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Digital Twin framework for automated fault source detection and prediction for comfort performance evaluation of existing non-residential Norwegian buildings

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

Numerous buildings fall short of expectations regarding occupant satisfaction, sustainability, or energy efficiency. In this paper, the performance of buildings in terms of occupant comfort is evaluated using a probabilistic model based on Bayesian networks (BNs). The BN model is founded on an in-depth analysis of satisfaction survey responses and a thorough study of building performance parameters. This study also presents a user-friendly visualization compatible with BIM to simplify data collecting in two case studies from Norway with data from 2019 to 2022. This paper proposes a novel Digital Twin approach for incorporating building information modeling (BIM) with real-time sensor data, occupants' feedback, a probabilistic model of occupants' comfort, and HVAC faults detection and prediction that may affect occupants' comfort. New methods for using BIM as a visualization platform, as well as a predictive maintenance method to detect and anticipate problems in the HVAC system, are also presented. These methods will help decision-makers improve the occupants' comfort conditions in buildings. However, due to the intricate interaction between numerous equipment and the absence of data integration among FM systems, CMMS, BMS, and BIM data are integrated in this paper into a framework utilizing ontology graphs to generalize the Digital Twin framework so it can be applied to many buildings. The results of this study can aid decision-makers in the facility management sector by offering insight into the aspects that influence occupant comfort, speeding up the process of identifying equipment malfunctions, and pointing toward possible solutions.

1. Introduction

The built environment is created and managed by the architecture, engineering, construction, and operation (AECO) sector to support human activities over time (i.e., work and accommodation). The influence of creating this environment on occupants is significant since they need buildings that are accessible, productive, healthy, and comfortable [1]. Since individuals spend 90% of their time inside, the role of occupant comfort within buildings in terms of environmental, social, and economic elements is crucial [2]. However, not all buildings successfully satisfy the comfort needs of their residents [3].

One of the most common causes of complaints from building residents is poor indoor air quality. Also, the amount of natural light that enters buildings and the amount of noise pollution have a psychological burden on the people living there, which reduces employees' productivity by up to 20% and increase errors caused by interruptions [4]. Thus, productivity includes the financial side of comfortable conditions, eventually impacting the company's finances [5]. Moreover, tolerable temperatures are determined by indoor environmental quality (IEQ) guidelines [6], but there is no correlation between these parameters stated in standards and what occupants experience as comfortable [7]. This is because people have different sensation levels for experiencing things. Therefore, gathering input from occupants and evaluating building performance is vital to enhancing occupants' comfort and productivity [8].

* Corresponding author.
E-mail address: haidarh@uia.no (H.H. Hosamo).

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Nomenclature

SVM	Support vector machine
FDD	Fault detection and diagnostics
ANN	Artificial neural network
BN	Bayesian network
API	Application programming interface
BIM	Building information modeling
BMS	Building management system
DT	Decision tree
LR	Linear regression
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
ASHRAE	American society of heating, refrigerating and air-conditioning engineers
RMSE	Root mean square error
NN	Neural network
RF	Random forest
BEM	Building energy management
BOT	Building ontology topology
SSN	Semantic sensor network
ML	Machine learning
BACnet	Building automation and control networks
COBie	Construction operations building information exchange
ANOVA	Analysis of variance
FM	Facility management
CMMS	Computerized maintenance management system

The rate at which the planet is warming is inextricably linked to the energy consumed by buildings. In the European Union, the building sector consumes 40% of all energy and produces 40% of all greenhouse gas emissions (GHG) [9]. In Norway, for instance, non-residential buildings (including vacation homes) make up around 62% of the entire building stock and 40% of the overall energy consumption in buildings (while residential and non-residential buildings make up 40% of Norway's total energy usage) [9]. Energy consumption in Norway's commercial and industrial sectors has risen by around 31% since 1990, while homes have risen by only 9% [10], underscoring the urgent need for a renovation strategy based on automated fault cause detection and prediction to enhance the efficiency of those buildings [11]. To drastically reduce our reliance on fossil fuels, we need to decarbonize our heating and cooling systems [12]. In addition, HVAC systems consume a disproportionate amount of energy in buildings, making it all the more important to offer techniques and advice to assist working professionals in developing and implementing high-quality deep energy rehabilitation centered on HVAC systems for better health, indoor environment quality, and energy performance in all buildings [13].

Predictive, preventive, and corrective maintenance procedures based on occupant comfort evaluations can contribute to building sustainability and introduce better operational plans [14]. This may be seen, for instance, in the trend toward using natural means of cooling and lighting instead of artificial ones [15].

Analysis of the indoor environment and what constitutes a comfortable setting has been the focus of research that has led to the development of methodologies and instruments for evaluating buildings' performance [16]. Post-occupancy evaluation (POE) is a process in which a building is surveyed after it has been occupied to assess how well it meets the needs of its occupants in terms of physical aspects like visual comfort, acoustic comfort, thermal comfort, as well as indoor air quality, and non-physical aspects like the workplace, and furniture [17].

These evaluation techniques are founded on deterministic models and hence fail to consider the variation in elements that affect indoor environmental conditions, including the building environment, building characteristics, spatial information, and user behavior [18].

Satisfaction with thermal conditions within a building is significantly influenced by how much control the occupants have over the indoor climate and how much their actions change the comfort condition [19]. Several factors, including the building envelope (like insulation and infiltration), the building systems (like HVAC and lighting), and the behavior of the occupants themselves, all contribute to the level of comfort in a given space [20]. Poor ventilation, brought on by HVAC system malfunction, emissions from building materials or misuse, can cause various health issues, including sick building syndrome [21]. Building comfort evaluations must consider the inherent uncertainty in the interaction between individual, societal, and building elements [22].

This gap can be bridged by employing a probabilistic strategy to evaluate indoor environmental quality [23]. Bayesian networks (BNs) are a type of probabilistic model that may predict a building's performance using a range of possible outcomes rather than a single value. Researchers have utilized BN to forecast thermal preferences [24] and to examine occupants' comfort with certain services [25]. To measure occupant satisfaction, however, a variety of data is needed, but this data generally exists in siloed systems that are neither studied nor integrated [1]. The application of BN to simulate occupants' comfort in terms of individual, societal, and physical building aspects is also rarely investigated.

Furthermore, the FM team may save time and effort using Digital Twin technologies, including BIM and sensor data, streaming real-time data from the building, and spatial information needed by the BN model. To the best of our knowledge, no previous research has integrated Digital Twin technology with risk assessment models to improve data collecting, feedback visualization from building occupants, and understanding of causal aspects that make occupants discomfort. The principle of the Digital Twin technology is shown in Fig. 1. The three main parts of the Digital Twin framework are the physical twin, the digital twin, and the decision-making process. The building, sensors (IoT), and equipment make up the physical twin; the sensors gather real-time data from buildings and communicate it to the digital twin, and the equipment puts into action the choices made by the facility managers.

The main objectives of this research are as follows:

1. Creating a BN model based on a satisfaction survey filled out by 850 users at the University of Agder and Tvedestrand Upper Secondary School and information gleaned from literature research and interviews with domain experts for evaluating buildings' ability to provide occupants with a comfortable indoor environment throughout a Digital Twin framework.
2. Build a Digital Twin framework to inform choices on maintenance (including predictive maintenance and automatic fault detection) and retrofitting conditioning to improve a building's serviceability and environmental pleasantness in real time.
3. Improve data visualization by incorporating occupants' feedback and the BN model into BIM.

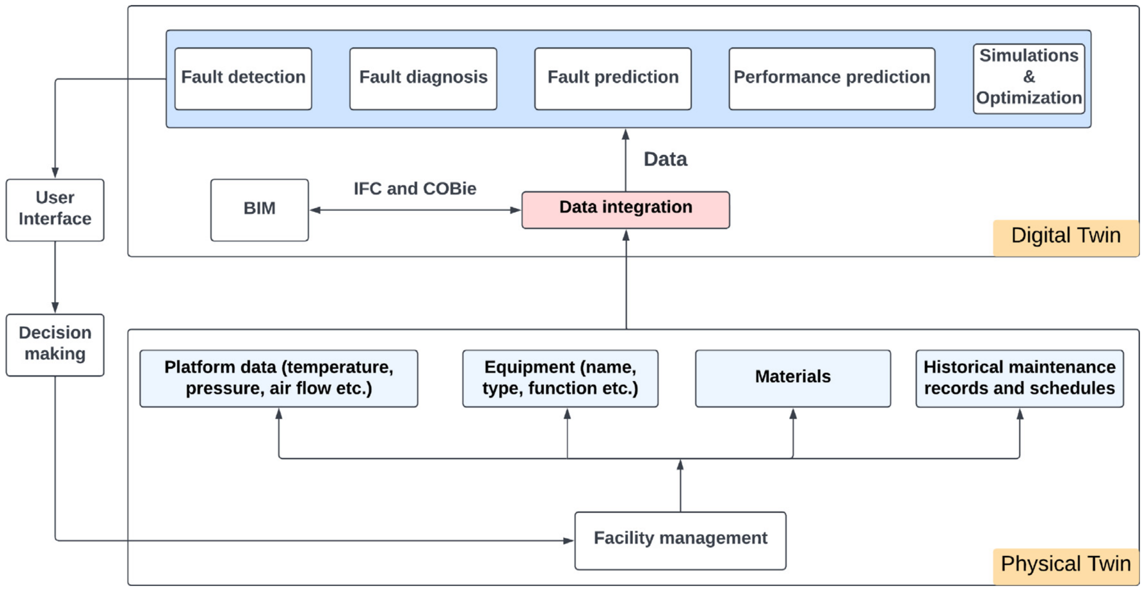

Fig. 1. Digital Twin concept for building operation to prevent future failures, reduce energy consumption and increase occupants' comfort.

4. Aid the FM team in developing strategies for optimal building operations by gain insight from prior failures to improve existing buildings' health, safety, and durability.
5. Maximize choices based on a predictive maintenance framework to predict the future cause that may make occupants uncomfortable and give a deep understanding of how the next building should be to avoid the aspects that led to occupants' discomfort.

2. Literature review

2.1. Fault detection, diagnosis, and prediction

Today's FM practices have resulted in several challenges, forcing the sector to undergo a paradigm change in recent years from looking for solutions to issues that have already happened to strategies to forecast what will happen [26]. As a result of this transformation, the move from corrective or planned measures to predictive strategies has occurred. Predictive maintenance, which involves studying condition data and records of previous maintenance, allows for the failure of building elements to be predicted. This improves building components' efficacy, reliability, and safety [27]. However, to achieve a good predictive maintenance strategy, it is necessary first to detect and diagnose the faults that make people uncomfortable correctly. The literature divides FDD research into three subfields: qualitative model-based [28], quantitative model-based [29], and process history-based [30] approaches. Under the process history-based approach, there are also qualitative and quantitative subfields. Expert systems fall under the qualitative subfield, while machine learning and statistics fall under the quantitative approach.

Regarding the expert systems, House et al. defined the AHU performance assessment rules (APAR) as a collection of 28 if-then rules that were evaluated based on an AHU's operational regime [31]. The APAR approach attracted much interest and was developed further by others [32,33]. Other researchers attempted to broaden the scope of APAR rules and create novel tools for fault detection; nevertheless, these tools only applied to a particular type of HVAC and required simulated data [34,35]. However, according to Trojanová et al., the creation of a universal model of HVAC is difficult [33].

On the other hand, artificial neural networks (ANN), support vector machines (SVM), random forests, and Markov chains are just a few machine learning methods that may be used to forecast the state of a building's components. Because of their propensity to forecast nonlinear time series patterns, ANNs have recently been deployed as decision support tools. For trend prediction of nonlinear time series, ANNs have been proven to perform better than traditional auto-regressive models [36]. Extensive research and documentation support ANNs' capacity to learn and preserve nonlinear patterns for future use [37]. In addition, SVM is a common statistical learning-based classification method [38]. When estimating the structural state of sewers, Sousa et al. found that ANNs and SVMs performed similarly well, and each had its advantages [39]. Ouadah et al. have also recommended using a "random forest" technique in predictive maintenance applications [40]. As the name indicates, a Random forest is an ensemble of numerous random decision trees whose predictions are averaged [41]. Both decision trees and random forests can reduce variance and improve generalization depending on the situation, as described in [42,43], respectively.

Carvalho et al. thoroughly evaluated the literature on machine learning approaches used for predictive maintenance, highlighting those being investigated in this area and the effectiveness of the most recent cutting-edge machine learning methods [44]. Additionally, Wang and Wang talked about how artificial intelligence (AI) would affect future predictive maintenance, which is a crucial component of sophisticated production systems in the future [45]. They specifically talked about the appeal of using deep learning technologies in predictive maintenance program plans. However, deep learning is only effective for some issues where large data sets are often needed for training. According to Hallaji et al. [46], and Carvalho et al. [44], the effectiveness of predictive maintenance applications depends on selecting the right machine learning approach.

In the context of risk modeling from uncertain data, the Bayesian network (BN) [1] is widely regarded as a powerful technique [24]. The BN can qualitatively and quantitatively characterize the interdependencies between building elements and systems, thus representing complex reasoning processes. Furthermore, unlike

[1] https://www.uib.no/en/rg/ml/119695/bayesian-networks

deterministic models, it may describe a building's status as a probabilistic process [47]. Bortolini and Forcada [47] created a BN-based probabilistic model for making decisions about building maintenance and retrofitting to boost building conditions. While the model can deal with uncertainty and make predictions, the necessary data is spread across different systems. In addition, the manual data transmission is time-consuming and ineffective [1]. Dynamic thermal models were calibrated using a novel Bayesian experimental calibration method by Raillon et al.[48].

Out of the above literature, there are two major roadblocks to the widespread use of machine learning [49]: firstly, a greater number of faults must be discovered, and for this reason, huge datasets are required. Secondly, others can not only rely on machine learning to create a universal system to detect faults in any building.

Therefore, this paper will combine machine learning (BN, ANN, SVM, and Random forest) with expert knowledge (APAR) to find and predict the faults in building systems that make people uncomfortable. By that, less data is needed, and a universal system can be built for several buildings.

2.2. Digital Twin technology for facility management

The Digital Twin technology draws from various domains, including the Internet of Things (IoT), artificial intelligence, cloud computing, and building information modeling (BIM) [50]. These technologies have made it possible to digitalize various building assets, allowing for the integration of a virtual item with a physical one over the entire life cycle [51].

The Digital Twin technology is employed in preventative maintenance approaches [2], where it is used to anticipate the state of an asset to reduce the number of operations and permit longer time intervals between them [52]. One further use for the Digital Twin is predictive maintenance [3]. This directly affects the Digital Twin's capability to keep an eye on the functioning of the entire system. The Digital Twin may see the operational data now being collected by the system as a virtual representation of the complete system. This makes it possible to monitor performance in real-time and ensure that operations are running smoothly.

The Digital Twin can provide notifications on maintenance and repairs. Consequently, issues may be discovered in advance and, ideally, fixed before they become serious and affect the occupants' comfort. As a result of predictive maintenance, maintenance operations may be planned ahead of time, and unplanned downtimes can be avoided. Because of this, both technology and human resources may be employed more effectively.

Out from that, building systems must be properly designed early on, taking into account both functional requirements and control strategies employing digital interfaces [53]. However, cause detection approaches for building systems and components (HVAC, envelope components, etc.) that combine semantic description with a Digital Twin approach (encompassing BIM, IoT, FMM, and machine learning) have yet to be discovered in the literature.

Maintaining HVAC systems may be difficult due to issues with information reliability and interoperability [54]. BIM is developing as a solution for maintenance tasks because it is a powerful tool for representing high-quality data and coordinating the use of several software programs [55]. A method for automatically scheduling maintenance work orders based on BIM and FM software was presented by Chen et al. [56]. Nojedehi et al. [57] connected BIM with maintenance management system logs using BIM as a common data environment and provided two ways for automatically transferring and displaying such data. Based on BIM and IoT technologies, Cheng et al. [58] created an integrated data-driven system for developing predictive facility maintenance. Although the deployment of BIM for maintenance operations has considerable potential advantages, there still needs to be more data integration for maintenance activities to identify the underlying causes of HVAC issues [59].

As a result, the article implements a Novel Digital Twin framework to determine the primary reason why occupants are dissatisfied with their spaces and devise a plan for predictive maintenance to stop further system and component failures in buildings and extend their lifespans.

2.3. Building factors and occupants' comfort

Both physical (IEQ) and non-physical factors affect the level of comfort experienced by building occupants, including thermal, visual, and acoustic environment, air quality, space layout, privacy, furnishing, and cleanliness [60].

The comfort of building occupants is influenced by location climate, building layout, building scale, building envelope, and ventilation [61]. The building envelope is the most important since its design determines how a structure will react to environmental factors [62]. Almost half of the energy used by HVAC systems in non-residential buildings is due to heat transfer via the building envelope [63]. The envelope shape, form, and construction are the key elements to consider in the early design stages to have a more satisfactory building. Building's orientation, shape, room arrangement, and other adjustable aspects are all in the building envelope form. The factors that make up the envelope shape are the window-wall design [64], and shading component size [65]. Some characteristics that affect envelope performance are envelope insulation, light transmission, and glazing insulation [66].

For thermal quality, studies have shown that climate, the characteristics of buildings, and the services provided significantly affect thermal comfort, in addition to the interior air temperature [67].

The level of thermal comfort is also affected by the HVAC system type. Radiant systems, for instance, can improve thermal comfort in the building [68]. Moreover, people who can adjust their thermal settings report feeling very comfortable [69]. According to research by [70], windows that can be opened and thermostats that can be adjusted are the two features that are requested the most. Buildings that rely on passive thermal techniques have a greater need for thermal features such as envelope insulation than other types of buildings [20]. A low U-value (thermal transmittance) envelope can thus help increase the times when people can feel comfortable without artificial air-conditioning [71].

The window to wall ratio (WWR) [4] is one quantitative measure that may be used to assess the effect of daylighting on the quality of light in buildings. There is a significant demand for daylight in workplaces, which may be directly attributed to the widespread perception that exposure to sunshine is more beneficial to people's health [4].

Physical characteristics, such as the external and interior sound insulation of walls, are connected to acoustic quality. The major reasons for occupants' dissatisfaction in this case, as shown by [72], are the same regardless of the type of office setting and include being able to overhear colleagues' private discussions, other employees' chats and the sound of people chatting in adjacent offices. Research has shown that machinery noise can also cause acoustic discomfort [73]. Unfortunately, exterior noise can be a problem in naturally ventilated buildings. Mechanical ventila-

[2] https://comparesoft.com/cmms-software/preventive-maintenance/

[3] https://spacewell.com/resources/blog/using-iot-sensor-data-for-asset-maintenance-smart-building-predictive-maintenance/

[4] https://www.hunker.com/13412499/how-to-calculate-a-wall-to-window-ratio

tion systems with acoustic attenuators have significantly lower airborne noise levels.

Regarding the appropriateness of the space, occupants' comfort may be affected by factors such as the room's dimensions, visual appeal, furnishings, and level of cleanliness [74]. Functional comfort for users may be ensured in the workplace by using ergonomic furniture, enclosed spaces for meetings, and collaborative work [75].

In facilities like schools and offices, where the indoor environment directly impacts the productivity of the building's occupants, it is extremely important to ensure their comfort and safety.

From there, the novelty of this study is that it will include physical (IEQ) and non-physical factors that may contribute to occupant discomfort in the cause detection process and learn from that for the next building.

2.4. Novelty of our research

Out of the above-reviewed research work, the gaps in the literature are as follows;

- Lack of a Digital Twin model for real-time causes detection of occupants' discomfort with whole building systems, including HVAC design, thermal comfort, visual comfort, acoustic comfort, and space adequacy.
- Lack of Digital Twin model for real-time predictive maintenance and workflow process for entire building.
- Lack of universally applicable of such Digital Twin system for facility management.

Based on the research gaps mentioned above, this study proposes an approach that integrates real-time sensor data, occupants' comfort survey results, BN model and machine learning via our developed plug-in in Revit and by using Dynamo to enable intelligent detection and prediction of faults that may make people dissatisfied in buildings. Thus, the originality of our work comes from the fact that it investigates the interaction of building envelope elements with HVAC systems and parameters with other critical design variables through real-time fault detection and prediction including in the Digital Twin framework to avoid occupants' dissatisfaction, which was previously unexplored in the literature. Hence, this paper:

- Describes a Digital Twin framework for the fault detection and prediction of whole building systems.
- Develops a plug-in in Revit that can receive real-time sensor data (temperature, pressure, etc.) from the equipment in I4Helse (University of Agder) and Tvedestrand upper secondary school buildings in Norway.
- Uses a Bayesian network for real-time fault detection in building systems.
- Uses a practical machine learning algorithm for predictive maintenance based on real-time data.
- Uses visual programming to create a new technique for fault detection and predicting in buildings, making feedback on the results in the BIM model and the building's management system easier.
- Develops a universal model based on ontologies that can efficiently run on a varied set of data from IoT sensors in buldings.
- Develops an integrated condition monitoring framework based on BIM technology for decision-making in FMM.

3. The proposed framework

As can be seen in Fig. 2, the proposed framework makes use of Digital Twin technology for fault detection and diagnostics, and it also predicts the condition of the building components, all to aid facility managers in making more informed decisions at the appropriate time. Integrating the latest technologies, such as building information modeling (BIM), the internet of things (IoT), and machine learning (ML), formed the basis for our system. Data input, fault detection and prediction, and information visualization and monitoring in BIM are the three primary phases of the framework. The BIM model may be used to acquire spatial data. By creating a plug-in extension for Autodesk Revit using C#, we connected the BIM model with fault detection and prediction findings to enhance the FM team's decision-making. The following sections will explain the three basic tiers that make up this framework.

3.1. Data input

This stage represents the box number one in Fig. 2.

3.1.1. Data from the BIM model

The proposed framework begins with the preparation of the BIM model for data extraction and the creation of a plug-in that streams real-time sensor data from the HVAC system and rooms in buildings into the BIM model, effectively transforming the BIM model into a database containing all of the information necessary to carry out the framework process. As part of the preliminary work, verifying that the BIM model has all the geometric and thermal properties necessary for the Digital Twin model is vital. A precise BIM model of the building in concern would help immensely with the data extraction process. Building envelope components can be created for structures that lack a BIM model through laser scanning [76] or 2D drawings.

In this paper, the BIM model serves a dual purpose: first, as input data for the fault detection and prediction procedure (box number two in Fig. 2), and second, as a visual representation of the findings from that procedure. To perform properly, the Digital Twin framework needs access to a BIM model database, including all necessary information. For this reason, it has to be precisely modeled, with each component receiving the precise allocation of the thermal and geometric characteristics of the building envelope's parts. Based on the definition of LOD provided by [77], a BIM model with a LOD of 300 or above is recommended for extracting the thermal and geometric data connected with the proposed framework. Autodesk Revitö 2022 [78] will be utilized as a BIM tool in this study due to its availability to researchers and its integration with an open-source visual programming environment (Dynamo) [79].

Data exchange protocols, such as the Industry Foundation Classes (IFC) and the Construction Operations Building Information Exchange (COBie), allow for data capture and transformation during a building's lifecycle [80]. The IFC data model includes geometric data, object classes, relations, and resources. Construction component costs and schedules are two examples of semantic data types that might be included in an IFC file [81]. COBie can also provide real-time data on how projects are run and managed [78]. Therefore, COBie should incorporate more data types and fields than IFC does, such as location data, asset details, documentation, and graphical data.

COBie relies on spatial data (space characteristics) for two main reasons: (1) Space objects are necessary for good space, occupant, and energy management, and (2) spaces are required for equip-

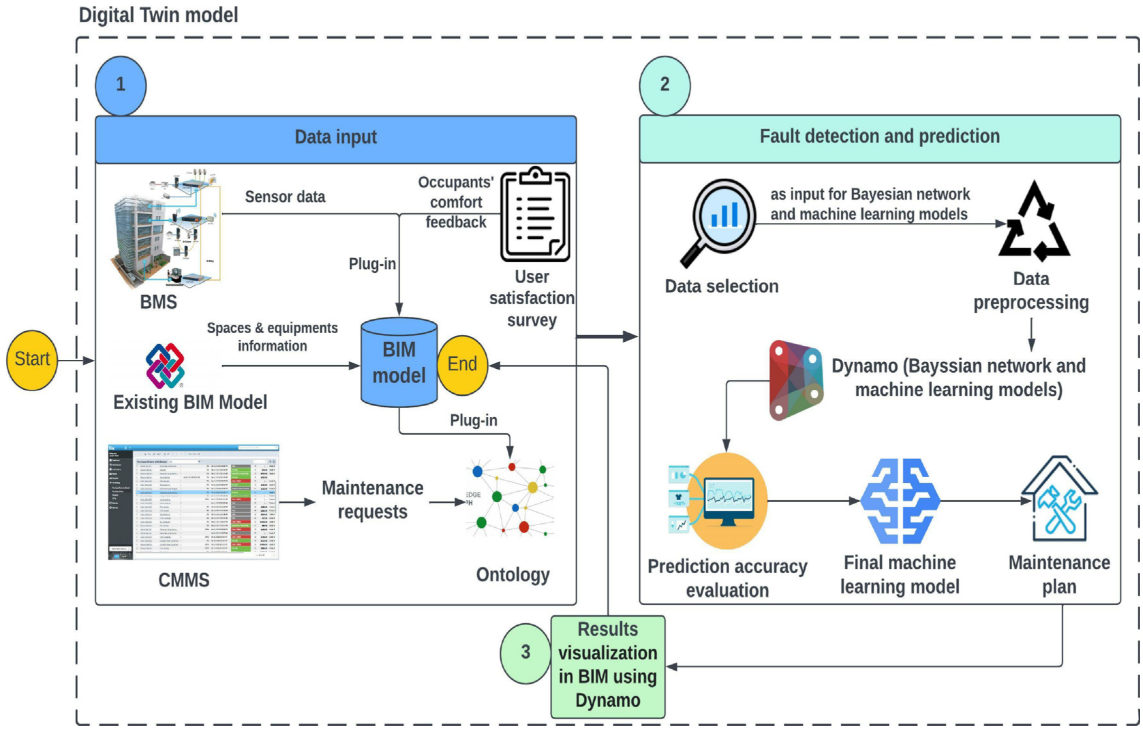

Fig. 2. The proposed Digital Twin framework for fault detection, prediction and data visualization.

ment installation. Moreover, the element ID from the BIM model (part of COBie) will be utilized to distinguish between elements when extracting fault detection and prediction information and feeding back the results into the BIM model.

Therefore, this article implemented a COBie plug-in for Revit to retrieve the required data from BIM models and send it to the BMS.

3.1.2. Integrate sensor data in BIM model

Throughout the building, several sensors have been placed in rooms and HVAC systems. These sensors monitor various environmental and operational variables, including supply and return air and water temperatures, flow rates, energy usage, control system setpoints, humidity, and ambient air temperature. In order to monitor and capture the crucial data from these sensors, we needed access to the BMS. However, getting data out of the BMS system quickly was not possible. Therefore, with the help of a development team, we created a Restful API (Application Programming Interface) to serve as an extra analytical layer on top of a traditional BMS system. It paves the way for several devices in a facility to be diagnosed by simply entering a URL (Uniform Resource Locator) to retrieve the necessary information. Using the RESTful API, the history of alerts and faults and the system for tracking routine maintenance can also be accessed. The whole system's principle is depicted pictorially in Fig. 3.

Next, a Revit plug-in was built using C sharp, and Windows Presentation Foundation (WPF) programming [82] in Microsoft Visual Studio Community 2022 to access the live sensor data and store it in an MSSQL database, all while maintaining an accurate BIM model. Additionally, the plug-in introduced a threshold to determine room coloration in response to occupant comfort levels. For the purpose of receiving and visualizing sensor data, many sensor blocks were employed in BIM model. The plug-in sensor block is displayed in Fig. 4.

3.1.3. Occupants survey

There are typically three basic stages involved when analyzing the aspects that contribute to a building's occupants' comfort level:

(1) Survey forms were developed and built for a user satisfaction survey that considers convenience factors (e.g., thermal comfort, acoustic comfort, indoor air quality, visual comfort, and space adequacy). Occupants were asked to identify their occupational setting in the POE survey by specifying the building, floor, and room. Occupants' feedback was scored on a 5-point Likert scale, with (5) indicating "very satisfied," and (1) indicating "very dissatisfied,". Participants were also questioned on how they felt about the visual, acoustic, and thermal comfort of their surroundings, as well as the quality of the indoor air during the winter and summer months. In addition, the survey provided a list of possible causes for discomfort and a free-form text box for further comments. Users were also surveyed on how they felt about the thermal comfort, indoor air quality, visual comfort, acoustic comfort, and space adequacy of the most frequently utilized common areas of the facility (such as corridors, conference rooms, classrooms, offices, kitchens, and laboratories).

(2) Occupant comfort causative variables were identified using a probabilistic model trained on a BN. The survey findings were used to design the BN model, which considers the most important factors contributing to occupants' feelings of discomfort in Norway's buildings. The BN model for occupant comfort was developed using the Python box in Dynamo. For each comfort factor, information about the building (such as its features or HVAC system) and the surrounding area (such as occupancy density) was gathered. Moreover, parameters were added to the BIM model to store the data that could not be acquired from the BIM model. This was done so the BN model could be used to its full potential.

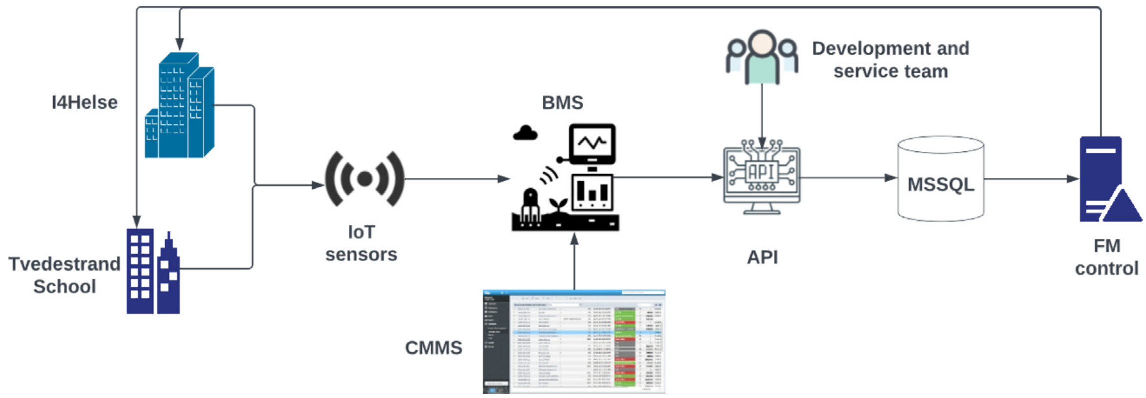

Fig. 3. IoT data gathering system including of API established by both the service and development teams.

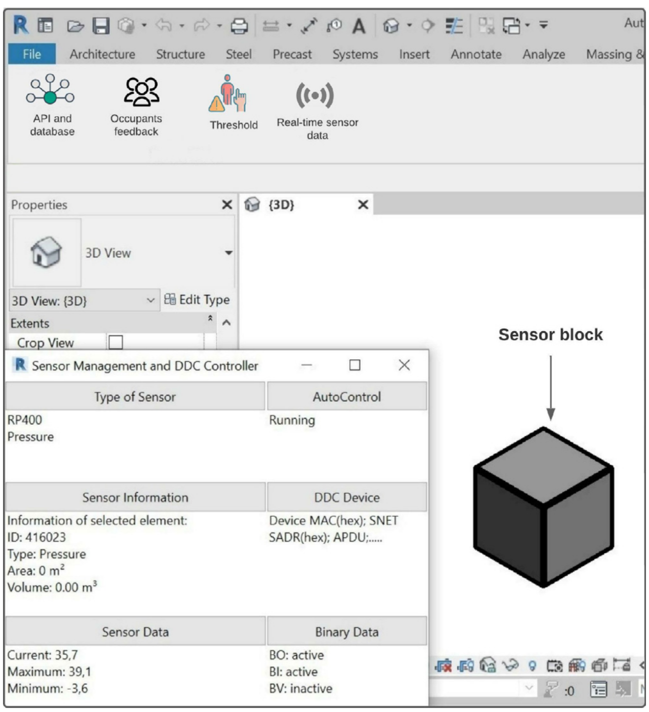

Fig. 4. Built-in sensor and occupants feedback management in Revit with the help of the developed plug-in.

(3) Our built plug-in and a visual programming interface for Autodesk Revit, Dynamo, and the Python programming language were used to connect the BIM model with occupants' feedback from the POE survey and the probabilistic model to support occupants' comfort. The BN is depicted in Fig. 5. The FM team can interpret the data thanks to the BIM visualization of occupant responses and the findings of the causative analysis.

3.2. Fault detection and prediction

This stage represents the box number two in Fig. 2.

3.2.1. Decision-making framework

Fig. 6 depicts the conceptual model and framework for making decisions to help facility managers identify the underlying causes of building issues and satisfy the demands of occupants. After getting the comfort issue, the framework will initially determine whether the HVAC system has an electrical issue. If not, the framework will use the BN network in Fig. 5 to automatically begin looking for HVAC design issues (thermal comfort issues). Whether there are any HVAC design issues, the framework will check to see if the HVAC system is inadequate, which indicates it cannot handle the thermal demands of the occupants. If the architectural and constructive design is properly established, the thermal load can be computed automatically, and the indoor unit capacity can be retrieved from the equipment database. There are two ways to deal with discomfort brought on by already installed, undersized HVAC components:

1. If at all feasible, insulate the room's façade, including the façade, windows, roof, and floor, to lower the thermal demand of the room.
2. The only alternative would be to use interior units with larger cooling or heating capacities if all envelope components fall under the insulation criteria. If these improvements are not feasible because of a limited budget, they might be suggested as ways to enhance the future building design.

If the indoor unit capacity is greater than the thermal load of the room, the framework will determine whether there is a failure in the indoor HVAC system equipment (fan, sensors, cooling and heating units, etc.) by applying the APAR rules as mentioned in Section (3.2.3), which are dependent on sensor data. Failures may occur from outside units if APAR cannot identify an issue with the inside equipment (e.g., frozen evaporator coils, dirty condenser coils, dirty filters). By determining whether the issue is with indoor or outdoor units, the framework enables the FM team to offer proper remedial steps.

The framework will also look for issues with comfort related to visual, acoustic, or spatial adequacy. The framework will examine the WWR, room lighting, and shade management for visual comfort. In a similar vein, the framework will look for internal and exterior acoustic insulation materials present in the building and an acoustic attenuator to determine whether there is an acoustic issue. The building's space needs are checked at the last stage of the framework by examining the rooms' cleanliness, adaptability, accessibility, and ergonomic furnishings.

3.2.2. Data selection and pre-processing

Feature selection is crucial when training a model with a machine learning method since it allows the methods to exclude irrelevant and noisy information. Several condition indices showed evidence of data noise; for example, (1) a sensor for chilled and heater water temperature, (2) the condition of the dampers, (3)

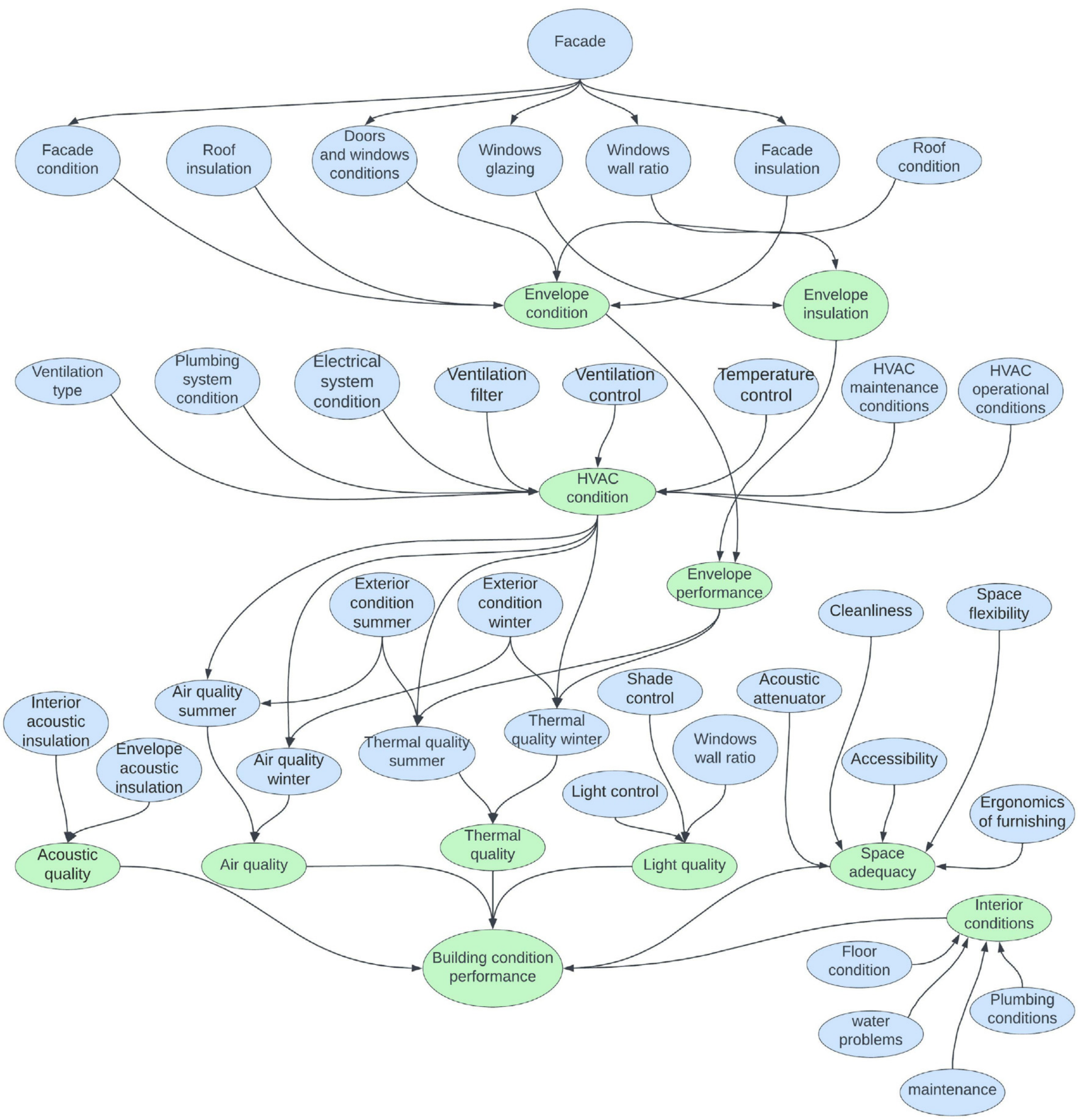

Fig. 5. The BN model for evaluating comfort performance in buildings.

the state of the heating and cooling valves, (4) the temperature in a given zone, (5) the status of the ventilation system, etc.

The dataset then undergoes data preparation, which entails data cleaning and standardization. Data normalization reduces the scale difference between different data sets, and the data cleaning removes the noisy and low variance data. Using the StandardScaler method [83], the data is translated into a range between 0 to 1. Data reduction eliminates extraneous information, whereas feature selection eliminates unnecessary information inside a dataset. This research will combine the ANOVA and SVM approaches to improve classification accuracy [84].

The ANOVA-SVM method produces many metrics, such as the ANOVA score, the accuracy score from each subset test, and the distance value from each data point to the decision boundary. While SVM boosts the classifier's performance, ANOVA analyzes the variation of each feature in the dataset. The data created by the ANOVA-SVM process includes the distance value of each feature to its decision border; the closer a feature is to its boundary, the more important it is. The closer the data is near the boundary, the better it fits the label.

3.2.3. AHU condition assessment and fault alarming

Fault detection and condition monitoring are two crucial steps in predictive maintenance. Equipment health and status may be tracked over time with the help of condition monitoring, which collects and analyzes key parameters to identify if a component's status has altered from its typical state.

Our work established a condition assessment system and implemented diagnostics in a larger number of devices using the expert rules by Nehasil et al. [85] based on the APAR approach by Schein et al. [86]. From 11 data points, Schein et al. [86] list 28 potential detection rules. The majority of the guidelines are conditional on the AHU's operational mode. The heater must undergo separate tests when the AHU is in heating or cooling mode. Once the time stamp's operating mode has been identified, the appropriate rules may be activated. Most rules are rather basic, requiring only elementary math to determine the outcome of a single determinable physical or regulatory event. All these rules were applied through the BN model; Fig. 7 shows a part of it.

Data points must be associated with diagnostic system inputs to operate properly. To achieve this, we employ a semantic descrip-

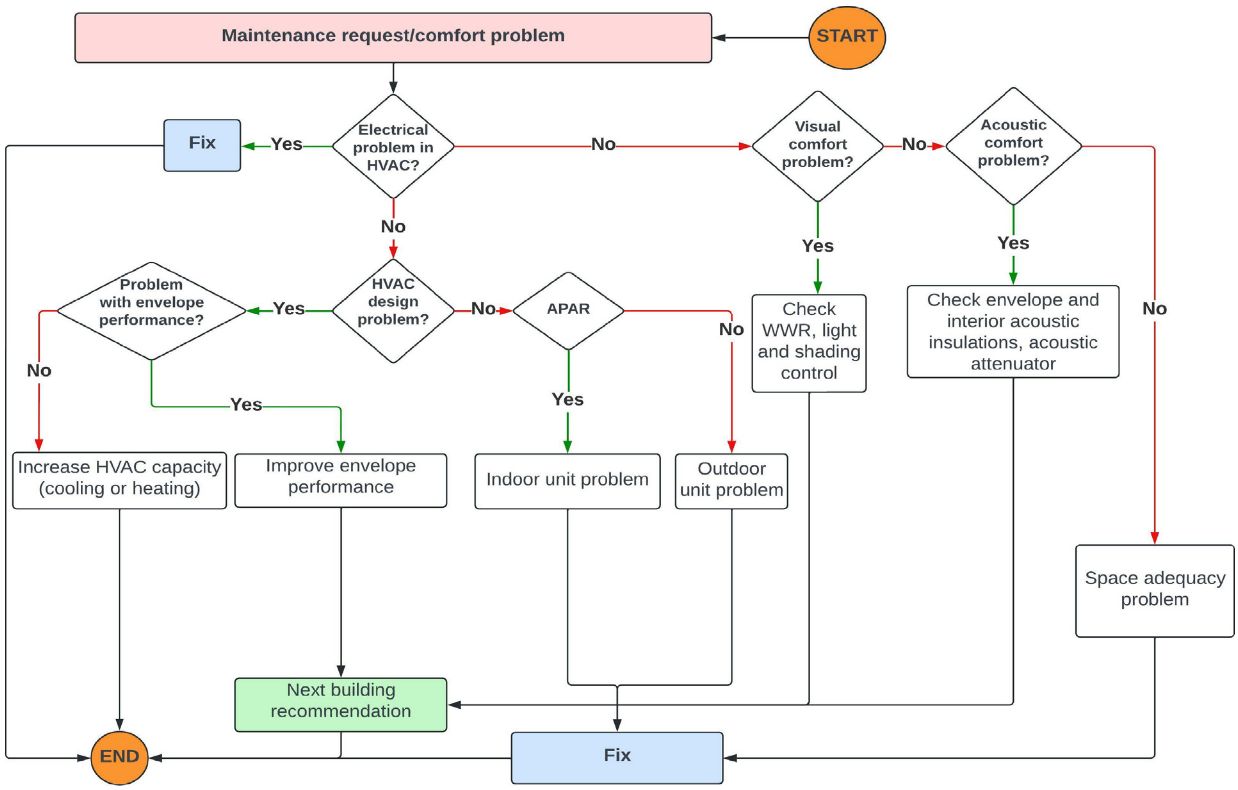

Fig. 6. The decision-making approach and framework to help facility managers detect building faults.

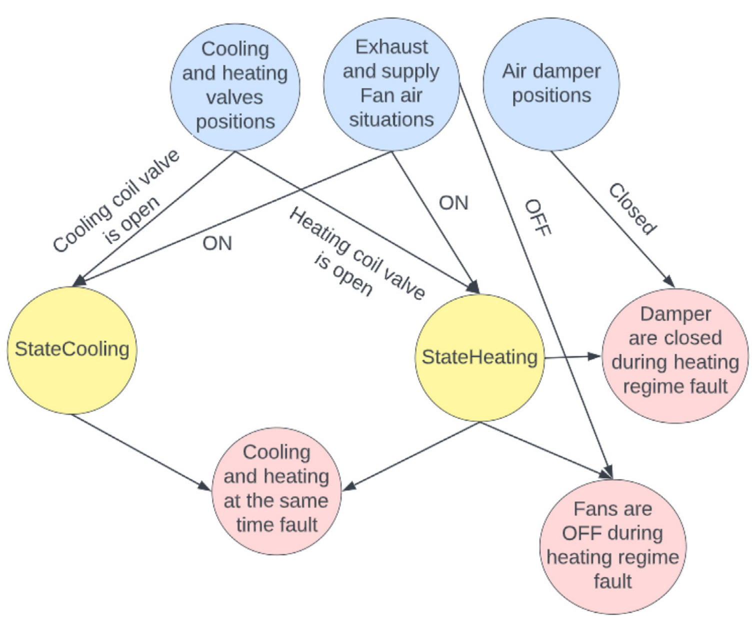

Fig. 7. An example of how the BN applies the APAR rules to check if there are any faults in the units inside the buildings. The blue nodes are the BMS data, the yellow nodes are the state nodes, and the red ones are the faults.

tion of data using BOT, Brick schema and SSN, as been mentioned before.

3.2.4. Comfort prediction using probabilistic modeling

Identifying the building and spatial information impacting occupants' comfort for each comfort component is necessary to determine the primary reasons for discomfort. Determining those reasons was accomplished by first picking which factors had the greatest impact on occupant comfort in a building through a review of the relevant literature. Second, a statistical analysis was performed on an 850-participants satisfaction survey in two buildings in Norway to determine the cause-and-effect relationships between various factors. Finally, the model structure was tested and improved by applying the Delphi technique [87]. In total, twenty-four specialists took part in the Delphi survey. According to the information type, each building and spatial information variable was designated as discrete (labeled, Boolean, discrete real, or ranked) or continuous in the BN model, represented by a node [88]. Certain nodes were designed to have only two possible values, called Boolean values, such as "Yes" and "No." Others were ranked in one of many states, including 'High,' 'Medium,' or 'Low.' To describe numerical statistical distributions as expressions, the truncated Normal distribution, also known as TNormal, was utilized [88]. Dynamo's Python box was chosen as the primary building block for the BN model for occupant comfort because of its robustness, adaptability, and user-friendliness.

The likelihood that a node will be in a given state is described by conditional probability tables (CPTs) [89]. The CPTs for each node and the significance of the parent nodes for occupants' comfort in several ways inside the BN model were selected based on [23]. When an observation is made for a given node, the BN performs the essential function of backward propagation by retracing the influence of the observation through the network to determine the marginal probabilities of unseen nodes [89]. Finally, a sensitivity analysis may be performed on a BN model to determine the most influential model inputs in light of observed data.

The ventilation system is a key factor in determining the air quality within a building, affecting how comfortable people feel inside. Those living in the building can adjust the temperature and humidity levels by simply opening windows. However, natural ventilation is weather-dependent [90] and may not be sufficient in extremely hot situations while it would lead to high heat losses in cold climate. An outside weather station's readings help understand how pleasant the air quality is outside.

The HVAC condition, which describes the status of the component, might be either high, medium, or low. For example, equipment in "high condition" is in pristine shape and may be put to its full intended use. However, the quality of the HVAC system is crucial for buildings with mechanical ventilation, as its inappropriate functioning can lead to inadequate ventilation and, in turn, health problems and discomfort [23]. Problems with indoor air quality and thermal comfort might result from improper HVAC design [91]. An effective HVAC system, for instance, must consider the building's layout. While centralized systems are ideal for single thermal zones, decentralized systems perform better in multi-zone structures.

Air quality comfort is also affected by the building's occupant density (m^2/person). In this paper, an external state is characterized by an externally labeled node (e.g., extreme cold, cold, mild for winters, and extremely hot, hot, and mild for summers). The BN model 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. The kind and features of HVAC systems (for example, the type of cooling and heating) and the options for thermal adaptation have been highlighted as important determinants in thermal comfort [92]. A building's thermal comfort may be affected by HVAC systems (boiler, chiller, etc.) age. Those with access to thermally adaptable opportunities, like opening windows and adjusting thermostats, report feeling quite comfortable [69]. The material and insulation that make up a building's facade, roof, and windows make up its envelope, which is one of the building's attributes that affect occupants' comfort [20].

Despite the importance of HVAC conditions, the availability of temperature control, and the efficiency of the envelope, faults in HVAC design and environmental variables have a greater impact on thermal comfort. Consequently, a low thermal transmittance envelope (U-value) can assist increase the periods during which occupants can feel comfortable without resorting to artificial cooling or heating [23]. Adjacent rooms also affect each other regarding thermal comfort in terms of the quality of their materials and insulation. The ability to regulate the temperature and the presence of opening windows are both examples of Boolean nodes.

Quantifying the effect of daylighting on visual comfort may be done by calculating the window-wall ratio (WWR) [93]. People strongly favor letting natural light into their workplaces, which correlates with the widespread consensus that natural light is healthier [94]. Given that the g-value of windows (glass) is low to avoid overheating or increasing cooling loads due to direct solar radiation, it is necessary to model the façade and window sizes in BIM and determine the WWR per area. Regarding occupant comfort, the availability of inside curtains and outside window shade is crucial for reducing glare and overheating [95]. Errors in design can affect occupants' visual comfort if, for instance, proper daylight controls are not implemented. The BN model defines the light and shade control options as Boolean nodes. WWR is a ranking node (i.e., low (10%), medium (10–40%), and high (>40%)) defined as the glazed area as a percentage of the envelope's total area.

Regarding space adequacy, space attributes, including flexibility, cleanliness, and accessibility, affect occupants' comfort [74]. The most important aspects of enough space are ergonomic furnishings, cleanness, and accessibility. Other aspects that impact occupant comfort include using ergonomic furniture and the availability of enclosed areas for meetings and collaborative work [96]. The BN model defines space adequacy data as a list of rated nodes.

Supply duct statistic pressure, differential pressure of the supply air filter, return air temperature, outdoor air temperature, mix air temperature, power consumption of the supply fans, power consumption of the returns fans, and supply air flow rate are all examples of sensors used in BN for the APAR method. Supply fan speed control signal, return fan speed control signal, supply duct statistic pressure setpoint, and supply air temperature setpoint are only some control signals and setpoints used by BN that may be easily retrieved from BMS. Fig. 8 depicts the primary building systems that were investigated for this study.

3.2.5. Maintenance strategy with multi-class classifier

Many reasons can cause failures in a building's systems, such as unskilled staff, a malfunctioning control system, improperly specified needs in the building management system (BMS), and so on. Faults in complex systems (like the AHU) that are not detectable by standard BMS tools (such as employing heating or cooling to balance the non-optimal heat recovery [97]) are unusual. It would be ideal to assign a failure severity to each problem depending on how much it affects the comfort of the building's occupants, how much energy is wasted, and how much danger there is to the machinery being used. From BMS, it is not feasible to obtain such information. If critical information is lacking, a severity index for each issue will become worthless. Instead, this study introduces a predictive maintenance framework to improve maintenance decisions through problem detection and system and component health forecasting.

Data from BN fault detection real-time system, the FM system, and the BIM will all be utilized in the forecasting procedure. Following Section 2.7., this investigation will employ the artificial neural network, support vector machine, and decision tree methods. Fig. 9 shows how the predictive maintenance method functions. This forecasting system considers several variables, including the findings from the Bayesian network's fault detection over three years of data collected at 5-min intervals. This forecasting method produces (1) building faults and (2) maintenance requests.

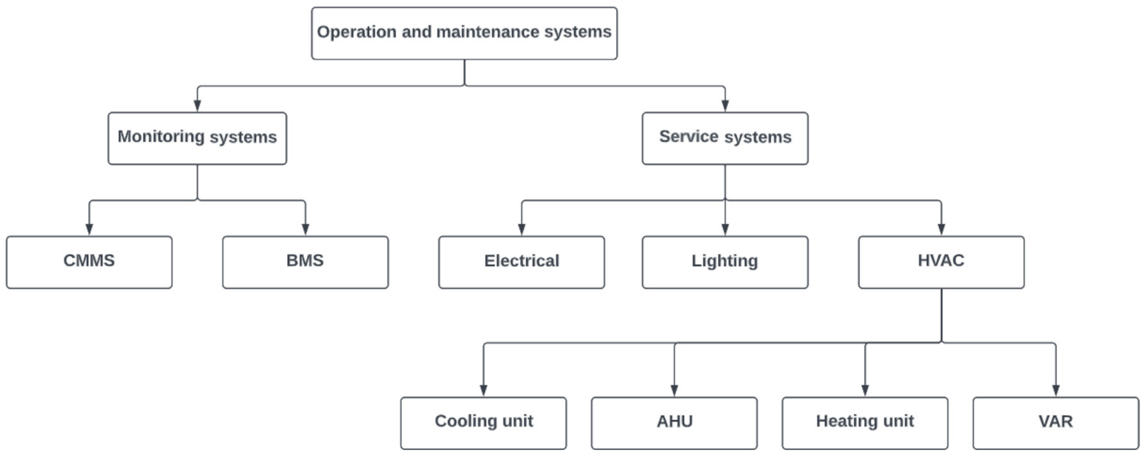

Fig. 8. Main buildings systems that have been included in this study.

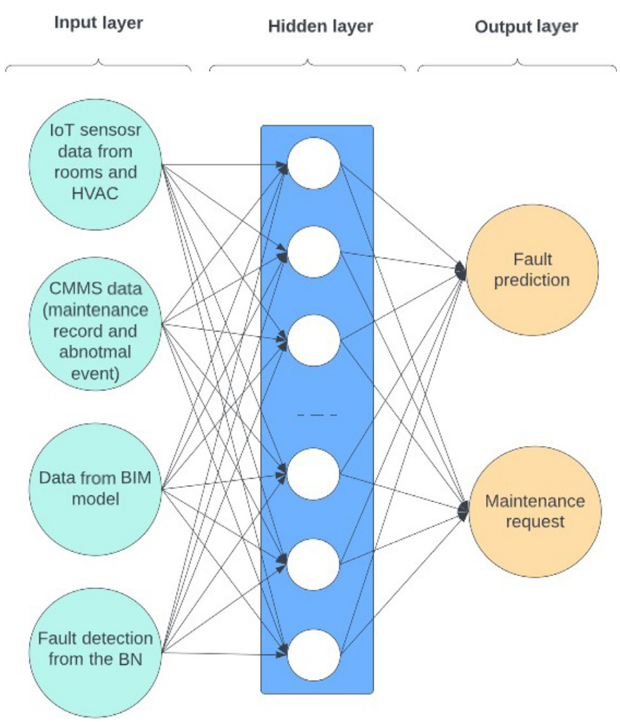

Fig. 9. The procedure of the prediction algorithm.

The proposed predictive maintenance system supports adaptive models training and prediction. Prediction models are trained with data from continually updated sensors and service logs. Parameters of the prediction models are adjusted to account for new information, as shown in Fig. 10.

The predictive method is shown in Fig. 10. Training, cross-validation, testing, and prediction are the four stages of the prediction process.

The ANN, SVM, and decision tree techniques are trained using data sets for the desired variables (input datasets), and the resulting prediction models are then utilized to make predictions. Input datasets are randomly divided into three categories: (1) 80% for model training, (2) 10% for validation, and (3) 10% for testing. A training set is used to train a machine learning model, while a testing set is used to evaluate and fine-tune the learned model over time by adjusting the weights of the algorithm's interconnected nodes. The remaining 10% of the data set must be used to verify the accuracy of the trained model. Adjusting the trained models based on dynamic updating data, such as the obtained dynamic sensor data and the updated maintenance records, leads to creating these models, which are then retrained. After the model has been run and a projected condition has been generated, the maintenance plan must be rescheduled to align with the condition. Last but not least, the well-trained models predict the long-term state of the various components (2 months ahead).

3.3. Data visualization

This stage represents the box number three in Fig. 2. Two types of visualization were examined when thinking about how to best present occupant feedback and causative factor findings. The former visually displays the findings of a user satisfaction survey, while the latter displays the results of a probabilistic model used to identify the root causes of occupants' dissatisfaction. (1) The originally proposed representation used a color scale ranging from "Very happy" to "Very dissatisfied" to represent occupants' opinions on various comfort levels. The BIM model featured a 3D representation of the tabular data gathered from Revit's schedule. The plug-in depicted in Fig. 4 was created to individually display the residents' feedback on each room's level of comfort. It is feasible for the FM team to observe the average comfort level of occupants by room by filtering comfort elements, and it is also possible to compare the comfort levels of occupants in other rooms using the same filtering criteria. The second suggested visualization

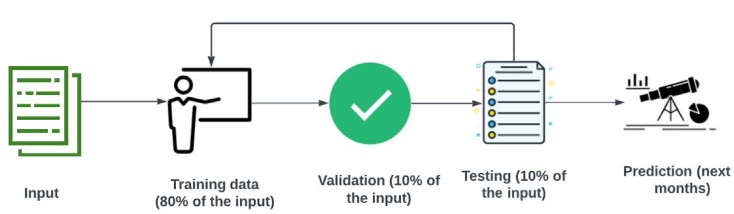

Fig. 10. The data-flow and implementation process for fault prediction.

would use Python scripts in Dynamo to present the probabilistic model's causal analysis of each room's data.

4. Case study

4.1. Background

I4Helse and Tvedestrand upper secondary school are the buildings used in this study to verify the proposed Digital Twin framework. Both buildings follow Norwegian TEK10 [98] and NS3701 standards [99]. I4Helse [100] was built in Grimstad, Norway, in 2017 with 1600 m^2 floor area, while Tvedestrand school [101] was built in Tvedestrand, Norway, in 2020 with 14500 m^2 floor area. Tables 1 and 2 show the main features of both buildings.

Numerous types of sensors, including but not limited to temperature, pressure, and flow rate sensors, have been installed to monitor the buildings. In order to process the information further, the signals were collected from the sensors and sent to the BIM models. Fig. 11 shows the BIM model for the I4Helse and Tvedestrand school buildings, wihle Fig. 12 illustrates the systems involved in this study.

In addition, the building users' satisfaction was assessed in various locations, including classrooms, offices, hallways, labs, conference rooms, and study rooms. This data was imported to the probabilistic model in Dynamo along with the spatial information of each room, such as occupancy density (m^2/person) and operable windows (yes/no), among other things. Fig. 13 shows the occupants' comfort level for indoor air quality in summer in part of the Tvedestrand school, where red color refers to people who feel discomfort, and green refers to a pleasant environment.

Table 1
Real values of the buildings envelopes following TEK10 and NS 3701.

Parameter	Initial value
External wall U-value (W/(m^2ůK))	0.15
Roof U-value (W/(m^2ůK))	0.11
External window, doors and glass U-value (W/(m^2ůK))	0.8
Ground floor U-value, W/(m^2.K)	0.06
Normalized thermal bridge (W/(m^2ůK))	0.03
Airtightness n_{50} (1/h)	0.35
g_t, Solar Heat Gain Coefficient (SHGC) (glass)	0.34 (3 layers glass)

Table 2
The HVAC systems in our case studies.

Operation	Features
Ventilation system	Mechanical balanced ventilation system
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 efficiency of 90%
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
Night ventilation	0.36 l/((m^2.s)

The BIM model was used to gather the 'evidence' of possible HVAC controls, HVAC design errors, occupancy densities, and environmental settings. The occupants' comfort probabilistic model in the BN model was then run using these parameters in Dynamo to determine the likely sources of comfort or discomfort. The user satisfaction survey that was incorporated into the BIM process (using the developed plug-in) and is considered "evidence" in the BN model was also used to determine the quality comfort level of each room.

For fault detection and prediction, the Digital Twin framework implemented in this paper has to have the right design, which includes the BIM model of HVAC, building spaces, envelope materials, maintenance records, and historical failure data. An algorithm for identifying faults is then trained using all this data. The trained algorithm utilizes inputs from the cyber-physical system to (1) determine if a failure will occur or (2) determine when there is sufficient data to forecast when the failure will occur. One of the skills offered by the Digital Twin is the ability to predict the reaction of the physical system to an unanticipated event before it occurs. By studying both the event itself and the present reaction to forecasts of behavior made in the past, it is possible to arrive at this forecast. Based on the data collected and the integration of the BIM and machine learning algorithms, a full instance of a Digital Twin may be built. Predictive maintenance using digital twins can be profitable because it can significantly cut the number of maintenance operations and the number of downtime machines experiences while also extending equipment lifetime.

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. 14 illustrates the HVAC layout in the buildings considered in this paper.

4.3. Data collection

As shown in Fig. 15, the BIM model may provide the FM manager with geometric and semantic data about the buildings. The FM system may also be used to access inspection reports and historical records of maintenance. The BN model uses this data in condition inspections and quality assessments. The damper position, the chiller valve position, the heater valve position, the water temperature from the heater, the water temperature of the return heating coil, and the flow rate of water are all examples of the real-time data collected by the IoT sensor. We gathered sensor data from the I4Helse building from August 2019 to July 2022 and from the Tvedestrand school building from October 2020 to July 2022 to show how long-term trends in sensor data may be used to predict future events. Some resample measurements made in Python in 2022's first two months are displayed in Fig. 16.

4.4. Feature selection for APAR and prediction process

The original dataset collected from buildings has many features, from which we have chosen 18 of the most important features for developing the APAR rules based on the ANOVA-SVM method. ANOVA is used for feature selection, reducing the feature space's high data dimensionality, and SVM is used to reduce the computational complexity and increase the classification's efficacy. The blue circles in Fig. 18 illustrates those features.

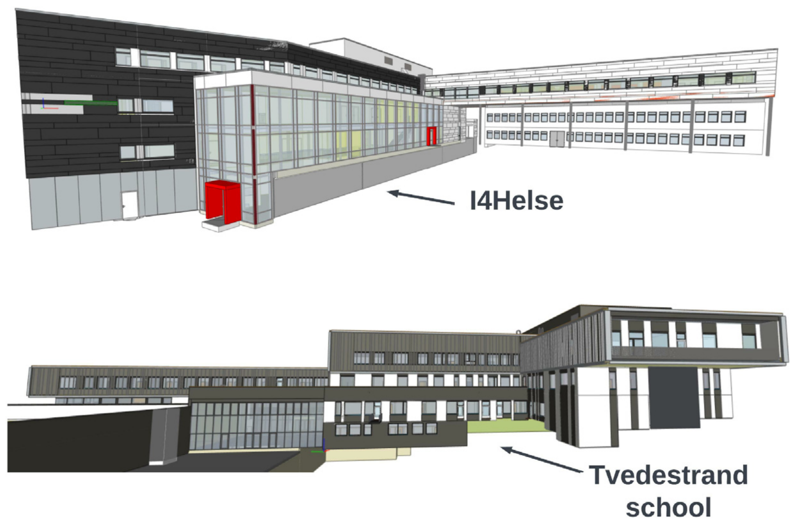

Fig. 11. I4Helse and Tvedestrand school as case studies in this paper.

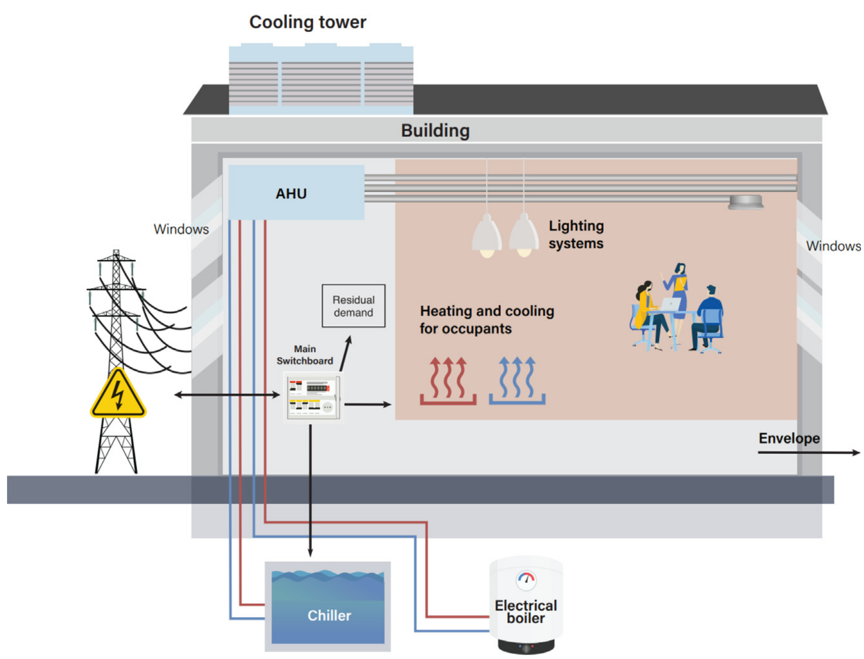

Fig. 12. The systems that are included in the Digital Twin framework through fault detection and prediction process to find occupants' discomfort reasons in buildings.

4.5. Faults detection

4.5.1. HVAC faults

As previously mentioned, various sensors are employed to track how well the buildings are functioning. Real-time sensor data and trends from the BIM model may be visually depicted, as seen in Fig. 15. The facility manager may use the sensors' data to assess each building system's current state. The FM system's recorded abnormal events and warnings serve as references for condition evaluation based on the outcomes of condition monitoring. In addition, after reviewing the findings of the field inspection, the FM team finished the building systems configuration list. At last, the facilities manager did a comprehensive check of the building's infrastructure to assess its state of repair.

Several severe faults were found through testing using our framework and the BN model, confirmed by facility management employees and by looking at the data gathered. While some errors are less severe than others, some need to be fixed immediately (simultaneous heating and cooling). The relevant control system algorithms need to be revised to fix these problems. An overview of operational faults is shown in Fig. 17.

One of the failures that were discovered using the APAR technique is seen in Fig. 18. The temperature deviates from the setpoint positively and negatively. The problem was that heat recovery was not at its maximum level during the colder months, which means it was not saturated (a saturated heating or cooling coil valve control signal for long duration points to issues like insufficient heating or cooling capacity or faulty valve actuators). In this rule, the supply fan signal is on, there is a significantly positive difference between the return and outdoor temperatures, and the heat recovery signal is not saturated.

When the supply air temperature drops to a little margin of the set point, heat recovery is raised to bring it back up to the desired level. The value of the fault can about make it over the 0.5 thresh-

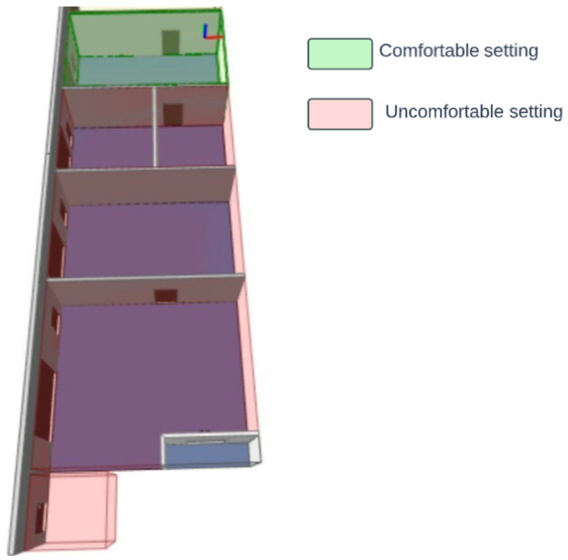

Fig. 13. Occupants' feedback of summertime indoor air quality in a part of Tvedestrand school.

old, which indicates that the temperature differential between the return air and the outside air is barely sufficient to cause the rule to be triggered. The control procedures might be modified if desired to allow this sort of conduct.

4.5.2. Acoustic quality

Several complaints have been received from occupants that the two buildings discussed here are too noisy to be comfortable. Table 3 provides a representation of the impact of the contributing components on the acoustics. When acoustic quality is quite good, the sensitivity analysis reveals the significance of the causative components. The likelihood of a building providing a high degree of acoustic comfort is shown to be most responsive to modifications to the envelope and internal acoustic insulation and least susceptible to modifications to the ventilation system.

Building and spatial information nodes were retrieved from BIM to evaluate acoustic comfort for each room based on the information about that space (such as the type of ventilation, acoustic attenuator, and occupants' acoustic comfort). No evidence could be established for the node in the probabilistic model of the acoustic insulation because no information about it was available. The backward propagation analysis in the BN model was utilized to acquire the findings of causal analysis and link to the associated rooms in BIM using Python scripts in Dynamo for unknown nodes (such as the envelope acoustic insulation). Using information from user satisfaction surveys for a given space, the probabilistic model determines the most likely values for the abovementioned variables. Then, BIM color-coded occupant satisfaction with acoustic comfort and displayed cause analysis findings in normalized stacked bar charts, as seen in Fig. 19.

The occupants of the Tvedestrand school classrooms reported high levels of acoustic comfort. Nonetheless, office occupants complained about the noise level. The bar charts for the offices reveal that the acoustic insulation of internal walls is the most likely source of acoustic discomfort (58%) rather than the ventilation system or the lack of attenuators.

The facility manager can generate hypothetical scenarios from the BIM visualization by changing the state of the causative elements and evaluating the likelihood that the occupants would be satisfied. Therefore, the causative analysis suggests that isolating an office's internal walls can increase its occupants' acoustic comfort. Nevertheless, if there is not enough money to accomplish that, putting acoustic attenuators in the ventilation systems of the office can be the most convenient choice.

4.5.3. Indoor air quality

A hypothetical situation about the pleasantness of the indoor air quality on the third floor of I4Helse is provided. To run the probabilistic model of occupant comfort in the BN model and identify the most likely causes of comfort or discomfort, the BIM model's definition of 'evidence' was used to retrieve the options of ventilation control, ventilation filter, occupancy density, and exterior conditions. Evidence in the BN model is derived from a user satisfaction survey embedded into BIM. This study revealed the quality comfort level of each room.

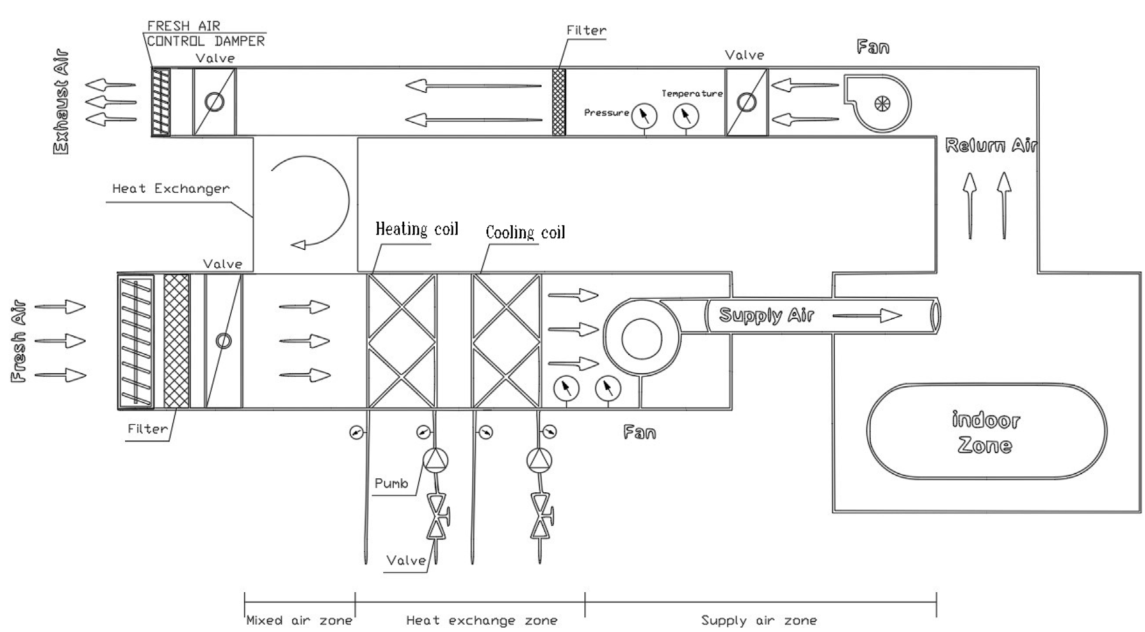

Fig. 14. Schematic illustration of HVAC from our case studies.

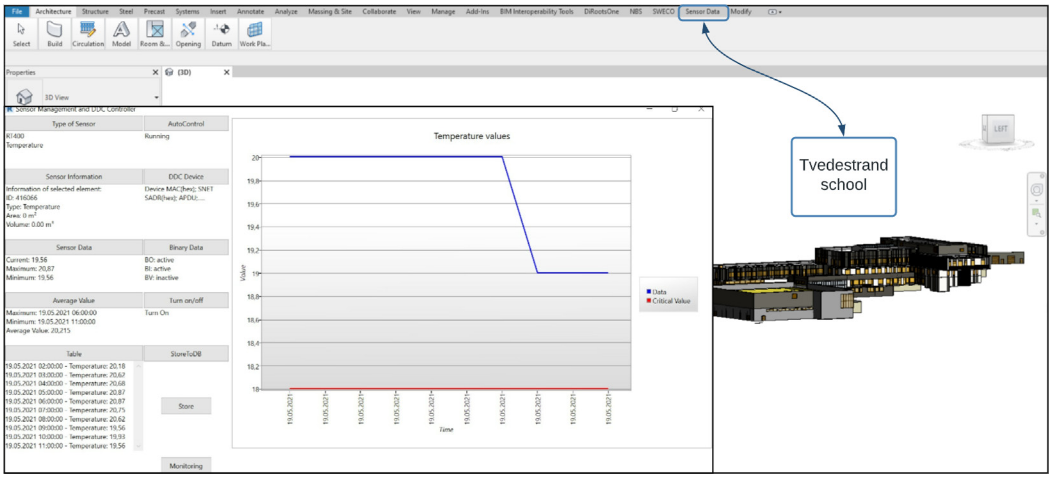

Fig. 15. The information about the building obtained via sensor data and the BIM model.

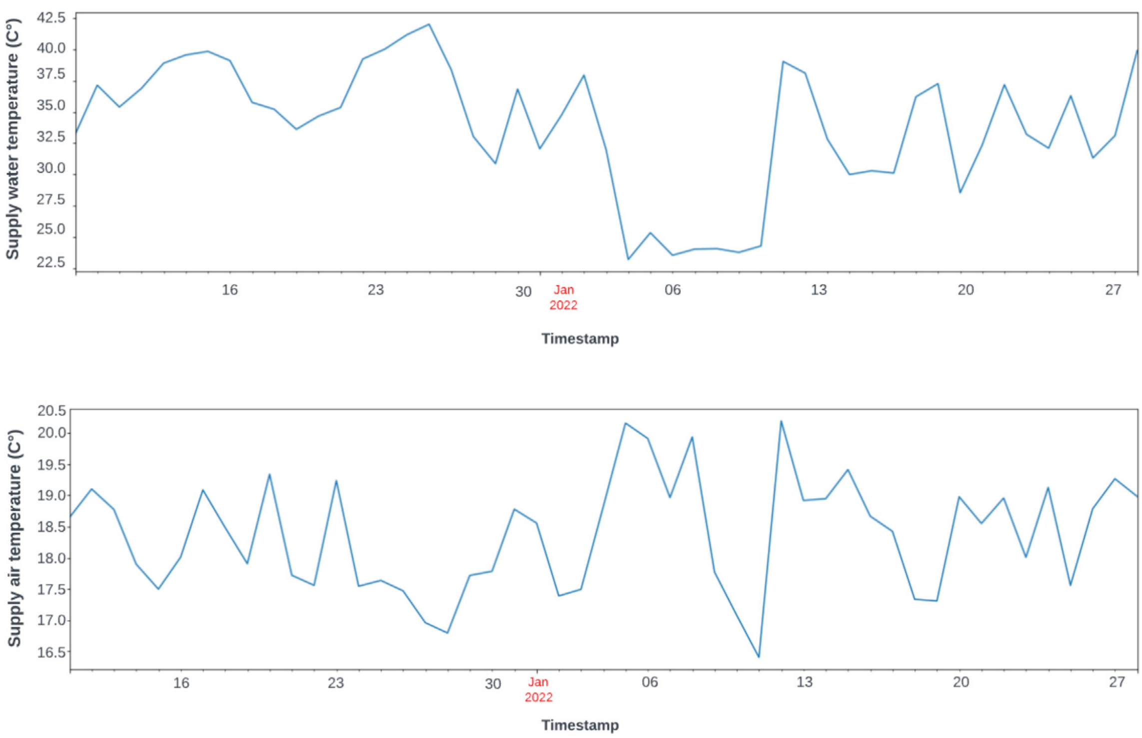

Fig. 16. A sample of the supply air temperature and supply water temperature for AHU at the Tvedestrand school during the months of December 2021 and January 2022.

The FM team can determine the likely causes of each room's air quality through BIM visualization. Probabilities of HVAC design faults or HVAC systems in high condition are displayed in Fig. 20. Indicating a high degree of comfort for residents in this room regarding indoor air quality, the findings show a 62% likelihood of the HVAC system operating without faults and being in a high condition in room No3039. However, occupants in rooms No3051, No3017, and No3016 reported being unhappy with the quality of the indoor quality. The model findings show a 74% chance that No3017, and No3016 contain significant HVAC design problems. These findings need to be compared to the requirements for the HVAC system to establish whether the ventilation system was operated appropriately. Occupancy density was also one of the primary reasons why people were unhappy with the air quality in these rooms.

In order to determine which parameters (previous nodes) were most important in improving the indoor air quality of uncomfortable rooms, a sensitivity analysis was conducted. Visually, the length of a bar reflects the weight that node has on the whole performance of the building's conditions (target node).

Fig. 21 depicts the effect of different nodes on indoor air quality in winter. It can be deduced that occupancy density and HVAC design faults have a greater impact on the likelihood of extremely high comfort levels in rooms No3016, No3051, and No3017, whereas ventilation control has the least impact. Those rooms have an HVAC system based on an AHU that services many rooms, which may be undersized. Even if the AHU has to be replaced, the high occupancy in these spaces suggests that lowering the number of occupants may improve the comfort level of the indoor environment.

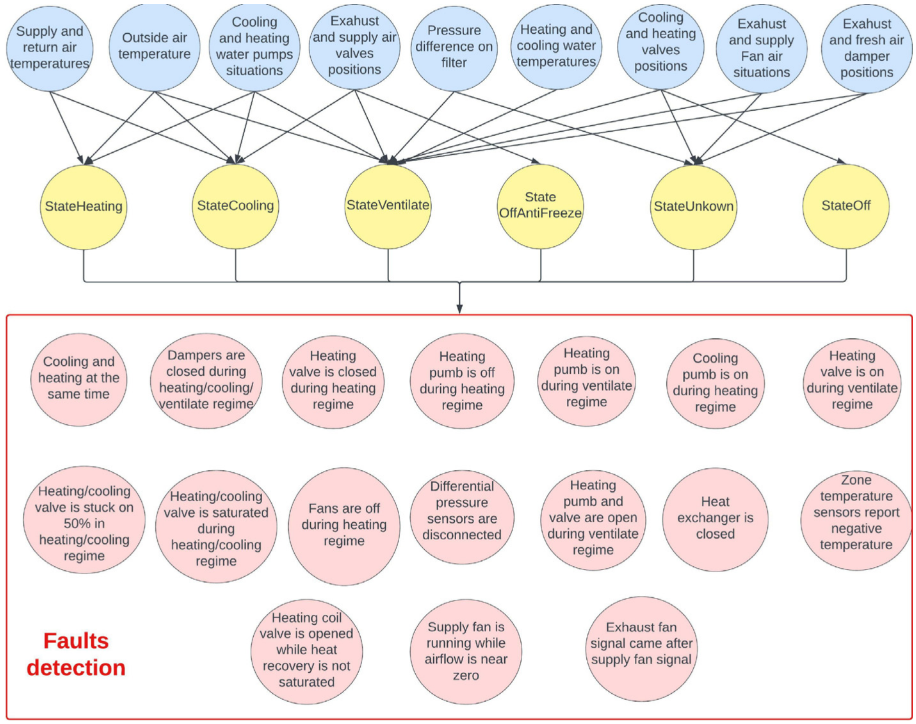

Fig. 17. The detected faults in our case studies.

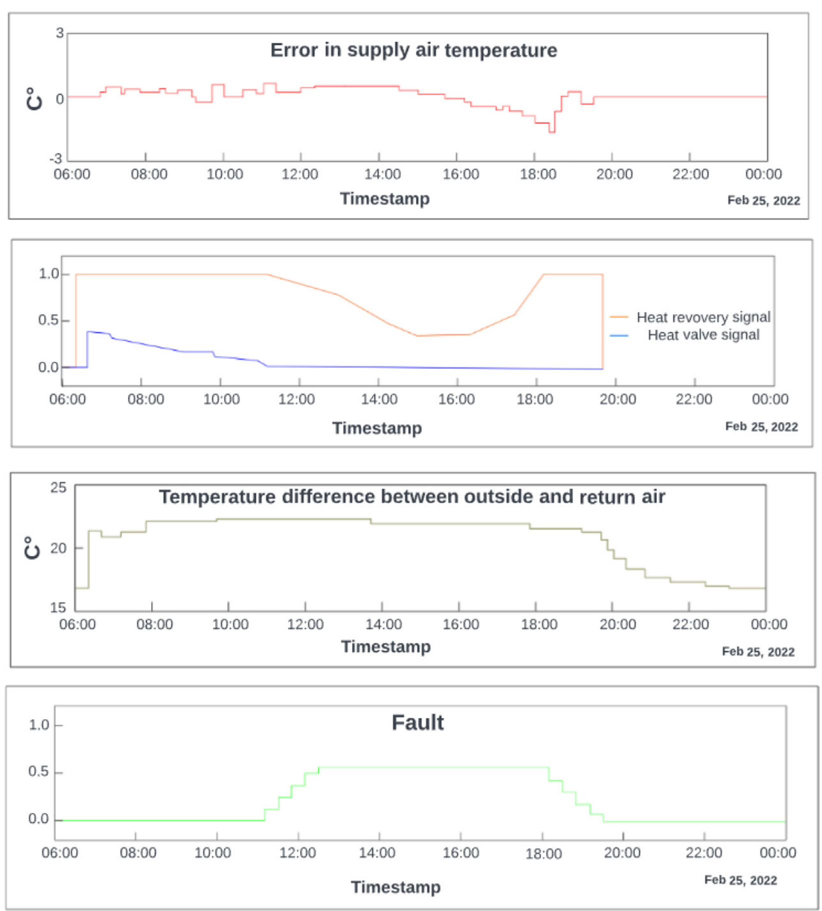

Fig. 18. Heat recover not saturated during one day in February. The fault is detected based on temperature setpoint, heat recovery signal and temperature difference between outside and returned air.

Table 3
Sensitivity analysis of acoustic quality.

Component	Probability
Acoustic quality (high)	0.042
Envelope acoustic insulation (low)	0
Envelope acoustic insulation (high)	0.121
Interior acoustic insulation (low)	0
Interior acoustic insulation (high)	0.108
Acoustic attenuator = not exist	0.016
Acoustic attenuator = exist	0.061
Ventilation type	0.036

4.5.4. Light quality

Fig. 22 illustrates the light quality of the buildings. In both buildings, the end user controls the artificial light; however, only occupants in Tvedestrand can control the glare from the sun through the blinds. Compared to building I4Helse, the possibility of attaining acceptable light quality at Tvedestrand school is significantly higher. According to this study, respondents were dissatisfied with the amount of daylight and artificial light in building I4Helse. The occupants' dissatisfaction with building I4Helse is likely because it has a low WWR. According to the satisfaction survey findings, occupants in the Tvedestrand school are more pleased with the light quality than those in the I4Helse.

Fig. 23 displays the results of the sensitivity study conducted on light quality. According to the formal interpretation, the chance of light quality being Very High given the outcomes of the parent nodes rises from 1.6% (when design faults are High) to 36.9% when there is a significant reduction in the number of design faults (when design errors are Low). The light quality is affected in a manner comparable to the various light control and shade management capabilities. The ratio of windows to walls has the biggest influence on the quality of light, which suggests that a window-to-wall ratio somewhere in the middle, between 10 and 40 percent, is the most pleasant choice.

4.6. Predictive maintenance

The four-step procedure used in the forecast was based on the BN faults shown in Fig. 17 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.

Artificial neural networks (ANN), support vector machines (SVM), and decision trees (DT) are the methods of choice for predicting and ranking the severity of faults. Class-specific indicators and a performance Trade-off Evaluation are used for comparative purposes in this study [102].

Conditions predicted by ANN, SVM, and decision trees are compared. Data sets are utilized for testing (10% of the overall data sets). ANN's 97% prediction accuracy was higher than that of SVM (96.5%) and Fine tree (94.7%). The comparative performance analysis and the condition prediction were carried out on the same datasets to ensure that the findings of the comparative performance analysis of these methods were applied to a diverse range of situations. However, accuracy is insufficient to determine which algorithm is best. In order to make a direct comparison between two variables, we will use the confusion matrix and the receiver operating characteristic curve (ROC). Accordingly, the AUC value

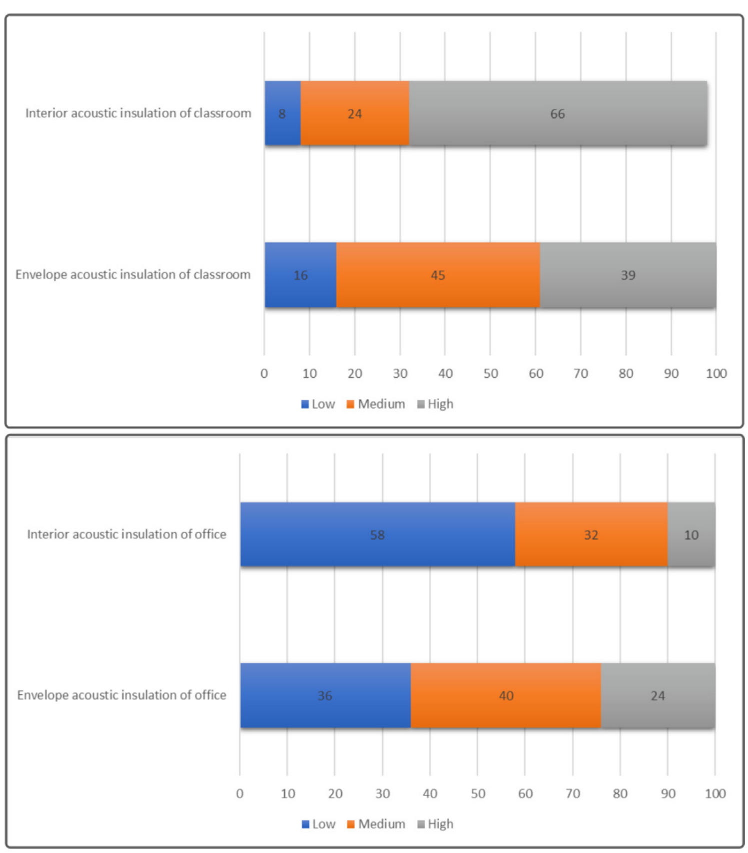

Fig. 19. acoustic comfort analysis of an office and classroom in Tvedestrand school.

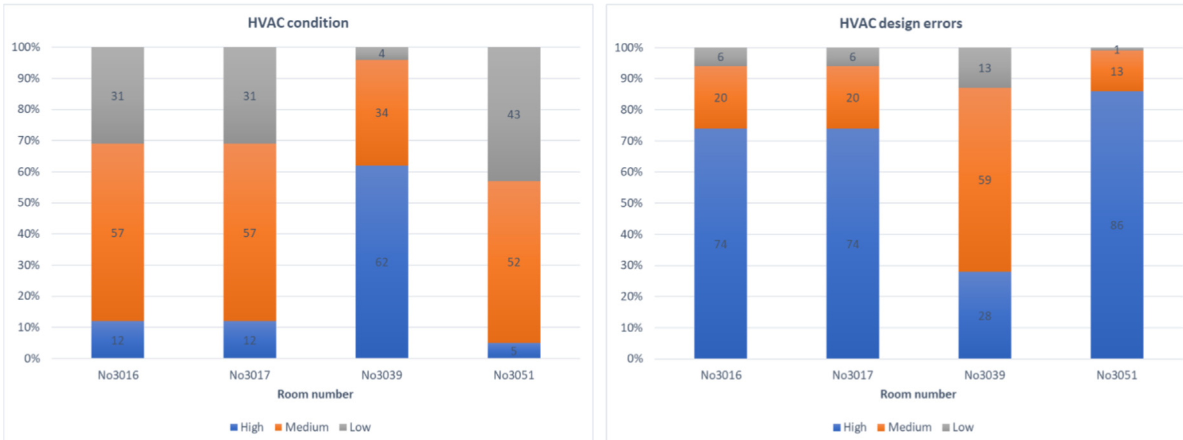

Fig. 20. The probability that each room has poor HVAC design or unsatisfactory HVAC conditions.

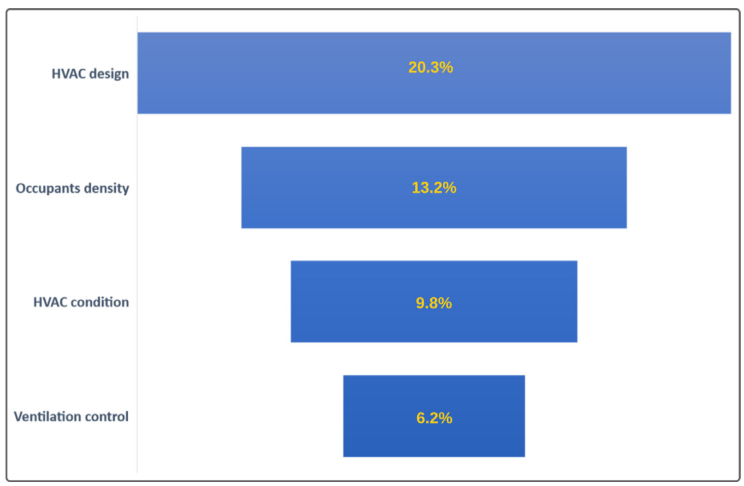

Fig. 21. The sensitive analysis of indoor air quality for rooms No3016, No3017, and No3051 in winter.

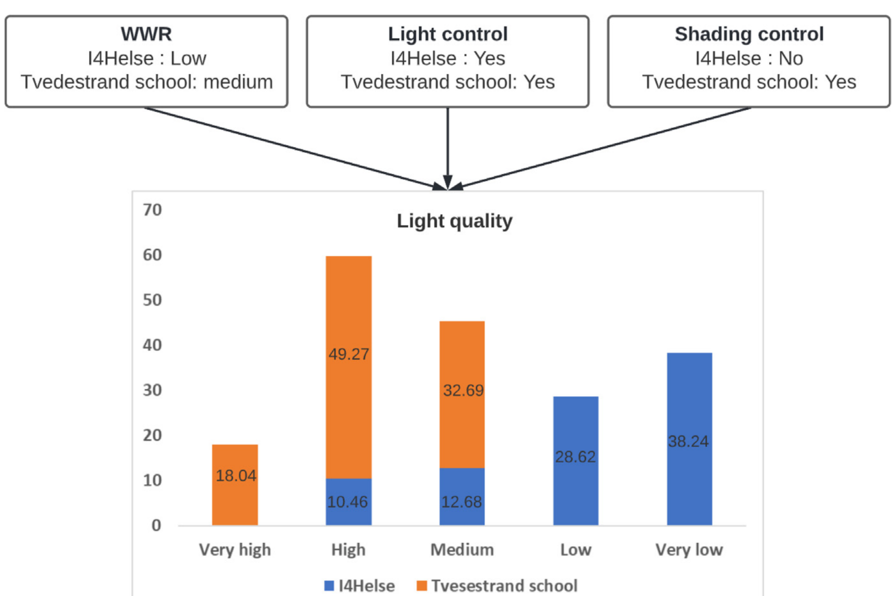

Fig. 22. Light quality probability percentage of I4Helse and Tvedestrand school.

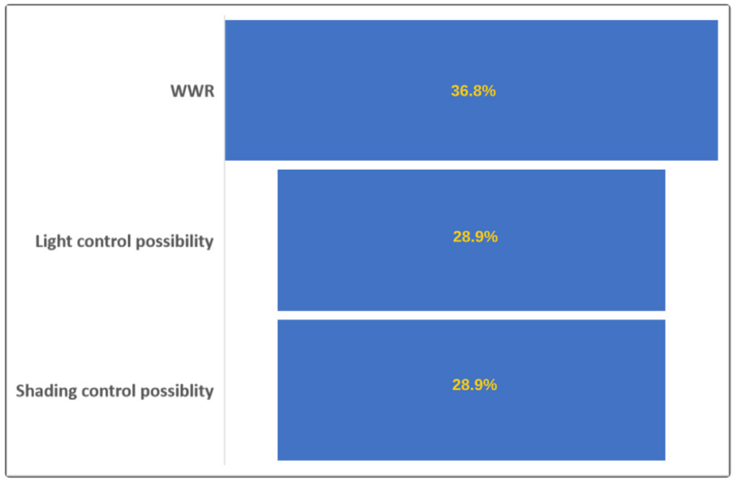

Fig. 23. Light quality sensitive analysis.

from the ROC was equal to 0.52, and the Fine tree incorrectly identified 3 faults (damper is closed during heating regime, heating pump is off during heating regime, and valve is opened during ventilation regime). Four faults (heat exchanger closed, heating pump off during heating regime, heating valve closed, and heating valve stuck in an intermediate position during heating regime) have been incorrectly identified as Class 1 using the SVM technique, yielding an AUC of 1. All faults, however, were accurately classified by ANN, and the area under the curve (AUC) was set to 1. The ROC curves confirm that ANN is superior to SVM and Fine trees; the area under the curve for Fine trees is just half of that for ANN. Consequently, the prediction accuracy and error indices of decision trees, ANN, and SVM all suggest that ANN beats the other two approaches, although it needs a longer time (287.05 s) than SVM (73.74 s) and Fine Tree (6.32 s).

After evaluating ANN, SVM, and decision tree methods, we settled on using the trained ANN model to make HVAC system predictions. The proposed framework can foresee situations at a later date. We utilize a time horizon of two months from now to demonstrate the dynamic nature of maintenance schedules in the future. The faults that were accurately recognized are shown in blue circles in Fig. 24, whereas the faults that were incorrectly predicted are shown in red circles.

Accordingly, based on the predicted condition, the facility manager should prepare maintenance equipment, supplies, and tools in advance as an alternative to restoring them after failure. Generally speaking, a predictive maintenance strategy enables the facility manager to monitor the state of the equipment and allocate resources and time accordingly. Changes in maintenance strategies are required for each new action plan.

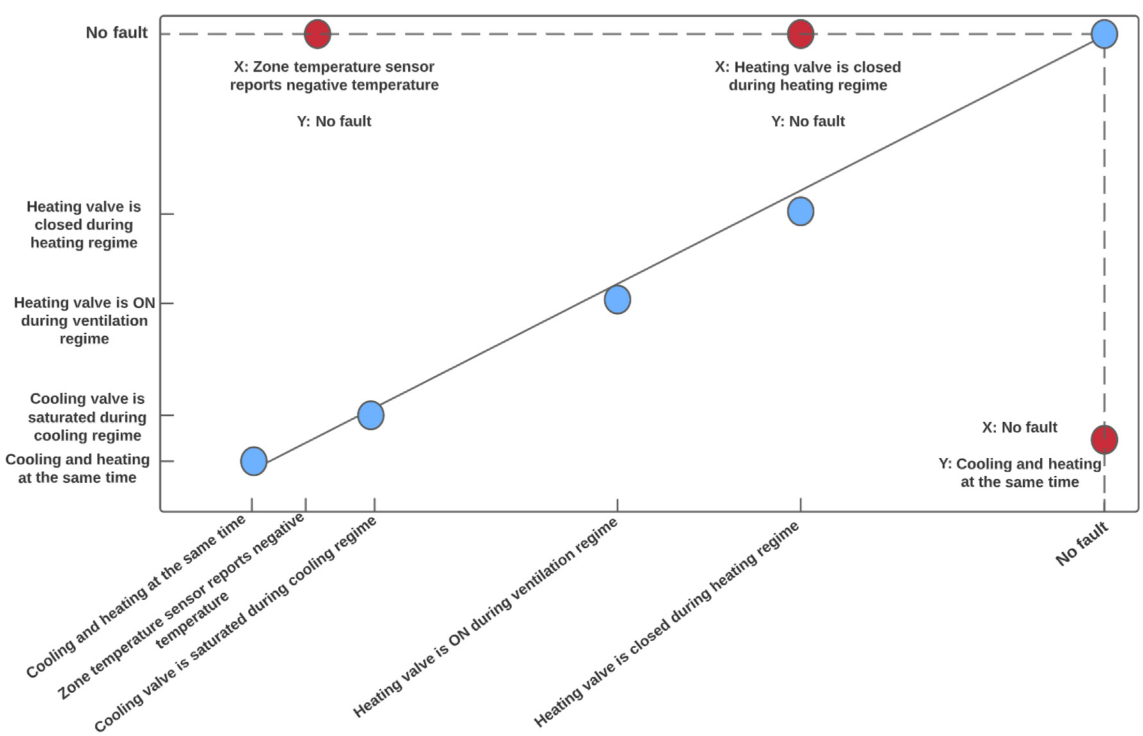

Fig. 24. Comparison between the actual and predicted faults for August and 2022 using ANN model (2 months ahead from the data that used for training and validation in Tvedestrand school) where x refers to the actual fault and y to the predicted fault.

5. Discussion

The classification of comfort aspects into thermal comfort, indoor air quality, visual comfort, acoustic comfort, and space adequacy is accomplished by integrating occupants' feedback and the occupants' comfort probabilistic model into the BIM model.

While some research has built a platform for merging building information modeling (BIM) with BN, a standardized technique must be used to evaluate the comfort performance of existing facilities. As a result, the probabilistic and predictive models can more easily acquire the necessary data thanks to the novel Digital Twin model proposed in this paper. It also helps the FM team deal with issues like data integrity, system compatibility, and labor efficiency.

The novel in our method presented in this paper focuses on real problems in uncomfortable spaces. It demonstrates occupants' feedback and detects and predicts the faults that contribute to occupants' discomfort in the form of a bar chart. This helps reduce the time spent looking for relevant information about the building, makes it easier to deal with the problem, and optimizes building operation strategies to increase occupants' comfort. Moreover, several studies have been on various techniques for identifying HVAC problems since the 1980s. Despite this, Fault detection is still not a standard part of HVAC operations. The reason is the restricted flexibility of fault detection methods and the high cost of fault detection systems. As a result, one purpose of this study is to present an automatic fault detection system to solve this problem. This system may be used with a wide variety of HVACs. On the other hand, the authors note that drawing comparisons and understanding the status of technology is challenging because each research effort has its unique dataset, test conditions, and measurement criteria. The purpose of this study is not to attain the maximum possible success rate in fault detection for a single HVAC system but rather to achieve a reasonable detection rate for many HVAC systems.

The wintertime indoor air quality issue was addressed, and it was shown that various people's judgments of the air quality might exist in the same room with the same heating, ventilation, and air conditioning (HVAC) system. More than 200000 data points were utilized to verify the suggested method from I4Helse and Tvedestrand school. Occupancy density (m^2/person) was found to have a major effect on how people perceive the air quality within a building, suggesting that rearranging furniture or decreasing the number of people there might increase indoor air quality comfort.

A plug-in, BOT, SSN, and Brick schema are used to facilitate the integration and flow of data in this investigation. On the other hand, Dynamo incorporates automation into the mapping information process, applies BN and a machine learning model, and is adaptable to and interoperable with the vast majority of current systems (e.g., Power BI). Incorporating a wide variety of sensors, equipment, and structural elements of a building into a single ontology is another approach to the data integration issue. Furthermore, the growing value of semantic data in BMSs will play a crucial role in advancing fault detection strategies.

The Digital Twin architecture utilized in this article can secure and verify the integrity of a system model by first gathering data from the operational environment, executing tests using that data, and finally realizing assessments, improvements, and forecasts. This might be helpful for decision-makers in supporting their decisions based on the information produced by the digital system regarding the project that is to be implemented in the actual world. In addition, the Digital Twin can forecast upcoming changes in the physical system since the digital system gives users the capacity to evaluate and simulate different scenarios to devise effective strategies. The framework has the potential to unearth new practical opportunities that can be incorporated into the physical system and its simulated variants. Just as the twin may show far-reaching plans and major benefits for the real-world system's output, so can the framework.

Using computer-aided design and artificial intelligence, the framework referred to as "Digital Twin" in this study can improve the performance of buildings, cut costs, lessen possible hazards, and optimize supply chains for building materials. When developing this Digital Twin, the dimensions of the conceptual space utilized for the workflow and the appropriate utilization of data and information interaction may make the incorporation of AI strategies much simpler.

On the other hand, an improved option can be addressed both now and in the not-too-distant future. Therefore, to bridge digital gaps and obtain a coherent and comprehensive process framework for designing and operating buildings and other facilities, digital twins need to be integrated within the architecture of existing construction companies. Such businesses are distinguished by their adaptable matrix organizational structure, revamped for each new venture, and heavy reliance on regional providers of resources and labor. The framework may also be utilized to determine where energy is wasted in the building and reduce environmental impacts.

The Digital Twin structure that has been adopted offers numerous benefits; nevertheless, certain issues need to be addressed. Because the Digital Twin works with artificial intelligence (AI) and the Internet of Things (IoT), these technologies face similar issues. The initial area of weakness is the IT infrastructure. Rapid AI development means we must provide a stable platform that can run cutting-edge software and hardware algorithms. It is vital for businesses to have a functioning and well-connected information technology infrastructure in order for this technology to be successful and for businesses to profit from it. The expense of putting these technologies in place and maintaining them is one of the most significant obstacles inside the infrastructure. For instance, the price of a Digital Twin for an office building around 60,000 square meters in size might be anywhere from 1.2 million to 1.7 million US dollars.

The following weakness in the modeling is that our Digital Twin model depends on the Internet of Things (IoT) technologies to receive data from smart devices. These technologies still have a long way to go before fully developed, impacting the standardization, resolution of sensor data, and large data capacity. In addition, the Building Information Modeling (BIM) models in companies used during the design phase are not appropriate for usage during maintenance. The issue arises because the employee who puts the order needs to be more informed about the correct usage of the BIM models and the extent to which they should require modeling. Further investigation is required to determine who will bring the BIM model up to date when significant alterations or additions have been made to the building. There needs to be someone available who can keep the model and all its data up to date. In addition, the maintenance of the model would require the competence of the staff members in charge of maintenance, which is generally not accessible. Another thing that stands in the way of using BIM is that the FM software utilized during the maintenance phase of the process cannot read the information directly from the BIM models at this time.

Another problem is that building owners need more incentives to invest in preventative maintenance, even though buildings lose energy due to poor maintenance and operation. Monitoring and prognostics must be performed without incurring additional costs or explaining the return on investment. In conclusion, most users would need to put in a significant amount of effort to successfully adopt the model that incorporates all of the information necessary for controlling potentially harmful circumstances, fire safety, and electrotechnical maintenance.

This study has some limitations: (1) the fault detection analysis was done in Dynamo, and the findings were mapped into BIM. The method does not consider any additional software in the market (r. g., Bayes Server). To fix this, it is important to write a new Python code in the block in Dynamo. (2) The occupants' age and physical condition significantly impact their degree of comfort. Other information requirements must be investigated to address these concerns, such as improving the probabilistic model by adding more elements impacting occupants' satisfaction. (3) Other types of problems, including firefighting, are not considered by the framework in this paper. (4) Since this framework was designed for usage in HVAC systems over their useful lifetimes, it is well suited to creating a building-wide deterioration scheme. (5) The choice of algorithm is based on the authors' prior knowledge, which affects the accuracy of the predictions. Alternative prediction methods will need to be looked into in further studies.

6. Conclusions

Analyzing several ambiguous factors is required to assess buildings' comfort performance. Using conventional methodologies to quantify and evaluate occupant comfort in buildings might be challenging based on such indeterminate factors. With such in mind, this research demonstrates creating a BN model for controlling the thermal comfort of existing buildings. The suggested BN may describe comfort in a building as a probabilistic process rather than a deterministic one and hence provide comfort performance levels in the form of probability distributions. The key benefit of BN is its adaptability, which allows it to include many types of data and evidence, including expert judgment.

Although the BN model may identify the causes of occupant discomfort, it is incompatible with BIM software, making the resulting data inaccessible and difficult to interpret. Moreover, the visualization and automated changes to component attributes and data management are only two ways BIM, as an integration tool, stands apart from other models. Hence, this paper introduces a novel Digital Twin approach that incorporates occupants' feedback (thermal comfort, indoor air quality, visual comfort, acoustic comfort, and space adequacy), real-time sensor data, the occupants' comfort probabilistic model, and predictive maintenance into BIM, categorized by comfort aspects. This visualization approach helps the FM team design the appropriate measures for increasing occupant comfort based on input from occupants and the findings of fault detection analysis.

This research also investigates the potential contributions of the Digital Twin to FMM-related predictive maintenance strategy. Predictive maintenance relies on the integration of three distinct but interdependent components: (1) operational fault detection, (2) condition prediction, and (3) maintenance planning. In addition, the status of the HVAC components is predicted using several machine learning approaches (artificial neural networks, support vector machines, and decision trees) to perform predictive maintenance and repairs promptly. The data integration and data flow mechanisms between BIM models, IoT sensor networks, and the FM system are built into the architecture of the proposed framework.

The proposed method aids FM operations and places tenants at the center of maintenance choices. With the help of the Digital Twin framework, the FM team can quickly and easily make decisions about occupant comfort-related building operational issues, removing a major obstacle to the collection of the necessary information during the operation and maintenance phase and thus paving the way for the much more widespread use of BN, BIM, and their associated benefits. Also, the visualization makes it easy to link various FM data (including architectural and geographical information) to these models. This means that buildings with considerably less effort may pursue the suggested technique, which is good news for research and can help drive commercial interest.

In order to improve the comfort of buildings and, by extension, the pleasure of their occupants, the suggested framework aids facility managers in making well-informed decisions. The results of two case studies of two buildings in Norway demonstrated that the suggested method could deepen our knowledge of the elements that influence occupants' levels of discomfort and the connection between those factors, the interior environment, and the physical properties of buildings. The Digital Twin framework in this paper could detect and diagnose more than 17 faults that the traditional BMS could not detect. Moreover, with very high accuracy, the framework could predict the faults that will happen in the next 2 months. In addition, the sensitive analysis of indoor air quality showed that occupancy density and HVAC design faults have the highest impact on comfort levels. Similarly, the windows to walls ratio has the biggest influence on the quality of light, suggesting that a window-to-wall ratio somewhere in the middle, between 10 and 40 percent, is the most pleasant choice.

Writing new Python code in the Dynamo block to compete with other market applications that use the Bayesian network is crucial for future research to increase the framework's popularity. In order to enhance the probabilistic model, further research into envelope materials, window control, windows to floor ratio instead of WWR, and the plumbing system are necessary. This paper's paradigm does not account for the complexity of other situations, such as firefighting. Since the authors' prior knowledge influences the accuracy of the predictions, other prediction approaches will need to be explored in future research. Finally, our methodology has yet to include the cost of all the solutions.

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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