self-contained and can be studied in isolation. Therefore, some ideas could be repetitive among the chapters. The content of each chapter in this thesis is summarised next:

Chapter 2: State of the Art

This chapter presents a general literature review about the energy-efficiency issues in the manufacturing industry and reviews the application of control systems to solve them. In this regard,

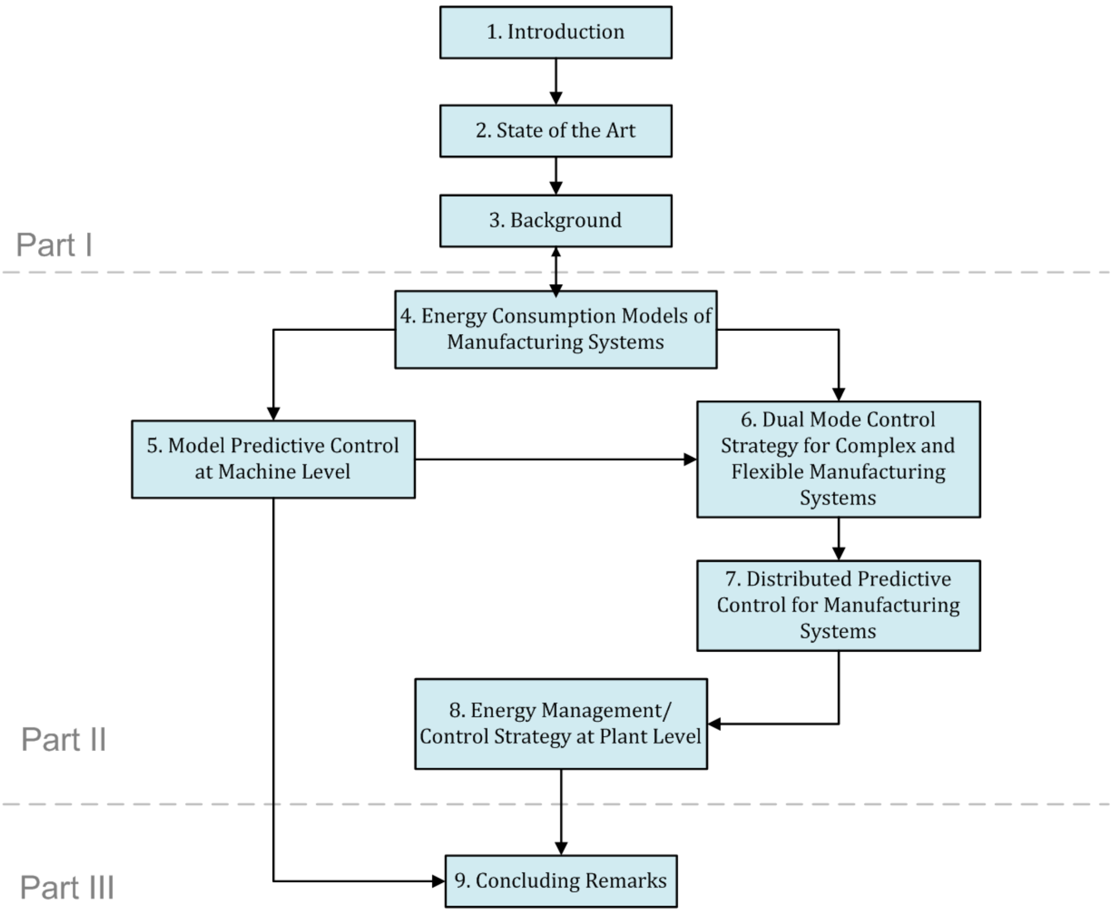


Figure 1.1: Outline of the thesis. Arrows indicate read-before relations.

the leading promoters of the transformation of manufacturing industry towards the smart manufacturing systems are discussed. Furthermore, it is proposed a division for manufacturing plants based on production units and their interactions such as machine, process line, and the whole plant to obtain manufacturing systems more treatable for designing control strategies. This chapter answers the key research questions *(Q1)* and *(Q2)* and is based on the following publication:

- Jenny L. Diaz C., Carlos Ocampo-Martinez, Energy efficiency in discrete-manufacturing systems: Insights, trends, and control strategies, *Journal of Manufacturing Systems*, Volume 52, Part A, 2019, 131-145.

Chapter 3: Background

This chapter provides the background and the preliminary concepts associated with the development of this doctoral dissertation. Besides, the proposed approach to improve the energy efficiency of manufacturing systems is presented. Thus, this chapter initiates the answering process to the key research questions *(Q3)* and *(Q4)*.

Chapter 4: Modelling of Energy Consumption and Discrete Domains

In this chapter, the methodology used to model the energy consumption of manufacturing systems is introduced and explained using a benchmark system. Besides, due to the nature of the actuators considered for the design of the proposed control strategies, three different approaches for modelling discrete sets are proposed and compared. All the results obtained in this chapter are used in the design of the control strategies presented in Chapters 5 to 8. This chapter answers key research question *(Q5)* and is partially based on the following publication:

- Jenny L. Diaz C., Sorin Olaru, Carlos Ocampo-Martinez, A comparison of modelling approaches for closed-loop decision making over discrete domains in manufacturing systems, *IEEE Conference on Control Technology and Applications (CCTA 2020)*. Submitted.

Chapter 5: Model Predictive Control at Machine Level

This chapter presents the formulation of the energy-efficiency problem of manufacturing systems at the machine level, which is extrapolated to higher levels in Chapters 6 to 8. Then, for the design of control strategies that do not affect the productivity of such systems, a classification of their constitutive elements is proposed. Based on such classification, a centralised MPC-based control strategy is designed using the energy consumption models and the modelling approaches of discrete sets presented in Chapter 4. In this regard, control objectives to minimise energy consumption and the operational constraints to guarantee the proper operation of manufacturing systems are proposed and deeply explained. This chapter answers the key research question *(Q6)*, and it is based on the following publications:

- Jenny L. Diaz, Miguel Bermeo, Javier Diaz-Rozo, Carlos Ocampo-Martinez, An optimisation-based control strategy for energy efficiency of discrete manufacturing systems, *ISA Transactions*, Volume 93, 2019, Pages 399-409.

- Jenny L. Diaz C. and Carlos Ocampo-Martinez, Energy efficiency improvement of machine tools via peripheral devices management: An optimisation-based control approach, *2019 American Control Conference (ACC)*, Philadelphia, PA, USA, 2019, pp. 3236-3242.

Chapter 6: Dual Mode Control Strategy for Complex and Flexible Manufacturing Systems

This chapter introduces a control strategy based on two control modes to minimise the energy consumption of manufacturing systems at the process line and to reduce the computational burden required. The main idea is to switch from a control mode based on MPC to an autonomous control mode that is not continuously solving an optimisation problem online. Taking advantage of the periodic behaviour of manufacturing systems, an algorithm to detect periodicity of the optimal sequences found in the first control mode is proposed and, once the periodicity is detected, the controller switches to the second control mode (or autonomous). Besides, a commutation protocol based on a prediction of the system behaviour is proposed to guarantee the system remains inside its feasible domain when the autonomous mode is on, and to detect when the controller should switch back to MPC-based control mode. This chapter answers the key research question *(Q7)*, and it is based on the following publication:

- Jenny L. Diaz C., Carlos Ocampo-Martinez, Sorin Olaru, Dual Mode Control Strategy for Complex and Flexible Manufacturing Systems, *Journal of Manufacturing Systems*, Submitted.

Chapter 7: Distributed Predictive Control for Manufacturing Systems

In this chapter, non-centralised control strategies are proposed, and their effectiveness to minimise energy consumption is tested and compared to the centralised control strategies presented in previous chapters. In this regard, a system partitioning is proposed based on the process line configuration and the coupled dynamics among the different machines and devices in a process line. Based on the system partitioning, local controllers are designed based on MPC to minimise the energy consumption of each sub-system. Afterwards, two algorithms based on the Alternating Direction Method of Multipliers (ADMM) are proposed to solve the optimisation problems in a distributed way in cooperative and non-cooperative control structures. Furthermore, a way to get the consensus among controllers with coupled dynamics taking into account the energy consumption is proposed. In this regard, this chapter answers the key research question *(Q8)*, and it is based on the following publication:

- Jenny L. Diaz C., Carlos Ocampo-Martinez, Design of non-centralised control architectures to the energy efficiency of flexible manufacturing systems, *IEEE/ASME Transactions on Mechatronics*, Submitted.

Chapter 8: Energy Management/Control Strategy at Plant Level

This chapter addresses the problem of minimising operational costs and maximising the profit of a manufacturing plant in real time. In this regard, two control strategies are proposed to determine the optimal operation of the plant, considering two different temporal scales. The first control strategy focuses on identifying the daily optimal production programming of the plant, taking into account the energy market and the piece demand. Then, based on the optimised production programming, an OBC strategy with a higher execution frequency is proposed to try minimising, even more, the operational costs. In the latter control strategy, the management of productive systems and the raw materials to be purchased are determined considering the current energy market, its price fluctuations, and the demand of resources from the process lines into the plant. Thus, both control strategies are designed based on the Economic Model Predictive Control (EMPC) approach due to the economic nature of the proposed control objectives. Besides, different control architectures, such as centralised and non-centralised, are considered. In this regard, this chapter answers the key research question *(Q9)*, and it is based on the following publications:

- Jenny L. Diaz C. and Carlos Ocampo-Martinez, Optimal production planning for flexible manufacturing systems: an energy-based approach, *21st IFAC World Congress, 2020*, Submitted.
- Jenny L. Diaz C., Carlos Ocampo-Martinez, Economic optimal operation of a manufacturing plant by using non-centralised control architectures, *International Journal of Production Economics*, Submitted.

Chapter 9: Concluding remarks

This chapter draws the concluding remarks regarding the results obtained and presented throughout this dissertation. Besides, the key research questions presented in Section 1.2 are addressed, and some open research questions are suggested as future work.

1.4 Other Publications

Some related publications associated with the research topic of this doctoral dissertation are outlined below.

- Jenny L. Diaz C., Carlos Ocampo-Martinez, Niklas Panten, Thomas Weber, Eberhard

Abele, Optimal operation of combined heat and power systems: An optimisation-based control strategy, *Energy Conversion and Management*, Volume 199, 2019, 111957.

- Jenny L. Diaz C., Thomas Weber, Niklas Panten, Carlos Ocampo-Martinez, and Eberhard Abele, Economic model predictive control for optimal operation of combined heat and power systems, *The 9th IFAC/IFIP/IFORS/IISE/INFORMS Conference Manufacturing Modelling, Management and Control MIM 2019*, Berlin, Germany, 2019.

- Sergi X. Ubach, Jenny L. Diaz C., Carlos Ocampo-Martinez and Miguel Antunez. Peak shaving through closed-loop optimisation applied to machine tools with periodic behaviour, *2017 IEEE 3rd Colombian Conference on Automatic Control (CCAC)*, Cartagena, 2017, pp. 1-7.

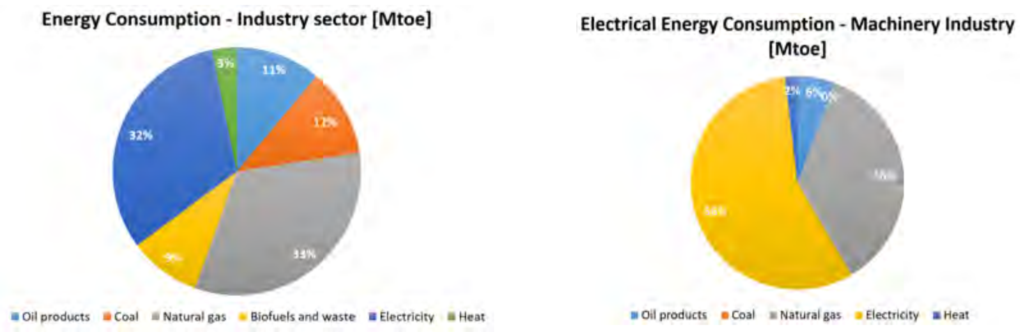
CHAPTER 2

STATE OF THE ART

Since the depletion of fossil energy sources, rising energy prices, and governmental regulation restrictions, the current manufacturing industry is shifting towards more efficient and sustainable systems [SHSB13, ZYXW17]. This transformation has promoted the identification of energy-saving opportunities and the development of new technologies and strategies oriented to improve the energy efficiency of such systems. In this chapter, a review of the research reported during the last decade regarding energy efficiency in manufacturing systems is presented considering the current technologies and strategies to improve that efficiency and identifying and remarking those related to the design of management/control strategies and their transformation towards Industry 4.0.

2.1 Discrete-Manufacturing Industry

The industrial sector accounts for more of 30% of the electrical energy consumption in the world, and the manufacturing industry consumed near to 50% of that energy, as shown in Figure 2.1 [IEA18]. Although the manufacturing industry represents an essential share of the world-wide economy, this industry has significant impacts to environmental dimension since its high consumption of both renewable and non-renewable materials and the production of solid, liquid, and gaseous (CO_2 emissions) waste streams. Due to the concern about climate change and the transformation towards sustainable systems, a paradigm shift towards efficient and smart systems has been promoted from the manufacturing industry. Thereby, the energy efficiency issue has gained attention during the last decade, from which new research trends from different



(a) - Industrial sector (b) - Machinery industry

Figure 2.1: Types of energy consumed by (a) industrial sector and (b) machinery industry until 2015 [IEA18].

points of view have arisen to try solving this concern.

Different approaches have been addressed, covering from energy sources and their distribution to industries up to the energy use in manufacturing processes carried out by industries. Some researches focus on finding a more efficient way to supply energy to the industries minimising the distribution losses and maximising the power production from renewable energy sources [FP15, LWK18, KWM+19]. Besides, from the environmental dimension, many of the reported studies focus on developing environmentally friendly technologies by the use of renewable or fewer contaminant materials [Bil14], while the economic and technological dimensions have received more attention, mainly due to the profits related to energy cost reductions [Ing17]. In this way, most of the reported improvements in energy efficiency are focused on proposing more efficient designs of the individual components of manufacturing systems.

In contrast, only a few strategies have addressed the design of energy management/control strategies in real time for manufacturing systems [DSD+12]. Some of the more recent works reported in [AAG+13, TCF16, XZ16, MSTK17, Yin13] present an overview of strategies for energy efficiency and sustainability developed so far for different industrial levels. Similarly, [Ing17] focuses on reviewing improvements proposed for manufacturing processes, while in [EBW16] a review of the new technologies of manufacturing sector focusing on remanufacturing, advanced and additive manufacturing is presented. Nonetheless, none of the proposed works so far looks at the identification of both control techniques and applications of control strategies in the manufacturing industry.

According to [Zei12], manufacturing is defined as *"a series of interrelated activities and operations involving the design, materials selection, planning, production, quality assurance,*

Figure 2.2: Input/output scheme of a manufacturing process.

management and marketing of the product, and controlling its industrial production". However, a more straightforward definition of manufacturing is proposed in [EBW16], in which manufacturing refers to the industrial production processes through which the raw materials are transformed into finished products to be sold in the market. In this sense, manufacturing can be considered as a set of processes for transforming resources and energy into industrial products and goods for consumers [Yin11]. According to the operation modes, the manufacturing industry can be classified into continuous manufacturing and discrete manufacturing.

In continuous manufacturing, the transformation of raw materials and energy into the desired products implicates changes in both physical and chemical properties of them during the technological processes, which can also constitute diverse operation modes as continuous, quasi-continuous and even batch processes. On the other hand, the discrete manufacturing industry is characterised by single part production, in a discrete-processing mode, and by either physical or mechanical treatments of the raw materials [Yin11]. In discrete manufacturing, usually, the raw materials are the products of other manufacturing processes, whereas the final consumers directly use its products. Some examples of the discrete-manufacturing industry are the automotive, aircraft, shipbuilding, and household appliance manufacturing industry.

Manufacturing processes are understood as the technological processes to transform raw materials into products, including their technical and engineering aspects [AAG+13, EBW16]. Thus, manufacturing processes involve a set of technologies and operations used to transform inputs (e.g., energy, material, information) into outputs (products and wastes), which take place in the process units that operate in an integrated and synergistic way to meet the final conditions of the desired products. Both inputs and outputs of manufacturing processes can be generalised, as shown in Figure 2.2. For the case of discrete manufacturing, the most common units used for the production of the parts are the machine tools, and the final conditions of products are mainly referred to physical properties, such as shape, surface, dimensions of the piece, among others.

In [DSD+12], manufacturing processes are classified into six categories: primary shaping, forming, separating, joining, coating/finishing and those that change the material properties. However, this classification could be limited when new technologies are considered, and due to this fact, in [NND+12] a classification based on the type of technology involved, namely, joining, dividing, subtractive, transformative, and additive technologies is proposed. Processes in which two or more workpieces are joint to form fewer workpieces are known as *joining technology*, while the opposite operation is named *dividing technology*, where the resulting number of workpieces is higher than the original one. In the *subtractive technology*, the processes are designed to remove material from a workpiece and forming a new part, for instance, by milling and turning [NND+12]. In the *transformative technology*, a single workpiece is used to produce a new work-piece without changing its mass during the operation, whereas in the *additive technology* the resulting workpiece has a volume higher than the pre-processed one since new material is either add or deposit for forming the new workpiece.

Additional to manufacturing processes, there exist other technical elements like industrial control systems, industrial robotics systems, assembly systems, material transportation systems, storage systems, among others, which guarantees the correct operation of a manufacturing plant [EBW16]. The industrial control systems that refer to all control systems that can be installed in an industrial plant have been an increasing research topic to achieve the objectives of both energy efficiency and production of discrete-manufacturing industry. According to [SPL+15], control systems encompass several types such as the Supervisory Control and Data Acquisition (SCADA) systems, Distributed Control Systems (DCS), and the Programmable Logic Controllers (PLC) modules. Indeed, industrial control systems are combinations of control components (e.g., electrical, mechanical, hydraulic, pneumatic) that act together based on set-points, control algorithms, variable and parameter constraints, and process data to achieve a common objective. In real applications, control systems can be typically configured to operate in open loop, closed-loop, or manual mode and, therefore, they can be automated or include the human intervention into the loop. The open-loop and closed-loop control systems can be differentiated based on the output effect over the input. In the closed-loop scheme, the output has a direct impact on the input to maintain the set-point or desired objective, while in the open-loop scheme, the output is controlled by established settings. On the other hand, in manual mode, the system is entirely controlled by humans [SPL+15].

In the work presented in [DSD+12], the study of energy efficiency in the manufacturing industry has been divided into levels to ease its comprehension and identification of energy-saving opportunities for both the whole plant and its different components. This approach by levels has remained through the works developed during the last decade for studying the energy

Table 2.1: Decomposition levels considered for the manufacturing industry based on [DSD+12].

Level	Description
Machine	Individual device or machine tool in the manufacturing system in which processes take place. Includes support equipment.
Line/multi-machine	Logical organisation of machines or devices that are acting either in series or parallel to execute a specific activity. Includes support equipment for the collection of devices as chip conveyors.
Plant/factory	Distinct physical entity housing multiple devices, which may or may not be logically organised into lines, cells, etc. Includes support equipment required at the facility.

efficiency of manufacturing systems since it allows performing a preliminary decomposition of the large-scale and complex systems in the manufacturing industry.

2.2 Classification by Organisational Levels

Due to the large-scale and complexity of manufacturing systems, these systems have been studied by using multi-scale and multi-level research methods [Yin11]. The energy efficiency in manufacturing systems has been analysed according to organisational levels, allowing researchers to identify saving opportunities, and propose improvements [HT09, SB13]. A first approximation was reported in [HT09], in which alternatives for improving the energy efficiency according to three layers, process and machine, the production system, and the Technical Building Services (TBS) are presented. Afterwards, in [RWVD10] a decomposition into four levels, covering from the product level up to supply chain of the factory, namely, product, machine/device, facility/line/cell and supply chain level is proposed, while in [DSD+12] a broader decomposition is propose based on [RWVD10] but including all activities of the manufacturing systems. On the other hand, in [AAG+13], four levels to study the energy efficiency in manufacturing systems were defined, namely, factory, line, machine and process levels, in which all improvements directly related to new technologies and parameters of the manufacturing process are considering into the process level. Nevertheless, to analyse the strategies and technologies of energy efficiency of manufacturing systems, only three levels have been considered combining the improvements at the machine and process level in only one level. The machine, line/multi-machine, and plant/factory levels are briefly explained in Table 2.1.

Manufacturing processes are related to the machine level, while the multi-machine production processes logically organised (sequence or parallel) refers to the line/multi-machine level, namely, manufacturing systems. Then, the association of manufacturing systems with technical equipment and personnel corresponds to the higher level of aggregation, the plant/factory level. A representation scheme of the hierarchy of these levels according to the configuration of devices in an automotive part manufacturing plant is presented in Figure 2.3. At the lowest level, manufacturing processes are performed in an arrangement of devices, namely, machine tool, which only does one kind of operation over a piece. More complex structures are found at the process line level, which corresponds to the aggregation of machines, auxiliary devices and buffer devices for producing a piece. At this aggregation level, machines are organised logically according to the required operations to process a piece entirely. Since the machines in a process line can have different operating cycles, buffers are required in order to maximise the production and avoid the simultaneous input of two or more pieces to one machine.

At both machine and line levels, auxiliary devices to guarantee the correct operation of machines and the suitable supply of resources to machines are required. Besides, if all the TBS and technical personnel are also considered, the higher level of aggregation (plant level) is achieved. Into the plant level, all devices involved in both value and non-value tasks in a factory are considered. According to Figure 2.3, it is possible to observe that the dynamics and interactions among the elements of a level can directly affect the components of higher levels and therefore, their energy consumption. From this fact, detailed knowledge of each level, its elements, and its interactions will be necessary for establishing a real context from which the improvements in energy efficiency can be developed.

Machine level

Machine level focuses on the machine tools, which are defined as complex systems composed of different components such as cooling units, pumps, spindles, drives, and peripheral devices (e.g., control units) that contribute to the total energy consumption of the machine [SZWW16]. This set of integrating parts and moving components enable the entire system to perform a complex function, such as the geometric forming, shaping or joining of workpieces by using the proper tools and technologies [Zei12]. This latter definition regards the machine tool as a type of metalworking machinery, which works for a fixed period (cycle) and have drive systems different from human effort.

The components of the machine tool can be divided into the primary-function and peripheral devices. The former refers to those devices directly involved in shaping or joining of workpieces

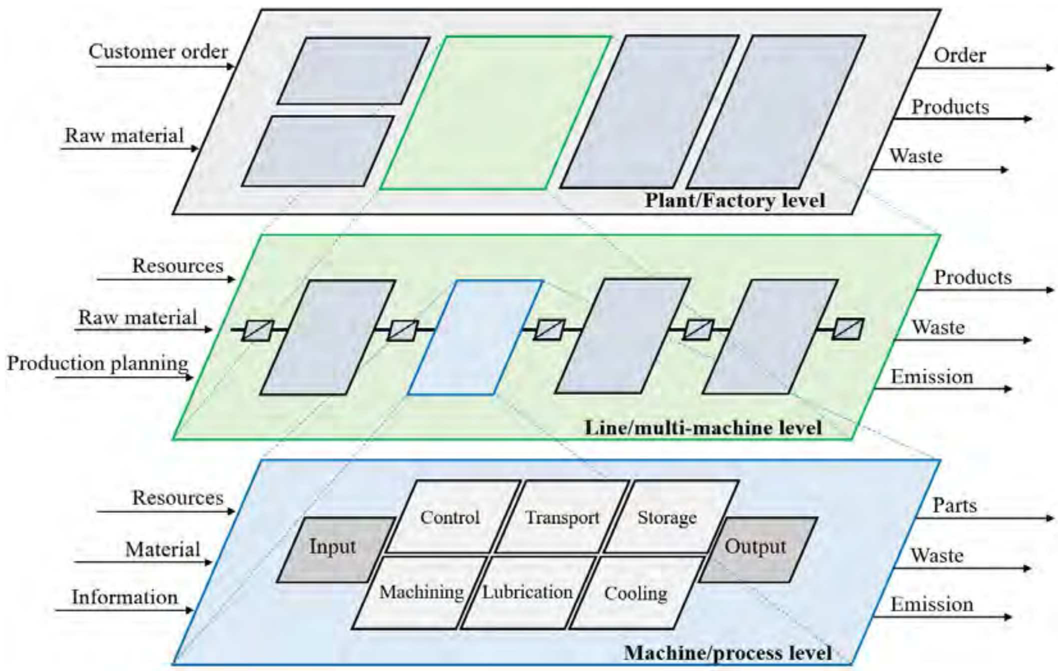


Figure 2.3: Classification by levels for manufacturing industry according to [Thi12].

while the peripheral devices guarantee the operating conditions needed for performing the primary function. Usually, the main components of a machine work according to a fixed activation sequence to process a piece, from which the machine cycle is defined. On the other hand, the peripheral devices could or could not work during a typical cycle of main devices, i.e., some of the peripheral devices can activate at each two or more cycles of normal operation. Indeed, switching on or off the peripheral components is a critical factor to reduce the energy consumption of machine tools.

According to [HLHH12], the activities with highest energy demand in a machine tool are the spindle rotation and the servo-driven axis motion, which are directly involved into the processing of a workpiece (cutting, milling, turning, among others). In Figure 2.4, the energy consumption of a machine tool is decomposed in low, medium, and high consumers, according to [ZLL+16, MWA15]. Based on primary consumers in a machine tool and its periodic behaviour, different operating modes can be distinguished during an operation cycle of a machine. These modes refer to the different processing stages (and of the energy consumption) of a machine to completely process a piece. Therefore, the energy consumption profile of a machine is determined by the process and individual machine features.

In [SZWW16], the operating modes of a machine tool are classified as *on, standby, process*

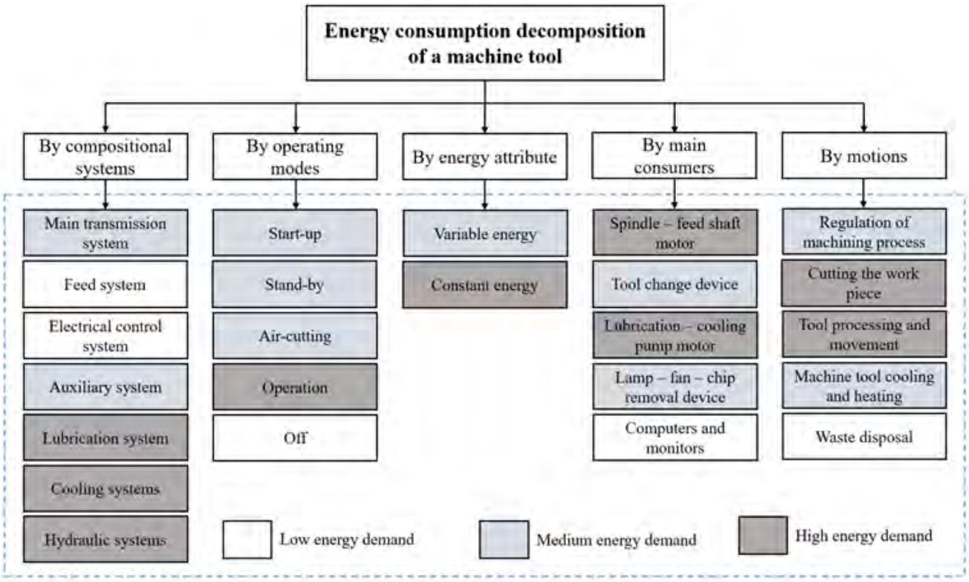


Figure 2.4: Energy consumption decomposition of a machine tool [ZLL+16, MWA15].

and *off* modes, while in [ZLL+16], a detailed classification of operating stages for a milling process such as *start-up, standby, air-cutting, operation*, and *off* status is proposed. These modes indicate the different power levels and activation times related to the operating machine states, where the start-up mode corresponds to the turning on of the machine, while the standby mode regards the electrical energy used to activate the machine components and to ensure the operational readiness of the machine. The air-cutting mode can occur several times during the machine operation, e.g., after the machine is started and before cutting, and between different cutting stages. Thus, more energy is required for the drives and spindle, e.g., to move, to change the tool, to clam the piece, to bring the tool, among others. Then, during the operation stage, the energy is consumed at the tool-tip to remove piece material, i.e., during the machining process. Finally, the off mode corresponds to switching off the machine, in which the power demand is null.

According to the technology employed and the operations performed, the operating modes of any devices could be determined from the energy consumption profile and through the information coming from the Computer Numerical Control (CNC). For instances, the operating modes of a machine tool can be identified based on the activation of its components for preparing the material removal, the waiting time of elements during changes of tools or pieces, as well as the spindle activation for removing the material. A typical energy consumption profile of the milling process with its operating modes is presented in Figure 2.5.

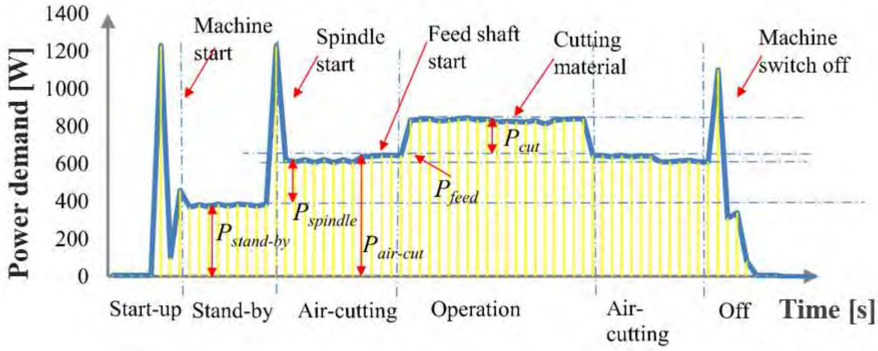
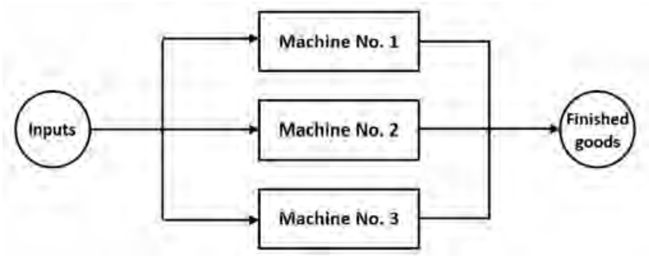


Figure 2.5: Energy consumption profile of a milling process with P_i the required power in each operating mode. Taken from [ZLL+16].

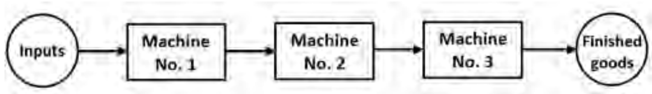
Moreover, the energy consumption of a machine tool can be divided into the constant and variable energies taking into account its operational modes. The former category is related to the energy consumption of both start-up and standby modes, such as activation of peripheral devices, unloaded motors, conveyors, control units, tool change, among others, while the variable energy refers to the power consumption during the machining process. In [HLHH12], the *variable energy* is defined as the energy used to cut materials, i.e., it depends on the machining process performed. In contrast, the constant energy is independent on machining and refers to the power consumed by the machine in a *ready-for-operating* mode. Indeed, depending on the type of machine tool, different energy consumption profiles, operating modes, and portions of constant and variable energy can be distinguished [DSD+12, Zei12, Thi12, ZLH+17]. Therefore, due to the different production processes performed in a machine and their associated operating modes, it is necessary to understand and analyse the energy consumption behaviour of such machine to propose improvements that allow reducing the energy consumption.

Line level

A process line refers to a collection of machines organised in a proper configuration for producing a finished piece. Among the machines that form a process line, it could exist other peripheral devices in addition to those that guarantee the operation of a machine tool. In [DSD+12], a process line is defined as a multi-machine ecosystem that describes a network of machines within a factory. According to the processes performed on each machine and its connections, process lines present different configurations such as serial and parallel structures as shown in Figure 2.6 or combinations of them. Based on the configuration of machines in a process line, the operation of one machine could depend on the correct operation of previous machines, as in serial



(a) - Parallel configuration



(b) - Serial configuration

Figure 2.6: Configuration in parallel (a) and serial (b) of machines in a process line.

configuration, while in a parallel configuration the operations of machines could be independent on other machines in the line.

Thereby, according to configurations in a process line, different energy and material flows, which represent either the interactions or relations between the machines in a line, could be existed. These relations add complexity to understand and model the energy consumption at this level. Therefore, factors as the diversity of components in a process line, their energy consumption behaviour, their interactions, and the intrinsic characteristics of each component should be considered to analyse and propose energy efficiency improvements at the process line level [EYME17].

Plant level

In the same way as the process line, the plant level consists of arrangements of process lines and auxiliary devices that guarantee the operating conditions of both each process line and its working environment. Thus, in [WCS+16], it is considered that most of the energy in a factory would be used for external applications and processes in non-value added sectors. Therefore, regarding energy flows at this level, the existing relations among machines and the working environment should be analysed. In [HT09], a production plant is defined as an integrated system that comprises three partial systems: the production system itself, the TBS and the building. The former refers to the interlinked machines and the personnel controlled through production management. On the other hand, TBS ensure the necessary production conditions of temperature, moisture, and purity through cooling/heating and conditioning of the air, besides of supplying energy, compressed air, steam or cooling water required for machines [FNA+17, PKK+09, ZZSW16].

Taking into account that in a manufacturing plant the energy costs are not only determined by its consumption but also by surcharges due to peak loads, the energy consumption profile of both the productive and non-productive systems in a manufacturing plant should be analysed. This latter fact is given by the simultaneous activation of different production processes, machines, and auxiliary devices, which results in a cumulative load that could increase the energy costs. Thus, in order to identify the critical components and propose measures for improving energy efficiency in a manufacturing plant, it is necessary to analyse the energy profile of all machines and the TBS to avoid both increases of the energy consumption and surpasses the contracted load.

2.3 Energy Efficiency of Manufacturing Systems

Due to the nature of manufacturing processes, manufacturing industry consumes both renewable and non-renewable resources, such as energy, water, metals, among others, producing a significant impact on the environment. As a consequence, solid, liquid, and gaseous waste are generated during the manufacturing processes. Based on this fact, nowadays, there exist an increasing interest of manufacturing enterprises to look for new technologies and strategies that allow reducing both the energy and production costs and making efficient use of resources. Traditionally, the performance of manufacturing systems has been addressed considering factors such as time, cost, quality, and flexibility, but in the new era of sustainable manufacturing, the resources and energy use should be considered into the efficiency analysis of manufacturing systems [SB13, ZLM+15]. Although the need for improving the energy efficiency of manufacturing systems is clear, there exist barriers and encouraging elements that limit and promote energy efficiency improvements, respectively. Different studies have focused on the identification of barriers and promoters for the implementation of energy reduction strategies in a factory [TCF16, MSTK17, SB13].

In general terms, the energy efficiency of manufacturing systems can be defined as the relationship between the productive output of production systems and the total energy supplied to them (e.g., oil, gas, electricity, heat) [SB13, OQL+16]. Nevertheless, depending on the industrial level, the systems, outputs, and inputs can be differently understood, and the energy efficiency definition will be different at each level.

2.3.1 Machine level

Although many energy efficiency definitions have been proposed in literature, they are not clear enough due to the diversity and complexity of machines in a manufacturing industry [AAG+13, Zei12, SB13, Thi12]. In [AAG+13], the energy efficiency at machine level is defined as the relation between the energy provided to the process and that consumed by the machine. Besides, in [Thi12] an energy efficiency definition based on the power demand was proposed and expressed as follows:

$$\eta_E = \frac{N_{wp}}{E_d\, t}, \tag{2.1}$$

being N_{wp}, E_d, t, the number of produced pieces, the electrical power demand, and time, respectively.

In [ZLL+16] a detailed definition of energy efficiency is introduced, which is divided into two types. First, the process energy efficiency refers to the relation between the effective energy and the energy consumed by the device in a finite time. Second, the instantaneous energy efficiency expresses the ratio of material removal cutting power and the machine input power. Indeed, and according to [Zei12], energy efficiency at machine level concerns the improvement of the input-output relations of existing transformation processes towards either minimum input or maximum output levels.

Besides, the use of evaluation indicators of energy efficiency of machines has been introduced for quantifying and tracking the machine efficiency. In [SZWW16], the energy efficiency indicators at machine level based on three strategies to foster environmental improvements in the context of sustainability have summarised and classified. Among these indicators, it can be highlighted the Energy intensity (EI), the Specific Energy Consumption (SEC), the Energy Efficiency Ratio (EER), the Energy Conversion Efficiency (ECE), and the Energy Efficiency Index (EEI). The SEC index has had a great application for determining the energy efficiency of a machine (or machining process efficiency) [DSD+12, ZLL+16, BSL+12, ISO14] since it is defined as the energy required to remove material per unit volume or mass, i.e., it expresses the relationship between energy consumption and process variables as follows:

$$SEC = \frac{E_d}{V_m}, \tag{2.2}$$

with E_d and V_m expressing the energy required by the machine in $[\mathrm{J}]$ and the total volume of removed material $[\mathrm{m}^3]$, respectively. Equation (2.2) is related to the energy efficiency of the entire machine since it considers both operational and non-operational modes. Also, V_m is directly related to the Material Removal Rate (MRR), which refers to the volume or quantity of removed material per unit of time. Besides, SEC is also used as a model of energy consumption since it expresses the energy efficiency level from the perspective of the machine effective input and output.

2.3.2 Process line and plant levels

Although at both the line and plant levels it is more difficult to define the energy efficiency due to both the diversity of machines and their configuration and the existence of more complex operational relationships among machines and both the peripheral devices and the working environment, the following simplified expression of the energy efficiency for both the process line and plant level is proposed based on [Thi12]:

$$\eta_E = \frac{N_{wp}}{E_{in}}, \tag{2.3}$$

being E_{in} the total energy fed to the system in [J], respectively. Even though (2.3) is quite general, the energy efficiency evaluation can be improved if the system boundaries (e.g., according to the manufacturing level selected) and both the input and output variables are correctly defined. Thus, based on (2.3), it is possible to observe that strategies that allow minimising the total energy input while keeping the production output or maximising the production output without increasing the energy consumed can contribute to improving the energy efficiency of manufacturing systems.

Regarding the process line and plant levels, the energy-efficiency indicators have been proposed in a similar way to (2.3) since the diversity of processes performed at these levels. Based on these, it is more convenient to compare the total energy consumption with the number of pieces produced along a fixed-time period. Thus, the use of key performance indicators depends on the level and application for which they will be employed since most of them are designed to express a relationship between one specific production activity and the energy consumed to achieve it. Then, a classification of the different energy efficiency indicators, their formulas, their application cases, and the more suitable application level is proposed in [BVS+11]. Moreover, since the complexity of the industrial processes and the different applications of energy efficiency indicators, in [SLT+16], a generalised calculation methodology by using templates for measuring the energy efficiency of manufacturing activities and covering from factory level to process and product levels is proposed.

2.4 Strategies and Technologies for Energy Efficiency

To produce a behavioural shift towards efficient and sustainable manufacturing industry, the relations between the companies and governmental institutions, as well as the technological developments, must be considered. From this fact, different studies have focused on the identification and categorisation of barriers and the encouraging elements of energy efficiency in manufacturing systems [BJT14, CT13]. Moreover, several studies have been developed throughout the last decade to provide a general context about the techniques and strategies implemented for improving the energy efficiency of manufacturing systems.

In [YKK+15], a review mainly focused on machine tools in manufacturing industries is performed, in which different techniques for assessing and modelling the fixed and variable energy consumption of these machines are presented. Besides, optimisation techniques to process planning, tool path generation, and scheduling of single devices are broadly reviewed, while analysing the impacts on both the energy efficiency of MRR and on assisted machining systems (e.g., Laser-Assisted Machining (LAM)). Then, the evolution of research in manufacturing systems from past and current trends to future developments have been studied in [EBW16]. This latter work mainly aims to review the current trends in manufacturing systems such as advanced, smart, cloud, and sustainable manufacturing, Cyber-Physical Systems (CPS), and re-manufacturing.

Furthermore, the work [ZLL+16] focuses on the identification of the main energy consumers in a machine tool and, based on this, different energy consumption models that take into account the process, machine tool, and tool features are presented. Other alternatives oriented to reduce the processing time by either increasing the process rate, optimising the machine tools architecture, and using control systems for the selective activation of machine tool components are presented in [Ing17, XZ16]. Additional to these works, several works have been developed with the same aim of collecting the strategies implemented by the manufacturing industry to satisfy its requirements of energy and resource savings. In Table 2.2, the identified categories for improving energy efficiency are summarised based on the reviewed works/papers and, according to the classification by levels previously presented in Section 2.2. From Table 2.2, it is possible to observe that most of the proposed approaches have been focused on the machine level, following the idea that an improvement in a lower level would be reflected in higher levels and, therefore, contribute to improving the energy efficiency of the entire system.

In [PKK+09], it is studied the energy policies, the energy-saving methods, and the energy

Table 2.2: Classification of relevant reported research about the current context of energy efficiency improvements in manufacturing industry regarding both the approaches addressed and the focusing level.

Reference	Key approaches		Focus level		
	Drivers and barriers	Strategies and methods	Machine	Line	Factory
[MSTK17]	x	x	x		
[TCF16]	x				x
[EBW16]		x	x	x	
[YKK+15]		x	x		
[CT14]	x				x
[BJT14]	x				x
[CT13]	x				x
[Ing17]		x	x		
[PKK+09]		x	x	x	x
[HT09]		x			x
[DSD+12]		x	x	x	x
[AAG+13]		x	x		
[Yin13]		x	x		
[SB13]		x	x		

consumption reduction strategies currently implemented in countries of the European Union (EU), Japan, and North America. Besides, the authors present the trends in research directions and identify the energy-saving opportunities for the manufacturing systems. According to this work, energy efficiency in manufacturing systems has been recognised as the most critical research issue shortly by the EU. Therefore, research topics such as energy-aware manufacturing processes (measurement and control), energy-efficient production management systems, advanced automation for demanding process conditions, maintenance concept for energy efficiency, electrical energy operations in off-peak hours, among others related to the emission reduction technologies (e.g., eco-design and environmental assessment) have gained attention into the industry. Most of these works attempt to introduce state-of-the-art regarding the strategies, methodologies, and technologies considered by levels, to get significant reductions in both energy and resource consumption in the domain of discrete manufacturing. However, a significant part of strategies studied focuses on machine level, in which three main research topics can be defined for classifying the reported research: optimisation of machine design, optimised process control, and process/machine selection. The improvements collected in these categories address topics related to the use of more efficient components for the machine tools, improvements of current technologies, the recovery of waste streams and heat losses within a machine tool, and the optimal energy and resource use that allow reducing energy waste.

Moreover, alternatives to manage the devices in a machine tool without modifying the design of either machine or peripheral devices have been developed focusing on integration or centralisation of peripheral devices, selective shutting off of devices, reduction of the idle time, optimisation of process parameters, and modelling, planning, and scheduling of processes. These latter strategies change the way as devices are managed without affecting the primary operation of the machine, and reuse the available technologies and machinery, avoiding significant increases in costs. Besides, since the diversity of machines and the machining processes, their complexity and their different components (primary-function and peripheral devices), strategies for optimising the machine configuration and components design, as well as optimisation of process parameters have been broadly studied during the last decade.

However, from the environmental perspective, other alternatives such as the implementation of recovery systems within machines, the use of alternative fluids for lubrication and coolant systems, the selection of more sustainable machining processes, and the optimal resources selection have gained attention in the manufacturing industry. Besides, several studies related to the implementation of control systems have been proposed for switching on/off of the machine components to reduce the idle times of machine when both centralised and non-centralised peripheral devices are included. This latter approach has promoted the research concerning more precise modelling techniques, simulation tools, and robust control systems to obtain improved energy consumption models and to consider predictive behaviours into the control systems design. In Table 2.3, a classification of the main technologies implemented at the machine/process level during the last decade is presented.

Continuing with the second level, due to the diversity of machines in a process line, besides of material removal different operations such as heat treatments, transportation and material handling, fluids transport, among others, can take place in the machines of a process line. Nonetheless, to obtain energy-efficient systems at line level, the improvements for each machine or individual device in the process line are not enough. Instead of that, the whole process line should be optimised to reduce its total energy consumption [UUG+16]. According to this fact, at the line or multi-machine level, some of strategies and technologies identified from literature are focused on the capture and track energy and material flows in a multi-machine ecosystem, the processes planning and scheduling of machines and their integration. Process planning and scheduling are essential and complementary factors regarding energy consumption and flexibility of manufacturing systems.

Conventionally, the scheduling is made after the processes planning stage, and in most of the cases, only a process planning is considered for the manufacturing of a piece. Regarding

Table 2.3: Research topics for improving the energy efficiency at machine level.

Category	Approach	Reference
Optimisation of the machine design	More efficient components	[ZZSW16, GSW15]
	Technological changes	[ZZSW16, Fra10, TRV17, SWW17, WZ15]
	Recovery systems for machines	[DCH+10, BCR17]
	Integrated or central peripheral devices	[MWA15, GSW15]
Optimised process control	Selective actuation of non-continuously-required devices	[GZWW12, LLTL17, ZTP+16, APM15, FM14, SOMGSOM14]
	Reduction of idle times and control of the activation sequence	[APM15, FM14, VKLS17, EV13]
	Optimised process parameters	[LLTL17, VKLS17, LKPM17, ZTP17, LTT+17, DZF+17, ZDF+17, LDZ+18, YLZ+16, KS14, Bhu13, MFIO11, HCMK11]
	Energy and resource efficient process modeling and planning	[SZWW16, HLHH12, ZLL+16, GZWW12, ZLH+17, ZTP+16, SOMGSOM14, DZF+17, YLZ+16, LLQ17, Alb17, EM17, LTJL16, BW12]
Process/machine selection	Process selection	[UTE17, NDW+12, HDK18]
	Optimal resource selection	[BCR17, GW17, ULP+17, KKK16]

this issue, the currently implemented strategies in manufacturing systems have focused on the development of adaptable and sustainable processes plans, which can be flexible regarding the energy and market requirements. In the work [BAPT12], an approach of integration between the Energy-Aware Scheduling (EAS) methodology and a reference schedule generated by an Advanced Planning and Scheduling (APS) system that does not consider energy-saving is proposed. This approach is employed together with a process model to control the power peaks in the shop floor for a given detailed schedule. Thus, the proposed method, which is based on a Mixed Integer Programming (MIP), modifies an original timetable of APS to reduce the power peaks in a process line.

Similarly, in [LGL+17], the energy-efficient Permutation Flow-shop Scheduling Problem

Table 2.4: Research topics to improve energy efficiency at the process line level.

Approach	Description	Reference
Energy efficient design	New designs (of machine components and peripheral devices) based on energy consumption simulation of whole process line	[UUG+16, EYME17]
Process planning and scheduling	Define process plans and machine sequences for optimal energy consumption	[ZTP+16, YLZ+16, BAPT12, LGL+17]
Control of peak power demand	Control of process scheduling to avoid peak load in flexible manufacturing systems	[SLFW14, SS16]

with Controllable Time (PFSPCT) to analyse the scheduling problem but including both transportation and processing times is studied. Thus, to formulate the problem scheduling, a multi-objective optimisation problem that considers both the makespan and the energy consumption of a machine cycle is proposed. Then, a Hybrid Multi-Objective Backtracking Search Algorithm (HMOBSA) is introduced to solve such an optimisation problem. A different approach that incorporates power models for a single machine and cutting parameters optimisation into the scheduling problems is developed in [YLZ+16]. In this work, the scheduling problem is solved by using a multi-level optimisation approach considering both the machine and line levels. At the machine level, the cutting parameters of each machine are optimised using grey relational analysis for determining the weight coefficient of the two objectives to be minimised: the cutting energy and cutting time. Then, based on an energy consumption model for a flexible flow-shop, a genetic algorithm is used to optimise both the makespan and the total energy consumption simultaneously.In another way, the issue of integration of processes planning and scheduling is studied in [ZTP+16]. In this work, an integration model based on Non-linear Process Planning (NLPP) is proposed to select suitable process planning and scheduling. The proposed model is used to predict the energy consumption of machine tools, while a genetic algorithm-based approach is adopted to solve the proposed problem. Some of the strategies previously discussed and the research topics at the line level are summarised and classified in Table 2.4.

At the plant level, the strategies to improve energy efficiency should consider the use of more efficient technologies and equipment, as well as the design of monitoring and control systems concerning the energy use in the manufacturing processes and TBS. Nonetheless, most of the optimisation methods for energy use proposed so far are focused on both machines and process lines with a specified configuration, while the entire factory with both the technical processes, its auxiliary devices and TBS has not usually been considered. Regarding plant level, the strategies mentioned in this thesis are classified into four categories, namely, improvements for the data acquisition, optimal energy design, optimal scheduling by flexible manufacturing systems (regarding energy consumption and peak power), and Smart Manufacturing (SM). This latter category focuses on the trends and new technologies introduced by Industry 4.0 [JMS+17a].

In order to design strategies that allow reducing the energy consumption of manufacturing systems from the viewpoint of the whole plant, the primary issue is to understand the energy consumption behaviour of the entire plant and its essential elements. However, for achieving a proper knowledge about the consumption behaviour of manufacturing systems, data acquisition tools, signal processing techniques, methodologies for processes modelling, and simulation tools are required. In this sense, some works have been developed to treat these concerns and provide better tools that allow acquiring and analysing the required information. Besides, some other strategies at the factory level, such as the production planning and scheduling, load control, demand response, and peak load minimisation at factory level have been analysed as strategies of energy management to avoid peak load surcharges and obtain an appropriate sizing of the infrastructure and the distribution load.

On the other hand, simulation tools are an essential research topic since they offer significant improvements for testing system design, models, control strategies, integration of the new system elements, and, in general, allow a better understanding of the manufacturing systems and their dynamics. According to [Thi12], based on discrete and continuous simulation models, four main simulations paradigms are highlighted, namely, Dynamic Systems Simulation (DSS), System Dynamic Simulation (SDS), Discrete Event Simulation (DES), Agent-Based Simulation (ABS), and the integrative application of two or more paradigms (Hybrid Techniques). The former refers to the description of the physical systems behaviour by using state variables and algebraic equations in standard tools like Matlab, Python, Octave, among others. SDS is mainly oriented to either ecological or economic models, in which the system is described based on both stocks and flows diagrams. In DES, the manufacturing system is modelled as a discrete sequence of events that determine a change in the system state. Each event occurs in a specific time instant and no changes are considered between events [PPC+18, RS16]. In ABS, each object of a defined environment is modelled based on inherent logic and considering the interactions with other objects and the effect over the whole environment [Thi12]. In addition to the mentioned simulation approaches, new approaches have been considering for the development of simulations tools, such as Artificial Intelligence (AI) techniques, Petri Nets (PN), and Monte Carlo Simulation (MCS). A detailed explanation of the simulation tools and some applications can be found in [KWM+19, VHDPG14, LBFJJM18, PLO19]. Besides, simulation software such as AnyLogic, Arena, and Flexsim, which are based on the mentioned approaches, have had a great application for the production assembly lines and supply chain in the manufacturing industry.

Currently, the manufacturing industry has had a paradigm shift with the aim to transform the industry into smart factories, a fact that confers higher flexibility and sustainability to manufacturing processes. The main promoter of this transformation has been the Industry 4.0 project. Several works have proposed different strategies of modelling, process planning and scheduling, and process design and control for improving the energy efficiency [SWW17, LLQ17, AKLS17]. Although many of the reported works consider strategies for flexible manufacturing at the plant level, the energy consumption is usually considered as an initial optimisation regarding the production planning of the existing devices in the plant. That is, these strategies determine an optimal sequence from the beginning, and therefore they cannot respond to the temporal variation of processes and working environment factors during the operation of the plant.

Based on the recent advances in sensing technology, connectivity, and computer science, systems in the new era of the manufacturing industry have transformed into CPSs, which refer to the new generation of systems that integrate computational and physical capabilities, while offering interoperability and resilience [BG11]. Thus, CPSs refer to systems that incorporate physical processes and embedded computing elements (e.g., smart sensors and actuators) allowing a real-time interaction, which eases the exchange of information for tasks such as monitoring, control, and management of these systems [BG11, MKB+16, JMS+17b]. Moreover, regarding connectivity, CPS can set up and use connections with the other systems (including human beings) in global networks for establishing cooperation and collaboration schemes among different systems [MKB+16, HUB15]. In Figure 2.7, a representation scheme of the concept of CPS as systems of systems is presented.

Since the complex dynamics of manufacturing systems, CPSs have been regarded as systems of systems that can be implemented at all levels of the manufacturing industry (machine, line, plant level) since they represent the physical and embedded computational parts that work cooperatively. Besides, the implementation of CPS together with Internet of Things (IoT) has fomented the transformation towards the Cyber-Physical Manufacturing Systems (CPMS), which represent the highest level of CPS application in manufacturing industry [JMS+17b]. This fact is given since the connectivity through IoT allows a better knowledge of the manufacturing systems, their energy consumption in real-time, and the behaviour of supply-chain markets related to the industrial activity. In this regard, IoT is considered as an integrated/enabled technology

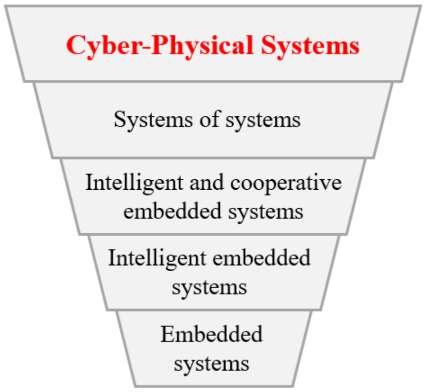


Figure 2.7: Conceptualisation scheme of Cyber-physical systems from systems of systems approach. Taken from [VHDPG14].

rather than a technology to improve the energy efficiency, which eases the design and implementation in real-time of control strategies to both the energy-efficiency and energy cost reductions [TNL17]. Therefore, based on IoT, a global connection of both the manufacturing systems within an industry and its supply chain can be established in order to consider most of the factors that affect the behaviour of a manufacturing plant.

One of the advantages of CPMS integration is the continuous data collection, which might be used to trigger and predict service activities (e.g., routine maintenance activities based on usage or wear, and tear of the equipment), as a way towards energy efficiency improvement in manufacturing systems. Although the implementation of CPMS opens new opportunities to introduce smart technologies in the control systems, the integration of all control resources seen from plant level (e.g., sensors and actuators, the PLC modules, SCADA modules) imposes new challenges for designing management/control strategies of energy demand at the plant level. Besides, regarding the flexibility and adaptability of manufacturing systems, new strategies that consider a high level of modularity to face any change in either production scheduling or the working environment will be required. The latter, for the suitable transformation towards Smart Manufacturing Systems (SMS).

2.5 Control Strategies in Manufacturing Systems

According to strategies mentioned in the previous section, control techniques have started to gain great application during the last decade in manufacturing systems, mainly due to introduction of smart systems, IoT, and the transformation towards Industry 4.0. Some of the potential applications of control systems have focused on both machine and process line levels since the large scale and complexity of both systems and the complex relationships at the plant level. Regarding the machine and line level, the control objectives have been mainly oriented to either process planning and scheduling to satisfy a production demand, quality of produced pieces by controlling machining processes, and reduction of peak load.

Thus, given the complexity of manufacturing systems due to the processes performed, the strong relations between the peripheral and machining devices, the time-varying constraints such as tool wear, the efficiency of each device (at machine, line, or plant level) and the changing-working environment, the most used control techniques in manufacturing systems are those based on optimisation. This fact is given since the control objectives, and the operational constraints of manufacturing systems can be included in an optimisation problem. Thus, either operating ranges, dynamic expressions for the relationships between machines and their environment, and any additional constraints that condition the performance of the system can be taken into account.

However, although few control applications consider energy objectives, most of them have been limited to analyse the individual system and not consider the interactions with both other devices and the TBS. Besides, most of these applications consist of designing closed-loop control schemes that minimise the difference between the real energy consumption and a reference behaviour, which is usually determined offline and without considering the temporal variations of its surroundings. According to the most relevant reported literature, the energy efficiency objectives usually considered for the design of control systems are focused on the following aspects [ASM16]:

- *Reduction of power peaks:* In this case, optimisation-based algorithms aim to reduce the occurrence of peaks produced by simultaneous activation of several devices or machines. Typical objective functions focus on minimising either the infinity norm of the power signal along a fixed period (e.g., a machine cycle) or the sum of penalties for the instantaneous power values that surpass a threshold value corresponding to a nominal power purchased.
- *Load-profile smoothing:* In this case, the optimisation-based algorithms search smoothing the global power consumption profile by minimising the difference between the instantaneous power consumption and the mean load demand of the machine tool during its operation. Although this approach allows obtaining smooth profiles, in some cases it implicates higher total energy demand when the instantaneous power will be lower than its

mean value.

- *Load reduction:* From this approach, significant cost reductions could be achieved since, in this case, optimisation-based algorithms are oriented to minimise the total load demand. Most of the proposed cost functions to achieve this objective consist of minimising the area under the curve of the total power consumption profile. On the other hand, for those cases in which some peripheral devices can be managed in real-time, a possible control objective is to minimise the difference between the global energy consumption and the fixed power from unmanaged devices in the machine.

Based on the works related to the design of control strategies, these control objectives have been of a high priority since they take into account how the electric companies sell energy to the manufacturing industries. Moreover, from these objectives, the energy costs could be minimised in the facility without modifying either the physical structure of the plant or the current design of devices. Some applications of these control objectives in the design of control strategies are presented in Tables 2.3 and 2.4 into the approaches named optimised process control, process planning and scheduling, and control of power-peak demand.

Additional to the objectives previously mentioned, their suitable combinations, technical constraints and algorithms to solve optimisation problems would be considered. Some examples of the technical constraints refer to limitations of running and idle times for devices, switching frequency, a time interval for switching on devices, among others [ASM16]. However, although these approaches have had a great application for designing control systems oriented to both energy efficiency and process planning and scheduling, in most of the cases, disturbances or changes in the working environment conditions are not considered. Therefore, and taking into account the current context of manufacturing industry and the introduction of SM and Industry 4.0, strategies able to respond in real-time to any changes in the system or its environment, besides to consider flexibility in the processes plan and schedule should be developed [APM15].

According to the U.S. National Institute of Standards and Technology (NIST), SM is defined as "*fully-integrated and collaborative manufacturing systems that respond in real-time to meet the changing demands and conditions in the factory, supply network, and customer needs*" [KLC+16]. Thus, SM can be understood as a collection of innovative technologies that can respond to complex changes in manufacturing systems in real-time, promoting the decision making in real-time through the introduction of Information and Communications Technologies (ICT), and the interaction among humans, technology, and information. Among the most well-known techniques to promote the transformation towards SM, it highlights cloud computing,

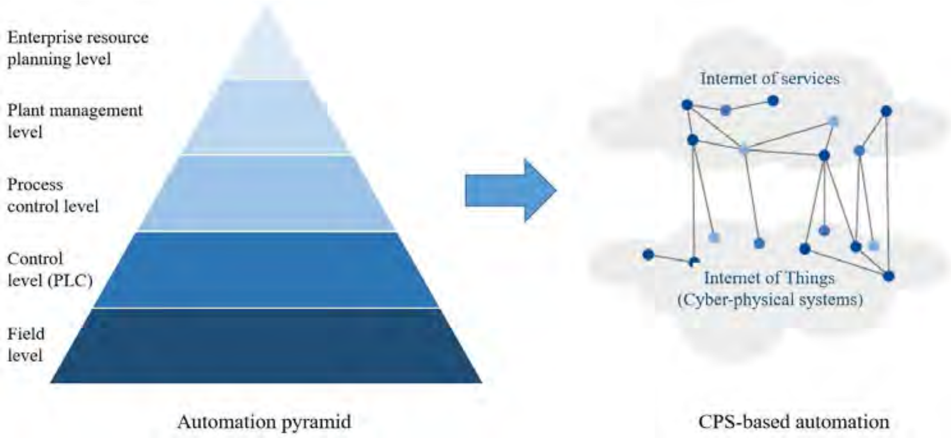


Figure 2.8: Transformation of automation structure by introducing the CPS concept. Based on [GJ13, FV16].

IoT, CPS, and big data [KLC+16]. CPSs have been recognised as useful tools for shifting of pyramid automation towards locally controlled modules without hierarchy, as shown in Figure 2.8. Thus, one of the advantages of CPS-based automation is that it allows companies a high degree of shared information at all levels, from which control systems could respond quickly on the appropriate level.

In this sense, from the developments in sensing technologies, the improvements in data acquisition and signal processing techniques, in the new era of the SM much information is available to be used in the monitoring and controlling these systems. Therefore, during the last years, more robust control systems able to treat and use the available information have been developed. For example, currently, control systems oriented to prognosis and maintenance of manufacturing systems, based on the historical data, have been developed to predict and program the required changes or maintenance activities [NDA+14, SWS+15, WLZ+17]. Besides, strategies such as receding horizon control and advanced methods of process control (e.g., Model Predictive Control (MPC)), have also started to gain attention in the manufacturing industry. Most of the application of these approaches are focused on problems of energy efficiency and flexibility for planning and scheduling of processes at the machine, line, and plant levels [UDOMA17, NCSS16, Kap17, CPS15].

2.5.1 Control systems at both machine and process line levels

Due to the periodic behaviour of the machine tools, the proposed control strategies had not had a great application since an optimal activation sequence for both peripheral and machining devices is determined off-line for the nominal operation of machines. Nonetheless, nowadays, it is considered that peripheral devices can be independently managed from machining devices in pro of energy efficiency and without to compromise the machining operation since these devices could or could not have a periodic behaviour. Based on this fact, the use of MPC controllers for selective on/off switching of peripheral devices, based on their process dynamics and the total energy consumption of the machine, has gained interest as a control strategy oriented to improve the energy efficiency of manufacturing systems [ZCAX17, UDOMA17, BHMA17].

As a consequence, most of the approaches addressed and related to the design of control systems at the machine level aim for the selective actuation of non-continuously-required devices, the reduction of the idle times, and improvements in the process planning and modelling for their application in advanced control systems. In this sense, in [FM14], an optimal switch-off policy for the energy consumption control of machine tools in the manufacturing industry is proposed, considering time-dependent warm-up duration and the random arrival of parts to the machine. This policy is based on the idea that once a part is finished, the machine remains in on-service status only for a short time. Then, if it passes a defined time interval without the entry of a new part, the machine will be switched off.

In [SOMGSOM14], a mathematical model of energy consumption considering three operational modes (processing, idle, and shut down) to minimise the total energy consumption of single-machine scheduling is proposed taking into account the continuous changes in energy prices. The general idea of this work is to provide a tool that helps to choose the most efficient production schedule for an individual machine, which could be useful like a reference or set-point for a control strategy. Thus, for designing advanced control systems based on optimisation, additional to available information, models of the electrical energy consumption of manufacturing systems that will be simple and precise enough to solve on-line the optimisation problem with short computing times are required. In this sense, the need of methodologies for correctly modelling both energy consumption of manufacturing systems and the dynamic relations with other devices and its environment, besides of integrating the available information from real processes, is highlighted.

In the same way, the control of peak power demand has been another research focus to improve the energy efficiency of manufacturing systems at the process line level. In [SLFW14], an advanced buffer inventory management method is proposed to reduce electricity consumption during peak periods of a multi-machine system and buffers. Moreover, the concepts of a processing mode and electric energy capacity plan for optimising the energy efficiency of processes in a flexible manufacturing system with several machine tools are introduced in [SS16]. In this sense, most of the strategies currently implemented regarding the peak power control consist of delaying the switching-on of some machines taking into account a threshold value. Usually, this last value corresponds to the contracted nominal power, which produces economic penalties if it is exceeded.

2.5.2 Control systems at plant level

At the plant level, in which there exist complex relationships and large-scale system schemes are considered, some of the main research topics for designing control strategies are focused on understanding the energy consumption of systems seen from this level. In this sense, a conceptual framework for energy efficiency based on an Event-Driven Architecture(EDA) and Complex-Event-Processing (CEP) is introduced in [SHSB13] to provide detailed information about the energy deviations of factory targets that can be useful for the production planning and control of manufacturing systems. In the same way, in [KM14], an approach for reducing energy consumption is proposed by providing a selection method of the more appropriate energy efficiency measures to be used by factory planning participants, intending to overcome the high efforts to acquire energy data. Thus, concerning the integration of control strategies at the plant level considering the available information from processes and the key technologies of Industry 4.0 (SM, IoT, etc.), some works have been developed regarding techniques for data acquisition, and data analysis and processing in real-time.

At highest levels, just a few of the control strategies implemented are directly related to the energy efficiency of manufacturing systems. In the work [TNL17], the problem of lack the real-time visibility of energy efficiency on the shop floor is treated. In this work, an IoT enabled software application for real-time monitoring of the energy efficiency of manufacturing factories, together with a data envelopment analysis technique to detect abnormal energy consumption patterns and quantify energy efficiency gaps is developed. This work shows a clear example of utility and application of the available technologies in Industry 4.0, from which it is possible to access the energy information and efficiently analysing it to extract key performance indicators that can be used as helpful tools in the energy management/control. Following the same way towards energy efficiency, the work proposed in [ZCAX17] presents a novel strategy for controlling the energy consumption of manufacturing systems. In this work, a data-driven stochastic manufacturing systems modelling method is proposed to achieve a predicting system that will be used later to design control systems. Then, from the obtained results, a real-time distributed feedback production control policy that integrates the current and predicted system

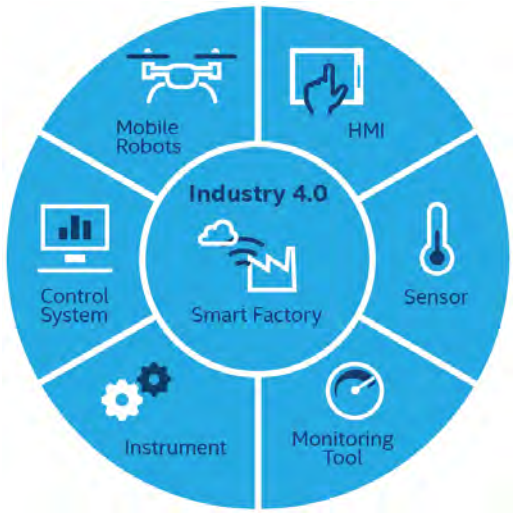


Figure 2.9: Integration architecture of fostering technologies of smart factories. Taken from [Int18].

performance to improve the overall profit and energy efficiency is presented.

Thus, by integrating the CPMS, IoT, and advances in sensing technologies, the design of advanced control strategies into the context of SM and Industry 4.0 could be improved. Thereby, the control strategies could be implemented in real-time with computing times small enough to solve the optimisation problem and execute the corresponding actions to keep the system in the desired state (i.e., the set-point). In this sense, the application of these technologies towards a more sustainable and flexible manufacturing industry, for instance, by reducing resources consumption (e.g. electrical energy) and custom services, promote and challenge, at the same time, the design of control systems robust enough to treat the complexity, large scale, and coupling of manufacturing systems at each levels (e.g., machine, line, and plant) and to establish communication scheme among different levels.

The integration of CPMS and IoT into the manufacturing systems towards Industry 4.0 requires the suitable synergy of several scientific and technological fields. Since the result of such interaction can yield in complex systems of systems, new challenges naturally arise in the technological dimension for the development of suitable architectures that support these systems. Thus, from a technical point of view, the embedded systems, sensor technology, actuation technology, decentralised data processing capacities (microcontroller), centralised data processing capacities (big data), communication interfaces (Ethernet, Wi-Fi, RFID, GPS, NFC, etc.), and communication protocols (IPv6, OPC UA, etc.) are required to the successful integration of CPMS and IoT into manufacturing systems [JBSR17]. Based on these approaches, systems can be transformed into smart entities with a defined identity, sensing capabilities of physical processes, actuation mechanisms, data processing ability and connectivity through network interfaces. Therefore, a digitisation stage of information collected about the physical conditions in the plant is required. Due to this fact, an essential factor is the installation of suitable sensors to cover the operating ranges of the process and with the expected precision. Into the context of Industry 4.0, sensors should have the features of durability, robustness, reliability, non-invasive installations, self-power, and wireless transmission [Dep15]. For instance, regarding energy consumption, the sensors commonly used by manufacturing industries are wireless current and voltage sensors. Besides, some industries integrate vibration sensors in order to analyse and predict possible equipment malfunctions, which increase their energy consumption. From these sensors is possible monitoring the phase-phase voltage, phase to neutral voltage, phase current, frequency, active power, reactive power, apparent power, active energy, reactive energy, power factor, instantaneous demand amps, instantaneous demand active power, instantaneous demand apparent power, maximum demand active power and maximum demand apparent power [MVC17, FMDC17].

Afterwards, the collected data need to be processed, analysed, and integrated to make decisions by using suitable communications platforms and protocols. In this regard, IoT is widely used to describe embedded systems through Internet connectivity in order to allow the interaction with other systems, human, or services, on a global scale [MS14, JBSR17]. According to [MS14], IoT can increase reliability, sustainability, and efficiency by improved access to information. However, to provide Internet to the whole facility is a high investment that should be carefully analysed. This fact had carried out that opponents to IoT started to question and criticise the return of investment (ROI) of the IoT implementation in the manufacturing industry. Following these critical voices, some researches have focused on analysing the real value of IoT integration in terms of time, flexibility, reliability, cost, and quality. In [JBSR17], different contributions regarding these issues are presented. Generally, the ROI is defined as the ratio between the nett gain and the costs of investment. However, regarding IoT investment, there exist hidden benefices that may provide critical evidence in favour of IoT, and which are usually not included when the ROI is computed. In [Mic16], a practical approach to calculate the return on investment for IoT is presented. Besides, it should be noted that following the *2017 Roundup of Internet of Things Forecasts* by FORBES, “the majority of enterprises adopting IoT today are using metrics and key performance indicators that reflect operational improvements, customer experience, logistics, and supply chain gains”.

2.6 Summary

In this chapter, a review of the current context of energy efficiency in manufacturing systems and the applied control strategies have been introduced and discussed aiming to identify the driver technologies for reducing the energy consumption and improving both energy efficiency and sustainability of these systems. Due to the large-scale of manufacturing systems and their complexity, an approach by levels has been addressed, allowing a better comprehension of their fundamental components and relationships. The first level considered was the machine, in which the manufacturing processes performed and the peripheral devices are included. Next, when interactions among machines in the same arrangement are considered, the second level (or process line) is defined. This level corresponds to an arrangement of machines, each one developing a defined operation and organised in a fixed sequence towards the production of a finished part. The third level addressed here is the factory or plant level, which is an extension of the previous levels and their complex interactions at each level and among them but which included the interactions of all manufacturing systems with the TBS and the rest of activities of a factory. This classification by levels is the guiding thread in the development of this thesis, and the control strategies proposed in Chapters 5, 6, 7, and 8 are based on the description by levels presented in this chapter.

Afterwards, at any level analysed, the identified strategies to improve the energy efficiency of manufacturing systems are presented and discussed. As results, improvements regarding data acquisition and processing techniques of the raw data are required if the new developments in sensing technology and the new CPS want to be included in the monitoring and control systems. Therefore, the inclusion of new technologies imposes challenges to the design of control systems, not only due to the complexity of such systems but also the requirements of computational time. Thereby, management/control systems should be able to predict the energy consumption behaviour of manufacturing systems, determine control actions and perform the changes in a reasonable time for their implementation in real time. In this sense, and taking into account the needed components towards the design of control systems (e.g., the system model, solver, control structure, etc.), improvements in each one of such components are required.

CHAPTER 3

BACKGROUND

This chapter points out the main topics addressed in the development of this dissertation. The concepts of CPS and CPMS, MPC, and EMPC are gathered in three sections. First, the CPS concept and its integration into the current context of the manufacturing industry towards CPMSs are briefly presented and discussed. Next, a review of the OBC techniques and their application to the design of control strategies for manufacturing systems are introduced. Then, a review of MPC is made focusing on non-centralised control architectures. Afterwards, the EMPC approach is presented and discussed, and some of its more important advantages and features are highlighted. Finally, according to the topics discussed, the main idea behind the development of this dissertation is presented and explained.

3.1 Cyber-Physical Systems

The CPSs refer to systems that integrate physical processes and embedded computing elements (e.g., smart sensors and actuators) allowing a real-time interaction, which eases the exchange of information for tasks such as monitoring, control, and management of such systems [BG11, MKB+16, JMS+17b]. CPSs have emerged to describe the integration of computation and physical processes that are characterised by tight integration and coordination, in which various embedded devices are networked to sense, monitor and actuate over physical elements in the real world [MKB+16]. Into the smart manufacturing industry, the interconnection of embedded elements is commonly performed through IoT. Thus, one of the potential advantages of CPS is that, from embedded computers and networks, physical processes are monitored and controlled by feedback loops, in which data management and smart analytic capabilities could be easily integrated. Based on this advantage, the raw data of the physical process might be transformed into predictive and prescriptive operations for monitoring and controlling CPSs [LBJ16, WTO15].

Based on the CPS structure and the nature of its elements (cyber and physical), these systems are characterised by the smartness, connectedness, and responsiveness towards internal and external changes. It means that the CPS are systems capable of acquiring information and act autonomously using smart actuators to interact with both the physical and digital world. On the other hand, regarding connectivity, CPS can set up and use connections with other systems (including human beings) and in global networks, for establishing cooperation and collaboration schemes among systems [MKB+16, HUB15]. Thus, CPSs have had a relevant application in the manufacturing industry since they ease the information acquisition and data-driven services to predict behaviours and establish manners of communication and cooperation among different systems.

Taking into account the size, interactions and connections among elements, and the complex dynamics of SMS, CPS can be regarded as *systems of systems* that can be implemented at all levels of the manufacturing industry (machine, line, and plant level). In this regard, the cyber (communication protocols, control systems, IoT, etc.) and physical (device, machines, process lines, etc.) systems of a manufacturing plant gather resources and capabilities to form a more complex, functional, and efficient system that offers better performance. Thus, the implementation of CPS, together with IoT, has fomented the transformation to the CPMSs, which represent the highest level of application of CPS in manufacturing industry [JMS+17b]. CPMS are considered as autonomous and cooperative sub-systems that are interconnected within and across all levels of production, i.e., from the processes developed in machines to production and logistics networks of a manufacturing plant [MKB+16]. The general idea of CPMS is to allow users to know and comprehend the invisible causal relationships among the manufacturing systems and to make optimised decisions oriented to satisfy a sustainable development [LBJ16]. According to [HUB15], one of the advantages of the CPMS integration is the continuous data collection, which might be used to trigger and predict service activities (e.g., routine maintenance activities based on usage or wear, and tear of the equipment) as a way towards energy efficiency of SMS. Many other advantages of CPMS, which results of integrating CPS in the manufacturing industry, are presented in [WTO15, HUB15].

Regarding the implementation of control strategies, CPMS requires designing reliable control networks to satisfy the global objectives, in which the smart sensors monitor the physical environments while smart actuators change the physical parameters of systems. However, due to the different levels of the manufacturing industry, communication architectures among the control systems in a manufacturing plant, in which smart sensors and actuators can be integrated into the either cooperating or collaborative way, should be analysed and selected according to the global objectives at the plant level [LBJ16, MKB+16, WTO15].

Although the implementation of CPMS opens new opportunities to introduce smart technologies into the design of control systems, the integration of all control resources seen from the plant level imposes new challenges for designing management/control strategies at each level of the manufacturing industry. That means that all sensors and actuators in a plant, the PLC modules, and SCADA modules should be suitably integrated. Besides, to confer more flexibility and adaptability capacities to manufacturing systems, control strategies should consider a high level of modularity to face any change in either production scheduling or the working environment. This last fact is quite important in the new era of SM, in which the flexible manufacturing is mandatory to improve the system productivity.

Flexible manufacturing

Into the new era of manufacturing systems and its transformation towards SM, flexibility to quickly respond to constant changes in the production programs is a mandatory requirement to satisfy the new designs and increasing the variety of products that can be processed in a manufacturing industry. In this regard, flexibility can be understood as the capacity of producing different parts or a wide variety of customised products of high quality and which can be fast enough delivery to the end-users. That means manufacturing systems with the ability to shift from one production program to another and to increase or reduce the production levels with the same equipment [Kap17, SRT17]. In [Kap17], two types of flexibility are distinguished as follows:

1. Tunability, which is related to the ability to manufacture a wide variety of products in multi-product production.
2. Adaptability to reconfigure the production processes when the production programs are changed.

However, flexible manufacturing is not only related to the ability to respond to changes in the production programs but also its ability to transform and adjust the production processes to changing conditions and the energy market. Therefore, manufacturing systems should be implemented by using flexible automated control system capabilities and software systems adaptive properties at all manufacturing levels. In this regard, a high level of modularisation for manufacturing processes and their modelling, to ease the flexibility/reconfiguration of control systems when changes happen. Besides, regarding energy consumption, control systems should suitably manage manufacturing systems to adapt their energy demands taking into account the current energy market [SBS+19].

3.2 Optimisation-Based Control

According to [Mur09], OBC refers to the control techniques that use the online generation of optimal trajectories as part of the feedback control algorithms. Indeed, this approach is applied to systems whose control objective can be defined as an optimisation problem. When appropriate, the OBC is implemented in receding horizon fashion, in which an optimal trajectory over a finite time horizon is determined by solving an online optimisation problem. Then, the generated trajectory is updated based on the current state of the system [Mur09, MHJ+03].

In general terms, the optimisation can be understood as the problem of choosing a set of variables that minimise or maximise a defined objective function (e.g., minimise costs or maximise production). However, in the context of OBC, the control problem is set up through an optimisation problem for selecting a set of variables for a control law that satisfies some performance condition [AS04, Mur09]. Hence, three elements are essential for designing optimisation-based controllers: an objective function, constraints, and a process model. Although the process model is considered as a primary element for the controller design into the optimisation problem, it is regarded as another type of constraints. The objective function refers to the mathematical expression of the control objectives that will be minimised or maximised. In contrast, constraints are functions of different nature that define the search space for the decision variables. On the other hand, the process model relates the inputs, states, and outputs of the process, and in the same way as constraints, it determines a search domain for the optimisation problem [PF16].

Since controllers designed based on optimisation solve an optimisation problem online, the objective function, the model, and the constraints can be updated to handle exogenous signals that affect the system behaviour. Therefore, if the objective function can be updated in real time, the changes in the production demand or the working environment could be updated at any time instant, which confers more flexibility and adaptability to controlled manufacturing systems. In the same way, changes in parameters and the operating conditions, or damage in either sensors or actuators could be considered by updating the process model and the set of constraints into the optimisation problem [MHJ+05].

Based on the high level of customisation of the OBC techniques, most of the time-varying factors that affect the energy consumption behaviour of a CPMS might be included into the design of energy management/control strategies. In this regard, the control systems must be robust enough to consider the most extensive set of constraints and possible uncertainties into the online optimisation [Mur09]. Then, once the optimisation problem is formulated, efficient numerical methods must be used to solve it and to obtain the values of optimal control inputs that satisfy the system dynamics and constraints and reach the control objectives. However, the selection of the numerical methods to solve the optimisation problem depends on the nature of decision variables (binary, integer, continuous), the kind of systems (linear or non-linear, constrained or unconstrained), and the number of constraints since these factors determine the computational time required to solve the related optimisation problem.

3.2.1 Model predictive control

MPC is a term that not only describes a specific control strategy but rather a set of control methods that make explicit use of a process model in order to obtain an optimal control sequence along a prediction horizon by minimising an objective function [CB07]. MPC has had an increasing development over the last decade, getting to extend the recent advances from the academic context to industrial applications. Thus, the general idea of MPC is to use a process model in order to predict and optimise future system behaviour along a finite control horizon. According to [CB07], the primary strategy of MPC consists of:

1. Prediction of the future outputs for a finite prediction horizon from a process model and the current inputs and outputs.
2. Calculation of the set of future control signals (control sequence) by optimising a defined function to remain the process as close as possible to the desired behaviour. The cost function could be expressed as a quadratic function of the errors between the predicted output signal and a reference trajectory.
3. The first control signal obtained for the current time is sent to the process while the remaining control signals of the calculated sequence are disregarded, and the procedure begins again displacing the prediction horizon towards the next time instant.

Some of the main advantages of the MPC are it can be implemented in several processes and industries and works for delayed and multi-variable systems. Besides, by using MPC, the control problem can be formulated in the time domain, and the set of constraints can be updated regularly [CB07]. However, since the formulation of MPC is based on an optimisation problem, its implementation could require a high computational burden to solve the problem and determine an optimal control law. Besides, since MPC considers the explicit use of a process model, from which the prediction is made and the optimal input sequences are determined, this control strategy is high dependently of the model accuracy to represent the system behaviour.

Formulation of MPC strategy

Several formulations of MPC strategy are reported in the literature for both continuous and discrete time [Kou16]. However, for the design of MPC-based controllers, the discrete time and the state-space representations of the process models have been more used [KM18, OM10]. Thus, consider a process model in the discrete-time domain as follows:

$$\mathbf{x}(k+1) = f\left(\mathbf{x}(k), \mathbf{u}(k), \mathbf{d}(k)\right), \tag{3.1}$$

with $k \in \mathbb{Z}_{\geq 0}$ the discrete-time index, and $\mathbf{x} \in \mathcal{X} \subseteq \mathbb{R}^{n_x}$, $\mathbf{u} \in \mathcal{U} \subseteq \mathbb{R}^{n_u}$, $\mathbf{d} \in \mathcal{D} \subseteq \mathbb{R}^{n_d}$ the vectors of system states, control inputs and disturbances, respectively. The function $g : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \mapsto \mathbb{R}^{n_x}$ refers to the mapping of system states and control inputs of a particular system. The sets $\mathcal{X}$ and $\mathcal{U}$ represent the feasible domains for system states and control inputs according to their operational and physical constraints. Allowing

$$\tilde{\mathbf{u}}(k) \triangleq \{\mathbf{u}(k|k), \mathbf{u}(k+1|k), \cdots, \mathbf{u}(k+H_p-1|k)\} \tag{3.2}$$

to be a feasible control input sequence over a fixed prediction horizon $H_p \in \mathbb{Z}_{\geq 0}$, the system state sequence resulting to apply $\tilde{\mathbf{u}}(k)$ to the system in (3.1) can be defined as follows:

$$\tilde{\mathbf{x}}(k) \triangleq \{\mathbf{x}(k+1|k), \mathbf{x}(k+2|k), \cdots, \mathbf{x}(k+H_p|k)\}. \tag{3.3}$$

Therefore, the MPC is based on the solution of the following open-loop optimisation problem [RM09]:

$$\min_{\tilde{\mathbf{u}}(k)} \quad J\left(\mathbf{x}_k(k), \mathbf{u}(k)\right) \tag{3.4a}$$

subject to

$$\mathbf{x}(k+1+j|k) = f\left(\mathbf{x}(k+j|k), \mathbf{u}(k+j|k), \mathbf{d}(k+j|k)\right), \forall j \in [0, H_p], \tag{3.4b}$$

$$\mathbf{x}(k+j|k) \in \mathcal{X}, \forall j \in [0, H_p], \tag{3.4c}$$

$$\mathbf{u}(k+j|k) \in \mathcal{U}, \forall j \in [0, H_p - 1], \tag{3.4d}$$

with $J : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \mapsto \mathbb{R}$ the cost function to be minimised along the prediction horizon H_p. Besides, $x(k+j|k)$ denotes the prediction of the system states at time instant $k+j$ performed at k. Then, assuming that the problem in (3.4) is feasible, there exists an optimal control input sequence defined by

$$\tilde{\mathbf{u}}^*(k) \triangleq \{\mathbf{u}^*(k|k), \mathbf{u}^*(k+1|k), \cdots, \mathbf{u}^*(k+H_p-1|k)\}. \tag{3.5}$$

Hence, according to the receding horizon philosophy [Mac02, RM09], only the first optimal control input $\mathbf{u}^*(k|k)$ of the optimal sequence $\tilde{\mathbf{u}}^*(k)$ in (3.5) is set to the system in (3.1). Thus, the final control input applied to the system corresponds to

$$\mathbf{u}^*_{MPC} \triangleq \mathbf{u}^*(k|k). \tag{3.6}$$

It is worth noting that the rest of the optimal control input sequence, i.e., from $k+1|k$ to $k+H_p-1|k$ is discarded, and the whole procedure is repeated for the next time instant after measuring/estimating the required information from the system. Several MPC algorithms have been proposed in the literature [CB07, Law14]. However, a general structure for the implementation of MPC algorithms is presented in Figure 3.1.

The main idea to guarantee the feasibility and stability of MPC consists of introducing terminal cost and constraints in the optimisation problem. Ideally, the MPC problem should be solved by using an infinite horizon. However, that is not possible, and it will require a high computational burden. Thus, MPC is designed as a finite horizon problem such that it approximates to the infinite horizon one. Therefore, the prediction horizon should be suitably selected since too short horizons could cause a deviation between the open-loop prediction and the closed-loop system. Thus, terminal cost and constraints, properly selected, are added to the optimisation problem behind the controller design to solve these issues. In [May14], the stability and recursive feasibility of nominal MPC by using a terminal stability constraint are studied and analysed. Other alternatives to the stability of MPC based on a terminal region of attraction have been studied and some of the obtained results to achieve stability are presented

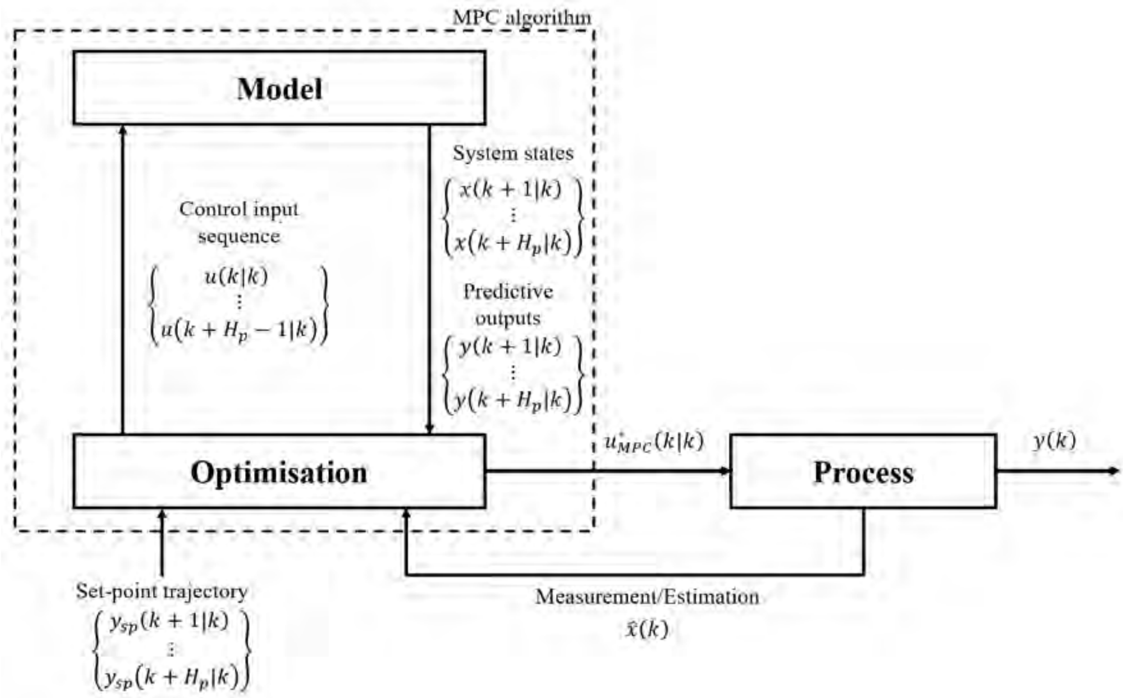


Figure 3.1: Structure of MPC strategy

and discussed in [Grü12].

The standard way to implement the MPC controller is by using a centralised MPC setup, where the global optimal control problem should be solved online concerning all actuators and taking into account the entire set of states. That means, all the primary decisions are performed in only one station or one controller. Thus, although this MPC configuration could be more straightforward because it is more intuitive, it requires significant computational efforts when the size of the system increases. Then, for large-scale systems such as CPMS, suitable control structures and fast computational resources are required to achieve global objectives. In this regard, the MPC approach could be suitably applied in real time if the optimal control problem is split into sub-problems. The last fact is because sub-problems are more straightforward to solve, even if they have coupled dynamics, cost functions or constraints [MN14].

Distributed model predictive control

The main idea of Distributed Model Predictive Control (DMPC) approaches is to divide the centralised problem into several parts whose control is assigned to a certain number of local controllers. In this scheme, not all controllers have a global vision, and therefore, depend on the interaction degree with the other local sub-systems. Indeed, each controller includes into its local optimisation problem the behaviour of other sub-systems to get in touch with the other controllers. Some of the advantages of the distributed control approaches are their easy implementation, their scalability and modularity, higher tolerance to failures and, besides, they require less computational resources than centralised architectures [Grü16, MN14].

For the implementation of a DMPC approach, the large-scale CPMS must be partitioned (or decompose) into sub-systems that could define the control sub-problems. Although the large-scale system decomposition into sub-systems is a difficult task due to the coupling dynamics of the elements of a system, traditionally, the decomposition issues have been addressed together with the modelling process. Nevertheless, the latter way of decomposition is not satisfactory when the complexity and coupling of systems increase since the communication among sub-systems for achieving the objectives is not guaranteed [OMP17]. Therefore, suitable partitioning methodologies must be used if the computational complexity and handling the possible communication issues want to be reduced and overcome, respectively.

In [BGOMQ17], a partitioning algorithm is developed considering an information-sharing graph that can be generated for any control strategy and for any large-scale dynamical system. This approach is tested for designing a distributed model predictive controller for a large-scale water supply system. Another approach, based on graph theory but combining the existing partition methods is proposed in [RPG+15] where a distributed balanced graph partitioning algorithm (called JA-BE-JA) is developed from the edge-cut and vertex-cut partitioning. On the other hand, [CA13] proposed an optimal partitioning methodology based on clusters for the decentralised thermal control of buildings. In this work, the controllers are locally designed according to the defined clusters and communicated to achieve the common control objective. However, when there is an exchange of data or communication between the sub-systems, distributed schemes can be classified into subclasses of cooperative and non-cooperative control [Grü16].

Once the global control problem has been divided into sub-systems, to obtain a better closed-loop control performance it is necessary to establish communication architectures between the different controllers (or entities). Taking into account the studies developed in the field of DMPC approaches, they can be classified based on the topology of the communication network, the different communication protocols used by the local controllers, and the cost function considered in the optimisation problems related to the local controllers [Sca09]. According to the cost function considered, if each local controller optimises the global cost function, cooperating or not with other controllers, there exist non-cooperative and cooperative MPC algorithms [CSlPL13].

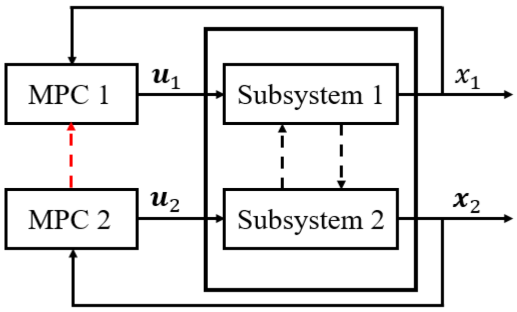


Figure 3.2: Sequential distributed MPC architecture.

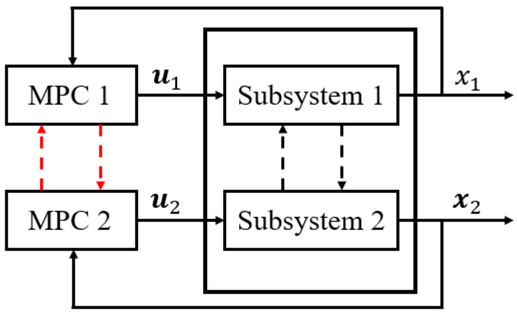


Figure 3.3: Parallel distributed MPC architecture.

For the non-cooperative MPC, each local controller optimises a local cost function, and the controllers can be evaluated in a sequential or parallel way, as shown in Figures 3.2 and 3.3. In a sequential architecture, the controller i is evaluated after the controller $i-1$ has been evaluated, while in a parallel way, all the controllers are assessed at the same time [CSlPL13].

On the other hand, for the cooperative DMPC approaches, each local controller optimises a global cost function taking into account the effects of its inputs on the entire plant. Besides, in the same way as the non-cooperative MPC, there exist two primary architectures according to the required information by controllers, sequential and iterative ones. The sequential cooperative architecture is based on the assumption that the full system state is available to all controllers at each time instant. Then, each controller sends the future trajectories to the next controller. For the case of the iterative architecture, each controller evaluates its future input trajectory according to the available measurements and the latest input trajectories received from all controllers. Then, controllers exchange their future input trajectories, and from this, each one computes the value of its cost function. When a stop criterion is satisfied, each controller sends its entire future input trajectory. A scheme for the iterative architecture is presented in Figure 3.4.

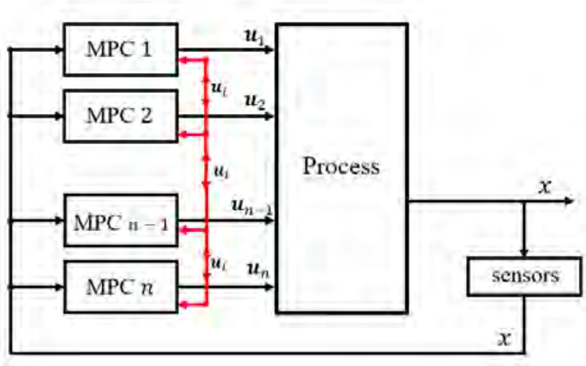


Figure 3.4: Iterative distributed MPC architecture [CSlPL13].

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At the plant level, the partitioning of large-scale CPMS could help to reduce the computational time and to ease the solution of the global control problem of the energy efficiency of CPMS. However, the sub-systems resulting from applying partitioning methodologies should be appropriately integrated and communicated for achieving the global objectives at the plant level. Based on the latter fact, by using DMPC approaches the control strategies at the line level can be integrated, and a supervisory management/control strategy at the plant level could be designed considering the control strategies at lower levels.

3.2.2 Economic model predictive control

The main idea that underlies the MPC is to transform a control problem into an optimisation problem so that a sequence of future control values is calculated at every moment [Sca09]. Usually, MPC is formulated using a quadratic objective function to penalise the deviations of the state and outputs of a system from their optimal steady-state values over a prediction horizon [EDC14, RM09]. However, when it is desired to optimise the economic performance of a process in real time, a control structure in two layers is required. First, a steady-state economic optimisation should be performed in real time to determine the economic-optimal reference that the predictive controller should follow in the second layer. Nonetheless, the steady-state operation may not necessarily be the economic best operation, and the hierarchical separation of economic analysis and control could be either inefficient or an inappropriate strategy for some applications [RAB12].

According to [RAB12], there is an increasing number of problems for which dynamic economic performance is crucial, and the hierarchical separation of economic analysis and control is either inefficient or inappropriate. Thus, in order to perform the process economic optimisation and process control simultaneously, a new MPC scheme has been proposed, in which an economical cost function replaces the normal tracking function. That approach is known as Economic MPC (EMPC). In this regard, given that the EMPC directly optimises an economic performance, it has been widely used in the context of the manufacturing industry to determine the optimal operation of manufacturing systems from an economic viewpoint.

Consider a discrete-time finite-dimensional system as in (3.1). Then, the instantaneous economic cost of implementing the control inputs $\mathbf{u_e}$ from the system states $\mathbf{x_e}$ is given by

$$l_e\left(\mathbf{x_e}(k), \mathbf{u_e}(k)\right), \tag{3.7}$$

with $l_e : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \mapsto \mathbb{R}$ used as a measure of the instantaneous process operating cost. Several economic costs have been considered such as the total profit, total operating cost, total revenues, as well as traditional indicator of chemical engineering as rates of desired products, desired product selectivity, and product yield. Similarly to (3.2) and (3.3), the feasible control input trajectory/sequence of the decision variables over H_p and the predicted state trajectory are given by

$$\tilde{\mathbf{u}}_\mathbf{e}(k) \triangleq \left\{\mathbf{u_e}(k|k), \mathbf{u_e}(k+1|k), \cdots, \mathbf{u_e}(k+H_p-1|k)\right\}, \tag{3.8}$$

$$\tilde{\mathbf{x}}_\mathbf{e}(k) \triangleq \left\{\mathbf{x_e}(k+1|k), \mathbf{x_e}(k+2|k), \cdots, \mathbf{x_e}(k+H_p|k)\right\}. \tag{3.9}$$

Thus, the EMPC approach along of H_p is characterised by the following optimisation problem [EDC14]:

$$\min_{\tilde{\mathbf{u}}_\mathbf{e}(k)} \sum_{k=0}^{H_p} l_e\left(\mathbf{x_e}(k), \mathbf{u_e}(k)\right) \tag{3.10a}$$

subject to

$$\mathbf{x_e}(k+1+j|k) = h\left(\mathbf{x_e}(k+j|k), \mathbf{u_e}(k+j|k), \mathbf{d_e}(k+j|k)\right) \tag{3.10b}$$

$$0 \geq g\left(\mathbf{x_e}(k+j|k), \mathbf{u_e}(k+j|k)\right), \forall j \in [0, H_p], \tag{3.10c}$$

$$\mathbf{x_e}(0) = \mathbf{x_e}(k), \tag{3.10d}$$

being $h(\cdot) : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \mapsto \mathbb{R}^{n_x}$ the mathematical expression for the nominal process model, $\mathbf{x_e}(0)$ the initial conditions on the dynamic model, $g(\cdot)$ the process constraints, and $l_e(\cdot)$ is the process economic cost function that the EMPC optimises through dynamic operation of the process. In addition to the process constraints, economics-based constraints should be added into the set of constraint in (3.10).

It should be noted that the EMPC is implemented in the same way as for the conventional MPC, i.e., in a receding horizon fashion. That means, at a sampling time, an optimal control input sequence $\tilde{\mathbf{u}}_{\mathbf{e}}^{*} = \{\mathbf{u_e}^{*}(k|k), \mathbf{u_e}^{*}(k+1|k), \cdots, \mathbf{u_e}^{*}(k+H_p-1|k)\}$ is determined, and only the first control action is sent to the system. Thus, the EMPC control law is defined as $\mathbf{u}_{EMPC}^{*} \triangleq \mathbf{u_e}^{*}(k|k)$. Afterwards, the information required by EMPC is updated, and the procedure is repeated for the next time instant. Several works related to the design of EMPC controllers, the theoretical background and stability analysis of EMPC have been proposed in the literature. A detailed explanation of the EMPC strategy can be found in [RAB12, ACT16]. Besides, in [EDC14], the closed-loop stability of EMPC is studied, and it presents a review of the various types of constraints and modifications to the objective function that have been proposed in the literature to guarantee the closed-loop stability. On the other hand, some relevant applications of EMPC in industrial environments are presented in [HPMJ12] for the building climate control in a smart grid, [LC18] boiler-turbine systems, and [TLG+19] for the mechanical pulping processes.

3.3 Energy-Efficient Strategy for CPMS

According to classification by levels proposed in Figure 2.3, at the machine level, different devices can be found. These devices can be classified into machining and peripheral devices. The former devices are directly involved in the primary tasks of the machine (i.e., machining operations). On the other hand, the peripheral devices work to guarantee the operating conditions of a machine tool or a set of them. Therefore, the operation of the peripheral devices might influence the sub-systems definition of each manufacturing level. For the cases in which peripheral devices are shared among two or more machines or process lines, the selection of sub-systems does not necessarily correspond to either the processes organisation or the plant configuration. In the same way, at line level, there are peripheral devices that, without being a part of the primary task of the process lines, guarantee the operating conditions for either a line or a set of them. Indeed, complex interactions between the same level and among different levels could exist, and all of them must be considered to design management/control strategies able to satisfy the requirements at the plant level.

Table 3.1: Classification of the systems and subsystems according to manufacturing levels.

Level	**System**	**Subsystems**
Machine	Machine	Set of machining devices and peripheral devices
Line	Line	Machine or set of them (maybe a process line)
Plant	Whole plant	Process line or set of them

The general aim of this classification by levels is to define the context for the possible systems and sub-systems that could be considered in the design of the energy management/control strategies. Based on Figure 2.3, system and sub-system concepts might be different from one level to another since systems for lower levels could be considered as sub-systems at higher levels. Therefore, keeping in mind that this thesis focuses on improving the energy efficiency and minimising the energy costs at the plant level, the existing interactions both into and among lower levels should be considered for the design of control strategies. Therefore, it is necessary to analyse every single level, determine its sub-systems, and establish its internal relationships as well as all interactions with other levels. As a consequence, the global objectives at the highest level could be achieved without compromise the individual goals at each level. In this regard, in Table 3.1, a classification into systems and sub-systems according to the defined levels is proposed.

Concerning the design of control systems, the control objectives are also defined by levels, in the same way as the systems and sub-systems classification is made. At the machine level, local objectives could refer to minimise, in real time, the energy consumption of a machine while its productivity is satisfied. Similarly, at both the line and plant levels, their particular objectives must consider the production requirements and flexibility for facing changes in production scheduling, while minimising their energy consumption in real time. However, besides the particular objectives of each level, the operational and working-environment constraints are different at each level, although some of them might affect two or more levels at the same time. Operational constraints refer to operational conditions of the processes, operating ranges of physical elements, intrinsic characteristics of systems (or devices), process sequences, among others, related to either the systems or sub-systems. On the other hand, regarding the working environment, all external factors to the system (or sub-systems) that directly affect its behaviour are considered into this class. Some examples belonging this latter category are either the addition of new devices to the process lines or the reconfiguration of processing sequences, which are produced as a result of changes in the design of products (flexibility).

Thus, to achieve global objectives at plant level, all objectives at lower levels must also be achieved. Hence, to reach the local objectives at the machine level, OBC techniques, such as MPC, can be used to design local control systems that minimise energy consumption while satisfying the production demand per machine. That means, the local objectives and both operating and working-environment constraints at machine level can be included in optimisation problems that are solved in real time. Besides, at the process line level, more sophisticated control structures could be considered, due to the resulting interactions among sub-systems within the same level and other levels. For example, when peripheral devices work to enable the proper operation of two or more machines, control strategies with predictive features could be desired to predict the process dynamics and to correctly manage such devices without endangering the operation and productivity of some machine.

Therefore, regarding the development of this dissertation, the general idea is to use MPC strategy for predicting the energy consumption behaviour of CPMS at line level and anticipating the control inputs for the cases in which either the process conditions or external factors of working environment change. Besides, from a predictive behaviour of energy consumption, the management of peripheral devices shared by different systems, which represent a significant saving opportunity for energy, could be improved regarding both energy and production requirements. Thus, considering the strategies proposed at machine level for minimising the energy consumption of machines, the controllers at line level must include the strategies at lower levels to trigger on or off devices in the line and smooth its energy consumption. Due to the complex relationships at the process line level and the size of these systems, the DMPC approach has been addressed to compare its performance regarding a centralised approach and the improvements concerning computational burden.

Similar behaviour as the line-level could be found at the plant level. That is, at the plant level, the interactions among different machines, process lines, or set of machines should be considered in the design of supervisory strategies. Therefore, the control objective at this level could be oriented to minimise the energy cost related to the operation of the plant, considering the energy consumption of both TBS and offices in the plant, as well as taking into account the energy market and its constraints. In this regard, the EMPC approach should be addressed in order to optimise the economic performance of the plant, taking into account the control objectives at the lower levels. Indeed, at the plant level, the process planning and scheduling can be determined according to the demand constraints and taking into account the energy-price profile during the plant operation. Then, based on the planning of the production programs at the plant level, the control strategy at process line level should be able to manage the changes in the production program while minimising its energy consumption and guaranteeing the system productivity. Moreover, the control strategy at machine level should guarantee the proper operation of machines in the process line.

Thus, aware of the necessity of improving the energy efficiency of manufacturing systems, the motivation of this doctoral thesis is to design energy management/control strategies by integrating of the concepts of the Industry 4.0 (SM, CPS, IoT, among others) and the OBC techniques. Thereby, according to the current needs of the manufacturing industry, the design of the control strategies should be oriented to reduce the energy consumption and to improve the energy efficiency and flexibility of the manufacturing industry, as a way of promoting/enabling the transformation of these systems towards SMS. Consequently, the control strategies to be developed should be able to process information in real-time to predict the energy consumption of an SMS taking into account their time-varying constraints. Then, based on the process prediction, the controller should be taken decisions that not compromise the quality and the number of the processed pieces.

3.4 Summary

This chapter has presented the main aspects for each one of the constitutive topics related to the development of this thesis, according to the literature review presented in Chapter 2. In the first section, the concept of CPS and the main ideas regarding flexible manufacturing are introduced. Then, OBC techniques, such as MPC, DMPC, and EMPC approaches have been presented and discussed in Section 3.2. In the third section, the main ideas behind the control strategy to be developed in this thesis are presented taking into account the manufacturing levels proposed in Chapter 2 and the control techniques discussed in this chapter. The control techniques and the concepts discussed in this chapter are used in the development of the control strategies in Chapters 5, 6 and 8 for the machine, process line, and plant levels, respectively. Besides, in Chapter 7, the distributed MPC approach is used to design a non-centralised control strategies and, the obtained results are compared with the centralised approaches.

Part II

Energy Efficiency Control Strategies

CHAPTER 4

MODELLING OF ENERGY CONSUMPTION AND DISCRETE DOMAINS

In this chapter, the manners in which the energy consumption has been modelled for manufacturing systems are reviewed, and the main approaches used by modelling energy efficiency of such systems are discussed. Then, based on this review, the modelling approach and the energy consumption models for the primary units of manufacturing systems, i.e., the machine tools, as well as the peripheral devices, are proposed. Besides, since the energy efficiency strategy to be developed in this dissertation is based on optimisation, which involve discrete and binary actuators, some modelling approaches for the decision models constrained to discrete sets are presented and discussed. Thus, in this chapter, the way the energy consumption models were obtained and how the discrete set can be modelled for the design of the control strategies in the next chapters are presented.

4.1 Energy Consumption Models of Manufacturing Systems

Since machine tools are the primary units in the manufacturing industry, most of the energy consumption models proposed in the literature are focused on these machines. Thus, at higher levels, the constructed energy consumption model is based on the superposition of the energy consumption of the machines and the peripheral devices. According to [ZLL+16], the energy consumption of a machine tool is equal to power multiplied by time, i.e., the area under the power load profile of the machine tool (see Figure 2.5). In general terms, the power can be computed as the force multiplied by speed. Thus, the strength reflects the deformation of metal material, and the speed accounts for the variation of processing parameters. Based on this statement, most of the used models for energy or power balance equation have been proposed based on the phenomena that govern the machining processes. Some of the approaches used to model the energy consumption at all levels of manufacturing industry are discussed in the next section.

4.1.1 Modelling approaches

According to [ZLL+16], at the machine level, the energy consumption models are mainly based on phenomena and can be roughly divided into three categories. The former class focuses on quickly get a linear relationship between the Specific Energy Consumption (SEC) and the material remove rate for estimating machine cutting energy consumption. The models of the second category analyse the relationship between energy consumption and the processing parameters, while the models of the third type calculate the energy consumption of the parts processing. At multi-machine or higher levels, due to the complexity and size of these systems, energy models can be built as either data-driven statistical model or detailed physical models, taking advantage of the advances in sensing technology [Fen16].

In this regard, different approaches have been addressed for modelling and designing control strategies in manufacturing systems. Among them, the Markov Chains (MC) and Petri Nets (PN) can be highlighted given their great application at both process line and plant levels [PLO19]. The main uses of these approaches have been oriented to model flow lines with a serial movement of jobs among workstations, job shops with more flexibility, assembly lines, among others, which serve as a foundation for design, scheduling, and control. Some applications and more in-depth explanations about these modelling approaches can be found in [DZ18, FLC+18, WFF+17]. Despite the prominent use of MC and PN in the manufacturing systems, they have been focused on modelling the production states of the machine instead of modelling the energy consumption behaviour of such systems. Thus, since the complexity to establish the different machine states, transitions between them, and their connections, data-driven models, such as those obtained from the SI methods, have gained attention into the manufacturing industry to model its energy consumption.

Due to the complexity of manufacturing systems, most of the models used for the design of control strategies are based on input-output correlations from data sets of energy consumption. This latter fact is given since the physical-based models require the full knowledge of several physical dynamics and parameters, which are often hard to represent, compute or estimate [DSD+12, ZLL+16, BPL+16]. As a way to overcome the drawback of requiring physical-based models, the process models obtained from Subspace Identification (SI) methods have gained attention in manufacturing systems management due to they directly deliver a state-space model [Qin06]. Besides, these state-space representations are quite useful for the design of model-based control strategies, in particular for MPC design. As a consequence, SI models have had significant application to the modelling of complex, large-scale, and time-varying-parameter systems [ZBD15, SV17, YLW18], and they have been widely used in manufacturing industries [KM18, MCAM17].

Then, due to the need to obtain suitable energy consumption models for the design of control strategies that can be implemented in real time, SI methods were selected to identify such models. These methods were preferred since linear state-space realizations can be obtained based on input-output data sets, and the design of control systems and the stability and feasibility conditions have been widely studied for such linear representations. Besides, in a manufacturing plant, it is quite difficult to measure/estimate many of the variables/parameters required to obtain phenomenological-based models, which often involve non-linearities that increase the complexity and the computational burden for the design of control strategies based on optimisation. However, the information about the energy consumed in a manufacturing plant usually is available and, for the case studied in this thesis, such information can be obtained in real time at high sampling frequencies. In this regard, given the simplicity of SI methods, the features of resulting models, and their great implementation in Identification Toolboxes, these methods will be used in this thesis for modelling of energy consumption of manufacturing systems.

4.1.2 Subspace identification methods

The SI methods have been used in this dissertation to determine the energy consumption models for manufacturing systems. Such modelling methods allow identifying the matrices of a state-space linear time-invariant (LTI) model of a real system based on input-output data sets. These algorithms are useful since state-space realisations are more convenient than others for estimation, control, and prediction tasks. Many SI methods are based on algorithms that use both observability and controllability matrices to determine the final model matrices from input-output data from a real system. Thus, given the measurements of $b \geq 1$ input signals and $p \geq 1$ output signals resulting from feeding a dynamic system with such inputs, the SI problem is defined next.

Consider a set of input-output measurements, which satisfies a linear state-space (unknown) realisation of order N for (3.1), i.e.,

$$\mathbf{x}(k+1) = A\mathbf{x}(k) + B\mathbf{u}(k) + \mathbf{w}(k), \tag{4.1a}$$

$$\mathbf{x}(k) = C\mathbf{x}(k) + D\mathbf{u}(k) + \mathbf{v}(k), \tag{4.1b}$$

being $\mathbf{w} \in \mathbb{R}^{\ell}$ and $\mathbf{v} \in \mathbb{R}^{p}$ the state noise and output measurement noise vectors, respectively. Then, in a deterministic case in which $\mathbf{w}$ and $\mathbf{v}$ are neglected, the SI problem consist of [ODM96]:

(a) Estimate the system order N.

(b) Estimate the systems matrices $A \in \mathbb{R}^{\ell\times\ell}$, $B \in \mathbb{R}^{\ell\times b}$, $C \in \mathbb{R}^{p\times\ell}$, and $D \in \mathbb{R}^{p\times b}$.

According to [ODM96], to determine both N and the system matrices (A, B, C, D), two different classes of SI algorithms have been proposed. The former class uses the state estimation $\hat{\mathbf{x}}$ to determine the systems matrices, while the second class uses the extended observability matrix O_i to first estimates the matrices A and C, and then, B and D. Some examples of the first class of algorithms are the Canonical Variate Analysis (CVA) and Numerical algorithm For Subspace Identification (N4SID), while a representative example of the second class is the Multi-variable Output Error State Space (MOESP) algorithm [DMVOF99]. The algorithms of the first class are based on concepts from system theory, the unifying theorem, linear algebra and statistics, and they can be generalised in two steps:

1. Determine N and a state sequence $\{\hat{\mathbf{x}}_1, \hat{\mathbf{x}}_2, \cdots, \hat{\mathbf{x}}_k, \hat{\mathbf{x}}_{k+1}\}$. For this end, the row spaces of data block Hankel matrices are projected, and then a singular value decomposition is applied.

2. Solve the least-squares problem to obtain the state-space matrices based on state estimation $\hat{x}$, and the measurements $\mathbf{u}$ and $\mathbf{y}$.

In this way, N and O_i are obtained directly from the singular value decomposition for the oblique projection (Θ_h). Based on this, N is fixed as the number of the singular values different to zero of Θ_h. Then, once N and O_i are determined, $\hat{\mathbf{x}}$ is obtained and, then, the model matrices A, B, C, D are computed. A summary of this procedure is presented in [VH16]. Likewise, general reviews of different SI algorithms and their implementations are introduced in [Qin06, ODM96, DMVOF99]. It is worth noting that the model states obtained by using SI methods lack physical sense and they are not directly related to the process variables.

To obtain a state-space representation of energy consumption models as the one shown in (4.1), the N4SID algorithm was selected due to its great application and implementation in software [Qin06, VH16]. The N4SID algorithm belongs to the family of projection-based algorithms since they determine state sequences through the projection of input and output data. Then, the state-space matrices are determined based on the state sequence. According to [OM94], the projection is crucial because it retains all the past information that is useful to predict the future. Besides, the state sequences are shown to be outputs of non-steady state Kalman filter banks, from which it is easy to determine the state space system matrices by solving a least-squares problem after the model order N is established. In the N4SID algorithm, the model matrices are computed as full state-space matrices in an almost optimally conditioned basis instead of in their canonical forms like in most of the proposed algorithms. This basis is uniquely determined, and therefore, there are not problems of identifiability. Besides, for the implementation, the observability/controllability index is not required in advanced. In Algorithm 4.1, the main steps for the N4SID algorithm are summarised.

Algorithm 4.1 Deterministic SI [OM94].

1: Determine the projection from input-output data sets
2: Determine the SDV
3: N equal to the number of non-zero singular values
4: Determine the least square solution to find model matrices

One of the main advantages of these algorithms is that additional parametrisation of the initial state is not required when the initial condition is different to zero. That means, in the N4SID algorithm, there is no difference between zero and non-zero initial state [OM94]. Besides, regarding computational burden, these algorithms are of non-iterative nature and do not involve non-linear optimisations. Thus, N4SID algorithm guarantees convergence, does not sensitive to initial conditions, and numerically stable since they only make use of QR decomposition and Singular Value Decomposition (SVD), which is used to determine the order model. This algorithm can be implemented by using the routine `n4sid` of the System Identification Toolbox™ provided by Matlab®. In this regard, to obtain power consumption models of peripheral devices, proper experiments should be performed for getting suitable input-output data sets.

4.1.3 Test bench of a machine tool and peripheral devices

In this section, some of the energy consumption models used in the development of this dissertation are presented. Since the machine tools are the primary units of the manufacturing industry, and the peripheral devices have great importance at all industrial levels considered, only energy consumption models were developed for these two elements. Thus, at higher levels, the energy consumption should be computed as the sum of the different parts that form each level. For instance, at the line level, the energy consumption will be calculated as the sum of the energy consumption of the machines and peripheral devices in the process line at each instant k.

In this regard, a test bench has been built to emulate the energy consumption behaviour of a manufacturing machine and its peripheral devices to extract data for the modelling process by using SI. Therefore, according to Figure 2.5, machine tools are characterised by a periodic behaviour in their energy consumption according to the different processing stages. This periodic behaviour corresponds to the operation cycle T_{M_i} of the machines to process a piece. Thus, to represent several processing stages and their energy consumption, different types of loads were considered to emulate the real power consumption of both manufacturing and peripheral devices.

Thus, the test bench is composed of a three-phase delta connection motor, a three-phase start connection motor, a heater, two Uninterruptible Power Supply (UPS) devices with different elements connected like loads (e.g., fans, lamps), and safety elements (e.g., regulators, relay). Moreover, a set of electronic devices, a PC, and a development board are included to control relays, allowing either activation or deactivation of the test-bench components according to an activation sequence sent. Besides, a data acquisition module with a sampling rate up to $250\,\mu$s is included to take data and send to both the development board and central PC, which receive the power signals according to the activation sequence informed to the test bench. An electrical diagram of the test bench with the connected loads is shown in Figure 4.1.

Due to the periodic behaviour of the considered systems, the test-bench components were classified as peripheral and manufacturing devices to design the machining sequence of a machine, and therefore, its associated energy consumption profile. Thus, the heater and a UPS with a lamp and a fan connected were selected to construct the periodic sequence since that selection allows modulating loads to represent the different manufacturing stages. On the other hand, the available motors and a UPS with two fans connected were considered as the peripheral devices since they usually produce instantaneous peaks when they are activated. Thus, this behaviour

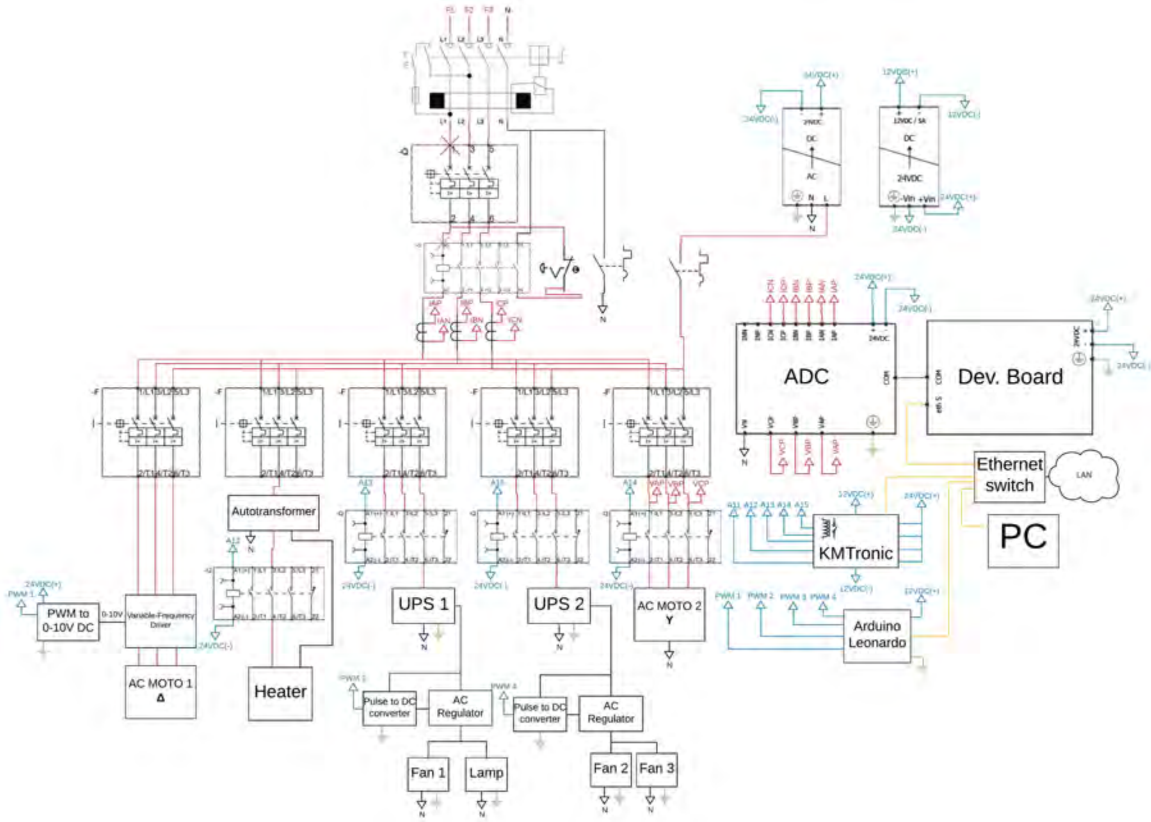


Figure 4.1: Electrical diagram of test bench of the machine tool emulator.

could be of interest when the suitable activation instants of peripheral devices should be determined. Besides, one of the UPS was also considered as a peripheral device to include a device in which the activation instant and the activation level should be determined. Therefore, based on the modulation in the load for the heater and UPS, machining sequences considering different processing stages, e.g., cutting, milling, drilling, forming, among others, were designed in the test bench.

The procedure followed to design a particular machining sequence is explained below. Considering a machine M_i with a fixed number of machining devices m, such as $l \in \mathcal{L} \triangleq \{1, 2, \cdots, m\}$. The activation sequences of machining devices $u_{M_{i,l}}$ along the machine cycle T_{M_i} define the machining sequence of the i-th machine, denoted as $\mathbf{\Lambda_{M_i}} \triangleq \{u_{M_{i,1}}(k), u_{M_{i,2}}(k), \ldots, u_{M_{i,m}}(k)\}$. Thus, a machining sequence $\mathbf{\Lambda_{M_1}}$ for machine the 1-st machine was created considering $T_{M_1} = 28$ s and different activation sequences for the two machining devices previously defined, i.e., one heater and one UPS with extra loads. In this regard, two processing stages were considered in addition to stages of start-up, stand-by, and

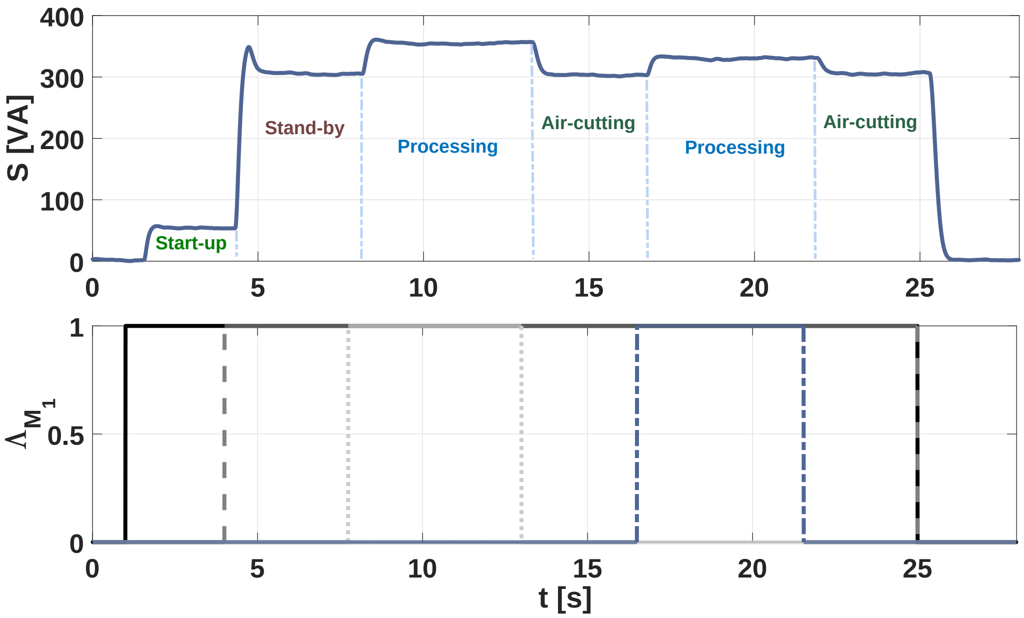


Figure 4.2: Machining sequence and its energy consumption profile for the first machine.

air-cutting, by using different activation levels for both the heater and the UPS with fans connected. Then, before to collect the data from the test bench, different tests were performed to determine the most suitable sampling rate for taking the data that will be used in the model identification. According to the tests performed, a sampling time of $\tau_s = 0.01$s was selected based on a trade-off between the temporal resolution of the signals and the computational burden for the design of the control strategies. The proposed machining sequence $\mathbf{\Lambda_{M_1}}$ and its energy consumption profile are shown in Figure 4.2. Besides, in this figure, the different processing stages are highlighted.

Once the peripheral and machining devices were classified and the machining sequence $\mathbf{\Lambda_{M_1}}$ was designed, different activation sequences of peripheral devices u_{P_j} (motors and UPS) and $\mathbf{\Lambda_{M_1}}$ were tested in the test bench in order to obtain their corresponding power consumptions, i.e., S_{P_j} and S_{M_i} for the j-th peripheral device and the i-th machine, respectively. Then, according to the inputs sent to the test bench, i.e., u_{P_j} and $\mathbf{\Lambda_{M_1}}$, and its associated outputs, suitable input-output data sets were obtained and used for the modelling process. The data sets used in the model identification for both machining and peripheral devices are presented in Figure 4.3. Based on these data sets, different values of N were tested by using the routine `n4sid` of the System Identification Toolbox™ provided by Matlab® with the aim to identify the suitable matrices A, B, C, and D, which allow the highest fit degree between the real and

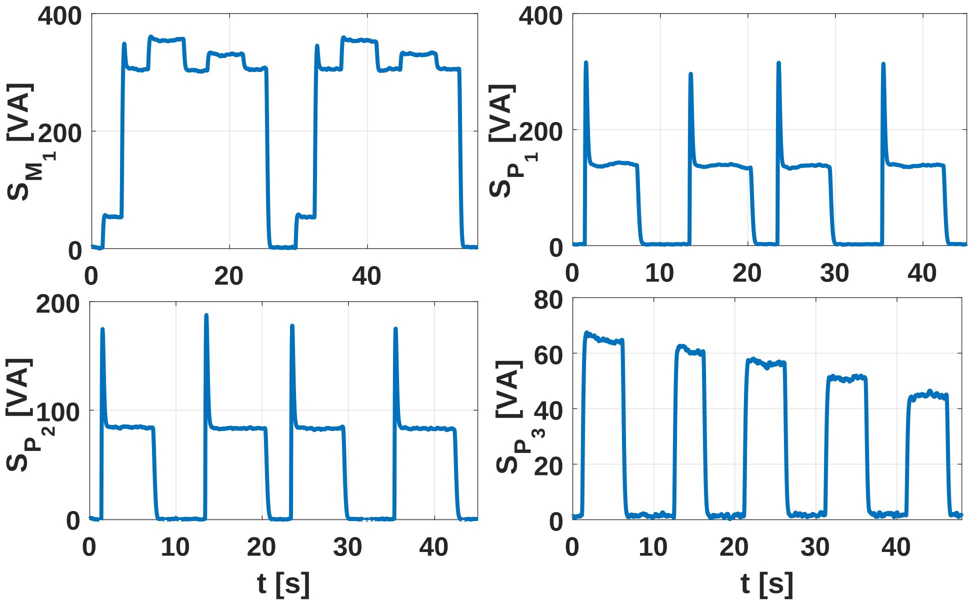


Figure 4.3: Real data of energy consumption of the 1-st machine and peripheral devices in the test bench.

modelled outputs. This procedure was performed for each one of the peripheral devices and the designed machining sequence, considering the three phases of the test bench according to Figure 4.1. However, since all devices in the test bench were connected to the phase B, only the corresponding results to this phase will be presented although all the analyses proposed in this dissertation can be properly extended for handling devices connected to all phases.

Then, according to the data set taken from the test bench and the state-space realisation in (4.1), the system inputs correspond to $\mathbf{\Lambda_{M_i}}$ and u_{P_j} for the machines and peripheral devices, respectively. Similarly, the system outputs refer to the instantaneous energy consumption S_{M_i} and S_{P_j} for the i-th machine and the j-th peripheral device resulting from applying the system inputs, respectively. Thus, according to the input-output data sets and Algorithm 4.1, the matrices in (4.1) for the energy consumption models of the machine and peripheral devices were computed and are presented next:

- Model matrices for the 1-st machine:

$$A_{M_1} = \begin{bmatrix} 0.9661 & 0.007732 & -0.03212 \\ -0.01149 & 0.9989 & -0.01347 \\ 0.1044 & 0.0183 & 0.944 \end{bmatrix} \tag{4.2}$$

$$B_{M_1} = \begin{bmatrix} 0.0001606 & 0.00319 & 0.0003486 & 0.0009717 \\ 9.138 \times 10^{-5} & 0.0008494 & 0.0002706 & 0.0004479 \\ -0.004008 & -0.01527 & -0.003393 & -0.0002734 \end{bmatrix} \tag{4.3}$$

$$C_{M_1} = \begin{bmatrix} 4.389 & -12.83 & -7.845 \\ 1985 & 5.402 & -18.28 \\ 52.81 & -51.87 & -1.532 \end{bmatrix} \quad D_{M_1} = 0 \tag{4.4}$$

- Model matrices for the delta-connection motor (P_1):

$$A_{P_1} = \begin{bmatrix} 0.9907 & 0.01979 & -0.05751 \\ -0.0092 & 0.981 & -0.01696 \\ 0.1179 & 0.04711 & 0.8358 \end{bmatrix} \tag{4.5}$$

$$B_{P_1} = \begin{bmatrix} -0.002313 & 0.0006303 \\ -0.009749 & 0.007604 \\ -0.1026 & 0.08011 \end{bmatrix} \tag{4.6}$$

$$C_{P_1} = \begin{bmatrix} 1102 & -47.29 & -28.02 \\ 1176 & -37.82 & -25.61 \\ 963.9 & 53.36 & -9.84 \end{bmatrix} \quad D_{P_1} = 0 \tag{4.7}$$

- Model matrices for the start-connection motor (P_2):

$$A_{P_2} = \begin{bmatrix} 0.9769 & -0.09587 & 0.04002 \\ 0.03737 & 0.9145 & 0.01567 \\ -0.03534 & 0.07357 & 0.9519 \end{bmatrix} \tag{4.8}$$

$$B_{P_2} = \begin{bmatrix} 0.01416 & 0.0006692 \\ -0.08568 & 0.09188 \\ 0.1041 & -0.1079 \end{bmatrix} \tag{4.9}$$

$$C_{P_2} = \begin{bmatrix} 580.4 & 47.48 & 40.89 \\ 669.4 & -35.38 & 3.535 \\ 554.8 & -38.06 & -34.75 \end{bmatrix} \quad D_{P_2} = 0 \tag{4.10}$$

Table 4.1: Model order and fitting percentage between real and modelled output.

Component	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{\Lambda_{M_1}}$
% fit	92.33	90.39	80.04	90.76
N	3	3	3	3

- Model matrices for UPS (P_3):

$$A_{P_3} = \begin{bmatrix} 0.9525 & -0.004772 & -0.001036 \\ -0.01279 & 0.9983 & -0.0001262 \\ -0.004169 & -0.0001779 & 0.9947 \end{bmatrix} \tag{4.11}$$

$$B_{P_3} = \begin{bmatrix} 1.266 \times 10^{-5} \\ 3.418 \times 10^{-6} \\ 1.119 \times 10^{-6} \end{bmatrix} \tag{4.12}$$

$$C_{P_3} = \begin{bmatrix} 37.34 & -99.63 & -106 \\ 1767 & 37.9 & 0.8116 \\ 127.7 & -474.6 & 26.17 \end{bmatrix} \quad D_{P_3} = 0 \tag{4.13}$$

It should be noted that for the motors, the matrices B_{P_1} and B_{P_2} that relate the model states and inputs were obtained considering two inputs. This fact is a result of adding a new pulse to model correctly the peaks produced in energy consumption profile when the motors are activated. In this regard, the second input for each device is equal to the first input delayed some samples, while the first input corresponds to the real activation/deactivation of the motor, i.e., $u_{2P_j}(k) = u_{P_j}(k - d_{P_j})$. The underlying idea behind the new input is to create an additional effect that allows achieving the heigh of power peaks according to the real data. Thus, the second input is delayed $d_{P_1} = 5$ and $d_{P_2} = 3$ samples with respect to the first input for the peripheral device P_1 and P_2, respectively. Then, based on the model matrices obtained, the model validation for energy consumption models of both peripheral devices and the machining sequence of M_1 are presented in Figure 4.4. Finally, the model order and the fit degree between the modelled and real output are summarised in Table 4.1.

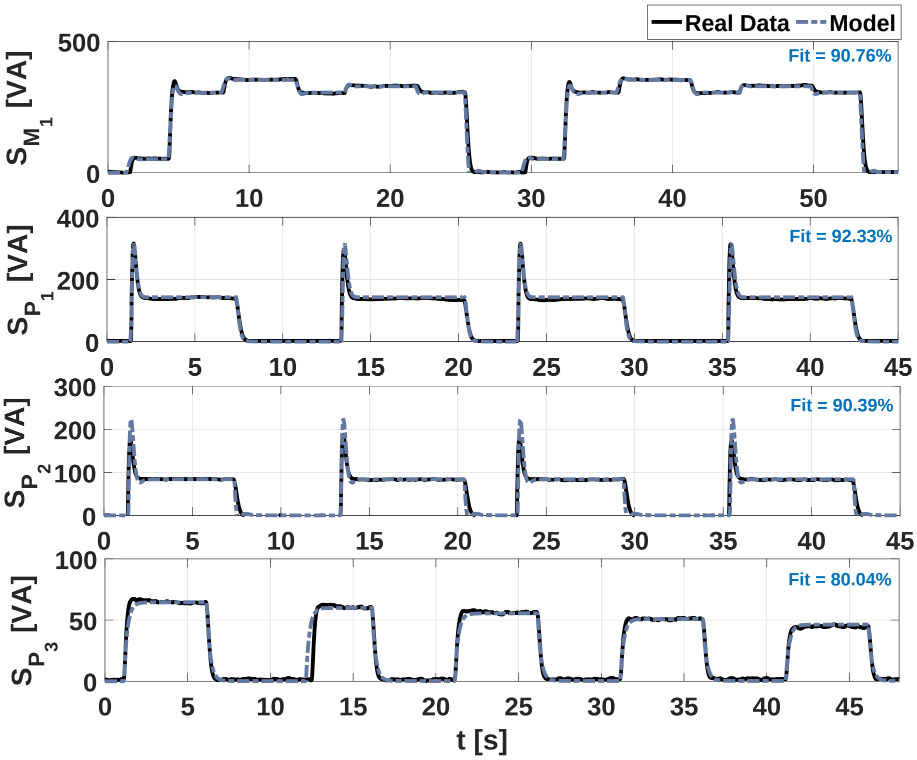


Figure 4.4: Validation of energy consumption models of peripheral devices (P_j) and machining sequence (M_1).

4.2 Modelling Approaches for Closed-loop Decision Making over Discrete Domains

In many industrial processes, both the optimal design and the implementation of optimisation-based control techniques often require variables constrained to a discrete set of admissible values. Some relevant applications of the use of discrete input signals can be found in chemical processes [NY16], process planning and scheduling [LGL+17], and on-off systems [GMC+10] (e.g., power electronics converters) in which the decision variable is constrained to binary selections. Thus, both the problem formulation and the discrete optimisation method are crucial to solve these optimisation problems in a proper and fast way. This last fact is critical to control applications subject to real-time implementation constraints [RM09].

However, the use of discrete decision variables would imply a high computational burden for the optimisation routines. In most of the control applications, the decisions that involve discrete actuators are removed from the control layer and dealt with logic rules and heuristic approximations [RR17, PSON12]. Moreover, with the advances in computer performance and optimisation software, the conventional manner to solve such problems is done by transforming them into a Mixed-Integer Linear Programming (MILP) problem and solving them by using branch-and-bound-based MILP solvers such as the ones available in packages like `cplex` [ILO13] and `gurobi` [GO19]. Based on this approach, to choose among n discrete values in an MIP problem, n binary variables that sum up to one are required [YV13]. Nonetheless, if the optimisation problem is not correctly formulated and the values of discrete terms are not restricted effectively to the feasible alternatives, this approach could lead to unbalanced branch-and-bound trees and it may result in long solution times [AFLN18].

Different approaches have been proposed in the literature to reduce the number of decision variables and the computational time to solve the related problem [PSON16]. However, in more complex cases these approaches imply the product of some polynomial terms, thus losing the linearity. In [LHF16], a set of equations for linearising the discrete cross-product terms is proposed to incorporate these terms into conventional MILP formulations. Similarly, a framework for reformulating Mixed-Integer Non-Linear Programming (MINLP) problems to a convex relaxed form is discussed in [LW18]. As common ideas, trying to avoid both bi-linear and non-linear terms into the problem reformulation is linked to the reduction of the number of decision variables and simplifying the nature of the proposed constraints from the definition stage of the optimisation problem. In this regard, three different ways to model discrete feasible sets will be introduced in this section, including the constraints and limitations to their implementation.

Thus, consider an open-loop optimisation problem as follows:

$$\min_{u_b, u_1, u_2, \ldots, u_d} \quad J\left(\xi(k), u_b, \underbrace{u_1, u_2, \ldots, u_d}_{u_r}\right) \tag{4.14a}$$

subject to

$$f\left(\xi(k), u_b, u_1, u_2, \ldots, u_d\right) = 0, \tag{4.14b}$$

$$g\left(\xi(k), u_b, u_1, u_2, \ldots, u_d\right) \leq 0, \tag{4.14c}$$

$$u_b \in \{0, 1\}^{n_b}, \tag{4.14d}$$

$$u_r \in \underbrace{\{s_{r_1}, s_{r_2}, \ldots, s_{r_n}\}}_{\boldsymbol{\Omega}_r}, \quad r = 1, 2, \ldots, d \tag{4.14e}$$

being $k \in \mathbb{Z}_{\geq 0}$ the discrete-time index, $\xi \in \mathbb{R}^{n_\xi}$ the state vector (assumed to be available at each time instant k), $J(\cdot)$ a cost function related to either tracking or economical objective, and f, g non-linear/linear maps relating the inputs $u_b, u_1, u_2, \ldots, u_d$ to the system states ξ. Besides, u_b corresponds to the vector of binary inputs of dimension n_b, $\{u_1, u_2, \ldots, u_d\}$ is the set of discrete inputs, and $\mathbf{\Omega}_r \subset \mathbb{R}$ is the discrete and countable finite set of cardinality n_r describing the feasible domain of u_r, with s_{r_n} the values (or symbols) that form the discrete (or alphabet) set $\mathbf{\Omega}_r$.

Taking into account the domain for the decision variables $u_b, u_1, u_2, \cdots, u_d$ in (4.14), suitable ways of modelling their domains are required to reduce the computational burden when the number of decision variables increases. This latter fact is important for the implementation of closed-loop control strategies based on optimisation, in which the optimisation problem should be solved fast enough at each instant k such that the controller can be implemented in real-time using the result of the optimisation (4.14). Therefore, to model discrete sets such as $\mathbf{\Omega}_r = \{s_{r_1}, s_{r_2}, \ldots, s_{r_n}\}$ (or alphabet sets when S_{r_n} represent some feature, state, decision, among others), the nature of the decision variables and suitable mathematical expressions to represent the admissible values should be determined and added to the optimisation problem.

In this regard, three different ways of modelling the decision variables constrained to discrete (or alphabet) sets are proposed. These approaches include different manners to model the domain of the decision variables and the required constraints to guarantee the selection of the admissible values according to their operating ranges. It should be noted that the different ways to model the discrete (or alphabet) sets have as ultimate goal the formulation of a compact 0-1 MILP problem. Thus, the decision variables constrained to belong to the set $\mathbf{M} = \{0, 1\}$ will be directly transposed to a binary variable. The main differences among the proposed approaches concern the number of both binary and continuous variables required and the suitable constraints to guarantee the discrete values for the decision variables. In particular, mathematical tools and representations such as rounding error and polyhedrons have been employed to constrain the discrete sets and to reduce the number of binary variables required. Thus, the proposed approaches to model the discrete domain for u_r, i.e. $\mathbf{\Omega}_r$, are presented below.

4.2.1 Approach 1: Rounding-error based strategy

In order to model a discrete set $\mathbf{\Omega}_r$ by using the rounding error, the following statement is assumed:

Assumption 4.1. *A discrete set* $\mathbf{\Omega}_r = \{s_{r_1}, s_{r_2}, \ldots, s_{r_n}\}$ *with* $s_{r_n} \in \mathbb{R}$ *is an ordered set in* *which all its elements have a regular spacing ρ.* □

Under this assumption, to model the discrete feasible set $\mathbf{\Omega}_r$ the following decision variable is required:

$$\tilde{u}_r \in [\underline{\varepsilon}, \overline{\varepsilon}] \text{, with } \overline{\varepsilon} = \max(\mathbf{\Omega}_\mathrm{r}), \underline{\varepsilon} = \min(\mathbf{\Omega}_\mathrm{r}).$$

Besides, to ensure that only the admissible values in $[\underline{\varepsilon}, \overline{\varepsilon}]$ could be selected, the rounding error should be added as a constraint into the optimisation problem in (4.14) as follows:

$$\left|\rho \left[\left(\frac{\tilde{u}_r}{\rho}\right)\right] - \tilde{u}_r\right| \leq 0, \tag{4.15}$$

with $[\cdot]$ the round operator and ρ the regular spacing among the elements of $\mathbf{\Omega}$. Based on the previous inequality, only the values in $[\underline{\varepsilon}, \overline{\varepsilon}]$ that satisfy $(x \mod \rho) \equiv 0$ can be chosen.

Remark 4.1. For the particular case in which zero belongs to $\mathbf{\Omega}_r$ and its distance to the next element in $\mathbf{\Omega}_r$ does not satisfy the spacing regularity of the rest of the elements, a new variable and an associated constraint will be introduced, e.g., when zero represents the off status and the rest of the elements refer to different activation levels. Thus, zero needs to be considered separately by its nilpotent properties within $\mathbf{\Omega}_r$, and an extra binary variable β_r and a new constraint are also required to represent the activation/deactivation of the discrete set as follows:

$$\underline{\varepsilon}\, \beta_r \;\leq\; \tilde{u}_r \;\leq\; \overline{\varepsilon}\, \beta_r, \tag{4.16}$$

with $\beta_r \in \{0, 1\}$ and $\tilde{u}_r \in [\underline{\varepsilon}, \overline{\varepsilon}]$. Furthermore, this approach could be extended to the case when the spacing ρ among the elements of $\mathbf{\Omega}_r$ is not regular. The original set is split into subsets with regular spacing, which are associated with one binary variable, rounding error equation, and additional constraints over binary variables to guarantee the selection of only one of them. Note however that the number of decision variables and constraints may significantly increases. □

4.2.2 Approach 2: Direct binary approach encoding

Given a set $\mathbf{\Omega}_r = \{s_{r_1}, s_{r_2}, \ldots, s_{r_n}\}$ with $s_{r_n} \in \mathbb{R}$ (or numerical values associated with an alphabet set), one can associate n decision variables such that

$$\gamma_1, \gamma_2, \ldots, \gamma_n \in \{0, 1\},$$

and reinforce the alternative of decision with the constraint

$$\gamma_1 + \gamma_2 + \cdots + \gamma_n = 1. \tag{4.17}$$

Indeed, to model $\mathbf{\Omega}_r$ and to guarantee the selection of only one of the values in this set, the decision variable u_r is computed according to

$$u_r = S_{r_1}\,\gamma_1 + S_{r_2}\,\gamma_2 + \cdots + S_{r_n}\,\gamma_n. \tag{4.18}$$

Remark 4.2. It should be noted that if zero belongs to $\mathbf{\Omega}_r$, $n-1$ binary variables are needed, and the constraint in (4.17) should be relaxed as

$$\gamma_1 + \gamma_2 + \cdots + \gamma_{n-1} \leq 1.$$

□

4.2.3 Approach 3: Geometrical representation of the feasible domain

In this case, the discrete set will be modelled through a polyhedron given as the intersection of inequalities and equalities (referred to as H-representation). In this regard, to get a polyhedron representation of a discrete set, the values of a discrete set $\mathbf{\Omega}_r$ should be fit to each of the vertices of the polyhedra. Thus, some auxiliary variables could be required to design the polyhedra vertices. This procedure is explained below considering a particular discrete set, e.g., $\mathbf{\Omega}_r = \{S_{r_1}, S_{r_2}, S_{r_3}, S_{r_4}\}$. In this case, to model $\mathbf{\Omega}_r$, two binary variables

$$\delta_1, \delta_2 \in \{0, 1\}$$

are required, while $\tilde{u}_r$ is relaxed to $\mathbb{R}$. Next, the discrete values of $\mathbf{\Omega}_r$ will be associated to the combinations of variables δ_1 and δ_2, which define the vertices set V of the polyhedron as

$$V = \{[0, 0, S_{r_1}]; [0, 1, S_{r_2}]; [1, 0, S_{r_3}]; [1, 1, S_{r_4}]\}. \tag{4.19}$$

Then, using suitable tools such as the MP Toolbox, the H-representation (inequality and equality matrices) of the polyhedron $P_v = \{v|A\,v \leq b,\ A_e\,v = b_e\}$, which corresponds to the convex hull of V, should be determined. Afterwards, these expressions should be added as constraints in the optimisation problem such that

$$[\delta_1, \delta_2, \tilde{u}_r]^T \in P_v. \tag{4.20}$$

Based on this formulation, for any combination of the binary variables, only the values in $\mathbf{\Omega}_r$ satisfy the inequality and equality matrices added as constraints. It should be noted that in this case, any assumption about regularity within the set $\mathbf{\Omega}_r$ was relaxed. Therefore, this formulation may be less restrictive when the number of binary variables and the vertices of the polytope is properly selected.

4.2.4 Comparative assessment

To test the approaches previously explained regarding their performance and computational burden, an optimisation-based controller, designed to improve the energy efficiency of a process line is studied[1]. It should be noted that the second manufacturing level has been considered for testing the proposed methods since, at this level, more complex relationships between machines and peripheral devices could exist. Besides, due to the large scale of manufacturing systems at this level, the number of decision variables might significantly increases, and the comparison of the proposed approaches could be more interesting.

In this regard, the proposed approaches will be used to model the decision variables constrained to discrete sets into the optimisation problem behind a predictive-like controller designed to manage the activation instants of the peripheral devices of a process line without affecting the process line productivity. A process line is a complex system including several machines and peripheral devices that work sequentially and subject to logic constraints. Machines correspond to a set of devices that are directly related to machining processes, while the peripheral devices are those devices that provide the resources required by the machine tools for their proper operation. Thus, there exist several functional relationships between machines and peripheral devices that determine the productivity of the process line. In Figure 4.5, a serial process line with b machines and divided into n sub-systems is shown. It should be noted that

[1]This control strategy is more in-depth explained in Chapter 6. However, it is briefly described in this section to present the results concerning the computational burden for the approaches proposed to model discrete sets.

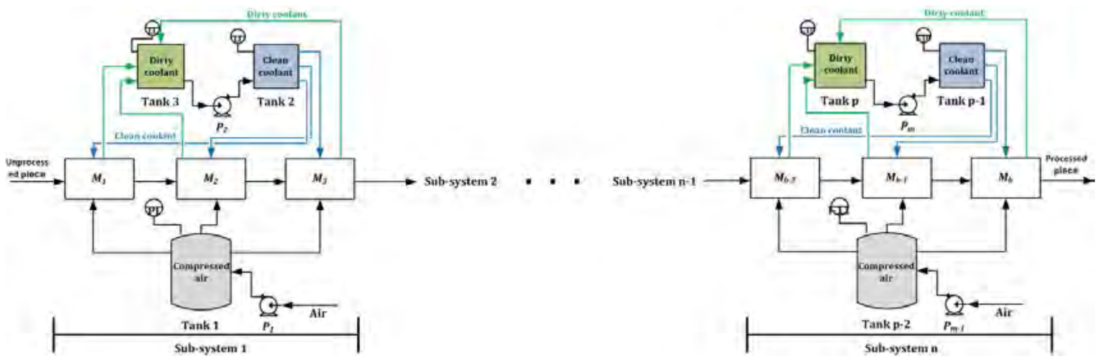


Figure 4.5: n-stage serial process line with its corresponding peripheral devices.

each sub-system is formed by the same set of three machines and two shared peripheral devices.

It is worth noting that to keep the same productivity of the process line that when the control strategy is not implemented, the machining sequences $\mathbf{\Lambda_{M_i}}$ have been considered as fixed and periodic over the time, assuming they are already optimised regarding energy consumption. This last fact implies that the time T_{M_i} to process a piece remains the same and, therefore, the process line can handle the same number of pieces as when the control/supervision strategy is not implemented. Besides, since $\mathbf{\Lambda_{M_i}}$ is considered fixed and periodic according to the machining sequence, its associated energy consumption will be also constant over any interval T_{M_i} and periodic along the time. On the other hand, peripheral devices in the process line could or could not operate in a periodic fashion, which could match with the machine cycle T_{M_i}.

Consider the first sub-system in Figure 4.5 with three machines and two peripheral devices as the whole process line. It is assumed that all machines in the the process line have the same period, i.e., $T_{M_i} = 28$ s $\forall\, i = 1, 2, 3$, and that the peripheral devices P_{G_1} and P_{G_2} are shared among the three machines in the process line. Then, an MPC controller has been designed based on an open-loop optimisation problem that minimises the global energy consumption S along a prediction horizon $H_p = T_{M_i}$, and taking into account the operating constraints of the machines and their peripheral devices as follows:

$$\min_{\mathbf{\Gamma_G(k)}} \quad J\left(\xi_{G_1}, \xi_{G_2}, u_{G_1}, u_{G_2}\right) \tag{4.21a}$$

subject to

$$\xi_{G_1}(k+r+1|k) = f_1\left(\xi_{G_1}(k+r|k), u_{G_1}(k+r|k)\right), \tag{4.21b}$$

$$S_{G_1}(k+r|k) = f_2\left(\xi_{G_1}(k+r|k)\right), \tag{4.21c}$$

$$\xi_{G_2}(k+r+1|k) = f_3\left(\xi_{G_2}(k+r|k), u_{G_2}(k+r|k)\right), \tag{4.21d}$$

$$S_{G_2}(k+r|k) = f_4\left(\xi_{G_2}(k+r|k)\right), \tag{4.21e}$$

$$Q_h(k+r+1|k) = q_h(Q_h(k+r|k), u_{G_1}(k+r|k), u_{G_2}(k+r|k), \mathbf{\Lambda_{M_i}}(k+r|k)), \tag{4.21f}$$

$$u_{G_1}(k+r|k) \in \{0,1\}, \tag{4.21g}$$

$$u_{G_2}(k+r|k) \in \mathbf{\Omega}_2 \triangleq \{0, 100, 120, 140\}, \tag{4.21h}$$

$$Q_h(k+r+1|k) \in \left[\overline{Q}_h\ \underline{Q}_h\right], \tag{4.21i}$$

and the logical constraints

$$\Delta u_{G_1}(k+r|k) \neq 0 \Longleftrightarrow u_{G_1}(k+r|k : k+r+5|k) = u_{G_1}(k+r|k), \tag{4.21j}$$

$$\Delta u_{G_2}(k+r|k) \neq 0 \Longleftrightarrow u_{G_2}(k+r|k : k+r+5|k) = u_{G_2}(k+r|k), \tag{4.21k}$$

with $r \in \{0, 1, 2, .., H_p - 1\}$ and $h = \{G_1, G_2\}$. Besides, in (4.21),

$$J(k) = \sum_{k=1}^{H_p} \left[\sum_{i=1}^{b} (S_{M_i}(k)) + S_{G_1}(k) + S_{G_2}(k) \right] \Delta k \tag{4.22}$$

represents the cost function defined as the integral of the energy consumption signal over the horizon H_p with $\Delta k = (t_k - t_{k-1})$ the temporal spacing, $S_{M_i} \in \mathbb{R}$ the instantaneous power consumption of the machines, $S_{G_j} \in \mathbb{R}$, $\forall j = 1, 2$, the instantaneous power consumption of peripheral devices, and

$$\mathbf{\Gamma_G}(k) \triangleq \{\mathbf{\Lambda_{P_G}}(k|k), \ldots, \mathbf{\Lambda_{P_G}}(k + H_p - 1|k)\} \tag{4.23}$$

refers to the sequence along H_p of the vector of decision variables $\mathbf{\Lambda_{P_G}}(k|k) = \{u_{G_1}(k|k), u_{G_2}(k|k)\}$. In addition, $\xi_{G_1} \in \mathbb{R}^{n_1}$ and $\xi_{G_2} \in \mathbb{R}^{n_2}$ are the system states related to energy consumption models for P_{G_1} and P_{G_2}, respectively, while $f_1 : \mathbb{R}^{n_1} \times \{0,1\} \mapsto \mathbb{R}^{n_1}$ and $f_3 : \mathbb{R}^{n_2} \times \mathbb{R} \mapsto \mathbb{R}^{n_2}$ are linear maps in function of both the current state and the inputs u_{G_1} and u_{G_2}. Moreover, $f_2 : \mathbb{R}^{n_1} \mapsto \mathbb{R}_{\geq 0}$ and $f_4 : \mathbb{R}^{n_2} \mapsto \mathbb{R}_{\geq 0}$ are the linear maps that relate the system states to the energy consumption for P_{G_1} and P_{G_2}. It should be noted that (4.21j) and (4.21k) are added to avoid damage in peripheral devices produced by high switching frequencies.

In addition, $Q_h(k)$ corresponds to states related to the dynamics of peripheral devices, with $q_h : \{0,1\} \times \mathbb{R} \mapsto \mathbb{R}_{\geq 0}$ the maps that consider the relationships between machines and peripheral devices. In this case, P_{G_1} is associated to the supply system of compressed air, which will be used for clamping pieces during the whole machining sequence. Besides, it is assumed that P_{G_1} has a nominal energy consumption whenever the device is turned on. Therefore, the q-relations associated to P_{G_1} correspond to the dynamics for the total change of mass M_{T_1} and pressure P_{T_1} inside a storage tank T_1, which are expressed in the discrete-time version as follows:

$$M_{T_1}(k+r+1|k) = M_{T_1}(k+r|k) + \tau_s\, \sigma(k+r|k), \tag{4.24a}$$

$$\sigma(k+r|k) = m_{in}\, u_{G_1}(k+r|k) - \sum_{i=1}^{b} m_{out_{M_i}}(k+r|k), \tag{4.24b}$$

$$P_{T_1}(k+r|k) = \frac{M_{T_1}(k+r|k)\, R\, T}{V_{T_1}\, W_{air}}, \tag{4.24c}$$

with τ_s the sampling time, $m_{out_{M_i}}$ the air consumption from M_i, m_{in} the air flow pumped by P_{G_1} towards the tank T_1, and, R, T, V_{T_1}, and W_{air} the gas constant, air temperature, volume of T_1, and the molecular weight of the air, respectively. Based on the physical dimensions of these systems, P_{T_1} must satisfy $\underline{P}_{T_1} \leq P_{T_1} \leq \overline{P}_{T_1}$.

On the other hand, P_{G_2} represents a coolant-supply system with re-circulation, from which a constant flow of coolant m_c is pumped from a dirty-coolant tank T_3 towards a clean-coolant tank T_2 passing through a filter in which the fine particles are separated. The coolant flows required by the machines are pumped from T_2. In this case, both the activation instant and the proper flow of coolant to satisfy the operating constraints must be selected. This latter fact means that the activation of P_{G_2} can be modulated along different energy consumption levels, such that $u_{G_2} \in \mathbf{\Omega}_2 \triangleq \{0, 100, 120, 140\}$. The dynamics for level changes in both tanks are

$$L_2(k+r+|k) = L_2(k+r|k) + \tau_s\, \gamma(k+r|k) \left(\frac{1}{\rho_c\, A_{T_2}}\right), \tag{4.25a}$$

$$\gamma(k+r|k) = m_c(k+r|k) - \sum_{i=1}^{b} m_{out,c_{M_i}}(k+r|k), \tag{4.25b}$$

$$L_3(k+r+1|k) = L_3(k+r|k) + \tau_s\, \theta(k+r|k) \left(\frac{1}{\rho_c\, A_{T_3}}\right), \tag{4.25c}$$

$$\theta(k+r|k) = \sum_{i=1}^{b} m_{in,c_{M_i}}(k+r|k) - m_c(k+r|k), \tag{4.25d}$$

$$P_{out}(k+r|k) = P_{in}(k+r|k) + \rho_c h_{f_{1\to 2}}(k+r) - \eta \left(\rho_c\, \frac{W(k+r|k)}{m_c(k+r|k)}\right), \tag{4.25e}$$

with $m_{out,c_{M_i}}$ the coolant flow required by the i-th machine, and $m_{in,c_{M_i}}$ the flow of the dirty coolant recovered. In addition, P_{in} and P_{out} correspond to the input and output pressure in the pipe system that transports the coolant from T_3 towards T_2, while, ρ_c, η, W and $h_{f_{1\to 2}}$ are the coolant density, efficiency of the pump, the work supply to the pump and the energy losses by friction, respectively.

Modelling of the discrete set $\mathbf{\Omega}_2$ for $\mathbf{u_{G_2}}$

Then, taking into account the variables to be optimised in (4.21), both nature and the total number of decision variables required, as well as constraints needed to model $\mathbf{\Omega}_2$ are presented below.

- ***Approach 1***: If zero is removed to the set $\mathbf{\Omega}_2$ and an extra variable is added to represent the switching off of P_{G_2}, i.e. $u_{G_2} = 0$, it is possible to fix $\rho = 20$ for the rest elements in $\mathbf{\Omega}_2$. Thus, three decision variables are required:

$$u_{G_1}(k), \beta_{G_2}(k) \in \{0, 1\},$$

and

$$\tilde{u}_{G_2}(k) \in [100, 140]\,,$$

with u_{G_1} related to P_{G_1}, and β_{G_2} and $\tilde{u}_{G_2}$ defined to model the discrete set $\mathbf{\Omega}_2$. Then, considering $\overline{\beta} = 100$, $\underline{\beta} = 140$, $\rho = 20$, and β_{G_2} for the switching off of P_{G_2}, the constraints

$$\left| 20 \left[\left(\frac{\tilde{u}_2(k)}{20} \right) \right] - \tilde{u}_2(k) \right| \leq 0, \tag{4.26}$$

$$100\, \beta_{G_2}(k) \;\leq\; \tilde{u}_2(k) \;\leq\; 140\, \beta_{G_2}(k), \tag{4.27}$$

should be added to the optimisation problem in (4.21). Based on this analysis, one binary variable and one continuous variable are required to model $\mathbf{\Omega}_2$.

- ***Approach 2***: In this *full* binary encoding, four binary variables are required to represent the domain of decision variables, i.e.,

$$u_{G_1}(k), \gamma_1(k), \gamma_2(k), \gamma_3(k) \in \{0, 1\}\,,$$

with u_{G_1} related to the activation/deactivation of P_{G_1}, and, according to Remark 4.2, three binary variables γ_1, γ_2 and γ_3 are required to model the discrete set $\mathbf{\Omega}_2$ together with the following constraint:

$$\gamma_1(k) \ + \ \gamma_2(k) \ + \ \gamma_3(k) \leq 1. \tag{4.28}$$

Finally, u_{G_2} is given by

$$u_{G_2}(k) = 100\gamma_1(k) \ + \ 120\gamma_2(k) \ + \ 140\gamma_3(k) \tag{4.29}$$

and, therefore, three binary variables are required to model $\mathbf{\Omega}_2$.

- ***Approach 3***: In this case, one binary variable for the activation/deactivation of P_{G_1} is required, i.e., $u_{G_1}(k) \in \{0,1\}$, while three variables are needed to model $\mathbf{\Omega}_2$:

$$\delta_1(k), \delta_2(k) \in \{0,1\}\,, \text{ and } \tilde{u}_{G_2}(k) \in \mathbb{R}.$$

Taking into account that every combination of the binary variables δ_1 and δ_2 is related to one element in the set $\mathbf{\Omega}_2$, a polyhedron with vertices

$$V_{G_2} = \{[0,0,0]\,[0,1,100]\,[1,0,120]\,[1,1,140]\}$$

is defined and shown in Figure 4.6. Next, using the MP Toolbox, the H-representation of the polyhedron could be obtained and, the following inequality matrix is added into the set of constraints on the optimisation problem in (4.21):

$$\begin{bmatrix} -0.768 & -0.640 & 0.006 & 0 \\ 0.986 & 0.164 & -0.008 & 0 \\ 0.371 & 0.928 & -0.009 & 0 \\ -0.436 & -0.218 & 0.011 & 0.873 \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \\ \tilde{u}_{G_2} \\ -1 \end{bmatrix} \leq \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}. \tag{4.30}$$

Thus, a total of two binary variables and one continuous variable are required to model $\mathbf{\Omega}_2$.

Simulation results

The control strategy was tested using each one of the proposed approaches to compare their performance and computational burden. All simulations were performed using an Intel Core

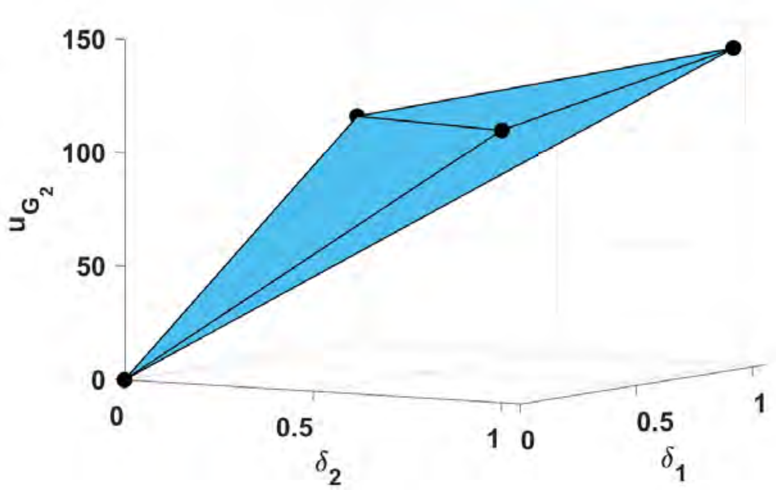
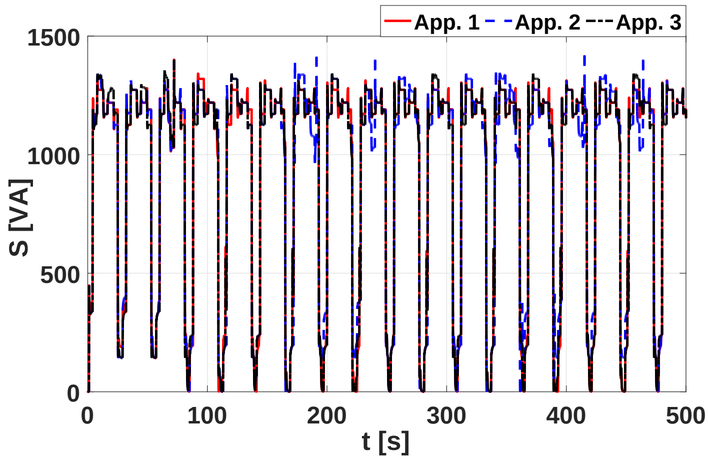


Figure 4.6: Polyhedron for the discrete set $\mathbf{\Omega}_2$.

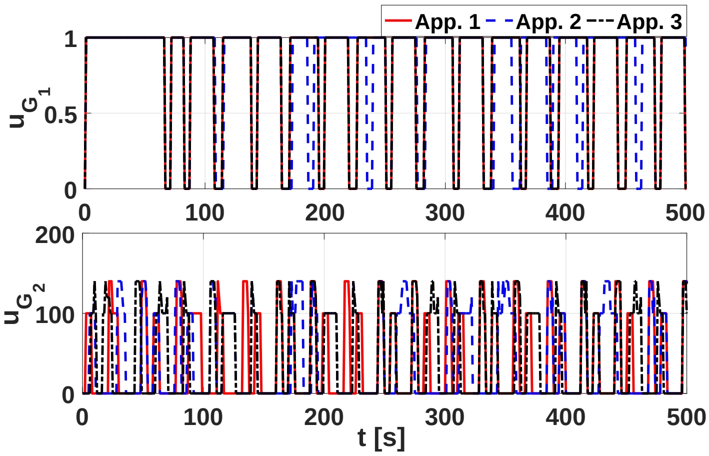
i7-55000U 2.4 GHz processor with 8G RAM and considering a sampling time equal $\tau_s = 0.1$ s. The simulation results were obtained in Matlab by using the software IBM ILOG CPLEX Optimisation Studio [ILO13] integrated to YALMIP toolbox [Löf04].

The resulting energy consumption profile and the optimal activation/deactivation sequence of peripheral devices are presented in Figures 4.7a and 4.7b,respectively, for the case in which only one sub-system is analysed, i.e., $n = 1$. In addition, in Figure 4.7c the dynamics corresponding to the devices P_{G_1} and P_{G_2} are shown. From these results, some differences can be observed for the peripheral device with a discrete domain, i.e., P_{G_2}, for which even when the device was turned on at the same time instant, the activation value $(100, 120, 140)$ was different according to the approach tested. Thus, although the stopping criteria of optimisation routine were the same for all approaches, these differences could be produced because the solver is not able to test all the possible combinations of each approach before reaching the stopping criteria. The latter is because of both the nature and the total number of decision variables are different for each approach and, therefore, the number of the possible combinations could be greater or fewer.

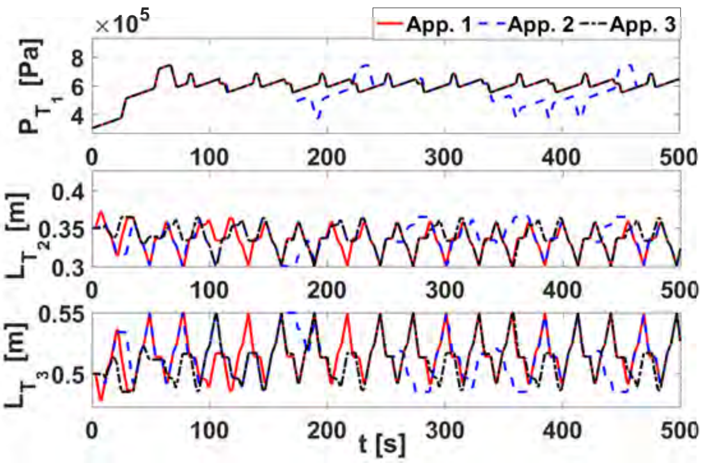
Next, to compare the computational burden when more decision variables are considered, a process line adding subsystems, as shown in Figure 4.5 is studied. It should be noted that for each one of the subsystems added, the operating conditions, machine cycles, energy consumption models, and dynamics of peripheral devices are assumed to be the same that for the first subsystem with three machines and two peripheral devices. In Table 4.2, a comparison of the proposed approaches concerning both the computational burden and the control objective is



(a) Total power consumption.



(b) Optimal input sequences.



(c) Dynamics of peripheral devices.

Figure 4.7: Simulation results of the control strategy using the proposed approaches.

presented when several subsystems are considered as the process line. Concerning the computational load for each approach, the decision variables (DV) along H_p, their classification, the number of equality and inequality constraints, the CPU time and the value of the cost function are shown in Table 4.2.

In Table 4.2, the auxiliary variables (AV) refers to the variables added to model the non-linear operators involved in the rounding error expression. Thus, the total number of decision variables considered by each approach corresponds to the set of both the decision and auxiliary variables. Besides, for Approach 1, all the auxiliary variables added to the decision model were defined as integer variables. Finally, the total number of continuous variables (CV) for Approaches 1 and 3 are summarised in the seventh column. From the results in Table 4.2, it should be noted that the equality constraints are the same for all approaches since they correspond to the initial conditions for both the process model and the machining sequences.

Based on the results in Table 4.2, it is possible to observe that even when the optimal activation sequences of peripheral devices obtained from each approach are different, the total energy consumption is similar for each one of the strategies tested. However, higher differences can be observed in the CPU time spent to solve the optimisation problem at each iteration. Thus, although the Approach 1 has a higher number of total decision variables, the solution is obtained faster than for the rest of the cases. This behaviour is related to the fact that Approach 1 has a lower number of binary variables, and therefore, fewer combinations should be tested, and the completion conditions are achieved faster. Thus, when the branch-and-bound algorithms are employed, the computational burden to evaluate all (or most of) the combinations increases as the binary variables increase. In this regard, by implementing the proposed Approach 1 with a fewer number of binary variables, the computational burden can be reduced even when auxiliary variables are required. However, although both Approaches 2 and 3 need more binary variables to model $\mathbf{\Omega}_2$ than Approach 1, the latter is more restrictive than the other approaches. Thus, when more complex discrete sets with no regular spacing are analysed, Approach 1 could require more binary variables than Approaches 2 and 3, in addition to the auxiliary variables due to both the rounding operator and absolute value.

Finally, according to the proposed formulations, ordered and non-ordered discrete sets could be modelled by using rounding error, binary variables or polyhedral approximations. Thus, based on the obtained results, it is possible to conclude that the total amount of binary variables is a crucial factor regarding the computational burden even when the total number of decision variables is lower. However, despite the computational cost, the approach using binary variables is useful to treat with non-ordered and non-regularly distributed symbol sets, which lead to optimisation problems that can be solved in an efficient manner and with a manageable computational burden.

4.3 Summary

In this chapter, the way the energy consumption models were obtained is presented and discussed. To this end, a test bench was built to emulate the energy consumption of a machine tool and its peripheral devices to collect real data. The energy consumption models were obtained based on SI methods, and the proposed methodology was the same employed to compute the energy consumption of elements of each one of the manufacturing levels considered in this dissertation. On the other hand, three different approaches to reformulate optimisation problems involving discrete and continuous variables into an MILP problem have been presented. According to the proposed formulations, ordered and non-ordered discrete sets could be modelled by using rounding error, binary variables or polyhedral approximations. Besides, necessary constraints to guarantee the selection of the discrete admissible values and the conditions for their implementation were presented and discussed. These approaches have been used to reformulate the decision models involves in the control strategies designed at machine, line and plant levels, which are presented in Chapters 5, 6, and 8.

Table 4.2: Comparison of the proposed approaches regarding their performance and computational burden.

App.	Subsystem n	No. Devices	No. DV along H_p	No. AV along H_p	No. BV along H_p	No. CV along H_p	No. inequality constraints	No. equality constraints	max CPU time per iteration (s)	CPU time (s)	S [VA]
1	1	2	87	58	**58**	29	1033	1977	0.157	**43.278**	1057389.179
2	1	2	116	0	116	0	975	1977	0.563	119.064	1057631.542
3	1	2	116	0	87	29	946	1977	0.390	84.978	1057389.179
1	2	4	174	116	**116**	58	2066	3954	0.875	**241.582**	2114885.914
2	2	4	232	0	232	0	1950	3954	1.172	424.487	2114843.857
3	2	4	232	0	174	58	1892	3954	1.609	661.855	2114506.408
1	3	6	261	174	**174**	87	3099	5931	2.375	**581.211**	3172410.754
2	3	6	348	0	348	0	2925	5931	3.078	1004.515	3171807.409
3	3	6	348	0	261	87	2838	5931	4.781	1019.072	3171530.959
1	4	8	348	232	**232**	116	4132	7908	2.953	**605.873**	4229758.495
2	4	8	464	0	464	0	3900	7908	2.891	1103.728	4229160.288
3	4	8	464	0	348	116	3784	7908	1.983	1105.196	4229503.581
1	5	10	453	290	**290**	145	5165	9885	2.844	**603.630**	5286723.512
2	5	10	580	0	580	0	4875	9885	2.562	1274.541	5286230.569
3	5	10	580	0	435	145	4730	9885	2.218	978.293	5286553.431

CHAPTER 5

MODEL PREDICTIVE CONTROL AT MACHINE LEVEL

5.1 General Considerations

At this level, manufacturing systems are understood as arrangements of different devices that work in a periodic, coordinated and sequential manner, e.g., a machine tool for manufacturing a piece. These devices can be classified into those directly involved into the manufacturing processes (e.g., forming, machining, joining), and those that guarantee the operational conditions of machining processes without their direct participation. These latter are known as peripheral devices and, at higher levels, e.g., in a process line, could be shared by two or more machines or manufacturing systems. According to this classification, most of the strategies implemented so far are mainly oriented to reduce the idle times and the total energy consumption through an off-line optimisation of a particular manufacturing sequence, i.e., process planing and scheduling [ZTP+16]. These approaches are essential and complementary factors regarding energy consumption and flexibility of manufacturing systems. Thus, the problem of process planning and scheduling has been usually formulated as a multi-objective optimisation problem that considers both the make-span and the energy consumption for a machine cycle [YLZ+16, LGL+17]. However, most of the applications of this topic have been mainly oriented to both process line and plant levels.

In addition to the global energy consumption in a fixed period, manufacturing systems can show additional energy costs when their energy consumption exceeds the maximum power purchased, fact that could occur due to the simultaneous activation of several devices, yielding in undesirable power peaks. Therefore, although the off-line optimisation of the activation sequence of manufacturing devices (including or not the peripheral devices) allows improving the energy efficiency of a manufacturing system by minimising its global energy consumption, other concerns must be taken into account to develop strategies that can be successful in real time and when disturbances take place. In this sense, strategies that avoid surpassing the nominal contracted power, e.g., by using selective on/off switching of the peripheral devices [UDOMA17] could be considered.

Some proposals for solving in real time the energy efficiency issue include the design of control systems, from which the peripheral devices can be managed taking into account the energy consumption of the whole set of devices. In this case, OBC techniques, such as MPC, have had a great application due to their high customisation level for defining control objectives, and including the operational constraints of both manufacturing and peripheral devices into the controller design. Likewise, due to the complexity of manufacturing systems, most of the models used for the design of control strategies are based on input-output correlations from data sets of energy consumption. This latter fact is given since the physical-based models require the full knowledge of several physical dynamics and parameters, which are often hard to represent, compute or estimate [DSD+12, ZLL+16, BPL+16].

Since machine tools work in a sequential way to process a piece during a fixed period of time, a periodic behaviour characterises these manufacturing systems according to the total time required for manufacturing a piece, i.e., the *operation cycle* of the i-th machine T_{M_i}. Thus, the energy consumption of devices straight related to manufacturing operations, such as manufacturing processes, transport, and handle of pieces, shows also a periodic behaviour. In addition to the devices directly involved in manufacturing operations, the peripheral devices guarantee the supply of resources (e.g., comprised air, water, coolant, lubricants) to the machining devices, and which might or might not show a periodic behaviour, which may match with T_{M_i}. Therefore, due to the nature of the operations performed in a machine tool (e.g., transport, rotational motions, axial motions, cutting, milling), there exist stages (or modes) of both high and low energy consumption along T_{M_i}.

Based on the stages of both higher and lower energy consumptions along T_{M_i}, peripheral devices must be correctly managed such that their activation time does not match with the time instants/slots of higher consumption of the manufacturing operations, avoiding also (if possible) the simultaneous activation of peripheral devices. Besides, the activation instants of each

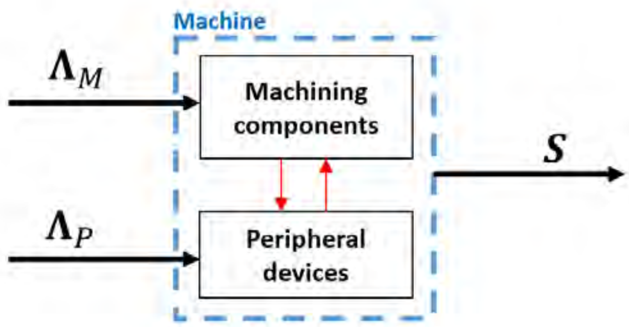


Figure 5.1: General scheme of inputs and outputs of machine tool.

peripheral device should be selected taking into account both its operational constraints and the dependency on the operation cycle of the machine. A machine tool and its associated set of peripheral devices can be represented as shown in Figure 5.1, being $\mathbf{\Lambda_{M_i}}$ the activation sequence of the machining devices of a particular machine i and $\mathbf{\Lambda_P}$ the activation sequence of peripheral devices related to the i-th machine. Besides, S refers to the apparent power consumed by the entire system.

Considering a fixed number of both manufacturing and peripheral devices related to a single[1] machine or system i, the activation sequences for both machining and peripheral devices can be defined as follows:

$$\mathbf{\Lambda_{M_i}}(k) = \{u_{M_{i,1}}(k), u_{M_{i,2}}(k), \ldots, u_{M_{i,m}}(k)\}, \tag{5.1a}$$

$$\mathbf{\Lambda_P}(k) = \{u_{P_1}(k), u_{P_2}(k), \ldots, u_{P_n}(k)\}, \tag{5.1b}$$

being $m = |\mathbf{\Lambda_{M_i}}|$ and $n = |\mathbf{\Lambda_P}|$ the number of manufacturing and peripheral devices in the machine, respectively. Besides, $u_{M_{i,l}}(k) \in \{0,1\}$ with $l \in \mathcal{L} \triangleq \{1, 2, \cdots, m\}$, and $u_{P_j}(k) \in \{0,1\}$ with $j \in \mathcal{J} \triangleq \{1, 2, \cdots, n\}$ are the activation signals of the l-th machining device and the j-th peripheral device, respectively. However, it should be noted that in cases in which the load of the peripheral devices can be modulated at different activation levels, then, u_{P_j} is subject to a discrete and finite set such $u_{P_j} \in \mathbf{\Omega_j} = \{s_1, s_2, \ldots s_n\}$.

For the case of machining devices, the execution times $T_{M_{i,l}}$ are usually fixed and their operation is constrained into T_{M_i} (with T_{M_i} as the upper bound). Therefore, $\sum_{l=1}^{m} T_{M_{i,l}} = T_{M_i}$ holds when only one manufacturing device is turned on and only once during T_{M_i}. On the other hand, since the peripheral devices might not show a periodic behaviour, their operation is

[1]Without lost of generality, this notation represents the case of non-shared peripheral devices. The extension is straightforward and it will address in Chapter 6.

not constrained into T_{M_i} and their execution times T_{P_j} are not necessarily upper bounded by T_{M_i}. Thus, given the periodicity of $\mathbf{\Lambda_{M_i}}$, its apparent power consumption, namely S_{M_i}, can be considered as fixed and periodic. Consequently, both $u_{M_{i,l}}(k)$ and $T_{M_{i,l}}$ are given by the machining processes and are known a priori. In this sense, Assumption 5.1 is established.

Assumption 5.1. *The machining sequence of a machine is previously known, i.e.,* $\mathbf{\Lambda_{M_i}}$ *along* T_{M_i}*, and hence its apparent power consumption, denoted by* $\bar{\beta}_i \triangleq \sum_{k=1}^{T_{M_i}} S_{M_i}(\mathbf{\Lambda_{M_i}}(k))\Delta k$*, will be constant over any interval when a periodic behaviour is considered.* □

It should be noted that in the case Assumption 5.1 is not considered, the activation sequence for the machining devices could also be considered as a decision variable and, then, the time to process a piece in a machine could be modified. That fact means the productivity of the machine tool could be decreased if the processing time is not considered as a control objective. Besides, if the machining sequence is modified, the operational relationships among the machine and peripheral devices will change over time according to the optimised sequences, and a higher computational load could be required to update the constraints every time the controller will be executed.

On the other hand, the energy consumption from peripheral devices S_{P_j} depends on the operational relationships between both manufacturing and peripheral devices, which are needed to guarantee the operating conditions of the whole manufacturing processes. Thereby, in order to select the optimal activation instants of the peripheral devices regarding the global energy consumption, the dynamics of both energy consumption and the processes represented by peripheral devices must be considered into the problem formulation because of the settling time of each element. In this regard, the control problem consists in determining the optimal $\mathbf{\Lambda_P}$ that minimises both S and the peaks of S that could exceed the nominal power purchased along a fixed period, e.g., $T = T_{M_i}$.

Operation of peripheral devices

Peripheral devices of manufacturing systems perform different processes to supply the necessary resources for the proper operation of machining devices, e.g., compressed air, lubricant, coolant. Mathematical expressions for defining relations between these devices and the machines they provide resources should be established considering both the resources consumption from machine tools and the process performed by the peripheral devices.

According to the manufacturing systems, some peripheral devices can or cannot be critical for the machining processes, and in this sense, some of these devices could be controlled either independently or dependently. Besides, some peripheral devices can have a buffer capacity, which could be enough to cover the whole operation cycle or even more. Thus, based on the analysed system, peripheral devices with different functionalities and capacities can be found. Due to this fact, three criteria are considered to establish the priorities to manage peripheral devices and to define the relationships to be considered in the design of control strategies. The factors considered are:

1. *Safety of machining processes*: A peripheral device is considered critical for the safety of processes if that device directly supplies one resource necessary for the machining process, e.g., compressed air, coolant, lubricant. An example of those devices/processes is the coolant feeding, which deliveries the coolant required for machining a piece in a machine tool.

2. *Buffer capacity:* Based on the particular design of peripheral devices, some peripheral devices could have capacity enough to cover the whole operation cycle without a real-time energy conversion during their operations. In addition, other devices may not have buffering capacity or not enough to cover an operation cycle, which implies that these devices perform their processes based on real-time energy conversion. Some example of these buffers are the pressure reservoirs, tanks, trays, among others.

3. *Control depending on main machining processes:* Based on the relationships between machining and peripheral devices, these latter could be controlled according to the machining processes when some event directly related to their operation triggered the activation/deactivation of peripheral devices. On the other hand, some devices can be controlled based on time and independent on machining process, indeed, their switching on/off is allowed only in fixed time intervals.

Based on the factors previously explained, it is possible to identify the devices that require a real-time energy conversion during their operation and those devices able to satisfy the requirements of machining process without being turned on at the same time. However, additional to these relations, there exist other operational limitations of peripheral devices, such as idle times, running times, and switching frequency, etc., that should be considered for the design of control strategies.

5.2 Control Problem Formulation

To improve the energy efficiency of manufacturing systems and to reduce the energy costs at the machine level, the control strategy should be focused on determining the way of reducing both energy consumption and the power peaks during the operation of a machine tool and its peripheral devices without affecting its productivity. At this level, productivity refers to the number of pieces processed by one machine in a fixed period, for instance, one hour, one day, or one month. Thus, it means that for remaining the machine productivity, the operation cycle should be the same.

In this regard, the control problem consists in determining the sequence $\mathbf{\Lambda_P}$ that minimises both S and the height of the power peaks that could exceed the nominal power purchased along a fixed period, e.g., T_{M_i}. Thus, according to Assumption 5.1, the proposed control policy does not affect the system productivity since the machining sequence $\mathbf{\Lambda_{M_i}}$ and its energy consumption $\bar{\beta}$ along the operation cycle T_{M_i} are fixed while only activation instants of the peripheral devices are modified (i.e., $\mathbf{\Lambda_P}$) according to the optimisation results. In this way, T_{M_i} for the i-th machine remains the same.

To this end, an optimisation-based controller is designed, considering both energy consumption models and operational constraints of peripheral devices into the optimisation problem behind the controller design. Thus, the general idea is to use the MPC approach (see [Mac02, RM09]) to anticipate either activation or deactivation of peripheral devices taking into account the current value of S, the dynamics of the processes related to the operation of peripheral devices, and the operational (mainly physical) constraints of these devices. In this case, the process dynamics for peripheral devices are the mathematical expressions that explicitly consider the functional relationships between the machine and its peripheral devices. Besides, these equations are mandatory for the controller design since they should be satisfied to guarantee the proper operation of the machine as well as its productivity.

It is worth noting that this dissertation focuses on energy objectives and, therefore, the modelling of machining processes is not addressed. Thus, only the energy consumption dynamics of these processes will be studied. However, the dynamics for the processes related to peripheral devices should be analysed because they considered the relationships to machining processes and are the devices that are manipulated in this proposal.

5.2.1 Control objectives

Different approaches have been proposed in the literature to improve the energy efficiency of manufacturing systems. Some of them are directly related to the minimisation of the associated energy costs using economic cost functions. On the other hand, many approaches have focused on the reduction of energy consumption of manufacturing systems using different control objectives such as minimisation of the load demand, smoothing of energy consumption profiles, and reduction of the processing time. Based on these proposals, two control objectives have been considered in this dissertation to improve energy efficiency and to reduce the energy costs of manufacturing systems at the machine level. The control objectives proposed are listed below:

- *Objective 1*: Minimisation of the total energy consumption of a machine and its peripheral devices along a fixed period, e.g., $T = T_{M_i}$ (J_1).
- *Objective 2*: Reduction of the height of the power peaks in the energy consumption profile along a fixed period, e.g., $T = T_{M_i}$ (J_2).

The first control objective refers to the minimisation of the area under the curve of the energy consumption profile for the machine and its peripheral devices along T. The latter fact is due to the energy consumed can be expressed as the power times the processing time. Regarding the second control objective, by minimising the highest power peak in the energy consumption profile, the height of the other power peaks in the profile will also be reduced. Thus, by using J_1 and J_2 as control objectives, it is possible to improve energy efficiency via energy consumption reduction if the system productivity is not affecting. Besides, based on these objectives, the energy costs can also be reduced by the minimisation of energy consumption and avoiding economic penalties for surpassing the nominal power purchased.

The variables related to the proposed control objectives are the instantaneous power consumption for both the i-th machine and the j-th peripheral device, i.e., $S_{M_i}(k)$ and $S_{P_j}(k)$, respectively. Then, the total energy consumption at each instant k can be computed according to

$$S(k) = S_{M_i}(k) + \sum_{j=1}^{n} S_{P_j}(k), \tag{5.2}$$

being $S_{M_i}(k)$ the sum of the instantaneous power consumption of all machining devices activated according to the sequence $\mathbf{\Lambda_{M_i}}$.

In order to compute S, power consumption models for both the machine (or its machining devices) and each peripheral device are required, i.e.,

$$S_{M_i}(k+1) = f_{M_i}(\xi_{M_i}(k), \mathbf{\Lambda_{M_i}}(k)), \tag{5.3a}$$
$$S_{P_j}(k+1) = f_j(\xi_{P_j}(k), u_{P_j}(k)), \tag{5.3b}$$

with $\xi_{M_i}(k) \in \mathbb{R}^r$ and $\xi_{P_j}(k) \in \mathbb{R}^p$ the state vectors of the energy consumption models of the i-th machine and the j-th device, $f_{M_i} : \{0,1\} \times \mathbb{R}^r \mapsto \mathbb{R}_{\geq 0}$ and $f_j : \{0,1\} \times \mathbb{R}^p \mapsto \mathbb{R}_{\geq 0}$ the maps that relates the input signals that activates/deactivates the machining sequence $\mathbf{\Lambda_{M_i}}$ and the j-th device to the power consumption, respectively. According to Chapter 4, the maps f_{M_i} and f_j are linear maps identified from real input-output data sets and by using subspace identification methods. Besides, it is worth noting that although the linear maps are defined in function of only binary sets (e.g., $\{0,1\}$), these can easily be extended to the case in which there are different activation levels by replacing $\{0,1\}$ by the suitable set, e.g., $\mathbf{\Omega}$.

According to the control objectives proposed to be optimised, two different approaches to formulating the optimisation problem are proposed below. The first approach considers the optimisation problem as one multi-objective, while the second one simplifies the problem to one of a single objective.

Case No. 1: Multi-objective optimisation

Multi-objective optimisation (MOO) can be defined as mathematical optimisation problems involving more than one objective function, which should be optimised simultaneously [Cha15]. According to [CMGGJ12], MOO is a useful technique for studying optimal trade-off solutions in the area of multiple-criteria decision making. Then, since the control problem consist of determining the optimal $\mathbf{\Lambda_P}$ that minimises both the global energy consumption S and the height of the power peaks, two cost functions are defined. Considering an operation time of length T, the first control objective is defined as the integral of the total energy consumption signal along T, i.e.,

$$J_1(k) = \sum_{k=1}^{T} \left(S_{M_i}(k) + S_P(k)\right) \Delta k, \tag{5.4}$$

being $\Delta k = (t_k - t_{k-1})$ the temporal spacing or the sampling time, $S_{M_i}(k)$ the instantaneous power consumption of the i-th machine, and $S_P(k) = \sum_{j=1}^{n} S_{P_j}(k)$ the total energy consumption of peripheral devices according to $\mathbf{\Lambda_P}(k)$. On the other hand, regarding the control objective 2, if the highest peak in the profile of the total energy consumption is minimised, then, the additional power peaks will also be reduced. Thus, the second control objective is defined as

$$J_2(k) = \|\mathbf{S}(k)\|_\infty, \tag{5.5}$$

being $\mathbf{S}(k) \triangleq \{S(k), \ldots S(k+T)\}$, for all $k \in \mathbb{Z}_{\geq 0}$, $S(k)$ as shown in (5.2), and $\|\cdot\|_\infty$ the infinity-norm operator. Then, to make optimal decisions in the presence of two or more objectives that may conflict, in many practical engineering applications, the multi-objective optimisation problem is formulated as a single-objective optimisation problem using the weighted sum of the multiple goals [Cha15]. Thus, according to (5.4) and (5.5), the final control objective cab be defined as follows:

$$J(k) = \phi_1\, \eta_1\, J_1(k) + \phi_2\, \eta_2\, J_2(k), \tag{5.6}$$

being ϕ_1 and ϕ_2 the weight coefficients and η_1 and η_2 the normalisation values for each objective, respectively.

Case No. 2: Single-objective optimisation

In this case, a combination of the two control objectives is proposed to reduce the optimisation problem to one of a single objective. Thus, considering an operation time with length T, the control objective can be defined as the minimisation of the energy consumption of peripheral devices according to the instantaneous energy consumption of $\mathbf{\Lambda_{M_i}}$, i.e.,

$$J(k) = \sum_{k=1}^{T} S_{M_i}(k)\, S_P(k)\, \Delta k. \tag{5.7}$$

According to (5.7), the total energy consumption of peripheral devices S_P is penalised according to the current energy consumption of the machine S_{M_i}, which is known along T_{M_i} according to Assumption 5.1. In this regard, S_P will have a greater penalisation at the highest values of S_{M_i} allowing to reduce the total energy consumption and the heigh of the power peaks at the same time.

5.2.2 Constraints

In general terms, the constraints considered in the optimisation problem correspond to the energy consumption dynamics for both the machine and peripheral devices, the process dynamics associated to the operation of peripheral devices, and the operational constraints of the peripheral devices and the machine. These constraints will be explained in detailed in sections 5.4.1 and 5.5.1 for the each one of the cases described in Section 5.2.1 according to the control objective.

5.3 Closed-Loop Control Strategy

Considering a prediction horizon H_p, the decision of switching on or off a peripheral device $j \in \mathcal{J}$ will depend on the operational relationships between the machine and its peripheral devices and the current value of $S_{M_i}(k)$. It means, although $\mathbf{\Lambda_{M_i}}$ along T_{M_i} is already given and hence its energy consumption, its consumption values discriminated along the time are important for making decisions regarding peripheral devices management. Thus, according to the control objective, the sequence for $\mathbf{\Lambda_P}$ along H_p is defined as

$$\mathbf{\Gamma}(k) \triangleq \{\mathbf{\Lambda_P}(k|k), \ldots, \mathbf{\Lambda_P}(k + H_p - 1|k)\}, \tag{5.8}$$

with $\mathbf{\Gamma}(k) \in \{0, 1\} \times \mathbf{\Omega_2}^{n\,H_p}$. Besides, denoting each one of the dynamic expressions related to the operation of peripheral devices as a q_j-relationship, the polytopic constraint of peripheral devices can represent by

$$\mathbb{Q} = \{Q_j \in \mathbb{R}^r |\, Q_j(k) \in [\underline{Q}_j, \overline{Q}_j]\, \forall\, k,\ \{\underline{Q}_j, \overline{Q}_j\} \in \mathbb{R}\}, \tag{5.9}$$

with j the index for the relation (or relationships) associated at each peripheral device, and Q_j the process variable in the maps $q_j(\cdot)$.

Thus, the design of the proposed predictive-like controller is based on the following finite-time open-loop optimisation problem:

$$\min_{\mathbf{\Gamma(k)}} \mathbf{J}\left(\mathbf{\Lambda_{M_i}}(k), \{u_{P_1}(k), u_{P_2}(k), \ldots, u_{P_j}(k)\}\right) \tag{5.10a}$$

subject to

$$S_{M_i}(k+r|k) = f_{M_i}(\xi_{M_i}(k+r|k), \mathbf{\Lambda_{M_i}}(k+r|k)), \tag{5.10b}$$

$$S_{P_j}(k+r|k) = f_{P_j}(\xi_{P_j}(k+r|k), u_{P_j}(k+r|k)), \tag{5.10c}$$

$$Q_j(k+r+1|k) = q_j(Q_j(k+r|k), u_{P_1}(k+r|k), \ldots, u_{P_j}(k+r|k)), \tag{5.10d}$$

$$u_{P_j}(k+r|k) \in \mathcal{U}_j, \tag{5.10e}$$

$$Q_j(k+r|k) \in \mathbb{Q}, \tag{5.10f}$$

$$\Delta u_{P_j}(k) \neq 0 \Longrightarrow \{u_{P_1}(k), \ldots, u_{P_j}(k+k_{saf}-1)\} = u_{P_j}(k), \tag{5.10g}$$

$\forall r = 0, 1, \cdots, H_p - 1$, with u_{P_j} the activation/deactivation signal of the peripheral device j and $\mathcal{U}_j$ its feasible domain. Besides, k_{saf} refers to the time steps equivalents to the safety time t_{saf} that the device j should keep on or off to avoid damage. It should be noted that according to the proposed control objective, the most intuitive solution is to remain the peripheral devices off. However, due to the presence of (5.10d) in the optimisation problem (5.10), peripheral devices should be switched on/off to keep the process variables Q_j into their operational ranges defined by $\mathbb{Q}$.

Assuming that the problem (5.10) is feasible, i.e., $\mathbf{\Gamma}(k) \neq \emptyset$, there will be an optimal solution for the activation sequence of peripheral devices defined by

$$\mathbf{\Gamma}^*(k) \triangleq \{\mathbf{\Lambda_P}^*(k|k), \ldots, \mathbf{\Lambda_P}^*(k+H_p-1|k)\}, \tag{5.11}$$

and, according to the receding horizon philosophy [Mac02, RM09], $\mathbf{\Lambda_P}^*(k|k)$ is sent to the machine and peripheral devices discarding the rest of the optimal sequence from $(k+1)|k$ to $(k+H_p-1)|k$. Then, the whole procedure is repeated for the next instant $k \in \mathbb{Z}_{\geq 0}$, after measuring/estimating the information from the plant required by the controller. Notice that the optimisation problem (5.10) explicitly considers the consumption models, in addition to the q-relationships that express the dynamic relationships between the machine and the peripheral devices. In Figure 5.2, the proposed closed-loop control scheme to determine $\mathbf{\Gamma}^*(k|k)$ along H_p is shown.

Based on Figure 5.2, the optimisation problem in (5.10) is solved into the controller module using a control-oriented model and suitable optimisation solvers. Afterwards, once $\mathbf{\Gamma}^*(k|k)$ is determined, the first component $\mathbf{\Lambda_P}^*(k|k)$ is sent to the plant and the state of the machine and its peripheral devices is updated. However, due to the nature of the energy consumption models identified, the model states lack physical sense and cannot be measured from the plant.

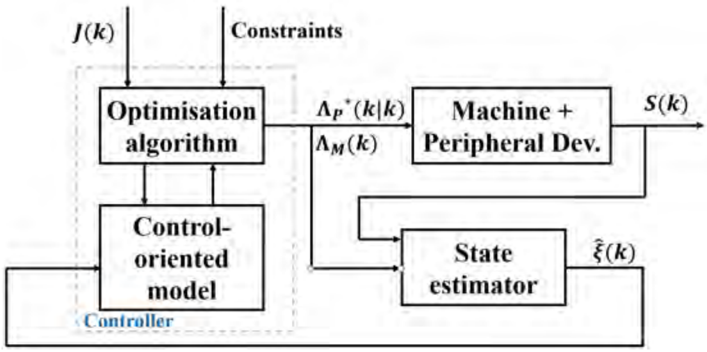


Figure 5.2: Control scheme of energy consumption for a machine tool and its peripheral devices.

Therefore, an observer is required to estimate the energy consumption states for the machine and its peripheral devices. Thus, the observer module uses the optimal activation sequence and the measurement about the power consumed from the plant to estimate the model states ξ at the instant $k + 1$. Then, this estimation is fed back to the controller at the next instant as the initial condition of the control-oriented model.

In [MRRS00], the sufficient conditions for stability for MPC of constrained dynamic systems (both linear and non-linear) are reviewed. In this case study, according to the design of the proposed controller, the sufficient conditions for both linear and constrained problems can be applied. However, it should be noted that according to the proposed control objectives, in the worst of the cases, the controller will get an optimal sequence with higher energy consumption. Still, the optimisation problem will be feasible. On the other hand, the optimisation problem in (5.10) could be infeasible only if some of the constraints related to the process dynamics of peripheral devices are not satisfied. Therefore, due to the periodic behaviour of these systems, the length selected for H_p and the execution time of the controller in a receding manner, it is possible to guarantee that the controller will be feasible at least for its next step of execution. In the next time step, the controller is run again and so on through the simulation horizon.

Design of observation module

According to Chapter 4, in which linear energy consumption models were obtained from input-output data sets using SI methods, a Kalman filter was designed to estimate the model states based on the current measurements from the plant. Thus, since the system is composed of the individual power consumption models for both the machining sequence and peripheral devices, the total output S can be defined as the sum of S_{M_i} and S_{P_j}, assuming there is no energy correlation between them. The latter fact is due to the only measurement available from the plant, corresponds to the total power consumption S, i.e., there are no single measurements for each peripheral device.

For the case of one machine with j peripheral devices, a total power consumption model can be defined by extending the matrices of each model as follows:

$$A_{kf} = \begin{bmatrix} A_{M_i} & 0 & \cdots & 0 \\ 0 & A_{P_1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & A_{P_j} \end{bmatrix}, \tag{5.12a}$$

$$B_{kf} = \begin{bmatrix} B_{M_i} & 0 & \cdots & 0 \\ 0 & B_{P_1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & B_{P_j} \end{bmatrix}, \tag{5.13a}$$

$$C_{kf} = \begin{bmatrix} C_{M_i} & C_{P_1} & \cdots & C_{P_j} \end{bmatrix}, \tag{5.14a}$$

$$D_{kf} = \begin{bmatrix} D_{M_i} & 0 & \cdots & 0 \\ 0 & D_{P_1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & D_{P_j} \end{bmatrix}. \tag{5.15a}$$

Notice that matrix C_{kf} has a different structure concerning the rest of the matrices of the extended model due to it is expressed as the sum of the energy consumption (outputs) of the individual devices and the machine. Next, considering

$$\mathbf{u}(k) \triangleq \left[u_{M_{i,1}}(k), \ldots, u_{M_{i,m}}, u_{P_1}(k), \ldots, u_{P_j}(k)\right]^T, \tag{5.16a}$$

$$\hat{\boldsymbol{\xi}}(k) \triangleq \left[\hat{\xi}_{M_i}(k), \hat{\xi}_{P_1}(k), \ldots, \hat{\xi}_{P_j}(k)\right]^T, \tag{5.16b}$$

as the extended input and state vectors, respectively, the estimation of the model states is performed according to

$$\hat{\boldsymbol{\xi}}(k+1) = A_{kf}\,\hat{\boldsymbol{\xi}}(k) + B_{kf}\,\mathbf{u}(k) + K\,\left(S(k) - \hat{S}(k)\right), \tag{5.17a}$$

$$\hat{S}(k) = C_{kf}\,\hat{\boldsymbol{\xi}}(k) + D_{kf}\,\mathbf{u}(k), \tag{5.17b}$$

being $\hat{S}$ the estimated output vector, K the filter gain matrix and S the measurement of total power from the plant. Therefore, consider a discrete plant given by

$$x(k+1) = A\,x(k) + B\,u(k) + G\,w(k), \tag{5.18a}$$

$$y(k) = C\,x(k) + D\,u(k) + H\,w(k) + v(k), \tag{5.18b}$$

being w and v the process and white measurement noise that satisfy

$$E\left(w(k)w(k)^T\right) = Q,\; E\left(v(k)v(k)^T\right) = R,\; E\left(w(k)v(k)^T\right) = N. \tag{5.19}$$

Then, the matrix K can be determined by solving the algebraic Riccati equation as follows:

$$K = \left(A\,P\,C^T + \bar{N}\right)\,\left(C\,P\,C^T + \bar{R}\right)^{-1}, \tag{5.20}$$

with

$$\bar{R} = R + H\,N + N^T\,H^T + H\,Q\,H^T, \tag{5.21}$$

$$\bar{N} = G\left(Q\,H^T + N\right), \tag{5.22}$$

and P should be determined in a way that solves the algebraic Riccati equation in (5.20).

5.4 Case No. 1: Multi-Objective Problem

In this case, it is considered that the system to be analysed is formed by one machine tool (M_1) and two on/off peripheral devices. Thereby, the machine cycle has a duration of $T_{M_1} = 28$ s and a periodic energy consumption profile as in Figure 4.2. Moreover, according to the designed test bench (see Figure 4.1), only the two motors in the test bench were considered as peripheral devices, while the UPS was neglected in this approximation. It should be noted that since this case refers to the multi-objective optimisation, the cost function J in (5.10) will be equal to (5.6).

5.4.1 Constraints

As mentioned in Section 5.2.2, to determine the optimal activations instants of the peripheral devices that minimise (5.6), the energy consumption models for both machine and peripheral devices are required. Besides, to ensure that resources can be supplied from the peripheral devices to machines at proper instants, the process dynamics of such devices, as well as their operational conditions, should be added into the set of constraints in (5.10). These constraints are explained below:

Operation of peripheral devices

It is worth noting that this case study was performed as a first approximation for the design of the control strategy. Thus, the q-relations mentioned in (5.10d) to express the relationships between the machine and peripheral devices are assumed to be expressions simplified of the real dynamics for the processes associated with the operation of peripheral devices. In this regard, it is assumed that some information about the resources consumed by the machine and provided by the peripheral devices is available. Thereby, based on a measured process variable (e.g., level of coolant in a tank, pressure of air in a reservoir, etc.), it is defined a linear expression as a function of the amount of some resource consumed by the machine and the amount provided by the peripheral device when is on. From this fact, the expressions $q_j(\cdot)$ in (5.10) for both motors, are established as follows:

$$Q_{P_j}(k+1) = Q_{P_j}(k) + \alpha_j(\mathbf{\Lambda_{M_i}}) + \eta_j \, u_{P_j}(k), \; \forall j = 1, 2, \tag{5.23}$$

being $Q_{P_j} \in \mathbb{R}$ a process variable related to the resource provided by the j-th device, e.g., the level of coolant in a storage tank, η_j the amount of resource provided by the peripheral device at each instant k i while it is on, and $\alpha_j(\mathbf{\Lambda_{M_i}})$ the amount of resource consumed by the machine at each instant k. It should be noted that, in this case, it is assumed that there is only one q-relation associated with each device and, therefore, it holds that $r = j$. Besides, it is assumed that the machine is continuously consuming the resources provided by the peripheral devices. In Table 5.1, the values of α_j, η_j and the operating ranges for $Q_{P_j}(k)$ are presented for each device.

Table 5.1: Simulation parameters for peripheral devices.

Device	α_j [ud/s]	η_j [ud/s]	$\underline{\mathbf{Q}}_{\mathbf{P_j}}$	$\overline{\mathbf{Q}}_{\mathbf{P_j}}$	$\mathbf{Q}_{\mathbf{P_j}}(0)$
$\mathbf{P_1}$	-3	5	50	150	55
$\mathbf{P_2}$	-5	7	60	180	65

Energy consumption models

According to the Subspace Identification method presented in Chapter 4, the linear models identified for the machine and the two motors in the test bench will be included into the set of constraints in (5.10). Thus, energy consumption models have the following form

$$\xi_p(k+1) = A_p\,\xi_p(k) + B_p\,u_p(k), \tag{5.24a}$$

$$S_p(k) = C_p\,\xi_p(k) + D_p\,u_p(k), \tag{5.24b}$$

with $p = M_i, P_1, P_2$, for the machine and both peripheral devices, and $\xi_p \in \mathbb{R}^{n_p}$ the model states. The model matrices for the machine and the two motors are presented in (4.2) to (4.10).

However, according to Assumption 5.1, $\mathbf{\Lambda_{M_i}}$ is already defined for T_{M_i} and, therefore, its associated energy consumption is assumed to be periodic and constant over time. Based on this fact, the energy consumption of the machine could be included in the optimisation as an offset value instead of considering the energy consumption model.

Operational constraints

Into this category are included the constraints related to the physical dimensions of peripheral systems, desired values of process variables as well as the safety constraints.

* ***Feasible domain for*** $\mathbf{u_{P_j}}$: Since both peripheral devices are considered as on/off actuators, u_{P_j} is a binary variable such that

$$u_{P_j} \in \{0,1\},\ j = 1,2. \tag{5.25}$$

* ***Safety constraints:*** It has been considered a minimum execution time for peripheral devices to avoid damages in them by a high switching frequency, which directly affects the inertia of each device. Thus, every time in which some peripheral device is turned on or

off, it should keep on its current state at least for a period equal $t_{saf} = 5$ s. In this regard, the following logic constraints should be included in the set of constraints:

$$\Delta u_{P_j}(k) \neq 0 \Longrightarrow \{u_{P_j}(k), \dots, u_{P_j}(k + k_{saf} - 1)\} = u_{P_j}(k), \tag{5.26}$$

with $\Delta u_{P_j}(k) = u_{P_j}(k) - u_{P_j}(k-1)$, and $k_{saf} = \frac{t_{saf}}{\tau_c}$, being τ_c the time-step size for making decisions.

5.4.2 Weighting and normalisation coefficients

Based on (5.6), the normalisation coefficients must be determined for each control objective. Thus, the main idea is to bring all the values for J_1 and J_2 to the range $[0, 1]$ according to

$$J_i' = \frac{J_1 - \underline{J_i}}{\overline{J_1} - \underline{J_i}}, \ i = 1, 2, \tag{5.27}$$

being J_i' the normalised value for J_i, and $\underline{J_i}$ and $\overline{J_i}$ the minimum and maximum value of J_i, respectively. The minimum and maximum for both J_1 and J_2 are defined based on the case study as follows:

- J_1: the minimum value of J_1 corresponds to the area under the energy consumption profile when only the machine is working, while the area under the energy consumption profile when the machine and both peripheral devices are working along the prediction horizon is considered as the maximum value for J_1.
- J_2: the higher peak in the energy consumption profile of the machine is considered as the minimum value of J_2. Besides, the height of the peak when both peripheral devices are activated at the same instant in which occurs the min of J_2 refers to the maximum value for J_2.

On the other hand, to determine the values of ϕ_1 and ϕ_2, a trial-and-error tuning procedure was used to find the trade-off between the proposed control objectives. For this purpose, several tests were performed changing the values of both ϕ_1 and ϕ_2, to analyse the variations in the control objectives J_1 and J_2. Thus, by using increments equal 0.05 for both ϕ_1 and ϕ_2, the obtained values for J_1 and J_2 are presented in Figure 5.3. According to these results, $\phi_1 = 0.9$ and $\phi_2 = 0.1$ were selected due to they corresponds to the best trade-off between the proposed

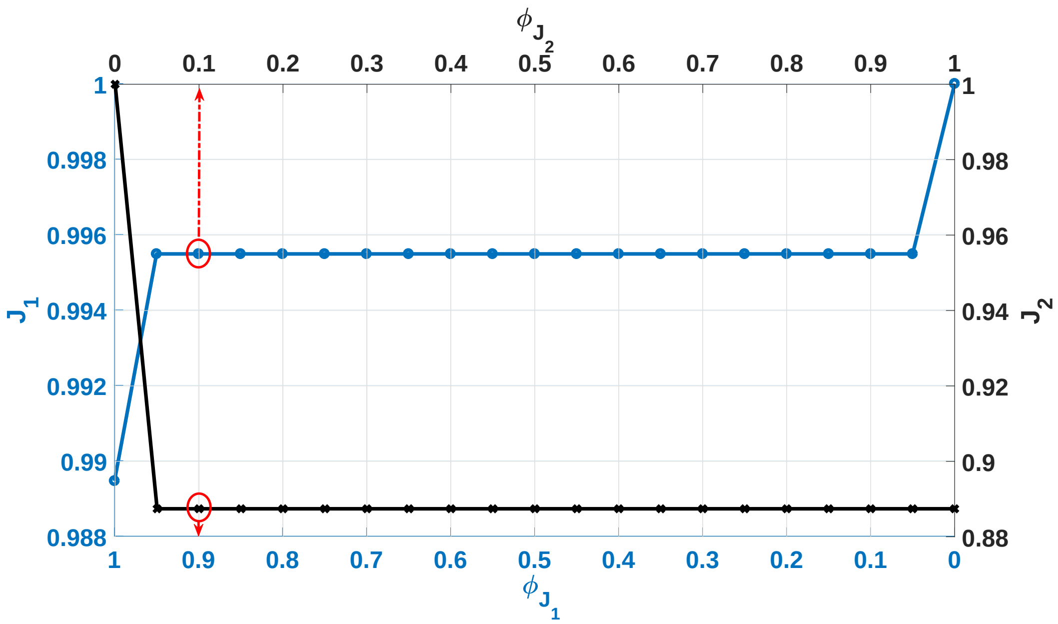


Figure 5.3: Comparative for normalised values of J_1 and J_2 for variations of ϕ_1 and ϕ_2.

control objectives. The latter fact taking into account that in this proposal, J_1 is prioritised since the costs by energy consumption are more expensive than the economic penalties for surpassing the nominal power.

From Figure 5.3, it is worth noting that when both control objectives are considered, i.e., the total energy consumption and the height of the peaks, the system is not quite sensitive to changes in both ϕ_1 and ϕ_2. Thus, according to the prediction horizon considered and the energy consumption profile for the machine, there are few combinations to activate peripheral devices that allow reducing the height of the peaks while satisfying the operational relationships among the machine tool and its peripheral devices. The latter fact is due to the existence of few instants along T_{M_i} in which $S(k)$ is lower than its mean value, and no all these instants allow satisfying the supply of resources to the machine at proper instants. Therefore, even when the weight of the peak-reduction term is prioritised, the controller should ensure firstly satisfying operational constraints before to minimise the height of the peaks. Besides, when only J_2 is considered in the cost function, the energy consumption increases since the controller probably finds activation instants for the peripheral devices in which J_2 is lower but such devices should be remained on for a longer time to satisfy the operational constraints. Based on the previous discussion, the values of ϕ_1 and ϕ_2 marked in Figure 5.3 were selected since they correspond to one of the best choices for the trade-off among the control objectives without penalising only one of the targets.

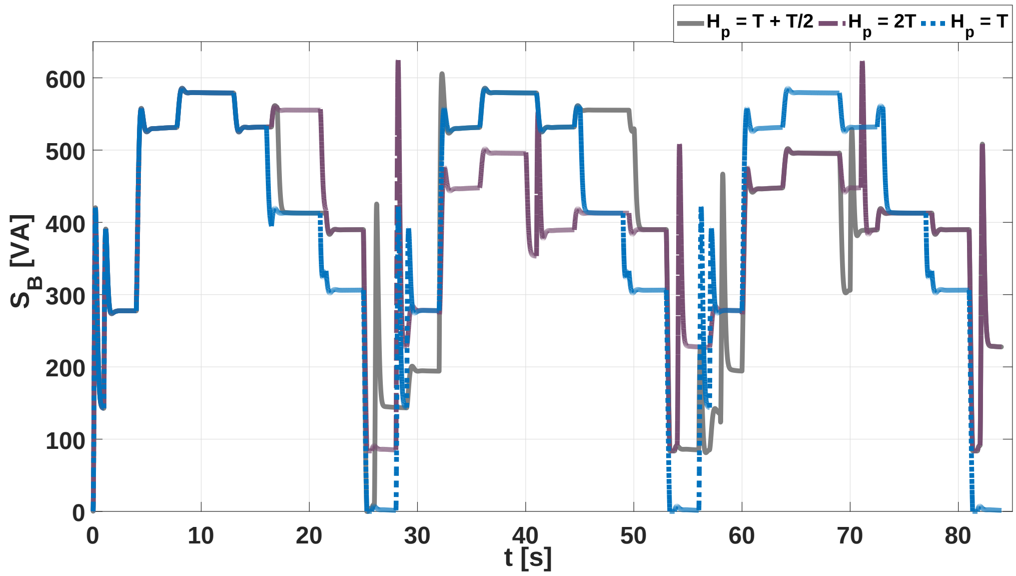


Figure 5.4: Comparative of different values of H_p for an initial optimisation.

5.4.3 Length of prediction horizon

In this case, it is assumed $T = T_{M_1}$. Thus, given the periodic behaviour of machine tools, values of H_p equal to T, $\left(T + \frac{T}{2}\right)$, and $2\,T$ were tested to determine the more suitable length of H_p. Thus, considering a fixed simulation period, the suitable length of H_p was selected according to the obtained values of J_1 and J_2 for the whole simulation. The obtained energy consumption profiles during a simulation time equal $T_s = 3\,T$ are shown in Figure 5.4. According to the results in Figure 5.4, it is possible to see that, for large values of H_p the height of peaks is increased, while the height of peaks is smaller when $H_p = T$. Besides, for shorter values of H_p, the resulting energy consumption profile is smoother.

Moreover, in Table 5.2, the values of J_1, J_2, and the larger computational time t_c spent by iteration are reported. Based on these results, $H_p = T$ was selected to test the proposed control strategy since by using that value, a suitable trade-off between both objectives with the lowest computational time is achieved. The last fact means, if $\tau_c = 1$ s, the controller will make 28 decisions along H_p.

5.4.4 Simulation results

In this section, the simulation results obtained to test the performance of the control strategy based on a multi-objective cost function are presented and discussed. Besides, given the nature

Table 5.2: Comparison of the performance of the proposed controller with respect to variations in the length of H_p.

Objective	$\mathbf{H_P = T}$	$\mathbf{H_P = T + \frac{T}{2}}$	$\mathbf{H_P = 2T}$
J_1[VA]	3.3416×10^4	3.4418×10^4	3.4050×10^4
J_2[VA]	585.69	605.76	624.79
t_c [s]	0.075	0.098	0.108

of the optimisation problem in (5.10), which is a mixed-integer linear programming problem, and the need to solve this problem fast enough to react in real time, it was chosen the solver IBM ILOG CPLEX Optimisation Studio [ILO13]. The simulations were developed in Matlab® using YALMIP interpreter [Löf04] for stating the problem optimisation in an intuitive format.

Based on the proposed control scheme and the found values for $\eta_1, \phi_1, \eta_2, \phi_2$ and H_p, the control strategy was tested by simulation based on parameters in Table 5.1 and considering a total simulation time $T_s = 8\,T$. It should be noted that although the sampling time for energy consumption models is $\tau_s = 0.01$ s, the proposed controller is executed to find optimal values of u_{P_j} at each second and to keep this value until the next one, i.e. $\tau_c = 1$ s. This way of implementing the controller is considered given the amount of data to be processed and the requirements of computing time for further real-time implementations.

Simulation results for the proposed control strategy are presented in Figures 5.5, 5.6, and 5.7. In this case, two different simulation horizons H_s were compared since the periodic behaviour of these machines and results in Table 5.2. Thus, in the first case, the conventional *MPC strategy*, in which only the first component is applied to the system ($H_s = 1$ s) is considered, while in the second one, the whole optimal sequence for the whole H_p is applied to system ($H_s = T$). Besides, all simulations were performed considering the same safety time for all the peripheral devices, $t_{saf} = 5$ s as it explained in Section 5.4.1.

In Figures 5.5, 5.6 and 5.7, the proposed predictive-like control (Energy-Efficiency Control, EEC) is compared to other rule-based control (RBC) that only considers the boundaries for $\overline{Q}_{P_j}$ and $\underline{Q}_{P_j}$ to make decision of switching on/off the peripheral devices. In Figure 5.5, it is possible to see that, according to the proposed control objectives, the height of power peaks is minimised concerning the RBC. Thus, the economic penalties for surpassing the nominal power could be avoided. This reduction in energy costs is related to the delay in the activation of peripheral devices to avoid their simultaneous activation. According to the reported results, the highest peaks registered using the EEC were $S_{max} = 623.2$ VA and $S_{max} = 585.7$ VA for $H_s = 1$ s and $H_s = T$, respectively, while for the RBC the highest peak was $S_{max} = 661.7$ VA. In this regard, improvements up to 6% were achieved concerning J_2 without affecting the machine

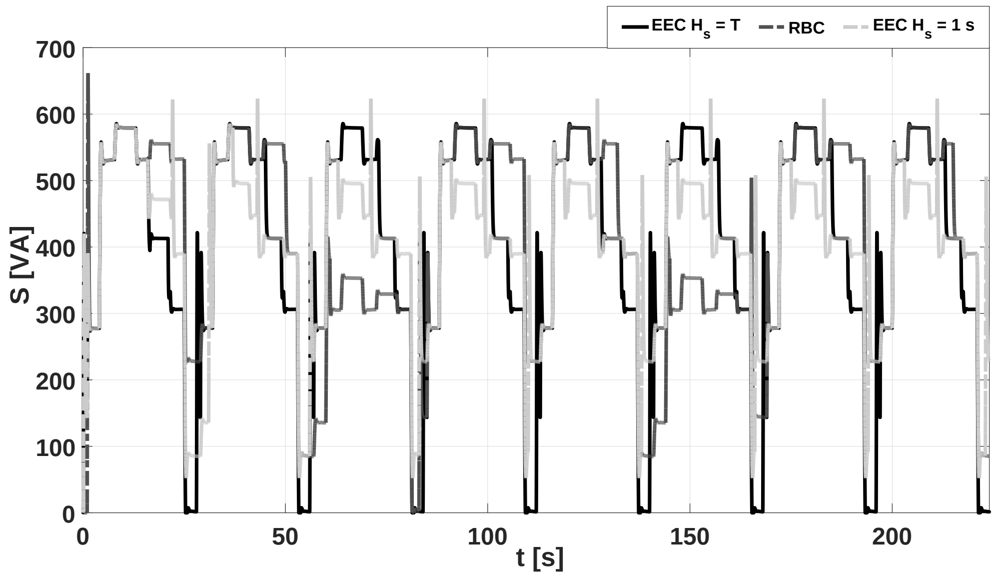


Figure 5.5: Total apparent power consumption during the machine operation.

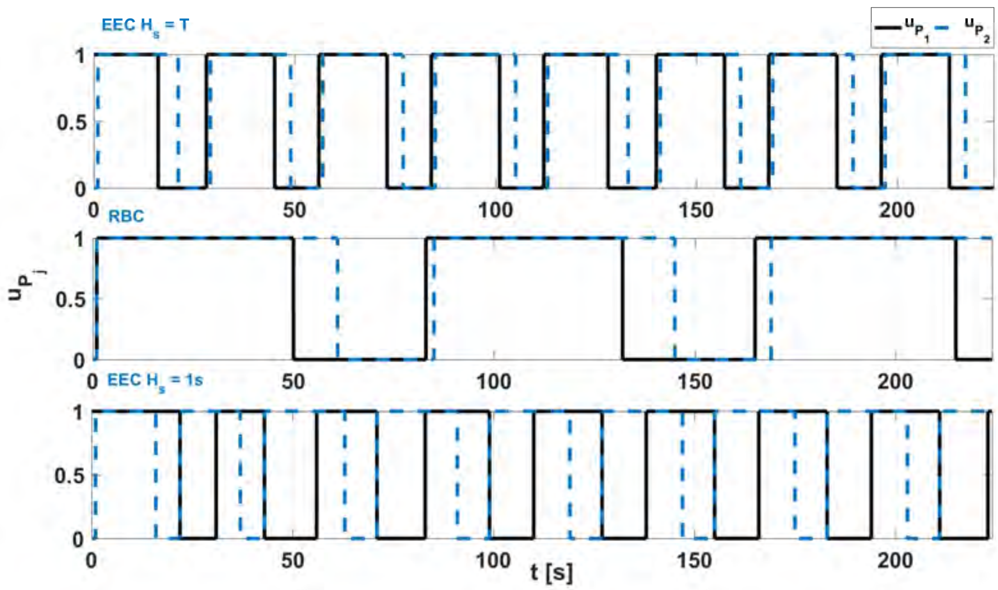


Figure 5.6: Input signals of the peripheral devices for the different control strategies tested.

production. The latter fact is due to the machining sequence for the machine was not modified and the time to process a piece remaining the same.

According to Figure 5.6, the signals u_{P_1} and u_{P_2} never turned on at the same time when the EEC was implemented. Besides, the ECC tries to turn off the peripheral device of higher consumption (P_1) always that it is not required and, therefore, this device has a higher switching

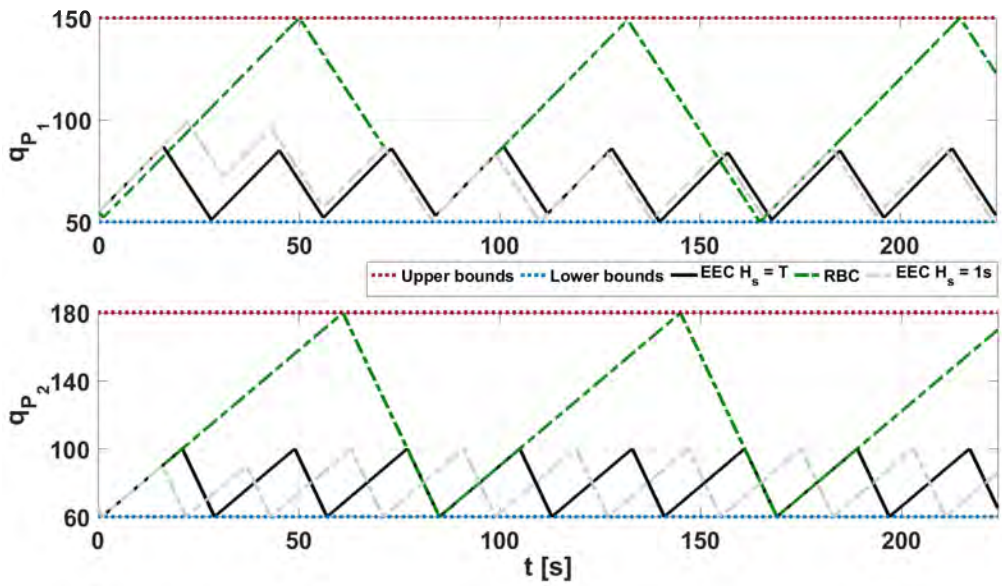


Figure 5.7: Dynamic of q_j for each one of considered peripheral devices.

frequency than in the results obtained using the RBC. A similar case can be observed for device P_2 in which the switching frequency is increased regarding the RBC. Thus, the EEC tries to keep the peripheral devices near the minimum values admissible for Q_{P_j} and, turned them off when they are far away from $\underline{Q}_{P_j}$ to avoid unnecessary energy consumption. Although the proposed strategy increases the switching frequency for both devices, the safety constraints and the operating relations represented here for q_1 and q_2 are always satisfied, as shown in Figure 5.7.

To evaluate the performance of the proposed control strategy, a key performance index named Specific Energy Consumption (SEC), which expresses the ratio of total energy consumption to the real output of a machining process, is calculated according to [LLTL17]:

$$SEC = \frac{E_{Total}}{N_{wp}} = \frac{1}{N_{wp}} \sum_{k=0}^{T_s} S(k)\Delta k, \tag{5.28}$$

being N_{wp} the total number of piece processed. The values of both SEC and J_1 for the proposed controller are presented in Table 5.3. Regarding J_1, global energy consumption is not significantly reduced since the energy consumption behaviour of the peripheral devices is not modified and, based on Figure 5.7, the operational cycle of peripheral devices T_{P_j} using the RBC strategy is larger than the considered prediction horizon $H_p = T$. This latter fact produces that the mentioned comparison will not be both realistic and fair since one of the proposed

Table 5.3: Assessment of SEC and J_1 values.

Index	EEC $(\mathbf{H_s} = 1\mathrm{s})$	EEC $(\mathbf{H_s} = \mathbf{T})$	RBC
$\mathbf{J_1}$ [VA]	8.9491×10^4	8.9210×10^4	9.1769×10^4
SEC [VA]	1.1186×10^4	1.1151×10^4	1.1471×10^4

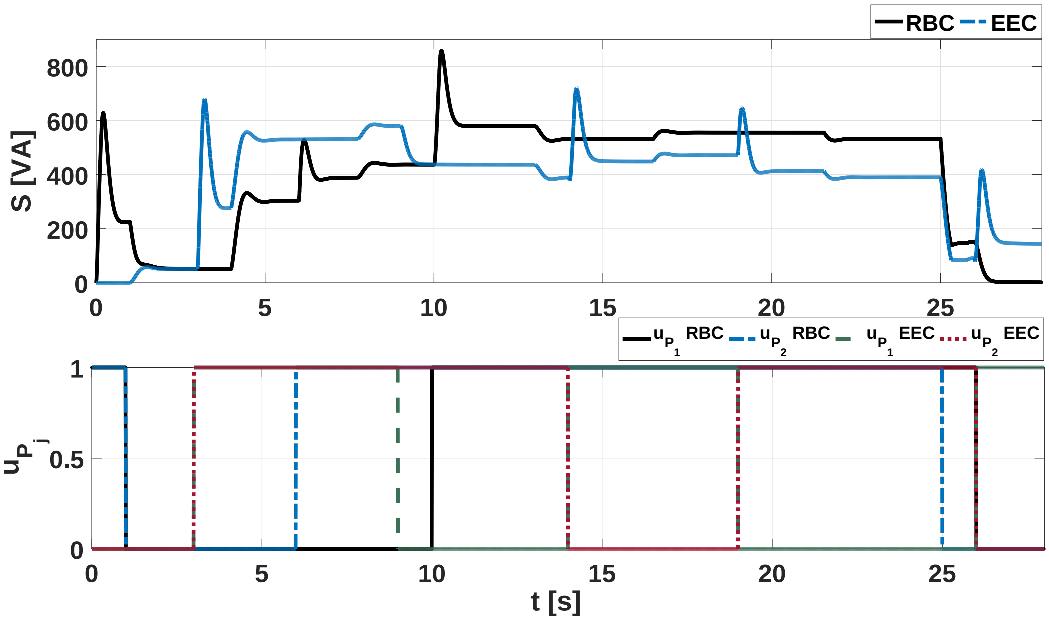


Figure 5.8: Comparative between EEC and RBC using $H_p = T_{P_j}$.

strategies could be favoured depending on the period tested. However, as a way of comparing the performance of both EEC and RBC approaches under the same conditions, in Figure 5.8 a hypothetical case in which $H_p = T_{P_j}$ is presented. From these results, it is possible to see that, when the optimisation is performed for the same length of T_{P_j}, better results can be obtained achieving improvements around 6.3% and 22% for J_1 and J_2, respectively.

5.4.5 Disturbances handling

To evaluate the performance of the proposed control strategy in a more complex situation, a case in which one unknown load is activated during some time intervals is analysed. In Figure 5.9, the activation signal of the unexpected load u_d and the resulting apparent power profile when both EEC and RBC are implemented are presented. It should be noted that although the disturbance is not explicitly considered in the optimisation problem, it is observed in the estimation of the states for energy consumption models. This estimation is performed based on the measurement of the total energy consumption, which includes the consumption related to

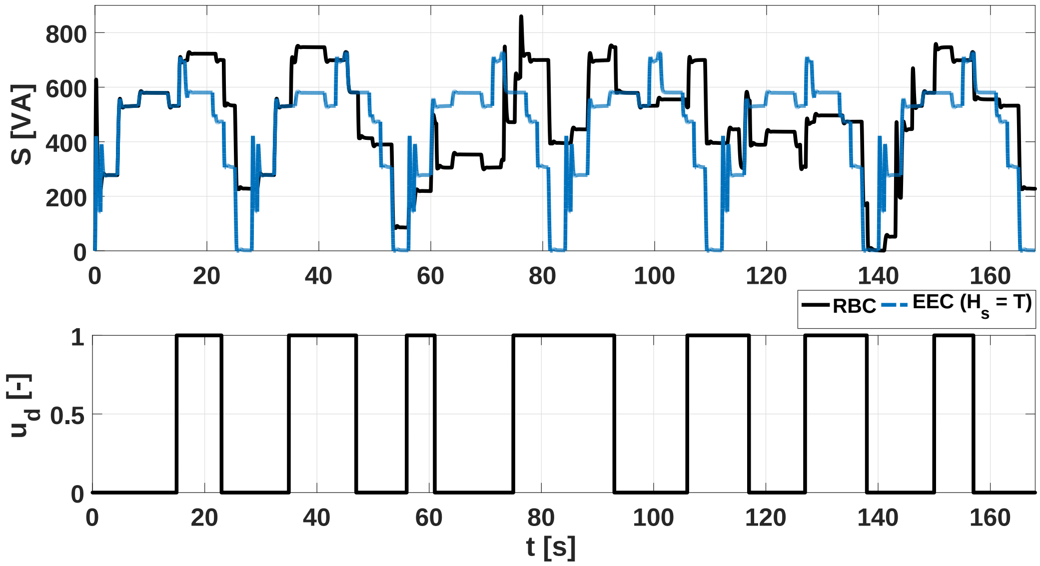


Figure 5.9: (a) Total power consumption. (b) Unknown input.

Table 5.4: SEC and J_i values for both ECC and RBC tested.

Index	$\mathbf{J_1}$ [VA]	$\mathbf{J_2}$ [VA]	**SEC** [VA]
EEC $(H_s = T)$	7.488×10^4	728.62	1.248×10^4
RBC	8.032×10^4	860.05	1.347×10^4

the unexpected load. Thus, based on this estimation, the prediction of the energy consumption will be higher, and the controller should make decisions that minimise such consumption. The obtained results for J_1, J_2 and SEC are summarised in Table 5.4.

According to Table 5.4, a reduction of 7.4% per machine cycle in the global energy consumption could be achieved using the EEC when disturbances are considered. This fact is given due to the inherent robustness shown by the optimisation-based controllers (as the predictive ones) and their non-static control law philosophy. On the other hand, regarding J_2, improvements of 15% are reached when disturbances affect the system since the proposed control can manage the activation instants of the peripheral devices taking into account both the energy consumption of the machining sequence and the difference between the measured and the estimated output. In this sense, although significant improvements were achieved for the nominal case, greater benefits are obtained when disturbance scenarios are considered.

5.5 Case No. 2: Single-Objective Problem

In this section, the results when a single control objective is used as a cost function in (5.10) are presented and analysed. Besides, the control strategy was implemented in the test bench to evaluate its performance in real time. However, at the moment in which these experiments were performed, some elements in the test bench had been modified concerning the initial configuration presented in Chapter 4. These changes were a result to replace some of the test-bench devices that had suffered damages. In this regard, both the motors and the machining sequence were modified, while the UPS remains the same as the initial configuration. Nonetheless, the models for the new motors and the machining sequence were identified following the same identification procedure explained in Chapter 4.

In this case, an operation cycle with two stages of manufacturing (cutting, milling, drilling, forming, etc.), was taken as the reference to represent the manufacturing sequence in the test bench. Thus, a sequence $\mathbf{\Lambda_{M_i}}$ was created with $T_{M_1} = 29$ s, which is constant along the time. On the other hand, the start-connection motor (P_1) and a UPS with two fans connected (P_2) were considered as the peripheral devices to include an on/off actuator and another in which the activation load could be modulated. In Figure 5.10, the proposed manufacturing sequence and the energy consumption profiles of peripheral devices are presented. It is worth noting that in this case, the second motor (P_3) will be used as an unknown load to evaluate the performance when disturbances take place.

5.5.1 Constraints

In the same way as the first case study, the constraints correspond to the energy consumption models, the dynamics related to the operation of peripheral devices, and the range constraints associated with the operation of both the machine and peripheral devices. However, in this case, the processes related to peripheral devices are adequately described and modelled to consider more realistic scenarios. The considered constraints are detailed below:

- ***Energy consumption models:*** According to Chapter 4 and the data in Figure 5.10, the models for the new devices in the test bench were also identified using SI methods. In this regard, the linear models for the machine (M_1)

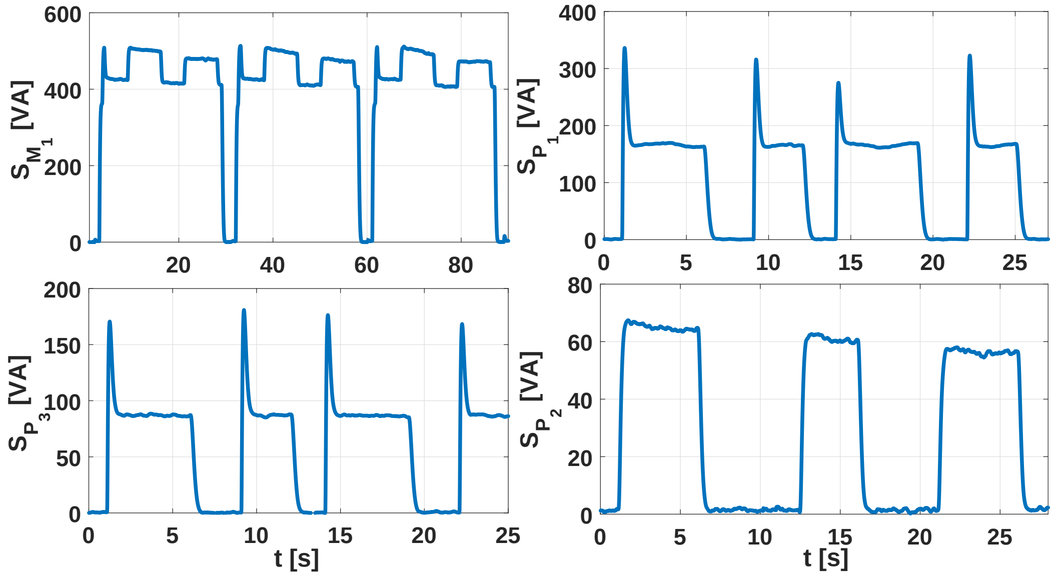


Figure 5.10: Energy consumption profile of (a) manufacturing sequence, (b) start-connection motor P_1, (c) UPS with fans P_2, and (d) delta-connection motor P_3.

$$\xi_{M_1}(k+1) = A_{M_1}\, \xi_{M_1}(k) + B_{M_1}\, u_{M_{i,l}}(k), \tag{5.29a}$$

$$S_{M_1}(k) = C_{M_1}\, \xi_{M_1}(k) + D_{M_1}\, u_{M_{i,l}}(k), \tag{5.29b}$$

the start-connection motor (P_1)

$$\xi_{P_1}(k+1) = A_{P_1}\, \xi_{P_1}(k) + B_{P_1}\, u_{P_1}(k), \tag{5.30a}$$

$$S_{P_1}(k) = C_{P_1}\, \xi_{P_1}(k) + D_{P_1}\, u_{P_1}(k), \tag{5.30b}$$

and the UPS (P_2)

$$\xi_{P_2}(k+1) = A_{P_2}\, \xi_{P_2}(k) + B_{P_2}\, u_{P_2}(k), \tag{5.31a}$$

$$S_{P_2}(k) = C_{P_2}\, \xi_{P_2}(k) + D_{P_2}\, u_{P_2}(k), \tag{5.31b}$$

should be included into the set of constraints of the optimisation problem. In (5.29), $\xi_{M_1} \in \mathbb{R}^r$ is the state vector, and $A_{M_1}, B_{M_1}, C_{M_1}$ and D_{M_1} are the model matrices identified. This notation is also extended to energy consumption models of peripheral devices in (5.30) an (5.31).

- ***Dynamics related to operation of peripheral devices:*** Since two peripheral devices (a start-connection motor and a UPS) are considered at this level, two different situations were established to represent the supply of resources from peripheral devices towards the machine tool. The supply systems, shown in Figure 5.11, are the following:

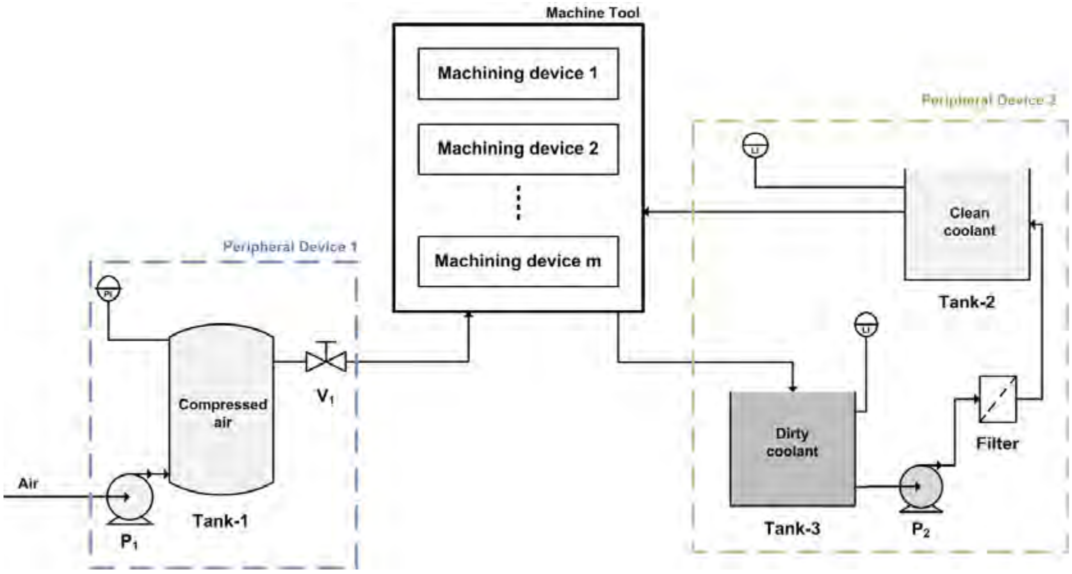


Figure 5.11: Scheme of a machine tool and its peripheral systems: (left) air-supply system and (right) coolant-supply system to machining processes.

1. ***Air-supply pump related to*** $\mathbf{P_1}$: One of the functions of pneumatic systems in manufacturing systems is to supply air at pre-defined conditions of pressure to clamp/unclamp pieces during machining operations. Thus, considering a supply system as shown in Figure 5.11, a pump provides to an air stream the energy required to achieve the desired conditions of pressure and, then, this stream is transported towards the machining devices that needed it. Due to the operational relationship between this system and the machining devices, the air-supply system is considered as critical, with buffer capacity, and coupled to the machining processes.

   According to Figure 5.11, the dynamics related to the operation of P_1 correspond to the total change of mass and pressure inside the Tank T_1, and they can be expressed in the discrete-time version based on Taylor's series expansions and the finite difference discretisation scheme as follows:

$$M_{T_1}(k+1) = M_{T_1}(k) + \tau_s\,\sigma(k), \tag{5.32}$$

   being τ_s[s] the sampling time, M_{T_1}[kg] the mass of air inside Tank T_1, and

$$\sigma(k) = m_{in,a}(k)\,u_{P_1}(k) - m_{out,a}(k), \tag{5.33}$$

   with u_{P_1} the activation signal of the pump P_1, $m_{out,a}\left[\frac{\text{kg}}{\text{s}}\right]$ the air flow consumed by the machining devices, and $m_{in,a}\left[\frac{\text{kg}}{\text{s}}\right]$ the air flow pumping by the pump P_1 to T_1.

On the other hand, the pressure dynamic inside T_1 can be related to the changes in M_{T_1} according to

$$P_{T_1}(k) = \frac{M_{T_1}(k)\, R\, T}{V_{T_1}\, W_{air}}, \tag{5.34}$$

being P_{T_1}[Pa] the air pressure inside T_1, $R\left[\frac{\mathrm{m}^3\ \mathrm{Pa}}{\mathrm{K\ mol}}\right]$ the universal gas constant, T[K] the temperature, $V_{T_1}[\mathrm{m}^3]$ the volume of T_1, and $W_{air}\left[\frac{\mathrm{kg}}{\mathrm{mol}}\right]$ the molecular weight of the air.

2. ***Coolant-supply pump related to $\mathbf{P_2}$:*** The supply of coolant is a critical task for machining process because if the coolant is not supplied in either sufficient quantity or at proper time instants, machining processes will not correctly work and the desired properties of the piece will not be reached. In many cases, coolant-supply systems are designed with re-circulation, filtering and re-use of coolant, as shown in Figure 5.11.

   Based on Figure 5.11, a constant flow of coolant $m_{cc}\left[\frac{\mathrm{kg}}{\mathrm{s}}\right]$ is pumped by P_2 from the tank with dirty coolant T_3 towards another tank with clean-coolant tank T_2. During the transport, the coolant flow passes through a filter in which the fine particles are separated. Afterwards, the coolant flow required for the different machining devices is supplied from Tank T_2. Next, after machining operations, the dirty coolant is collected and delivered to Tank T_2 with dirty coolant, in which the gross chip particles are separated by gravity, and the procedure is repeated. In this case, the pump P_2 corresponds to the peripheral device of interest, which must be activated to supply the coolant flow required to guarantee both the proper operation of machining devices and the reference levels at each tank. Therefore, in this case, both the activation instant and the proper flow of coolant to satisfy the operating constraints must be selected.

   The level dynamics at each tank are the following:

   - Clean tank T_2:

   $$L_{T_2}(k+1) = L_{T_2}(k) + \tau_s\, \gamma(k) \left(\frac{1}{\rho_c\, A_{T_2}}\right), \tag{5.35}$$

   being

   $$\gamma(k) = m_{cc}(k) - m_{c,M}(k), \tag{5.36}$$

   with L_{T_2}[m] the level of coolant stored in T_2, $m_{c,M}\left[\frac{\mathrm{kg}}{\mathrm{s}}\right]$ the coolant flow required by machine according to $(\mathbf{\Lambda_{M_i}})$, $\rho_c\left[\frac{\mathrm{kg}}{\mathrm{m}^3}\right]$ the coolant density, and

$A_{T_2}[\mathrm{m}^2]$ the cross-sectional area of T_2. The coolant flow required by the machine is expressed as a function of the flows required by the tool (m_{tool}) and the work-piece (m_{wp}) such that

$$m_{c,M} = m_{tool}(k) + m_{wp}(k). \tag{5.37}$$

It should be noted that according to the designed machine sequence, $m_{tool}(k)$ and $m_{wp}(k)$ will be different to zero only during the two machining stages of the machine cycle. The rest of the time, the coolant flow required by both the machine and work-piece is equal to zero.

- Dirty tank T_3:

$$L_{T_3}(k+1) = L_{T_3}(k) + \tau_s\, \theta(k) \left(\frac{1}{\rho_c\, A_{T_3}}\right), \tag{5.38}$$

being

$$\theta(k) = m_{dc,M}(k) - m_{cc}(k), \tag{5.39}$$

with $L_{T_3}[\mathrm{m}]$ the level of dirty coolant stored in T_3, $m_{dc,M}\left[\frac{\mathrm{kg}}{\mathrm{s}}\right]$ the flow of dirty coolant recovered from the machine, and $A_{T_3}[\mathrm{m}^2]$ the cross-sectional area of T_3. In this case, it is assumed that $m_{dc,M} \approx m_{c,M}$ due to the coolant losses during the recovery process.

Then, the coolant flow to be cleaned m_{cc}, and pumped from T_3 towards T_2, can be determined based on

$$P_{out,2}(k) + \eta\,(\rho_c\, \omega(k)) = P_{in,2}(k) + \rho_c h_{f_{1\to 2}}(k), \tag{5.40}$$

being $P_{in,2}[\mathrm{Pa}]$ and $P_{out,2}[\mathrm{Pa}]$ the inlet and output pressure in the pump P_2, respectively. Besides, η is the efficiency of pump, $h_{f_{1\to 2}}\left[\frac{\mathrm{m}^2}{\mathrm{s}^2}\right]$ refers to the energy losses by friction, and

$$\omega(k) = \frac{W(k)}{m_{cc}(k)}, \tag{5.41}$$

is the specific work per time unit with W [W] the work supply to the pump P_2. In this regard, the activation instants and the coolant flow could be determined to satisfy the operating levels at each tank. Thus, W is directly related to the activation signal of the pump P_2, i.e., $W = u_{P_2}$. Then, based on (5.40) and (5.41), m_{cc} can be determined according to

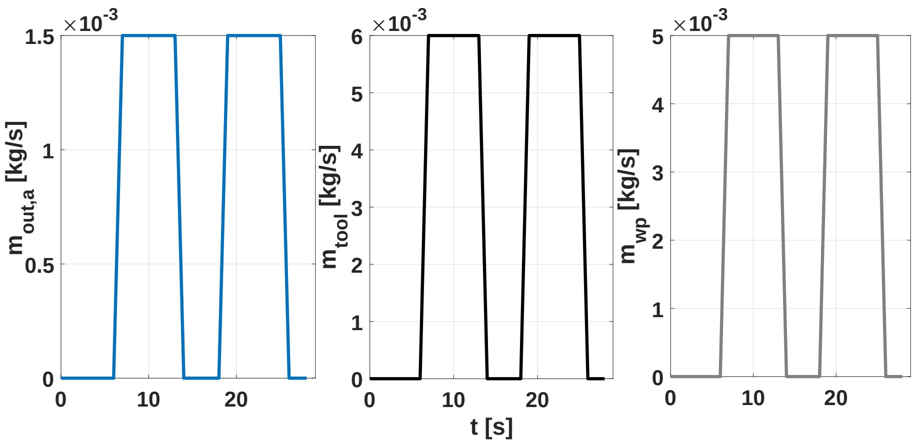


Figure 5.12: Profile of the resource consumption of air and coolant from the machine according to $(\mathbf{\Lambda_{M_1}})$.

$$m_{cc}(k) = \frac{\eta\, \rho_c\, u_{P_2}(k)}{P_{in,2}(k) + \rho_c h_{f_{1\to 2}}(k) - P_{out,2}(k)}, \tag{5.42}$$

with $h_{f_{1\to2}}$ considering the energy losses by friction in the pipeline and the pressure drop due to pass through the filter (ΔP_{filter}). Therefore, according to the energy provided to the pump P_2, more or less flow m_{cc} can be transported. Strictly speaking, energy losses should be computed in two parts, the first one related to the energy losses in fittings and the second one for the losses through pipes with a circular cross-section. In [Bir07] and [Hoo81], suitable ways to compute energy losses as a function of the fluid properties, its velocity, the pipe and fittings dimensions and the friction factor are proposed. However, in this thesis, the energy losses are considered to be constant, assuming the turbulent regime to fix the friction factor due to the nature of the process performed by peripheral systems. Thus, based on the selected friction factor and the higher velocity allowed through the pipeline, constant values for the energy losses were fixed to avoid including the non-linearities in mathematical expressions into the computation of the friction factor and the energy losses.

In Figure 5.12, the consumption profile of both air and coolant from the machine along T_{M_1} and according to $(\mathbf{\Lambda_{M_1}})$ is presented.

- ***Operational constraints:*** In this category, constraints related to physical dimension of peripheral systems, desired values of process variables as well as safety constraints are included.

* ***Pressure range**:* According to machining processes performed in the machine, the air flow $m_{out,a}$ should satisfy an operational range

$$\underline{P}_{T_1} \leq P_{T_1}(k) \leq \overline{P}_{T_1}, \tag{5.43}$$

with $\underline{P}_{T_1}$ and $\overline{P}_{T_1}$ the lower and upper bounds of P_{T_1}, respectively. The latter fact to guarantee the proper operation of associated operations in the machine.

* ***Coolant level in tanks**:* Based on the design of the tanks to storage both dirty and clean coolant, and to guarantee the supply of the coolant from one tank to the other one, the level of coolant at each tank must satisfy its operational ranges as follows:

$$\underline{L}_{T_2} \leq L_{T_2} \leq \bar{L}_{T_2}, \tag{5.44}$$

$$\underline{L}_{T_3} \leq L_{T_3} \leq \bar{L}_{T_3}, \tag{5.45}$$

being $\underline{L}_{T_i}$ and $\overline{L}_{T_i}$ the lower and upper bounds for the level in the tank T_i, respectively,

* ***Feasible domain for $\mathbf{u_{P_1}}$**:* According to the operation of compressed-air supply system, u_{P_1} could be activated or deactivated, but its load could not be modulated. Therefore, u_{P_1} is a binary variable such that

$$u_{P_1} \in \{0, 1\}. \tag{5.46}$$

* ***Feasible domain for $\mathbf{u_{P_2}}$**:* As explained for the coolant-supply system, both the activation instant, as well as the amount of coolant flow to be pumped, should be determined. In this regard, u_{P_2} can be activated at different levels to pump more or less coolant flow. Therefore, u_{P_2} is a discrete variable subject to belong to a discrete set such that

$$u_{P_2} \in \mathbf{\Omega_2} \triangleq \{0, 100, 120, 140\}. \tag{5.47}$$

Besides, according to the approaches proposed in Chapter 4 to model the discrete-finite sets, the following variables and constraints should be included into the optimisation problem to guarantee that the values of u_{P_2} belong to $\mathbf{\Omega_2}$,

$$\left| 20 \left[\left(\frac{\tilde{u}_{P_2}(k)}{20} \right) \right] - \tilde{u}_{P_2}(k) \right| \leq 0, \tag{5.48}$$

$$100\, \beta_2(k) \ \leq \ \tilde{u}_{P_2}(k) \ \leq \ 140\, \beta_2(k), \tag{5.49}$$

Table 5.5: Model order and fitting percentage between real and modelled output.

Component	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{\Lambda_M}$
% fitting	92.33	90.39	90.70

being $[\cdot]$ the round operator, ρ the regular spacing among the elements of $\mathbf{\Omega_2}$, $\beta_2 \in \{0, 1\}$ an auxiliary binary variable for the activation/deactivation of the second peripheral device P_2, and $\tilde{u}_{P_2} \in [100\ 140]$ the new variable for the activation level when the device P_2 is turned on.

* ***Safety constraints**:* In order to avoid damages in the peripheral devices by a high-switching frequency that directly affects the inertia of each device, constraints in the execution time have been considered. Thus, at each second in which some peripheral device is turned on/off, it should remain its current state at least for a time period $t_{saf} = 5$s. In this regard, the following logic constraints are included into the set constraints:

$$\Delta u_{P_1}(k) \neq 0 \Longrightarrow \{u_{P_1}(k), \ldots, u_{P_1}(k + k_{saf} - 1)\} = u_{P_1}(k), \tag{5.50a}$$

$$\Delta u_{P_2}(k) = 1 \Longrightarrow \{u_{P_2}(k), \ldots, u_{P_2}(k + k_{saf} - 1)\} > 0, \tag{5.50b}$$

$$\Delta u_{P_2}(k) = -1 \Longrightarrow \{u_{P_2}(k), \ldots, u_{P_2}(k + k_{saf} - 1)\} \leq 0, \tag{5.50c}$$

with $\Delta u_{P_j}(k) = u_{P_j}(k) - u_{P_j}(k-1)$, and k_{saf} the number of discrete time intervals related to t_{saf}. For the case of u_{P_2}, the constraints have been referred to zero due to this peripheral device can be activated at different levels, and changes in the activation level are allowed while the device remains turned on.

5.5.2 Model identification

According to the SI method presented in Chapter 4, the model validation for both the machine and peripheral devices are shown in Figures 5.13 and 5.14, respectively. Besides, in Table 5.5, the fitting percentages of each model output concerning the available real data are presented. From these results, it is possible to observe that identified models can represent the dynamic behaviour of both peripheral devices and the proposed manufacturing sequence with a quite accuracy and fitting values higher than 80%. It should be noted that in this case, all the models had the same order model, i.e., $N = 3$.

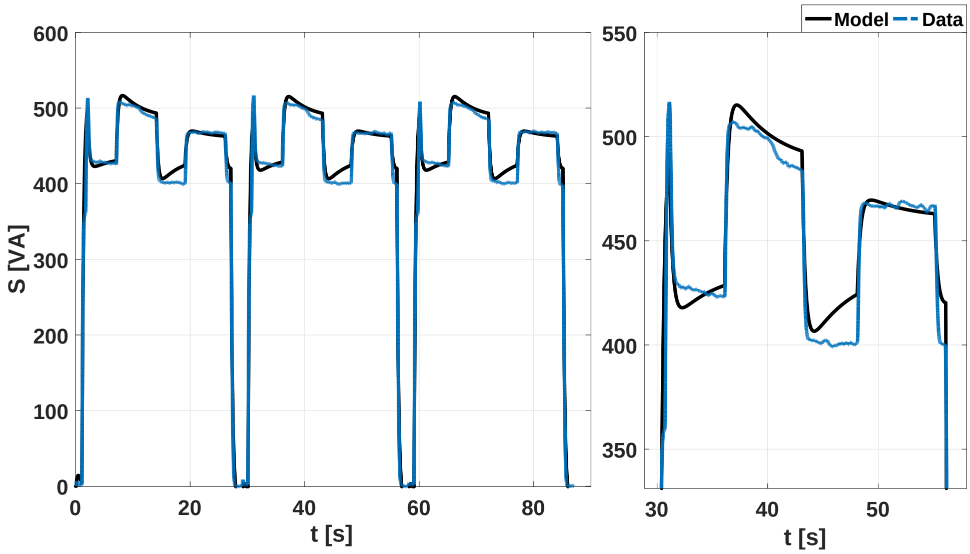


Figure 5.13: Validation of the energy consumption model for the new machine cycle with $T_{M_1} = 29$ s.

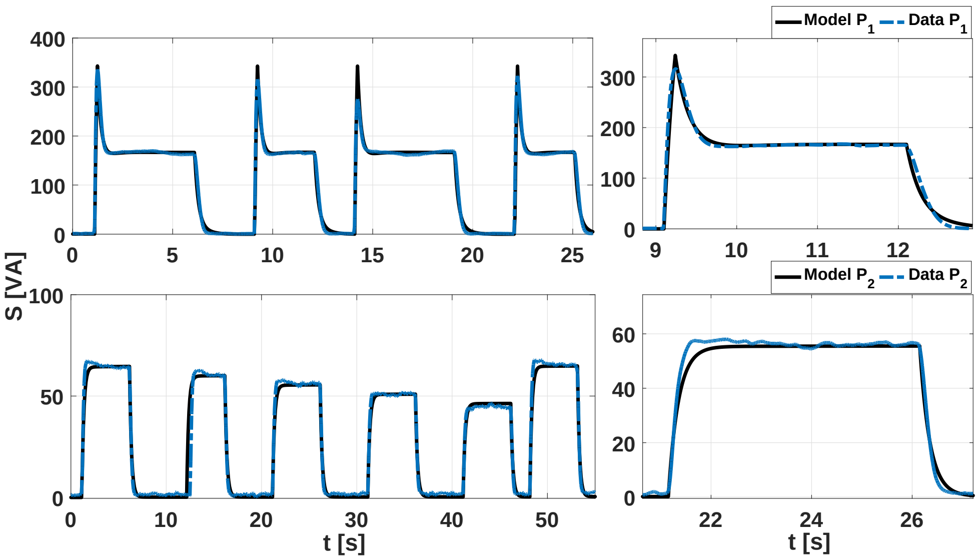


Figure 5.14: Validation of energy consumption models of the peripheral devices in the test bench (P_j).

5.5.3 Test-bench implementation

Given the mixed-integer linear programming nature of the proposed optimisation problem in (5.10) and the tools considered to solve it, preliminary simulations were developed in Matlab® to test the performance of the proposed controller before its implementation in the test bench.

Table 5.6: Simulation parameters for peripheral devices.

Parameter	Value	Parameter	Value
V_{T_1}	0.005m^3	A_{T_2}	0.0314m^2
$m_{out,a}$	$0.0015\frac{\text{kg}}{\text{s}}$	A_{T_3}	0.0314m^2
$m_{in,a}$	$0.0025\frac{\text{kg}}{\text{s}}$	η	0.85
T	$25°\text{C}$	m_{tool}	$0.005\frac{\text{kg}}{\text{s}}$
$\overline{P}_{air}$	6.5bar	m_{wp}	$0.006\frac{\text{kg}}{\text{s}}$
$\underline{P}_{air}$	5bar	$h_{1\to 2}$	$0.06\frac{\text{m}^2}{\text{s}^2}$
P_{atm}	101325Pa	ΔP_{filter}	10000Pa
ρ_c	$1042.5\frac{\text{kg}}{\text{m}^3}$	$\overline{L}_{T_2}$	0.5m
$\overline{L}_{T_3}$	0.8m	$\underline{L}_{T_2}$	0.3m
$\underline{L}_{T_3}$	0.6m	R	$8.1314\frac{\text{J}}{\text{Kmol}}$

It is worth noting that both the simulations and the test bench implementation were performed according to the parameters in Table 5.6 for the operation of the peripheral devices and using $H_p = 29$ s, which corresponds to T_{M_1} in this case. Besides, although the tests performed in the test bench were developed using a sampling time of $\tau_s = 0.01$s, the proposed controller is executed at each second, finding optimal values of u_{P_j} at each second and keeping this values up to the next second. Thus, in this case, $\tau_c = 1$ s and the controller makes 29 decisions along H_p.

As the same for the case No. 1, in addition to the proposed Optimisation-Based Controller (OBC), a Rule-Based Control (RBC) scheme, in which the peripheral devices are turned on/off according to the limit values for Q_j, was tested and compared to the proposed approach. Thereby, every time that the minimum allowed value for a peripheral device is reached, this device is turned on, whereas if the maximum allowed value is achieved, the device will be turned off. Thus, the proposed OBC, RBC and the observer were implemented in an embedded system using the C++ language, the Basic Linear Algebra Sub-programs (BLAS) [BPP+02], and Linear Algebra Packet (LAPACK) [ABD+90] libraries. These libraries and packets were used to perform linear algebra operations in parallel to reduce as much as possible the computational time. Besides, the optimisation problem (5.10) was implemented in ILOG CPLEX C++ API [ILO13] that is an interface to use the CPLEX solver.

5.5.4 Key performance indicators (KPI)

In order to evaluate the energy efficiency and performance of the considered control strategies, the following KPIs were selected and computed:

Maximum peak

The maximum consumption or peak value for a test is expressed as

$$\mathbf{KPI}_1 = \|\mathbf{S}\|_\infty, \tag{5.51}$$

with $\mathbf{S} = \{S(1), S(2), ..., S(N_\mathbf{S})\}$ the set of measurements, and $N_\mathbf{S} = |\mathbf{S}| = \frac{T_s}{\tau_s} \in \mathbb{R}_{\geq 0}$ is the number of the measurements. Thus, based on $\mathbf{KPI}_1$, the supply capacity or availability of electrical power to be contracted with an energy company can be suitably determined.

Load factor

The load factor is understood as a ratio of the average load during a given period and the maximum demand in the same period, i.e., the amount of energy used concerning the maximum capacity in a certain period (e.g., month, days, hours). Thus, the load factor is then defined as follows:

$$\mathbf{KPI}_2 = \frac{1}{N_\mathbf{S}\,\mathbf{KPI}_1}\sum_{k=1}^{T_s} S(k), \tag{5.52}$$

being $\mathbf{KPI}_2$ the load factor percentage derived by the average energy along T_s regarding to the equivalent energy consumption at maximum load $(N_\mathbf{S}\ \mathbf{KPI}_1)$. In this regard, if $\mathbf{KPI}_2$ is greater than 50%, the use of energy is relatively constant, and the contracted capacity is then properly used. Otherwise, energy demand might be reduced.

Variance of energy consumption profile

The management of the peripheral devices in an intelligent way to have an approximately constant consumption can be reached avoiding the sum of several power peaks and turning on the peripheral devices when the manufacturing process shows a low consumption. Thus, achieving an efficient distribution of energy over time with a low variation, the adequate supply capacity to be contracted could be determined. In this sense, the variance of energy consumption is defined as follows:

$$\mathbf{KPI}_3 = \frac{1}{N_\mathbf{S}}\sum_{k=1}^{T_s}(S(k) - \bar{\mathbf{S}})^2, \tag{5.53}$$

Table 5.7: KPI values for the OBC and RBC controllers.

Controller \ KPI	$\mathbf{KPI}_1$	$\mathbf{KPI}_2$	$\mathbf{KPI}_3$
OBC ($H_p = T$)	831.6273 VA	60.53%	13485 VA
OBC ($H_p = 2T$)	831.6273 VA	60.53%	13492 VA
OBC ($H_p = 3T$)	831.6273 VA	60.53%	13508 VA
RBC	911.1758 VA	55.09%	29328 VA

being $\bar{\mathbf{S}}$ the mean value of energy consumption along T_s.

5.5.5 Experimental results

Once the initial conditions of the observer and the q-relations are established, four tests were carried out to compare both control strategies and determine the performance of OBC at different H_p. In this regard, three different values of H_p were tested, i.e., $H_p = T$, $H_p = 2\ T$ and $H_p = 3\ T$. Based on these tests, the proposed KPIs were calculated, and the obtained results are presented in Table 5.7. It should be noted that in these cases all simulations were performed considering a simulation time equal $T_s = 41$ minutes that corresponds to 86 operation cycles. Then, according to the results in Table 5.7, $H_p = T$ was established for testing the control strategy in the test bench since increasing it does not bring great benefits in KPIs.

Next, in Table 5.8, a comparative of KPIs values for the implementation of the proposed OBC and RBC is shown as the improvement in the percentage of the OBC concerning the RBC. It should be noted that since $\mathbf{\Lambda}_{\mathbf{M_i}}$ is not modified, i.e., the total time for manufacturing a piece is the same, the productivity of the system is not affected when the proposed control strategy is implemented. This fact is a consequence of the independent management of peripheral devices regarding global energy consumption in which the dynamics of these devices are considered as restrictions into the optimisation problem. From this approach, it is possible to guarantee that peripheral devices are energy-efficient managed in a way in which the resources required for the machine operation are supplied in quantity and at the proper time instant. Based on the obtained results, it is possible to see that regarding $\mathbf{KPI_1}$, the peak using OBC is reduced by 7.63% concerning RBC, while for $\mathbf{KPI_2}$ improvements close to 5.40% were achieved. In this regard, 86 pieces were produced when both OBC and the RBC are implemented, taking into account the total simulation time. Therefore, the proposed OBC improves energy efficiency without productivity losses. On the other hand, the variation of the energy consumption profile is reduced by 46.79%, which means a more constant energy consumption profile can be reached using the proposed controller while the system productivity remains.

Table 5.8: Improvement in KPI values of OBC with respect to RBC in the test bench.

Controller \ KPI	**KPI$_1$**	**KPI$_2$**	**KPI$_3$**
RBC ($H_p = T$)	899.00 VA	66.66%	30948 VA
OBC ($H_p = T$)	830.37 VA	70.25%	16466 VA
% improvement	7.63%	5.40%	46.79%

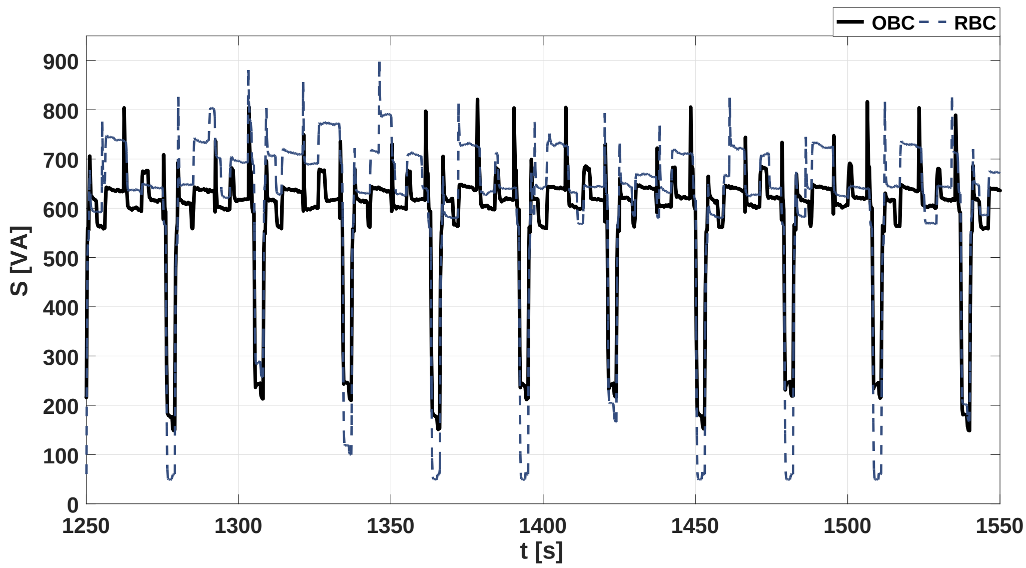


Figure 5.15: A zoom of energy consumption profile for both OBC and RBC.

Besides, in Figure 5.15 a representative part of the energy consumption profile resulting from the application of the OBC and RBC controllers is presented. Based on these results, the power peaks obtained by using RBC were always higher than the peaks resulting from using OBC, in concordance with results in Table 5.7. This behaviour is mainly due to the RBC does not take into account the current stage of the manufacturing process for deciding between switching on/off any peripheral devices. Besides, the proposed OBC can modulate the load of P_2 to satisfy operating constraints and reach a lower energy consumption.

Representative parts of both the optimal input sequence $\mathbf{\Gamma}^*(k)$ for OBC and the activation/deactivation sequence for RBC are presented in Figure 5.16. From these results, it is possible to see that even when the safety constraints are satisfied, the switching frequency of OBC is higher than the obtained when RBC is implemented. Thus, the OBC strategy avoids to turn devices on at the same time instant, and in the cases that both devices must switch on the activation of one of them is delayed or advanced to avoid their simultaneous activation. Besides, when the load can be modulated (like for P_2), OBC never decides to turn devices on at the maximum capacity, instead of that, it increases the switching frequency at lower consumption levels.

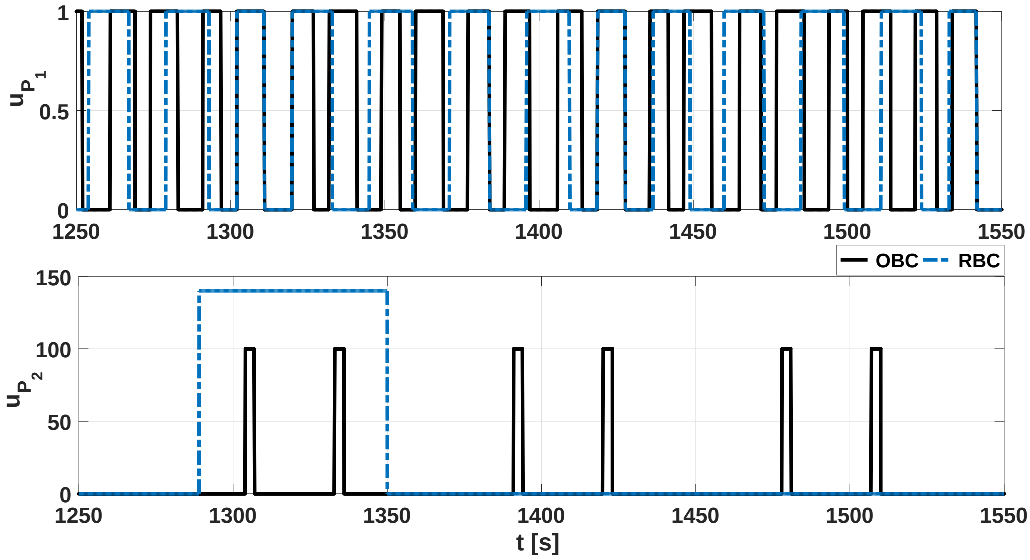


Figure 5.16: Input signals for the peripheral devices.

On the other hand, the dynamics of q-relations for the two processes selected and depicted by peripheral devices are shown in Figure 5.17. From these results, and according to the optimal sequences found, it can seem that for both cases, the operation of peripheral devices remains inside the considered operating ranges. However, for the case of the coolant-supply system, which shows the slowest dynamics, P_2 is activated to keep the level in the clean tank continues near its lower limit. Therefore, most of the recovered coolant is stored into the dirty tank, i.e., it remains near the upper boundary, as shown in Figure 5.18. This behaviour could be a consequence of energy losses considered at each section of the process, since the system requires more energy to transport the fluid through the filter and pipeline up to T_2. Thereby, the OBC decides to store the coolant in the dirty tank and to pump the refrigerant towards the particle filter and the clean tank only when it is required.

5.6 Summary

This chapter is focused on proposing an energy reduction control approach to periodic manufacturing systems in which their peripheral devices can be independently managed. The proposed control strategy is designed based on OBC techniques and the *receding horizon philosophy* to transform the control problem into an optimisation problem that considers power consumption models, operational constraints and the operational relationships among the machine and its

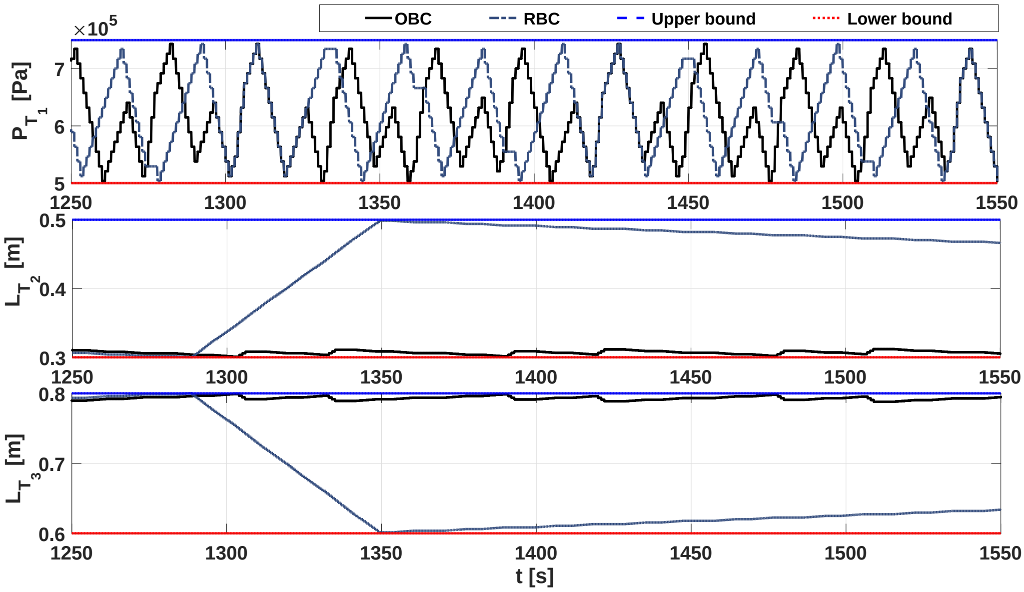


Figure 5.17: Dynamics of q-relations for P_1 and P_2.

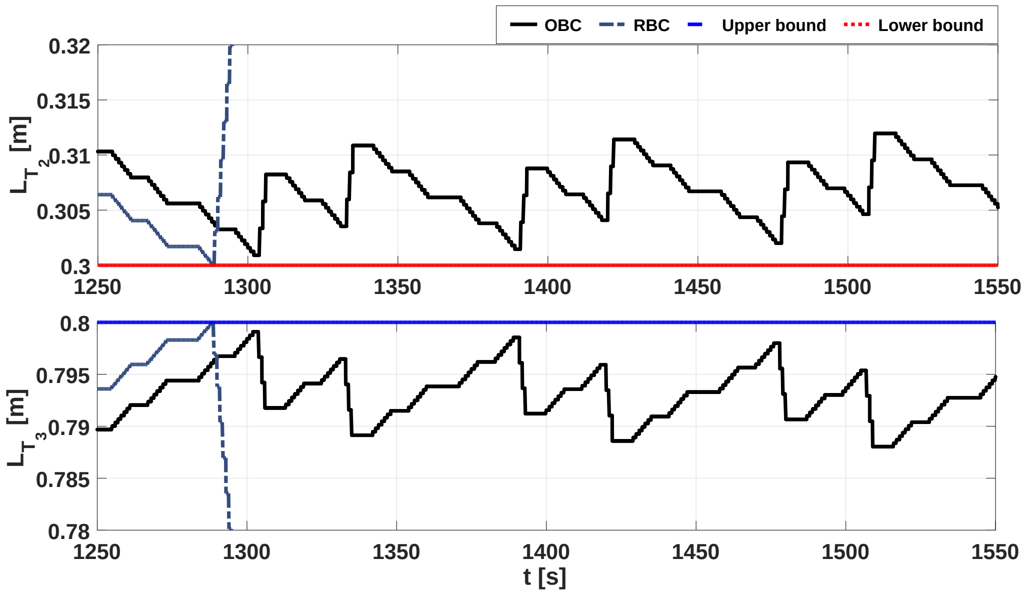


Figure 5.18: Zoom of q-relations dynamics for P_2 presented in Figure 5.17.

peripheral devices. Thus, the main idea is to predict the time instants at which the peripheral devices will be required and, based on this prediction, selecting the time instant in which those devices must be switched on/off to minimise the total energy consumption. Besides, the control strategy aims to avoid the simultaneous activation of the peripheral devices, while guaranteeing the time-varying operational conditions of manufacturing processes, and remaining their productivity.

Two different case studies were addressed in this Chapter. According to Section 5.1, the control strategy using a multi-objective cost function was tested only by simulation, while the proposal using a single control objective was implemented in the test bench explained in Chapter 4. It is worth noting that the case No. 1 (multi-objective) was developed as a first approximation to valid the control strategy and, therefore, the q-relationships for the process dynamics of peripheral devices were simplified. However, based on the obtained results for the case 1, the simplification from a multi-objective problem to one of a single objective and the selection of the prediction horizon can be explained. Thus, suitable modifications were performed to the control strategy and, based on them, the case No. 2 was designed and implemented in the test bench to check the effectiveness of the control strategy in real-time.

Regarding the first case study, significant improvements in reducing the power peaks magnitude were achieved when the proposed control strategy was implemented, without affecting the machine operation and its productivity. The latter fact due to Assumption 5.1, from which the machining sequence is not modified and therefore, the machine can process the same number of pieces than when the control strategy is not implemented. Nonetheless, concerning global energy consumption, significant reductions were not achieved because of the energy consumption behaviour of peripheral devices is not modified or modulate. Thus, in the second case study, peripheral devices with different power consumption levels were included to test the energy reductions that could be achieved when the energy consumption of peripheral devices can be modified.

Based on the obtained results for the second case study, the peripheral devices can be managed appropriately regarding energy efficiency without compromising the proper operation and the productivity of the manufacturing processes. Thus, according to the KPIs computed, the proposed control strategy allows achieving reductions in energy costs avoiding the economic penalties, which can be produced if the nominal power purchased is surpassed. Besides, the use of loads that can be modulated represents an energy-saving opportunity since in this way, it is possible to modify its energy consumption without change the physical configuration of the peripheral devices.

CHAPTER 6

DUAL MODE CONTROL STRATEGY FOR COMPLEX AND FLEXIBLE MANUFACTURING SYSTEMS

The manufacturing industry is shifting towards SM, in which both energy efficiency and flexibility are some of the main objectives of this digital transformation. In this regard, the control strategies for manufacturing systems should be able to support the requirements of this transformation with a low computational burden towards their implementation in real time. In this chapter, a dual-mode control strategy based on two control approaches is proposed to minimise the energy consumption of manufacturing systems without affecting their productivity, even when scenarios of flexible manufacturing are considered. The first control mode is based on MPC to determine an optimisation-based strategy for the constrained behaviour of the system. This mode is a extension of the proposed control strategy in Chapter 5 to the process line level. On the other hand, the second mode builds on the assumption that the system exhibits a periodic behaviour and, thus, it will be able to switch to an autonomous control mode that avoids the resolution of an optimisation problem online.

6.1 Motivation

In the previous chapters, energy consumption models and a centralised control strategy have been proposed to improve the energy efficiency of the lower aggregation level in the manufacturing industry, i.e., the machines level. However, machines are only the basic process units in the manufacturing industry, and at higher levels, more complex structures and interactions exist. Besides, into the new era of manufacturing systems and their transformation towards smart manufacturing, these systems and the control strategies should be able to respond to changes in the production programs to be capable of processing pieces with different design specifications, allowing a higher level of customisability for the final users [DOM19].

At process line level, manufacturing systems refer to a collection of machines and devices organised in a proper configuration for producing a finished piece, commonly named as process line. Complex structures are found in a process line, which corresponds to the aggregation of machines, peripheral devices, and buffer devices for producing a piece. At this aggregation level, machines are organised logically according to the required operations to process a piece entirely. Besides, since the machines in a process line could have different operating cycles, buffers might be required in order to maximise the production and avoid the simultaneous input of two or more pieces to one machine. As the same for the machine level, peripheral devices refer to those devices that are not directly related to machining operations but are necessary to guarantee the correct operation of machines and the suitable supply of resources to machines in the process line. Some resources required by machines are, for instance, water to clean pieces, the coolant to be used during machining operations, air or hydraulic fluids to clamp/unclamp of pieces according to the design of the machine, among others.

According to the processes performed on each machine and its connections, process lines present different configurations, such as serial and parallel structures. Based on the configurations in a process line, different energy and material flows, which represent either the interactions or relations between the machines and peripheral devices in the process line, could exist. These relationships add complexity to understand and modelling the energy consumption as well as designing control/management strategies at this level. Therefore, factors as the diversity of components in a process line, their energy consumption behaviour, their interactions, and the intrinsic characteristics of each component should be considered to analyse and propose energy efficiency improvements at the process line level [EYME17].

However, to reduce the energy consumption of manufacturing systems, the improvements for single machine or device in the process line are not enough and, instead of this, the whole process line should be optimised to reduce its total energy consumption [UUG+16]. Although many works consider strategies for flexible manufacturing at the plant level, energy consumption is usually considered as an initial optimisation regarding the production planning of the existing devices in the plant. That is, these strategies determine an optimal sequence from the beginning, and therefore they cannot respond to the temporal variation of processes and working environment factors during the operation of the plant [DOM19].

Given the complexity of manufacturing systems due to the processes performed, the strong relationships between the peripheral and machining devices, the time-varying constraints such as tool wear, the efficiency of each device and the changing-working environment, the most used control techniques in manufacturing systems are those based on optimisation. This fact is given since the control objectives, operating constraints of either devices or machines involved, their operating ranges, dynamic expressions for the relationships between machines and their environment, and any additional constraints that condition the performance of the system to be controlled can be included into an optimisation problem.

However, although few control applications in manufacturing systems consider energy objectives, most of them have been limited to analyse the individual system and not consider interactions with both other devices and machines. Besides, most of these applications consist of designing closed-loop control schemes that minimise the difference between the real energy consumption and a reference behaviour, which is usually determined offline and without considering the temporal variations of its surroundings. Thus, in most of the case studies, disturbances or changes in the working environment are not considered. Therefore, and taking into account the current context of manufacturing industry, strategies able to respond in real time to any changes in the system or its environment, besides to consider flexibility in the processes plan and schedule should be developed [APM15].

Thus, in this chapter, a dual mode control strategy based on two control approaches is designed to minimise the energy consumption of manufacturing systems without affecting their productivity. The main idea behind the design of the dual control strategy is to reduce the computational burden by switching from a control mode based on online optimisation to an autonomous mode without optimising. The last fact with the objective that the proposed control strategy can be suitable for its implementation in real time, considering both flexible manufacturing scenarios and disturbances management, but without sacrificing the closed-loop performance of the controller.

6.2 Control Problem Formulation

In the current context of flexible manufacturing, process lines should be able to produce different finished parts, in which the line has the flexibility to react to changes in the product being manufactured, both in type and quantity. In this regard, a process line is a complex (and large-scale) system including several machines and peripheral devices that work synchronously and logically up to getting a finished part. Machines in a process line (M_i) correspond to a set of devices that are directly related to machining processes (e.g., milling, cutting, turning, grinding, drilling), while the peripheral devices are those devices that provide the resources required to machines for their proper operation. Thus, the classification into manufacturing devices and peripheral devices proposed in Chapter 5 is extended to the process line, in which the manufacturing devices now refer to the machine tool, i.e., the set of all devices that form the machine. However, it should be noted that, although at the process line are also considered peripheral devices, these can even exist at the machine level at the same time.

According to Chapter 5, the machines in a process line are characterised by a periodic behaviour according to the total time required for manufacturing a piece, which corresponds to a *operation cycle* that will be denoted by T_{M_i} henceforth since several machines form a process line. Then, the energy consumption of devices straight related to manufacturing operations in each machine, such as manufacturing processes, transport, and handle of pieces, shows also a periodic behaviour. Besides, due to the nature of the operations performed by machine devices (e.g., rotational motions, axial motions, cutting, milling), there exist stages of both high and low energy consumption along T_{M_i}.

On the other hand, since peripheral devices supply resources to machines in the process line, there exist several functional relationships between machines and peripheral devices that determine the productivity of the process line. When the machines in a process line have different values of T_{M_i}, the throughput of the process line level is determined based on the machine with the longest T_{M_i}, i.e., $\mathtt{max}(T_{M_i})$. Thereby, process lines are designed with the aim of processing a complete piece up to achieve the desired physical properties (e.g., shape, weight, volume, surface, among other) in the shortest possible time. However, peripheral devices might or might not show a periodic behaviour, which may match with T_{M_i}, as a consequence of the design of peripheral devices in the process line as well as the way they are managed. Therefore, to improve the energy efficiency of a process line, peripheral devices must be correctly managed such that their activation time does not match with the time instants/slots of higher energy consumption while satisfying the operating constraints of machines.

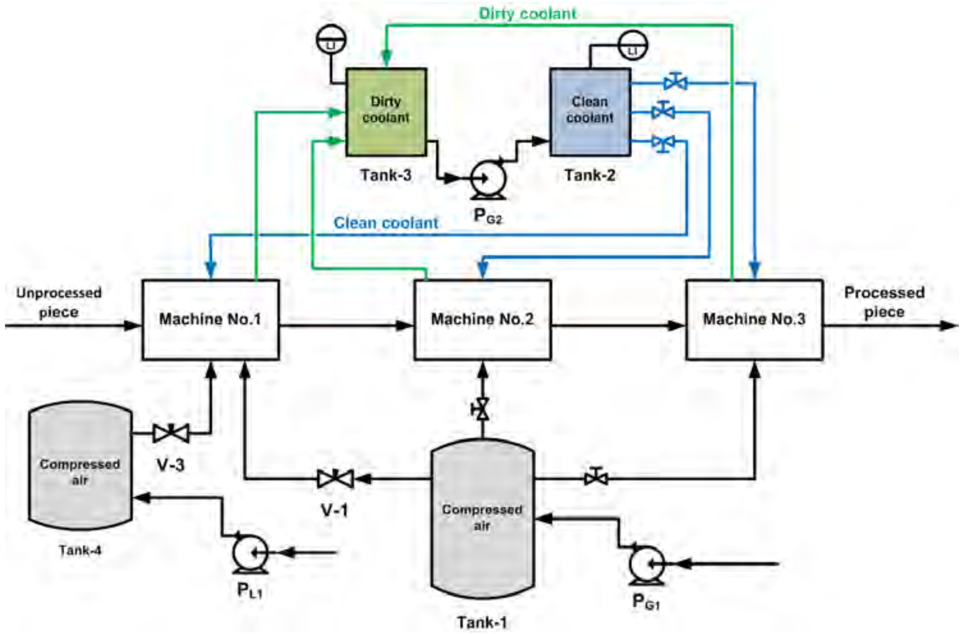


Figure 6.1: Three-stage serial process line with its corresponding peripheral systems.

At the process line level, the functional relationships between machines and peripheral devices could be quite complex since some peripheral devices can be shared between two or more machines, provide the same resource to all the machines in the line, or even supply the same resource provided by another global peripheral device to a particular machine. Besides, peripheral devices in the process line should be able to adapt their operation to the changes in the production program and the new functional relationships imposed by these programs. In these cases, a consensus based on the management objectives (e.g., energy consumption, energy costs, productivity) should be established to guarantee the satisfaction of the operating constraints among machines and peripheral devices as well as the proposed control objectives. In Figure 6.1, a serial process line is shown, which consists of three machines and three peripheral devices. Based on the configuration of peripheral devices in the process line, they can be classified as:

- *Global* peripheral device if it is shared among two or more machines of the process line, and
- *Local* peripheral device of the machine i when the device works only for the i-th machine in the process line.

According to the stages of higher and lower energy consumptions along T_{M_i}, the activation instants of each peripheral device should be selected taking into account both its operating constraints and its dependency on the activation sequence of machines $\mathbf{\Lambda_{M_i}}$. Thus, according to

(5.1a), considering a fixed number of both machines and peripheral devices in a process line, their activation sequences can be defined as

$$\mathbf{\Lambda_{M_i}}(k) = \{u_{M_{i,1}}(k), u_{M_{i,2}}(k), \ldots, u_{M_{i,m}}(k)\}, \tag{6.1a}$$

$$\mathbf{\Lambda_P}(k) = \{u_{P_1}(k), u_{P_2}(k), \ldots, u_{P_n}(k)\} \tag{6.1b}$$

being $m = |\mathbf{\Lambda_{M_i}}|$ and $n = |\mathbf{\Lambda_P}|$ the number of manufacturing devices of the i-th machine and the number of peripheral devices in the process line, respectively. Usually, the activation signals of both machine devices and peripheral devices are constrained to $u_{M_{i,l}}(k) \in \{0,1\}$, $l \in \mathcal{L} \triangleq \{1, 2, \cdots, m\}$, and $u_{P_j}(k) \in \{0,1\}$, $j \in \mathcal{J} \triangleq \{1, 2, \cdots, n\}$. However, for the cases in which the activation load of devices can be modulated, the activation signal will be constrained to $u_{M_{i,l}}, u_{P_j} \in \mathbb{Z}_{\geq 0}$.[1]

Due to the activation instants of the machine devices $u_{M_{i,l}}$ and their execution times $T_{M_{i,l}}$ given by the manufacturing process and known a priori from the process planning and scheduling designed for each piece, both the machining sequences of each machine $\mathbf{\Lambda_{M_i}}$ and its associated power consumption S_{M_i} can be considered as fixed and periodic over the time (see Assumption 5.1). Otherwise, the power consumption of peripheral devices S_{P_j} depends on the operational relationships between them and machines in the process line since they must guarantee resources required for the manufacturing processes. Thus, to select the suitable activation instants of the peripheral devices that allow minimising the global energy consumption S of the process line, the dynamics of both energy consumption and the process performed by the peripheral devices, and operating constraints between they and machines should be taken into account for the design of control strategies. In this regard, the control problem consists of determining the optimal $\mathbf{\Lambda_P}$ that minimises the global S along a fixed period T. Indeed, the control objective can be defined as the minimisation of the integral of the energy consumption signal, i.e.,

$$J = \sum_{k=1}^{T} \left[\sum_{i=1}^{b} S_{M_i}(k) + \sum_{j=1}^{n} S_{P_j}(k) \right] \Delta k, \tag{6.2}$$

being b the total number of machines in the process line and $\Delta k = (t_k - t_{k-1})$ the temporal spacing, which is assumed equal to τ_s. Then, to compute the global apparent power consumption $S(k) = \sum_{j=1}^{n} S_P(k) + \sum_{i=1}^{b} S_{M_i}(k)$, power consumption models for each machine

[1] Regarding the notation, it is worth noting that some letters are re-defined at each chapter as required.

$$\xi_{M_i}(k+1) = h_1\left(\xi_{M_i}(k), \{u_{M_{i,1}}(k), u_{M_{i,2}}(k), \cdots, u_{M_{i,l}}(k)\}\right) \tag{6.3a}$$

$$S_{M_i}(k) = h_2(\xi_{M_i}(k)), \tag{6.3b}$$

and each peripheral device are required, i.e.,

$$\xi_{P_j}(k+1) = f_1(\xi_{P_j}(k), u_{P_j}(k)), \tag{6.4a}$$

$$S_{P_j}(k) = f_2(\xi_{P_j}(k)), \tag{6.4b}$$

being $\xi_{P_j}(k) \in \mathbb{R}^p$ and $\xi_{M_{i,l}}(k) \in \mathbb{R}^r$ the system states of the energy consumption models related to P_j and $M_{i,l}$, respectively. Besides, $f_1 : \mathbb{R}^p \times \{0,1\}^n \mapsto \mathbb{R}^p$ and $f_2 : \mathbb{R}^p \mapsto \mathbb{R}_{\geq 0}$ are the maps in function of both the current state and the activation signal of P_j, while $h_1 : \mathbb{R}^r \times \{0,1\}^m \mapsto \mathbb{R}^r$ and $h_2 : \mathbb{R}^r \mapsto \mathbb{R}_{\geq 0}$ are the maps for $M_{i,l}$. Moreover, mathematical expressions for the dynamics of processes performed by peripheral devices, i.e.,

$$Q_{P_j}(k+1) = q_{P_j}(Q_{P_j}(k), u_{P_j}(k), \mathbf{\Lambda_{M_i}}), \tag{6.5}$$

are also required to express the operational relationships between machines and peripheral devices. In (6.5), $Q_{P_j}(k)$ corresponds to states related to the dynamics of peripheral devices P_j, with $q_{P_j} : \mathbb{R} \times \{0,1\}^{n+m} \mapsto \mathbb{R}$ the maps that consider the relationships between machines and peripheral devices.

6.3 A Benchmark System

According to Figure 6.1, a process line with three machines and three peripheral devices will be studied to test the performance of the control strategy to be proposed. In order to analyse a scenario of flexible manufacturing, two different production programs to process two different types of pieces will be considered. The difference between the production programs concerns to the first machine, for which the resource consumption at each instant k will be higher when the second production program is executed. Besides, two case studies will be analysed in this chapter. In the former, it is assumed that all machines in the process line have the same cycle time, i.e., $T_{M_i} = 28$ s $\forall\, i = 1, 2, 3$ and their machine sequences[2] $\mathbf{\Lambda_{M_i}}(k)$ are fixed and periodic over the time. On the other hand, the second case study considers the scenario in which not all the machines in the process line have the same cycle time, i.e., $T_{M_i} \neq T_{M_p}$ for some $i \neq p$.

[2] It corresponds to the sequence of processes performed by the machining devices of a machine to process a piece.

Concerning the peripheral devices, P_{G_1} and P_{G_2} are considered as global peripheral devices since they are shared among the three machines in the process line. In contrast, P_{L_1} is a local device that only provides resource to M_1. Thus, for the first production program, the global devices P_{G_1} and P_{G_2} are able to supply the resources demand of machines. However, when the second production program is executed, an extra peripheral device (P_{L_1}) is required since the device P_{G_1} is not able to supply the new demand of compressed air required by machines activated in the second program.

It should be noted that at this level, the processes related to the operation of peripheral devices are inherited of the machine level. Thus, both P_{G_1} and P_{L_1} are associated to the supply system of compressed air, which will be used for clamping pieces during the whole machining sequence. Besides, it is assumed that both P_{G_1} and P_{L_1} have a nominal energy consumption whenever the device is turned on. It is worth noting that the local peripheral device P_{L_1} works only for M_1 and its operation depends on the production program executed in the process line. Thus, in order to consider a flexible manufacturing scenario, it is assumed that P_{L_1} will be inactivated during the first production program, and will be activated when the second production program is executed since the resource consumption of M_1 during the second program is significantly higher than its consumption in the previous production program. For the case in which the second production program will be executed because a different part should be processed in the process line, new decision variables to determine the optimal flow to be taken from each device are required. Thus, according to Figure 6.1 the aperture of the valves v_1 and v_3 should also be optimised according to the new sequences of resources consumption from machines for the new production program. It should be noted that the other valves in the process line are not directly manipulated since it is assumed that they are opened/closed when required, and they can provide the flows demanded by the machines. Thus, without loss of generality, in this case, only the valves involved in coupled dynamics will be addressed in the extended operation range.

On the other hand, P_{G_2} is related to a coolant supply system for the machining operations at each machine, and its activation could be modulated to different energy consumption levels. According to this, both the activation instant and the activation level for P_{G_2} should be optimised taking into account the resources consumption from machines. It is worth noting that the consumption of resources from machines depends on $\mathbf{\Lambda_{M_i}}$ and the production program. However, although in this dissertation the machining sequences are not presented in detail since they are assumed to be fixed and constant over the time, in Figures 6.2 and 6.3, the consumption profiles of compressed air and coolant from the machines are presented for the two cases considered. Based on these figures, it is possible to observe that the unique difference between the

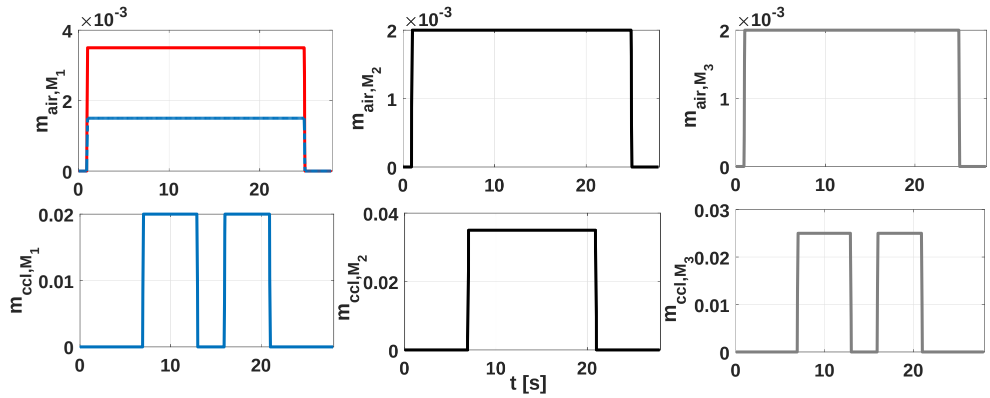


Figure 6.2: Sequences for resource consumption from machines in the process line along T_{M_i} for the first case study in $\left[\frac{\text{kg}}{\text{s}}\right]$. For the case of M_1, the blue line refers to the air consumption when the first production program is executed, and the red line corresponds to the consumption when the second production program is activated.

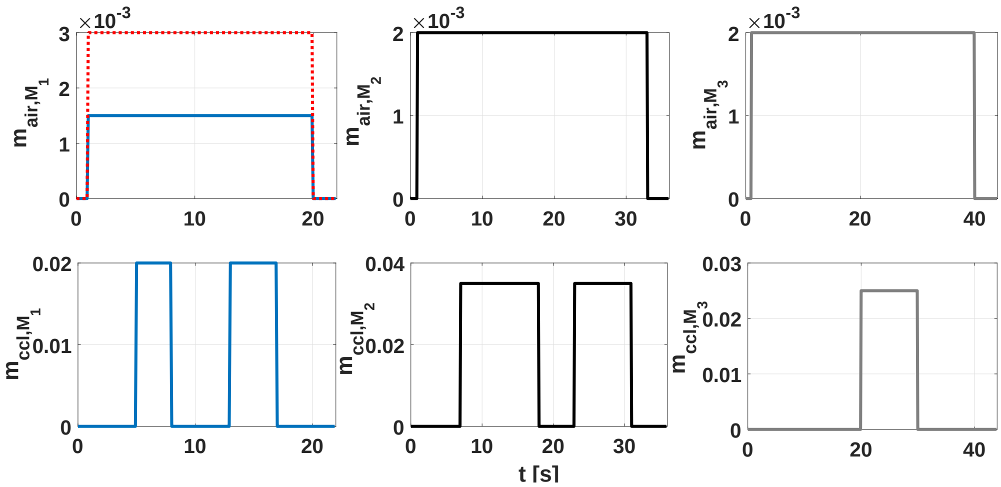


Figure 6.3: Sequences for resource consumption from machines in the process line along T_{M_i} for the second case study in $\left[\frac{\text{kg}}{\text{s}}\right]$. For the case of M_1, the blue line refers to the air consumption when the first production program is executed, and the red line corresponds to the consumption when the second production program is activated.

production programs regards the machine M_1, in which the resource consumption is duplicated, as shown in the figures with a red line.

Operational constraints

As the same for the machine level, the operational constraints refer to the process dynamics related to the operation of peripheral devices, the operational relationships between machines and peripheral devices, the energy consumption models, and the physical limitations of the machine tools and peripheral devices. It should be noted that although the processes of peripheral devices are the same at the machine level, the physical dimensions of these systems are different at both levels due to at this level higher capacity is required.

Air-supply system

For both P_{G_1} and P_{L_1}, the dynamics for the total change of mass M_{T_1} (M_{T_4}) and pressure P_{T_1} (and P_{T_4}) inside a storage tank T_1 (and T_4) can be expressed in the same way as presented in Chapter 5 for the supply system of compressed air. Such dynamics can be expressed in the discrete-time version as follows:

$$M_{T_1}(k+1) = M_{T_1}(k) + \tau_s\, \sigma(k), \tag{6.6a}$$

$$\sigma(k) = m_{in}\, u_{G_1}(k) - m_{G_{1\,M_1}} - \sum_{i=2}^{b} m_{air,M_i}(k), \tag{6.6b}$$

$$P_{T_1}(k) = \frac{M_{T_1}(k)\, R\, T}{V_{T_1}\, W_{air}}, \tag{6.6c}$$

being m_{air,M_i} the air consumption from machine M_i, m_{in} the air flow pumped by P_{G_1} (and P_{L_1}) towards the tank T_1 (and T_4), and, R, T, V_{T_1} and W_{air} the gas constant, air temperature, volume of T_1 (and T_4), and the molecular weight, respectively. In addition, the pressure P_{T_1} (and P_{T_4}) must satisfy $\underline{P}_{T_1} \leq P_{T_1}(k) \leq \overline{P}_{T_1}$ (and $\underline{P}_{T_4} \leq P_{T_4}(k) \leq \overline{P}_{T_4}$), with $\underline{P}_{T_1}$ and $\leq \overline{P}_{T_1}$ the lower and upper bounds for P_1, respectively. Moreover, since P_{L_1} is a local device of M_1, the second term in the right-hand side in (6.6b) does not exist and the only output of T_4 is $m_{L_{1\,M_1}}$. Although (6.6a) to (6.6c) were presented with respect to Tank 1, a similar set of equations can be written for Tank 4.

It should be noted that for the case in which both P_{L_1} and P_{G_1} provide compressed air to M_1 at the same time, the sum of $m_{G_{1\,M_1}}$ and $m_{L_{1\,M_1}}$ should be equal the flow required by M_1 at each instant k, namely $m_{air,M_1}(k)$. Thus the following relation should be satisfied:

$$m_{air,M_1}(k) = m_{G_{1\,M_1}}(k) + m_{L_{1\,M_1}}(k), \tag{6.7}$$

being $m_{air,M_1}(k)$ the sequence shown in Figures 6.2 and 6.3 for each production program.

In this regard, two valves with modulated aperture (v_1 and v_3) are considered into the process scheme to determine how much flow of compressed air could be provided from P_{G_1} and P_{L_1}.

The domain for variables v_1 and v_3 should be defined taking into account the maximum flow that can supply each device when the valves are 100% open as well as the admissible values into its domain to guarantee a feasible solution. Thus, the flows of compressed air provided by P_{G_1} and P_{L_1}, according to the values of both v_1 and v_3, can be compute according to the following equations:

$$m_{G,1_{M_1}}(k) = \varepsilon_{v_1}\ v_1(k), \tag{6.8a}$$

$$m_{L,1_{M_1}}(k) = \varepsilon_{v_3}\ v_3(k), \tag{6.8b}$$

with ε_{v_1} and ε_{v_3} the maximum capacity of v_1 and v_3, respectively.

Coolant-supply system

At this level, a coolant-supply system with re-circulation is also considered. Thus, according to the related discussion in Chapter 5, the pump $P_{G,2}$ corresponds to the peripheral device of interest, and both the activation instant and the suitable flow of coolant to satisfy the operating constraints must be selected. Therefore, $u_{G_2} \in \mathbb{V}_2 \subset \mathbb{Z}$ such that $\mathbb{V}_2 \triangleq \{0, 100, 120, 140\}$. The dynamics for level changes in both tanks are the following:

$$L_2(k+1) = L_2(k) + \tau_s\ \gamma(k) \left(\frac{1}{\rho_c\ A_{T_2}}\right), \tag{6.9a}$$

$$\gamma(k) = m_c(k) - \sum_{i=1}^{b} m_{ccl,M_i}(k), \tag{6.9b}$$

$$L_3(k+1) = L_3(k) + \tau_s\ \theta(k) \left(\frac{1}{\rho_c\ A_{T_3}}\right), \tag{6.9c}$$

$$\theta(k) = \sum_{i=1}^{b} m_{dcl,M_i}(k) - m_c(k), \tag{6.9d}$$

$$\tag{6.9e}$$

with m_c given by

$$m_c(k) = \frac{\eta\ \rho_c\ W(k)}{P_{in}(k) + \rho_c\ h_{f_{1\to 2}}(k) - P_{out}(k)}, \tag{6.10}$$

with $m_{ccl_{M_i}}$ the coolant flow required by the i-th machine, and $m_{dcl_{M_i}}$ the flow of the dirty coolant recovered. In addition, P_{in} and P_{out} correspond to the input and output pressure in

Table 6.1: Model order and fitting percentage for the energy consumption models identified by SI methods.

Component	$\mathbf{M_1}$	$\mathbf{M_2}$	$\mathbf{M_3}$	$\mathbf{P_{G,1}}$	$\mathbf{P_{L,1}}$	$\mathbf{P_{G,2}}$
N	5	7	5	6	6	3
% fitting	95.32	95.95	95.32	98.82	97.83	94.22

the pipe system that transport the coolant from T_3 towards T_2, while, ρ_c, η, W and $h_{f_{1\to2}}$ (see Section 5.5.1) are the coolant density, efficiency of the pump, the work supply to the pump $P_{G,2}$ and the energy losses by friction, respectively.

Energy Consumption Models

Based on the test bench presented in Chapter 4, three new machining sequences were created using different activation instants and load modulations for both the heater and one of the UPS. Different test were performed to collect data with the aim be used in the model identification according to the Subspace Identification methods presented in the same chapter. It should be noted that, initially, the data were collected using the same sampling frequency, $\tau_s = 0.01$ s. However, at this level, once the models were identified using τ_s, the models for both peripheral devices and machines were re-sampled to a new sampling time $\tau_s = 0.1$ s in order to reduce the computational burden. In this case, since P_{G_1} and P_{L_1} have a fix energy consumption whenever they are turned on, they were associated with the motors in the test bench. On the other hand, since for P_{G_2} the activation load can be modulated, it was related to the UPS with some extra loads.

In this regard, different sequences of $\mathbf{\Lambda_P}$ and $\mathbf{\Lambda_{M_i}}$ were tested in the test bench. Afterwards, the energy consumption models for the three machines and the three peripheral devices in the process line were identified by using the `n4sid` routine of the System Identification Toolbox™ provided by Matlab®. In Table 6.1, the model order and the fitting percentages between the model and real outputs are presented for each one of the machines and peripheral devices. Besides, in Figures 6.4 and 6.5, the model validation with respect to the real data is presented for both machines and peripheral devices, respectively. Then, the the obtained matrices for the energy consumption models of both peripheral devices and machines, at the new $\tau_s = 0.1$ s, are presented in Appendices A.1 and A.2.

In addition to the energy consumption of peripheral devices and machines, it was assumed that the valves related to P_{G_1} and P_{L_1} also imply an associated energy consumption. Thus, the

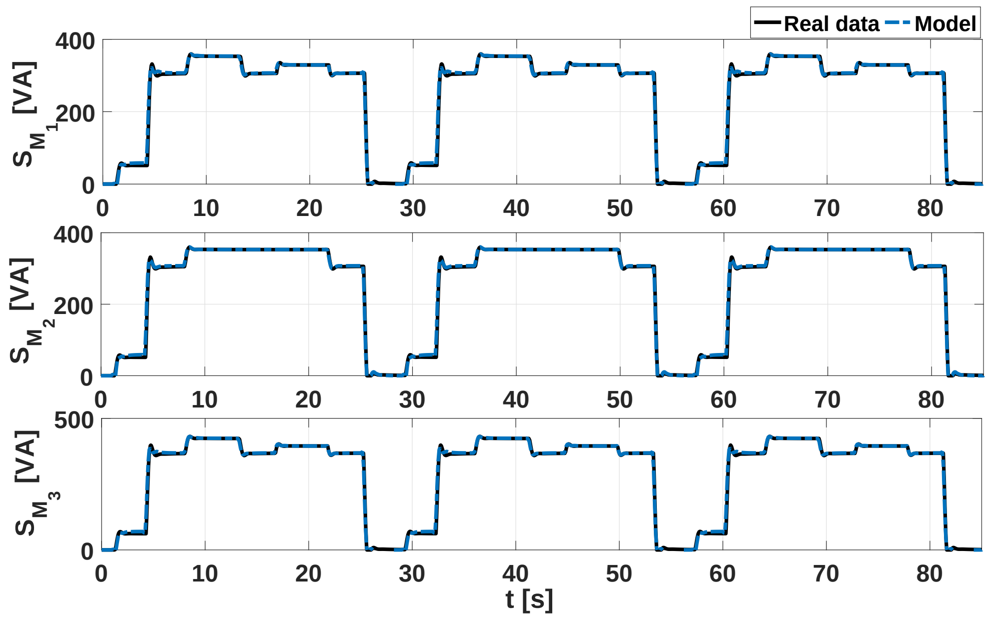


Figure 6.4: Model validation for machines in the process line.

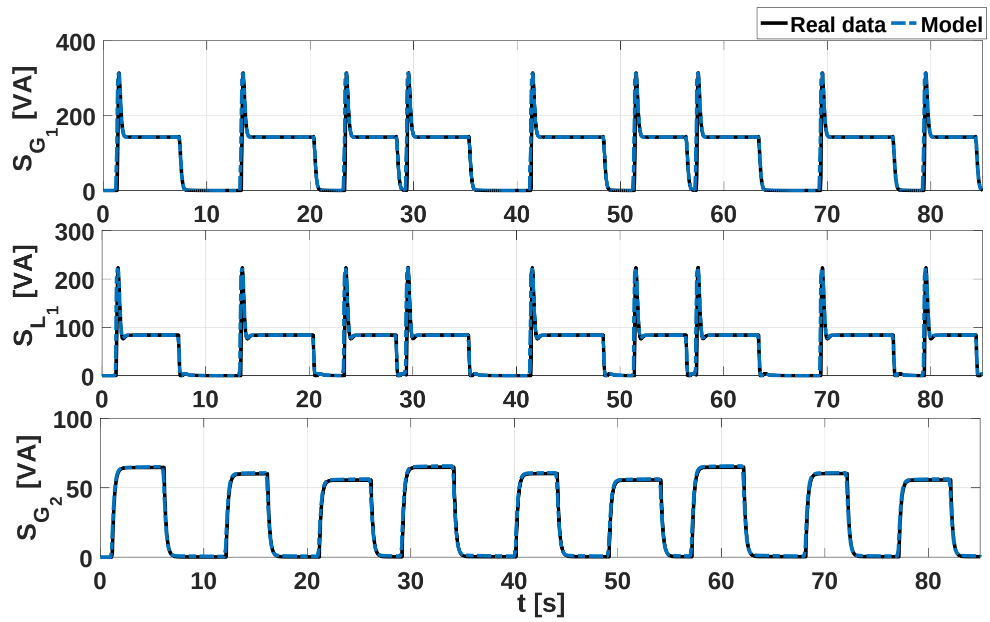


Figure 6.5: Model validation for peripheral devices in the process line.

energy consumption concerning valves is computed according to

$$S_{v_1}(k) = \alpha_{v_1}\ v_1(k), \tag{6.11a}$$

$$S_{v_3}(k) = \alpha_{v_3}\ v_3(k), \tag{6.11b}$$

being α_{v_1} and α_{v_3} the constant energy consumption of valves v_1 and v_3, respectively.

6.4 Control Mode Switching Strategy based on MPC

Based on the stages of both high and low energy consumption into the corresponding profile for a machine, peripheral devices must be correctly managed in order to minimise the total energy consumption and to avoid also (whenever possible) their simultaneous activation. Thus, to design a control strategy such that it does not affect the productivity of the process line, the machining sequences $\mathbf{\Lambda_{M_i}}$ of each machine for each production program will be considered as fixed and periodic over the time, assuming they are already optimised regarding energy consumption. This latter fact implies that the time T_{M_i} to process a piece at each M_i remains the same and, therefore, the process line has the capacity to handle the same number of pieces as when the control/supervision strategy is not implemented. Thus, since the operation of machines cannot be modified, only peripheral devices will be managed to minimise the total energy consumption (machines and peripheral devices) taking into account the operational relationships among machines and peripheral devices.

In this regard, an OBC strategy that allows minimising the global energy consumption of a process line is proposed taking into account its dynamics, the global energy consumption S and, the operational relationships between machines and peripheral devices in the process line. Besides, the control strategy should be able to respond to changes in production programs and to adapt its operation according to the new operating constraints, relationships among the process-line components, and the new energy consumption profiles of machines. Therefore, the proposed control strategy is designed considering two different control modes:

- *Predictive control mode:* This mode is based on the design of a prediction-based controller according to the MPC approach to determine the optimal activation sequence of peripheral devices in the process line $\mathbf{\Lambda_P^*}$ at the current production program. For the case of the second production program, the optimal sequences for the aperture of valves $\mathbf{\Lambda_V^*}$ should also be determined.
- *Autonomous control mode:* The second control mode will be implemented only if the peripheral devices exhibit a periodic behaviour after a time period of running the predictive control mode. Then, if some peripheral device has a periodic behaviour, its periodicity should be detected and the activation sequence previously optimised in the first control

mode (i.e., $\mathbf{\Lambda}^*_{\mathbf{P}}$ and $\mathbf{\Lambda}^*_{\mathbf{V}}$) will be sent to the system. That means, every time the energy response of a peripheral device is detected as periodic, it will be removed from the optimisation problem underlying the controller design in the former control mode with the aim to decrease the computational burden.

The predictive control mode is based on both energy consumption models and operating constraints of peripheral devices embedded in an optimisation problem behind the design of the controller. The general idea of this mode is to anticipate either activation or deactivation of peripheral devices that allow minimising the global energy consumption of the process line taking into account their dynamics, the global energy consumption S and the operational relationships with the machines in the process line. Then, considering a prediction horizon $H_p = T$ (with $T = \mathtt{max}(T_{M_i})$), the decision of switching on or off a device j depends on the current value of the energy consumption of machines $S_{M_i}(k)$, i.e., although the manufacturing sequences for machines in the process line are already given and hence its energy consumption profile along T_{M_i}, its real consumption values discriminated along the time are important for making decisions regarding real-time peripheral devices management.

According to the control objective defined in (6.2), the sequences for $\mathbf{\Lambda_P}$ and $\mathbf{\Lambda_V}$ along H_p are defined as

$$\mathbf{\Gamma}(k) \triangleq \{\mathbf{\Lambda_P}(k|k), \dots, \mathbf{\Lambda_P}(k + H_p - 1|k)\}, \tag{6.12a}$$

$$\mathbf{\Pi}(k) \triangleq \{\mathbf{\Lambda_V}(k|k), \dots, \mathbf{\Lambda_V}(k + H_p - 1|k)\}, \tag{6.12b}$$

with $\mathbf{\Lambda_V}(k) = \{v_1(k), v_3(k)\}$, $\mathbf{\Gamma}(k) \in \{0,1\} \times \mathbb{V}_2^{n\,H_p}$, and $\mathbf{\Pi}(k) \in \{0,100\}^{n\,H_p}$.

Subsequently, the design of the proposed prediction-based controller is based on the following finite-time open-loop optimisation problem:

$$\min_{\mathbf{\Gamma(k)},\mathbf{\Pi(k)}} \quad J(k) \tag{6.13a}$$

subject to

$$\xi_{G_1}(k + r + 1) = f_1\left(\xi_{G_1}(k + r), u_{G_1}(k + r)\right), \tag{6.13b}$$

$$S_{G_1}(k + r) = f_2\left(\xi_{G_l}(k + r)\right), \tag{6.13c}$$

$$\xi_{G_2}(k + r + 1) = f_3\left(\xi_{G_2}(k + r), u_{G_2}(k + r)\right), \tag{6.13d}$$

$$S_{G_2}(k + r) = f_4\left(\xi_{G_2}(k + r)\right), \tag{6.13e}$$

$$\xi_{L_1}(k+r+1) = f_5\left(\xi_{L_1}(k+r), u_{L_1}(k+r)\right), \tag{6.13f}$$

$$S_{L_1}(k+r) = f_6\left(\xi_{L_1}(k+r)\right), \tag{6.13g}$$

$$S_{v_1}(k+r) = \alpha_{v_1}\; v_1(k+r) \tag{6.13h}$$

$$S_{v_3}(k+r) = \alpha_{v_3}\; v_3(k+r), \tag{6.13i}$$

$$Q_{G_1}(k+r+1) = q_{G_1}\left(Q_{G_1}(k+r), u_{G_l}(k+r), \mathbf{\Lambda_{M_i}}\right), \tag{6.13j}$$

$$Q_{G_2}(k+r+1) = q_{G_2}\left(Q_{G_2}(k+r), u_{G_2}(k+r), \mathbf{\Lambda_{M_i}}\right), \tag{6.13k}$$

$$Q_{L_1}(k+r+1) = q_{L_1}\left(Q_{L_1}(k+r), u_{L_1}(k+r), \mathbf{\Lambda_{M_i}}\right), \tag{6.13l}$$

$$m_{air,M_1}(k+r) = m_{G_{1M_1}}(k+r) + m_{L_{1M_1}}(k+r), \tag{6.13m}$$

$$u_{G_1}(k+r) \in \{0,1\}, \tag{6.13n}$$

$$u_{G_2}(k+r) \in \mathbb{V}_2, \tag{6.13o}$$

$$u_{L_1}(k+r) \in \{0,1\}, \tag{6.13p}$$

$$v_1(k+r) \in \{0,100\}, \tag{6.13q}$$

$$v_3(k+r) \in \{0,100\}, \tag{6.13r}$$

$$Q_{G_1}(k+r) \in \left[\overline{Q}_{G_1},\, \underline{Q}_{G_1}\right], \tag{6.13s}$$

$$Q_{G_2}(k+r) \in \left[\overline{Q}_{G_2},\, \underline{Q}_{G_2}\right], \tag{6.13t}$$

$$Q_{L_1}(k+r) \in \left[\overline{Q}_{L_1},\, \underline{Q}_{L_1}\right], \tag{6.13u}$$

and the following logical constraints to avoid the high switching frequency of system actuators:

$$\Delta u_{P_j}(k+r) \neq 0 \Longleftrightarrow u_{P_j}(k+r+l) = u_{P_j}(k+r),\ \forall l = 1, \cdots, 4, \tag{6.13v}$$

for $r \in \{0,1,2,..,H_p-1\}$, and being ξ_{G_1}, ξ_{G_2} and ξ_{L_1} the states of energy consumption models for P_{G_1}, P_{G_2} and P_{L_1}, respectively, Q_{G_1}, Q_{G_2} and Q_{L_1} the states of peripheral devices, and $\Delta u_{P_j}(k) = |u_{P_j}(k) - u_{P_j}(k-1)|$ the activation/deactivation indicator of the j-th peripheral device. The q_{P_j}-dynamics in (6.13) correspond to the process dynamics for the compressed air supply system and the coolant supply system previously explained in Section 6.3 for the peripheral devices in the process line, i.e., P_{G_1}, P_{L_1} and P_{G_2}. It should be noted that when the first production program is running, the device P_{L_1} is deactivated, and therefore, its activation sequence is restricted to be null along the time.

If it is assumed that the problem in (6.13) is feasible, i.e., $\mathbf{\Gamma}(k) \neq \emptyset, \mathbf{\Pi}(k) \neq \emptyset$, and thus it exists an optimal solution for the activation sequences of peripheral devices and valves defined by

$$\mathbf{\Gamma}^*(k) \triangleq \{\mathbf{\Lambda_P}^*(k|k), \ldots, \mathbf{\Lambda_P}^*(k+H_p-1|k)\},$$

$$\mathbf{\Pi}^*(k) \triangleq \{\mathbf{\Lambda_V}^*(k|k), \dots, \mathbf{\Lambda_V}^*(k+H_p-1|k)\}.$$

According to the receding horizon philosophy [Mac02, RM09], $\mathbf{\Lambda_P}^*(k|k)$ and $\mathbf{\Lambda_V}^*(k|k)$ are sent to the process line discarding the rest of the optimal sequences from $(k+1)|k$ to $(k+H_p-1)|k$, while the whole process is repeated at the next instant $k \in \mathbb{Z}_{\geq 0}$ after the updates on the measurements/estimations of the state information from the plant for both the energy consumption models and process dynamics considered in (6.13).

On the other hand, the second control mode (or the autonomous mode) will be activated when a periodic behaviour in the optimal activation/deactivation signal of each peripheral device is identified. Once the periodic behaviour of any device is detected, it will be removed from the optimisation problem in (6.13) to reduce both the number of decision variables and the computational burden. Then, the periodic sequence detected is sent to the corresponding plant at each time instant k, while the optimisation for the other peripheral devices keeps taking also into account the energy consumption resulting from the devices that now entered in a periodic behaviour. Finally, if the periodicity is detected for all peripheral devices in the process line, the control commutes to a completely autonomous mode in which there is no optimisation in real time. Thus, the optimal and periodic sequences for the activation/deactivation of peripheral devices are fixed and sent to the plant and the control unit entering a monitoring phase where the performance indices are checked to verify the functioning according to the predefined pattern. In the case a mismatch is detected, a change of mode is triggered.

When the system is on autonomous mode, the computational burden is reduced since no online optimisation is required. However, in this mode it is not possible to manage any disturbance or change that might affect the operation of the peripheral devices and the machines in the process line. Therefore, the protocol for commuting from the autonomous mode to the predictive/optimisation mode is required. Since in the autonomous mode per se is not able to predict and find the activation/deactivation sequence of peripheral devices, a switching protocol is implemented while the autonomous mode is running, in which a prediction of the process is performed considering both the current measurements of the plant and the predefined periodic control sequences. Thus, this protocol aims to verify that the system constraints will be satisfied in the future according to the current state of the system. In this regard, any change or disturbance appreciated in the measurements from the plant could produce an abnormal behaviour in the future if the same activation sequence is kept and sent to the plant. If it happens, the monitoring and commutation protocol should detect these abnormalities and should indicate that, at the current system conditions, the system state will be out of its feasible domain and, therefore the control sequence should be recomputed to enforce feasibility of operation and optimise the performance. Practically, when abnormalities are detected, the controller switch to the predictive (or first control) mode with the aim to determine on-line the new optimal activation/deactivation signals of peripheral devices at the current state of the process line.

In the next sections, both the strategy for the detection of the periodicity of peripheral devices and the commutation protocol will be explained in detail.

6.4.1 Periodicity detection

To determine the periodicity pattern within the operation of peripheral devices and to commute to the autonomous mode, Algorithm 6.1 is proposed based on signal processing tools such as autocorrelation. Thus, after a time period N_u of operating under the first control mode, the activation/deactivation sequence of each peripheral device that has been sent to the system $\mathbf{u}_j$ is used to determine its periodicity. At time instant $k \geq N_u$, a pre-processing of the activation/deactivation signal $\mathbf{u}_j$ is performed to remove its mean value and capture the more relevant changes of the signal ($\hat{\mathbf{u}}_j$). It should be noted that this procedure is more important for those peripheral devices in which the activation load could be modulated since their periodicity should be detected taking into account both the activation instant and the level of activation. Thus, removing the mean value, the small changes associated with the load modulation gain relevance and the periodicity could be detected easier using autocorrelation. It is worth noting that the mean value is removed only for the periodicity-detection procedure. Once periodicity is found, the sequence to be sent to the process line will be taken from the original one without removing the mean value.

It should be pointed out that, in this case, autocorrelation was selected since it allows identifying repetitive patterns in a signal such as its periodicity. The autocorrelation is a measurement of the correlation/similarity between a signal and a delayed version of itself. In this regard, correlation coefficients are calculated considering different values of the signal delays with respect to itself. If the signal is periodic, it will be perfectly correlated with a version of itself if the time delay is an integer number of periods [Gaj03]. Thus, given a discrete-time signal $y(k)$, the discrete autocorrelation R_{yy} at lag τ_y is defined by

$$R_{yy}(\tau_y) = \sum_{n \in \mathbb{Z}} y(k)\, y(k - \tau_y), \tag{6.14}$$

Algorithm 6.1 Periodicity detection of the system actuator dynamics.

procedure PERIODICITY DETECTION($\hat{\mathbf{u}}_\mathbf{j}$)
  Define N_u
  while $T_{u_j} = 0$ **do**
    Define $\hat{\mathbf{u}}_\mathbf{j}(:) = \mathbf{u}_\mathbf{j}(k - N_u : k)$
    Remove mean value of $\hat{\mathbf{u}}_\mathbf{j}(:)$
    Compute $\mathbf{ux}_\mathbf{j} = \texttt{xcorr}\,(\hat{\mathbf{u}}_\mathbf{j}, \hat{\mathbf{u}}_\mathbf{j})$
    Compute $\overline{ux}_j = \texttt{max}\,(\mathbf{ux}_\mathbf{j})$
    Fix μ
    Define $\xi = \mu\, \overline{ux}_j$
    $[\mathbf{pk}, \mathbf{lc}] = \texttt{findpeaks}\,(\mathbf{ux}_\mathbf{j}, \text{'MinPeakheight'}, \xi)$
    $\mathbf{D}_\mathbf{pk} = |$ lc(1) - lc(2:end)$|$ ▷ distance among peaks
    Set $h = 1$
    while $h \leq \texttt{length}\,(\mathbf{D}_\mathbf{pk})$ **do**
      $T_h = \mathbf{D}_\mathbf{pk}\,(h)$
      if $|Q_{P_j}\,(k - T_h) - Q_{P_j}\,(k)\,| \leq \varepsilon$ **then**
        $T_{u_j} = T_h$ ▷ periodicity device j
        Display T_{u_j}
      else
        $h = h + 1$
        $k = k + 1$
      end if
      end
    end while
    end
  end while
  end
end procedure
return T_{u_j}

where R_{yy} is the correlation coefficient at the lag τ_y. Thus, high values of R_{yy} correspond to lags over which the the signal presents similar patterns. Then, in order to detect the periodicity, the autocorrelation of the signal is computed for all possibles lags and, the values in which it is higher are identified as possible periods of the signal.

Once the signal is pre-processing, the autocorrelation $\mathbf{ux}_\mathbf{j}$ of the pre-processed signal of $\hat{\mathbf{u}}_j$ is computed and the vectors of both correlation coefficients and lags are determined. Due to the nature of the activation/deactivation signal (step signal), some patterns that do not correspond to the real period of the signal could be also identified and have significant values of $\mathbf{ux}_\mathbf{j}$. Therefore, the periodicity condition should be verified for the different lags obtained from autocorrelation. In this regard, the maximum value $\overline{ux}_j = \mathbf{ux}_\mathbf{j}$ is determined, and then, only the peaks $\mathbf{pk}$ in $\mathbf{ux}_\mathbf{j}$ above the μ percentage of $\overline{ux}_j$ are considered to check the periodicity constraint, i.e.,

$$|x(k) - x(k + pT_x)| \leq \varepsilon,$$

$\forall p \in \mathbb{Z}$, being T_x the period of the signal and ε the tolerance value.

According to peaks $\mathbf{pk}$ and the corresponding values of lags **lc**, the distance between the first lag and the rest of the lags in **lc** is calculated. Then, the periodicity condition is verified for all distance previously computed, which represent the different alternatives to be chosen as the period of the signal. To this end, one of the signals for the dynamics of the processes associated to the operation of the peripheral device is considered. Thus, the period of the peripheral device T_{u_j} will be defined equal to the distance in $\mathbf{D_{pk}}$ for which the periodicity condition is satisfied. Afterwards, this device is removed from the optimisation problem considered in the first control mode. Finally, if the periodicity is found for all devices in the process line, then, the control system can commute to the autonomous control mode. It should be noted that if more than one value in $\mathbf{D_{pk}}$ satisfies the periodicity condition, T_{u_j} will be chosen according to the longer period to ensure the selection of the real period and not one of the smaller periods inside the first one. It should be noted that in the case the production program changes, the controller should automatically switch back to the control mode based on MPC. In this regard, given the new production program and the operational constraints, new activation/deactivation sequences for peripheral devices are optimised and, using these signals, Algorithm 6.1 should detect the new periodicity.

6.4.2 Commutation protocol

Once the period for all devices is detected, a supervision protocol should start to run with the aim to identify when the controller should commute again to the predictive control mode. During the autonomous control mode the optimal sequences previously determined are sent to the process and, the operational constraints are verified for the current instants to guarantee that the system keeps in its feasible region. However, if there is some change in the system or any disturbance takes place, then the system could reach a state of higher energy consumption or even an infeasible state. In the worse case, if there is some abnormal behaviour of the system and the activation/deactivation sequence of peripheral devices is not updated at the suitable time instant, the system state might violate the boundary of the feasible region. If infeasibility occurs, it will not be possible to come back to the first control mode, such as the optimisation problem behind the controller design will be infeasible for the current state of the process line. Therefore, the supervision module needs to predict the system behaviour in order to anticipate these undesirable behaviours based on the current state of the process line and the optimal sequences found in the first control mode.

In this regard, whenever the autonomous mode is running, a prediction of the behaviour of the process line is performed taking into account the models for both machines and peripheral devices and the current measurements from the available sensors. In this case, the prediction horizon has the same length as for the predictive control mode, i.e., $H_{p,c} = 28$ s. Based on the system prediction, it is verified that the process variables Q_{P_j} remain inside its boundaries $\overline{Q}_{P_j}$ and $\underline{Q}_{P_j}$, and that the the energy consumption for the current prediction does not exceed the optimal energy consumption found in the first control mode. Then, if for some time instants along the prediction horizon the variables Q_{P_j} are out of their boundaries or the energy consumption along the prediction horizon surpasses a percentage η_s of the optimal energy consumption, the commutation indicators will be activated at the current instant k for switching to the first control mode at the instant $k+1$. Thus, the commutation protocol from the autonomous mode to the predictive control mode is based on a prediction of the behaviour of the process plant to guarantee that the dynamics of peripheral devices remain inside their feasible region and the energy consumption is not increasing. It should be noted that the commutation indicators are flag variables designed based on the results obtained from the first control mode, which correspond to the optimal values used for the comparison in the autonomous mode.

Thus, at each instant k, for any instant r in the prediction for the commutation protocol, i.e., $r, r+1, \ldots, r+H_{p,c}-1$, an index I_{Q_j} is defined to check whether process variables remain inside their feasible domains such that

$$\text{If } Q_{P_j}(r) \notin \left[\overline{Q}_{P_j},\ \underline{Q}_{P_j}\right] \text{ then } I_{Q_j}(r) = 1. \tag{6.15}$$

Then, considering $\bar{\mathbf{S}}$ as the total energy consumption predicted along $H_{p,c}$, the commutation indicators at each instant k are defined as

$$\omega_{Q_j}(k) = \sum_{r=k}^{k+H_{p,c}} I_{Q_j}(r), \tag{6.16}$$

$$\text{If } \bar{\mathbf{S}}(k) \geq \eta_s\, \mathbf{S}^* \text{ then } \omega_S(k) = 1, \tag{6.17}$$

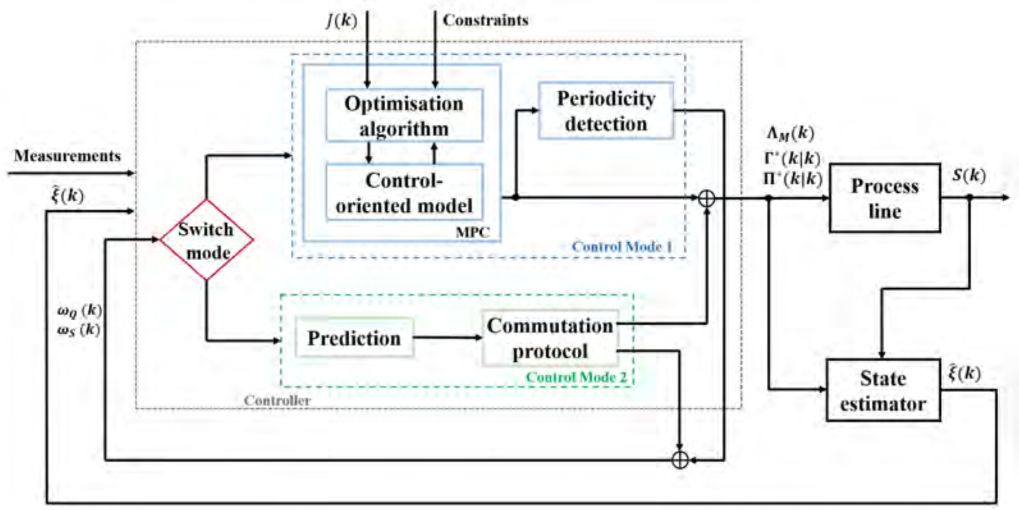


Figure 6.6: Real-time implementation scheme for the dual control strategy.

being $\mathbf{S}^*$ the optimal energy consumption along H_p obtained in the first control mode, and ω_{Q_j} and ω_S the commutation indicators, which should be initialised every time the protocol is executed. Then, if either $\omega_{Q_j}(k) \geq 1$ or $\omega_S(k) \geq 1$ while the autonomous control mode is on, the controller should switch to the MPC-based control mode at the instant $k+1$. In Figure 6.6, the control scheme proposed for the implementation in real time of the dual control strategy is shown. Therefore, according to the value of the commutation indicators ω_{Q_j} and ω_S, the control mode to be run will be selected.

6.5 Simulation Results

In order to test the effectiveness of the proposed control strategy to improve the energy efficiency of manufacturing systems in flexible scenarios, the following production programs are considered:

- *Production program 1* (PP_1): In this program only the two global peripheral devices are required since the installed capacity is enough to supply the resources consumption of machines in the process line. It means that during the execution of PP_1, the sequences $u_{L_1}\{1 : H_p\}$ and $v_1\{1 : H_p\}$ should be null, and added to the optimisation problem in (6.13) into the set of constraints. Besides, the energy consumption model and the process dynamics related to the device P_{L_1} will not be considered into the set of constraints since this device remains inactive during the execution of PP_1. This production program will be executed during 800 s, and then, it is assumed that a change in the production program occurs since a new piece will be processed. The resources consumption of both compressed air and coolant of machines along $\mathbf{\Lambda_{M_i}}$ during this program are shown in figures 6.2 and 6.2 for the two cases studied.

- *Production program 2* (PP_2): During this program, the consumption of compressed air from M_1 is increased from $0.0015\frac{\text{kg}}{\text{s}}$ to $0.003\frac{\text{kg}}{\text{s}}$ while keeping the same for the other two machines in the process line. Since the maximum capacity of the global peripheral device P_{G_1} when is turned on is $0.006\frac{\text{kg}}{\text{s}}$, it is not able to provided the air stream required by all the machines in the process line, and therefore the local device P_{L_1} should be activated to help supplying the air stream required by the first machine. The pipe system that connects P_{L_1} to M_1 to allow a maximum flow of $0.003\frac{\text{kg}}{\text{s}}$, while the maximum flow thorough the connection between P_{G_1} and M_1 remains equal to $0.0015\frac{\text{kg}}{\text{s}}$ as for the first program. In addition, when PP_2 is running, the dynamics for the device P_{L_1} and its energy consumption model should be considered into the set of constraints of the optimisation problem in (6.13). It should be noted that the resource consumption for the rest of machines in the process line keep the same as for PP_1.

Based on the previous description of production programs, PP_1 was executed during the first 800 s of simulation, and then, the production program was commuted to PP_2. In this case, simulations along 2000 s were performed using a execution time of the controller equals 1 s. This latter fact means that the controller makes decision every second along $H_p = 28$ s, and the required information for the controller is also updated every second before to run the controller again. All simulations were performed using an Intel Core i7-55000U 2.4 GHz processor with 8G RAM and considering a sampling time $\tau_s = 0.1$ s. The simulation results were obtained in Matlab by using the software IBM ILOG CPLEX Optimisation Studio [ILO13] integrated to YALMIP toolbox [Löf04]. Moreover, according to Algorithm 6.1, the `xcorr` routine of Matlab was used to compute the autocorrelation $\mathbf{ux_j}$ of the pre-processed signal of $\hat{\mathbf{u}}_j$, from which were obtained the vectors of both correlation coefficients and lags. The physical dimensions of the coolant system and the two air supply systems are presented in Table 6.2.

6.5.1 Machines with same $\mathbf{T_{M_i}}$

The obtained optimal activation sequences for both peripheral devices and the percentage of aperture valve for v_1 and v_3 are shown in Figures 6.7 and 6.8, respectively. According to these

Table 6.2: Simulation parameters for the supply systems of compressed air and coolant.

Parameter	Value	Units	Parameter	Value	Units
V_{T_1}	0.015	m^3	V_{T_4}	0.01	m^3
A_{T_2}	0.015	m^2	A_{T_3}	0.015	m^2
T_{air}	25	°C	R	8.1314	$\frac{\mathrm{J}}{\mathrm{Kmol}}$
W_{air}	28.966	$\frac{\mathrm{g}}{\mathrm{mol}}$	ΔP_{filter}	10000	Pa
P_{atm}	101325	Pa	η	0.95	–
ρ_c	1042.5	$\frac{\mathrm{kg}}{\mathrm{m}^3}$	$h_{1\to 2}$	0.12	$\frac{\mathrm{m}^2}{\mathrm{s}^2}$
$m_{in,1}$	0.006	$\frac{\mathrm{kg}}{\mathrm{s}}$	$m_{in,3}$	0.004	$\frac{\mathrm{kg}}{\mathrm{s}}$
α_{v_1}	2.5	VA	α_{v_3}	2.5	VA
ε_{M_1}	1.5×10^{-5}	–	ε_{M_3}	3.0×10^{-5}	–
$\underline{P}_{T_1}$	300	kPa	$\overline{P}_{T_1}$	750	kPa
$\underline{P}_{T_4}$	300	kPa	$\overline{P}_{T_4}$	750	kPa
$\underline{L}_{T_2}$	0.3	m	$\overline{L}_{T_2}$	0.6	m
$\underline{L}_{T_3}$	0.4	m	$\overline{L}_{T_3}$	0.7	m

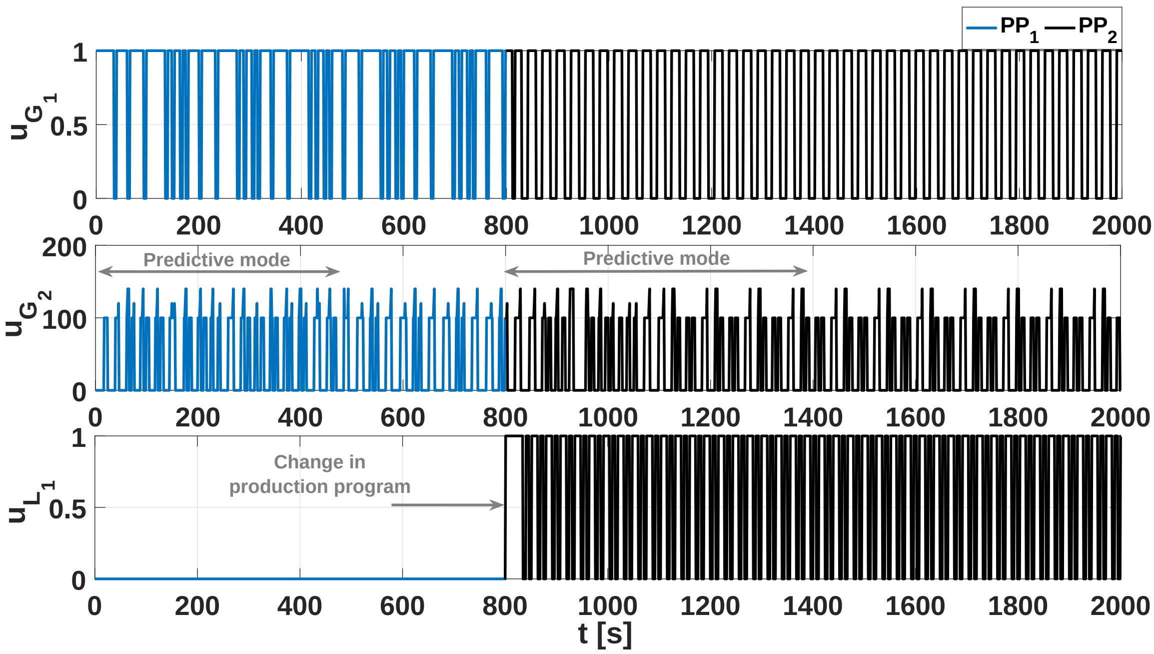


Figure 6.7: Optimal activation sequences of peripheral devices in the process line.

results, the device P_{L_1} is activated only when PP_2 is executed, and the periodic behaviour of all devices in the process line can be observed. In Figure 6.7, the time slots in which the predictive control mode is running are marked, while for the rest of the time the controller is in the autonomous mode. When the controller is in the autonomous mode, the periodicity of each device has been already determined during the predictive mode, and therefore, the periodic

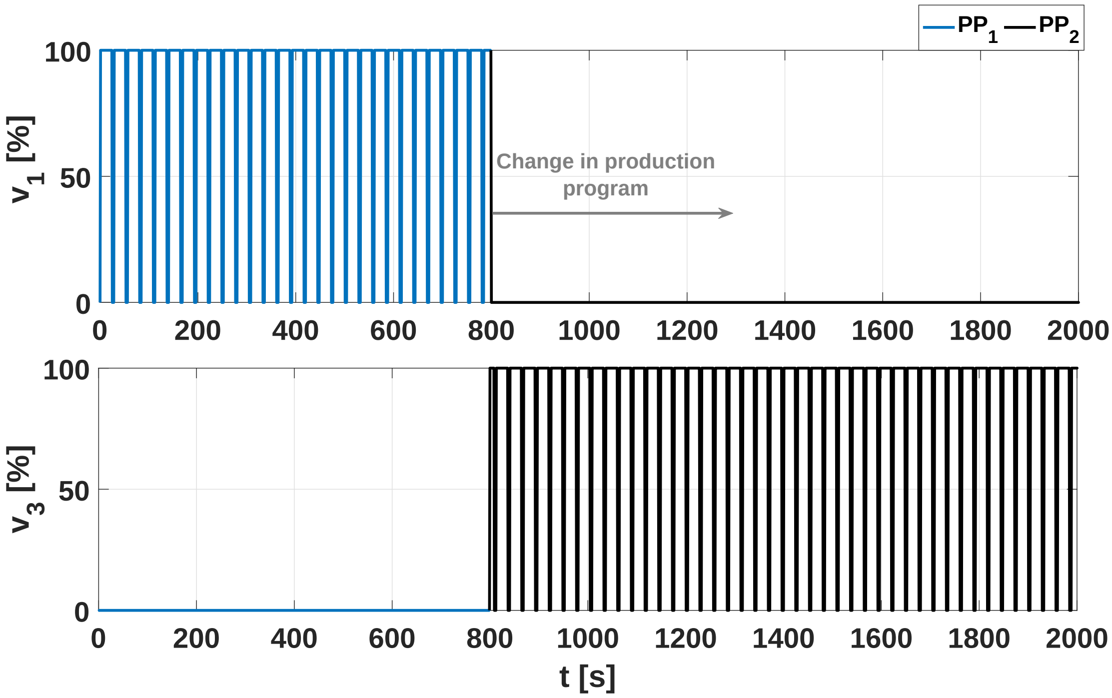


Figure 6.8: Optimal sequences for the valve aperture of v_1 and v_3.

behaviour in the activation sequence is also appreciated in the final part of the predictive control mode. It should be noted that, only during the predictive control mode the controller solves the optimisation problem in (6.13), and in the autonomous mode, the periodic sequences are sent to the plant and only it is verified that the system remains inside the feasible domain found in the optimisation-based mode. The latter procedure corresponds to the communication protocol.

Besides, concerning the change in the production program, from Figure 6.8, it can observe that since the energy consumption of P_{G_1} is higher than the energy consumption of P_{L_1}, the controller decides supplying all the compressed air required by M_1 from P_{L_1} reducing the demand for P_{G_1}, and allowing this latter device remains turned on for less time to minimise the global energy consumption. In this regard, P_{L_1} is responsible for providing all the demand of M_1, while v_1 is totally closed and P_{G_1} supplies only to machines M_2 and M_3. Next, according to the obtained activation sequences, in Figures 6.9 and 6.10, the resulting energy consumption of the process line and the particular energy consumption of each device obtained when the proposed control strategy is implement are presented, respectively. From these results, it is also possible to see that the peripheral device P_{L_1} starts to consume energy only when the second production program is activated and, therefore, the global energy consumption of the process line increases after this moment.

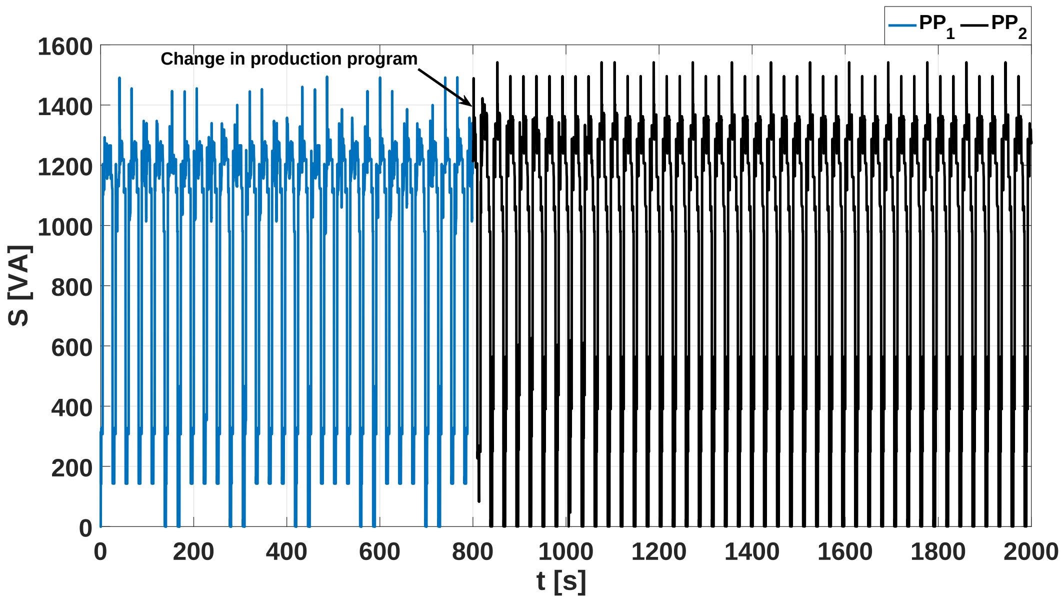


Figure 6.9: Energy consumption profile for the whole process line.

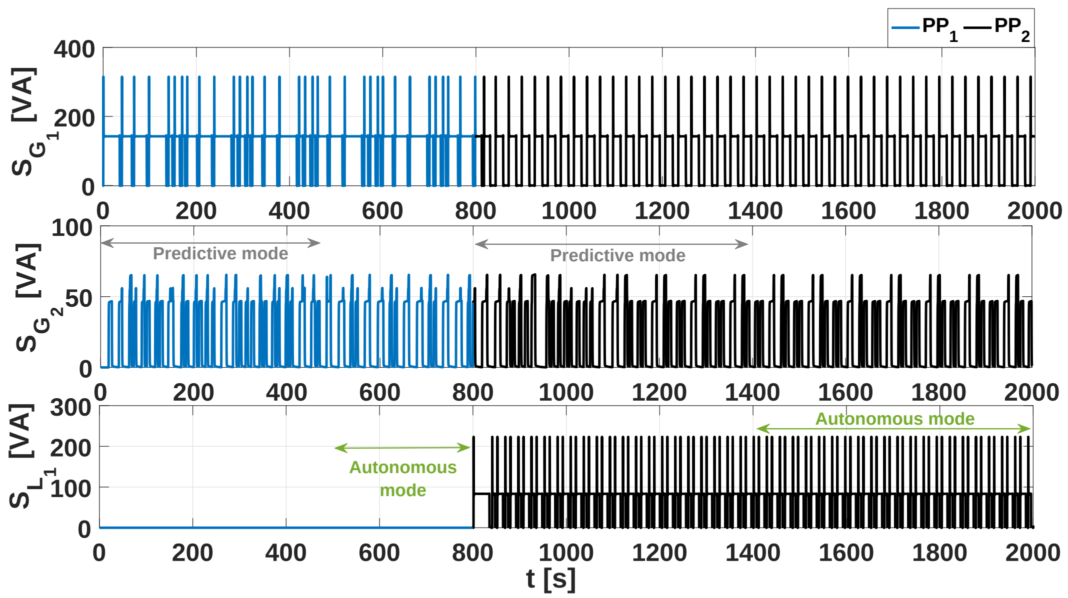


Figure 6.10: Energy consumption profile for the peripheral devices P_{G_1}, P_{G_2} and P_{L_1}, respectively.

In the same way, in Figures 6.11 and 6.12, the dynamics for the supply systems of compressed air and coolant associated to peripheral devices in the process line are presented. Based on these results, it can be seen that both the pressure and level dynamics remain inside their

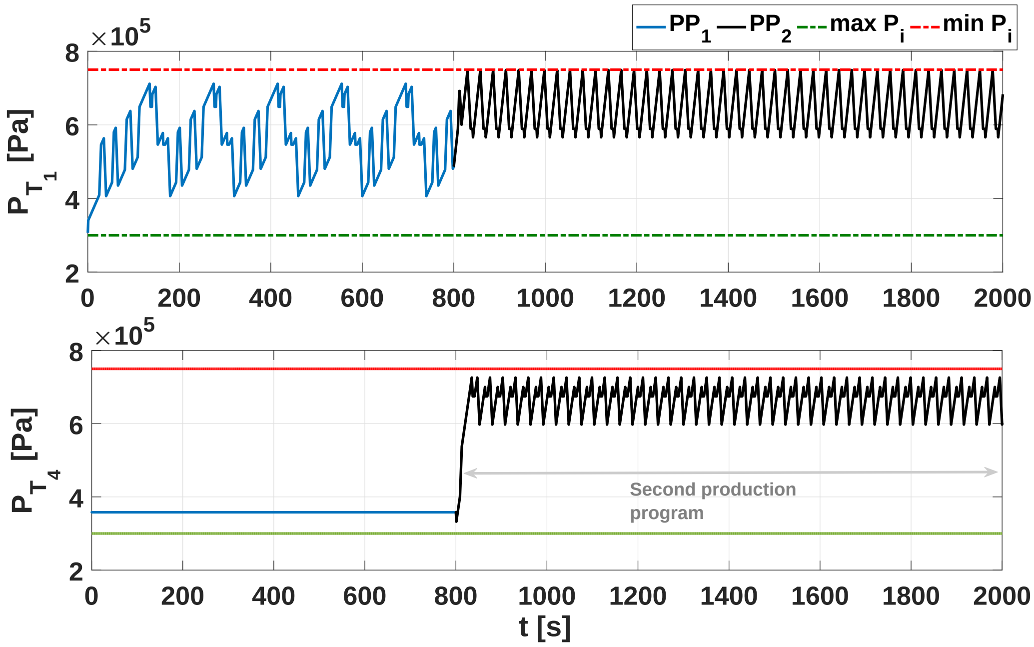


Figure 6.11: Pressure dynamics for both P_{L_1} and P_{G_1}.

upper and lower bounds while either of the production programs is executed. Besides, the periodic behaviour can also be detected from these dynamics (for each production program)after the predictive control mode is activated. Thus, due to the nature of these dynamics, both pressure and level dynamics were employed to check the periodicity condition as shown in Algorithm 6.1. The last fact is because when using the activation sequences of peripheral devices, which are usually constrained to $\{0, 1\}$, the periodicity condition could be verified for values of T_{u_j} that are not the real period for the devices. Then, based on the obtained results for the optimal sequences of u_{P_j} and process dynamics Q_{P_j}, the values of $T_{u_{G_1}}$ and $T_{u_{G_2}}$ detected while PP_1 was ran were equal to 140 and 84 s, respectively. For the case in which PP_2 was executed, the periods identified for P_{G_1}, P_{G_2} and P_{L_1} were 28s, 84s and 28s, respectively.

Next, to verify the computational burden and the suitability to implement the proposed control strategy in real time, the computational time spent by iteration is presented in Figure 6.13. Based on these results, it can be seen that even when the predictive control mode is on, the maximum time spent is lower than one second. Besides, it should be noted that when the autonomous mode is on, the computational time significantly decreases since, in this mode, it should not solve an optimisation problem. Thus, the time spent in the autonomous mode refers to the time required for the commutation protocol to predict the system behaviour and to verify that the system remains into its feasible domain for the whole prediction. Then, according

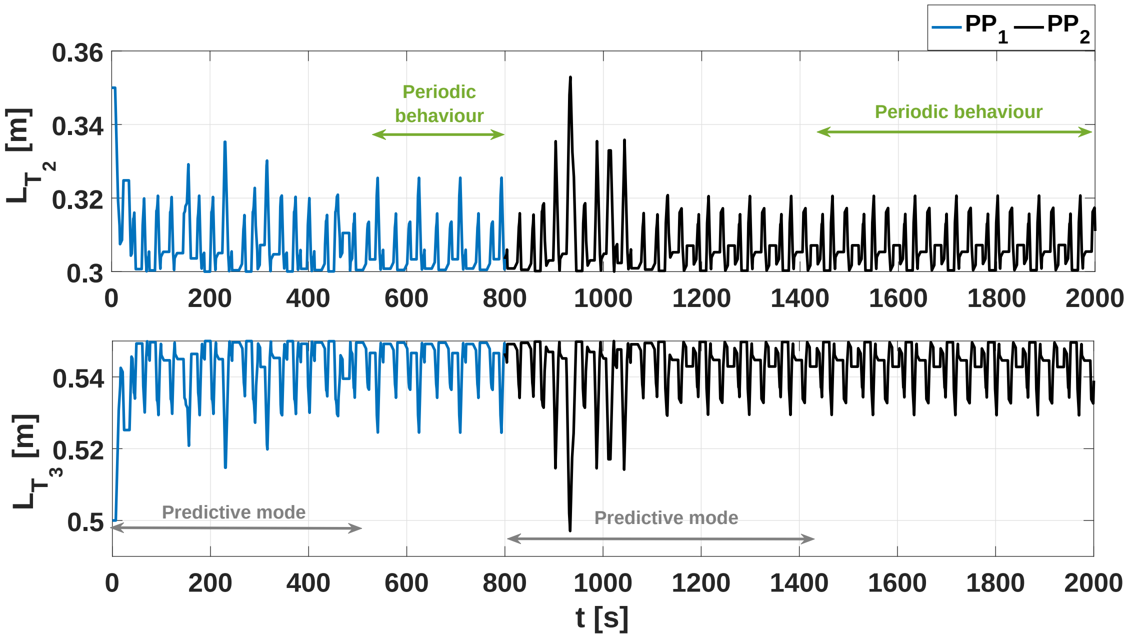


Figure 6.12: Level dynamics for both clean and dirty coolant tanks.

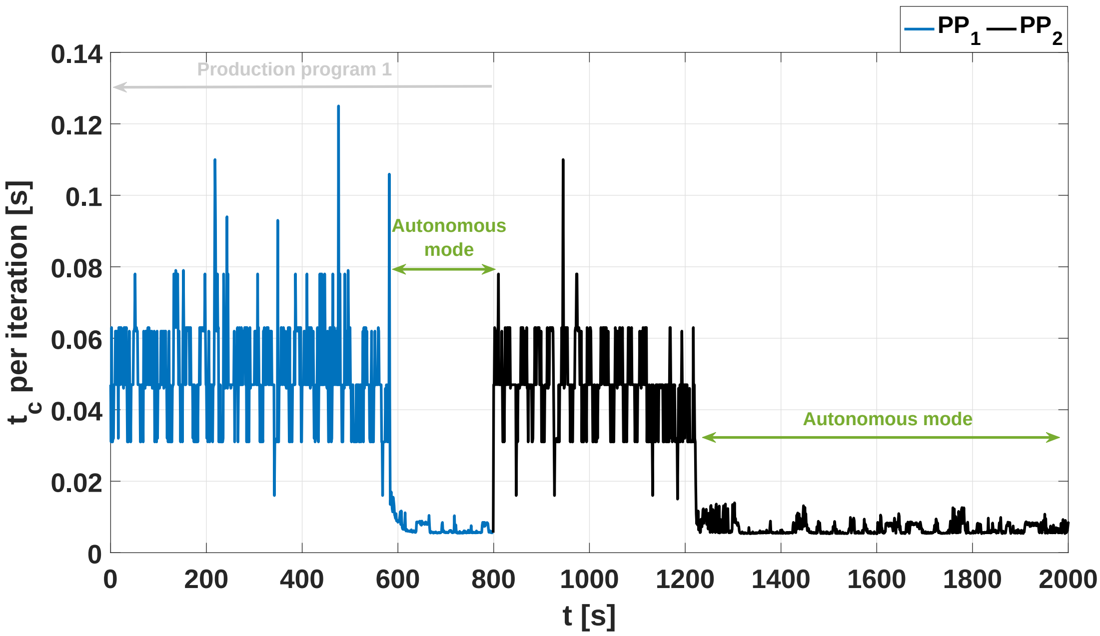


Figure 6.13: Computational time spent by iteration to solve the optimisation problem at the process line level.

to these results, it is possible to conclude that the proposed control strategy is suitable to be implemented in real time.

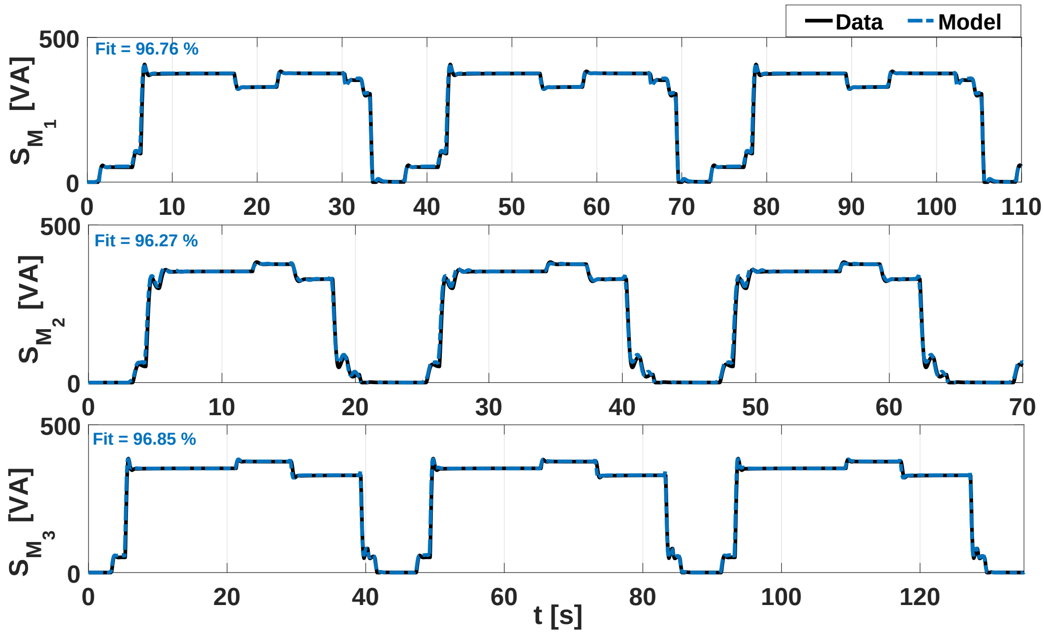


Figure 6.14: Model validation of machines in the process line with different T_{M_i}.

6.5.2 Machines with different $\mathrm{T_{M_i}}$

In this case, it is assumed that the three machines in the process line have different cycle time T_{M_i}. In these cases, usually, some buffer elements are required to compensate for the production rates among the machines in the process line. Since this dissertation focuses on the energy consumption of manufacturing systems and not address the problem of process programming and scheduling, which is deep studied and explained in the literature, only the machines and the peripheral devices are considered since they are the main energy consumers. Thus, a process line as shown in Figure 6.1 is analysed but considering the following cycle times: $T_{M_1} = 22$ s, $T_{M_2} = 36$ s, and $T_{M_3} = 44$ s. Therefore, the productivity of the process line will depend on the machine with the longest time, i.e., T_{M_3}. Based on this machine, the total number of finished parts in a specific period can be computed.

For this case study, new machining sequences $\boldsymbol{\Lambda}_{M_i}$ were designed and, then, energy consumption models were identified using SI methods. In Figure 6.14, the model validation is presented for the three machines in the process lines. On the other hand, the peripheral devices, and their associated process dynamics remain the same that in the case in which all the machines had the same cycle time. Besides, the sequences for the consumption of compressed air and coolant from the machines are presented in Figure 6.3. It should be noted that the matrices for the energy consumption models of machines are shown in Appendix A.3.

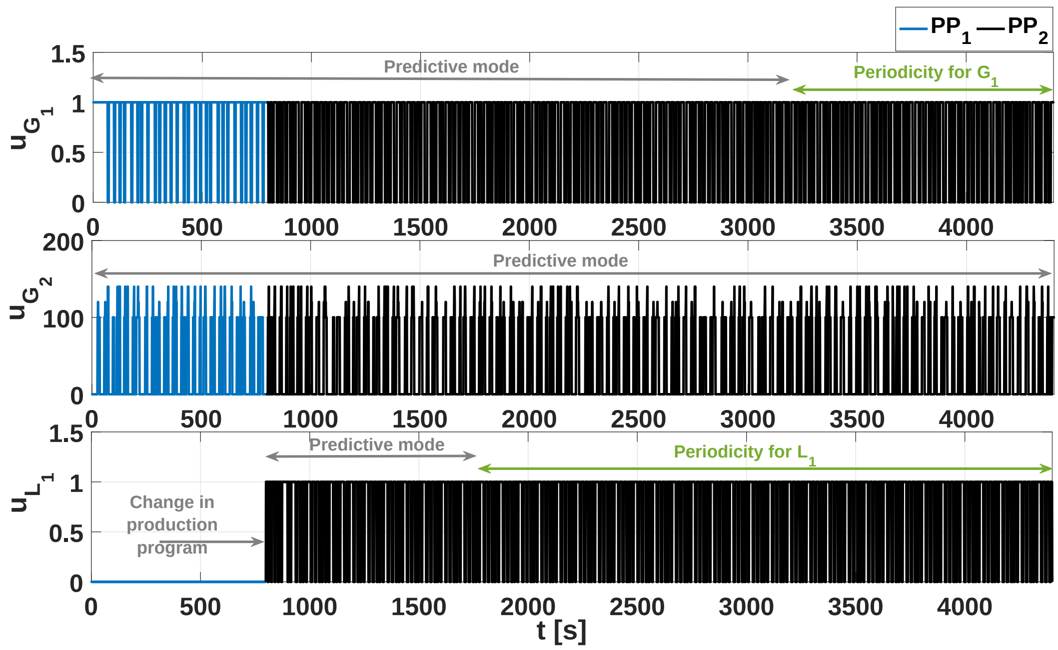


Figure 6.15: Optimal activation sequence for peripheral devices in a process line with machines with different T_{M_i}.

Then, the proposed control strategy was tested considering the new values of T_{M_i} and the same simulation parameters for the operation of peripheral devices presented in Table 6.2. Since machines with longer T_{M_i} were considered, in this case, the detection of the system periodicity took more time than in the case in which the machines have the same value of T_{M_i}. This behaviour could be a consequence of the combination of the different periodicities of the machines and their resources consumptions. Besides, for some devices, it was not possible to find periodic behaviour, at least up to the time that the simulations were executed. In Figures 6.15 and 6.16, the optimal activation sequence of peripheral devices and the total energy consumption profile for the process line are shown, respectively. In this case, during the first production program, periodicity for any device was not detected, and the controller had run in the MPC-based control mode. However, after the change in the production program and the inclusion of the local peripheral device for the 1-st machine, i.e., P_{L_1}, the periodicity for some of the peripheral devices in the process line can be detected.

As the same in the first case, once the local peripheral device P_{L_1} is activated, it provides all the flow of compressed air required by M_1 while P_{G_1} is responsible for supplying the airflow to M_2 and M_3. In Figure 6.17, the valve aperture related to both P_{L_1} and P_{G_1} is shown. On the other hand, in Figures 6.18 and 6.19, the q-relations associated with the operation of peripheral devices are presented. From these results, it is possible to see that even when some devices are

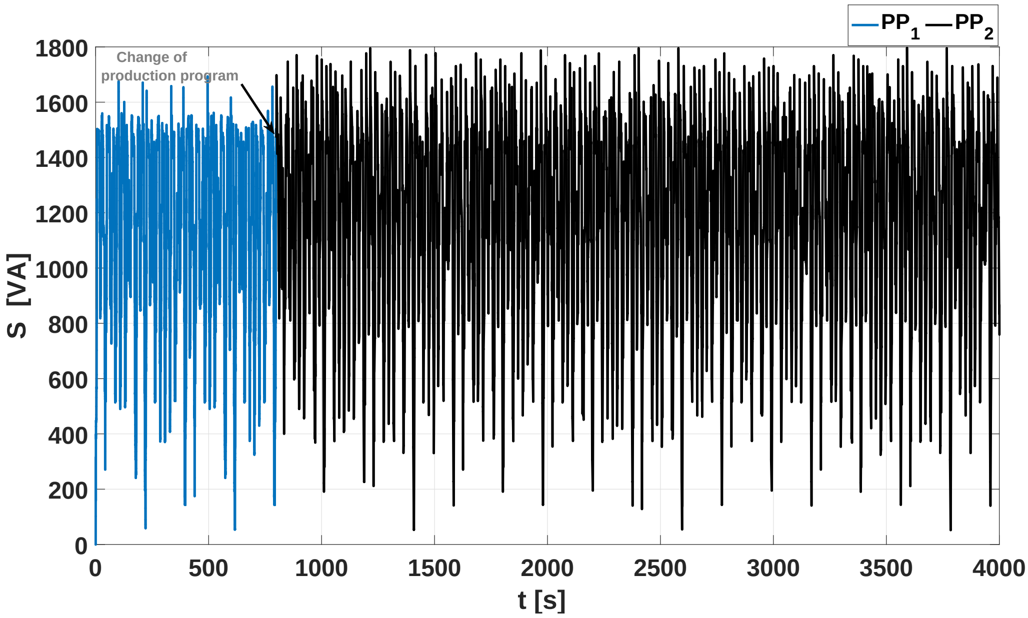


Figure 6.16: Energy consumption profile of a process line with machines with different T_{M_i}.

in autonomous mode, the proper operation of these devices is guaranteed and, therefore, the machines can keep operating adequately. Besides, from the dynamics of process related to the peripheral devices, it is easier to observe the periodic behaviour of these devices. For the case of P_{L_1}, the detected period was equal $T_{u_{L_1}} = 88$ s while for P_{G_1} the period was $T_{u_{G_1}} = 1118$ s. These periods were detected in the time instants $t = 1691$ s and $t = 3175$ s, respectively. In contrast to the case in which all the machines in the process line have the same T_{M_i}, the periods were longer and, therefore, the control mode based on MPC was running during more time. The last fact is because to detect the periodicity through autocorrelation, the section of the signal to analyse should be large enough to contain at least two times the period of the signal.

According to the optimal activation sequences for the peripheral devices, their energy consumption profiles are shown in Figure 6.20. From the obtained results for the case in which the machines in the process line have different T_{M_i}, it can be concluded that detecting periodicity is easier for the local peripheral devices since they only consider an energy consumption profile and a consumption sequence of resources from the machine. Moreover, when the number of sequences to be satisfied increases, the periodic behaviour is longer since there exist a superposition of periodic behaviours of the machine tools. In concordance to the above, for the case of P_{G_2}, it was not possible to detect a periodic behaviour in its activation/deactivation sequence. The latter fact could be a consequence of the different sequences of resources consumption that

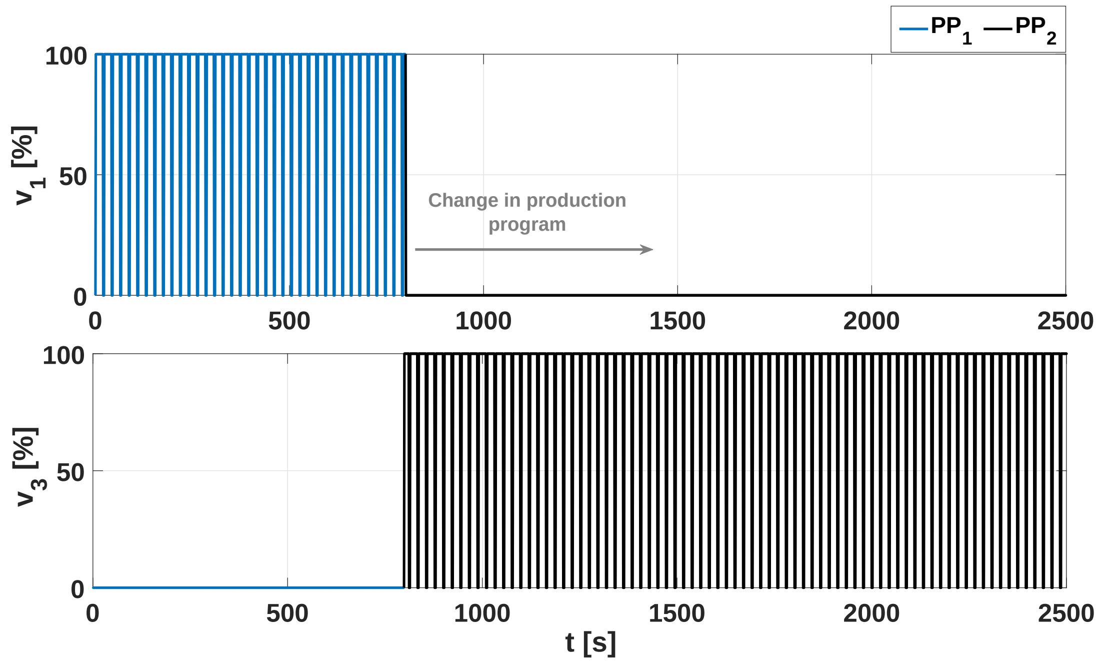


Figure 6.17: Activation sequence of valves for the process line with machines with different T_{M_i}.

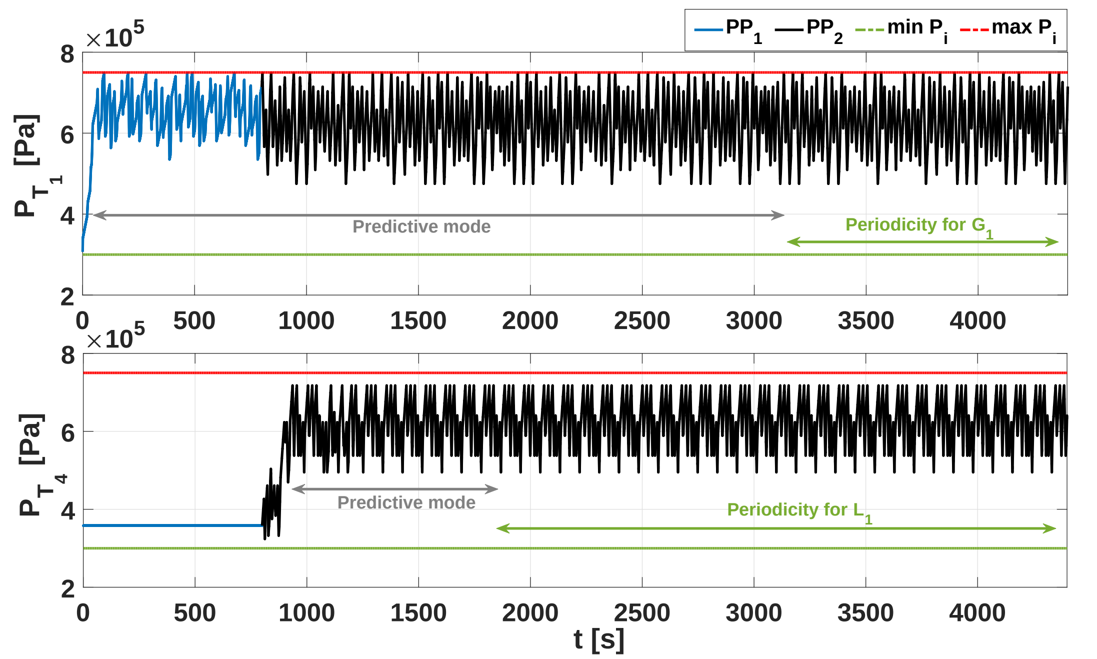


Figure 6.18: Pressure dynamics for peripheral systems of the process line when the machines have different T_{M_i}.

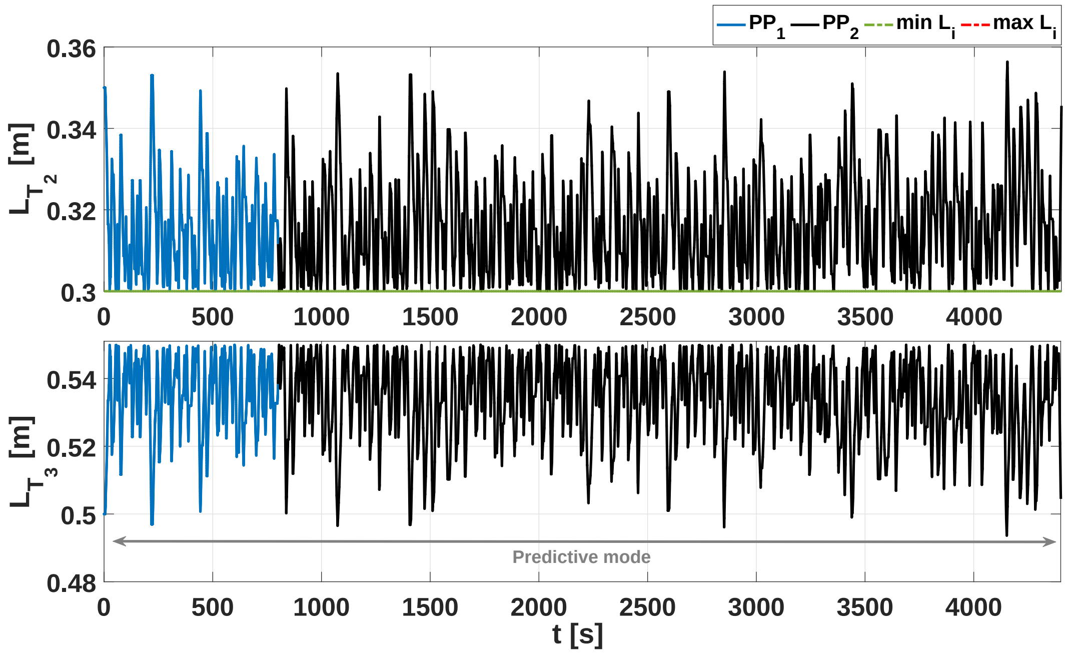


Figure 6.19: Level dynamics for peripheral systems of the process line when the machines have different T_{M_i}.

must be satisfied while the activation instants that minimise the energy consumption are determined according to the different energy consumption profiles of the machines. Then, due to the long duration of the periods detected for P_{L_1} and P_{G_1} and the fact that a periodic behaviour for P_{G_2} was not determined, the computational burden was not significantly reduced. In Figure 6.21, the CPU time spent by iteration to solve the optimisation problem is presented. Although the differences between both control modes are not too significant, it could be of exciting check the performance of the proposed control strategy in systems that consider more decision variables.

6.5.3 Performance degradation

In this section, the proposed control strategy based on two different control modes is compared with a conventional MPC controller with the aim to evaluate the performance degradation when a periodic behaviour is detected and the autonomous mode is switched on. In this regard, a predictive-like controller based on the MPC approach and the same optimisation problem in (6.13) was designed and used to determine the optimal activation sequences of peripheral devices when the optimisation problem is solved during the whole simulation. The MPC controller

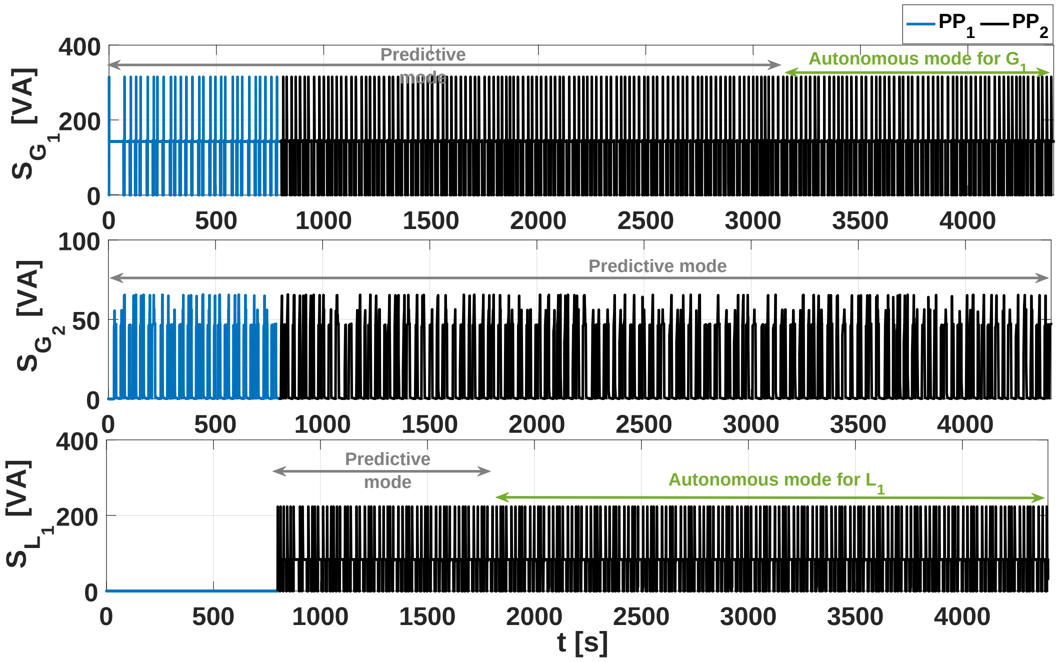


Figure 6.20: Energy consumption profile of peripheral systems of the process line when the machines have different T_{M_i}.

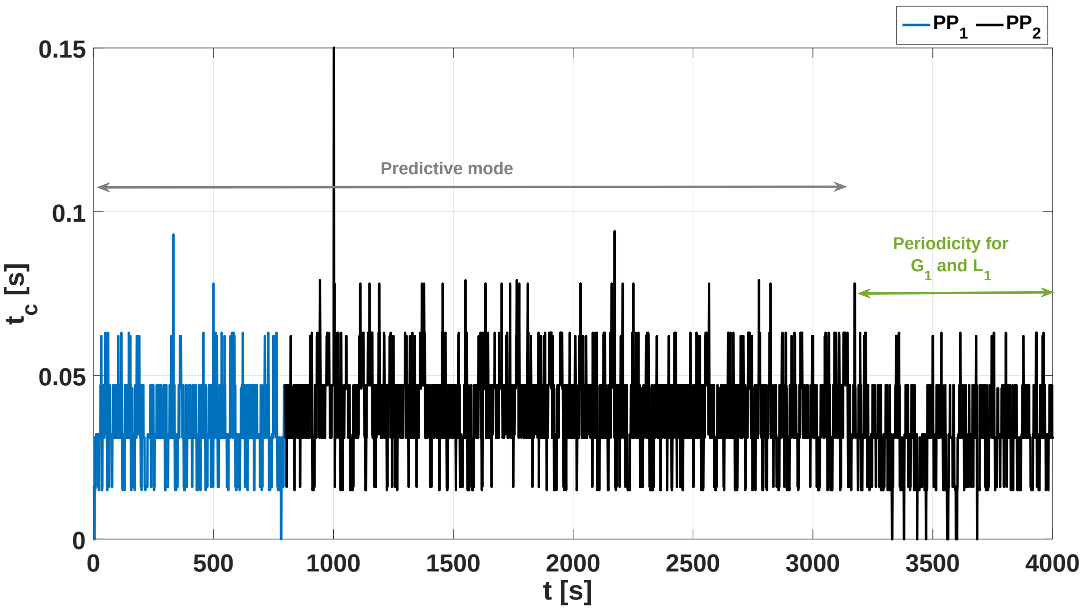


Figure 6.21: Computational time spent by iteration to solve the optimisation problem at the process line level when the machines have different T_{M_i}.

Table 6.3: Performance degradation with respect to a conventional MPC.

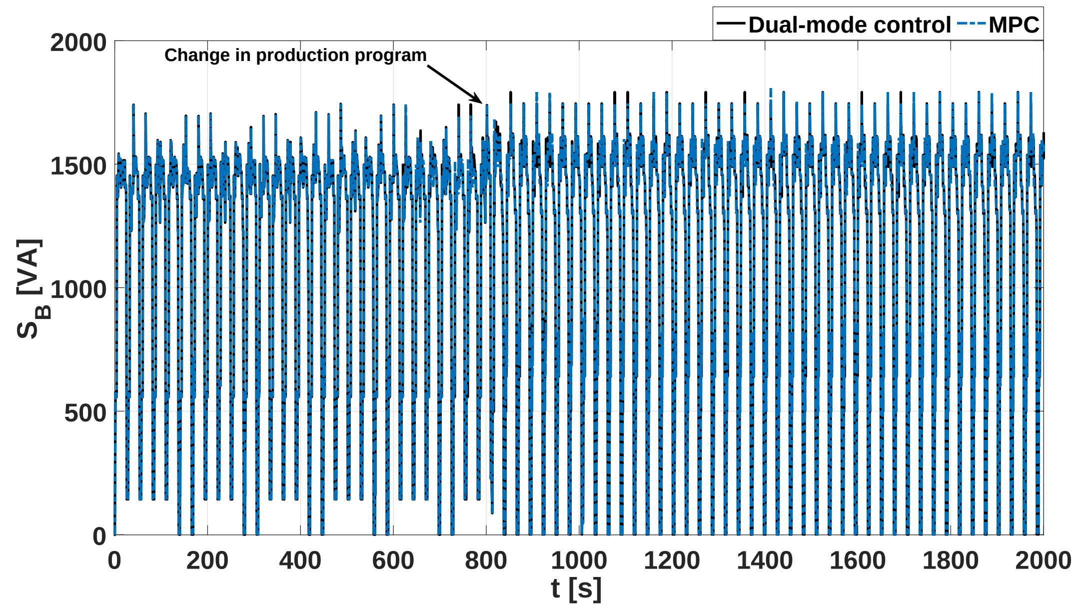
Controller	**Energy consumption** $[\mathrm{VA}]$	**Simulation time** $[\mathrm{s}]$
MPC	3299596.872	169.470
Dual control	3299578.348	60.681

was tested at the same operational conditions as for the dual control mode strategy and considering the same flexibility scenario presented in the previous section. It should be noted that the results shown in this section were performed only for the first case study since in such a case study, the periodicity was detected for all the peripheral devices. However, since a periodic behaviour is achieved even when all the machines in the process line do not have the same cycle time, these analysis is also extended to these cases.

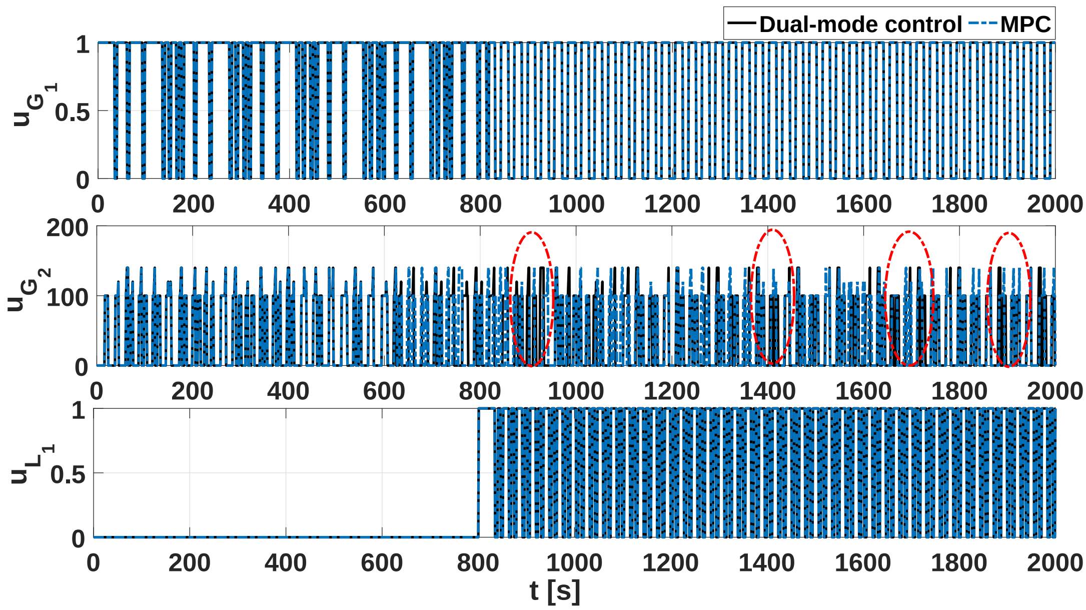
The obtained results for energy consumption profile are presented in Figure 6.22 and summarised in Table 6.3. From these results, it is possible to observe that the main differences in the activation sequences of peripheral devices are related to the device P_{G_2}, for which the activation load can be modulated. These small variations in the modulation of u_{G_2} could be a consequence of the termination criteria defined by default for the solver `cplex` and the current state of the system. That means, depending on the current state of the system, i.e., the current state of energy consumption models and process dynamics of peripheral devices, the termination criteria might be achieved at different values of the feasible domain for the decision variables. Thus, regarding the performance of control strategies in closed-loop, the degradation of the performance when the proposed dual control strategy is implemented with respect to a control strategy that is constantly optimising online is almost none, with differences near $5.6 \times 10^{-4}\%$. However, regarding the computational burden, when the system exhibits a periodic behaviour and it is used to commute to autonomous mode, the time spent is significantly lower and the possibilities to implement the strategy in real time increases. Besides, by implementing the commutation protocol during the autonomous mode to check that the system remains inside its feasible domain, the computational burden is reduced without affecting significantly the effectiveness of the control strategy.

6.5.4 Comparative assessment and disturbances management

In this section, the performance of the proposed dual control mode strategy is compared with an MPC controller that is constantly optimising for the whole simulation when disturbances take place and affect the operation of the process line. As in Section 6.5.3, in this Section,



(a) Profile of the total energy consumption.



(b) Optimal activation sequences of devices P_{G_1}, P_{G_2} and P_{L_1}.

Figure 6.22: Simulation results of the comparison between the dual control mode strategy and the conventional MPC.

it was studied the case in which the machines in the process line have the same T_{M_i}. The underlying idea of this comparative study is to understand how conservative the dual control strategy should be before to commute to the predictive control mode when some disturbance happens. As explained in Section 6.4.2, a prediction horizon of $H_{p,c} = 28$ s is made at each iteration while the autonomous control mode is running, and, if it detects that the system reaches

Table 6.4: Comparative assessment for different values of $H_{p,c}$.

$\mathbf{H_{p,c}}$ [s]	**Controller**	**Energy consumption** [VA]	**Simulation time** [s]
		Disturbance 1	
-	MPC	1363532.825	77.139
28	Dual control	1363447.325	84.265
14	Dual control	1363447.325	74.062
7	Dual control	Infeasible	-
		Disturbance 2	
-	MPC	1364306.771	83.680
28	Dual control	1363872.542	50.975
14	Dual control	1364225.510	50.530
7	Dual control	1364325.510	51.643

out of its feasible domain (determined from the predictive control mode) in any moment along the prediction horizon, the system should commute to the predictive control mode. That means if, at the current instant, the prediction shows that at the instant $t = 28$ s, the systems surpasses some of its boundaries, the control commutes. However, this is the most conservative possible scenario, since for the case in which the disturbance remains, for instance along three seconds from the current instant and then disappears, the control mode switching would be unnecessary, and the computational burden increases. In this regard, the proposed control strategy is tested considering scenarios with disturbances and different values of $H_{p,c}$ to evaluate its effectiveness regarding the conventional MPC. Then, base don the obtained results, the suitable length of $H_{p,c}$ can be determined, from which a proper performance can be achieved without increasing the computational burden.

Two different disturbances were considered and three different lengths of $H_{p,c}$ were tested in order to compare the performance and computational burden of the proposed control strategy with respect to the conventional MPC. For the former, a fault in the device G_2 is assumed, considering a reduction of its efficiency from 95% to 85% along 25 s. Thus, the real flow of coolant pumps from T_3 to T_2 will be lower that the flow considered into the control-oriented model (in the controller design). The second disturbance is applied to modify the operation of G_1 and emulates a fault of its operation. Thus, an air leak equals to $0.0023\frac{\text{kg}}{\text{s}}$ was added during 25 s. Based on the previous description of the considered disturbances, different simulations using the proposed dual control mode switching strategy were performed modifying the value of $H_{p,c}$ to compare both the resulting energy consumption and the time spent in the simulations with respect to the control strategy that is constantly optimising. The obtained results for the total energy consumption along 1400 s and the total simulation time are presented in Table 6.4.

Based on the obtained results, it is possible to conclude that for choosing the length of $H_{p,c}$ both the nature of the disturbances applied as well as its duration should be considered. However, to analyse most of the possible situations, in magnitude and duration, is a tedious task. For the case of disturbance 1, the first time that the commutation protocol detects that the system will be outside of its feasible domain corresponds to the instant 13 s in the prediction horizon. Thus, for lengths of $H_{p,c}$ shorter than nine seconds the commutation protocol was not able to detect that the system will violate the boundary of the feasible domain well in advance. Therefore, the optimisation problem in the second mode was infeasible at the time in which the commutation protocol decided to switch to the first control mode. Regarding the second disturbance, its effects on the operation of peripheral devices were only observed after the disturbance disappears. Thus, when the controller switched to the predictive control mode, the system is at the normal operational conditions again, and the MPC can reach faster the periodic behaviour. Therefore, in contrast to the scenario of the first disturbance, in this case, the length of $H_{p,c}$ was not critical since when the disturbance was detected, there were not unexpected behaviours that try to move the system outside of its feasible domain. In this regard, when selecting $H_{p,c}$ in the commutation protocol equals to H_p for the first control mode, it is possible to avoid the system to reach infeasible domains while the autonomous mode is running even when disturbances take place. Besides, according to the results in Table 6.4, the performance of the proposed control strategy is not significantly improved if the length of $H_{p,c}$ is shorter.

6.6 Summary

In this chapter, a dual control mode switching strategy is proposed to improve the energy efficiency of complex manufacturing systems without affecting their productivity. In this regard, machines in the process line and their corresponding energy consumption were assumed constant over the time to process the same number of pieces as when the control strategy is not implemented. Thus, the strategy was designed based on two control modes. In the former, a predictive-like controller is executed up to a periodic behaviour of the optimised system is detected (if such behaviour occurs). Then, once the periodicity is detected, the system commutes to an autonomous control mode to reduce the computational burden. However, to avoid undesirable behaviour of the process line, a prediction and a commutation protocol in which it is verified that the system remains into its feasible domain are performed while the autonomous mode is running. Besides, due to the nature of system actuators, the centralised MPC controller is designed based on a mixed-integer linear programming problem, in which both energy consumption models and the process dynamics performed by peripheral devices are included in the constraints set.

According to the obtained results, the proposed control strategy allows managing the peripheral devices to minimise global energy consumption and reducing the computational burden without decreasing the productivity of the process line, even when flexible-manufacturing scenarios are considered. Besides, in some cases, it is possible to reduce the computational burden when the controller switches from the MPC-based control mode to the autonomous one. In comparison to a control strategy based only on MPC, the performance of the proposed approach is not affected by switching to autonomous control mode. Besides, the proposed approach can manage disturbances due to the prediction and commutation protocol that is executed during the autonomous control mode.

Based on the obtained results for both cases studies, it can be concluded that when the controller should coordinate the periodic behaviours of both energy and resources consumption, the periodicity detection is more complicated or takes more time. Therefore, control strategies in which the global control problem can be divided in smaller control problems and with lower complexity could be tested to check whether it is possible to achieve a periodic behaviour faster than the one with a centralised control structure. In this regard, in Chapter 7, distributed control architectures will be tested in cases of higher complexity to check the viability of implementing these control strategies in complex and flexible manufacturing systems.

CHAPTER 7

DISTRIBUTED PREDICTIVE CONTROL FOR MANUFACTURING SYSTEMS

In Chapters 5 and 6, centralised control strategies have been designed to minimise the energy consumption of manufacturing systems at both machine and process line levels, respectively. However, at higher manufacturing levels, such as the process line and plant levels, more complex coupling dynamics could exist among the different elements as the size of these systems increases. Thus, for large-scale manufacturing systems, a higher computational load could be required to achieve a solution fast enough to be able to implement the control strategies in real time. In this regard, by using non-centralised control schemes, the computational burden could be reduced and, besides, control systems might be modularised to confer more flexibility to such systems.

This chapter deals with the design of non-centralised control architectures to improve the energy efficiency of manufacturing systems. Thus, based on both the configuration of manufacturing systems and their coupling dynamics, such large-scale systems are partitioned into sub-systems, from which smaller control problems can be stated. Then, by using suitable distributed optimisation techniques such as ADMM algorithms, the outputs from all controllers are optimally coordinated through a central coordinator associated with the Lagrange multipliers. Finally, based on the obtained results, a comparative assessment of centralised and non-centralised control structures proposed so far is presented.

7.1 Non-centralised MPC Schemes

The large-scale and complex systems can be difficult to control using centralised control architectures since they require a high computational burden to guarantee an optimal control input when a large number of decision variables and constraints are involved. An example of these systems is the manufacturing systems at both process line and plant levels, in which some peripheral devices can be shared between machines or process lines. Commonly, these large-scale systems have been addressed as a set of many interacting sub-systems to divide the original control problem intro smaller control problems, which could be solved separately and with a lower computational load.

However, when the large-scale systems are divided into sub-systems, there exist some complex and coupling constraints that represent the relationships among the sub-systems that cannot be separated. Thus, although the whole system can be divided into sub-systems, the coupling constraints require the exchange information among all the systems involved. In the manufacturing industry and the context of this dissertation, the coupling constraints are usually referred to the operational interactions between machines and peripheral devices, which corresponds to the supply of resources to several machines from only one peripheral device, and the multi-suppliers of one resource to one machine. In addition to the latter constraints, the changes in the configuration of manufacturing systems are also considered, for instance, when new peripheral devices should be included to process a new type of piece (this fact related to flexible manufacturing).

In this regard, centralised control approaches can be able to address these coupling interactions by adding them into the set of constraints of the optimisation problem behind the controller design. Nonetheless, these control schemes require the availability of information about the whole system and a high computational burden to achieve a solution. Then, to overcome the computational-burden issues of centralised approaches, the non-centralised control schemes have emerged as an alternative to compute the control inputs of large-scale systems. According to the idea of dividing the whole system into n_l different sub-systems and the centralised controller into smaller controllers, different non-centralised control approaches have been proposed in the literature based on the communication among the controllers and their control objectives [CSlPL13, MN14]. Among them, there exist the completely decentralised structures, distributed control systems with exchanging of information and hierarchical structures [TOCP18, TM17, FLT18, RMC+15].

Decentralised architectures refer to those controllers that are designed to operate in a completely independent fashion. It means that there is no communication among the local controllers designed for each sub-system. Therefore, these control architectures are based on the assumption that the interactions among sub-systems are weak to achieve closed-loop stability and the desired performance. Thereby, once the large-scale system had been divided into disjoint sub-systems, the local controllers can be designed based on the non-overlapping pairs of manipulated and controlled variables at each sub-system [CSlPL13, Sca09]. Then, due to the limited closed-loop performance of decentralised control systems given the lack of communication or information exchange among the local controllers, the design of control architectures that allows communication among the controllers to coordinate their actions have been deeply studied.

As explained in Chapter 3, distributed control architectures refer to those controllers among which exist some level of communication. It is worth noting that for the case of the local controllers designed based on the MPC approach, the information usually shared among the controllers corresponds to the prediction of the state or input variables [Sca09]. Besides, concerning the design of distributed control structures based on MPC, several algorithms have been proposed and reported in the literature. In the works of [Sca09] and [CSlPL13], a classification of DMPC algorithms is proposed based on the communication topology among local controllers and the cost function to be optimised.

Regarding the cost function, DMPC algorithms can be classified as cooperative and non-cooperative. In the former, each local controller optimises a global cost function that requires information of all sub-systems. In contrast, for the non-cooperative case, each controller optimises a local cost function with information only from the related sub-system. Based on the previous discussion, it should be noted that communication is an essential feature in distributed architectures since it is the way how the local controller get information about the other sub-systems. Thus, due to the communication among the local regulators, in general, the distributed approaches can achieve a better performance than the decentralised architectures. In fact, according to [CSlPL13], distributed methods, in which each local controller knows the current state of all sub-systems, can reach the performance of centralised structures. An example of the latter architectures is the cooperative DMPC.

Afterwards, according to the nature of coupling constraints among the sub-systems, some control architectures are more suitable than others regarding their implementation. Concerning the manufacturing industry and from manufacturing processes, most of the relationships among the systems cannot be assumed to be weak since the interactions among sub-systems are strictly necessary to guarantee the desired physical properties of the piece and the continuity of the processes. However, from the energy point of view, some sub-systems could be independently managed if the operational constraints are guaranteed. The latter fact means that if the sub-systems are adequately defined, according to the operational interactions of machining processes, some systems can be controlled separately to minimise their energy consumption. Thus, in this chapter, both cooperative and non-cooperative control architectures will be tested and compared with respect to the centralised controller proposed in Chapter 6 to minimise the total energy consumption of manufacturing systems at the process line level. Moreover, the idea of implementing controllers in a distributed manner is in concordance with the required modularity of flexible manufacturing. Modularised structures add robustness to manufacturing systems to face the changes in production demand by reconfiguration of manufacturing processes and their control systems without affecting the rest of the sub-systems.

7.1.1 Distributed optimisation

Then, once the sub-systems and the related local control problems have been defined, suitable optimisation algorithms should be selected to handle MPC problems distributively. Most of the algorithms proposed in the literature are iterative and require that some specific conditions are satisfied to converge to an optimal solution [Boy10]. Some of the most used algorithms of this type are those based on the Lagrangian approach such as dual decomposition [YMKT08, GR10, BSA13], ADMM [Boy10, LFJ13], and the Accelerated Distributed Augmented Lagrangian (ADAL) [LCZ18, ZZ18]. All these algorithms are based on the Lagrange dual theory, and the main difference among them concerns to the way they are used to decompose the augmented Lagrangian.

Regarding systems with coupled cost functions and constraints, the underlying idea behind the algorithms based on Lagrangian multipliers is to relax the coupling constraints to make separable the optimisation problem. Thus, a Lagrange multiplier is added per each coupling constraint. In this dissertation, the ADMM algorithm is employed to solve the optimisation problems behind the design of local controllers based on MPC in a distributed way. These algorithms were selected due to their great implementation in large-scale systems and the extensive literature related to them [WGY10, WO12, DMS18, HBK+18].

7.1.2 Alternative direction method of multipliers (ADMM)

The ADMM is a robust algorithm well suited to distributed convex optimisation [Boy10]. In general, ADMM solver large-scale optimisation problems by breaking them into smaller problems, which are easier to handle. Thus, it takes the form of a decomposition-coordination procedure in which the solutions to those smaller problems are coordinated to find a solution to the global problem [Eck12].

Consider an optimisation problem as follows:

$$\min_{s,y} \quad f(s) + g(y) \tag{7.1a}$$

subject to

$$F\, s + G\, y = M, \tag{7.1b}$$

being $f(s)$ and $g(y)$ two convex functions, $s \in \mathbb{R}^n$ and $y \in \mathbb{R}^m$ two sets of decision variables with separable objectives, and $F \in \mathbb{R}^{p\times n}$, $G \in \mathbb{R}^{p\times m}$ and $M \in \mathbb{R}^p$ the matrices of the linear constraints that define a non-empty set. If (7.1) is feasible, then, the optimal solution can be denoted as follows:

$$\{s^*, y^*\} = \mathtt{Inf}\{f(s) + g(y) | F\, s + G\, y = M\}. \tag{7.2}$$

The underlying idea behind the Lagrangian duality is to consider the problem constraints by augmenting the cost function. Thus, the Augmented Lagrangian of the problem in (7.1) is defined by [Boy04]

$$\mathcal{L}_\rho\,(s, y, \lambda) = f(s) + g(y) + \lambda^T\,(F\, s + G\, y - M) + \frac{\rho}{2}\|F\, s + G\, y - M\|_2^2, \tag{7.3}$$

being λ the dual variable or Lagrange multiplier and $\rho > 0$ a predefined parameter in ADMM to obtain convergence. Besides, it should be noted that the last term in (7.3) is added to yield convergence without assumptions like strict convexity or finiteness of f or g [Boy10]. Then, the problem in (7.1) can be rewritten as follows:

$$\min_{s,y}\ \max_{\lambda}\ \mathcal{L}_\rho\,(s, y, \lambda)\,, \tag{7.4}$$

being $\{s, y\}$ and λ the primal and dual variables, which aim for decreasing and increasing $\mathcal{L}_\rho\,(\cdot)$,

Algorithm 7.1 Standard ADMM algorithm for problem in (7.1).

Define s, y, ρ
Convergence $= 0$
Initialise λ
while Convergence $= 0$ **do**
  $s \leftarrow \min_{s} \; f(s) + \lambda^T \left(F\, s + G\, y - M\right) + \frac{\rho}{2}\|F\, s + G\, y - M\|_2^2,$
  $y \leftarrow \min_{y} \; g(y) + \lambda^T \left(F\, s + G\, y - M\right) + \frac{\rho}{2}\|F\, s + G\, y - M\|_2^2,$
  $\lambda = \lambda + \rho\,(F\, s + G\, y - M),$
  if $\|r\|_2 < \epsilon$ **then**
    Convergence $= 1$
  end if
end while

respectively. Then, to solve (7.4), a balance point among the dual and primal variables should be determined such that s and y cannot decrease $\mathcal{L}_\rho$, while λ cannot increases it. In this regard, the ADMM algorithm consists of the following iterative procedure [Boy10, Eck12]:

$$s^{k+1} = \min_{s} \; \mathcal{L}_\rho\left(s, y^k, \lambda^k\right), \tag{7.5a}$$

$$y^{k+1} = \min_{y} \; \mathcal{L}_\rho\left(s^{k+1}, y, \lambda^k\right), \tag{7.5b}$$

$$\lambda^{k+1} = \lambda^k + \rho\left(F\, s^{k+1} + G\, y^{k+1} - M\right). \tag{7.5c}$$

The first two stages in (7.5) correspond to the s-minimisation step and y-minimisation step, while the third step refers to the update of the dual variable. It is worth noting that the separation of the minimisation stages for s and y is what confers the decomposition feature when the cost function is separable [Boy10]. The detailed procedure to find an optimal solution of (7.1) by using ADMM is presented in Algorithm 7.1.

7.2 DMPC Design at Process Line Level

Consider a process line as the shown in Figure 7.1. In this case, it is assumed that all machines in the process line have different cycle time T_{M_1}, i.e., $T_{M_i} = 22$ s, $T_{M_2} = 36$ s, $T_{M_3} = 44$ s, and $T_{M_4} = 28$ s. In addition to machine tools, three global peripheral devices and one local device for M_1 are included, which supply the resources required by the machines to perform the machining processes. Similarly to the benchmark system presented in Chapter 6, devices P_{G_1} and P_{L_1} provide the flows of compressed air required by some of the machines in the line while P_{G_2} and P_{G_3} are responsible to supply the coolant flows required for all machines in the

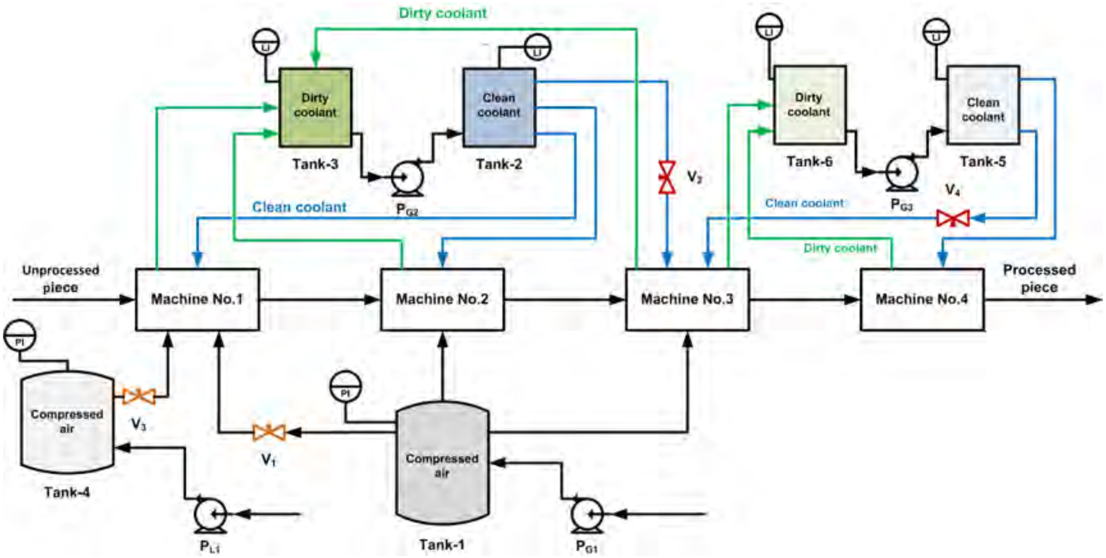


Figure 7.1: Four-stage serial process line with four peripheral devices.

process line. It worth noting that both P_{G_1} and P_{L_1} can supply the airflow to M_1, while the rest of machines can only take the air from P_{G_1}. In the same way, both P_{G_2} and P_{G_3} can provide the coolant required by M_3 while P_{G_2} must also supply the coolant flows required by M_1 and M_2 while, in turn, P_{G_3} is responsible for the coolant demand of M_4. It should be noted that in this case it is supposed that M_4 does not require compressed air for its operation.

Due to the operational relationships among machines and peripheral devices, manufacturing systems exhibit strong coupling dynamics that should be satisfied to guarantee the proper operation of the machine tools in the process line. According to Figure 7.1, the coupling dynamics refer to the cases in which there exist multi-providers to one machine or when the resources should be shared among different machines. In both cases, it must be guaranteed that the required flow of either coolant or air is supplied at the proper time instants and quantity according to the machining sequence of each machine. Thus, besides to determine the optimal activation instants for peripheral devices, the control strategy should be able to select from which device it will supply the resources demand of machines when they have multi-suppliers. However, in some cases, several devices could be required to satisfy the demand of one machine when it cannot be met by using only one peripheral device. In addition to the case of multiple suppliers, some peripheral devices in the process line should be managed appropriately to meet the resources demand of several machines at the same time. Therefore, it is necessary to ensure that these peripheral systems have the capacity enough to provide such resources during the operation of machines. In this regard, a consensus among the different suppliers should be established to guarantee that the resources required by machines can be supplied as well as that the peripheral devices are suitably activated to ensure the machines can work without interruptions.

The process dynamics related to the operation of both P_{G_1} and P_{L_1} correspond to the same mass and pressure dynamics presented in Chapter 7. They are adapted here for Tanks 1 and 4 according to Figure 7.1 as follows:

$$M_{T_1}(k+1) = M_{T_1}(k) + \tau_s\, \sigma_{T_1}(k), \tag{7.6a}$$

$$\sigma_{T_1}(k) = m_{in,G_1}\, u_{G_1}(k) - m_{G_1 \to M_1}(k) - \sum_{i=2}^{3} m_{air,M_i}(k), \tag{7.6b}$$

$$P_{T_1}(k) = \frac{M_{T_1}(k)\, R\, T}{V_{T_1}\, W_{air}}, \tag{7.6c}$$

and for the local peripheral device

$$M_{T_4}(k+1) = M_{T_4}(k) + \tau_s\, \sigma_{T_4}(k), \tag{7.7a}$$

$$\sigma_{T_4}(k) = m_{in,L_1}\, u_{L_1}(k) - m_{L_1 \to M_1}(k) \tag{7.7b}$$

$$P_{T_4}(k) = \frac{M_{T_4}(k)\, R\, T}{V_{T_4}\, W_{air}}, \tag{7.7c}$$

being $u_{G_1} \in \{0, 1\}$ the activation signal of P_{G_1}, $u_{L_1} \in \{0, 1\}$ the activation signal of P_{L_1}, m_{air,M_i} the air consumption from machine M_i, m_{in,G_1} the air flow pumped by P_{G_1} (and P_{L_1}) towards the tank T_1 (and T_4), and, R, T, V_{T_1} and W_{air} the gas constant, air temperature, volume of T_1 (and T_4), and the molecular weight, respectively.

Since both P_{G_1} and P_{L_1} can provide the airflow required by M_1, the following balance equation should be satisfied:

$$m_{air,M_1}(k) = m_{G_1 \to M_1}(k) + m_{L_1 \to M_1}(k), \tag{7.8}$$

with

$$m_{G_1 \to M_1}(k) = \varepsilon_{v_1}\, v_1(k), \tag{7.9a}$$

$$m_{L_1 \to M_1}(k) = \varepsilon_{v_3}\, v_3(k), \tag{7.9b}$$

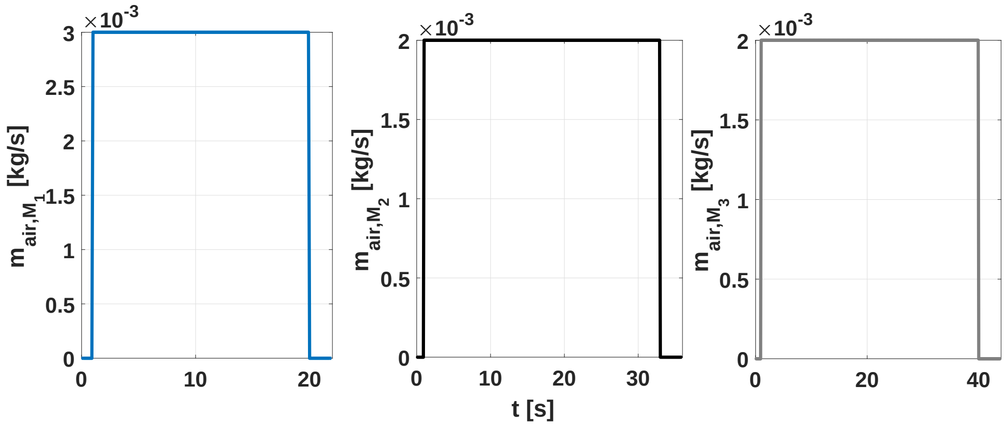


Figure 7.2: Sequences for the air consumption from machines in the four-stage process line along T_{M_i}.

being v_1 and v_3 the valve aperture to allow the flow from P_{G_1} and P_{L_1}, respectively. Moreover, as explained in Chapter 6, the pressure in both tanks (P_{T_1} and P_{T_4}) must remain inside an operational range to avoid damage in the peripheral systems and to ensure that there will be enough capacity to provide the resources during the operation of machines. Thus, $\underline{P}_{T_1} \leq P_{T_1}(k) \leq \overline{P}_{T_1}$ (and $\underline{P}_{T_4} \leq P_{T_4}(k) \leq \overline{P}_{T_4}$) should be satisfied, with $\underline{P}_{T_1}$ and $\overline{P}_{T_1}$ the lower and upper bounds for P_1, respectively. The sequence for the consumption of compressed air from machines according to their machining sequences are presented in Figure 7.2

On the other hand, since the coolant supply to machines in the process line depends on both P_{G_2} and P_{G_3}, the level dynamics for the tanks with clean and dirty coolant presented in Chapter 6 are also extended to Tanks $2, 3, 5$ and 6 according to Figure 7.1. Thereby, the dynamics for level changes related to the operation of P_{G_2} are the following:

$$L_2(k+1) = L_2(k) + \tau_s\, \gamma_{T_2}(k) \left(\frac{1}{\rho_c\, A_{T_2}} \right), \tag{7.10a}$$

$$\gamma_{T_2}(k) = m_{c,G_2}(k) - m_{cc,M_1}(k) - m_{cc,M_2}(k) - m_{cc,G_2 \to M_3}(k), \tag{7.10b}$$

$$L_3(k+1) = L_3(k) + \tau_s\, \theta_{T_3}(k) \left(\frac{1}{\rho_c\, A_{T_3}} \right), \tag{7.10c}$$

$$\theta_{T_3}(k) = \sum_{i=1}^{3} m_{dc,M_i}(k) - m_{c,G_2}(k), \tag{7.10d}$$

$$\tag{7.10e}$$

with m_{c,G_2} given by

$$m_{c,G_2}(k) = \frac{\eta\, \rho_c\, u_{G_2}(k)}{P_{in,G_2}(k) + \rho_c\, h_{f_{G_2,1\to 2}}(k) - P_{out,G_2}(k)}, \tag{7.11}$$

being $u_{G_2} \in \{0, 100, 120, 140\}$ the activation signal of P_{G_2}. On the other hand, the process dynamics related to P_{G_3} are the following:

$$L_5(k+1) = L_5(k) + \tau_s\, \gamma_{T_5}(k) \left(\frac{1}{\rho_c\, A_{T_5}} \right), \tag{7.12a}$$

$$\gamma_{T_5}(k) = m_{c,G_3}(k) - m_{cc,G_3\to M_3}(k) - m_{cc,M_4}(k), \tag{7.12b}$$

$$L_6(k+1) = L_6(k) + \tau_s\, \theta_{T_6}(k) \left(\frac{1}{\rho_c\, A_{T_6}} \right), \tag{7.12c}$$

$$\theta_{T_6}(k) = m_{dc,M_3}(k) + m_{dc,M_4}(k) - m_{c,G_3}(k), \tag{7.12d}$$

$$\tag{7.12e}$$

with m_{c,G_3} given by

$$m_{c,G_3}(k) = \frac{\eta\, \rho_c\, u_{G_3}(k)}{P_{in,G_3}(k) + \rho_c\, h_{f_{G_3,1\to 2}}(k) - P_{out,G_3}(k)}, \tag{7.13}$$

being $u_{G_3} \in \{0, 70, 140\}$ the activation signal of P_{G_3}.

In (7.10) and (7.12), $m_{cc,j\to M_i}$ refers to the coolant flow supplied by the j-device to the i-th machine, and $m_{dc_{M_i}}$ is the flow of dirty coolant recovered from machines. In addition, $P_{in,j}$ and $P_{out,j}$ correspond to the input and output pressure in the pipe system that transport the coolant from the tanks with clean coolant towards the tank with dirty coolant, while, ρ_c, η, ω and $h_{f_{j,1\to 2}}$ are the coolant density, efficiency of the pump, specific work per time unit and the energy losses by friction, respectively. It should be noted that for the third machine there exists a consensus between P_{G_2} and P_{G_3} to provide the coolant flow required. Thus, the following constraint is also required

$$m_{cc,M_3}(k) = m_{cc,G_2\to M_3}(k) + m_{cc,G_3\to M_3}(k), \tag{7.14}$$

with

$$m_{cc,G_2\to M_3}(k) = \varepsilon_{v_2}\, v_2(k), \tag{7.15a}$$

$$m_{cc,G_4\to M_3}(k) = \varepsilon_{v_4}\, v_4(k), \tag{7.15b}$$

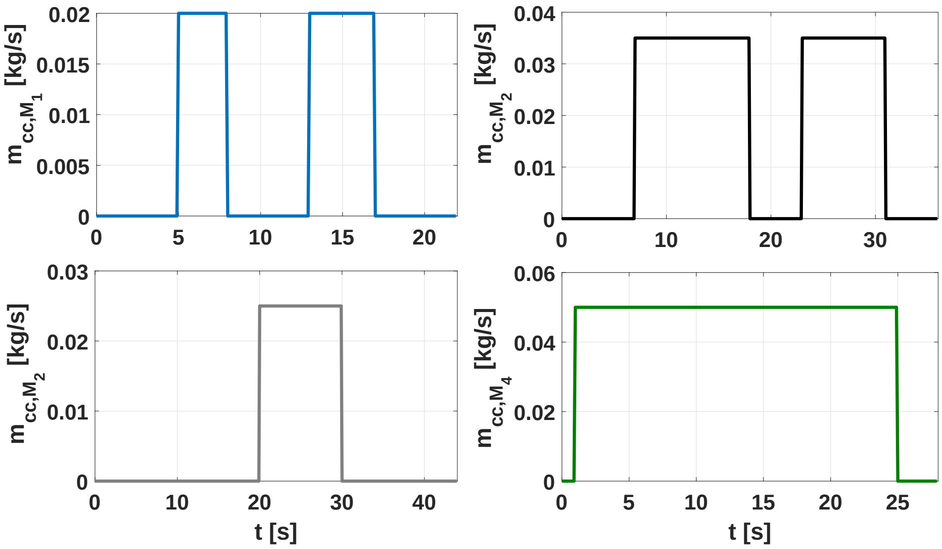


Figure 7.3: Sequences for the coolant consumption from machines in the four-stage process line along T_{M_i}.

being v_2 and v_4 the valve aperture related to each coolant supply system. In addition to the level dynamics, the operational ranges for these levels must also be considered with the aim to be able to satisfy the demand during the whole operation of machines. In this regard, $\underline{L}_{T_i} \leq L_{T_i}(k) \leq \overline{L}_{T_i}$ hold $\forall\ i = 2, 3, 5, 6$. In Figure 7.3, the sequences for the coolant consumption from machines are shown.

Then, into the context of this dissertation, besides to satisfy the operational relationships among machines and peripheral devices, these devices should be suitably managed to minimise the energy consumption of the whole process line. To this end, in Chapter 6, a centralised control architecture was proposed, in which all the coupling dynamics among machines and peripheral devices are considered and satisfied. However, since the complexity and the size of the manufacturing systems at both process line and plant levels, non-centralised control architectures will be tested in this chapter to compare them with the centralised one. It is worth noting that the non-centralised control structures are also more compatible with the new smart manufacturing systems since they allow the division of the control problem into smaller ones.

Thus, in the following sections, the control problem and the proposed controllers are presented. All the proposed controller below were designed considering non-centralised control architectures and the ADMM algorithm to solve the distributed optimisation problem. The latter taking into account that since the nature of the coupling dynamics in these systems and the control objective of minimising energy consumption, these coupling constraints cannot be considered as weak and, therefore, distributed architectures in which there exist some communication among controllers are more recommended.

7.2.1 Control problem formulation

Ideally, the machines in the process line should be operated without interruptions. Consequently, the required resources for machining operations performed at every machine should be supplied at the proper instant and in the appropriate quantity to guarantee the continuous operation of the machines. Similarly to the control strategies proposed at both the machine and process line levels in Chapters 5 and 6, the activation instant and activation level of peripheral devices should be determined to satisfy the operational relationships while minimising the energy consumption of the whole manufacturing system. Then, considering a fixed number of machines and peripheral devices as in the process line shown in Figure 7.1, the activation sequences for these devices can be defined as

$$\mathbf{\Lambda_{M_i}}(k) = \{u_{M_{i,1}}(k), u_{M_{i,2}}(k), \dots, u_{M_{i,m}}(k)\}, \ \forall i = 1,2,3,4 \quad (7.16a)$$

$$\mathbf{\Lambda_P}(k) = \{u_{G_1}(k), u_{G_2}(k), u_{G_3}(k), u_{L_1}(k)\}, \quad (7.16b)$$

$$\mathbf{\Lambda_V}(k) = \{v_1(k), v_2(k), v_3(k), v_4(k)\}, \quad (7.16c)$$

with m equal the number of machining devices of each machine in the process line. According to the control strategies proposed so far, $\mathbf{\Lambda_{M_i}}$ and their associated energy consumption are considered fixed and periodic along the time to keep the same the productivity of the process line. Then, in concordance with the centralised control strategy in Chapter 6, the control objective is defined as the minimisation of the integral of the total energy consumption profile along a period T, i.e.,

$$J(k) = \sum_{k=1}^{T} S(k)\,\Delta k = \sum_{k=1}^{T} \left[\left(\sum_{i=1}^{4} S_{M_i}(k) \right) + \left(\sum_{j=1}^{4} S_j(k) \right) \right] \Delta k \quad (7.17)$$

being $\Delta k = (t_k - t_{k-1})$, $S_{M_i} \in \mathbb{R}$ and $S_j \in \mathbb{R}$ the energy consumption of the machines and peripheral devices, respectively. It should be noted that the energy consumption models for both machines and peripheral devices will also be required to compute J at each time instant $k \in \mathbb{Z}_{>0}$. As in the previous chapters, the energy consumption models for both the machines and peripheral devices were obtained by using the SI method and the real data from the test

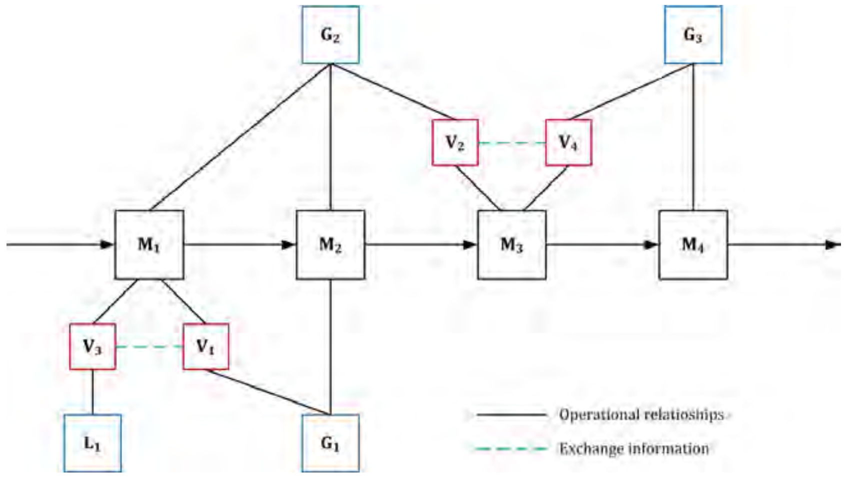


Figure 7.4: Simplified structure of the four-stage serial process line in Figure 7.1.

bench. The obtained models have the following structure:

$$\xi_l(k+1) = h_l\left(\xi_l(k), u_l(k)\right) \tag{7.18a}$$

$$S_l(k) = g_l(\xi_l(k)), \tag{7.18b}$$

with $l = \{M_1, \cdots, M_i, P_1, \cdots, P_j\}$ the index for either machine or peripheral device, $\xi \in \mathbb{R}^n$ the model states, and $h(\cdot) : \mathbb{R}^n \times \mathbb{V}_j \mapsto \mathbb{R}^n$ and $g(\cdot) : \mathbb{R}^n \mapsto \mathbb{R}$ the linear maps of energy consumption models identified by SI methods. It is worth noting that, in this case, the models for both peripheral devices and machines are the same that those presented in Chapter 6.

According to the process description, the activation signals for P_{G_1} and P_{L_1} are constrained to the set $u_j \in \{0, 1\}$ since these devices are of on/off type. On the other hand, since for devices P_{G_2} and P_{G_3} the activation level can be modulated, u_j is constrained to a finite set such as $\mathbb{V}_j = \{n_1, n_2, \cdots, n_p\}$, $n_p \in \mathbb{R}$. Then, according to Figure 7.1, the activation of u_j will depend on the current energy consumption of the whole process line, the operational relationships between machines and peripheral devices, and the physical constraints of peripheral systems. Therefore, peripheral devices should be suitably managed to guarantee the proper operation of the machines and to minimise the total energy consumption, while keeping the productivity of the process line. The latter fact means operating peripheral devices without affecting the processing time and the machining operations performed by the machines.

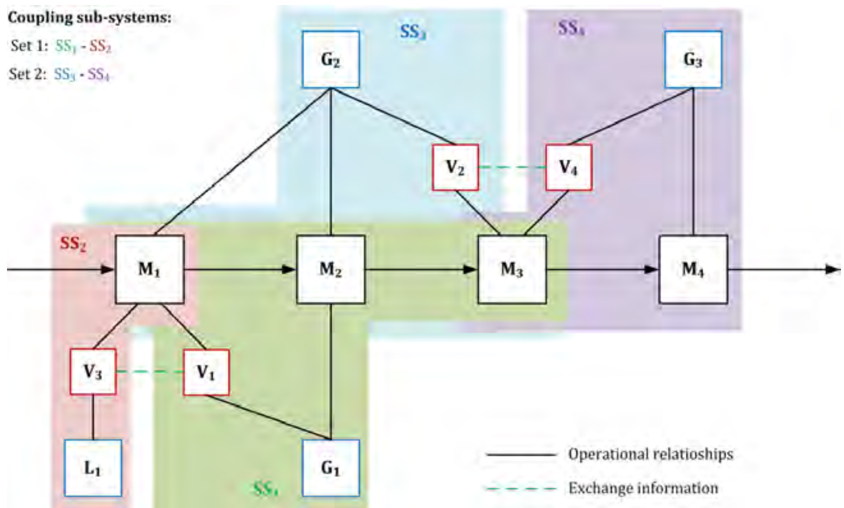


Figure 7.5: Proposed sub-systems division for the four-stage serial process line in Figure 7.1.

7.2.2 System partitioning

In Figure 7.4, a simplified representation of the process line in Figure 7.1 is presented showing the operational relationships among machines and peripheral devices. From this figure, it is possible to observe that there exist multi-providers for both M_1 and M_3, while P_{G_1} and P_{G_2} must supply resources to two or more machines. In these cases, it should exist a consensus to select the supplier and to determine the amount of a resource that should be provided in such a way that the energy consumption can be minimised. Thus, when several devices can cover the demand of a particular machine, the controller should decide which peripheral device is more suitable to supply this demand taking into account the consumption from the other machines and the current levels in the supply systems. Besides, the maximum flow that can be provided when the valves are entirely opened ($v_j = 100$) must be considered to get a consensus among the values of v_j when more than one device is needed to supply resources to one machine.

Then, according to the process line configuration and the coupling dynamics among the different machines and peripheral devices, the process line is divided into four sub-systems, as shown in Figure 7.5. Sub-system 1 (SS_1) is formed by the machines M_1, M_2, M_3, the device P_{G_1}, and the valve v_1. This sub-system deals with the supply of compressed air to most of the machines in the process line. However, M_1 has also as a supplier the device L_1. Thus, the second sub-system (SS_2) is composed of P_{L_1}, v_3 and only M_1 since P_{L_1} is a local peripheral device for this machine. From these two sub-systems, communication is required to supply the exact flow of compressed air required by M_1 as in (7.8).

The third (SS_3) and fourth (SS_4) sub-systems were defined concerning the supply system of coolant to machines in the process line. Thus, SS_3 consists of the machines M_1, M_2, and M_3, the device P_{G_2} and the valve v_2. This sub-system represents the main coolant-supply system of the process line. Then, the sub-system SS_4 concerns to machines M_3 and M_4, the device P_{G_3} and v_4. This sub-system is responsible for satisfying the requirements of M_4 and should also coordinate with SS_3 to supply the coolant demand of M_3. Although there exists clear operational relationships among SS_1 and SS_2, and SS_3 and SS_4, it should be noted that there is not coupling dynamics among the supply systems of compressed air and coolant. That means, in this case study, it is not necessary to establish communication among the supply systems of different resources to machines. This fact could help to reduce the complexity of centralised control architectures.

It should be noted that the system partitioning is performed based on the configuration of the process line and the coupled dynamics among machines and peripheral devices to reduce the number of coupled sub-system and, therefore, the communication among controllers. However, other sub-systems could be defined depending on the information exchange among the local controllers, the optimisation algorithm to be used, and the computational capacity to solve such algorithms.

7.2.3 Non-cooperative DMPC (NCDMP)

According to the proposed system partitioning in the previous section, one local controller is designed for each sub-system using a local cost function. Then, considering a prediction horizon H_p, each local controller l is based on the following open-loop optimisation problem[1]

$$\min_{\mathbf{\Gamma^l(k)},\mathbf{\Pi^l(k)}} \quad J^l(k) \tag{7.19a}$$

subject to

$$\xi^l_{M_i}(k+1+r) = f^l_{M_i}\left(\xi^l_{M_i}(k+r), \mathbf{\Lambda^l_{M_i}}\right), \tag{7.19b}$$

$$S^l_{M_i}(k+r) = g^l_{M_i}\left(\xi^l_{M_i}(k+r)\right), \tag{7.19c}$$

$$\xi^l_j(k+1+r) = f^l_j\left(\xi^l_j(k+r), u^l_j(k+r)\right), \tag{7.19d}$$

$$S^l_j(k+r) = g^l_j\left(\xi^l_j(k+r)\right), \tag{7.19e}$$

$$S^l_{v_j}(k+r) = \alpha^l_{v_j}\; v^l_j(k+r), \tag{7.19f}$$

[1]Regarding the notation, it is worth noting that some letters are re-defined at each chapter as required.

$$Q_j^l(k+1+r) = q_j^l\left(Q_j^l(k+r), u_j^l(k+r), \mathbf{\Lambda^l_{M_i}}\right), \tag{7.19g}$$
$$m_{M_i}^l(k+r) = m_{j\to M_i}^l(k+r) + m_{b\to M_i}^l(k+r), \tag{7.19h}$$
$$u_j^l(k+r) \in \{n_1, n_2, \cdots, n_p^l\}, \tag{7.19i}$$
$$v_j^l(k+r) \in \{d_1, d_2, \cdots, d_p^l\}, \tag{7.19j}$$
$$Q_j^l(k+r) \in \left[\overline{Q}_j^l,\ \underline{Q}_j^l\right], \tag{7.19k}$$

$\forall r = 0, 1, \cdots, H_p - 1$, with i and j the indices for the machines and peripheral devices in each sub-system SS_l, respectively. Moreover, b refers the index for the other sub-systems with coupled dynamics, J_l is the local cost function, and being $\mathbf{\Gamma^l}$ and $\mathbf{\Pi^l}$ the activation sequence of peripheral devices and valves along H_p. These sequences can be defined as follows:

$$\mathbf{\Gamma^l}(k) \triangleq \{\mathbf{\Lambda^l_P}(k|k), \ldots, \mathbf{\Lambda^l_P}(k+H_p-1|k)\}, \tag{7.20a}$$
$$\mathbf{\Pi^l}(k) \triangleq \{\mathbf{\Lambda^l_V}(k|k), \ldots, \mathbf{\Lambda^l_V}(k+H_p-1|k)\}, \tag{7.20b}$$

with $\mathbf{\Lambda^l_P}$ and $\mathbf{\Lambda^l_V}$ as in (7.16b) and (7.16c), respectively.

It is worth noting that in (7.19), expressions in (7.19b), (7.19c), (7.19d), and (7.19e) refer to the linear maps for the energy consumption of the machines and peripheral devices involved in SS_l, while (7.19f) accounts for the constant energy consumption related to v_j^l. Besides, (7.19g) corresponds to the different process dynamics associated to the supply systems of either coolant or compressed air for the peripheral devices involved in SS_l. Moreover, expressions from (7.19i) to (7.19k) correspond to the range constraints for the decision variables and the operating ranges for the dynamics of processes related to operation of peripheral devices.

On the other hand, (7.19h) concerns the coupling dynamics among the sub-system l, i.e., SS_l, and some other sub-systems, denoted here with the sub-index r. Thus, these expressions refer to the balance conditions when a machine has multiple suppliers for the same resource. Concerning this case study, these coupling dynamics exist between SS_1 and SS_2 to provide compressed air to M_1, and between SS_3 and SS_4 to supply the coolant required by M_3. Thus, the sub-systems related to the air supply are not interacting with the sub-systems related to the supply of coolant.

Then, to make the sub-systems with coupling dynamics (SS_1-SS_2 or SS_3-SS_4) separable and to use the ADMM algorithm, a new variable z_j is introduced. Then, the optimisation problem in (7.19) is transformed as follows:

$$\min_{\mathbf{\Gamma^l(k)},\mathbf{\Pi^l(k)}} \quad J^l(k) \tag{7.21a}$$

subject to

$$h(\{u_j(k+r), v_j(k+r)\}^l) \preceq b^l, \tag{7.21b}$$

$$u_j^l(k+r) \in \mathcal{U}_j^l, \tag{7.21c}$$

$$v_j^l(k+r) \in \mathcal{V}_j^l, \tag{7.21d}$$

$$v_j^l(k+r) = z_j(k+r), \tag{7.21e}$$

where (7.21b) gather all the operational constraints and the energy consumption models of the devices and valves involved in SS_l, while (7.21c) and (7.21d) refer to the range constraints for the decision variables. Note that by adding the new variable z_j, the balance expression in (7.19h) is removed from the optimisation problem and it will be replaced by (7.21e). Besides, it should be noted that this constraint is only related to the sub-system l and does not consider the interactions with the other sub-systems explicitly. Nonetheless, the variable z_j, which is considered as the consensus variable of the sub-system l, has the information about the valve aperture v_j required to satisfy (7.19h) taking into account the amount of flow provided by the other sub-systems related to the same resource and machine. Thereby, z_j should be suitably determined since it accounts for the compliment of the equation of balance in (7.19h) to provide resources to machines with multiple suppliers. It is worth noting that the main advantage of this transformation is that since z_j could be considered as an external variable for SS_l, every local control problem can be solved separately if the value of z_j is known. A way to determine the values of z_j will be presented in Section 7.2.3.

Then, according to the ADMM algorithm, (7.21e) is relaxed into the cost function by using of the Lagrange multipliers. Then, the augmented Lagrangian for each sub-problem (7.21) can be defined as follows:

$$\mathcal{L}_\rho^l\left(\{u_j, v_j\}^l, z, \lambda\right) = J^l(\{u_j, v_j\}^l) + g_v(z) + (\lambda)^T\left(v_j^l - z_j\right) + \frac{\rho}{2}\|v_j^l - z_j\|_2^2, \tag{7.22}$$

with J^l the local cost function given by

$$J^l(\{u_j, v_j\}^l) = \sum_{k=1}^{H_p}\left[S_{M_i}^l(k) + S_j^l(k) + S_{v_j}^l(k)\right]\Delta k, \tag{7.23}$$

and being $g_v(\cdot)$ a regularisation term for $z = [z_1, z_2, \cdots, z_j]$, and $\lambda = [\lambda_1, \cdots \lambda_j]$ the Lagrange multipliers for all the coupling constraints in SS_l, e.g., the balance equation in (7.21b). Moreover, $\left(v_j^l - z_j\right)$ is the consensus constraint. Then, (7.22) is the optimisation problem with two sets of decision variables, i.e., $\{u, v\}$ and z, and with separable cost functions.

According to the ADMM algorithm, first, variables $\{u, v\}^l$ are updated for each sub-system l considering an initial condition for z and λ. This step can be performed in parallel or in sequential way. Next, based on the updated values for $\{u, v\}^l$, the consensus variable z is also updated. Finally, the Lagrange multiplier λ (or dual variable) is updated by using the Gauss-Seidel method [Boy10], and the procedure is repeated up to reach the convergence. These steps can be summarised as follows:

$$\{u_j, v_j\}_{k+1}^l = \min_{\{u_j, v_j\}^l} \left[J^l(\{u_j, v_j\}^l) + (\lambda_k)^T \left({v_j}^l - {z_j}_k\right) + \frac{\rho}{2} \|{v_j}^l - {z_j}_k\|_2^2 \right], \tag{7.24a}$$

$$z_{k+1} = \min_z \left[g_v(z) + \sum_{l=1}^{b} (\lambda_k)^T \left({v_j}_{k+1}^l - z_j\right) + \frac{\rho}{2} \|{v_j}_{k+1}^l - z_j\|_2^2 \right], \tag{7.24b}$$

$$\lambda_{k+1} = \lambda_k + \rho \left({v_j}_{k+1}^l - {z_j}_{k+1}\right). \tag{7.24c}$$

Regarding this case study, steps in (7.24) are developed for each one of the sets with coupled sub-systems. Thus, the ADMM algorithm is implemented for sub-systems SS_1 and SS_2, and also to solve the optimisation problems for SS_3 and SS_4. The latter means that the local controllers for coupled sub-systems will be solved in a distributed way using the ADMM algorithm, but also in a decentralised way concerning the other set of coupled sub-systems.

Consensus stage

Usually, the consensus problem based on the ADMM algorithms considers the regularisation term $g_v(\cdot)$ as averaging of the variable z concerning the number of sub-systems [Boy10]. However, in this case, in addition to the amount of resource to be supplied from each peripheral device to satisfy (7.19h), the consensus stage should consider the energy consumption associated to the valve operation and the peripheral devices. In this regard, the regularisation term $g(\cdot)$ in (7.24) is defined as follows:

- *Balance constraint:* The first term in $g_v(\cdot)$ penalises the error related to the balance constraint. Thus, the error at each instant k is defined as

$$e_{M_i}(k) = \left(\varepsilon_{v_j}\, z_j^l(k) + \varepsilon_{v_b}\, z_b^r(k) - m_{M_i}(k)\right), \tag{7.25}$$

with j and b the indices related to the peripheral devices of the sub-systems l and r, which can supply the same resources to M_i. Besides, ε_{v_j} refers to the maximum flow that can be transported thought v_j when it is fully opened, and $\mathbf{E_{M_i}} = [e_{M_i}(1), e_{M_i}(2), \cdots, e_{M_i}(H_p)]^T$ is the error vector for (7.25) along H_p. Notice that in this case, the real constraint in (7.19h) is expressed in function of the consensus variable z, which is sent to the local controllers to guarantee the flow required by the machine. In this regard, $g_1(\cdot)$ is defined as follows:

$$g_1(z) = \mathbf{E_{M_i}}^T\, I_e\, \mathbf{E_{M_i}}, \tag{7.26}$$

being I_e the weighting matrix for (7.25) along H_p.

- *Energy consumption:* Since each valve has an associated energy consumption, the second term to be included in the regularisation term accounts for the total energy consumption related to the operation of the valves. Thus, the energy consumption associated to the operation of v_j is given by

$$S_{z_j}(k) = \alpha_{v_j}\, z_j(k), \tag{7.27}$$

and the total energy consumption for the manipulation of the valves can be computed according to

$$S_z(k) = \sum_{j=1}^{p} S_{z_j}(k), \tag{7.28}$$

being p the number of peripheral devices involved in (7.19h). Next, similar to the first case, the second term is defined along H_p as follows:

$$g_2(z) = \mathbf{S_z}^T\, I_{S_v}\, \mathbf{S_z}. \tag{7.29}$$

Finally, the whole regularisation term is given by

$$g_v(z) = \underbrace{\mathbf{E_{M_i}}^T\, I_e\, \mathbf{E_{M_i}}}_{g1} + \underbrace{\mathbf{S_z}^T\, I_{S_v}\, \mathbf{S_z}}_{g2}. \tag{7.30}$$

From (7.30), both the strong coupling constraints among sub-systems and a penalisation for the energy consumption, which is the main objective of this dissertation, are considered. The underlying idea behind (7.30) is to determine the values of z that no only allow satisfying the flow requirements from machines but also minimising the energy consumption. To this end, matrices I_e and I_{S_v} should be suitably selected since it is necessary to guarantee that (7.19h) and (7.21e) are satisfied even when they were relaxed into the cost function. It should be noted that, in addition to the weighting matrices I_e and I_{S_v}, it was also considered a matrix for the quadratic term $\|{v_j}_{k+1}^l - z_j\|_2^2$, i.e.,

$$\|{v_j}_{k+1}^l - z_j\|_2^2 = \left({v_j}^l(k) - z_j(k)\right)^T \; I_{v_j} \; \left({v_j}^l(k) - z_j(k)\right). \tag{7.31}$$

In this dissertation, different ways to define the weighting matrices were considered to achieve lower energy consumption while satisfying the balance constraints. The proposed manners for setting the weighting matrices will be described in deep in Section 7.3.1 along with the simulation results.

Stopping criteria

Based on the coupling constraints among the different sub-systems, the new consensus variable and the resulting consensus constraint, the following stopping criteria are defined:

1. *Balance equation:* It is defined such that the difference between the sum of the flows provided by peripheral devices and the real flow required by the machine will be less or equal to a predefined tolerance value

$$\sum_{j=1}^{p} \varepsilon_{v_j} \; v_j(k) - m_{M_i}(k) \leq \epsilon_1, \tag{7.32}$$

   with ϵ_1 being the tolerance value near zero.

2. *Consensus constraint:* It is defined to guarantee that each local controller takes into account the decisions made in the consensus stage. It is defined as follows:

$$v_j(k) - z_j(k) \leq \epsilon_2, \tag{7.33}$$

   being ϵ_2 a value significantly small with respect to the magnitude of variables v_j and z_j.

Algorithm 7.2 Non-cooperative distributed model predictive control.

1: Initialise sequences of $z(k)$ and $\lambda(k)$ along H_p
2: **repeat** for each set of coupling sub-systems
3: Broadcast the current values of $z(k)$ and $\lambda(k)$ among the set of coupling sub-systems
4: Solve the optimisation problem of each local controller l separately under the current values of $z(k)$ and $\lambda(k)$

$$\min_{\mathbf{\Gamma}^{\mathbf{l}}(k),\mathbf{\Pi}^{\mathbf{l}}(k)} \left[J^l(\mathbf{\Gamma}^{\mathbf{l}}(k), \mathbf{\Pi}^{\mathbf{l}}(k)) + \lambda(k)^T \left(v_j(k)^l - z_j(k) \right) + \frac{\rho}{2} \| v_j{}^l(k) - z_j(k) \|_2^2 \right],$$

subject to

$$h(\{u_j(k), v_j(k)\}^l) \preceq b^l,$$
$$u_j^l(k) \in \mathcal{U}_j^l, \; v_j^l(k) \in \mathcal{V}_j^l,$$

with $\mathbf{\Gamma}^{\mathbf{l}}$ and $\mathbf{\Pi}^{\mathbf{l}}$ the activation sequences of peripheral devices and valves along H_p
5: Get the local solutions $\bar{\mathbf{\Gamma}}^{\mathbf{l}}, \bar{\mathbf{\Pi}}^{\mathbf{l}}$ and sent to the consensus stage
6: Solve the consensus problem under the optimal sequences $\bar{\mathbf{\Gamma}}^{\mathbf{l}}, \bar{\mathbf{\Pi}}^{\mathbf{l}}$ previously obtained

$$\min_{z(k+1)} \left[g_v(z) + (\lambda(k))^T \left(\bar{v}_j(k) - z_j(k) \right) + \frac{\rho}{2} \| \bar{v}_j(k) - z_j(k) \|_2^2 \right]$$

7: Compute the stopping criteria

$$S_{c,1}(k : k + H_p) = \sum_{j=1}^{p} \varepsilon_{v_j} \, v_j(k : k + H_p) - m_{M_i}(k : k + H_p),$$
$$S_{c,2}(k : k + H_p) = v_j(k : k + H_p) - z_j(k : k + H_p)$$

8: Update the Lagrange multiplier

$$\lambda(k + 1) = \lambda(k) + \rho \left(\bar{v}_j(k) - \bar{z}_j(k) \right)$$

9: **until** $S_{c,1}(k : k + H_p) \leq \epsilon_1$ and $S_{c,2}(k : k + H_p) \leq \epsilon_2$
10: Gather all the optimal solutions from the other local controllers, which could be coupled or not to other controllers
11: Apply the first component of the optimal solution
12: Increase k to $k + 1$ and repeat the procedure from step 1

It should be noted that the stopping criteria are checked for each time instant in the prediction horizon. Finally, the procedure previously explained for the non-cooperative control architecture (NCDMPC) is presented in Algorithm 7.2.

7.2.4 Cooperative DMPC (CDMPC)

For the case of a cooperative control architecture, the system partitioning is performed in the same way that for the case of non-cooperative architecture. However, in this case, each local controller is designed to minimise the global cost function. It means that each local controller should determine the optimal activation of its peripheral devices and valves but minimising the energy consumption of the whole process line. Thus, each local controller needs to know the optimal sequences obtained by the other local controllers. Then, for a defined H_p, the design of each local controller is based on the same open-loop optimisation problem in (7.19) but changing the local cost function J^l by the following global cost function:

$$J(\{u_j, v_j\}^l, \{u_b, v_b\}^r) = \sum_{k=1}^{H_p} \left[\underbrace{S^l_{M_i}(k) + S^l_j(k) + S^l_{v_j}(k)}_{\texttt{current sub-system}} + \underbrace{S^r_{M_i}(k) + S^r_b(k) + S^r_{v_b}(k)}_{\texttt{other sub-systems}} \right] \Delta k, \tag{7.34}$$

with j and b the indices for the peripheral devices and valves related to the sub-system l and for the devices and valves of the other sub-systems r, respectively. Thus, $\{u_j, v_j\}$ is the set of variables directly involved in SS_l, and $\{u_b, v_b\}^r$ is the set of variables required from the other controllers. Besides, since (7.34) refers to the energy consumption, the energy consumption models of the other sub-systems should be added into the set of constraints in (7.19).

In the same way as the non-cooperative case, one extra variable is added, and the local optimisation problems are solved using the ADMM algorithms for the sub-systems with coupling dynamics. However, in this case, once the local controllers obtain an optimal sequence for the activation of peripheral devices and valves, they exchange the information with the other local controllers and compute the global cost function. Then, the value of $J(\cdot)$ for each local controller is compared with respect to those obtained from the other controllers. Next, if the difference among the values of J is less or equal to a predefined tolerance, the algorithm is finished, and the optimal sequences of each controller are equal to the last sequences obtained. In this regard, to the convergence of the CDMPC architecture, a new stopping criterion is defined:

$$|J_l(k) - J_r(k)| \leq \epsilon_J, \; \forall \, j \neq r. \tag{7.35}$$

being ϵ_J a small-enough value.

Thus, after the stopping criteria in (7.32) and (7.33) are reached for the sub-systems with

Algorithm 7.3 Cooperative distributed model predictive control.

1: Initialise sequences of $z(k)$ and $\lambda(k)$ along H_p
2: **while** $S_{c,J} > \epsilon_J$ **do**
3: **repeat** for each set of coupling sub-systems
4: Broadcast the current values of $z(k)$ and $\lambda(k)$ among the set of coupling sub-systems
5: Solve the optimisation problem of each local controller l separately under the current values of $z(k)$ and $\lambda(k)$

$$\min_{\mathbf{\Gamma^l}(k),\mathbf{\Pi^l}(k)} \left[J(\cdot) + \lambda(k)^T \left(v_j(k)^l - z_j(k)\right) + \frac{\rho}{2} \|v_j{}^l(k) - z_j(k)\|_2^2 \right],$$

subject to

$$\begin{aligned} &h(\{u_j(k), v_j(k)\}^l) \preceq b^l, \\ &u_j^l(k) \in \mathcal{U}_j^l,\ v_j^l(k) \in \mathcal{V}_j^l, \end{aligned}$$

with $J(\cdot)$ as in (7.34), $\mathbf{\Gamma^l}$ and $\mathbf{\Pi^l}$ the activation sequences of both peripheral devices and valves along H_p for sub-system l, and $\mathbf{\Gamma^b}$ and $\mathbf{\Pi^b}$ the sequences from other sub-systems
6: Get the local solutions $\bar{\mathbf{\Gamma}}^{\mathbf{l}}, \bar{\mathbf{\Pi}}^{\mathbf{l}}$ and sent to the consensus stage
7: Solve the consensus problem under the optimal sequences $\bar{\mathbf{\Gamma}}^{\mathbf{l}}, \bar{\mathbf{\Pi}}^{\mathbf{l}}$ previously obtained

$$\min_{z(k+1)} \left[g_v(z) + (\lambda(k))^T \left(\bar{v}_j(k) - z_j(k)\right) + \frac{\rho}{2} \|\bar{v}_j(k) - z_j(k)\|_2^2 \right].$$

8: Compute the stopping criteria

$$\begin{aligned} S_{c,1}(k : k + H_p) &= \sum_{j=1}^{p} \varepsilon_{v_j}\, v_j(k : k + H_p) - m_{M_i}(k : k + H_p), \\ S_{c,2}(k : k + H_p) &= v_j(k : k + H_p) - z_j(k : k + H_p) \end{aligned}$$

9: Update the Lagrange multiplier,

$$\lambda(k + 1) = \lambda(k) + \rho\left(\bar{v}_j(k) - \bar{z}_j(k)\right)$$

10: **until** $S_{c,1}(k : k + H_p) \leq \epsilon_1$ and $S_{c,2}(k : k + H_p) \leq \epsilon_2$
11: Gather all the optimal solutions from the other local controllers, which could be coupled or not to other controllers.
12: Exchange optimal solutions and compute the value the global cost function $J(\cdot)$
13: **end while**
14: Apply the first component of the optimal solution
15: Increase k to $k + 1$ and repeat the procedure from step 1

coupled dynamics by using the ADMM algorithm, (7.35) is computed for all local controllers. Then, if (7.35) is satisfied, the optimal activation sequences are found and defined as those obtained for the last iteration. This procedure and the modifications concerning the non-cooperative architecture are shown in Algorithm 7.3.

7.3 Comparative Assessment: Centralised vs. Non-centralised Control Architectures

In this section, the centralised control architecture proposed in Chapter 6 will be compared with the non-centralised control structures proposed in this chapter. It is worth noting that all the simulations were performed considering $H_p = 22$ s, which corresponds to the shorter machine cycle (i.e., T_{M_i}) among all machines in the process line. As the same of the control strategies previously proposed, the controllers were executed every second while the sampling time for energy consumption models and process dynamics was $\tau_s = 0.1$s. The simulation parameters, according to the process line in Figure 7.1, are presented in Table 7.1. Moreover, as the same for the previous cases, simulations were performed using an Intel Core i7-55000U 2.4 GHz processor with 8G RAM, and the simulation results were obtained in Matlab by using the software IBM ILOG CPLEX Optimisation Studio [ILO13] integrated to YALMIP toolbox [Löf04].

7.3.1 Weighting matrices

As explained in Section 7.2.3, weighting matrices need to be suitably defined to include the energy consumption into the consensus stages, besides, to bring all the terms in the cost function to the same magnitude. In this regard, matrices I_e and I_{S_v} for the consensus stage kept the same during the whole simulation, while two different ways of defining I_{v_j} were considered. According to system partitioning and the ADMM method, two consensus stages are required, one for the coupling sub-systems SS_1 and SS_2 and another for the sub-systems SS_2 and SS_4. In both cases, I_e was defined as follows:

$$I_e = 1 \times 10^4 I_{H_p}, \tag{7.36}$$

being I_{H_p} the identity matrix with dimension equal to H_p. It should be noted that the factor 1×10^4 is required since the magnitude order of the air and coolant flows is significantly smaller than for the rest of the terms in the cost function.

On the other hand, according to Table 7.1, for the first pair of coupled sub-systems, the manipulation of the valves implies the same energy consumption since $\alpha_{v_1} = \alpha_{v_3}$. Therefore, in this case, the energy consumption will be the same independently of selection of v_1 and v_3. However, for the second pair of coupled systems, $\alpha_{v_2} \neq \alpha_{v_4}$ and, therefore, the term related

Table 7.1: Physical dimensions and parameters for the supply systems of compressed air and coolant.

Parameter	Value	Units	Parameter	Value	Units
T_{M_1}	22	s	T_{M_2}	36	s
T_{M_3}	44	s	T_{M_4}	28	s
V_{T_1}	0.015	m^3	V_{T_4}	0.01	m^3
A_{T_2}	0.015	m^2	A_{T_3}	0.015	m^2
A_{T_5}	0.015	m^2	A_{T_6}	0.015	m^2
T_{air}	25	°C	R	8.1314	$\frac{\mathrm{J}}{\mathrm{Kmol}}$
W_{air}	28.966	$\frac{\mathrm{g}}{\mathrm{mol}}$	ΔP_{filter}	10000	Pa
P_{atm}	101325	Pa	η	0.95	–
ρ_c	1042.5	$\frac{\mathrm{kg}}{\mathrm{m}^3}$	$h_{1\to2}$	0.12	$\frac{\mathrm{m}^2}{\mathrm{s}^2}$
$m_{in,1}$	0.006	$\frac{\mathrm{kg}}{\mathrm{s}}$	$m_{in,3}$	0.004	$\frac{\mathrm{kg}}{\mathrm{s}}$
α_{v_1}	2.5	VA	α_{v_3}	2.5	VA
α_{v_2}	2.25	VA	α_{v_4}	2.75	VA
ε_{v_1}	1.5×10^{-5}	–	ε_{v_3}	3.0×10^{-5}	–
ε_{v_2}	2.5×10^{-4}	–	ε_{v_4}	2.5×10^{-4}	–
$\underline{P}_{T_1}$	300	kPa	$\overline{P}_{T_1}$	750	kPa
$\underline{P}_{T_4}$	300	kPa	$\overline{P}_{T_4}$	750	kPa
$\underline{L}_{T_2}$	0.3	m	$\overline{L}_{T_2}$	0.6	m
$\underline{L}_{T_3}$	0.4	m	$\overline{L}_{T_3}$	0.7	m
$\underline{L}_{T_5}$	0.3	m	$\overline{L}_{T_5}$	0.6	m
$\underline{L}_{T_6}$	0.4	m	$\overline{L}_{T_6}$	0.7	m
ρ^1	0.1	–	ρ^2	0.01	–
λ_0^1	$[1,1,\cdots,1]\in\mathbb{R}^{H_p}$	–	λ_0^2	$[1,1,\cdots,1]\in\mathbb{R}^{H_p}$	–
z_{1-2}^0	$[0,0,\cdots,0]\in\mathbb{R}^{H_p}$	–	z_{1-2}^0	$[0,0,\cdots,0]\in\mathbb{R}^{H_p}$	–

to the energy consumption in this consensus stages will be important. Based on the previous discussion, the weighting matrices for both sets of coupled sub-systems were defined as follows:

$$I_{S_v}^1 = 10\, I_{H_p}, \tag{7.37}$$

$$I_{S_v}^2 = 5\times10^3\, I_{H_p}, \tag{7.38}$$

with $I_{S_v}^1$ related to the consensus between SS_1 and SS_2, and $I_{S_v}^2$ for the consensus stage between SS_3 and SS_4. It should be noted that these weighting matrices were adjusted by a trial and error procedure taking as reference the obtained results for the centralised control architecture. Besides, for the case in which the valves have the same energy consumption, the energy-consumption term in the regularisation function $g_v(z)$ losses relevance since in any case the energy consumption will be the same. In contrast, for the case in which the valves imply different energy consumptions, $I_{S_v}^2$ was defined to make relevant this term with respect to the other terms of the regularisation function.

On the other hand, two different ways of fixing matrices I_{v_j} into the quadratic term of $g_v(\cdot)$ are proposed. The idea with these matrices is to include an extra penalisation based on the current capacity of the peripheral devices to provide resources without real-time energy conversion. In the former case, the weighting matrices I_{v_j} were defined and remained the same for the whole simulation, while in the second case, the values of I_{v_j} were updated at each iteration according to the current state of the process variables. The last fact is because if any process variable, e.g., pressure or the coolant level in the tanks, is near to its lower boundary and the controller decides to supply the required flow from this system, then, the related peripheral device must be activated. For both the fixed and adaptive cases, matrices I_{v_j} are presented below:

- *Fixed matrices I_{v_j}:* Due to the introduction of a new variable z_j in each sub-problem and the addition of the consensus constraint to each local control problem, there is a matrix I_{v_j} for each local control problem that penalises the consensus constraints along H_p. For the case of both coupling sub-systems, i.e., SS_1-SS_2 and SS_3-SS_4, the matrices I_{v_j} are defined as follows:

$$I_{v_j} = 10\ I_{H_p}, \tag{7.39}$$

  with $j = 1, 3$ for the case of the coupling SS_1 and SS_2, and $j = 2, 4$ for SS_3 and SS_4. It is worth noting that in this case, the matrices I_{v_j} are the same at both the local controllers and the consensus stage, and there is not an extra penalisation related to the process dynamics related to the peripheral devices.

- *Adaptive matrices I_{v_j}:* In this case, the penalisation regarding the process dynamics related to the peripheral devices is only considered into the consensus stage. That means, for each local problem, the matrices I_{v_j} remain the same with respect to the previous case. However, in the consensus stage, these matrices are modified to update the variable z considering the current capacity of peripheral systems. Thus, for each local controller,

$$I_{v_j}^l = 10\ I_{H_p}. \tag{7.40}$$

  Then, based on the optimal solution of each local controller, a prediction for the process dynamics of peripheral devices is made, i.e., pressure dynamics for SS_1 and SS_2 and level dynamics for SS_3 and SS_4. Next, according to the prediction for the pressure and the coolant levels at each tank, a vector of weights is created in the following way. At each k along H_p, the value of the process variable Q_j is normalised as follows:

$$\hat{Q}_j(k) = \frac{Q_j(k) - \underline{Q}_j}{\overline{Q}_j - \underline{Q}_j}, \tag{7.41}$$

being $\overline{Q}_j$ and $\underline{Q}_j$ the maximum and minimum values allowed for Q_j (with Q_j equal to the pressure in Tanks 1 or 4, or the level in Tanks 2, 3, 5, or 6). Once the normalised value $\hat{Q}_j(k)$ is computed, the extra weight to penalise the selection of v_j according to the level of Q_j at instant k is defined as follows:

$$w_{Q_j}(k) = 1 + (1 - \hat{Q}_j(k)). \tag{7.42}$$

Based on (7.42), when Q_j is near $\underline{Q}_j$, the peripheral device and the valve related to this process dynamics will have a higher penalisation since if the associated valve v_j opens, then, the peripheral device should be turned on early than if the resource is provided from another device. In contrast, if Q_j is close to $\overline{Q}_j$, the penalty for supplying resources from v_j will be less to promote the use of this device before other devices with less capacity. Thereby, the matrices I_{v_j} at the consensus stages are defined as follows:

$$I_{v_j} = W_{Q_j}\, I^l_{v_j}, \tag{7.43}$$

being W_{Q_j} the vector of weights along H_p, which multiplies each component of the matrix $I^l_{v_j}$.

7.3.2 Simulation results

Inclusion of energy consumption in consensus stage

In this section, the proposed control strategy by using a non-cooperative control architecture is tested to compare the effectiveness of including the energy consumption into the regularisation term $g_v(z)$ for the consensus stages. Thus, in the first case, denoted as NCDMPC$_1$, the regularisation term was defined without considering the energy consumption of valves

Table 7.2: Comparison of the total energy consumption for NCDMPC_1 and NCDMPC_2.

Controller	Energy consumption [VA]	Maximum $\mathrm{S(k)}$ [VA]	SEC [VA]
NCDMPC_1	1974467.706	2595.879	65815.591
NCDMPC_2	1972591.431	2257.714	65753.048

$$g_v(z) = \underbrace{\mathbf{E_{M_i}}^T\, I_e\, \mathbf{E_{M_i}}}_{g1}.$$

For the second case (denoted NCDMPC_2), the regularisation term $g_v(\cdot)$ is given by (7.30), i.e.,

$$g_v(z) = \underbrace{\mathbf{E_{M_i}}^T\, I_e\, \mathbf{E_{M_i}}}_{g1} + \underbrace{\mathbf{S_z}^T\, I_{S_v}\, \mathbf{S_z}}_{g2},$$

in which both the balance constraints and the energy consumption are included.

It should be noted that in this analysis, matrices I_e and I_{S_v} for both sets of coupled subsystems were defined as explained in Section 7.3.1. However, only for the case of NCDMPC_1, $I_{v_4} = 60\ I_{H_p}$ was defined to penalise the use of v_4 higher than the use of v_2. The last fact is because in this case, the energy consumption of valves was not considered into $g_v(\cdot)$. For the rest of the valves in the process line, matrices I_{v_j} were defined as in (7.40).

In Figures 7.6 and 7.7, portions of the activation sequences for the peripheral devices and the valve aperture are shown. Results in Figure 7.7 refer the consensus variable and the selection of the suppliers in a way such that operational constraints are satisfied and the energy consumption minimised. Then, to compare the effectiveness of the tested control strategies, in Table 7.2, the total energy consumption along 30 cycles of the longest T_{M_i} for the machines in the process line are shown. Besides, since $\texttt{max}(T_{M_i}) = 44$ s, the Specific Energy Consumption (SEC) indicator (see (5.28)) is also computed and presented in Table 7.2. From these results, it is possible to see that when the energy consumption is also considered into the consensus stage, small reductions can be achieved with differences near 1876.274 VA.

Cooperative vs. non-cooperative architectures

In this section, both cooperative and non-cooperative control architectures will be compared according to Algorithms 7.3 and 7.2, respectively. Besides, both architectures were tested using

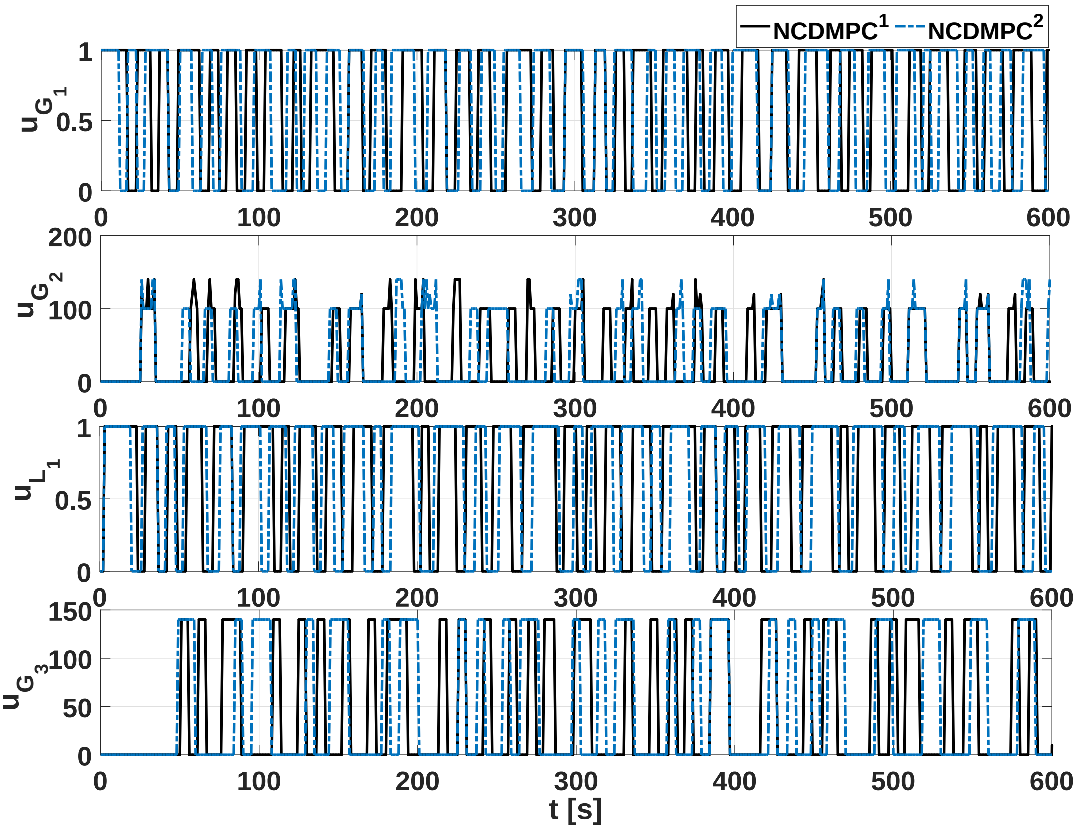


Figure 7.6: Comparison of the activation/deactivation sequences of peripheral devices using the control strategies NCDMPC_1 and NCDMPC_2.

the two ways proposed for defining matrices I_{v_j} into the consensus stages. Thus, the control strategy denoted as NCDMPC_2 in the previous section will be now marked as NCDMPC, while the cooperative architecture with the same fixed weighting matrices will be referred to CDMPC. Besides, both the cooperative and non-cooperative architectures considering the adaptive weighting matrices will be denoted as Ad-CDMPC and Ad-NCDMPC, respectively.

In Figure 7.8, the resulting energy profile for the process line is shown for each one of the control strategies tested. It should be noted that although the total simulation time was $T_{sim} = 1320$ s, only a portion of the full signal is shown in this figure to observe better the differences among the results obtained from each control strategy. Besides, all the simulations were performed considering the same value of T_{sim}, which corresponds to 30 operating cycles for the machine with the longest T_{M_i}. Regarding energy consumption, a comparison of the total energy consumption for the whole simulation, the highest peak in the energy consumption profile and the SEC indicator are shown in Table 7.3.

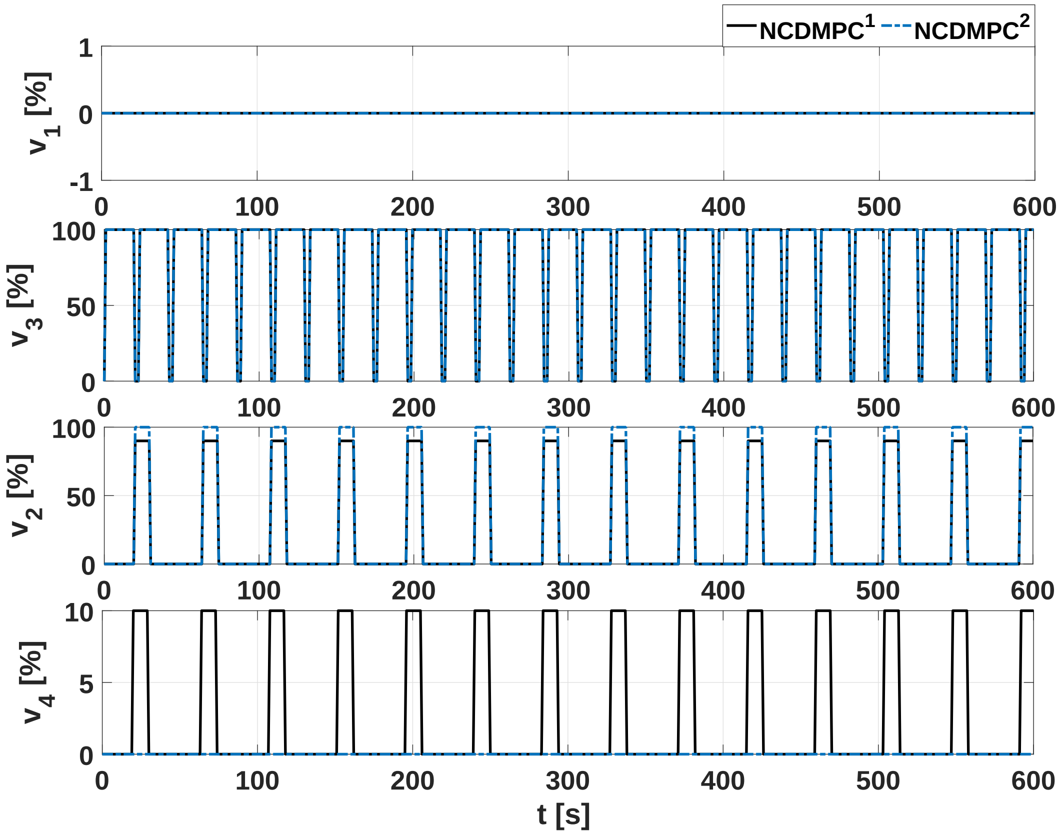


Figure 7.7: Comparison of the sequences for the valve aperture using the control strategies $NCDMPC_1$ and $NCDMPC_2$.

Table 7.3: Results for the comparison of cooperative and non-cooperative control architectures.

Controller	Energy consumption [VA]	Maximum $S(k)$ [VA]	SEC [VA]
NCDMPC	1973736.762	2356.931	65791.225
CDMPC	1972503.098	2489.896	65750.103
Ad-NCDMPC	1973857.628	2376.881	65795.254
Ad-CDMPC	1972556.607	2304.056	65751.887

From results in Table 7.3, it can be concluded that in the way as the adaptive matrices are defined, they do not allow significant improvements. Instead of that, by using adaptive matrices, the total energy consumption for the cooperative and non-cooperative architectures is a little bit higher than in the case in which the matrices are fixed. However, these differences correspond to variations less than 0.01% among the proposed approaches. In this regard, at least for the nominal cases without disturbances, all the proposed control strategies have a similar performance in closed loop. Besides, regarding cooperative and non-cooperative structures,

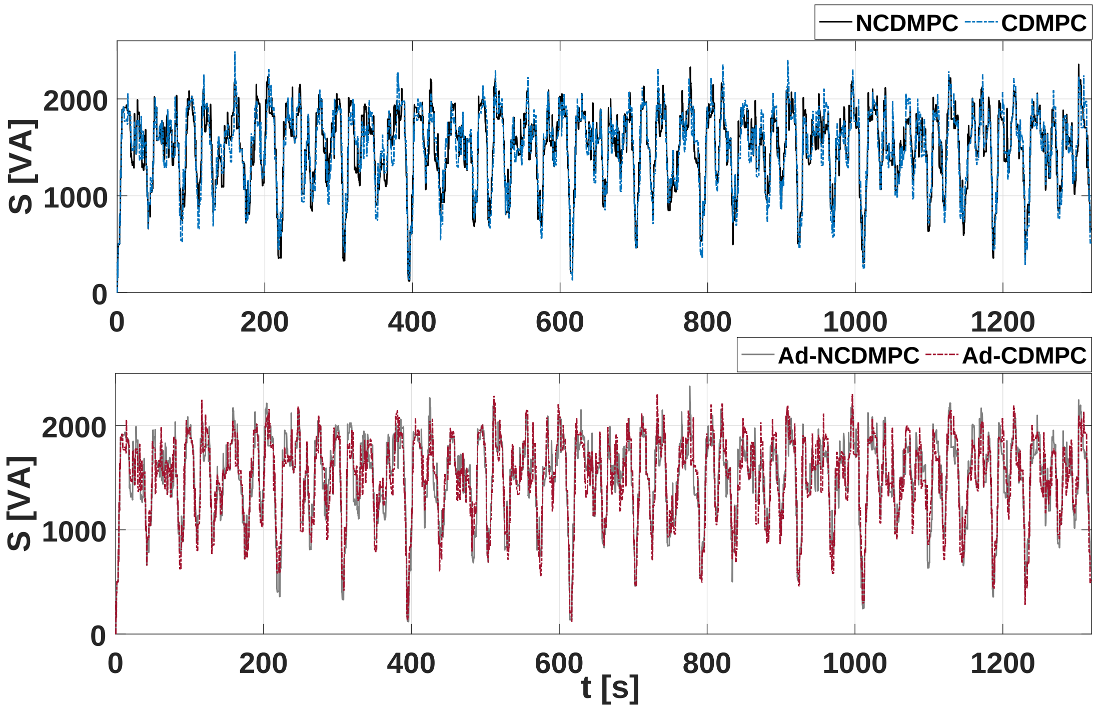


Figure 7.8: Energy consumption profile of a four-stage serial process line for the comparison between cooperative and non-cooperative control architectures.

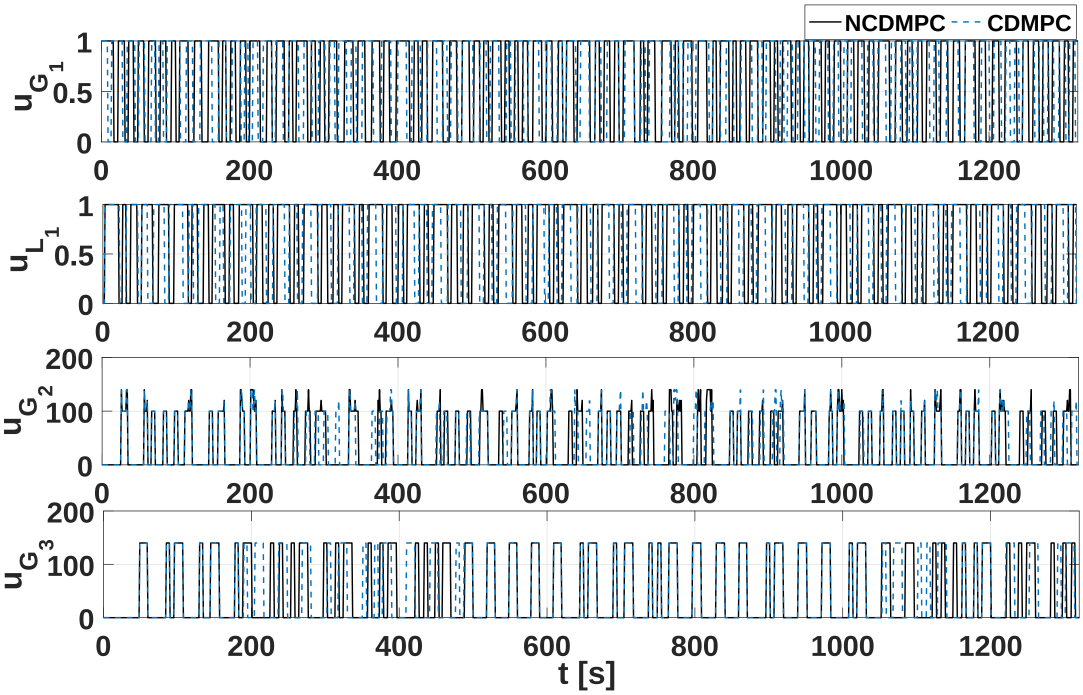
in the best case, energy-consumption reductions near 0.06% were achieved when cooperative architectures are implemented. These results could be a consequence of the defined control objectives and the way they are computed at each controller and the assumption that both the machining sequences of machines and their energy consumption are periodic and constant along the time. Thus, although each local controller should minimise the energy consumption of its peripheral devices and valves, they could know the energy consumption of its machines or all machines in the process line like an offset value into the cost function. In this regard, each controller coordinates the activation of its devices, taking into account the energy consumption profile of all machines in the process line.

The obtained activation sequences for peripheral devices are shown in Figures 7.9a and 7.9b for the cases of fixed and adaptive weighting matrices, respectively. In the same way, in Figures 7.10a and 7.10b the activation sequences are shown for the aperture of the valves for the cases of fixed and adaptive weighting matrices, respectively. From these results, it is possible to see that for both cooperative and non-cooperative control strategies, the optimal activations for the valve aperture was the same. Thus, in both cases, the controller decides to use only one device instead of a combination of the possible providers when there are more than one available. For the case of the compressed air, the obtained solution was expected since the feasible domains for both v_1 and v_3 are the set $\{0, 100\}$. Then, since both valves have the same energy consumption, the controller decides to provide the airflow required by M_1 using v_3 and P_{L_1} since the latter device has an energy consumption lower than the one of P_{G_1}. Besides, it is worth noting that since P_{L_1} is a local device for M_1, if P_{G_1} does not have to be responsible of the demand for M_1 it could be able to supply resources to the other machines during more time without a real-time energy conversion.

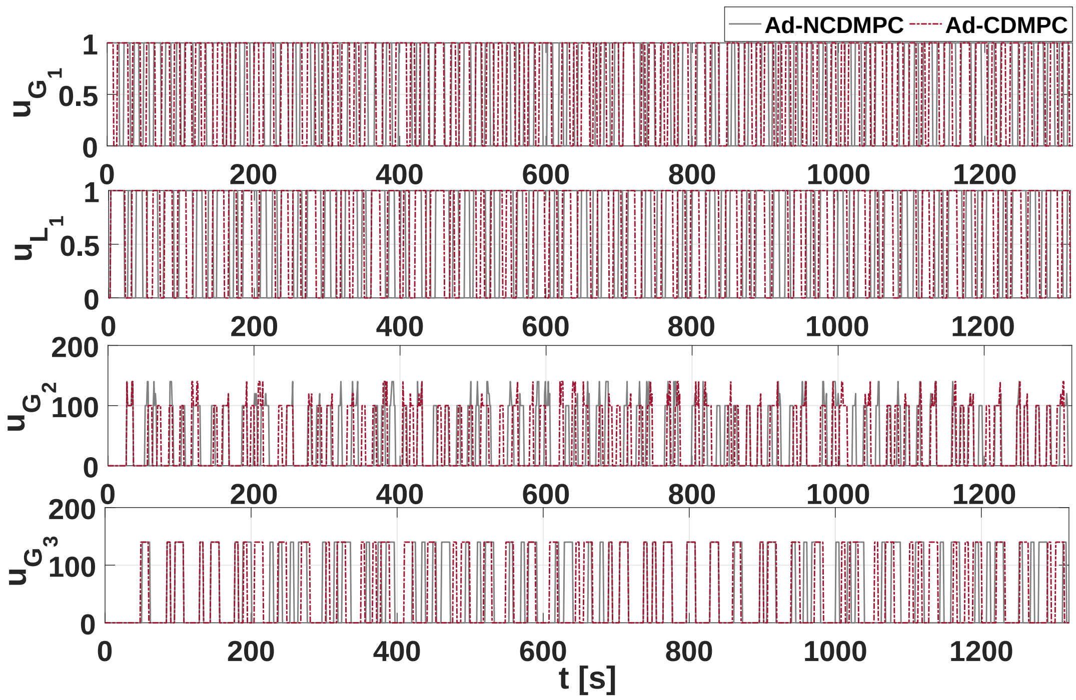
On the other hand, regarding v_2 and v_4, the consensus is a little bit more complex since there are more possible combinations for the valve apertures and the energy consumptions of valves are different. The last fact is due to the feasible domains for both v_2 and v_4 are given by the set $\{0, 10, 20, \cdots, 90, 100\}$. Besides, although P_{G_2} and P_{G_3} have the same energy consumption model, P_{G_3} is more constrained than P_{G_2} with respect to the activation level, i.e., $u_{G_2} \in \{0, 100, 120, 140\}$ and $u_{G_3} \in \{0, 70, 140\}$. Thus, it could occur the case in which P_{G_3} should always be activated at the highest level to be able to satisfy the demand of machines, which could imply a higher energy consumption than P_{G_2}. Therefore, regarding the coolant-supply system, the controller should make decisions based on both the energy consumption of the valves and the peripheral devices. As a consequence of the previous discussion and since the control objectives are defined for minimising the energy consumption, the controller always decides using v_2 and P_{G_2} to supply the flow of coolant required by M_3.

Although the optimal activation sequences for v_j were the same using both cooperative and non-cooperative architectures, the main differences between these control strategies can be seen in the results for the activation sequences of peripheral devices. For these devices, cooperative structures with information exchange among all sub-systems in the process line allow achieving better results that the non-cooperative architectures. This exchange of information concerns to the two sets of sub-systems that not have coupled dynamics (i.e., the supply system of compressed air and the coolant-supply system) to compute the total energy consumption of the whole process line.The last fact taking into account that by using the proposed ADMM-based algorithms, there is always an information exchange among the sub-systems with balance constraints. Thus, based on the activation sequence for all the variables v_j, the activation of peripheral devices of each sub-system is adapted and modulated when possible with the aim to minimise the total energy consumption from the knowledge of the particular energy consumption of each sub-system.

The process dynamics related to the operation of peripheral devices, according to the obtained activation sequences for both peripheral devices and valves, are shown in Figures 7.11

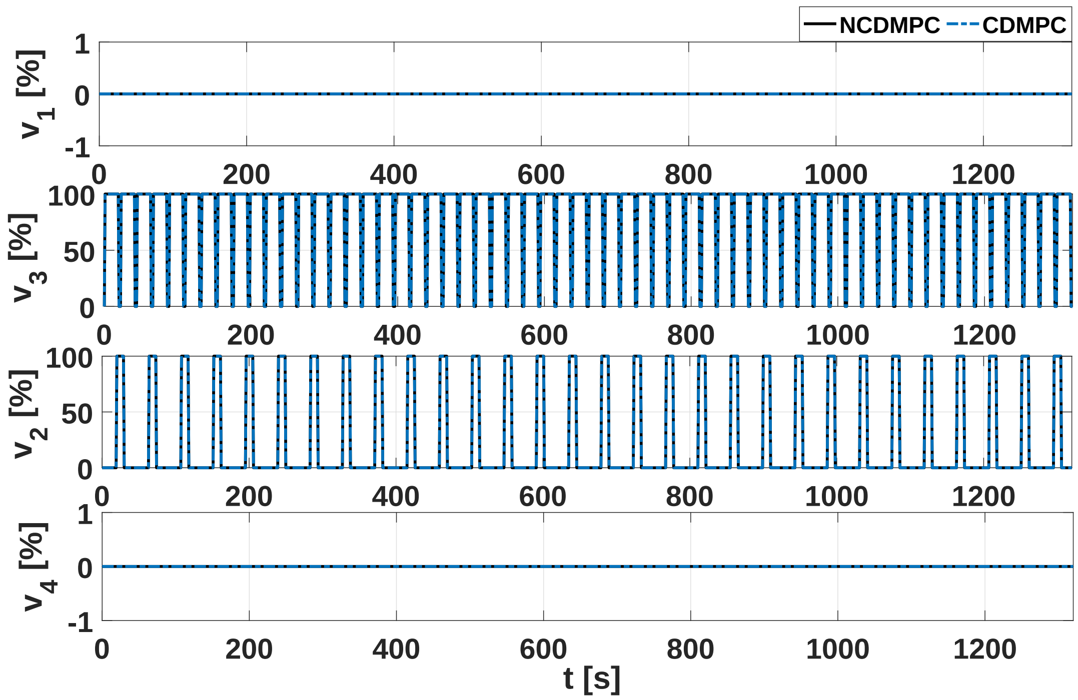


(a) Activation sequences using fixed weighting matrices.

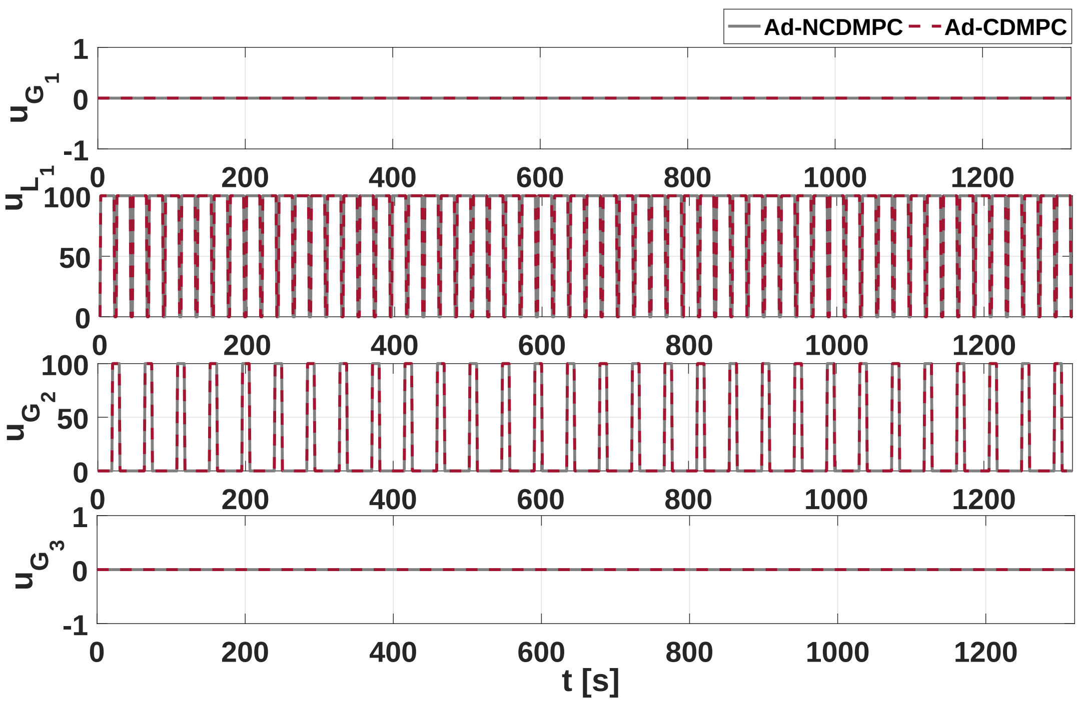


(b) Activation sequences using adaptive weighting matrices.

Figure 7.9: Activation sequences of peripheral devices using cooperative and non-cooperative control architectures.



(a) Valves aperture using fixed weighting matrices.



(b) Valves aperture using adaptive weighting matrices.

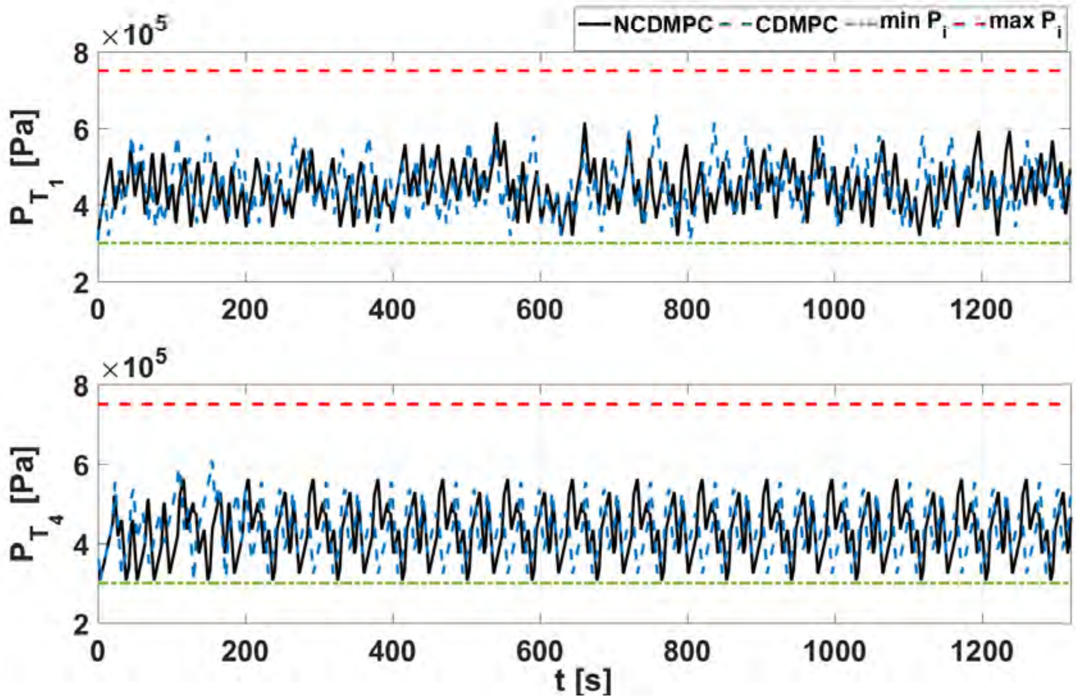
Figure 7.10: Activation sequences for the valves aperture using cooperative and non-cooperative control architectures.

and 7.12. The main observed result from these figures refers to the fact that when using the proposed control strategies, the process variables always remain inside their feasible domains and near the lower boundaries to avoid unnecessary energy consumptions. It means that peripheral devices are switched on only when the process variables could go out of their feasible domains in the future, and they remain on only until they reach a minimum level that guarantees the demand can be covered. Finally, a comparison of the CPU time spent to find an optimal solution per iteration (in the simulation loop), and the number of iterations made up to achieve the stopping criteria are shown in Figure 7.13 and 7.14, respectively.

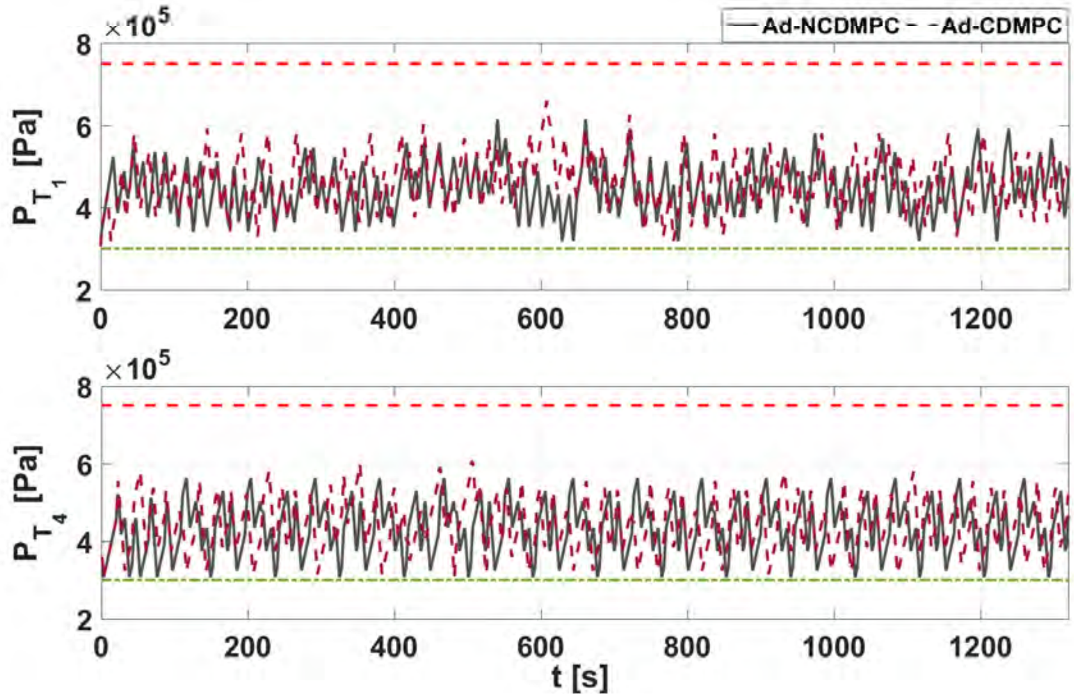
From results in Figures 7.13 and 7.14, it is possible to see that, as is expected, the cooperative control architectures spent more time and iterations to reach an optimal solution that satisfied all the stopping criteria. However, these control structures allow improvements with respect to the non-cooperative architectures for these manufacturing systems. It should be noted that the number of iterations shown in Figure 7.14, for the case of cooperative control strategies, corresponds to the sum of the number of iterations performed for the ADMM algorithm per each external iteration performed until satisfying the stopping criterion of the cooperative architectures according to Algorithm 7.3. Remember that this criterion concerns the differences between the total energy consumption computed by each local controller. Besides, at the bottom of Figure 7.14, the total number of iterations made for the external loop (see algorithm 7.3) is shown. Then, according to the results presented in this section, the energy consumption is more reduced when cooperative structures are employed than when non-cooperative architectures are used. However, these reductions are not significant, and the use of cooperative control strategies imply substantial increments in the computational burden to get a solution. Thus, in this case, it is recommendable to implement the non-cooperative architectures since, by using schemes in which only there exists information exchange among the sub-systems with coupled dynamics, it is possible to achieve a performance similar to that of cooperative architectures.

Centralised vs. non-centralised architectures

In this Section, a comparison among the centralised control architecture proposed in Chapter 6 and the best non-centralised control strategies studied in Section 7.3.2, is presented. The results presented here correspond to both the cooperative and non-cooperative architectures that consider the adaptive matrices of I_{v_j}, denoted as Ad-NCDMPC and Ad-CDMC, and the proposed centralised MPC (C-MPC) applied to the process line in Figure 7.1. It is worth noting that the cooperative and non-cooperative approaches using the adaptive weighting matrices were

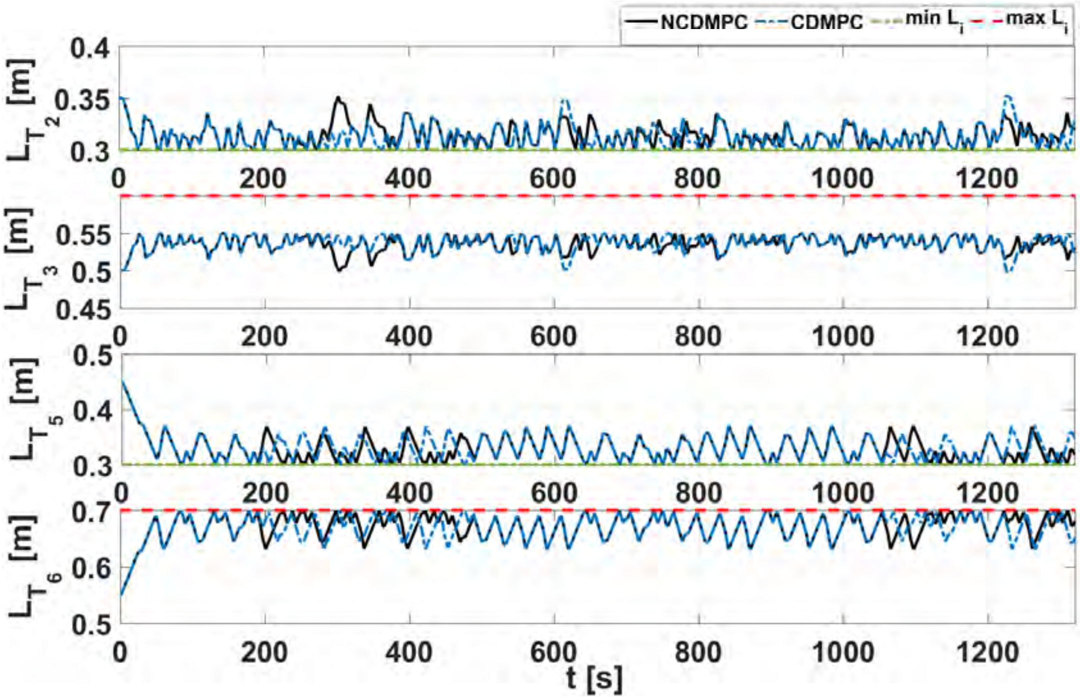


(a) Pressure of compressed air in T_1 and T_4 using fixed weighting matrices.

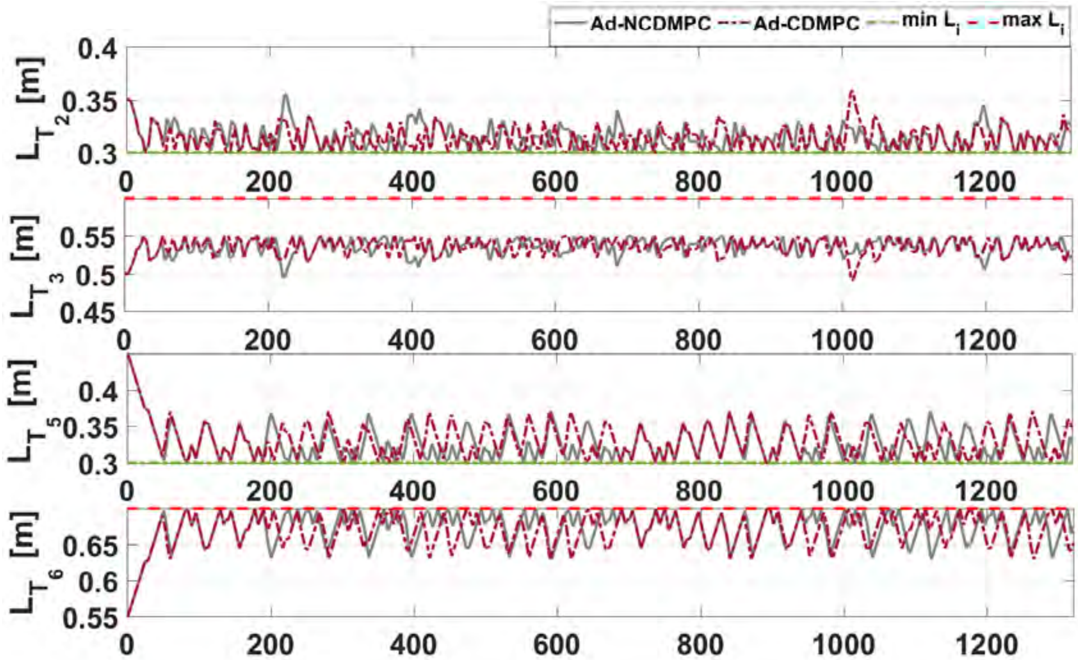


(b) Pressure of compressed air in T_1 and T_4 using adaptive weighting matrices.

Figure 7.11: Process dynamics related to the supply system of compressed air using cooperative and non-cooperative control architectures.



(a) Coolant level in the tanks using fixed weighting matrices.



(b) Coolant level in the tanks using using adaptive weighting matrices.

Figure 7.12: Process dynamics related to the coolant-supply system using cooperative and non-cooperative control architectures.

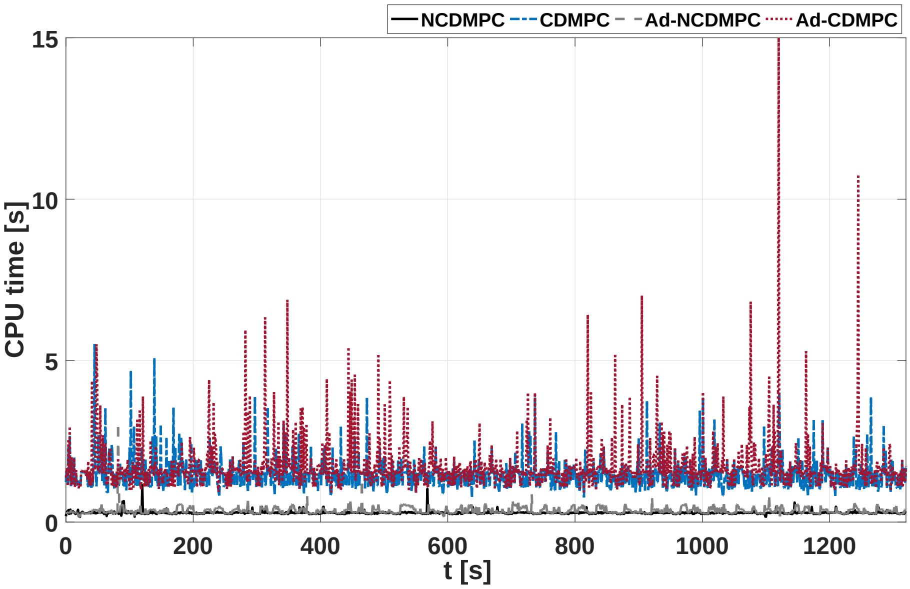


Figure 7.13: Comparison of the CPU time spent to find an optimal solution per iteration in the simulation loop.

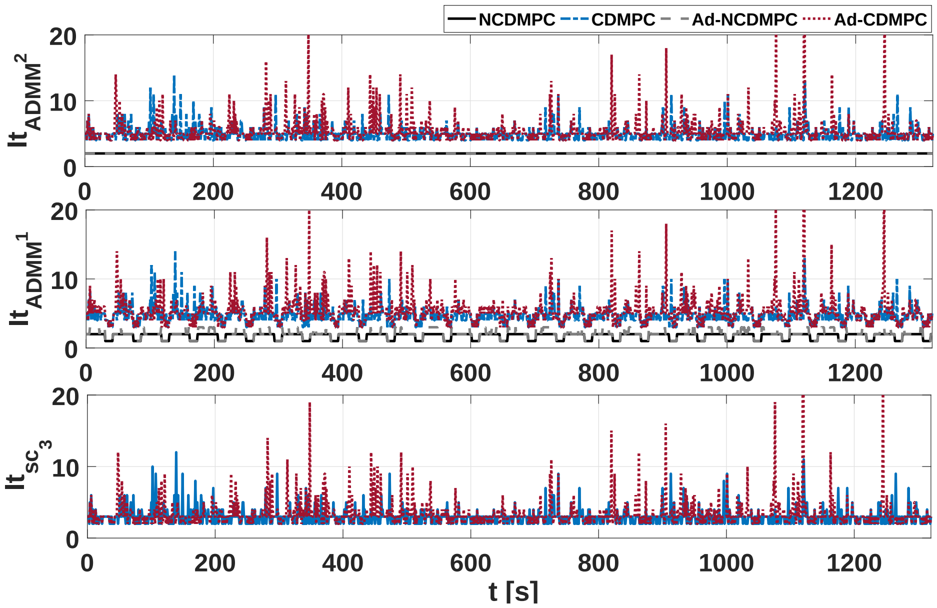


Figure 7.14: Comparison of the total number of iteration required until reach an optimal solution that satisfies all the stopping criteria.

selected since they achieve similar performance to the other strategies tested and allow an automatic tuning if there is some change in the system. Again, all the simulation were performed during 30 machine cycles, based on the machine with the longest cycle time, and according

Table 7.4: Comparison among centralised and non-centralised control architectures.

Controller	Energy consumption [VA]	Maximum $\mathrm{S(k)}$ [VA]	SEC [VA]
C-MPC	1973528.069	2344.263	65784.269
Ad-NCDMPC	1973857.628	2376.881	65795.254
Ad-CDMPC	1972556.607	2304.056	65751.887

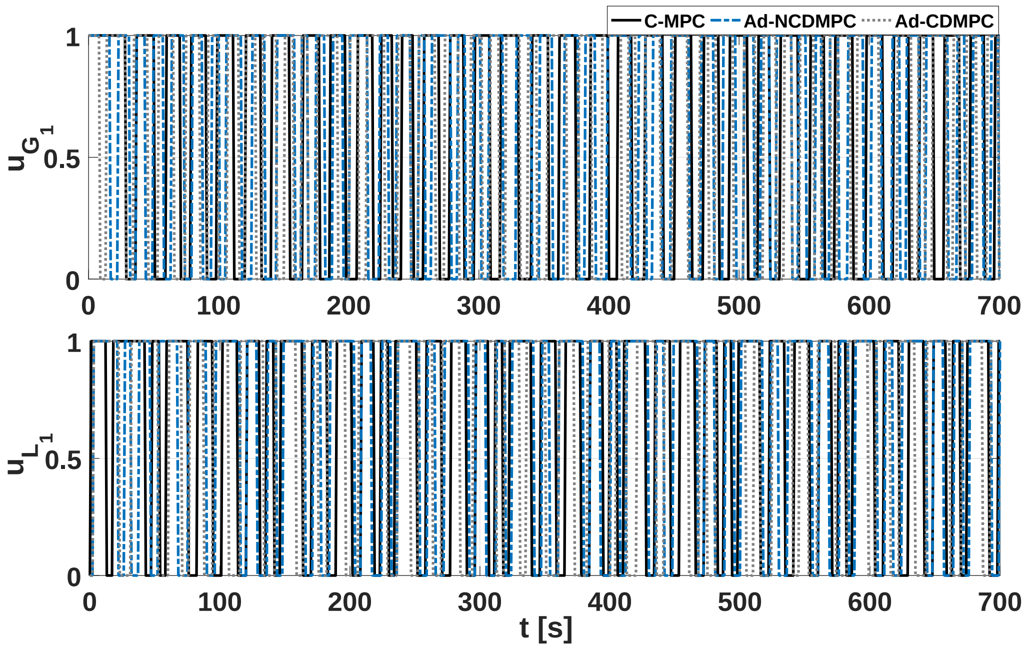


Figure 7.15: Activation sequences for peripheral devices P_{G_1} and P_{L_1} by using centralised and non-centralised control architectures.

to the parameters presented in Table 7.1. The results obtained by using the centralised and non-centralised control strategies are summarised in Table 7.4.

The optimal activation/deactivation sequences of peripheral devices obtained when the proposed centralised and non-centralised control architectures are used are shown in Figures 7.15 and 7.16, respectively. Moreover, according to these sequences, the resulting energy consumption profile for the whole process line is presented in Figure 7.17. Based on these results, although the effectiveness of both the centralised and non-centralised control approaches is similar, their activation sequences are different, and the main differences refer to the activation sequence for the valve apertures as shown in Figures 7.18 and 7.19. It should be noted that for the case of the supply system of compressed air, the optimal sequences obtained for both control architectures was the same, mainly since this system is more constrained that the coolant-supply system. However, for the supply system of coolant, in which more solutions for both v_2 and v_4

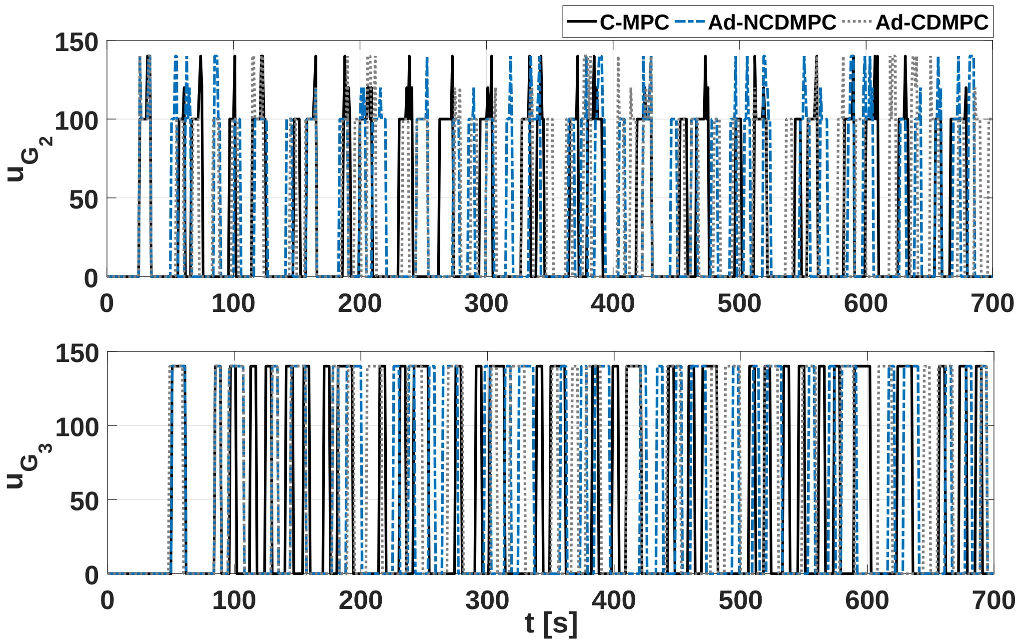


Figure 7.16: Activation sequences for peripheral devices P_{G_2} and P_{G_3} by using centralised and non-centralised control architectures.

are allowed, the centralised control strategy decides to use both P_{G_2} and P_{G_3} to satisfy the coolant demand from M_3. Then, as a consequence of these differences regarding the variables with coupled dynamics, the activation sequences for peripheral devices were also different since the controller should keep trying to minimise the energy consumption and satisfying the process constraints according to the current status of the process line.

It should be noted that, according to the literature regarding centralised and non-centralised control architectures, the former are those that can achieve the optimal solution, and the non-centralised control structures could match the centralised behaviour if there exists cooperation among the local controllers. However, in this case, comparing the values of the total energy consumption, it could be said that the non-centralised control strategies allow achieving better results. Thus, based on the above and taking into account that the differences obtained among all the control strategies do not surpass 0.05%, it can be said that these differences are due to numerically issues more than related to the performance of the control strategies in closed loop. Thus, since the number of decision variables the centralised control approaches should consider, the discrete and binary nature of these variables, and the number of possible combinations, the solver selected is not able to test all the possible solutions before to reach the predefined stopping criteria of the solver. Based on this fact, the division of the global control problem into smaller ones could represent an advantage regarding the centralised approaches for the modularisation of

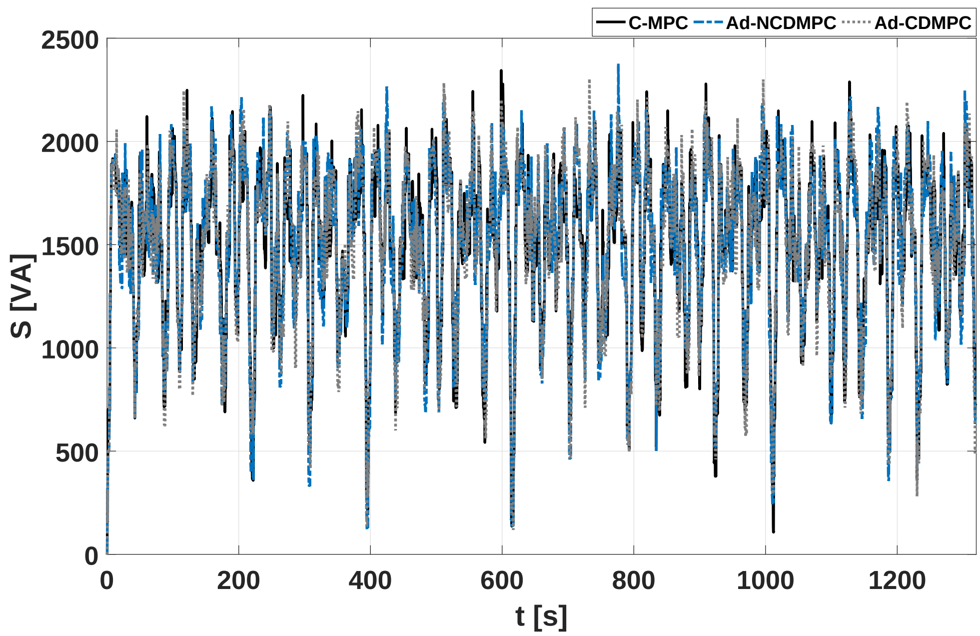


Figure 7.17: Energy consumption profile obtained by using centralised and non-centralised control architectures.

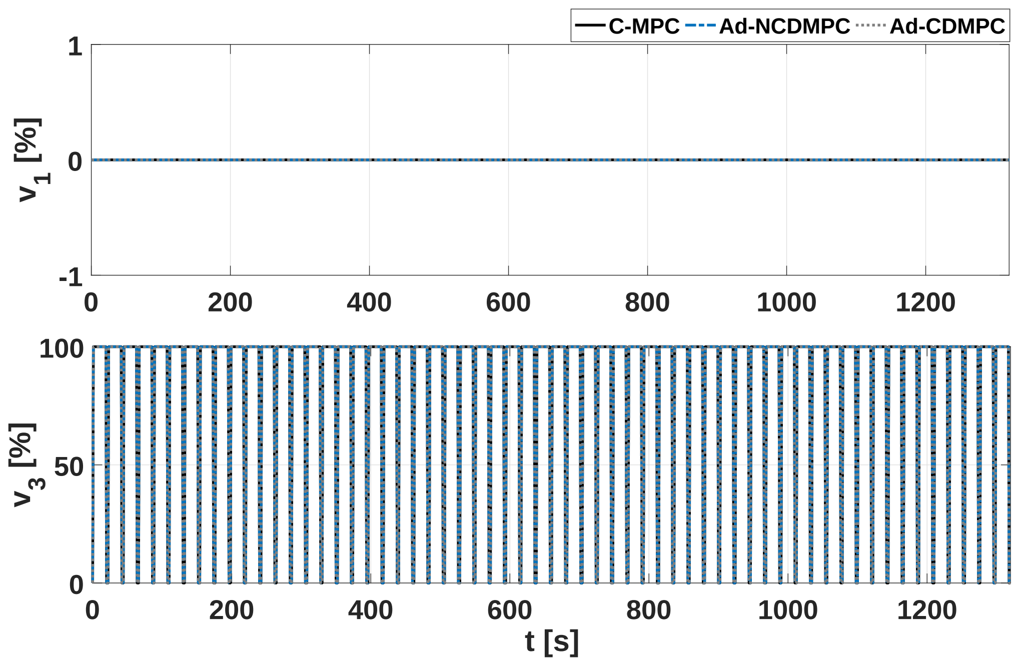


Figure 7.18: Sequence for the aperture of valves v_1 and v_3 by using centralised and non-centralised control architectures.

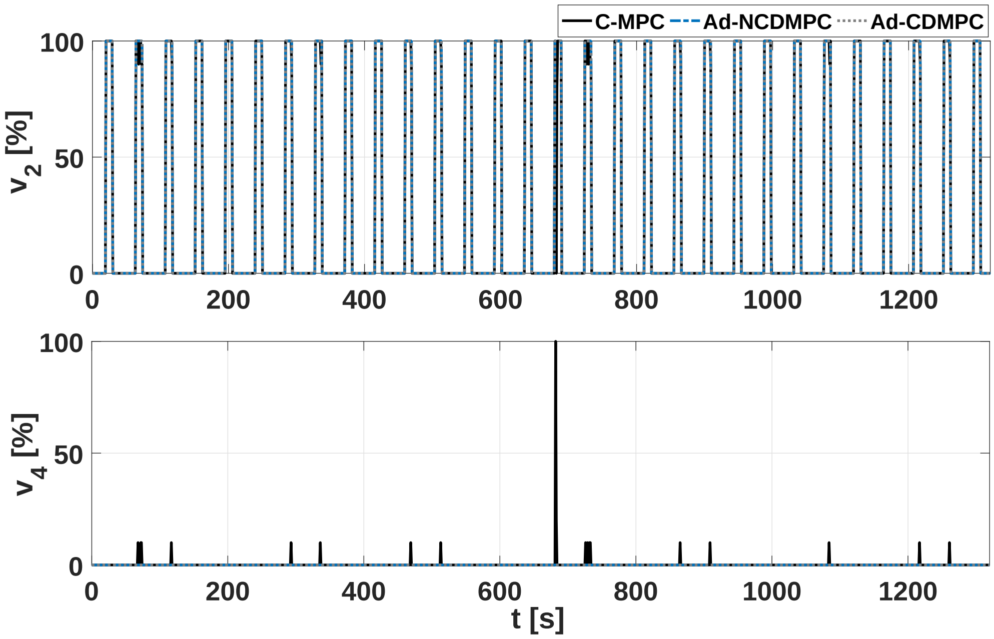


Figure 7.19: Sequence for the aperture of valves v_2 and v_4 by using centralised and non-centralised control architectures.

the control systems. The latter could contribute to the transformation of manufacturing systems towards a smart and flexible manufacturing industry.

In Figure 7.20, the CPU time spent by iteration for each one of the control strategies tested is shown. In this figure, the time spent to find an optimal solution per iteration for the centralised approach is compared with the time spent to achieve a solution by the slower set with coupled sub-systems in Ad-NCDMPC, and the time needed by Ad-CDMP to find the optimal solution. Thus, based on the obtained results, both C-MPC and Ad-NCDMPC find an optimal solution faster than the Ad-CDMP strategy, which requires more iterations to reach a consensus among all local controllers that satisfies the stopping criteria regarding the global cost function. Although the local controllers in the case of non-centralised control structures have a lower dimension than in the centralised one, the computational burden increases since the solution method employed (ADMM) is iterative, there is an exchange of information among the local controllers, and a consensus among such controllers is required. Thus, even when each local controller reaches a solution faster than the centralised case, they require more than one iteration to satisfy stopping criteria. To improve those issues, the non-centralised control strategies proposed in this Chapter could also be integrated to the dual-mode control strategy proposed in Chapter 6 to switch to an autonomous mode once the periodic behaviour for peripheral devices is detected.

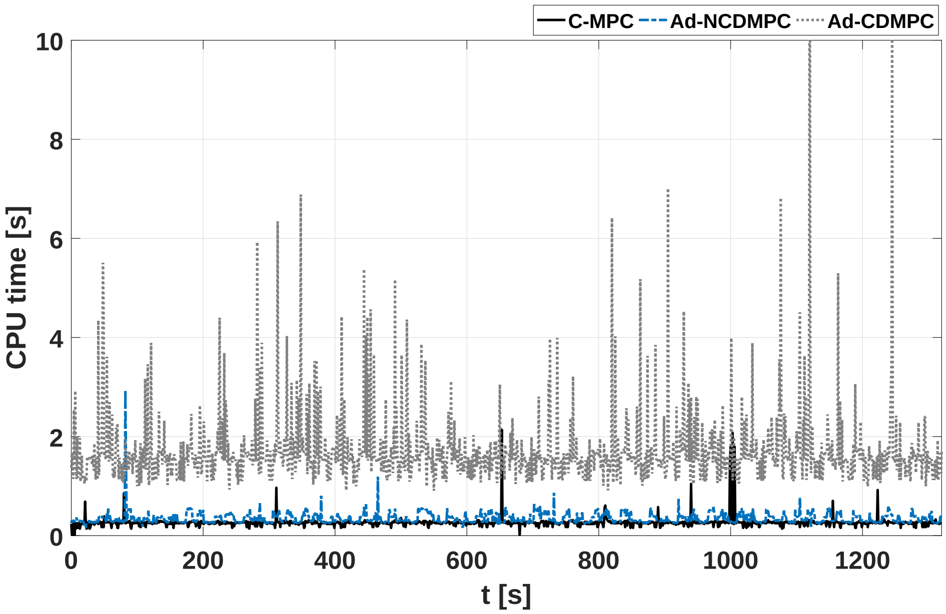


Figure 7.20: CPU time spent by iteration to find an optimal solution by using centralised and non-centralised control architectures.

7.4 Summary

This chapter deals with the system partitioning and design of non-centralised control architectures for manufacturing systems, from which the control systems could also be modularised (as the plant design) for their integration into the new era of flexible and smart manufacturing. Cooperative and non-cooperative architectures were designed and tested to minimise the total energy consumption of a process line with coupled dynamics. The obtained results were compared with the centralised control strategy considered so far to minimise the energy consumption of manufacturing systems. It should be noted that due to the strongly coupled dynamics, two algorithms based on ADMM were proposed to solve the local optimisation problems in a distributed fashion. In this regard, some modifications regarding the conventional consensus stages were introduced to include energy consumption into this stage. The obtained results showed that although the non-centralised architectures have a similar closed-loop performance to that of the centralised strategy, the cooperative control architectures need a high computational burden to get an optimal solution. Therefore, an improved procedure to fit the convergence parameters of the proposed algorithms should be performed and even trying to test non-iterative methods to reduce the computational burden.

Chapter 8

Energy Management/Control Strategy at Plant Level

This chapter deals with the design of control strategies to program the plant production and to minimise the operational costs related to the added value tasks in a manufacturing plant. Since in the previous chapters control strategies to reduce the total energy consumption at both machine and process line were proposed assuming that the production programs to be executed in the machine tools are already known, at plant level, the production programming for a fixed period (e.g., hours, days, weeks) should be determined to satisfy the demand of pieces from the costumers. In this regard, taking into account that at the plant level the productive systems and the systems responsible for providing the services to the offices and non-added value tasks are included, the management at this level is divided into two parts. First, a control/management strategy to program the plant production is proposed. The main idea behind this strategy is to determine what production program should be executed at each moment to satisfy the pieces demand while maximising the plant profit taking into account the energy market. Then, according to the optimal production program (for hours, days or weeks), a control strategy is designed to minimise the operational costs related to both the energy and resources consumption from the TBS. Since the TBS directly accounts for the expense of resources in the plant, the amount of coolant or compressed air to be used in the manufacturing processes could be minimised at the same time the energy consumption is reduced according to the current energy market and its fluctuations. Therefore, this chapter concerns to the design of predictive-like controllers based on the EMPC approach, from which the production programming in the plant is determined and the TBS are suitable managed to minimise the operational costs of the plant.

8.1 General Considerations

A manufacturing plant can be understood as an integrated system that comprises three partial systems: the production system itself, the TBS and the building [HT09]. The former refers to the interlinked machines and the personnel controlled through production management. On the other hand, TBS ensure the necessary production conditions of temperature, moisture, and purity through cooling/heating and conditioning of the air, besides of supplying energy, compressed air, steam or cooling water required for production systems [FNA+17, ZZSW16]. Thus, at the plant level, all devices involved in both value and non-value tasks in a factory are included.

At the plant level, most of the reported research works have focused on the design of production programs and process scheduling to minimise the processing time or, in other words, to maximise the production of the parts. This last fact is given since, in a manufacturing plant, the incomes are mainly a result of the sale of the produced parts. However, strategies that confer more flexibility to manufacturing systems and allow improving their energy efficiency are required. A suitable way to add more flexibility to manufacturing systems is through the design of modular processes and control strategies that can respond to changes in the product demand or design. The last fact is in turn given to achieve a higher level of customisation according to customer requirements.

Although many works reported in the literature focus on strategies for flexible manufacturing at the plant level, the energy consumption has been usually considered as an initial optimisation to minimise operational costs for a fixed demand [BAPT12, LGL+17]. Based on these strategies, an optimal production program is determined at the beginning for specific operational conditions and, therefore, it is not possible to respond to the temporal variation of processes, demand, and working environment during the whole plant operation. Besides, despite all the recent advances and the new generation of CPMS, few strategies have taken the energy market and its fluctuations into account for minimising energy costs and improving the energy efficiency of a manufacturing plant.

In this regard, the design of control strategies that allow taking advantage of energy-price fluctuations to minimise in real time the energy costs of a manufacturing plant without affecting the plant productivity could be a suitable way to improve the energy efficiency of manufacturing systems. Thus, in Section 8.2, an OBC strategy is proposed to determine the daily production program that maximises the plant profit taking into account the energy-market information and the control strategies aimed at the lower manufacturing levels. Then, due to the nature of the objective to be minimised (energy costs or operational costs), the proposed controller is designed according to the EMPC approach that directly optimises an economical cost function. The main idea is to predict the instants of time in which the production program should be executed considering the product demand, the energy prices in the market, and the operational constraints of the plant. It should be noted that the control strategy is based on the assumption that production programs have already been designed and optimised to minimise processing time and their energy consumption at the same time that the parts are designed. Thereby, the proposed controller can be implemented as a complementary strategy to the optimal production programming to improve both the plant productivity and its profitability.

Once the production program for the plant is determined, which refers the instants and execution time for production program, the elements in the TBS should be suitably managed to satisfy the production processes and the rest of non-added value task in a manufacturing plant. Thus, a control strategy is proposed to minimise in real time the operational costs concerning energy and other resources required by manufacturing processes following the same idea of the control strategies at both machine and process line levels. Thus, based on the production program executed in the plant and its demand of energy and resources, the central systems that provide resources to the peripheral systems at both machine and line levels are activated/deactivated to satisfy the operational constraints while minimising the operational costs of the plant. In this regard, the energy market and the price fluctuations are also considered into the controller design to mitigate the operational costs when unexpected scenarios in the energy market take places, even when the production plant has been already defined.

8.2 Economic Production Programming of a Manufacturing Plant

8.2.1 Problem statement

A manufacturing plant consists of arrangements of process lines and auxiliary devices that guarantee the operating conditions of each process line and its working environment. Thus, the energy costs in a manufacturing plant are related to the energy consumption of the productive and non-productive processes in addition to the surcharges produced by surpassing the nominal power purchased. Hence, the energy consumption profile of both the productive and non-productive systems in a manufacturing plant should be analysed and considered into the design of the production program to minimise the operational costs. A scheme of a manufacturing plant

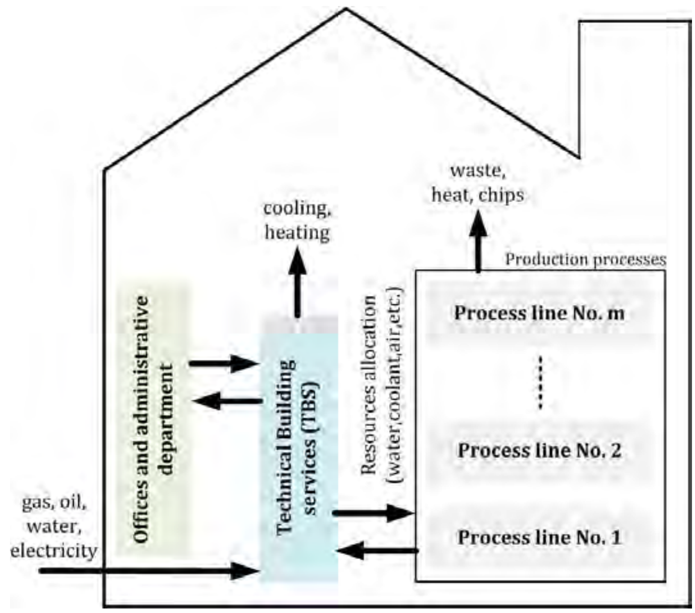


Figure 8.1: Representation of a manufacturing plant and its constitutive elements. Based on [DSD+12].

considering the TBS and process lines is shown in Figure 8.1.

In addition to the energy spent by the TBS and the process lines in a manufacturing plant, the energy consumed in the offices by the company workers should also be considered. Thus, according to the workday of each company, the energy consumption profile from offices could change along the day, and even, it could have small differences from one day to the other. In the same way, the energy consumption profile of the TBS will depend on the production programs currently executed in the process lines since the requirements of resources can change from one production program to others. In this regard, the energy consumption from the offices could be considered as fixed while the energy expenditure related to both the production processes and TBS is regarded as a variable one since it will depend on time-varying product demand.

Besides, taking into account the current context of manufacturing industry and its transformation towards SM, the production programming should be developed in real time to respond fast enough to changes in either the demand or the product design. It means that the flexibility in the manufacturing industry requires a regular updating of the decisions making to adapt it to the changing demand and to take advantage of the time-varying energy market. Thus, considering these fluctuations into the design of control strategies that can be implemented in real time, the energy cost could be minimised while satisfying the flexibility requirements of Industry 4.0.

Hence, consider a manufacturing plant with a fixed number of process lines, i.e., m, as shown in Figure 8.1. Then, assuming that each process line i (with $i = 1, 2, \ldots, m$) involves a fixed number of machines n that perform different processes according to a pre-defined configuration (sequential or parallel), different parts could be processed in the same process line. The sequence of processes required to process a piece corresponds to the production program PP of the piece l. Thus, assuming that each machine in the process line performs only one machining operation (e.g., cutting, milling, turning, among others), the production program for the piece l in the process line i, $PP_{i,l}$, involves the operation of n machines in the process line according to the machining processes required. Besides, since each machine j (with $j = 1, 2, \ldots n$) in the i-th process line has its own processing time $T_{i,j}$, the time spent to produce a finished part by $PP_{i,l}$ is computed based on the machine with the longer processing time, i.e., $T_{PP_{i,l}} = \mathtt{max}\,(T_{i,j})$. That means, in the continuous operation of $PP_{i,l}$, the number of pieces produced in a fixed period (e.g., minute, hour, day) is calculated according to $T_{PP_{i,l}}$, which is usually referred to as the productivity of the process line.

Although the processing times of the machines are minimised offline, a real-time production programming that maximises the plant profit is required to face the new challenges imposed by SM. In this regard, the production program of a manufacturing plant should consider the energy consumption and its associated costs, the changes in the product demand, and customisation requirements from customers. This latter fact rises to improve both the energy efficiency of the plant and its flexibility by mean of constant updates of product demand and the temporal variations of energy prices. Thus, the plant profit should be optimised, taking into account the energy consumption of both value and non-value tasks in the plant, the changing energy market and product demand, besides, the processing times. The last fact takes into account that a reduction in processing times and, therefore, the energy consumption of a manufacturing plant do not guarantee that energy costs are also reduced. Thus, reductions in energy costs can be achieved if the energy price profile is considered. Thereby, to determine the economic-optimal operation of a manufacturing plant along an operation period T, the following control objectives are proposed:

- ***Revenues for sale of parts:*** According to the type of piece processed, the amount of finishing parts and their commercial value, the manufacturing plant can obtain incomes for the sale of parts as follow. At each process line i, the total number of produced pieces of type l is determined according to

$$N_{i,l}(k) = \frac{T}{T_{PP_{i,l}}} u_{i,l}(k), \tag{8.1}$$

being $N_{i,l} \in \mathbb{Z}_{\geq 0}$ the total number of pieces of type l processed in the i-th process line along T, and $u_{i,l} \in \{0,1\}$ the activation/deactivation signal of the production program PP_l. Consider that p production programs can be executed in the i-th process line, based on $\gamma_{p,l} \in \mathbb{R}_{\geq 0}$ the selling price for the piece l, the total revenues are computed according to

$$\phi_1(k) = \sum_{k=1}^{T} \left[\sum_{i=1}^{m} \left[\sum_{l=1}^{p} \left[\gamma_{p,l} \; N_{i,l}(k) \right] \right] \right]. \tag{8.2}$$

It is worth noting that each process line can only run one production program at a time. Still, depending on the plant configuration, a production program can be executed at the same time in different process lines.

- ***Energy costs of manufacturing processes:*** Regarding the operation of a manufacturing plant, the energy costs related to the productive or value-added tasks are defined as follows:

$$\phi_2(k) = \sum_{k=1}^{T} \left[\sum_{i=1}^{m} \left[\gamma_e(k) S_{L_i}(k) \right] \right], \tag{8.3}$$

being γ_e the energy price in the current market and S_{L_i} the instantaneous power consumption in the i-th process line. It should be noted that the power consumption of a process line will depend on the production program that it is being executed. Therefore, S_{L_i} can be expressed as

$$S_{L_i}(k) = u_{i,1} \; S_{PP_{i,1}}(k) + u_{i,2} \; S_{PP_{i,2}}(k) + \cdots + u_{i,p_i} \; S_{PP_{i,p_i}}(k), \tag{8.4}$$

being p_i the total number of production programs that can be executed in the i-th process line, $S_{PP_{i,l}}$ the power consumption of production program l in the i-th process line, and $\sum_{l=1}^{p_i} u_{i,l} \leq 1$.

- ***Energy costs for non-value added tasks:*** In this item are included the costs related to the energy consumption of the TBS and the offices in the manufacturing plant as follows:

$$\phi_3(k) = \sum_{k=1}^{T} \left[\gamma_e(k) \; \left(S_{TBS}(k) + S_{off}(k) \right) \right], \tag{8.5}$$

with $S_{TBS} \in \mathbb{R}$ and $S_{off} \in \mathbb{R}$ the instantaneous power consumption from the TBS and offices, respectively.

According to (8.2), (8.3) and (8.5), to determine the optimal production program that maximises the plant profit, the following economic cost function is proposed:

$$J(k) = -\left(\phi_1(k) - \phi_2(k) - \phi_3(k)\right), \tag{8.6}$$

being $J \in \mathbb{R}$ the total profit of the plant during an operation period T. Therefore, to maximise (8.6), the control problem consists of determining the optimal activation/deactivation sequences $u_{i,l}$ of production programs at each process line, taking into account the demand of pieces, the energy market and its fluctuations, as well as the operational constraints in the manufacturing plant. Among these constraints could be considered the work shifts, the maximum execution time for the production programs, and the incompatibility to run some production programs at the same time (even in different process lines) such as occurs in a real manufacturing plant in which the resources and the availability for using the machines can be constrained. Besides, regarding the scenarios of flexible manufacturing, the time instants in which the changes in the production programs will be allowed can also be included as constraints.

8.2.2 EMPC design

To design a strategy of production programming in a manufacturing plant from which the plant profit can be maximised in real time, in this work an optimisation-based controller is proposed. The proposed controller is designed taking into account the energy market to minimise energy costs and the changes in the product demand to satisfy the requirements of flexible manufacturing. Thus, to determine an optimal production programming in a manufacturing plant from an economic point of view, the EMPC approach was addressed to design an optimisation-based controller that allows maximising the revenue for the sale of processed pieces while minimising the operational costs along a prediction horizon H_p. Thus, due to the economic nature of the control objectives to be treated, the use of EMPC has been preferred concerning other approaches, such as the conventional MPC, since it directly optimises the economic of the process [EDC14] as explained in Chapter 3. It should be noted that the implementation strategy of EMPC is the same as for the conventional MPC, i.e., in a receding horizon fashion [Mac02].

Thus, the general idea is to predict what production program PP_l should be executed at each process line along H_p, such that the plant profit can be maximised taking into account the product demand, the operating constraints and the time-varying price profiles. Thereby, the decision to activate/deactivate the l-th production program in the i-th process line, i.e., $u_{i,l}$, will depend on the current value of the demand of pieces of type l and the energy price in the market. In this regard, the energy consumption of each production program must be known. Therefore, assuming that in each process line only a fixed number p_i of production programs can be executed, the activation signal of the i-th process line can be expressed as

$$\boldsymbol{\upsilon_i}(k) \triangleq \{u_{i,1}(k), u_{i,2}(k), \dots, u_{i,p_i}(k)\},\ \forall i = 1, 2, \dots, m, \tag{8.7}$$

with $u_{i,l} \in \{0, 1\}$ indicating that PP_l is being executed in the i-th process line if $u_{i,l} = 1$, or that it is deactivated when $u_{i,l} = 0$. Then, according to the defined control objectives in (8.6), the sequences for J and $\boldsymbol{\upsilon_i}$ along H_p are defined as

$$\mathbf{J}(k) \triangleq \{J(k|k), \dots J(k + H_p - 1|k)\}, \tag{8.8a}$$

$$\mathbf{U_i}(k) \triangleq \{\boldsymbol{\upsilon_i}(k|k), \dots, \boldsymbol{\upsilon_i}(k + H_p - 1|k)\}, \tag{8.8b}$$

with $\mathbf{J} \in \mathbb{R}^{H_p}$ and $\mathbf{U_i} \in \{0, 1\}^{H_p}$. Thereby, the economic predictive-like controller is based on the following open-loop optimisation problem:

$$\max_{\mathbf{U_i}(k)\ \forall\ i=1,2,\dots,m} \quad \mathbf{J}(k) \tag{8.9a}$$

subject to

$$S_{L_i}(k + r + 1|k) = f_l\left(S_{L_i}(k + r|k), u_{i,l}(k + r|k)\right), \tag{8.9b}$$

$$g_i(\mathbf{U_i}(k + r|k)) \leq 0, \tag{8.9c}$$

$$N_{i,l}(k + r|k) \geq \alpha_l, \tag{8.9d}$$

$$u_{i,l}(k + r|k) \in \{0, 1\},\ l = 1, 2, \dots, p_i, \tag{8.9e}$$

for $r = 0, 1, 2, \dots, H_p - 1$, and being $f_l : \mathbb{R} \times \{0, 1\}^{p_i} \mapsto \mathbb{R}$ the linear map for the energy consumption of the i-th process line, $g_i(\cdot) : \{0, 1\}^{p_i} \mapsto \mathbb{R}$ the linear maps that express the logical and operational constraints among the production programs allowed in the i-th process line, and $\alpha_l \in \mathbb{Z}$ the demand for the piece l. In addition to these constraints, safety times for the minimum execution time of a production program in a certain process line can be considered imposing constraints on $\Delta u_{i,l}$. In this regard, every time that $\Delta u_{i,l} = |u_{i,l}(k) - u_{i,l}(k - 1)|$ will be different to zero, the current state of PP_l should be kept along for a period equal to the safety time t_{saf}.

Assuming that the optimisation problem in (8.9) is feasible, i.e., $\mathbf{U_i}(k) \neq \emptyset$, the optimal sequence $\mathbf{U_i}^*(k)$ exists and, according to receding horizon approach [Mac02], the first component $\boldsymbol{v_i}^*(k|k)\ \forall\, i = 1, 2, \ldots, m$ is sent to the process lines. Then, this procedure is repeated for the next instant once measurements of input signals and estimation of the required information about the plant are updated. Taking into account the nature of variables to be optimised, the optimisation problem in (8.9) is an MILP problem, for which suitable solvers should be chosen to solve the problem with a low computational burden.

Since the proposed approach focuses on programming the plant productivity to minimise the operating costs according to a required demand, it is assumed that the production programs are previously designed and optimised offline regarding the processing time. Thus, the controller should decide the programs to execute in each process line to minimise energy costs, maximise revenues, and satisfy the daily product demand. Besides, it is worth noting that in most of the cases, process lines are defined according to the plant configuration, i.e., based on the disposition of machines into the plant. However, in some cases, manufacturing plants can exhibit a non-fixed configuration considering processes/machines in other plants. Therefore, the plant configuration must be taken into account when the production programs are designed, and their machines are selected. Hence, at the moment to define what production program should be executed to minimise operational costs, additional constraints could be included in the optimisation problem to add the complex relationships of non-fixed plant configurations into the control strategies. Such constraints could refer to the transporting costs to move the pieces from one plant to another, the time slots available for using machines in other companies, among others.

On the other hand, according to (8.9), suitable energy consumption models for each production program are required. However, at the plant level, the maps $f_l(\cdot)$ in (8.9) could be addressed as mathematical correlations between the processing time and the known energy consumption of machines involved with every production program, which have been already designed. Then, based on the production programs and machines involved, energy consumption models for the machines can be used to estimate or predict the total energy consumption of a process line. How the energy consumption models were defined and used at plant level is explained in Section 8.2.3.

8.2.3 Benchmark system

According to Figure 8.1, a manufacturing plant with three process lines will be analysed to test the proposed control strategy. The manufacturing process lines are detailed in Figure 8.2, in

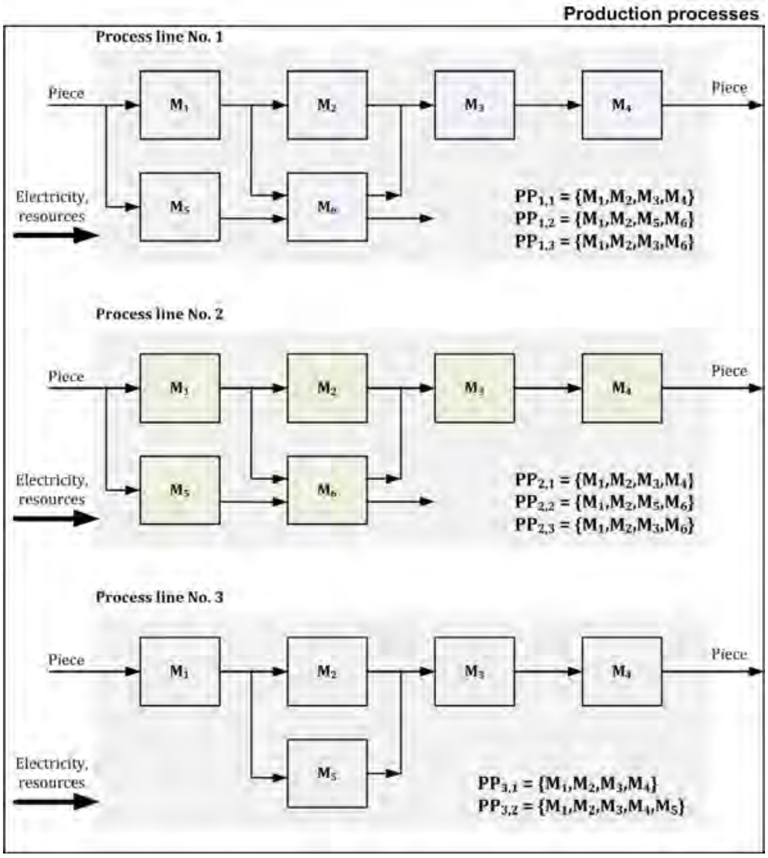


Figure 8.2: Process lines in a manufacturing plant.

which every line is drawn with its respective machines. Based on Figure 8.1, to process pieces in the machines, electricity and resources for machining operations, such as coolant and compressed air, are required, and, according to the production program executed (or the type of piece processed), these consumptions will be different. Thus, both electricity and all resources required for the proper operation of the manufacturing plant are managed into the TBS, which includes the required technical elements and actuators to store and distribute the resources among the different productive and non-productive units of the plant. Among the non-productive areas are considered the offices and rest of areas for the usage of the workers. Usually, it is assumed that the office has a known energy consumption profile along the day, which is repeated over time with small variations. In this regard, both the electricity consumption of the plant and the purchase of resources will be variable and depend on the current production programs executed in the different process lines. The last fact since based on the pieces demand, the production programs and their execution times will be different and should be programmed to maximise the plant incomes.

Based on the customer requirements, pieces are designed, taking into account the available machines in the plant and the type of machining operations that they can perform. Thus, a sequence of machining operations is defined to achieve the desired physical properties of a piece and, then, proper machines in the process line are selected. These sequences, with their corresponding processing and transport times, refer to the production programs. Since there exist several strategies to design these production programs by optimising directly the machining parameters, in this case, it is assumed that these programs are designed and optimised offline by the design team of the company. Then, based on the production programs and the current demand, the daily production programming of the plant consists of selecting which production program should be executed at each moment to satisfy the demand and maximise the plant profit.

In this case, a plant with fixed configuration is considered, in which the machines have been organised taking into account the machining operations required to produce the pieces that the company can sale. According to Figure 8.2, the first and the second process lines have the same configuration for the machines and can process the same type of parts. That means the production programs that can be executed in these lines are the same. Besides, machines in these process lines have the same processing time, i.e, $T_{1,j} = 28$ s, $j = 1, 2, \ldots, p_1$ and $T_{2,j} = 28$ s, $j = 1, 2, \ldots, p_3$. The latter fact implies that in the process lines, the same number of pieces can be processed during a fixed period. On the other hand, the third process line is formed by five machines, most of them with different processing times. Thereby, $T_{3,1} = 28$ s, $\mathrm{T}_{3,2} = 44$ s, $T_{3,5} = 44$ s, $\mathrm{T}_{3,4} = 22$ s and $T_{3,6} = 36$ s. In this case, the productivity of the line is computed based on the machines with the longest processing time, i.e., $T_{3,2}$ or $T_{3,5}$. Thereby, based on the number of pieces produced and their sale price, the company incomes can be computed.

Operational constraints

Due to the configuration of process lines, the capacity of the TBS and the current demand of pieces and resources from the added value tasks, some operational constraints should be considered to program the plant production. Some examples of these constraints are detailed below:

- Every time that a program is activated, it should be kept on for at least four hours, i.e., $t_{on} = 4$ hours.
- The program $PP_{i,2}$ cannot be executed at the same time in both process lines 1 and 2. It is given since this program has the highest energy consumption among the allowed programs in the process lines 1 and 2.

- Changes in the production program for the next day are allowed until four hours prior the next day. The last fact is given since the TBS should also be prepared to provide the required resources to the process lines.
- The daily energy-price profile will be updated every 30 minutes according to the fluctuations in the energy market. Based on this, the controller decisions will be updated every 30 minutes.
- The program $PP_{3,2}$ cannot be executed at the same time that the program $PP_{1,1}$ in the first line. This scenario considers the case in which some programs cannot operate at the same time because it is not possible to provide all the resources required by both programs from the TBS.
- The production of pieces per day can be only 10% higher than the daily demand. This constrain is added to avoid unnecessary production of pieces with the sole objective of increasing revenue from the sale of parts.

In addition to operational constraints and iterations among process lines, energy consumption models are required to compute the total energy costs in (8.6) of both added and non-added value tasks in the manufacturing plant. The models used are presented below.

Energy consumption models

Since the production programs have been designed offline focused on minimising the processing time and maximising the number of processed pieces according to the customer requirements, the energy consumption for each one can be known. In this section, the procedure to determine energy consumption models of production programs and TBS is explained. Besides, regarding the consumption from the offices, it is assumed that the energy consumption follows a daily pattern with small variations between days, which will be added as white noise.

Thus, using the real data from the energy consumption of each machine, its energy consumption model can be obtained based on SI methods [ODM96], as explained in Chapter 4. Then, from the knowledge of the energy consumption profile of machines, and taking into account the design of the PPs, the energy consumption of each program can be considered as the sum of the single energy consumption of the machines involved. Indeed, summing up the instantaneous energy consumption of each machine at each instant k, the energy consumption profile for the whole process line (at nominal and continuous operation) can also be determined. Next, based on the energy consumption profile for each $PP_{i,l}$, correlations to compute the cumulated energy consumption over time when $PP_{i,l}$ is being executed are defined as follows:

$$\tilde{S}_{PP_{i,l}}(u_{i,l}, t_{on_{i,l}}) = \theta_{i,l}\, t_{on_{i,l}}(k) + \delta_{i,l}\, u_{i,l}(k), \tag{8.10}$$

being $\tilde{S}_{PP_{i,l}}$ the cumulation of power consumed while $PP_{i,l}$ is kept on, $t_{on_{i,l}}$ is the cumulate operation time for $PP_{i,l}$, and $\theta_{i,l}, \delta_{i,l}$ the coefficients for each $PP_{i,l}$. Thus, based on the energy consumption profile of the process line, the total energy consumption for a fixed sampling time τ_s can be computed as the integral of the energy consumption profile. Indeed, as the execution time of $PP_{i,l}$ increases, its cumulative $\tilde{S}_{PP_{i,l}}$ also increases. Then, by using the data of processing time and the integral of the energy consumption at each τ_s, a simple linear correlation can be obtained to expresses the energy consumption of the whole process line based on the execution time of any $PP_{i,l}$. It should be noted that these models are obtained assuming a normal and continuous operation of the machines in the process line involved while $PP_{i,l}$ is being executed. Thus, assuming a sampling time τ_s equal 10 minutes, along 30 minutes of operation of $PP_{i,l}$, the cumulation of power consumed satisfies $\tilde{S}_{PP_{i,l}}(u_{i,l}, 10) \leq \tilde{S}_{PP_{i,l}}(u_{i,l}, 20) \leq \tilde{S}_{PP_{i,l}}(u_{i,l}, 30)$. Besides, it is worth noting that since $t_{on_{i,l}}$ is the cumulation of execution time of $PP_{i,l}$ while $PP_{i,l}$ is remained on, it should be updated as

$$t_{on_{i,l}}(k) = \left[t_{on_{i,l}}(k - \tau_s) + \tau_s\right]\; u_{i,l}(k). \tag{8.11}$$

It is worth noting that (8.11) is multiplied by $u_{i,l}(k)$ since if $PP_{i,l}$ is switched off, $t_{on_{i,l}}$ should be reinitialised to zero when it will be activated again. Besides, according to (8.10) and (8.11), the energy consumed at every τ_s can be computed as the difference between the current value of $\tilde{S}_{PP_{i,l}}(\cdot)$ and the previous one. As an example of the previous procedure, the energy consumption profile for $PP_{1,1}$ is presented in the top of Figure 8.3 according to the machines involved and their corresponding energy consumption models.

Afterwards, based on the energy consumption profile of the whole process line, data about the total energy consumption corresponding to vector of operational times such $t_{PP_{i,l}} = [\tau_s, 2\tau_s\ , 3\tau_s\ , \cdots, n\tau_s]$ can be computed as the integral of the energy consumption profile from the beginning up to each one of the values in $t_{PP_{i,l}}$. In the bottom of Figure 8.3, the cumulative energy consumption for $PP_{1,1}$ during 24 hours of continuous operation is shown. Then, based on this plot, the parameters $\theta_{i,l}$ and $\delta_{i,l}$ in (8.10) have been identified. It should be noted that the

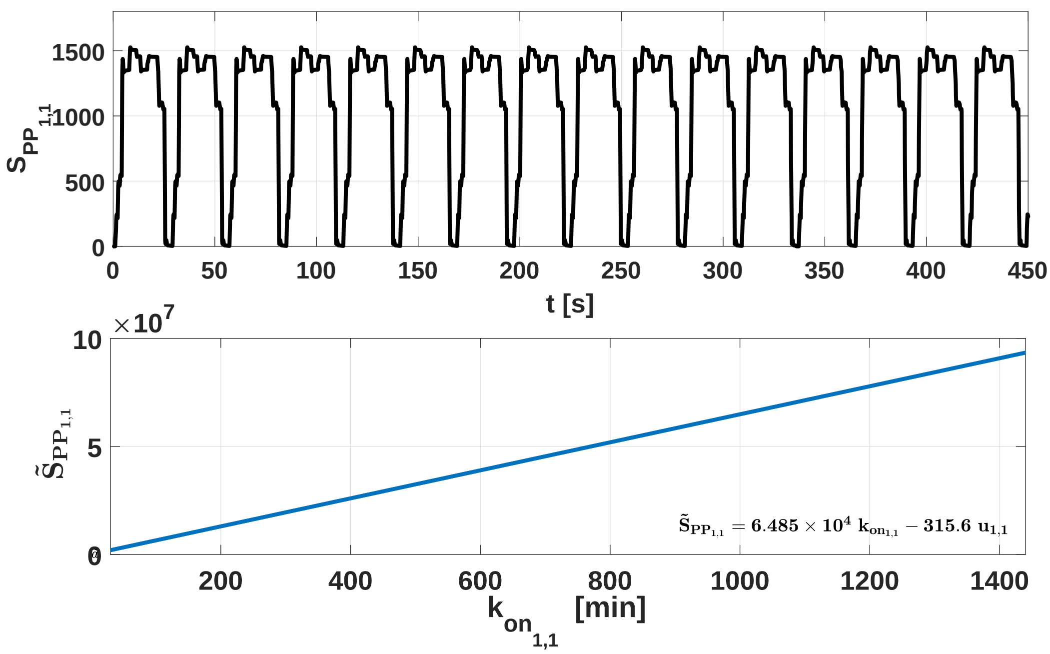


Figure 8.3: Energy consumption profile for $P_{1,1}$ along 24 hours of operation and the corresponding cumulative energy consumption.

linear behaviour of the cumulative energy consumption is due to the periodic behaviour of the machines since, for every τ_s, the total number of cycles performed by each machine is almost the same.

On the other hand, since the TBS provide the required resources to the machines in the process lines, the energy consumption of the elements of the TBS will be defined as a function of the production programs that are being executed and a constant portion related to the environmental conditions of the plant. Thus, the energy consumption of TBS is given by

$$S_{TBS}(k) = S_{f,o}(k) + \sum_{l=1}^{3} \beta_{1,l}\, u_{1,l}(k) + \sum_{l=1}^{3} \beta_{2,l}\, u_{2,l}(k) + \sum_{l=1}^{2} \beta_{3,l}\, u_{3,l}(k), \tag{8.12}$$

being $S_{f,o}$ the constant consumption related to the environmental conditions of the plant and $\beta_{i,l}$ the correlation coefficients that account for the energy consumption of the element in TBS responsible to provide the resources to the i-th process line when the l-th program is executed. Finally, the simulation parameters are presented in Table 8.1, in which the costs are presented in economic units (e.u.).

Table 8.1: Simulation parameters for the manufacturing plant studied.

Parameter	Value	Units	Parameter	Value	Units
$T_{1,j}$	28	s	$T_{2,j}$	28	s
$T_{3,1}$	28	s	$T_{3,2}$	44	s
$T_{3,3}$	22	s	$T_{3,4}$	36	s
$T_{3,5}$	44	s	$\gamma_{p1,1}$	2.5	e.u.
$\gamma_{p1,2}$	3.0	e.u.	$\gamma_{p1,3}$	2.8	e.u.
$\gamma_{p2,1}$	2.5	e.u.	$\gamma_{p2,2}$	3.0	e.u.
$\gamma_{p2,3}$	2.8	e.u.	$\gamma_{p3,1}$	2.0	e.u.
$\gamma_{p3,2}$	2.8	e.u.	$\theta_{1,1}$	6.485×10^4	–
$\delta_{1,1}$	-315.6	–	$\theta_{1,2}$	8.005×10^4	–
$\delta_{1,2}$	-1063	–	$\theta_{1,3}$	6.463×10^4	–
$\delta_{1,3}$	-898.3	–	$\theta_{3,1}$	6.238×10^4	–
$\delta_{3,1}$	-171.2	–	$\theta_{3,2}$	7.903×10^4	–
$\delta_{3,2}$	-115.6	–	H_p	24	hours
t_{on}	4	hours	τ_s	30	minutes

8.2.4 Simulation results

According to the case study presented in Section 8.2.3 and the proposed control strategy (denoted as EMPC) to minimise energy costs in a manufacturing plant, some simulations were performed to test the effectiveness of the proposed controller. The results presented below were obtained considering a total simulation time $T_s = 7$ days with a execution time for the controller as $\tau_s = 30$ minutes. Besides, a prediction horizon $H_p = 24$ hours was considered, which means the controller makes decision 48 times along H_p according to the value of τ_s. Thereby, the total number of decision variables corresponds to $|\mathbf{U_i}(k)| = 48$ per each process line i. The obtained results using EMPC were compared with another EMPC (denoted as EMPC$_2$), in which the fluctuations of the energy-price profile are not considered. Thus, for the last case, a constant energy price of $\gamma_e = 0.04$ e.u./kW was considered.

To determine the optimal production programming of the plant from an economic point of view, at each τ_s, the predictions for the energy consumption from offices, the demand of pieces, and the current energy-price profile are updated when the proposed EMPC is implemented. Since the controller is executed every 30 minutes using a prediction horizon of one day ahead, the piece demand for the next day will begin to be considered into the optimisation problem in (8.9) just four hours before the current day finishes. Therefore, according to the receding horizon implementation strategy, the constraints to satisfy the daily demand of parts should be suitably adjusted to constrain the demand for the current day and the next one, when the latter starts to appear in the prediction horizon.

Then, taking into account the constraints in Section 8.2.3, the problem in (8.9) is re-written as follows:

$$\max_{\mathbf{U_i}(k)\ \forall\ i=1,2,3} \quad \mathbf{J}(k)$$

subject to

$$\begin{aligned}
\tilde{S}_{PP_{i,l}}(k+r|k) &= \theta_{i,l}\, t_{on_{i,l}}(k+r|k) + \delta_{i,l}\, u_{i,l}(k+r|k),\\
u_{1,1}(k+r|k) &+ u_{1,2}(k+r|k) + u_{1,3}(k+r|k) \leq 1,\\
u_{2,1}(k+r|k) &+ u_{2,2}(k+r|k) + u_{2,3}(k+r|k) \leq 1,\\
u_{3,1}(k+r|k) &+ u_{3,2}(k+r|k) \leq 1,\\
u_{1,2}(k+r|k) &+ u_{2,2}(k+r|k) \leq 1,\\
u_{3,2}(k+r|k) &+ u_{1,1}(k+r|k) \leq 1,\\
N_{1,l}(k+r|k) &\geq \alpha_{1,l}(k+r|k),\\
N_{2,l}(k+r|k) &\geq \alpha_{2,l}(k+r|k),\\
N_{3,l}(k+r|k) &\geq \alpha_{3,l}(k+r|k),\\
u_{1,l}(k+r|k) &\in \{0,1\},\ l=1,2,3,\\
u_{2,l}(k+r|k) &\in \{0,1\},\ l=1,2,3,\\
u_{3,l}(k+r|k) &\in \{0,1\},\ l=1,2,
\end{aligned}$$

for $r = 0, 1, 2, \ldots, H_p - 1$ and being $\alpha_{i,l}$ the demand of the l-th piece processed in the i-th process line. In this case, it is considered that the values of $\alpha_{i,l}$ will change over time according to the demand from the customers. In this regard, $\alpha_{i,l}$ should be properly updated based on the demand matrices for each process line M_{L1}, M_{L2} and M_{L3}, given by

$$M_{L1} = \begin{bmatrix} 1024 & 850 & 250 & \mathbf{1000} & 800 & 960 & 1000\\ 1024 & 1000 & 500 & 850 & 950 & 800 & \mathbf{650}\\ 1024 & 550 & 800 & 600 & 1024 & 900 & 780 \end{bmatrix}, \tag{8.14}$$

$$M_{L2} = \begin{bmatrix} 1024 & 850 & 250 & 1000 & 800 & 580 & 700\\ 1024 & 1000 & 500 & 850 & 950 & 600 & 860\\ 1024 & 550 & 800 & 600 & 1024 & 780 & 900 \end{bmatrix}, \tag{8.15}$$

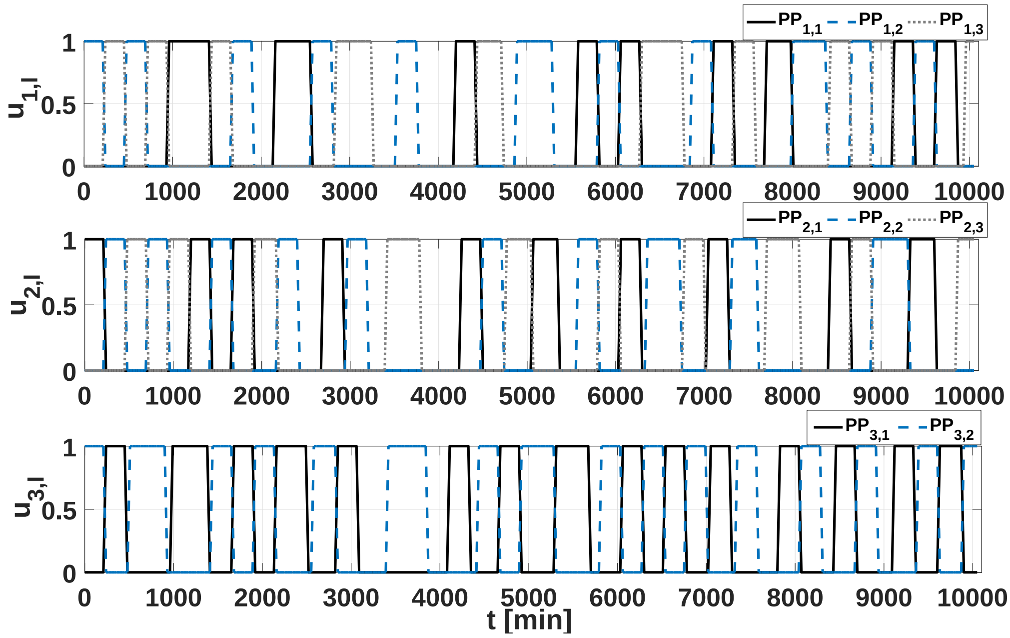


Figure 8.4: Activation sequences for each production programs by using EMPC.

$$M_{L3} = \begin{bmatrix} 880 & 850 & \mathbf{250} & 900 & 800 & 650 & 760 \\ 880 & 1000 & 580 & 850 & 950 & 600 & 820 \end{bmatrix}, \tag{8.16}$$

with the rows corresponding to the type of piece l and the columns refer to the day. The values in bold correspond to the changes that will be introduced in the product demand during the simulations. Thus, these values will be modified at suitable instants to 600, 1000, and 550 pieces, respectively. Afterwards, given the hybrid nature of the optimisation problem in (8.13), simulations were developed using the same simulation tools that in previous chapters.

In Figures 8.4 and 8.5 the simulation results of the activation sequences for each process line are shown for both controllers tested. Besides, the corresponding total energy consumption by process lines according to the obtained activation sequences is presented in Figure 8.6. Based on these results and the logical constraints included into the optimisation problem in (8.9), it is possible to see that the second program was never turned on at the same time in the process lines 1 and 2. In the same way, the programs $PP_{1,1}$ and $PP_{3,2}$ were always turned on at different moment along the day to guarantee that the TBS was able to provide the required resources to both process lines 1 and 3. Based on these results, it is possible to see that all logical constraints concerning the operational relationships among process lines are satisfied while the plant production is programmed to maximise the plant profit.

Next, in Figure 8.7, the total energy consumption of the plant, the energy consumption from

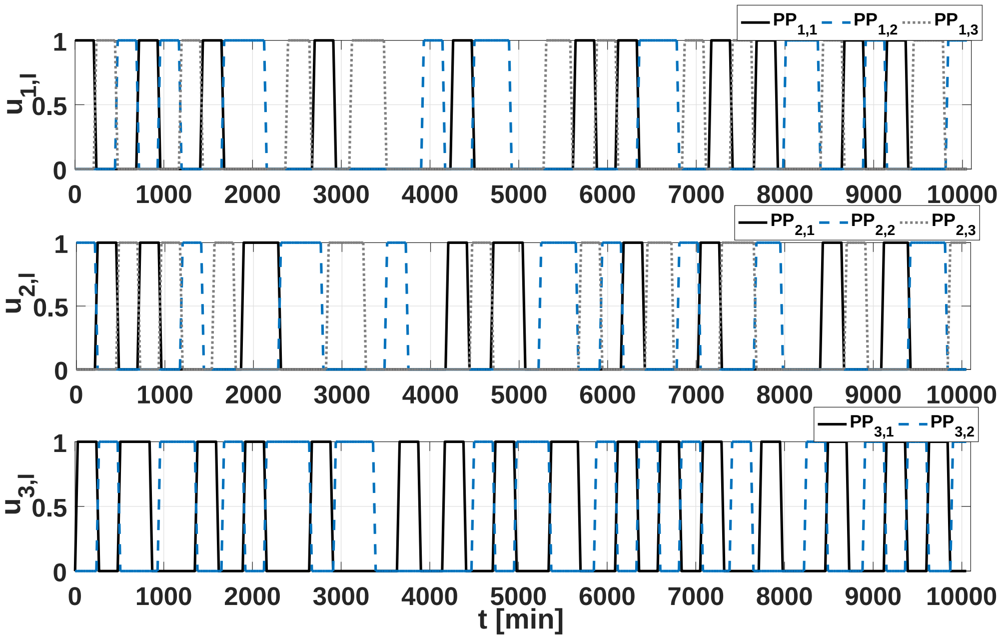


Figure 8.5: Activation sequences for each production programs by using EMPC$_2$.

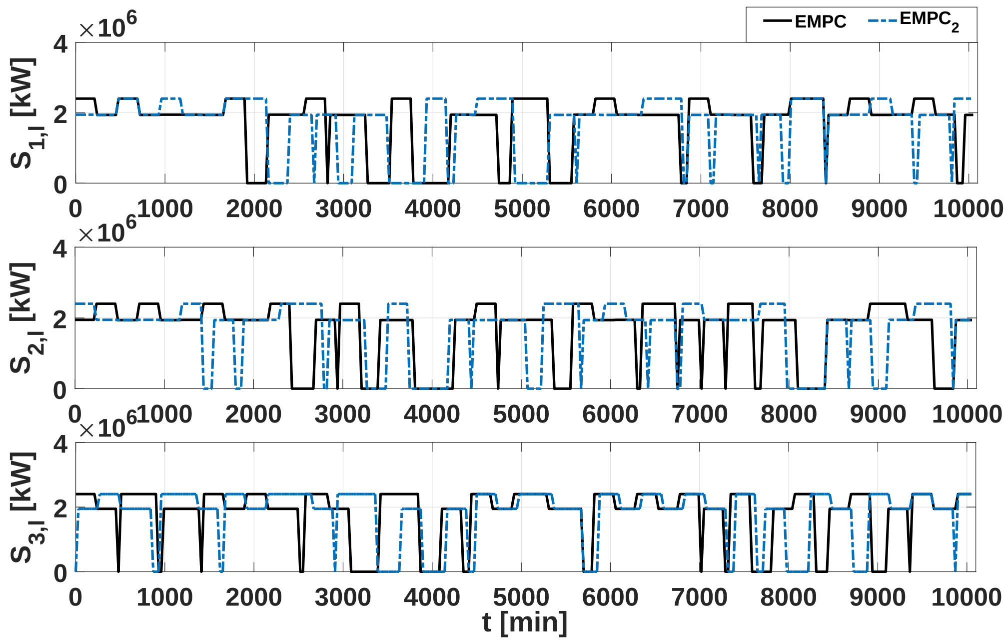


Figure 8.6: Comparison of the energy consumption of each precess line by using EMPC and EMPC$_2$.

offices and the TBS obtained using the proposed EMPC and EMPC$_2$ are presented. Besides, at the bottom of this figure, the energy-price profile is also shown. Then, from results in Figures 8.4, 8.5 and 8.7, it can be observed that the proposed EMPC tries to switch off the production programs at the moments of higher energy prices or to switch to programs of lower energy

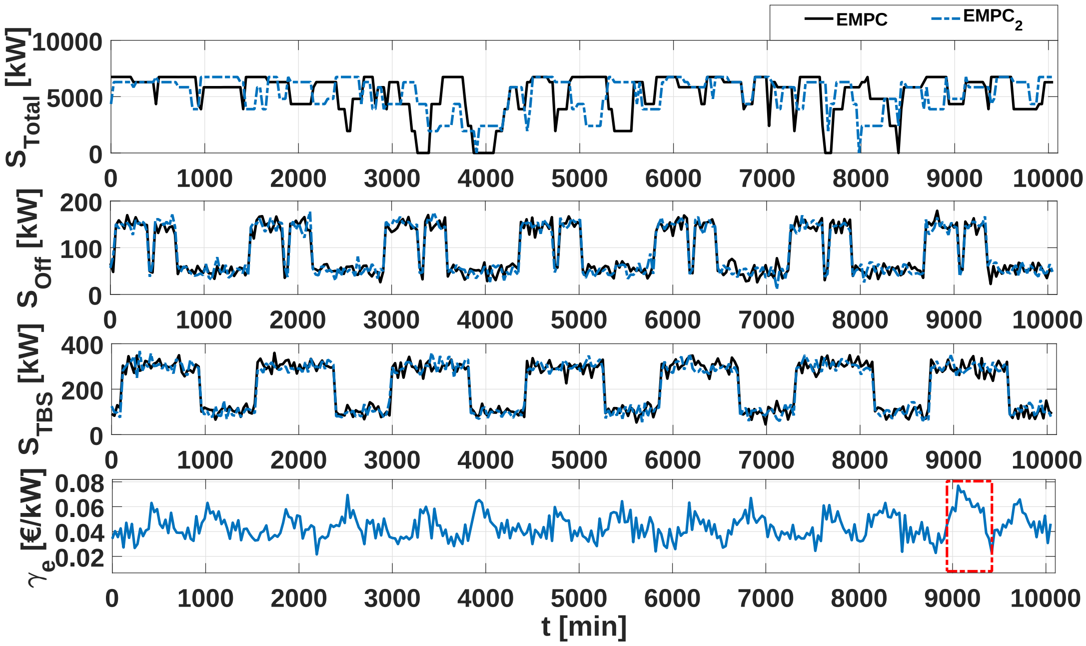


Figure 8.7: Comparison of the total energy consumption for both value and non-value added tasks by using EMPC and EMPC$_2$.

consumption. In contrast, the EMPC without including the energy prices only decides to switch on/off the productions programs once the demand of pieces has been completed. This behaviour is also appreciated when an increment in the energy prices happen during six hours (highlighted with a red square), which was added to test the effectiveness of the proposed control strategy under disturbing scenarios. In concordance, during this event, the proposed controller tries to switch to the production programs with lower energy consumption, and only after the energy prices come back to their typical values, the second program in each process line was again executed. Therefore, since by using EMPC a typical energy-prices profile is updated every 30 minutes, the proposed control strategy can re-program the production of the plant according to the energy market and its fluctuations. It should be noted that, according to (8.12), the total energy consumption of TBS was computed according to the requirements of each production program, while the energy consumption from offices was considered as a constant daily profile with small variations.

On the other hand, based on the execution time of each production program, a comparison of the pieces demand and the real production per day using both control strategies are presented in Figures 8.8a, 8.8b and 8.8c. From these results, it is possible to see that both controllers decide to maximise the revenues for the sale of parts to mitigate the energy costs by producing the maximum number of pieces allowed. However, the proposed EMPC activates the production

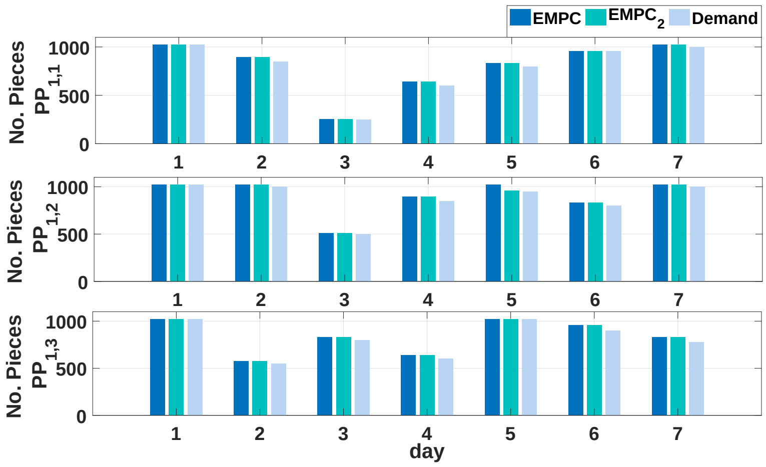
Table 8.2: Total costs and plant profit per day.

Day	**Costs** $[\times 10^3 \text{e.u.}]$	**Revenue** $[\times 10^4 \text{e.u.}]$	**Profit** $[\times 10^4 \text{e.u.}]$
1	7.0320	2.1722	1.4690
2	7.1564	2.1658	1.4502
3	6.9344	2.1472	1.4538
4	6.8515	2.1775	1.4924
5	7.1112	2.1722	1.4610
6	7.0143	2.1542	1.4528
7	7.8561	2.1722	1.3865

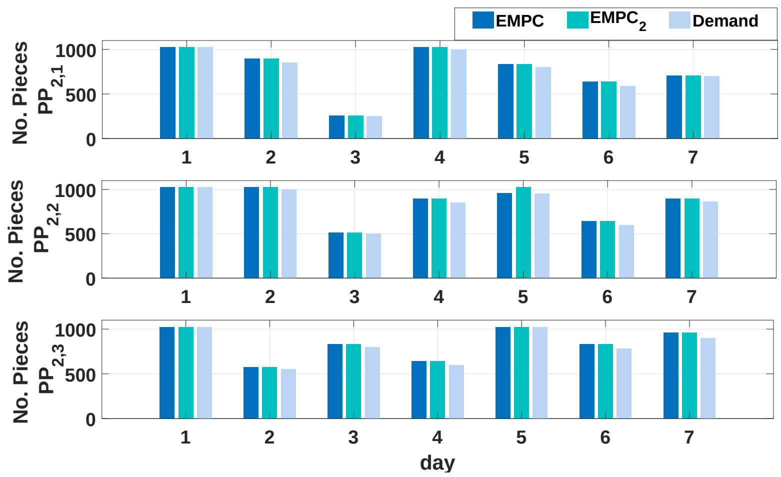
programs of higher energy consumption during the periods of cheapest energy. Besides, it should be noted that according to the constraints for the maximum production of pieces, the excess in the production never surpasses 10% of the real demand.

According to the production of pieces and the energy consumed, in Figure 8.9 and Table 8.2, the total revenues, energy costs, and profit per day are presented for each one of the control strategies tested. Based on these results it is possible to see that, by including the energy-price fluctuations into the optimisation problem, energy costs can be reduced, and the plant profit can be increased in 2% per day, approximately, without affecting the processing times of machines. However, it is worth noting that since both controllers try to maximise the parts production, the incomes for their sale were quite similar. Afterwards, in Figure 8.10, the computational time spent by iteration as well as the obtained values for J in (8.6) are presented for the proposed EMPC. It should be noted that, according to the proposed cost function, the negative values of J correspond to the profit after discounting the energy costs to the incomes achieved by the sale of the produced parts. Besides, based on the sampling time and the maximum value of t_c, it can be concluded that the proposed control strategy is suitable to be implemented in real time.

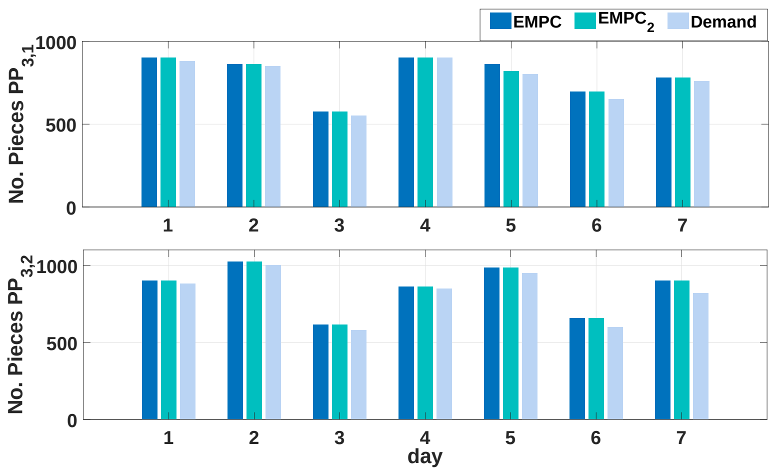
Finally, in this section, an OBC strategy has been proposed to determine the optimal economic production programming of a manufacturing plant. Thus, depending on the production program and the programming of machines to process a type of part, the proposed controller finds the suitable instants in which the production program must be executed taking into account the energy market, its fluctuations, and the demand of parts. According to the obtained results, considering updates in the energy prices and changes in the demand of pieces, energy costs were minimised without affecting the system productivity since the design of production programs (assuming optimised) was not modified. Besides, by implementing a control strategy in real time, changes in the demand of parts according to the customer requirements could also be considered, adding more flexibility to the plant operation.



(a) Production in process line 1.



(b) Production in process line 2.



(c) Production in process line 3.

Figure 8.8: Comparison between demand and production of pieces for the process lines.

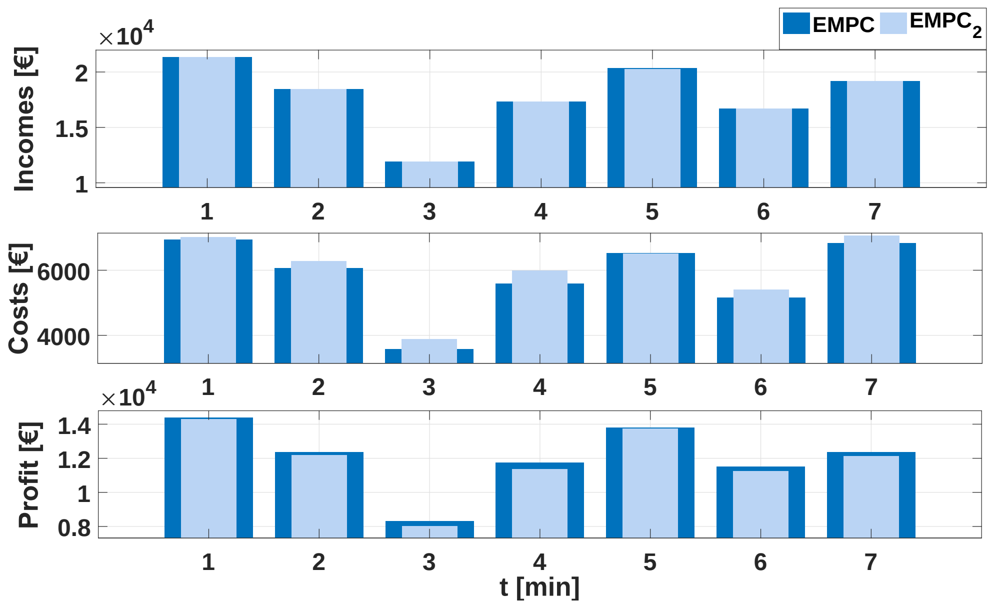


Figure 8.9: Plant profit per day according to the total energy costs and incomes for the sale of parts.

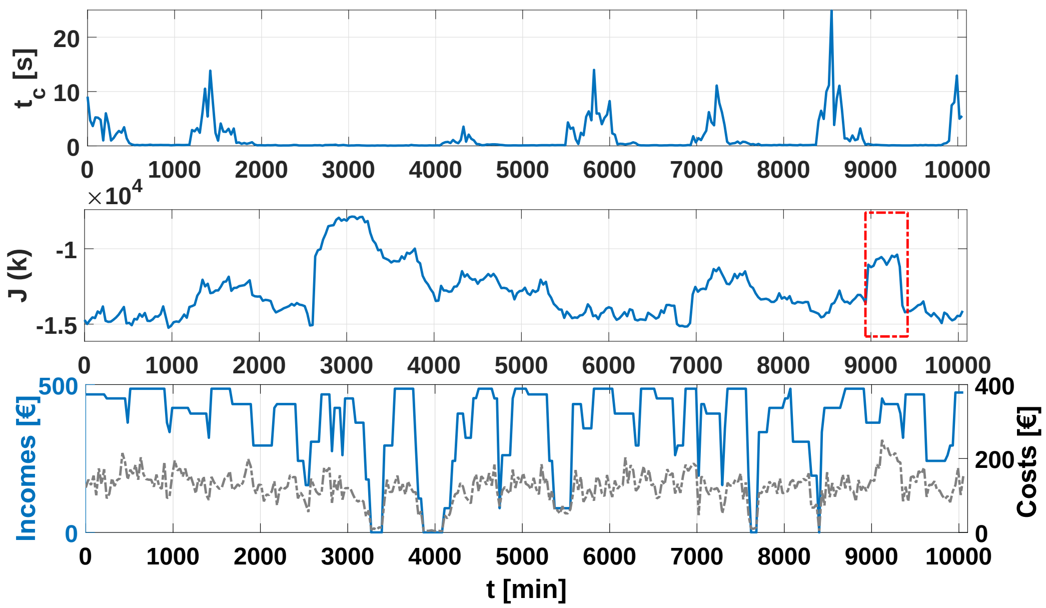


Figure 8.10: Simulation results for the computational burden, cost function, and total costs and revenues per day.

8.3 Economic Optimal Operation of the TBS

Once the plant production is determined and the machines selected are ready to operate, peripheral devices at both machine and process line levels should also be ready to supply the required resources to machining devices. Therefore, resources such as coolant and compressed air should be purchased and prepared to desired conditions to distributed among the productive areas of the plant. Although the energy consumption of TBS is considered when production programming is performed, they can be managed in real time to try minimising energy costs. Thus, in this section, a control strategy to manage the elements in the TBS related to productive tasks is designed taking also advantage of energy market fluctuations and minimising in real time the operational cost by energy and resources consumption.

As shown in Figure 8.11, the centralised systems that provide the resources to machines and productive systems integrate the TBS. Thereby, all the raw materials are collected and processed in the TBS to achieve the desired operating conditions and, then, these material and resources are sent to the production systems that required them. For instance, the main components to get the mixture of coolant are purchased, mixed and stored in tanks. In these tanks, the mix remains in desired conditions, and when it is required, the coolant is pumped to the production systems. In this regard, the productive systems refer to process lines in which machining operations take places, and the pieces are processed. Then, the flows of coolant that arrived at peripheral systems of the process lines and machines are processed again to reach the final operating conditions and, they are sent to machines when they required. It should be noted that the supply of resources from TBS to machines is performed in stages due to the possible energy and material losses during their transport, and the different production programs with their corresponding demand of resources from process lines. Besides, manufacturing plants usually purchase the raw materials in specific periods and, therefore, there should be enough resources in the plant to be able to cover the demand when different productions programs are scheduled.

In this regard, as the same for the machine and process line levels, these peripheral systems should be suitably managed to guarantee that the resources can be available when they are required in the process lines. However, contrary to the lower levels, the management of peripheral systems at plant level is oriented to minimise the total energy costs as well as the costs of raw materials. To this end, a control strategy is proposed to manage the centralised peripheral systems to minimise the operational costs, i.e., energy and raw material. The proposed controller is based on the EMPC approach since the control objective is one of economical type. Thus, both the activation instant and the amount of both coolant and air to be purchased should be determined to take into account the demand of resources from productivity units in the plant (machines and process lines) and the current energy prices in the market. It should be noted that according to the control strategy presented in Section 8.2, the production program of the plant

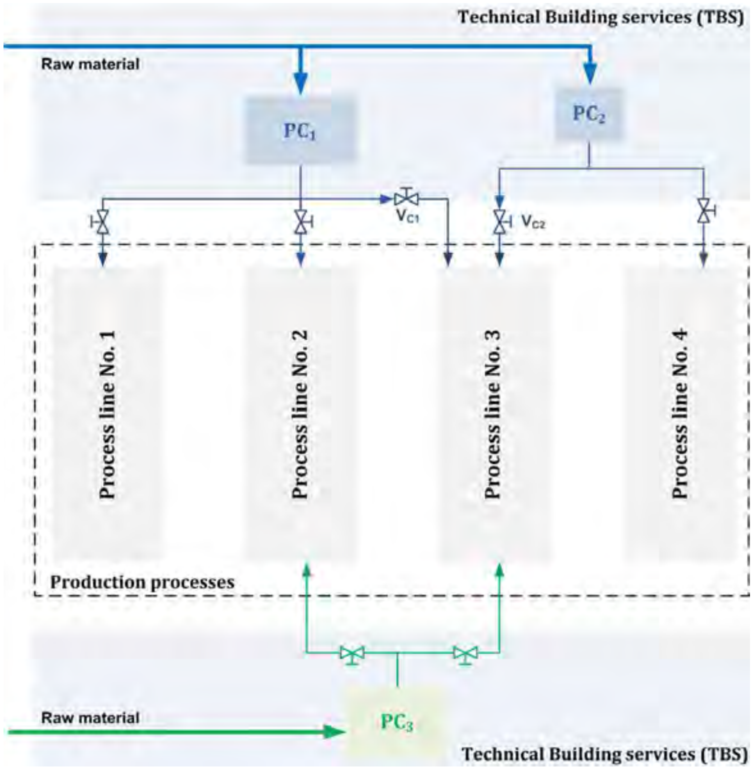


Figure 8.11: Process lines in a manufacturing plant.

was determined considering an associated energy consumption for the TBS and logical constraints that guarantee that the TBS will be able of supply all the required resources. Contrary to this, the main objective of the control strategy proposed below is to manage peripheral systems suitably to satisfy the resources demand while trying to keep the optimal operation of the plant and even to try of minimising more the energy cost taking advantage of the energy-market fluctuations.

8.3.1 Control problem formulation

Considered a connection scheme among the TBS and process lines in a manufacturing plant, as shown in Figure 8.11. Connections in blue correspond to the supply system of compressed air to process lines while the connection in green refers to the coolant-supply systems. These systems were considered to continue with the same process dynamics studied in the previous chapters. In this case, only two process lines in the plant require coolant for the machining operations performed in machines, i.e., the process lines 2 and 3. On the other hand, since all the machines in the process line need compressed air for their machining operations, two centralised peripheral systems are required to satisfy the demand. Due to these two systems are assumed to be of different size, the first supply system of compressed air P_{C_1} must satisfy the demand of the process lines L_1, L_2 and, in some cases, of L_3. Similarly, the second system P_{C_2} must supply the airflow required by L_4 all the time, and some times, it could also satisfy the demand of L_3. The latter fact means that at each instant k, the following relation should be satisfied:

$$m_{air,L_3}(k) = m_{air,C_1 \to L_3}(k) + m_{air,C_2 \to L_3}(k), \tag{8.17}$$

being $m_{air,L_3} \in \mathbb{R}_{\geq 0}$ the demand of air from the third process line, and $m_{air,C_1 \to L_3} \in \mathbb{R}_{\geq 0}$ and $m_{air,C_2 \to L_3} \in \mathbb{R}_{\geq 0}$ the flows of air supply for both P_{C_1} and P_{C_2}, given by

$$m_{air,C_1 \to L_3}(k) = \delta_{C_1}\ v_{C_1}, \tag{8.18a}$$

$$m_{air,C_2 \to L_3}(k) = \delta_{C_2}\ v_{C_2}, \tag{8.18b}$$

being δ_{C_1} and δ_{C_2} the maximum flows allowed when v_{C_1} and v_{C_2} are 100% opened, respectively.

It is worth noting that the demand considered at this level is the result of the control strategies implemented at lower levels. That means, at both machine and process line levels, peripheral devices are managed to feed the required resources at the tanks in each local and global peripheral system and, then, the streams are sent to machines. However, in those cases, it was assumed that the resources were always available when the peripheral devices required them. Thus, the centralised peripheral systems in the TBS are responsible for guaranteeing the availability of resources.

In Figures 8.12 and 8.13, some sequences for the consumption of compressed air and coolant from process lines are presented. For the case of L_3, both P_{C_1} and P_{C_2} can cover the whole demand of compressed air individually, but also they could exist a consensus among them to satisfy the total demand. In this regard, in addition to the management of peripheral systems, the single supplier or the aperture of valves v_{C_1} and v_{C_2} when both system jointly work to supply the demand of L_3 should be selected. It should be noted that the rest of the valves are not studied in depth since it is assumed that they are always available and can provide the required flow to each machine they are connected with. Then, to minimise the operational costs of the plant subject to the current production programs executed in the different process lines and their resulting demand for resources, the following operational costs are considered:

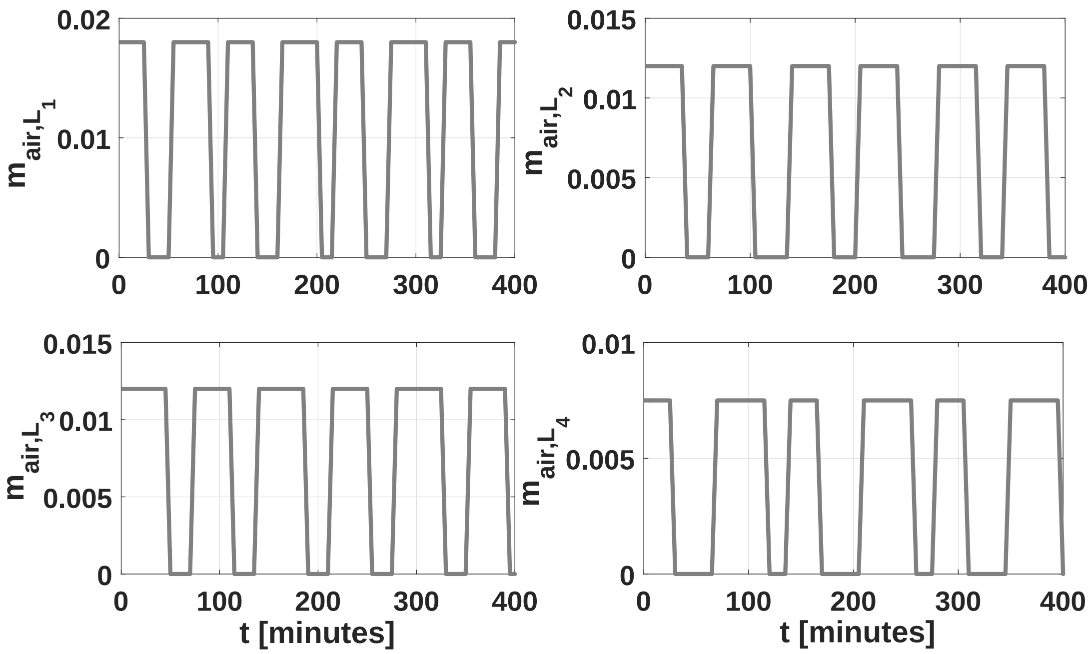


Figure 8.12: A portion of the sequences of flow of compressed air demanded from the process lines in $[\mathrm{kg/minute}]$.

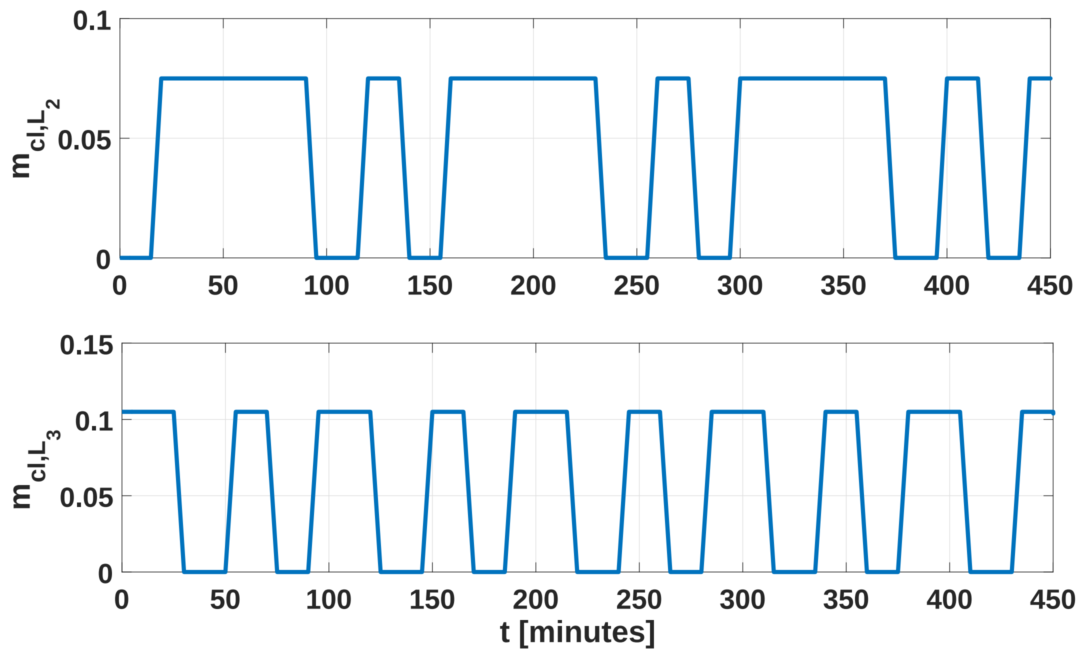


Figure 8.13: A portion of the sequences of flow of coolant demanded from L_2 and L_3 in $[\mathrm{kg/minute}]$.

- ***Costs for raw materials:*** In this case, costs related to the consumption of coolant and compressed air will be considered. For the compressed air consumption, the related costs are given by

$$\varphi_{air}(k) = \gamma_{air} \left(\frac{1}{\rho_{air}}\right) m_{in,air}(k), \tag{8.19}$$

being $\gamma_{air} \in \mathbb{R}$ in $\left[\frac{\text{e.u.}}{\text{m}^3}\right]$ the purchase price, ρ_{air} the density of the air, and $m_{in,air} = m_{air,C_1} + m_{air,C_2} \in \mathbb{R}$ in $\left[\frac{\text{kg}}{\text{s}}\right]$ the total airflow consumed on the plant at eat instant k. On the other hand, the costs related to consumption of coolant can be computed according to

$$\varphi_{cl}(k) = \gamma_{cl} \left(\frac{1}{\rho_{cl}}\right) m_{in,cl}(k), \tag{8.20}$$

where $\gamma_{cl} \in \mathbb{R}$ is the price of coolant in $\left[\frac{\text{e.u.}}{\text{m}^3}\right]$, ρ_{cl} the coolant density, and $m_{in,cl} \in \mathbb{R}$ in $\left[\frac{\text{kg}}{\text{s}}\right]$ is the total coolant required by machining operations.

- ***Energy costs:*** The total energy cost will depend on the energy consumed in the process lines $S_L \in \mathbb{R}$ and by the elements in the TBS, denoted here as $S_{C_j} \in \mathbb{R}$, and the current energy price $\gamma_e \in \mathbb{R}$ in $\left[\frac{\text{e.u.}}{\text{kWh}}\right]$ as follows:

$$\varphi_e(k) = \gamma_e(k) \left(\sum_{i=1}^{4} S_{L_i}(k) + \sum_{j=1}^{3} S_{C_j}(k)\right). \tag{8.21}$$

According to (8.19), (8.20), and (8.21), both γ_{air} and γ_{cl} are constant prices for the raw materials while γ_e is time-varying according to the current energy market.

Then, the total operational costs at each instant k are given by

$$J(k) = \varphi_{air}(k) + \varphi_{cl}(k) + \varphi_e(k), \tag{8.22}$$

with $J \in \mathbb{R}$. Therefore, to minimise the operational costs of the plant in (8.22), the mass of resources to be purchased to guarantee the proper operation of the process lines should be determined as well as the activation instant of peripheral systems to achieve the desired conditions of resources while minimising the total energy costs. The last fact is because every time that new resources are purchased, the peripheral systems should be activated to process those raw materials and, therefore, there will be an associated energy consumption (S_{C_j} in (8.21)).

8.3.2 EMPC for the TBS management

Two control architectures will be proposed in order to compare their closed-loop performance and their computational burden to achieve an optimal solution. Thus, both centralised and non-centralised control architectures are proposed in this section based on the control strategies proposed in the previous chapters.

Centralised EMPC

Considering a fixed number of centralised peripheral systems as shown in Figure 8.11, the activation sequence of peripheral devices and valves as well as for the flows of raw material to be purchased at each instant k can be defined as follows:

$$\mathbf{\Lambda}_{P_C}(k) = \{u_{C_1}(k), u_{C_2}(k), u_{C_3}(k)\}, \tag{8.23a}$$

$$\mathbf{\Lambda}_{V_C}(k) = \{v_{C_1}(k), v_{C_2}(k)\}, \tag{8.23b}$$

$$\mathbf{\Lambda}_{m}(k) = \{m_{air,C_1}(k), m_{air,C_2}(k), m_{in,cl}(k)\}, \tag{8.23c}$$

with $u_{C_1}(k) \in \{0,1\}$ and $u_{C_2}(k) \in \{0,1\}$ the activation/deactivation signal for peripheral systems of compressed air P_{C_1} and P_{C_2}, respectively. Besides, $u_{C_3} \in \mathbb{V}_{C_3} = \{0, 100, 200\}$ is the activation signal for the coolant-supply system P_{C_2}. In addition, $v_{C_1} \in \mathbb{V}_{C_1} = \{0, 10, \cdots, 100\}$ and $v_{C_2} \in \mathbb{V}_{C_2} = \{0, 10, \cdots, 100\}$ refer to the valve apertures for the connections among P_{C_1}, P_{C_2} and L_3. Then, the decisions of switching on centralised peripheral systems in TBS and buying raw material to be processed in peripheral systems will depend on the current energy consumption from process lines in the plant as well as the demand of resources from them. Then, considering a prediction horizon H_p, the activations sequences in (8.23) are defined as follows:

$$\mathbf{\Gamma}_{P_C}(k) = \{\mathbf{\Lambda}_{P_C}(k|k), \mathbf{\Lambda}_{P_C}(k+1|k), \cdots, \mathbf{\Lambda}_{P_C}(k+H_p-1|k)\}, \tag{8.24a}$$

$$\mathbf{\Gamma}_{V_C}(k) = \{\mathbf{\Lambda}_{V_C}(k|k), \mathbf{\Lambda}_{V_C}(k+1|k), \cdots, \mathbf{\Lambda}_{V_C}(k+H_p-1|k)\}, \tag{8.24b}$$

$$\mathbf{\Gamma}_{m}(k) = \{\mathbf{\Lambda}_{m}(k|k), \mathbf{\Lambda}_{m}(k+1|k), \cdots, \mathbf{\Lambda}_{m}(k+H_p-1|k)\}, \tag{8.24c}$$

where $\mathbf{\Gamma}_{P_C} \in \{0,1\} \times \mathbb{V}_{C_3}^{n\ H_p}$, $\mathbf{\Gamma}_{V_C} \in \mathbb{V}_{C_1} \times \mathbb{V}_{C_2}^{l\ H_p}$, and $\mathbf{\Gamma}_m \in \mathbb{R}^{m\ H_p}$. According to the proposed control objective in (8.22), the total operational cost along H_p is given by

$$\mathbf{J}(k) = \sum_{k=1}^{H_p} J(k), \tag{8.25}$$

with $\mathbf{J} \in \mathbb{R}_{\geq 0}$. Afterwards, the proposed controller is based on the following open-loop optimisation problem:

$$\min_{\mathbf{\Gamma}_{P_C}(k), \mathbf{\Gamma}_{V_C}(k), \mathbf{\Gamma}_m(k)} \quad \mathbf{J}(k) \tag{8.26a}$$

subject to

$$S_{C_j}(k+r|k) = f_j\left(u_{C_j}(k+r|k)\right), \forall j = 1,2,3 \tag{8.26b}$$

$$Q_{C_j}(k+r+1|k) = g_{C_j}\left(Q_{C_j}(k+r|k), u_{C_j}(k+r|k), v_{C_j}(k+r|k)\right), \tag{8.26c}$$

$$m_{air,L_3}(k+r|k) = \delta_{C_1}\, v_{C_1}(k+r|k) + \delta_{C_2}\, v_{C_2}(k+r|k), \tag{8.26d}$$

$$m_{in,air}(k+r|k) \in \mathbb{R}_{\geq 0}, \tag{8.26e}$$

$$m_{in,cl}(k+r|k) \in \mathbb{R}_{\geq 0}, \tag{8.26f}$$

$$u_{C_i}(k+r|k) \in \{0,1\},\ i = 1,2, \tag{8.26g}$$

$$u_{C_3}(k+r|k) \in \mathbb{V}_{C_3}, \tag{8.26h}$$

$$v_{C_1}(k+r|k) \in \mathbb{V}_{C_1}, \tag{8.26i}$$

$$v_{C_2}(k+r|k) \in \mathbb{V}_{C_2}, \tag{8.26j}$$

$$Q_{C_i}(k+r|k) \in \left[\underline{Q}_{C_i}, \overline{Q}_{C_i}\right], \forall i = 1,2,3 \tag{8.26k}$$

being $f_j : \{0,1\} \mapsto \mathbb{R}$ the maps for the energy consumption of peripheral systems, Q_{C_i} the states of process dynamics related to the operation of P_{C_i}, and $g_{C_i} : \{0,1\} \times \mathbb{V}_{C_i} \times \mathbb{R} \mapsto \mathbb{R}$ the process dynamics for P_{C_i}. Besides, (8.26d) refers to the balance condition for the demand of L_3 according to its available suppliers, while (8.26e) to (8.26k) refer to both the range constraints of decision variables and the physical constraints of the supply systems of both compressed air and coolant.

Then, if the optimisation problem, jointly solved it, is feasible, i.e., $\mathbf{\Gamma}_{P_C}(k) \neq \emptyset$, $\mathbf{\Gamma}_{V_C}(k) \neq \emptyset$, and $\mathbf{\Gamma}_m(k) \neq \emptyset$, the optimal sequences for P_{C_j} and m_i are given by

$$\mathbf{\Gamma}^*_{P_C} \triangleq \{\mathbf{\Lambda}^*_{P_C}(k|k), \cdots, \mathbf{\Lambda}^*_{P_C}(k+H_p-1|k)\},$$

$$\mathbf{\Gamma}^{*}_{V_C} \triangleq \{\mathbf{\Lambda}^{*}_{V_C}(k|k), \cdots, \mathbf{\Lambda}^{*}_{V_C}(k+H_p-1|k)\},$$

$$\mathbf{\Gamma}^{*}_{m} \triangleq \{\mathbf{\Gamma}^{*}_{m}(k|k), \cdots, \mathbf{\Gamma}^{*}_{m}(k+H_p-1|k)\},$$

and the first components $\mathbf{\Lambda}^{*}_{P_C}(k|k)$ and $\mathbf{\Gamma}^{*}_{m}(k|k)$ are sent to the systems following the receding horizon philosophy. In this case, simplified energy consumption models were considered as follows:

$$S_{C_j}(k) = \vartheta_j \, u_{C_j}, \tag{8.27}$$

being $\vartheta_j \in \mathbb{R}$ a constant related to the energy consumption of P_{C_j} when this latter is turned on. On the other hand, regarding process dynamics for the operation of peripheral systems, similar expressions to ones used in the previous chapters were used as constraints in (8.26k) in the optimisation problem in (8.26). Thus, q-relations related to both P_{C_1} and P_{C_2} correspond to the mass and pressure dynamics into a reservoir tank:

- *Peripheral system P_{C_1}:* The mass balance inside the tank T_{C_1} is given by

$$M_{T_{C_1}}(k+1) = M_{T_{C_1}}(k) + \tau_s \, \mu_{C_1}(k), \tag{8.28a}$$

$$\mu_{C_1}(k) = \left(m_{air,C_1}(k) - m_{air,L_1}(k) - m_{air,L_2}(k) - \delta_{C_1} \, v_{C_1}(k)\right), \tag{8.28b}$$

  being m_{air,L_1} and m_{air,L_2} the airflow required by L_1 and L_2, respectively. Then, based on the mass inside T_{C_1}, the pressure of air is computed according to

$$P_{T_{C_1}}(k) = \frac{M_{T_{C_1}}(k) \, T_{air} \, R}{V_{T_{C_1}} W_{air}}, \tag{8.29}$$

  with $P_{T_{C_1}}$ [Pa], $M_{T_{C_1}}$ [kg], and being T_{air}, R, $V_{T_{C_1}}$ and W_{air} the temperature inside T_{C_1}, the universal gas constant, the volume of T_{C_1}, and the molecular weight of the air, respectively.

- *Peripheral system P_{C_2}:* Since both systems provide the same resource, the process dynamics for P_{C_2} will be the same as P_{C_1} and are expressed as follows:

$$M_{T_{C_2}}(k+1) = M_{T_{C_2}}(k) + \tau_s\, \mu_{C_2}(k), \tag{8.30a}$$

$$\mu_{C_2}(k) = \left(m_{air,C_2}(k) - \delta_{C_2}\, v_{C_2}(k) - m_{air,L_4}(k)\right), \tag{8.30b}$$

$$P_{T_{C_2}}(k) = \frac{M_{T_{C_2}}(k)\, T_{air}\, R}{V_{T_{C_2}} W_{air}}. \tag{8.30c}$$

Otherwise, for the case of the coolant-supply systems, the process dynamics refer to mass exchange into a tank T_{C_2}, which is expressed in terms of the level change as follows:

$$L_{T_{C_2}}(k+1) = L_{T_{C_2}}(k) + \frac{\tau_s}{\rho_{cl}\, A_{T_{C_2}}}\left(m_{in,cl}(k) - m_{cl,L_2}(k) - m_{cl,L_3}(k)\right), \tag{8.31}$$

with $L_{T_{C_2}}[\mathrm{m}]$ the coolant level in T_{C_2}, and being $\rho_{cl}[\mathrm{kg/m^3}]$ and $A_{T_{C_2}}[\mathrm{m^2}]$ the coolant density and the cross-sectional area of T_{C_2}.

Distributed EMPC

In order to solve the optimisation problem in (8.26) in a distributed way, a non-cooperative control strategy will be proposed in this section, according to the algorithm proposed in Chapter 7 for non-centralised control architectures. Based on the configuration of the TBS and the process lines in the plant, the whole system is divided into three sub-systems, i.e., SS_1, SS_2 and SS_3, as shown in Figure 8.14. According to that figure, the first sub-system is formed by the centralised peripheral system P_{C_1}, the valve v_{C_1}, and the process lines L_1, L_2 and L_3, while SS_2 consists of the small supply system of compressed air P_{C_2}, v_{C_2}, and the process lines L_3 and L_4. It should be noted that these two systems present some coupled dynamics, which concerns the balance condition to satisfy the demand for compressed air in L_3, as shown in (8.26d). In this regard, a consensus should exist to decide the supplier or the valve aperture of both v_{C_1} and v_{C_2} when both systems will be required to cover the demand.

On the other hand, SS_3 refers to the coolant-supply systems with P_{C_3} and the process lines L_2 and L_3. It is worth noting that the last system does not have operational dynamics related to the other sub-systems. Therefore, it might be independently controlled without exchanging information with the other sub-systems. However, for the case of SS_1 and SS_2, information exchange is required to achieve a consensus about the best way to cover the resource demand from L_3, from which the energy consumption could be minimised. Then, to made the problem in (8.26) separable concerning SS_1 and SS_2, a new variable (z^l) is added and constrained to be equal to v_{C_i} and the coupling constrain in (8.26d) is removed from the optimisation problem,

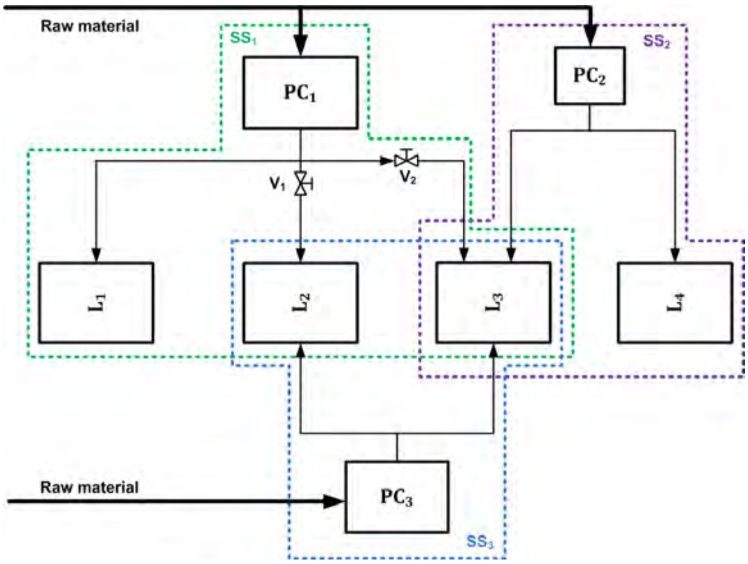


Figure 8.14: System partitioning based on the connection between in TBS and process lines in a manufacturing plant presented in Figure 8.11.

such as it was explained in Chapter 7. Thus, the local controllers for the first and second sub-systems (i.e. $l = 1, 2$) are based on the following optimisation problem:

$$\min_{\boldsymbol{\Gamma}^l_{P_C}(k),\boldsymbol{\Gamma}^l_{V_C}(k),\boldsymbol{\Gamma}^l_{m}(k)} \quad \mathbf{J}^l(k) \tag{8.32a}$$

subject to

$$S^l_{C_j}(k+r|k) = f^l_j\left(u^l_{C_j}(k+r|k)\right), \tag{8.32b}$$

$$Q^l_{C_j}(k+r+1|k) = g^l_{C_j}\left(Q^l_{C_j}(k+r|k), u^l_{C_j}(k+r|k), v^l_{C_j}(k+r|k)\right), \tag{8.32c}$$

$$v^l_{C_j}(k+r|k) = z_j(k+r|k), \tag{8.32d}$$

$$m^l_{in,air}(k+r|k) \in \mathbb{R}_{\geq 0}, \tag{8.32e}$$

$$u^l_{C_j}(k+r|k) \in \{0,1\}, \tag{8.32f}$$

$$v^l_{C_j}(k+r|k) \in \mathbb{V}_{C_j}, \tag{8.32g}$$

$$Q^l_{C_j}(k+r|k) \in \left[\underline{Q}^l_{C_j}, \overline{Q}^l_{C_j}\right], \tag{8.32h}$$

being $z_j \in \mathbb{R}$ the consensus variable with the information about the another sub-system with coupled dynamics. It should be noted that for the case of $l = 3$, constraint (8.32d) is removed since SS_3 is not coupled to any other sub-system. Then, for the case of SS_1 and SS_2, the coupled constraint (8.32d) is relaxed to the cost function by using of Lagrange multipliers. In this regard, the augmented Lagrangian is defined as follows:

$$\mathcal{L}_\rho^l\left(\{u_{C_j}, v_{C_j}\}^l\right) = J^l(k) + g(z) + (\lambda)^T\,(v_j^l - z_j) + \frac{\rho}{2}\|v_j^l - z_j\|_2^2, \tag{8.33}$$

where $g(\cdot)$ is a regularisation term for $z = [z_1, z_2]$, which is defined as the balance constrained removed from (8.32) but in terms of z as follows:

$$e_z(k) = \left[\delta_{C_1}\, z_1(k) + \delta_{C_2}\, z_2(k) - m_{air,L_3}(k)\right], \tag{8.34a}$$

$$g(z) = e_z(k)^T\,\mathbf{I}_z\, e_z(k). \tag{8.34b}$$

being e_z the error vector related to the compliment of balance constraint in (8.26d), and $\mathbf{I}_z$ the identity matrix of suitable dimensions.

Then, using (8.33) as cost function, the relaxed optimisation problem in (8.32) is separable in both constraints and cost function regarding the set of variables $\{u_{C_j}, v_{C_j}\}^l$ and z. Next, according to the ADMM algorithm, (8.32) is solved in the following way:

$$\{u_{C_j}, v_{C_j}\}_{k+1}^l = \min_{\{u_{C_j}, v_{C_j}\}^l}\left[J^l(\{u_{C_j}, v_{C_j}\}^l) + (\lambda_k)^T\,(v_{C_j\,k+1}^l - z_{j\,k}) + \frac{\rho}{2}\|v_{C_j\,k+1}^l - z_{j\,k}\|_2^2\right], \tag{8.35a}$$

$$z_{k+1} = \min_z\left[g(z) + \sum_{l=1}^{b}(\lambda_k)^T\,(v_{C_j\,k+1}^l - z_j) + \frac{\rho}{2}\|v_{C_j\,k+1}^l - z_j\|_2^2\right], \tag{8.35b}$$

$$\lambda_{k+1} = \lambda_k + \rho\left(v_{C_j\,k+1}^l - z_{j\,k+1}\right). \tag{8.35c}$$

According to (8.35a), the sequences for the activation of devices, the valve apertures, and the amount of raw material required are locally determined for each sub-system based on a initial condition for z_j. Subsequently, the consensus variable z_j is updated in (8.35b). Finally, the Lagrangian multipliers are updated according to (8.35c). Since the ADMM algorithm is an iterative procedure, the following stopping criteria are defined:

$$\delta_{C_1}\, v_{C_1}(k) + \delta_{C_2}\, v_{C_2}(k) - m_{air,L_3}(k) \leq \epsilon_1, \tag{8.36}$$

$$v_{C_j}(k) - z_j(k) \leq \epsilon_2, \tag{8.37}$$

where (8.36) refers to the balance constraint to satisfy the demand of L_3 while (8.36) is related to the consensus constraint in each sub-system. The tolerance values ϵ_1 and ϵ_2 should be suitably

Table 8.3: Physical dimensions and parameters for the supply systems of compressed air and coolant.

Parameter	**Value**	**Units**	**Parameter**	**Value**	**Units**
$V_{T_{C_1}}$	0.15	$\mathrm{m^3}$	$V_{T_{C_2}}$	0.085	$\mathrm{m^3}$
$A_{T_{C_2}}$	0.05	$\mathrm{m^2}$	ρ_c	1042.5	$\frac{\mathrm{kg}}{\mathrm{m^3}}$
T_{air}	25	$^\circ\mathrm{C}$	R	8.1314	$\frac{\mathrm{J}}{\mathrm{Kmol}}$
W_{air}	28.966	$\frac{\mathrm{g}}{\mathrm{mol}}$	ρ_{air}	1.225	$\frac{\mathrm{kg}}{\mathrm{m^3}}$
δ_{C_1}	1.2×10^{-4}	$\frac{\mathrm{kg}}{\mathrm{s}}$	δ_{C_2}	1.2×10^{-4}	$\frac{\mathrm{kg}}{\mathrm{s}}$
γ_{air}	0.06	$\frac{\mathrm{e.u}}{\mathrm{m^3}}$	γ_{cl}	1.5	$\frac{\mathrm{e.u}}{\mathrm{m^3}}$
ϑ_{C_1}	0.06	W	ϑ_{C_1}	1.5	W
$\underline{P}_{T_{C_1}}$	500	kPa	$\overline{P}_{T_{C_1}}$	700	kPa
$\underline{P}_{T_{C_2}}$	400	kPa	$\overline{P}_{T_{C_2}}$	650	kPa
$\underline{L}_{T_{C_3}}$	0.5	m	$\overline{L}_{T_{C_3}}$	0.75	m
ρ	0.1	–	λ_0	$[1, 1, \cdots, 1] \in \mathbb{R}^{H_p}$	–
z_0^1	$[0, 0, \cdots, 0] \in \mathbb{R}^{H_p}$	–	z_0^2	$[0, 0, \cdots, 0] \in \mathbb{R}^{H_p}$	–
ϵ_1	0.5	–	ϵ_2	1.0×10^{-6}	–

selected according to the magnitude of the involved variables and the desired accuracy.

8.3.3 Simulation results

In this section, simulation results are presented to compare the effectiveness of the proposed control strategies, their closed-loop performance and the computational burden of both centralised and non-centralised control architectures proposed in Section 8.3.2. In the same way as in Chapter 7, all the simulations were performed using an Intel Core i7-55000U 2.4 GHz processor with 8G RAM, and the simulation results were obtained in Matlab by using the software IBM ILOG CPLEX Optimisation Studio [ILO13] integrated to YALMIP toolbox [Löf04]. However, at this level, the controllers were executed every five minutes, i.e., $\tau_s = 5$ minutes. The latter is also the sampling time of both process dynamics and energy consumption models. Moreover, in this case, a prediction horizon $H_p = 8$ hours was considered according to the usual work shifts, which means that along H_p the controller makes 96 decisions. Besides, simulations were performed for a total simulation of $T_{sim} = 5$ days according to the simulation parameters presented in Table 8.3.

In Figures 8.15, 8.16, and 8.17, a comparison of the optimal sequences for the decision variables by using both the centralised and non-centralise control architectures is presented, which will be denoted as CEMPC and DEMPC, respectively. Besides, it is worth noting that these

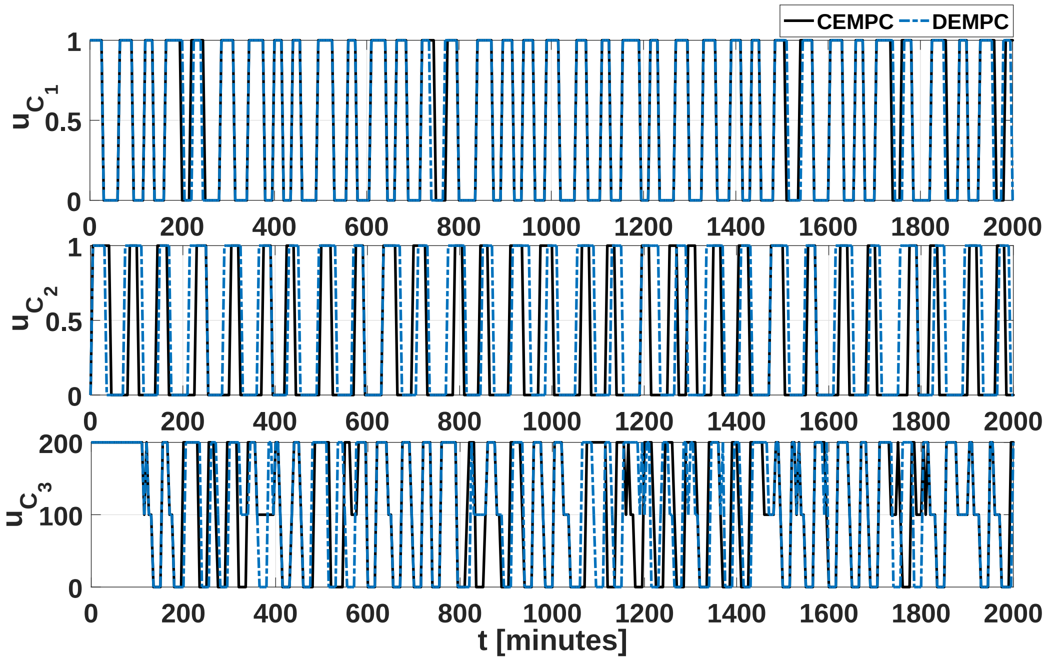


Figure 8.15: Comparison of the optimal activation sequences of peripheral systems using the control strategies CEMPC and DEMPC.

results were obtained using a typical daily energy-price profile but adding white noise to emulate the price fluctuations. Thus, the optimal activation sequence of peripheral devices and the valve apertures to select the supplier of L_3 are shown in Figures 8.15 and 8.16, respectively. Although there are some differences in the activation of peripheral systems, the main discrepancies between the centralised and non-centralised control strategies concern the valve aperture. From results in Figure 8.16, it can be observed that for the case of CEMPC, there exists a modulation of the valve apertures during the whole simulation. In contrast, when DEMPC is implemented, P_{C_2} was always selected as the supplier of compressed air for L_3. The last results are a consequence of how the consensus stage was defined, and the fact P_{C_1} has a higher energy consumption than P_{C_2}.

On the other hand, in Figure 8.17, the optimal sequences of the required flow of compressed air for both P_{C_1} and P_{C_2}, and coolant for P_{C_3} are presented. Due to the differences for the valve apertures, the main differences between the control strategies refer to the sub-systems with coupled dynamics. Thus, when CEMPC is implemented, the consumption of air from P_{C_1} is higher than the consumption for P_{C_2}, while if DEMPC is implemented the consumption from P_{C_1} is lower since in this case P_{C_2} is always used as the provider of compressed air for L_3 and, therefore, the demand of resources for P_{C_1} decreases. Then, according to the sequences for

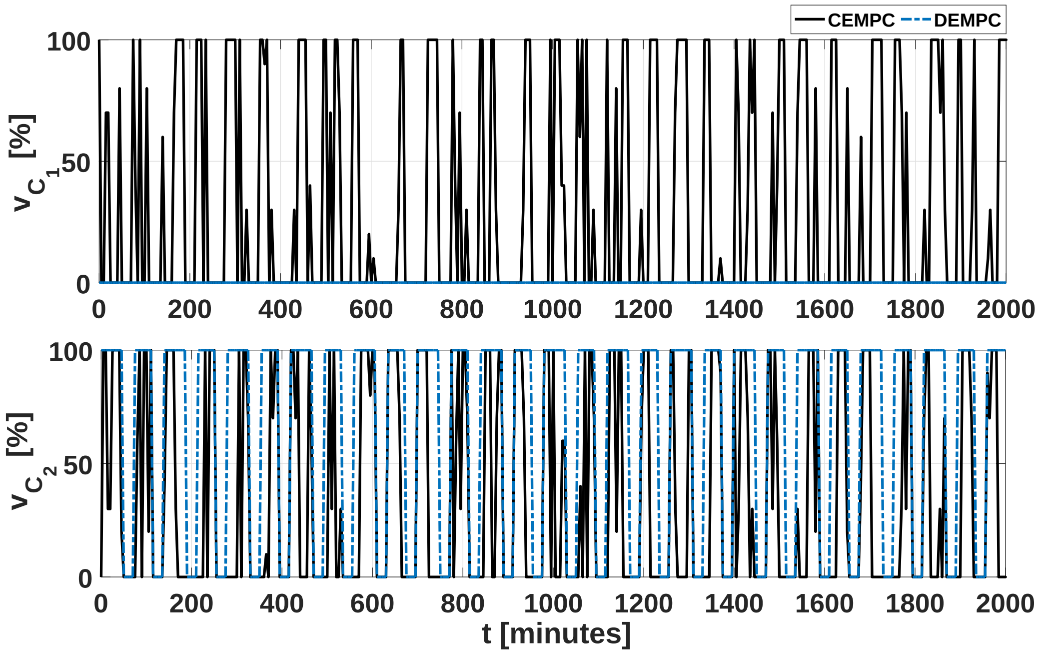


Figure 8.16: Comparison of the optimal valve apertures of peripheral systems using the control strategies CEMPC and DEMPC.

the decision variables, the process dynamics related to the operation of peripheral devices are shown in Figure 8.18. From these results, it is possible to see that operational constraints are always satisfied while the activation of peripheral devices, the valve apertures, and the inlet flow of resources are optimised to minimise the total operational costs.

Since the proposed control strategies were designed to minimise the operational costs during the plant operation, the operational costs related to raw material and energy consumption as well as the total operating costs for the whole simulation are summarised in Table 8.4. Besides, the costs discriminated along of the whole simulation, and the time-varying profile for the energy price are shown in Figure 8.19. Based on these results, it can be observed that for both the raw materials (i.e., compressed air and coolant) and energy, the obtained costs are quite similar when the proposed control strategies were tested. Nonetheless, the main differences concern the energy costs, which are a consequence of the noise added to the considered energy-price profile. Thus, although in the simulation case the total energy costs using DEMPC was lower than when CEMPD was implemented, these differences are lower than 0.06% and are related to the energy costs, for which the white noise the energy prices was considered. Finally, in Figure 8.20, the CPU time spent by each one of the proposed approaches to find an optimal solution is presented. In this case, the computational time spent by iteration of the centralised

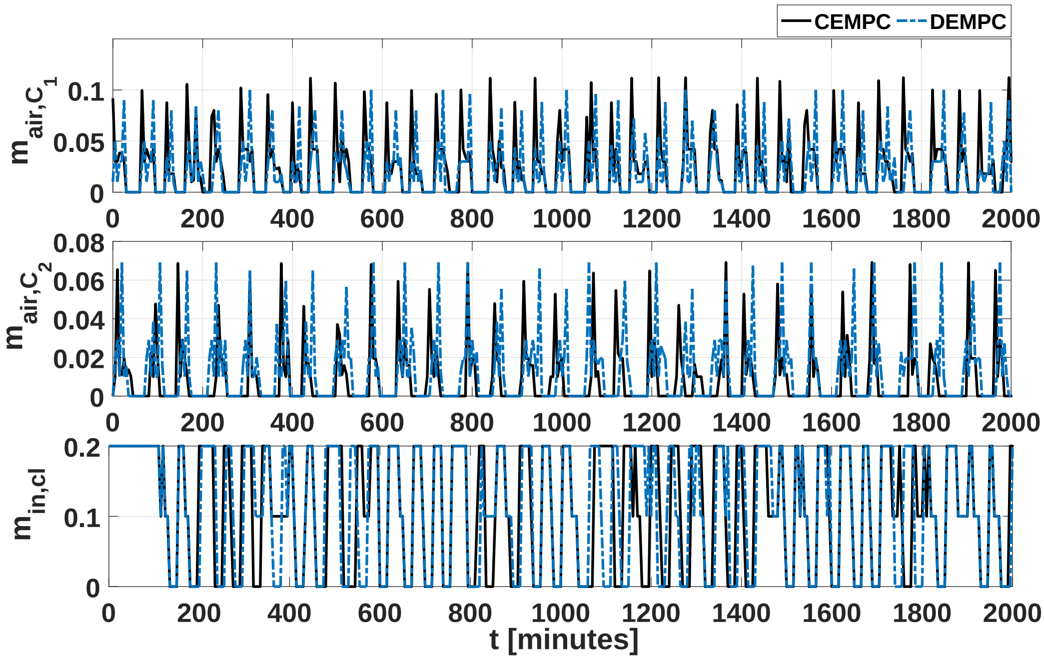


Figure 8.17: Comparison of the flow of both compressed air and coolant to be purchased to satisfy the resources demand of the process line using both CEMPC and DEMPC.

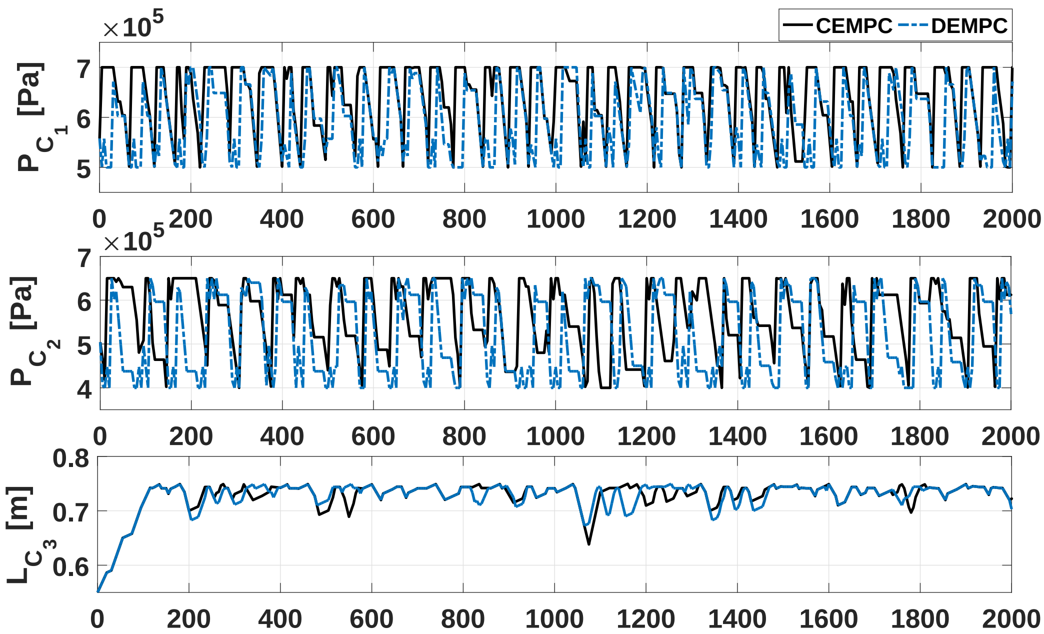


Figure 8.18: Comparative of the process dynamics related to the operation of peripheral devices using both CEMPC and DEMPC.

Table 8.4: Comparison of the operational costs using both CEMPC and DEMPC control strategies.

Controller	Energy costs [e.u.]	Costs of raw materials [e.u.]	Total costs [e.u.]
CEMPC	6642.658	11.821	6654.479
DEMPC	6638.306	11.821	6650.128

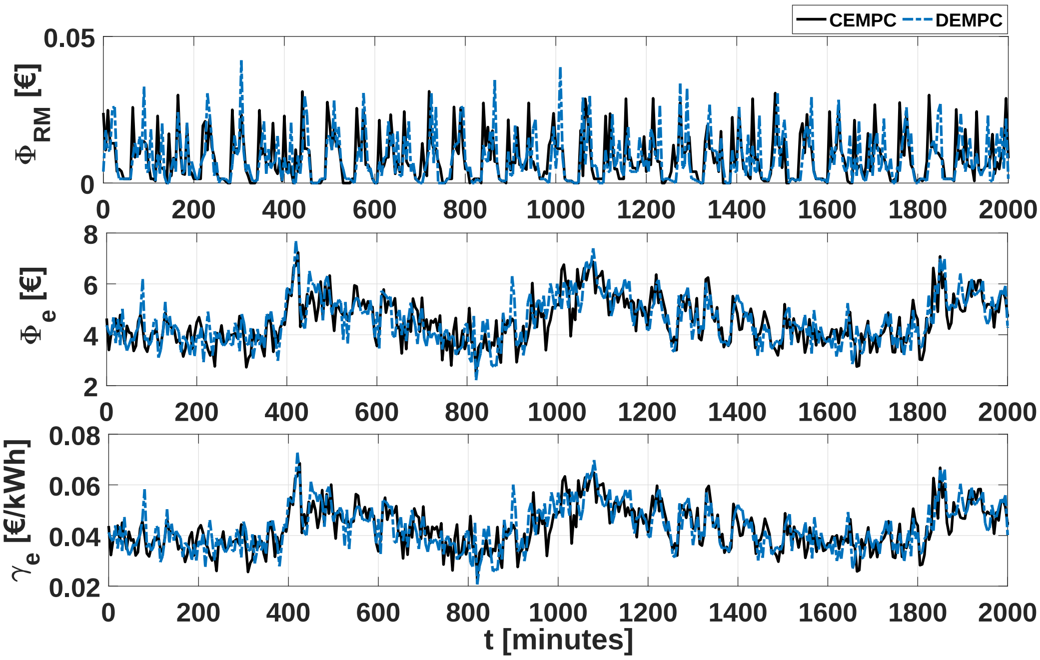


Figure 8.19: Comparative of energy consumption profile for a four-stage serial process line using the control strategies CEMPC and DEMPC.

approach is compared with the longer time of each local controller in the DEMPC strategy to satisfy stopping criteria and reach an optimal solution. Based on the obtained results, it can be concluded that using non-centralised control architectures, in which there exists communication exchange only for the sub-systems with coupled dynamics, the computational burden can be reduced. Therefore, the control strategy is suitable for its implementation in real time without decreasing its closed-loop performance significantly.

8.4 Summary

In this chapter, control strategies to determine the economical optimal operation of manufacturing systems at plant level have been proposed. At the plant level, control objectives were

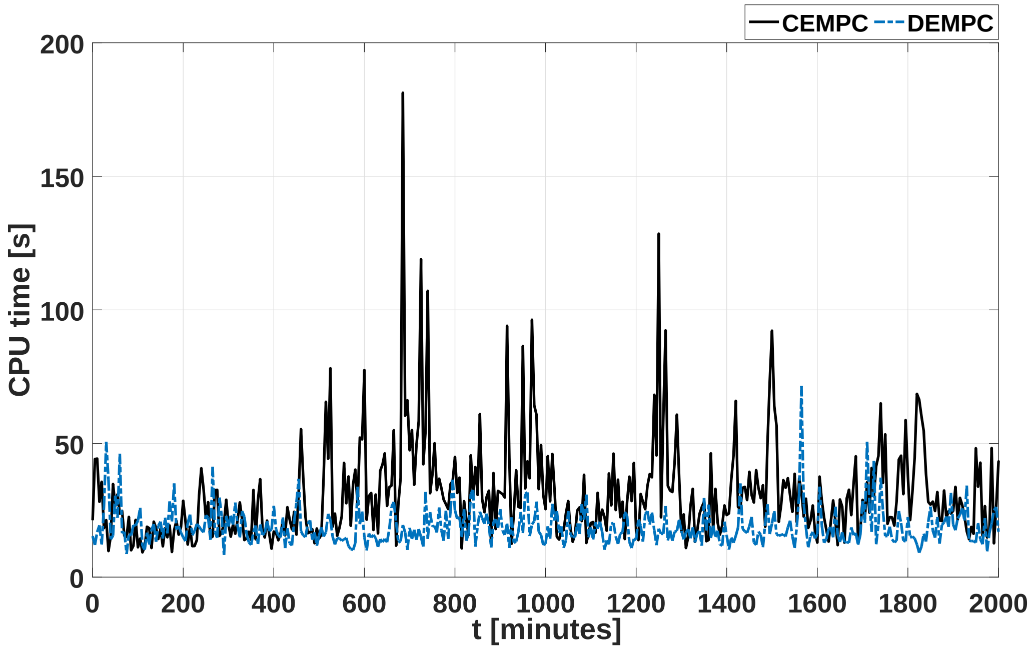


Figure 8.20: Comparison of the required computational burden using both CEMPC and DEMPC.

focused on maximising the plant profit, taking advantage of the energy market and their price fluctuation around the day. Thus, the production program of the plant consists of determining the optimal instants and execution time for the available production programs in the plant that maximise the plant profit, taking into account the energy consumption of non-added value tasks in the plant and the demand of pieces. Next, based on the production program, a new control strategy was also proposed to minimise the operational costs for raw materials and energy spent by TBS to satisfy the demand of resources in the process lines according to the current production program executed. In this regard, in the second control strategy, the controller makes decisions faster than in the first strategy to respond in real time to any disturbances or fluctuations in the energy prices. Therefore, although the production in the plant is programmed, the energy costs could be more minimised if there exists reductions in energy prices, or mitigate the total costs when there are unexpected increments in these prices.

Part III

Concluding Remarks

CHAPTER 9

CONCLUDING REMARKS

9.1 Contributions

In this thesis, energy management/control strategies have been presented to improve the energy efficiency of manufacturing systems without negatively affecting their productivity. Motivated by the transformation of manufacturing industries towards smart and flexible systems, optimisation-based controllers (mainly MPC and EMPC), under either centralised and non-centralised control architectures, have been designed to cope with the requirements of energy efficiency and flexibility of new manufacturing industry. Thus, as the first contribution of this thesis, a framework for the classification of manufacturing systems and the design of control strategies, which do not modify the processing times of the machines has been presented in Chapter 3. Based on this, the control strategies presented in Chapters 5 to 8 were developed.

Based on the proposed framework to address manufacturing systems, a centralised control strategy to minimise the total energy consumption of such systems by managing peripheral systems/devices (depending on the level analysed) separately of the machining processes has been proposed as the second contribution of this dissertation. The control strategy is based on MPC, and the control objective is defined as the integral under the curve of the energy consumption profile of the manufacturing system during a fixed period. Besides, the operational relationships among peripheral devices and machines are defined as a set of constraints into the optimisation problem behind the MPC-based controller design. The proposed control strategy is presented in Chapters 5 and 6 for both machine and process line levels, respectively. However, as the size of manufacturing system increases (when higher levels are studied), the proposed centralised control strategy requires higher computational burden, and it could not be suitable of implementing in real time. In this regard, a dual mode control strategy has been proposed in Chapter 6 for the process line level as the third contribution of this dissertation. The control strategy is based on an MPC-based control mode to determine the optimal behaviour of the manufacturing system. Next, taking advantage of the periodic behaviour of such systems, the controller switches to an autonomous control mode without on-line optimisation that uses the optimal sequences determined by the first control mode.

To reduce the energy consumption of manufacturing systems when the complexity of operational relationships increases, the problems of multi-providers for a machine and the shared resources among several machine tools in a process line are addressed in Chapter 7. In this regard, two distributed algorithms based on ADMM are proposed for cooperative and non-cooperative control architectures. Thus, a consensus stage including both the energy consumption and the coupled dynamics as regularisation terms, besides to include adaptive weighting matrices, have been proposed in Chapter 7 as the fourth contribution of this dissertation. It is taken into account that the consensus among the local controllers should consider the distribution of resources in a way that the global energy consumption can be minimised.

Finally, in Chapter 8, the problem of determining the optimal production programming of a manufacturing plant for minimising the operational costs, as well as to maximising the plant profitability has been addressed. It is given since the control strategies at lower levels (machine and process lines) follow the directrices determined at the plant level, in which the best economic performance is searched. Then, as the last contribution of this dissertation, two control strategies have been proposed for solving these issues in Chapter 8. The former determines the production programming of the plant that maximises its profit according to the current energy market and takes into account the energy consumption of both added and no-added value tasks in the plant. Then, a second control strategy based on EMPC is proposed to manage the centralised peripheral systems (into the TBS) such a way the operational costs related to the added value tasks are minimised, i.e., the consumption of the raw materials and energy. Through this separation, although an optimal production programming is determined, operational costs (and therefore the plant profit) are reduced even more with the second control strategy, since the last strategy updates the energy-market information more frequently than the first strategy. Thus, the second strategy can manage the peripheral systems to take advantage of the reduction in energy prices, while mitigating the total costs when there are increments in the price of energy.

9.2 Answering the Research Questions

The main conclusions of this thesis are presented below as the answers to the key research questions addressed in Chapter 1.

(Q1) *What is the current context of energy efficiency in the manufacturing industry, and what are the main research gaps regarding their energy efficiency?*

The manufacturing industry is suffering a paradigm-shifting toward smart, efficient, and flexible manufacturing systems. Into this transformation, the digitalisation and modularised plant designs form part of the main objectives. Thus, the optimisation of plant design, the process planning and scheduling, and the maximisation of plant productivity have gained special attention during the last years. On the other hand, researches regarding the energy efficiency of such systems have focused on the minimisation of the processing times required by machine tools to process a piece and on the design of machines and machining devices with less energy consumption. However, all these strategies only consider the energy consumption as an objective during the design stages, and not address the design of management/control strategies of manufacturing systems that can react in real time to unexpected behaviours, such as occurs in a real manufacturing plant. Besides, due to conventional manufacturing systems are not managed in real time, it is not possible to take advantage of the energy market and the price fluctuations to minimise the total energy costs during the operation of manufacturing systems.

Then, taking into account the recent advances in sensing technology, data management, and techniques for the information exchange, the main research gaps regarding the energy efficiency of manufacturing systems concern all steps needed for the tasks of modelling, monitoring, and control of such systems in real time, with objectives mainly focused on minimising their energy consumption. Thus, according to Chapter 2, there is a need for designing energy management/control strategies that face the new challenges of the new era of manufacturing industry, taking advantage of the current technological developments (e.g., CPS, IoT, etc.) and the available information of energy market to also minimise the energy costs during the operation of manufacturing plants.

(Q2) *How OBC techniques can contribute to improving the energy efficiency of manufacturing systems?*

Since the more natural way to improve the energy efficiency of a particular system is by either reducing the total energy consumption or increasing the number of value-added outputs with the same energy amount, these objectives can be directly addressed as the cost function in an optimisation problem when using OBC techniques. Thus, the operational constraints and the operational relationships among the different elements of manufacturing systems could also be included in the optimisation problem as a set of constraints to guarantee the proper operation of manufacturing systems. Moreover, according to the receding horizon philosophy for the implementation of these strategies in real time, the available information about manufacturing processes and the energy market could be continuously updated to achieve better results according to the current status of the manufacturing systems and the external factors that affect them. In this regard, OBC techniques, mainly those based on prediction such as MPC (and, in turn EMPC) were considered along this thesis for the development of the energy-efficiency control strategies presented in Chapters 5 to 8.

(Q3) How the energy efficiency of manufacturing systems could be improved and which control techniques could be useful to this end?

An important fact for the design of strategies that allow improving the energy efficiency of manufacturing systems is to avoid affecting the productivity of such systems while attempting minimising their energy consumption. In this regard, as explained in Chapters 2 and 3, the compositional elements of manufacturing systems have been divided into separable sets of machining and peripheral devices for the design of control strategies that minimise their energy consumption without affecting their productivity. The former group is directly related to machining operations performed at the machine tools. On the other hand, the latter group refers to those processes that guarantee the supply of required resources by the machines or their machining devices. Therefore, based on the proposed classification, an energy management/control strategy in which the peripheral devices can be handled independently of the machining devices was proposed in Chapter 5. Thus, keeping the operation of the machining devices the same and, through the management of the peripheral devices to minimise their operation and their energy consumption, the productivity of manufacturing systems can remain the same.

In this regard, using OBC techniques, operational relationships among machining and peripheral devices can be include into the set of constraints of the optimisation problem behind the controller design to guarantee the proper operation of machining devices and, therefore, to remain the productivity. Moreover, due to the periodic behaviour of manufacturing systems and the need to manage the peripheral devices for minimising their energy consumption, by means of a prediction of the energy consumption of both machining and peripheral systems, these latter could be suitably managed to minimise the energy consumption as well as the energy costs. Thus, both MPC and EMPC were selected for the design of the control strategies proposed in this thesis. Based on these approaches, the energy consumption of the whole manufacturing systems can be predicted using suitable process models, and according to the prediction of their behaviour, the peripheral devices can be managed for guaranteeing the proper operation of the whole systems.

(Q4) *How can manufacturing systems be addressed for the design of control strategies?*

For the design of control strategies that can be implemented in real time, first, the manufacturing industry was classified by levels as shown in Figure 2.3 and explained in Table 3.1. Thereby, three manufacturing levels were considered, i.e., machine, process line, and plant levels, viewing from the lower aggregation level (the machine) to the higher one (the plant). This classification is useful since it allows separating the large-scale manufacturing systems and makes them more treatable for designing management/control strategies with different temporal scales and control objectives. In addition to the classification by levels, the compositional elements of the manufacturing systems (at each level) were classified into machining and peripheral devices as it was discussed in the answer of *(Q2)* and presented in Assumption 5.1 in Chapter 5. Then, based on the different ways for improving the energy efficiency of manufacturing systems, and the size and complexity of such systems at each industrial level defined, control objectives of different nature are required. Thus, at lower levels, the control objectives were focused on reducing the total energy consumption of machines and process lines, such as presented in Chapters 5, 6 and 7. In contrast, at the plant level, in which the process planning and scheduling are performed, the goals are usually related to either improving the economics performance or maximising the plant profit, such as proposed in Chapter 8.

(Q5) *How to model the energy consumption of manufacturing systems for the design of control strategies that can be suitable for being implemented in real time?*

According to Chapter 4, different approaches have been studied to model the energy consumption of manufacturing systems and their main components. Most of these models have been mainly used to optimise the energy consumption of manufacturing devices during their designing stages. Among them, phenomenological-based models have been deeply addressed primarily in the design of new and improved devices by optimising the physical dimensions, the process parameters, or the operating conditions to reduce the energy consumption of such components. However, for the design of control strategies, this type of models could require a high computational burden to be implemented in real time.

Besides, the models based on physical phenomena usually require the accurate knowledge of a considerable number of variables and parameters, which are difficult to measure or estimate in a real factory/plant. In this regard, based on the advances in sensing technology and data management and processing, data-driven models have gained attention in manufacturing industry to model both their process dynamics and their energy consumption. Thus, based on the available information about the energy consumption of each machine, machining device, or peripheral device, the energy consumption of manufacturing systems can be modelled based on available data sets of the energy consumption from a manufacturing plant, such as the information available for the energy bills. Then, as shown in Chapter 4, the subspace identification algorithms were considered to model the energy consumption of manufacturing systems since they allow obtaining state-space realisations based on input-output data sets obtained using suitable sensing devices. Besides, it is well known that the state-space models are more suitable for the design of control strategies based on models. Thereby, selecting an appropriate sampling time to capture all behaviours of interest concerning energy consumption of manufacturing systems, proper energy consumption models can be identified for the design of control strategies with lower computational burden at each one of the considered industrial levels.

(Q6) How to design and implement an energy management/control strategy for manufacturing systems without affecting their productivity?

The productivity of manufacturing systems refers to the number of parts processed in a fixed period. Thereby, to design control strategies without affecting the productivity of manufacturing systems, first, the compositional elements of such systems were classified as machining devices and peripheral devices. Then, a control strategy to manage peripheral devices separately of machining sequences of each machine to keep them constant and to ensure that the machines in the plant can process the same number of pieces than when the control strategy is not implemented was introduced in Chapter 5.

Based on the considered classification for the compositional elements, the proposed control strategy determines the suitable activation/deactivation instants of peripheral devices according to the operational relationships among them and their related machining devices. The latter procedure is followed in order to guarantee the machine tools obtain the required resources at suitable instants to ensure the proper and continuous operations of all machines. In this regard, the control strategies proposed in Chapters 5 and 6 for both machine and process line level, respectively, were designed based on Assumption 5.1, from which the machining sequence and the time required to process a piece remain the same while the peripheral devices are managed. Besides, by using MPC, the energy consumption of the whole system and all the operational relationships among machines and peripheral devices are considered as the cost function and constraints of the optimisation problem behind the controller design.

(Q7) How to reduce the computational burden of centralised MPC-based architectures when large-scale manufacturing systems are studied?

As the aggregation degree of manufacturing systems increases, the size of such systems and the complexity of their operational relationships also significantly increase. In this regard, a dual control mode strategy is proposed in Chapter 6 to take advantage of the periodic behaviour of manufacturing systems and to switch from an MPC-based control mode to a different mode without online optimisation. Besides, non-centralised control architectures are introduced in Chapters 7 and 8 to compare their effectiveness, their closed-loop performance, and the computational burden concerning the obtained results for the centralised control architectures, such as the one presented in Chapter 6 for the process line level. First, manufacturing systems are divided into sub-systems, taking into account their coupled dynamics to split the centralised control problem into smaller problems solved locally for each sub-system. However, due to the dynamic coupling of such systems, there should exist communication among the local controllers to achieve the control objectives and satisfy the coupled constraints. Therefore, to reduce the computational burden, communication exchange among local controllers is limited to those controllers with coupled dynamics. Based on the results presented in Chapter 6, the computational burden can be significantly reduced if it is possible to detect a periodic behaviour for the operation of peripheral devices. Furthermore, as presented in Chapter 8, the implementation of non-cooperative control architectures can contribute in reducing the computational burden without strongly affecting the effectiveness and performance of the proposed control strategies.

(Q8) Can the non-centralised MPC-based approaches help to confer more flexibility to manufacturing systems while improving its energy efficiency?

Modularised and reconfigurable plant configurations can contribute manufacturing systems to respond faster to changes in the production programs or piece demand by substituting modules according to the new requirements instead of redesign all the production programs. These modules could be defined by grouping similar machining operations, complementary operations, or according to the physical distribution to minimise transport times. In this regard, by using non-centralised control architectures, defining local controller according to the operational modules and establishing proper communications schemes among them, the control systems of a manufacturing plant could also be modularised. The last fact allows that control systems could be suitably activated/deactivated and reconfigured according to the changes in production programs for processing pieces in the machines. Thus, when a local controller should be modified, using non-centralised architectures, each local controller could be updated without affecting the other controllers.

(Q9) How to improve the profit of a manufacturing plant taking advantage of available information about the energy market?

As shown in Chapter 8, at the plant level, control objectives are usually focused on either reducing the operational costs or maximising the added-value outputs of the plant by using economic cost functions. Thus, using the EMPC approach and including the information about the daily energy price profile and their fluctuations, energy costs might be minimised in real time even after defining the production programming of the plant. In this regard, in the second part of Chapter 8, a control strategy based on EMPC that take advantage of the fluctuations in the energy price was proposed. Thus, when the energy price decreases, the controller decides to produce more pieces or execute the production programs with higher energy consumption while trying to mitigate the total costs when unexpected increments in the energy price occur. Therefore, by using the available information regarding the energy market and its prices fluctuations, the plant profit can be improved designing control strategies that directly optimises the economic performance of a manufacturing plant.

9.3 Directions for Future Research

This thesis has been focused on how to improve the energy efficiency of manufacturing systems without affecting the plant productivity through the design of optimisation-based controllers in either centralised and non-centralised control architectures. However, there are still many open problems regarding the design and implementation of energy management/control strategies into the context of the new smart manufacturing. Some ideas for future directions are outlined below:

- Regarding the Algorithms 7.2 and 7.3 for both non-cooperative and cooperative control strategies, the adaptive procedure of defining the weighting matrices in the consensus stage could be improved considering both the energy consumption and the operational ranges for the process dynamics of the peripheral devices in a joint manner. It is given since the control objectives in this thesis are mainly focused on reducing energy consumption.

- The non-centralised control architectures were developed considering a fix sub-system partitioning based on the plant configuration. However, due to the transformation towards reconfigurable manufacturing systems, suitable methodologies for the time-varying system partitioning and the reconfiguration of the control systems could be tested and analysed to check the implementation viability of the proposed control strategies in such systems.

- Non-iterative methods could be tested to solve the distributed optimization problems faster than in the case of non-centralised control strategies proposed in this thesis. Besides, a better procedure to fit the convergence parameters of ADMM algorithm, i.e., ρ and the initialisation of λ^0, could be performed since in this work they were fitted by a trial and error procedure.

- It is well known that in manufacturing systems, the energy consumption profile of both devices and machines change along the time due to their wear or damage. Therefore, related to energy consumption models, a procedure to re-identify such models while the plant is operating should be developed and integrated. Thus, every time that the difference between the model and real output exceeds a threshold value, the SI algorithm should be rerun (possibly offline). Thereby, a new model based on the current energy consumption profile that takes into account the wear or damage of the devices and machines is obtained and updated into the controller.

- Maintenance tasks in the plant could be scheduled according to the faults identified in the plant, taking advantage of the procedure to detect when energy consumption models should be re-identified. Thus, the differences between the modelled and real energy consumption could also contribute to identifying the abnormal operation of devices and machines to schedule maintenance tasks well in advance to minimise the adverse effects on plant productivity.

- The contributions regarding the design of OBC strategies have been developed for linear systems since linear state-space realisations were obtained for energy consumption models, and the non-linear terms in the process dynamics related to the operation of peripheral devices were simplified. Thus, the proposed strategies could be extended to the non-linear case in which the nonlinearities in the process dynamics related to the operation of peripheral devices are considered.

Part IV

Appendices

APPENDIX A

MATRICES OF ENERGY CONSUMPTION MODELS

In Chapter 4, the way energy consumption models were obtained based on the test bench and using SI methods was presented. However, at the process line level, new energy consumption models were obtained using $\tau_s = 0.1$ s. The obtained model matrices are presented below.

A.1 Machines with the same T_{M_i}

- Model matrices for the 1-st machine with $T_{M_1} = 28$ s:

$$A_{M_1} = \begin{bmatrix} 0.6359 & -0.1838 & 0.05086 & -0.0541 & 0.002193 \\ 0.6793 & 0.3444 & -0.3249 & 0.04497 & -0.03021 \\ 0.1073 & 0.7592 & -0.1182 & -0.0395 & 0.586 \\ 0.1903 & 0.7731 & 0.7324 & 0.4395 & -0.349 \\ 0.1836 & 0.4071 & 0.5642 & -0.3085 & 0.5174 \end{bmatrix} \tag{A.1}$$

$$B_{M_1} = \begin{bmatrix} -0.00298 & 0.04056 & 0.005922 & 0.00809 \\ -0.02989 & -0.1384 & -0.02115 & -0.01427 \\ 0.1208 & -0.005341 & 0.02813 & -0.05182 \\ -0.02277 & 0.04464 & -0.0111 & 0.02418 \\ -0.02168 & 0.0144 & -0.01614 & 0.01853 \end{bmatrix} \tag{A.2}$$

$$C_{M_1} = \begin{bmatrix} 2323 & 912.6 & 426.5 & 695.5 & -60.91 \end{bmatrix} \quad D_{M_1} = 0 \tag{A.3}$$

- Model matrices for the 2-nd machine with $T_{M_2} = 28$ s:

$$A_{M_2} = \begin{bmatrix} 0.7325 & 0.21 & 0.006873 & 0.03084 & -0.0163 & -0.0004119 & 0.01072 \\ -0.6065 & 0.3775 & -0.3195 & 0.04666 & -0.1687 & 0.005885 & 0.1201 \\ -0.03711 & 0.7804 & 0.2524 & 0.02012 & 0.1486 & -0.271 & -0.181 \\ -0.04295 & 0.1089 & 0.6123 & -0.5457 & -0.3615 & 0.05965 & 0.3229 \\ -0.02771 & -0.1345 & 0.01392 & -0.1982 & -0.1145 & -0.7343 & -0.1242 \\ -0.01317 & 0.004019 & 0.07568 & 0.06458 & -0.5836 & 0.3465 & -0.7281 \\ -0.08859 & 0.1507 & 0.3688 & 0.2427 & 0.3726 & 0.4271 & 0.09172 \end{bmatrix} \tag{A.4}$$

$$B_{M_2} = \begin{bmatrix} -0.007007 & 0.01635 & 0.004062 & 3.286 \times 10^{-15} \\ 0.02134 & 0.1249 & 0.0211 & -8.884 \times 10^{-17} \\ -0.09391 & -0.05626 & -0.007111 & -1.004 \times 10^{-16} \\ 0.1139 & -0.03842 & -0.00385 & -1.594 \times 10^{-17} \\ -0.03278 & 0.05112 & 0.01736 & 1.637 \times 10^{-17} \\ -0.04206 & 0.03805 & 0.01406 & -5.453 \times 10^{-19} \\ 0.003614 & 0.006 & 0.006078 & 9.569 \times 10^{-19} \end{bmatrix} \tag{A.5}$$

$$C_{M_2} = \begin{bmatrix} 2584 & -748.7 & -686.8 & -224.1 & 38.59 & -17.05 & -292.7 \end{bmatrix} \quad D_{M_2} = 0 \tag{A.6}$$

- Model matrices for the 3-rd machine with $T_{M_3} = 28$ s:

$$A_{M_3} = \begin{bmatrix} 0.6359 & -0.1838 & 0.05086 & -0.0541 & 0.002193 \\ 0.6793 & 0.3444 & -0.3249 & 0.04497 & -0.03021 \\ 0.1073 & 0.7592 & -0.1182 & -0.0395 & 0.586 \\ 0.1903 & 0.7731 & 0.7324 & 0.4395 & -0.349 \\ 0.1836 & 0.4071 & 0.5642 & -0.3085 & 0.5174 \end{bmatrix} \tag{A.7}$$

$$B_{M_3} = \begin{bmatrix} -0.00298 & 0.04056 & 0.005922 & 0.00809 \\ -0.02989 & -0.1384 & -0.02115 & -0.01427 \\ 0.1208 & -0.005341 & 0.02813 & -0.05182 \\ -0.02277 & 0.04464 & -0.0111 & 0.02418 \\ -0.02168 & 0.0144 & -0.01614 & 0.01853 \end{bmatrix} \tag{A.8}$$

$$C_{M_3} = \begin{bmatrix} 2788 & 1095 & 511.8 & 834.6 & -73.1 \end{bmatrix} \quad D_{M_3} = 0 \tag{A.9}$$

A.2 Peripheral devices

- Model matrices for the delta-connection motor (P_{G_1}):

$$A_{G_1} = \begin{bmatrix} 0.2767 & -0.2891 & 0.009459 & 0.0004373 & 0.01101 & 0.001158 \\ -0.4725 & -0.04262 & 0.5009 & -0.001896 & -0.004211 & -0.0005016 \\ 0.6169 & -0.3929 & -0.1953 & -0.01401 & -0.07714 & -0.005914 \\ 0.4641 & 0.09513 & 0.794 & 0.2848 & -0.007988 & -0.04228 \\ -0.328 & -0.8366 & 0.2048 & -0.2702 & -0.9245 & 0.05518 \\ -0.06346 & -0.07257 & -0.2008 & 1.037 & 1.245 & 0.4445 \end{bmatrix} \tag{A.10}$$

$$B_{G_1} = \begin{bmatrix} -0.1333 & 0.1379 \\ -0.01909 & 0.06852 \\ 0.03028 & 0.1666 \\ 0.07546 & -0.1778 \\ -2.543 & 2.449 \\ 2.156 & -1.979 \end{bmatrix} \tag{A.11}$$

$$C_{G_1} = \begin{bmatrix} 146.2 & 657.8 & -241.3 & -1461 & -1300 & -1464 \end{bmatrix} \quad D_{G_1} = 0 \tag{A.12}$$

- Model matrices for the start-connection motor (P_{L_1}):

$$A_{L_1} = \begin{bmatrix} 0.6516 & 0.4684 & -0.1411 & 0.133 & 0.0298 & 0.02003 \\ -0.4772 & 0.7274 & 0.2483 & -0.2889 & 0.002229 & -0.001723 \\ -0.2171 & -0.1745 & -0.6648 & -0.5858 & 0.05864 & 0.03707 \\ -0.405 & -0.18 & 0.354 & 0.2391 & 0.1322 & 0.08848 \\ 0.02545 & 0.2399 & -0.0438 & -0.139 & -0.506 & 0.546 \\ -0.08759 & -0.25 & 0.01577 & 0.1762 & -0.7284 & 0.1577 \end{bmatrix} \tag{A.13}$$

$$B_{L_1} = \begin{bmatrix} 0.0718 & -0.06258 \\ -0.05692 & 0.04774 \\ 0.05255 & -0.05339 \\ 0.1729 & -0.1563 \\ 0.08786 & 0.1316 \\ -0.06282 & 0.03418 \end{bmatrix} \tag{A.14}$$

$$C_{L_1} = \begin{bmatrix} -1756 & -254.8 & -59.57 & 667.7 & 13.06 & 20.04 \end{bmatrix} \quad D_{L_1} = 0 \tag{A.15}$$

- Model matrices for UPS (P_{G_2}):

$$A_{G_2} = \begin{bmatrix} 0.778 & 0.1579 & -0.01131 \\ -0.5545 & 0.09045 & -0.162 \\ -0.03048 & 0.0825 & 0.9925 \end{bmatrix} \tag{A.16}$$

$$B_{G_2} = \begin{bmatrix} 3.614 \times 10^{-5} \\ 8.618 \times 10^{-4} \\ -3.222 \times 10^{-5} \end{bmatrix} \tag{A.17}$$

$$C_{G_2} = \begin{bmatrix} 785.7 & 16.09 & 30.85 \end{bmatrix} \quad D_{G_2} = 0 \tag{A.18}$$

A.3 Machines with different T_{M_i}

- Model matrices for the 1-st machine with $T_{M_1} = 36$ s:

$$A_{M_1} = \begin{bmatrix} 0.6221 & -0.189 & 0.06219 & -0.04441 & -0.03154 & 0.03574 \\ 0.66 & 0.3085 & -0.396 & 0.006705 & -0.06619 & 0.04316 \\ 0.1003 & 0.5231 & -0.2752 & -0.2951 & 0.4609 & 0.2251 \\ -0.001171 & 0.5212 & 0.1855 & 0.4084 & -0.2387 & -0.1068 \\ 0.08429 & 0.2675 & 0.2939 & -0.5832 & 0.4331 & -0.5827 \\ -0.1405 & -0.244 & -0.4531 & -0.4262 & -0.01461 & 0.294 \end{bmatrix} \tag{A.19}$$

$$B_{M_1} = \begin{bmatrix} -0.002645 & 0.03967 & 0.007252 & 0.01675 \\ -0.03788 & -0.1408 & -0.02827 & -0.01494 \\ 0.124 & 0.03522 & 0.01835 & -0.1138 \\ 0.006524 & 0.04902 & 0.0333 & 0.01568 \\ -0.03644 & 0.02931 & 0.03952 & 0.03016 \\ 0.003094 & 0.01858 & 0.03493 & -0.005426 \end{bmatrix} \tag{A.20}$$

$$C_{M_1} = \begin{bmatrix} 2150 & 859.7 & 441.3 & 542.4 & 389.8 & -906.1 \end{bmatrix} \quad D_{M_1} = 0 \tag{A.21}$$

- Model matrices for the 2-nd machine with $T_{M_2} = 22$ s:

$$A_{M_2} = \begin{bmatrix} 0.8122 & 0.1444 & 0.07154 & -0.009067 & 0.02995 \\ -0.5447 & 0.6381 & -0.3743 & -0.03961 & -0.06527 \\ 0.0826 & 0.7733 & 0.1676 & -0.1163 & 0.03395 \\ 0.2505 & 0.1025 & 0.2716 & 0.7077 & 0.7449 \\ -0.02584 & -0.2478 & -0.1302 & -0.1668 & -0.4874 \end{bmatrix} \tag{A.22}$$

$$B_{M_2} = \begin{bmatrix} 7.466 & -5.145 & -1.767 & -0.6868 \\ 10.75 & -7.336 & -2.534 & -0.9854 \\ -20.75 & 14.9 & 5.149 & 1.442 \\ 137.9 & -94.42 & -32.31 & -13.46 \\ -18.13 & 9.228 & 3.016 & 3.817 \end{bmatrix} \tag{A.23}$$

$$C_{M_2} = \begin{bmatrix} 1807 & -407.1 & 34.41 & -62.81 & -14.67 \end{bmatrix} \quad D_{M_2} = 0 \tag{A.24}$$

- Model matrices for the 3-rd machine with $T_{M_3} = 44$ s:

$$A_{M_3} = \begin{bmatrix} 0.6059 & -0.1486 & -0.01081 & 0.07929 \\ 0.7329 & 0.2724 & -0.2021 & -0.02237 \\ 0.1546 & 0.6038 & 0.6595 & 0.2604 \\ -0.04367 & -0.5062 & 0.01074 & 0.713 \end{bmatrix} \tag{A.25}$$

$$B_{M_3} = \begin{bmatrix} 0.009006 & 0.05006 & 0.01336 & 0.006815 \\ -0.04345 & -0.2421 & -0.00738 & -0.01753 \\ 0.02766 & 0.08551 & -0.03246 & -0.005898 \\ -0.007627 & -0.08222 & 0.01492 & -0.00536 \end{bmatrix} \tag{A.26}$$

$$C_{M_3} = \begin{bmatrix} 1846 & 755 & 509 & -621.3 \end{bmatrix} \quad D_{M_3} = 0 \tag{A.27}$$

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NOMENCLATURE

A list of the symbols used in this thesis is presented below.

Symbols

α_{v_1}	Constant energy consumption of valve v_1 when is 100% opened
α_{v_3}	Constant energy consumption of valve v_3 when is 100% opened
$\bar{\mathbf{S}}$	Integral of the energy consumption along H_p
$\mathbf{\Omega}_r$	Discrete and countable finite set
η	Pump efficiency
η_E	Energy efficiency
$\hat{x}$	Estimation of system states
$\mathbf{\Gamma}$	Sequence of $\mathbf{\Lambda_P}$ along H_p
$\mathbf{\Lambda_P}$	Activation sequence of peripheral devices
$\mathbf{\Lambda_{M_i}}$	Machining sequence of the i-th machine. Activation sequence of machining devices along T_{M_i}
$\mathbf{\Lambda_P^*}$	Optimal activation sequence of peripheral devices
$\mathbf{\Lambda_V^*}$	Optimal activation sequence for the valve apertures
$\mathbf{\Omega_j}$	Discrete set for u_{P_j}
$\mathbf{\Pi}$	Sequence of $\mathbf{\Lambda_V}$ along H_p
$\tilde{\mathbf{u}}_\mathbf{e}$	Feasible control input sequence in EMPC
$\tilde{\mathbf{u}}_\mathbf{e}^*$	Optimal control input sequence in EMPC
$\tilde{\mathbf{u}}$	Feasible control input sequence
$\tilde{\mathbf{u}}^*$	Optimal control input sequence
$\tilde{\mathbf{x}}_\mathbf{e}$	System state sequence related to $\tilde{\mathbf{u}}_\mathbf{e}$
$\tilde{\mathbf{x}}$	System state sequence related to $\tilde{\mathbf{u}}$
$\mathbf{D_{pk}}$	Distance vector among the first lag and the rest of the lags in $\mathbf{lc}$
$\mathbf{d}$	Vectors of disturbances in MPC

$\mathbf{lc}$	Vector of lags among the peaks of $\mathbf{ux_j}$
$\mathbf{pk}$	Peaks of in $\mathbf{ux_j}$
$\mathbf{S}^*$	Integral of the optimal energy consumption along H_p
$\mathbf{u_e}$	Vector of control inputs in EMPC
$\mathbf{u}$	Vector of control inputs in MPC
$\mathbf{u}^*_{EMPC}$	Control law from EMPC
$\mathbf{u}^*_{MPC}$	Control law from MPC
$\mathbf{v}$	Measurement noise vector
$\mathbf{w}$	State noise vector
$\mathbf{x_e}$	Vector of system states in EMPC
$\mathbf{x}$	Vector of system states in MPC
$\mathbf{y_{sp}}$	Set-point sequence in MPC
$\mathbf{y}$	Vector of system outputs in MPC
$\mathbf{ux_j}$	Vector of autocorrelation coefficients of signal $\hat{\mathbf{u}}_\mathbf{j}$
ω_S	Commutation indicator related to the energy consumption
ω_{Q_j}	Commutation indicator related to process dynamic Q_j
$\overline{ux}_j$	Maximum autocorrelation coefficient of $\mathbf{ux_j}$
ρ_c	Coolant density
τ_c	Time step for controller decisions along H_p
τ_s	Sampling time
Θ_h	Oblique projection
ε_{v_1}	Maximum flow of air provided through the valve v_1
ε_{v_3}	Maximum flow of air provided through the valve v_3
ξ_{M_i}	State vector of the energy consumption model for the i-th machine
ξ_{P_j}	State vector of the energy consumption model for the j-th peripheral device
A_{T_2}	Transverse area of T_2
A_{T_3}	Transverse area of T_3
d_{P_j}	Delay in time steps among u_{P_j} and $u_{2_{P_j}}$
E_d	Electrical power demand
E_{in}	Energy fed
G_1	Index for the global peripheral device 1
G_2	Index for the global peripheral device 2
H_p	Prediction horizon
H_s	Simulation horizon for MPC strategy
$h_{f_{1\rightarrow 2}}$	Energy losses by friction

$H_{p,c}$	Prediction horizon in the commutation protocol
J	Cost function
k	Discrete-time index
k	Discrete-time index
k_{saf}	Time steps corresponding to t_{saf}
L_1	Index for the Local peripheral device 1
L_2	Level of clean coolant in Tank 2
L_3	Level of dirty coolant in Tank 3
l_e	Economic cost function
$m_{c,M}$	Coolant demand from M_1 for the machine level
m_{cc}	Coolant flow pumped by P_2 to M_1 for the machine level
m_c	Flow of coolant pumped by $P_{G,2}$
M_{T_1}	Mass of air in Tank 1
M_{T_4}	Mass of air in Tank 4
m_{tool}	Coolant demand from tools in M_1 for the machine level
m_{wp}	Coolant demand for the work piece processed by M_1 for the machine level
m_{ccl,M_i}	Demand of coolant required from M_i
m_{dcl,M_i}	Flow of dirty coolant recovered from M_i
N	Model order by SI methods
n_i	Dimension of vector $i = x, u, d$
N_u	Time to start running periodicity detection
N_{wp}	Number of produced pieces
O_i	Extended observability matrix
P_{in}	Input pressure in the pipe system
P_{out}	Output pressure in the pipe system
P_{T_1}	Pressure of air inside Tank 1
P_{T_4}	Pressure of air inside Tank 4
Q_{P_j}	State vector of the process dynamic related to the j-th peripheral device
R	Gas constant
S	Total power consumption
S_{M_i}	Instantaneous power consumption of the i-th machine
S_{P_j}	Instantaneous power consumption of the j-th peripheral device
S_P	Total energy consumption of all peripheral device
S_{v_1}	Energy consumption related to the valve v_1
S_{v_3}	Energy consumption related to the valve v_3

T	Temperature
t	Continuous time
t_c	Computational time spent per iteration
T_s	Simulation time
T_{M_i}	Operation cycle of the i-th machine
$T_{M_{i,l}}$	Operation time of the l-th machining device of the i-th machine
T_{P_j}	Execution time of the j-th peripheral device
t_{saf}	Safety time for activation/deactivation of peripheral devices
T_{u_j}	Period of the j-th peripheral device
u_b	Vector of binary inputs
u_r	Vector of discrete inputs
$u_{2_{P_j}}$	Delayed input signal with respect to u_{P_j}
$u_{M_{i,l}}$	Activation/deactivation signal of the l-th machining device of the i-th machine
u_{P_j}	Activation/deactivation signal of the j-th peripheral device
v_1	Valve aperture related to the peripheral device G_1
v_3	Valve aperture related to the peripheral device L_1
V_m	Volume of removed material
V_{T_1}	Volume of Tank 1
V_{T_4}	Volume of Tank 4
W	Work supply to the pump
W_{air}	Molecular weight of the air
M_i	Index for the i-th machine
m_{air,M_1}	Demand of airflow from M_1
m_{air,M_i}	Consumption of air from the i-th machine
$m_{in,a}$	Air flow pumped by P_1 to M_1 for the machine level
m_{in}	Air flow pumped by P_{G_1} or P_{L_1}
$m_{out,a}$	Air demand from M_1 for the machine level
$m_{G_{1M_1}}$	Airflow pumped from P_{G_1} to the 1-st machine
$m_{L_{1M_1}}$	Airflow pumped from P_{L_1} to the 1-st machine