UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH

PhD program in Construction Engineering

Building Information Modeling for Facility Managers

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Barcelona, September 2022

Acknowledgment

First, I would like to express my sincere gratitude to my advisor Prof. Núria Forcada for her patience, motivation, immense knowledge, and valuable supervision throughout my PhD studies. I have been extremely lucky to have an advisor who supported me so much not only in my work but also in molding my professional life. She kindly offered me many opportunities to improve my academic career and thus follow my dream to become a professor. I can never repay you for your remarkable contribution to my growth and development.

I would like to gratefully acknowledge my colleagues and friends in Universitat Politècnica de Catalunya as well as other universities throughout the world with whom I have worked. I would like to thank all my Spanish and Iranian friends, and all members of the Group of Construction Research and Innovation (GRIC) for their assistance. I also want to express my gratitude to Prof. David J. Edwards for his valuable and constructive suggestions during the development of the research work.

To my father Malak, my mother Zari, and my siblings, thank you for your love, support, and unwavering belief in me. Without you, I would not be the person I am today.

Also, I would like to express my deepest gratitude to my wife Rezvan for her unconditional love, constant support, and for putting up with me writing one more paper. Thanks for being my best friend. I owe you everything.

I acknowledge the funding received towards my PhD from the Government of Catalonia, Agència de Gestió d'Ajuts Universitaris i de Recerca (AGAUR), under Grant 2019 FI_B00064. Moreover, this thesis has been partially supported by funds from the City Hall of Terrassa (Spain), for which I am grateful.

Summary

A Decision Support System (DSS) can help facility managers to improve building performance, occupants' comfort, and energy efficiency during the Operation and Maintenance (O&M) phase. These DSSs are normally data-intensive and have specific data requirements. Building Information Modeling (BIM) has the potential to advance and transform facilities O&M by providing facility managers with a digitalized virtual environment that allows them to retrieve, analyze, and process such data. However, the implementation of BIM in O&M phases is still limited. The majority of issues in the BIM-O&M context lie in the interoperability between different software that requires different data structures and formats. In a BIM environment, there are issues associated with extracting, storing, managing, integrating, and disseminating data so that interoperability is assured.

Considering the aforementioned aspects, the aim of this thesis is to enable interoperability between BIM models and the DSSs for building performance aspects such as building condition, maintenance, and occupants' comfort. This integration automatizes the data transfer process which can assist Facility Management (FM) team in properly establishing the necessary measurements to moderate the negative consequences on buildings and thereby improve their performance and occupants' comfort. The approach can also provide FM teams with an effective platform for data visualization in a user-friendly manner that can assist in integrating digital insights into FM decision-making processes and converting them into positive strategic actions. The proposed approach is validated in existing software as a case study. It is possible to demonstrate the applicability of this approach by ensuring that its interactions and outcomes are feasible using case studies. Case studies also identify how much the task efficiencies are in comparison with the manual method, helping facility managers to optimize operation strategies of buildings in order to enhance their performance. Verification tests are also performed on the information exported from a software program.

The results demonstrate an efficiency increase in high-quality FM data collection for different kinds of DSS, reducing the time and effort that the FM team spends on searching information and entering data. A Dynamo script is designed to allow administrators to include as much information as they wish in BIM models. Moreover, a novel approach is proposed to create a new category in BIM to assist public and business administrations with managing assets efficiently. In addition, building performance aspects can also be analyzed using the proposed method of integrating occupants' feedback into BIM models. By implementing the proposed approach, FM teams are able to correctly establish measurements which can be applied to mitigate the negative effects on buildings, thus improving their performance and enhancing their occupants' comfort. Besides, the proposed approach enables BIM to be a more useful tool for visualization by using the most appropriate charts and formatting options to display data in a very sensible manner, guiding decision-makers in addressing building operational issues.

Keywords: Building Information Modeling (BIM), Decision Support System (DSS), Facility Management (FM), building performance, building condition, occupants' comfort, maintenance management, data integration, probabilistic models, Bayesian networks, visualization.

Contents

List of Acronyms

AECO	Architecture, Engineering, Construction and Operation
AR	Augmented Reality
BEMS	Building Energy Management System
BIM	Building Information Modeling
BMS	Building Management System
BN	Bayesian Network
CAD	Computer-aided Design
CEN	European Committee for Standardization
CMMS	Computerized Maintenance Management Systems
COBie	Construction Operations Building information exchange
FM	Facility Management
FMEA	Failure Mode and Effect Analysis
FTA	Fault Tree Analysis
GIS	Geographic Information System
HVAC	Heating, Ventilation, and Air-Conditioning
IDM	Information Delivery Manual
IEQ	Indoor Environmental Quality
IFC	Industry Foundation Classes
IFMA	International Facility Management Association
ISO	International Organization for Standardization
KPI	Key Performance Indicator
LOD	Level of Development
MC	Markov Chain
MVD	Model View Definition
NBIMS	National Building Information Modeling Standard
O&M	Operation and Maintenance
PAS	Publicly Available Specification
POE	Post-Occupancy Evaluation
RFID	Radio-Frequency Identification
XML	eXtensible Markup Language

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Chapter 1

Introduction

This chapter provides an introduction to the thesis, which is focused on the BIM implementation at O&M phases. This chapter outlines the problem, describes the research aim and objectives, and provides an outline of the scope and limitations of this study, as well as the overall structure of the dissertation.

1.1 Problem statement

In the life cycle of a project, the operation and maintenance (O&M) phases are critically important. Compared with other phases, the highest costs occur during the O&M phase (Rafael Sacks, Eastman, Lee, & Teicholz, 2018), which shows the importance of Facility Management (FM) activities. In the broad context of FM, building maintenance is generally recognized as the main activity, since more than 65% of the total cost of FM comes from facility maintenance management (W. Chen, Chen, Cheng, Wang, & Gan, 2018). In O&M phase, the FM team and owners are responsible for the upkeep of building elements/systems to prevent functional failures by applying corrective and preventive maintenance plans with the aim of achieving energy efficient and improving occupants' comfort (Chiantore, P. V.; Papaecomou, V.; Degner, 2018; H. Alavi, Forcada, Bortolini, & Edwards, 2021). For buildings to remain in appropriate conditions for use and to meet a minimum standard or level of performance, they require continuous operating expenses, including periodic maintenance (Grussing & Liu, 2014). A poorly maintained building will deteriorate even faster in the long run (Heo, Choudhary and Augenbroe, 2012). Hence, the lack of a proper maintenance plan along with the building's natural aging accelerates the degradation of existing buildings (Bortolini & Forcada, 2020; Garyaev & Ayoub, 2020).

Among the building systems, the HVAC systems have a significant impact on thermal comfort and, if it is improperly maintained, may result in health problems, and discomfort for occupants (Yang & Ergan, 2016). The occupants' comfort within buildings is essential in terms of environmental, social, and economic aspects, (Nawawi & Khalil, 2008) since people spend approximately 90% of their time indoors (Klepeis et al., 2001; El-Sharkawy, 2014; Ferreira & Cardoso, 2014). In addition, the HVAC systems account for one of the highest percentage of energy use in a building (Fadzli Haniff, Selamat, Yusof, Buyamin, & Sham Ismail, 2013; Pritoni, Salmon, Sanguinetti, Morejohn, & Modera, 2017). The use of HVAC energy in unoccupied spaces is sometimes higher than in occupied spaces in commercial buildings (Martani, Lee, Robinson, Britter, & Ratti, 2012). Moreover, standards based on indoor environmental quality (IEQ) factors are used to define the acceptable ranges of comfort (S. Wang, Yan, & Xiao, 2012). However, due to the variations in individual sensation levels, there is a poor relationship between the comfort conditions defined in the standards and those perceived by the occupants (Wagner, Gossauer, Moosmann, Gropp, & Leonhart, 2007). It is therefore necessary to put occupants at the center of maintenance decisions through the implementation of an occupant-centric approach by collecting occupants' feedback to improve building performance, including occupants' comfort and productivity (Mallory-Hill, Preiser, & Watson, 2012).

To improve building performance based on occupant-centric approach Decision Support Systems (DSS) can be used, making decisions in an early design development stage and during the O&M phase. The former helps designers to identify multiple technical and commercial options that are compliant with pre-determined specifications and the latter help facility managers to optimize building operations techniques (Corneli, Meschini, Villa, Di Giuda, & Carbonari, 2017). The DSS for maintenance activities with the appropriate information, modeling, and planning can have a significant impact on occupants' comfort as well as building performance, allowing buildings to maintain serviceability before deterioration propagates, prevent defects and failure of the building elements, extend their service life (Wong, Ge, & He, 2018; Wu & Lepech, 2020). Various types of historical data, including inspection records, and sensor data, are frequently used by the FM team to make decisions on building condition assessment, HVAC problems analysis and occupants' comfort evaluation (El Ammari & Hammad, 2019). Some building maintenance systems, like computerized maintenance management systems (CMMS) are typically used for capturing such data to perform maintenance activities (Motamedi, Hammad, & Asen, 2014). However, the current systems are based on deterministic models (Catalina & Iordache, 2012; Agha-Hossein, El-Jouzi, Elmualim, Ellis, & Williams, 2013) and do not take into account the effects on occupants' comfort of building information (e.g., building characteristics) and spatial information (e.g., occupancy density) (Van Gelder, Janssen, & Roels, 2014; J. Chen, Augenbroe, Wang, & Song, 2017). Some factors such as climate conditions and building operational conditions are intrinsically uncertain, making accurate predictions of building performance difficult (Holmes & Hacker, 2007). It is therefore essential to increase predictability by incorporating these uncertainties in order to identify strategies and methods to improve the performance of buildings and occupants' comfort (Douglas, Ransom, & Ransom, 2013).

To incorporate these uncertainties, Bayesian Networks (BN) can be used. BN are a type of probabilistic graphical model that provide a formalism for reasoning about partial beliefs under conditions of uncertainty (Neuberg, 2003). It is considered a powerful tool by which to model risks with uncertainty data (Langevin, Wen, & Gurian, 2013; Nguyen, Tran, & Chandrawinata, 2016; Seungjae Lee, Bilionis, Karava, & Tzempelikos, 2017). BN can model building comfort as a probabilistic process, to give the most probable performance level of a building using probability distributions (Bortolini & Forcada, 2019a). In addition, it can model a building's condition as a probabilistic process, contrary to deterministic models (Bortolini & Forcada, 2019b). Bortolini and Forcada (Bortolini & Forcada, 2019b) developed a probabilistic model based on BN that covers several interconnected elements for assisting decision-making on building maintenance and retrofitting measures to improve building conditions and support occupants' comfort (Bortolini & Forcada, 2019a). Although the models can handle uncertainty and make predictions, the data that is required is dispersed among platforms. Besides, the data is transferred manually, which is a laborious, inefficient process (Cavka, Staub-French, & Poirier, 2017; Roberts, Edwards, Hosseini, Mateo-Garcia, & Owusu-Manu, 2019; H. Alavi, Forcada, Bortolini, et al., 2021).

To address the challenges of data reliability and automatize the data transfer process, a Building Information Modeling (BIM) has been emerging as a potential solution (Cavka et al., 2017; H. Alavi, Forcada, Fan, & San, 2021) for guiding decision-makers concerning building maintenance. BIM is "an approach to design, construction, and facilities management, in which a digital representation of the building process is used to facilitate the exchange and interoperability of information in digital format" (R. Sacks et al., 2018). BIM constitutes an effective platform by which to depict high-quality information and integrate different platforms. BIM utilizes 3D, parametric and object-based models to create, store and use coordinated and compatible data throughout the life cycle of a facility (B Becerik-Gerber, Jazizadeh, Li, & Calis, 2012). Acting as a central resource for decision-makers, BIM has the ability to provide better documentation, improved collaboration and work flexibility, and updated information through the building life cycle (Volk, Stengel, & Schultmann, 2014; H. Alavi, Forcada, Bortolini, et al., 2021). BIM integrated with a DSS, may constitute a powerful tool to support the selection of effective maintenance strategies (A. Carbonari, Giretti, Corneli, Villa, & Di Giuda, 2017; Alessandro Carbonari, Corneli, Di Giuda, Ridolfi, & Villa, 2019). Nevertheless, the greatest obstacle of the integration of BIM with a DSS is the lack of interoperability in the O&M context (S. H. Alavi & Forcada, 2019; Gao & Pishdad-Bozorgi, 2019). The interoperability issue caused a delay in transferring the FM information into DSS during O&M phase even though the required data is available in the BIM model (Pishdad-Bozorgi, Gao, Eastman, & Self, 2018). It is estimated that inadequate interoperability and incompatibility between systems result in a $15.8 billion total increase in project costs, according to a study conducted by the National Institute of Standards and Technology (Gallaher, O'Connor, Dettbarn, & Gilday, 2004).

To address the interoperability issues, this thesis presents a conceptual model to integrate BIM models into DSS (e.g., the probabilistic models based on BN). This thesis focuses on improving both maintenance efficiency, and occupants' comfort by integrating DSS into BIM to optimize building operation strategies and support decision-making on FM activities. This integration facilitates data transfer and reduces the time and effort that the FM team spends on manual input. It also allows BIM tools to visualize in an integrated, interactive way for decision-makers. Moreover, the FM team can make decisions on building operational problems centered on occupant comfort with minimal effort, overcoming a key barrier to collecting required information during the O&M phase.

1.2 Aim and Objectives

The primary aim of this thesis is to enable the interoperability between DSS and BIM for the O&M phase, allowing an efficient building performance and supporting FM activities.

The objectives for this thesis are the following:

Objective 1: Identify and analyse shortcomings of the implementation of BIM in the O&M phase.

Objective 2: Identify and devise a solution for generic interoperability problems.

Objective 3: Develop a conceptual model to enable interoperability between BIM models and probabilistic models.

Objective 4: Establish an effective platform for data visualization.

Objective 5: Evaluate the conceptual model.

1.3 Scope of the research, limitations, and delimitations

The scope of this research includes the development of a conceptual model to enable interoperability between BIM models and the DSS for building performance. It also includes the visualization of building condition, and occupants' comfort during O&M phase. The BIM visualization is designed in a user-friendly manner that can assist facility managers in incorporating digital insights into FM decision-making processes and converting these insights into effective strategic actions. Nevertheless, other FM activities (e.g., energy management) are out of the scope of this thesis.

Facility managers are in charge of the performance management of the buildings to evaluate and prioritize building renovations. Various stakeholders (e.g., owner, occupants) are involved in different types of buildings such as Business (e.g., offices, banks), Educational (e.g., schools, universities), and Mercantile (e.g., department stores, markets). Residential buildings and certain types of non-residential buildings, such as hospitals are outside of this investigation due to their strict requirements and characteristics.

A generic integration model is developed but only implemented in one specific Risk analysis (AgenaRisk) and BIM software (Revit). This is a limitation of this research and different Python code blocks are required to implement it in other software.

In addition, the proposed approach is limited regarding the complexity of building elements. For example, while the façade can be defined by the exterior wall at each level, it cannot be presented by each individual room to evaluate building performance for the specific room. In this case, Dynamo scripts should be developed to deal with evaluating the performance of each room.

The methodology of integration is semi-automated because a user is recommended between each step of extraction to ensure that the exported files are stored in the right location with the correct names. BN results, for example, can only be read by Python scripts in the BIM model if their names and locations are matched.

Moreover, set of characters defining a search pattern in a Python code block, are designed to create a new category in BIM. This approach relies on text to execute pattern matching and search-and-replace operations; therefore, it could be adapted to specific contexts and purposes as needed

The use of Augmented Reality (AR) to improve the usability and accessibility of BIM information, is also proposed. Consequently, AR can be used to provide a superimposed geometric representation over the physical space along with the relevant BIM-based FM information. However, the programming tasks and technical specifications of data integration are out of the scope of this thesis.

1.4 Thesis structure

This thesis is structured in eight chapters as follows:

Chapter 1 describes a background to the problem, provides an overview of the aims and objectives of the research study, and outlines the scope of the study as well as its limitations and delimitations.

Chapter 2 presents the state of the art about facility management, DSS, BIM and AR.

Chapter 3 provides a description of the research method, including the steps involved in the BIM integration.

Chapter 4 details the work undertaken to develop the DSS, identify relevant data, indicators and provides a BIM integrated with DSS for detecting the root cause of HVAC problems.

Chapter 5 details the work undertaken to develop the DSS, identify relevant data, indicators and provides a BIM integrated with DSS for assessing building condition.

Chapter 6 details the work undertaken to develop the DSS, identify relevant data, indicators and provides a BIM integrated with DSS for enhancing occupants' comfort.

Chapter 7 presents the main conclusions of this thesis and its contributions both on a theoretical and practical level. Potential future research topics are also discussed.

The outline of this thesis is illustrated in Figure 1.

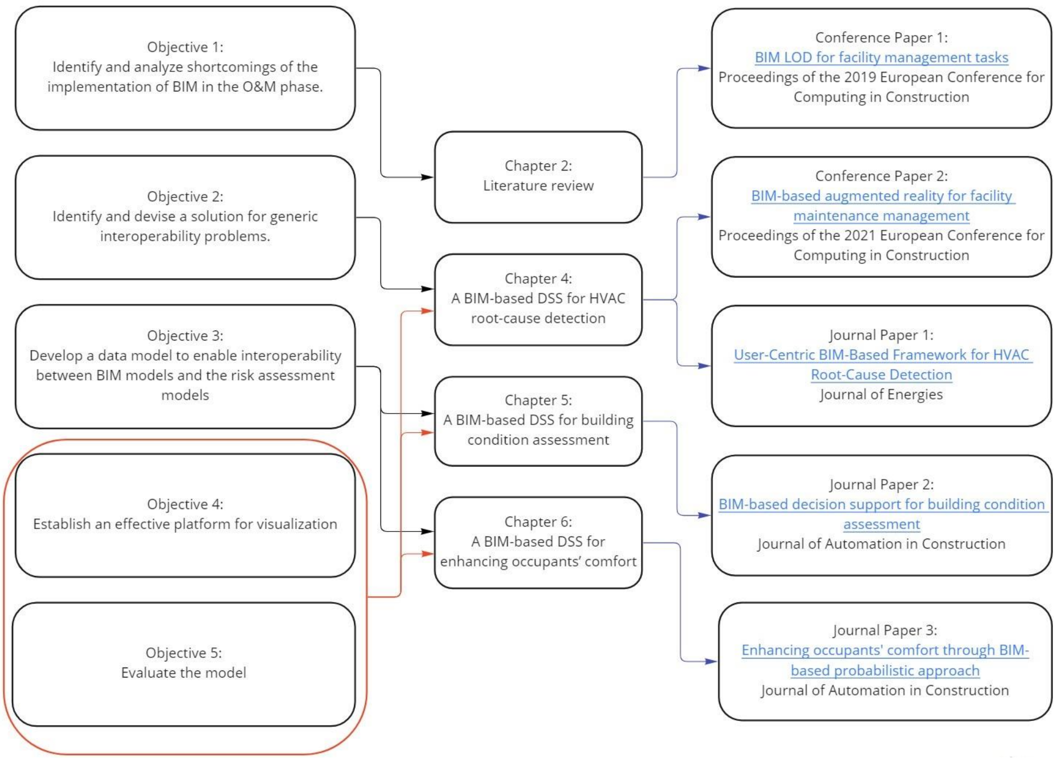


Figure 1. Thesis outline

Chapter 2

State of the art

This chapter presents a complete literature review carried out to gather the existing knowledge within the subject of research. First, the concept of DSS is explained followed by the explanation of facility management and probabilistic models. Then, the applications of BIM for O&M phase and the need for the integration of BIM and DSS are discussed. The BIM information standards for addressing interoperability during O&M, are presented. Furthermore, benefits of the implementation of Augmented Reality to evaluate building performance and occupants' comfort are discussed. Finally, the complexity of the research subject is summarized, establishing the basis for this thesis.

2.1 Decision Support System

2.1.1 DSS concept

A DSS is "a computer-based information system that supports either a single decision-maker or a group of decision-makers when dealing with unstructured or semi-structured problems. A DSS supports one or more decision-making activities carried out in a decision process. Moreover, it mainly supports managerial tasks at different levels and is intended to improve the effectiveness of the decision-making process (e.g., timeliness, accuracy, and quality) (O'Sullivan, 1985; Liang, Lee, & Turban, 2008).

A DSS may offer assistance for both multiple independent and interdependent choices. The decision-makers should engage with a DSS actively, which means they initiate every instance of their use and are in control of all aspects of the decision-making process. In addition, the decision-makers can be trained to perform better in upcoming decision-making circumstances, thanks to a DSS with the capability of learning from the past (O'Sullivan, 1985; Liang et al., 2008). A DSS enables decision-makers to cope with changing conditions; therefore, it should be adaptable and flexible in order to meet their requirements. The following are the benefit of using a DSS (Power, 2002; Liang et al., 2008): 1) Improve individual productivity; 2) Improve decision quality and problem solving; 3) Facilitate interpersonal communication; 4) Improve decision-making skills; 5) Increase organizational control.

2.1.2 DSS and facility management

The building industry began to face pressure in the 1980s from government institutions, clients, and increased international competition to improve the quality of their buildings, increase their construction speeds, and reduce their costs (de Wilde, 2018). This pressure led to the emergence of the new discipline of Facilities Management (FM) (Cohen, Standeven, Bordass, & Leaman, 2001). The International Facility Management Association (IFMA, 2015) defines FM as "a profession that encompasses multiple disciplines to ensure functionality of the built environment by integrating people, place, process and technology", illustrated in Figure 2.

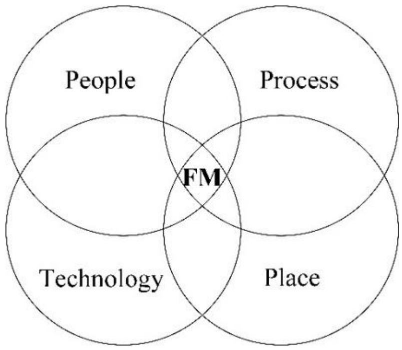


Figure 2. Facility Management (Source: IFMA, 2015)

Figure 3 illustrates the organizational levels of FM. Strategic, tactical, and operational processes are a set of processes with which FM team ought to deal (CEN, 2011). The main objective of FM is the operational level (Chotipanich, 2004) which consists various tasks such as maintenance management, asset managemen, energy management, safety management, security management, and user satisfaction. In the operational level, this study focuses on maintenance management and occupants' comfort which are the main activities of facility managers (W. Chen et al., 2018). This operational role assists in meeting an organization's fundamental routine and regular demands (CEN, 2011). The performance of any building depends on the FM's ability to operate effectively and provide a productive working environment (Chotipanich, 2004). Operators monitor the efficiency of the building and notify senior management of any performance discrepancies (Ruparathna, Hewage, & Sadiq, 2017). This involves gathering data through the measurement of physical characteristics (e.g., CO2 level), gathering user perceptions (e.g., the perceived level of thermal comfort), or combining both (Talamo & Bonanomi, 2015; Lai & Man, 2017). A number of documents (e.g., drawings, plans, data sheets) contains this data which could lead to time-consuming tasks to locate and validate data during O&M phase. Furthermore, facility managers utilize different types of systems such as Building Management System (BMS) and Computerized Maintenance Management System (CMMS) to operate and manage buildings. However, information obtained from FM systems may be scattered, unconnected, managed by different teams, and not readily available (Shalabi & Turkan, 2017). Therefore, this data need to be stored in a mixture of electronic formats such as electronic documents, drawings, file folders of management and maintenance records (P. E. D. Love, Matthews, Simpson, Hill, & Olatunji, 2014; Pishdad-Bozorgi et al., 2018). In addition, while FM information systems are complicated and supply high quality data, they do not provide interoperability and visualization capabilities to support FM needs (Shalabi & Turkan, 2017).

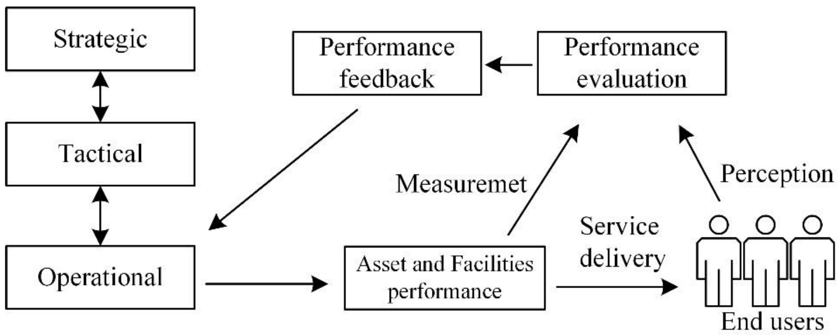


Figure 3. Organizational levels of FM (based on CEN 2011; Lai and Man 2017)

Regarding maintenance management, there are some challenges in current FM practices that have required a paradigm shift in the sector in recent years. Clients are demanding strategies for predicting events instead of responding to problems (Wong et al., 2018). This shift marks the transition from corrective or planned strategies to preventive and predictive strategies. For instance, the failure of building elements can be predicted by preventive maintenance through an analysis of condition data and historical maintenance records. This increases their efficiency, reliability and safety (Gunay, Shen, & Yang, 2019).

In this case, a DSS can be utilized to assist facility managers in optimizing building operations techniques (Corneli et al., 2017). The DSSs are becoming increasingly important for assessing and controlling building performance and a variety of methods have been used to support multi-criteria decision making. For example, Matos et al. (Matos, Rodrigues, Rodrigues, & Costa, 2021) prioritized maintenance actions, using Key Performance Indicators (KPI) and DSS to support decision-making on building performance. The term performance implies that the buildings should meet the requirements of occupants, providing a conducive, safe, comfortable, healthy and secure indoor environment to carry out different activities, including work, study, leisure, family life, and social interactions (Bakens, Foliente, & Jasuja, 2005; Ibem, Opoko, Adeboye, & Amole, 2013).

2.1.3 DSS and probabilistic models

Risk is traditionally defined as a combination of the probability (or likelihood) of something occurring as well as its positive and negative consequences (Duffuaa & Ben-Daya, 2009; Weber, Medina-Oliva, Simon, & Iung, 2012). The ISO 31010:2009 defines risk assessment as "that part of risk management which provides a structured process that identifies how objectives may be affected, and analyses the risk in term of consequences and their probabilities before deciding on whether further treatment is required". A risk assessment is intended to provide evidence-based information and analysis to enable informed decisions to be made regarding how to mitigate particular risks and how to decide between alternative approaches to mitigation (ISO 31010:2009).

In maintenance activities, well-known probability techniques include the Fault Tree Analysis (FTA), Markov chains (MCs), Failure Mode and Effect Analysis (FMEA), and Bayesian Networks (BNs) (Weber et al., 2012; Chemweno, Pintelon, Van Horenbeek, & Muchiri, 2015). Among them, BN (a type of probabilistic graphical model) has a much more flexible structure (Khakzad, Khan, & Amyotte, 2011). In a reasoning process, the BN can represent complicated linkages among building elements and systems, and qualitatively and quantitatively characterize variable dependencies. It also models multi-state variable and evaluates several output variables in the same model (Weber et al., 2012). In complex processes, BN provides an easy way to calculate the joint probability distribution of all variables involved (Celeux, Corset, Lannoy, & Ricard, 2006). Hence, incorporating BN into a DSS can have a significant effect on making decisions in the context of building performance since facility managers generally face the challenge of uncertain or incomplete information. The probabilistic models for improving building condition and enhancing occupants' comfort are considered in this study.

During the O&M phase, some studies developed probabilistic models for improving building condition. Frederik et al. (Auffenberg, Snow, Stein, & Rogers, 2017) created a probabilistic model that learns from user feedback and adapts to the users' specific preferences over time to analyze building conditions. Yang et al. (Y. Zhao, Wen, Xiao, Yang, & Wang, 2017) developed a probabilistic model based on a comprehensive survey of air handling unit (AHU) fault detection and diagnosis methods. Lee et al. (Seungjae Lee et al., 2017) developed a Bayesian method for probabilistic occupant thermal preference categorization and prediction in office buildings, to provide predictions for personalized thermal preference profiles. Furthermore, Bortolini and Forcada (Bortolini & Forcada, 2019b) developed a model for assessing the condition of a building using a Bayesian network (BN) method. They utilized TNormal distribution to determine the probability distribution which is a suitable distribution when the mean (μ) and variance (σ^2) are determined and it allows for the creation of many distribution forms (Fenton & Neil, 2018). The BN structure was constructed by identifying the causal relation between the variables based on the data available and expert judgment. A panel of experts provided feedback on the causal relations constructed by data, which helped to identify key variables or processes that were overlooked and fix potential errors of the model. Conditional probability tables for the variables can be consulted in (Bortolini & Forcada, 2019b).

Moreover, other studies developed the probabilistic models for improving occupants' comfort. Yang et al. (Y. Zhao et al., 2017) developed a probabilistic model based on a comprehensive survey of air handling unit (AHU) fault detection and diagnosis (FDD) methods. Zhe et. al. (Z. Wang & Hong, 2020) used Bayesian inference approach to derive new occupant comfort temperature ranges for U.S. office buildings using the ASHRAE Global Thermal Comfort Database. Lee et al. (Seungjae Lee et al., 2017) developed a Bayesian approach for probabilistic classification and inference of occupant thermal preferences in office buildings to provide predictions for personalized thermal preference profiles. Frederik et al. (Auffenberg et al., 2017) created a probabilistic model to learn from a user's feedback, allowing it to adapt to the users' individual preferences over time to assess occupants' comfort.

Despite the fact that these researchers have made a significant contribution to the improvement of building condition and occupants' comfort, none of them automatized the data transfer process or integrated BIM into their probabilistic models, which would facilitate data transfer due to the interoperability issues (Burcin Becerik-Gerber, Asce, Jazizadeh, Li, & Calis, 2012). Another obstacle is that the data is not processed and analyzed in a way that the decision-makers need and not visualized in an easily accessible, and refined way (Motawa & Almarshad, 2013; Motamedi et al., 2014).

2.2 Building Information Modeling

2.2.1 BIM concept

Building Information Modeling (BIM) is a technology-driven methodology used to improve performance and efficiency during the design, construction, operation and maintenance of assets (P. E. D. D. Love, Simpson, Hill, & Standing, 2013). The National BIM Standard (NBIMS-US™, 2015) defines BIM as "a digital representation of physical and functional characteristics of a facility and as such it serves as a shared knowledge resource for information about a facility forming a reliable basis for decisions during its life cycle from inception onwards". The key idea for understanding BIM is the concept of parametric objects and its differentiation from traditional 2D objects (Eastman et al., 2008).

The main applications of BIM processes and technologies include: 3D visualization of the project; cost estimations; conflict interference and collision detection (C. Eastman et al., 2008); visualization of quality risks in construction projects (Forcada et al., 2014); site logistics planning and construction sequencing planning (Bortolini, Shigaki and Formoso, 2015); and facilities management (Cavka et al., 2017; Pishdad-Bozorgi et al., 2018).

2.2.2 BIM for O&M

In order to enable BIM functionality for O&M stage, widely diverse kind of data are essential (B Becerik-Gerber et al., 2012). According to and Nicolle and Cruz (2011), detailed data is also required for installed component in buildings. These kind of data might not be available in many existing buildings due to imperfect and deficient, obsolete or disintegrated building information(Gursel, Sariyildiz, Akin, & Stouffs, 2009). Becerik et al. (2012) defined application areas for enabling BIM for FM and revealed that each one of these areas demanded precise data requirements. For instance, Maintenance management is an example of FM activities which leads to not only reduce the cost of maintenance and plan the preventive maintenance, but also has a positive impact on the productivity of occupants. The importance of BIM in O&M buildings has been analyzed by Mayo et al. and Thabet et al. (2016) and several case studies were used to reinforce that BIM can facilitate decision making during this stage (Akcamete, Akinci, & Garrett, 2010; Sattenini, Azhar, & Thuston, 2011). Other researchers categorized FM data and products to help the transfer of design data to the handover stage (Pishdad-Bozorgi et al., 2018). The significant difference between enabling BIM for FM in new buildings and existing buildings is the lack of as-built , CAD files as well as insufficient and outdated information of the buildings (Gursel et al., 2009; B Becerik-Gerber et al., 2012). Missing this kind of information might lead to ineffective building management, uncertain process results and time loss or cost increases in FM processes.

Efforts to extend BIM beyond the design and construction phases of the buildings are significant. Researchers focus on implementing BIM in O&M phase for different FM activities, such as: maintenance of warranty and service information (Arayici, 2008; Singh, Gu, & Wang, 2011; Haidar Hosamo Hosamo et al., 2022); quality control (Boukamp & Akinci, 2007; Choi & Lee, 2018); asset management and monitoring (Arayici, 2008; B Becerik-Gerber et al., 2012; S. H. Alavi & Forcada, 2019); energy management (Dave, Buda, Nurminen, & Främling, 2018; H. Wang, Pan, & Luo, 2019; H. Alavi & Forcada, 2022); sustainability (Barnes & Castro-Lacouture, 2009; R Sacks, Treckmann, & Rozenfeld, 2009; Arayici et al., 2011; Matos et al., 2021); space management (Cho, Alaskar, & Bode, 2010; B Becerik-Gerber et al., 2012; S. H. Alavi & Forcada, 2019); emergency management (Wetzel & Thabet, 2015; S. H. Alavi & Forcada, 2019; Marocco & Garofolo, 2021); and retrofit planning (Mill, Alt, & Liias, 2013; L. Zhao, Zhang, Wang,

& Wang, 2021). BIM implementation can be further extended to: preventive maintenance planning (Burcin Becerik-Gerber et al., 2012; W. Chen et al., 2018; H.H. Hosamo, Svennevig, Svidt, Han, & Nielsen, 2022); building systems analysis (Weygant, 2011; Burcin Becerik-Gerber et al., 2012; Quinn et al., 2020); commissioning processes (Burcin Becerik-Gerber et al., 2012; Jiao et al., 2013); and strategy planning (Zou & Wang, 2009; Burcin Becerik-Gerber et al., 2012; H.H. Hosamo et al., 2022).

A few studies have integrated probabilistic models into BIM for facility managers (Hu & Castro-Lacouture, 2018; McArthur et al., 2018; T. K. Wang & Qin, 2018; Micolier, Taillandier, Taillandier, & Bos, 2019). Di Giuda et. al. (Di Giuda, Pellegrini, Schievano, Locatelli, & Paleari, 2020) demonstrates the benefits of using BIM for increasing occupants' comfort, such as (1) obtaining feedback for the design process, (2) reducing energy consumption, and (3) reduction of operational phase's costs. Göçer et. al. (Göçer, Hua, & Göçer, 2015, 2016) have integrated BIM with occupants' feedback by extracting spatial information from the BIM model into a graphic information system (GIS) tool and then link occupants' feedback with ArcGIS so as to visualize the results. However, the applications of BIM in operation and maintenance phase are still under development, and the research in this area, while growing, is still at a very early stage (Pishdad-Bozorgi et al., 2018; J. C. P. Cheng, Chen, Chen, & Wang, 2020).

2.2.3 BIM information standards for O&M

The implementation of BIM depends on its application in which the Level of Development or Details (LOD) must be defined. The LOD designation for project milestones determine geometric and non-geometric attribute information offered by a model component ((AIA), 2008). Enabling BIM for O&M phase requires precise LOD (Leite, Akcamete, Akinci, Atasoy, & Kiziltas, 2011) for each FM activities. However, LOD specification does not target what FM activities will require as FM data (Dias & Ergan, 2016).

During O&M phase, standards and specifications regarding the transmission, availability, and integrity of data have been developed (Re Cecconi, Maltese, & Dejaco, 2017). The PAS 1192-6:2018 standard, recommends using BIM models to store and retrieve facility data for the cooperative sharing of structured health and safety data throughout the project and asset life-cycles. BuildingSMART, the worldwide industry body, has developed a standard data format, the Industry Foundation Classes (IFC). The IFC conceptual model is intended to describe architectural, building and construction industry data and has been mostly used as the data exchange schema between BIM and other systems such as Computerized Maintenance Management Systems (CMMS) (Dong, O'Neill, & Li, 2014;

Zhou, Love, Matthews, Carey, & Sing, 2015; Göçer et al., 2016; Wong et al., 2018; Marmo, Polverino, Nicolella, & Tibaut, 2020).

The Construction Operations Building Information Exchange (COBie), a subset of IFC data, is an international standard for exchanging data from the design phase to the O&M phase using a formal spreadsheet. The version of COBie for the FM handover Model View Definition (MVD), (BuildingSMART Team, 2020) is the MVD delivered in a file format that can be viewed and edited in Microsoft Office Excel (East et al., 2013). However, it allows for the storage of a large volume of different kinds of data, which results in overloading (Thabet et al., 2016). Accordingly, COBie needs to be customized for facility information as a means to building operation (Dias & Ergan, 2016). Becerik-Gerber et al. (B Becerik-Gerber et al., 2012) showed that each FM activity is data-intensive and demands specific data. Kim et al. (K. Kim et al., 2018) focused on identifying specific data for FM maintenance activity and proposed a data management approach to integrate IFC objects, COBie data, and maintenance work information from the FM system database.

2.2.4 BIM interoperability for O&M

Efforts to address BIM interoperability for O&M have been made by many researchers. Gouda et al. developed a framework by employing semantic web technology to store maintenance information and BIM data using COBie (Gouda Mohamed, Abdallah, & Marzouk, 2020). Cheng et al. (2020) determined FM information requirements referring to the Information Delivery Manual (IDM) and developed an integrated data-driven system based on BIM and IoT technologies for predictive maintenance of building facilities using COBie and the IFC extension. To enhance decision-making in FM, Chen et al. (2018) proposed a system for automated maintenance work order scheduling, based on BIM and FM software using COBie and the IFC extension. Marmo et al. developed a framework to address the interoperability issue by mapping the IFC into a relational database for maintenance and performance management (Marmo et al., 2020). Other researchers developed applications on BIM by integrating various systems to execute maintainability analysis (Shen, Hao, & Xue, 2012; Motamedi et al., 2014; Alireza Golabchi, Akula, & Kamat, 2016; Shalabi & Turkan, 2017), indoor localization (Papapostolou & Chaouchi, 2011), fire emergency simulation and analysis (S. H. Wang, Wang, Wang, & Shih, 2015; M. Y. Cheng et al., 2017; Y. J. Chen, Lai, & Lin, 2020), fault detection and diagnosis (Zimmermann, Lu, & Lo, 2012; Yang & Ergan, 2016), sustainability assessment (McArthur, 2015; H. Wang et al., 2019), and energy simulation and forecast (Gerrish, Ruikar, Cook, Johnson, & Phillip, 2017; Gerrish, Ruikar, Cook, Johnson, Phillip, et al., 2017; Galiano-Garrigós, García-Figueroa, Rizo-Maestre, & González-Avilés, 2019).

The variety of standards and technologies available (i.e., building automation protocols such as BACnet, Modbus, ZigBee and C-Bus) is one of the BIM–O&M interoperability problems (Gao & Pishdad-Bozorgi, 2019). Hence, many researchers have focused on system-based approaches to address the specific interoperability issue between BIM and software systems, standards or protocols in the O&M phase (Volk et al., 2014; Galiano-Garrigós et al., 2019; Matarneh, Danso-Amoako, Al-Bizri, Gaterell, & Matarneh, 2019; Ozturk, 2020). The system-based approaches propose a systematic architecture for data integration (Kang & Hong, 2015). Such approaches make full use of open libraries, components and commercial software tools, and implement data integration architecture (Kang & Hong, 2015). Kang and Hong (Kang & Hong, 2015) proposed system architecture to effectively integrate BIM into geographic information system (GIS)-based FM software. Such approaches make full use of open libraries, components and commercial software tools, and implement data integration architecture (Kang & Hong, 2015). Motawa et al. (Motawa & Almarshad, 2013) developed system architecture to collect data and knowledge about building maintenance activities while and after they are performed. Lee and Cheng et al. (J. Lee et al., 2013; M. Y. Cheng et al., 2017) presented a system architecture to integrate BIM with Barcodes and Radio-Frequency Identification (RFID) tags to enable timely data access. Quinn et al. (Quinn et al., 2020) proposed system architecture to extract data from a Building Automation System (BAS) and incorporate it in BIM using a linked data structure. Ani et al. (Ani, Johar, Tawil, Razak, & Hamzah, 2015) integrated information from a survey on a water ponding defect on a flat roof to the BIM model to identify the flat roof condition.

When BIM is integrated with other software, there may be confusion in communication if the visualization is not appropriate. Hence, different types of visualization should be considered in the BIM model for displaying the results (H. Alavi, Forcada, Bortolini, et al., 2021). Tashakkori et al. (Tashakkori, Rajabifard, & Kalantari, 2015) integrated BIM-based 3D indoor navigation functions with the proposed emergency management systems. Moreover, Wang et al. (S. H. Wang et al., 2015) applied the same approach to find the escape route to support fire safety management of buildings. Oti et al. (Oti, Kurul, Cheung, & Tah, 2016) utilized color scheme visualization in BIM to visualize data related to the energy management systems, to reflect time-dependent energy consumption information. Regarding maintenance activities, some researchers utilized BIM 3D visualizations to locate building components and support troubleshooting in proposed maintenance systems (S. H. Wang et al., 2015; H. Alavi, Forcada, Fan, et al., 2021).

2.2.5 BIM-based Augmented Reality for O&M

Augmented Reality (AR) is an innovative technology that can enable digital information such as 3D models, images, and animations to be overlaid on the real world to facilitate natural contact between users and their surroundings (J. C. P. Cheng, Chen, & Chen, 2017). For years, AR has been applied to the Architecture, Engineering, Construction and Operation (AECO) industry (Dunston & Wang, 2011). AR makes user information readable and manipulable surrounding facilities by mixing virtual and the real world.

In order to improve the effectiveness of BIM applications, some studies have shown that incorporation of the AR technology would be beneficial for improving the usability and accessibility of BIM information (Y. J. Chen et al., 2020). Hence, to further improve FM activities, it is necessary to implement BIM and AR jointly to access high-quality information and visualize the required information. AR provides a suitable interface for FM fieldwork support (Sanghoon Lee & Akin, 2011; Koch, Neges, König, & Abramovici, 2014) by providing the superimposed geometric representation on the physical space along with the relevant BIM-based FM data (Gao & Pishdad-Bozorgi, 2019).

Researches have been developed AR to facilitate FM tasks. For example, Irizarry et al. (2014) proposed an AR system for facility managers to provide FMM information, proved to be able to improve efficiency during FMM. Lee et al. (2011) presented a system of an AR-based equipment O&M fieldwork support application to improve efficiency in FMM. Hou et al. (2014) presented a framework in which AR combined with photogrammetry to manage information for FMM. Ting et al. (2019) developed a facility risk assessment and maintenance system prototype enabling facility managers to select the maintenance policy for a single piece of equipment. Chen et al. (2020) integrated AR with BIM to improve safety and reduce error for FM activities. FM activities frequently require multiple users to communicate and interact with each another. For instance, when occupants report a problem, the facility manager comes to the office of the employee and inspects the problem on site. After identifying the problem, the facility manager makes decision and calls the administrative affairs manager, reports the problem, and requests a work order. To deal with this issue, AR can give a UI to FM staff and occupants to straightforwardly communicate with surrounding facilities (K. Chen, Chen, Li, & Cheng, 2019).

2.3 Summary

The literature review demonstrates the growing use of BIM for O&M phase to help FM team. In this sense, addressing interoperability between existing systems and the BIM model, is crucial to provide high-quality data for FM activities. A literature analysis also emphasizes the necessity of the probabilistic DSS for the improvement of FM activities (e.g., building performance) dealing with uncertainty, managing risks, identifying, analyzing, evaluating, and mitigating factors that may influence the performance of the building. Nevertheless, these DSSs are not integrated nor interoperable with BIM to automatized the data transfer process.

While the numerous benefits offered by BIM, its utilization for the O&M phase remains significantly limited due to the interoperability issues. Thus, the DSS integration into BIM needs to be investigated to facilitate data transfer, reducing the time and effort that the FM team spends on manual input. BIM has the potential to advance and transform facilities O&M by providing a platform for facility managers to retrieve, analyze, and process building information in a digitalized 3D environment. The greatest advantage of BIM application in FM is the integration of data systems over the life cycle of a facility.

Literature review also highlighted the potential benefits of implementing BIM and AR jointly during O&M phase and empirical results from existing studies also corroborate these findings. The use of AR technology as a visualization platform represents a great potential to support FM, regarding the enhancement of building performance. Consequently, facilities managers will be in a better position to make decisions about the building and provide better outcomes.

Chapter 3

Research Method

This chapter explains the research method adopted to achieve the objectives of this thesis. First, the global approach is explained followed by three DSS to be integrated in BIM during the O&M activities. Afterwards, the method to integrate DSS into BIM is presented in three steps to implement the DSS and enable the BIM visualization for desired purposes. Finally, the proposed method is validated in existing software as a case study.

3.1 Global approach

The global approach of this research consists of three main steps as illustrated in Figure 4.

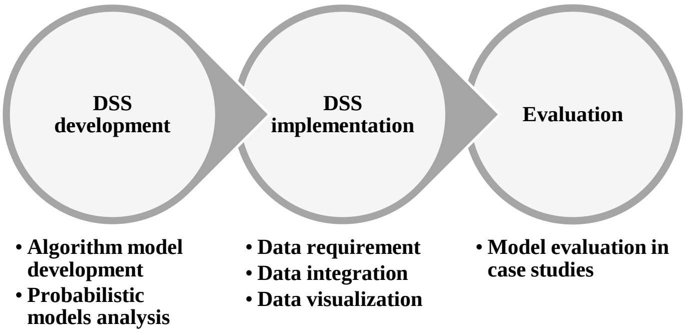


Figure 4. Global approach of this research

The first step is to develop DSS by creating an algorithm model and analysing the existing probabilistic tools when necessary. The next step is to implement these DSS in the BIM models by following three steps shown in Figure 5. These steps are: data requirement, data integration and data visualization.

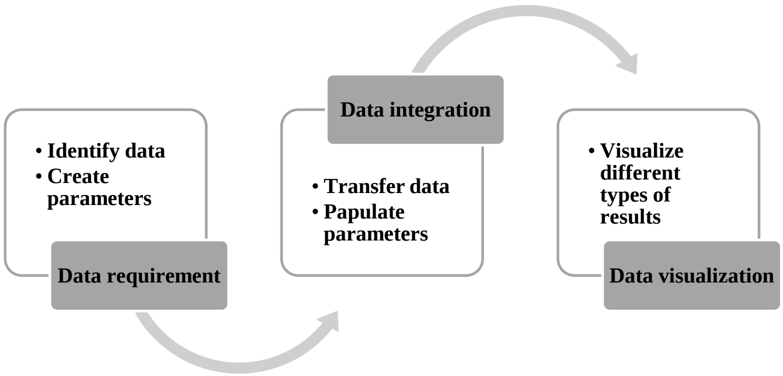


Figure 5. Process of DSS implementation

The required data is identified and transferred to the BIM model to implement DSS followed by visualizing different types of results. Finally, the proposed model is evaluated in the case studies.

3.2 DSS analysis and development

Although many different DSS can be implemented during the O&M activities, this thesis presents three DSS to be integrated in BIM. These DSS are: (1) HVAC problems analysis based on the algorithm model. (2) Building condition assessment, and (3) occupants' comfort evaluation, both of which are based on probabilistic models (i.e., probabilistic models) as illustrated in Figure 6.

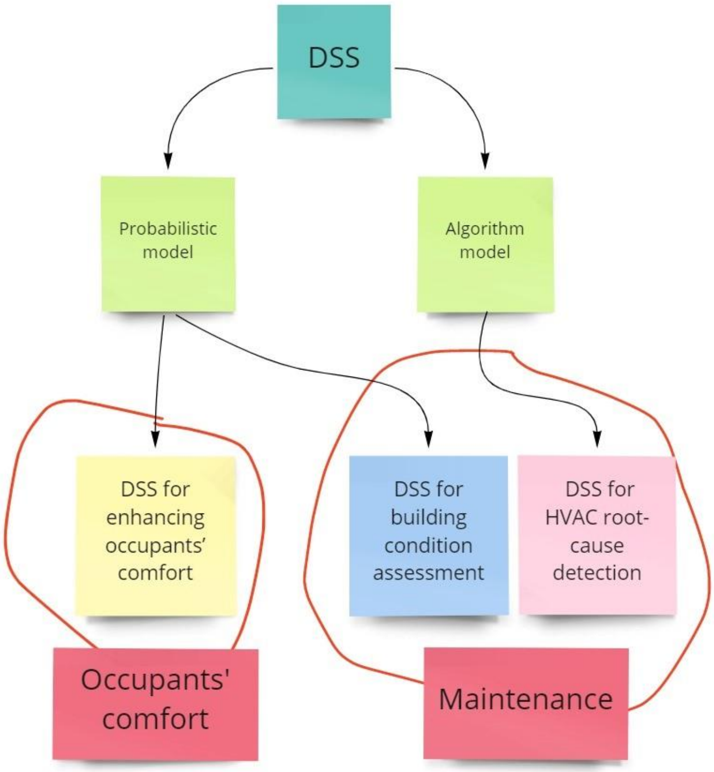


Figure 6. Three DSS applications covered in this thesis

The algorithm model for HVAC root-cause detection is created and implemented into the BIM model directly. In contrast, the probabilistic models for building condition assessment and occupants' comfort evaluation are analysed based on existing probabilistic DSS. The probabilistic models are based on BN and require a BN modeling tool (e.g., AgenaRisk, one of the most common and powerful tools for BN modeling) to be implemented. In this case, a conceptual model is designed to integrate the probabilistic models into the BIM models enabling bidirectional data transfer between BIM and BN. The conceptual model is then implemented in Autodesk Revit which is one of the most popular BIM tools in the AEC sector.

3.3 DSS implementation

To implement the DSS, different steps are required as illustrated in Figure 7. First, the required data is defined based on the DSS, and the relevant parameters are created in the BIM model. Next, the required data is transferred to the BIM model to populate the relevant parameters by integrating various systems (i.e., data integration). Then, the BIM visualization is constructed in user-friendly ways which can assist users in integrating digital insights into FM decision-making processes and converting them into positive strategic actions.

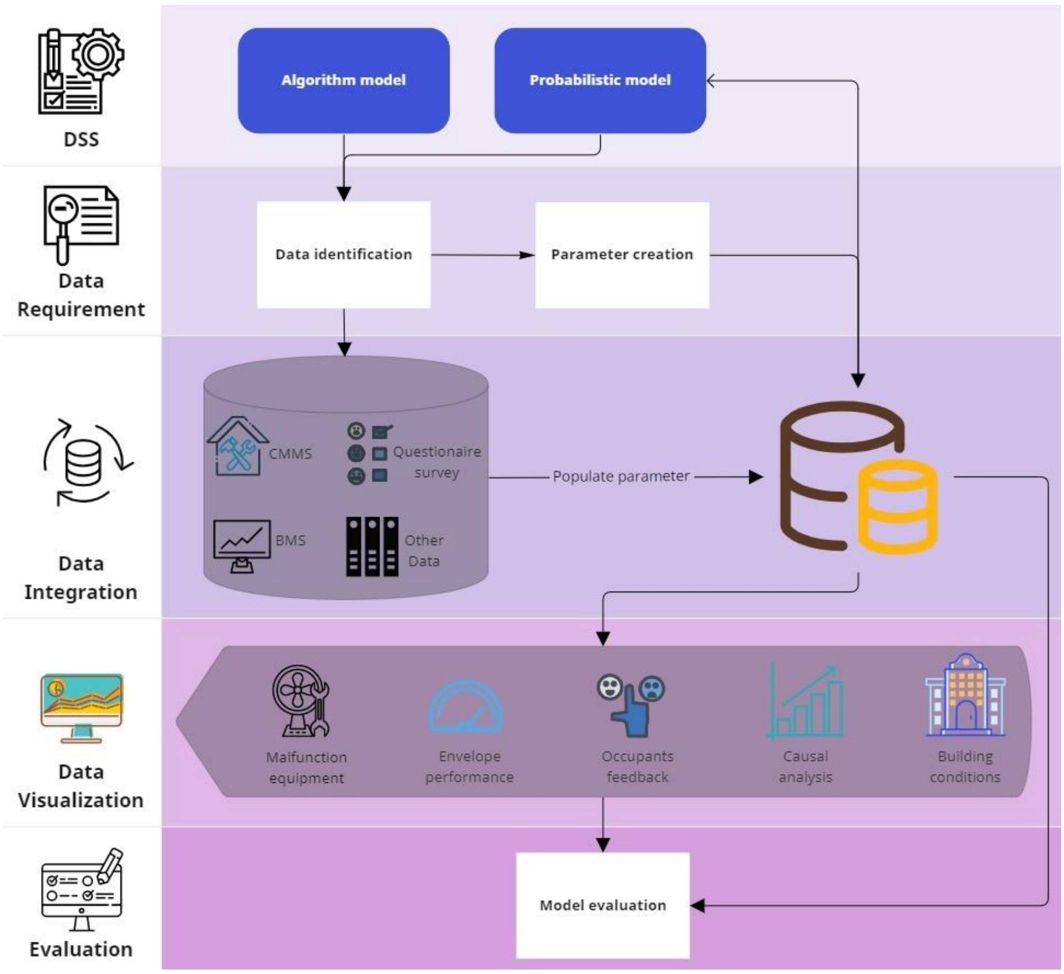


Figure 7. Process of the DSS implementation in BIM

3.3.1 Data requirement

Even though BIM provides building and spatial information, it still cannot represent complete information on FM applications (e.g., building condition assessment, HVAC problems analysis and occupants' comfort evaluation) in which the FM team can make decisions. Therefore, the Industry Foundation Classes (ifc), an open international standard for BIM, introduced the IfcPropertySet allowing BIM models to contain additional data. The IfcPropertySet known as "IfcPset" is a container class that holds properties within a property tree" ("buildingSMART International Standards Server: IfcPropertySet," 2022).

To create parameters in BIM, spatial information should be assigned into rooms, while building information should be assigned into their corresponding family. Building information for each component in a building is different; thus, it is crucial to assign the IfcPset into their relevant families in BIM. 'Ventilation control', for instance, should be assigned to a mechanical family but not a wall family.

In Autodesk Revit, shared parameter can also be utilized to allow BIM models to contain such information. Shared parameter is a Revit term that can be added to the Revit family for custom data fields creating parameters for data that could not be obtained from the BIM model. It can also be accessible for any project due to holding parameters in a separate file (H. Alavi, Forcada, Bortolini, et al., 2021). The process of creating shared parameters can be done both manually and semi-automated using Dynamo, a visual programming extension for Autodesk Revit.

3.3.2 Data integration

To populate the parameters, various systems (e.g., CMMS, BMS) should be integrated into the BIM model using Dynamo and Python scripts. Afterwards, the BIM model will run the DSS (e.g., algorithm model and probabilistic models) to obtain the results, shown in Figure 8.

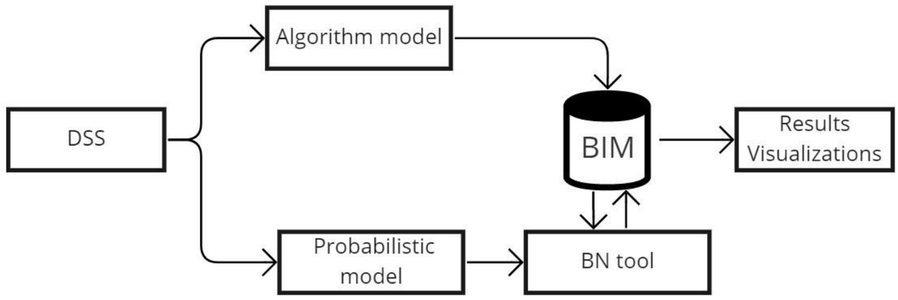


Figure 8. Data integration of different DSS types in BIM

The BIM model will directly run the algorithm model to obtain the results. However, the probabilistic models require a BN modeling tool (e.g., AgenaRisk) to obtain the results. Thus, the required data should be extracted from the BIM model using Dynamo and Python scripts, by creating a dataset in either Microsoft Excel as an intermediate format or a JavaScript Object Notation (.Json) format, which is a lightweight format for storing and transferring data. Subsequently, the dataset (.Json or comma-separated value (CSV)) containing all the required data should be imported into the BN modeling tool where the FM team can acquire the results of different analysis (e.g., building condition and occupants' comfort). Finally, the results can be extracted from the BN tool into either a .Json or a .CSV format and imported into the BIM model using Dynamo and Python to visualize the results in a 3D model.

3.3.3 Data visualization

The BIM model can visualize the results from the algorithm model instantaneously. For probabilistic models, however, it requires bidirectional data transfer between BIM and the BN tool to visualize the results. Thus, the results obtained from the BN tool should be imported into the BIM model using a Python programming language in Dynamo. A Python code block queries the results to match with corresponding spaces/building elements. For instance, the results related to a building element (e.g., Fan coil) with corresponding equipment codes are imported and sorted to match relevant families (e.g., mechanical equipment) in BIM. Besides, the results related to spaces are also imported and sorted to match relevant rooms in BIM. Then, the results of each element and space can be mapped to their corresponding elements and rooms in the BIM model using GetItemAtIndex and SetParameterByName nodes in Dynamo.

Once the results from the BN tool are mapped, the BIM capabilities are utilized to visualize the results with different colors for both spaces and building elements. The tabulated data taken from Revit's schedule are visualized in a 3D format in the BIM model by applying view filters. The FM team would be able to filter the elements or rooms in the BIM model to view the color associated with them based on the desired purposes. It is also possible to compare building elements and rooms between different buildings.

3.4 Evaluation

Model evaluations aim to ensure that the model's interactions and outcomes are realistic (S. Chen & Pollino, 2012). An evaluation of a model can be divided into two general categories: validation and verification (Sargent, 2013). A validation is the process of ensuring that a product, service, or system meets the requirements of its intended customers and other stakeholders (Engel, 2010). A verification is to demonstrate that the model has been transformed from a problem formulation to a model specification with sufficient accuracy (Balci, 1997). In this research, therefore, the proposed approach to integrate BIM and DSS, is validated by implementing them in case studies to ensure that the tasks are performing as efficiently as possible. In this case, the same approach as Kang and Hong (Kang & Hong, 2015) is used to identify how much the task efficiencies in comparison with the manual method.

In addition, information exported from software programs should be verified according to Eastman (T. Eastman & Sacks, 2011) by checking the syntax and structure of project exchange files and checking the completeness of the contents of a project exchange file (objects, parameters, and their values) between two applications. In this respect, the syntax and the value of the transferred data are checked in the case studies to ensure that there is no missing data to meet the data completeness criterion. Data completeness concerns the degree to which all data relevant to an application domain has been recorded in an information system (Gertz, Özsu, Saake, & Sattler, 2004).

The case studies include different buildings of the Terrassa campus from the Universitat Politècnica de Catalunya (UPC). The campus includes 25 buildings with classrooms, offices, laboratories, dining rooms, restrooms, common areas and study areas. The campus is located in a small urban area in the city of Terrassa (Barcelona) with a Mediterranean climate characterized by hot, dry summers and cold, wet winters. It includes 25 buildings involving classrooms, offices, laboratories, dining rooms, restrooms, common areas, and study areas. The TR5 building was constructed in 1960 in Terrassa campus; it has 11,492 m^2 and five floors with a concrete structure, a brick façade, and an inverted roof. The majority of the windows are single glazed, and the interior partitions are plain brick walls. When TR5 was built, only a radiant system was installed, with two boilers and four air handling units (AHU) (one for each floor) located in the underground. A duct network brought the heated air from the underground to the habitable areas. There was no cooling system at all, and the ventilation was only natural, by opening windows. In the 1990s, splits providing both cooling and heating were installed in some offices. Later, the boilers were substituted by condensing boilers with high efficiency. Finally, by 2010 most of the third floor, which includes both offices and classrooms, was reconditioned, and an air-water system was installed to provide both heating, ventilation, and air conditioning. A chiller was installed in the roof while the existing boilers were also connected to the new HVAC system for the third floor. Then, several fan coils were installed in each room (offices, classrooms, and corridors) of this floor. TR5 has been using a CMMS Archibus called FACIL since 2012. The FACIL allows tracking all infrastructure and equipment inventories, as well as the management of preventive and corrective maintenance of the equipment. Whenever there is an incidence in any of the equipment, it can be reported by UPC staff and administrative personnel through the FACIL. Furthermore, TR5 has been using a BMS Schneider, comprising a set of products and software, multi-sensor probes for rooms, to improve its energy efficiency and provide the real-time building data.

Chapter 4

A BIM-based DSS for HVAC root-cause detection

This chapter presents the work undertaken to define an algorithm model to determine the causes of HVAC problems as the main contributors to excessive energy consumption in the building operation phase. Afterwards, the algorithm model is implemented in BIM to visualize malfunction equipment and assist FM team to determine the most probable cause of an HVAC problem, reducing the time to detect equipment faults and providing potential actions to solve them. HVAC system failures would result not only in energy waste, but also in low occupants' comfort. This implies that important energy as well as high occupant comfort can be achieved by applying proper maintenance plan for improving the efficiency of the HVAC systems. A case study in a university building is used to demonstrate the applicability of the approach.

4.1 DSS for HVAC root-cause detection

The algorithm model to assist facility managers in identifying the root cause of HVAC problems and thus meet occupants' needs is shown in Figure 9. The HVAC system is one of the most important factors affecting thermal comfort and when it is improperly operated, it may result in poor ventilation, cause health problems and discomfort to the occupants. Therefore, it is imperative to determine the causes of HVAC problems to know what actions can be taken by FM team. When thermal comfort in a building room is not achieved it might be attributed to either the undersized HVAC components (i.e., HVAC design problem) or the equipment failure (Yang & Ergan, 2017; Ilango, 2019). In such circumstances, end-users might complain for not having the desired indoor comfort (H. Alavi, Forcada, Bortolini, et al., 2021). Therefore, HVAC problems are categorized under two groups: a) undersized HVAC components or HVAC design problem; and b) failure of the equipment which is related to either an indoor or outdoor unit (Yang & Ergan, 2017; Ilango, 2019).

These problems can be reported by occupants who are discomfort in terms of thermal sensation (H. Alavi, Forcada, Bortolini, et al., 2021). To address discomfort due to already installed undersized HVAC components two options are possible (H. Alavi & Forcada, 2022): a1) reduce the thermal demand of the room by insulating the envelope including façade, windows, roof and/or floor, if possible; and a2) substitute indoor units for those with the correct cooling/heating capacity. On the other hand, the location of the specific equipment is needed to address the failure of an HVAC equipment. Failures can stem from outdoor units (e.g., frozen evaporator coils, dirty condenser coils, dirty filters) and indoor unit (e.g., motor fans failure, air outlet obstruction). Therefore, the algorithm model identifies whether the problem is related to indoor units or outdoor units to enable FM team to provide practical corrective actions.

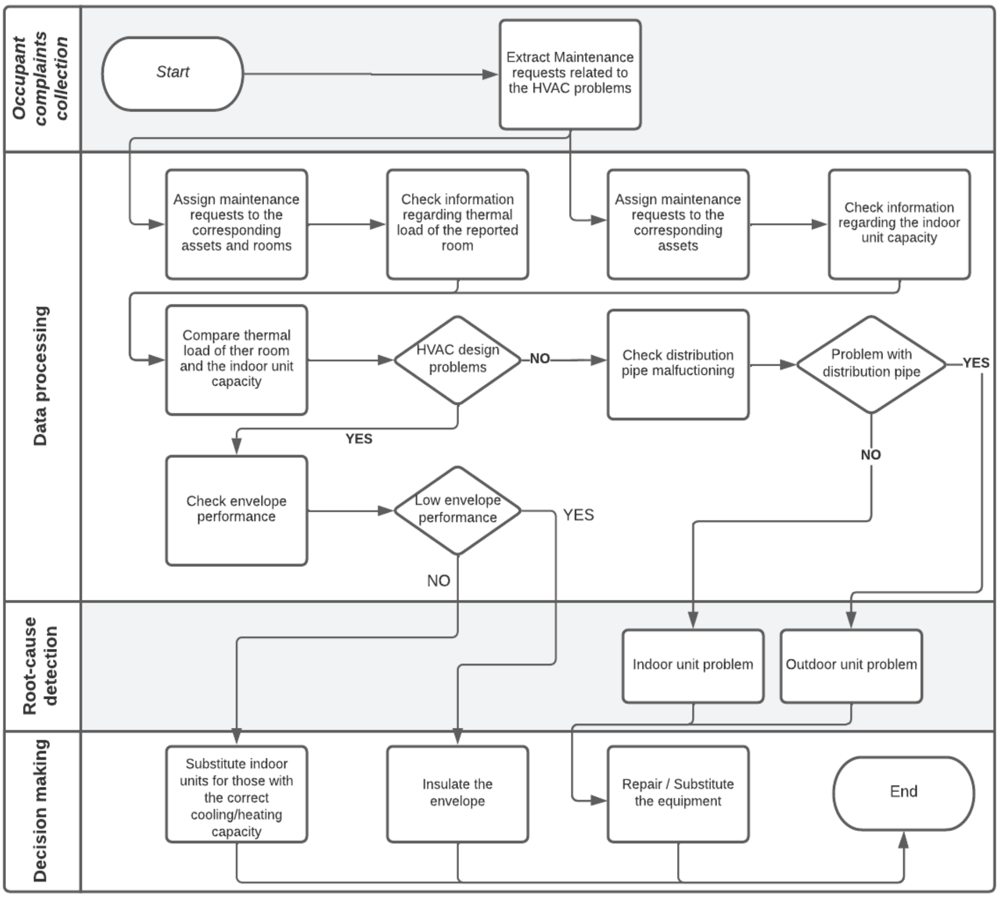


Figure 9. Algorithm model for HVAC root-cause detection

To analyse if the HVAC system is correctly designed, the indoor unit capacity against the thermal load of the room should be compared. To do so, the indoor unit capacity can be obtained from the equipment database while the thermal load can be automatically calculated if the architectural and constructive design is correctly defined. If the indoor unit capacity is higher than the thermal load of the room, then the thermal discomfort might be attributed to the failure of the equipment. However, if the indoor unit capacity is lower than the thermal load of the room, facility managers should check if the heat transfer through the envelope can be improved. To do so, all envelope elements (façade, windows, roof, floor) insulation should be evaluated. If all envelope elements are within the insulation threshold, then the only option would be substitute indoor units for those with the correct cooling/heating capacity. However, if any of the envelope elements have lower insulation properties, insulation refurbishment should be considered.

If the envelope insulation is within the limits and the HVAC components are correctly designed, the probable main cause of thermal discomfort might be attributed to a failure of any of the HVAC system equipment. To determine if the failure is attributed to the outdoor unit or the indoor unit, information about the pressure and temperature from the Building Management System (BMS), a computer-based system for managing, monitoring and controlling of building services, should be analysed. If both pressure and temperature are within the acceptable values, then the failure might come from the outdoor unit. If not, the failure might be related to the indoor unit.

4.2 DSS implementation

Once the algorithm model is created, the BIM capabilities are utilized to: a) implement the algorithm model; and b) provide the FM team with color-coded visualization to indicate the root cause of a certain failure or problem.

Figure 10 shows the process of the algorithm model implementation in BIM by following three main steps. (1) Data requirement: the required data for the algorithm model is defined. (2) Data integration: the required data from various sources (e.g., CMMS) is integrated with the BIM model to implement the algorithm model detecting the root cause of HVAC problems. (3) Data visualization: the BIM visualization is used to add red colour in malfunction equipment.

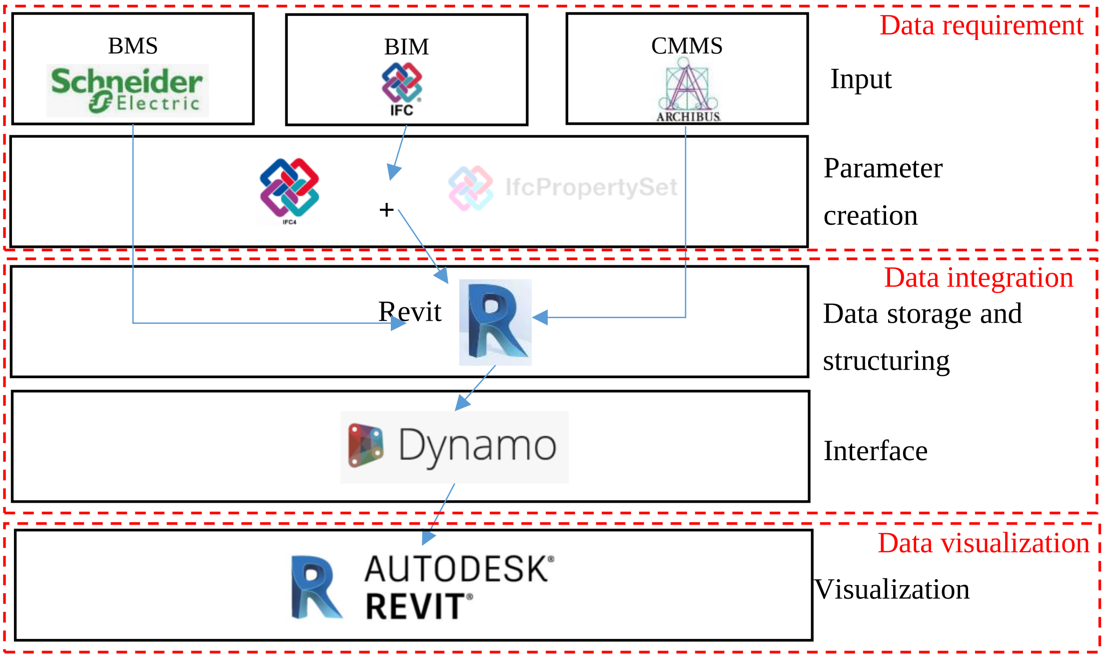


Figure 10. Process of the algorithm model implementation in BIM

4.2.1 Data requirement

As described in Section 3.3.1, the BIM cannot represent complete information on maintenance activities in which the algorithm model can be implemented. Therefore, the data requirement for the algorithm model is defined from various sources such as CMMS and BMS, shown in Table 1.

Table 1. Data requirement for the algorithm model.

Required information		**Source**
Room data	Number	BIM
	Area	
	Thermal load	
	Facade material	
	U-value of envelope elements	

	Type of heating (Radiators / Air water / Splits / VRV) Type of cooling (Air-water / Fan coils and AHU / Splits / VRV) Description of the problem Location of the problem Date of the reported problem	CMMS
System data	Equipment ID Cooling capacity Heating capacity	BIM
	Temperature Pressure	BMS

The occupants' complaints (i.e., maintenance requests) regarding the thermal comfort might come from the CMMS and should include information about the building, the room, the date and the hour. From this information, data about the indoor unit related to that room can be obtained. Moreover, other relevant data such as temperature and pressure of the malfunction equipment's pipes can also be obtained from the BMS or Building Energy Management System (BEMS) or Building Automation System (BAS).

4.2.2 Data integration

To populate the parameters that are created in section 4.2.1, the CMMS and BMS are integrated into the BIM model. To do so, the HVAC problems are extracted from CMMS and stored in Microsoft Excel. Then, the HVAC problems with corresponding equipment codes are imported and sorted to match relevant mechanical equipment in BIM by using Dynamo and scripts of Python. Figure 11 shows the process of mapping HVAC problems into the BIM model.

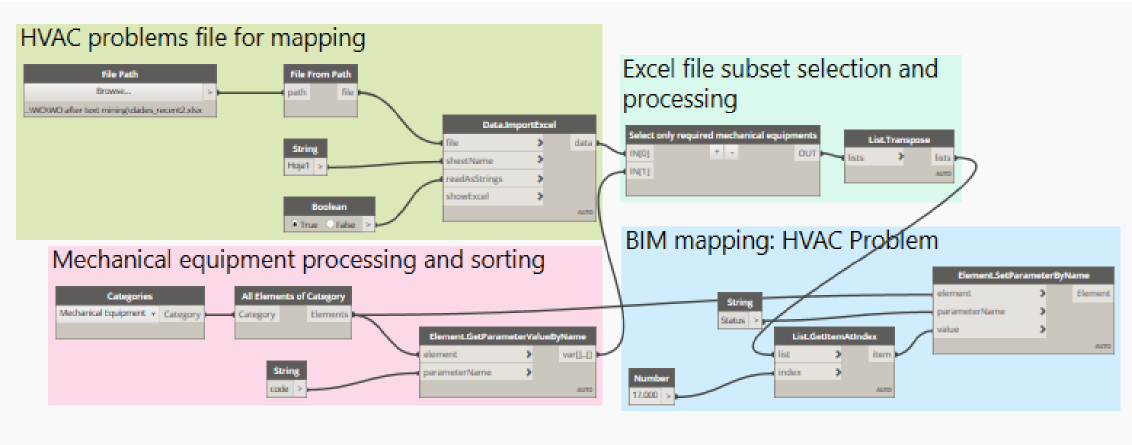


Figure 11. Dynamo scripts to map HVAC problems into BIM

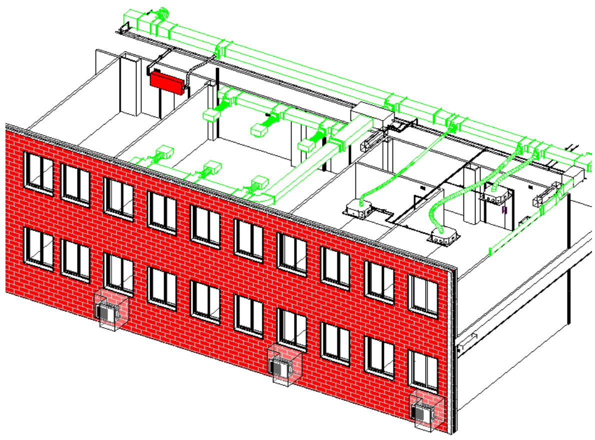
The column of equipment code in HVAC problems in the Excel file is connected to the Python code block as an input (input#0), whilst the mechanical equipment in the BIM model is also connected as inputs input#1. Next, a Python code block queries input#1 to find equipment that match those from the HVAC problems (input#0) and create a new list with HVAC problems and their corresponding information.

To integrate the BMS with the BIM model, the similar approach to Dong et al. (Dong, Oneill, Luo, & Bailey, 2014) is utilized to acquire data regarding temperature and pressure of HVAC equipment and incorporated them into the BIM model.

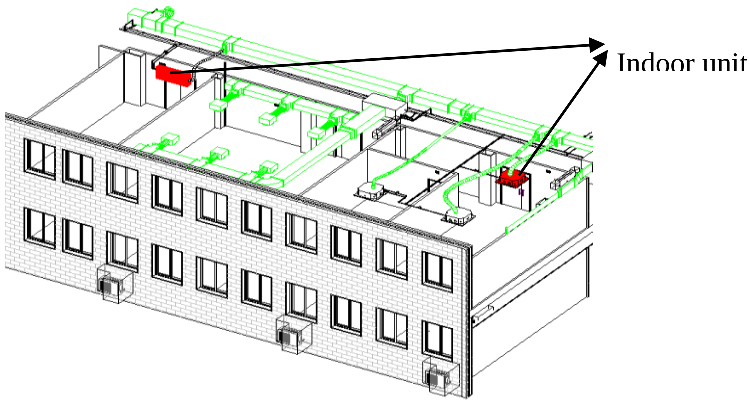
4.2.3 Data visualization

Once the "maintenance requests" concerning the HVAC problems is being reported, BIM integrated CMMS/BMS provides various kind of information such as the building, the room and the date. Hence, the algorithm model utilizes these data as initial inputs to analyse the root cause of HVAC problems. When the HVAC problems and their causes are determined, the BIM model provides the visualization of the malfunction equipment. Thus, the tabulated data taken from Revit's schedule (e.g., Calculated Value) is visualized in a 3D format in the BIM model by applying view filters. The BIM visualization for HVAC equipment problems is shown in Figure 12.

(a) an under design of the indoor unit



(b) a malfunctioning of the indoor unit



(c) a malfunctioning of the outdoor unit

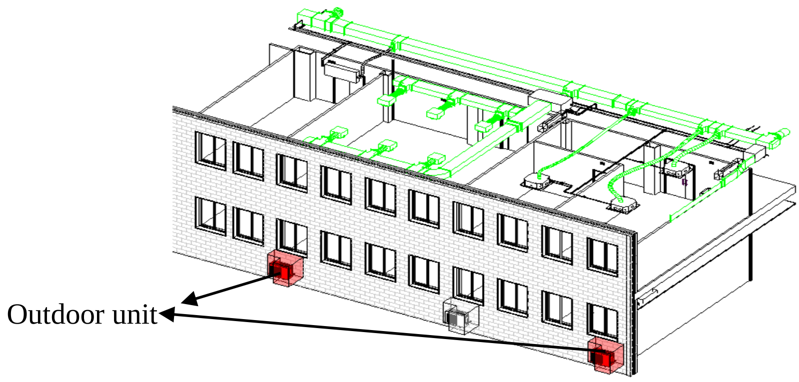


Figure 12. BIM visualization of malfunction HVAC equipment.

The FM team can filter the malfunction equipment in the BIM model to view its corresponding necessary information to facilitate decision making.

4.3 Evaluation

In this chapter, the evaluation is based on the validation, thus the TR5 building is used as a case study. In order to identify HVAC problems for the TR5 building, all maintenance requests are exported from FACIL into Microsoft Excel as an intermediate format, including the following information: equipment ID, floor code, space code, request code, and description of the problem. Table 2 shows some examples of HVAC problems in the TR5 building.

Table 2. Example of HVAC maintenance requests in TR5.

No.	Equipment ID	Floor code	Space code	Maintenance request	Description
1	TR-CLIFC0082	P03	310	33325	The fan-coil fan does not stop.
2	TR-CLIFC0083	P03	312	40504	The air conditioning does not cool.
3	TR-CLISI0304	P03	318	51823	The radiator does not work
4	TR-CLISI0045	P0E	055	71944	It does not cool the air conditioning
5	TR-CLIFC0094	P03	329	79299	The previous incident occurs again, this time so that the noise is not continuous. This is a very annoying sound.
6	TR-CLISI0250	P03	307	80962	Heating equipment not working
7	TR-CLISI0215	P01	130	83738	HEATING DOESN'T WORK !!!!!!!
8	TR-CLISI0238	P03	306	98316	The 3.06 air conditioner does not work
9	TR-CLIFC0073	P01	158	106728	The air conditioning does not cool.
10	TR-CLISI0237	P03	305	115297	Hot air does not work. A warning LED has been lit, perhaps for filter cleaning.

11	AA-PROVA			120025	The heating doesn't seem to work. The radiators are cold.
12	TR-CLISI0003	P00	0128	126853	Disassemble and remove Climate equipment.

Among these HVAC maintenance requests, a maintenance request (No. 8) is considered as a scenario in this study to implement the algorithm model. The occupants located in building TR5, room 306 experience thermal discomfort and report a problem associated with the split in that room through the FACIL portal explaining the equipment is not working properly. This HVAC maintenance request is extracted from the FACIL and imported into the BIM model to match with the corresponding mechanical equipment using Dynamo and scripts of Python. When the maintenance request is assigned to its corresponding equipment, the relevant data of the equipment and the room, where the equipment is placed, is provided by the integrated BIM model to implement the algorithm model.

The algorithm model then queries the possible causes of the problem by comparing the required cooling load (calculated in Revit) with the cooling capacity of the split to identify whether or not the problem is related to HVAC design. A “Calculated Value” within a Revit schedule is used to define formula driven reporting values by modifying existing parameter values through the use of mathematical (e.g., Volume / Area) or conditional expressions. The energy demands for the room 306 is calculated in Revit and compared with the characteristic of the split obtained from the BIM model (e.g., cooling capacity) using “Calculated Value”. Since the cooling capacity of the split is higher than the required cooling load for that room, there are no HVAC design problems or undersized HVAC components. In the next step, the algorithm model monitors the temperature and the pressure of equipment’s pipes to determine whether indoor unit or outdoor unit has a problem. Both the temperature and the pressure of the split’s pipes are not within the acceptable values; therefore, the algorithm model determines that the problem is related to the energy production (i.e., outdoor unit). As a result, the outdoor unit corresponding with the reported split is turned to red colour to assist facility managers, illustrated in Figure 13. Therefore, the results of the algorithm model suggest that the problem is probably related to the outdoor unit. Then the FM team should move directly to where the outdoor unit is located and find a refrigerant leak. They repair it and solve the problem without moving to the room where the end-user make the complaint.

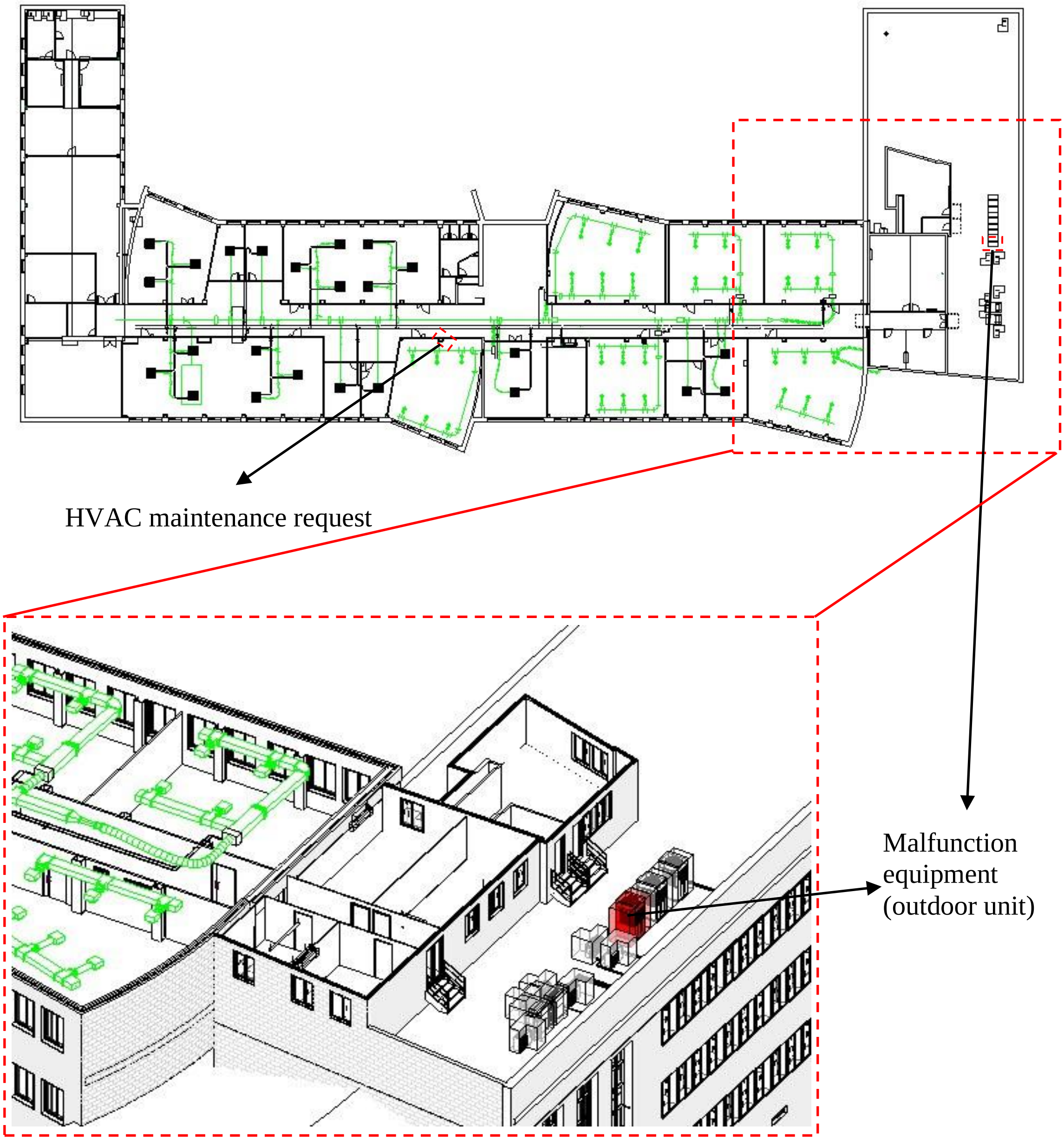


Figure 13. BIM visualization of the possible causes of the problem

4.4 Discussion

The proposed algorithm model allows to semi automatically detect which are the causes of occupants' complaints about thermal comfort in specific rooms. The proposed approach integrates CMMS and BMS into the BIM model to identify the root cause of HVAC problems. When the end user reports a problem (e.g., too cold), the algorithm model queries the possible causes of the problem. It enables the FM team to address the challenges of information reliability, interoperability, and usability.

Although some studies integrate BIM with other FM software, they do not provide a root-cause detection to deal with HVAC problem in buildings, which allows the causes of occupants' discomfort (in thermal comfort) to be properly understood. Existing studies focus on the visualization of equipment condition or building performance in different platforms (A. Golabchi, Akula, & Kamat, 2013; Motamedi et al., 2014; H. Alavi, Bortolini, & Forcada, 2022). However, they only considered spatial information of the reported problem. The approach of this visualization focuses on malfunction equipment illustrating in red colour, so that the effort of looking for the location of the real problem, is minimized. This type of visualization allows for a more intuitive detection of the reasons of occupant discomfort and makes it easier to address the issue, resulting in a significant improvement in occupants' comfort and the optimization of building operation techniques to enhance occupant comfort and energy efficiency.

The case study is used to validate the proposed algorithm model. For the scenario of a maintenance request, it is highlighted that although the occupants in room 306 are dissatisfied in terms of thermal comfort and reported a problem associated with the split, the real problem is for outdoor unit and no actions are required for the split. This helps FM team to plan corrective actions without going through the building physically. It also provides the relevant data for facility managers to perform maintenance activities on HVAC systems, reducing the time and effort that the FM team spends on searching appropriate and reliable information.

4.5 Conclusions

The proposed approach defines the algorithm model and integrates various sources of data while considering BIM as a central database. Existing studies neither detect the causality of HVAC problems nor provide a real problem visualization to have easily accessible data. This chapter presents an automated approach that provides an algorithm model for identifying problems and integrates CMMS and BMS into the BIM model in order to streamline the process of resolving HVAC problems. There are two key benefits of this integration: 1) BIM performs as a data repository, providing relevant data for the proposed algorithm model; 2) BIM can visualize malfunction equipment and provides a potential solution for improving occupants' comfort. The algorithm model semi-automatically detects which are the causes of HVAC problems. Based on the proposed algorithm model, a case study is developed to show how this approach may be used to visually analyse the potential causes of HVAC problems in a room. This visualization approach focuses on real problems in discomfort spaces and assists the FM team to establish the necessary measurements for improving occupants' comfort and energy efficiency.

The contributions of this chapter include: (1) an approach that enables integrated representation of HVAC troubleshooting–related information, which is typically stored in BIM, CMMS, and BMS; and (2) the algorithm model that identifies possible causes and visualizes them in order to solve a problem. The proposed approach assists the FM team in identifying the most probable cause of a particular HVAC problem, ensuring that they do not overlook the main cause or spend time tracing and locating components on the site. It also provides the FM team with the relevant and required data about these reasons, allowing them to determine the real problem. The FM team can make decisions on building operational problems cantered on occupants' comfort with minimal effort which overcomes a key barrier both to location of the problem and collection of relevant data within the operation and maintenance phase.

Chapter 5

A BIM-based DSS for building condition assessment

This Chapter presents a conceptual model to integrate probabilistic DSS into BIM for building condition assessment. A condition assessment system is used primarily to facilitate the analysis of all elements of an asset in order to determine the extent of the necessary repair that is detected during an inspection and to predict failure of building elements. The BIM and BN models are integrated, based on the proposed conceptual model to assess building condition, and visualize the current condition of the building elements and systems by employing a color scale. Finally, the conceptual model is validated in existing software as a case study considering the integration of BIM and the building condition probabilistic model.

5.1 DSS for building condition assessment

With the aim of assessing the entire condition of a building, Bortolini and Forcada (Bortolini & Forcada, 2019b) developed a probabilistic model based on BN for building condition assessment. This model is created using cause-and-effect relationships between uncertain elements that impact building conditions. The condition of building elements and systems is categorized as high, medium, or low. For example, the term "high condition" refers to a piece of equipment that is in high working order and can be used to its maximum potential for its intended function. The BN model to assess building conditions is presented in Figure 14. Hierarchical levels could be visualized in the model that include all the general civil and architectural elements, as well as MEP (mechanical, electrical, and plumbing) systems.

The BN model is divided into building elements and systems. The building elements are classified as: 1) structure, 2) façade, 3) roofing, 4) flooring, 5) interior partitions and 6) doors/windows. The building systems are also defined as follows: 1) electrical systems, 2) plumbing systems, 3) HVAC systems, 4) elevator and 5) fire systems.

Variables that impact the performance of building elements and systems are classified as: design and construction errors; policy for building operation and maintenance; defects in building elements/systems; environmental agents; and building properties including age, type of elements, and whether preventive maintenance actions are planned. Weather conditions, the surrounding environment, the danger of natural catastrophes and geological conditions are examples of environmental agents.

In the BN model, variables that impact the condition of building elements and systems are represented as nodes. Depending on the data type, they are defined as discrete (labeled, Boolean, discrete real or ranked) or continuous (Fenton & Neil, 2018). Some nodes are defined as ranked and had various states such as 'High', 'Medium', and 'Low'. Others are specified as Boolean, with binary states like 'Yes' and 'No'. For whatever element or system condition, the model can be queried by inserting evidence in the BN model and setting its state (i.e., low condition). Then, the BN calculates the probability function of the parent nodes by conducting backward propagation, and estimates the most likely causes (e.g., age of the equipment, lack of preventive maintenance and design errors).

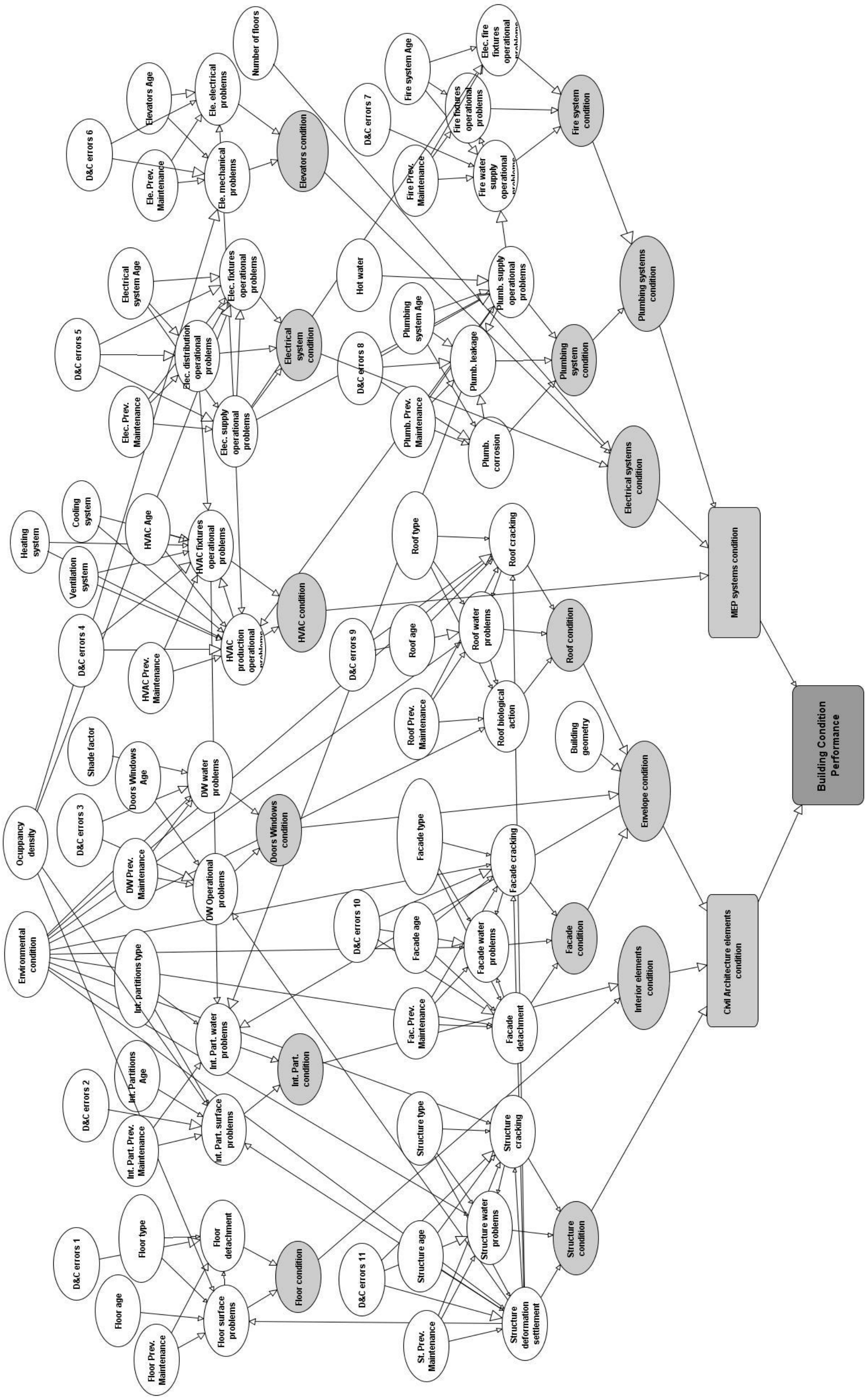


Figure 14. BN model for assessing a building's condition (Bortolini & Forcada, 2019b)

The BN is constructed in AgenaRisk for building condition assessment, due to its power, versatility and user-friendly interface (Pérez-Miñana, 2016). It can visualize the sensitivity analysis for the BN model to represent the importance of causal factors.

5.2 DSS implementation

To integrate the building condition probabilistic model based on BN in the BIM model, a conceptual model is designed enabling bidirectional data transfer between BIM and BN. The conceptual model is then implemented in Autodesk Revit. The system architecture of implementing the conceptual model into Autodesk Revit (i.e., a BIM tool) to facilitate the assessment of building conditions consists of three main steps, illustrated in Figure 15. (1) Data requirement: the parameters for the Revit model are created as IfcPset, based on the required data for building condition assessment. (2) Data integration: the Revit model is integrated with the BN model to evaluate building condition using Dynamo. (3) Data visualization: the BN results of the building condition assessment are exported to local storage and visualized in Revit in a way that the FM team can easily understand the data.

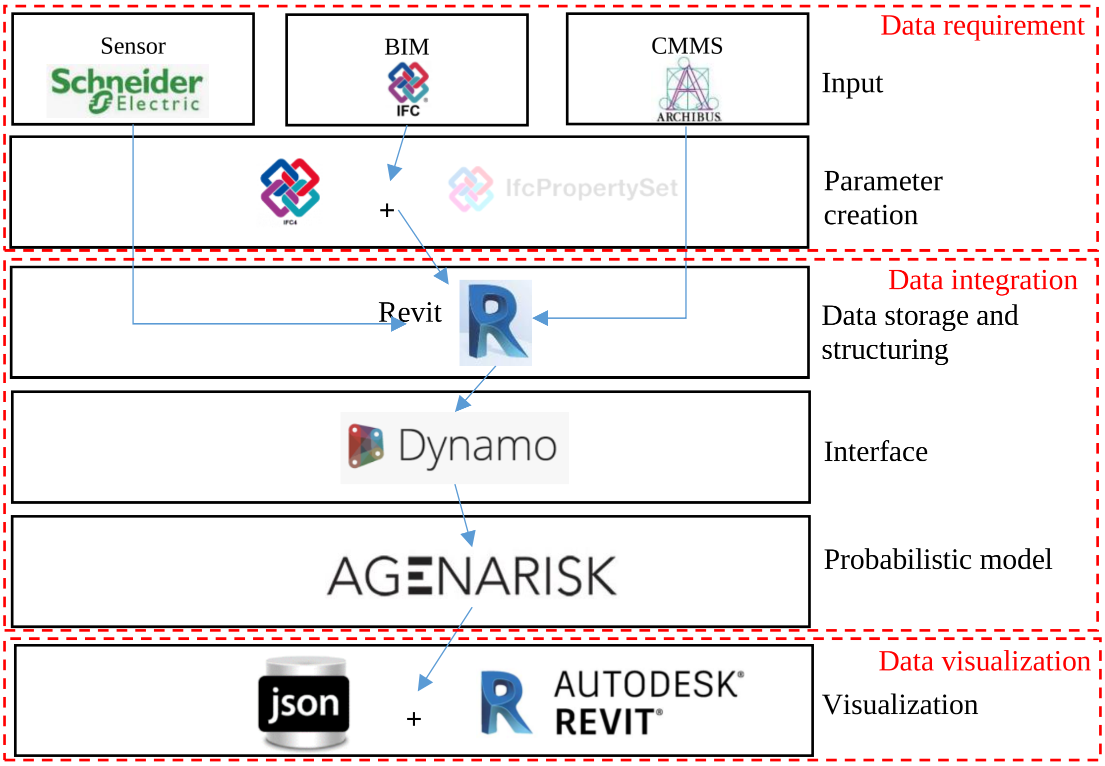


Figure 15. Process of the probabilistic model implementation in BIM for building condition assessment

5.2.1 Conceptual model

The conceptual model consists of seven thematic classes, namely: “BuildingCondition”, “CMMS”, “EnvironmentalCondition”, “IfcBuilding”, “IfcPset”, “Interface” and “Visualization”. A Unified Modeling Language (UML) class diagram, which is a worldwide industry standard (Weilkiens, 2007), is employed to present the conceptual model. A class diagram in the UML is a type of static structure diagram that describes the structure of a system by showing its classes, attributes, and behavior (e.g., operations). Figure 16 highlights the conceptual design of the proposed model for BIM and BN integration. In Figure 16, the “interface” class for building elements/systems merges all data sources and transforms them into the appropriate format by creating new attributes to support compatibility of BIM and BN models. To create new attributes, algorithms for various data types such as Number, Boolean and String are created. These attributes are then required by the “BuildingCondition” class, using an interface to assess a building’s condition.

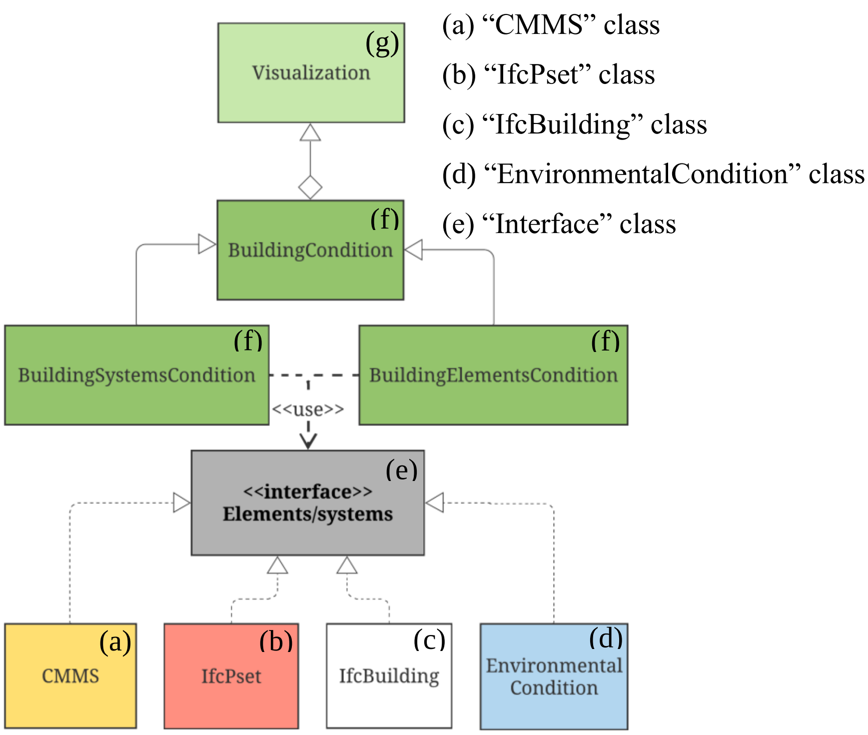


Figure 16. Conceptual design of the UML diagram

To enhance the readability of the UML diagrams, classes are depicted in different colors, considering different data sources. The “CMMS” class (in yellow, [a]) includes maintenance requests and preventive maintenance records, which play an important role in identifying defects in building elements/systems. The “EnvironmentalCondition” class contains a sensor to obtain the weather conditions (in blue, [d]). Figure 17 shows the UML diagram for “CMMS” and “EnvironmentalCondition” classes.

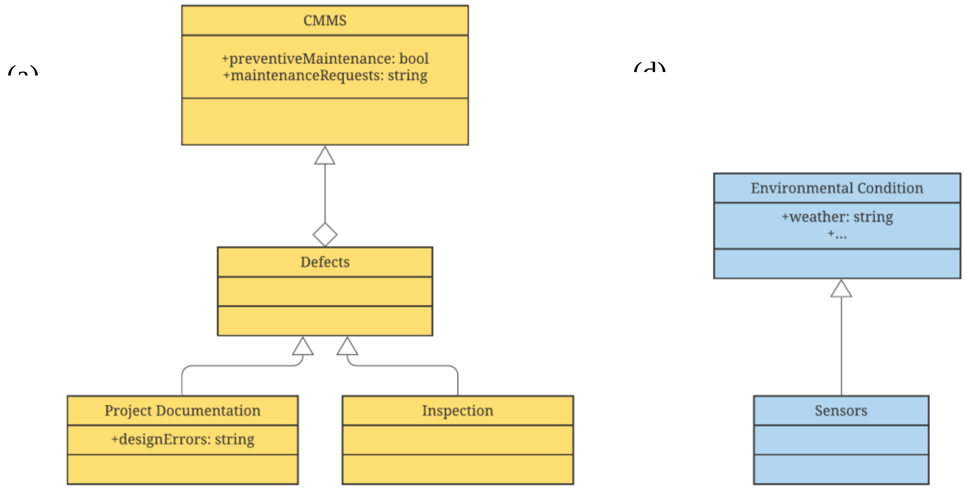


Figure 17. UML diagram of (a) “CMMS” class and (d) “EnvironmentalCondition” class

The “IfcBuilding” class (in white, [c]) is considered a major data exchange schema standard for BIM (BuildingSMART, 2020). The IFC Property Set known as “IfcPset” is a class (in red, [b]) that contains required data on building condition assessments. These data are assigned to an IFC model object and their class names are preceded by the prefix IfcPset.

The “BuildingCondition” classes (in green, [f]) are divided into building system condition and building element condition for ease of reading, as shown in Figure 18 and Figure 19. Due to the complexity of the model and limitations of space, the attributes are not illustrated in the class diagrams (for the complete conceptual model, see Appendix B).

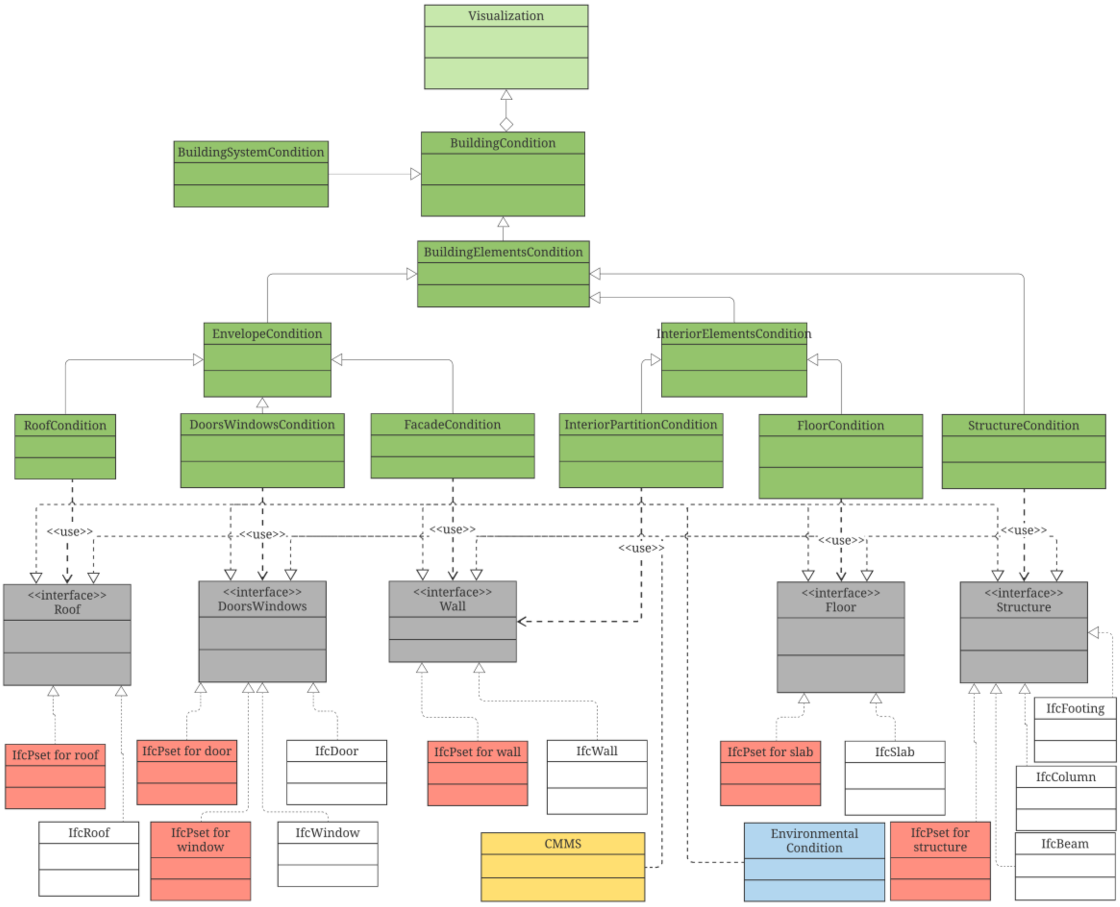


Figure 18. Conceptual model of the building element condition using UML diagram

The “BuildingCondition” classes that are based on causality analysis use “interface” class (in grey, [e]) to assess a building’s condition. This requires the acquisition of data from various sources such as “CMMS”, “IfcBuilding”, “IfcPset” and “EnvironmentalCondition” classes, followed by the transformation of these data into an appropriate format.

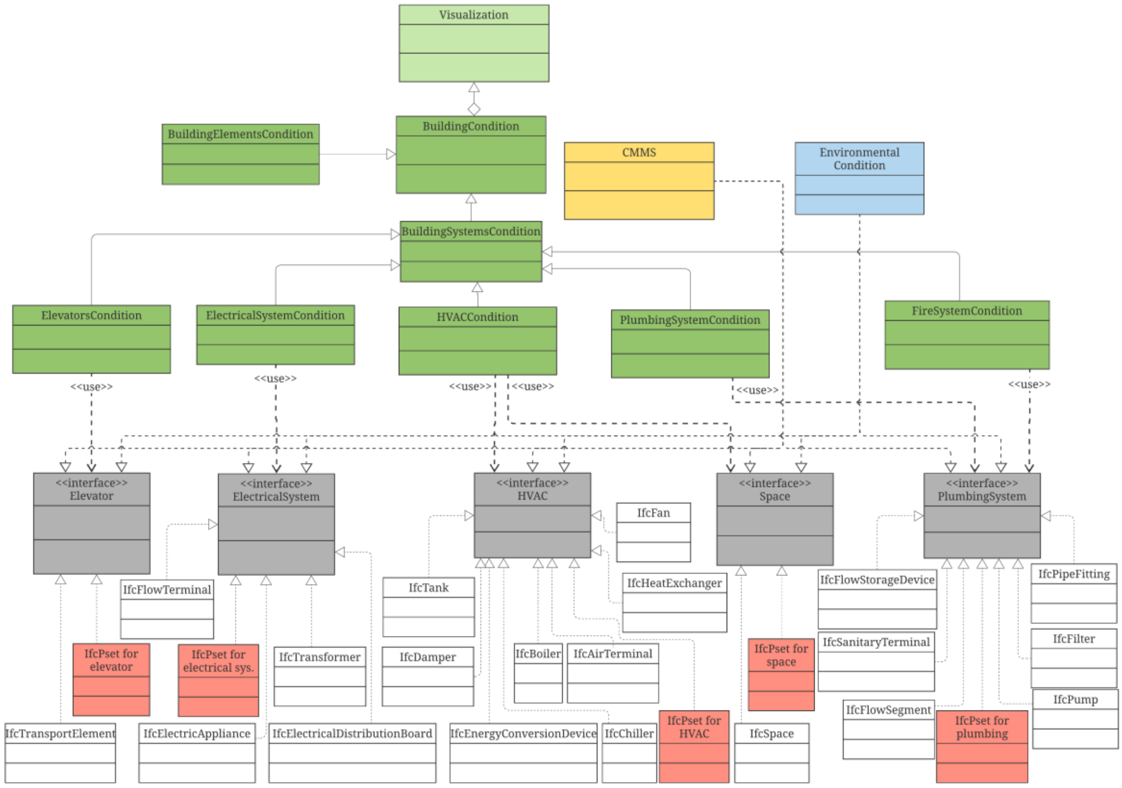


Figure 19. Conceptual model of the building system condition using UML diagram

UML diagrams for building system condition and building element condition differ according to their characteristics. For instance, the “IfcBuilding” class for building element condition is comprised of IFC for elements such as IfcDoor, IfcWindow, Ifcwall and IfcRoof, while for building system condition it consists of various IFC with respect to systems (e.g., IfcChiller, IfcDamper and IfcBoiler).

Finally, among all the thematic classes, the “Visualization” class (light green, [g]) represents a link through which the results of the building condition assessments can be imported into any possible data visualization tool.

5.2.2 Data requirement

To allow BIM models to contain the required data on building condition assessments, a Dynamo script is used to create parameters for data that could not be obtained from the BIM model, such as the age of each building element and system. All variables of the BN model are considered parameters in Dynamo. Figure 20 shows the process of creating parameters to host relevant data in BIM using a Dynamo script.

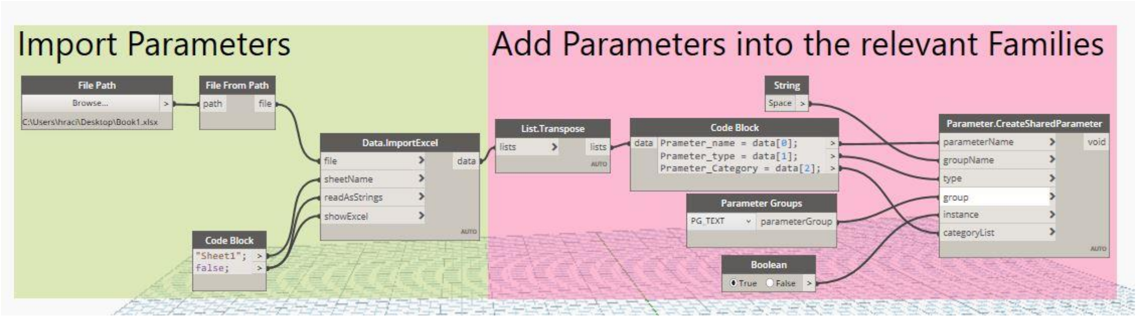


Figure 20. Dynamo scripts to create parameters

The parameter name of the required data is exported from the BN model as an .XML file converted into Microsoft Excel (.xls), an intermediate format, before mapping it to the BIM model. Then, authors manually define the parameter types and families to assign the required data into their relevant families in BIM. There are different kinds of parameter types, including Numbers, Strings and Yes/No Boolean. For example, the "HVAC age" parameter requires a numeric value since it contains the age of equipment. Therefore, its type is considered as "Numbers" and its corresponding family is defined as "Mechanical Equipment" in the BIM model. Next, the .xls file containing the parameter's name, type (i.e., data type) and family for each item of data, is imported into the Dynamo through a Data.ImportExcel node. Eventually, all the parameters are created in the BIM model based on the required data from the BN model to host relevant data using a ParameterCreateSharedParameter node in Dynamo.

The options of whether or not to have preventive maintenance, cooling, heating, and different kinds of data such as building properties (e.g., age, type of elements) are then added to the BIM model from which can be extracted. However, before extracting these data from the BIM model, they must be transformed into an appropriate format so as to be compatible with the BN model. To achieve this, a bunch of Python scripts is designed in Dynamo to transform data from the BIM into the appropriate format. Dynamo is a scalable way to extract data from centralized spreadsheets and update common parameters with a range of data types including Boolean, Strings and Numbers. Table 3 shows all the parameters that need to be transformed to be utilized in the BN model.

Table 3. Parameters in the BN model for building condition assessments

Type	**Parameters**		**States in the BN model**
Boolean	Façade prev. maintenance Roof prev. maintenance Doors/windows prev. maintenance Cooling Heating HVAC prev. maintenance Electrical prev. maintenance	Elevators prev. maintenance Structure prev. maintenance Floor prev. maintenance Interior partitions prev. maintenance Plumbing–hot water Plumbing prev. maintenance Fire system prev. maintenance	Yes, No
String	Façade type		Concrete panels/masonry, metal panels, glazed, others
	Roof type		Flat concrete, flat metal panels, glazed, others
	Ventilation		Forced, natural
	Structure type		Concrete, masonry, steel, others
	Floor type		Continuous, discontinuous, others
	Interior partition type		Masonry walls, light partition walls, others
Number	Façade age Roof age Doors/windows age	Elevator age Electrical age	<10, 10 to 20, >20
	Structure age Floor age	Interior partitions age	<10, 10 to 30, >30
	Plumbing age HVAC age	Fire system age	<3, 3 to 10, >10

For those data expressed in numbers (e.g., roof age, floor age), a Python code block is used to calculate the average age of all elements in BIM since the BN model evaluates the condition of entire buildings rather than a single element. For example, when one floor of a building is renovated, the “floor age” is determined by the Python code block calculating the average age of all floors in a building and transforming the results into an appropriate format for the BN model which is “<10” if the average age is less than 10 years, “10 to 30” if the average age is between 10 to 30 years, and “>30” if the average age is greater than 30 years.

For data expressed in a Boolean form (e.g., “Yes” having or “No” not having preventive maintenance, cooling, or heating), a Python code block is designed to enumerate all the “Yes” and “No” for each Boolean to determine which one is repeated more than the other. For instance, for data on Having or not having heating in a room, all the rooms are considered in a Python code block and all “Yes” and “No” are enumerated to find out whether the building has heating or not. The most repeated answer is considered the result for the question of whether or not there is heating in the building. If the number of “Yes” and “No” are equal, the result would be considered “No”.

A similar approach to Boolean and numbers can be used for strings (e.g., ventilation). For example, the ventilation type in the BN model for buildings is either forced or natural. A Python code block recognizes whether the building has forced ventilation or not. If not, the type of ventilation is considered natural. If there are more than two options (e.g., façade type), the “if…elif…else” statement could be used (i.e., the same as floor age). Table 4 shows an example of Python code blocks for floor age as numbers, floor preventive maintenance as Boolean, and ventilation as strings.

Table 4. Examples of Python code blocks for transforming data

Nodes	**Type**	**States in BN**	**Locate in BIM**	**Python code block in Dynamo**

Floor preventive maintenance	Boolean	Yes / No	Spaces	Yes_Count = list.count(data, 'Yes')
				No_Count = list.count(data, 'No')
				if Yes_Count > No_Count:
				result = "Yes"
				else:
				result = "No"

Floor age	Numbers	<10
		10 to 30
		>30
			Building elements	average = sum(data)/len(data)
				if average < 10:
				result = “< 10”
				elif average > 20:
				result = “> 20”
				else:
				result = “10 to 20”

Ventilation	String	Forced/Natural	Spaces	if data == Forced result = “Forced” else: result = “Natural”

5.2.3 Data integration

To transfer data between BIM and BN models bidirectionally, firstly the required data is extracted from the BIM model using Dynamo and Python scripts, by creating a dataset in a JavaScript Object Notation (.Json) format, which is a lightweight format for storing and transferring data. The dataset containing all the required data is then imported into the BN tool, AgenaRisk, which utilizes the data as ‘evidence’. Then, the FM team could run the BN model straightaway to acquire the results of analyzing the condition of a building. Secondly, the assessment results of a building’s condition are extracted from the AgenaRisk tool into a Json format and imported into the BIM model using Dynamo and Python to visualize the results in a 3D model.

In accordance with the BN model, the BN results assess conditions of entire buildings, comprising various groups of elements. For example, all windows and floors (i.e., different elements) in the building must be considered to evaluate the condition of the window and floor respectively. Therefore, various categories are designed using the “Categories” node in Dynamo to match the results of the building condition assessment with the corresponding groups of elements in the BIM model.

Even though categories in BIM provide various groups of elements, some categories on building condition assessments based on the BN model still cannot be represented. Hence, Dynamo and Python scripts are used to create a new category for BIM to be compatible with the BN results. For instance, the BN model assessed the condition of either façade or interior partitions individually, both of which have the same category in the BIM model called “wall category”. In this example, regular expressions, a sequence of characters that specifies a search pattern in a Python code block are designed to distinguish the wall category between the interior partitions and façade, to create new categories in BIM for both. Regular expressions utilize text to conduct pattern matching and “search-and-replace” operations. Figure 21 illustrates an example of creating a new category in BIM for façade.

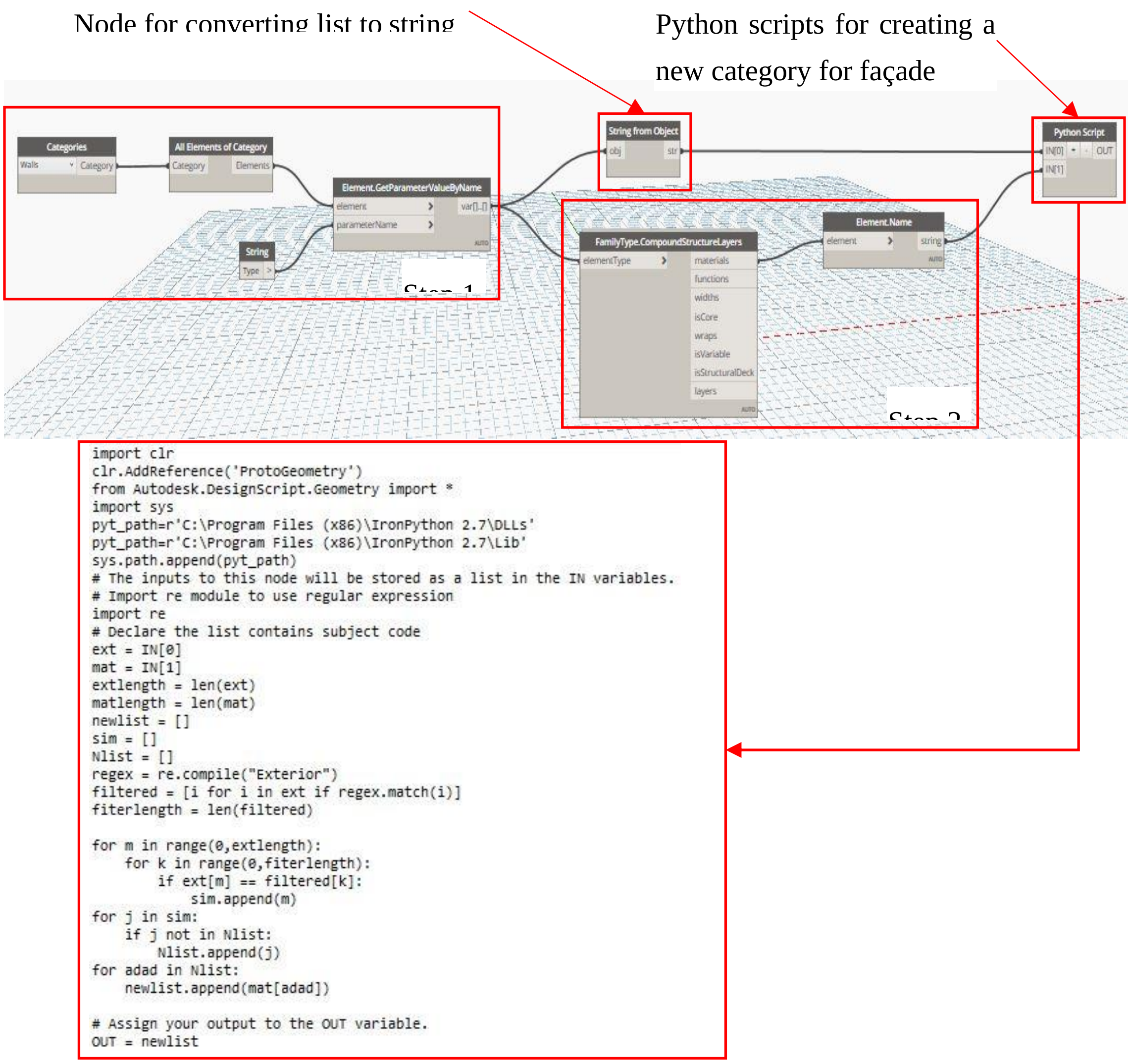
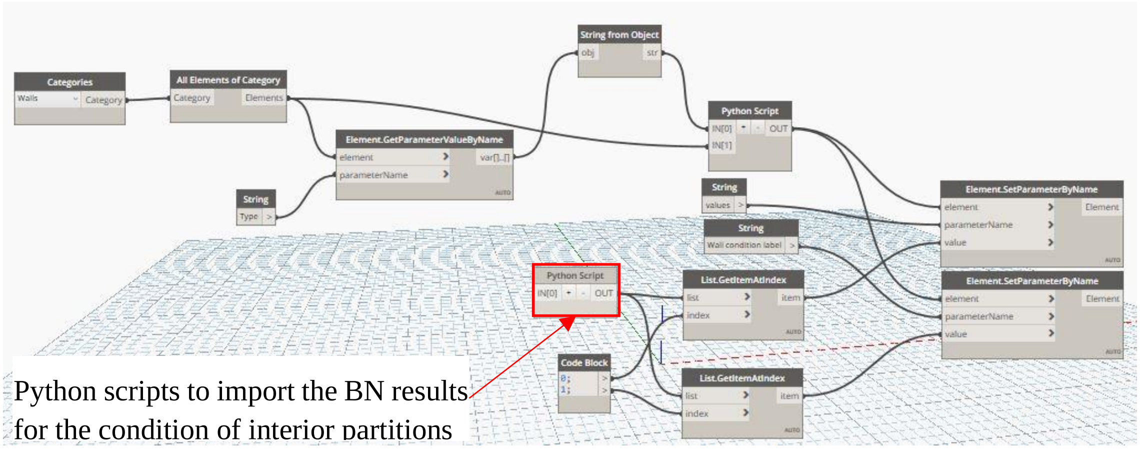


Figure 21. Dynamo scripts to create a new category in BIM for façade as an example

Three steps are imperative to create a new category for façade as an example. Firstly, a list of all wall elements for the building is created in the first step. Then, this list is converted to string using the “String from Object” node as a regular expression supports strings. A regular expression is used to find the “exterior walls” among the list by string-searching algorithms. Secondly, the material of all walls is obtained using FamilyType.CompoundStructureLayers and Element.Name nodes in Dynamo, creating a list of material (Step 2). Thirdly, the list of all wall elements is connected to the Python code block as input#0, and the list of material is connected as input#1. Next, a Python code block queries input#0 to filter a list by exterior walls (i.e., façade). Then, it queries input#1 to find materials that match those from the exterior walls (input#0) and create a new list with the exterior walls and their corresponding material. Eventually, the category for façade is created to be consistent with the BN results of building condition assessments.

5.2.4 Data visualization

As described in Section 3.3.3, the results of the building condition assessments are extracted from the AgenaRisk tool into Json format and imported into Revit using a Python programming language in Dynamo to be matched with corresponding building elements. A Python code block queries the BN results to find the condition of elements categorized as high, medium, or low. Then, the condition for each element is mapped to its corresponding elements in the BIM model using GetItemAtIndex and SetParameterByName nodes. Figure 22 illustrates the process of mapping the BN results for interior partitions as an example.




```
import clr
clr.AddReference('ProtoGeometry')
from Autodesk.DesignScript.Geometry import *
import sys
pyt_path=r'C:\Program Files (x86)\IronPython 2.7\DLLs'
pyt_path=r'C:\Program Files (x86)\IronPython 2.7\Lib'
sys.path.append(pyt_path)
# The inputs to this node will be stored as a list in the IN variables.
import json
lis_value = []
lis_label = []
with open('C:\Hamid\PhD Hamidreza\BN model\Export results for visualization\All visualization\Scenario 6 Safety Int. Part. condition.json', 'r+') as file:
    data = json.load(file)

for res in data['dataSets']:
    for resv in res['results']:
        for val in resv['resultValues']:
            lis_value.append(val['value'])
            lis_label.append(val['label'])
            for i in range(0,len(lis_value)):
                for j in range(0,len(lis_label)):
                        if lis_value[i] == max(lis_value):
                                x = lis_label[i]
                        else:
                                continue

# Assign your output to the OUT variable.
OUT = max(lis_value), x
```

Figure 22. Dynamo scripts to map the BN results for interior partitions as an example

Lastly, the BIM model visualizes the results with different colors to vary from ‘High’ to ‘Low’. The tabulated data taken from Revit’s schedule are visualized in a 3D format in the BIM model by applying view filters. For a given element, the relevant results of the building condition assessment are identified. Figure 23 illustrates the BIM visualization of the building’s condition as an example.

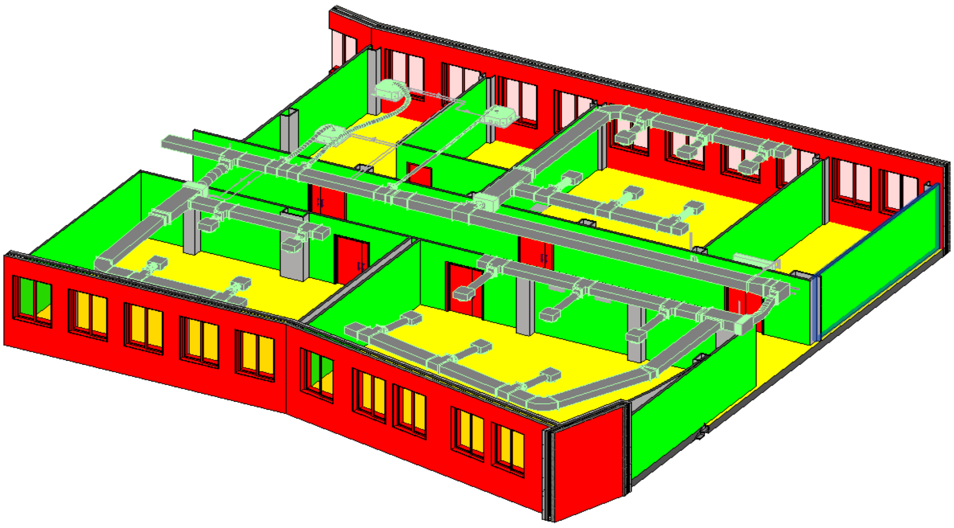


Figure 23. BIM visualization of a building's condition

BIM visualization allows the FM team and owners to evaluate building and system elements based on the causality analysis using different color codes, where red represents a low performance condition, yellow a medium performance condition, and green a high-performance condition.

5.3 Evaluation

In this chapter, the evaluation is based on the validation and verification. To validate the conceptual model, three buildings (TR5, TR11 and TR14) of the Terrassa campus are used as case studies (Figure 24). Furthermore, to verify data completeness of the conceptual model, information exported from the BIM model is checked, ensuring that there is no missing data.

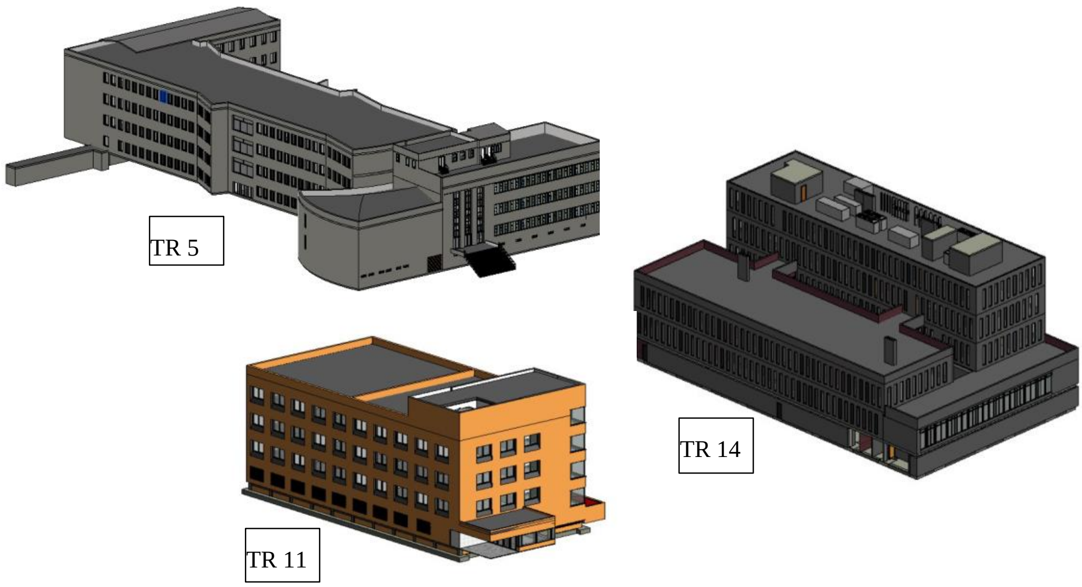


Figure 24. Case study projects

The consistency of the conceptual model is validated by running the proposed system architecture in TR5, TR11 and TR14 and comparing the condition assessment results with those obtained from the existing manual method (e.g., AgenaRisk) in which the FM is required to perform the data transfer process manually. Furthermore, 18 scenarios per building are simulated and compared with the results obtained from the existing manual method.

The completeness of the conceptual model is verified by (Afsari, Eastman, & Castro-Lacouture, 2017): a) checking the Json data formatting, b) checking either an empty or null value for each data item in the Json file.

The first step verifies the Json data for correctness and provides a list of missing data in the validation report one after another, until all the required data is complete. In this study, a Json validator (e.g., http://jsonlint.com/) is used to verify Json data for formatting. If the data in the Json file is incorrect or incomplete, the verification will report a failure to assist in the debugging of Json data (Wickham, 2018).

The second step ensures that all data have their value, demonstrating the data completeness. Once the Json data formatting had been evaluated, the value of the transferred data is checked to meet data completeness. If the value for data is missing, it should be presented either as empty (“”) or a null value in the Json file. Therefore, the Json file is parsed using the json.load() method in Spyder (Spyder, 2018). The Python script is then used to check whether the value for each data is empty (null) or not.

The benefits of using the proposed system architecture (task efficiency analysis) are analyzed in terms of time reduction in comparison with the manual method. The advantages of the visualization in terms of intuitiveness are discussed.

All buildings are maintained by the same FM company. Therefore, all have the same maintenance protocols. TR5 was constructed in 1960, it has five floors with 11,492 m2; TR11 was built in 1997 and has 4 floors with a total area of 2,779 m2; and TR 14 was built in 2011 and is a six-story building with one parking lot and 7,378 m2.

Both TR5 and TR11 have a reinforced concrete structure, flat roofs, and masonry façades, while TR14 has a metal panel façade. Regarding HVAC in TR5, most classrooms and offices have radiators, air-water systems and multi splits while TR14 is heated and cooled by fan coils, one chiller and two boilers. In TR11, there is no cooling system at all, and the ventilation is only natural, by opening windows.

To run the proposed system architecture, many parameters are created, such as the age of elements and whether or not they have preventive maintenance or ventilation. The Python code blocks are used to calculate the data required by the BN (square meters, average age, etc.). Other parameters are created to adapt the classification of the elements obtained from the BIM model to those required by the BN model. For example, the façade type is classified as “concrete panels/masonry”, “metal panels”, “glazed” and “others”.

As an example, to allow data integration and interoperability regarding the ventilation system, the algorithm for “HVAC interface” creates new attributes to be compatible with the BN model considering the entire buildings. In TR5, for instance, since most rooms (e.g., offices, classrooms, and corridors) have an air-water system, the new “Forced” attribute is created while in TR11 the new attribute is “Natural”. For TR14, it is also considered as “Forced” on account of having air handling units (AHU) and fan coils in all rooms.

With respect to flooring, the algorithm for floor “interface” creates new attributes for buildings. In TR14, the floor is “discontinuous” as it is constructed in various phases. For other buildings (TR5, TR11), the attribute is “continuous”.

The BN results (condition of the building elements and systems) are visualized in the BIM model (Figure 25) by the proposed system architecture and compared with those obtained using the AgenaRisk in which data are introduced manually. The system architecture shows the same results as the existing manual method but in a user-friendly way, allowing the FM team to quickly identify problems in buildings. Besides, 54 different scenarios for all three buildings (i.e., 18 scenarios for each building) are simulated in the proposed system architecture and the existing manual method. After running all these scenarios, the results in both methods are the same and thus confirms the data consistency.

Regarding the task efficiency analysis, the same approach as Kang and Hong (Kang & Hong, 2015) is used in this study. To achieve this, two tasks are classified as follows. (1) BIM Data Transfer Process (BDTP), which transfers data from the BIM into the BN model. (2) Mapping BN results into BIM (MBB), which imports the BN assessment results into the BIM model to visualize a building's condition. Then, each task is timed and compared with the others listed in Table 5.

Table 5. Task efficiency analysis

Building	**Task**	**Time to perform each task (minutes [hours])**	
		AgenaRisk (manual)	**Proposed system architecture (automated)**
TR5	BDTP	1845 (30.7)	44 (0.7)
	MBB	530 (8.8)	15 (0.25)
TR11	BDTP	1390 (23.2)	40 (0.7)
	MBB	510 (8.5)	13 (0.2)
TR14	BDTP	1000 (16.6)	37 (0.6)
	MBB	495 (8.2)	10 (0.2)

The time for performing the "BDTP" task, which is known as the most time-consuming, decreases nearly 100% in all buildings when the proposed system architecture is used. This shows the importance of automation of data transfer. In general, using the existing manual method, it takes 39.5 hours for TR5, 31.7 hours for TR11 and 24.8 hours for TR14 to perform "BDTP" and "MBB" tasks. When the system architecture is used, the same task takes 0.95 hours, 0.9 hours, and 0.8 hours for each building respectively to check that all algorithms are running correctly.

Regarding data completeness, the results from a Json validator shows that the Json data (containing BIM data) formatting is correct and there is no incorrect Json syntax or missing data. Once the Json data formatting is found to be correct, the value of the transferred data is checked to meet the data completeness criterion. To achieve this, the Python script is used for all 54 scenarios. The results demonstrates that there are 1,728 data items, all of which had a specific value, explaining that data from the BIM model are transferred to the BN model completely without losing data.

With regard to the transfer of the assessment results of a building's condition to the BIM model, the same approach is applied. Firstly, the Json data formatting is checked for the Json file containing the results of the building condition assessments, which are correct. Secondly, the Python script reveals that none of the values are empty (null). Besides, if a value is missing, the Dynamo will report an error while it runs for the visualization. Hence, it is concluded that the process of data transfer from the BN model to the BIM model is also performed properly and thus shows no data loss.

From a sensitivity analysis of the TR5 roof, cracks in the tiles due to age and a lack of preventive actions are found to be the main causes of this poor condition. Substituting tiles, painting them with a waterproof coating to avoid efflorescence and sealing them are found to be appropriate corrective actions for the poor roof condition, while periodic inspections of roof tiles (cracked or chipped tiles) and replacement when necessary are implemented as preventive maintenance actions.

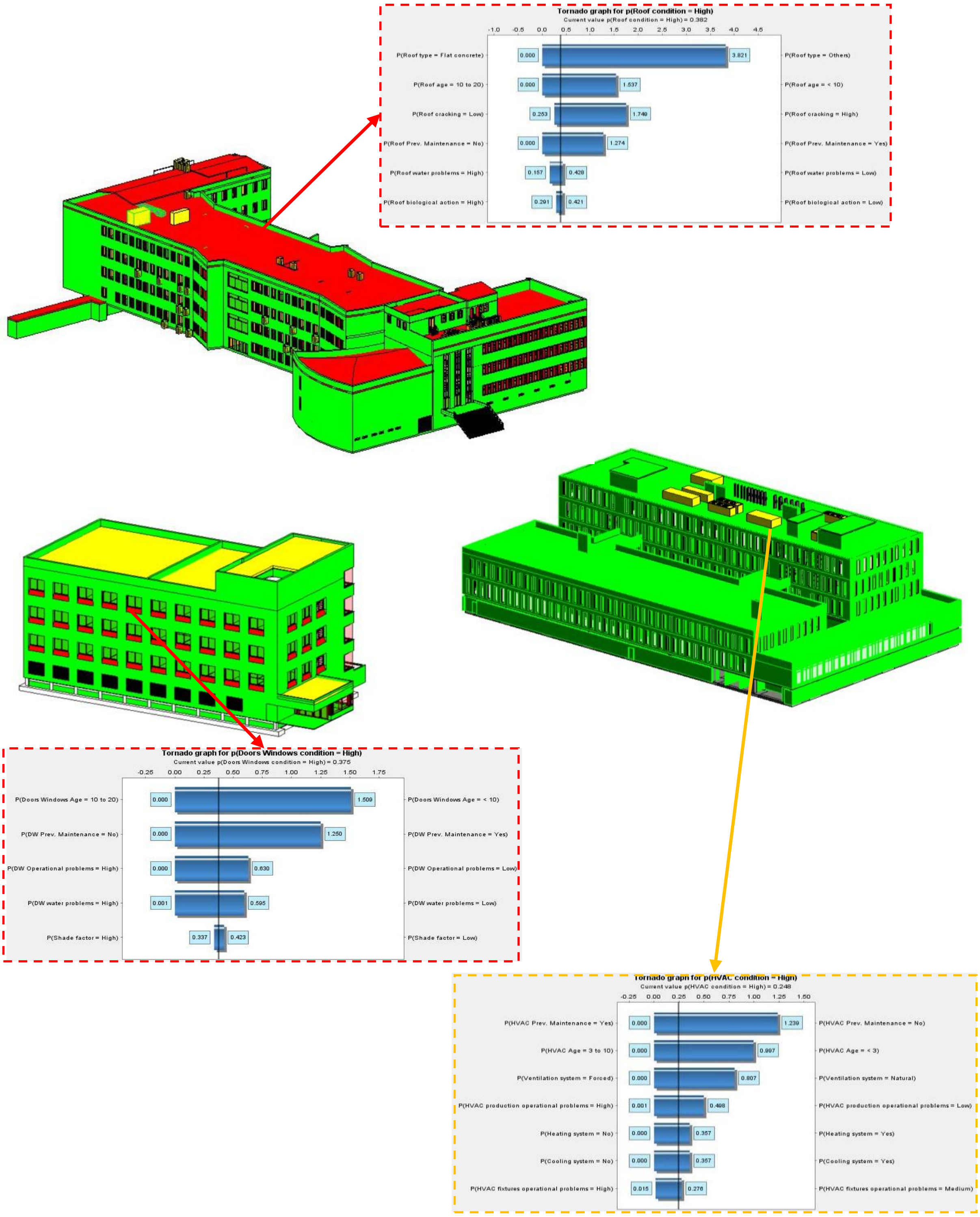


Figure 25. BIM visualization of building conditions and causality analysis results

5.4 Discussion

This chapter presents a conceptual model to enable interoperability between BIM models and the building condition probabilistic model based on BN. The research provides the system architecture to implement the conceptual model in a case study. The integration of BIM with BN models facilitates data transfer and reduces the time and effort that the FM team spends on manual input. It also allows BIM tools to visualize the building elements/systems in an integrated, interactive way for decision-makers.

The conceptual model allows bidirectional transfer data between BIM and the BN models. It integrates BIM with the probabilistic model based on BN for building condition assessment. Therefore, it enables the FM team to address the challenges of information reliability, interoperability, usability, and minimization of labor time. It also helps the FM team to optimize building operation strategies and supports decision-making on FM activities (e.g., predictive maintenance) to improve building performance.

The conceptual model is implemented in Autodesk Revit and AgenaRisk. However, both the process of data extraction from AgenaRisk and the process of mapping the results in the BIM model are based on Python and Dynamo respectively, allowing a high level of customization and interoperability with the majority of existing platforms.

The case study is used to validate the proposed approach. The visualization of the condition of the elements and systems from the campus buildings facilitates prioritization of investments in buildings. In the case of the three campus buildings, the roof from TR5 is found to require renovation and thus prioritization. Furthermore, the BN results allow an evaluation of the causal factors of the condition of the elements, using sensitivity analysis. The length of the bars is a measure of the influence of parameters on the building condition assessment. Therefore, the FM team can evaluate the most probable cause of those building elements/systems associated with poor condition to implement corrective actions and plan future preventive measures.

5.5 Conclusions

The conceptual model allows interoperability between the BIM and probabilistic model to evaluate building elements and systems. The proposed system architecture automatizes the data workflows to increase the use efficiency of the BN model, reducing the time and effort that the FM team spends on manual input. Enabling interoperability between BIM and the

BN model allows transformation of the data into an appropriate format automatically to run the BN model. Automating data transfer enables the FM team to take advantage of the BN model in favor. Thus, the FM team could use the proposed system architecture to prioritize the work order to improve maintenance activities, extend the lifespan of building elements or systems and increase building durability. The conceptual model can be applied to any building typology and is very relevant because its application allows the assessment of building conditions in a semi-automated way.

The method of visualization in this approach focuses on the condition of building elements and systems, which is demonstrated on a color scale where red indicates urgency in building elements and systems intervention, yellow indicates deteriorating performance condition, and green indicates satisfactory condition of the building elements and systems. This visualization makes it possible to detect the condition of current building elements and systems more intuitively, and potentially makes it easier to deal with the problem. This will result in a considerable improvement in building performance. Overall, the workflow for the FM team to use the system architecture is:

1) Run the system architecture in all buildings managed by the FM company
2) Visualize the condition of the building elements/systems for those buildings
3) Check sensitivity analysis to determine the most probable causes for the building elements/systems with low-performance condition
4) Make corrective action plans
5) Propose preventive maintenance plans

Chapter 6

A BIM-based DSS for enhancing occupants' comfort

This chapter describes the process of BIM integration with an occupants' comfort probabilistic model as well as occupants' feedback with respect to the comfort aspects: thermal comfort, acoustic comfort, indoor air quality, visual comfort, and space adequacy. Hence, a satisfaction survey and an occupants' comfort probabilistic model are utilized to evaluate the causal factors of occupants' discomfort. The required data for the occupants' comfort probabilistic model is then identified. Afterwards, BIM is integrated with the probabilistic model and occupants' feedback to enable the visualization of average occupants' comfort level, employing a color scale in rooms. This integration can also assist facility managers and owners in identifying causal factors of occupants' discomfort and properly establishing the necessary measurements to moderate the negative consequences on occupants and thereby improve their comfort. Finally, a case study is used to validate the proposed approach.

6.1 DSS for occupants' comfort

To evaluate the causal factors of occupants' discomfort, Bortolini and Forcada (Bortolini & Forcada, 2019a) developed a probabilistic model based on BN for occupants' comfort. This model is created using cause-and-effect relationships between uncertain elements that impact occupant's comfort in non-residential buildings, illustrated in Figure 26.

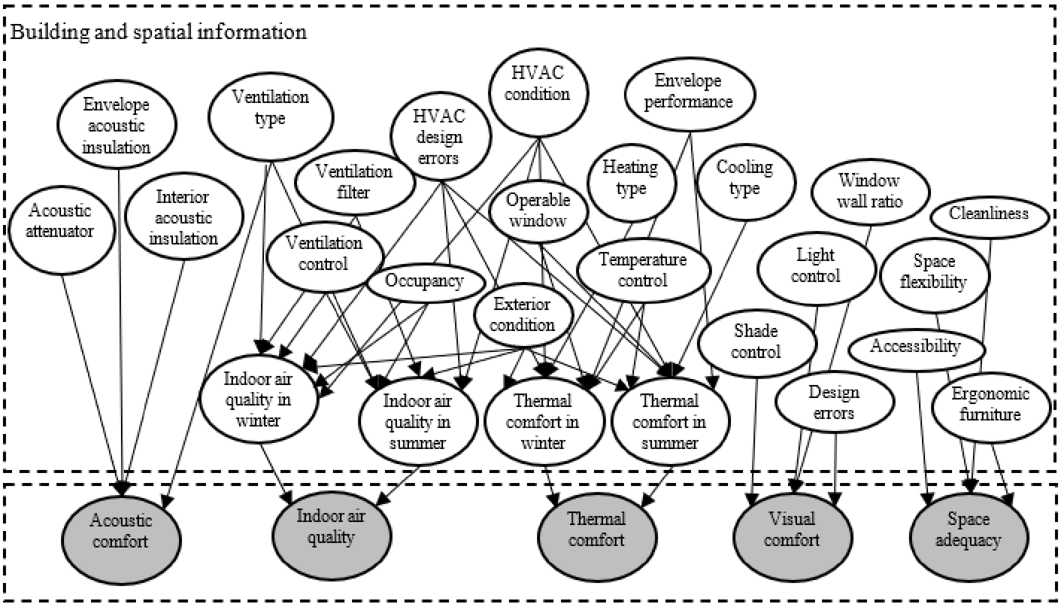


Figure 26. BN model for occupants' comfort

In the BN model, variables that impact the occupants' comfort for various aspects (e.g., thermal comfort, visual comfort, acoustic comfort, and indoor air quality) are described as follows. Indoor air quality is one of the primary disturbances among the occupants. Additionally, daylight penetration in buildings and harmful noise level straightforwardly affect the occupants' psychology. Thus, disturbing physical aspects slow down occupants' job levels and raise the number of mistakes due to interruption (Korkmaz, Messner, Riley, & Magent, 2010; Chidiac, Catania, Morofsky, & Foo, 2011). The physical condition of the workplace influences 15-20% of the occupants' productivity. Productivity thus constitutes the economic dimension of comfort conditions by ultimately impacting the business financially (Rostron, 2008; Shrestha & Kulkarni, 2013).

For acoustic comfort, the insulation characteristics of all walls, windows, and doors of each room are contributing factors in the BN model. Acoustic attenuators used in mechanical ventilation systems can reduce noise from air systems and are considered as a contributing factor to understanding occupants' acoustic discomfort. Buildings with natural ventilation might lead to discomfort due to outside noise; hence the type of ventilation system is identified as a further factor affecting acoustic comfort. Factors such as building and spatial information are considered as nodes in the BN model (e.g., causal factors). The type of ventilation system is defined as a labeled node with the following states: natural, forced, and mixed. Envelope and interior acoustic insulation are defined as ranked nodes. Finally, an acoustic attenuator is defined as a Boolean node (Yes/No). Regarding the importance of the parent nodes, interior acoustic insulation, envelope acoustic insulation, and acoustic attenuator have the same impact on acoustic comfort.

Indoor air quality depends on the type of ventilation system which can influence occupants' comfort perception. Generally, naturally ventilated buildings have higher rates of comfort than air-conditioned buildings (Rostron, 2008). The occupants can open windows and thus vary the indoor environment to some extent. However, natural ventilation is dependent on weather conditions (Chilton et al., 2012), and might not be adequate in environments with extreme temperatures. Obtaining information on outdoor conditions from an exterior meteorological station is, therefore, a relevant factor for determining the air quality comfort.

On the other hand, for buildings with mechanical ventilation, the condition of the HVAC system is an essential factor, as its improper operation may lead to poor ventilation and cause health problems and discomfort (Rostron, 2008; Au-Yong, Ali, & Ahmad, 2014; Bortolini & Forcada, 2019a). The HVAC condition, which refers to the condition of the component, is categorized as high, medium, or low. For instance, high condition would describe an item of equipment in excellent condition, capable of being used to its fully specified utilization for its designated purpose. HVAC design errors (wrong design of the system) might have an impact on occupants' discomfort in indoor air quality and thermal comfort (Roulet et al., 2006; Aghemo, Blaso, & Pellegrino, 2014). For example, a good HVAC system design depends on the architecture of the building. If there are single thermal zones, then centralized systems are the best option, whereas, for buildings with different thermal zones, decentralized systems are a better option.

Furthermore, occupancy density (m^2/person) affects air quality comfort, so it is also considered as a contributing factor in indoor air quality. In the BN model, HVAC design errors, HVAC condition and occupancy density are defined as ranked nodes and ventilation control and filter are considered as Boolean nodes. Exterior condition is defined as a labelled node (e.g., extreme cold, cold, and mild for winters and extreme hot, hot, and mild for summers). HVAC condition and HVAC design errors are the most important factors that affect indoor air quality, while ventilation filter has the least impact on indoor air quality.

With respect to thermal comfort, thermal sensation is the condition of mind that expresses comfort with the thermal environment. The exterior conditions play an essential role in thermal sensation. The type and characteristics of HVAC systems (e.g., cooling and heating type) and thermal adaptive opportunities are also identified as relevant factors in thermal comfort (Hua, Göçer, & Göçer, 2014; Bortolini & Forcada, 2018). Radiant systems, for example, can provide higher comfort levels for indoor temperature (Karmann, Schiavon, Graham, Raftery, & Bauman, 2017). The age of HVAC components (such as splits, boiler, chiller, etc.) can affect their performance and thus the thermal comfort. Occupants with thermal adaptive opportunities such as operable windows and thermostats present high levels of comfort (J. Kim & De Dear, 2012; Al-Atrash, Hellwig, & Wagner, 2018). The characteristics of a building include envelope material and insulation, comprising both façade, roof, and windows (Catalina & Iordache, 2012). In this sense, an envelope with a low thermal transmittance (U-value) can help extend the periods of thermal comfort without reliance on mechanical air-conditioning (Al-Homoud, 2005; Bortolini & Forcada, 2019a). The material and insulation properties of partitions also play an important role when the adjacent rooms do not keep thermal comfort characteristics. In the BN model, the heating and cooling types are defined as labeled nodes with the statement of radiant, all-air, others, and not applicable. Both the possibility of controlling temperature and operable windows are considered as Boolean nodes. Although HVAC conditions, temperature control possibility, and envelope performance are classed as essential factors, thermal comfort is mostly affected by HVAC design errors and exterior conditions.

For visual comfort, the impact of daylighting can be considered quantitatively through the window-wall-ratio (WWR) (Li, Zhang, Edwards, & Hosseini, 2019). There is a strong preference for daylight in workplaces, which is closely associated with the belief that daylight is better for health (Galasiu & Veitch, 2006). Therefore, dimensions of façade and windows should be modeled in BIM, and the WWR per space calculated. The availability of interior curtains and/or exterior window shading (louvers) is a critical component in controlling glare and overheating, both of which affect occupants' comfort (Galasiu & Veitch, 2006). Design errors might also have an impact on occupants regarding visual comfort; for example, failure to design appropriate daylight controls can affect visual comfort. The light and shade control possibilities are defined as Boolean nodes in the BN model. The WWR is defined as the ratio of the glazed area to the entire area of the envelope and considered as a ranked node (i.e., low (<10%), medium (10-40%), and high (>40%)).

Regarding the importance of parent nodes for visual comfort, the ‘design error’ factor is more effective than light and shade control factors.

As described in 51, each variable of building and spatial information is represented as a node in the BN model, and depending on data type, they are defined as discrete or continuous. Due to the underlying numerical scale of the ranked nodes, the truncated Normal distribution (TNormal) is used for defining numerical statistical distributions as expressions (Fenton & Neil, 2018).

6.2 DSS implementation

There are three main steps to implement the occupants' comfort probabilistic model based on BN in the BIM model, making the analysis of occupants' comfort causal factors easier. (1) Data requirement: firstly, a satisfaction survey is developed and designed in Google forms, based upon comfort aspects (e.g., thermal comfort, acoustic comfort, indoor air quality, visual comfort, and space adequacy). Secondly, the probabilistic model is utilized to determine occupants' comfort causal factors based on BN, obtained from (Bortolini & Forcada, 2019a). In order to take advantage of the BN model, building information (e.g., building characteristics or HVAC system) and spatial information (e.g., occupancy density) are collected for each comfort aspect. Some of this information (e.g., building characteristic) could be obtained from a BIM model, but for that information which is not, parameters are created in the BIM model to host it. (2) Data integration: the BIM model is integrated with occupants’ feedback from the POE survey and the occupants’ comfort probabilistic model to support occupants’ comfort, utilizing a visual programming extension for Autodesk Revit, Dynamo, and the Python programming language. (3) Data visualization: The feedback of occupants and the BN results of occupants' discomfort causal factors are exported to local storage and visualized in Revit in a way that allows the FM team to comprehend the information. Figure 27 illustrates the process of integrating occupants’ feedback and the occupants’ comfort probabilistic model into the BIM model.

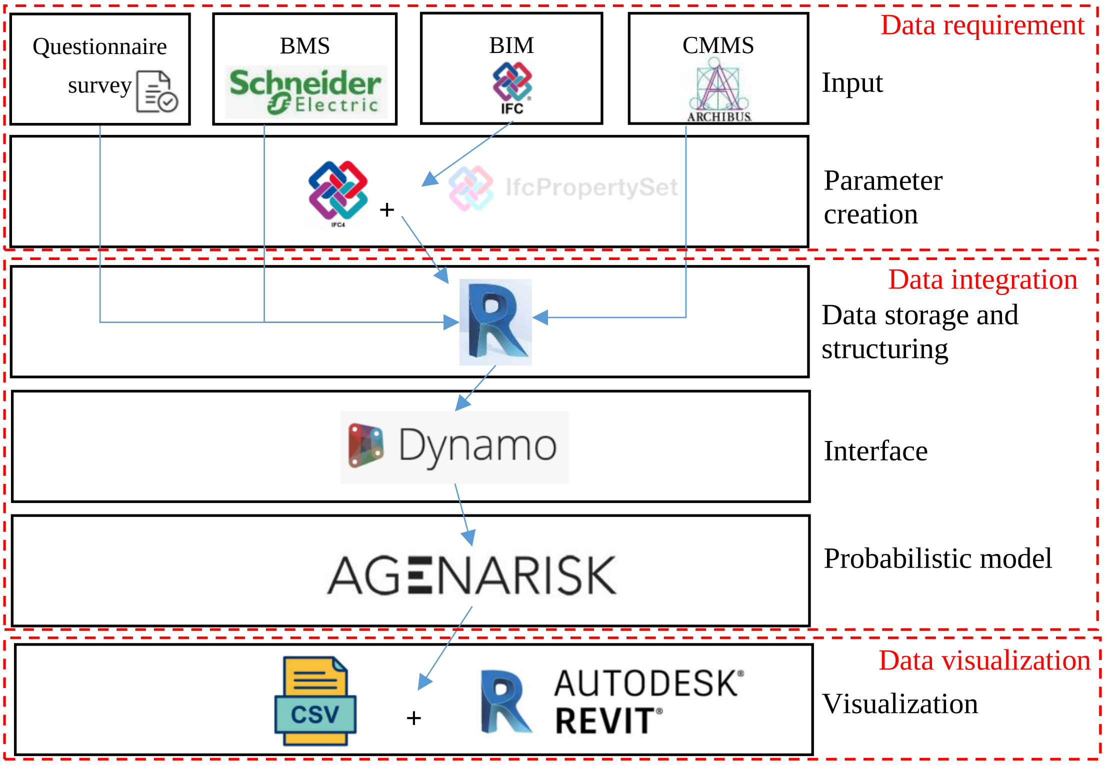


Figure 27. Process of the probabilistic model implementation in BIM for occupants' comfort

6.2.1 Data requirement

As described in 3.3.1, shared parameter is utilized to allow BIM models to contain information regarding occupants' comfort. In this case, occupants' feedback is collected through a questionnaire survey consisting of three sections (see Appendix A):

Section 1. Occupants are asked to select their workplace location, as defined by building, floor and room.

Section 2. Occupants are asked to rate their satisfaction in relation to various workplace comfort aspects, including thermal comfort in winter and summer, indoor air quality in winter and summer; visual comfort; acoustic comfort; and space adequacy. The survey used a 5-point Likert rating scale to rate occupant feedback, ranging from 'very satisfied' (5) to 'very dissatisfied' (1), with a neutral midpoint (3). The survey also asked the reasons for discomfort given the predefined options, and included a text entry box for respondents to add other reasons.

Section 3. Occupants are also asked to rate their satisfaction in relation to comfort aspects of the common spaces of the building that they used most (e.g., corridors, conference rooms, restrooms, and dining rooms), including thermal comfort in winter and summer; indoor air quality in winter and summer; visual comfort; acoustic comfort; and space adequacy.

Since occupants' feedback is reported by the spaces, the rooms are suitable hosts for the satisfaction survey. Hence, all comfort aspects of the satisfaction survey (e.g., indoor air quality and visual comfort) are created, defined, and linked to the rooms in BIM to host occupants' feedback. The same approach is used to create parameters for hosting building and spatial information with respect to the BN model for each comfort aspect that is not available in BIM (e.g., occupancy density).

After creating parameters, occupants' feedback, and the occupants' comfort probabilistic model are integrated into BIM. First, the occupants' feedback from the satisfaction survey is mapped into the corresponding parameters in BIM concerning each room. Second, bidirectional data transfer is implemented from BIM to a BN tool (AgenaRisk) and vice versa to integrate the occupants' comfort probabilistic model into BIM. Finally, the occupants' feedback from the satisfaction survey and the occupants' comfort probabilistic model is visualized in BIM using different color codes for the spatial distribution and Archi-lab_Mandrill package in Dynamo, respectively.

6.2.2 Data integration

6.2.2.1 Integration of occupants' feedback into BIM

The process of mapping occupants' feedback into BIM consisted of three steps. First, the occupants' feedback is exported into Microsoft Excel as an intermediate format, prior to its mapping within BIM. Then, the occupants' feedback for each comfort aspect is imported and sorted to match relevant rooms in BIM by using Dynamo and scripts of Python respectively. Finally, all occupants' feedback is mapped into the appropriate spaces using dynamo scripts as shown in Figure 28.

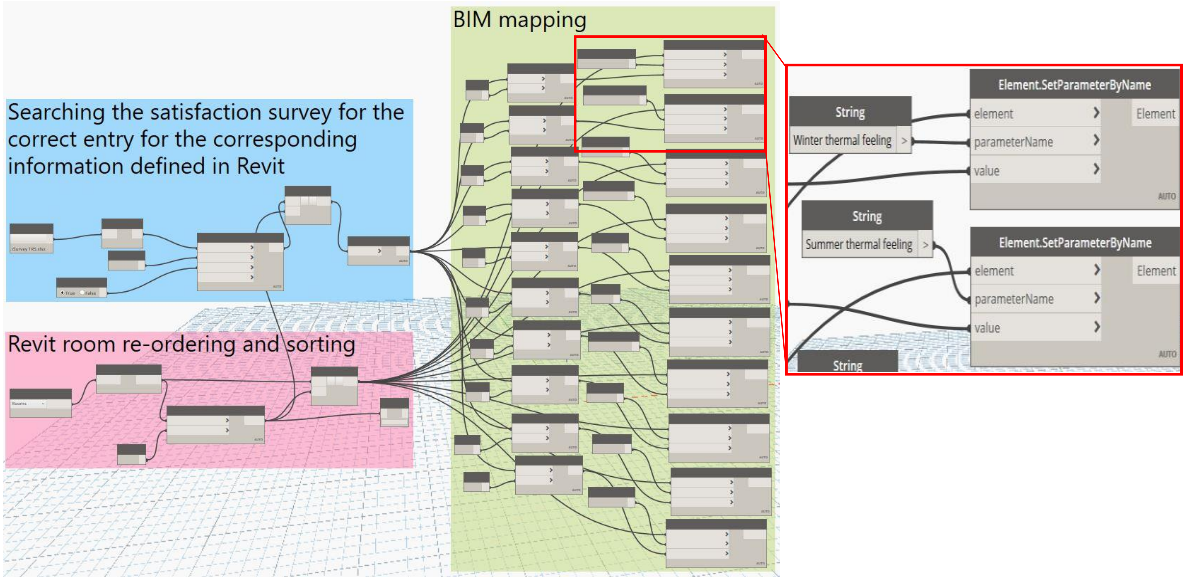


Figure 28. Dynamo script to map occupants' feedback into BIM

Occupants' feedback is imported in Dynamo from the .xls file and classified to different comfort aspects using ReadFromFile and GetItemAtIndex nodes respectively. At the same time, the list of all rooms is extracted from the Revit file and sorted to match the room numbers in the occupants' feedback using code blocks developed in Python, a similar approach to Bortoluzzi (Bortoluzzi, Efremov, Medina, Sobieraj, & McArthur, 2019). Python code block queries the occupants' feedback (the spreadsheet file) to find room numbers that match those from the Revit file. Eventually, the final list is mapped to BIM using the SetParameterByName node to match occupants' feedback to the proper parameter names with corresponding rooms.

6.2.2.2 Integration of occupants' comfort probabilistic model into BIM

To integrate BIM and the occupants' comfort probabilistic model, the building and spatial information concerning each comfort aspect together with occupants' feedback is extracted from the BIM model using Dynamo, by creating a dataset in a comma-separated value (CSV) format. Figure 29 shows the extraction of the building and spatial information from BIM regarding different comfort aspects.

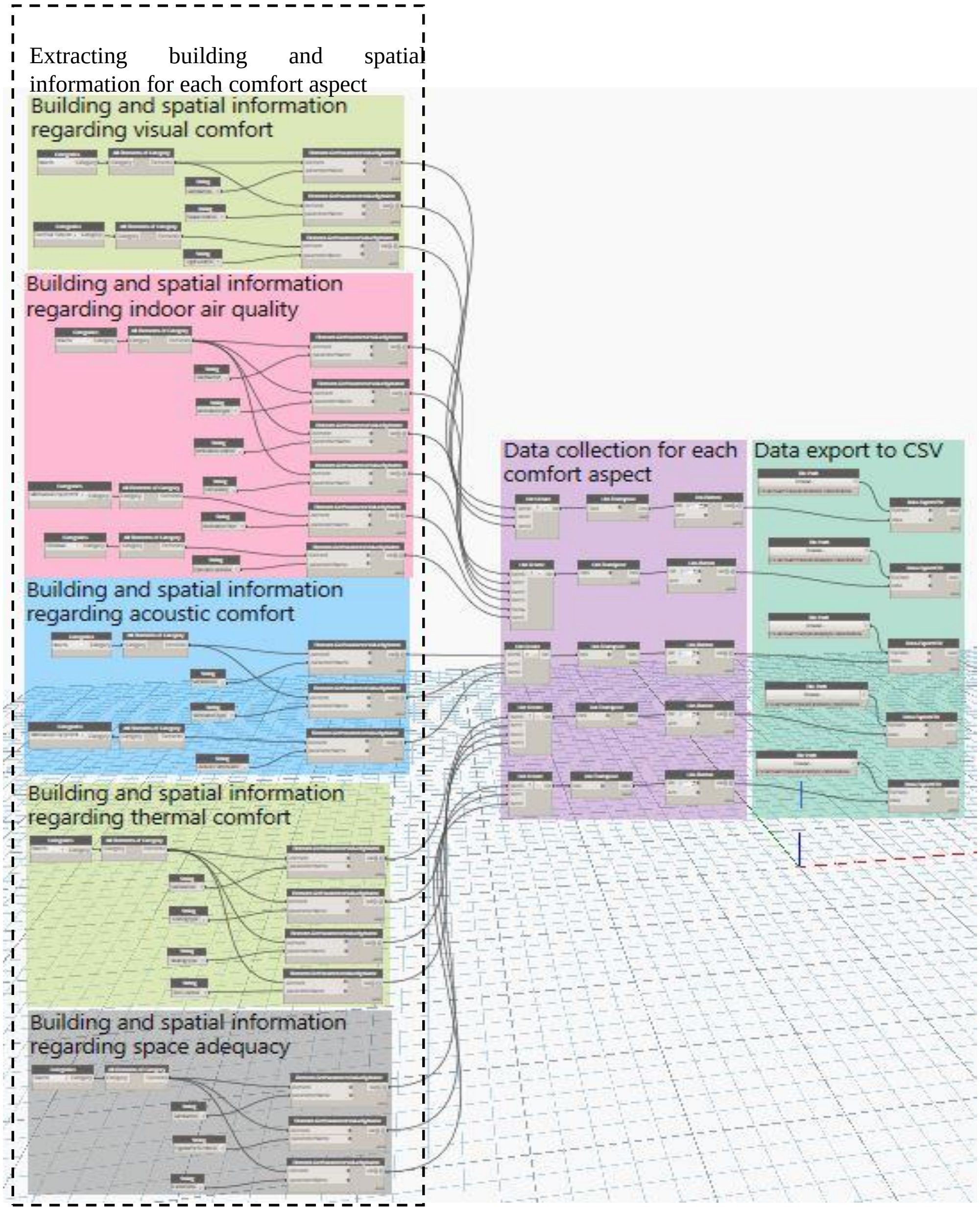


Figure 29. Dynamo script to extract information from BIM

Next, the dataset containing building and spatial information as well as occupants' feedback, is imported into the BN tool AgenaRisk, which utilizes the information as 'evidences' to run the occupants' comfort probabilistic model as backward propagation to find out the probable causes of comfort or discomfort. The results of causal analysis are then extracted from the AgenaRisk tool into a CSV format and imported into BIM using Dynamo to be matched with corresponding rooms.

Further, Python code block is used to assign the results of causal analysis to the corresponding rooms, considering the building and spatial information in that room. For a given room, the relevant results of the causal analysis are identified. This data supports the integration of customized sliders in the visualizations to permit the appraisal of each room. The Dynamo script and Python code blocks support this functionality and are presented in Figure 30 (for indoor air quality).

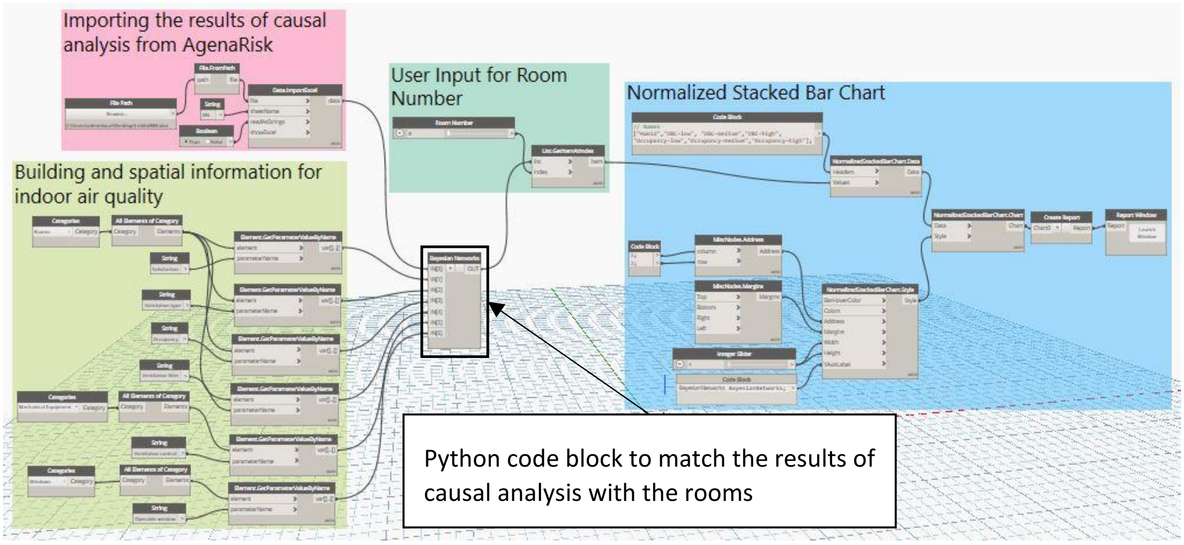


Figure 30. Dynamo script to integrate occupants' comfort probabilistic model into BIM

The results of causal analysis are connected to the Python code block as an input (input#0), whilst the building and spatial information for each room are also connected as inputs (from input#1 to input#6 regarding indoor air quality). Then, a Python code block queries from input#1 to input#6 to find building and spatial characteristics in rooms that matches those from the results of causal analysis (input#0) and filters these to create a final multi-dimensional list with the required room numbers and their corresponding parameter data.

6.2.3 Data visualization

Two kinds of visualization are considered for displaying occupants' feedback and the results of causal factors. The former visualizes the results of the satisfaction survey and the latter visualizes the information coming from the probabilistic model to determine the causal factors of dissatisfaction. (1) The first proposed visualization mapped occupants' feedback with different colors to vary from 'Very satisfied' to 'Very dissatisfied', considering comfort aspects. The tabulated data taken from Revit's schedule is visualized in a 3D format in the BIM model. The visualization of the occupants' feedback by rooms for each comfort aspect is implemented by applying view filters. The FM team would be able to filter comfort aspects in order to view the average level of occupants' comfort by room, and it is also possible to compare occupants' comfort between different rooms. (2) The second proposed visualization is to visualize the relevant results of the causal analysis coming from the probabilistic model, as related to each room (using Python scripts), which is then connected to the NormalizedStackedBarChart.Data node as values in Dynamo in order to visualize the normalized stacked bar chart for each room using the Archi-lab_Mandrill package. For a given selected room, the results of causal analysis (i.e., the importance of causal factors) are then displayed in BIM.

To give an example and illustrate it, the main factors affecting acoustic comfort are analyzed (see Figure 31).

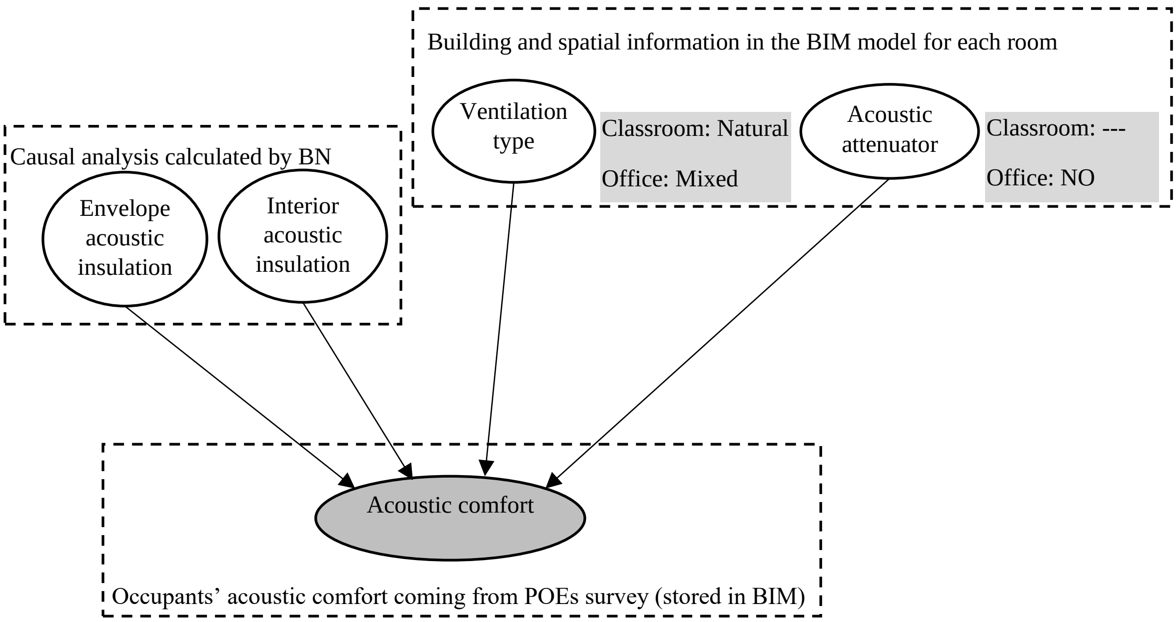


Figure 31. BN model for "acoustic comfort" as an example

The importance of the causal factors on the acoustic quality can be visualized in Figure 32. The sensitivity analysis shows the importance of the causal factors when acoustic quality is very high. It can be visualized that the probability of a building having a high acoustic comfort level is more sensitive to changes in the states of envelope and interior acoustic insulation, and least sensitive to changes in the type of ventilation.

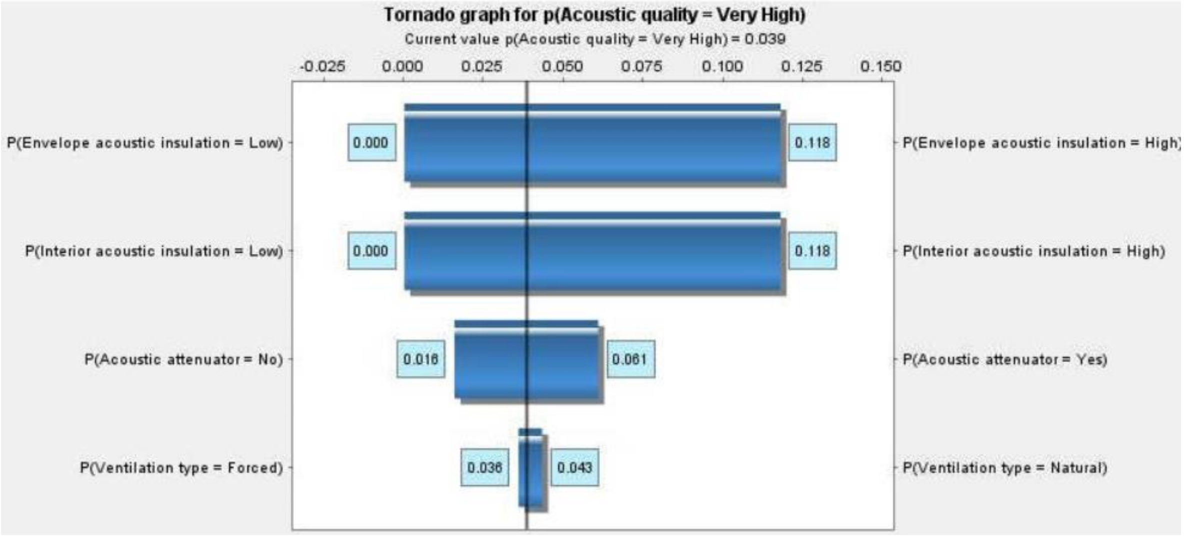


Figure 32. Tornado graph to analyze the sensitivity of acoustic quality as an example

For this example, as-built information is not updated, so not all information is available. The information about the acoustic insulation is unknown, so no evidence would be established for that node in the probabilistic model. In this example, to evaluate acoustic comfort for each room, the nodes (i.e., building, and spatial information) that are known in that room (such as type of ventilation, acoustic attenuator, and occupants' acoustic comfort) are obtained from BIM. For those nodes that are unknown (e.g., envelope and interior acoustic insulation), the backward propagation analysis in the BN model is used to obtain the results of causal analysis and link to the corresponding rooms in BIM using Python scripts. When including the results of the satisfaction survey as evidence for a specific room, the probabilistic model calculates the most probable state of the unknown variables. Then, BIM visualized the average comfort of occupants regarding acoustic comfort in a color scale and the results of causal analysis in normalized stacked bar charts to facilitate future analysis. Figure 33 illustrates an example of occupants' feedback regarding acoustic comfort and the results of causal analysis visualized in BIM.

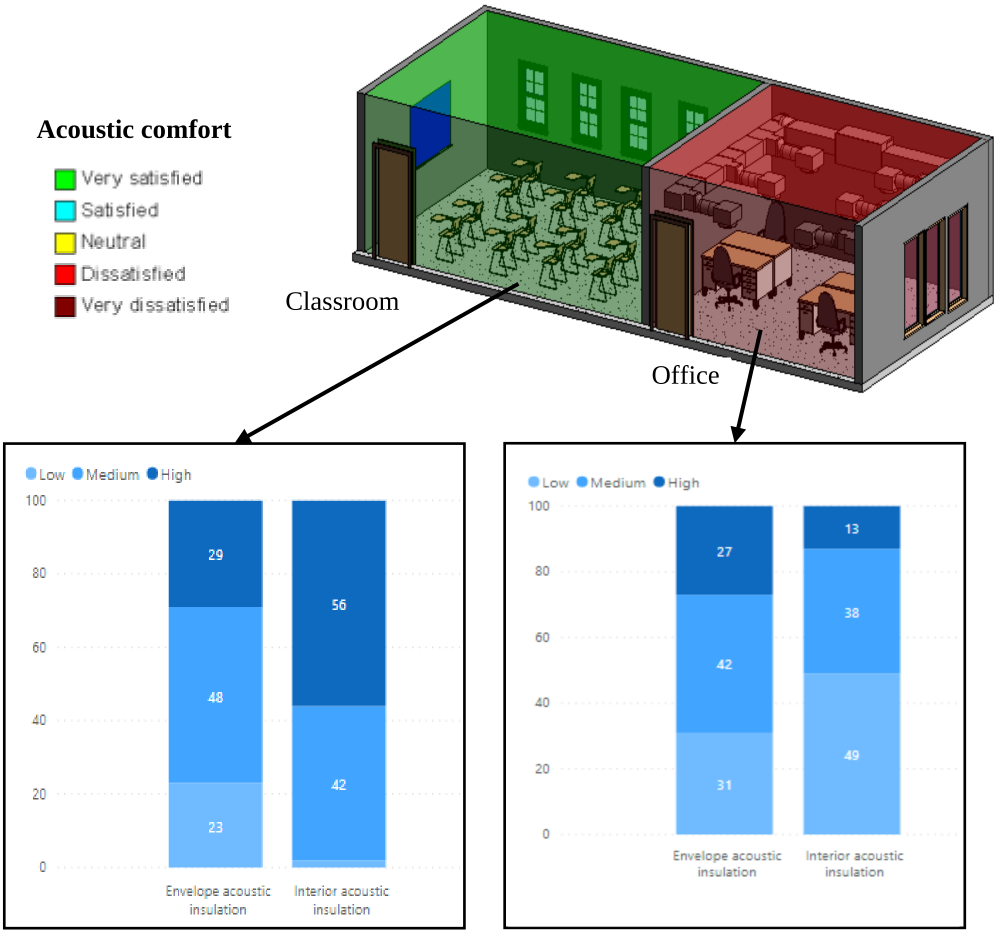


Figure 33. BIM visualization for "acoustic comfort" as an example

In this example, although the classroom has natural ventilation, which might lead to discomfort due to outside noises, occupants are very satisfied regarding acoustic comfort. On the other hand, occupants are not satisfied with the acoustic in the office. The stacked bar charts for the office shows that the cause of acoustic discomfort, apart from the ventilation system and not having attenuators, is the acoustic insulation of interior partitions, having a probability of 49% of being low.

From the visualization on BIM, the facility manager can provide hypothetic scenarios by modifying the state of the causal factors and check the probable occupants' satisfaction under these conditions. Therefore, results of the causal analysis suggest that although having the same acoustic insulation of interior partitions, insulating the interior partitions of the office can improve occupants' acoustic comfort in that room. However, installing acoustic attenuators in ventilation systems is the most comfortable solution for the office.

6.3 Evaluation

In this chapter, the evaluation is based on the validation. To validate the applicability of integrating occupants' feedback and occupants' comfort probabilistic model into BIM, Building TR5 is used as a case study.

The satisfaction survey is conducted in different TR5 building spaces including classrooms, offices, corridors, restrooms, laboratories, conference rooms, study rooms and dining rooms. This information is integrated into the BIM model and imported to the probabilistic model together with the building and spatial information of each room (e.g., occupancy density (m2/person), operable windows (yes/no) and ventilation type, among others).

Figure 34. Occupants' comfort level for indoor air quality in summer

The indoor air quality comfort in one part of the third floor of TR5 is presented as a scenario. Figure 34 shows the occupants' comfort level for indoor air quality in summer. The options of ventilation control, ventilation filter, occupancy density, and exterior conditions are obtained from the BIM model defined as 'evidences' to run the occupants' comfort probabilistic model in the BN model and find out the probable causes of comfort or discomfort. The quality comfort level in each room is also obtained from the satisfaction survey integrated into BIM and defined as "evidence" in the BN model. The BN model for indoor air quality in summer is shown in Figure 35.

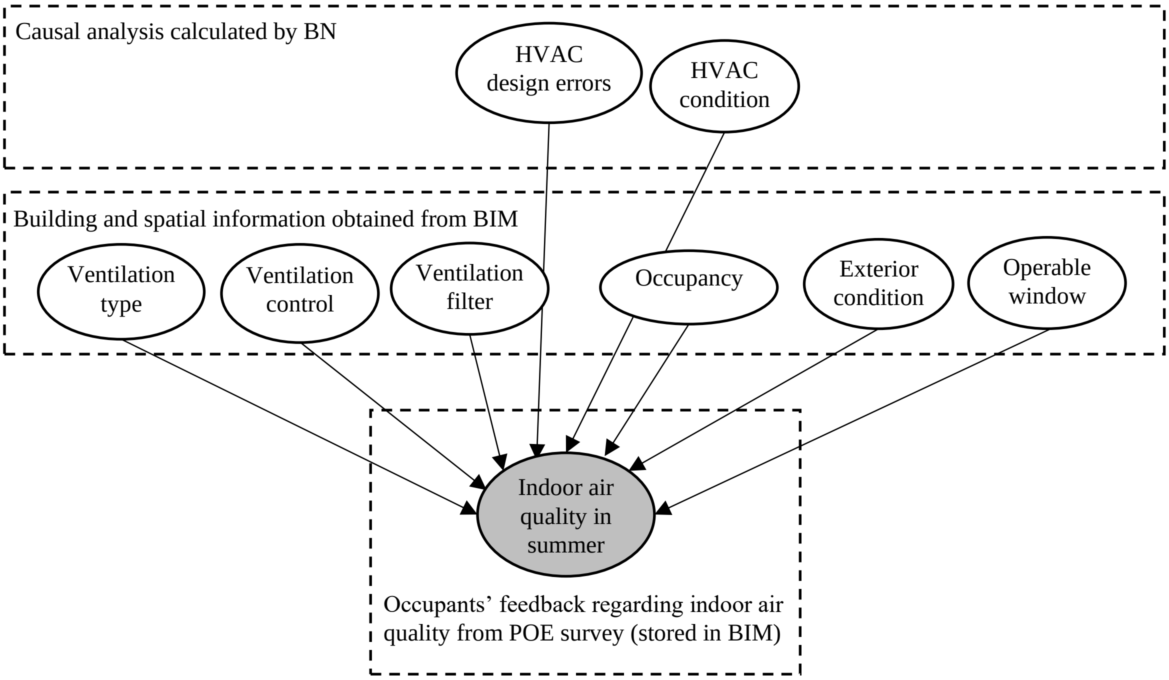


Figure 35. BN model for indoor air quality in summer

The building and spatial information for indoor air quality obtained from the BIM model for the third floor of building TR5 is shown in Table 6.

Table 6. Room information for indoor air quality obtained from BIM

Room	**Indoor air quality satisfaction in summer**	**Ventilation type**	**Ventilation control**	**Ventilation filter**	**Occupancy density (m2/person)**	**External condition**	**Operable windows**
301 (office)	V. Satisfied	Mixed	Yes	Yes	2.86 (Medium)	Hot	Yes
302 (office)	Dissatisfied	Mixed	Yes	Yes	5.15 (Low)	Hot	Yes

303 (classroom)	Dissatisfied	Mixed	No	Yes	0.48 (High)	Hot	Yes
304 (office)	V. Satisfied	Natural	No	No	5.84 (Low)	Hot	Yes
305 (classroom)	Neutral	Mixed	No	Yes	1.92 (Medium)	Hot	Yes
306 (classroom)	Dissatisfied	Mixed	No	Yes	0.61 (High)	Hot	Yes

BIM visualization allows the FM team and owners to obtain the probabilities of causal factors for indoor air quality comfort or discomfort in each room. The probabilities of having design errors in the HVAC or have a high condition for the HVAC system for each room is presented in the BIM model (see Figure 36). The results demonstrate that room 301 has a 56% probability of the HVAC being in a high condition (i.e., HVAC system operation without problems), which provides proof for the high comfort level for occupants in this room regarding indoor air quality. On the other hand, occupants in rooms 302, 303, and 306 are not satisfied with indoor air quality. The model results indicate that HVAC design errors is the most probable cause for rooms 303 and 306 since they have an 81% probability of having high design errors in HVAC system. These results must be contrasted with the HVAC requirements (air renovation requirements, pressure of the fan, etc.) to determine if the ventilation system is correctly designed. The second most probable cause, high occupancy density, is also found to be one of the major causes of air quality dissatisfaction in these rooms. These results are coherent with those obtained for room 305 with the same construction characteristics but medium occupancy where occupants reveal to have a neutral indoor air satisfaction.

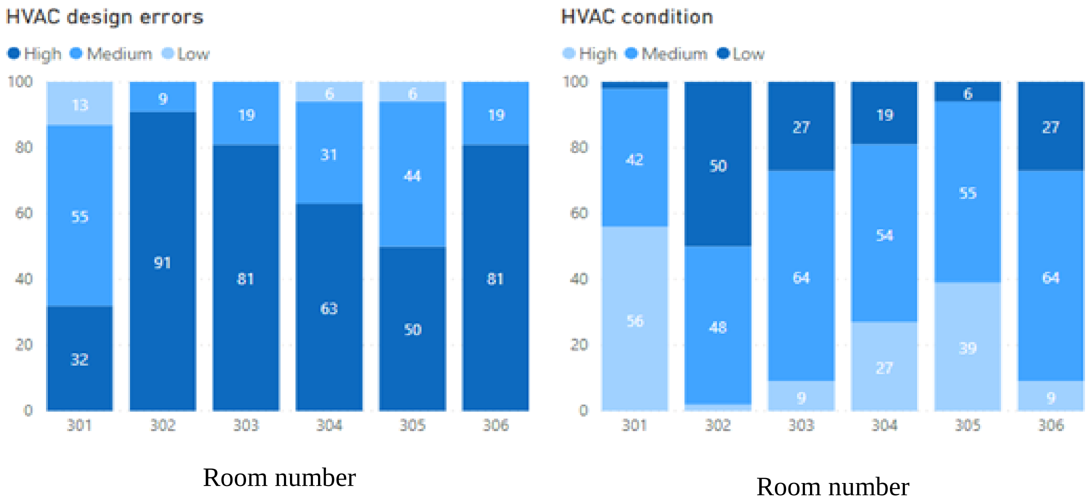


Figure 36. Probabilities of having HVAC design errors or having a high HVAC condition for each room

For those rooms with a low level of indoor air quality comfort, a sensitivity analysis is carried out to determine which parameters (previous nodes) have more impact in achieving a 'very high indoor air quality comfort'. From a purely visual perspective, the length of a bar represents the measure of the impact of that node on the building condition performance (target node).

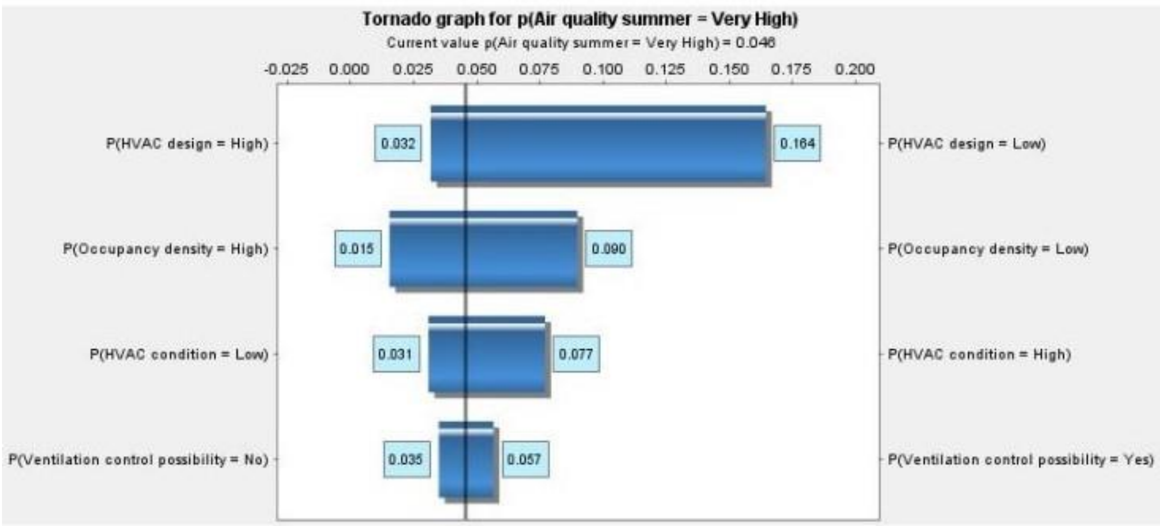


Figure 37. Tornado graph to analyze the sensitivity of indoor air quality for rooms 303 and 306 in summer (Very high = 4.6%)

Figure 37 shows the probability of the indoor air quality comfort performance being 'very high' (4.6%). It can be concluded that the probability of rooms 303 and 306 having very high comfort levels is more sensitive to occupancy and HVAC design errors and least sensitive to ventilation control possibility. The HVAC system of rooms 303 and 306 is based on general AHU for all classrooms, which might be under dimensioned. However, the occupancy is high in these rooms, and instead of changing the AHU, which is costly, reducing the occupancy might bring higher levels of comfort in terms of indoor air quality.

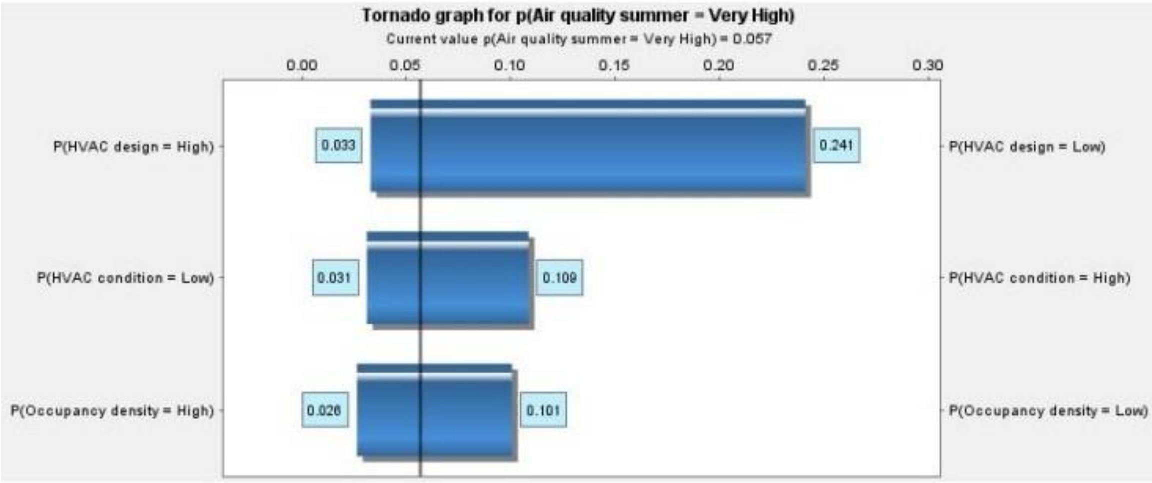


Figure 38. Tornado graph to analyze the sensitivity of indoor air quality for room 302 in summer (Very high = 5.7%)

The sensitivity analysis for indoor air quality for room 302 in summer is also carried out. Figure 38 shows the impact of three factors when the indoor air quality in summer is 'very high' (5.7%). The formal interpretation is that the probability of indoor air quality being very high, given the results of the parent nodes, rises from 3.3% (when HVAC design errors are 'high') to 24.1% (when HVAC design errors are 'low'). The HVAC condition and occupancy density did not significantly affect occupants' comfort in this room regarding indoor air quality in summer. Therefore, the most probable cause of discomfort in room 302 is 'HVAC design errors' which has a 91% probability of being high. Hence, a good design would include different equipment (changing the fan coil) to improve occupants' comfort in room 302 in terms of indoor air quality.

6.4 Discussion

The proposed approach of integrating occupants' feedback and the occupants' comfort probabilistic model into the BIM model classifies comfort aspects into thermal comfort, indoor air quality, visual comfort, acoustic comfort, and space adequacy, referred to each room of a building. The visualization of the probabilistic model results is implemented in

Revit. However, the automation process of extracting and mapping information is incorporated in Dynamo allowing customization and interoperability with most existing platforms (e.g., Power BI).

This approach presents a novel integration to facilitate data collection for the probabilistic model to evaluate the comfort performance of existing buildings, which allows the causes of occupants' discomfort in specific comfort aspects to be properly understood. It also enables the FM team to address the challenges of information reliability, interoperability, usability, and minimization of labor time.

Existing studies focus on the visualization of occupants' comfort in different platforms (Göçer et al., 2015, 2016). However, they only considered spatial information. The method of visualization in this approach focuses on real problems in discomfort spaces, demonstrating occupants' feedback in a color scale, and the results of causal factors of occupants' discomfort in a stacked bar chart, so that the effort of looking for appropriate information (e.g., building, and spatial information) is minimized. The visualization of causal factors makes it possible to detect the causes of occupants' discomfort more intuitively and potentially makes it easier to deal with the problem, which will result in a considerable improvement in occupants' comfort and optimize building operation strategies to increase occupants' comfort.

The case study is used to validate the proposed approach. For the scenario of indoor air quality in summer, it is highlighted that although there are similar rooms with the same HVAC system, occupants presented different perceptions of the indoor air quality. It is identified that occupancy density (m^2/person) has a considerable impact on indoor air quality perception and that redesigning these spaces, or reducing the occupancy, might improve indoor air quality comfort.

6.5 Conclusions

The assessment of building performance involves the analysis of multiple factors together with the occupants' feedback. This chapter presents the process of BIM integration with occupants' feedback and the occupants' comfort probabilistic model, organized by comfort aspects including thermal comfort, indoor air quality, visual comfort, acoustic comfort, and space adequacy. There are three key benefits of this integration: 1) BIM performs as a data repository, providing building and spatial information; 2) BIM can visualize causal factors of occupants' discomfort using an occupants' comfort probabilistic model and provides a potential solution for improving occupants' comfort; 3) BIM intrinsically supports data management and visualization (e.g., the visualization of occupants' feedback in color). The integration process can be used for other building performance aspects such as building condition, energy efficiency, in which occupants' feedback combined with building technical information might help FM decisions. Unlike existing models, using BIM as an integration tool allows automatic updates of the components' characteristics and data management, and enables visualization. This visualization method, based on occupants' feedback and the results of causal analysis, focuses on real problems in discomfort spaces and assists the FM team or owners to establish the necessary measurements for improving occupants' comfort. Scenarios to evaluate the comfort of different groups of occupants could also be performed.

The results and a case study show that the proposed approach could yield a better understanding of the dependent factors of discomfort and the relationship between occupants' comfort, indoor environment and building characteristics. This integration and visualization process is likely to be valuable to facility managers and owners who will be able to make a more precise analysis of building performance based on occupants' feedback; adopt building operational adaptations, and propose retrofit actions. Designers can also utilize the information to create future buildings that consider the real needs of occupants. This process will also be of interest to other researchers who are integrating and visualizing different operational data into BIM.

Chapter 7

Conclusions

This chapter concludes the thesis with an overview of the key contributions. The objectives of the study are reviewed to determine if they have been reached. Finally, on the basis of the limitations in this work, several additional future research possibilities are also recommended.

7.1 Main contributions

This study presents an approach to enable interoperability between DSSs and BIM for the O&M phase which leads to the improvement of a building's performance including building condition assessment, maintenance management (e.g., HVAC problems analysis) and thus occupants' comfort. Addressing interoperability will leverage the BIM tool as a data repository to automate the data transfer process and improve its consistency and reliability. This approach presents innovative techniques to facilitate data transfer which enables the FM team to address the challenges of information reliability, interoperability, usability, and minimization of labor time. It also allows automatic updates of the components' characteristics, and data management. Enabling interoperability between BIM and the DSSs allows bidirectional data transfer and transformation of the data into an appropriate format automatically to take advantage of DSSs.

The approach enables BIM as a more effective platform for visualization to guide decision-makers in addressing building operational problems. The visualization translates the data into a form that would be easy to understand for facility managers, highlighting useful information and eliminating the noise. Although the visualization is implemented in Revit, the automated procedure for data extracting and mapping are based on Python and Dynamo, allowing a high level of customization and interoperability with the majority of existing platforms (e.g., Data studio).

The pragmatic findings of this study are two-fold. First, the integration of DSS into BIM models facilitates data transfer and reduces the time and effort that the FM team spends on manual input which also overcomes a key barrier to data collection within the O&M phase, optimizing building operation strategies. The proposed approach can assist FM team in properly establishing the necessary measurements to moderate the negative consequences on buildings and thereby improve their performance and occupants' comfort. Moreover, it could be used to prioritize the work order to improve maintenance activities, extend the lifespan of building elements or systems and increase building durability. Second, the visualization permits a much broader range of FM data (i.e., building, and spatial information) to be mapped to such models, with a minimum of effort. The proposed approach utilizes BIM to deliver visualization to the FM team, allowing them to provide practical maintenance plans to improve building performance and occupants' comfort. The implication of this is that the approach will become much easier for buildings to pursue, enabling academic work, and encouraging business adoption to increase. It also supports facility managers to keep their team engaged in the process and enabling any concerns to be easily addressed.

The applications of the proposed approach provide benefits for the different stakeholders. Facility managers can use it to analyze the economic aspects that support the decision-making regarding renovation and retrofit actions, and prioritize maintenance actions to enhance the performance of the buildings. Owners and FM team can easily understand data through the method of visualization in which useful information would be highlighted and the noise would thus be eliminated from the data. They can use it find out how their investments on the problem may impact their building performance, occupants' comfort, and energy efficiency.

Public and business administrations can benefit of several tools proposed in this thesis, such as the method to add parameters in the BIM model with Dynamo. This approach is way faster than the shared parameter and it can be used to include data as much as their wish in the BIM models. Furthermore, organizations usually design their own data classification models and categories. In this respect, they can use the proposed method of creating a new category in BIM (e.g., distinguish the wall category between the interior partitions and façade) to help business manage assets effectively.

Researchers can also take advantage of the proposed method of transforming data into an appropriate format to be compatible with other software by applying it for different research objectives. For example, they can develop different types of DSSs in whatever data format and utilize this approach to make it compatible with BIM. In addition, they can analyze other building performance aspects in which occupants' feedback combined with building technical information thanks to the method of occupants' feedback integration into the BIM models.

In addition, the contributions of this thesis are also compared with the primary objectives. The first objective was to identify and analyze shortcomings of the implementation of BIM in the O&M phase. In this sense, Chapter 2 imparted the findings of a literature review carried out regarding existing DSS to evaluate building performance, including probabilistic models. After identifying different BIM information standards, the problem related to the BIM interoperability is explored. Based on a critical review of the related literature, Chapter 2 also presented the identification of the challenges and obstacles faced by facility managers during the O&M phase. A literature review regarding the use of BIM and AR at the O&M phase is also provided.

The second objective was to identify and devise a solution for generic interoperability problems. In this regard, Chapter 4 developed the DSS to determine the causality of HVAC problems, aiming to optimize positive interactions between occupants and buildings. Firstly, the DSS and the necessary information to develop the HVAC causality framework is defined. Then, the framework is integrated in to the BIM model. Finally, a color and friendly visualization is incorporated into the model. The framework allowed to detect semi automatically which are the causes of occupants' complaints (i.e., maintenance requests) about thermal comfort in specific rooms. Furthermore, it helps the FM team to optimize building operation strategies and supports decision-making on maintenance activities to enhance both occupants' comfort and energy efficiency.

The third objective of this thesis was to develop a conceptual model to enable interoperability between BIM models and probabilistic models. In this respect, Chapter 5 and Chapter 6 developed a conceptual model to integrate probabilistic DSSs based on BN into the BIM model. First, the required data for the BN model is identified. Then, BIM and BN models are integrated, based on the proposed conceptual model to assess building condition, and enhance occupants' comfort. The method of integrating occupants' feedback into the BIM models are also explored in Chapter 6.

The fourth objective was to establish an effective platform for data visualization. In this sense, the development of the model for the visualization presented in Chapters 4, 5 and 6 to display data in a very sensible way by using the most appropriate chart and formatting options. In Chapter 4, the model developed to visualize malfunction equipment to determine the most probable cause of an HVAC problem. In Chapter 5, the model is developed to visualize the current condition of the building elements and systems, established within Revit Software. In Chapter 6, the model developed to visualize the occupants' feedback and the results of causal factors related to the occupants' comfort, providing an effective platform for data visualization.

The fifth objective was to evaluate the proposed model. In this regard, case studies are used to validate the proposed approach and presented in separated chapters. Case studies allow to illustrate the applicability of the model for ensuring that its interactions and outcomes are feasible and the tasks are performing as efficiently as possible. In addition, the quality of data in the integration process, is checked through the use of case studies to meet the data completeness criterion.

7.2 Future research

A list of future research directions that could build on the current investigation are outlined below.

More case studies with greater volume of information could be assessed in order to validate the findings of the current project. Moreover, investigating the integrity of an IFC file generated by a BIM software application may provide insight into the overall decision-making process during O&M phase.

Since the integration process is based on Python, it can be used for different types of DSSs. Thus, further development of this integration can analyze other building performance aspects, such as energy performance and accessibility.

As highlighted across this thesis, the proposed approach can be implemented into most existing platforms. Hence, future work could be performed in this area by implementation of this approach not only in other BIM software but also in other visualization platform such as Power BI. In this regard, most BIM software do not provide a direct link to Power BI. Accordingly, further development of a plug-in for BIM software can automatically imports required data and visualizes real-time data in a user-friendly way.

Buildings of the future will offer a wide array of "smart technologies" – networked technology that controls aspects of occupants' comfort and improves building performance; therefore, future steps will include:

1) integrating wearable technologies (e.g., sensor-based networks) that allow them to plug into the building system automatically and control their comfort.
2) employing Artificial Intelligence (AI) and Internet of Things (IOT) technologies, which would coalesce together to create a fully integrated and automated solution.
3) using machine learning, a subset of AI that trains a machine on how to learn from data and identify patterns. It could then make independent decisions on how to improve occupants' comfort. People would thus live in a truly smart built environment that automatically caters for the needs of every citizen.

It could also move further still towards dark factory environments where a building is controlled by robots without any human intervention.

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Appendix

A. Satisfaction survey

Section 1: Interviewee's details

1. Please specify the subject of your degree
- Technical degree subjects (Architect/Engineer)
- Administrative degree subjects (Business and Finance)
- Technician
- Other:

2. Please specify your work experience type
- Owner side
- Facility service side
- Professor/Researcher
- Other:

3. Please specify your work experience activity
- Designer
- Construction manager
- Maintenance
- Facility manager
- Energy manager
- Asset manager
- Consultant
- Other:

4. Please specify the years of your working experience
- Less than 10 years
- Between 11 and 19 years
- More than 20 years

Section 2. Building performance categories

Performance can be described as behavior in service of a facility for a specified use. The table below shows the main important areas to consider when assessing the performance of a building based on a literature review and experts opinion.

Areas	Description
Safety and Assets working properly	It is related to structural and physical condition of the building and the correct functioning of its elements
Health and Comfort	It is related to the air quality, thermal comfort, light and acoustic quality in building spaces
Suitability of space	It is related to the availability of space to perform activities, including its accessibility and ergonomic aspects
Cleanness of spaces	It is related to the cleaning of spaces
Energy efficiency	It is related to the control of the growth in energy consumption

5. Are all the terms understandable?

- 1 (Not understandable)

- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5 (Very understandable)

6. Do you think these areas represent the most significant aspects for assessing the performance of a building?
- ☐ Yes
- ☐ No

7. If not, please justify:

Section 3: Definition of factors

Environmental agents
Environmental agents might affect the performance of a building. This is related to different factors related to the building location and type of exterior condition, as show in the table below.

Environmental agents	Description
Weather condition	Solar radiation, wind, temperature, humidity, snow and rain water loads
Surrounding environment	Type of environment such as industrial, seaside, and if there is vegetation, pollutants, chemicals
Natural disasters	Storms, fire, landslide, earthquakes
Geological conditions	Type of soil such as clay, sand, loam

8. Are all the terms understandable?

- ☐ 1 (Not understandable)
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5 (Very understandable)

9. Do you think these terms cover the most relevant environmental agents that might affect the performance of a building in general?
- ☐ Yes
- ☐ No

10. If not, please justify:

Building properties
The performance of a building can also be affected depending on the characteristics of the building. The table below shows the properties that might influence the performance of a building in general.

Building properties	Description
Type of structure/façade/roof	Type of material and its properties (i.e., porosity, acoustical absorption, resistance, thermal conductivity, etc)
Age	The period of time the building was built until the present
Type of heating/cooling system	The type of system/equipment to heat and cool the building (i.e., gas-fired heaters, electric heaters, central heat, split unit, etc)
Geometry	The shape of the building including height
Orientation	Solar orientation of façades
Type of use	The building typology (i.e., schools, shopping centers, offices, government buildings, etc)

11. Are all the terms understandable?

- ☐ 1 (Not understandable)
- ☐
- ☐
- ☐
- ☐ 5 (Very understandable)

12. Do you think these terms cover the main building properties that might affect the performance of a building in general??

- ☐ Yes
- ☐ No

13. If not, please justify:

Section 4: Defects on construction elements and systems.

The detection of building defects is an important task to assess the performance of a building. The aim of this section is to determine the most influential defects on the performance of a building. This classification aims to be generic to be applied to any type of construction solution.
Think back over all the years of your experience and choose a building that you worked with.

14. Select the building typology you are thinking (not residential)

- ☐ Academic building
- ☐ Office building
- ☐ Government building
- ☐ Commercial building
- ☐ Other:

Structure:

15. In the structure, which defects influence majoritarily the performance of a building?

- ☐ Biological action and change (e.g., mold, microbiological and plants growth)
- ☐ Chemical action and change (e.g., corrosion in metalic structure, bars with corrosion)
- ☐ Cracking (e.g., cracks in pillars)

- ☐ Deformation/Settlement (e.g., deflection in a beam, pillar deformed, fatigue, landslip)
- ☐ Structural vibration
- ☐ Surface problems (e.g., honeycombs in concrete, efflorescence, delamination, discoloration of concrete)
- ☐ Water problems (e.g., excess moisture in slabs)
- ☐ Detachment/Broken (e.g., part of the concrete broken)
- ☐ Other:

Façade:

16. In the façade, which defects influence majoritarily the performance of a building?
- ☐ Biological action and change (e.g., plants, algae growth)
- ☐ Chemical action and change (e.g., oxidation of metalic components)
- ☐ Cracking (e.g., fissure in panels of the covering)
- ☐ Surface problems (e.g., efflorescence, bumps, dips, graffiti, discoloration of the painting,
- ☐ deposit of dirt, uneven covering)
- ☐ Water problems (e.g., condensation, rising damp from floor, penetration damp)
- ☐ Detachment/Broken (e.g., tile broken, detachment of façade covering)
- ☐ Other:

Roofing:

17. In the roofing, which defects influence majoritarily the performance of a building?
- ☐ Biological action and change (e.g., birds action, gutters clogged with leaves)
- ☐ Chemical action and change (e.g., oxidation of metal components)
- ☐ Cracking (e.g., cracks in roof covering)
- ☐ Deflection (e.g., deflection of roof structure)
- ☐ Surface problems (e.g., efflorescence, bumps, dips, uneven covering, discoloration, deposit of dirt)
- ☐ Water problems (e.g., leaks, entrapped water, accumulation of moisture)
- ☐ Detachment/Broken (e.g., waterproofing detached)
- ☐ Other:

Flooring:

18. In the flooring, which defects influence majoritarily the performance of a building?
- ☐ Chemical action and change (e.g., change of color due to cleaning with chemical product)
- ☐ Cracking (e.g., cracks floor covering)
- ☐ Surface problems (e.g., efflorescence, soiled, hitch/scratch, discoloration, uneven surface of covering)
- ☐ Water problems (e.g., entrapped water, accumulation of moisture)
- ☐ Detachment/Broken (e.g., floor covering broken)
- ☐ Other:

Interior partitions:

19. In the interior partitions, which defects influence majoritarily the performance of a building?
- ☐ Cracking (e.g., fissures in plaster boards)
- ☐ Surface problems (e.g., dips, discoloration, paint peeling, blister)
- ☐ Water problems (e.g., moisture due to a broken pipe, condensation due to not insulated window)
- ☐ Detachment/Broken (e.g., detachment of a plaster wall)
- ☐ Other:

Doors/windows:

20. In the doors/windows, which defects influence majoritarily the performance of a building?
- Biological action and change (e.g., lichens in windows)
- Chemical action and change (e.g., corrosion of the window frame and ironmongery)
- Surface problems (e.g., uneven door, paint peeling)
- Water problems (e.g., moisture concentration in wood window frame)
- Detachment/Broken (e.g., window glass broken)
- Operational faulty functioning (e.g., door do not close, broken rolling window shutter)
- Other:

Electrical system:

21. In the electrical system, which defects influence majoritarily the performance of a building?
- Operational fault functioning of electrical supply elements (e.g., transformer problems, voltage, frequency, stoppage of electricity supply)
- Accumulation of dirt in electrical distribution elements
- Insulation problems in electrical distribution elements (e.g., cables insulation damaged)
- Operational faulty functioning of electrical distribution elements (e.g., electric sparks, short circuit)
- Operational faulty functioning of electrical fixtures (e.g., faulty functioning of equipment, light burnt)
- Other:

Plumbing system:

22. In the plumbing system, which defects influence majoritarily the performance of a building?
- Algae in water supply tanks
- Corrosion in water supply elements (e.g., corrosion of solar panel)
- Leakage in water supply elements (e.g., leakage in water tanks)
- Operational faulty functioning of water supply elements (e.g., equipment malfunction, problems with temperature, pressure, water level, vibration)
- Microorganisms in water distribution elements (e.g., microorganisms in pipes)
- Corrosion in water distribution elements (e.g., corrosion of pipes and valves)
- Accumulation of dirt in water distribution elements (e.g., pipes clogged)
- Insulation problems in water distribution elements (e.g., pipes insulation damaged)
- Leakage in water distribution elements (e.g., pipes leakage)
- Plumbing fixtures broken (e.g., sanitary equipment broken)
- Leakage in plumbing fixtures (e.g., leakage in water tap)
- Operational faulty functioning of plumbing fixtures (e.g., water tap not working)
- Other:

HVAC system:

23. In the HVAC system, which defects influence majoritarily the performance of a building?
    - Algae in water tanks
    - Corrosion in HVAC production elements
    - Leakage in HVAC production elements
    - Operational faulty functioning of HVAC production elements (e.g., chiller malfunction, noisy boiler, mechanical problems, fan motor failure)
    - Microorganisms in HVAC distribution elements (e.g., microorganisms in pipes)
    - Corrosion in HVAC distribution elements (e.g., corrosion of ducts and pipelines)
    - Accumulation of dirt in HVAC distribution elements (e.g., dirt in filters and ducts)
    - Insulation problems in HVAC distribution elements (e.g., pipes insulation damaged)
    - Leakage in HVAC distribution elements (e.g., pipes leakage)

- ☐ Leakage in HVAC fixtures elements (e.g., leakage in air unit, condensation dripping from diffuser)
- ☐ HVAC fixtures broken (e.g., grills broken)
- ☐ Operational faulty functioning in HVAC fixtures elements (e.g., excessive noise and vibration of air unit, thermostat malfunction)
- ☐ Other:

Fire system:

24. In the fire system, which defects influence majoritarily the performance of a building?
    - ☐ Algae in water supply tanks
    - ☐ Corrosion in water supply elements
    - ☐ Operational faulty functioning of water supply elements (e.g., equipment malfunction, pressure problems)
    - ☐ Microorganisms in water distribution elements (e.g., microorganisms in pipes)
    - ☐ Corrosion in water distribution elements (e.g., corrosion of valves)
    - ☐ Leakage in water distribution elements (e.g., pipes leakage)
    - ☐ Accumulation of dirt in water distribution elements (e.g., pipes clogged)
    - ☐ Leakage in fire fixtures (e.g., water leakage in sprinkler)
    - ☐ Fire fixtures broken (e.g., sprinkler broken)
    - ☐ Operational faulty functioning of fire fixtures (e.g., smoke detector not working, fire alarm malfunction, fire hose not working, fire extinguisher not working)
    - ☐ Other:

Elevator:

25. In the elevator, which defects influence majoritarily the performance of a building?
    - ☐ Corrosion in the distribution elements (e.g., cables with corrosion)
    - ☐ Operational faulty functioning of distribution elements (e.g., mechanical problems, electric motor with excessive noise, abrupt landing, overheating of control system)
    - ☐ Accumulation of dirt in elevator cabin
    - ☐ Elevator cabin parts broken (e.g., buttons broken)
    - ☐ Operational faulty functioning of elevator cabin elements (e.g., doors not closing properly)
    - ☐ Other:

26. Do you agree that these terms cover all potential defects that might appear in a building?
    - ☐ Yes
    - ☐ No

27. If not, please justify:

28. Additional comments:

B. Conceptual model