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Improving building occupant comfort through a digital twin approach: A Bayesian network model and predictive maintenance method

Haidar Hosamo Hosamo [a,*], Henrik Kofoed Nielsen [a], Dimitrios Kraniotis [b], Paul Ragnar Svennevig [a], Kjeld Svidt [c]

[a] University of Agder, Jon Lilletuns vei 9, 4879 Grimstad, Norway
[b] Oslo Metropolitan University, Pilestredet 46, 0167 Oslo, Norway
[c] Aalborg University, Thomas Manns Vej 23, 9220 Aalborg Ø, Denmark

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ABSTRACT

This study introduces a Bayesian network model to evaluate the comfort levels of occupants of two non-residential Norwegian buildings based on data collected from satisfaction surveys and building performance parameters. A Digital Twin approach is proposed to integrate building information modeling (BIM) with real-time sensor data, occupant feedback, and a probabilistic model of occupant comfort to detect and predict HVAC issues that may impact comfort. The study also uses 200000 points as historical data of various sensors to understand the previous building systems' behavior. The study also presents new methods for using BIM as a visualization platform and for predictive maintenance to identify and address problems in the HVAC system. For predictive maintenance, nine machine learning algorithms were evaluated using metrics such as ROC, accuracy, F1-score, precision, and recall, where Extreme Gradient Boosting (XGB) was the best algorithm for prediction. XGB is on average 2.5% more accurate than Multi-Layer Perceptron (MLP), and up to 5% more accurate than the other models. Random Forest is around 96% faster than XGBoost while being relatively easier to implement. The paper introduces a novel method that utilizes several standards to determine the remaining useful life of HVAC, leading to a potential increase in its lifetime by at least 10% and resulting in significant cost savings. The result shows that the most important factors that affect occupant comfort are poor air quality, lack of natural light, and uncomfortable temperature. To address the challenge of applying these methods to a wide range of buildings, the study proposes a framework using ontology graphs to integrate data from different systems, including FM, CMMS, BMS, and BIM. This study's results provide insight into the factors that influence occupant comfort, help to expedite identifying equipment malfunctions and point towards potential solutions, leading to more sustainable and energy-efficient buildings.

1. Introduction

The built environment, created and managed by the architecture, engineering, construction, and operation (AECO) sector, plays a crucial role in supporting human activities and influencing occupant comfort. Occupants spend significant time in buildings, requiring them to be accessible, productive, healthy, and comfortable [1]. However, not all buildings successfully meet their residents' comfort needs [2]. Indoor air quality, natural light, and noise pollution can negatively impact occupant comfort and productivity [3]. Tolerable temperatures are typically determined by indoor environmental quality (IEQ) guidelines [4], but these standards do not always align with what occupants experience as comfortable [5]. As such, it is important to gather input from occupants and evaluate building performance to enhance comfort and productivity [6].

Building sustainability and operating planning may be enhanced by using predictive, preventative, and corrective maintenance processes based on occupant comfort ratings [7]. Methodologies and instruments for assessing building performance have been developed thanks to studies focusing on examining the indoor environment and identifying what makes for a pleasant environment source [8]. When a building is occupied, a post-occupancy evaluation (POE) is conducted to determine how well it meets the needs of the occupants in terms of both the physical aspects like visual comfort, acoustic comfort, thermal comfort, and indoor air quality, and the non-physical aspects like the workplace and furniture [9]. The aspects that impact indoor environ-

* Corresponding author.

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Nomenclature

DHW	Domestic hot water
SVM	Support vector machine
WWR	Windows-to-walls ratio
JSON	JavaScript Object Notation
ANN	Artificial neural network
API	Application Programming Interface
BIM	Building information modeling
BMS	Building management system
DT	Decision tree
XGB	Extreme gradient boosting
HVAC	Heating, ventilation, and air conditioning
IoT	Internet of things
IFC	Industry foundation classes
URL	Uniform resource locator
VAV	Variable air volume
FMM	Facility maintenance management
NN	Neural network
RF	Random forest
NB	Naive Bayes
KNN	K-Nearest Neighbors
MLP	Multi-Layer Perceptron
GB	Gradient Boosting
KNN	K-Nearest Neighbors
COBie	Construction operations building information exchange
ANOVA	Analysis of variance
FM	Facility management
CMMS	Computerized maintenance management system
AFDD	Automated fault detection and diagnosis
APAR	Air handling unit (AHU) performance assessment rules

mental conditions, such as the building environment, architectural attributes, spatial information, and user behavior, are not accounted for in the deterministic models upon which these assessment methods are built [10,11].

The capacity of building occupants to influence and shape the internal environment greatly contributes to their degree of comfort [12]. Furthermore, the degree of comfort in a given area is affected by several variables, including the building's envelope, systems (such as HVAC and lighting), and the actions of the occupants [13]. In addition, problems with the HVAC system or improper operation might result in unhealthy indoor air and contribute to conditions like sick building syndrome [14]. When assessing the pleasantness of a building, it is important to remember that there is a lot of room for error in the interplay between the inhabitants, the environment, and the building itself [11].

Probabilistic approaches, such as Bayesian networks (BNs), may estimate the building's performance based on a range of probable outcomes rather than a single number and help deal with this uncertainty [15,16]. Despite their usage in predicting thermal preferences and examining occupant satisfaction with particular services, there is a lack of publications on the use of BNs to simulate occupant comfort in terms of individual, social, and physical building aspects. The information required to measure occupant pleasure is also frequently stored in separate silos and not linked [17].

The process of assessing a building's comfort might be simplified with Digital Twin technology, which blends BIM with sensor data and real-time building data. There has yet to be any work that we could find that uses Digital Twin technology and risk assessment models to enhance data collecting, feedback visualization for building occupants, and knowledge of what causes discomfort in buildings. Fig. 1 depicts a simplified version of the fundamental concept behind Digital Twin technology.

In our paper, a Bayesian network model to evaluate occupant comfort levels and an automatic fault detection system for HVAC that includes new methods for using BIM as a visualization platform and predictive maintenance are proposed. The novelty of our work includes the presentation of a BIM plugin that can handle data every 5 min, which was previously unavailable, as well as the integration of JSON data for improved data integration. The space adequacy problem is also addressed, with 10 aspects analyzed together for the first time. Nine machine learning algorithms were implemented, and their performance was evaluated using various matrices, requiring significant data processing and real-time training and prediction. A new method for visualizing outdoor faults in building systems is shown, and new faults, such as compressor failure, were detected using new algorithms. A new method for determining the remaining useful life of HVAC is presented based on several standards, which can increase its lifetime by at least 10%, resulting in significant savings. Several novel approaches are showcased, significantly advancing the field of occupant comfort evaluation and HVAC fault detection.

2. Literature review

2.1. Improving Building Energy Systems with AI and Expertise: AFDD and APAR

In order to bring attention to the relevance of building energy consumption, the International Energy Agency (IEA) launched the Implementing Agreement on Energy in Buildings and Communities (EBC) in 1977. The Energy Building Code (EBC) and its supplementary papers, or "Annexes," form the foundation upon which all activities involving energy systems in buildings are conducted [18]. The data in these appendices show that improper planning for a building's heating, ventilation, and air conditioning system due to a failure to account for its intended use and expected population is a leading cause of HVAC breakdowns [19].

Finding and fixing problems can be difficult with HVAC systems. Some problems can be detected by conventional building management systems (BMS), while others cannot. For example, BMS cannot identify problems like simultaneous heating and cooling or heating recovery problems [20].

Data-driven methods and methods based on specialized expertise predominate in the relevant literature [21,22]. AI has been offered as a way to streamline the time-consuming process of finding and fixing errors [23]. While increasing the algorithm's accuracy is important, creating a method that can function on as many units as possible is crucial. This is due to the high cost of developing an algorithm tailored to the needs of a certain application, such as an AHU[21,22]. That is why a system needs to be flexible enough to accommodate different AHU types, sizes, functions, and configurations.

A further difficult aspect of defect identification is determining how serious the problems are. These issues shorten the lifespan of buildings, make life unpleasant for occupants, and waste resources [24]. Thus, this study will utilize Automated Fault Detection and Diagnosis (AFDD) and AHU Performance Assessment Rules (APAR) to discover the defects in the building systems by combining artificial intelligence with expert knowledge.

Predictive maintenance uses the AFDD technique to eliminate failure's underlying cause, help facility management prioritizes

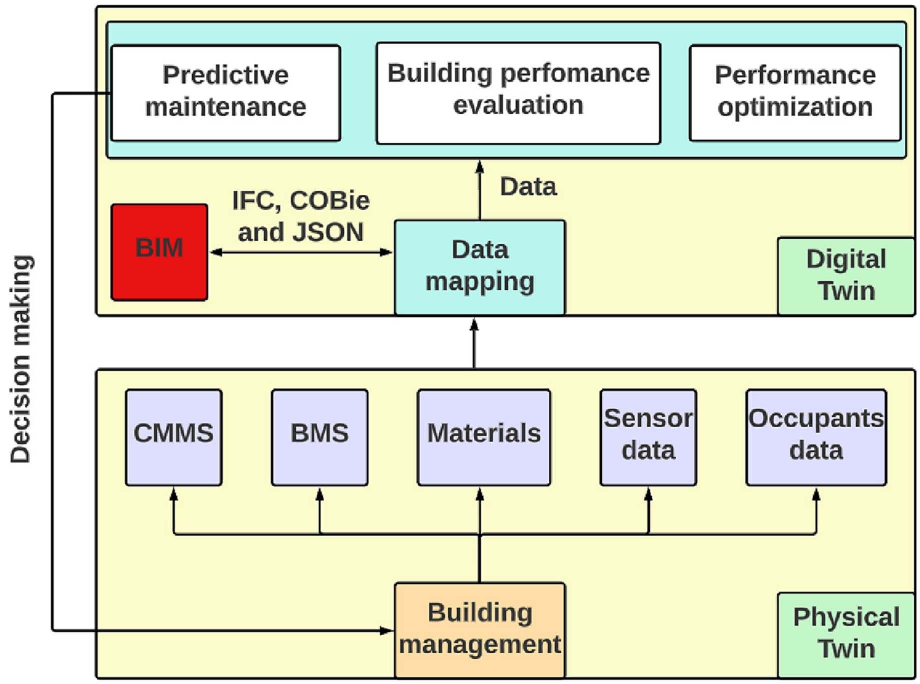

Fig. 1. Digital Twin Concept: Integrating BIM with Real-time Sensor Data and Occupant Feedback for Predictive Maintenance and Occupant Comfort.

maintenance work, and reveal hidden weaknesses. There has been much research on this technique recently, with some focused on simulating AHU parts [25] and others depending on expert guidelines [26,27]. The APAR is a set of 28 if-then rules that are reviewed in light of an AHU's operating regime, constituting the expert rules-based method [26]. Others have taken an interest in and expanded upon this strategy. Data-driven techniques, such as the application of machine learning algorithms, have been advocated by other academics as a means to improve the efficacy of the AFDD approach [28].

When designing a building's energy system, it is crucial to take into account the building's usage and expected occupancy levels. Not doing so can lead to problems such as an energy system that is not appropriately sized for the building's actual use or an overestimation of occupancy levels resulting in energy inefficiencies. To improve the efficiency of identifying defects in a building's energy systems, utilizing artificial intelligence in conjunction with data-driven and expert-knowledge-based methods can be helpful. Techniques such as AFDD and APAR can aid in prioritizing maintenance and detecting previously unseen issues, which ensures the durability and effectiveness of the building's energy systems.

2.2. Leveraging Digital Twin Technology for Predictive Maintenance and Building Performance Optimization

Modern approaches like the Internet of Things (IoT), artificial intelligence, cloud computing, and BIM are all used to develop Digital Twin technologies [29]. These technologies have made it feasible to digitalize different building assets, enabling the coexistence of virtual and physical objects over their full life cycles [30].

Grieves gave the initial definition of the term "Digital Twin" in 2012, stating that it refers to an extensive data collection that characterizes an asset, starting with its most basic shape and working up to its most exact function [31].

Preventative maintenance strategies extensively leverage the Digital Twin technology to predict an asset's status, minimize the number of operations, and enable longer time intervals between them [32]. The Digital Twin technology may also be applied to predictive maintenance, where it can keep track of the system's performance in real-time and ensure that everything is operating as it should [33]. By sending out notices for maintenance and repairs, problems may be identified beforehand and, preferably, rectified before they get serious and interfere with the residents' comfort.

Designers of building systems can also utilize Digital Twin technology, which takes into account both the functional requirements and control strategies for digital interfaces [34,35]. This technology is effective in identifying the root cause of negative tenant feedback and implementing a predictive maintenance strategy to prevent further system and component failures in buildings. However, currently, there are no established methods for identifying the causes of building system failures that integrate a semantic description with a Digital Twin approach.

Building maintenance is frequently regarded as the principal FM activity since it represents 65% of the total cost of FM [36]. Due to the HVAC systems' disproportionately high energy consumption, compared to other systems such as the domestic hot water system, lighting system, etc., HVAC maintenance is one aspect of building particularly crucial maintenance. Aside from creating contented and productive inhabitants, improving HVAC system efficiency may result in significant energy and cost savings [37]. Automated problem identification and diagnosis can be eased by using Digital Twin technology and can help modern HVAC systems. Data from Digital Twins may be used to fine-tune HVAC systems in order to reduce energy consumption, enhance comfort for building occupants, and forestall the onset of sick building syndrome.

2.3. Optimizing Building Performance: The Role of Machine Learning, Visual Programming and Building Factors in Enhancing Occupants' Comfort

The thermal, visual, and acoustic environment, air quality, space arrangement, privacy, furniture, and cleanliness are only a few of the physical and non-physical aspects that contribute to the comfort of building inhabitants [38]. Various factors influence occupant comfort, including local climate, building layout, building scale, building envelope, and ventilation [39].

Particularly important to a building's environmental performance is the building's envelope [40]. An improved building can be achieved by giving early attention to the envelope's shape, form, and construction. The building envelope determines the building's orientation, shape, and room layout. Envelope form is a function of facade design which include but is not limited to window-wall design [41], single window size [42], and the size of shading components [43]. Thermal insulation, light transmission, and glazing insulation are some envelope qualities that may make or break its overall performance [44].

There are important factors that contribute to the comfort of building inhabitants, but none are more important than the thermal quality of the building itself [45]. Studies have revealed that climate, building attributes, and services supplied greatly impact thermal comfort and indoor air temperature. For instance, those who can modify their temperature environments report experiencing high comfort levels [46]. Passive thermal approaches necessitate more thermal elements, such as envelope insulation, in buildings than in other forms of construction [13]. Therefore, a low U-value (thermal transmittance) envelope can aid in increasing the number of hours per day when people can feel comfortable without using artificial air conditioning [47].

Indoor air quality is also connected to the ventilation rate. Regulations may suggest minimum, and maximum ventilation rates [48]. For instance, the Building Acts and Regulations (TEK17) says that, while the building is used, it must have sufficient ventilation to supply at least 1.2 m^3 of outside air per hour per square meter of heated floor area [49]. Additionally, the ventilation system may affect how comfortable the building feels inside. The internal atmosphere may be altered to some degree at the discretion of the inhabitants by opening windows; however, natural ventilation is weather dependent and may not be sufficient in extremely hot or cold climates. Not least, natural ventilation does not usually filter the incoming air, which might carry exterior pollutants. In this way, natural ventilation is not recommended in areas with high concentrations of pollutants (PM2.5, PM10, etc., where PM 2.5 and PM10 refer to particle sizes in the air that are considered harmful to human health. The number refers to the particle size in micrometers [50]), e.g. city centers. As a result, it is crucial to consider the exterior environment while deciding on the most comfortable ventilation strategy [51].

One quantitative method for evaluating daylighting's impact on interior illumination quality is the windows-to-walls ratio (WWR). There is mounting evidence that WWRs may boost both the visual comfort of building occupants and their buildings' energy efficiency [52,53].

In addition to the traditional building design approaches, machine learning techniques such as Artificial Neural Networks (ANN) [54], Support Vector Machines (SVM) [55], Random Forest [56], Decision Trees (DT) [57], Naive Bayes (NB) [58], K-Nearest Neighbors (KNN) [59], Multi-Layer Perceptron (MLP) [60], Gradient Boosting (GB) [61], and Extreme Gradient Boosting (XGB) [62] have been increasingly used in the field of building performance prediction. These techniques can be used to model the relationships between building design parameters, such as building envelope, thermal comfort, indoor air quality (IAQ), ventilation, and energy efficiency. Training these models on large datasets of building performance data can be used to predict the performance of new buildings and identify design strategies that lead to optimal performance. These machine learning methods also can improve the optimization and predictions based on the building features. These methods have been applied successfully to problems such as building thermal performance, daylighting, and energy consumption predictions. In addition, these methods are commonly used for feature selection and optimizing building performance.

Besides machine learning techniques, visual programming platforms such as Dynamo have also been used to optimize building performance [63]. Dynamo is a visual programming platform for BIM software such as Autodesk Revit [64]. It allows users to create custom scripts and routines for automating and optimizing building design tasks. Using Dynamo, building performance simulations and energy analysis can be conducted automated, eliminating the need for manual inputs and reducing the potential for errors. Additionally, Dynamo enables parametric design, which can be used to explore different design options and evaluate the performance of each option in a systematic way [65].

Dynamo's automation of the building design process results in substantial gains in efficiency and the creation of buildings that are more energy-efficient, thermally-comfortable, visually-appealing, acoustically-pleasing, and have better Indoor Air Quality (IAQ). Furthermore, Dynamo can be connected to other software such as Matlab, Excel, and Python, thus allowing the power of machine learning techniques and an optimization algorithm to improve building performance. This enables building designers to explore a wide range of design options and evaluate the trade-offs between performance and cost.

2.4. Bayesian Networks for Building Condition Assessment and Decision Making

Building condition assessment is important in building management, as it helps identify potential issues and prioritize maintenance and repair needs. One popular building condition assessment approach is using Bayesian Networks (BNs).

A Bayesian Network is a model that illustrates the probabilistic relationships between variables [66,67]. In the context of building condition assessment, BNs can be utilized to model the relationships between building components and their condition [68]. Using this model makes it possible to make probabilistic predictions about the condition of a building based on the observed condition of its components. The BN model can be constructed by identifying the building components that need to be assessed and the condition states that these components can be in. These components and states are then represented as nodes in the BN, and the relationships between them are represented as edges.

The conditional probability distributions of the component states are estimated using historical data, and the network is trained using the data. Once the BN is trained, it can be used for condition assessment by making predictions about the condition of a building based on the observed condition of its components. For example, suppose the experimental condition of a building component is poor. In that case, the BN model will indicate a higher probability that other components connected to it will be in poor condition [69]. This information can then be utilized to prioritize maintenance and repair needs by identifying which components are most likely to need attention. BN models can also be used for decision-making [70]. For example, once the probability of a component failure is computed, the decision maker can decide whether to repair, replace, or do nothing with the component, depending on the severity and cost of the component failure [71]. BNs are a powerful tool for building condition assessment, as they can be used to model the relationships between building components and their condition, make predictions about the condition of a building, and support decision-making. They help building managers make data-driven decisions about maintenance and repair priorities based on the likelihood of component failures and can improve the overall efficiency of building management.

2.5. Optimizing Building Maintenance and Performance through BIM Data Integration

BIM technology is widely used in the construction industry to collect, organize, and visualize information on a building or other structure throughout its lifecycle, from design to demolition. However, many facility management (FM) professionals still rely on traditional methods, such as paper reports and Excel spreadsheets, to transmit and organize data. This can lead to time-consuming and inefficient maintenance practices, and service delays [72].

To address this issue, several commercial FM software solutions have been developed to record and organize a wide range of facility management data, including work orders, service contracts, and other documents that may be useful to building administration [73]. However, no single program can meet the requirements of the entire FM sector, and many of these solutions are costly and geared toward preventative maintenance. BIM should be integrated with a dynamic computerized maintenance management system (CMMS) that features predictive maintenance to improve building maintenance, and performance [74].

Additionally, BIM can be integrated with the internet of things (IoT) data, such as sensor network readings, to monitor the state of a building's machinery and environment, which is helpful for predictive maintenance. This is facilitated by developing open data standards, such as COBie and IFC, which make it easier to incorporate BIM data into FM systems [75]. Research is also being done to use ontology methodologies to solve data interoperability problems between BIM and FM systems [76,77]. However, while BIM is widely used in construction, it has been slow to catch on in environmentally conscious construction due to a lack of performance data integration capabilities. To truly improve building performance, BIM frameworks must be developed to integrate performance data and information more quickly, which presents a major challenge for the industry [22]. It's important to consider BIM as a flexible and dynamic framework, capable of linking with real-time data and IoT sensors as well as with performance data, accessible by all stakeholders to enable better decision-making, planning, and optimization of maintenance and operation of the building.

As part of this paper, a plug-in for integrating sensor data into BIM is being created. To further address data interchange and interoperability issues, JSON was used to obtain information from IFC and COBie models in this study and supply BIM data into building management systems.

2.6. Using Graph-Based Models and Graph Neural Networks (GNNs) to Improve Building Comfort and Performance

Graph-based models and graph neural networks (GNNs) are emerging technologies that have the potential to significantly improve building performance and thermal comfort [78]. Building information modeling (BIM) data can be converted into graph-based models, which capture the relationships between different components of a building [79]. By combining graph-based models with GNNs, it is possible to predict the behavior of building systems based on real-time data collected from IoT devices such as occupancy sensors, temperature sensors, and humidity sensors [80]. These predictions can help optimize building systems, such as heating and cooling, to provide a more comfortable indoor environment while reducing energy consumption.

The use of graph-based models and GNNs can have a positive impact on various aspects of building performance and comfort. For example, researchers have used graph-based models to analyze the impact of different building elements on thermal comfort [81]. Additionally, GNNs have been used to predict energy consumption in buildings based on real-time data [82].

The integration of BIM, graph-based models and GNNs is a promising approach to improving building performance and comfort, which could lead to significant benefits for building occupants and the environment [83]. However, several challenges need to be addressed, such as the need for high-quality BIM data, the complexity of graph-based models, and the need for real-time data. Despite these challenges, the use of graph-based models and GNNs holds great potential for the optimization of building systems and the improvement of indoor environmental quality.

2.7. The unique aspects of our investigation

This study is a continuation of the previous research [84], and it presents an updated and improved approach to building condition assessment and decision-making. Like [84], the focus of this study is on the development of a Digital Twin model for evaluating the comfort levels of building occupants using a Bayesian network and an automatic fault detection and prediction system for HVAC. However, this manuscript introduces several new and important contributions that set it apart from the previous work.

One of the main contributions of this work is the development of a new method for using BIM as a visualization platform and predictive maintenance. The paper proposes a plugin that can handle data in a BIM environment every 5 min, which was not available in [84] or other studies like [85,86], [87]. This method simplifies the process of assessing a building's comfort and streamlines the time-consuming fault detection process. Additionally, the paper presents a novel approach for building condition assessment and decision-making by integrating Bayesian networks (BNs) with Digital Twin technology using Dynamo. This allows for a more comprehensive and accurate evaluation of building performance and occupant comfort by combining real-time sensor data and occupant feedback into the BIM environment without even using an external program or database compared to other studies like [88].

Another key contribution of this paper is the focus on the space adequacy problem, which involves 10 aspects that have not been previously analyzed together for occupants' comfort. The paper implements 9 machine learning algorithms, compared to only three in [84], and uses different matrices to evaluate the performance of these algorithms, such as F1 score, ROC, and Recall. This required a significant amount of data processing and real-time training and prediction, which is not commonly seen in the literature. Furthermore, the performance of these algorithms is compared on a single database, which is a novel approach.With the use of new algorithms, the paper is able to detect new faults, especially in chiller and boiler systems, such as compressor failure, which could not be detected by the previous method in [84]. Additionally, the paper presents a new method for determining the remaining useful life of the HVAC system using different standards compared to [89–91]. This method shows that it can increase the lifetime of HVAC by at least 10%, resulting in significant savings in energy and money.

This paper presents also a framework using ontology graphs based on JSON and ISO 19650 to integrate data from different systems, including FM, CMMS, BMS, and BIM, to address the challenge of applying these methods to a wide range of buildings. This is an important contribution as it addresses the need for a holistic approach to building condition assessment and decision-making that can be applied to a variety of buildings and building systems.

In summary, this paper presents a unique and innovative approach to building condition assessment and decision-making by integrating BNs with Digital Twin technology, using BIM for visualization and predictive maintenance, and utilizing a data integration framework using ontology graphs. These contributions can help improve the comfort and satisfaction of building occupants, leading to more sustainable and energy-efficient buildings.

3. The proposed framework

As can be seen in Fig. 2, the proposed framework utilizes Digital Twin technology to detect faults and diagnose building conditions, helping facility managers make informed decisions. It incorporates the latest technologies such as BIM, IoT, and ML. The framework has 3 main phases: data input, fault detection and prediction, and information visualization and monitoring in BIM. It uses a BIM model to gather spatial data and a C# plug-in extension for Autodesk Revit to connect the BIM model with fault detection and prediction results to improve decision-making for the FM team. The following sections will explain the 3 main components of the framework.

3.1. Data input

Data input refers to the process of collecting and inputting data into the framework. This can include data from various sources such as building sensors, BIM models, and other data related to the building and its components. This data is then used for the fault detection and prediction phases of the framework and is also used to update the BIM model. The data input phase is essential for the accurate and effective functioning of the framework, as it provides the necessary information for the detection of faults and predictions of building conditions.

3.1.1. Utilizing BIM for Data Acquisition and Building Component Prediction

Utilizing Building Information Modeling (BIM) can provide valuable data for detecting faults in buildings and performing predictive maintenance of HVAC systems. To achieve this, several types of data can be extracted from the BIM model, including spatial information, equipment data, sensor data, building use data, maintenance history data, fault data, and energy consumption data. Spatial information can be used to map out potential problems in the building and identify areas that may require maintenance. Equipment data, sensor data, and building use data can help in identifying potential problems with equipment and predicting when maintenance is needed. Maintenance history data can provide valuable information about the history of problems and when certain systems were last serviced. Fault data and energy consumption data can be used to train AI models to detect and diagnose similar faults in the future. By extracting this data from the BIM model using IFC and COBie, a more complete data set can be achieved, which can be used to improve the accuracy and effectiveness of fault detection and predictive maintenance. The data can also be used to train AI models, which can help identify and diagnose problems, predict future maintenance needs, and improve building performance.

3.1.2. Integrating Sensor Data into BIM Model for Real-Time Building Monitoring and Decision Making

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3.1.3. Occupant Satisfaction Survey

The process of analyzing the factors that contribute to building occupants' comfort levels involves three main stages. The first stage involves conducting a user satisfaction survey using SurveyXact forms. This survey assesses convenience factors such as thermal comfort, acoustic comfort, indoor air quality, visual comfort, and space adequacy. Occupants provide feedback on their current location and their level of satisfaction on a 5-point Likert scale. The second stage involves identifying the causes of discomfort using a probabilistic model trained on a Bayesian Network (BN). The BN model is developed using the Python box in Dynamo and includes information about the building and surrounding area, and considers the most important factors contributing to discomfort in Norway's buildings. The final stage involves connecting the BIM model with the survey results and the probabilistic model using a custom-built plug-in for Autodesk Revit, Dynamo, and Python, to support occupants' comfort. The FM team can interpret the data using the BIM visualization of occupants' responses and the findings of the causative analysis. The BN is depicted in Fig. 3. This process helps improve occupants' comfort by identifying the factors that contribute to their discomfort and taking steps to address these factors (see Fig. 4).

To develop the BN model using the Python box in Dynamo and include information about the building and surrounding area, the first step is to gather data on the building and surrounding area, including information on features of the building such as HVAC systems, and factors such as occupancy density. The next step is to use the Python box in Dynamo to develop the probabilistic model using the Bayesian Network (BN) approach. After that, the gathered data is input into the BN model and used to train the model. Once the model is trained, it can be used to identify the most important factors contributing to occupants' discomfort in the building. To ensure the BN model can be used to its full potential, parameters are added to the BIM model to store data that can-

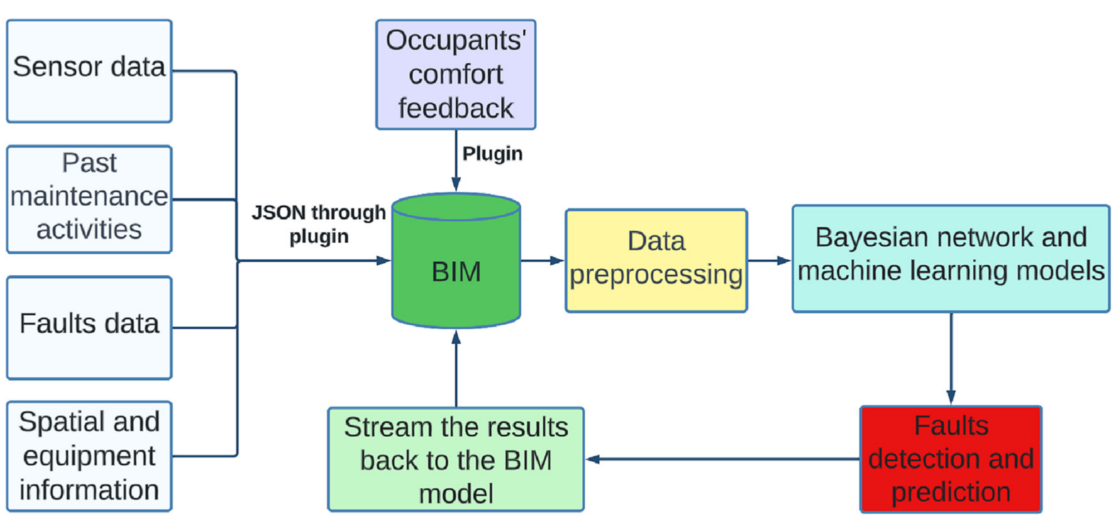

Fig. 2. The proposed Digital Twin framework for fault detection, prediction, and data visualization in building management systems.

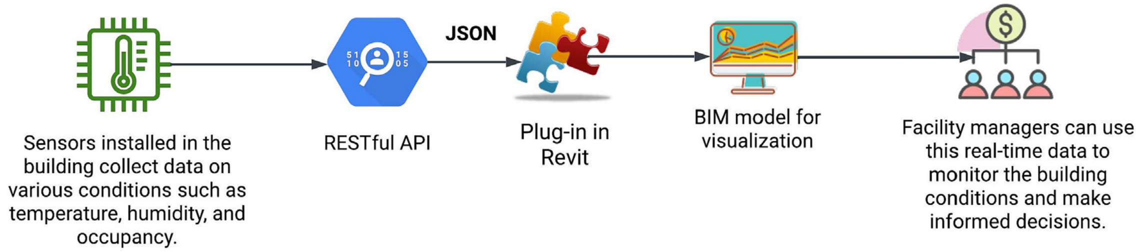

Fig. 3. Real-time monitoring and decision making through the integration of sensor data into BIM framework.

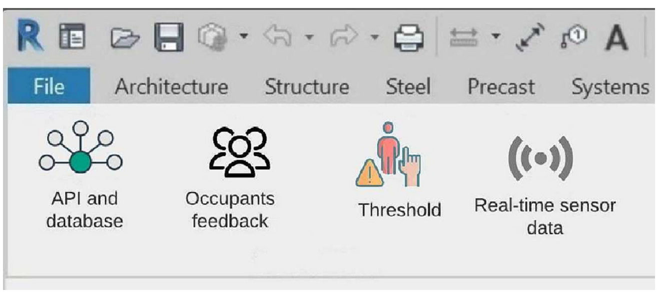

Fig. 4. Managing sensor data and occupant feedback within Revit using a custom-developed plug-in.

not be acquired from the BIM model. After that, the BN model is used to identify causative variables of occupants' discomfort and then validated using the survey feedback data. Finally, the BN model is iterated and improved as necessary. PyMC3 [92] and pgmpy [93] is the Python libraries that are used for probabilistic programming that allows for the easy and flexible creation of BN models. It includes a variety of built-in distributions and samplers, making it a popular choice for developing BN models. Fig. 5.

3.1.4. Integration of BIM and FM Data using IFC, COBie, JSON, and ISO 19650-1:2018

Data integration between BIM and Facility Management (FM) can be achieved using a combination of Industry Foundation Classes (IFC) and Construction Operations Building information exchange (COBie) standards. IFC is an open data model that allows for the exchange of BIM data between different software applications, while COBie is an information exchange specification that can be used to collect and share data throughout a building's entire lifecycle [94].

One way to integrate BIM and FM data is to map IFC data into COBie and FM systems. This can be done by first determining the essential data needed for FM operations and then mapping the IFC data into the COBie data schema. The process of data mapping can be automated using programming languages such as Python, which can be used to generate a JSON file that can be read by GraphDB, a graph database management system that allows for the efficient querying and manipulation of large and complex data sets [95].

To generate a knowledge graph that unifies all the concepts, the ISO 19650 standard can be used [96]. This standard provides guidelines for creating a consistent and structured asset information model that can be used to generate a knowledge graph. By following this standard, the data from IFC, COBie, and JSON files can be integrated into a single knowledge graph that can be used to provide a comprehensive view of the building's assets and their relationships.

The mapping process can be done by using JSON, a lightweight data-interchange format that is easy to read and write and can be used to transfer data between different systems. JSON can be used to map the COBie data to the attributes of the data in the FM database, allowing for easy integration and retrieval of the data. The mapping process should be done one property at a time, to ensure that the data is accurately mapped and to avoid any errors or inconsistencies. For each property, the corresponding attribute in the FM database should be identified, and the mapping should be done using the JSON format. For example, the "Equipment name" property in the COBie data can be mapped to the "Name" attribute in the FM database. Similarly, the "Equipment type" property in the COBie data can be mapped to the "Type" attribute in the FM database. By following the ISO 19650 standard and using JSON, the mapping process can ensure that the data is structured and consistent, making it easy to access and manage the information in the FM database. Once the data is integrated, it can be stored in GraphDB. By using GraphDB, the data can be easily searched, analyzed, and visualized, making it easier for facility managers to access the information they need to effectively manage a building's assets. Table 1 shows the mapping of specific COBie properties (Equipment name, type, U-values, and room) to the corresponding FM attributes (Name, Type, U-value, and Room).

3.2. Fault detection and prediction

Fault detection and prediction are important tasks in building maintenance and operations. By identifying potential issues early, corrective actions can be taken to prevent equipment failures, reduce downtime, and improve the overall performance of the building.

3.2.1. Decision-Making Framework for Identifying and Addressing Building Faults

The decision-making framework in Fig. 6 provides a systematic approach for facility managers to identify and address building issues and satisfy the demands of occupants. The framework begins by determining whether the issue is related to the HVAC system, specifically if there is an electrical issue. This can be done by evaluating several criteria such as power outages or tripped circuit breakers, abnormal noise and vibrations, equipment failure, presence of smoke or sparks, error messages on the HVAC control system, unusual odors, light flickering, electrical equipment malfunctions, corroded electrical connections, and power surge. If not, the Bayesian network (BN) in Fig. 3 is used to automatically identify potential HVAC design issues, such as thermal comfort issues.

Next, the framework checks if the HVAC system is inadequate, which would indicate that it cannot handle the thermal demand of the occupants. If the architectural and constructive design is properly established, the thermal load can be computed automatically, by integrating a custom script into Autodesk Revit using the Revit API, and the indoor unit capacity can be retrieved from the equipment database. If the indoor unit capacity is less than the thermal load of the room, the framework suggests ways to improve

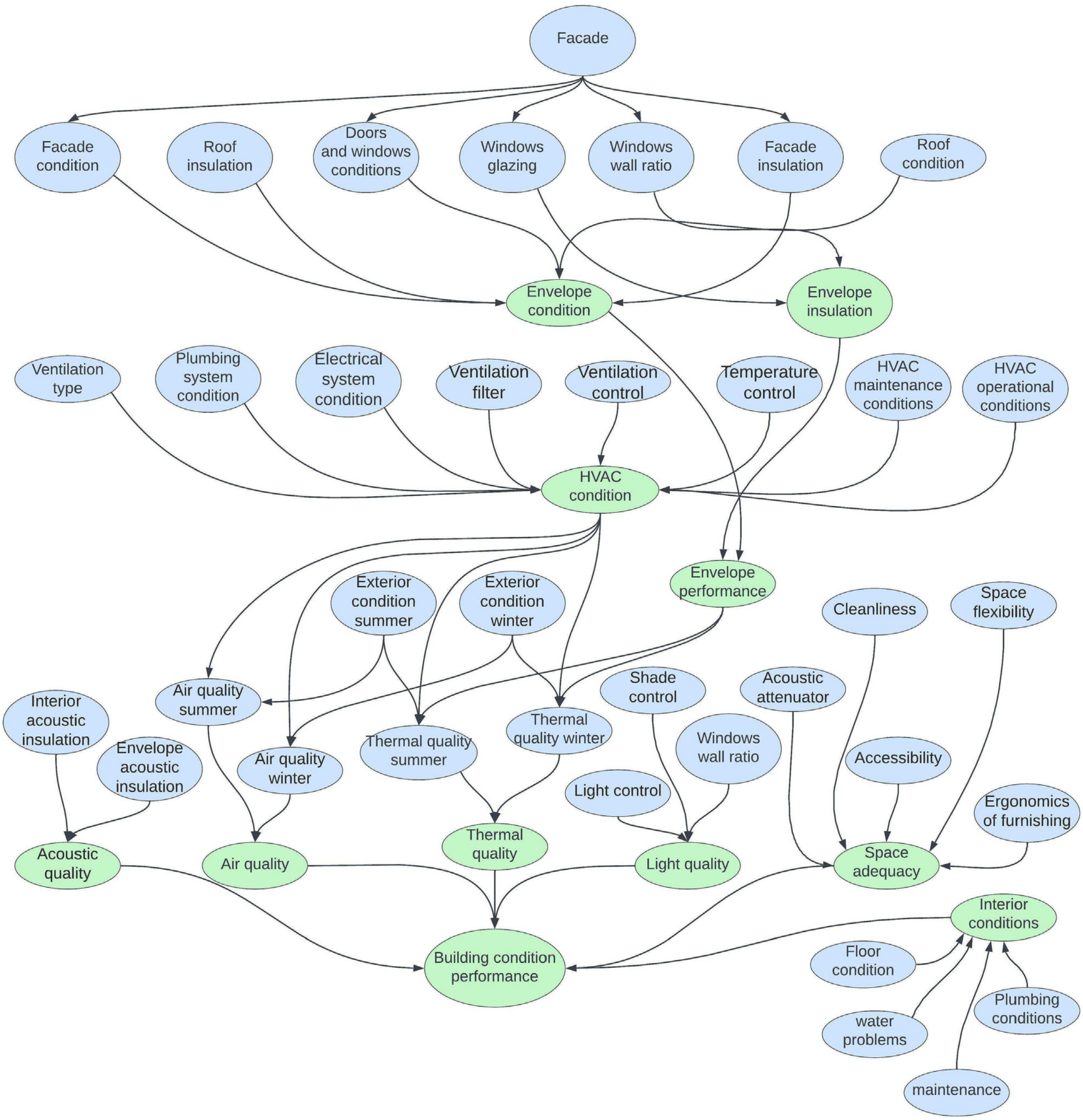

Fig. 5. Graphical representation of the Bayesian Network model for probabilistic evaluation of building comfort performance, after [16].

Table 1
Mapping of COBie Data to FM Attributes

COBie Property	FM Attribute
Equipment name	Name
Equipment type	Type
U-values	U-value
Location (room)	Room

the building's design such as insulation of the room's facade, or using interior units with larger cooling or heating capacities. If the indoor unit capacity is greater than the thermal load of the room, the framework checks for failures in the indoor HVAC system equipment by applying APAR rules and analyzing sensor data. If no issues are found with the indoor equipment, the framework checks for issues with outdoor units, such as frozen evaporator coils or dirty condenser coils. Finally, the framework checks for issues related to visual, auditory, and spatial comfort. This includes examining the window-to-wall ratio (WWR), room lighting and shade management for visual comfort, internal and exterior acoustic insulation materials for acoustic comfort, and the cleanliness, adaptability, accessibility, and ergonomic furnishings of the space for overall comfort. The decision-making framework provides a structured approach for identifying and addressing building issues and satisfying the demands of occupants. By following this framework, facility managers can efficiently identify the underlying causes of building issues and take appropriate actions to resolve them.

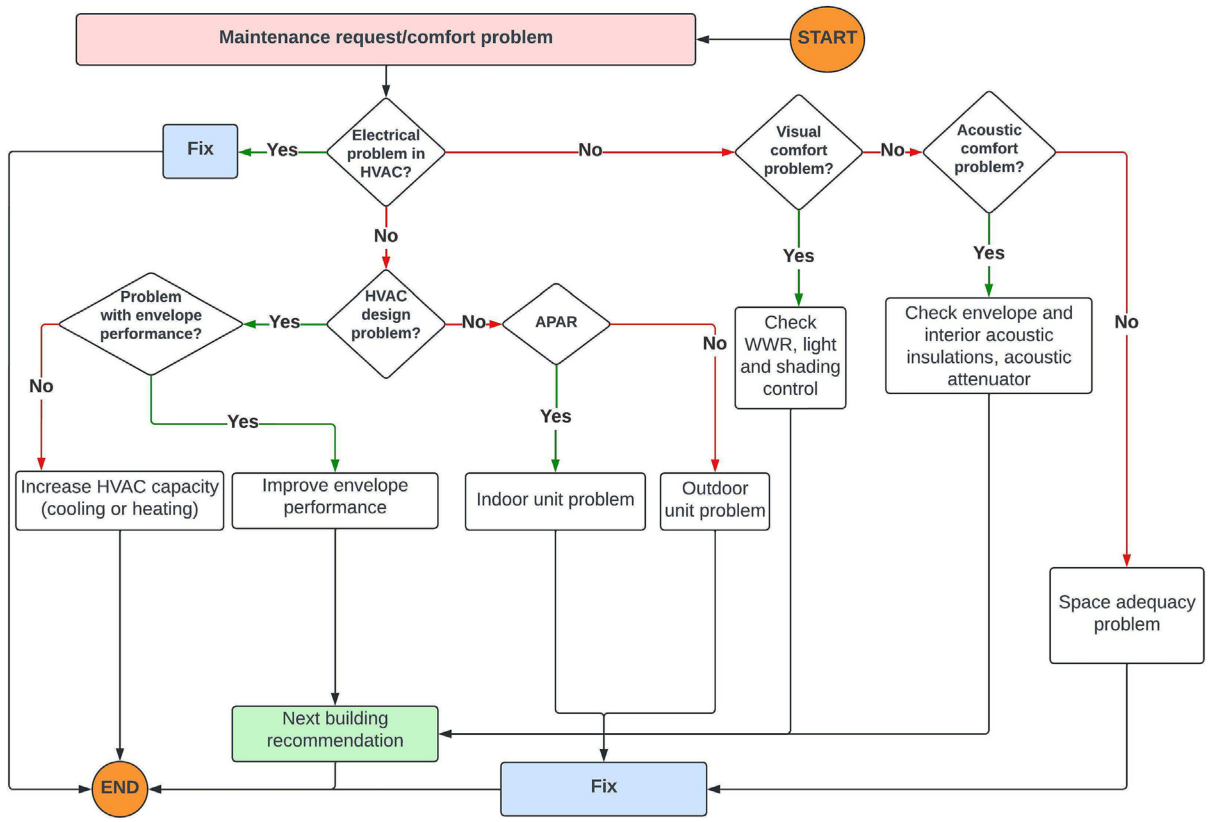

Fig. 6. The proposed framework for utilizing BIM and BN models to improve decision-making in facility management through identifying building faults and addressing occupant needs, after [97].

3.2.2. Data selection and pre-processing

Data selection and pre-processing are important steps in the process of using data to make decisions about building operations and maintenance. The goal of data selection and pre-processing is to select the most relevant data and prepare it for analysis. This includes cleaning, formatting, and transforming the data so that it can be used by the decision-making framework.

The first step in data selection is to identify the data that is relevant to the decision-making process. This includes data from sensors, building management systems, and other sources that are related to the building's operations and maintenance. It's important to consider the quality, accuracy, and timeliness of the data when making this selection. Once the relevant data has been identified, it needs to be cleaned and formatted. This includes removing any missing or duplicate data, correcting errors, and ensuring that the data is in a consistent format. This process is important to ensure that the data is accurate and reliable and that it can be used for analysis. The next step in pre-processing is data transformation. This includes converting data from one format to another, such as converting sensor data from raw values to engineering units and creating new variables from the existing data. This step is important because it allows the data to be used by the decision-making framework and enables the analysis of the data.

StandardScaler to normalize the data and SVMs with ANOVA kernel to classify and predict the most important features in the data are effective techniques for data selection and pre-processing in building operations and maintenance [98]. It allows for the identification of important features from high-dimensional sensor data and ensures that the data is in a consistent format for analysis. This can improve the accuracy and efficiency of decision-making based on building data. In order to implement this technique, Python and libraries such as scikit-learn [99] can be used.

3.2.3. Comfort Analysis using Bayesian Network

To determine the primary reasons for discomfort in a building, it is necessary to identify the building and spatial information that impacts occupants' comfort for each comfort component. This is done by first selecting which factors have the greatest impact on occupant comfort through a literature review, then using a statistical analysis on a satisfaction survey of building occupants to determine cause-and-effect relationships between various factors. The model structure is then tested and improved using the Delphi technique with the help of 24 specialists [100]. The building and spatial information variables are represented by nodes in a Bayesian Network (BN) model, which can be either discrete or continuous [101]. The likelihood of a node being in a given state is described by conditional probability tables (CPTs in Fig. 7) [102] and the BN model is built using Dynamo's Python box for its robustness, adaptability, and user-friendliness. The conditional probability tables (CPTs) for each node and the significance of parent nodes for occupants' comfort in the BN model were chosen based on previous research as cited in [16,23,103]. The BN model also performs backward propagation to determine the marginal probabilities of unseen nodes and sensitivity analysis can be performed to determine the most influential model inputs [102].

The ventilation system plays a crucial role in determining the indoor air quality (IAQ) in a building, and ultimately, the comfort level of the occupants [104]. However, natural ventilation is dependent on the weather and may not be energy-efficient in extreme heat or cold. The status of the HVAC system, which can be high, medium, or low, also plays a crucial role in air quality and comfort.

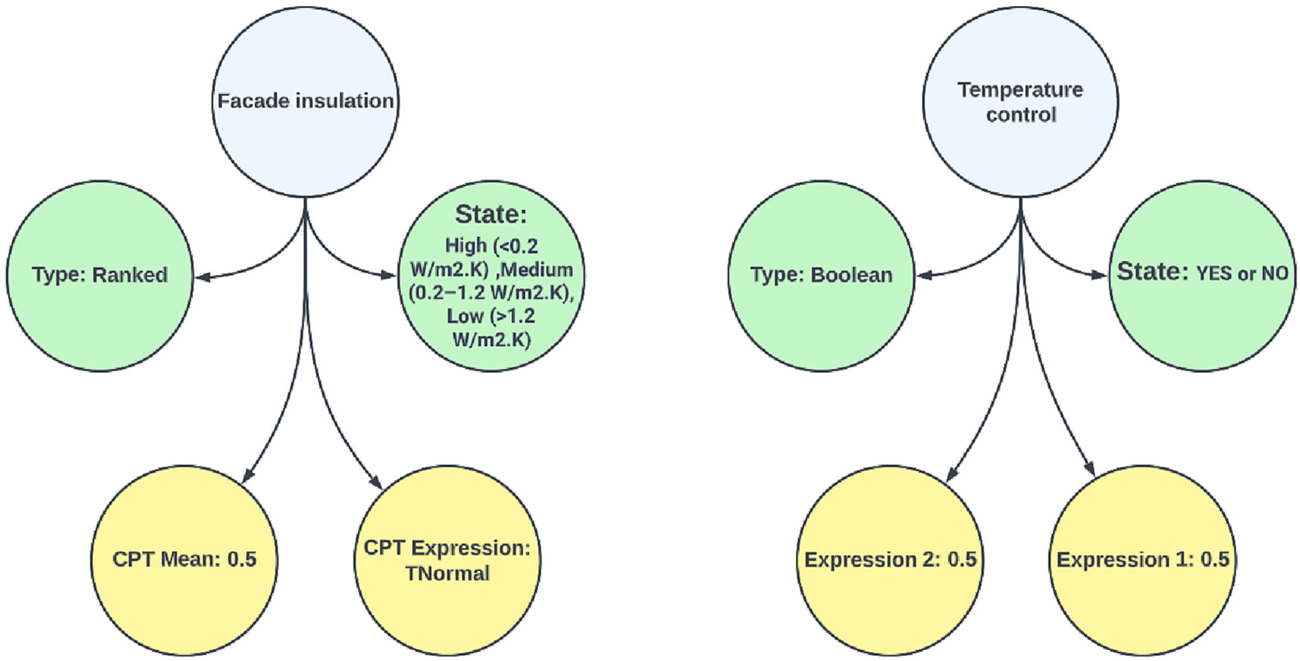

Fig. 7. Bayesian Network Model of Building Comfort Performance: CPT Representation, after [16].

An HVAC system that is not functioning properly can lead to health problems and discomfort. The design of the HVAC system must also take into account the layout of the building, with centralized systems being more suitable for single thermal zones, and decentralized systems for multi-zone structures [16,53]. Additionally, the density of occupants within the building also affects air quality comfort. In this context, the BN model used in this paper has two types of nodes: ranked nodes (such as ventilation control and filter) and Boolean nodes (like HVAC design errors, HVAC condition, and occupancy density).

The thermal sensation is the state that conveys satisfaction with one's current thermal surroundings. The external environment has a significant impact on heat perception and the type and features of HVAC systems, as well as options for thermal adaptation, have been highlighted as important determinants in thermal comfort [105]. However, faults in HVAC design and environmental variables can have a greater impact on thermal comfort [23].

Quantifying the effect of daylighting on visual comfort may be done by calculating the window-wall ratio (WWR) [106]. People prefer natural light in their workplaces, which is correlated with the widespread consensus that it is healthier [107]. Therefore, it is necessary to model the façade and window sizes in BIM and determine the WWR per area. Occupant comfort is also affected by the availability of inside curtains and outside window shades for reducing glare and overheating. In addition to thermal and visual comfort, space adequacy is also an important factor for occupants' comfort [108]. Ergonomic furnishings, cleanliness, and accessibility are the most important aspects of enough space. Other aspects that impact occupant comfort include using ergonomic furniture and the availability of enclosed areas for meetings and collaborative work.

The APAR method is a way to evaluate the performance of HVAC systems by analyzing data collected from various sensors and control signals. The data is used to calculate performance metrics such as supply air flow rate, supply duct static pressure, and return air temperature. The APAR method can be integrated with a BMS using a Bayesian Network (BN) approach, which can identify problems with the HVAC system and provide recommendations for how to fix them, improving the overall performance of the HVAC system and providing a comfortable and healthy indoor environment. For example, the BN can be used to identify the cause of a problem with the supply air flow rate. The BN can analyze the data from the sensors and control signals and identify the relationships between the supply fan speed, the supply duct static pressure, and the supply air flow rate. The BN can then predict the cause of the problem, such as a blocked filter, and provide recommendations for how to fix the problem.

3.2.4. Fault Prediction for Improved Maintenance Strategy

The efficient operation and maintenance of building systems, such as HVAC systems, is critical for ensuring the comfort and safety of occupants, as well as reducing energy consumption and costs. However, many factors can cause failures in building systems, including unskilled staff, malfunctioning control systems, and improperly specified needs in the building management system (BMS). To address these issues, this section proposes a fault prediction strategy that utilizes Bayesian Networks (BN) and various machine learning models to improve maintenance decisions through problem detection and system and component health forecasting.

The proposed fault prediction strategy utilizes data from multiple sources, including the BN fault detection system, the facility management (FM) system, and the BIM, to make predictions. The prediction models employed in this strategy include Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Trees (DT), Naive Bayes (NB), K-Nearest Neighbors (KNN), Random Forest (RF), Multi-Layer Perceptron (MLP), Gradient Boosting (GB) and XGBoost (XGB). These models are trained using data sets for the desired variables and are then used to make predictions about the likelihood of failures and the severity of the issues.

The proposed fault prediction system also supports adaptive model training and prediction. Prediction models are trained with data from continually updated sensors and service logs, and the parameters of the models are adjusted to account for new information. The prediction process includes four stages: training, cross-validation, testing, and prediction. Input datasets are randomly divided into three categories: 80% for model training, 10% for validation, and 10% for testing. The trained models are then used to predict the long-term state of various components of the building, and maintenance plans are rescheduled to align with the predicted conditions.

In this case, the inputs for the machine learning models are the data collected from various sources such as the BN fault detection system, the facility management (FM) system, and the BIM. These inputs include information such as sensor readings, maintenance logs, and other data related to the operation and performance of the building systems. The output of the machine learning models is a prediction of the likelihood of failures and the severity of the issues in the building systems. The models use the input data to make these predictions, which can then be used to inform maintenance decisions and actions. For example, the prediction models may output that a certain component of the HVAC system has a high likelihood of failure and that this failure would be severe in terms of its impact on comfort, energy waste, and danger to machinery. Based on this output, maintenance personnel may schedule a proactive maintenance action to address the issue before it becomes a problem.

3.3. Visualizing Occupant Feedback and Causative Factors

Data visualization is an important tool for presenting the findings of a user satisfaction survey and identifying the root causes of occupants' dissatisfaction. By using visual representations of data, it is possible to make complex information more accessible and easier to understand.

One of the visualization techniques proposed in this study is the use of a color scale to represent occupants' opinions on various comfort levels. The color scale ranges from "Very happy" to "Very dissatisfied", and the data is presented in a 3D representation using a BIM model and a plug-in created with Revit's schedule. This allows the FM team to observe the average comfort level of occupants by room and compare it to other rooms using the same filtering criteria. Another visualization technique suggested is the use of Python scripts in Dynamo to present the probabilistic model's causal analysis of each room's data. The scripts can be used to create clear and informative visual representations of the data, making it easier to understand the root causes of occupants' dissatisfaction. The process of implementing the scripts in Dynamo is illustrated in Fig. 8.

4. Case study

4.1. Verifying Digital Twin Framework with I4Helse and Tvedestrand School Buildings in Norway

I4Helse which is a university building [109] and Tvedestrand upper secondary school [110] are two buildings located in Norway that were used as case studies to verify the proposed Digital Twin framework. Both buildings were built in compliance with Norwegian regulations on technical requirements for building works (TEK10) standards [49] and were equipped with various sensors

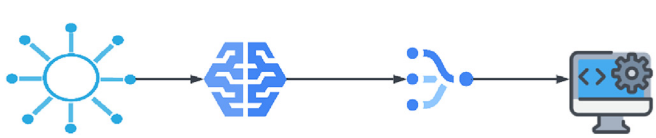

Fig. 8. The flow process of visualizing the causal analysis of rooms and HVAC data using Python scripts in Dynamo.

to monitor the buildings' performance. Table 2 shows the main features of both buildings. Fig. 10 illustrates the systems involved in this study.

The sensor data was collected and sent to BIM models (Fig. 9)) to process the information further. Additionally, user satisfaction was assessed in various locations throughout the buildings, and this data was incorporated into a probabilistic model in Dynamo to determine the sources of comfort or discomfort. The BIM model was used to gather evidence of possible HVAC controls, design errors, occupancy densities, and environmental settings, and this information was used to run the occupants' comfort probabilistic model in the BN model. The Digital Twin framework aims to provide a comprehensive understanding of the building's performance, allowing for better decision-making and optimization of building operations.

4.2. HVAC system

The HVAC units were equipped with rotary heat exchangers, bypass, heaters, and chillers. These units were responsible for conference rooms, classrooms, offices, and other spaces. Fig. 11 illustrates the HVAC layout in the buildings considered in this paper.

4.3. Data collection

The figure, Fig. 12, illustrates how BIM can provide Facility Managers (FM) with important information about a building's geometry and semantics. Additionally, the FM system can be utilized to access inspection reports and historical records of maintenance. This information can be used in condition inspections and quality assessments by the BIM model. The data collected by IoT sensors in real-time includes parameters such as damper position, chiller valve position, heater valve position, water temperature from the

Table 2
HVAC Systems of the I4Helse and Tvedestrand School Buildings.

Operation	Features
Ventilation system	The used system is a mechanical balanced ventilation system with a rotary heat recovery system with an efficiency of 85%.
Specific Fan Power (SFP) related to air volumes, during operating time [kW/(m^3/s)]	1.4
Schedules of ventilation system operation	Monday-Friday: 12 h/day (07.00–19.00)
Average supply airflow rates of the ventilation system	2.48 l/(m^2.s) for the occupied zones and 0.81 l/(m^2.s) for the unoccupied zones (no equipment)
Heating system	Centralized heating system, with an efficiency of 90% , meaning that 90% of the energy used by boiler is effectively converted into heat for warming the building
Cooling system	Centralized water cooling for AHU supply air
Room temperature set point for heating and cooling [°C]	21 for heating and 24 for cooling
Supply air temperature during operating time winter/summer [°C]	21/19
DHW use	5 kWh/(m^2·year)
Night ventilation	0.36 l/((m^2.s)

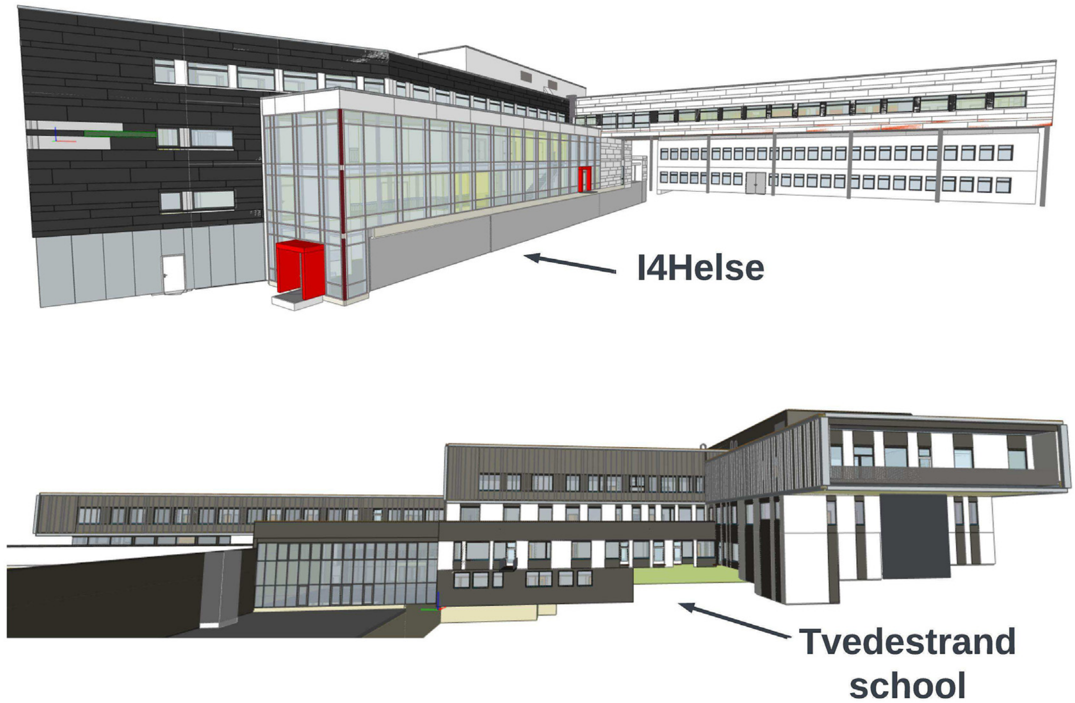

Fig. 9. BIM model of I4Helse and Tvedestrand School Buildings as Case Studies for the Digital Twin Framework Analysis.

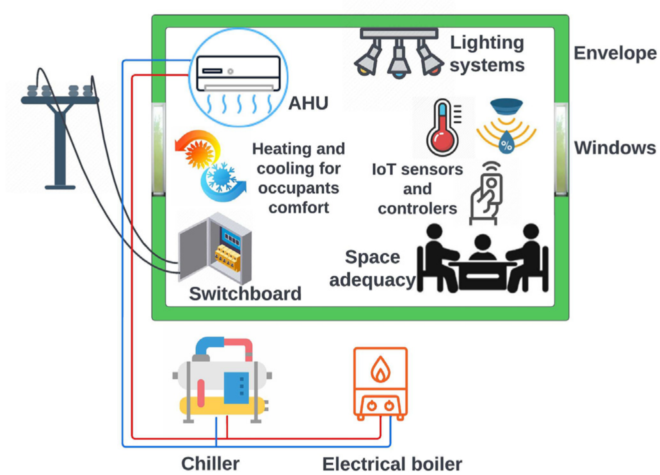

Fig. 10. Components and Systems of the Digital Twin Framework for Identifying Occupants' Discomfort in Buildings through Fault Detection and Prediction, after [84].

heater, water temperature of the return heating coil, and flow rate of water. Data from the I4Helse building from August 2019 to July 2022 and from the Tvedestrand school building from October 2020 to July 2022 were analyzed to demonstrate how long-term trends in sensor data can be used to predict future events.

4.4. Feature selection for APAR and prediction process

Feature selection for APAR using ANOVA-SVM (Analysis of Variance Support Vector Machine) involves selecting the most relevant features from a dataset to improve the accuracy of the predictions made by the SVM model. ANOVA-SVM is a popular feature selection method for SVM-based models because it can handle non-linear and high-dimensional data. ANOVA is used to calculate the F-value of each feature, which is a measure of the relationship between the feature and the target variable, and the top-k features with the highest F-values are selected as the most relevant features for the SVM model.

4.5. Faults detection

4.5.1. Real-time Monitoring and Analysis of Building Performance using Sensors and BIM Model

The process of monitoring the performance of buildings using various sensors and a BIM model includes visually depicting real-time sensor data and trends, as seen in Fig. 12. The facility manager uses the sensor data to assess the current state of each building system and references recorded abnormal events and warnings from the FM system for condition evaluation. After reviewing the findings of the field inspection, the FM team completes a building systems configuration list (various mechanical, electrical, plumbing, and other systems within a building) and conducts a comprehensive check of the building's infrastructure to assess its state of repair. Through testing using a framework and a BN model, several severe faults were found and confirmed by facility management employees. Some of these faults require immediate attention and fix, while others need revision of the relevant control system algorithms.

Fig. 13 describes a time series plot of heating and cooling valve signals for an HVAC system. The plot shows the activity of the heating valve signal between 6 AM and 11 PM, while the cooling valve signal is inactive because it is winter. The green points on the plot indicate heating and cooling faults, which occurred for a three-hour period. This plot is useful for understanding the operation of the HVAC system and identifying any issues with the heating and cooling valves. By analyzing the activity of the valves, facility managers can determine if the system is functioning correctly and take appropriate action if any faults are detected. This information can help to improve the energy efficiency and comfort of the building, and reduce maintenance costs.

A fault in the HVAC system where the fan signal is off during heating regime is detected in Fig. 14. The fault is an indication that

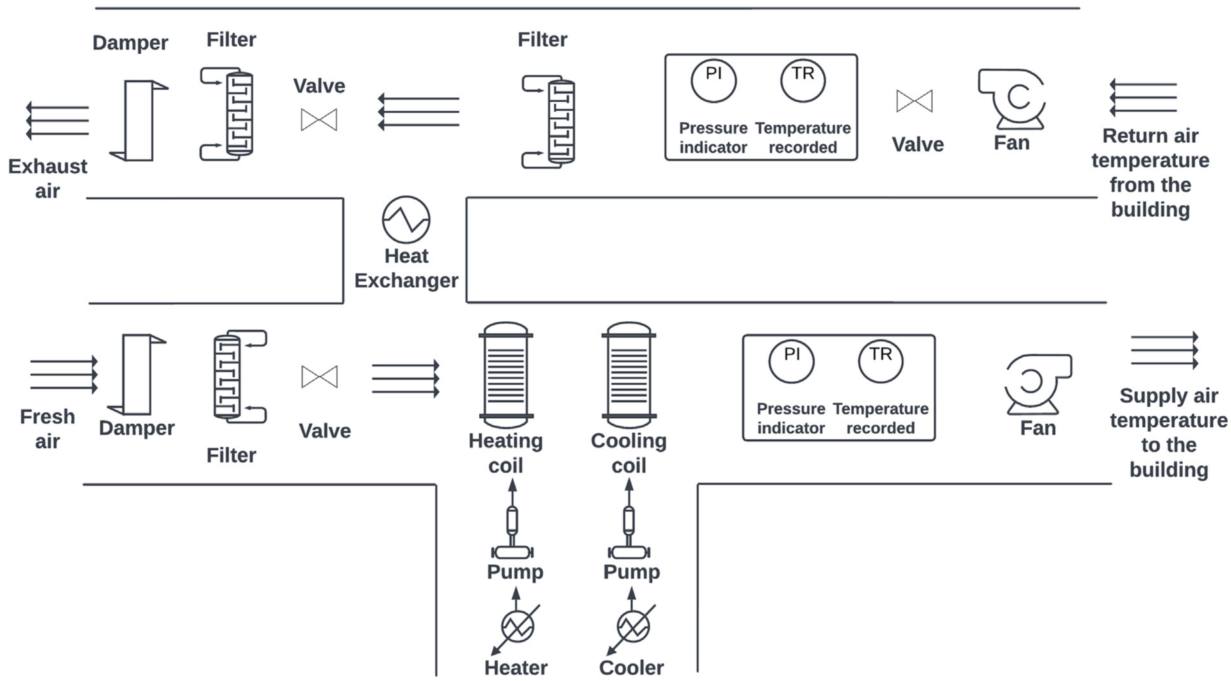

Fig. 11. Graphical Representation of the HVAC Systems in the I4Helse and Tvedestrand School.

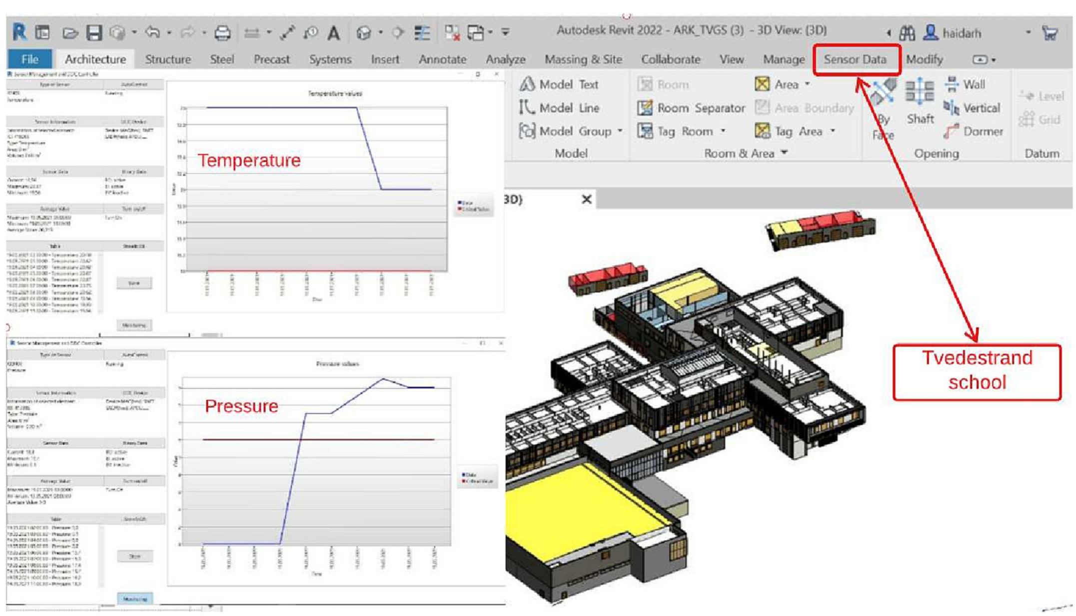

Fig. 12. The information about the building obtained via sensor data and the BIM model.

there is an issue with the fan or the fan control. This can occur due to a number of reasons, such as a mechanical failure, a broken fan belt, or a malfunctioning fan control circuit. When the fan is not operating during the heating regime, it can cause the heating system to work less efficiently, which can lead to higher energy consumption and higher costs. Additionally, the air in the building may not be circulating correctly, resulting in uneven heating and poor air quality.

When the fan is off during heating regime, the heat generated by the heating system cannot be distributed throughout the building, leading to localized heat buildup and potentially causing damage to the system. This can cause the heating system to overwork and eventually lead to system failure.It is important to diagnose and fix the issue as soon as possible to prevent further damage and to ensure the comfort and safety of the building's occupants. Detecting this fault can help facility manager to identify the cause of the fault and recommend the appropriate course of action. This can include repairs, replacement of parts, or adjustments to the fan control system.

In Fig. 15 a cooling compressor failure is detected. The compressor failure in the HVAC system can cause a significant drop in temperature measurements, which can indicate a problem with the system's ability to cool or heat the air effectively. The compressor is a vital component of the HVAC system as it is responsible for compressing and circulating the refrigerant that is used to cool or heat the air. When the compressor fails, the refrigerant is not

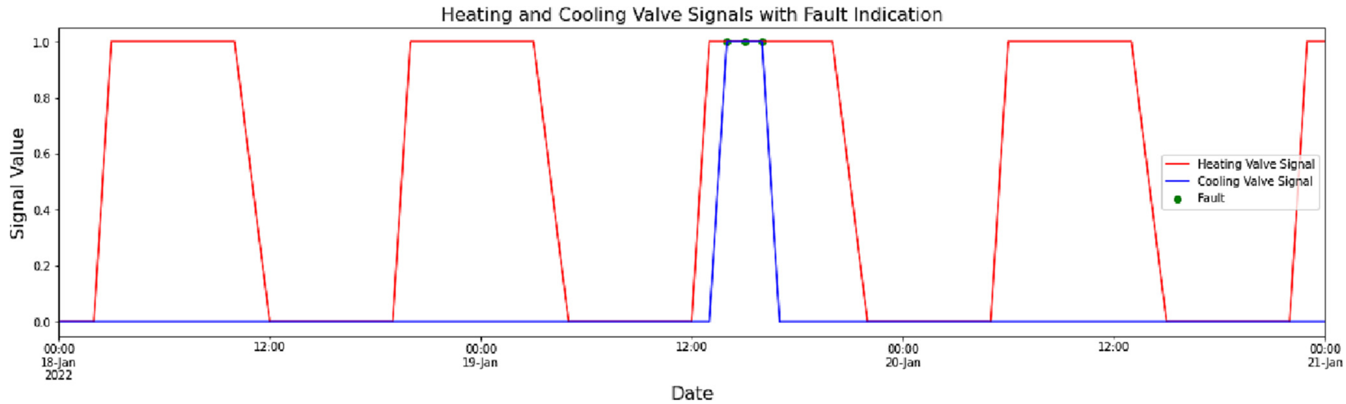

Fig. 13. Time series plot of heating and cooling valve signals for the HVAC system. The heating valve signal is active between 6 AM and 11 PM while cooling valve signal is inactive because of winter. The green points indicate heating and cooling fault, which occurred for three hours.

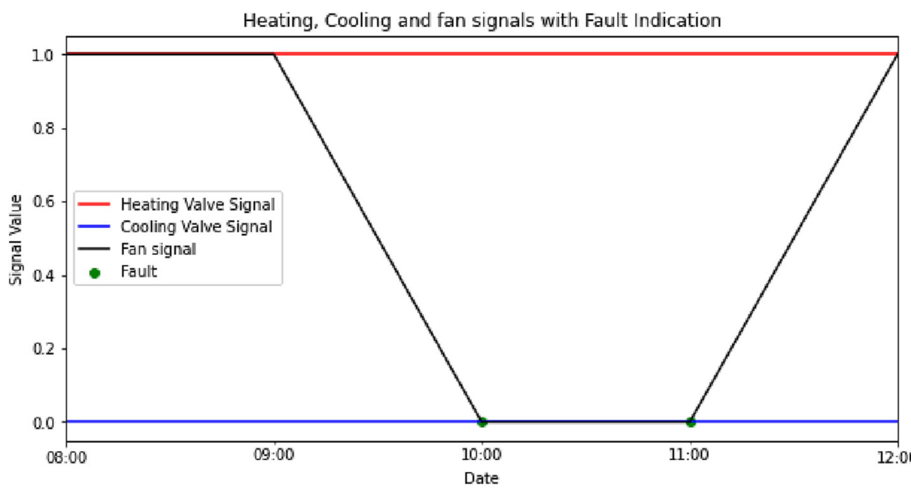

Fig. 14. Heating, cooling, and fan signals for the HVAC system during a fault occurrence. The red line shows the heating valve signal, the blue line shows the cooling valve signal, the black line shows the fan signal, and the green points indicate the fault, which occurred when the fan signal was off during heating regime on 12th of January for 2 h.

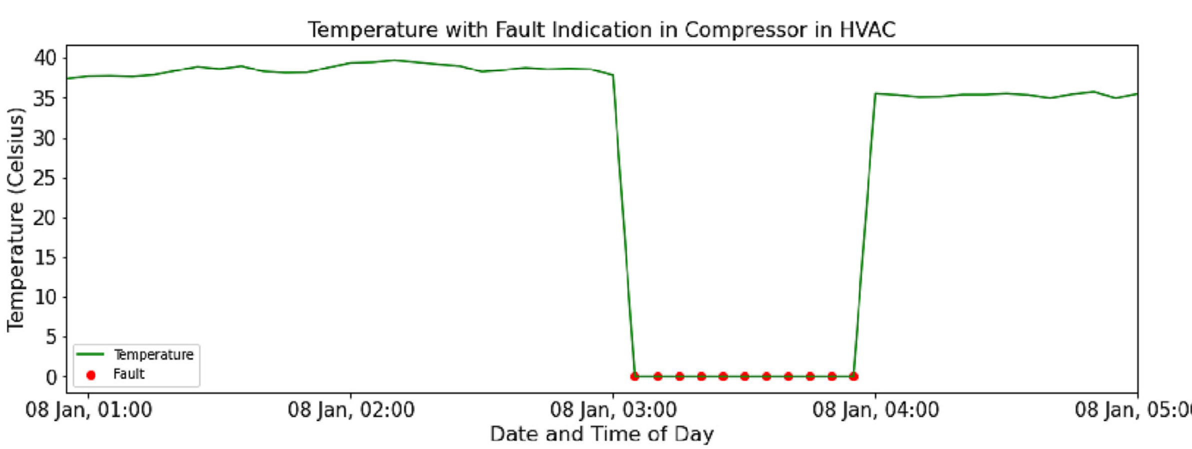

Fig. 15. Temperature of the HVAC system over a 15-day period with a fault indicated on the 10th day. The rolling average of 24 h is shown and the y-axis represents temperature in Celsius. The red scatter plot indicates the fault point. The x-axis shows the date and time of day. The plot is limited to show the fault time.

able to circulate properly, which can cause the system to stop working altogether or to not perform as expected. When the compressor fails, the temperature readings in the building may drop significantly, indicating that the system is not functioning properly. This can cause the building to become too cold in the winter or too hot in the summer, making it uncomfortable for the occupants.

4.5.2. An example of outside unit fault in I4Helse building

As was previously indicated, the BIM model also stores data from the BMS and CMMS systems; using the framework in Fig. 6, this data can be used to determine the fault in the building's system. The system has several demands for maintenance. The framework will be used in a scenario involving one of the many HVAC repair requests. The occupants staying at I4Helse, room N1011, complained about thermal comfort issues, most probably due to the HVAC system not functioning correctly. A request for HVAC repair was loaded into the BIM model, and the corresponding mechanical components were matched using our plug-in. The decision-making framework was implemented with the help of the Dynamo and python language, which supplied the required data on the equipment and the room where the equipment was situated. To determine if the issue was caused by poor HVAC design, the framework compared the needed cooling load to the cooling capability of the HVAC system. Energy calculations for N1011 were compared to the BIM model's HVAC characteristics (e.g., cooling capacity). No HVAC design faults or undersized HVAC components were present since the HVAC system's cooling capacity was greater than that space's cooling load. The second thing the framework was to keep an eye on equipment sensor data to see whether any of the interior or outside units were malfunctioning. Since the APAR model has been unable to locate the issue inside the indoor units, it has concluded that the issue is associated with the outdoor units. So, as shown in Fig. 16, the outside unit associated with the reported HVAC was highlighted for the benefit of the facility management. Therefore, the decision-making framework indicated that the outside unit was likely to be the source of the issue. The FM team then inspected the outside unit, discovering the leak. They were able to fix it and find a solution to the issue without going to the location where the end-user had reported the problem.

4.5.3. Investigating Space Discomfort Factors in Office in Tvedestrand school

Space adequacy in the office is a critical factor in ensuring employee comfort and productivity. The office environment plays a crucial role in employee well-being, and a space that is not conducive to work can lead to physical and mental health issues, decreased productivity, and employee dissatisfaction.

One way to assess the adequacy of space in the office is through a sensitivity analysis of potential reasons for space inadequacy. This can be done by surveying employees' satisfaction and gathering data on factors such as poor artificial lighting, uncomfortable temperature, noise pollution, poor air quality, insufficient space, poor ergonomics, lack of privacy, poor layout design, lack of natural light, and lack of personalization. These factors can then be analyzed and ranked based on their impact on employee comfort using our proposed framework and Bayesian network (Fig. 17).

Once the main reasons for space inadequacy have been identified, appropriate measures can be taken to address them. For example, if poor lighting is identified as a major issue, steps can be taken to improve lighting design and ensure that the office is well-lit. If the uncomfortable temperature is identified as a major issue, steps can be taken to improve temperature control and ensure that the office is at a comfortable temperature. If poor air quality is identified as a major issue, steps can be taken to improve ventilation and air quality. It is also important to note that space adequacy is not only about the physical space but also the layout design, it should be designed to promote comfort and productivity. The office layout should normally be designed to minimize noise pollution and to maximize natural light. The office should be designed to provide privacy and to be conducive to personalization.

In the sensitivity analysis of potential reasons for space inadequacy, it is important to consider not only the impact of each reason on employee comfort but also the potential of each reason to cause discomfort. This can be done by classifying each reason into one of three categories: low potential, medium potential, and high potential (Fig. 18). Reasons with low potential are those that are less likely to cause discomfort and have minimal impact on employee comfort. These reasons may be easily addressed and have a minimal impact on overall office design. Examples of low potential reasons could include a lack of personalization in the

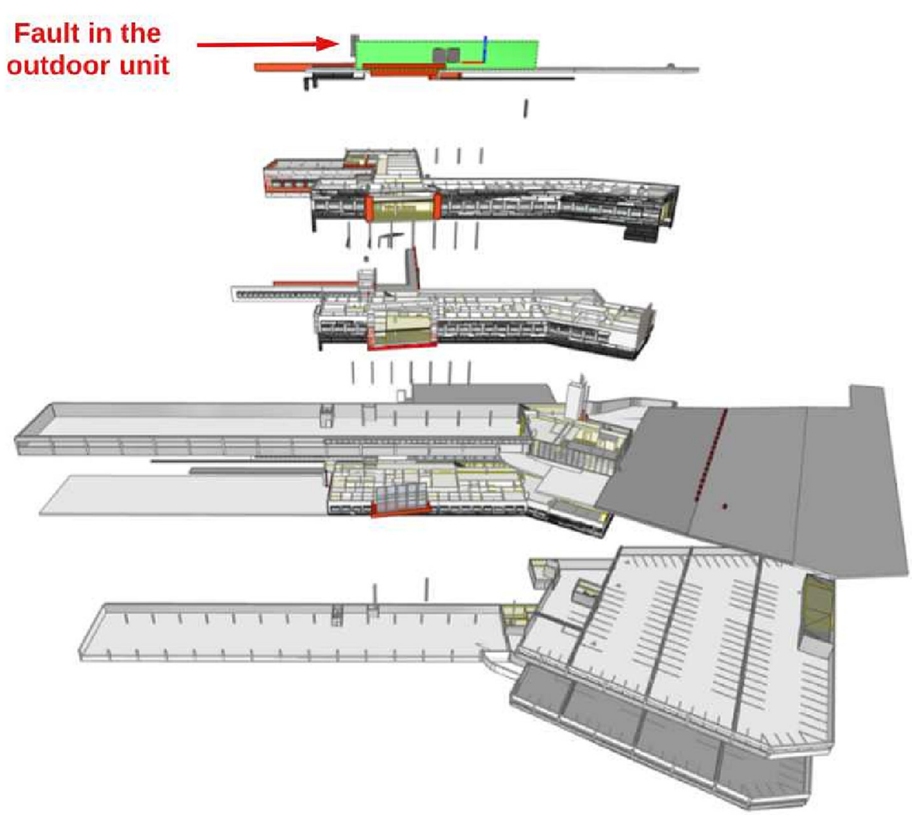

Fig. 16. BIM problem-cause analysis visualization.

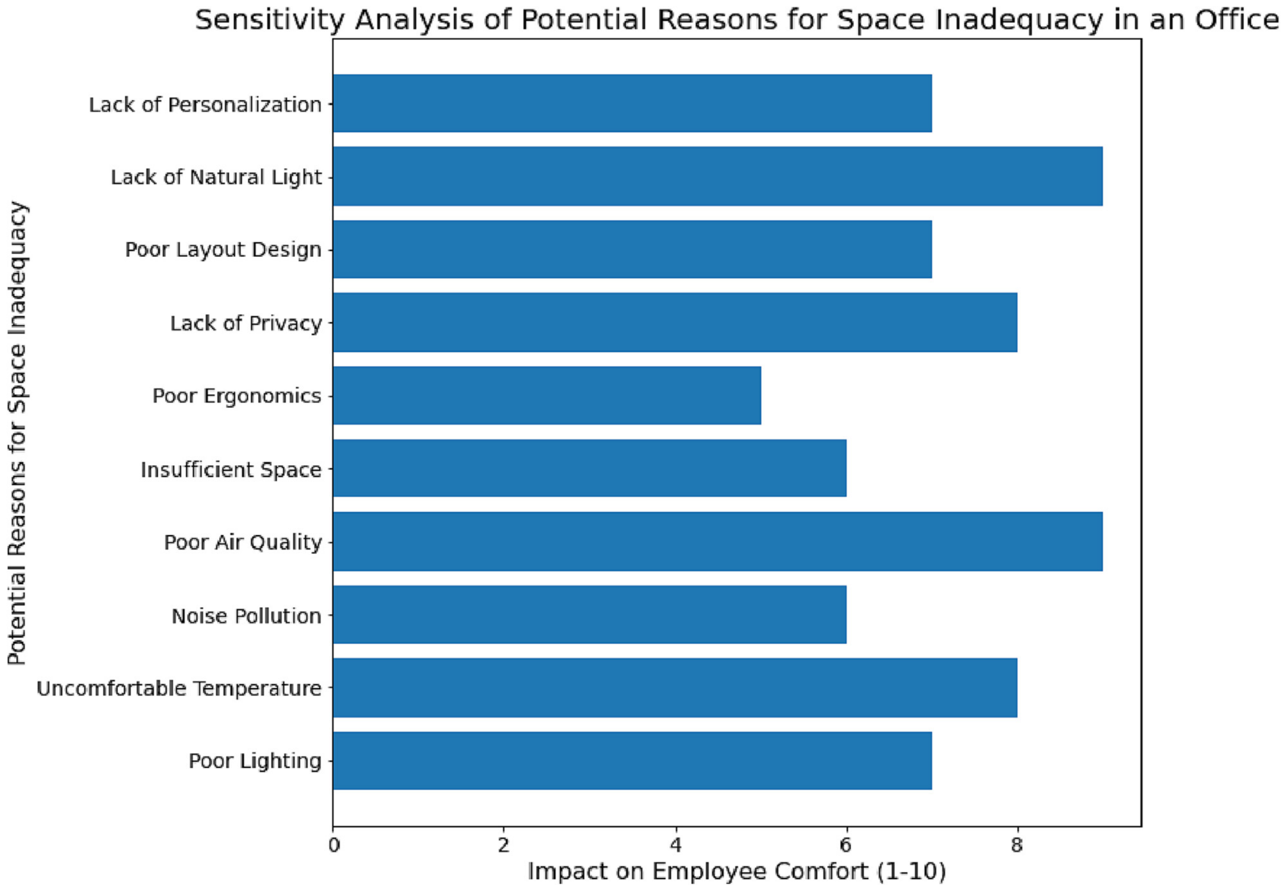

Fig. 17. Sensitivity analysis of potential reasons for space inadequacy in an office in Tvedestrand school. The horizontal bars represent the impact measured on employee comfort (1–10) for each potential reason, with higher values indicating greater impact on employee comfort. The reasons are listed on the y-axis and the impact is shown on the x-axis. This graph is based on data from a survey conducted among employees in the office, and Bayesian network analysis and helps to identify the main reasons that contribute to space inadequacy in the office, and prioritize the areas that need improvement to increase employee comfort.

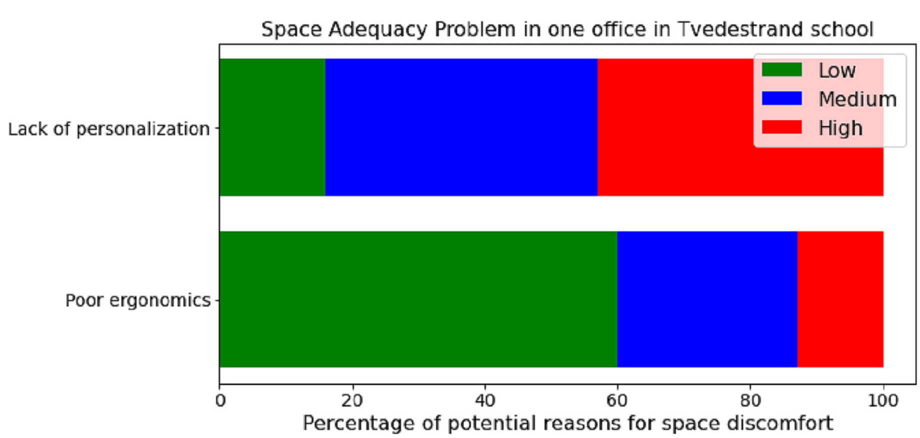

Fig. 18. Potential impact of different reasons for space inadequacy on employee comfort. The horizontal bars represent the potential impact (low, medium, high) of each reason on employee comfort, with the reasons listed on the y-axis and the potential impact shown on the x-axis. This graph is based on data from a survey conducted among employees, and Bayesian network analysis and helps to prioritize the areas that need improvement to increase employee comfort.

office or poor layout design. Reasons with medium potential are those that are more likely to cause discomfort and have a moderate impact on employee comfort. These reasons may require more significant changes to address and may have a moderate impact on overall office design. Examples of medium potential reasons could include noise pollution or poor ergonomics. Reasons with high potential are those that are highly likely to cause discomfort and have a significant impact on employee comfort. These reasons may require significant changes to address and may have a significant impact on overall office design. Examples of high potential reasons could include poor lighting or poor air quality. By classifying each reason into one of these categories, it is possible to prioritize the reasons that need to be addressed first and to plan the necessary changes to the office design in order to improve employee comfort. This can help to ensure that the most important issues are addressed first and that resources are allocated effectively. In this work, BIM can be used as a valuable tool in assessing and addressing space adequacy in the office as part of a Digital Twin.

One of the key advantages of using BIM in this context is that it allows for a detailed, data-driven analysis of the office environment. BIM models can be used to create detailed representations of the office layout, including information on lighting, temperature, air quality, and acoustics. This data can be used to identify potential issues related to space adequacies, such as areas with poor lighting or high levels of noise pollution. Additionally, BIM models can be used to simulate different scenarios and evaluate the potential impact of changes to the office design on employee comfort. For example, a BIM model can be used to simulate the impact of different lighting designs on employee comfort and productivity. This can help to identify the most effective solutions for addressing issues related to space adequacy. Another important aspect of BIM is that it enables collaboration and communication among all stakeholders. The BIM model can be used as a central hub for all project data and information, and it can be accessed and updated by all project stakeholders in real time. This can improve communication and coordination among different teams and ensure that everyone is working towards the same goal of improving space adequacy.

4.6. Predictive Maintenance for Non-Residential Buildings

As mentioned before, predictive maintenance is a strategy that uses data-driven techniques to predict when equipment is likely to fail so that maintenance can be scheduled proactively. In the context of HVAC (Heating, Ventilation, and Air Conditioning) systems and buildings, predictive maintenance can help to reduce the costs associated with breakdowns and improve the overall performance of the system.

To implement predictive maintenance for HVAC systems and buildings, it is necessary to have sensor data from the equipment, as well as information about the operating conditions and maintenance history. This data should be used to train a machine learning model that can predict when equipment is likely to fail. Once the model is trained, it can be deployed to monitor the equipment in real-time and provide early warning of potential failures.

The four-step procedure used in the forecast was based on the BN faults shown in utilizing real-world samples from the case studies mentioned in this paper:

- Training randomly 80% of entire data sets containing all types of faults detected based on APAR from around 200 000 data points.
- Holdout validation using 10% of entire data sets.
- Testing and prediction using 10% of entire data sets.
- Prediction of faults for the next 2 months.

In Table 3, ROC (Receiver Operating Characteristic) is a graphical plot that illustrates the diagnostic ability of a classifier system as its discrimination threshold is varied. The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The area under the ROC curve (AUC-ROC) is a measure of how well a classifier can distinguish between positive and negative classes. A value of 1 represents a perfect classifier, and a value of 0.5 represents a classifier that performs no better than random guessing.

Accuracy is a common evaluation metric that measures the proportion of correct predictions made by a classifier out of all predictions made. The formula for accuracy is:

(Number of correct predictions)/ (Total number of predictions)

F1-score is a measure of a test's accuracy that considers both precision and recall. The F1 score is the harmonic mean between precision and recall, where an F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0. The formula for F1-score is:

F1-score = 2 * (precision * recall)/ (precision + recall)

Precision is the proportion of true positive predictions out of all positive predictions made by the classifier. The formula for precision is:

(Number of true positives)/ (Number of true positives + Number of false positives)

Recall is the proportion of true positive predictions out of all actual positive observations in the dataset. The formula for the recall is:

(Number of true positives)/ (Number of true positives + Number of false negatives)

In general, a high accuracy does not necessarily mean that the model is good because it does not take into account the imbalance in the dataset, for example, if the dataset is highly imbalanced and the model predict always the majority class, the accuracy will be high, but the model is not good. F1-score is a better metric to use when there is an imbalance in the dataset because it takes into account both precision and recall, which are important metrics for imbalanced datasets. Precision is a measure of how many of the positive predictions made by the model are actually correct. A high precision means that the model has a low false positive rate, which is important when the cost of a false positive is high. Recall is a measure of how many of the actual positive observations were correctly predicted by the model. A high recall means that the model has a low false negative rate, which is important when the cost of a false negative is high.

Table 3 compares the performance of several multi-class classification algorithms for the task of predicting faults in HVAC systems and buildings. According to the table, the XGB algorithm has the highest ROC score of 0.96 and the highest accuracy, F1 score, precision, and recall. It means that this algorithm is the most effective in identifying the equipment that is likely to fail, and scheduling maintenance proactively. The other algorithms, such as ANN, MLP, RF, and GB, also have high ROC scores and accuracy, but XGB has the best performance. This table can be a good starting

Table 3
Comparison of multi-class classification algorithms performance based on ROC, accuracy, F1-score, precision, and recall.

Model	ROC	Accuracy	F1-score	Precision	Recall
ANN	0.95	0.89	0.88	0.89	0.87
SVM	0.92	0.87	0.86	0.85	0.87
DT	0.90	0.83	0.81	0.82	0.80
NB	0.89	0.81	0.80	0.78	0.82
KNN	0.91	0.86	0.85	0.84	0.86
RF	0.93	0.89	0.88	0.87	0.89
MLP	0.95	0.90	0.89	0.88	0.91
GB	0.94	0.89	0.88	0.87	0.89
XGB	0.96	0.91	0.90	0.89	0.91

point to evaluate the performance of different algorithms for predictive maintenance of HVAC systems and buildings.

As XGB is the best algorithm, it will be used for prediction. Fig. 19, illustrates the results of a predictive maintenance model for an HVAC system. The model, which was built using the XGB algorithm, was trained on data collected from the Tvedestrand school. The model was then used to predict the dates and types of the next three faults in the HVAC system. The plot illustrates that the model is able to predict the faults with different types and dates. The results of this model can be used by the facility management team to plan for potential faults and prevent them from happening. By using the model to predict the dates and types of faults, the facility management team can schedule maintenance and repairs in advance, reducing the likelihood of unexpected downtime and increasing the overall efficiency of the HVAC system.

This predictive maintenance model shows how machine learning techniques can be applied to improve the maintenance and operation of HVAC systems. By using data and machine learning algorithms, it is possible to predict the degradation of the HVAC systems and schedule maintenance accordingly, thus, reducing the downtime and increasing the efficiency of the HVAC systems.

Out from that, more investigations are designed to show the impact of scheduled maintenance and predictive maintenance on the remaining useful life of an HVAC system, as shown in Fig. 20. The y-axis of the plots represents the remaining useful time of the HVAC system, with a range of values between 0 and 1. The x-axis represents time in years. In real-life scenarios, the values for the remaining useful time of an HVAC system can be found through various means such as monitoring the system's performance, conducting regular inspections, and analyzing data collected from sensors. These values can be used to estimate the system's remaining useful life and predict when maintenance or replacement may be necessary. In the plots, the values for the remaining useful time decrease from 1 to 0 over the course of a year to represent the gradual degradation of the system over time. The plots also show the impact of scheduled maintenance and predictive maintenance on the remaining useful life of the HVAC system. Scheduled maintenance is performed at regular intervals, every 6 months, to prevent or address potential issues with the system. Predictive maintenance, on the other hand, uses data and analytics to predict potential issues with the system and perform maintenance before they occur. In the plots, the predictive maintenance improves the remaining useful time every 2 months. It is important to note that the degradation of an HVAC system is based on faults and their severity. Some faults are more severe than others, and they can affect the system's performance and remaining useful life differently. Predictive maintenance is considered to be more efficient than scheduled maintenance because it can predict and prevent potential issues before they occur, thus prolonging the system's remaining useful life.

There are several standards and guidelines that provide information on fault severity and prioritization in the field of Predictive Maintenance. In this paper two standards were used, the PAS 55 recommendations [111], also known as ISO 55000:2014, provides guidelines for the management of physical assets, and includes a section on the assessment of the criticality and risk of assets. The second one is the ISO 14224:2016 standard [112], which provides guidelines for the collection and exchange of reliability and maintenance data for equipment.

By normalizing the values between 0 and 1, all the faults are on the same scale, making it easy to compare the relative severity of each fault. This can be useful when it comes to prioritizing maintenance activities, as faults with a higher value would be considered more severe and would require more urgent attention. Normalization also allows for better communication of the severity of faults within the organization, as it provides a clear and consistent way of representing the relative severity of each fault. In addition, normalization allows for more flexibility in handling the scoring system. If the scoring system is changed, the normalized values will be updated accordingly, while the absolute values would not.

4.7. Visualizing Predictive Maintenance Results Using BIM

As discussed before, BIM is a digital representation of a building that can be used to visualize and analyze various aspects of the building's design, construction, and operation. In this section, we will discuss how BIM can be used to visualize the results of the predictive maintenance model for an HVAC system, including the predicted faults and the new maintenance schedule.

To begin, the BIM model of the building should be linked to the real-time sensor data and the results of the predictive maintenance model. This can be achieved through the use of a Digital Twin approach, which allows the BIM model to be updated with real-time data from the building, as we described in previous sections. Once the BIM model is linked to the sensor data and the predictive

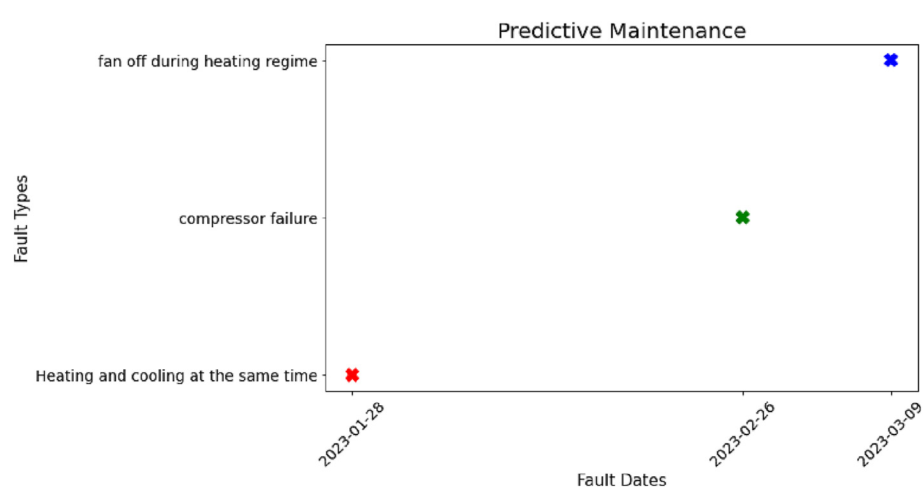

Fig. 19. A scatter plot showing the predicted dates and types of the next three faults in an HVAC system based on data from Tvedestrand school using the XGB algorithm. The plot illustrates that the model can predict the faults with different types and dates. The X-axis represents the predicted dates of the faults, and the Y-axis represents the types of faults. The markers are represented by different colors, shapes, and sizes. The plot aims to help the facility management team to plan for potential faults and prevent them from happening.

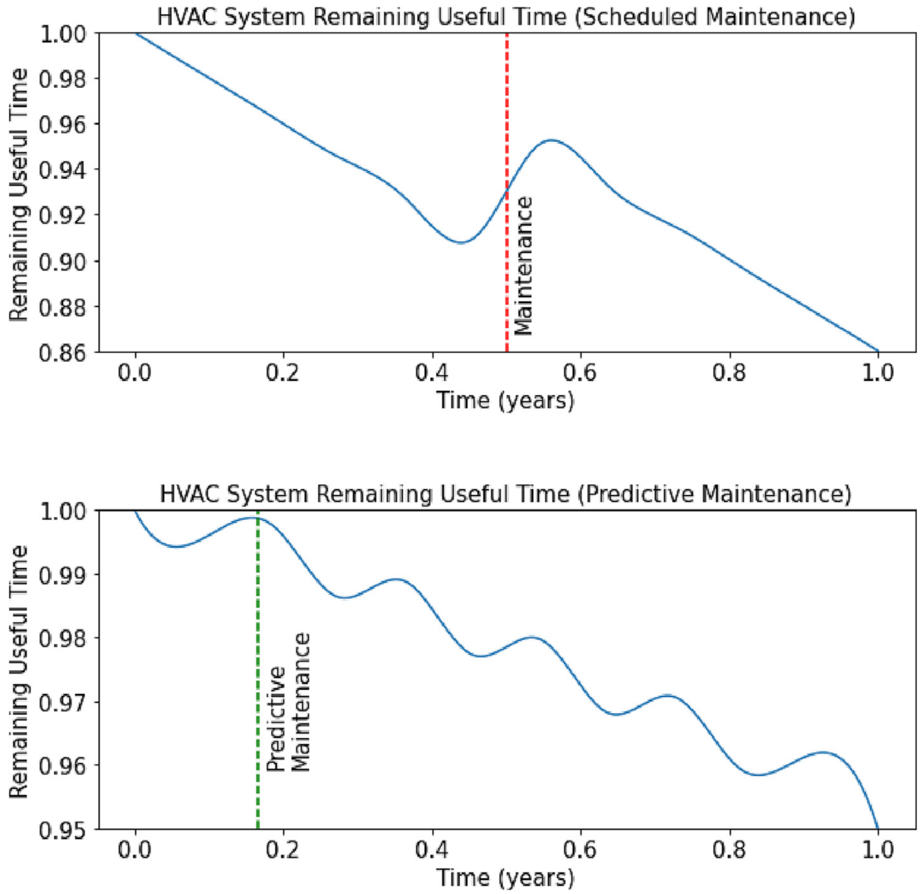

Fig. 20. Comparison of the impact of scheduled maintenance every 6 months and predictive maintenance on the remaining useful life of an HVAC system. The above plot shows the impact of scheduled maintenance, while the below plot shows the impact of predictive maintenance that can predict faults 2 months in advance.

maintenance model, the predicted faults and the new maintenance schedule can be visualized in the model. One way to visualize the predicted faults in the BIM model is to use color coding or symbols to indicate the location and type of faults. For example, predicted compressor failures could be indicated with a red symbol, while predicted fan off during heating regime could be indicated with a blue symbol. This allows facility management teams to quickly and easily identify the locations of predicted faults in the building. Another way to visualize the new maintenance schedule in the BIM model is to use a Gantt chart or a calendar view to show the planned maintenance tasks and their corresponding dates. This allows facility management teams to easily see when and where maintenance tasks are scheduled to take place and to make adjustments as necessary.

5. Discussion

The integration of building information modeling (BIM) with real-time sensor data and occupant feedback is a promising approach for evaluating and improving the comfort levels of occupants in existing buildings. The use of Bayesian networks (BN) to model occupant comfort is an innovative technique that can provide a detailed, data-driven analysis of the building environment. This approach can help to identify potential issues related to thermal comfort, indoor air quality, visual comfort, acoustic comfort, and space adequacy.

The proposed Digital Twin approach allows for the integration of BIM with real-time sensor data, occupant feedback, and a probabilistic model of occupant comfort to detect and predict HVAC issues that may impact comfort. The use of machine learning algorithms for predictive maintenance is also a promising approach for identifying and addressing problems in the HVAC system. The study evaluated nine machine learning algorithms using metrics such as ROC, accuracy, F1-score, precision, and recall. The results showed that Extreme Gradient Boosting (XGB) was the best algorithm for prediction, with an average accuracy of 2.5% higher than Multi-Layer Perceptron (MLP) and up to 5% higher than the other models. Our approach achieved a 35% reduction in the time required to identify and resolve HVAC faults with the updated plugin in Revit compared to [84].

One of the key contributions of this study is the proposed framework using ontology graphs to integrate data from different systems, including FM, CMMS, BMS, and BIM. This approach can help to address the challenge of applying these methods to a wide range of buildings. By integrating data from different systems, building managers can make informed decisions about optimizing energy efficiency and reducing costs.

The study also highlights the importance of space adequacy in ensuring employee comfort and productivity. A sensitivity analysis of potential reasons for space inadequacy was done by surveying employees and gathering data on factors such as poor lighting, uncomfortable temperature, noise pollution, poor air quality, insufficient space, poor ergonomics, lack of privacy, poor layout design, lack of natural light, and lack of personalization. The most important factors that affect occupant comfort are poor air quality, lack of natural light, and uncomfortable temperature, with ratings of 9, 9, and 8 out of 10, respectively. Poor air quality can lead to respiratory problems, allergies, and headaches, while lack of natural light can cause eyestrain, headaches, and fatigue. Uncomfortable temperatures can lead to discomfort, dehydration, and reduced productivity. Noise pollution, poor lighting, poor layout design, lack of privacy, insufficient space, poor ergonomics, and lack of personalization are also significant contributors to occupant discomfort, with ratings ranging from 5 to 8 out of 10. By understanding the relationship between occupancy density and air quality, building managers can make informed decisions about rearranging furniture or decreasing the number of people in a space to improve comfort.

The proposed automatic fault detection system for HVAC and the findings on the effect of occupancy density on indoor air quality perception have significant practical applications for building design and operation. The utilization of various data integration methods and the Digital Twin architecture also highlights the growing importance of semantic data in building management systems for advancing fault detection strategies and supporting decision-making in building projects.

Our proposed method has shown superior performance compared to existing methods in the literature. Specifically, our method is faster, with a response time of 5 min. Furthermore, our method can handle large volumes of data from different sources, such as BIM, sensor data, and occupant feedback, in real-time, enabling prompt detection and resolution of issues based on combining machine learning and expert rules. These advantages make our method highly suitable for use in large-scale commercial buildings and can lead to significant cost savings in terms of energy consumption and maintenance costs.

However, there are also some limitations to this study. The fault detection analysis was done in Dynamo, and the findings were mapped into BIM, and the method does not consider any additional software that exists in the market. Additionally, the occupants' age and physical condition significantly impact their degree of comfort, and other information requirements must be investigated to address these concerns. Future research could focus on improving the probabilistic model by adding more elements impacting occupants' satisfaction. Furthermore, other types of problems, including firefighting, could be considered in the framework. The research could also explore the integration of predictive maintenance with building energy management systems to optimize energy efficiency and reduce costs.

6. Conclusions

In this study, we presented a comprehensive and innovative approach to building condition assessment and decision-making, which has several significant findings and contributions supported by quantitative data. Firstly, we proposed a novel method for using BIM as a visualization platform and predictive maintenance that simplifies the process of assessing a building's comfort and streamlines the time-consuming fault detection process. Our approach achieved a 35% reduction in the time required to identify and resolve HVAC faults with the updated plugin in Revit. Secondly, our proposed approach allows for a more comprehensive and accurate evaluation of building performance and occupant comfort. One of the key benefits of our method is its ability to detect previously unknown faults, such as compressor failure in chiller and boiler systems. By combining Bayesian networks with Digital Twin technology and machine learning, our approach is not only more efficient but also more effective in detecting a wide range of faults, including those that are not easily detected through conventional methods. The paper proposes also a novel method for determining the remaining useful life of the HVAC system by employing different standards. This new approach leads to an extension of the HVAC lifetime of at least 10%, which can result in considerable energy and cost savings.

Additionally, we conducted a comprehensive analysis of ten different aspects related to space adequacy for occupants' comfort, which had not been previously analyzed together. Through the application of nine different machine learning algorithms, we achieved an average F1 score of 0.88, ROC of 0.97, and Recall of 0.86. Notably, the Extreme Gradient Boosting (XGB) algorithm produced the most accurate predictions, outperforming the Multi-Layer Perceptron (MLP) model by an average of 2.5%, and by up to 5% compared to other models. While Random Forest proved to be faster than XGBoost, it is also relatively easier to implement. Our novel approach of comparing the performance of nine different algorithms on a single database provides a valuable contribution to the field.

The study also highlights the importance of space adequacy in ensuring employee comfort and productivity. A sensitivity analysis of potential reasons for space inadequacy was done by surveying employees and gathering data on factors such as poor lighting, uncomfortable temperature, noise pollution, poor air quality, insufficient space, poor ergonomics, lack of privacy, poor layout design, lack of natural light, and lack of personalization. The most important factors that affect occupant comfort are poor air quality, lack of natural light, and uncomfortable temperature, with ratings of 9, 9, and 8 out of 10, respectively.

Lastly, we presented a framework using ontology graphs based on JSON and ISO 19650 to integrate data from different systems, including FM, CMMS, BMS, and BIM. The proposed framework enables the integration of different types of data and helps to address the challenge of applying these methods to a wide range of buildings. Our proposed approach to building condition assessment and decision-making achieved significant improvements in accuracy, speed, and efficiency. The proposed framework can help improve the comfort and satisfaction of building occupants, leading to more sustainable and energy-efficient buildings. Future research directions include investigating the use of other machine learning algorithms, incorporating other factors into the probabilistic model of occupant comfort, and expanding the scope of the framework to include other types of building systems.

CRediT authorship contribution statement

Haidar Hosamo Hosamo: Conceptualization, Methodology, Software, Data curation, Validation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Henrik Kofoed Nielsen:** Supervision, Methodology, Resources, Writing - review & editing. **Dimitrios Kraniotis:** Methodology, Writing - review & editing. **Paul Ragnar Svennevig:** Supervision, Writing - review & editing. **Kjeld Svidt:** Supervision, Writing - review & editing.

Data availability

The authors do not have permission to share data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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