Digital Twin technology toward more sustainable buildings Predictive maintenance, energy optimization and occupants' comfort in non-residential buildings

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UiA University of Agder

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Preface

> "If the facts don't fit the theory,
> change the facts."
>
> Albert Einstein

The research described in this dissertation was conducted as part of a doctoral study jointly supported financially by the Department of Engineering Science at the University of Agder (UiA) and the European Union Interreg project through Scandinavian Sustainable Circular Construction (S2C). Haidar Hosamo Hosamo carried out the research from the first of August 2020 as part of a three-year contract. The author wishes to express his profound gratitude to UiA and S2C for the great opportunity they have offered. The author would also like to thank Aalborg County and Steinar Roppen Olsen from Agder County, as well as Eva Hjälmered and Ida Thomsson from Alexanderson Institute for their support and collaboration.

An extended summary and papers 1–7 (in the appendices) have been incorporated into the thesis. The extended summary represents the work as a whole and makes it easy to fully comprehend the study field, objectives, and contributions without going to the appendices. The seven papers offer various contributions and go into further depth on the research technique and the findings.

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Abstract

The integration of digital technologies in the form of sensor networks and automation systems has a significant impact on the Architecture, Engineering, and Construction-Facility Management (AEC-FM) industry in terms of data monitoring and management. By combining the real and digital worlds, developments in digital technologies like Digital Twin provide a high-level depiction of buildings and their assets. This thesis covers a wide range of topics, including building information management and the interaction of building systems, where the Digital Twin technology becomes a solution to organizing data and generating new study lines on data interchange and BIM (Building Information Modeling)-FM interoperability. In order to contribute to digitalization and automation solutions for building management, the initial step in this thesis was to prepare a review of research on study patterns, gaps, and trends in the AEC-FM industry. After a complete bibliometric search of Google Scholar, Web of Science, and Scopus and following selection criteria, 77 academic publications about the Digital Twin application in the AEC-FM industry were labeled and clustered accordingly. The results demonstrate that information standardization, predictive maintenance, users' comfort, and optimizations are the marked fields where the Digital Twin in the AEC-FM industry should be implemented to reach Zero Emission Buildings (ZEB). This work suggests several novel frameworks for Digital Twin for building management as a place to start a further investigation.

In order to get around the shortcomings of the facility maintenance management (FMM) systems now used in buildings, the next stage in this research was to develop a Digital Twin predictive maintenance framework for the Air Handling Unit (AHU). BIM, IoT (internet of things), and semantic technologies are used as a part of the Digital Twin technology, which is still in its infancy in the facility management sector, to improve building facility maintenance strategies. Three modules are used to develop a predictive maintenance framework: maintenance planning, condition prediction using machine learning, and operating fault detection in AHU based on the APAR (Air Handling Unit Performance Assessment Rules) approach. Inspection data and past maintenance records may also be acquired through the FM system. In order to confirm that the strategy was workable, the suggested framework was also put to the test in a real-world case study using data from August 2019 to October 2021 for an educational building in Norway (I4Helse). The integration of BIM with predictive maintenance resulted in a powerful solution for decision-making in facility management. A RESTful API and plug-in extension were developed for Autodesk Revit using C sharp, seamlessly connecting the BIM model with sensor data

and enhancing understanding and analysis. A RESTful API served as an additional layer, enabling the extraction of data from individual devices in the building, granting access to a wide range of diagnosed devices, maintenance records, and historical alarms and faults. The fully-featured plug-in empowered facility managers to access real-time sensor data through the RESTful API, update the BIM model, and save it in the relevant condition database. The COBie extension plug-in converted BIM data to COBie spreadsheets, while the mapping of COBie data attributes with the FM database was achieved using the Brick Schema. The implementation of the APAR method led to the identification of 25 faults in AHU systems. Machine learning algorithms, including ANN, SVM, decision trees, and based on data from BIM, BMS, CMMS, and sensor data, were compared to predict the faults, with ANN outperforming others in accuracy. Therefore, ANN was used to predict the future faults within one and 4.5 months ahead which could predict most of the faults in AHU. This integrated approach enabled facility managers to effectively monitor degradation, plan resources, save energy, and improve thermal comfort for occupants, creating a comprehensive solution for optimized facility management.

The heating, ventilation, and air conditioning Digital Twin (HVACDT) system was presented as the third study area in this thesis to minimize energy consumption while enhancing thermal comfort. The framework is designed to make it easier for facility managers to comprehend how a building operates and improve HVAC system performance. The Digital Twin framework is based on BIM. It includes a newly developed plug-in for Matlab programming that allows for real-time sensor data, thermal comfort, and optimization processes. Data were gathered from a Norwegian non-residential building (I4Helse) between August 2019 and October 2021 and used to test the framework to see if it is viable. The HVAC system is then enhanced using a multiobjective genetic algorithm (MOGA) and an artificial neural network (ANN) in a Simulink model. The HVAC system includes, among other things, air distributors, hydronic cooling and heating units, pressure regulators, valves, air gates, and fans. In this context, numerous features are considered choice variables, including temperature, pressure, ventilation, cooling, heating operation management, and other elements. In this study, Post-occupancy evaluation (POE) was utilized to create a user satisfaction survey focusing on thermal comfort. The survey included both physical and non-physical comfort aspects, and participants were asked to provide feedback on various comfort parameters related to their workplace. Additionally, respondents were requested to rate their satisfaction with the thermal characteristics of common areas in the building. To organize the spatial data, room information from the building's incomplete BIM model was supplemented with laser scanner data. The point cloud model was processed in Autodesk ReCap Pro and Autodesk Revit to create an accurate representation for collecting occupants' feedback. The predicted mean vote (PPD) and HVAC energy consumption are calculated to derive objective functions. The decision factors and objective function of ANN were hence highly connected. The accuracies of wavelet neural network (WNN), random forest (RF), support vector machine (SVM), and artificial neural network (ANN) forecasting models were compared using R^2 and

Root Mean Square Error (RMSE) metrics. The ANN model exhibited the highest R^2 value (0.93) and the lowest RMSE value (0.027), surpassing the performance of the WNN, SVM, and RF models. These results indicate that the ANN model achieved the best prediction fitting outcomes and had the lowest forecast fitting error, highlighting its superiority in accuracy compared to the other models. Additionally, MOGA offers a variety of design elements that may be utilized to find the greatest thermal comfort and energy-saving options. The Pareto optimum solution for minimizing energy consumption and Predicted Percentage of Dissatisfied (PPD) was presented, with an optimization process that took approximately 7.055 hours. It revealed the trade-off between the two objective functions. Reducing energy consumption from 62.8 kW to 46.4 kW resulted in an increase in PPD from 6.2% to 27% during winter while reducing energy consumption from 59 kW to 42.9 kW led to an increase in PPD to 22.4% during summer. The minimum PPD values were 6.2% for winter, indicating maximum thermal comfort. However, this came with the highest energy consumption of 62.8 kW in winter and 59 kW in summer. On the other hand, the lowest energy consumption was 46.4 kW in winter and 42.9 kW in summer, but with high PPD (27% in winter and 22.4% in summer). The choice of the best solution depends on whether energy, thermal comfort, or both were considered the main priority. The findings indicate that the average cooling energy savings for four summer days are around 13.2%. For the three summer months (June, July, and August), they are 10.8%, maintaining the PPD below 10%. Regarding data handling, the HVACDT framework exhibits a higher level of automation than conventional methods. Another plug-in was developed to stream the optimization results back to the BIM model.

In order to explore how building components affect energy use and determine the best design, this research then proposed a method that integrates BIM, machine learning, and the non-dominated sorting genetic algorithm-II (NSGA II). A plug-in is being created to receive sensor data and export the required data from BIM to MSSQL and Excel. To run an energy consumption simulation, the BIM model of Tvedestrand VGS was loaded into IDA Indoor Climate and Energy (IDA ICE). The model in IDAC ICE was validated using the sensor data. To explore the potential solutions, we initially generated 1,236,912 combinations of decision variables. However, by employing pairwise testing, we effectively reduced the combinations to 8000, covering all possible solutions more efficiently. Each combination was used as input for IDA ICE, running one simulation to obtain the annual energy consumption. Completing all simulations required approximately 16 days. The resulting database, consisting of the 8000 combinations and their respective energy consumption values, was then utilized as input for machine learning algorithms through visual programming (Dynamo). The optimization process took a wide range of input variables into account. The most significant characteristics in the literature guided the selection of the initial set of variables related to the building envelope, such as U-values. Additionally, variables like minimum air supply, window-wall ratio, solar heat gain coefficient (SHGC), load (lighting), activation of shading, reflectance, night ventilation, shading factor, air infiltration, supply air temperature setpoints in AHU, supply water temperature setpoints from the central heating system, and heat exchanger efficiency in AHU were considered. The optimization of the latter variables, in combination, was absent from the literature, and no research investigated the combined control of these two types of variables for the optimization process, i.e., HVAC with building envelope variables. Although there were over 40 variables that could be included based on the literature, the ANOVA-SVM method was employed to identify and prioritize the most important variables for consideration in the optimization process. Eleven machine learning algorithms are utilized to analyze the 8000 simulations and create a prediction model between building characteristics and energy use including Linear Regression (LR), ANN with one layer and 10 neurons, ANN with one layer and 100 neurons, Support Vector Machine (SVM), Gaussian Process Regression (GPR), Deep Neural Network (DNN), Random Forest (RF), Extreme Gradient Boosting (XGB), Artificial Neural Network-Support Vector Machine (ANN-SVM), Least Square Support Vector Machine (LSSVM), Group Method of Data Handling (GMDH), and Group Least Square Support Vector Machine (GLSSVM). The best algorithm was Group Least Square Support Vector Machine (GLSSVM), which was eventually used in NSGA II as the fitness function for calculating building energy consumption. According to the findings, the results indicate that the energy consumption and PPD of the Pareto optimum solutions are frequently lower, with values below 50 kWh/m^2.year and 9%, respectively, compared to the original design solution's energy consumption of 61.17 kWh/m^2 and PPD of 18.5%. This suggests that the NSGA-II solutions have the capability to effectively reduce the building's energy consumption while simultaneously improving thermal comfort. The results show that building energy consumption and thermal comfort may be successfully improved by the GLSSVM-NSGA II hybrid technique, which reduces energy consumption by 37.5% and increases thermal comfort by 33.5%, respectively. Brick, BOT, and SSN, which are based on COBie and IFC data were used for data integration in this part of the thesis. In addition, the results show that the energy-efficient design of the building envelope should prioritize the U-value of exterior walls, followed by roofs, windows, and the window-to-wall ratio. By utilizing the innovative GLSSVM-NSGAII multi-objective technique, design modifications can be implemented to enhance building energy consumption and thermal comfort performance even before construction. This approach aids in selecting suitable building materials and designs. Additionally, factors such as shading, solar heat gain coefficient (SHGC), reflectance, and activation play a crucial role and are determined based on solar radiation and outer window air infiltration. Other important input parameters for achieving optimal solutions include envelope settings and efficient heat exchangers in the air handling unit (AHU). Subsequently, adjustments can be made to the ventilation supply air temperature and flow rate in the AHU, as well as the supply water temperature from the central heating plant to the local radiators.

The next stage was to assess the application of Digital Twin for fault detection in buildings, considering various building systems and aiming to enhance occupants' comfort across various aspects. Firstly a new review study was implemented to discover this area which led to the following research. A probabilistic model based on Bayesian networks (BNs) was used to assess the performance of two buildings in this case, I4Helse and Tvedestrand VGS. The analysis of factors contributing to occupants' comfort in a building involved three stages. Firstly, survey forms were developed for a user satisfaction survey, capturing convenience factors such as thermal comfort, acoustic comfort, indoor air quality, visual comfort, and space adequacy. Occupants provided feedback on various aspects using a Likert scale and had the opportunity to provide additional comments. Secondly, a probabilistic model based on a Bayesian Network (BN) was developed, considering survey findings and important factors for discomfort in buildings. The BN model incorporated building and environmental information, complemented by parameters added to the BIM model. Lastly, a plug-in and visual programming interface were used to connect the BIM model, occupants' feedback, and the probabilistic model, enabling the FM team to interpret data through BIM visualization and causal analysis. Then the research work in this thesis provided a framework that follows a systematic approach to address comfort issues in buildings. Firstly, it checks for electrical issues in the HVAC system, and if none are found, it utilizes a Bayesian Network (BN) to identify HVAC design issues related to thermal comfort. If there are design issues, it examines whether the HVAC system is inadequate to meet occupants' thermal demands. Proper architectural design allows for automatic computation of the thermal load and retrieval of indoor unit capacity from the equipment database. In cases where undersized HVAC components cause discomfort, options include insulating the room's façade or using interior units with larger cooling or heating capacities. If the indoor unit capacity exceeds the thermal load, the framework applies the APAR rules to identify failures in indoor or outdoor HVAC system equipment. The framework also addresses issues related to visual comfort, acoustic comfort, and spatial adequacy, considering factors such as window-to-wall ratio, room lighting, shade management, acoustic insulation materials, room cleanliness, adaptability, accessibility, and ergonomic furnishings. This comprehensive decision-making framework assists facility managers in detecting and addressing building faults effectively. To improve the predictive maintenance framework, the forecasting procedure considers fault detection findings from a Bayesian network over three years of data, generating building faults and maintenance requests. The proposed predictive maintenance system supports adaptive model training and prediction, continuously adjusting parameters based on updated sensor data and service logs. The study's results indicate that acoustic discomfort is primarily attributed to inadequate internal wall insulation rather than ventilation or the absence of attenuators. Using BIM visualization, facility managers can simulate different scenarios by manipulating causal elements to assess occupants' satisfaction likelihood. Isolating internal walls can enhance acoustic comfort, but if budget constraints exist, incorporating acoustic attenuators into the ventilation systems is a more practical option. The sensitivity analysis implemented in this work shows that occupancy density and HVAC design faults are identified as crucial factors influencing indoor air quality. Visual dissatisfaction with the building I4Helse is linked to its low window-to-wall ratio (WWR), while occupants of Tvedestrand School express greater satisfaction with light quality. Window-to-wall ratio plays a vital role in light quality, with an optimal range of 10 to 40 percent. The trained ANN model is chosen for HVAC system predictions, demonstrating the framework's ability to anticipate future scenarios up to two months in advance, emphasizing the dynamic nature of maintenance schedules.

This study was extended to explore the space adequacy problem and advance the predictive maintenance process by testing 9 machine learning algorithms. The sensitivity analysis categorizes potential reasons for space inadequacy into low, medium, and high potential based on their likelihood to cause discomfort and impact employee comfort. Reasons with low potential have minimal impact and are easily addressed, such as a lack of personalization. Reasons with medium potential require more significant changes, like noise pollution or poor ergonomics. Reasons with high potentials, such as poor lighting or air quality, have a significant impact and require substantial modifications. By prioritizing these reasons, resources can be allocated effectively to improve employee comfort. BIM is valuable for assessing and addressing space adequacy as part of a Digital Twin. For predictive maintenance, the Extreme Gradient Boosting (XGB) algorithm outperforms others, while Random Forest is faster and easier to implement. The study introduces a method to determine HVAC's remaining useful life, potentially extending it by at least 10% and resulting in cost savings. Poor air quality, lack of natural light, and uncomfortable temperature emerge as the most influential factors affecting occupant comfort.

By employing the Digital Twin architecture, this study utilizes operational data, testing, and assessments to ensure the integrity of the system model. Decision-makers can rely on the information generated by the digital system to support their real-world project decisions. Furthermore, the Digital Twin can forecast upcoming changes in the physical system by allowing users to evaluate and simulate various scenarios and devise effective strategies. This framework has the potential to uncover new practical opportunities that can be implemented in both the physical system and its simulated counterparts, offering significant benefits and enhancing system performance in the real world.

Sammendrag

Digital tvilling for prediktivt vedlikehold, energieffektivisering, og personkomfort i kommersielle bygg er et forskningsområde som setter søkelys på å utnytte teknologi for å øke effektiviteten til bygninger innenfor disse områdene. Gjennom å bruke digital tvilling-teknologi, kan man simulere og analysere driften av et bygg, og bruke dette til å forutsi mulige feil og identifisere muligheter for energieffektivisering. Dette kan bidra til å øke levetiden og energieffektiviteten til bygningen.

I tillegg til å forbedre vedlikehold og energieffektivisering, kan digital tvilling også bidra til å øke personkomforten for de som bruker bygningen. Dette kan gjøres ved å bruke teknologi for å optimalisere temperaturen, luftfuktigheten, og andre faktorer som påvirker komforten. Ved å holde disse faktorene innenfor best mulige nivåer, kan man bidra til å redusere stress og øke produktiviteten til brukerne av bygningen. I forskningen vår har vi brukt prediktivt vedlikehold for ventilasjonssystemet ved å kombinere regler funnet ved hjelp av litteratursøk og av eksperter som har erfaring med drift av ventilasjonssystemer (det vil si AHU performance assesment rules eller APAR) på maskinlæring, basert på to års data fra Tvedestrand videregående skole og I4Helse (universitetsbygning) i Norge. APAR-reglene gir en metodisk tilnærming for å vurdere ytelsen til ventilasjonsaggregater basert på målte data fra systemet, og kan bidra til å identifisere potensielle problemer og feil før de oppstår. Disse reglene brukes sammen med maskinlæringsmetoder for å analysere kontinuerlig oppdaterte data fra ventilasjonssystemet, og for å forutsi fremtidige tilstander og potensielle feil. Dette gjør det mulig å utføre prediktivt vedlikehold og planlegge vedlikeholdsarbeid før det oppstår alvorlige problemer som kan føre til driftsfeil og energitap. Dette viser at prediktivt vedlikehold ved hjelp av digital tvilling-teknologi kan være en formålstjenlig metode for å øke effektiviteten og levetiden til ventilasjonssystemet i kommersielle bygg.

I neste steg av forskningen vår, bygget vi en digital tvilling av et varme- og ventilasjonssystem i Matlab. Deretter brukte vi bygningsinformasjonsmodellering, tingenes internett, maskinlæring, og multiobjektive genetiske algoritmer for å utvikle systemet ytterligere. Når det gjelder databehandling, viser den digitale tvillingen for varme- og ventilasjonssystemet et høyere nivå av automatisering enn vanlige metoder. I denne studien ble evaluering av bygninger i bruk (Post-Occupancy Evaluation, POE) benyttet for å lage en brukertilfredshetsundersøkelse med fokus på termisk komfort. Undersøkelsen inkluderte både fysiske og ikke-fysiske komfortaspekter, og deltakerne ble bedt om å gi tilbakemelding på ulike komfortparametere knyttet til arbeidsplassen deres. I tillegg ble respondentene bedt om å vurdere sin

tilfredshet med de termiske egenskapene til fellesområdene i bygningen. Rominformasjon fra bygningens ufullstendige BIM-modell ble supplert med laserskannerdata for å organisere romdata. Punktsky-modellen som kom fra laserskanner ble behandlet i ReCap Pro og Revit for å lage en nøyaktig representasjon for å samle inn tilbakemelding fra brukerne. Nøyaktighetene til forskjellige prognosemodeller, inkludert wavelet neural network (WNN), random forest (RF), support vector machine (SVM), og artificial neural network (ANN), ble sammenlignet. ANN-modellen overgikk alle andre modeller i nøyaktighet. Den Pareto optimale løsningen for å minimere energiforbruket og PPD ble presentert, med en optimaliseringsprosess som tok omtrent 7,055 timer. Den avdekket avveiningen mellom de to målene. Redusert energiforbruk førte til en økning i PPD både om vinteren og sommeren. Valget av den beste løsningen avhenger av om energi, termisk komfort, eller begge deler ble vurdert som hovedprioritet. Resultatene indikerer at gjennomsnittlig kjøleenergibesparelse for fire sommerdager er rundt 13,2%, og for de tre sommermånedene er det 10,8%, med PPD under 10%. I forhold til databehandling, viser HVACDT-rammeverket et høyere nivå av automatisering enn tradisjonelle metoder. En annen plugin ble utviklet for å sende optimaliseringsresultatene tilbake til BIM-modellen.

For å utforske hvordan bygningskomponenter påvirker energibruken og for å bestemme det beste designet, foreslo denne forskningen en metode som innpasser varme- og ventilasjonssystemet med andre bygningskomponenter som fasader, tak, belysning, og andre relevante komponenter. Den digitale tvillingen ble bygget i programmet IDA ICE, som ble koblet med bygningsinformasjonsmodellen og 12 maskinlæringsalgoritmer, samt en rask ikke-dominerende sorteringsalgoritme. Resultatene viser at bygningens energiforbruk og personkomfort kan forbedres med denne hybridteknikken som kombinerer maskinlæring og optimalisering. Modellen i IDAC ICE ble validert ved hjelp av sensordata. For å utforske mulige løsninger genererte vi opprinnelig 1,236,912 kombinasjoner av beslutningsvariabler. Ved å bruke parvise tester reduserte vi imidlertid kombinasjonene til 8000, noe som dekket alle mulige løsninger mer effektivt. Hver kombinasjon ble brukt som input for IDA ICE, som kjørte en simulering for å beregne årlig energiforbruk. Fullføring av alle simuleringene tok omtrent 16 dager. Den resulterende databasen, bestående av de 8000 kombinasjonene og deres respektive energiforbruksverdier, ble deretter brukt som input for maskinlæringsalgoritmer gjennom visuell programmering (Dynamo). Optimaliseringsprosessen tok hensyn til et bredt spekter av inputvariabler. De mest betydelige egenskapene i litteraturen veiledet utvalget av det første settet med variabler relatert til bygningskroppen, som U-verdier. I tillegg ble variabler som minimum luftforsyning, vindu-vegg-forhold, solvarmevinningskoeffisient (SHGC), last (belysning), solskjerming, reflektanse, nattventilasjon, luftinfiltrasjon, lufttemperaturinnstilling i AHU, vannforsyningstemperaturinnstilling fra sentralvarmesystemet, og varmevekslerens effektivitet i AHU vurdert. Totalt ble elleve maskinlæringsalgoritmer brukt til å analysere de 8000 simuleringene og lage en prediksjonsmodell mellom bygningsegenskaper og energibruk. Den beste algoritmen var Group Least Square Support Vector Machine (GLSSVM), som til slutt ble brukt i NSGA II som fitness-funksjonen for å beregne bygningens energiforbruk. Resultatene viser at energiforbruket og PPD i de Pareto-optimale løsningene ofte er lavere, med verdier under 50 kWh/m^2.år og 9%, henholdsvis, sammenlignet med det opprinnelige designets energiforbruk på 61,17 kWh/m^2.år og PPD på 18,5%. Dette tyder på at NSGA-II-løsningene har evnen til effektivt å redusere bygningens energiforbruk samtidig som termisk komfort forbedres. Resultatene viser at bygningens energiforbruk og termisk komfort kan forbedres betydelig ved hjelp av GLSSVM-NSGA II hybridteknikken, som reduserer energiforbruket med 37,5% og øker termisk komfort med 33,5%, henholdsvis. Videre viser resultatene at det energieffektive designet av bygningskroppen bør prioritere U-verdien av yttervegger, etterfulgt av tak, vinduer, og vindu-vegg-forholdet. Ved å bruke den innovative GLSSVM-NSGAII multi-objektive teknikken, kan designendringer implementeres for å forbedre bygningens energiforbruk og termisk komfortytelse før konstruksjonen starter. Dette hjelper med å velge egnede byggematerialer og design.

Siste trinn i forskningen vår var å vurdere bruken av digital tvilling for feildeteksjon i bygninger, med tanke på ulike byggesystemer. En Bayesianske nettverksbasert sannsynlighetsmodell ble brukt for å vurdere ytelsen til bygninger med hensyn til termisk komfort, visuell komfort, akustisk komfort og romlig funksjonalitet for personkomfort. BN-modellen er basert på en detaljert undersøkelse av bygningens ytelsesegenskaper og svar på spørsmål om tilfredshetsundersøkelse. I tillegg tilbyr denne studien en bygningsinformasjonsmodell -kompatibel brukervennlig visualisering for å gjøre datainnsamling enklere for Tvedestrand videregående skole og I4Helse, ved hjelp av data fra 2019 til 2022. Studiens funn kan hjelpe beslutningstakere i anleggsadministrasjonsindustrien ved å finne faktorene som påvirker brukerkomforten, akselerere prosessen med å oppdage utstyrsproblemer, og foreslå mulige løsninger. Analysen av faktorer som bidrar til beboernes komfort i en bygning involverte tre trinn. Først ble spørreskjemaer utviklet for en brukertilfredshetsundersøkelse, som fanget opp bekvemmelighetsfaktorer som termisk komfort, akustisk komfort, inneluftkvalitet, visuell komfort, og romtilstrekkelighet. Beboerne ga tilbakemelding på ulike aspekter ved hjelp av en Likert-skala og hadde muligheten til å gi tilleggs kommentarer. For det andre ble en probabilistisk modell basert på et Bayesisk nettverk (BN) utviklet, der undersøkelsesfunn og viktige faktorer for ubehag i bygninger ble tatt i betraktning. BN-modellen inneholdt bygnings- og miljøinformasjon, supplert med parametere lagt til BIM-modellen. Til slutt ble et plugin og et visuelt programmeringsgrensesnitt brukt for å koble BIM-modellen, beboernes tilbakemelding, og den probabilistiske modellen, noe som muliggjorde at FM-teamet kunne tolke data gjennom BIM-visualisering og kausal analyse.

Denne studien ble utvidet for å utforske problemet med romtilstrekkelighet og forbedre den prediktive vedlikeholdsprosessen ved å teste 9 maskinlæringsalgoritmer. Følsomhetsanalysen kategoriserer potensielle årsaker til romtilstrekkelighet i lav, middels, og høy potensial basert på deres sannsynlighet for å forårsake ubehag og påvirke ansattes komfort. Årsaker med lavt potensial har minimal innvirkning og er lette å løse, som for eksempel mangel på personlig tilpasning. Årsaker med middels potensial krever mer betydelige endringer, som støyforurensning eller dårlig ergonomi. Årsaker med høyt potensial, som dårlig belysning eller luftkvalitet, har en betydelig innvirkning og krever omfattende modifikasjoner. Ved å prioritere disse årsakene, kan ressursene allokeres effektivt for å forbedre ansattes komfort. BIM er verdifullt for å vurdere og håndtere romtilstrekkelighet som en del av en digital tvilling. For prediktivt vedlikehold presterer den ekstreme gradientøkningsalgoritmen (XGB) bedre enn andre, mens Random Forest er raskere og lettere å implementere. Studien introduserer en metode for å bestemme HVACs gjenværende nyttige levetid, noe som potensielt kan forlenge den med minst 10% og resultere i kostnadsbesparelser. Dårlig luftkvalitet, mangel på naturlig lys, og ubehagelig temperatur fremkommer som de mest innflytelsesrike faktorene som påvirker beboernes komfort.

For å oppsummere, denne forskningen har undersøkt bruken av digital tvilling-teknologi for å forbedre prediktivt vedlikehold, energieffektivisering, og komfort i kommersielle bygg. Vi har vist at det er mulig å finne feil og forutsi fremtidig tilstand for ventilasjonssystemets komponenter ved å bruke kontinuerlig oppdaterte data, APAR, og maskinlæringsmetoder. Dette kan bidra til vedlikeholdsplanlegging og eliminering av driftsfeil, noe som førte til en årlig energibesparelse. Vi har også vist at ved å innpasse varme- og ventilasjonssystemet med andre bygningskomponenter, og bruke hybridteknikker som kombinerer maskinlæring og optimalisering, kan bygningens energiforbruk og termisk komfort føre til en reduksjon i energiforbruket på 37,5 % og en økning i termisk komfort på 33,5 %. Videre har vi vurdert bruken av digital tvilling for feildeteksjon i bygninger ved hjelp av en sannsynlighetsmodell basert på Bayesianske nettverk, og vist at denne modellen kan gi informasjon om hvilke faktorer som påvirker brukerkomforten, og hjelpe med å oppdage problemer på utstyr, som gjør det enklere for driftsorganisasjonen å ta valg. Alt i alt viser vår forskning at digital tvilling-teknologi kan være et nyttig verktøy for å forbedre vedlikehold, energieffektivisering, og komfort i kommersielle bygg.

Publications

This thesis is composed of the author's published journal papers and one submitted paper, which are listed below:

Paper 1: H. H. Hosamo, A. Imran, J. Cardenas-Cartagena, P. R. Svennevig, K. Svidt, H. K. Nielsen, "A Review of the Digital Twin Technology in the AEC-FM Industry," Advances in Civil Engineering, vol. 2022, Article ID 2185170, 17 pages, 2022. https://doi.org/10.1155/2022/2185170

Paper 2: H. H. Hosamo, P. R. Svennevig, K. Svidt, D. Han, H. K. Nielsen, "A Digital Twin Predictive Maintenance Framework of Air Handling Units based on Automatic Fault Detection and Diagnostics," Energy and Buildings (2022) 111988. doi: 10.1016/j.enbuild.2022.111988

Paper 3: H. H. Hosamo, M. H. Hosamo, H. K. Nielsen, P. R. Svennevig, K. Svidt, "Digital Twin of HVAC system (HVACDT) for multiobjective optimization of energy consumption and thermal comfort based on BIM framework with ANN-MOGA," Advances in Building Energy Research (2022) 1–49, publisher: Taylor & Francis. doi:10.1080/17512549.2022.2136240.

Paper 4: H. H. Hosamo, M. S. Tingstveit, H. K. Nielsen, P. R. Svennevig, K. Svidt, "Multiobjective optimization of building energy consumption and thermal comfort based on integrated BIM framework with machine learning-NSGA II," Energy and Buildings 277 (2022) 112479. doi: 10.1016/j.enbuild.2022.112479.

Paper 5: H. H. Hosamo, H. K. Nielsen, A. N. Alnmr, P. R. Svennevig, K. Svidt, "A review of the Digital Twin technology for fault detection in buildings," Frontiers in Built Environment 8 (2022). https://doi.org/10.3389/fbuil.2022.1013196

Paper 6: H. H. Hosamo, H. K. Nielsen, D. Kraniotis, P. R. Svennevig, K. Svidt, "Digital Twin framework for automated fault source detection and prediction for comfort performance evaluation of existing non-residential buildings," Energy and Buildings (2023). doi: 10.1016/j.enbuild.2022.112732.

Paper 7: H. H. Hosamo, H. K. Nielsen, D. Kraniotis, P. R. Svennevig, K. Svidt, "Improving Building Occupant Comfort through a Digital Twin Approach: A Bayesian Network Model and Predictive Maintenance Method," Energy and Buildings (2023). doi: 10.1016/j.enbuild.2023.112992.

Contents

List of Figures

List of Tables

Nomenclature

Notations

a	Air
cw	Cold water
hi	Heat in
ho	Heat out
hw	Hot water
i	In
o	Out
ot	Outside
r	Room
wi	Water in
wo	Water out

Abbreviations

AFDD Automated fault detection and diagnostics

AHU Air handeling unit

ANN Artificial neural network

ANOVA Analysis of variance

APAR Air handling unit performance assessment rules

API Application programming interface

BACnet Building automation and control networks

BEM Building energy management

BIM Building information modeling

BMS Building management system

BN Bayesian network

BOT Building ontology topology

CMMS Computerized maintenance management systems

COBie Construction operations building information exchange

DNN Deep neural network

FDD Fault detection and diagnostics

FFNN Feed forward neural network

FM Facility manager

FMM Facility maintenance management

GA Genetic algorithm

GB Gradient boosting

GBM Gradient boosting machines

GLSSVM Group least square support vector machine

GMDH Group method of data handling

GMM Gaussian mixture modelling

GPR Gaussian process regression

HVAC Heating, ventilation, and air conditioning

HVACDT Heating, ventilation, and air conditioning Digital Twin

IEQ Indoor environmental quality

IFC Industry foundation classes

IoT Internet of things

KNN K-nearest neighbors

LR Linear regression

LSSVM Least squares support vector machine

LSTM Long short-term memory

ML Machine learning

MLR Multiple linear regression

NN Neural network

NSGA Non-dominated Sorting Genetic Algorithm

PM Predictive maintenance

PMV Predicted mean vote

PPD Predicted percentage of frustrated

RDF Resource description framework

RF Random forest

RMSE Root Mean Square Error

RNN Recurrent neural networks

ROC Receiver operating characteristic curve

SSN Semantic sensor network

SVM Support vector machine

SVR Support vector regression

URL Uniform resource locator

VAV Variable air volume

WFR Windows to floor ratio

WWR Windows to wall ratio

XGB Extreme gradient boosting

Symbols with units

η Efficiency [-]

ν_{Fan} fan efficiency [-]

$\rho_{density}$ Density [kg/m^3]

$\rho_{occupants}$ Occupants density [m^2/person]

θ_s Saturation water vapour content [kg/kg]

C_P Specific heat capacity [kJ/kg K]

f_{cl} Body's surface area when fully clothed to the body's total surface area while naked [-]

I_{cl} Thermal resistance of clothing [m^{2}K/W]

M_{ai} Mass airflow rate [kg/s]

M_{cw} Mass water flow rate for cooling [kg/s]

M_{hw} Mass water flow rate for heating [kg/s]

P_a Partial vapour pressure [Pa]

R_a Ventilation rate to dilute contaminants generated by building-related sources [m^3/s]

R_p Ventilation rate to dilute pollutants created by occupants [m^3/s]

T_i Temperature after rotary heat exchanger [°C]

T_{ai} Ambient air temperature [°C]

T_{cl} Clothing's surface temperature [°C]

T_{hi} Supply heating water temperature [°C]

T_{ho} Return heating water temperature [°C]

T_{ui} Supply air temperature to zones [°C]

T_{uo} Return air temperature [°C]

T_{wi} Supply cooling water temperature [°C]

T_{wo} Return cooling water temperature [°C]

V^0 Volume flow rate [m^3/s]

V_{air} Air volume delivered by the fan [m^3/s]

V_{ot} Minimal ambient airflow rate to building [m^3/s]

A Area [m^2]

COP The coefficient of performance [-]

inf Infiltration [m^3/s]

L Body thermal load [-]

M Metabolic rate [met]

Q Cooling or heating load [kW]

RH Relative humidity [-]

Tr Average radiant temperature [°C]

W External work [W]

Chapter 1

Introduction

> "You've achieved success in your field when you don't know whether what you're doing is work or play."
>
> Warren Beatty

In the context of building design and operation, the importance of studying energy consumption and occupants' comfort cannot be overstated. Not only does optimizing energy usage contribute to environmental preservation, but it also offers significant benefits in terms of reducing energy costs for organizations and individuals. At the same time, providing occupants with comfortable indoor environments is crucial for their overall well-being and productivity. Elements such as pleasant temperatures, good air quality, and appropriate lighting directly influence occupants' satisfaction, performance, and health. Research efforts aim to strike a balance between energy-saving measures and maintaining optimal comfort levels, recognizing that these factors are integral to sustainability, economic considerations, and the quality of indoor spaces. The term "spaces" refers to indoor spaces or enclosed environments where people live, work, or spend time. It includes buildings, offices, homes, schools, and any other constructed areas where individuals reside or carry out various activities.

By implementing energy-efficient technologies and strategies that do not compromise occupants' comfort, it becomes possible to achieve both environmental responsibility and optimal living and working conditions. This aligns with the broader goals of sustainability, as reducing carbon footprints and minimizing energy waste are essential for mitigating climate change. Simultaneously, prioritizing occupants' comfort creates healthier and more productive indoor environments, benefiting individuals and organizations alike. Through research endeavors, the emphasis on energy-saving measures and comfort is justified, as these critical aspects not only align with sustainability objectives but also address economic considerations and the overall quality of indoor environments.

In this thesis, the focus lies on developing a Digital Twin framework that integrates real-time data, expert rules, and machine learning algorithms to optimize energy usage and enhance occupants' comfort in non-residential buildings. By considering factors such as HVAC systems, building envelopes, and spatial design, the framework aims to provide practical solutions for reducing energy consumption while improving the indoor environment. The investigation includes case studies of I4Helse and Tvedestrand VGS buildings in Norway, which serve as real-world examples to showcase the effectiveness of the framework in achieving energy efficiency and occupants' comfort. Through this research, valuable insights will be gained, contributing to a better understanding of how to optimize building performance, enhance occupant well-being, and guide decision-making processes in non-residential buildings.

1.1 Motivation

The present rate at which the planet is warming is inextricably linked to the energy consumed by buildings. As a whole, the building sector is responsible for 40% of all energy used in the EU and 40% of all GHG emissions in the EU [16, 17, 18]. Roughly 62% of buildings in Norway are non-residential, which includes vacation homes, and 40% of Norway's overall energy usage goes toward buildings (including homes and businesses) [19]. The percentage of energy usage by non-residential buildings in Norway accounts for approximately 14% of the total energy consumption in mainland Norway (31 TWh in 2019) [20]. Figure 1.1, represents the energy consumption breakdown in different categories. The combined figure, consisting of two pie charts, provides a visual representation of the energy consumption breakdown in different categories for both office buildings and school buildings. Figure (a) illustrates the distribution of energy consumption within office buildings, with categories such as room heating, lighting, and technical equipment accounting for varying percentages. Figure (b) highlights the energy consumption breakdown in school buildings, showcasing categories like room heating, ventilation heating, and lighting. The pie charts allow viewers to quickly grasp the proportional distribution of energy consumption among these categories, aiding in understanding the key contributors to overall energy usage. The visual presentation of the data facilitates informed decision-making and enables stakeholders to identify areas for potential energy efficiency improvements or targeted conservation efforts.

The critical need to improve the energy performance of non-residential buildings is further emphasized by the fact that energy consumption in Norway's non-residential sector has increased by around 31% since 1990, while residential building energy use has increased by about 9% [19]. Cold-climate countries face additional challenges regarding the improvement of energy efficiency in buildings due to the high heating needs and low average temperatures. This means that the construction industry is one of several that might benefit from investigating energy efficiency measures to achieve complete sustainable development [21, 22, 23].

Energy efficiency has been a major topic of discussion. However, the emergence of automated building analytics and big data technologies has expanded facility managers' ability to predict future conditions and not only react to the faults in buildings after they occur. This is what is called predictive maintenance. Given that

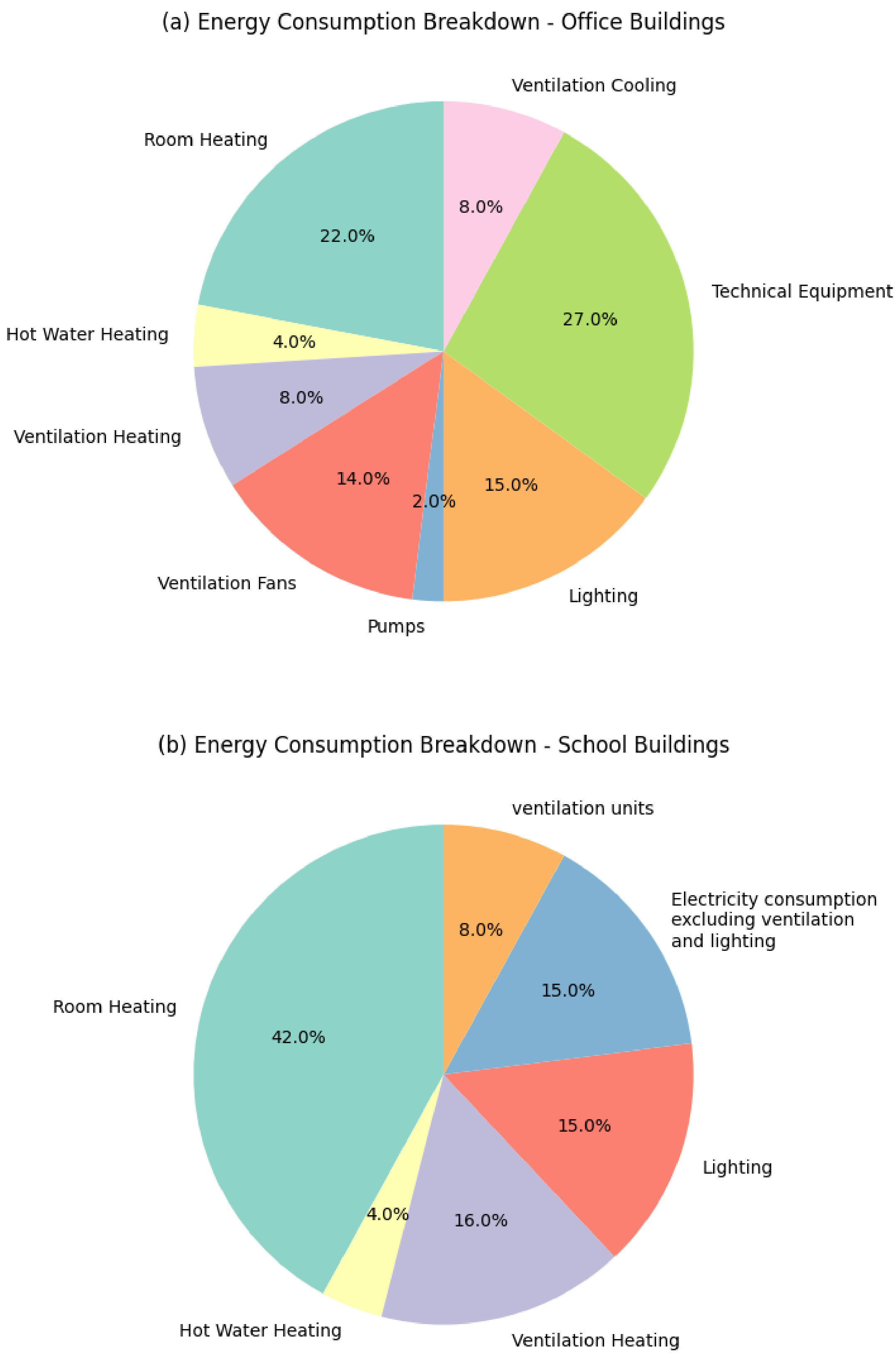


Figure 1.1: Pie chart showing the percentage distribution of energy consumption in Norwegian (a) office buildings based on TEK10 [8], and (b) school buildings [8].

a significant portion, around 65%, of yearly facility management costs is dedicated to maintenance, implementing a predictive maintenance strategy is crucial [24, 25]. Predictive maintenance may result in longer equipment life, less energy consumption, better performance, and lower labor expenses.

However, in buildings like schools and offices, where the interior climate may significantly impact the productivity of those who work or study there, it is crucial to consider the comfort and well-being of the building's users when evaluating the building's energy efficiency. Improving a building's energy performance toward zero emission buildings (ZEB) while maintaining thermal comfort is a formidable challenge, where better indoor climate control might lead to more power use [26, 27, 28]. For this reason, a solution has been proposed in this work by using the Digital Twin technology, a digital replica of the physical objects in real-time [29, 30] to help facility managers reduce energy consumption, increase users' comfort, and predict future situations in building systems.

1.2 Objective and research questions

The primary objective of this thesis research is to develop a Digital Twin framework specifically designed for non-residential buildings. This framework aims to optimize the operation and design phase of these buildings by reducing energy consumption, enhancing occupants' comfort, and providing accurate forecasts of future conditions such as fault detection. By utilizing the Digital Twin approach, the framework will enable real-time monitoring, analysis, and simulation of building performance, facilitating data-driven decision-making and enabling the implementation of energy-efficient strategies. Ultimately, the goal is to create a comprehensive solution that contributes to sustainable and efficient building operations, resulting in reduced energy usage and improved user experiences. Figure 1.2 illustrates the overarching goals that drive our research and serve as the foundation for the study. These objectives provide a roadmap for the investigation and guide the subsequent chapters of this thesis.

The logic between the four steps, starting from AHUs (Air Handling Units) and progressing to HVAC (Heating, Ventilation, and Air Conditioning), building envelope, and space, revolves around the holistic optimization and predictive maintenance of indoor environments in buildings. AHUs are initially focused on for predictive maintenance, ensuring efficient and reliable operation. Moving forward, the optimization scope expands to encompass the entire HVAC system, enabling energy efficiency and occupant comfort. Additionally, attention is directed towards the building envelope, which includes elements like walls, windows, roofs, and insulation. The building envelope plays a crucial role in controlling heat transfer, water vapor transform, and air leakage, impacting energy consumption and indoor environmental quality. Finally, the concept of "space" in buildings refers to the physical areas within a structure, encompassing rooms, corridors, and open areas. Optimizing and maintaining spaces involve considerations such as temperature con-

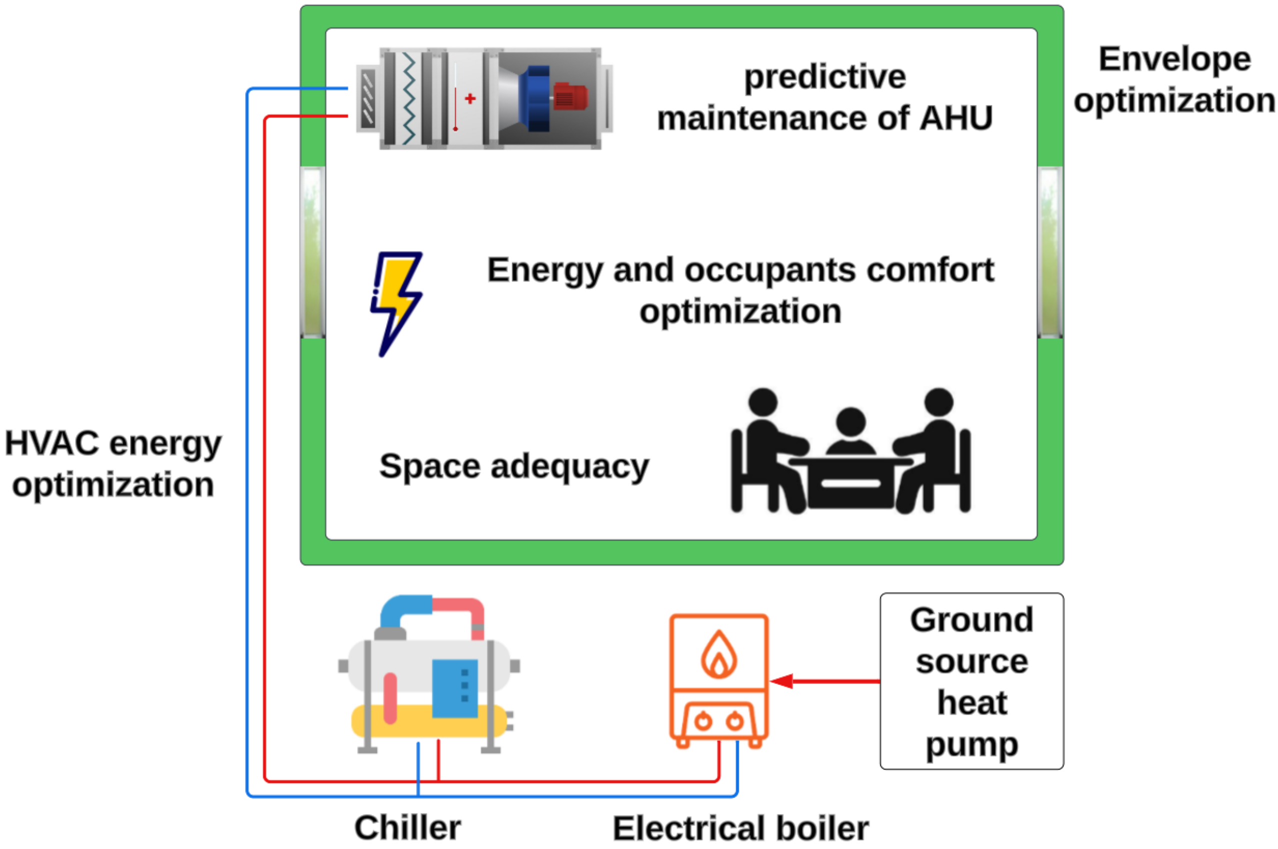


Figure 1.2: The main objectives of this thesis.

trol, air quality, lighting, acoustics, and overall occupant well-being. By integrating these steps, a comprehensive approach is established, ensuring the optimization and predictive maintenance of AHUs, HVAC systems, building envelope, and spaces to achieve energy efficiency, comfort, and a healthy indoor environment.

Energy saving and comfort are essential aspects that hold significant importance in research related to AHUs, HVAC systems, building envelope, and spaces. These factors have been highlighted as key objectives and questions due to their substantial impact on both environmental sustainability and occupant well-being. Energy saving is crucial to address the global challenge of reducing carbon emissions and mitigating climate change. By optimizing the operation of AHUs, HVAC systems, and building envelope, significant energy savings can be achieved, leading to reduced carbon footprints and increased energy efficiency. This not only contributes to environmental preservation but also helps organizations and individuals reduce energy costs. Simultaneously, occupant comfort is paramount for creating healthy and productive indoor environments. Comfortable indoor temperatures, good air quality, and adequate lighting contribute to occupant satisfaction, productivity, and well-being. By incorporating energy-saving measures without compromising comfort, research endeavors aim to strike a balance between environmental responsibility and providing occupants with optimal living and working conditions. Thus, the emphasis on energy saving and comfort is justified as they represent critical aspects that align with sustainability, economic considerations, and the quality of the indoor environment.

Out from that, the research aims to achieve the following objectives in the context of Digital Twin technology:

1. Investigate the current state and potential of Digital Twin technology in the Architecture, Engineering, and Construction (AEC) industry, specifically focusing on its application in non-residential buildings. This objective involves examining the existing literature, case studies, and industry practices to understand the implementation, challenges, and benefits of Digital Twins in the AEC sector.

2. Develop a comprehensive Digital Twin framework specialized in predictive maintenance for non-residential buildings, utilizing real-time data, expert rules, and machine learning algorithms. The objective is to enhance operational efficiency, improve occupants' thermal comfort, and establish a generalized framework that can be applied to various building types and contexts. This includes integrating BIM, IoT devices, and Facilities Management (FM) systems into the framework to enable data integration and decision-making.

3. Expand the Digital Twin framework to encompass the entire HVAC system, integrating multiobjective optimization techniques to minimize energy consumption and enhance thermal comfort for building occupants. This objective involves developing algorithms and methodologies to optimize HVAC system operation, control strategies, and parameter settings in real-time based on data collected from sensors, BIM models, and machine learning algorithms.

4. Explore the interaction between building envelope components, HVAC systems, and critical design variables within the Digital Twin framework, utilizing IDA Indoor Climate and Energy (IDA ICE) software [31], machine learning, and NSGA II. The objective is to optimize energy performance, improve indoor thermal comfort, and reduce overall energy usage by analyzing the impact of different design variables, such as glazing parameters, shading factors, and air infiltration, on the building's performance.

5. Develop a unified framework that maximizes the potential benefits of Digital Twin technology in thermal comfort, visual quality, acoustic performance, and spatial design. This objective involves integrating various comfort factors and their interdependencies into the Digital Twin framework, utilizing Bayesian network modeling and machine learning techniques to capture and analyze complex relationships between different comfort aspects.

6. Investigate the utilization of ontology for systems integration within the Digital Twin framework, aiming to facilitate seamless integration of various building systems, data sources, and domains. This objective involves developing ontologies and data models that enable interoperability and data exchange between different components of the Digital Twin, ensuring efficient communication and integration of information from diverse sources.

Based on that, Figure 1.3 provides a conceptual diagram of the systems used in this thesis.

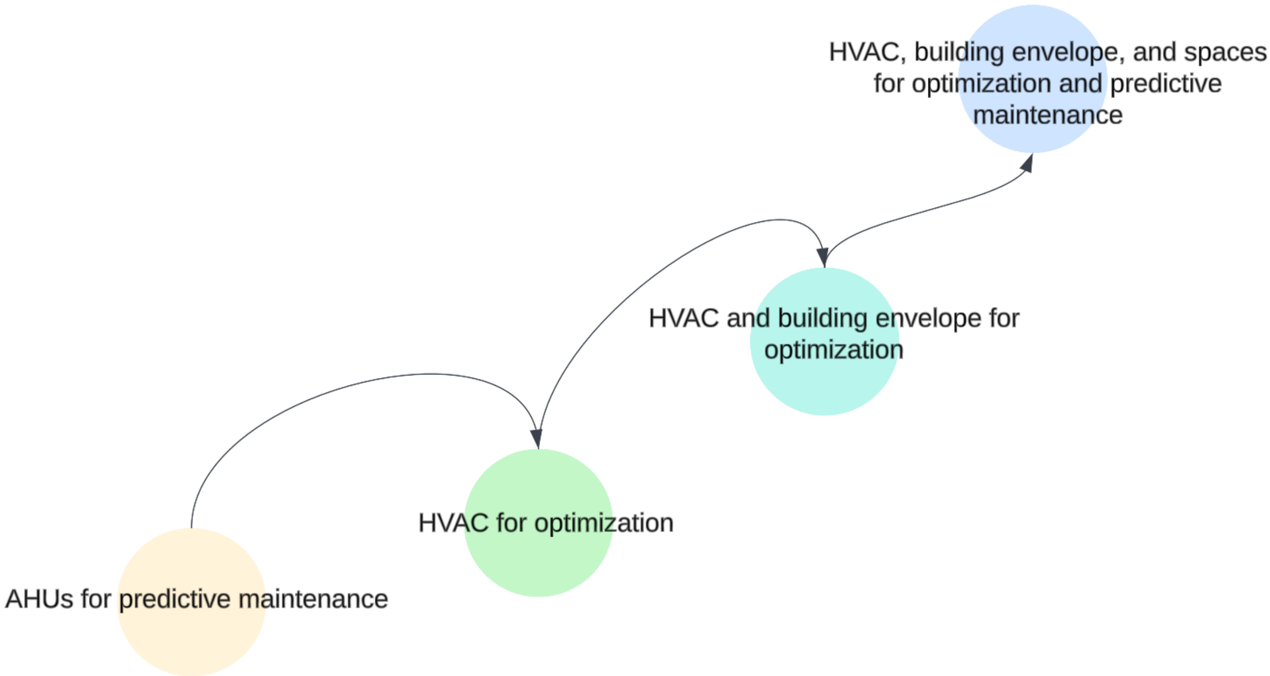


Figure 1.3: A schematic representation of the primary systems and processes investigated in this thesis. An AHU typically consists of a fan, heating and cooling coils, filtration devices, and dampers to control airflow. HVAC, on the other hand, typically includes an AHU, as well as ductwork, controls, and other components to distribute conditioned air throughout the building. So, AHU is a part of the HVAC system that is responsible for treating and distributing air in a building.

These objectives aim to contribute to the knowledge and understanding of Digital Twin technology's potential in optimizing building performance, enhancing occupant comfort, and guiding decision-making processes in the operation and maintenance of non-residential buildings.

Consequently, this thesis is driven by the following research question:

How can implementing Digital Twin technology improve the performance of non-residential buildings in terms of energy and comfort?

This research question will be addressed and answered through a comprehensive analysis of the primary systems and processes related to this thesis, as shown in Figure 1.4.

To investigate the impact of implementing Digital Twin technology, the research will focus on several key aspects. First, the research will explore the integration of real-time data, BIM, and machine learning algorithms within the Digital Twin framework. This will enable accurate predictions and fault detection, leading to improved energy efficiency and occupant comfort.

Additionally, the research will examine the optimization of HVAC systems through real-time monitoring and control. By utilizing Digital Twin technology, the performance of HVAC systems can be optimized to enhance energy efficiency and thermal comfort.

Furthermore, the research will investigate the interaction between building envelope components and HVAC systems. This includes analyzing the influence of factors such as glazing parameters, shading factors, and air infiltration on energy consumption and occupants' thermal comfort.

The research will also address the importance of considering multiple comfort factors and their interdependencies in building operations. By utilizing Bayesian network modeling, the probabilistic nature of comfort aspects such as thermal comfort, indoor air quality, visual comfort, acoustic comfort, and space adequacy can be captured and integrated into the Digital Twin framework.

Figure 1.4 shows how each study relates to the overarching research question. Paper 1 provides a review paper to define the gaps in the body of knowledge. Paper 1 led to papers 2, 3 and 4. Paper 2 presents a Digital Twin framework for the predictive maintenance of four AHUs in a Norwegian University building. Paper 3 provides a real-time optimization framework using Digital Twin technology for HVAC systems in the same building. Studies on the optimization of the building envelope and HVAC simultaneously are followed by taking an upper secondary school as a case study (paper 4). Another review paper is then followed to extend our research scope (paper 5). This led to papers 6 and 7, which extended the work from thermal comfort to include visual, acoustic, and space comfort in the university and school buildings mentioned above.

- The bibliography and appendices with published papers close out the thesis.

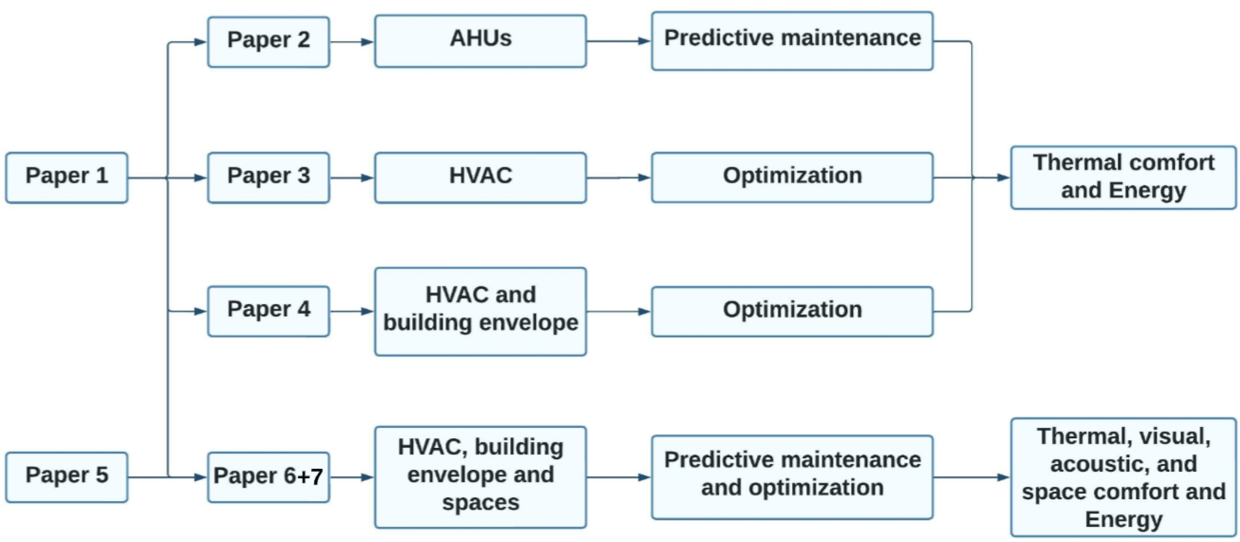


Figure 1.4: A graphical depiction of the published research papers concerning this thesis's primary systems and processes.

Out from that, the following research sub-questions have been addressed:

1. How to create a universal Digital Twin framework for predictive maintenance of AHUs based on IoT, BIM technology, and machine learning for decision-making in FMM?

   - **Motivation:** Efficient facility maintenance management (FMM) is motivated by the need for predictive maintenance strategies to optimize AHU performance, energy consumption, and occupants' comfort. AHUs are critical components of building HVAC systems, and their proper functioning directly affects energy usage and occupant satisfaction. By leveraging IoT sensors, BIM technology, and machine learning algorithms within a Digital Twin framework, it becomes possible to monitor AHUs in real-time, detect anomalies, and predict potential failures. This framework enables proactive maintenance planning, optimized decision-making, and resource allocation, leading to improved AHU performance, energy efficiency, and occupant comfort.
   - **Approach:** The approach to address the sub-question involves the utilization of IoT sensors, BIM technology, and machine learning algorithms within a Digital Twin framework. The framework enables real-time monitoring of AHUs, anomaly detection, and prediction of potential failures. IoT sensors collect data on AHU performance parameters, which is integrated with BIM models and analyzed using machine learning algorithms. By combining these technologies, the framework facilitates predictive maintenance planning, enabling timely interventions and preventing costly breakdowns. This approach optimizes AHU operation, improves energy efficiency, and ensures occupant comfort through informed decision-making based on real-time data and predictive insights.
   - **Article:** The article that addressed the sub-question is "A Digital Twin Predictive Maintenance Framework of Air Handling Units based on Automatic Fault Detection and Diagnostics" which focused on the importance of efficient facility maintenance management (FMM) through predictive maintenance strategies for AHUs.

2. How to use Digital Twin technology to reduce energy consumption and increase users' thermal comfort through real-time optimization of HVAC systems?

   - **Motivation:** This sub-question recognized the importance of energy efficiency and occupant thermal comfort in non-residential buildings. The aim was to create sustainable and comfortable indoor environments by prioritizing these aspects. The research leveraged the capabilities of Digital Twin technology to optimize HVAC system performance by integrating real-time data from sensors with building simulation models. This approach enabled continuous monitoring of key performance indicators, such as indoor temperature, humidity, and occupancy, facilitating dynamic adjustments and control strategies in response to changing conditions. By focusing on energy efficiency and occupant thermal comfort, the research aimed to enhance building performance and user satisfaction.

- **Approach:** The approach to address this sub-question involved harnessing the capabilities of Digital Twin technology in non-residential buildings. Real-time data collected from sensors was integrated with building simulation models in Simulink within the Digital Twin framework. This integration allowed for continuous monitoring of key performance indicators related to energy efficiency and occupant thermal comfort. By analyzing the data using machine learning and employing optimization algorithms, dynamic adjustments and control strategies were implemented in real-time. The objective was to reduce energy consumption while ensuring occupants' thermal comfort, ultimately enhancing building performance and user satisfaction.
- **Article:** The article titled "Digital Twin of HVAC system (HVACDT) for multiobjective optimization of energy consumption and thermal comfort based on BIM framework with ANN-MOGA" addressed this sub-question.

3. How can Digital Twin technology reduce energy consumption and increase users' thermal comfort by optimizing HVAC systems and building envelope components?

   - **Motivation:** This sub-question addressed the holistic optimization of both HVAC systems and building envelope components within the Digital Twin framework. Recognizing the significant impact of the interaction between HVAC systems and the building envelope on energy consumption and occupants' thermal comfort, the research aimed to optimize these elements together. By integrating simulation models of HVAC systems and building envelopes within the Digital Twin, it became possible to analyze various configurations, insulation strategies, and control parameters. The objective was to identify the most energy-efficient and comfortable solutions by considering the interplay between these elements. This comprehensive optimization approach aimed to improve energy performance and enhance occupants' thermal comfort in non-residential buildings.
   - **Approach:** The approach to address this sub-question involved integrating simulation models of both HVAC systems and building envelope components within the Digital Twin framework. By combining these models, the Digital Twin could analyze the interaction between these elements and evaluate different configurations, insulation strategies, and control parameters. Through this analysis, the framework aimed to identify solutions that simultaneously optimized energy consumption and occupants'

thermal comfort. The use of machine learning-based optimization algorithms, such as NSGA II, enhanced the efficiency and effectiveness of the optimization process. The goal was to achieve multiobjective optimization, considering both energy performance and occupants' thermal comfort, within the integrated BIM framework.

- **Article:** The article titled "Multiobjective optimization of building energy consumption and thermal comfort based on integrated BIM framework with machine learning-NSGA II" addressed this sub-question.

4. How to use Digital Twin technology to detect the reasons to discomfort in buildings, including thermal, visual, acoustic, and space comforts?

   - **Motivation:** This sub-question highlighted the importance of considering occupant comfort beyond thermal aspects and expanded the application of Digital Twin technology to encompass multiple comfort parameters. Recognizing that occupant comfort is influenced by various factors such as thermal conditions, lighting, acoustics, and spatial constraints, the research aimed to address these concerns comprehensively. By integrating sensor data, occupant feedback, and simulation models within the Digital Twin framework, it became possible to identify and understand the factors contributing to discomfort. This understanding enabled proactive detection and mitigation of comfort issues, allowing for targeted improvements in building design, operation, and maintenance. The motivation was to enhance occupant satisfaction, well-being, and productivity through the proactive management of multiple comfort parameters.

   - **Approach:** The approach to address this sub-question involved the integration of sensor data, occupant feedback, and simulation models within the Digital Twin framework. By leveraging these components, the Digital Twin could identify and analyze various factors that impacted occupant comfort, including thermal conditions, lighting, acoustics, and spatial constraints. This integration enabled the proactive detection of discomfort issues, allowing for targeted improvements in building design, operation, and maintenance to enhance occupant comfort. The approach focused on a comprehensive understanding of multiple comfort parameters and utilized the capabilities of the Digital Twin to address occupant concerns beyond thermal aspects.

   - **Article:** The articles that addressed this sub-question were "Digital Twin framework for automated fault source detection and prediction for comfort performance evaluation of existing non-residential Norwegian buildings" and "Improving Building Occupant Comfort through a Digital Twin Approach: A Bayesian Network Model and Predictive Maintenance Method".

Two review articles, namely "A review of the Digital Twin technology for fault detection in buildings" and "A Review of the Digital Twin Technology in the AEC-FM Industry," played a significant role in defining the research questions. These articles provided valuable insights into the application of Digital Twin technology in the context of fault detection in buildings and the Architecture, Engineering, Construction, and Facility Management (AEC-FM) industry. By examining the existing literature and industry practices, these review articles helped to shape the research questions by highlighting the potential, challenges, and benefits of Digital Twins in the specific domains. The knowledge and understanding gained from these review articles contributed to the formulation of focused and relevant research questions for the study.

1.3 Thesis outline

The research questions serve as the framework for the thesis's structure, which was designed to provide a logical sequence to the issues covered and facilitate easy reading. The intended layout is as follows:

- **Chapter 1** introduces the thesis's research motivation, objectives, questions, and outline.

- **Chapter 2** places this study within the context of the current state-of-the-art literature and outlines the research gaps this thesis addresses.

- **Chapter 3** details the methodology, discusses its significance and introduces the tools and techniques employed in the research efforts.

- **Chapter 4** provides a short overview of the research papers included in the thesis's Appendices.

- **Chapter 5** provides an in-depth discussion and analysis of the research findings.

- **Chapter 6** provides the findings, difficulties, and possible future directions that stem from this thesis.

Chapter 2

Background Theory

"Each problem that I solved became a rule which served afterwards to solve other problems."

Rene Descartes

Creating a harmonious balance between energy consumption and occupant comfort is a key objective in the design and operation of non-residential buildings. The efficient use of energy is essential for sustainability, cost-effectiveness, and reducing environmental impact. At the same time, ensuring a comfortable indoor environment for occupants is vital for their well-being, productivity, and satisfaction.

In this section, we delve into the crucial factors that contribute to occupant comfort in non-residential buildings, including indoor air quality, thermal comfort, acoustics, visual comfort, and ergonomic considerations. We explore how these elements play a significant role in creating a comfortable environment that supports occupants throughout their daily activities.

Moreover, we examine the challenges associated with energy consumption in non-residential buildings, focusing on factors such as building design, HVAC systems, lighting, and plug loads. Understanding the impact of these factors is crucial for implementing energy-efficient strategies and optimizing building performance.

To bridge the gap between energy consumption and occupant comfort, we introduce the concept of Digital Twin technology. Digital Twin technology offers a comprehensive solution by integrating real-time data, advanced control algorithms, and predictive modeling techniques. It enables the design and operation phases of buildings to be seamlessly interconnected, facilitating informed decision-making and optimized performance.

Throughout this section, we highlight the role of Digital Twin technology in achieving a balance between energy consumption and occupant comfort. We explore its applications in the design phase, where it aids in evaluating design options and selecting the most efficient solutions. Additionally, we delve into its role in the operation phase, where it enables real-time monitoring, control, and predictive maintenance of building systems. This holistic approach fosters sustainable building practices, improves occupant well-being, and aligns with the goals of environmental responsibility and resource conservation.

2.1 The revolution of Digital Twin for the built environment

In recent years, a revolutionary concept has emerged in the field of technology and construction known as the "Digital Twin" [32]. This groundbreaking concept has the potential to transform the way we design, construct, and operate buildings and infrastructure [33]. To understand the significance of the Digital Twin, it is important to first grasp its origins and how it differs from other related concepts such as BIM, digital models, digital shadows, and digital control.

In the built environment, the Digital Twin concept builds upon the foundation of BIM, which is a process that utilizes digital representations of the physical and functional characteristics of a building or infrastructure project [34]. BIM has been widely adopted in the construction industry as a means to create and manage a comprehensive digital representation of a project throughout its lifecycle [35]. However, BIM primarily focuses on the design and construction phases, providing a static digital model of the physical asset [36].

In contrast, the Digital Twin, which was first introduced by Dr. Michael Grieves in 2003 at the University of Michigan, takes the concept of BIM to a whole new level [37, 32]. A Digital Twin is a dynamic virtual representation of a physical asset, such as a building or infrastructure system, that mirrors its real-world counterpart throughout its entire lifecycle. It combines real-time data from sensors, IoT devices, and other sources to create a virtual replica that evolves alongside the physical asset [38]. This means that the Digital Twin is not only a static representation but also an interactive and responsive model that captures the asset's current state and behavior.

Digital Twins enable a wide range of applications and benefits in the built environment. By integrating real-time data, they allow for predictive analysis [39], simulations to optimize operational performance [40], energy efficiency [41], and maintenance strategies [2].

In addition, it is important to distinguish the Digital Twin from other related concepts as shown in Figure 2.1. The Digital Twin concept revolutionizes the built environment by incorporating real-time data and interactivity, unlike static digital models. A digital model represents an asset without automated data exchange between the physical and virtual environments, although it can receive state-altering inputs [9]. In contrast, a digital shadow refers to a digital model with a unidirectional data flow from the physical to the virtual environment, while digital control involves a unidirectional flow from the virtual to the physical [9]. The Digital Twin is distinguished by its bidirectional data flow, enabling a comprehensive exchange between the physical and virtual environments [42].

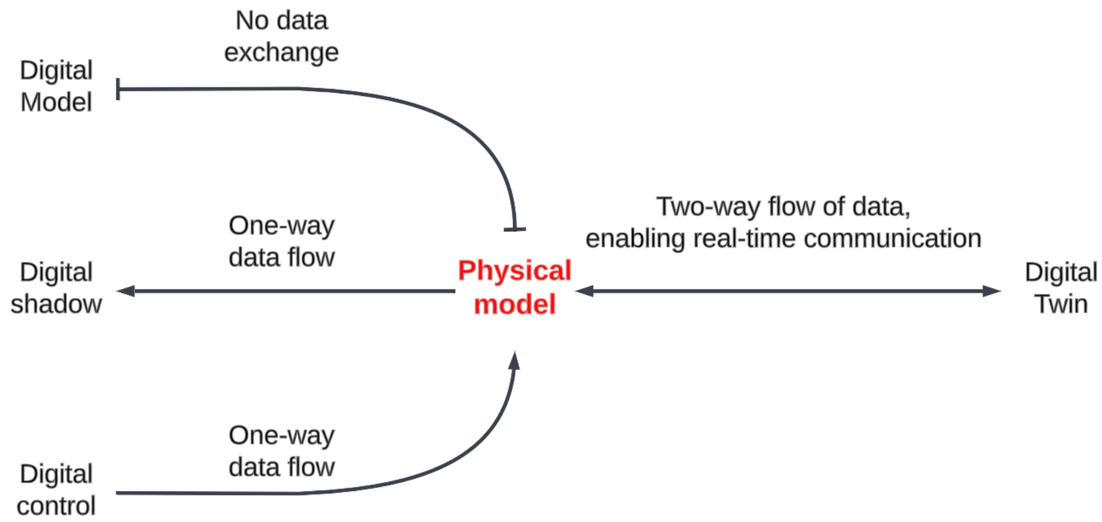


Figure 2.1: Flowchart illustrating the distinctions between Digital Model, Digital Shadow, Digital Control, and Digital Twin in relation to data flows and change of state between the physical and virtual environments. Inspired by [9].

Furthermore, BIM and IoT play vital roles in the development of Digital Twins [43]. BIM provides a comprehensive digital representation of a physical asset, capturing its geometry and relevant information, while IoT devices and sensors collect real-time data from the asset and its surroundings [44]. The integration of BIM and IoT enables the Digital Twin to mirror the behavior of the physical asset, allowing for predictive analysis, optimization and informed decision-making [45]. The bidirectional data flow between the Digital Twin and the physical asset (Figure 2.2) ensures continuous updates and synchronization, enhancing performance and efficiency throughout the asset's lifecycle [46].

Figure 2.2: Flowchart depicting the relationship between BIM, IoT, and the Digital Twin. BIM and IoT serve as integral components of the Digital Twin concept, with BIM providing a comprehensive digital representation of the physical asset and IoT collecting real-time data.

This thesis leverages a higher level of the Digital Twin that combines sensor data, BIM, data integration techniques, and machine learning algorithms, as shown in Figure 2.3. This integrated approach offers substantial advantages in both the design and operation phases of the built environment. By incorporating sensor data, real-time monitoring of parameters like temperature, occupancy, and energy consumption is enabled, providing valuable insights into the asset's actual performance and occupants' comfort. BIM ensures a comprehensive and accurate representation of the asset's geometry and attributes, serving as the foundation for the Digital Twin. Through data integration techniques, the sensor data and BIM are combined to create a unified representation, facilitating effective analysis and decision-making. Machine learning algorithms are then applied to process and analyze the integrated data, uncovering patterns, trends, and correlations that can further optimize occupant comfort. This Digital Twin framework allows for improved design processes, such as optimizing energy efficiency and predicting performance outcomes, while also considering occupant comfort factors. One key advantage is the ability to learn from previous buildings and use that knowledge to enhance the design of future buildings. By validating simulation models with real-time sensor data and conducting multiple simulations, designers can optimize the design and achieve the best results. Additionally, the Digital Twin framework promotes enhanced collaboration and decision-making through multidisciplinary collaboration and information sharing among designers, engineers, and other stakeholders. This facilitates better communication, coordination, and decision-making throughout the design process, leading to more effective and efficient outcomes. During the operation phase, it supports predictive maintenance, energy management, and performance optimization to enhance operational efficiency, reduce energy waste, and ensure a comfortable indoor environment for occupants.

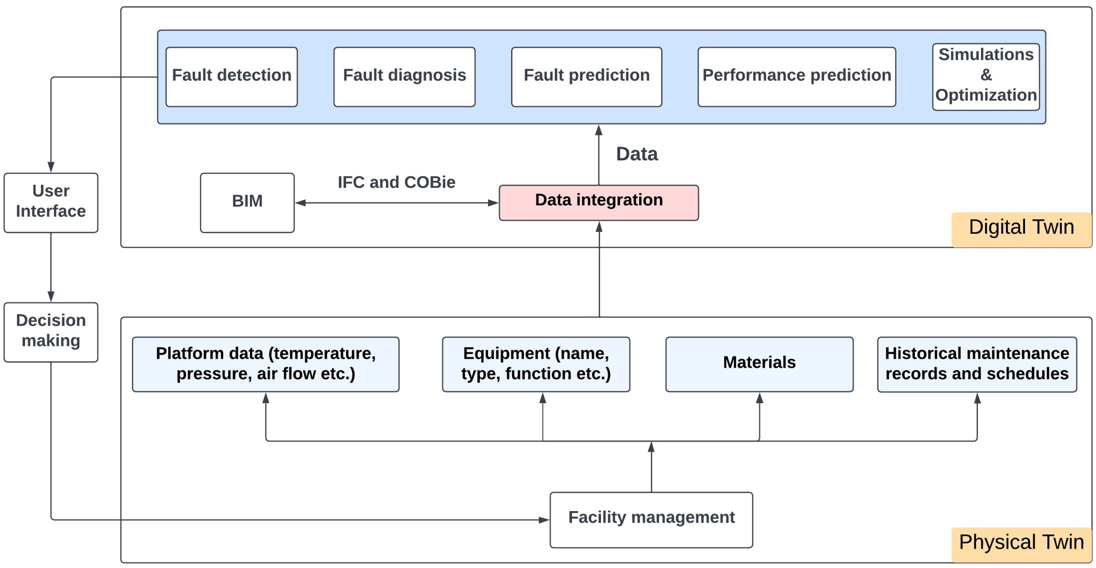


Figure 2.3: Digital Twin model for building management to avoid future faults, decrease energy usage, and enhance user comfort [6].

2.2 Energy consumption in non-residential buildings

Energy consumption in non-residential buildings is a pressing concern with significant environmental and economic implications. In this section, we provide an overview of the key factors influencing energy consumption, including building design, HVAC systems, lighting, and plug loads. We explore the importance of energy-efficient practices and sustainable design principles in reducing energy demand. Additionally, we discuss the role of advanced HVAC technologies, energy-efficient lighting solutions, and strategies for managing plug loads to achieve substantial energy savings. Furthermore, we introduce the concept of passive energy design, which utilizes natural resources (natural lighting, natural ventilation techniques, natural heat stored beneath the Earth's surface, etc.,) and renewable energy sources to minimize energy consumption.

2.2.1 Building Design, Energy Consumption, and HVAC Systems

The energy consumption of a non-residential building is heavily influenced by its design, including factors such as building orientation, insulation, glazing, and overall layout [47]. These design elements directly impact the energy requirements for heating, cooling, lighting, and ventilation within the building [48, 49]. Therefore, energy-efficient building design strategies focus on maximizing natural daylight, optimizing insulation, reducing thermal bridging, and utilizing efficient HVAC (Heating, Ventilation, and Air Conditioning) systems [50]. By incorporating these sustainable design practices, non-residential buildings can effectively minimize their energy demand while ensuring occupant comfort and operational efficiency.

2.2.2 HVAC Systems

HVAC systems account for a significant portion of energy consumption in non-residential buildings [51]. These systems are responsible for maintaining comfortable indoor temperatures, humidity levels, and air quality for occupants [52]. However, inefficient HVAC systems can lead to excessive energy usage and increased operating costs [53].

One of the primary factors contributing to HVAC energy consumption is system design [54]. The selection of equipment, such as boilers, chillers, piping, and air handling units, plays a crucial role in energy efficiency. High-efficiency equipment, such as condensing boilers and variable refrigerant flow (VRF) systems, can significantly reduce energy consumption compared to their conventional counterparts [55]. Additionally, properly sized equipment ensures optimal performance and avoids energy waste [56].

Another aspect impacting HVAC energy consumption is control strategies [57]. Implementing advanced control systems, such as building automation systems (BAS) and energy management systems (EMS) [58], allows for precise monitoring and regulation of HVAC equipment. Smart controls enable the adjustment of temperature setpoints, ventilation rates, and equipment schedules based on occupancy patterns and environmental conditions [59]. Additionally, demand-controlled ventilation (DCV) systems can optimize air exchange rates, matching ventilation to actual occupancy needs and reducing energy waste [60].

2.2.3 Lighting

Lighting represents an important portion of energy consumption in non-residential buildings, amounting to approximately 15% as evidenced by Figure 1.1. Traditional lighting systems, such as incandescent or fluorescent lights, are energy-intensive and less efficient compared to modern alternatives [61]. Replacing outdated lighting technologies with energy-efficient options like LED (Light Emitting Diode) lights can result in substantial energy savings [62]. Additionally, incorporating daylighting strategies, such as large windows, skylights, and light shelves, can minimize the need for artificial lighting during daylight hours [63].

2.2.4 Plug Loads and Equipment

Plug loads, including appliances, electronics, and office equipment, contribute to a considerable portion of energy consumption in non-residential buildings [64]. The increasing prevalence of computers, printers, televisions, and other electronic devices in modern workplaces has amplified this issue [65]. Managing plug loads through energy-efficient devices, smart power strips, and effective power management strategies can help reduce energy consumption associated with these loads [66].

2.2.5 Passive Energy Design in Buildings

Passive energy design revolutionizes the way we approach building construction by prioritizing energy efficiency and sustainability [50]. It embraces the idea that a building can be intelligently designed to utilize the potential of natural resources and optimize occupant comfort without relying heavily on mechanical systems. By integrating climate analysis, passive heating, passive cooling, daylighting, and renewable energy, passive energy design aims to minimize energy consumption, reduce environmental impact, and create spaces (rooms, offices, common areas, and other designated areas within a building where occupants work, interact, or reside) that are both environmentally friendly and conducive to the well-being of the occupants [67]. This approach not only benefits the planet but also promotes long-term cost savings and a healthier indoor environment.

2.2.5.1 Climate Analysis and Comfort

Before designing a building, a thorough climate analysis is essential. Factors such as temperature, humidity, solar radiation, wind patterns, and seasonal variations need to be taken into account [68]. This analysis helps determine the specific passive design strategies required to optimize comfort and reduce energy consumption. For example, understanding the prevailing winds can help determine the best orientation and layout of the building to enhance natural ventilation [69].

2.2.5.2 Passive Heating

Passive heating techniques aim to capture, store, and distribute solar heat to warm the building during colder periods [70]. Passive heating strategies include:

- **Building Orientation:** proper alignment of the building in relation to the sun can maximize solar gain [71]. In the Northern Hemisphere, for instance, south-facing windows receive more sunlight throughout the day [72].

- **Thermal Mass:** incorporating materials with high thermal mass, can absorb and store heat during the day, releasing it slowly at night when temperatures drop [73].

- **Insulation:** effective insulation reduces heat loss, minimizing the need for active heating systems. Proper insulation of building envelope is crucial to prevent heat transfer [74].

2.2.5.3 Passive Cooling

Passive cooling techniques focus on reducing heat gain and enhancing natural ventilation to maintain comfortable indoor temperatures [75]. Some strategies related to passive cooling include:

- **Building Design:** Shading elements such as overhangs, louvers, or awnings can block direct sunlight during hot seasons while allowing sunlight during colder periods [76].

- **Natural Ventilation:** Building design should encourage cross-ventilation by incorporating windows, vents, and adjustable openings to facilitate airflow and enhance cooling through the stack effect [77].

- **Reflective Surfaces:** Light-colored or reflective roofing materials can reduce heat absorption and lower the cooling load [78].

2.2.5.4 Daylighting

Daylighting maximizes the use of natural light to illuminate interior spaces, reducing the need for artificial lighting [79], this includes:

- **Window Placement:** proper placement and sizing of windows allow for ample natural light penetration while minimizing glare and heat gain [80]. Light shelves or light tubes can be used to distribute daylight deeper into the building [81].

- **Interior Layout:** designing spaces with open floor plans, interior glazing, and light-colored surfaces can help optimize the distribution of daylight throughout the building [82].
- **Automated Controls:** sensors and automated systems can be installed to regulate artificial lighting based on available natural light, further optimizing energy usage [83].

2.2.5.5 Renewable Energy

While passive design strategies significantly reduce energy consumption, integrating renewable energy sources can further enhance a building's sustainability [84]. Common renewable energy systems include:

- **Solar Photovoltaic (PV) Panels:** these panels convert sunlight into electricity, providing a clean and renewable source of power [85].
- **Solar Thermal Systems:** these systems utilize the sun's energy to heat water for domestic use or space heating [86].
- **Ground source Systems:** ground source heat pumps utilize the constant temperature of the earth to provide heating and cooling for a building [87].

The aforementioned aspects emphasize the significance of studying energy consumption in buildings. By understanding the factors that contribute to energy usage, such as building design, HVAC systems, lighting, and other related components, researchers can identify opportunities for improvement and develop strategies to enhance energy efficiency.

It is important to note that while renewable energy is a crucial aspect of sustainable building practices, it is not the main focus of this Ph.D. thesis. Nonetheless, it is important to acknowledge the potential benefits and significance of renewable energy integration in achieving long-term energy efficiency and sustainability in non-residential buildings.

2.3 Occupant comfort in non-residential buildings

Creating a comfortable indoor environment for occupants is a crucial aspect of non-residential building design. Occupant comfort directly affects well-being, productivity, and overall satisfaction. This section explores the various factors that contribute to occupant comfort in non-residential buildings, including indoor air quality, thermal comfort, acoustics, visual comfort, and ergonomic considerations.

2.3.1 Indoor Air Quality

Indoor air quality plays a vital role in occupant comfort and health [88]. Poor air quality can lead to issues such as allergies, respiratory problems, and reduced cognitive function [89]. Non-residential buildings' design must ensure proper ventilation, filtration, and control of pollutants to maintain high indoor air quality [90]. This involves effective HVAC system design [91], regular maintenance [92], and monitoring of pollutant levels [93]. Implementing strategies like the use of low-VOC (volatile organic compounds) materials and adequate outdoor air supply can significantly enhance indoor air quality and occupant comfort [89].

2.3.2 Thermal Comfort

Achieving optimal thermal comfort is essential for occupant satisfaction and productivity. The thermal environment in non-residential buildings should be carefully managed to provide a comfortable temperature range, determined by the operative temperature which results from surface temperature, air velocity, and occupants' activities. [94]. Factors such as insulation, glazing, shading devices, and HVAC systems influence thermal comfort [95]. Building design should consider occupant preferences and local climate conditions to ensure thermal comfort throughout the year [96]. Individual control options, such as adjustable thermostats and operable windows, can further enhance occupant satisfaction by allowing personal temperature preferences [97].

2.3.3 Acoustics

Noise levels significantly impact occupant comfort and concentration in non-residential buildings. Excessive noise can cause stress, reduce productivity, and hinder effective communication [7]. Proper acoustic design involves controlling noise transmission from external sources and minimizing internal noise sources [98]. Sound-absorbing materials, strategic placement of walls and partitions, and acoustic treatments in open spaces can help create a quieter and more comfortable environment [99]. Additionally, incorporating private spaces, meeting rooms, and designated quiet zones can provide occupants with options for focused work or relaxation [100].

2.3.4 Visual Comfort

Visual comfort refers to the quality of lighting and visual conditions within a non-residential building [101]. Inadequate lighting, glare, or poor color rendering can cause eyestrain, fatigue, and discomfort [102]. Effective lighting design should consider both natural and artificial lighting sources [103]. Optimizing daylight access, utilizing appropriate window treatments, and employing energy-efficient lighting systems with proper color rendering and glare control can enhance visual comfort [104]. Additionally, incorporating task lighting and adjustable lighting controls allows occupants to personalize their lighting preferences, further promoting visual comfort [105].

2.3.5 Ergonomics

Ergonomic considerations in non-residential buildings focus on designing spaces and furniture to support occupant well-being and productivity [106]. Proper workstation design, adjustable furniture, and ergonomic accessories contribute to improved posture [107], reduced musculoskeletal issues [108], and increased comfort [109]. Providing ergonomic guidelines, training, and promoting movement throughout the workspace can help enhance occupant comfort and productivity [110]. Additionally, creating spaces for relaxation, socialization, and physical activity supports overall well-being and reduces stress levels [111].

Figure 2.4 highlights the complex relationship between various factors and their impact on the overall performance of buildings.

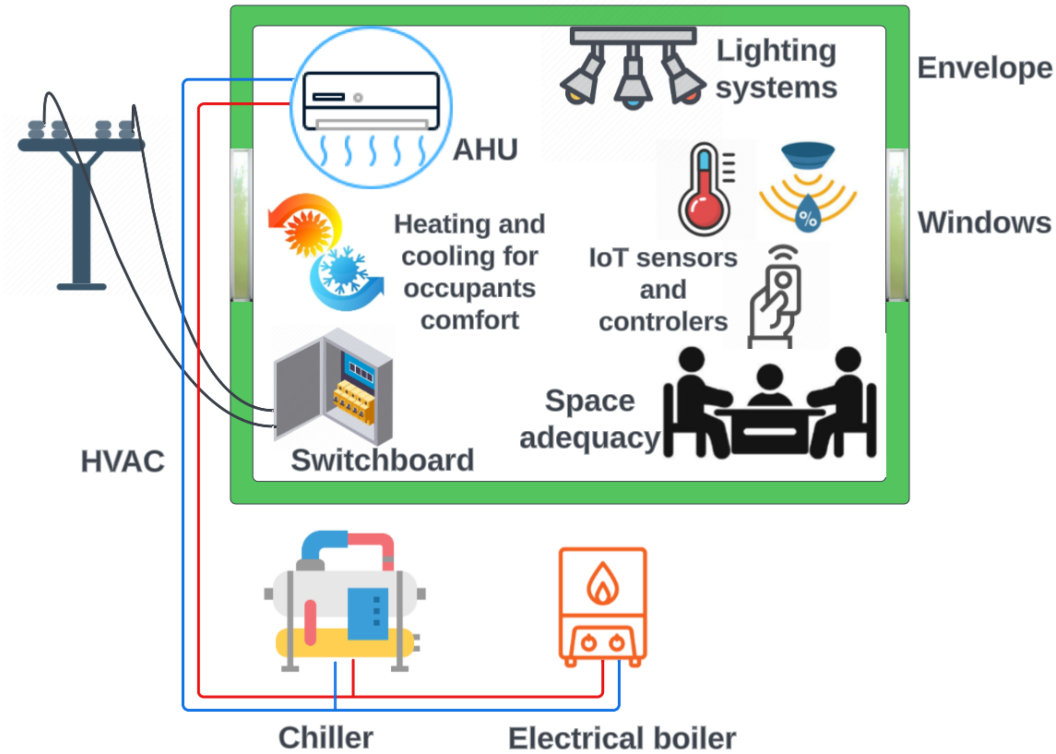


Figure 2.4: Interconnected factors influencing energy consumption and occupant comfort in non-residential buildings [6].

2.4 Achieving a balance between energy consumption and occupant comfort: the role of Digital Twin technology in building design and operation

Designing non-residential buildings that strike a balance between energy consumption and occupant comfort is a multifaceted challenge. It entails the need to minimize energy usage and promote sustainability, while simultaneously ensuring a comfortable indoor environment for occupants' well-being. The conventional approach of treating design and operation phases as separate entities often results in less-than-optimal outcomes. However, Digital Twin technology presents a promising solution to address this challenge. In this section, we will explore the role of Digital Twin in overcoming these challenges during both the design and operation phases of non-residential buildings.

2.4.1 During the design phase

Digital Twin technology provides valuable insights by simulating and analyzing various design scenarios [4, 112]. Architects, engineers, and stakeholders can collaborate within the Digital Twin environment to evaluate design aspects such as building orientation, envelope design, HVAC system selection, and lighting design [113]. This enables informed decision-making to choose the best design options that optimize both energy performance and occupant comfort.

2.4.2 During the operation phase

The Digital Twin serves as a central platform for real-time monitoring and control of building systems [114]. Integrated with building automation systems, it enables automated controls to adjust HVAC settings [115, 116, 117, 118, 119], lighting levels [120, 121], and other systems based on occupancy, time of day, and environmental conditions [122, 123]. This dynamic optimization ensures energy-efficient operation while preserving occupant comfort [124].

In addition, the Digital Twin facilitates occupant engagement and education. Through user interfaces connected to the Digital Twin, occupants receive real-time feedback on energy consumption and occupant comfort metrics [125, 126, 127]. This personalized information and recommendations promote energy-conscious behaviors and empower occupants to make informed choices.

Predictive maintenance is another key aspect enabled by Digital Twin. Leveraging real-time sensor data and performance analytics, the Digital Twin enables Predictive management of building systems [128, 129]. It can detect potential issues or anomalies in advance, allowing for predictive maintenance strategies. This Predictive approach helps prevent equipment failures, optimize maintenance schedules, and reduce downtime, ultimately optimizing energy consumption while ensuring uninterrupted occupant comfort [130, 131].

Furthermore, data integration is a fundamental capability of the Digital Twin. It seamlessly integrates data from various building systems and sensors, enabling comprehensive analysis and decision-making [132]. Energy audits, post-occupancy evaluations, and performance assessments can be conducted using data from the Digital Twin, providing valuable insights into energy consumption patterns and occupant comfort levels [133]. Furthermore, the Digital Twin can integrate with other industry-standard systems, such as Computerized Maintenance Management

Systems (CMMS) [134], Building Management Systems (BMS) [135], and BIM exchange schemas like Industry Foundation Classes (IFC) [136], and Construction Operations Building Information Exchange (COBie) [137]. This integration, facilitated by ontology-based approaches, ensures semantic interoperability and efficient data exchange, enhancing collaboration, data sharing, and accurate information within the Digital Twin [138, 139, 140].

By using the Digital Twin technology, designers can make informed decisions in the design phase, considering various scenarios and choosing the best design options that achieve a balance between energy consumption and occupant comfort. In the operation phase, the Digital Twin enables real-time monitoring, control, and optimization of building systems, promoting energy efficiency while ensuring occupant comfort. This holistic approach, supported by the Digital Twin, fosters sustainable and occupant-centric building performance throughout the entire lifecycle.

2.5 Uncovering the research gaps through state-of-the-art review

To identify the research gaps in the field of energy-saving and comfort improvement, a systematic literature review was conducted without any specific years limit, utilizing the Google Scholar, Web of Science, and Scopus databases. This rigorous review encompassed a comprehensive search across a wide range of sources, including academic journals, conference proceedings, and industry reports.

The search strategy incorporated keywords related to energy efficiency, comfort enhancement, building performance, maintenance, data integration, ontology, and digital twin technology. A total of 123 articles were included in the review, encompassing a diverse range of studies from both hot and cold climate regions. This ensured a comprehensive analysis of the research landscape surrounding energy-saving and comfort improvement, without any limitations in terms of publication years.

A quantitative analysis of the literature was then performed to identify the most important and frequently discussed areas. This analysis involved quantifying the frequency of specific topics, methodologies, and key findings within the selected literature. Through this quantitative review, it became evident that there was a significant knowledge gap regarding the implementation of Digital Twin technology to improve the performance of non-residential buildings in terms of energy and comfort.

Subsequently, a qualitative analysis was conducted to gain deeper insights into this specific area. The qualitative analysis involved a thorough examination of the selected literature from various disciplines, including architecture, engineering, and computer science, to identify common themes, emerging trends, and critical insights. This process enabled a comprehensive understanding of the challenges, opportunities, and potential benefits associated with implementing Digital Twin technology in non-residential buildings.

The qualitative analysis revealed several research gaps that necessitate further exploration and innovation. Firstly, there is a need for comprehensive and integrated approaches that consider the synergy between energy efficiency and multiple aspects of comfort, including thermal, acoustic, visual, and space comfort [141, 142, 13, 143]. While some studies have focused on energy-saving measures or comfort enhancement strategies individually, few have explored the holistic impact of integrating both aspects through Digital Twin technology for facility management.

Secondly, the development and implementation of advanced control algorithms and predictive modeling techniques within the Digital Twin framework require attention [144, 145, 146, 147]. Many existing studies have relied on simplified control strategies or static models, neglecting the dynamic nature of building systems and occupant behavior [148, 149]. Advancing the field requires the exploration of more sophisticated and adaptive control algorithms that optimize energy consumption while maintaining occupant comfort [150, 151, 152].

Moreover, one research gap that emerged in our study pertains to optimizing both the building envelope and HVAC systems simultaneously during the design phase. While numerous studies have individually focused on enhancing the energy efficiency of building envelopes or optimizing HVAC systems, there is a lack of comprehensive research exploring the synergistic benefits of optimizing both aspects together to reduce energy consumption and increase occupants comfort [153, 56, 154, 155]. Integrating the building envelope and HVAC systems in a holistic manner has the potential to significantly improve energy performance and occupant comfort. However, there is a need for further investigation and development of methodologies that consider the interaction between these components, taking into account factors such as insulation, air tightness, thermal bridging, ventilation strategies, and heating/cooling loads.

Lastly, effective integration and interoperability of data within the Digital Twin framework are areas that require attention [156, 157, 158]. While some studies have explored data-driven approaches in energy-saving and comfort-improvement research, many have focused on specific aspects or subsystems of buildings, resulting in fragmented datasets and limited cross-domain analysis. Addressing the challenges associated with data integration from various sources, standardizing data formats, and enabling seamless interoperability between different systems and platforms is essential for comprehensive analysis and informed decision-making.

These identified research gaps, which emerged through a systematic literature review, have led to the formulation of the following research question:

"How can implementing Digital Twin technology improve the performance of non-residential buildings in terms of energy and comfort?"

This research question aims to explore the potential of Digital Twin technology in addressing the identified gaps and advancing the field of energy-saving and comfort improvement in non-residential buildings. By investigating this question, the study seeks to uncover new approaches, novel strategies, and practical recommendations for utilizing Digital Twin technology to optimize building performance, enhance energy efficiency, and improve occupant comfort.

The identified research gaps, along with the research question, will guide the methodology chapter of the research study. The methodology will focus on using Digital Twin technology, supported by BIM, machine learning, data integration, and the IoT, to enhance buildings in terms of energy efficiency, occupant comfort, and predictive maintenance.

The methodology chapter will outline the step-by-step approach to be followed in the research study. It will describe how the Digital Twin framework will be developed, incorporating BIM models, sensor data, and other relevant building information. Machine learning algorithms will be employed to analyze the collected data and extract meaningful insights for optimizing energy consumption and improving occupant comfort.

Additionally, the methodology will address the integration of various data sources and systems within the Digital Twin framework, ensuring compatibility, standardization, and seamless interoperability. The use of IoT devices and sensors will facilitate real-time data acquisition, enabling continuous monitoring and control of building systems.

Furthermore, the methodology will encompass predictive maintenance strategies within the Digital Twin framework. By analyzing historical data, machine learning algorithms can identify patterns and anomalies, enabling the prediction of maintenance needs and proactive measures to prevent equipment failures and optimize building performance.

Hence, the methodology chapter will provide a comprehensive plan for implementing Digital Twin technology, supported by BIM, machine learning, data integration, and IoT, to enhance the performance of non-residential buildings in terms of energy efficiency, occupant comfort, and predictive maintenance. It will detail the data collection, analysis, and decision-making processes, ensuring that the research objectives are effectively addressed.

Chapter 3

Methodology

"An opinion should be the result
of thought, not a substitute for it."

Jef Mallett

Chapter 3 of this thesis presents the methodology employed to address the research objectives and answer the research questions. This chapter outlines the systematic approach and framework used to develop and implement the proposed Digital Twin framework for optimizing building energy efficiency and indoor thermal comfort. The methodology encompasses various stages, including data collection, model development, optimization algorithms, and implementation in the Digital Twin environment.

The primary aim of this chapter is to provide a comprehensive overview of the steps taken to achieve the desired outcomes and demonstrate the reliability and validity of the research findings. The chapter begins by detailing the data collection process, which involves gathering information from building sensors and BIM models. Special attention is given to data security and privacy considerations, emphasizing the measures taken to anonymize and protect participants' personal information in accordance with relevant data protection regulations. The methodology also highlights the importance of informed consent and ethical approval obtained from the appropriate authorities.

Next, the chapter thoroughly explores the model development phase, focusing on the use of machine learning algorithms and the utilization of historical and real-time data to predict energy consumption and thermal comfort metrics, providing a basis for optimization.

The optimization process is then explained, incorporating multi-objective genetic algorithms such as MultiObjective Genetic Algorithm (MOGA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II). These algorithms enable the generation of Pareto-optimal solutions that balance energy efficiency and thermal comfort objectives while considering constraints and trade-offs.

Furthermore, the chapter describes the implementation of the proposed Digital Twin framework in the Dynamo environment, utilizing the Optimo package in Dynamo to compute the optimal Pareto solutions. This stage includes the replacement of Revit (which is a BIM software developed by Autodesk [159]) elements and control of indoor conditions to meet the desired level of thermal comfort.

Throughout the methodology, an emphasis is placed on the reliability, validity, and ethical considerations of the research. The chapter concludes by highlighting the importance of following a rigorous methodology to ensure the integrity and credibility of the research outcomes.

3.1 Case studies

The proposed Digital Twin framework in this thesis is validated through two case studies: I4Helse [160] and Tvedestrand upper secondary school [161], which serve as practical examples to assess and demonstrate the effectiveness of the framework in real-world scenarios. Both buildings adhere to Norwegian TEK10 "Teknisk forskrift for byggverk" (Technical Regulation for Buildings) [162] and NS3701 standards "Criteria for passive houses and low energy buildings - Non-residential buildings" [163].

I4Helse, constructed in Grimstad, Norway, in 2017 [160], is a mixed-use building that houses various facilities. It includes university offices, physiotherapy and occupational therapy laboratories, a home-based service center, service offices, a habilitation unit, and an e-health center. This versatile building serves multiple purposes, providing spaces for academic activities, healthcare services, and administrative functions, with a floor area of 1600 m^2. Tvedestrand VGS school [161], built in Tvedestrand, Norway, in 2020, has a larger floor area of 14500 m^2. These buildings were selected to align with the research objectives and provide significant contributions to the implementation and effectiveness assessment of the Digital Twin framework.

The case studies were selected based on their alignment with the research objectives, which aim to reduce energy consumption and enhance comfort using the proposed Digital Twin framework. Additionally, these case studies were chosen due to their affiliation with the University of Agder (UIA) and the Scandinavian Sustainable Circular Construction (S2C) project (through the previous project Green building A-Z from 2016 to 2019 [164]), which provides collaborative opportunities and easy access to relevant data, enabling a comprehensive exploration of the Digital Twin framework. Both buildings in the case studies comply with TEK10 [162] and NS3701 standards [163], ensuring that the evaluation of the Digital Twin framework takes into account the specific regulatory framework of Norway, making the research findings practically relevant. Furthermore, the availability of sensor data in these buildings, along with features such as energy wells (Figure 3.1) [165], heat pumps, and extensive solar panels, provides valuable insights for developing and validating the Digital Twin framework [166].

Furthermore, the local climate conditions were taken into account, which have a significant impact on the mean temperature in the case studies areas. Based on data from the Landvik station, the average annual temperature for the study

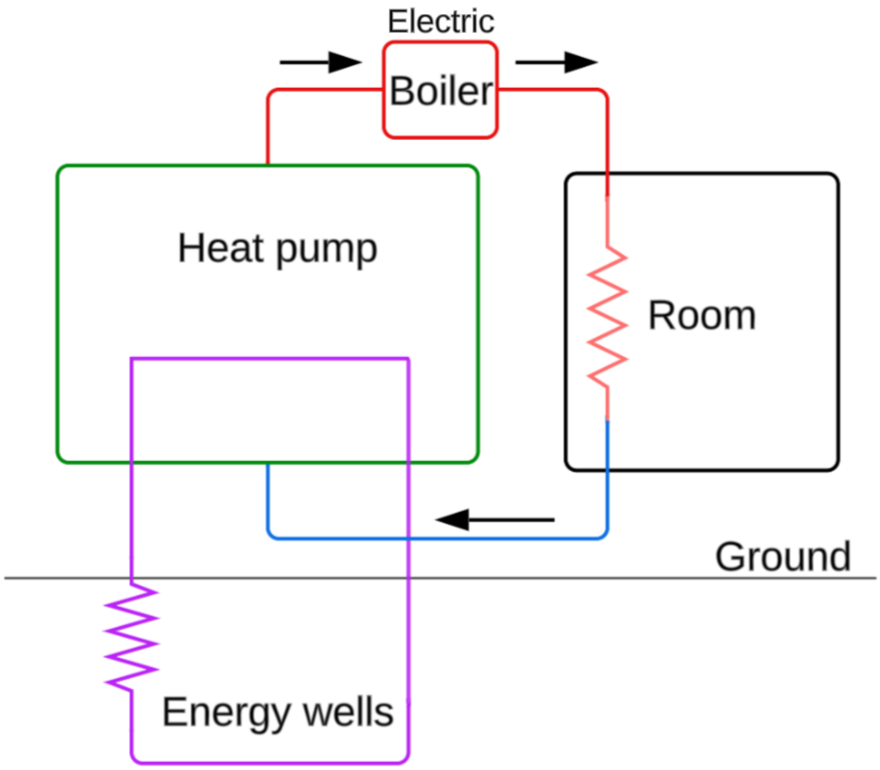


Figure 3.1: Illustration of a Ground Source Heat Pump (GSHP) system includes energy wells drilled deep into the ground, heat pump unit, supplementary electric boiler, and multiple rooms benefiting from the system's thermal comfort and energy efficiency. Inspired by [10]. This system is separated from the neighboring buildings of the University of Agder.

period, from August 2020 to May 2023, was around 8.05°C [167]. It was crucial to consider this climate factor when designing and operating buildings' Digital Twin HVAC systems and implementing energy-efficient measures. We incorporated real-time weather data into the Digital Twin method to ensure accurate analysis and optimization of the HVAC systems. Hence, information like temperature, humidity, solar radiation, wind speed, and precipitation were collected. This data was then processed and used as input to the Digital Twin model algorithms. This allowed the system to dynamically adjust HVAC settings and parameters based on the current weather conditions.

On the other hand, obtaining the necessary data for the Digital Twin framework was challenging. Although sensors were already installed in both buildings, accessing and extracting the data proved to be complex. Extensive communication and coordination with the responsible companies were required, involving multiple rounds of discussions. Furthermore, the BIM model for HVAC systems was not readily available, necessitating the construction of the models from scratch. The existing BIM models for the entire buildings were also found to be insufficient, requiring substantial modifications and rebuilding to ensure accuracy and compatibility with the Digital Twin framework.

Table 3.1 provides an overview of the various sensors employed in the building and HVAC system and used for the validation of the Digital Twin framework. These sensors played a crucial role in monitoring and collecting data related to different parameters and variables to enable accurate modeling and simulation within the Digital Twin environment. In order to further process the information, the signals from the sensors were collected and delivered to the BIM models. Figure 3.2 depicts the BIM models for the I4Helse and Tvedestrand school buildings, whereas Figure 3.3 depicts the systems involved in this thesis. Tables 3.2 and 3.3 provide detailed information about the primary characteristics of both buildings.

In the case studies of I4Helse and Tvedestrand VGS, it is important to note that the historical data collected from the sensors were available from 2019 for I4Helse and from 2020 for Tvedestrand VGS. Hence, when referring to the dataset throughout this thesis, I specifically mean those sensor data collected during the periods of 2019 and 2020 until 2023. This historical dataset provides a valuable foundation for analyzing and evaluating the performance of the Digital Twin framework over time, allowing for a comprehensive assessment of its effectiveness in optimizing energy consumption and maintaining comfort levels in these buildings, and making smarter algorithms for real-time prediction.

In addition, as part of the evaluation process, the satisfaction of the building's users was assessed across various spaces within the buildings, including classrooms, offices, hallways, labs, conference rooms, and study rooms, among others. This assessment aimed to capture the subjective experiences and feedback of the occupants, providing valuable insights into their comfort levels, overall satisfaction, and perception of the indoor environment.

It is important to note that the proposed Digital Twin framework discussed in this chapter refers to a methodology rather than specific results. The Digital Twin serves as a methodological approach for integrating real-time data, advanced modeling techniques, and optimization algorithms to enhance the energy efficiency and indoor comfort of buildings.

Table 3.1: Sensors used in the case studies and their HVAC systems

Sensor Type	**Location/Usage**
Temperature sensors	Indoor spaces, HVAC supply and return ducts
Humidity sensors	Indoor spaces, HVAC supply and return ducts
CO2 sensors	Indoor spaces, HVAC supply and return ducts
Lighting sensors	Rooms, offices, common areas
Solar radiation sensors	Building facades, windows
Air velocity sensors	HVAC supply and return ducts
Pressure sensors	HVAC system, air handling units
Air and water flows sensors	HVAC system, pumps, water distribution
Water temperature sensors	Chilled water supply/return, hot water supply/return
Energy meters	Building, HVAC and heat pump
Fault detection sensors	HVAC system, equipment, pumps, motors
Vibration sensors	HVAC system, equipment, fans, compressors
Occupant presence sensors	Offices, meeting rooms, common areas
Occupant activity sensors	Workstations, desks, common areas

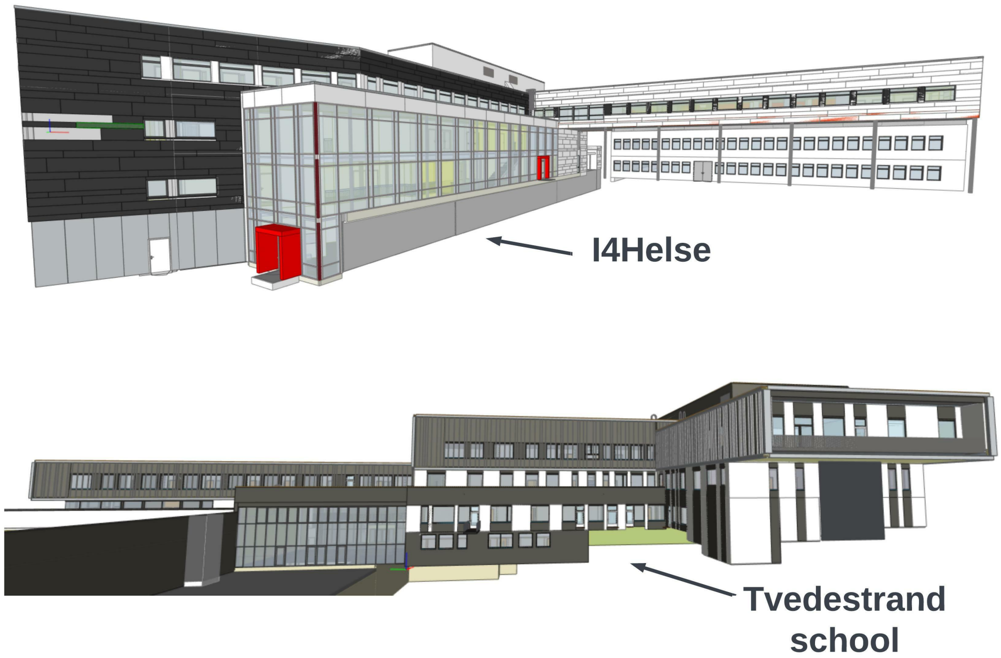


Figure 3.2: I4Helse and Tvedestrand school as case studies in this thesis [6].

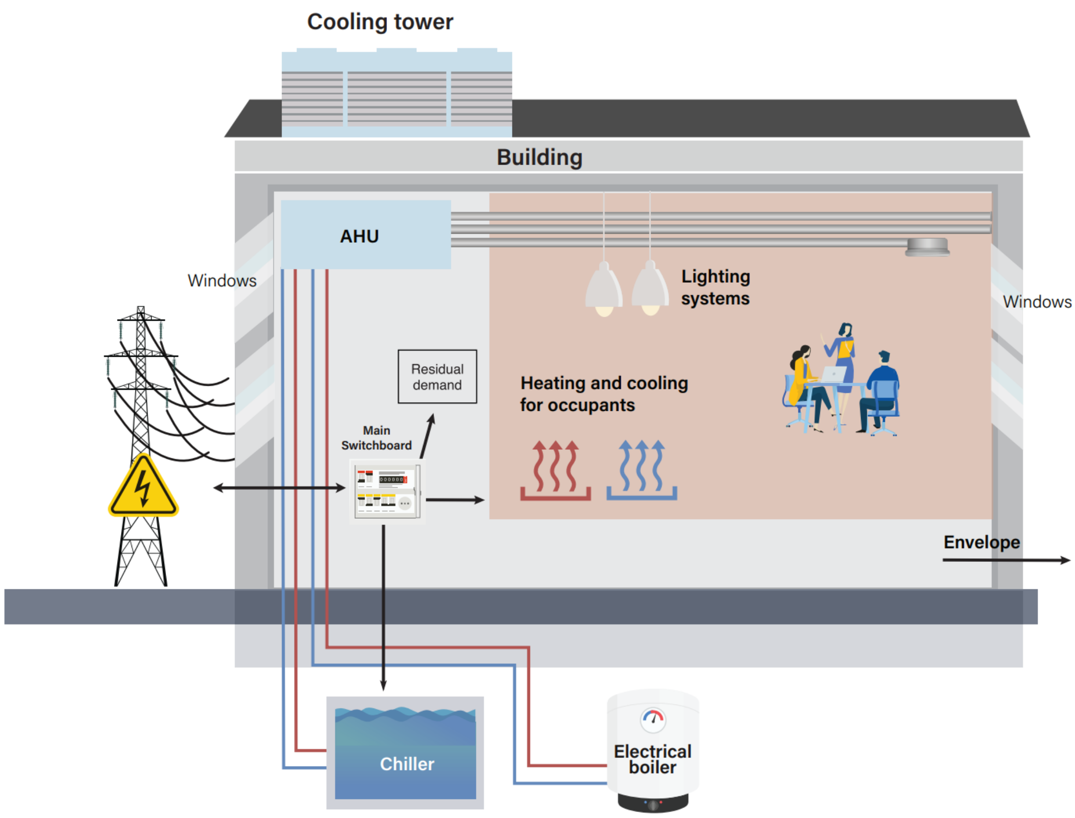


Figure 3.3: The components incorporated in the Digital Twin framework, including the building's envelope, lighting, and HVAC systems [6].

Table 3.2: Building envelope performance values for the two case studies where TEK10 and NS 3701 Standards requirements are followed. The term 'initial values' refers to the actual values of the building and serves as the starting point for the optimization process.

Parameter	**Initial value**
External wall U-value (W/(m²·K))	0.15
Roof U-value (W/(m²·K))	0.11
External window, and doors (W/(m²·K))	0.8
Floor U-value, W/(m².K)	0.06
Normalized thermal bridge (W/(m²·K))	0.03
Airtightness n_{50} (1/h)	0.35
g_t, Solar Heat Gain Coefficient (SHGC) (glass)	0.34 (3 layers glass)

Table 3.3: The HVAC systems in our case studies including setpoints.

Operation	**Features**
Ventilation system	Mechanical balanced ventilation system
Schedules of ventilation system operation	Monday-Friday: 12 hours/day (07.00–19.00)
Average supply airflow rates of the ventilation system	2.48 l/(m².s) for the occupied zones and 0.81 l/(m².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 setpoint 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/((m².s)

3.2 Methodological Approach: utilizing Digital Twin for Energy Efficiency and Indoor Comfort

The methodological approach utilized in this thesis aims to utilize Digital Twin technology to address existing gaps in research (see section 2.5) and practice concerning operational efficiency, energy optimization, and occupant comfort in non-residential buildings. Focusing on these key areas, the approach seeks to provide practical solutions and contribute to closing the existing knowledge and gaps.

BIM is an essential component of the methodological approach utilized in this thesis. BIM is incorporated due to its capability to provide a digital representation of the building, facilitating accurate modeling and simulation of building geometry, systems, and components. It served as a central repository of information that enables seamless collaboration among stakeholders involved in the building management process, including architects, engineers, contractors, and facility managers.

The BIM methodology involved creating a detailed 3D model of the building, which included information about its physical characteristics, such as dimensions, materials, and structural elements. This model served as a Digital Twin of the physical building, allowing stakeholders to visualize and analyze the building's various systems and components. BIM enabled stakeholders to identify potential clashes or conflicts in the design phase, resulting in improved coordination and reduced errors during the construction and maintenance stages.

Furthermore, BIM supported data integration and management by providing a structured framework to store and organize information related to the building's lifecycle. This included information about equipment, maintenance schedules, energy consumption, and performance data. The integration of BIM with other technologies, such as IoT sensors, enabled the collection of real-time data linked to the digital model, facilitating continuous monitoring and analysis of the building's performance.

IoT (Internet of Things) technology played a crucial role in the methodological approach adopted in this thesis. IoT was employed to capture real-time data from sensors deployed throughout the building, enabling comprehensive monitoring of various parameters. This continuous monitoring and data acquisition provided valuable insights into the building's operational performance.

By utilizing the IoT, our framework enabled predictive fault detection and maintenance. The utilization of IoT sensors allowed to collect real-time data, empowering facility managers to identify any anomalies or deviations from desired performance thresholds. This predictive approach played a crucial role in detecting potential issues before they escalated, enabling timely interventions and maintenance activities. Additionally, IoT technology enabled the implementation of predictive analytics algorithms. These algorithms utilized historical data analysis to uncover patterns and trends, enabling the system to make accurate predictions and provide early warnings about potential faults or operational inefficiencies.

In addition, ML algorithms played a vital role in the methodology employed in this thesis. Several types of ML were used, as indicated in Table 7 of [4]. The selection of data was a crucial step in the research process, guided by its relevance to the research objectives and the availability of data sources within the selected case studies. Careful consideration was given to the data sources that aligned with the specific focus of the research, which aimed to improve operational efficiency, energy optimization, and occupant comfort in non-residential buildings. The research objectives determined the types of data required for analysis and prediction. Various data sources were considered, including sensor data (refer to Table 3.1), BIM data, comfort data (from the survey), and Computerized Maintenance Management System (CMMS) data.

To facilitate the analysis and application of ML algorithms, MATLAB Simulink [168] was utilized for developing the HVAC Digital Twin model, analyzing and predicting the outputs. Simulink provided a comprehensive platform for modeling and simulating the HVAC system, enabling an accurate representation and analysis of its behavior. Python [169], on the other hand, was used for implementing other ML algorithms and analyzing the collected data. Python's rich ecosystem of ML libraries and tools enabled advanced data analysis, feature engineering, and model training. The integration of both MATLAB Simulink and Python allowed for a comprehensive and effective approach to analyzing and predicting the performance of the HVAC system within the Digital Twin framework.

Furthermore, the ML algorithms were trained on historical data, which not only facilitated the development and optimization of the algorithms but also enabled the framework to make real-time predictions more efficiently. The training process involved optimizing the parameters of the ML algorithms to enhance their accuracy and effectiveness in predicting potential faults and optimizing maintenance activities.

The framework, as shown in Figure 3.4, consists of two main stages: the Data Input stage and the Predictive Maintenance and Optimization stage. These stages play integral roles in the overall functionality of the framework and will be discussed in detail below.

3.2.1 Data input as the first stage

The data input stage of the framework encompasses the integration of various types of data, including BIM, sensor data, and building users' feedback. These data sources collectively provide essential information for analysis and decision-making processes within the framework. Figure 3.5 illustrates the Data input stage, which involves the integration of various data sources into the framework.

3.2.1.1 BIM model data

Validating the data in a BIM model was a crucial step in ensuring its accuracy and reliability. The validation process involved reviewing and cross-referencing various types of data within the BIM model. One important type of data was geometric data, which included information about the building's physical elements such as walls, roof, floors, doors, and windows. The geometric data were validated in this work by comparing the dimensions, positions, and orientations of these elements

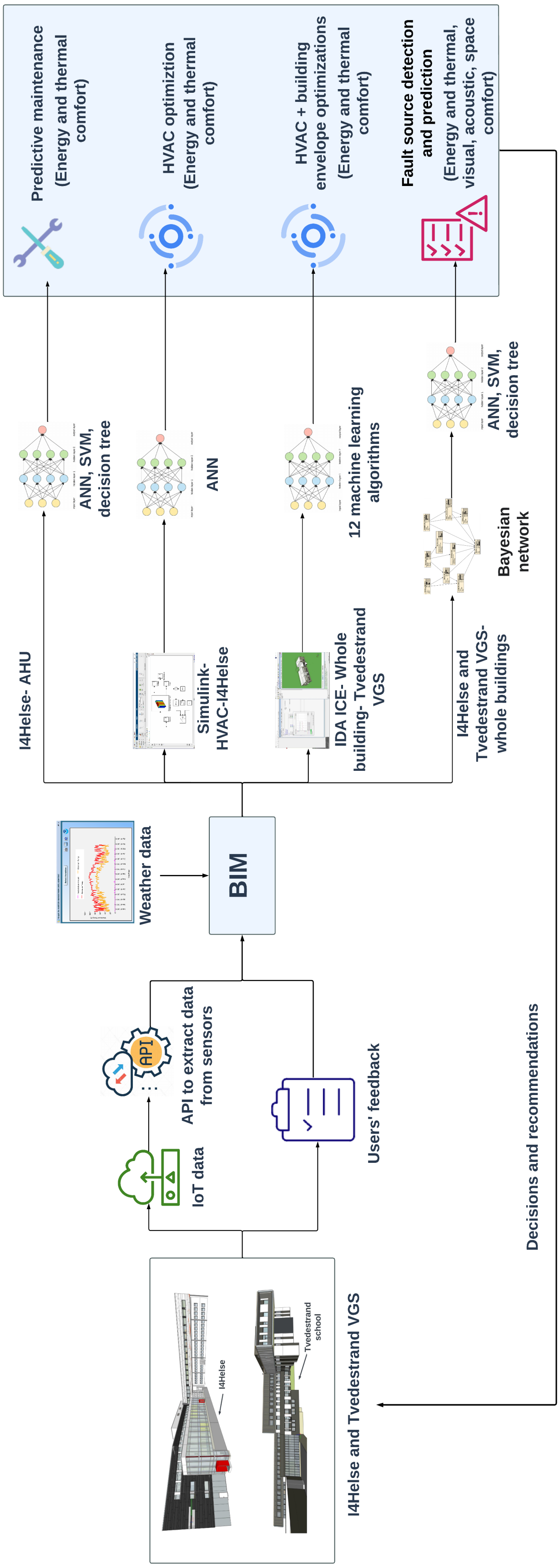


Figure 3.4: Methodological framework of the Digital Twin used in this thesis.

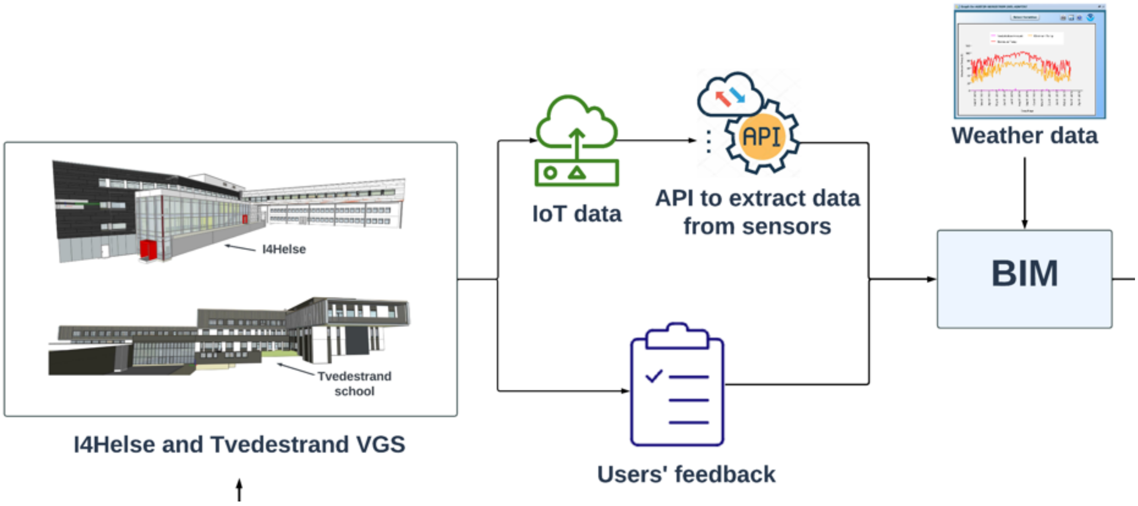


Figure 3.5: The Data input stage.

with the actual physical measurements taken on-site. Tools like laser scanners, Autodesk ReCap, Autodesk Navisworks, Revit, and Solibri Model Checker were used to identify geometric inconsistencies and clashes within the BIM model.

Another type of data in a BIM model was material data, which included information about the properties and characteristics of construction materials used in the building. Validating material data involved cross-referencing it with the specifications and documentation provided by the facility manager. This was done manually by reviewing the BIM model's material information.

System data was another important aspect of the BIM model, which included information about the building's HVAC systems, plumbing systems, and other components. To ensure the accuracy of this data, a validation process was conducted by comparing the information in the BIM model with the actual installed systems and their specifications. This validation involved verifying equipment sizes, capacities, and connections. In this work, Autodesk Revit was utilized for this purpose. Additionally, data sheets provided by the facility manager were used as a valuable source of information during the comparison process. By cross-referencing the BIM data with the physical components and their specifications, the accuracy and reliability of the BIM model were assessed, ensuring that it faithfully represented the real-world building systems.

Thermal performance data was also significant in the BIM model, as it evaluated the building's ability to maintain desired temperature levels and thermal comfort. It included parameters such as insulation properties, U-values, air leakage rates, and solar heat gain coefficients. Validating thermal performance data involved comparing these values with actual measurements obtained from on-site data collection. In this thesis, the actual measurements were obtained from [170].

In this work, the BIM model served two important purposes. Firstly, it acted as input data for predictive maintenance and optimization techniques. Secondly, it served as a visual representation of the results obtained from these procedures. For the Digital Twin framework to operate effectively, it required access to a complete

BIM model database. This necessitated a detailed modeling effort, ensuring that the thermal and geometric properties of various building envelope components were accurately allocated to each element.

The Level of Development (LOD) of a BIM model played a crucial role in extracting the thermal and geometric data necessary for the proposed framework. As defined by [171], a preferred LOD of 300 or higher was recommended. LOD referred to a standardized measure of completeness and detail within a BIM model across different project stages. It specified the reliability and accuracy of the BIM data, enabling analysis, visualization, and construction activities. The LOD scale ranged from LOD 100 (conceptual) to LOD 500 (as-built). A higher LOD ensured that the BIM model contained the necessary level of detail and accuracy to effectively extract thermal and geometric data for the Digital Twin model.

Given its accessibility to academics and integration with an open-source visual programming environment such as Dynamo [172, 173], Autodesk Revit® 2022 [174] was used as the BIM authoring tool in this thesis. Its compatibility and functionality made it a suitable choice for creating and managing the BIM model within the proposed framework. The use of Autodesk Revit® 2022 provided a robust platform for modeling, analyzing, and simulating the building's elements and systems.

3.2.1.2 Incorporate sensor information into the building information model

To gather essential data regarding the building's operational and environmental conditions, sensors were already in place throughout the rooms and HVAC systems. This was done by Laugstol company [175] for I4Helse and by Bravida [176] for Tvedestrand VGS. These sensors effectively monitored a wide range of variables as shown in Table 3.1. However, extracting the necessary data from the Building Management System (BMS) presented challenges, as direct data extraction was not possible due to system limitations.

To address this challenge, an approach was taken within the BIM environment to seamlessly incorporate the sensor data. A new sensor family was developed, which refers to a collection of sensor components specifically designed to represent the physical sensors within the Digital Twin model. In the context of a BIM model, a "family" is a term used to describe a group of related components with similar characteristics, functions, or properties. In this case, the sensor family comprises components that emulate the physical sensors used in the real-world building or system being modeled. These sensor components within the family are created to accurately represent the behavior and attributes of their real-world counterparts within the Digital Twin model. This new sensor family enabled the accurate representation and visualization of the sensor elements within the BIM model.

The Revit plug-in played a critical role as the bridge between the sensor data and the BIM model. By integrating the URL of the RESTful API into the C# code of the plug-in, a direct connection was established. This connection allowed for the automatic retrieval of real-time data from the sensors through the RESTful API and the mapping of that data to the appropriate sensor elements within the BIM model (Figure 3.6). The plug-in facilitated the synchronization of the sensor data with the corresponding sensor elements in real-time, ensuring that the BIM model accurately reflected the current conditions of the building.

The integration of sensor data into the BIM model was implemented in this work, granting facility managers direct access to real-time information on building conditions. This implementation involved the development of a custom plug-in that seamlessly streamed real-time sensor data from the HVAC system and individual rooms into the BIM model. This solution enabled facility managers to actively monitor the building's performance and make data-driven decisions to enhance operations and occupant comfort.

One key feature of the plug-in was the implementation of a threshold mechanism that color-coded rooms based on occupant comfort levels. Utilizing the collected sensor data, the plug-in categorized each room within the BIM model and assigned color codes such as green, yellow, or red, representing optimal, moderate, or uncomfortable conditions respectively. This visual representation enabled facility managers to swiftly identify areas that required attention, allowing them to proactively address comfort-related issues and allocate necessary resources accordingly.

The facility managers used the solution and expressed their intention to share it with their companies. They recognized the value and potential benefits of the integrated sensor data and saw the opportunity to implement the solution across their companies. Their intention to recommend this approach to their company highlighted their confidence in the solution's effectiveness and its potential to optimize building performance and occupant comfort.

By seamlessly incorporating sensor data into the BIM model, the proposed framework enabled real-time monitoring of building conditions and provided facility managers with the necessary information to make informed decisions. This integration enhanced the value and utility of the Digital Twin model by empowering facility managers to utilize real-time data in optimizing energy consumption, improving maintenance practices, and ensuring occupant comfort.

Figure 3.7 and 3.8 depict the functionality of the plug-in within the BIM environment, showcasing its role in visualizing sensor data and enabling real-time monitoring and analysis of building conditions. This integration of sensor data through the Revit plug-in and the BIM model not only enhanced the accuracy and timeliness of the information available to facility managers but also streamlined their decision-making processes, contributing to improved building performance and occupant satisfaction. By having real-time access to comprehensive data on building conditions, facility managers were able to proactively identify areas requiring attention, such as rooms with suboptimal comfort levels or potential maintenance issues. This timely awareness empowered them to take prompt actions, implement targeted adjustments, and optimize system operations to ensure optimal energy efficiency, thermal comfort, and indoor air quality. Consequently, the integration of sensor data facilitated a proactive approach to building management, resulting in improved performance, reduced energy waste, enhanced occupant comfort, and overall increased satisfaction with the building environment.

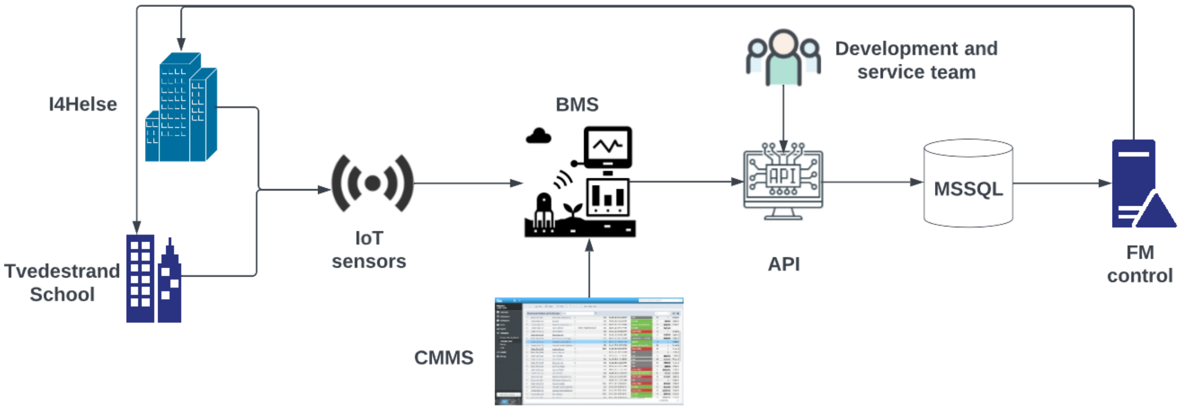


Figure 3.6: IoT data gathering system including API established by both the service and development teams [6].

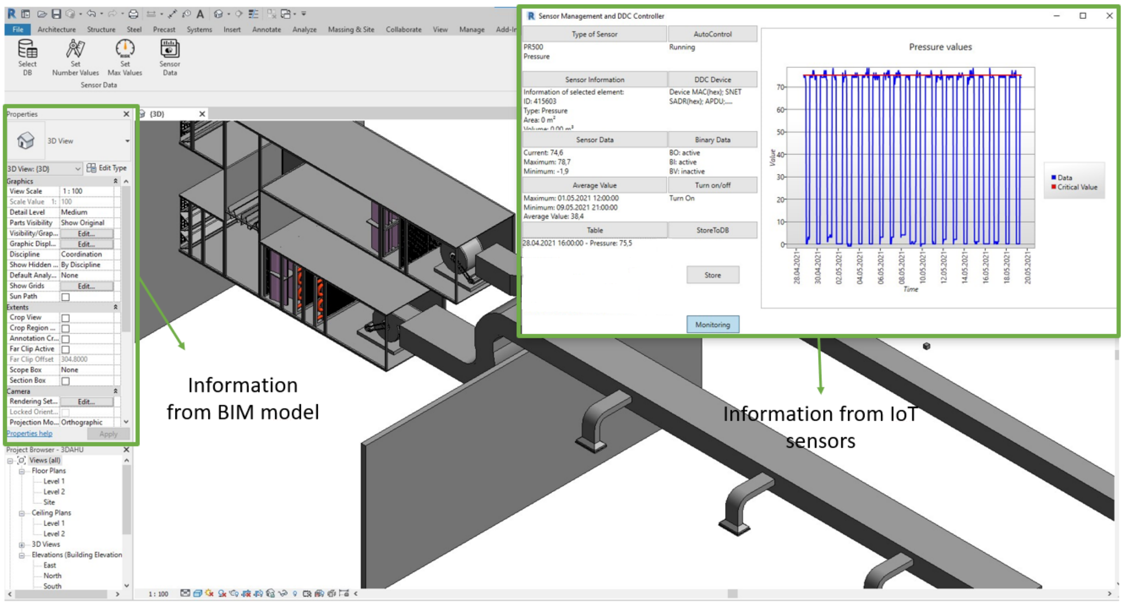


Figure 3.7: The AHU information from sensor data and BIM model (the first version of the plug-in used in paper 2) [2].

3.2.1.3 Survey of building users

The exploration of factors affecting users' comfort is essential in the context of the thesis research topic, which focuses on energy saving and comfort improvement in non-residential buildings. Users' comfort is a crucial aspect as it directly influences their satisfaction, well-being, and productivity within the built environment. Understanding and addressing the factors that impact users' comfort are fundamental to creating sustainable environments.

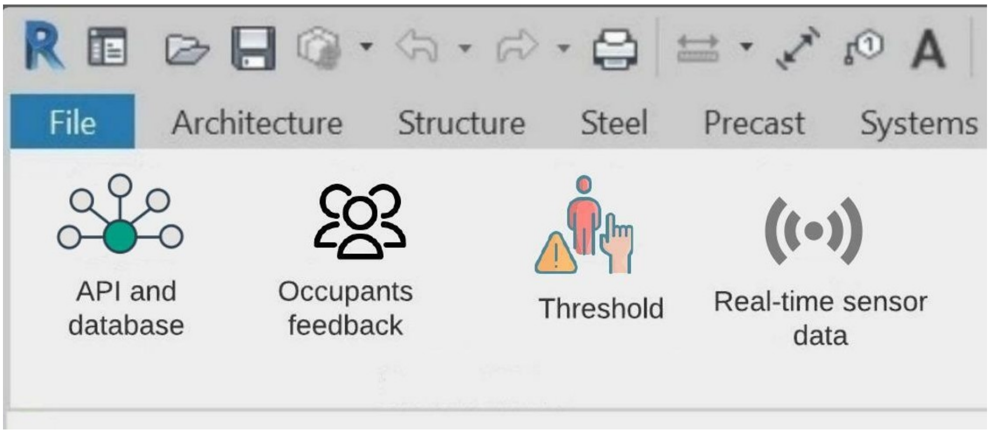


Figure 3.8: Managing sensor data and occupant feedback within Revit using a custom-developed plug-in (last version of the plug-in) [6].

The research aims to explore the potential of Digital Twin technology and other methodologies in optimizing energy consumption while prioritizing occupants' comfort. By conducting a thorough examination of the factors that influence users' comfort, the study seeks to develop practical strategies and tools that effectively enhance indoor environmental quality and promote occupants' well-being.

Analysis of the factors that affect users' comfort in a building entails three primary steps:

1. With the user's comfort in mind, we designed and created survey forms (an example can be found in Annex H) using the SurveyXact tool [177] to measure buildings' users' satisfaction (e.g., thermal comfort, acoustic comfort, indoor air quality, visual comfort, and space adequacy) throughout the cold and hot months. In the survey, respondents were questioned about the building, floor, and room number where they spent most of their time at work. Using a 5-point Likert scale where a score of 5 indicates "very satisfied" and a score of 1 indicates "very dissatisfied." The survey also included a list of possible causes for discomfort and a free text box for additional comments.

   The survey design process began with a comprehensive literature review to identify factors influencing occupant comfort in non-residential buildings. Building upon this research, an interesting survey formed by researchers in the occupants' comfort field from Spain served as a foundation for developing the survey used in this thesis [13, 178]. To ensure its validity and relevance, the survey was then reviewed and edited by researchers from Norway, Spain, Germany, Cyprus, and Italy, who provided diverse perspectives and insights from different geographical contexts. Additionally, the perspectives of building department leaders and school administrators in our case studies were incorporated to address the specific needs and requirements of the occupants. The objective of this process was to determine the discomfort factors to include in the survey, aligning them with both the existing literature and the input from experts. The resulting comprehensive list of discomfort causes formed the basis for the survey questions, allowing occupants to provide feedback and highlight any potential discomfort issues they may have experienced.

Moreover, in order to gain valuable insights into the interplay between occupant comfort and system control, additional measures were implemented during the survey process to incorporate real-time comfort considerations. Colleagues occupying different rooms within the I4Helse building were invited to provide feedback on their comfort levels specifically during the summer season. Simultaneously, I made targeted adjustments to the controller settings for temperature and airflow to closely observe the direct impact on comfort perception. This approach provided a deeper understanding of how occupant comfort is influenced by system control and enabled us to uncover important insights for optimizing both comfort and energy efficiency.

2. The survey's results were utilized in developing the BN model, which considers the most significant aspects contributing to the discomfort experienced by users in buildings located in Norway. A probabilistic model trained on a BN was utilized to identify the users' comfort causal factors. For each comfort factor, details on the building were obtained, including its features and HVAC system, as well as information about the surrounding, including occupancy density. The Python box in Dynamo was utilized in developing the BN model for users' comfort.

3. Connecting the BIM model with users' feedback from the survey and the probabilistic model to support users' comfort was achieved with a plug-in developed in C Sharp, visual programming for Autodesk Revit in Dynamo, and the Python programming language. The FM team could make sense of the information owing to the BIM representation of user responses and the results of the causal analysis.

   The process of connecting the BIM model with users' feedback involved integrating the information gathered from the occupants' responses with the Digital Twin model. The specific type of information connected was the feedback provided by the building users regarding their comfort perceptions, potential discomfort causes, and any specific issues they experienced within the building.

   To connect this feedback with the BIM model, a data integration approach was employed using C Sharp and visual programming for Autodesk Revit in Dynamo. The information collected from the surveys, including user feedback, was processed and transformed into a format compatible with the BIM model. This involved mapping the feedback data to the corresponding elements within the BIM model, such as specific rooms and systems.

   The purpose of connecting the BIM model with users' feedback was to enhance the Digital Twin model's capabilities in monitoring and analyzing building conditions. By incorporating the occupants' feedback, the Digital Twin model could be enriched with real-time user experience data, enabling facility managers and stakeholders to gain insights into the performance and comfort levels of different areas within the building.

This integration served multiple purposes. Firstly, it provided a holistic view of the building's performance by combining sensor data and users' feedback, allowing for a comprehensive analysis of the factors influencing comfort and energy consumption. Secondly, it facilitated the identification of specific areas or systems within the building that required attention or optimization based on user-reported issues or discomfort causes. This information could guide facility managers in making informed decisions to improve occupant comfort and overall building performance.

3.2.2 Predictive maintenance and optimization as the second stage in the framework

The second stage of the framework, as depicted in Figure 3.9, focuses on predictive maintenance and optimization.

In this stage, the framework utilizes several techniques and algorithms to drive predictive maintenance and optimization efforts. By analyzing the data collected in the Data Input stage, the framework detected several faults, achieved predict maintenance needs, and optimized various aspects of building performance.

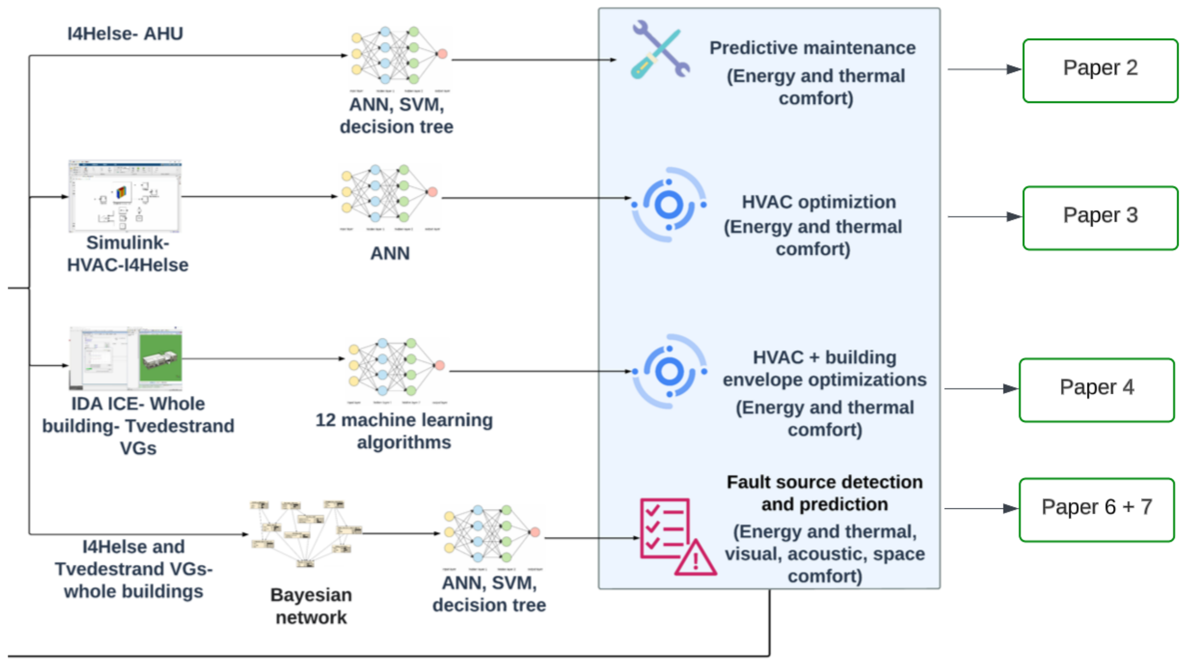


Figure 3.9: The second stage of the framework.

3.2.2.1 Enhancing comfort by predictive maintenance: AHU condition assessment rules for identifying building issues

Predictive maintenance plays a crucial role in ensuring optimal comfort and operational efficiency in non-residential buildings. One of the key processes in predictive maintenance is the identification of faults and monitoring of conditions, which involves collecting and analyzing critical parameters to assess the status of building components. In line with this objective, the proposed framework in this thesis aims to assist facility managers in identifying the root causes of building issues and addressing the needs of occupants. To achieve this, the framework employs a systematic approach that begins by determining if a reported comfort issue is related to an electrical problem within the HVAC system. If not, the framework utilizes a Bayesian Network (BN) to investigate potential issues with the HVAC system design, including assessing its capacity to meet the thermal demands of the occupants. This analysis considers factors such as architectural and construction design, thermal load calculations, and equipment database information. If the HVAC system is found to be undersized, the framework provides recommendations such as facade insulation or upgrading to larger capacity interior units. Conversely, if the indoor unit capacity is deemed sufficient, the framework utilizes APAR rules to further investigate potential equipment failures within the HVAC system. Additionally, the framework considers visual, acoustic, and spatial comfort factors, such as window-to-wall ratio, room lighting, and space functionality, in order to comprehensively address the occupants' comfort needs.

Our study constructed a condition assessment system and executed diagnostics in various devices using the expert rules developed by Nehasil et al. [179] based on the APAR technique developed by Schein et al. [180]. Schein et al. [180] identify 28 possible detection rules in AHU. The majority of the rules depend on how the AHU is being used. Depending on whether the AHU is cooling or heating, a separate test must be performed on the heater. It is possible to activate the necessary rules after the operating mode of the time stamp has been determined. Most rules are rather simple, using only basic mathematics to predict the result of a single determinable physical or regulatory event as can be seen in Table 3.4. A portion of the BN model used to apply all of these principles is shown in Figure 3.10.

The ANN, SVM, and decision tree approaches are trained using data sets for the selected variables (including the faults detected by APAR). The well-trained, validated, and tested models predict the long-term state of the various components (2 to 4 months ahead). Based on the prediction, the maintenance plan must be rescheduled to align with the condition.

The validation process for the ANN, SVM, and decision tree approaches involves training the models using carefully selected datasets based on Table 3.1, including the faults detected by the APAR method. These models are then subjected to a rigorous validation procedure to ensure their accuracy and reliability in predicting the long-term state of various building components.

The validation involves comparing the model's predictions with actual data obtained from real-world scenarios. By comparing the predicted values with the observed values, including mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R-squared), the model's accuracy was assessed, and any discrepancies or deviations were identified and addressed.

Once the models have been well-trained, validated, and tested, they were utilized to predict the long-term state of various building components. These predictions provided valuable insights into the future condition of the components, allowing for more informed decision-making regarding maintenance planning and scheduling. Based on these predictions, the maintenance plan was adjusted and rescheduled to align with the predicted condition, enabling predictive maintenance and minimizing potential failures or disruptions.

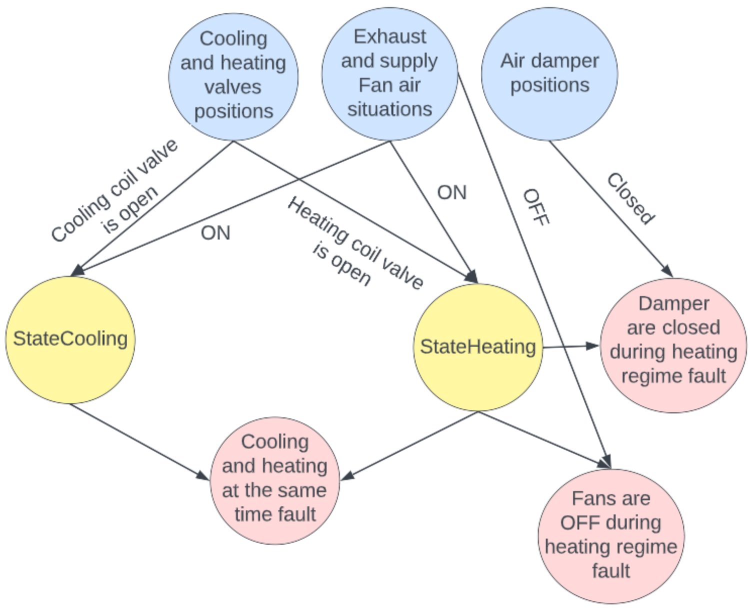


Figure 3.10: An example of how the BN applies the APAR rules to check if there are any faults in the units inside the buildings. The blue nodes are the BMS data, the yellow nodes are the state nodes, and the red ones are the faults [6].

3.2.2.2 HVAC Digital Twin (HVACDT) model

A Digital Twin model of the HVAC system is depicted in Simulink, and intelligent operations are performed using these models (Figure 3.11). While there is theoretically no limit to the many network topologies that may be used, it is computationally efficient to go with the simplest possible design.

The primary equations for the mathematical modeling in Simulink are as follows based on [181] and [182], where Tables 3.2 and 3.3 show the general information regarding the reference case building:

Cooling load (kW):

$$Q_{cooling} = (M_{cw} \times C_{pwater} \times (T_{wo} - T_{wi})) \qquad [kW] \tag{3.1}$$

Table 3.4: Summary of some expert rules for fault detection in air handling units.

Mode	Rule No.	Description
Heating (mode 1)	1	Supply air temperature is less than air temperature after heat exchanger plus the difference between the supply air temperature set point and threshold for errors in temperature measurements
Heating (mode 1)	2	Ratio of outdoor air flow rate to supply air flow rate is outside of acceptable range which indicate an air leakage
Mechanical cooling with 100% outdoor air (mode 3)	8	Outdoor air temperature is less than supply air temperature set point minus the difference between the supply air temperature set point and and threshold for errors in temperature measurements

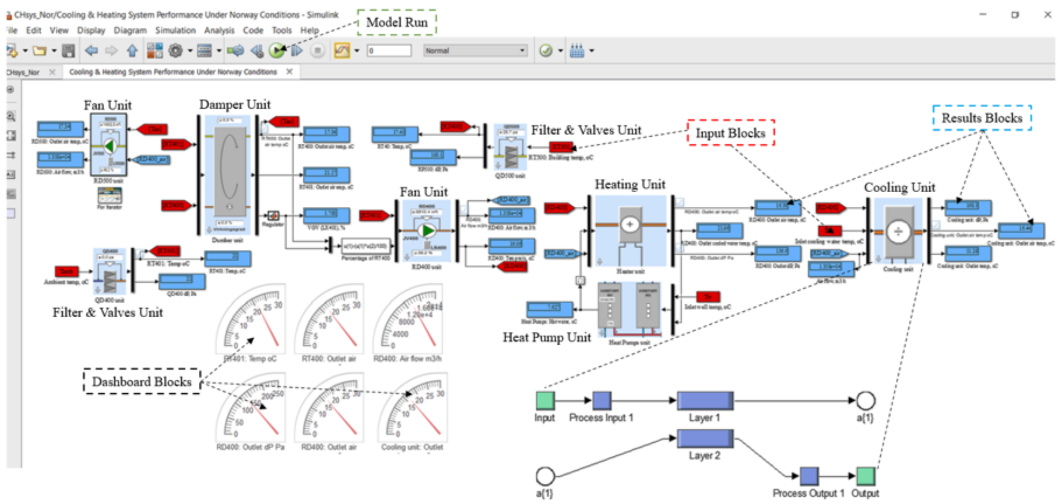


Figure 3.11: The developed HVACDT using Simulink toolbox [3].

Heating load (kW):

$$Q_{heating} = (M_{hw} \times C_{pwater} \times (T_{hi} - T_{ho})) \qquad [kW] \tag{3.2}$$

In summer (kW):

$$Q_{air} = (M_{ai} \times C_{pair} \times (T_{ui} - T_{ai})) \qquad [kW] \tag{3.3}$$

In winter (kW):

$$Q_{air} = (M_{ai} \times C_{pair} \times (T_{ui} - T_i)) \qquad [kW] \tag{3.4}$$

$$\eta = \frac{Q_{cooling/heating}}{Q_{air}} \qquad [-] \tag{3.5}$$

$$Q_{power} = \frac{Q_{cooling/heating}}{COP} \qquad [kW] \tag{3.6}$$

$$\begin{aligned} C_{pwatersummer} = (4.218103) + (-0.0050041 \times (T) + (0.000827196 \times \\ (T)^{1.5}) + (-7.44273 * 10^{-6} \times (T)^{2.5}) + \\ (4.15557 \times 10^{-7} \times (T)^3) \qquad [kJ/kgK] \qquad [182] \end{aligned} \tag{3.7}$$

$$\begin{aligned} C_{pwaterwinter} = (4.218103) + (-0.0050041 \times (T) + (0.000827196 \times \\ (T)^{1.5}) + (-7.44273 * 10^{-6} \times (T)^{2.5}) + \\ (4.15557 \times 10^{-7} \times (T)^3) \qquad [kJ/kgK] \qquad [182] \end{aligned} \tag{3.8}$$

$$C_{Pair} = 1.005 + (x \times 1.82) \qquad [kJ/kgK] \tag{3.9}$$

$$x = RH \times \theta_s \qquad [kg/kg] \tag{3.10}$$

Where,

T: The average temperature between the inlet and outlet temperatures from the chiller and heater [°C]

T_{ui}: Supply air temperature to zones [°C]

T_{uo}: Return air temperature [°C]

T_{hi}: Supply heating water temperature [°C]

T_{ho}: Return heating water temperature [°C]

T_{ai}: Ambient temperature [°C]

T_i: Temperature after rotary heat exchanger [°C]

M_{ai}: Mass airflow rate [kg/s]

M_{hw}: Mass water flow rate for heating [kg/s]

M_{cw}: Mass water flow rate for cooling [kg/s]

T_{wi}: Supply cooling water temperature [°C]

T_{wo}: Return cooling water temperature [°C]

C_P: Specific heat capacity [kJ/kg K]

Q: Cooling or heating load [kW]

η: Efficiency [-]

COP: The coefficient of performance [-]

Density: [kg/m³]

θ_s: Saturation water vapour content [kg/kg]

RH: Relative humidity [-]

x: mass humidity ratio of the air [kg/kg]

These equations are used to model the cooling and heating loads in the building.

Equation (3.1) calculates the cooling load by multiplying the mass flow rate of chilled water (M_{cw}), the specific heat of water (C_{pwater}), and the difference between the temperature of the water leaving the cooling coil (T_{wo}) and the temperature of the water entering the cooling coil (T_{wi}).

Equation (3.2) calculates the heating load by multiplying the mass flow rate of hot water (M_{hw}), the specific heat of water (C_{pwater}), and the difference between the temperature of the water entering the heating coil (T_{hi}) and the temperature of the water leaving the heating coil (T_{ho}).

Equation (3.3) and (3.4) calculates the air load, which is the amount of energy required to heat or cool the air in the building. It is calculated by multiplying the mass flow rate of air (M_{ai}), the specific heat of air (C_{pair}), and the difference between the temperature of the air entering the room (T_{ui}) and the ambient temperature (T_{ai}) in summer and the difference between (T_{ui}) and temperature after rotary heat exchanger (T_i) in winter.

Equation (3.6) calculates the power required to run the cooling or heating system by dividing the cooling or heating load by the COP.

Equation (3.7) and (3.8) calculates the specific heat of water for cooling and heating.

Equation (3.9) calculates the specific heat of air.

Equation (3.10) calculates x which is the mass of water vapor present in one unit mass of dry air(kg/kg). x is used in the specific heat of air calculation. x is calculated by multiplying the relative humidity (RH) and the saturated water vapour content (θ_s).

By using measurement data from Landvik station [167], we could calculate monthly averages for temperature and relative humidity, which are converted to x-values using saturated air table. Also, 1.005 in equation 3.9 is the dry air heat capacity in kJ/kgK by normal temperature. It is worth mentioning that Landvik station refers to a specific weather station located in Grimstad, Norway close to the I4Helse building. It is equipped with instruments and sensors to collect weather data such as temperature, relative humidity, wind speed, and precipitation. The station continuously measures and records these weather parameters, providing a reliable source of data for meteorological analysis and research purposes.

In the equation (3.9), 1.82 is a constant value that is used to adjust the dry air heat capacity (1.005 kJ/kgK) to take into account the effect of air humidity on the specific heat of air. The value of x, which is calculated by multiplying the relative humidity (RH) and the saturated water vapour content (θ_s) as shown in equation (3.10), is multiplied by this constant value (1.82) in equation (3.9). The result is added to the dry air heat capacity (1.005 J/kgK) to get the specific heat of air (Cpair) taking into account the humidity effect.

The development and validation of the HVAC Digital Twin (HVACDT) model involved several important steps to ensure its accuracy and reliability. In order to create a comprehensive and realistic model of the HVAC system, each component, such as the rotary heat exchanger, filters, fans, cooling units, and heating units, underwent thorough validation in Simulink. This validation process involved comparing the inputs and outputs of each component within the Simulink model to real-world data and observations from the HVAC system in I4Helse.

The selection of data for the validation process was undertaken to encompass a range of operating conditions and scenarios that the HVAC system could encounter. This involved collecting data from different time periods, varying weather conditions, variations in temperature setpoints, airflow rates, fan speeds, damper positions, and load conditions. The aim was to cover a broad spectrum of typical operational scenarios and ensure that the model's responses aligned with real-world observations.

To validate the inputs and outputs, machine learning techniques were employed. The models shown in Figure 3.12 played a crucial role in this procedure. These models were trained and validated using relevant datasets and machine learning algorithms to ensure that they accurately represent the behavior and performance of the HVAC system components.

The HVACDT model integrates real-time data, which is continuously updated in an Excel sheet every 10 minutes. This real-time data serves as the input for the Simulink model, enabling dynamic simulations and analysis. Within the Simulink model, an artificial neural network (ANN) is utilized to verify the performance of each component. The ANN compares the inputs and outputs of each unit within the HVACDT model with the corresponding inputs and outputs of the real system. This validation process ensures that the simulated behavior aligns with the actual behavior of the HVAC system.

In addition to the validation through machine learning, the energy results of the

HVACDT model are further validated using the physical equations mentioned in the thesis. These equations provide a basis for validating the energy consumption of the fans, cooling units, heating units, and other components within the HVAC system. By comparing the simulated energy results with the expected energy consumption based on the physical equations, the accuracy and reliability of the HVACDT model are verified.

To elaborate more, the data sets were randomly split into three groups: 80% for training, 10% for validation, and 10% for testing. The training phase utilized a Levenberg-Marquardt optimization technique to adjust the network based on the generated error. The energy consumption and Predicted Percentage of Dissatisfied (PPD) estimated and forecasted by the model showed strong consistency with the actual results.

The accuracy and performance of the ANN model were further validated by comparing it with other forecasting models such as the wavelet neural network (WNN), random forest (RF), and support vector machine (SVM). The ANN model outperformed the others in terms of R^2 values and Root Mean Square Error (RMSE), demonstrating its superior prediction fitting outcomes and lower forecast fitting error.

Based on the successful validation of the ANN model in accurately predicting energy consumption and thermal sensation, it was selected as the objective function for the multi-objective optimization process.

The objective function is a fundamental component of the multiobjective optimization process, serving as a mathematical representation of the goals and constraints to be considered in the optimization problem. In the context of this research, the objective function plays a crucial role in integrating energy consumption and thermal comfort objectives.

To elaborate further, the objective function combines the predicted energy consumption and thermal comfort metrics derived from the ANN model. These metrics are based on various input parameters, such as outdoor weather conditions, indoor setpoints, occupancy patterns, and HVAC system configuration. The ANN model uses historical data and machine learning techniques to generate predictions that reflect the behavior of the building under different scenarios.

The objective function itself can take different forms depending on the specific optimization goals and constraints. One common approach is to use a weighted sum formulation, where the energy consumption and thermal comfort metrics are multiplied by corresponding weights and summed together. These weights reflect the relative importance assigned to each objective, allowing decision-makers to prioritize energy efficiency or thermal comfort based on their specific needs and preferences.

For instance, if the objective is to minimize energy consumption while maintaining a certain level of thermal comfort, the objective function may assign a higher weight to energy consumption and a lower weight to the comfort metric. This would guide the optimization algorithm to focus more on reducing energy usage while ensuring that comfort requirements are met.

The objective function is dynamic and continuously updated as new sensor data becomes available and the ANN model generates updated predictions. This ensures that the optimization process takes into account real-time information and adjusts its decisions accordingly. By incorporating the objective function into the multiobjective optimization algorithm, a range of Pareto-optimal solutions were generated, representing different trade-offs between energy consumption and thermal comfort.

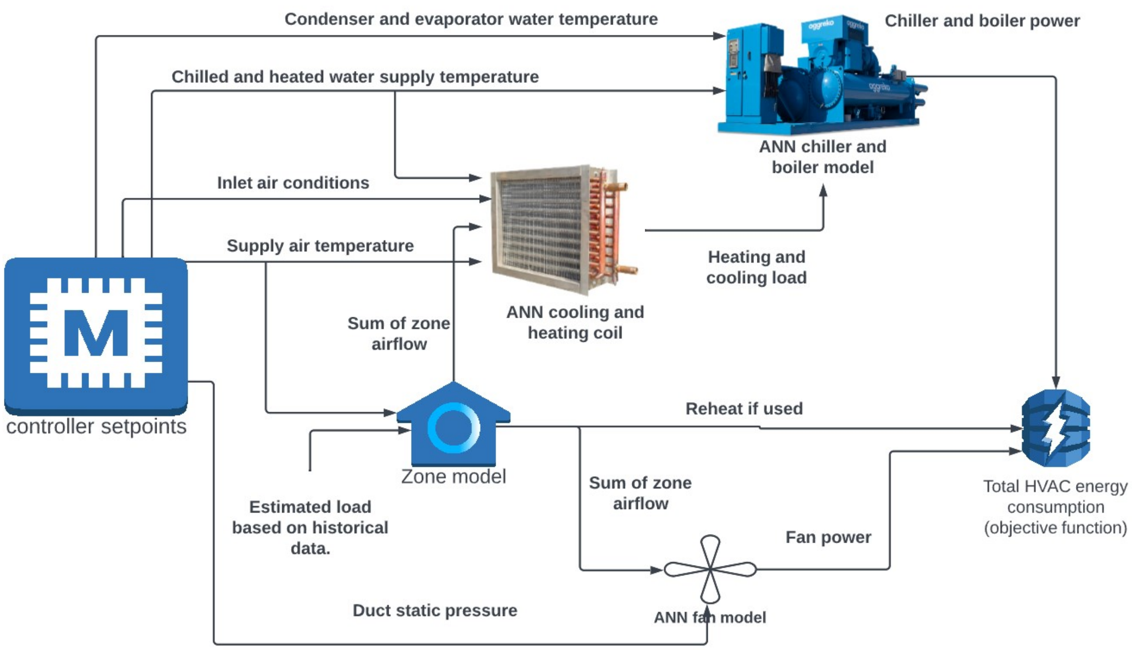


Figure 3.12: ANN components model flow chart, after [11].

3.2.2.3 HVAC and building envelope optimizations

EnergyPlus [183], TRNSYS [184, 185], and IDA ICE [186, 187], are only a few of the building energy performance tools often referenced in the literature.

The studies mentioned above show that improving a building for energy efficiency and thermal comfort simultaneously requires attention to the features and use of the building envelope and the HVAC system. Despite this, previous optimizations ignored important factors, including envelope characteristics and HVAC controls.

Consequently, this thesis fills a gap in the literature by optimizing for HVAC parameters and considering the interaction of building envelope components with HVAC system parameters with other crucial design variables. This was achieved by optimizing energy performance while considering users' comfort levels utilizing the Simulink model in MATLAB and IDA ICE software with machine learning algorithms.

This thesis considers many factors, such as window area, temperatures, U-values, airflow, and more, all of which are crucial to a building's performance but difficult to measure and pinpoint in the early stages of design [188, 189]. Energy use and occupants' comfort are modeled by setting up the building's parameters and environmental factors to reflect the actual conditions of the buildings. For each simulation, the result is the yearly energy demand given to the building for heating, cooling, ventilation, and lighting, expressed in kWh/m^2 floor space.

Several machine learning algorithms are analyzed to predict the energy a building uses. These algorithms were chosen based on how prevalent they were in the academic literature and how highly they were recommended. In this thesis, we compare various algorithms on the same dataset because none of the approaches that we select have ever been explicitly compared on a single dataset in any of the previous research that has been done. We selected the algorithms that demonstrated greater performance in the literature than those included in the same table. Each method includes several customizable aspects, such as the accuracy and the amount of work required by the computer. Some examples of this include convergence criteria, tuning parameters, and fitting procedures. Based on the theoretical basis and the program documentation, we make an effort to locate the settings that are the most relevant. In addition to this, the framework for the prediction of energy consumption was composed of four primary stages, which are as follows: (1) Data preprocessing; (2) Feature Selection; (3) Model development (training, validation, and testing); and (4) Model evaluation. These stages are depicted in Figure 3.13.

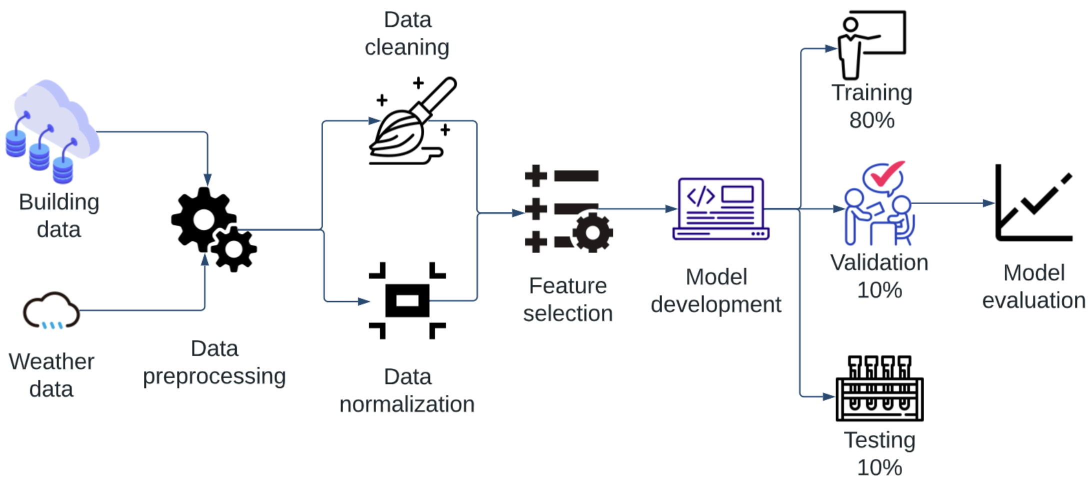


Figure 3.13: Prediction framework flowchart.

This work implements regression prediction methods for energy consumption as an alternative to the traditional mathematical functions employed as the objective function in optimization algorithms. These techniques are useful when a single formula cannot capture the intricate nonlinear connection between input variables and desired outcomes.

Indoor thermal comfort is the second object function considered in this work. It describes how comfortable most users are in a controlled indoor setting. The Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) are two important indicators of thermal comfort in this field; they measure how people within a building feel about the temperature of the air around them. The PMV has seven different ratings, from -3 to +3. Positive and negative numbers indicate warm and cool temperatures, respectively, whereas scores closer to zero indicate better thermal comfort. The PPD may be estimated after the PMV is known.

The equations (3.11), (3.12), (3.13), and (3.14) for the thermal comfort indicators (PMV and PPD) are developed according to ISO 7730 [190].

$$PMV = (0.303 \cdot e^{0.036 \cdot M} + 0.028) \cdot L \tag{3.11}$$

$$\begin{aligned} L = (M - W) - 0.00305 \cdot (5733 - 6.99 \cdot (M - W) - P_a) - 0.42(M - W - 58.15) \\ - 0.000017(5867 - P_a) - 0.0014 \cdot M \cdot (34 - T_a) - 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot ((T_{cl} + 273)^4 \\ - (T_r + 273)^4) - f_{cl} \cdot hc \cdot (T_{cl} - T_a) \end{aligned} \tag{3.12}$$

$$\begin{aligned} T_{cl} = 35.7 - 0.028 \cdot (M - W) - 0.155 \cdot I_{cl} \cdot (3.96 \cdot 10^{-8} \cdot f_{cl}((T_{cl} + 273)^4 \\ - (T_r + 273)^4) + f_{cl} \cdot hc \cdot (T_{cl} - T_a)) \end{aligned} \tag{3.13}$$

$$PPD = 100 - 95 \cdot e^{-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2} \tag{3.14}$$

Where,

PMV : Predicted mean vote [-]

PPD : Percentage of people dissatisfied [-]

M: Metabolic rate [met] = 1.2 (sedentary activities (office, home, school)) [181]

L: Body thermal load [-]

W: External work [W]

T_{cl}: Clothing's surface temperature [°C]

P_a: Partial vapour pressure [Pa]

f_{cl}: Body's surface area when fully clothed to the body surface area while naked [-]

I_{cl}: Thermal resistance of clothing [m² °C/W]

T_a: Indoor temperature [°C]

h_c: Convective heat transfer coefficient [W/m²K]

In equation (3.12), the various factors contributing to heat loss are represented by terms on the right side of the equation. These terms are then multiplied by specific coefficients and constants, such as 0.00305 and 3.96*10⁻8, in order to adjust the relative importance of each factor. Similarly, in equation (3.14), coefficients 95 and 100 are utilized to adjust the range of the PPD value, in order to accurately predict the percentage of people who would be dissatisfied with the thermal conditions.

In IDA ICE, which is a software tool used for building energy simulation, PPD is calculated by taking the average value of each zone in the building. The software simulates the thermal conditions in a building and uses a comfort model to predict the percentage of people in a given zone who would be dissatisfied with the thermal conditions. The PPD value is then used to evaluate the thermal comfort of the building and identify areas for improvement.

IDA ICE uses the adaptive comfort model which is based on the adaptive thermal comfort theory [191], this theory proposes that people have an adaptive range of comfort temperature, that can change based on activity, clothing, and air movement. The software calculates the PPD, which is based on the indoor temperature, humidity, air velocity, and mean radiant temperature. These parameters are then used to predict the percentage of people who would be dissatisfied with the thermal conditions in a given zone.

In this thesis, IDA ICE is used to calculate PPD by simulating the thermal conditions in buildings and using comfort models to predict the percentage of people in each zone who would be dissatisfied with the thermal conditions. By utilizing this value, we assessed the thermal comfort within the building and pinpoint areas that require optimization.

3.2.2.4 Multi-Objective Genetic Algorithm (MOGA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II)

In this thesis, Multi-Objective Genetic Algorithm (MOGA) [192] and Non-dominated Sorting Genetic Algorithm II (NSGA-II) [193] are used as optimization techniques in the proposed Digital Twin framework.

MOGA is a type of evolutionary algorithm that is used to find the optimal solutions for problems with multiple conflicting objectives. In the context of this thesis, MOGA was used to optimize the building's systems and components, such as HVAC, to improve energy efficiency and indoor comfort. MOGA works by using a population of possible solutions and repeatedly applying genetic operators, such as crossover and mutation, to evolve the population towards better solutions. The solutions in the final population are considered Pareto optimal, meaning that they are the best solutions for the given objectives, but they may not be the best solution for all objectives simultaneously.

NSGA-II is an improvement to the original NSGA algorithm, which is a type of MOGA. NSGA-II is particularly useful for handling problems with a large number of objectives and constraints. It uses a non-dominated sorting approach to sort the solutions into different levels of non-domination, called fronts. The solutions in each front are considered to be equally good in terms of the objectives, and the solutions in the lower fronts are considered to be better than those in the higher fronts. NSGA-II is able to balance the trade-offs between the different objectives and constraints to find the best overall solutions.

Both MOGA and NSGA-II are powerful optimization techniques that applied to the Digital Twin framework to optimize the building's systems and components. By using these algorithms, it is possible to improve the energy efficiency and indoor comfort of the building, while also satisfying other constraints, such as budget and maintenance requirements.

Table 3.5 provides a more comprehensive comparison between MOGA and NSGA-II. Both methods are used for multi-objective optimization and can find Pareto optimal solutions. Both methods can handle constraints. NSGA-II uses non-dominated sorting which MOGA does not. NSGA-II is better on high-dimensional problems, but MOGA is slightly less computationally complex. NSGA-II is better at preserving diversity and is more popular and highly recommended in the literature.

3.2.2.5 Pareto front solution in Dynamo

Using the previously stated plugin developed using C Sharp in Revit, the first step in this section is to transfer real-time sensor data from the building to the BIM model in Autodesk Revit. The BIM model always has the most up-to-date data for these attributes since they are streamed in real time via the Internet of Things devices.

In the second stage (Figure 3.14), the Optimo package in Dynamo was used to compute the optimum Pareto solution. Since the Dynamo API supports python nodes, we could easily translate the objective functions from the machine learning model and PPD to Dynamo.

Outputs from the optimization loop include the Pareto Optimal Set ((Figure 3.15) and CSV files containing the solution lists and population lists generated by the optimization process.

The optimal outcomes are used to replace Revit elements and control the indoor conditions to uphold PPD less than 10%.

3.2.3 Data Security and Privacy Considerations

The proposed Digital Twin framework relied heavily on the collection and analysis of data from various sources, including building sensors and BIM models. Therefore, it was imperative to address the security and privacy implications associated with this data collection and analysis.

Special attention was given to de-identifying any data that could potentially identify individuals. By removing personally identifiable information, the privacy of the building occupants was protected, and the risk of re-identification was minimized. Compliance with relevant data protection regulations, such as the General Data Protection Regulation (GDPR) in the European Union, was ensured to maintain the highest standards of data privacy [194].

Table 3.5: Comparison of Multi-Objective Genetic Algorithm (MOGA) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) in terms of objectives, Pareto optimality, handling constraints, non-dominated sorting, performance, scalability, diversity preservation, computational complexity, and popularity.

Method	**MOGA**	**NSGA-II**
Objective	Multi-objective optimization	Multi-objective optimization
Pareto Optimality	Pareto optimal solutions	Pareto optimal solutions
Handling Constraints	Handling constraints is possible	Handling constraints is possible
Non-dominated Sorting	No	Yes
Performance	Good performance on low-dimensional problems	Better performance on high-dimensional problems
Scalability	Can handle a moderate number of objectives	Can handle a large number of objectives
Diversity Preservation	Good diversity preservation	Excellent diversity preservation
Computational Complexity	Moderate computational complexity	Higher computational complexity
Popularity	Widely used	Widely used and highly recommended in literature

It is important to note that when collecting data on the comfort of building occupants, obtaining the appropriate approvals and permissions is crucial. In this thesis, the process of obtaining approval from the Norwegian Centre for Research Data (Sikt now) [195] was a significant and time-consuming task. The process of obtaining approval from Sikt took around 4 months, and it is important to factor in this time when planning research involving the collection of sensitive data.

Obtaining approval from Sikt ensured that the data collection and analysis were conducted in accordance with ethical guidelines and regulations. It also provided

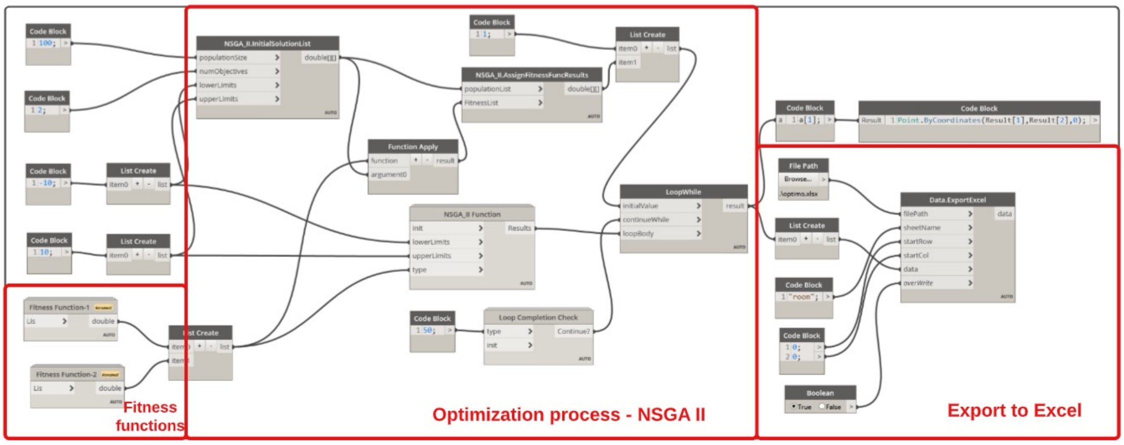


Figure 3.14: An overview of the optimization method in Dynamo, after [12].

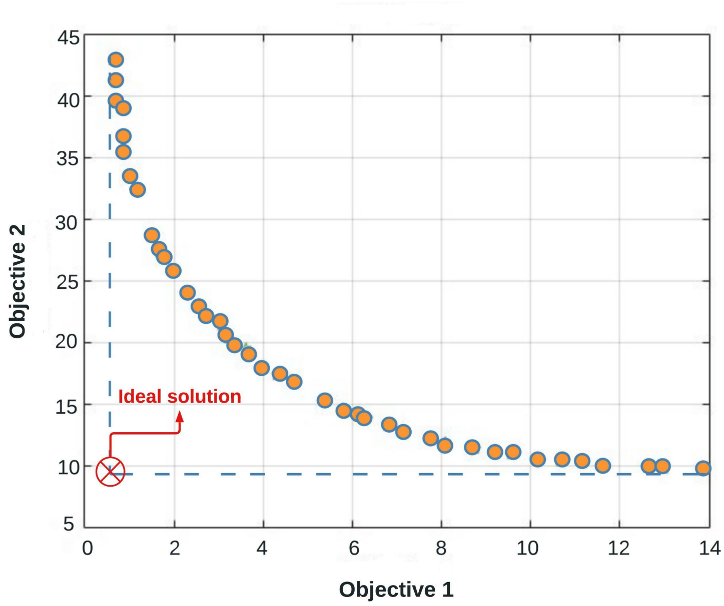


Figure 3.15: The Pareto front's optimal solution [4].

assurance to the building occupants that their personal data would be handled appropriately and that their privacy would be protected.

It is important to acknowledge that obtaining approval from Sikt was not the only step taken to ensure data security and privacy. A more detailed explanation is provided in the following sections.

3.2.3.1 Informed consent in the study

Informed consent was a fundamental aspect of this study to ensure the ethical treatment of participants. Before collecting any data, participants were provided with comprehensive information about the study, including its purpose, procedures, potential risks and benefits, and how their data would be handled. This information was approved by Sikt in a clear and understandable manner.

Participants were given sufficient time to review the provided information and were encouraged to ask questions to clarify any concerns or doubts they may have had (please check the information letter to participants in Annex H). The researchers ensured that participants had a full understanding of what their involvement would entail, allowing them to make an informed decision about participating in the study.

Voluntary consent was emphasized, and participants were informed that their participation was entirely voluntary. They were assured that declining to participate or withdrawing from the study at any point would not result in any negative consequences or impact their relationship with the researchers or the organization involved.

Consent was obtained in a documented manner, either through electronically recorded consent approved by the ethics committee. Participants were provided with a copy of the consent form for their records.

Respecting the principles of informed consent was crucial to ensure that participants had autonomy over their involvement in the study and were fully aware of how their data would be used. It aimed to uphold their rights, privacy, and well-being throughout the research process.

3.2.3.2 Data anonymization and confidentiality

In this study, specific measures were taken to ensure data anonymization and maintain confidentiality, with the primary goal of protecting participant privacy.

To begin with, any personal or sensitive information collected from participants during the study was subjected to a process of anonymization. This involved removing or encrypting identifiable information, such as names, contact details, and other personally identifiable data. By doing so, the data was transformed into a format that could no longer be linked to individual participants, thus preserving their privacy.

Furthermore, strict protocols were implemented to ensure the secure storage and handling of the collected data. Identifiable data was stored separately in SurveyXact [177] from the research findings and stored in a secure and controlled environment. Access to this data was limited only to authorized personnel who were bound by confidentiality agreements. These measures helped prevent unauthorized access or disclosure of participant information.

Confidentiality was a top priority throughout the study. All research results, analyses, and reports were presented in an aggregated and anonymized format. Individual participant data was not disclosed in any published materials or presentations, further safeguarding the privacy and confidentiality of participants.

3.2.3.3 Compliance with data protection regulations

The study placed a strong emphasis on compliance with data protection regulations, particularly the General Data Protection Regulation (GDPR) and Sikt data privacy.

To ensure compliance, data handling practices, storage, and processing were conducted in accordance with the guidelines outlined in the relevant regulations. This included obtaining informed consent from participants prior to data collection, clearly communicating the purpose and scope of data processing, and providing participants with the right to access their data, request its deletion, or make corrections if necessary.

3.2.3.4 Ethical approval

Ethical approval for this research study was sought and obtained from the Ph.D. program committee in engineering (PPCE) at the University of Agder. This approval was obtained to ensure that the study was conducted in compliance with ethical guidelines and principles, with a primary focus on safeguarding the rights, welfare, and privacy of the participants involved.

The ethical approval process involved submitting a detailed research proposal outlining the study's objectives, methodology, data collection procedures, and measures taken to protect participants. The PPCE committee carefully reviewed the proposal to assess its ethical implications and determine whether the study met the necessary ethical standards.

To respect the principle of autonomy, I obtained informed consent from all participants, providing them with comprehensive information about the study, its objectives, potential risks, and benefits. Participants were given the freedom to voluntarily decide whether or not to take part in the research, safeguarding their autonomy and privacy.

In line with the principle of beneficence, I carefully considered and minimized any potential risks to the participants. The research design incorporated measures to protect their well-being and welfare. I also maximized the benefits of the study by ensuring that the data collected would contribute to advancing knowledge and potentially improving practices in the relevant field.

Moreover, I adhered to the principle of justice by ensuring fair and equitable selection and recruitment of participants. I strived to include a diverse range of participants, considering accessibility, inclusivity, and representation. This approach fostered fairness and avoided any form of discrimination or undue influence.

Chapter 4

Main contributions

"If you would be a real seeker after truth, it is necessary that at least once in your life you doubt, as far as possible, all things."

Rene Descartes

This chapter summarizes the primary findings that show the novelty of the work introduced in this thesis, based on the research presented in seven peer-reviewed scientific articles. Please refer to the Appendices for the full texts of the articles.

4.1 Paper 1- A Review of the Digital Twin Technology in the AEC-FM Industry [1]

The Digital Twin technology may improve AEC-FM operations by enhancing data management and processing through synchronizing and integrating massive amounts of data, information, and knowledge. Through its use, data and information may be dynamically integrated and used effectively throughout a facility asset's lifecycle. Decision-making throughout a building's lifecycle may benefit greatly from combining a virtual information model with real-time data. Connecting IoT sensors and devices to the physical system enables real-time data integration, which improves adaptive updating to provide the data needed for further artificial intelligence integration, which coordinates and automates the physical counterpart of the digital model in response to operational changes.

The originality of this article rests in its exploration of three databases, the Web of Science, Scopus, and Google scholar, concerning the Digital Twin in the AEC-FM industry, where there are few review papers on Digital Twin technology in the AEC-FM sector. As more people in the AEC-FM industry learn about the concept, the technology, and the present state of the art, knowledge of the Digital Twin will rise. This study also proposes a conceptual framework for Digital Twin technology in the AEC-FM sector, which may be used as a roadmap for further study in this area.

This paper provides a quantitative analysis of the number of publications published annually in Scopus, Google Scholar, and Web of Science by the AEC-FM sector on Digital Twin research from 2016 to 2022. Journals of Digital Twin Application Research in the AEC-FM Industry and Active Nations are also included. An additional qualitative analysis was performed to assess the development of Digital Twin research through time and identify research gaps and trends. Of these results, the most significant impact of Digital Twin research is discovered under "Digital Twin in Facility Lifecycle Management." At the same time, there is a wide gap in research that looks into "Digital Twin-Information Integration Standards," "Digital Twin-Based users-Centric Building Design," "Digital Twin-Based Predictive Maintenance," "Semantic Digital Twin for Facility Maintenance," and "Digital Twin-Based Human Knowledge."

In fact, the areas mentioned above shaped my dissertation and provided me with ideas for future research, where my next publication dealt with Digital Twin-based predictive maintenance and information integration for facility management and then with users-centric building design.

4.2 Paper 2- A Digital Twin Predictive Maintenance Framework of Air Handling Units based on Automatic Fault Detection and Diagnostics [2]

A digital twin predictive maintenance framework for air handling units based on automatic fault detection and diagnostics is a system that uses digital twin technology to analyze data from air handling units (AHUs) and predict when maintenance is needed. The system uses machine learning algorithms to analyze data from sensors and other sources to identify patterns and anomalies that may indicate the presence of a fault or issue. The framework typically includes a digital twin of the AHUs, a virtual representation of the physical units based on data collected from sensors and other sources. The digital twin is used to simulate the behavior and performance of the AHUs under different operating conditions and to analyze data from the physical units to identify potential issues. The system also includes a fault detection and diagnostics (FDD) component, which uses machine learning algorithms to analyze data from the AHUs and identify patterns and anomalies that may indicate the presence of a fault. When a fault is detected, the system generates an alert. It provides diagnostic information to maintenance technicians, who can use this information to determine the cause of the fault and take appropriate action to fix it. By using a digital twin predictive maintenance framework based on automatic fault detection and diagnostics, organizations can improve the reliability and efficiency of their AHUs and reduce the risk of unexpected downtime. It can also help reduce maintenance costs by enabling technicians to address potential issues before they become more serious proactively.

In addition, the digital twin predictive maintenance framework for AHU can save energy and enhance thermal comfort in buildings in several ways:

1. Improved efficiency: By continuously monitoring and analyzing the performance of the air handling units (AHUs), the Automated Fault Detection and Diagnostics (AFDD) system can identify and address any issues that may be affecting the efficiency of the AHUs. This can reduce energy consumption and improve the overall efficiency of the building's HVAC (heating, ventilation, and air conditioning) system.

2. Early detection of issues: By detecting potential issues with the AHUs before they become more serious problems, the AFDD system can help to prevent unexpected downtime and ensure that the AHUs are operating at optimal performance levels. This can reduce energy consumption and improve the thermal comfort of the building by ensuring that the temperature and humidity levels are properly controlled.

3. Predictive maintenance: By predicting when maintenance is needed for the AHUs, the AFDD system can help optimize the timing of maintenance activities and reduce energy consumption by minimizing emergency repairs and unscheduled downtime.

4. Enhanced control: By providing real-time data and analytics about the performance of the AHUs, the AFDD system can help build managers make more informed decisions about optimizing the HVAC system's operation. This can improve the thermal comfort of the building and reduce energy consumption by ensuring that the AHUs operate in the most efficient settings.

Overall, a digital twin predictive maintenance framework based on AFDD can help to improve the energy efficiency and thermal comfort of a building by optimizing the performance of the AHUs (Figure 4.1), detecting and addressing potential issues, and minimizing downtime.

This paper's originality lies in its attempt to bridge knowledge gaps in the workflow process and generally applicable AFDD system, as well as a need for a Digital Twin model for predictive maintenance of HVAC systems, notably Air Handling Units (Figure 4.2).

This paper builds on that foundation by outlining a Digital Twin framework for implementing predictive maintenance, describing the use of AHU performance Assessment Rules (APAR) and a practical machine learning algorithm (specifically, ANN, SVM, and decision trees) for predictive maintenance based on real-time data. It also describes the use of a universal AFDD tool that can efficiently run on a diverse set of data from IoT sensors in AHUs and outlines the development of an integrated condition monitoring BIM framework based. To elaborate, we developed a generalized approach for AHU failure detection by fusing expert guidelines with machine learning. Therefore, this study aims to achieve a better possible success rate in defect detection for a single AHU rather than achieving a fair detection rate for multiple AHUs.

Within the next few years, semantic data will likely become a standard feature of enterprise management platforms. Moreover, the growing importance of semantic data in BMSs will play a pivotal role in advancing fault detection strategies. In our work, a plug-in using C Sharp and Brick schema are used to facilitate the integration and flow of data, including various sensors, equipment, and building components in a single ontology as a potential solution to the data integration issues.

This research shows that automated fault detection in AHUs is useful and efficient. The system may detect a wide range of issues in AHUs with a high degree of accuracy.

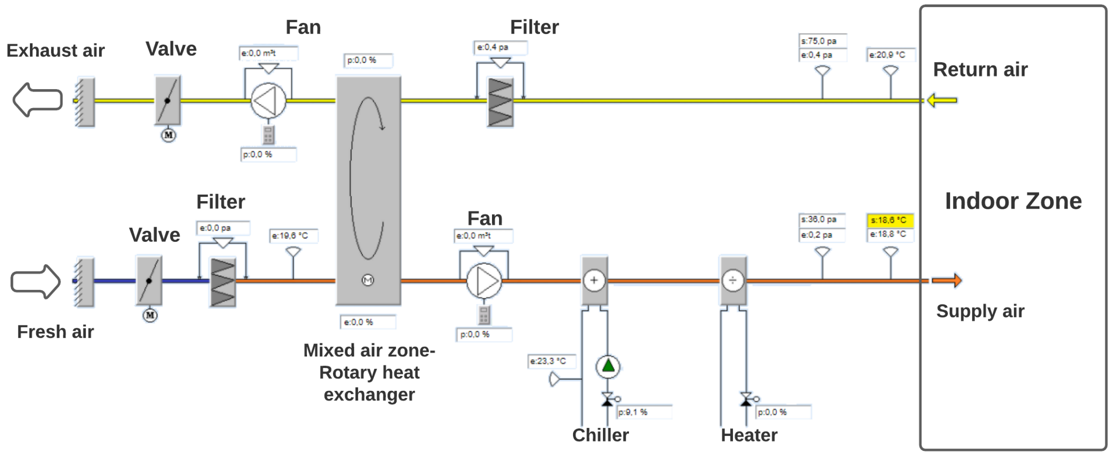


Figure 4.1: Schematic illustration of an AHU from I4Helse [2].

4.3 Paper 3- Digital Twin of HVAC system (HVACDT) for multiobjective optimization of energy consumption and thermal comfort based on BIM framework with ANN-MOGA [3]

Multi-objective optimization is a method of finding a solution that optimizes multiple objectives simultaneously. In the context of energy consumption and thermal comfort, multi-objective optimization involves finding a balance between the two objectives, as they may often be conflicting. For example, optimizing energy consumption may involve setting the temperature of a building lower, which may not be optimal for thermal comfort. On the other hand, optimizing thermal comfort may involve setting the temperature higher, which may result in higher energy consumption. To perform multi-objective optimization of energy consumption and thermal comfort, a variety of techniques can be used, such as:

1. Multi-objective optimization algorithms: These algorithms, such as multi-objective genetic algorithms (MOGA), can be used to identify the optimal

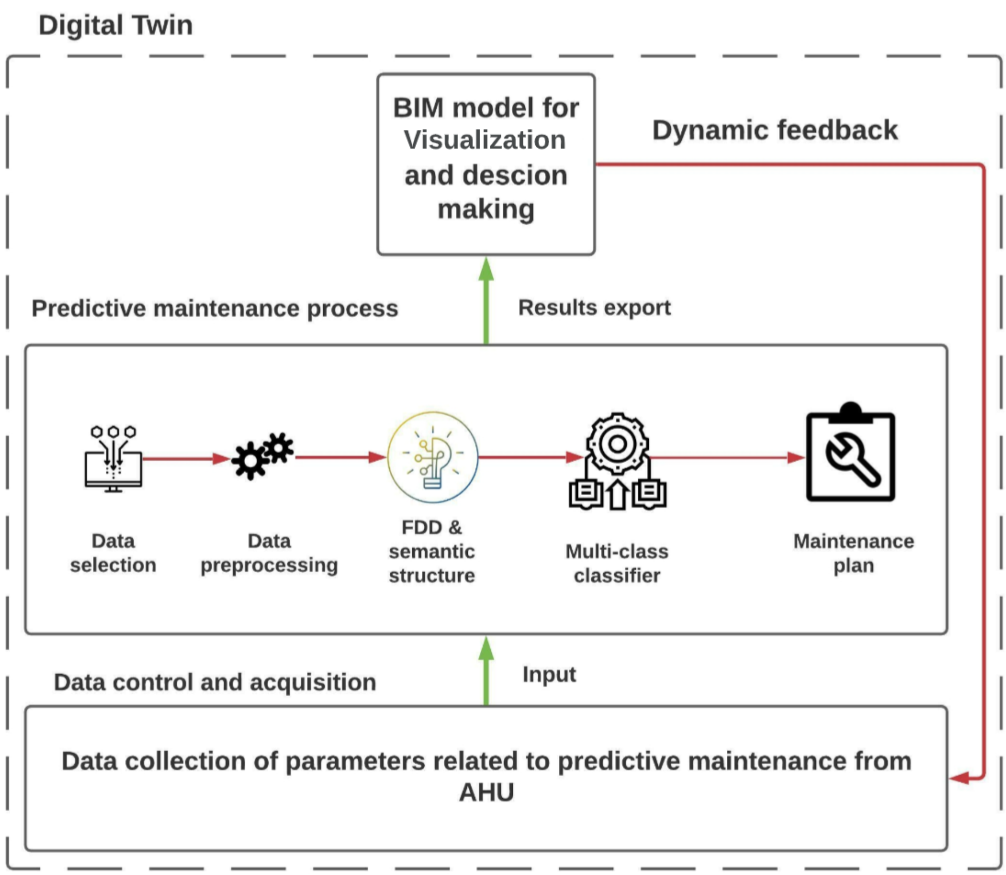


Figure 4.2: The Proposed Digital Twin predictive maintenance framework based on expert rules, Machine Learning, BIM and IoT for AHU [2]

solution for multiple objectives.

2. Artificial neural networks (ANN): ANNs can be used to analyze and interpret HVAC system data and identify optimization opportunities.

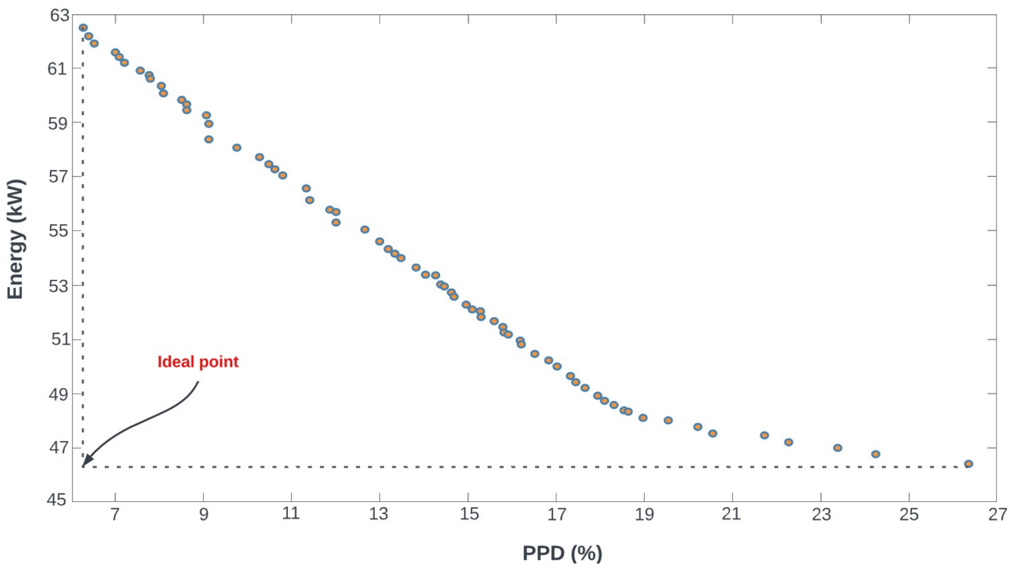
3. Building information modeling (BIM): BIM can be used to create a detailed model of the HVAC system, including its components, operation, and performance. This can be used to analyze the system and identify opportunities for optimization. The BIM model is also used to stream the final results in BIM so the best operational conditions of HVAC can be implemented.

It is important to consider the trade-offs between energy consumption and thermal comfort when optimizing the performance of an HVAC system. By using multi-objective optimization techniques, it is possible to find a solution that balances both objectives and maximizes overall performance.

In this paper, a digital twin of an HVAC, or HVACDT, is a virtual representation built in Simulink MATLAB of the physical HVAC system. It can simulate and analyze the system's performance in real-time, optimizing energy consumption and thermal comfort. The digital twin can be created using a BIM framework, which allows for integrating data from various sources such as design plans, sensor data, and operational data. This data can be used to create a detailed model of the HVAC system, including its components, operation, and performance. Artificial neural networks (ANN) and multi-objective genetic algorithms (MOGA) are used to optimize the performance of the HVACDT based on energy consumption and thermal comfort objectives. ANNs can be used to analyze and interpret the data from the HVACDT and used as a fitness function for MOGA instead of traditional mathematical methods. At the same time, MOGA can identify the optimal solution for the given objectives. Using an HVACDT in combination with ANNs and MOGA can provide valuable insights into the performance of the HVAC system and allow for the optimization of its operation. It can also identify opportunities for energy savings and improve the overall comfort of the building.

The optimization procedure took around 7.055 hours to run on a gaming laptop. The optimization results are represented using the Pareto optimal solution for reducing energy consumption and PPD in the I4Helse building depicted in Figure 4.3. It represents how the two objectives are fundamentally in conflict with one another. Winter PPD increased by 6.2% to 27.0% as energy use dropped from 62.8 kW to 46.4 kW. The minimal percentage point difference (PPD) for optimal thermal comfort in the winter is 6.2%.

The best solution (ideal point) between the two objectives is depicted in Figure 4.3, wherein wintertime energy consumption and PPD are depicted as 46.4 kW and 6.2%, respectively. Compared to the typical annual energy use of 55 kW, this represents savings of around 22% in the summer and 15.6% in the winter. The same is true for PPD, where the initial value is 15.7% in winter and 10.6% in summer, resulting in a decrease of 6.05% in winter and 6.7% in summer.



(a)

Figure 4.3: optimization results for winter [3]

4.4 Paper 4- Multiobjective optimization of building energy consumption and thermal comfort based on integrated BIM framework with machine learning-NSGA II [4]

MOGA (Multiobjective Genetic Algorithm) and NSGA II (Non-dominated Sorting Genetic Algorithm II) are both types of evolutionary algorithms that can be used to solve multiobjective optimization problems. Both algorithms use genetic operators (e.g., crossover and mutation) to search for solutions in a population of potential solutions, to find a set of solutions representing a trade-off between the conflicting objectives rather than a single "optimal" solution. One key difference between MOGA and NSGA II is how they handle multiple objectives. MOGA uses a scalarization approach, in which the multiple objectives are combined into a single scalar value using a weighting scheme. This scalar value is then used to guide the search for solutions. NSGA II, on the other hand, uses a non-dominated sorting approach in which solutions are ranked based on how many other solutions they dominate (i.e., how many other solutions they are better than in at least one objective). This allows NSGA II to identify a set of solutions representing a trade-off between the conflicting objectives rather than finding a single "optimal" solution. Another difference between MOGA and NSGA II is how they handle constraints. MOGA can handle equality and inequality constraints, but it does so by adding penalty functions to the objective function. This can make it more difficult to find feasible solutions, especially if the constraints are complex or nonlinear. NSGA II, on the other hand, uses a constraint handling technique called "constraint domination" to identify and eliminate infeasible solutions from the search space. This can make it easier to find feasible solutions, but it may also result in a larger set of solutions that need to be evaluated.

Therefore, we changed from MOGA to NSGA II in this paper. We used eleven supervised machine learning algorithms based on regression to forecast annual energy consumption: LR, ANN, SVM, GPR, DNN, RF, XGB, ANN-SVM, LSSVM, GMDH, and GLSSVM. First, we did 8000 simulations on a set of inputs, including building envelope and HVAC system parameters in IDA ICE, and the output was the energy consumption and users' comfort. Based on that, we have a good database representing the performance of Tvedestrand secondary school in Norway. We implement the eleven machine learning algorithms on it to check which one can be the best to represent the building performance.

The results showed that the GLSSVM model is the most accurate and produces the best forecast for energy consumption. It also reduced the simulation time from days to seconds. This is because it employs a hybrid model instead of the more traditional approaches that rely solely on one model. The GMDH and the LS-SVM are both components of the GLSSVM [196, 197]. Using the input data of the cutting-edge hybrid forecasting model that the GMDH model selects, the LS-SVM model makes predictions about the signal's future behavior. Every possible combination of the two input variables is considered at each layer, and regression is carried out using a polynomial function for each such combination. The data from the GMDH model's output (which has the smallest error) is used as input for the LS-SVM model and the original set of variables. GLSSVM is often iterated between three and five times to provide the most accurate results. Compared to the ANN-SVM hybrid model, the GLSSVM model performs better. This is because GMDH picks an optimal structure of the model or network until it finds the best one, while ANN has a fixed structure, and LSSVM, an upgraded version of SVM that improves the prediction faster, is a key component of GLSSVM. Therefore, GLSSVM may be employed as the fitness function of multiobjective optimization (NSGA II), leading to more effective optimization.

As previous paper, we used the Pareto front to find the optimal solution (Figure 4.4). Comparing the optimal design strategy to the initial design solution, energy consumption is reduced by 37.5% while 33.5% increases thermal comfort. The roof's U-value, the windows' U-value, and the window-to-wall ratio should all be considered. However, the U-value of the outer walls should be the primary emphasis of the energy-efficient design of the building envelope. Modifying the building's design before construction can improve energy consumption and thermal comfort performance using the cutting-edge GLSSVM-NSGAII multi-objective approach. Its purpose is to help in the choice of construction methods and materials. Further, the optimal solution was also reached by gathering data on the best envelope settings and the parameters in the HVAC.

4.5 Paper 5- A review of the Digital Twin technology for fault detection in buildings [5]

The main aim of this review paper was to explain more about the overlooked information in my thesis and to extend the scope of the thesis. In this paper, we found that the Digital Twin can be used to analyze and optimize various aspects of the building, including thermal, visual, acoustic, and space comfort. Thermal comfort refers to the temperature and humidity levels within a building that are perceived as comfortable by the users. The Digital Twin can simulate a building's energy efficiency to determine what changes should be made to maximize users' sense of thermal comfort. For example, the Digital Twin can help determine the optimal insulation and heating and cooling systems to maintain a comfortable indoor temperature. Moreover, visual comfort refers to the lighting levels and quality within a building that are perceived as comfortable by the users. The lighting performance of a building may be modeled using the Digital Twin to increase users' visual comfort. For example, the Digital Twin can help determine the optimal location and size of windows and artificial lighting sources to provide sufficient light for tasks and activities while minimizing glare and shadows. Furthermore, acoustic comfort refers to the sound levels and quality within a building that are perceived as comfortable by the users. A Digital Twin can be used to model the acoustic performance of

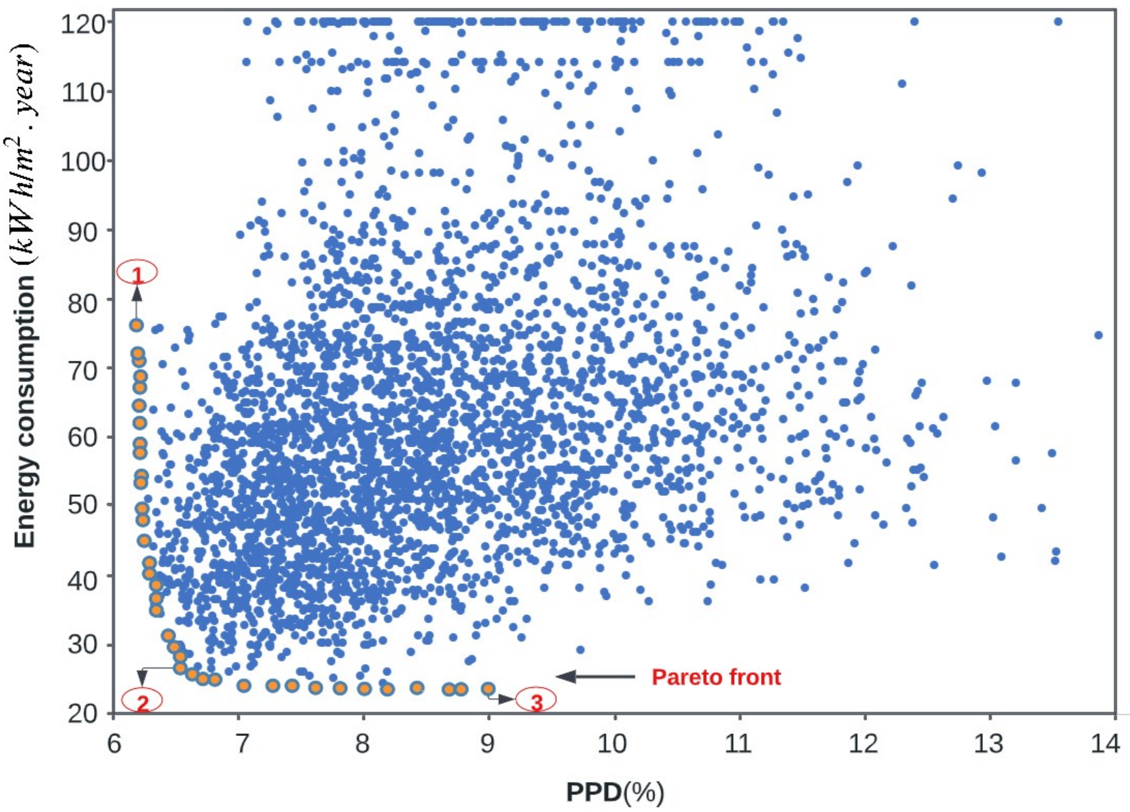


Figure 4.4: The Pareto front of energy consumption optimization, where points (1) and (3) represent the anchor points that refer to the optimal points of the individual objective functions and the worst value for the other objective function in multi-objective optimization. Point (2) refers to the knee point, which indicates the most satisfactory solution but not the ideal one. Every blue point in the figure represents a possible solution [4].

buildings. For example, the Digital Twin can help determine the optimal location and type of sound-absorbing materials to reduce noise levels and improve speech intelligibility. Space comfort refers to the layout and functionality of the spaces within a building that are perceived as comfortable by the users. The Digital Twin can be used to model the layout and functionality of a building and identify areas where adjustments need to be made to improve space comfort. For example, the Digital Twin can help determine the optimal arrangement of furniture and equipment to optimize space use and improve traffic flow. In General, a Digital Twin can be a powerful tool for optimizing the comfort and functionality of a building by allowing designers and building managers to analyze and adjust various aspects of the building in a virtual environment before implementing changes in the physical world.

Out of that, various types of faults or problems in buildings can cause discomfort for the users. Some examples include:

1. Thermal discomfort: This can be caused by problems with the HVAC system, such as a malfunctioning thermostat, air handling unit, or leaky ductwork.

2. Visual discomfort: This can be caused by problems with the lighting, such as windows-to-wall ratio, flickering or dimming lights, or an inadequate amount of light for tasks and activities.

3. Acoustic discomfort: This can be caused by problems with noise levels, such as excessive noise from HVAC equipment, construction work, or neighboring units.

4. Space discomfort: This can be caused by problems with the layout and functionality of the spaces within the building, such as poorly designed or crowded spaces or inadequate storage or workspace.

To detect faults causing discomfort in a building, it is important to monitor the various systems and components of the building regularly and gather feedback from the users. This can be done manually through inspections and surveys, or it can be done automatically using sensors and other monitoring devices that are integrated into the building's Digital Twin. Once a fault has been detected, it is important to diagnose and fix the problem as soon as possible to minimize discomfort for the users. This may involve repairing or replacing faulty equipment, adjusting settings or controls, or making other necessary repairs or improvements.

In the context of fault detection in buildings, BIM can identify potential issues or problems with the building's systems and components before they occur. For example, a BIM model can simulate the performance of the building's HVAC, lighting, and other systems under various conditions, such as different weather patterns or occupancy levels. This can help identify potential problems, such as overheating or insufficient lighting and allow them to be addressed before they cause discomfort for the users. BIM can also be used to monitor the performance of the building in real-time using sensors and other monitoring devices integrated into the BIM model. This can allow for early detection of problems as they occur and allow for timely maintenance and repairs to be carried out to minimize discomfort for the users.

One important piece of fault detection is machine learning which can be used to help optimize the comfort of building users in several ways:

1. Thermal comfort: Machine learning algorithms can be used to analyze data from temperature and humidity sensors, as well as from surveys of the users' comfort levels, to identify patterns and relationships that can be used to improve the heating, ventilation, and air conditioning (HVAC) system's performance. For instance, a building's HVAC system may be optimized with the help of machine learning algorithms by taking into account the outside temperature and humidity as well as the building's occupancy and the time of day.

2. Visual comfort: With machine learning algorithms, we can evaluate data from light sensors and comfort surveys to find patterns and correlations that may be utilized to optimize the lighting system. For instance, the lighting system may be programmed with machine learning algorithms to automatically modify

brightness and color temperature based on various variables, including the time of day, the type of work being done, and the preferences of the building's inhabitants.

3. Acoustic comfort: Machine learning algorithms can be used to analyze data from sound level sensors and surveys of the users' comfort levels to identify patterns and relationships that can be implemented to enhance the acoustics of buildings. For instance, machine learning algorithms may be used to predict the optimal sound absorption and insulation levels based on factors such as the type of space, the type of activity being performed, and the time of day and to adjust the building's materials and construction accordingly or recommend it for the next building.

4. Space comfort: Machine learning algorithms can be used to analyze data from sensors that measure the occupancy and usage of different spaces within the building, as well as from surveys of the users' comfort levels, to identify patterns and relationships that can be used to improve the layout and functionality of the building. For instance, machine learning algorithms can be used to predict the optimal arrangement of furniture and equipment based on factors such as the type of activity being performed, the time of day, and the users' preferences and to adjust the layout accordingly.

In addition, Bayesian networks play an important role in fault detection in buildings. Bayesian networks are probabilistic graphical models that can be used to represent complex systems and relationships between variables. They are often used in fault detection and diagnosis (FDD) applications to model the dependencies and uncertainties of different system components or subsystems and identify the most likely causes of failures or malfunctions based on available data. In the context of fault detection in buildings, a Bayesian network can be used to model the various systems and components of the building, such as the HVAC system, the lighting system, and the electrical system. The network can include variables that represent the different states or conditions of these systems and components, such as "functioning correctly" or "faulty," as well as variables that represent the external conditions that may affect the system, such as temperature and humidity. To use a Bayesian network for fault detection, data from sensors and other monitoring devices can be input into the network, and the network can be used to calculate the probabilities of different states or conditions for each variable. This can allow the network to identify the most likely causes of any observed failures or malfunctions and to provide recommendations for repairs or maintenance based on the probabilities of different failure modes.

On the other hand, Digital Twin faces many of the same obstacles as a technology that exists in tandem with AI and the IoT. The difficulties of deploying Digital Twin technology were also the subject of this paper's analysis.

The current state of the IT system causes the initial difficulty. A robust infrastructure of regularly updated software and hardware is required to keep up with the rapid development of AI. The high cost of implementing and maintaining such systems is one of the largest obstacles in the infrastructure's way. For instance, a Digital Twin for a 60,000-square-foot office building can cost between 1.2 and 1.7 million dollars [198]. Having a well-connected, stable, and secure information technology infrastructure is crucial to the success of this technology, and the reaping of its benefits by businesses [199, 200].

The second obstacle is modeling a Digital Twin itself, as the process needs to be standardized. Standardized approaches facilitate user comprehension and the free flow of data across the various phases of creating and deploying the Digital Twin. As for gathering information from connected gadgets, Digital Twin is wholly reliant on Internet of Things innovations. Unfortunately, the standardization of Digital Twin technology is hindered by the need for extensive revisions to existing IoT standards [201, 202, 203].

Furthermore, [204] states that BIM models used during the design phase are unsuitable for use throughout the maintenance phase. The issue arises when the individual placing the order does not understand the proper use of the BIM models and the extent to which they should require modeling. This causes models to miss key details. It needs to be clarified, too, who would be responsible for re-creating the model when substantial changes were made to the building [205]. There is currently no one accessible to maintain the model and its associated data. On top of that, the model's upkeep needs the assistance of the maintenance crew, who are often unavailable.

Another challenge to implementing BIM in operations is that software currently needs to be created to use the modeled data. Currently, the FM software used during the maintenance phase cannot pull the necessary data directly from the BIM models [206].

Finally, a model that incorporates all the data needed for fire safety, electrotechnical maintenance, and controlling potentially dangerous circumstances would require much work for most users to apply successfully [207]. Every job requires a unique set of maintenance models, and those models should only include the information directly applicable to that task.

4.6 Paper 6- Digital Twin framework for automated fault source detection and prediction for comfort performance evaluation of existing non-residential buildings [6]

Based on the outcomes of paper 5, paper 6 aims to fill the gap in the literature by addressing the need for a Digital Twin model for real-time cause detection of user discomfort with whole building systems, such as HVAC design, thermal comfort, visual comfort, acoustic comfort, and space adequacy. As an added complication, no Digital Twin model is available for the complete building to use in predictive maintenance activities happening in real-time.

As a response to the gaps mentioned above in the literature, this paper proposes a method for intelligently detecting and predicting faults that may make people dissatisfied in two Norwegian buildings, I4Helse and Tvedestrand secondary school, by integrating real-time sensor data, users' comfort survey results, a BN model, and machine learning. Thus, this paper contributes to the body of knowledge by exploring, for the first time, 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 prevent user dissatisfaction.

Facility managers may utilize the decision-making framework depicted in Figure 4.5 to understand the origins of building issues better and meet their users' needs. As soon as the framework gathers information about the comfort issue, it will determine if the HVAC unit has an electrical problem. The framework will then utilize the BN network shown in Figure 4.6 to search for HVAC design problems if this is not done manually (thermal comfort issues). The probability of a node being in a certain state is represented by conditional probability tables (CPTs) [208]. The CPTs for each node and the importance of parent nodes for occupant comfort were chosen using [178, 13] within the Bayesian network model.

The HVAC system will be checked to determine if it is insufficient, which would mean that it cannot meet the thermal needs of the users, regardless of any design defects in the HVAC system. It is possible to calculate the thermal load automatically and get the indoor unit capacity from an equipment database if the architectural and construction design is specified correctly. A lack of comfort caused by inadequate HVAC systems can be addressed either by insulating the façade to reduce the thermal demand of the room or by using interior units with larger cooling or heating capacities if all envelope components fall under the insulation criteria to remedy a lack of comfort caused by inadequate HVAC systems. Future building designs may incorporate these enhancements if the current ones are not financially viable.

The capacity of the indoor unit might be more than the heat demand of the space. In that instance, the framework will use the APAR to determine if there is a problem with the interior HVAC system equipment (fan, sensors, cooling and heating units, etc.). If APAR cannot detect a problem with the internal machinery, it may be necessary to rely on external units, which tend more to be broken (e.g., frozen evaporator coils, dirty condenser coils, dirty filters). The framework allows the FM team to provide appropriate corrective procedures by distinguishing between problems with indoor and outdoor units.

The framework will also investigate problems with visual, acoustic, or spatial comfort. The framework will analyze the WWR, room lighting, and shade management for optimal visual comfort. Similarly, if there is an acoustic problem, the framework will check for acoustic attenuator and acoustic insulation materials on the inside and outside of the structure. In the framework's last phase, we ensure the building has enough space by checking the rooms for cleanliness, flexibility, accessibility, and ergonomic furniture.

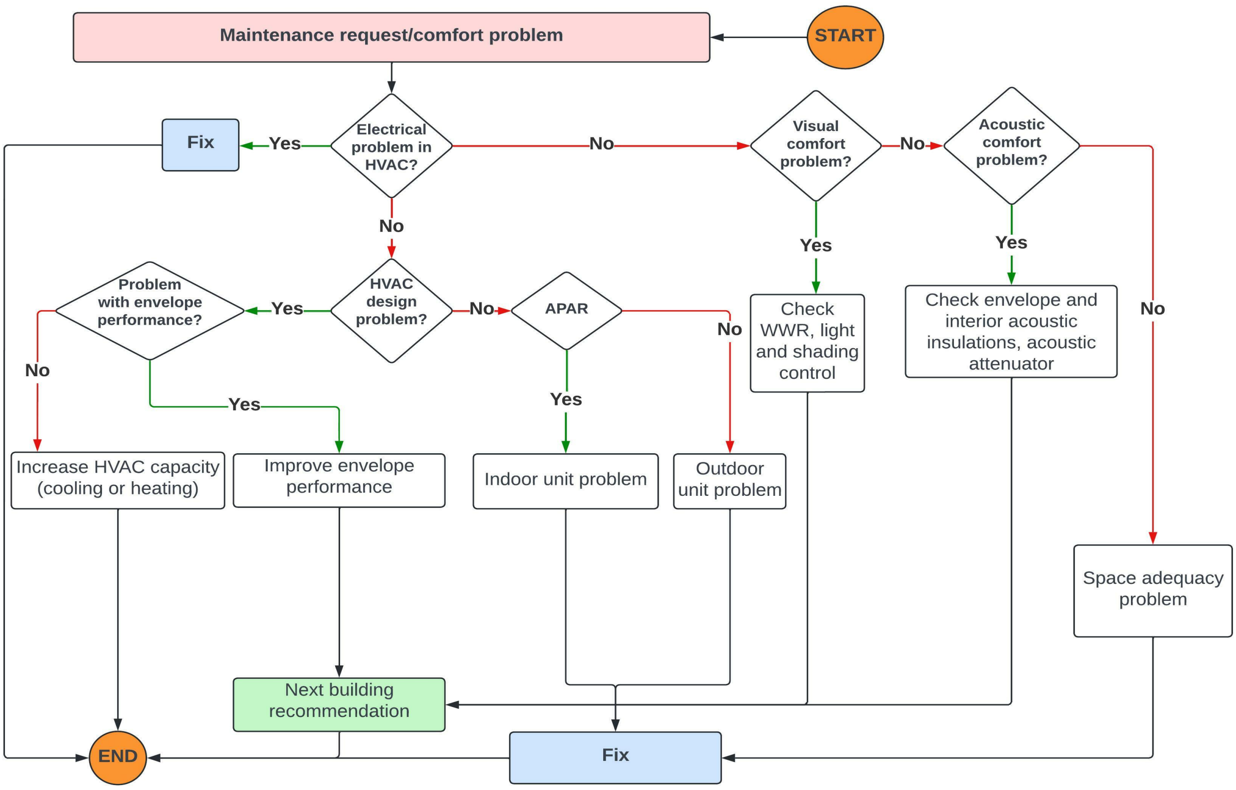


Figure 4.5: The decision-making approach and framework to help facility managers detect building faults, after [13].

Various sensors monitor the buildings' efficiency, as was previously described. As shown in Figure 4.7, the BIM model may create a visual representation of real-time sensor data and trends. The facility manager may use the data collected by the sensors to determine the status of all building systems. References for condition evaluation based on monitoring results can be found in the FM system's recorded abnormal occurrences and alerts. Furthermore, the FM team completed the building systems configuration list after examining the field inspection results. The facilities manager finally inspected the building's systems thoroughly to determine their current repair status.

Our framework and the BN model were tested, the results were validated by facility management staff, and the data revealed many serious faults. Although some faults are less serious than others, they need to be corrected immediately (simultaneous heating and cooling). These issues can be resolved by updating the appropriate control system algorithms. Figure 4.8 provides an overview of operational defects.

Figure 4.9 depicts an example of a fault found using the APAR method. There are both positive and negative deviations in temperature from the target. The difficulty was that heat recovery was not fully saturated until late in the colder months (a saturated heating or cooling coil valve control signal for a long duration points to issues like insufficient heating or cooling capacity or faulty valve actuators). If the supply fan signal is on and the difference between the return and outside

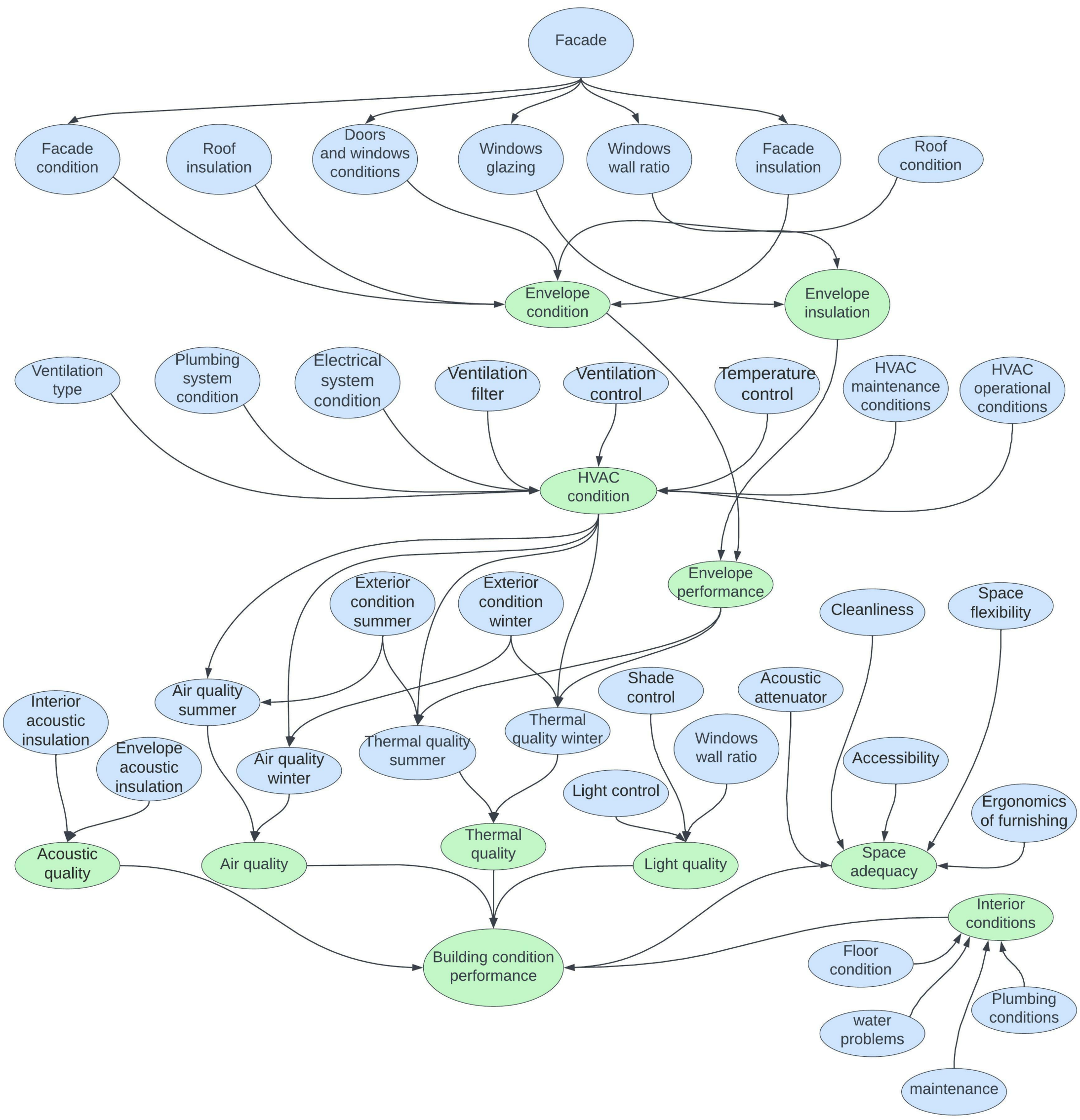


Figure 4.6: The BN model for evaluating comfort performance in buildings, after [13, 14]

temperatures is large enough, then the heat recovery signal is not at its maximum, and the rule applies.

Heat recovery is increased when the supply air temperature falls within a narrow range of the set point. The temperature difference between the return air and the outside air is high enough to activate the rule, as the fault value is barely above the 0.5 threshold. Adjustments to the control mechanisms permit such behavior.

The FM team can pinpoint the root reasons for poor ventilation in each space thanks to BIM visualization. Figure 4.10 shows the likelihood of HVAC design errors or poorly functioning HVAC systems. The results suggest that room No3039 has a 62% chance of having an HVAC system that is both fault-free and in excellent condition, ensuring a high level of comfort for users concerning indoor air quality. Nevertheless, users in rooms No3051, No3017, and No3016 have complained about

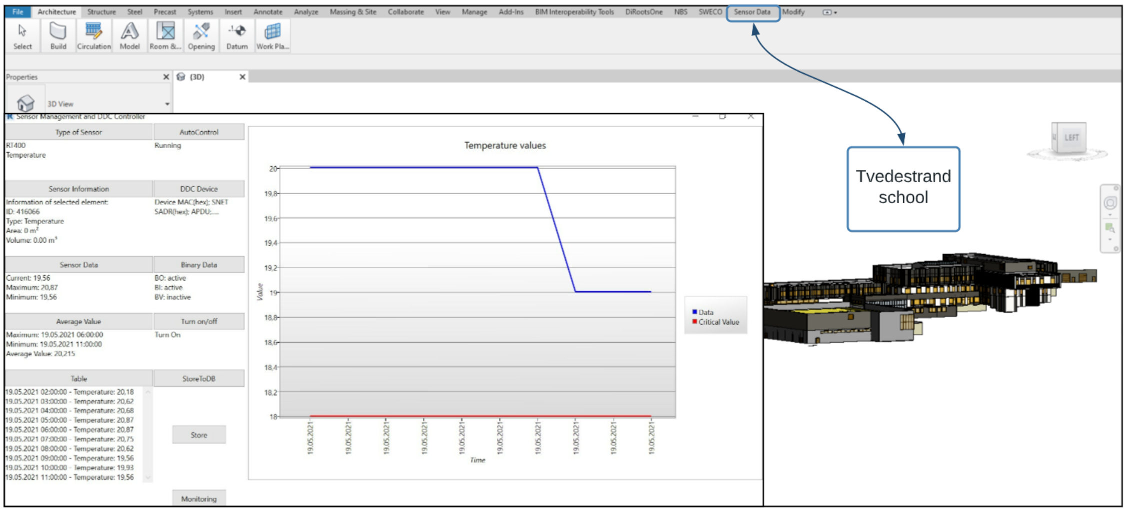


Figure 4.7: The information about the building obtained via sensor data and the BIM model [6].

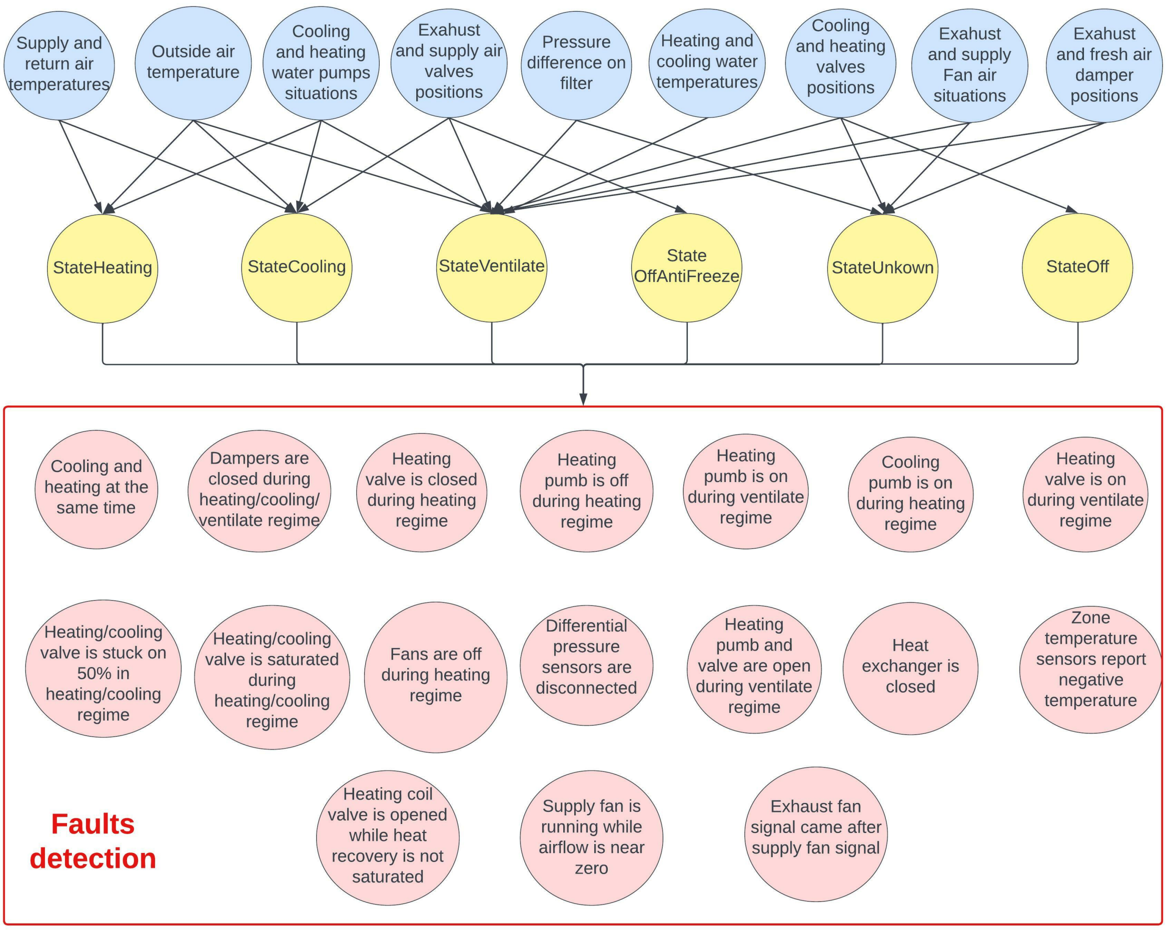


Figure 4.8: The detected faults in our case studies [6].

indoor air quality. The results of the model indicate that there is a 74% possibility that rooms No3017 and No3016 have major HVAC design flaws. These findings must be compared to the HVAC system's specifications to determine whether the

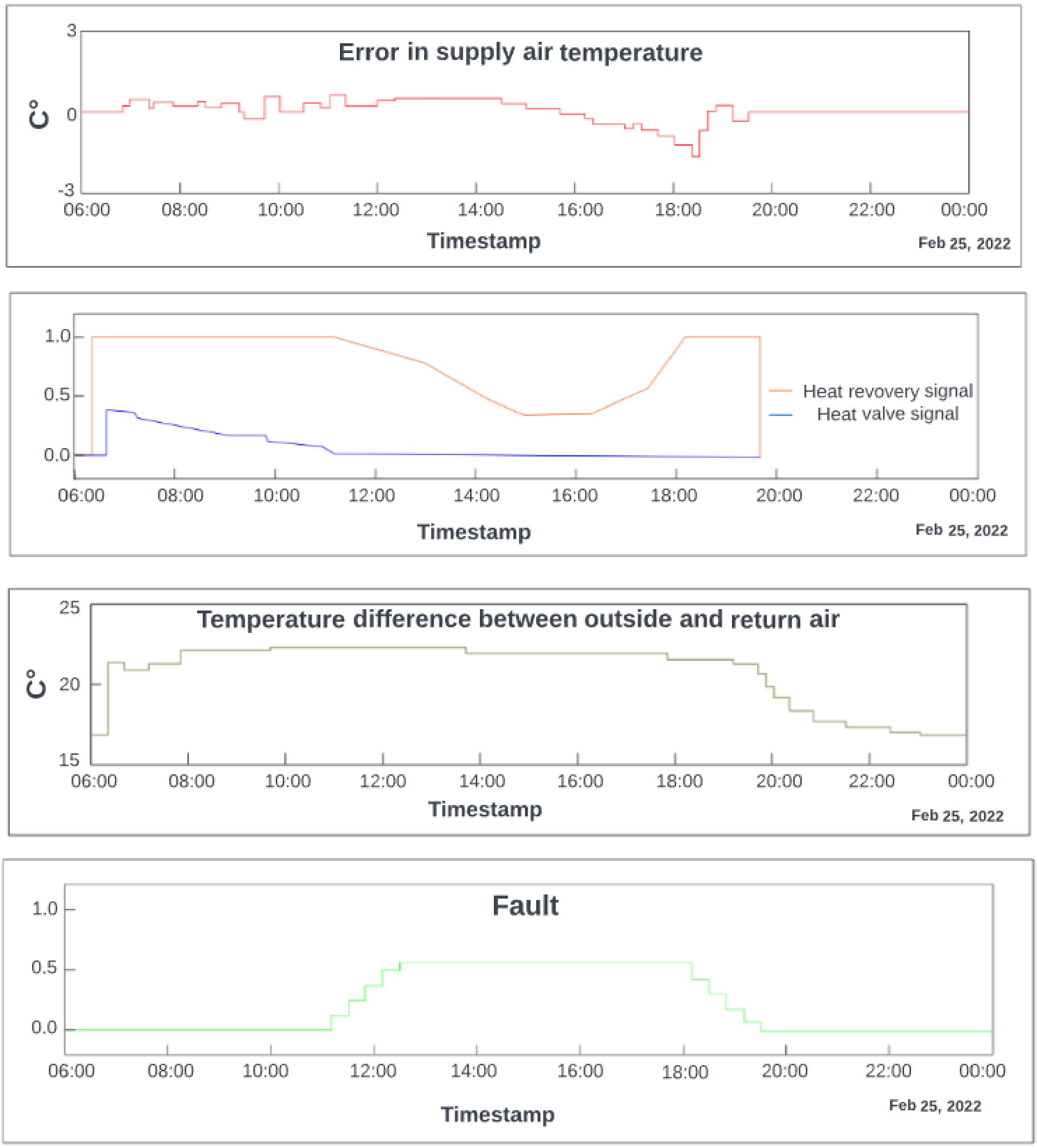


Figure 4.9: Heat recovery not saturated during one day in February. The fault is detected based on temperature setpoint, heat recovery signal, and temperature difference between outside and returned air, (the fault concept inspired by [15]).

ventilation system was run properly. Also, one of the key reasons people were uncomfortable with the air quality in these rooms was the high occupancy rate.

A sensitivity analysis was undertaken to discover which factors (prior nodes) were most relevant for enhancing the indoor air quality of uncomfortable rooms. The length of a bar visually represents the influence a node has on the overall performance of the building's conditions (target node).

Figure 4.11 demonstrates the impact of various nodes on wintertime indoor air quality. It can be determined that users' density and HVAC design flaws have a bigger influence on the chance of rooms No3016, No3051, and No3017 having

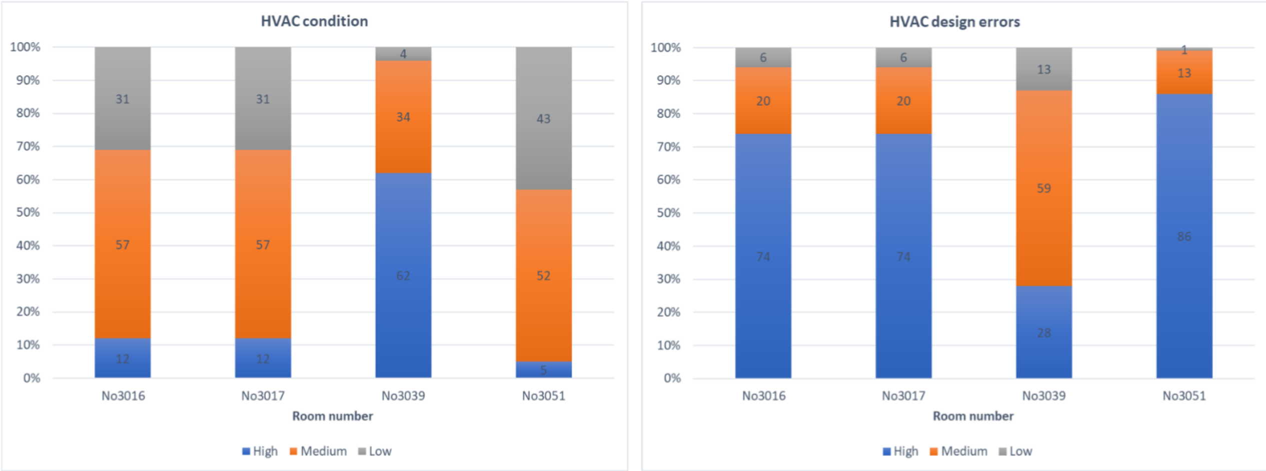


Figure 4.10: The probability that each room has poor HVAC design or unsatisfactory HVAC conditions [6].

exceptionally high comfort levels, whereas ventilation control has the least impact. The HVAC system in these rooms is based on an AHU that supports many rooms that may be inadequate. Even if the AHU has to be changed, the high occupancy in certain areas shows that reducing the number of users may enhance internal comfort.

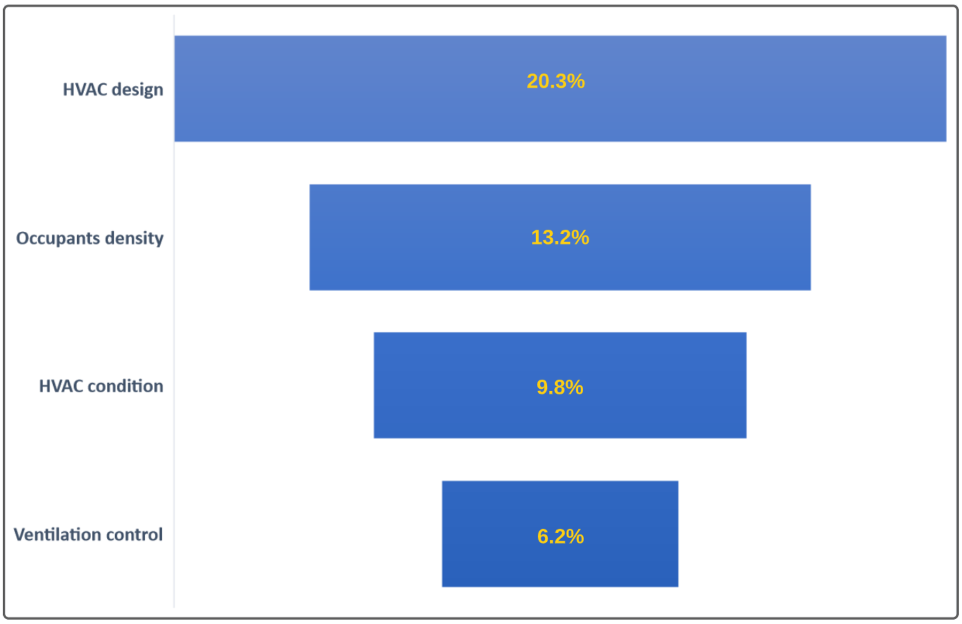


Figure 4.11: The sensitive analysis of indoor air quality for rooms No3016, No3017, and No3051 in winter [6].

4.7 Paper 7- Improving Building Occupant Comfort through a Digital Twin Approach: A Bayesian Network Model and Predictive Maintenance Method [7]

In Paper 6, we proposed a method for intelligently detecting and predicting faults that may cause discomfort in existing non-residential buildings using real-time sensor data, user comfort survey results, a Bayesian network (BN) model, and machine learning. The method was demonstrated in two Norwegian buildings, I4Helse and Tvedestrand secondary school. In this continuation of Paper 6, we further develop and expand upon the proposed method by introducing a Bayesian network model to make a sensitive analysis of the space adequacy and comfort of buildings' occupants. Nine machine learning algorithms were evaluated for predictive maintenance and rest of life of buildings components using metrics such as ROC, accuracy, F1-score, precision, and recall, where Extreme Gradient Boosting (XGB) was the best algorithm for prediction.

To address the challenge of applying these methods to a wide range of buildings, we propose a framework using JSON to integrate data from different systems, including FM, CMMS, BMS, and BIM. The results of this study can be beneficial for decision-makers in the facility management sector by providing insight into the factors that influence occupant comfort, expediting the process of identifying equipment malfunctions, and pointing towards potential solutions, leading to more sustainable and energy-efficient buildings.

Out from that, Paper 7 builds upon the foundation laid in Paper 6 by introducing a Bayesian network model and expanding upon the proposed method for improving building occupant comfort through a Digital Twin approach, including the use of BIM, predictive maintenance, and ontology graphs.

BIM and FM data integration can be achieved by using IFC and COBie standards. IFC is an open data model for exchanging BIM data between different software, while COBie is a specification for collecting and sharing data throughout a building's lifecycle. The data can be mapped into COBie and FM systems using programming languages such as Python, and then stored in a graph database management system like GraphDB for efficient querying and manipulation. The ISO 19690 standard provides guidelines for creating a consistent and structured asset information model that can be used to generate a knowledge graph, allowing for easy access and management of the building's assets. The mapping process should be done one property at a time, using JSON to ensure accurate and consistent data.

Table 4.1 shows the mapping of specific COBie properties such as "Equipment name", "Equipment type", "U-values", "Location (room)", "Manufacturer", "Serial number", "Warranty expiration date" to the corresponding FM attributes "Name", "Type", "U-value", "Room", "Vendor", "Serial No.", "Warranty Exp. Date" respectively.

In addition, assessing space adequacy in the office is critical for employee comfort

Table 4.1: Mapping of COBie Data to FM Attributes

COBie Property	FM Attribute
Equipment name	Name
Equipment type	Type
U-values	U-value
Location (room)	Room
Manufacturer	Vendor
Serial number	Serial No.
Warranty expiration date	Warranty Exp. Date

and productivity. A sensitivity analysis of potential reasons for space inadequacy is implemented, 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, by surveying employees and gathering data. These factors are analyzed and ranked based on their impact on employee comfort, and appropriate measures that can be taken to address them. BIM can be used as a valuable tool in assessing and addressing space adequacy in the office as part of a Digital Twin model. It allows for a detailed, data-driven analysis of the office environment to identify potential issues and prioritize changes to improve employee comfort. Figure 4.12 and Figure 4.13 show the sensitive analysis results.

The BIM model can store data from BMS and CMMS systems and use it to determine faults in the building's system using the framework in Figure 4.5. In the scenario of an HVAC repair request at the I4Helse building, room N1011, the BIM model was used to match the mechanical components and energy calculations were compared to the BIM model's HVAC characteristics to determine if poor design was the cause. The framework then checked sensor data for malfunctioning units and found that the outside unit was likely the source of the issue. The FM team inspected the unit and found a leak, fixing the problem. Figure 4.14 shows BIM problem-cause analysis visualization.

Table 4.2 compares the performance of different multi-class classification algorithms for predicting faults in HVAC systems and buildings. The ROC (Receiver Operating Characteristic) is a graphical plot that illustrates the diagnostic ability of a classifier system as its discrimination threshold is varied. The area under the ROC curve (AUC-ROC) is a measure of how well a classifier can distinguish between positive and negative classes. The accuracy, F1-score, precision, and recall are also used as evaluation metrics. The XGB algorithm has the highest ROC score and highest accuracy, F1-score, precision, and recall, indicating it is the most effective in identifying equipment likely to fail and scheduling maintenance proactively. Other algorithms like ANN, MLP, RF, and GB also have high ROC scores and accuracy, but XGB has the best performance. This table can be used as a starting point to evaluate the performance of different algorithms for the predictive maintenance of HVAC systems and buildings.

Investigations are being done to determine the effect of scheduled and predictive

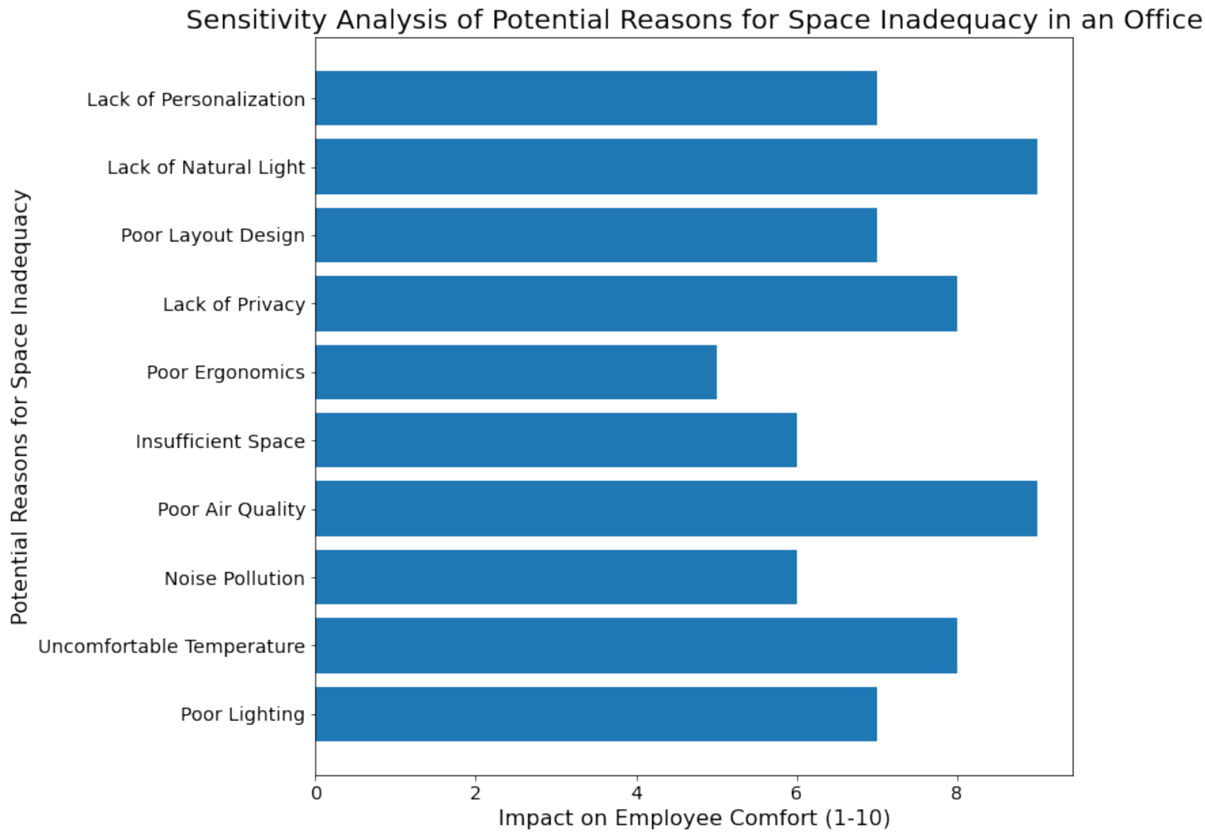


Figure 4.12: Sensitivity analysis of reasons for space inadequacy in Tvedestrand school office. Horizontal bars represent impact on employee comfort (1-10), with higher values indicating greater impact. Reasons listed on y-axis and impact on x-axis. Based on survey data and Bayesian network analysis, helps identify main reasons and prioritize areas for improvement to increase comfort [7].

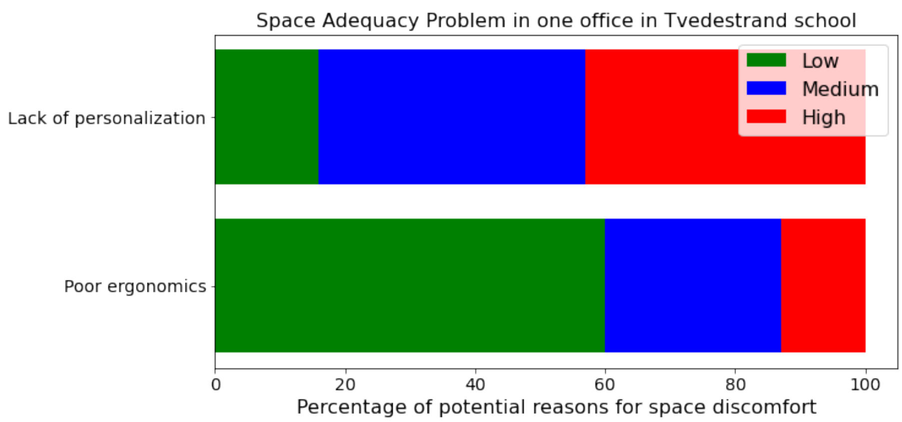


Figure 4.13: Potential impact of different reasons for space inadequacy on employee comfort. Horizontal bars represent potential impact (low, medium, high) of each reason on employee comfort, reasons listed on y-axis and potential impact on x-axis. Based on survey data and Bayesian network analysis, helps prioritize areas for improvement to increase comfort [7].

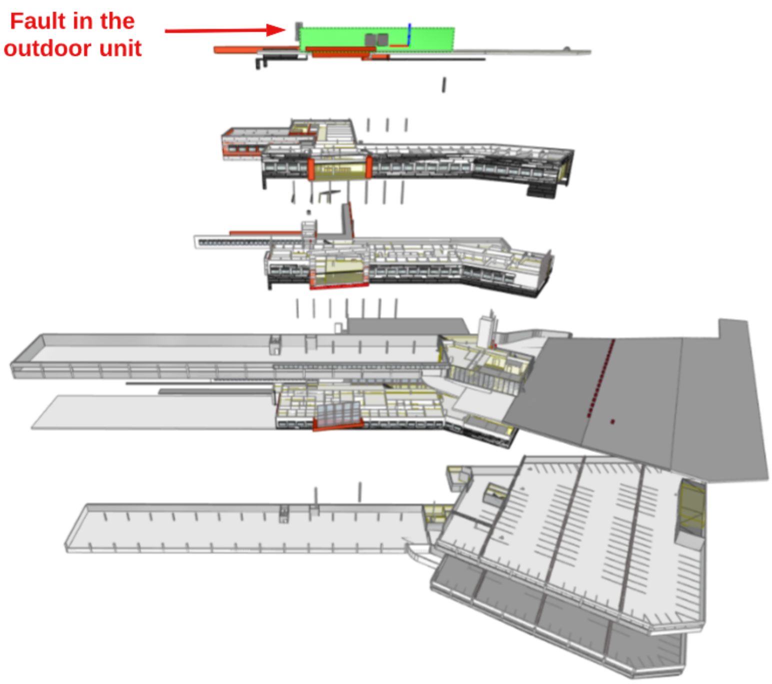


Figure 4.14: BIM-assisted analysis of HVAC fault in I4Helse building, showing the specific outside unit identified as the likely source of the problem [7].

Table 4.2: 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

maintenance on the remaining useful life of HVAC systems. The remaining useful time is shown on the y-axis, with a range of 0 to 1. The x-axis represents time in years. Real-life values for remaining useful time can be found through monitoring, inspections, and sensor data. Scheduled maintenance is done every 6 months, while predictive maintenance uses data and analytics to predict and prevent potential issues, prolonging the system's remaining useful life. The impact of these maintenance methods is shown in Figure 4.15.

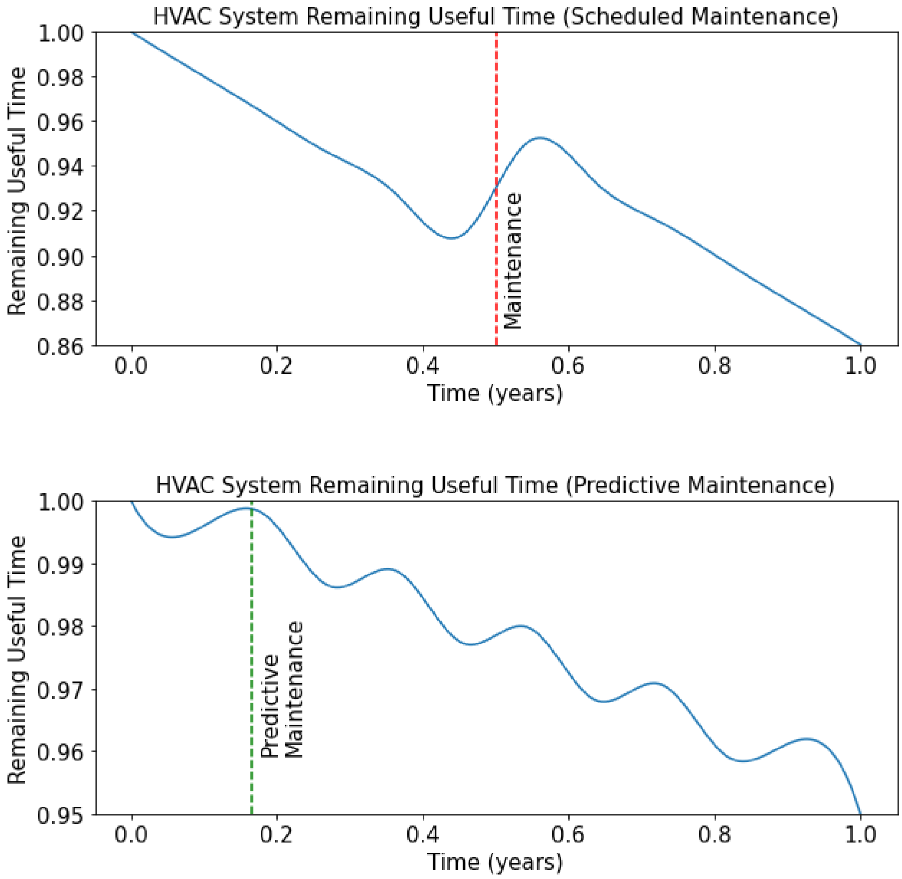


Figure 4.15: Comparison of the impact of scheduled maintenance every 6 months and predictive maintenance on the remaining useful life of an HVAC system. The above plot shows the effect of scheduled maintenance, while the below plot demonstrates the advantage of predictive maintenance in prolonging the HVAC system's useful life by predicting and preventing potential issues before they occur [7].

Chapter 5

Discussion

"The future belongs to those who believe in the beauty of their dreams."

Eleanor Roosevelt

In this chapter, the discussion revolves around the contribution of this thesis.

The thesis makes a unique contribution to the field of energy optimization, occupants' comfort improvement, and fault detection in non-residential buildings by integrating various analysis methods into a comprehensive framework that incorporates Digital Twin technology that offers a holistic approach to building performance evaluation and management. While it is true that various analysis methods already exist, the thesis goes beyond utilizing these methods by integrating them into a comprehensive framework incorporating Digital Twin technology. This integration facilitates a holistic approach to building performance evaluation and management, enabling real-time monitoring, predictive maintenance, and multiobjective optimization.

The work presented here encompassed quantitative and qualitative studies to identify the research gaps in the existing literature. The identified research gaps included topics such as Information Integration Standards, Occupants Centric Building Design, Predictive Maintenance, and energy optimization. This led to the following research sub-questions, which demonstrate the contribution of this thesis.

Sub-question 1: How to create a universal Digital Twin framework for predictive maintenance of AHUs based on IoT, BIM technology, and machine learning for decision-making in FMM?

One notable contribution of the thesis is the implementation of predictive maintenance strategies enabled by Digital Twin technology. This thesis focused on three essential elements that were crucial for deploying a practical predictive maintenance program: big data collection from sensors (from 2019 to 2021), an AFDD and machine learning algorithms for automatic fault detection and diagnostics, and the use of BIM to transfer and visualize data in a 3D model. The thesis addressed the obvious limitations of reactive and preventive maintenance strategies in keeping up with the advancements in building automation and maintenance operations [209, 210], which are already in use in BMS systems and utilize static CMMS [211, 212].

The integration of BIM with FM systems was implemented as a solution using a newly developed plugin in C# that can implement the APAR rules for fault detection, as BIM served as a source and repository of information for planning and managing building maintenance. The thesis proposed the integration of BIM with historical and real-time data from the Internet of Things (IoT) and the faults detected using APAR as input to machine learning, including ANN, SVM, and decision trees, to enable the monitoring of building equipment and environmental conditions, thus facilitating predictive maintenance. This integration addressed the limitations of current fault detection methods [213, 214] in complex systems like Air Handling Units (AHUs) and achieved high accuracy in predicting the faults in AHUs for up to 4.5 months ahead.

Combining machine learning with APAR in this work led to a framework that can be implemented in many buildings as it does not depend on machine learning alone which can predict specific systems as can be seen in the literature nowadays [215, 216], but also combine that with expert rules that can be implemented to many buildings. Despite this advancement, the type of input data to these algorithms remains a problem in the literature. Therefore, an ontology-based solution has been used in this work.

The thesis highlighted the importance of ontology methodologies to overcome challenges in information interoperability and addressed the lack of research on integrating BIM and FM data using ontology techniques [156, 217, 218]. To tackle the issues related to data exchange and interoperability, the thesis implemented the use of brick ontology based on COBie data, which allowed for the retrieval of information from an IFC model and its transfer into the COBie data standard for delivery into FM systems.

By combining BIM, IoT, Facility Maintenance Management (FMM), and machine learning for HVAC systems, the thesis presented a novel framework that filled the gap in the literature and provided facility managers with practical techniques for predicting future conditions.

Sub-question 2: How to use Digital Twin technology to reduce energy consumption and increase users' thermal comfort through real-time optimization of HVAC systems?

The work presented in this thesis made significant contributions compared to previous literature through real-time optimization of HVAC systems and by recognizing the importance of smart control systems [219, 220]. The thesis introduced the utilization of Simulink to build a Digital Twin of the HVAC system based on real-time data. This approach enabled the development of a dynamic model that accurately represented the behavior of the actual HVAC system and helped in reducing energy consumption while keeping occupants satisfied.

Machine learning techniques were employed to learn and predict the behavior of the Simulink model, enhancing the optimization process. The thesis showcased the implementation of a multiobjective Genetic Algorithm (MOGA) to use the best machine learning model as a fitness function, optimizing both the HVAC system and energy consumption. This integration of Simulink, machine learning, and optimization algorithms represented a novel approach in the field.

The thesis presented compelling data that demonstrated the effectiveness of the proposed optimization approach. By implementing the optimization findings derived from the Digital Twin, the thesis showed that it was possible to maintain the Predicted Percentage of Dissatisfied (PPD) below 10%, resulting in significant energy savings. The results indicated an average energy savings of 13.2% for cooling over four summer days and 10.8% for the three summer months of June, July, and August. This level of control enabled adaptive and responsive building environments, aligning with occupants' needs and preferences, ultimately improving thermal comfort.

Sub-question 3: How can Digital Twin technology reduce energy consumption and increase users' thermal comfort by optimizing HVAC systems and building envelope components?

To improve the accuracy of performance evaluation and expedite the implementation of optimization results, the thesis emphasized the utilization of building components as optimization variables by combing both building envelope and HVAC aspects which are rarely found in literature [153, 56, 154]. To address this, the thesis utilized IDA ICE software to simulate the imported BIM model, generating a comprehensive dataset of energy consumption data based on 8000 simulations. This approach ensured the availability of sufficient data for precise analysis of building energy usage. The simulation results were then verified with sensor measurements for energy and indoor climate.

The thesis also focused on multiobjective optimization, considering both energy consumption and thermal comfort as objective functions. The genetic algorithm NSGA II was selected as the optimization algorithm due to its efficiency in finding optimal solutions and preserving superior individuals from the parent generation. The implementation of NSGA II was carried out using visual programming (Dynamo) and the Optimo tool. Machine learning algorithms, including LR, ANN, SVM, GPR, DNN, RF, XGB, NN-SVM, LSSVM, GMDH, and GLSSVM, were compared to identify the most accurate model for the optimization process. To my knowledge, there is no single study in the literature that combined those types of machine learning in Dynamo on such a huge database of 8000 simulations of both HVAC and building envelope.

The combination of machine learning and NSGA II provided an adaptable and efficient optimization approach for building energy consumption. Surrogate models developed through machine learning served as fitness functions, improving the accuracy and computational efficiency of the optimization process [221, 222]. In addition, using Dynamo allowed for seamless streaming of optimization results back into the BIM model. By doing so, the framework provided facility managers and designers with a practical and user-friendly tool to make informed decisions and optimize energy consumption while considering thermal comfort requirements. This approach led to reducing energy consumption by about 37.5% and increased occupants' comfort by about 33.5%.

The thesis extended the use of the ontologies by combining BrickSchema, BOT, and SSN to enable the representation of building assets, sensors, and building topology, facilitating the integration of BIM, energy management, and thermal comfort data into a unified framework.

Sub-question 4: How to use Digital Twin technology to detect the reasons for discomfort in buildings, including thermal, visual, acoustic, and spatial comforts?

This thesis proposed a comprehensive framework that integrated various components and methodologies to achieve the goal of using Digital Twin technology to detect the reasons for discomfort in buildings in real time, including thermal, visual, acoustic, and space comfort. This approach was not found in the literature and recommended by several researchers [143, 141, 223].

Firstly, the thesis developed a Digital Twin framework that incorporated real-time sensor data, occupants' comfort survey results, and Bayesian network (BN) models. By combining these elements, the framework enabled the intelligent detection and prediction of faults that contributed to occupants' dissatisfaction.

Secondly, a BIM plugin was created within the framework, allowing for the seamless integration of data every 5 minutes. This plugin is new in terms of its ability to process data in a shorter period compared to every 10 minutes to the previous one, handle occupants' comfort data, and show the faults' position in the BIM model for indoor and outdoor units which made it easier for facility managers to find the fault that caused discomfort and fix it faster.

Furthermore, the research addressed the analysis of space adequacy, considering 10 aspects simultaneously, including lack of personalization, lack of natural light, poor layout design, etc. (please check Figure 17 in Annex G). This holistic approach provided a comprehensive understanding of the factors influencing occupants' comfort in terms of spatial considerations.

Additionally, the thesis presented new algorithms for fault detection, including the detection of compressor failure, implemented different machine learning algorithms on the same database (Table 3 in Annex G), and proposed a method for determining the remaining useful life of HVAC systems based on multiple standards which can increase the HVAC system life by at least 10%. These contributions enhanced the field of occupant comfort evaluation and HVAC fault detection. In addition, JSON was used for data integration instead of ontologies-based solutions which showed that it is much easier to work with and more effective in including all types of information needed (Section 3.1.4 in Annex G).

Overall, the thesis contributed to the body of knowledge by offering a comprehensive framework that utilized Digital Twin technology, BN models, machine learning algorithms, and BIM integration to detect and understand the reasons for discomfort in buildings. The integration of real-time data, advanced algorithms, and visualization techniques enhanced the understanding of building performance and facilitated informed decision-making for maintenance and retrofitting activities, ultimately improving occupants' comfort and well-being.

Chapter 6

Concluding Remarks

> "If I have seen further it is by standing on the shoulders of giants."
>
> Isaac Newton

This thesis addressed various aspects of developing a sustainable building approach for the existing non-residential Norwegian buildings. The approach was implemented using Digital Twin technology and provided further insights towards achieving more sustainable buildings.

6.1 conclusions

In the AEC-FM sector, Digital Twin technology marks the beginning of a new era of digital information. The research shows that the AEC-FM sector is already working to adopt the Digital Twin idea. Although, at this point, these initiatives are still in the exploratory phase. There is much work that has to be done in order to introduce a high-fidelity Digital Twin model into the AEC-FM industry. In addition, the AEC-FM industry is using Digital Twin simultaneously with attempts to improve BIM by including the operation and management phase. Although there are difficulties in combining BIM with IoT and processing the gathered data, BIM has the advantage that it has previously been applied for many assets. The solid data processing and BIM integration foundations of Digital Twins are a major plus. However, the AEC-FM sector needs to catch up regarding developing and applying Digital Twin technologies.

In this thesis, the author analyzed existing non-residential buildings in Norway to show how implementing Digital Twin technology may improve prediction and knowledge integration, users' comfort, ontologies, and human-based technologies across the building lifecycle.

The research has addressed the following research sub-questions:

Sub-question 1: How to create a universal Digital Twin framework for predictive maintenance of AHUs based on IoT, BIM technology, and machine learning for decision-making in FMM?

The integration of Digital Twin technology in the Facility Maintenance Management (FMM) process offers significant benefits, particularly in the realm of predictive and dynamic maintenance strategies. The proposed framework in this thesis incorporates various data integration and flow mechanisms, such as Building Information Models (BIM), Internet of Things (IoT), and Facilities Management (FM) systems, to facilitate the effective implementation of Digital Twin. To achieve predictive maintenance in Air Handling Units (AHUs), machine learning approaches, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and decision trees, are utilized to predict the status of AHU components and schedule maintenance or repairs in advance. This predictive approach not only extends the lifespan of AHU parts but also ensures high accuracy in automated fault detection. AHU performance assessment rules (APAR) are applied, leveraging sensor data to identify potential issues with AHU equipment, such as fans, sensors, cooling and heating units, and more. By combining IoT, BIM technology, machine learning, and APAR, the proposed universal Digital Twin framework provides decision-making support in FMM, enabling efficient and effective maintenance strategies for AHUs.

Sub-question 2: How to use Digital Twin technology to reduce energy consumption and increase users' thermal comfort through real-time optimization of HVAC systems?

In order to optimize HVAC system efficiency and enhance users' thermal comfort, this thesis presents the HVACDT prototype system that integrates C# programming and multi-objective algorithm optimization into a unified BIM-based workflow. The HVACDT framework, specifically designed for I4Helse, enables the evaluation of energy efficiency and thermal comfort in buildings. The implementation of the HVACDT system involves several steps, including the generation of a BIM model for data extraction, MATLAB programming to adapt Artificial Neural Networks (ANN) and Multi-Objective Genetic Algorithm (MOGA) to the case study, and the incorporation of the optimal solution back into the BIM model for visualization.

The proposed ANN setup demonstrates exceptional accuracy in forecasting energy consumption and Predicted Percentage of Dissatisfied (PPD). The multi-objective optimization significantly improves HVAC operation, ensuring thermal comfort while minimizing energy usage, compared to the real design. The Pareto front solution offers a range of options, allowing building managers to select the most suitable control method for their HVAC systems. The presented data show that by implementing the optimization findings, it is possible to maintain the PPD below 10%, resulting in an average energy savings of 13.2% for cooling over four summer days and 10.8% for the three summer months of June, July, and August. Through real-time optimization of HVAC systems using Digital Twin technology, both energy consumption and users' thermal comfort can be effectively improved.

Sub-question 3: How can Digital Twin technology reduce energy consumption and increase users' thermal comfort by optimizing HVAC systems and building envelope components?

Furthermore, this thesis provided a multi-objective optimization framework based on Building Information Modeling (BIM) and machine learning-NSGAII algorithms to reduce energy consumption and improve buildings' thermal comfort by investigating multiple building factors. An integrated optimization strategy was implemented to achieve this, which considered the building's envelope, glazing parameters, HVAC settings, shading factors, and air infiltration.

In order to validate the simulation model in IDA ICE and gain a realistic understanding of sensor values, all building sensor data is imported into the BIM model using a Revit plugin and then exported to MSSQL and Excel. The established BIM model is then imported into the IDA ICE, and a pairwise test is carried out to obtain a sufficient sample dataset of building energy consumption through simulation. Several machine learning models are trained on the sample dataset to establish a nonlinear mapping between the energy consumption and influencing factors; GLSSVM was the best algorithm in terms of R^2, RMSE, MSE, and MAE; and a case study of a secondary school in Tvedestrand, Norway, was used to verify the efficacy of the proposed method. The school was constructed according to the Norwegian building standard TEK10. It has been determined that the hybrid GLSSVM-NSGA-II is the superior approach to improving internal comfort in the building under consideration.

The best design strategy using GLSSVM-NSGA II improves thermal comfort by 33.5% and decreases energy consumption by 37.5% compared to the original design solution. Moreover, the U-value of the outside walls should be the primary emphasis of the energy-efficient design of the building envelope, followed by the U-values of the roof and windows and the window-to-wall ratio. The solar radiation and air infiltration on the outer side of the windows were used to establish the proper shading factor, SHGC, reflectance, and activation.

Sub-question 4: How to use Digital Twin technology to detect the reasons for discomfort in buildings, including thermal, visual, acoustic, and spatial comforts?

In addition, the effort in this work is intended to substitute existing approaches to quantify and assess user comfort in buildings, which may be difficult due to unknown aspects. With this goal in mind, this work presented the development of a BN model for regulating the indoor climate of existing buildings. The proposed BN may offer comfort performance levels in the form of probability distributions since it describes comfort in a building as a probabilistic process rather than a deterministic one. Adaptability is BN's strongest suit because it allows for the incorporation of not only empirical evidence but also expert opinion.

Although the BN model has the potential to pinpoint the root of building users' complaints, it is not compatible with building information modeling (BIM) programs, making the generated data unavailable and difficult to comprehend. In addition, BIM is unique as an integration tool because of its visualization capabilities and automatic modifications to component properties and data management. Accordingly, this work presented a novel Digital Twin approach that integrates users' feedback (categorized by comfort aspects such as thermal comfort, indoor air quality, visual comfort, acoustic comfort, and space adequacy), real-time sensor data, the users' comfort probabilistic model, and predictive maintenance into building information modeling (BIM). Based on users' feedback and problem detection analysis results, this visualization method guides the FM team in developing effective methods to improve users' satisfaction.

The proposed techniques help FM operators and building designers and put users at the center of decisions. The FM team can make informed decisions about user comfort-related building operational issues much more quickly and easily with the help of the Digital Twin framework, which removes a major barrier to the collection of the necessary information during the operation and maintenance phase and paves the way for much more widespread use of BN, BIM, and their associated benefits. The visualization also facilitates linking many types of FM data (such as architectural and geographical information) to these models. Buildings may explore the proposed method with much less work, which is great for research and can help stimulate commercial interest.

6.2 limitations and future work

The findings of this thesis will aid academics and professionals in the AEC-FM industries by raising the visibility of the current research aims, research gaps, and long- and short-term future trends in the field of Digital Twin research. However, a more holistic perspective is needed in future studies to address the issues raised in this thesis.

Thanks to recent breakthroughs in artificial intelligence (AI), the Internet of Things (IoT), software, and hardware, digital twinning in civil engineering is on the cusp of a major technological advancement. Because of its potential impact on the sustainability of buildings, the Digital Twin deserves further study into the best ways to link real and digital components using the cutting-edge connection and integration methods. Additionally important is the widespread use of the Digital Twin across several technological domains in computation, analysis, optimization, and decision-making.

The limitations of this thesis, as well as the potential directions for further research, are as follows:

1. The developer's prior experience affects the prediction results by choosing the

AI algorithms. It will be important for future researchers to examine other methods of prediction.

2. In order to provide a standardized data integration solution across different sensors and application systems, future studies should use a new ontology-based method to construct new data mapping and integration models between BIM, BMS, CMMS, and optimization software.

3. The HVACDT's efforts here were concentrated only on HVAC system. There is room for improvement in the decision-making process by incorporating other factors such as Energy use intensity (EUI), daylighting, life cycle costs, and the effectiveness of natural ventilation.

4. Post-processing lighting and Computational Fluid Dynamics (CFD) simulations may be utilized to investigate more thermal and optical comfort elements. Dynamic visual comfort parameters, such as daylight autonomy or useable daylight illuminance, must be used to identify the optimal placement of the shade device.

5. The distribution of thermal and visual comfort indices is more interesting to be compared at different places in the room instead of taking the average value of the whole room.

6. Examining the effect of the solar panel (PV) at the building site is necessary for on-site power production.

7. Understanding the control model of windows and shading requires a deeper look at the impacts of indoor air temperature, CO2, direct sunshine, and wind velocity setpoints, as well as the controls for shading and window openings. Visual comfort must be taken into account during optimization.

8. Future studies must focus on expanding the framework's user base by developing additional Python code in the Dynamo block to compete with other market apps that employ the Bayesian network.

9. The model presented in this work needs to consider the nuances of more complicated settings, such as firefighting.

10. The probabilistic model might be improved by studying the windows-to-floor ratio (as an alternative to windows-to-wall ratio (WWR)) and the plumbing system.

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Appendix A

Paper 1- A Review of the Digital Twin Technology in the AEC-FM Industry

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Review Article

A Review of the Digital Twin Technology in the AEC-FM Industry

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The Architecture, Engineering, Construction, and Facility Management (AEC-FM) industry is increasingly affected by digital technologies that monitor sensor network data and control automation systems. Advances in digital technologies like Digital Twin offer a high-level representation of buildings and their assets by integrating the physical and digital world. This paper examines patterns, gaps, and trends in the AEC-FM sector and contributes to digitalization and automation solutions for building management. This work covers a broad range of research topics, from intelligent information management of complex models to building information management and the interaction of building systems, where researchers are increasingly interested in using the Digital Twin to manage their information and in developing new research lines focused on data interchange and the interoperability of building information modeling (BIM) and facility management (FM). After a complete bibliometric search of several databases and following selection criteria, 77 academic publications about the Digital Twin application in the AEC-FM industry were labeled and clustered accordingly. This study analyzed in detail the concept of key technologies, including "Digital Twin in Facility Lifecycle Management," "Digital Twin-Information Integration Standards," "Digital Twin-Based Occupants Centric Building Design," "Digital Twin-Based Predictive Maintenance," "Semantic Digital Twin for Facility Maintenance," and "Digital Twin-Based Human Knowledge." The findings show that information standardization is the first major hurdle that must be overcome before the actual use of Digital Twin can be realized in the AEC-FM industry. Based on that, this paper provides a conceptual framework of Digital Twin for building management as a starting point for future research.

1. Introduction

The AEC-FM industry may enter the fourth industrial revolution with the aid of Digital Twin technology. This technology is considered revolutionary because of its various purposes, including simulating, helping to make decisions, and the possibility of autonomy. Therefore, the AEC-FM industry faces an unavoidable transformation to the fourth industrial revolution [1, 2]. Digital Twin aims to improve asset design, project execution, and asset operation by incorporating information and data throughout an asset's lifespan [3, 4].

Digital Twin has become a trend in many sectors. The term has been expanded to include various uses, from basic digital models that focus on visualization to sophisticated cyber-physical systems. For the AEC-FM industry, Digital Twin is a broad concept with many implications. Very often, the concepts of BIM and Digital Twin are confused. The fundamental purpose of BIM is to create a 3D-model extension of a real-world item, while the significant function of a Digital Twin is to emulate the thing it reflects. By incorporating data and information throughout the lifespan of an asset, it is possible to exchange it with other Digital Twin simulators and programs. These interactions allow the Digital Twin to be a vital decision-making source during the asset's lifetime.

1.1. Definition of Digital Twin. Having a digital model for an asset is not enough to provide whole-life cycle asset management, especially in the maintenance and operation phase.

Therefore, there is ongoing research on how to incorporate the Digital Twin concept that integrates Artificial Intelligence, Machine Learning, and Big Data Analytics to create dynamic models that can learn and update the status of the physical counterpart from multiple heterogeneous data sources [5].

What can Digital Twin offer to the building sector? To answer this question, it is necessary to first look into what a Digital Twin is. As several industries are using this concept (e.g., space and air force, marine, offshore, and aerospace industry), there are multiple definitions of the term. However, the CIRP Encyclopedia of Production Engineering [6] released a definition of the term Digital Twin in 2019 that seems to cover most use cases: *"A digital twin is a digital representation of a unique active product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors through models, information, and data within a single or even across multiple life cycle phases."*

The definition uses the phrase "unique product." The reason for this is to emphasize the need for a Digital Twin to represent only one asset because of the accumulation of information. The product's history is essential as previous damage or repairs will significantly affect how the product will respond to loads in the future. Another aspect that is worth looking into in the definition is the following phrase: "[\enleadertwodots] or even across multiple life cycle phases." It is to underline the possibility of letting the Digital Twin follow the product even after the end of its life cycle in the event of refurbishing or reusing some of the components in other projects, and the history of the components will be valuable.

1.2. The Origin of Digital Twin. Using models to represent the real world is not new within the engineering field. NASA built physical "twins" of the spacecraft in the Apollo program in 1967-1972 [7]. However, it is only in the last quarter of the 20^{th} century that it has been possible to create virtual replicas within computers' digital space. The origin of the Digital Twin concept is by many [8–10] credited to Michael Grieves, who in 2002 held a presentation about product life cycle management. In the presentation, Grieves showed all of the essential parts of a Digital Twin model: the real object, the virtual object, and the gathering and processing of data between the physical asset and the digital replica. Grieves initially referred to it as a "conceptual ideal for product life cycle management." Later on, Grieves changed it to "Mirrored Spaces Model" and then called it "Information Mirroring Model." [6] Finally, Grieves wrote an article in 2011 with John Vickers, who worked for NASA, and in this article, the term "Digital Twin" was used [6]. The main parts of Digital Twin can be seen in Figure 1, where the simulation model must be validated by the measurements from the physical object using technology, such as laser scanners, drones, sensor data, etc. Once the model is validated, it can give insight into how the physical object acts under various simulated situations, making better decisions and streamlining operations and predictions.

Michael Grieves recently published research about the common misunderstanding that the Digital Twin does not exist unless there is a physical object [11]. According to Grieves, the primary criterion for determining if a digital model is a Digital Twin is whether the model is designed to become a physical product with a physical counterpart. Grieves gives an excellent example here. A flying carpet Digital Twin will never become a Digital Twin because we cannot make it a physical object.

1.3. Scope and Structure of the Paper. The AEC-FM industry is in the midst of the fourth industrial revolution, a period of unavoidable digital transformation [1]. Digital Twins can usher in the fourth industrial revolution in the AEC-FM industry. The aerospace sector began using the Digital Twin roughly a decade ago to develop new planes and vehicles. However, the Digital Twin idea is mainly used in designed goods, manufacturing equipment, and production lines to manage product lifecycles and meet Industry 4.0 criteria. It is viewed as an innovative method of integrating and controlling an asset throughout its lifespan because of its numerous applications, including simulation, decision support, and the possibility for autonomy. However, to compete in the AEC-FM industry, businesses must find new and inventive ways to revolutionize their work [12]. The subject matter is critical in allowing the digital and physical elements to be appropriately integrated. Digital Twin may help offer more successful asset design, project execution, and asset operation by integrating data and information throughout the lifespan of an asset [13, 14].

Information-based systems, such as BIM, which seamlessly integrate information, will allow advances in AEC-FM operations and increase the project's efficiency and effectiveness throughout the project's lifetime. However, BIM will not satisfy the need for an automation solution in the AEC-FM industry alone, nor will it deal with the intelligent data revolution and interoperability issues. BIM must be combined with emerging technologies that are only partly applied in the AEC-FM industry, where there is minimal research to close this gap to enhance building management and design.

The Digital Twin activities may enhance AEC-FM operations by improving data management and processing using large-scale data, information, knowledge integration, and synchronization. It does this by dynamically integrating data and information throughout an asset's lifespan. Combining a virtual information model with real-time data might significantly improve decision-making over the whole building's lifespan. The integration of real-time data via IoT sensors and devices on the physical system enhances adaptive updating to serve the information for further machine learning and artificial intelligence integration to coordinate and automate the physical counterpart of the digital model, following operational changes.

This paper's novelty lies in investigating three databases, namely the Web of Science, Scopus, and Google scholar, about the Digital Twin in the AEC-FM industry facing the manufacturing and automotive industry. Compared to other

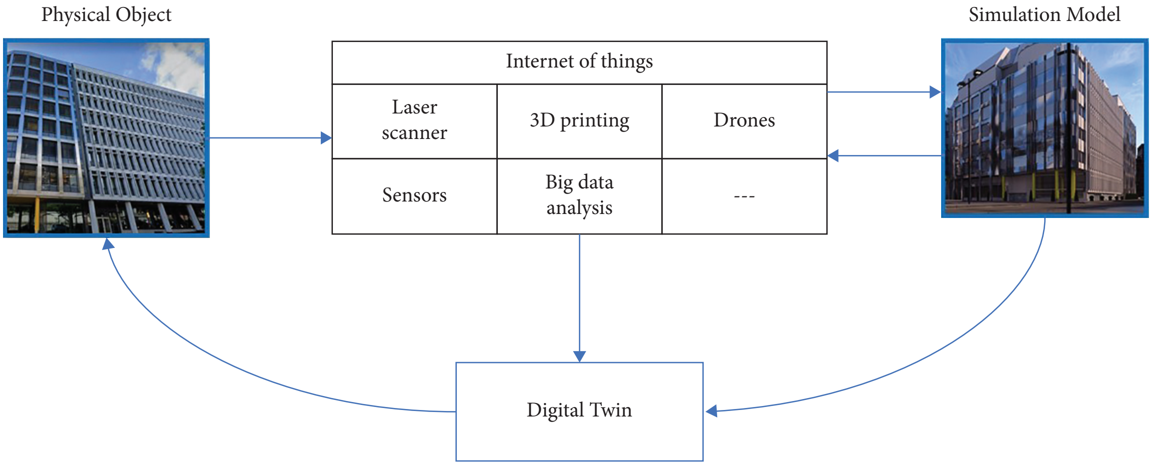

Figure 1: Digital Twin technology

review papers [13, 15, 16], this study is one of the few studies that focus on Digital Twin technology within the AEC-FM industry.

In addition, there are similar works to our paper that have been published recently. Deng et al. [17] performed an extensive assessment to identify the developing technologies aiding the transition from BIM to Digital Twins in built environment applications. The emphasis was on BIM rather than supporting technologies like Digital Twin information transmission systems. Our work focuses more on the ideal digital twin model for AEC-FM. Fjeld [18] examines the state of Digital Twin knowledge in the Norwegian AEC-FM industry to establish a standard definition of "Digital Twin" technology. However, only Scopus was used as a database in her study. Caramia et al. [19] conducted a systematic literature study to examine the Digital Twin in AEC/FM. They chose a limited period for their study (2018 to 2020). Moreover, there are various gaps in the use of Digital Twin, such as occupant comfort, predictive maintenance, etc., that are not addressed in their research.

The awareness of the Digital Twin in the AEC-FM industry will improve as more people get familiar with the idea, the technology, and the current state of the art. A conceptual framework for an ideal Digital Twin AEC-FM industry is also proposed in this study, which will serve as a guideline for future research.

The following sections of the study investigate the current status of Digital Twin research in the AEC-FM industry to identify patterns, trends, and gaps in this area.

2. Methodology

This study examines whether technologies and applications in the AEC-FM sector are ideal for Digital Twin technology. There is currently no comprehensive inquiry focusing on understanding how specific cutting-edge technologies complement Digital Twin to reach their full potential or whether there is any chance of combining more than one technology to assist Digital Twin.

This article's technique is divided into three steps, as shown in Figure 2. Data collection (stage 1) involves retrieving an initial number of articles, deleting extraneous publications, and selecting just particular publications and relevant categories. Stage 2 includes a scientometric analysis, followed by the findings (stage 3). The following are further details about these stages:

2.1. Data Collection. Literature exploration was performed on the Scopus, Web of Science, and Google scholar databases to ensure more comprehensive and robust findings rather than just gathering data from a single one. The OR and AND search benchmark was used to do the keyword-based search, for example, LIMIT-TO (EXACT KEYWORD, "Digital Twin") OR LIMIT-TO (EXACT KEYWORD, "Life Cycle") OR LIMIT-TO (EXACT KEYWORD, "Architectural Design") OR LIMIT-TO (EXACT KEYWORD, "Construction Industry") OR LIMIT-TO (EXACT KEYWORD, "Information Management"), etc. The study examines publications published between 2016 and 2022 (ending on 12th February). The reason for choosing this time interval is because there were no pieces of research about Digital Twin in AEC-FM before 2016. The result of the first stage was 158 research publications. A refinement of the search followed this to exclude many irrelevant papers that may have no bearing on this study. The papers selected were based on published articles, conferences, and reviews, as these publications can give a thorough overview of extant research [20]. For instance, only English-language articles were collected since VOSviewer was used to evaluate scientometric data, which only supported English-language papers. VOSviewer software was employed to do bibliometric data analysis on the databases' information (Figure 2). VOSviewer is a visualization application that uses natural language processing methods and text mining techniques to help analyze massive networks. It is frequently used in scientific research [21, 22]. The VOSviewer application may be used to do scientometric analyses, which may entail studying citation links between articles or journals, cooperation ties between researchers, and co-occurrence interactions between scientific terms. However, VOSviewer has a limitation in consolidating data duplication. As a result, we manually eliminate duplicate studies to avoid any noise in the data. After that, new groups

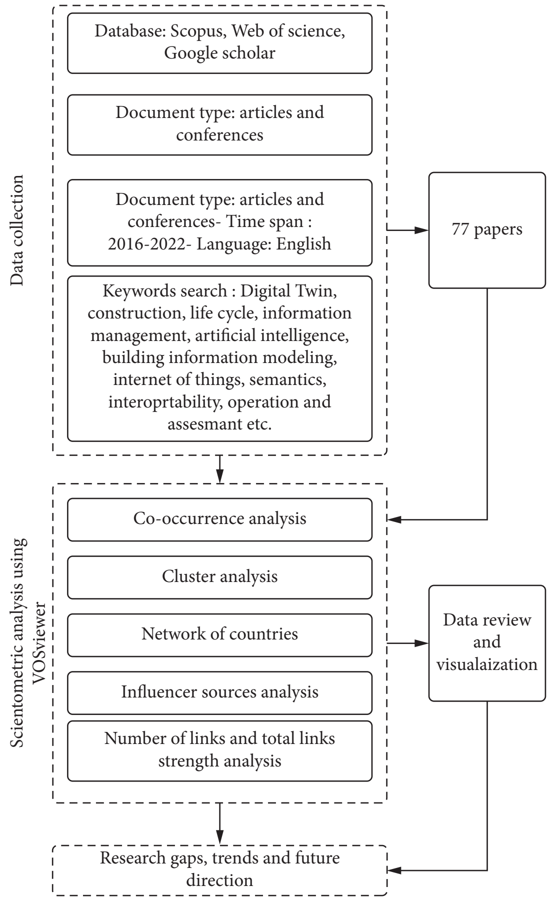

Figure 2: Investigation workflow of AEC-FM digital twin research.

were selected for this article based on other refining criteria, including subject area (engineering, environment, etc.) and source type (journal and conference proceedings). The final literature volume was 77 papers.

2.2. Scientometric Analysis. Analyzing articles by hand is becoming increasingly difficult because of the rapid growth of research. As a result, this study used the VOSviewer® as an analytical tool and classified and evaluated the literature using a conventional quantitative and qualitative manner. The program supports Distance-based maps, and the user can select the sort of analysis to do. This software's capabilities include the analysis of coauthorship, co-occurrence, citations, bibliographic coupling, and cocitations. There is a wide range of uses for each of these. Aside from that, this study is primarily concerned with determining the link between current technology and the Digital Twin. Consequently, this paper's goal necessitates that the primary focus is co-occurrence analysis and link analysis. Citation analysis is one sort of analysis that can be used in the future. Firstly, co-occurrence analysis is used to examine the co-occurrence of terms in at least two separate publications [23]. The relationships between keywords are determined by the frequency with which they are used in documents [24]. The study themes were determined using cluster analysis (Section 3.1). Secondly, the number of links reveals how many times a term is linked to other keywords. The overall link strength metric measures the strength of a keyword's linkages to other keywords. Additionally, the average publication year of the papers that contain a term provides context for the keyword's presence in the associated literature. The more recent the average year of publication, the more current the keyword and subject of the study.

Moreover, influencer source evaluations were conducted to include all critical publications from the most prestigious journals, such as automation in construction, applied science, etc.

2.3. Research Gaps, Trends, and Future Direction. To provide a thorough insight into the Digital Twin technology in AEC-FM and the future research in this domain, this stage includes a discussion of the application fields of Digital Twin.

3. Results

3.1. Science-Based Keyword Mapping and Analysis. The main features in the study are identifiable by keyword search [25]. The knowledge of words and phrases was gained using text mining and natural language processing techniques used in VOSviewer [24]. For authors who fail to include relevant keywords, a few databases employ subject headers to help prevent overlooking relevant terms. In this study, keywords generated by the authors and indexes were utilized for scientific analysis. A keyword filter was used to count the number of phrases used in the study. The extent of a document is shown by the number of times a term appears.

The network of terms co-occurrence is made visible in Figures 3–5 using bibliometric data analysis. The technique used to develop the graphic is based on a minimum of four keywords that are close to one another.

The circles and labels in Figures 3–5 indicate the keywords in the respective figures. The weight of a term is represented by the circle's size and the label's size. The distance between two keywords in a network is used to determine how closely they are linked to one another. Because of their significant correlation, two keywords are placed closer together in the network, whereas their lesser correlation brings them farther apart. Moreover, colors represent the groups of related keywords (clustering).

As seen in Figures 3–5, the analysis of keywords from findings indicates that four main terms form together with the Digital Twin concept in the AEC-FM industry: BIM, IoT, ML, and Building Management System (BMS).

The keywords employed in this study were both author-generated and index keywords, which were combined to complete the analysis. A total of 52 keywords out of 1244 passed the criteria of 6 co-occurrences. Following the consolidation of the keyword list, 41 keywords were selected, which are presented in Table 1.

The study patterns, gaps, and trends in Digital Twin research were explored further in light of the research findings on the field's evolution. The following sections of the article discuss research trends and highlight research gaps in the field of Digital Twins.

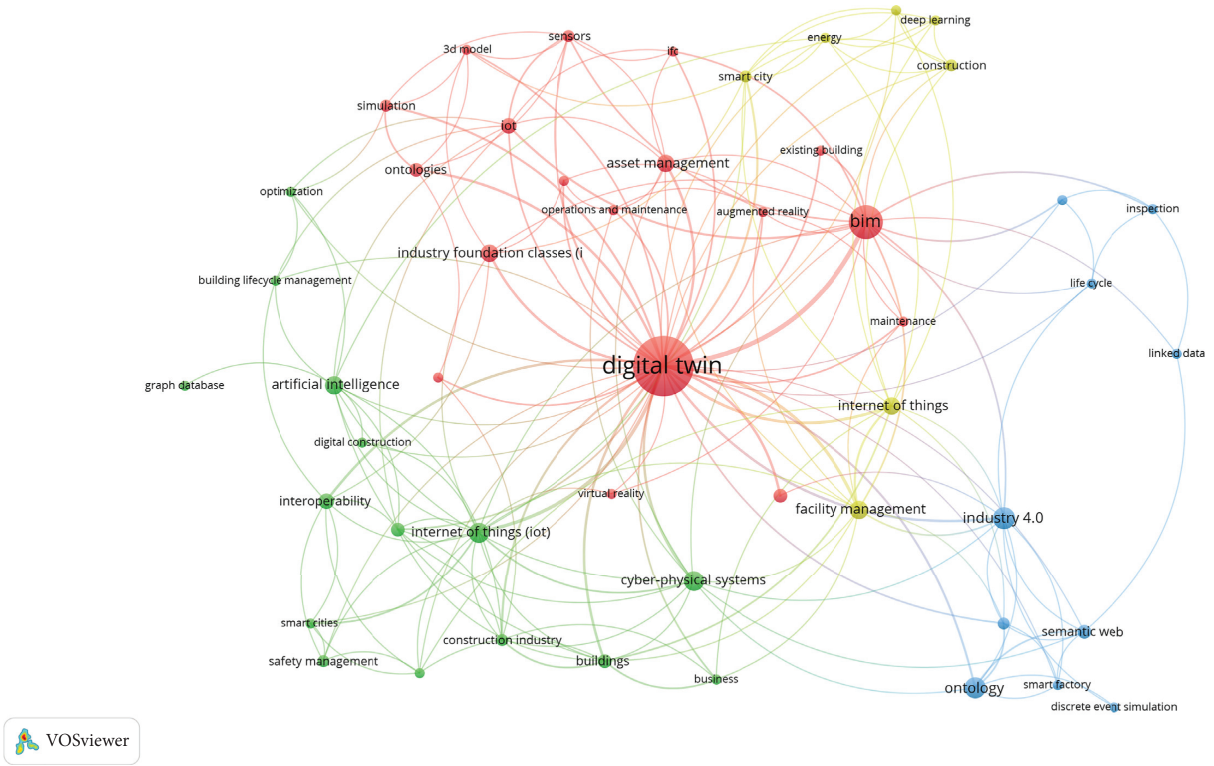

Figure 3: Network representation of keyword co-occurrence extracted from the Web of Science of Digital Twin research in the AEC-FM industry from 2016 to 2022.

3.2. Total Link Strength and Average Year Published. The most important keywords in the Digital Twin study undertaken in the AEC-FM industry have high overall link strength and a high occurrence frequency. Table 1 shows the findings of the scientometric study, which revealed that the keyword Digital Twin had the highest overall link strength (123). The lifecycle (38), architectural design (37), and information management (25), respectively, came next. Decision making, constructing information models, project management, and artificial intelligence were the terms with the subsequent most significant overall link strengths. However, there is a significant gap in Digital Twin research in the areas of predictive maintenance (10), interoperability (8), information systems (7), energy utilization (7), ontology (6), asset management (5), safety engineering (5), life cycle management (5), semantics (5), data fusion (5), and linked data (3).

For years, the AEC-FM industry's attention has focused on Digital Twin research as a product lifecycle management technique, and these two terms have become the most important in research. In the building construction industry, Digital Twins are now used across the whole project lifetime, which explains why this term is so important. Every building project generates complex data. Using modern Digital Twin research in the AEC-FM industry, we can put this massive amount of data to good use in facility management. As a consequence of the AEC-FM industry's digital transition, a cognitive-capable Digital Twin of the building as a physical asset was created. Digital Twin study promises to enhance building information models, data processing, and efficiency in information administration. One of the most challenging tasks in the project lifecycle is gathering and analyzing data. Thus, information management is critical in Digital Twin research.

In addition, energy utilization, built environment, facility management, building information model, and artificial intelligence are relatively new keywords that have become increasingly popular in association with Digital Twin research in recent years, as shown in the right-most column of Table 1. The chronological sequence of the keywords implies that researchers are more likely to investigate information use using BIM-based procedures than through traditional methods.

3.3. The Reviewed Sample Size. As shown in Figure 6, the quantity of papers produced between 2016 and 2022 is presented annually. During this period, the quantity of articles linked to Digital Twin in AEC-FM has increased. The trend is even more evident in 2019 with the growing quantity of research publications. The total number of papers published in the past seven years was approximately 77 when this paper was prepared. Thus, the exponential increase of Digital Twin research in AEC-FM demonstrates the dramatic influence on the AEC-FM community.

Several engineering and computer science journals have published articles on Digital Twin research outputs, according to the distribution of Digital Twin research outputs in the Table 2. Among the primary reasons for this

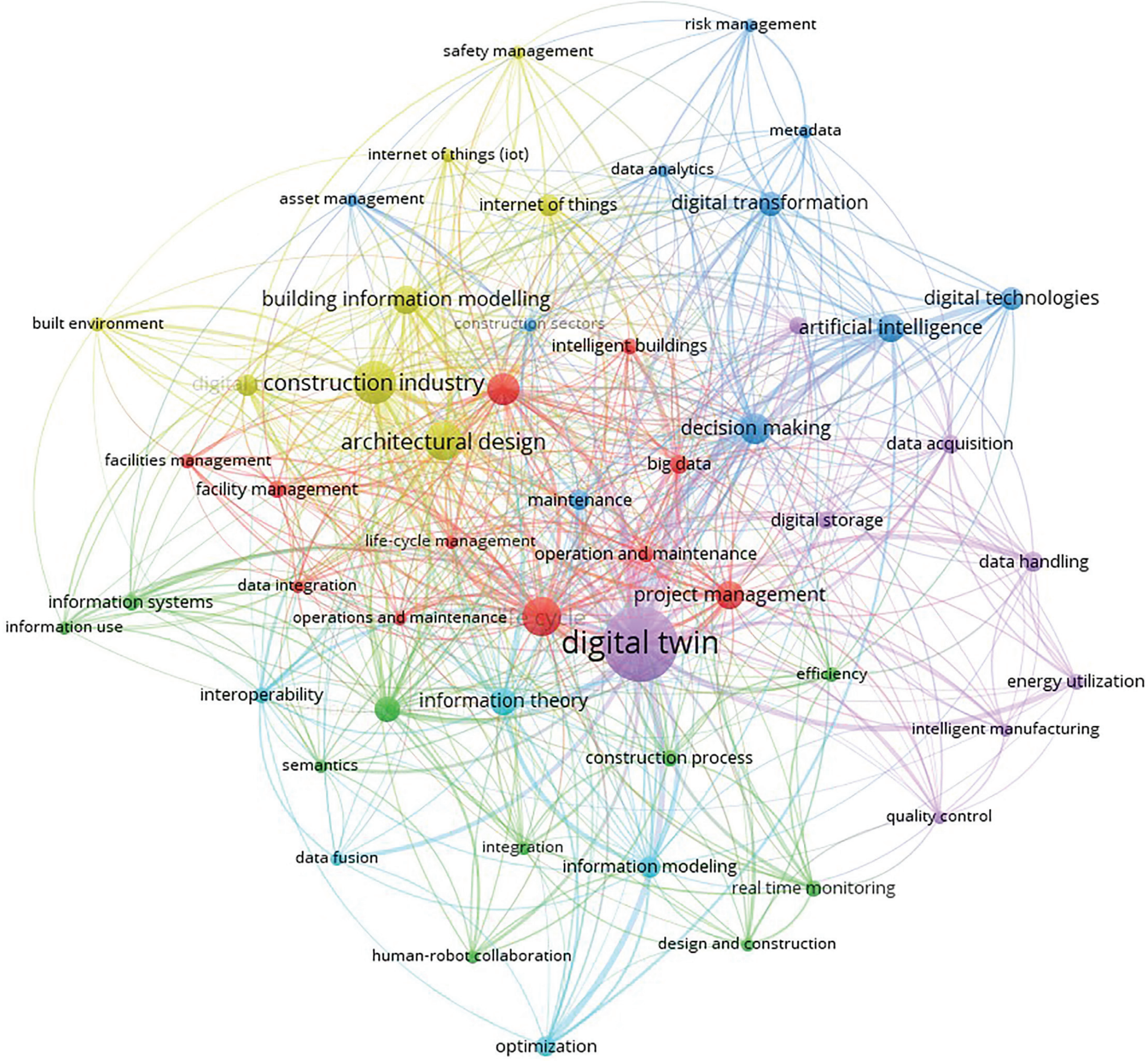

Figure 4: Network representation of keyword co-occurrence extracted from Scopus of the Digital Twin research in the AEC-FM industry from 2016 to 2022.

development is that digitalization and automation are primarily achieved via the use of tools and techniques created in those fields [9].

3.4. Active Nations in the AEC-FM Industry Digital Twin Application Research. To discover which nations are most involved in the AEC-FM industry digital twin research, the study employed the "coauthorship" analysis, "country" unit of analysis, and "fractional counting" as the counting technique. Fractional counting was used to limit the influence of highly cited articles in the bibliographic coupling network and to minimize the impact of publications with numerous authors. A minimum of one document and one reference per nation was used to establish the optimal network. In the investigation, 13 nations met the criteria and were thus included in the resulting network. In Figure 7, the network indicates that the United Kingdom, United States, Italy, and Australia were the major contributors to Digital Twin research in the AEC-FM industry.

There is a limitation of international cooperation in the AEC-FM sector in Digital Twin research. Many of the papers have been published recently because of the relative infancy of the Digital Twin and the delayed acceptance of new technologies in the AEC-FM sector. Because of this, it is necessary to foster stronger cooperation across nations to facilitate global knowledge exchange and transmission.

3.5. Scientific-Based Analysis of Sources. Scientific-based analyses were utilized to find sources on the topic of Digital Twin that was published in the AEC-FM sector. The threshold for the minimum number of documents was one. A total of 20 sources matched the criterion. Furthermore, for each of the 20 sources, the overall strength of the citation connections with other sources was determined.

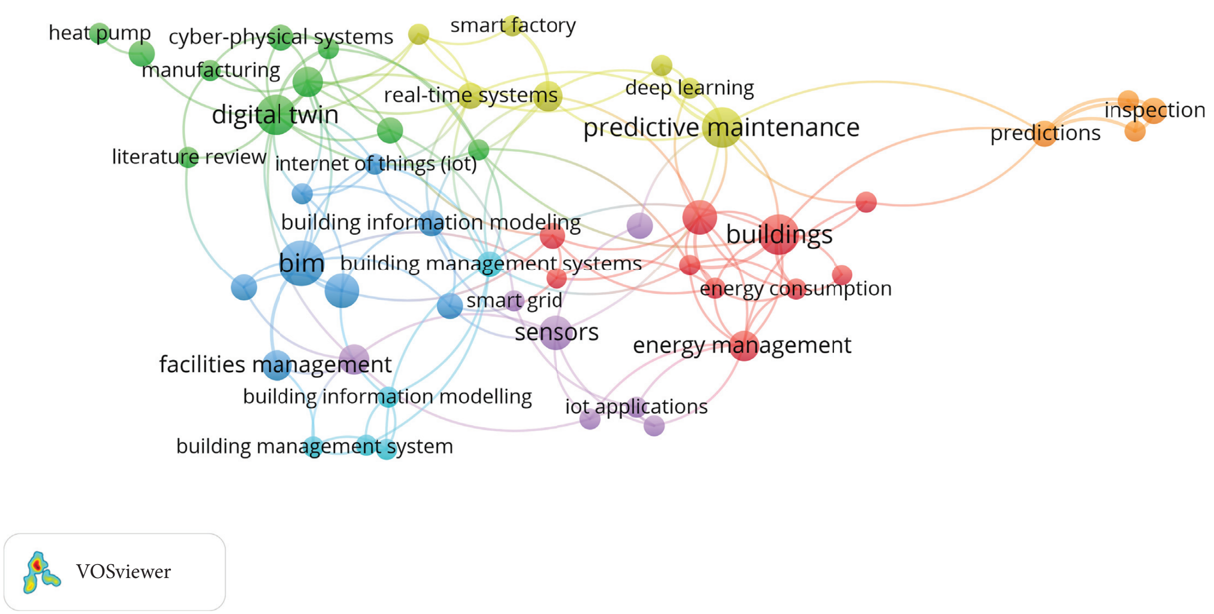

Figure 5: Network representation of keyword co-occurrence extracted from Google Scholar of the Digital Twin research in the AEC-FM industry from 2016 to 2022.

Table 1: A scientometric study of items related to Digital Twin research in the AEC-FM industry from 2016 to 2022.

Keywords	Cluster	Number of Links	Total link strength	Average published year
Big data	Digital twin in facility life cycle management	27	9	2019.67
Facility management		21	8	2020.75
Information management		42	25	2020.16
Life cycle		45	38	2020.18
Life cycle management		18	5	2019.60
Project management		33	20	2019.90
Data fusion	Digital twin-information integration standards	11	5	2020.40
Information modeling		24	11	2020.55
Information theory		35	17	2020.24
Interoperability		20	7	2020.00
Optimization		14	10	2020.80
Data acquisition	Digital twin-based occupants centric building design	24	9	2020.22
Data handling		17	10	2020.10
Digital storage		24	8	2020.38
Digital twin		51	123	2020.32
Energy utilization		14	7	2020.86
Intelligent buildings		21	7	2020.29
Energy management		15	9	2020.12
Construction process	Semantic digital twin for facility maintenance	19	7	2020.14
Embedded systems		33	16	2020.19
Human-robot collaboration		9	5	2020.00
Information systems		19	7	2020.14
Information use		13	5	2020.40
Real-time monitoring		14	7	2020.14
Semantics		15	5	2020.20
Ontology		16	6	2020.12
Linked data		18	3	2020.30

Table 1: Continued.

Keywords	Cluster	Number of Links	Total link strength	Average published year
Artificial intelligence		27	19	2020.32
Asset management		16	5	2019.60
Data analytics		18	5	2020.00
Decision making		41	23	2020.26
Digital technologies	Digital twin-based predictive maintenance	19	13	2020.23
Maintenance		24	10	2020.30
Metadata		15	5	2018.80
Risk management		13	5	2018.60
Predictive maintenance		22	8	2018.72
Architectural design		46	37	2020.32
Building information modeling		36	20	2020.25
Built environment	Digital twin-based human knowledge	15	6	2020.83
Digital twins		28	12	2020.92
Internet of things		30	11	2020.27
Safety management		15	5	2020.60

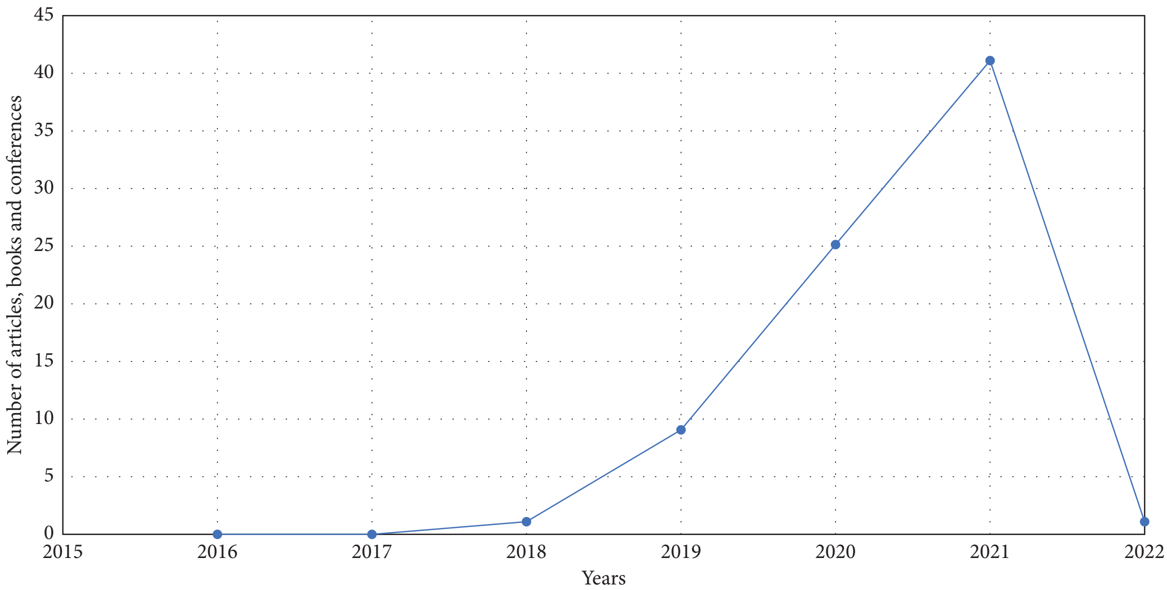

Figure 6: The number of articles published each year in the AEC-FM industry regarding Digital Twin research from 2016 to 2022.

Four major quantitative factors are listed in Table 2. Several articles highlight the importance of the sources' contribution to the field of study. Links indicate the relationship between the specified source to other sources. Total link strength reflects how strong a journal's link with other journals is. Finally, the total number of citations is tallied for each reference across all years.

A network diagram illustrates the outcome of journal citation analysis (Figure 8). Automation in Construction, Applied Sciences, Engineering Construction, and Architectural Management, Journal of Information Technology in Construction, Construction Innovation, and IEEE Access publishes the most significant number of papers in Digital Twin in AEC-FM. In contrast, Automation in Construction, Applied Sciences, Engineering Construction, Architectural Management, Construction Innovation and the Proceeding of the 34th Annual Arcom 2018 are the top sources with the highest citation. Therefore, according to these comparisons, Automation in Construction, Applied Sciences, Engineering Construction, and Architectural Management is the most influential source in Digital Twin in AEC-FM.

4. Discussion

The evolution of Digital Twin research throughout time, research patterns, gaps, and trends were evaluated and addressed in this part based on study findings. The sections that follow highlight research trends and define research needs in the field of Digital Twin research. Of these results, the most notable impact of Digital Twin research is found under the topic, "Digital Twin in Facility Lifecycle Management." At the same time, there is a wide gap in research

Table 2: The AEC-FM industry's sources' quantitative measures concerning the digital research.

Source title	Number of articles	Links	Total links strength	Citation
Automation in construction	11	9	14	169
Applied sciences Switzerland	4	3	5	17
Engineering construction and architectural management	4	5	6	22
Journal of information technology in construction	4	5	7	4
Construction innovation	3	1	1	24
IEEE access	3	1	1	3
Sensors	2	1	1	3
Smart and sustainable built environment	2	4	4	11
Buildings	2	2	3	3
Electronics Switzerland	2	2	2	3
IEEE engineering management review	2	1	1	8
IFAC papersonline	2	1	1	1
International journal of safety and security engineering	2	1	1	6
Journal of asian architecture and building engineering	2	1	1	2
Journal of computing in civil engineering	2	2	2	0
Journal of building engineering	1	2	3	0
Proceeding of the 34th annual arcom 2018	1	1	1	15
Sensors Switzerland	1	1	1	3
Tunnelling and underground space technology	1	1	1	0

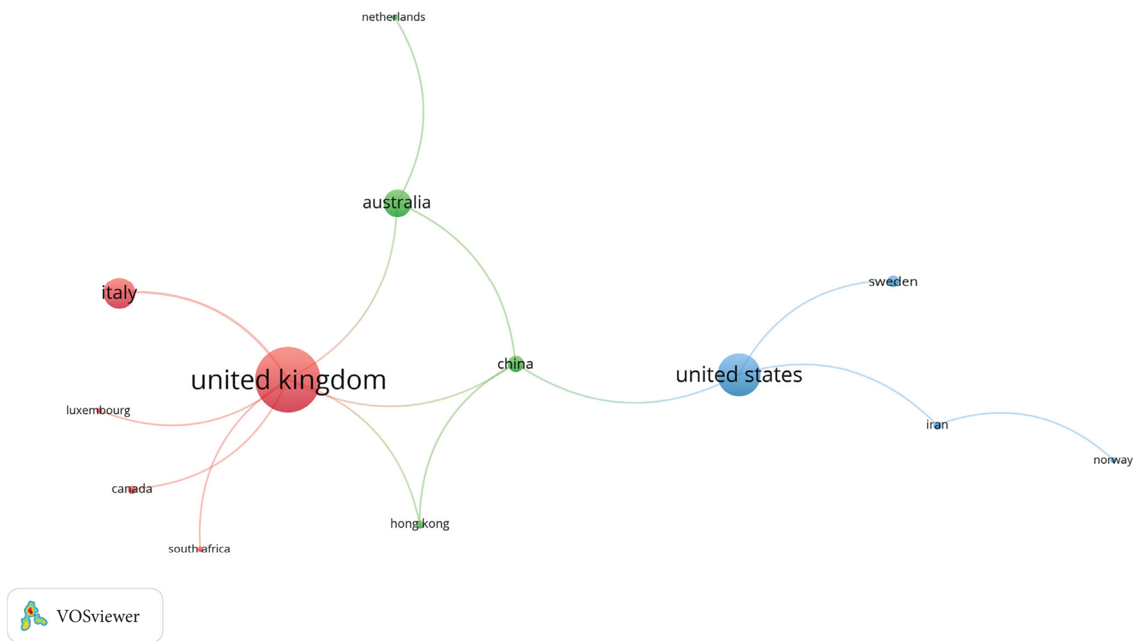

Figure 7: Countries making important contributions to the Digital Twin research in the AEC-FM industry.

that looks into "Digital Twin-Information Integration Standards," "Digital Twin-Based Occupants-Centric Building Design," "Digital Twin-Based Predictive Maintenance," "Semantic Digital Twin for Facility Maintenance," and "Digital Twin-Based Human Knowledge" (Figure 9).

4.1. Digital Twin in Facility Lifecycle Management. Facility management (FM) accounts for almost two-thirds of the overall cost of a building's entire life cycle [26]. FM is a multidisciplinary approach to ensuring the built environment's efficiency by incorporating individuals, locations, procedures, and technologies. Maintenance management, energy management, space management, asset management, building performance, control management, sustainability management, emergency management, and other building management tasks are all included in FM. However, FM managers always struggle to access details using 2D drawings and conventional facility management systems [27, 28].

4.1.1. Asset Management and Monitoring. Asset management refers to a group of management processes and structures covering all aspects of asset management during

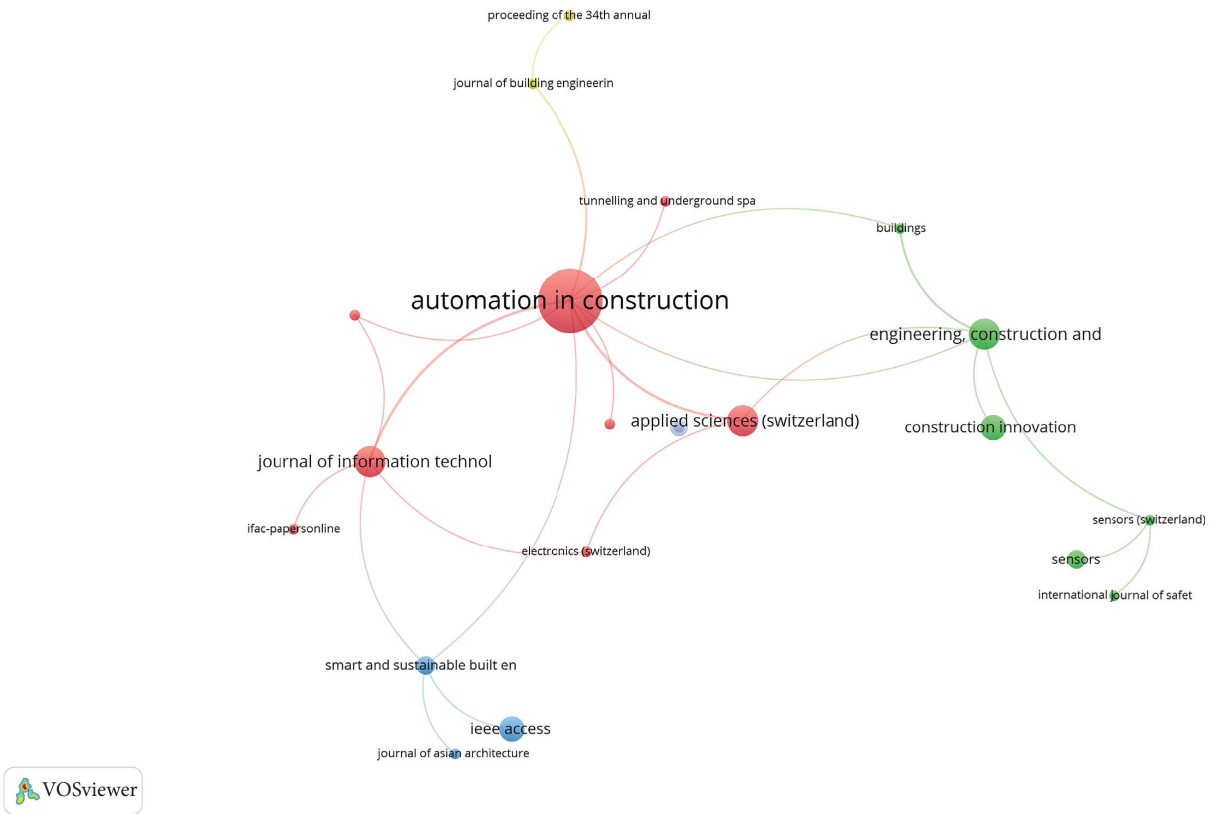

Figure 8: Digital Twin for AEC-FM activities uses scientific-based mapping of influencer sources.

its life cycle. It involves the management of the physical asset and the associated digital knowledge within the scope of the project [5, 29]. Likewise, BIM considers the entire life cycle of an asset, including quality control and asset management [30–34]. BIM has potential applicability and benefits in the service and maintenance stage, according to many types of research [35–37], and some leading FM organizations are pushing the use of BIM in this stage. Lee & Lin [38] explored how the BIM approach is used to construct 3D information models for building management and maintenance. However, while using BIM alone, there is no automatic condition monitoring to allow facility managers to make quick maintenance decisions. In addition, a lack of knowledge in using BIM alone will make it difficult to define asset management criteria during the design process [5]. It brings us to the power of Digital Twin technology to improve facility management maintenance and operational performance. The use of a Digital Twin would speed up the advantages and growth of BIM and other digital innovations in the asset management industry [39]. However, a well-defined and well-organized Digital Twin model is also needed to oversee current implementations, identify gaps, and include roadmaps for future progress.

4.1.2. Maintenance of Mechanical, Electrical, and Plumbing Components. The maintenance of a building could benefit from Digital Twin by platforms assisting with checking maintainability and real-time data access. The related studies of operation and maintenance were summarized as three main categories, including identification of physical components linked with BIM by RFID (radio-frequency identification) tags, linking physical with digital objects by connecting BIM and building management system (BMS), in addition to the visualization of problems by augmented reality or mobile BIM tools [40]. Augmented reality can be described as a real-time view of a physical world with included digital information, which enhances the user's perception of the real world [41].

The maintenance of mechanical, electrical, and plumbing (MEP) is often reactive or preventive, however, failure or future conditions cannot be prevented. Cheng et al. [27] conducted a study based on IoT and BIM to improve the maintenance strategy for building facilities. The study collected data from IoT sensors monitoring the building facilities and environment in the operation period. The future conditions of MEP components were predicted by ML algorithm, and an illustrative example stated that this method could efficiently predict the condition of MEP components.

4.2. Digital Twin-Information Integration Standards. With the rise of new technologies, information diversity and overload can happen, all of which can lead to system fragmentation throughout the building project, difficulties for workers to consume the information timely and effectively, and burden the workers with too much or irrelevant information [42]. Integrating the buildings' information

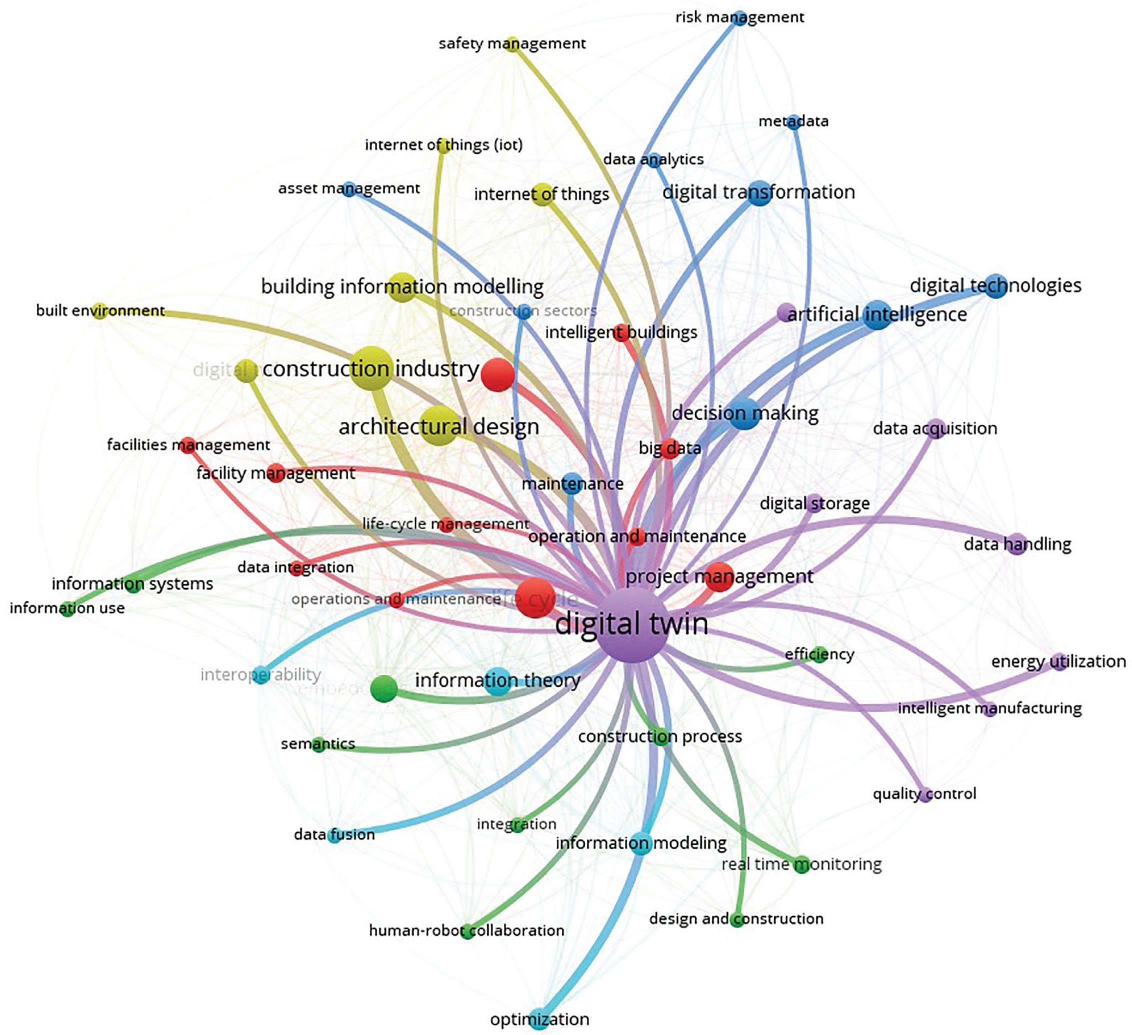

Figure 9: The AEC-FM industry's "Digital Twin" item co-occurrence network visualization map from 2016 to 2022 (up to February 2022).

with the live data is not easily accessible for potential users. The problem is attributable to the difficulty in accessing the building information and the challenge to integrate this information with the live data from heterogeneous sources [43]. Bischof et al. [44] present the challenges arising from the nature of different data sources and emphasize providing semantic interoperability and data integration.

McGlinn et al. [45] developed an ontology to integrate heterogeneous data using artificial neural network, genetic algorithm, and data mining for addressing the issue of providing intelligent control suggestions to facility managers. Their findings indicate that, while BIM and IoT are promising technologies that result in broader data sets, standardization of such policies and procedures arises to be an unexpected challenge. Some efforts have been made to solve standardization issues. However, McGlinn et al. [45] have not fully tackled the challenges mentioned above in their research. The main reason is that currently, there are many BIM software with different format types. One of the proposed solutions is a cloud-based BIM system that adopts the IFC format as the BIM file upload format with a developed web interface using WebGl [46]. On the other hand, cloud IoT can merge Cloud Computing and IoT, partially solving most IoT issues. Cloud can provide the intermediate layer between things and applications, interoperability of very high heterogeneity of devices, and real-time data analysis [47, 48].

Hence, the initial challenge to facing the practical application of Digital Twin in the AEC-FM industry is information standardization. Poorly designed and implemented information integration makes sorting large and heterogeneous data sets into useable data challenging, and doing so is more complex than anticipated. This process is very time-consuming and will hinder the future of the Digital Twin revolution [49].

In general, IoT sensors are dynamic, and FM-BIM contains static data. The standard integration method that is used for static and dynamic data is known as linked data [50, 51]. The method stores each data source effectively separately and creates a data lake that can be accessed through the data management system. When working with this method, there are two approaches to consider: ontology linked and directly linked. An ontology-linked approach uses a query processor to make this data accessible. In the case of a directly linked approach, standardized naming formats can be used to create a direct link between BIM data points and IoT [52]. The second approach links BAS and IoT to BIM using standardized naming formats and is much simpler. In the AEC-FM industry, the information exchange protocol COBie was developed to establish a standard naming format. This was used to facilitate the integration of computerized data into BIM. This approach requires no manual tagging. Instead, connecting BIM and BAS data stores and other data sets will define the input data structure.

4.3. Digital Twin-Based Occupants Centric Building Design. Human-building interaction is one of the least developed aspects of building science, even though most buildings are built for human occupants with the functions of delivering comfortable, healthy, accessible, and secure spaces to satisfy a variety of uses [53, 54]. However, numerous post-occupant assessments show that buildings often fail to meet occupant expectations [55]. As a result, a paradigm shift is necessary to recognize that occupants and buildings have a complex and dynamic bi-directional relationship that enables new technologies and approaches to raise awareness of the importance of healthy and comfortable environments. Therefore, research is needed for the use of existing data sources such as BIM, BAS, and IoT and how to integrate them with technologies like ML and statistical modeling to build the Digital Twin model that will aid facility managers in decision-making, obtaining knowledge on occupant behavior and indoor climate and the relation between them. The following knowledge gaps have been identified in the literature:

(i) The different domains of environmental exposure have been treated in isolation in previous studies on human comfort and behavior in buildings, especially indoor air quality and acoustic, thermal, and visual comfort [56–60]. Thus, it is necessary to build a framework that investigates the effect of all those aspects on occupant comfort.

(ii) Data-driven modeling of occupant presence and activities are required to achieve new knowledge. In particular, data mining and artificial intelligence. New techniques and tools are rapidly developing and gaining traction due to Artificial Intelligence and data mining that is capable of identifying patterns and learning from the past, have improved properties and performance, or make analytical and predictive approaches more available [61]. In this domain, deep learning has emerged as a promising strategy for occupant detection in recent years [62]. The best data processing techniques should be investigated in future research for predicting occupant presence [63] or for model-predictive control [64, 65].

(iii) Integrating BIM with ML and statistical approaches with sensor data to build a Digital Twin that makes data collection more manageable and allows for the visualization of occupant feedback and HVAC conditions results to support decision-makers. There have been very few studies in this domain, and one of the limited examples is by Alavi & Forcada [34] where the authors incorporate occupant feedback from a questionnaire survey and a probabilistic model of occupant comfort into BIM.

(iv) Although many methods of calculation can provide reliable simulation approximations of building energy performance, the key source of uncertainty still lies in the occupant actions [66, 67]. Hence, it is vital to develop an occupancy ontology that enables occupant behavior and activities to be represented within construction spaces. In addition, streaming real-time data through ontology to draw patterns of occupants is missing in the reviewed literature.

4.4. Semantic Digital Twin for Facility Maintenance. To conduct analysis, predict the probability of failure, and prevent failure through systemic maintenance, facility maintenance requires various data, including location, historical maintenance records, and temperature and pressure data of facility components such as HVAC systems. Even though facility maintenance operators automated application systems, these systems still appear to them as black boxes. Furthermore, Microsoft Excel spreadsheets are still commonly used, resulting in a late response to service requests and inefficient maintenance management. However, since facility maintenance approaches are highly varied in their requirements, no single system fits all applications. As a result, researchers are increasingly focused on improving the effectiveness of information management in facility maintenance.

BIM, FM databases, and IoT networks are examples of technologies that can help build the Digital Twin, which helps with data collection, storage, and management. Early research on BIM-based FM [35, 37, 68, 69] demonstrated how BIM could be used to improve FM operations. However, the integration is difficult because each of the systems uses different data formats [70]. The lack of an information integration technique between BIM and FM is well known in the literature [71, 72]. On the other hand, developing an IoT data representation standard and a methodology for incorporating this standard with the BIM and FM systems is necessary. As a result, a strategy for simplifying and optimizing the querying process between BIM, FM, and IoT is essential. In this integration, ontology can be a solution to the complexity of Industry Foundation Classes (IFC) from BIM, lack of extracted information using Construction Operations Building Information Exchange (COBie) from FM, and different IoT formats [73, 74]. The ontology is a tool for converting domain knowledge into information that a computer can understand [75]. Hence, more research is required for the following:

(i) Development of ontologies for IoT, BIM, and FM information.

(ii) Building a relationship between the three presented ontologies.

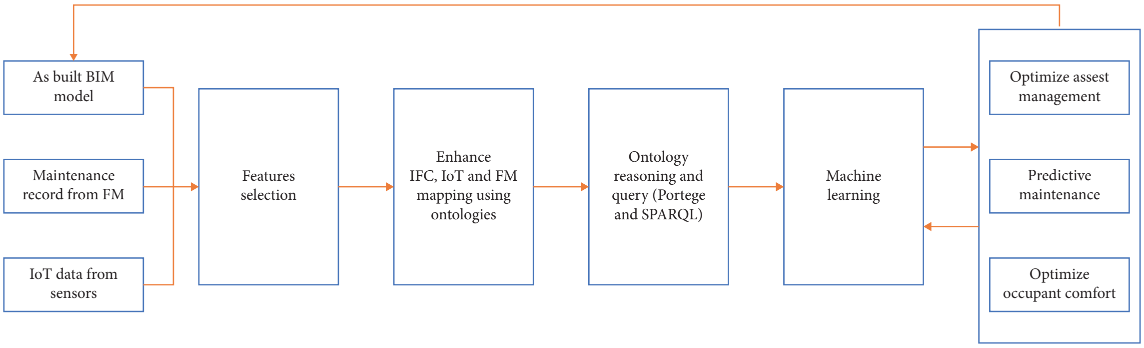

FIGURE 10: A preliminary architecture for information integration based on ontology.

(iii) Reasoning-based querying to make information more accessible for FM.

Combining ontologies, relationships, and retrieval queries create a semantic Digital Twin represented by a knowledge graph that aids in information integration and bi-directional information transfer between BIM, IoT, and FM. This paper proposes a methodology framework for data integration and facility maintenance in Figure 10. In Figure 10, the data from BIM, FM, and IoT will be exported first. Then, the most crucial feature from this data will be selected using a statistical method such as Analysis of Variance (ANOVA). After that, to map the remaining data in one system, we need to use the ontology concept. ML classification can then be applied over those ontologies to achieve several goals like predictive maintenance.

4.5. Digital Twin-Based Predictive Maintenance. Effective maintenance techniques can minimize building maintenance costs and increase building components' service life. In building maintenance management, reactive and proactive maintenance are currently implemented [76, 77]. However, reactive maintenance cannot avoid failure. Furthermore, proactive maintenance cannot forecast the future conditions and repair components to prolong their life in advance [78]. A number of studies reviewed predictive maintenance aspects [79–82]. In addition, several algorithms have been used for data processing to predict the condition of building components [83–86]. Although most of the findings investigated predictive maintenance, they provided facility managers with no accurate and practicable method to predict a building's future condition. Hence, a comprehensive method of implementing BIM and IoT with data processing to build a Digital Twin for predictive building maintenance is required. In Figure 11, we propose a Digital Twin framework of a chiller for predictive maintenance and fault detection. The data will be streaming to the building management system and then built an API in this figure. By extracting the data using the API, a digital twin model can be built in Simulink in MATLAB and then validate the MATLAB model's outcomes by using machine learning techniques. After validation, we can use the model to do several parametric studies. For example, suppose we want to predict the remaining useful life of the chiller for optimizing maintenance schedules. In that case, we use the MATLAB model to update the model in the building management system constantly. Similarly, we can inject different faults and simulate the chiller behavior under different fault conditions using the MATLAB model.

4.6. Digital Twin-Based Human Knowledge. The predictive capabilities of Digital Twin are very promising in the building sector. Nevertheless, these features are still unable to react to unexpected events [87]. To handle this issue, the human knowledge with Digital Twin must be combined to build what is called Cognitive Twin [88]. Besides, each Digital Twin has different models, which are difficult to identify their interrelationships [89]. Cognitive Twin can solve this problem by linking the knowledge from multiple Digital Twin across several domains. In these domains, combining semantic models with Digital Twin is the core principle to capture complex systems in an intuitive fashion, which can be summarized in standardized ontology languages [90–92]. More sophisticated techniques like knowledge graphs are used to speed up the implementation of Digital Twin [93, 94]. It includes cognition elements, such as reasoning, planning, and learning [95, 96]. However, many gaps remain to be bridged, such as the absence of a logical implementation framework and the integration of empowering technologies and instruments. This subject requires additional research efforts.

5. Research Limitations and Future Studies

While this study contributes to the body of knowledge, it also has limitations. Although a comprehensive search was conducted for relevant material, not all search terms were likely found. Only Scopus, Web of Science, and Google Scholar databases were utilized. Consequently, more papers about the deployment of Digital Twin in the AEC-FM industry have not been addressed. Since the research has these limitations, the results may not accurately represent the literature on Digital Twin applications in the AEC-FM industry. Subjective evaluations may have been applied in the study to find the most relevant publications and identify their use in various lifecycle phases of the literature. In addition, new natural language processing advances are necessary to automatically avoid duplication from various

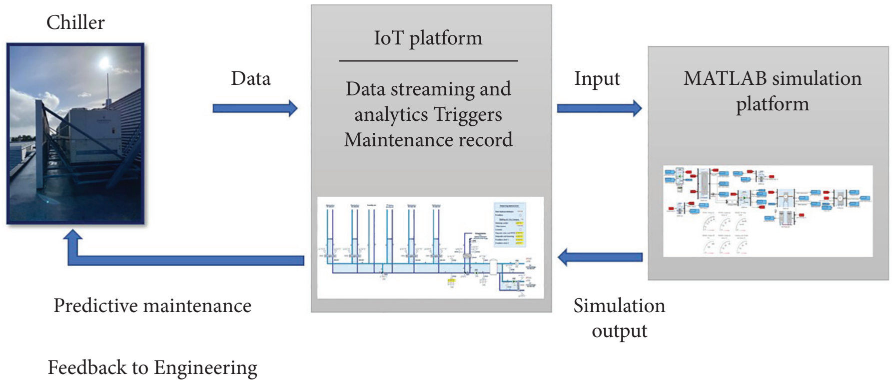

FIGURE 11: Digital Twin predictive maintenance framework of a chiller.

databases, gathering data from all languages and encapsulating them to provide a picture of research from a worldwide perspective. The limitations mentioned above generate grounds for further research and should be considered when interpreting the research findings.

6. Conclusion

The transition to a new era of digital information in the AEC-FM industry comes with Digital Twin technology. Based on the literature review, there are already efforts to implement the Digital Twin concept in the AEC-FM industry. However, these efforts seem to be in a preliminary stage. Much research is needed to successfully add a full-scale high-fidelity Digital Twin model to the AEC-FM industry. Additionally, there seem to be parallel efforts to upgrade BIM to involve the operation and management phase by implementing Digital Twin to the AEC-FM industry. It seems that BIM has the benefit of already being implemented for many assets, even though there are challenges with integrating BIM and IoT and processing the accumulated data. Digital Twin has the benefit of having a good foundation for data processing and integrating BIM. However, the Digital Twin technology is further behind regarding research and implementation in the AEC-FM industry.

Digital Twin research in the AEC-FM industry saw a significant upswing in 2019. Despite being associated with many issues, such as sharing data limitations, project inefficiencies, and the absence of a collaborative approach throughout the lifespan, the implementation and adoption of Digital Twins are expected to grow. This article dealt with the developments in the AEC-FM industry's Digital Twin research and suggested future research paths by doing a scientometric analysis and mapping.

Automation in Construction, Applied Sciences, Engineering Construction, and Architectural Management is the most influential journal in Digital Twin for the AEC-FM industry. The keyword clusters from scientometric analysis results suggested that there are six mainstream research fields in which the AEC-FM industry is studied "Digital Twin in Facility Lifecycle Management," "Digital Twin-Information Integration Standards," "Digital Twin-Based Occupants-Centric Building Design," "Digital Twin-Based Predictive Maintenance," "Semantic Digital Twin for Facility Maintenance," and "Digital Twin-Based Human Knowledge."

Analysis and mapping demonstrated that it is essential to enhance prediction and knowledge integration, occupants' comfort, ontologies, and human-based technologies across the project lifecycle in the near future.

Future research should include a comprehensive viewpoint to deal with the difficulties mentioned in the study. The AEC-FM industry stakeholders and academics will all benefit from the results of this research, which serves to broaden the awareness of present research goals, research gaps, and long- and short-term future research trends in the field of Digital Twin research.

While the study had a limited sample of sources, the data gleaned from them was subject to bibliometric limitations. In addition, only academic research is utilized in scientometric mapping and analysis. It means that practical and commercial innovations are excluded. To gather better findings, future research may use data from practitioners and businesses.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Appendix B

Paper 2- A Digital Twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics

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A Digital Twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics

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Air handling unit

ABSTRACT

The building industry consumes the most energy globally, making it a priority in energy efficiency initiatives. Heating, ventilation, and air conditioning (HVAC) systems create the heart of buildings. Stable air handling unit (AHU) functioning is vital to ensuring high efficiency and extending the life of HVAC systems. This research proposes a Digital Twin predictive maintenance framework of AHU to overcome the limitations of facility maintenance management (FMM) systems now in use in buildings. Digital Twin technology, which is still at an initial stage in the facility management industry, use Building Information Modeling (BIM), Internet of things (IoT) and semantic technologies to create a better maintenance strategy for building facilities. Three modules are implemented to perform a predictive maintenance framework: operating fault detection in AHU based on the APAR (Air Handling Unit Performance Assessment Rules) method, condition prediction using machine learning techniques, and maintenance planning. Furthermore, the proposed framework was tested in a real-world case study with data between August 2019 and October 2021 for an educational building in Norway to validate that the method was feasible. Inspection information and previous maintenance records are also obtained through the FM system. The results demonstrate that the continually updated data combined with APAR and machine learning algorithms can detect faults and predict the future state of Air Handling Unit (AHU) components, which may assist in maintenance scheduling. Removing the detected operating faults resulted in annual energy savings of several thousand dollars due to eliminating the identified operating faults.

1. Introduction

Buildings' contribution to world energy use, both residential and commercial, has continuously grown, with estimations ranging from 20% to 40% [1,2]. The heating, ventilation, and air conditioning (HVAC) system is utilized as the heart of any structure to keep the indoor climate comfortable for people. However, HVAC accounts for about half of a building's total energy use [2,3]. As a result, there is an urgent need to reduce HVAC energy usage. It is concluded that the installation of basic and sophisticated controls measures, as well as the elimination of frequent faults in HVAC systems, may save up to 30% of energy consumption [4–6].

Much of the discussion has focused on energy savings, but the rise of automated building analytics and big data applications extended the scope to allow facility managers to implement predictive maintenance. Predictive maintenance is essential since maintenance costs are around 65% of the annual facility management costs [7]. Increased equipment life, higher efficiency, and cheaper labor costs are all possible benefits of predictive maintenance.

Nowadays, there are two common ways to manage building maintenance systems. The Facility Manager (FM) either implements reactive maintenance, where the action is taken after the failure happens, or preventive maintenance, where a predetermined approach to replace building elements is utilized. In both cases, these trends do not keep pace with the development process that began in the last 20 years of building automation and maintenance operations in HVAC. The reason for that is that reactive maintenance cannot prevent failure, and preventive maintenance wastes time and money by replacing equipment in a good situation, so it can not predict the future condition. On the other hand, predictive maintenance uses historical data to capture the components' conditions and predict failure and degradation in the system [8]. In this work, we are using the predictive maintenance strategy to predict the faults in the AHU units.

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Nomenclature

ANN	artificial neural network
APAR	air handling unit performance assessment rules
AHU	air handling unit
AR	augmented reality
API	application Programming Interface
ANOVA	analysis of variance
BIM	building information modeling
BMS	building management system
CMMS	computerized maintenance management systems
DT	digital twin
FMM	facility maintenance management
FM	facility manager
FDD	fault detection and diagnosis
HVAC	heating, ventilation, and air conditioning
IoT	internet of things
IFC	industry foundation classes
PM	predictive maintenance
RDF	resource description framework
ROC	receiver operating characteristic curve
SVM	support vector machine
URL	uniform resource locator
VAV	variable air volume

1.1. Computer-based systems and data integration

In multi-stakeholder construction projects, data interoperability is essential to the project's success as a whole. Building maintenance and everyday operations can only be successful if they are supported by accurate and timely information. Facilities management (FM) is a good example, where 80 percent of the time is spent seeking relevant information [9]. In FM, data is still widely transmitted through building maintenance systems like computerized maintenance management systems (CMMS) using paper reports and Excel spreadsheets. Traditional transfer methods might lead to service delays and wasteful maintenance procedures [10].

A variety of commercial FM software (e.g., EcoDomus, Onuma system and ARCHIBUS, and IBM Tririga and BIM 360 field) has been developed to keep track of everything from maintenance activities to work orders and service contracts to anything else that might be helpful to management or maintenance workers. While these software options are available to fulfill the needs of facilities management, no single application can address all of the needs of the industry [11]. Furthermore, static CMMS systems with preventative maintenance are a feature of these solutions, but they are also costly [12]. As a result, an as-built BIM with a Level of Detail (LOD) of 400 to 500 necessitates a dynamic CMMS system incorporating predictive maintenance [13].

Building Information Modelling (BIM) is intended to provide a way to allow the seamless interchange of information throughout the lifespan of a building by integrating various technologies and supporting the activities of industry stakeholders [14]. BIM may contribute to FM by serving as a source and repository of information to aid in the planning and administration building maintenance operations in both new and existing structures. Ding et al. [15] provided additional support for these findings, revealing that BIM allows for a 98 percent decrease in the amount of time required to update FM databases. In addition, data from the Internet of things (IoT), such as sensor networks, can be integrated with BIM to monitor the conditions of building equipment and the building environment, which is valuable for predictive maintenance. This integration is needed to build what is called Digital Twin to maintain the system. Fig. 1 shows the principle of a Digital Twin.

Developing techniques to incorporate BIM data into the FM system has become critical as data specifications like COBie and IFC (Industry Foundation Classes) open standards arise. COBie and IFC are open data specifications. The Sydney Opera House case study showed how current FM systems (such as Mainpac, HARDEST, and TRIM) could provide FM data consistency and information interchange through IFC and BIM [16]. Researchers in the AEC/FM business is now using ontology methodologies to overcome the challenge of information interoperability [17,18]. However, there is a lack of research on using ontology techniques to integrate BIM and FM data.

To address the issues of data exchange and interoperability, this paper used brick ontology based on COBie data, to help retrieve information from an IFC model, transfer data into COBie data standard, and finally deliver BIM data into FM systems.

Based on that, three elements are needed to deploy a practical predictive maintenance program.

- Big data collection from sensors such as temperatures, pressure, and air volume, are essential to learning how the equipment works.
- A platform that can implement automatic fault detection and diagnostics (AFDD) algorithms and conclude how to improve the maintenance system and predict the faults.
- Building information modeling to avoid traditional methods (2D models) in transfer data and visualize the results in a 3D model.

In this paper, those three elements have been used to build our predictive maintenance framework. In the next paragraphs, the above mentioned elements will be explained in details.

1.2. Fault detection and diagnosis

The International Energy Agency began a project in 1977 to recognize the importance of energy usage in buildings by establishing an Implementing Agreement on Energy in Buildings and Communities (EBC-formerly known as ECBCS). All work is done via a set of 'Annexes,' so-named because they are annexes to the EBC Implementing Agreement [19]. The Annexes provide significant results about typical HVAC systems and fault detection and diagnosis (FDD) techniques [20–22]. The Annexes confirm that one of the critical reasons for failures in HVAC is that buildings design without any information about future use, such as space occupancy. This lack of knowledge will make it very difficult to design the correct system accordingly.

Even if some failures can be easily detected through the alarm system of Building Management System (BMS), however, in systems like Air Handling Unit (AHU) which is considered as a complex system, many faults can not be detected by BMS, for example (heating and cooling at the same time and heating recovery issues) [23].

Artificial intelligence is one of the methods to solve the complicated fault detection process [24–26]. In literature, we can generally find two approaches, data-driven methods, and methods based on a priory knowledge from experts [20,27]. The authors in [20,27] confirmed that developing a general algorithm that can work on many units as possible is more critical than improving

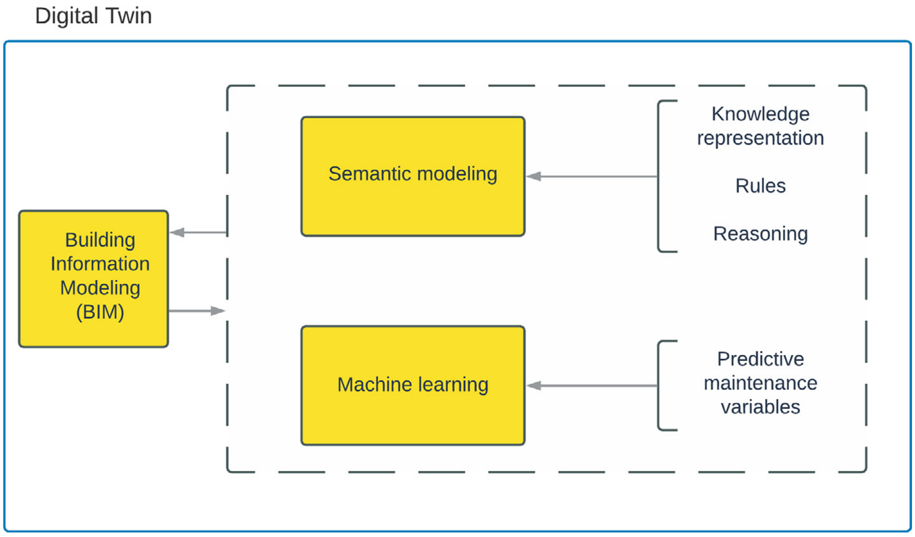

Fig. 1. The Digital Twin model.

the algorithm's accuracy. That is because it is not economical to develop an algorithm that works to only one Air handling unit, for example. Hence, there is a need for a system that can cover various AHU schemes, dimensions and purposes, and different configurations. This algorithm also must cover the different communication protocols like BACnet that comes from different hardware in the building, which belongs to different provider companies. A solution for that may be by using BrickSchema. The BrickSchema introduces a semantic structure for the description of the physical, logical and virtual assets [28].

Another big issue within the fault detection process is to evaluate the severity of those faults. In other words, how these faults affect lifespan degradation, occupants' comfort, and wasted energy [29].

1.3. Literature review

1.3.1. Digital Twin for predictive maintenance

Digital Twin technology relies on several areas like the Internet of things (IoT), Artificial Intelligence, Cloud computing, and BIM [30–32]. These technologies have empowered the digitalization of the different assets to integrate a virtual object with a physical one through the entire life cycle [33].

The literature on Digital Twin has a variety of definitions. For instance [34–36]; however, Grieves defined the idea of Digital Twin for the first time in 2012. A few years later, Grieves clarified that he was referring to a set of data that thoroughly characterizes an asset, from its most basic geometry to its most specific function [37].

Digital Twin technology is utilized in preventive maintenance methods, where it is used to forecast the status of an asset in order to minimize the number of operations and allowing for longer time intervals between them [38,39]. Predictive maintenance is another use for the Digital Twin. This is directly connected to the Digital Twin's capacity to monitor the whole system's operation. The Digital Twin, being a virtual image of the entire system, has access to the system's present operational data. This allows for real-time monitoring of performance and operation assurance. The Digital Twin can alert to maintenance and repairs. As a result, problems may be identified in advance and, preferably, corrected before they become severe. Maintenance procedures can be scheduled, and downtimes avoided as an outcome of using predictive maintenance. As a result, both technological and human resources may be better used.

Systems must be appropriately designed in the early phases of development to realize the maximum potential, considering both functional needs and control techniques using digital interfaces [40]. However, complete descriptions for HVAC systems that address these ideas do not yet exist. A combination of semantic description and Digital Twin approach (including BIM, IoT, FMM, and machine learning) for HVAC Systems has not been found in the literature. Hence, this paper applies a novel framework for Digital Twin Design to HVAC systems, initially using a detailed Air Handling Unit (AHU) model.

1.3.2. BIM-based predictive maintenance

Several researchers have studied how BIM models can be used for visualization and maintaining building facilities. However, these studies are limited because no automatic condition monitoring was provided [41,42]. Chen et al. [43] proposed a framework to integrate the BIM model with FM systems for automatic facility maintenance planning. However, this framework can not be used for predictive maintenance. Other researchers tried to use other technologies with BIM for facility maintenance. For example, [44,45] used Augmented Reality (AR) technology for roads maintenance and condition of components.

In addition, the application of BIM to predictive maintenance has been investigated by several researchers [46,47], However, no case study was presented to support the suggested framework's viability. Wang et al. [48] investigated a cloud-based paradigm for predictive maintenance of an electric motor but did not provide a prediction algorithm for condition prediction. Schmidt and Wang [49] considered cloud technology for the predictive maintenance process. Other researchers also mentioned the challenges of using big data for predictive maintenance due to the need for up-to-date and correct component data [50,51]. Deep learning and predictive algorithms for predictive maintenance have also been investigated, but without any integration with BIM applications [52,53].

Most of the above studies looked at BIM as visualization and extracting data tool; however, facility condition evaluations and maintenance plans are not included. In other words, the studies mentioned above did not provide facility managers with accurate and practical techniques for predicting future conditions, and no practical case studies were presented in these studies.

1.3.3. Machine learning (ML) for predictive maintenance

Artificial neural networks (ANN), support vector machines (SVM), Markov chains and decision trees are machine learning methods that may be used to forecast the state of building components. ANNs, unlike standard statistical approaches, can anticipate nonlinear time-series trends and maintain nonlinear failure patterns [54,55]. ANNs have been used to predict the corrosion of pipelines and estimate the service life of a facade coating; however, statistical data cannot be used for such studies [56,57]. Wind turbine problem detection was made possible thanks to the development of test equipment by [58]. The authors gathered vibration data in both a healthy and a degraded state. Healthy and faulty conditions were characteristics by using ANN. The paper's findings show that the categorization accuracy is 92.6 percent.

SVM is another commonly used statistical learning theory-based classification algorithm. ANNs and SVMs both rely on particular examples in the training and testing samples, with the SVM approach being more sensitive to parameter values. Carvalho et al. [59] provide a systematic literature review of machine learning methods applied to predictive maintenance.

The Markov chain model was also utilized to forecast the bridge's service life [60]. On the other hand, the Markov chain is not suitable for complex systems such as HVAC systems because it implies that the future state is only determined by the present situation, not by the previous condition, and the model uses discrete parameters.

A Bayesian network is a valuable tool in artificial intelligence. It can depict and diagnose complicated systems with inadequate or contradictory data. The Bayesian network has been effectively employed in information discovery and probabilistic inference since Pearl presented it in the early 1980s [61,62]. MUNIN [63], and Sleep Consultant [64] are commercial computer-aided diagnostic decision support systems that use Bayesian Belief Network (BBN). Industrial applications of BBN-based diagnostic systems include nuclear power systems [65], sensor failure detection [66], and others. Mokhtari et al. [67] used Bayesian Inference to calibrate a wind speed sensor in a thermal power plant. Raillon et al. [68] used a unique Bayesian experimental calibration approach to calibrate dynamic thermal models. Najafi et al. [69] and Wall et al. [70] Both efforts used machine learning to train Bayesian networks with fault-free data. Other applications included chiller FDD [71] and VAV terminal FDD [72]. Liu et al. [73] suggested a unique Bayesian fault detection algorithm. The approach employed a modest quantity of measurement data to estimate the statistical properties of fault levels. Zhao et al. [24] suggested a diagnostic Bayesian network-based technique to diagnose 28 AHU defects. However, there is no commonly acknowledged Bayesian network construction approach, and no clear winner has emerged to this point [74,75]. This weakness has two distinct drawbacks: designing a Bayesian Network takes much time, as a result, Bayesian Networks can only utilize causal influences identified by their programmer. On the other hand, neural networks may learn any pattern and are not constrained by the programmer.

Random forest is another approach that has been proposed by Leo [76]. As the name implies, a Random forest assembles many randomized decision trees into a "forest" (ensemble) and averages their predictions. In Predictive maintenance applications, Random forest is the most often used machine learning technique. The primary justifications are as follows: decision trees allow a large number of observations to be included in the forecast, as mentioned in [77]; and Random forest can minimize variance and enhance generality in particular circumstances, as detailed in [78]. The Random forest technique, on the other hand, has certain disadvantages. The Random forest technique, for example, is complicated and takes longer to compute than other ML methods.

As a result of the datasets obtained in this study, and the methodologies we examined, the ANN, SVM, and decision trees algorithms were chosen as machine learning models to predict future conditions for this study.

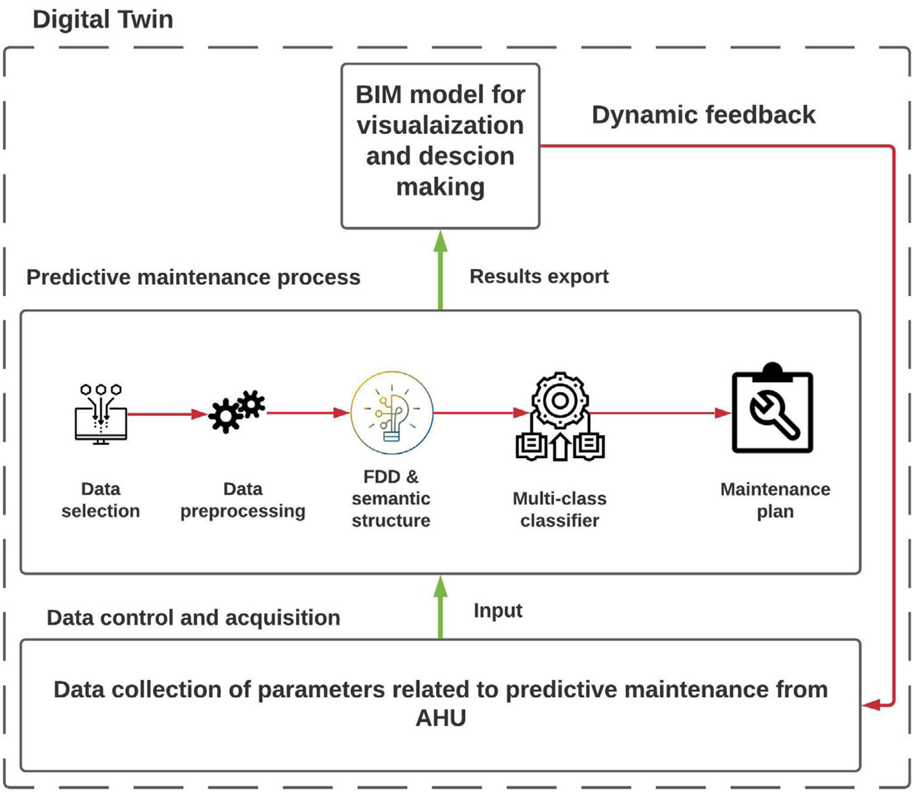

Fig. 2. The Proposed Digital Twin predictive maintenance framework based on expert rules, Machine Learning, BIM and IoT for AHU.

1.3.4. AFDD of AHU

To plan maintenance before failure, preventative maintenance programs use BMS data and a CMMS. However, AFDD is used in predictive maintenance programs to eliminate the fundamental cause of failure before it occurs, help facility management staff prioritize maintenance activities, and identify defects that might otherwise go undetected by traditional methods.

Several researches have been conducted recently of AFDD of AHU. Some focused on simulation specific parts of AHU [79,80], while the others used expert rules rather than complicated calculations [81]. Regarding expert rules manner, AHU performance assessment rules (APAR) were defined by House et al. [81] as a set of 28 if-then rules assessed based on an AHU's operational regime. The APAR technique drew much attention and was later expanded upon by others [82,83]. Other researchers tried to extend APAR rules and develop new tools for faults detection; however, their tools were for a specific type of HVAC and with simulated data [84,85]. However, according to Trojanová et al. [83], it is challenging to develop a general model-based for HVAC.

In recent years, researchers focused on machine learning and data mining for fault detection [86]. However, machine learning alone can not be adopted for two critical reasons [87]:

- The need for large datasets to increase the number of faults that can be detected.
- It is not possible to build a universal system based on machine learning alone.

1.4. Novelty of our research

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

- Lack of a Digital Twin model for predictive maintenance of HVAC system and specifically Air Handling Unit.
- Lack of practical degradation system and workflow process.
- Lack of universally applicable AFDD system.

Based on the research gaps mentioned above, this study:

- Describes a Digital Twin framework for the predictive maintenance implementation process.
- Uses of practical machine learning algorithm for predictive maintenance based on real-time data.
- Uses of universal AFDD tool that can efficiently run on a varied set of data from IoT sensors in AHUs.
- Develops an integrated condition monitoring framework based on BIM technology for decision-making in FMM.

2. The proposed framework

The proposed framework utilizes Digital Twin technology for fault detection and diagnostics and predicts the condition of the building components so that the facility management staff can make better decision at the right time, as shown in Fig. 2. This framework is based on our developed method by integrating the new technologies, particularly BIM, IoT, semantic metadata and expert rules, and ML. The framework includes three main steps, Data acquisition, predictive maintenance process, and BIM model for information visualization and monitoring. Spatial information can be obtained from the BIM model. The BIM model was integrated with predictive maintenance results to support decision-making by developing a plug-in extension for Autodesk Revit using C sharp so that the FM team can easily understand the data. The three main levels of this framework will be explained in detail in the following sections.

2.1. Data control and acquisition

Based on the literature review (for example, [88,89]), component parameters related to predictive maintenance are identified. Hence, the necessary knowledge to complete the working framework is classified into three groups:

(1) BIM model to give information of building components, such as dimensions, materials, and installation year, illustrates the deteriorating tendency over time.
(2) Sensor data from the IoT sensor network to monitor facility conditions, the trend of sensor data, and the usage behavior of the components. For example, temperature, pressure, and flow rate are collected from sensors in AHU.
(3) Usage age, maintenance record, and irregular intervals for inspection data for the FM system, including how long it has been since the last inspection.

2.1.1. Data in BIM model

The BIM model will be used in two directions in this study, i.e., as input for predictive maintenance and to visualize the results. FM and predictive maintenance benefit from a BIM model's geometric and semantic features (non-geometric). So, as-built BIM models should have certain graphical and non-graphical information for predictive maintenance, such as component size, materials, and installation year.

For facility management, COBie (Construction Operations Building Information Exchange) and Industrial Foundation Classes (IFC) are information exchange specifications for the lifetime capture and transfer of information [90,91]. In IFC files, information about building components and their interrelationships is stored. Classes of objects, relations, and resources make up the IFC file structure. In terms of geometry, IFC can express information like length and height. Various semantic information may be stored in IFC, such as a construction component cost and timeline [92]. In addition, COBie may instantly provide information on the operation, maintenance, and management of projects to facility managers [93]. Hence, IFC may provide geometric and semantic information in BIM models; however, COBie should supply more information such as spatial information, asset details, documentation, and

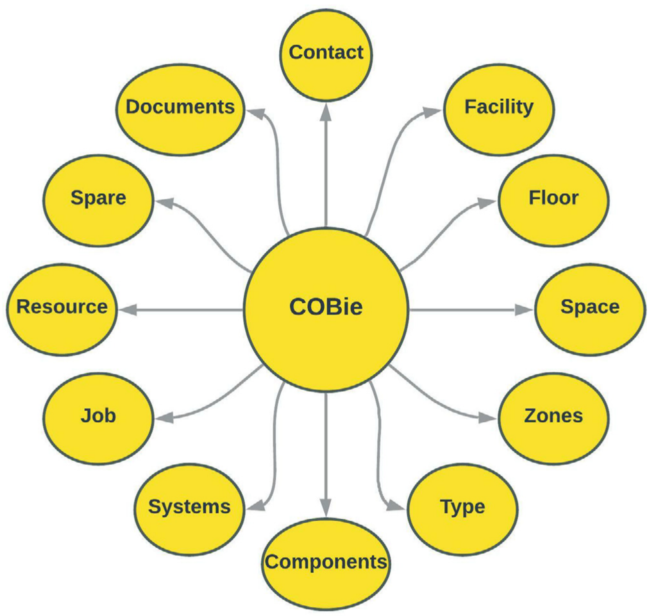

Fig. 3. Standard COBie components.

Føler	Type	Dimensioner	Følerelement (NTC 12k@25°C)	Materiale	Anvendelse
	ETF-122	Ø6,5x30mm, 2,5 m kabel	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Polyolefin Keramik Rustfri AISI 316	Universalføler Eks. gulvføler
	ETF-144/99A	Ø6,5x30mm, 2,5 m kabel	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	ABS plastic PVC insulated	Universalføler Eks. gulvføler
	ETF-422	Ø6,5mm, L100mm 1/4" pipe, 2,5 m kabel Max pressure 6 atm.	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Galv. messing	Ikke-aggressive væsker og medier
	ETF-522	Ø6,5mm, L50mm 2,5 m kabel Max pressure 0.5 atm.	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Galv. messing	Universalføler Maskindele
	ETF-622	8 x 12mm Hole Ø3.5mm 2,5 m kabel	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Kobber	Maskindele Overflader
	ETF-744/99	86 x 45 x 35mm	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	ABS plastic Melamin	Fugtige områder Udendørs
	ETF-822	Ø6,5mm, L200mm 1/4" pipe, 2,5 m kabel Max pressure 6 atm.	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Galv. messing	Ikke aggressive væsker og medier
	ETF-944/99H	80 x 80 x 16 mm IP20	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	Bayblend noryl	Rumføler Tørre rum Indendørs
	ETF-1133/44/55	Ø6,5x200mm Flange 2,5 m kabel	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	Galv. messing	Ikke-aggressive væsker og luftarter
	ETF-1633/44/55	60 x 30 x 30mm Max pipe diameter 50mm Inkl. fastgørelse IP54	NTC 12k +25°C = 12kΩ Område -50°C-+70°C	Polycarbonat Rustfri AISI 316	Overflader på rør
	ETF-1733/44/55	55 x 52 x 27mm IP54	NTC 12k +25°C = 12kΩ Område -40°C-+70°C	Polycarbonat	Fugtige områder Udendørs Ikke-aggressive
	ETF-1899A	Ø12,0 x 40mm, 2.5 m kabel Flad på følerside Ekskl. fastgørelse	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	Polycarbonat	Universalføler til overflader
	ETFL-2	Ø8mm L100mm ¼" RG		Galv. messing	Følerlomme ikke-aggressive

NTC 12k modstandstabel						
-20°C = 112246Ω	11°C = 22300Ω	16°C = 17750Ω	21°C = 14238Ω	26°C = 11506Ω	35°C = 7978Ω	60°C = 3201Ω
-10°C = 63929Ω	12°C = 21292Ω	17°C = 16974Ω	22°C = 13636Ω	27°C = 11035Ω	40°C = 6569Ω	70°C = 2306Ω
0°C = 37942Ω	13°C = 20335Ω	18°C = 16237Ω	23°C = 13064Ω	28°C = 10587Ω	45°C = 5442Ω	80°C = 1692Ω
5°C = 29645Ω	14°C = 19428Ω	19°C = 15537Ω	24°C = 12519Ω	29°C = 10159Ω	50°C = 4535Ω	90°C = 1263Ω
10°C = 23364Ω	15°C = 18567Ω	20°C = 14871Ω	25°C = 12000Ω	30°C = 9752Ω	55°C = 3800Ω	100°C = 958Ω

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Fig. 4. AHU sensors datasheet.

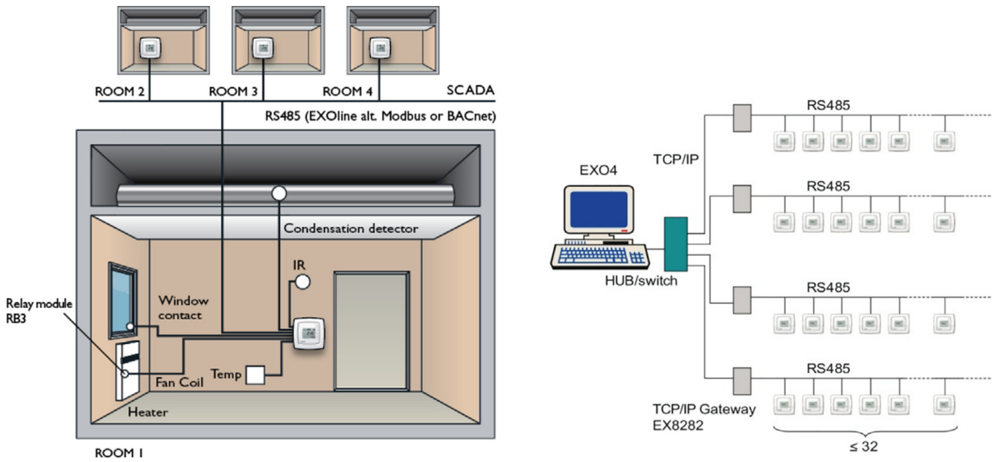


Fig. 5. An example of the application system [94].

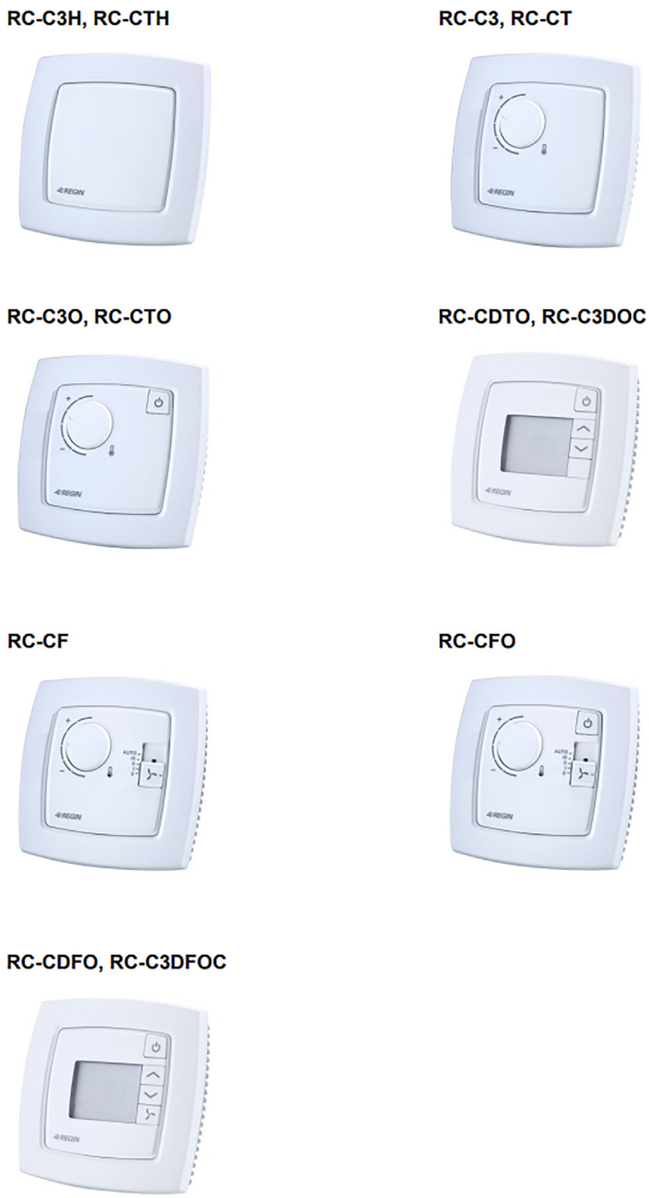


Fig. 6. System controllers [94].

graphical information, among other features. Therefore, a COBie extension for Revit was utilized in this article to extract the necessary information from the BIM models for predictive maintenance and transmit it to the FM system. Fig. 3 shows COBie components.

2.1.2. Sensor data collection and maintenance record

A Restful API (Application Programming Interface) has been built as an additional analytical layer over a conventional BMS system. This allows using a specific URL (Uniform Resource Locator) to extract data from each device in the building, which will, in turn, allows to reach of a large number of diagnosed devices. The restful API also allows reaching the maintenance record system and previous alarms and faults. Fig. 7 is a schematic representation of the principle of the whole system. During the operating phase, Internet of Things sensors network is constructed to collect sensors data from the building's facilities and the surrounding environment. These sensors include NTC-12 K-sensors for temperatures, PTH-3202-DR for peressure, TTH-6040–0 for outdoor temperature and the IVL10 temperature-sensitive airflow transmitters. A data sheet of sensors is shown in Fig. 4. In addition, Regio controllers have been used to handle everything from temperature, lighting, humidity, CO2 levels, and even blinds. Additionally, Regio provides online and Internet services. A PC linked to the workplace network may be used to regulate the temperature and other operations of a room. Fig. 5 and Fig. 6 show the application system and the controllers, respectively.

Also, Plugin is built in the BIM model with Microsoft Visual Studio Community 2019, allowing for the visualization and storage of real-time sensor data directly in the BIM model. The Application base class implements an external application interface to create the tab, the ribbon, and the buttons of the plugin. This fully-featured plugin is excellent for facility managers since it allows them to access real-time sensor data and save it in the relevant condition database (MSSQL DB) while keeping BIM up to date. The "Sensor Data" button allows FM managers to view the current sensor data as well as the historical sensor data's maximum and minimum values. The condition database also allows FM managers to verify the sensor's average value and historical value. By pressing the "Store" button, the sensor data is saved in real-time, as shown in Fig. 8. In the last step, the sensor data are employed in the FMM process for condition monitoring and prediction.

The BACnet (Building Automation and Control Networks) protocol is extensively used as a data communication protocol among various equipment, devices, and sensors to get real-time operational data from the IoT sensor network [95]. The Regio display tool can modify the protocol and then return the protocol to Modbus.

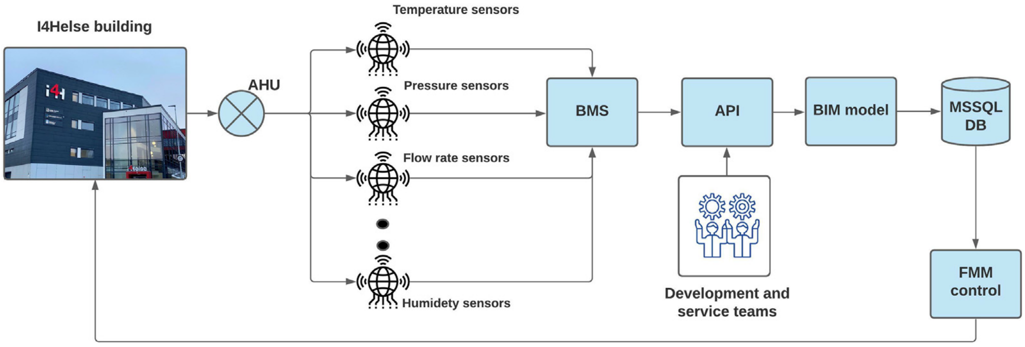


Fig. 7. IoT data collection system including API developed by service and developed teams.

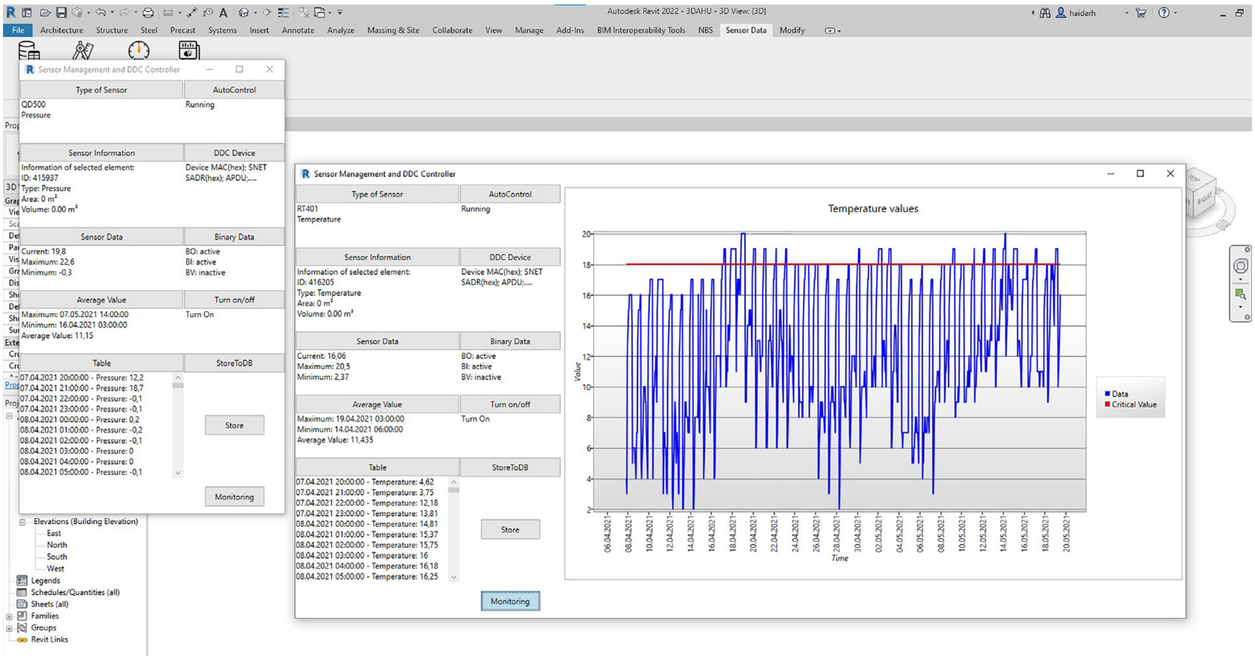


Fig. 8. The plugin for sensor management.

Table 1
Analogue inputs.

Object name	Object-ID	Description
RC_Actual_R.RegioRoomTemp	Analog input, 0	Room temperature
RC_Actual_R.RegioAIChangeOver	Analog input, 1	Change over temperature
RC_Actual_R.RegioAnaIn1	Analog input, 2	Value of analogue input 1
RC_Actual_R.RegioUAnaIn1	Analog input, 3	Value of universal analogue input 1
RC_Actual_R.RegioRoomCO2	Analog input, 4	CO2 input value

Setpoints, control parameters, trend logs, and alarms are all examples of operational data. Setpoint data and sensor-derived condition data will be the focus of this study to provide information on the present state of the equipment and facilities. Temperature, pressure, flow rate, and ON/OFF state are all supported by BACnet in an IoT sensor network. Modeling a wide range of sensor-derived operational information is accomplished by using eight different types of objects and their attributes: (1) Analogue inputs, (2) Analogue values, (3) Binary inputs, (4) Binary values, (5) Loop, (6) Multistate inputs, (7) Multistate values and (8) Device. Table 1 and Table 2 illustrate analog inputs, and a binary signal, respectively.

2.2. Data integration

2.2.1. Data integration between BIM and FM

For facility managers, COBie serves as an information exchange specification for data lifetime capture and distribution [90]. Despite this, compatibility between IFC and COBie is still a problem because of the FM system's data structure, which differs from BIM models' data syntax. BIM data may be integrated with FM data using COBie. COBie spreadsheets are used to import data from BIM models that have been pre-selected according to user-defined parameters. The names of characteristics in COBie spread-

Table 2
Binary inputs.

Object name	Object-ID	Description
RC_Actual_L.RegioDIOpenWindow	Binary input, 0	Indicate open window
RC_Actual_L.RegioDICondenseAlarm	Binary input, 1	Indicate condense alarm
RC_Actual_L.RegioDIPresences	Binary input, 2	Indicate presence from digital input
RC_Actual_L.RegioDIChangeOver	Binary input, 3	Indicate change over from digital input
RC_Actual_L.RegioRoomTempHighTempAlarm	Binary input, 4	Room high temperature alarm

Table 3
The information for data integration between IFC, COBie and FM.

System	Class
IFC	Equipment name Size(length – width -height) Material Elevation Equipment number Location (area/floor/room) Equipment type Equipment function Equipment units
COBie	Price Purchase date Responsible person Equipment specification Equipment professional information Warranty Manufacture information
FM	Appearance description Special detail of model Assembly process Operation manual 2D drawing Equipment performance table Damages History maintenance records Maintenance schedule Replacement

sheets are frequently distinct from those found in FM system data, which can be problematic. Because of this, the COBie data must be mapped into FM systems using the FM relational data structure.

This integration effort is divided into two components: (1) data mapping between the IFC schema and a portion of the COBie data schema, and (2) the whole COBie data schema. COBie data may be collected from BIM models following data mapping.

The first step in mapping IFC data into COBie and FM systems is determining what information is necessary for FM operations. An initial study was conducted to assess the support of asset register information needs by IFC/COBie data entities based on the definition of asset information requirement ISO 19650-1:2018 [96], standards of PAS 1192-3:2014 [97], and buildingSMART 2021 [98]. Table 3 presents the BIM-FM model's information checklist in light of this. Table 3 shows that information for FM is backed by BIM models, COBie data, and an FM system. Data from BIM models may be sent in IFC format using an ontology-based strategy for FM data encoding, outlined in this paper. In order to create an ontology file that can be read using GraphDB [99], Python was utilized to finish an entire automated mapping procedure.

In Graph DB, entities and entity relations may be readily generated, as demonstrated in Fig. 9. SPARQL, an RDF query language that uses Internationalized Resource Identifiers (IRI) to identify the location of the ontology, may be used to query the file.

Autodesk Revit was chosen in this paper as the BIM software, with Laugstol's ENS-portal [100] chosen as the FM system. Data from BIM models are extracted, and the COBie extension plug-in for Revit is used to convert data from BIM models to COBie spreadsheets. Part of the information for facility information requirements for maintenance operations is exported from BIM models based on IFC.

The attributes of COBie data and attributes of data in the FM database should be mapped one by one after getting COBie data from BIM models. Using the COBie connector code we wrote in Python, the attributes of the components in the COBie spreadsheet are translated to the equivalent attributes in the FM system. Data from COBie spreadsheets may be imported into the FM system column by column using the connector code.

2.2.2. Sensor data integration into BIM model

A Revit plug-in is needed to receive, store, and display real-time sensor data because Revit and other BIM design applications do not have these capabilities. The data from the sensors is shown in a BIM model thanks to this Revit C#.NET API add-in plug-in. The system.net object is used to transfer sensor data into the Revit model. The System.net object uses the URL from the sensor data API to bring the data into the BIM model [101].

The IFC entity does not include a sensor type. Sensors may be represented using IfcSensor and IfcSensorType. IfcSensor type transfers sensor data into the BIM model when we establish the sensor family in Revit for a neutral data format.

On the other hand, the BIM model can only record transitory data from sensors. Thus, every sensor data will end up in the condition DB at some point (Fig. 7). The sensor data is then combined into a BIM model and rendered for visual display using Revit's new plug-ins. Finally, the sensor data may be conveniently accessible in the BIM model for condition evaluation.

2.3. Predictive maintenance process

In predictive maintenance, faults in the building components are found and predicted early. The FM system gathers the FM data, while its specific sensors (Fig. 7) measure the condition monitoring data.

2.3.1. Data selection and pre-processing

When using machine learning approaches, feature selection is critical since it allows the techniques to filter out redundant and noisy data throughout the training process. The noisy data was observed at several condition indexes, including (1) chilled and heater water temperature sensor, (2) dampers condition, (3) heating and cooling valves conditions, (4) zone temperature, (5) fan conditions, and so on.

The dataset is entered into the data preparation process, which includes two steps: data cleaning and data normalization. The

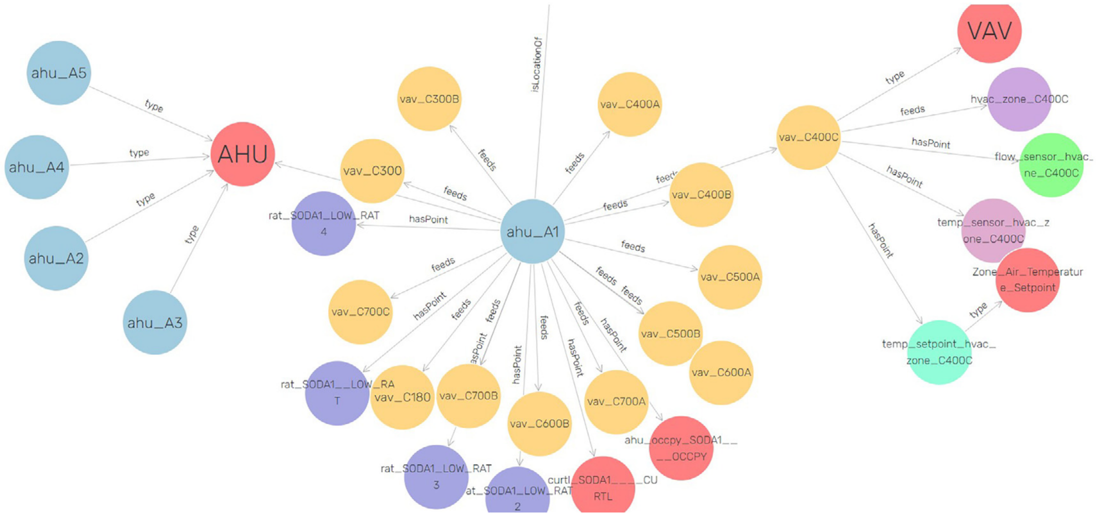


Fig. 9. Part of the ontology graph in GraphDB.

noisy and low variance data are deleted during the data cleaning process, and data normalization is utilized to decrease the scale disparity between each data set. The data is transformed into a range between 0 and 1 using the StandardScaler technique [102]. Feature selection is used to eliminate unwanted features from a dataset, whereas data reduction removes unneeded data. This study will integrate the Analysis of Variance (ANOVA) approach with Support Vector Machine (SVM) to increase classification performance [103,104]. ANOVA examines the variance of each feature in the dataset, whereas SVM improves the classifier's performance. Several metrics are generated by the ANOVA-SVM approach, including the ANOVA-SVM score, the accuracy score from each subset test, and the distance value between each data point and the decision border. The distance value of each feature to its decision border is the generated data from the ANOVA-SVM process, and the closer each feature is to its boundary, the more critical it is. The more relevant the data is to its label, the closer it is to the decision border.

2.3.2. AHU condition assessment and fault alarming

Condition monitoring and fault alerting are two essential phases in the process of predictive maintenance. Condition monitoring gathers and interprets important component parameters to determine whether a component's status has changed from its usual state and whether the equipment's health has changed over time.

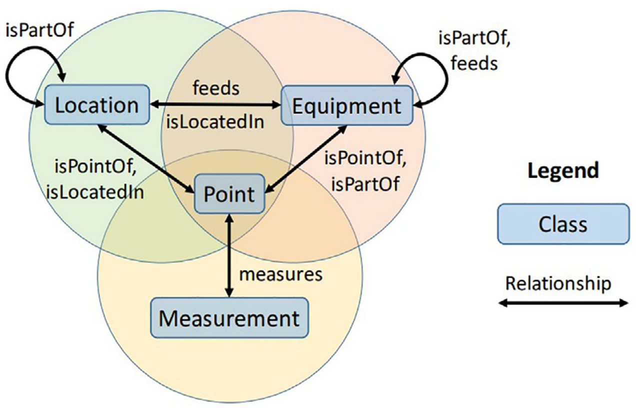


Fig. 10. Brick Schema concepts and their relationship to a data point [107].

The expert rules in by Nehasil et al. [29] based on the APAR method by Schein et al. [105] was used to establish our condition assessment system and deploy diagnostics in a broader number of devices in our study. Schein et al. [105] provide a list of 28 different detection rules developed from only 11 data points in their study. The majority of the rules are dependent on the mode of operation of the AHU. It is necessary to test the heater differently depending on whether the AHU is heating or cooling. Once the operating mode for a given timestamp has been determined, the relevant set of rules can be triggered for that timestamp. In most cases, the regulations are not sophisticated and rely on uncomplicated calculations covering a specific physical or regulatory event.

It is also important to link data points to the diagnostic system's inputs for the system to function correctly. This is accomplished by using a semantic description of data: metadata (tags) that have been given to data points by human specialists following the standard established by the Haystack Project [106] and Brick Schema [107] to retain the highest level of possible compatibility. Fig. 10 defines Brick Schema concepts to which a Point can be linked to: Location, Equipment and Measurements [107].

2.3.3. Metadata

Data regarding physical, spatial, and virtual assets and their interactions inside a structure are essential to building operation analytics because it offers semantic information about the assets and their relationships. We utilized a Brick schema to store the information about the AHU models we created. Brick is a data format that is open-sourced and intended to offer consistent semantic descriptions for construction assets. It was necessary to construct a single Brick model. The Brick model is expressed in the Turtle (TTL) file format using the Resource Description Framework (RDF) language and the Resource Description Framework (RDF) language. RDFS (Resource Description Framework) is a general-purpose language that may be expressed in a concise and natural text format. Fig. 11 depicts the entity classes that exist in the building, as well as their connections. There may be many instances of each entity class. When the Variable air volume (VAV) system class interacts with the AHU class, the "Feed" relationship between the two classes is established. A single "AHU" instance can feed many "VAV" instances in the same building model. The "hasPoint" reltion is a term used to indicate telemetry related with equipment, for example, VAV hasPoint zone air temperature sensor.

Fig. 11. Brick schema model of AHU.

2.3.4. Multi-class classifier and maintenance plan

Many factors can cause HVAC system failures, the most common of which include insufficiently educated or untrained operators, a lack of regular maintenance, a problem with the control system, or incorrectly set requirements in the building management system (BMS). It is relatively uncommon to find faults in complicated systems (e.g., the AHU) that cannot be discovered using ordinary BMS tools (e.g., using heating or cooling to balance the non-optimal heat recovery [23]). Ideally, the severity of a failure for each fault identified might be determined based on occupants' discomfort, wasted energy, and the risk to the equipment operated. Obtaining such data is not possible from BMS. A severity index for each problem will eventually become meaningless if the relevant data is missing. Instead, this research presents a framework for predictive maintenance, which attempts to enhance maintenance decisions by identifying faults and forecasting the status of AHU components.

A combination of data from the condition monitoring sensors, the FM system's data, and BIM data will be employed in the prediction process. According to Section 1.3.3., ANN, SVM, and decision tree algorithms are used in this work to forecast the faults of AHU components. In Fig. 12, it can be seen how the algorithm for predictive maintenance works in action. Sixteen factors are fed into this forecasting algorithm from three different systems, including BIM models, FM systems, and IoT sensor networks. The following is a list of the 16 different variables: (1) AHU type, (2) location, (3) capacity, (4) material, (5) dimension, (6) installation year, (7) temperature sensors values (supply and return air to the building, zone temperature, outside temperature, supply and return temperature from the chiller, and supply and return temperature from the heater), (8) pressure sensors values, (9) flow rate sensors values, (10) usage age, (11) valves positions, (12) abnormal event times per year, (13) minor repair times per year, (14) significant repair times per year, (15) problem type, and (16) operational regime

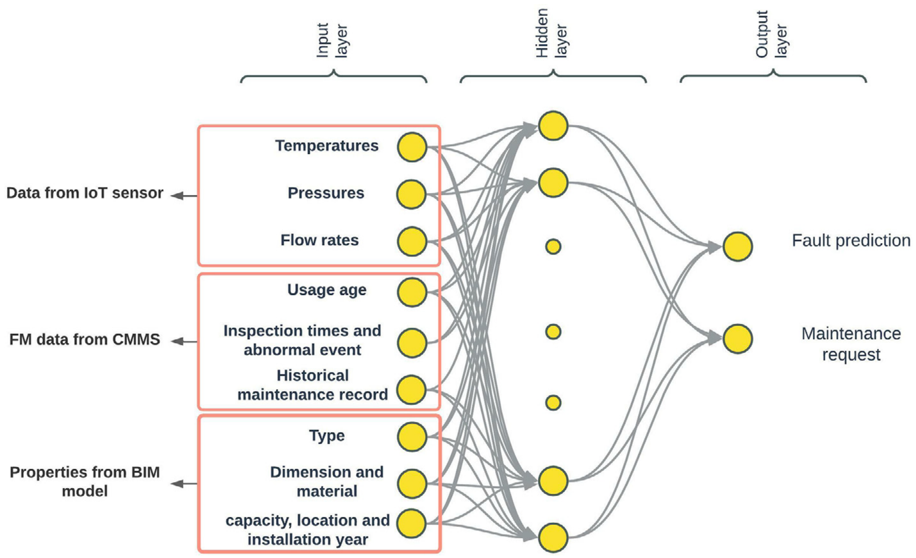


Fig. 12. The prediction algorithm process.

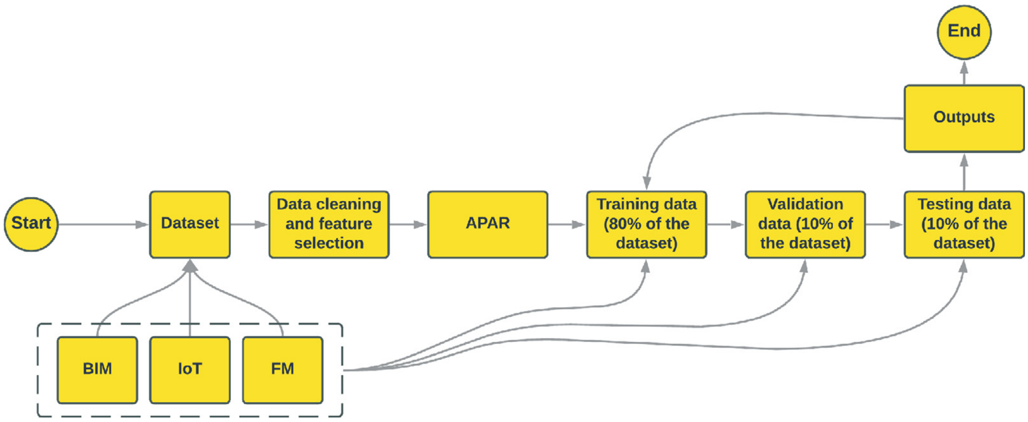


Fig. 13. The data-flow and implementation process for fault prediction.

(ventilation, heating or cooling). The output of this prediction process includes (1) the faults of AHU components based on APAR and (2) maintenance requests.

The suggested predictive maintenance system allows for dynamic model training and prediction. Prediction models are trained using real-time sensor data that is updated in real-time and maintenance records gathered over time. As seen in Fig. 13, the parameters of the prediction models are gradually updated to reflect the changing situations.

Fig. 13 depicts the prediction technique in action. There are four steps in the prediction process: (1) training, (2) cross-validation, (3) testing, and (4) prediction. The preparation steps include (1) datasets collection (Section 2.1.1 and Section 2.1.2), (2) Data selection and pre-processing (Section 2.2.1), (2) APAR (Section 2.2.2), and (3) machine learning algorithm selection. The 16 variables, the input datasets, are utilized for training and testing the prediction model, as indicated above.

The data sets for the specified variables (input datasets) are used to train the ANN, SVM, and decision trees methods, which result in prediction models. A random distribution of input datasets is used to divide them into three groups: (1) 80 percent for model training, (2) 10 percent for validation, and (3) 10 percent for testing the models. Machine learning models are taught using a training set; on the other hand, a testing set is used to test the trained models and continually correct them by modifying the weights of the machine learning algorithm linkages. It is necessary to use the remaining data set (10 percent) to validate the trained model. These models are created by adjusting the trained models based on dynamic updating data, including the acquired dynamic sensor data and the updated maintenance records, and then retraining the models. Following that, the maintenance plan must be rescheduled to coincide with the predicted condition produced by the model, as described above. Last but not least, the well-trained models are put to use to estimate the future status of various components (one and 4.5 months later).

3. Case study

3.1. Background

A study of an educational building on the University of Agder campus (I4Helse building), Grimstad, Norway, was conducted to verify the proposed Digital Twin predictive maintenance framework. A total of 4 AHUs serves this campus building. In order to monitor the AHUs, many types of sensors have been placed, including but not limited to (1) temperature sensors, (2) pressure sensors, and (3) flow rate sensors. The signals were gathered from the sensors and transmitted to the BIM models for further processing. In Fig. 14, the BIM model generated for the I4Helse building has been chosen to serve as an example.

3.2. Tested AHU units

The tested units were equipped with a rotary heat exchanger, as well as a bypass, a heater, and a cooler. These units were in charge of conference rooms, classrooms, offices, corridors, laboratories, and other facilities. Fig. 15 illustrates a typical layout of the AHU in the buildings.

3.3. Data collection

The FM manager and maintenance technicians can obtain the geometrical and non-geometrical of the AHU from the BIM model, as shown in Fig. 16. This information is used for condition inspection and condition assessment. The real-time data is gathered from the IoT sensor, including supply air pressure and temperature, exhausted air pressure and temperature, supply air temperature setpoint, damper position, chiller valve position, heater valve position, water temperature from the heater, temperature of return heating coil and flow rate of water. In order to demonstrate how long-term patterns in sensor data may be utilized to forecast future circumstances, we collected sensor data between August 2019 and August 2021 for I4Helse building. Fig. 17 shows some resample measurements in python during January and February 2020. Inspection information and previous maintenance records are also obtained through the FM system.

3.4. Selected features for expert rules

There are 74 features in the original dataset gathered from buildings, from which we have selected 18 of the most critical features for the expert rules implementation done in this part. The top 18 vital features (Table 4) are selected using a combination of Analysis of Variance (ANOVA) for feature selection, which reduces the high data dimensionality of the feature space, and SVM algorithms for classification, which reduces the computational complexity and increases the effectiveness of the classification [108].

3.5. Faults detection

As previously stated, several sensors are used to monitor the performance of each AHU. As seen in Fig. 16, the sensor data and trends may be represented graphically in the BIM model. Based on the sensor data, the facility manager may determine the opera-

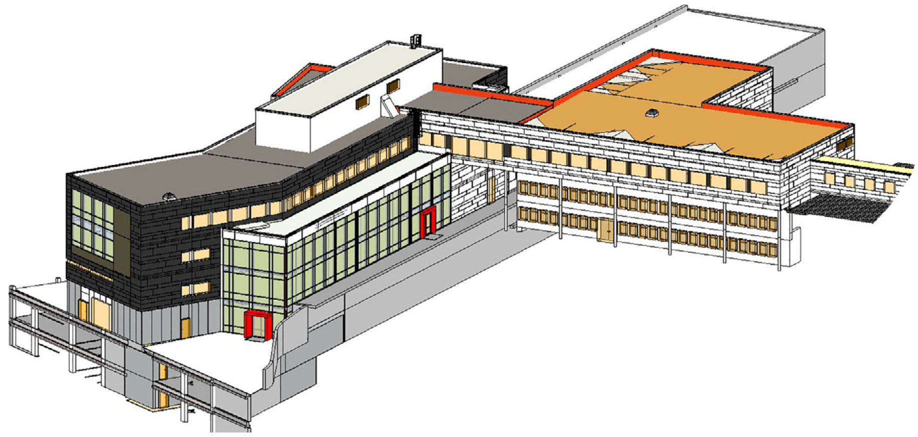


Fig. 14. I4HELSE BIM model.

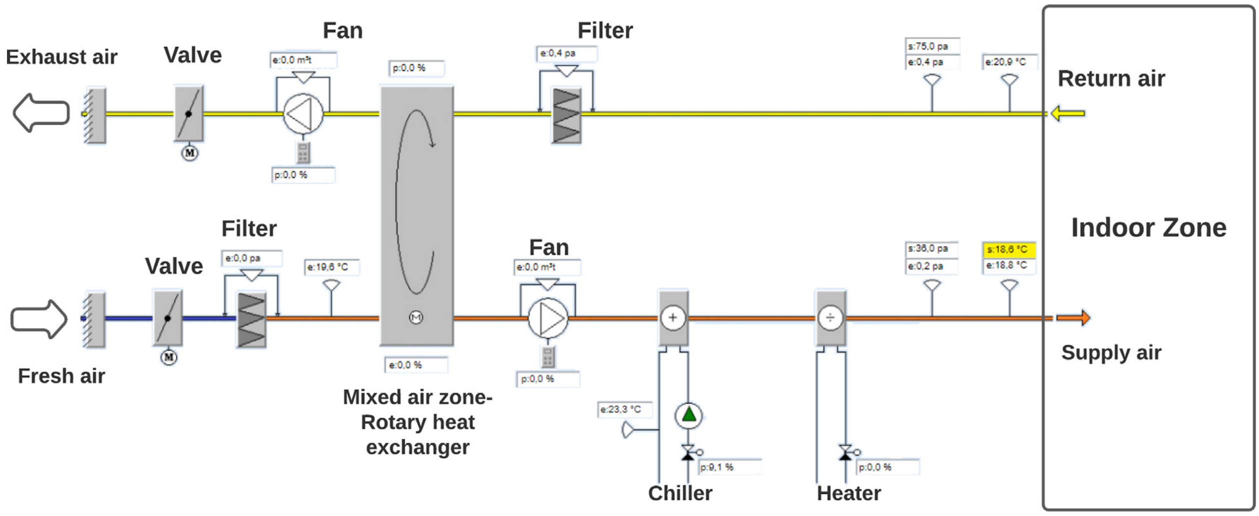


Fig. 15. Schematic illustration of an AHU from I4Helse.

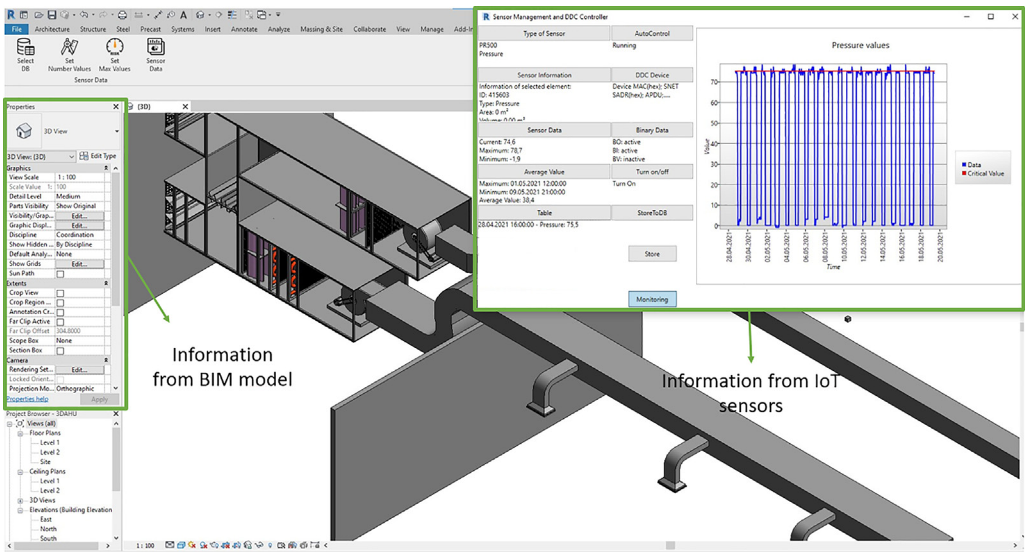


Fig. 16. The AHU information from sensor data and BIM model.

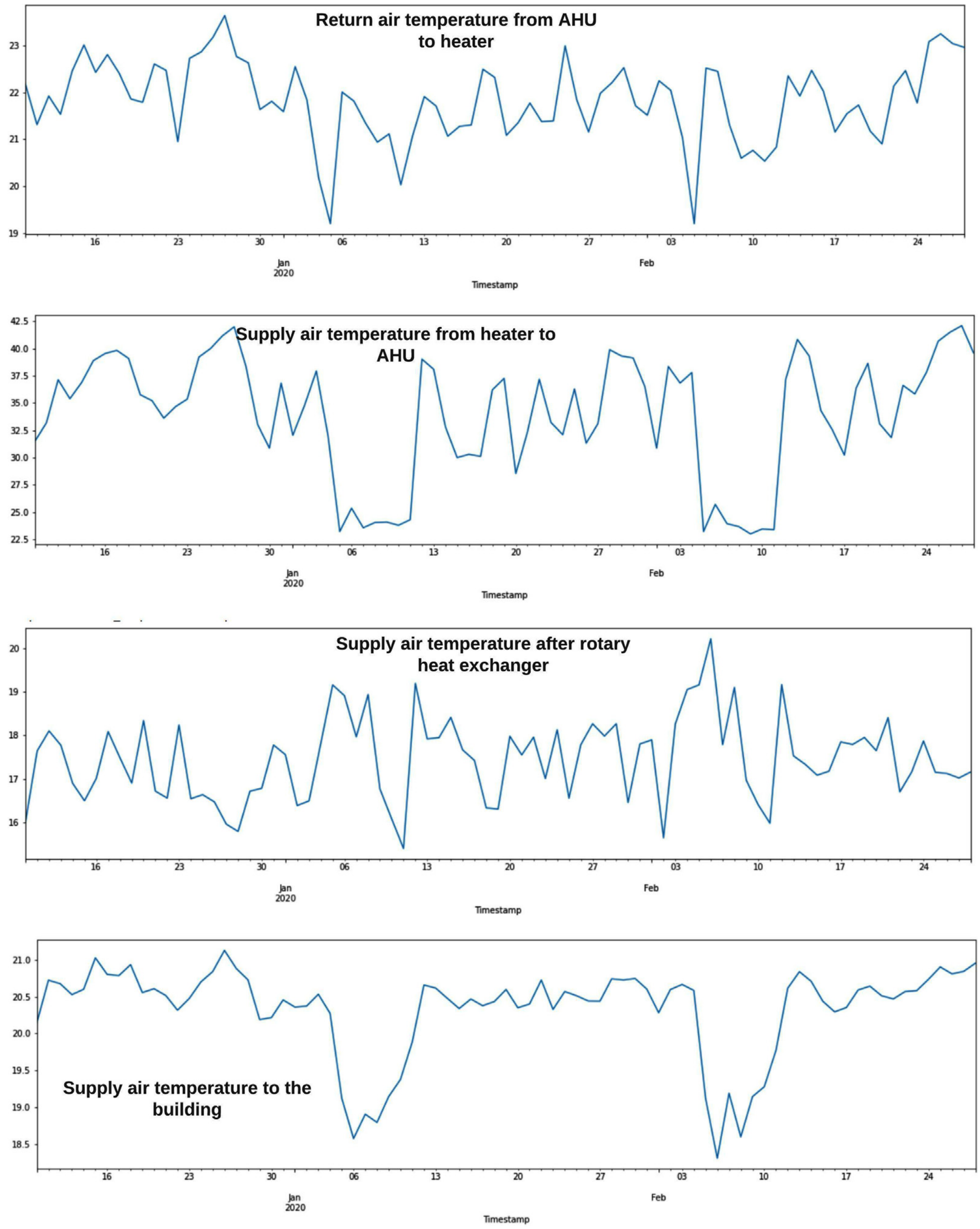


Fig. 17. Sample of sensor data from a single AHU.

tional status of each AHU in the building. The abnormal occurrences and alerts that have been recorded in the FM system are utilized as references for condition evaluation based on the results of condition monitoring. Furthermore, FM staff completed the AHU configuration list in accordance with the results of the field inspection, as shown in Fig. 18. Finally, the facility manager inspected the AHU to determine its general condition.

Several serious faults were discovered during testing based on the export rules mentioned in [105,29], which were validated by facility management staff and by analyzing the collected data. Table 5 provides an overview of operational faults. The frequency with which the problem arises can be determined based on the duration. Even though some mistakes are less severe than others, some must be corrected as quickly as possible (simultaneous heating and cooling or troubles with recuperator control). It is necessary to revise the appropriate algorithms in the control system to resolve these issues.

In the next section, examples of the most severe operational errors in detail, including their subsequent solution, are illustrated. A shorter period is displayed for clarity.

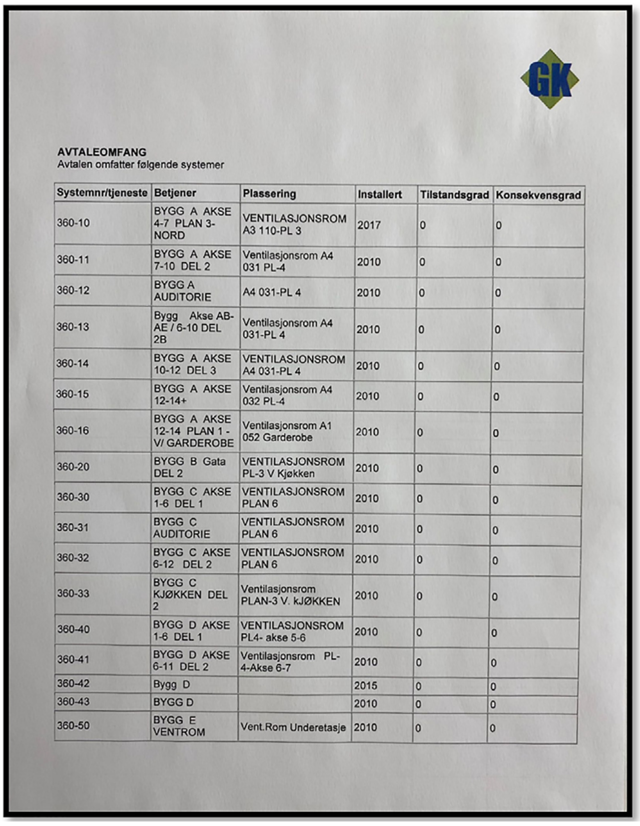
3.6. Diagnosis of the detected faults-examples

3.6.1. Heating and cooling

Fig. 19 shows the detection of simultaneous heating and cooling in a day in winter season (29th of January 2021).If the supply air temperature setpoint is greater than the external air temperature, the air handling unit is configured to operate in the winter season. As a result, the AHU is presumed to be operating in the winter mode, as the outdoor air must be heated before being delivered

Table 4
Top important feature variables for AHU FDD using ANOVA.

Index	Description
1	Return air temperature
2	Supply air temperature
3	Pressure difference on filter outdoor air
4	Cooling water valve position
5	Heating water temperature
6	Heating water valve position
7	Outside air temperature
8	Cooling water temperature
9	Exahust air valve position
10	Fresh air valve position
11	Fan exhaust air situation
12	Fan fresh air situation
13	Cooling water pumb situation
14	Heating water pumb situation
15	Heat recovery bypass position
16	Pressure difference on filter return air
17	Exhaust air damper position
18	Fresh air damper position



AVTALEOMFANG
Avtalen omfatter følgende systemer

Systemnr/tjeneste	Betjener	Plassering	Installert	Tilstandsgrad	Konsekvensgrad
360-10	BYGG A AKSE 4-7 PLAN 3-NORD	VENTILASJONSROM A3 110-PL 3	2017	0	0
360-11	BYGG A AKSE 7-10 DEL 2	Ventilasjonsrom A4 031 PL-4	2010	0	0
360-12	BYGG A AUDITORIE	A4 031-PL 4	2010	0	0
360-13	Bygg Akse AB-AE / 6-10 DEL 2B	Ventilasjonsrom A4 031-PL 4	2010	0	0
360-14	BYGG A AKSE 10-12 DEL 3	VENTILASJONSROM A4 031-PL 4	2010	0	0
360-15	BYGG A AKSE 12-14+	Ventilasjonsrom A4 032 PL-4	2010	0	0
360-16	BYGG A AKSE 12-14 PLAN 1 - V/ GARDEROBE	Ventilasjonsrom A1 052 Garderobe	2010	0	0
360-20	BYGG B Gata DEL 2	VENTILASJONSROM PL-3 V Kjøkken	2010	0	0
360-30	BYGG C AKSE 1-6 DEL 1	VENTILASJONSROM PLAN 6	2010	0	0
360-31	BYGG C AUDITORIE	VENTILASJONSROM PLAN 6	2010	0	0
360-32	BYGG C AKSE 6-12 DEL 2	VENTILASJONSROM PLAN 6	2010	0	0
360-33	BYGG C KJØKKEN DEL 2	Ventilasjonsrom PLAN-3 V. kJØKKEN	2010	0	0
360-40	BYGG D AKSE 1-6 DEL 1	VENTILASJONSROM PL4- akse 5-6	2010	0	0
360-41	BYGG D AKSE 6-11 DEL 2	Ventilasjonsrom PL-4-Akse 6-7	2010	0	0
360-42	Bygg D		2015	0	0
360-43	BYGG D		2010	0	0
360-50	BYGG E VENTROM	Vent.Rom Underetasje	2010	0	0

Fig. 18. Example of a service report from GK Inneklima AS for AHU in I4Helse.

to the inhabitants. When the AHU is in fault-free mode, the following requirements must be met: (1) The cooling valve (SB402) should be closed; (2) The supply air setpoint temperature should be higher than the outside air temperature; (3) The temperature of the air after the heating coil should be approximately equal to the temperature of the supply air minus the temperature rise due to the supply air fan. However, as can be seen in Fig. 19, both heater valve (SB401) and chiller valve (SB402) are opened. While simultaneous heating and cooling do not affect interior comfort, it is very wasteful in terms of energy usage. Clearly, there is a severe flaw in the control system, and this should never have happened.

Table 5
Total detected faults based on APAR method.

Number of fault	Name of Fault
Fault 1	Dampers are closed during heating regime
Fault 2	Dampers are closed during cooling regime
Fault 3	Dampres are closed during ventilate regime
Fault 4	Heating valve is closed during heating regime
Fault 5	Cooling valve is closed during cooling regime
Fault 6	Heating pump is OFF during heating regime
Fault 7	Heating pump is ON during ventilate regime
Fault 8	Cooling pump is ON during heating regime
Fault 9	Heating valve is ON during ventilate regime
Fault 10	Heating valve is stuck on 50 % during heating regime
Fault 11	Heating valve is open to the maximum level during heating regime
Fault 12	Fans are OFF during heating regime
Fault 13	Both tubes of differential pressure sensor disconnected
Fault 14	Tube of differential pressure sensor disconnected (negative pressure)
Fault 15	Quick regimes cycling
Fault 16	Heating pump is ON and valve is opened during ventilate regime
Fault 17	Heating pump is OFF during humidifying regime
Fault 18	Heating valve is OFF during humidifying regime
Fault 19	Zone inlet temperature sensor reports −20°C
Fault 20	Zone inlet temperature sensor reports 150°C
Fault 21	Zone outlet temperature sensor reports −20° C
Fault 22	Zone outlet temperature sensor reports 150°C
Fault 23	Heat exchanger is closed
Fault 24	Cooling valve is stuck on 50 % during cooling regime
Fault 25	Cooling valve is open to the maximum level during cooling regime

3.6.2. Unexpected heating

Test checks states of heater, chiller, humidifier and recuperation. AHU is in a heating regime (25th of February 2021). A fault is reported if the heater valve is closed (SB401), the heating pump is off, the chiller valve is opened (SB402), the cooling pump is on, or the full potential of recuperation is not used (LX401). The pressure of exahust air (PR500) and supply air pressure (RP400) are shown in Fig. 20. The supply air temperature (RT400) is much higher than the setpoint (supply air temperature setpoint) (Fig. 20). All supply air should flow through the bypass damper, and the heating valve (SB401) should be closed. None of this is happening.

3.6.3. Heat conservation cool

Test checks if there is an uncontrolled transfer of heat, cold or moisture to the supply air when flowing through the air handling unit. A fault is reported if the AHU is in the cooling regime and supply air temperature (RT400) is higher than the outside temperature (AHU1 odata) (Fig. 21). This fault often happened in November and December 2020 and January 2021 (before the significant change on 10th February 2021). In this case, the chiller valve (SB402) should be closed. The outside temperature is low enough to cool supply air.

3.7. Failure prediction in AHUs

3.7.1. Key metrics for evaluation

We tested the suggested AHU predictive maintenance technique using real-world samples from our buildings with data augmentation methods. Data from BIM models, IoT sensor networks, and FM systems are collected in three groups in each data set. There are four steps in the prediction process:

- Training randomly 80% of entire data sets containing 25 types of faults (Table 5) detected based on APAR from around 150 000 data points.

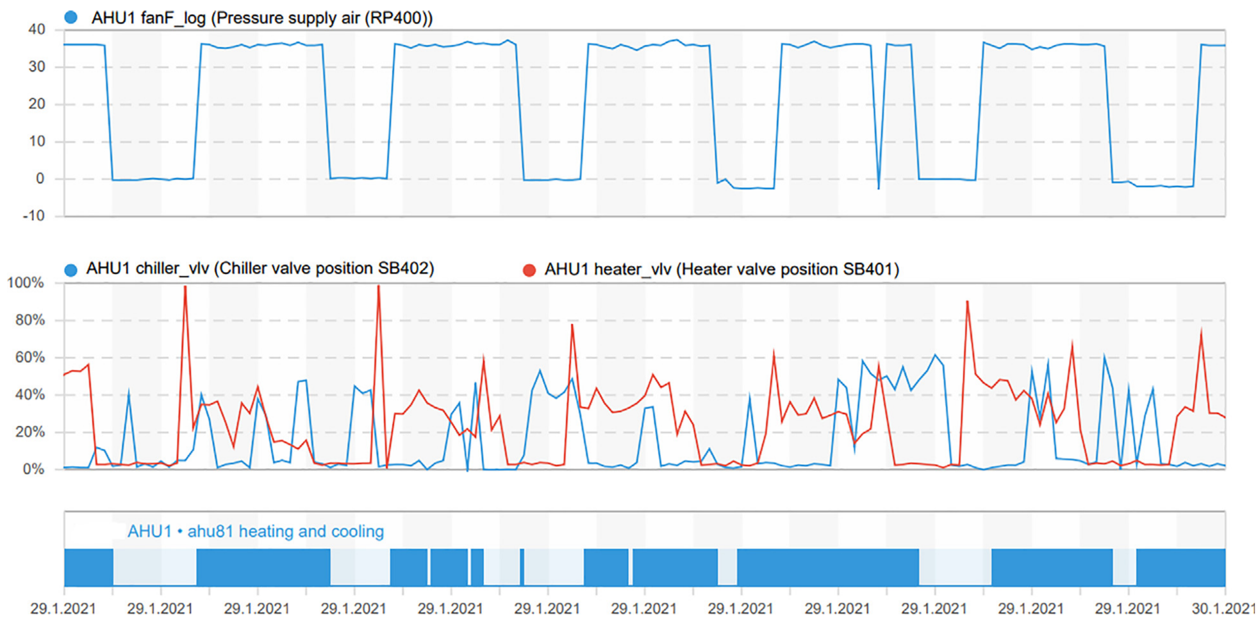


Fig. 19. Simultaneous heating and cooling fault.

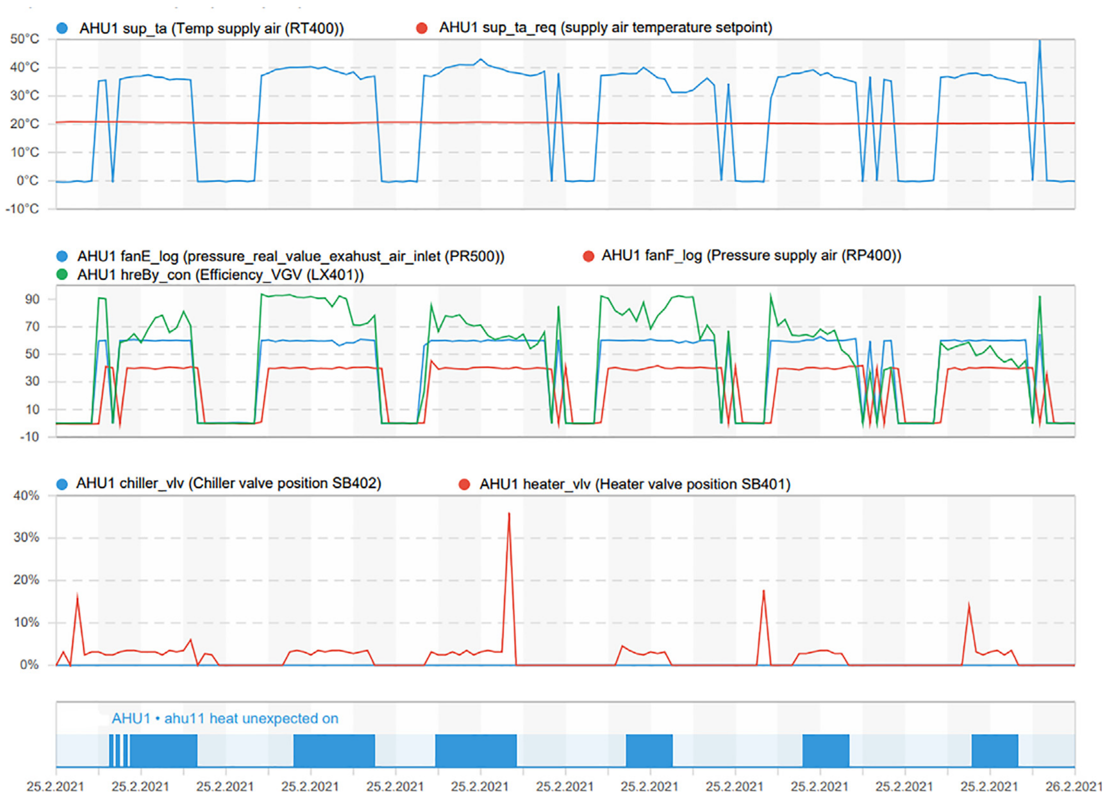


Fig. 20. Heat unexpected on fault.

- Holdout validation using 10% of total data sets.
- Testing and prediction using 10% of total data sets.
- Prediction of faults for the next month and 4.5 months.

The algorithms artificial neural network (ANN), support vector machine (SVM), and decision trees are used to predict and evaluate severe AHU faults.

Two specific assessment measures are utilized for experimental comparison, namely class-specific metrics and performance Trade-off Evaluation.

Consider that there are N classes, each with an index ranging from 1 to N. Class-specific metrics measure the classifier's performance concerning a given class k, where k: $1 \leqslant k \leqslant N$. The positive class is k, while the rest of the classes are grouped as a negative

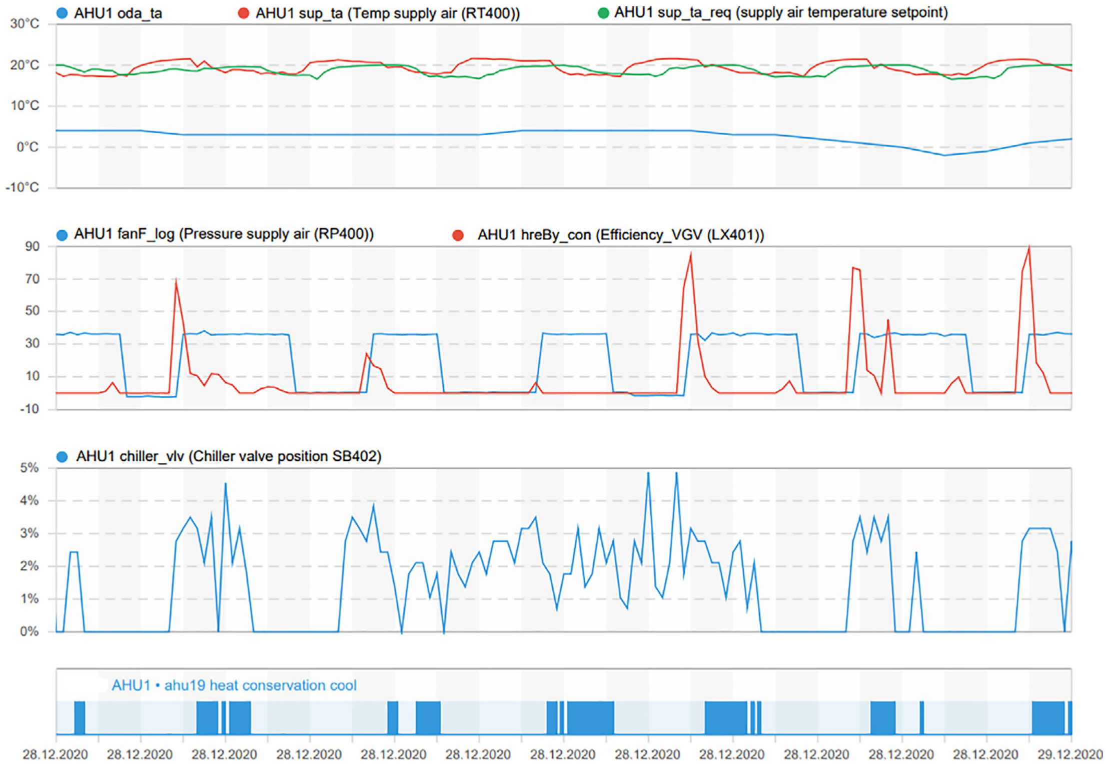


Fig. 21. Heat conservation cool fault.

Table 6
Predictive totals by class. The confusion matrix can be used to determine the predicted totals for class k. True Positives are contained within the diagonal entry row k, column k, False Negatives are contained within the remaining entries in row k, False Positives are contained within the remaining entries in column k, and True Negatives are included within the remaining entries in the matrix.

True Positives	TPk	The number of responses equal to class k that were correctly predicted as class k.
True Negatives	TNk	The number of responses not equal to class k that were correctly predicted as not equal to class k.
False Positives	FPk	The number of responses not equal to class k that were incorrectly predicted as class k.
False Negatives	FNk	The number of responses equal to class k that were incorrectly predicted as not class k.

class. The metrics measure the classifier's performance with class k, one vs. all others. (Table 6). The confusion matrix concept can be seen in Fig. 22. In addition, The Receiver Operating Characteristic curve (ROC) for class k and the Area Under the Curve for class k are frequently used to evaluate a model and its trade-off as functions of the threshold value [109].

3.7.2. An evaluation of predictive maintenance strategies

The predicted conditions of AHU using the ANN, SVM and decision trees algorithms are compared. Data sets (10% of the total data sets) are used for testing. The prediction accuracy of the best decision tree was Fine Tree is 99.9% better than SVM (99.5%) and ANN (99.7%). The condition prediction was carried out on the same datasets as the comparative performance analysis to guarantee that the results of the comparative performance analysis of these approaches were applicable to a wide range of situations. However, accuracy alone is not a reliable predictor of which algorithm is the most effective. As previously said, we will compare two variables using the confusion matrix and the receiver operating characteristic (ROC). Based on that, the Fine tree misclassified 4 faults (damper are closed during heating regime, heating pump is off during heating regime, heating pump is on and valve is opened during ventilation regime, and quick regime cycling) and AUC value from the ROC was equal to 0.49. The SVM method has also misclassified 5 faults (heat exchanger is closed, heating pump is off during heating regime, heating valve is closed during heating regime, heating valve is stuck in intermediate position during heating regime, quick regime cycling) with AUC value equal to 1. However, ANN was able to classify all faults correctly and with AUC equal to 1. Hence, ANN outperforms both SVM and Fine trees, and the ROC curves also indicate this, with the area under the curve for Fine trees being half that of the area under the curve for the ANN. So the prediction accuracy and error indices of decision trees, ANN, and SVM all indicate that ANN outperforms the other two methods even if it requires a longer time (147.05 s) than SVM (53.756 s) and Fine Tree (3.8745 s).

3.7.3. Maintenance planning

The trained ANN model is chosen to forecast the future state of the AHUs based on a comparison of ANN, SVM, and decision trees techniques. The suggested framework is capable of predicting future conditions at a certain point in time. We use one month

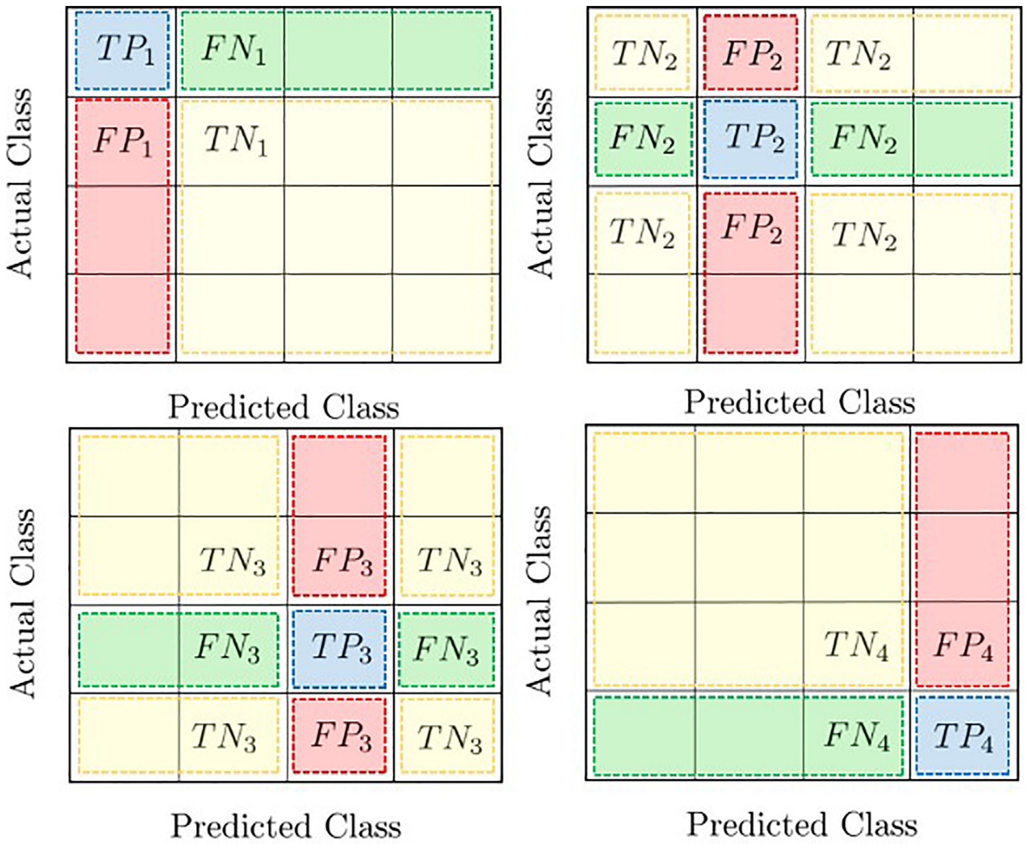


Fig. 22. Multiclass confusion matrix [109].

and 4.5 months later as an example for future maintenance planning and illustrate the dynamic maintenance planning that goes with it. For one month scenario, Table 7 and Fig. 23 show the detected faults and the faults that were wrongly predicted, where x refers to the actual case and y to the predicted case. For example, during one month scenario, it was predicted that the dampers will be closed during the cooling regime, where in actual case, no fault was detected. In the same way, for 4.5 months scenario, Table 8 and Fig. 24 shows the predicted faults, where the algorithm misclassified some faults comparing to the actual case like the faults in heat exchanger.

As a result, the facility manager should prepare maintenance equipment, materials, and tools ahead of time rather than repairing after failure, depending on the expected condition. Because the situation will deteriorate gradually over the following nine months, monthly examination and minimal maintenance will suffice. Overall, a predictive maintenance approach allows the facility manager to track changes in degradation and condition and plan tools and time accordingly. Each expected action causes a change in maintenance planning.

Table 7
Fault prediction for one month later; 29-05-2021 to 29-06-2021

Type	Accuracy%	Error%
Cooling valve is closed during cooling regime	87.5	12.5
Damper are closed during cooling regime	80.0	20
Heating valve is ON during ventilation regime	100	0
No faults	99.8	0.2

4. Discussion

There have been several studies on various techniques for identifying HVAC problems since the 1980s. Despite this fact, Fault detection is still not a standard part of HVAC operations. The rea-

Table 8
Fault prediction for 4.5 months later; 29-05-2021 to 15-10-2021

Type	Accuracy%	Error%
Cooling pump is ON during heating regime	100	0.0
Cooling valve is closed during cooling regime	87.5	12.5
Damper are closed during cooling regime	80.0	20
Damper are closed during ventelation regime	80.0	20
Heater exchanger is closed	71.4	28.6
Heating pump is ON, and valve is opened during ventelation regime	100	0.0
Heating valve is ON during ventelation regime	100	0.0
Heating valve is open to the maximum level during cooling regime	0.0	100
Heating valve is open to the maximum level during heating regime	0.0	100
No faults	99.9	0.1

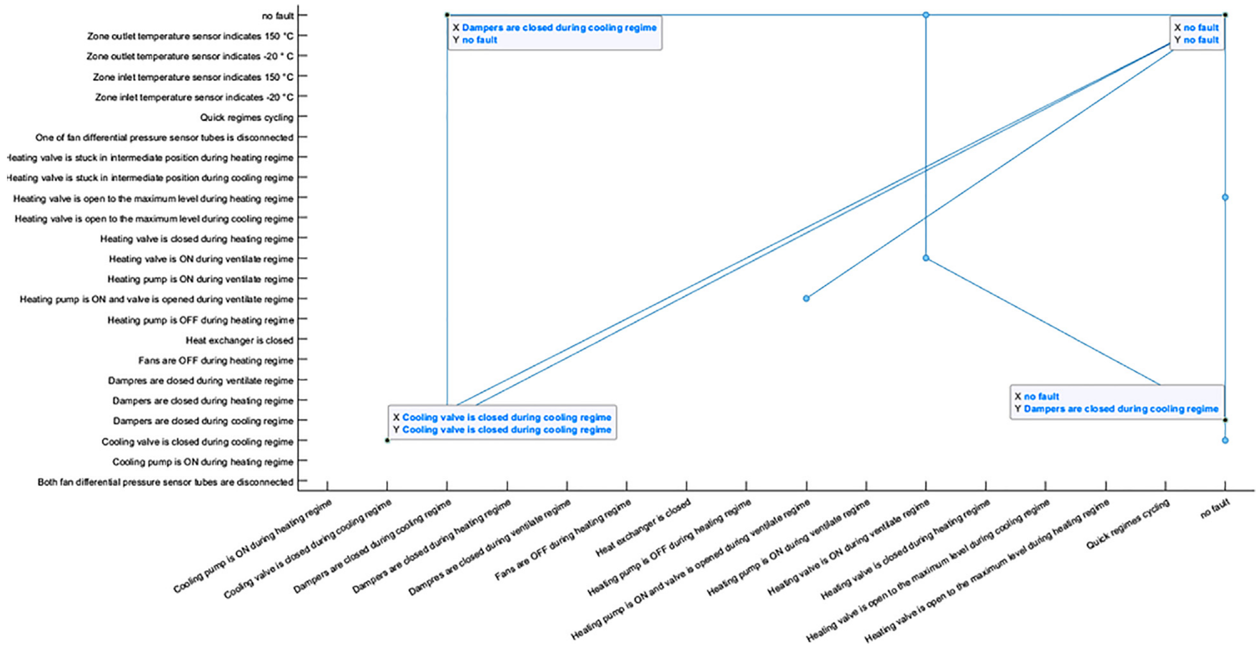


Fig. 23. Comparison between the actual and predicted faults for June 2021 using ANN model (one month ahead from the data that used for training and validation between August 2019 and May 2021) where x refers to the actual fault and y to the predicted fault.

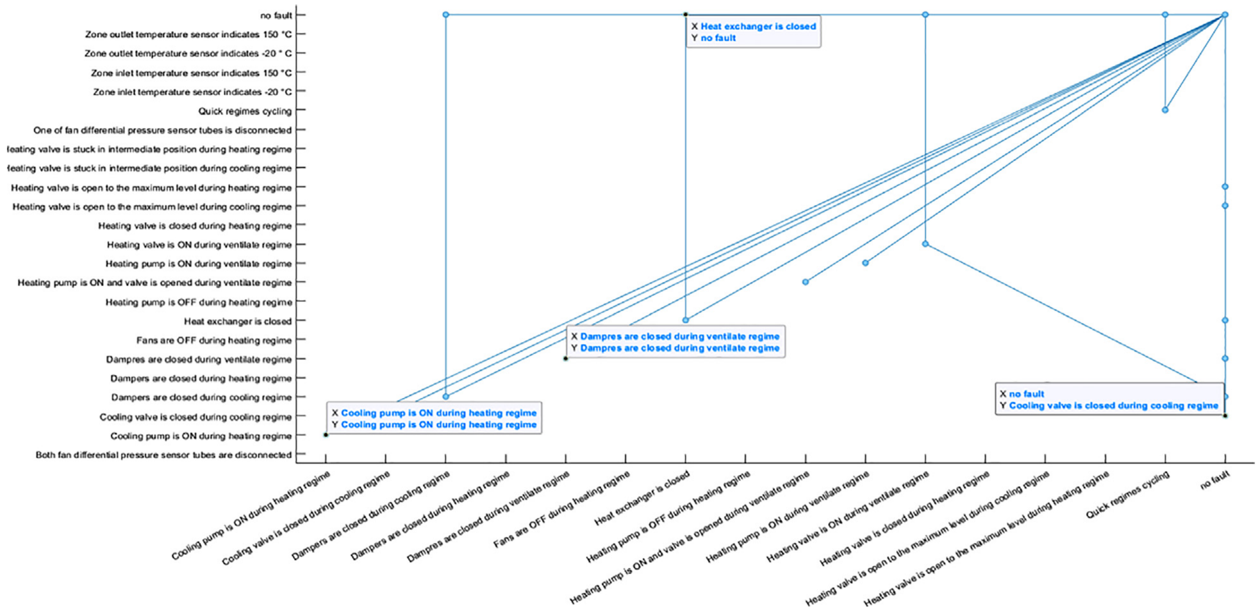


Fig. 24. Comparison between the actual and predicted faults for June, July, August, September and October 2021 using ANN model (4.5 months ahead from the data that used for training and validation between August 2019 and May 2021) where x refers to the actual fault and y to the predicted fault.

son is the restricted flexibility of fault detection methods and the high cost of fault detection systems. As previously indicated, to solve this issue, we used a modular AHU fault detection system that can be utilized with a wide range of AHUs.

This article describes a rule-based system for FDD. It is appropriate for AHU and other HVAC system components, such as the electrical and plumbing systems. This work aims not to obtain the highest possible success rate in fault detection for a single AHU but rather to achieve a fair detection rate for many AHUs. However, the authors state that making comparisons and comprehending the overall condition of technology are complex tasks since each study project uses a particular dataset, test settings, and measurements.

When the facility manager employs the suggested framework in the practical process, it is not required to compare different prediction techniques. Predictive maintenance strategies utilizing ANN, decision trees and SVM techniques are demonstrated in this study to show how to implement a predictive maintenance plan using this framework. It can be seen from the comparative example that different prediction algorithms will produce results with varying accuracy and processing times. Furthermore, the results of the predictions are dependent not only on the quality and the number of datasets gathered but also on the algorithms that have been chosen.

In this study, data integration and flow is accomplished through the use of a plug-in and Brick schema. Other possible solutions to the data integration problems are to include different sensors, equipment, and building components, among other things, in one ontology. Even more significantly, the rising relevance of semantic data in building management systems will be critical in expanding fault detection approaches. It is anticipated that semantic data will become a common element of business management systems within a few years. Agarwal et al. [110] identified many critical ideas from several popular ontologies that may be used for data integration, such as, Semantic Sensor Networks (SSN). As a result, the ontology-based approach may prove to be a viable option for data integration, standardization, and synchronization in the future, among other things. It is expected that as a consequence, the use of fault detection technologies will become extremely easy, inexpensive, and a common element of building management systems.

5. Conclusions

The article examines how the Digital Twin may assist predictive maintenance and dynamic maintenance strategy in the FMM process. The design of the proposed framework includes the data integration and data flow processes between BIM models, IoT sensor networks, and the FM system. The use of three modules implements predictive maintenance: (1) operational fault detection, (2) condition prediction, and (3) maintenance planning. Furthermore, several machine learning techniques (ANN, SVM, and decision trees) are used to forecast the components' state to maintain or repair them in advance and to increase the lifetime of AHU components.

According to the findings of this study, the method of automated fault detection in AHUs has proven to be both functional and beneficial. The system has a high success rate even though it detects a wide variety of different problems and a variety of different AHUs. Moreover, the authors discuss data sources and a semantic definition of data and methods for fault detection and repair.

The limitations of this paper are as follows: The selection of the algorithm depends on the developer's previous experience, which will impact the prediction outcomes. In future investigations, it will be necessary to investigate alternative prediction approaches. Future research should adopt an ontology approach to build a new data model that will establish a standardized data integration solution among various types of sensors and application systems. It is also crucial to further investigate the incremental learning methods of the prediction models to extend the existing model's knowledge, i.e., to train the model further and keep updating the input data.

CRediT authorship contribution statement

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

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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Appendix C

Paper 3- Digital Twin of HVAC system (HVACDT) for multiobjective optimization of energy consumption and thermal comfort based on BIM framework with ANN-MOGA

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Digital Twin of HVAC system (HVACDT) for multiobjective optimization of energy consumption and thermal comfort based on BIM framework with ANN-MOGA

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ABSTRACT

This study proposes a novel Digital Twin framework of heating, ventilation, and air conditioning (HVACDT) system to reduce energy consumption while increasing thermal comfort. The framework is developed to help the facility managers better understand the building operation to enhance the HVAC system function. The Digital Twin framework is based on Building Information Modelling (BIM) combined with a newly created plug-in to receive real-time sensor data as well as thermal comfort and optimization process through Matlab programming. In order to determine if the suggested framework is practical, data were collected from a Norwegian office building between August 2019 and October 2021 and used to test the framework. An artificial neural network (ANN) in a Simulink model and a multiobjective genetic algorithm (MOGA) are then used to improve the HVAC system. The HVAC system is comprised of air distributors, cooling units, heating units, pressure regulators, valves, air gates, and fans, among other components. In this context, several characteristics, such as temperatures, pressure, airflow, cooling and heating operation control, and other factors are considered as decision variables. In order to determine objective functions, the predicted percentage of dissatisfied (PPD) and the HVAC energy usage are both calculated. As a result, ANN's decision variables and objective function correlated well. Furthermore, MOGA presents different design factors that can be used to obtain the best possible solution in terms of thermal comfort and energy usage. The results show that the average cooling energy savings for four days in summer is roughly 13.2%, and 10.8% for the three summer months (June, July, and August), keeping the PPD under 10%. Finally, compared to traditional approaches, the HVACDT framework displays a higher level of automation in terms of data management.

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Nomenclature

η	Efficiency
ω_0	Humidity ratio of the air outside
ω_r	Humidity ratio of the air in a room
ρ	Density
θ_s	Saturation water content
C_P	Specific heat capacity
h_{fg}	Evaporation heat energy
V^0	volume flow rate
A	Area
a	Air
AHU	Air handeling unit
ANN	Artificial neural network
API	Application Programming Interface
ASHRAE	American society of heating, refrigerating and air-conditioning engineers
BIM	Building information modelling
BMS	Building management system
COP	The coefficient of performance
DT	Digital Twin
FM	Facility manager
GA	Genetic algorithm
HVAC	Heating, ventilation, and air conditioning
i	In
IFC	Industry foundation classes
inf	Infiltration
IoT	Internet of things
lat	Latent
Mai	Supply airflow rate
Mcw	Supply water flow rate in summer
Mcw	Supply water flow rate in winter
Mhw	Supply water flow rate in summer
Mhw	Supply water flow rate in winter
MLP	Multilayer perceptron network
MOGA	Multi-objective genetic algorithm
o	Out
PMV	Predicted mean vote
PPD	Predicted percentage of dissatisfied
Q	Cooling/heating load
q	Energy per unit of floor area
r	Room
RH	Relative humidity
RMSE	Root Mean Square Error
s	Sensible
Tai	Ambient temperature
Thi	Supply heating water temperature
Tho	Return heating water temperature
Ti	Temperature after rotary heat exchanger
Tui	Supply air temperature to zones
Tuo	Return air temperature
Twi	Supply cooling water temperature
Two	Return cooling water temperature
URL	Uniform resource locator
VAV	Variable air volume

1. Introduction

A lack of clean and fresh air is a fatal flaw in human health. Our health may suffer if we spend much time indoors working or studying, depending on our job. Having properly-ventilated rooms in any populated building is therefore necessary. Depending on the time of year or the building's purpose, it may be necessary to use heating or cooling. It is impossible to maintain a suitable interior temperature without a properly functioning heating, ventilation, and air conditioning (HVAC) system. However, as the world's population expands, so does the world's need for energy (Nasruddin et al., 2016). The International Energy Agency (IEA) reported in 2013 that buildings had become the third-largest worldwide energy user (International Energy Agency, 2013). Several researchers have stated that HVAC systems are the most common source of energy use in a building, with more than half of the building energy (T. Li et al., 2021; Poel et al., 2007). Therefore, an optimization process is needed for the HVAC system to reduce energy consumption while keeping occupant comfort in mind.

To make the optimization process more effective and user-friendly, Building Information Modelling (BIM) can be utilized in this domain to digitally model complex systems with correct information, which can then be used for various performance assessments and design decision-making applications. Developing an Application Programming Interface (API) in BIM will allow the user to add new functions to automate repetitive operations, analyze deeper, and solve complicated issues (e.g. building thermal performance optimization) (Lim et al., 2019; Mehndi & Chakraborty, 2020). As an additional benefit of BIM, data from the Internet of things (IoT), such as sensor networks, and occupants' feedback may be connected with BIM to monitor the status of the building's equipment and the surrounding environment, which is helpful for the optimization process. This connection is required to create what is referred to as the Digital Twin of the HVAC system (HVACDT).

In the construction sector, the operations of Facilities Management (FM) are handled by a large number of stakeholders. The ability of facility managers to make effective and timely decisions is essential to the functioning of the FM industry. During this process, facility managers present and leave at various times over the building's operating life cycle. This procedure can cause the information to be lost or misconstrued if it is not managed effectively (ATD, 2010).

Because it plays such an essential part in the long-term viability of buildings and the built environment, the energy consumption and performance of the HVAC system need to be monitored with as much precision as possible. Facility managers' inappropriate decisions may lead to wasted energy, excessive expenses, and thermal dissatisfaction (Sagnier, 2018). Thermal complaints are one of the most common complaints (Goins & Moezzi, 2013), and the developed MLP model demonstrated that it could assist facility managers in planning for the staffing resources needed to handle these complaints, thereby improving both the satisfaction of occupants and the performance of the building (Assaf & Srour, 2021). Therefore, the sustainability context in the FM business has to utilize advanced intelligent digital technologies since these technologies can assist improve the flow of information and can also conclude forecasts based on sensor data (Araszkiewicz, 2017; Xu et al., 2020). In this paper, the HVACDT was developed as a real-time system to assist facility managers in making better decisions during the operation phase of building life-cycle management.

The Internet of Things (IoT), Artificial Intelligence (AI), and BIM are all used in Digital Twin technology (Boje et al., 2020; Han et al., 2021; H. Hosamo et al., 2021; Mabkhot et al., 2018; Madni et al., 2019; Rolfsen et al., 2021; Shabani et al., 2021). These technologies have enabled the digitization of many assets, allowing a virtual item to be integrated with a physical object during its entire life span (Qi & Tao, 2018). There are several definitions for Digital Twin in the literature. For example, Kritzinger et al. (2018), Autiosalo et al. (2020), J. Lee et al. (2013), H. H. Hosamo and Hosamo (2022), and H. H. Hosamo, Imran, et al. (2022); nevertheless, Grieves first articulated the concept of Digital Twin in 2012. Grieves emphasized a few years later that he meant a bundle of data that completely describes an asset, from its most fundamental geometry to its most particular function (Grieves & Vickers, 2017). The initial step in this paper will be to create a BIM plug-in to accept real-time data from sensors as well as occupants' feedback. Then, all of the information from the BIM will be sent into the Matlab-built Digital Twin model in Simulink. The Digital Twin model will be validated using machine learning by comparing the energy consumption and thermal comfort results with actual data. The Simulink model's outputs will then be inputs to an optimization algorithm to discover the best strategy for reducing energy usage while maintaining occupant thermal comfort.

1.1. Artificial neural network (ANN) applications for HVAC

Numerous architectural and civil engineering challenges have been handled effectively during the last three decades, thanks to the emergence of soft computing techniques such as artificial neural networks (ANNs) and fuzzy systems. For instance, Abdo-Allah et al. (2018) developed a fuzzy logic controller (FLC) for a central air handling unit (AHU) in Canada. Numerous further investigations have incorporated Diagnostic Bayesian network (DBN) (T. Li et al., 2021), Artificial Neural Network (ANN) (Seo et al., 2019), fuzzy logic algorithm (Khan et al., 2015) were used to enhance HVAC performance. Additionally, Beccali et al. (2017) have shown that ANN might be a valuable tool for energy-efficient building renovation.

Table 1 summarizes a few studies that used machine learning to predict thermal comfort and energy consumption in buildings, including some of the most used Regression methods like SVR, LR, and DT. Out from the Table 1, it is obvious that investigating the best energy use prediction remains a complex task, as there is no general agreement on the most suitable algorithm for energy prediction. According to Olofsson and Andersson (2002), ANN outperforms other approaches for calculating energy usage in buildings. In a similar study (Bui et al., 2020) calculated the energy consumption, including the heating and cooling load, by combining an ANN model and the firefly method (EFA). Additionally, the EFA-performance ANN's was confirmed by comparing the acquired findings to those obtained using other approaches. According to the research findings mentioned in this paper, the ANN model can aid civil engineers and construction managers in the early design of energy-efficient structures. Thus, in this paper, ANN will be employed as a machine learning model to validate the Simulink Digital Twin model (HVACDT).

Table 1. Summary of machine learning approaches used in literature to predict the energy consumption and thermal comfort in buildings.

Reference	Algorithm type	Description
H.-x. Zhao and Magoulès (2012)	ANN,SVM, LR	This paper focuses on applying new models to solve prediction challenges and improving model parameters or input samples for improved performance. Other factors of load prediction are broken down into meteorological conditions, building attributes, and occupancy behavior in the study.
Amasyali and El-Gohary (2018)	SVM, ANN, Decision trees, Data driven models	This study examines the scopes of prediction, data attributes, and pre-processing data methods, including machine learning algorithms for prediction and performance metrics for assessment.
Mat Daut et al. (2017)	ANN, SVM, Hybrid ANN, Hybrid SVM	According to this study, artificial intelligence is the most appropriate strategy for managing nonlinear elements since it can deliver higher predicting performance. A hybrid of two forecasting methods, as opposed to a single forecasting approach might potentially produce more exact findings than a single forecasting method.
Z. Wang and Srinivasan (2015)	ANN, SVM, Ensemble model,LR	The authors evaluate AI-based building energy prediction approaches, focussing on ensemble models. The ideas and applications of multiple linear regression, artificial neural networks, support vector regression, and ensemble prediction models have been covered. This paper also discusses the benefits and drawbacks of each model type.
Edwards et al. (2012)	LR, FFNN, SVR, LS-SVM and others	Seven machine learning approaches were evaluated on two different data sets. The authors evaluated each approach's pros, drawbacks, and technical advantages. The results indicate that LS-SVM is the optimal approach for estimating the future energy usage of each home.
Rahman et al. (2018)	RNN, LSTM	Models for medium- to long-term projections of power consumption patterns in commercial and residential buildings are proposed in this work using two innovative deep RNN with LSTM models. Compared to a 3-layer multi-layered perceptron (MLP) model, the suggested RNN model fails to estimate aggregate load profiles over a 1-year time horizon.
J. Xue et al. (2012)	Hybrid NN-SVM	A unique method for forecasting hourly energy load in a short time, as well as forecasting the daily consumption for the upcoming months, is presented in this paper. The technique is based on the NN-SVM with RGA optimization. Based on the findings, this new technique thoroughly depicts daily and weekly load changes and a reliable prediction of upcoming month consumption with high accuracy.
Dong et al. (2016)	ANN, SVR, LS-SVM, GPR, GMM	This paper aims to provide an innovative hybrid modelling technique for estimating residential building energy use. This study combines data-driven techniques with forward physics-based models. The analysis described here predicts power consumption using five-minute interval data. The results of the final data analysis suggest that hybrid modelling is marginally superior to conventional data-driven methods for hourly forecasting.
Fan et al. (2017)	DNN, RF, SVR, GBM, XGB, MLR, ELN	The potential of deep learning in building cooling load prediction is investigated using seven different algorithms. The results demonstrate that the extreme gradient boosting (XGB) technique demonstrates superior prediction to other methods.
Olu-Ajayi et al. (2022)	DNN, ANN, GB, SVM, KNN, DT, LR	The accuracy of nine machine learning approaches for forecasting yearly energy usage was examined in this study. DNN outperformed other models in predicting energy usage. ANN, GB, and SVM are also considered efficient prediction methods in this study.
Ahmad et al. (2014)	SVM, ANN, LSSVM, GMDH, GLSSVM	This study demonstrates that NN and SVM are the most often employed artificial intelligence models in building energy use prediction. A GMDH-LSSVM hybrid model was suggested in this research, and it was discovered to have a promising forecasting potential when applied to different time series forecasting areas.

(*Continued*)

Table 1. Continued.

Reference	Algorithm type	Description
Østergård et al. (2018)	OLS, RF, SVR, GPR, NN, MARS	This study puts a variety of machine learning algorithms to the test in the context of 'building performance simulations'. the results show that GPR generated the most accurate models in general, followed by NN and MARS.

1.2. Optimization methods

Green building design and performance optimization are two examples of large-scale challenges for which optimization methods have been created (Elbeltagi et al., 2005). Combining energy consumption modelling with other optimization methods, such as simulation-based optimization for performance optimization, may be worth investigating to minimize building energy consumption (Nguyen et al., 2014). As shown in past studies, employing high-performance approaches can assist researchers in optimizing building energy use (Griego et al., 2015). Foucquier et al. (2013) assessed three alternative optimization techniques: 'white box', 'black box', and 'grey box'. On the other hand, Magnier and Haghighat (2010) used TRNSYS and ANN to maximize thermal comfort and energy usage in an office building. The resulting findings demonstrated that using a Genetic Algorithm (GA) as an optimization tool may successfully minimize building energy usage.

Pombeiro et al. (2017) optimized the AHU system using a programming model and GA. The GA model employed EnergyPlus to simulate interior temperature. To improve energy efficiency and interior comfort, Alcalá et al. (2003) developed evolutionary algorithms for constructing cleverly tuned fuzzy logic controllers. Similarly, Congradac and Kulic (2009) proposed a GA for typical HVAC systems. The GA design aimed to maximize performance, especially power savings. A simulation model was created to show how much electricity may be saved by controlling CO2 concentration in a standard HVAC system. Kusiak et al. (2013) used data mining to reduce the HVAC system's energy usage. The results revealed a 23% reduction in energy use. Ferdyn-Grygierek and Grygierek (2017) utilized the EnergyPlus toolbox to model and optimize building operations. The research is done for two building types: heating and cooling and heating only. The life cycle expenses decreased by 7–34%, depending on the case. Seong et al. (2019) employed the GA to optimize HVAC system management. Using the optimum control factors, the building's overall energy usage was lowered by 5.72%. Qiao et al. (2021) employed the GA to improve HVAC systems. The optimization was done using Fanger's comfort approach and GA (Fanger, 1973). Nassif et al. (2005) employed GA to optimize two AHU control objectives. Nasruddin et al. (2019) used ANN and multiobjective GA to optimize a two-chiller system.

Several other approaches have also been tested in addition to the genetic algorithm for optimization. An innovative demand response management and thermal comfort optimization control system for three buildings was devised by Korkas et al. using the Principal Component Analysis Optimization (PCAO) algorithm (Korkas et al., 2016). R-PCAO (Rule-based Parameterized Cognitive Optimization) was utilized by Baldi et al. to improve building energy consumption and occupant comfort (composition of interacting rooms, with the interconnection of HVAC sensing) (Baldi et al., 2018). A new Distributed Demand Management System (D-DMS) and multi-objective optimization were presented by Korkas et al. to minimize energy consumption and fulfill thermal comfort levels to improve the user-driven energy performance of the building and the district (Korkas et al., 2018). C. J. Lin et al. (2022) suggests combining ANN with a multi-objective whale optimization algorithm (MOWOA) to maximize thermal comfort and reduce energy consumption to regulate air-conditioning and mechanical ventilation systems. Thermal comfort, operating costs, and system efficiency of a university campus in Tianjin, China, were optimized using a multi-objective particle swarm optimization (PSO) method (Ding et al., 2019). Yong et al. (2020) integrated a novel algorithm based on the basic particle swarm optimization and EnergyPlus to reduce energy consumption and enhance comfort levels in many buildings in China. Kim and Hong (2020) employed multi-objective optimization for an office building in Seoul to establish the ideal interior set-point temperature that solves the trade-off between HVAC energy savings and labour productivity. Using the Mode Frontier and the Passive House Planning Package (PHPP), B. Lee et al. (2020) developed a combined automated simulation framework for reducing heating demand in a passive house design approach. Dhariwal and Banerjee (2017) presented a strategy to circumvent the heavy computing of building simulation-based optimization by integrating the design of experiment (DOE) and response surface methodology (RSM).

Out of the above studies, several optimization approaches were used to enhance building performance and energy consumption. However, most studies have implemented the genetic algorithm, which can be divided into Single Objective Genetic Algorithm and multiobjective genetic algorithms (MOGA). Using the Single Objective Genetic Algorithm technique, Wright and Alajmi (2016) found the best HVAC system and building envelope parameter set that produced the optimal yearly energy usage. Harun et al. (2017) identify the optimum materials for minimal OTTV in building exterior retrofit optimization. Yigit & Ozorhon's (2018) employed the Single Objective Genetic Algorithm technique using MATLAB to discover the ideal building thermal design. However, despite Single Objective Genetic Algorithm speed in tackling single-objective optimization issues, it is severely constrained in solving complicated problems involving several competing criteria. Multiobjective genetic algorithms (MOGA) are therefore utilized when a single goal approach is not as practical as it may be. Compared to GA, MOGA offers a framework for handling several conflicting objective functions (Vachhani et al., 2015). Another common use of MOGA is to enhance the efficiency of a building's mechanical systems. Jeong et al. (2019) employed MOGA to optimize multi-family housing complexes and reduce carbon dioxide emissions. In a case study, Nasruddin et al. (2019) coupled MOGA with an Artificial Neural Network (ANN) to improve the performance of a two-chiller system. Chang et al. (2020) determined the optimal materials for a renovated building based on its current constructed form using MOGA. Hence, MOGA will be used as an optimization algorithm in this paper.

1.3. Combine machine learning with a multi-objective optimization algorithm

An appropriate fitness function for MOGA is required to speed convergence and locate the optimum solution. Empirical formulae or computer simulations are usually used to determine the fitness functions. Zhang constructed mathematical models that serve as a fitness function for a genetic algorithm based on empirical formulae to optimize the parameters (K. Zhang, 2020). Naderi et al. used EnergyPlus to improve the design and control characteristics of a smart shading blind (Naderi et al., 2020). Bruno et al. utilized the minor yearly energy usage and minimum construction cost from EnergyPlus as fitness functions (Zemero et al., 2019). However, the empirical equations cannot be changed to unique building circumstances, and calculating the fitness values of several individuals using simulation software is computationally costly while reducing optimization efficiency. In order to overcome the restrictions of the previously utilized fitness functions, it was recommended that ML be used as the fitness function of the optimization method (Østergård et al., 2018). Lin et al. employed neural networks to generate thermal comfort and overall energy consumption metamodels (Y.-H. Lin et al., 2016). Nasruddin et al. used an artificial neural network and a multi-objective GA to optimize the operation of a two-chiller system in a building (Nasruddin et al., 2019). Wang et al. used Gradient Boosting Decision Trees (GBDT) to generate building performance metamodels (R. Wang et al., 2020). In conclusion, intelligent algorithms as fitness functions can increase optimization algorithms' adaptability and efficiency (J. Zhang et al., 2019). The current work provides a multi-objective optimization approach for HVAC energy consumption and thermal comfort in buildings that combines machine learning and MOGA.

1.4. BIM as a tool for sustainability

There are several ways in which a BIM-based design process may be used throughout the building life cycle to undertake various analyzes and enhance teamwork. Researchers suggest that the BIM method and tools may be used to conduct early-stage sustainability analysis and decision-making (Azhar et al., 2011; Carvalho et al., 2019; H. H. Hosamo, Svennevig, et al., 2022). It was argued by Freitas et al. (2020) that BIM may also be used to help make decisions about the energy efficiency of existing structures. According to Lim et al. (2021), BIM is still not utilized effectively in building activities. Hence, further research is required in order to address many issues in the green building environment.

Recently, researches have shown a growing interest for using BIM with text-based programming to advance their studies. Many research fields have benefitted from this combination, including process automation (Liu et al., 2021), facility management (B. Wang et al., 2021), and building performance analysis (Abbasi & Noorzai, 2021). In addition, text-based programming scripts allow designers to enhance the capabilities of current BIM tools by designing new features to automate, extract, and manage the data of a BIM model more efficiently.

Furthermore, BIM project property information cannot be transmitted directly between BIM authoring tools and simulation software when using data interchange protocols like Industry Foundation Classes (IFC) (Natephra et al., 2018). Consequently, in order to use data collected from a BIM model in energy modelling programs, manual data entry is necessary (Z. Chen et al., 2020). Out from that, there is a significant benefit to building a Revit API for automated BIM data extraction and administration.

1.5. Scope

It has been shown from the literature that many techniques can optimize the HVAC systems. They vary between ANN, FLC, GA, data mining, and probabilistic method. That would indicate the importance of using optimization toolboxes to enhance the performance of HVAC systems. However, it is of practical importance to develop a simple yet accurate and reliable model to match better the actual behavior of the subsystems and overall system over the entire operating range. Moreover, ideally, it is almost impossible to develop a model based on physical knowledge. Therefore, this paper proposes the HVACDT method that integrates BIM, a new plug-in in Revit, Simulink, and a multiobjective optimization algorithm (MOGA) in one novel workflow for the HVAC system. Based on the research gaps mentioned above, this study:

- Develops a new plug-in for Revit to receive the sensor data and occupants' feedback and then feed them to the optimization process in Simulink.
- Describes a Digital Twin framework for the optimization process using inputs from the BIM model to Simulink in Matlab.
- Uses of ANN algorithm for validating the Simulink model based on IoT data.
- Uses multiobjective optimization algorithm (MOGA) to find the optimal energy consumption and thermal comfort solution.
- Streams the final results in BIM so the best operational conditions of HVAC can be implemented.

2. Methodology

The novel HVACDT method is developed to reduce the energy consumption of HVAC and increase the thermal comfort of occupants in buildings. The HVACDT method process depicted in Figure 1 begins by extracting the appropriate data from the BIM model and ends by sending the optimal design option data back to the BIM model. The method was structured in several steps:

- The initial stage of the HVACDT method (the green area in Figure 1) consists of preparing the BIM model for data extraction. The preparation process involves checking that all the required dimensions, materials, and installation year, are available in the BIM model. In addition, a Revit plug-in is developed using C sharp to stream the data from sensors in HVAC to the BIM model; for example, temperature, pressure, and flow rate are collected from sensors in HVAC.

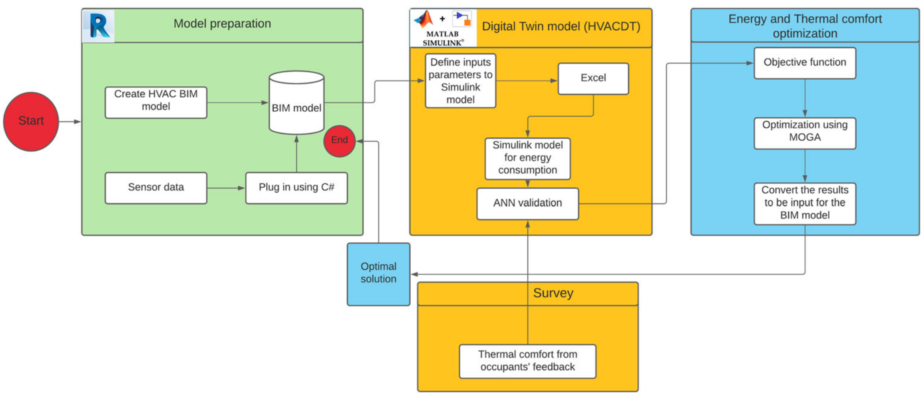


Figure 1. The Digital Twin framework for the optimization process.

- The second stage (the yellow area in Figure 1) involves extracting the input parameters for the optimization problem from the BIM model. The same plug-in is used to extract data from Revit. An Excel template is used to store the gathered data. This data is used as inputs for the Simulink model. The output parameters from Simulink using ANN is the energy consumption, which is validated with the actual data from the building.
- Furthermore, a questionnaire survey about thermal comfort was distributed to get the predicted mean vote (PMV) and the predicted percentage of dissatisfied (PPD), chosen as the thermal comfort indexes. PMV and PPD are two popular indices of thermal comfort (Deshko et al., 2020). The PMV scale ranges from −3 (very cold) to +3 (very hot). Comfortable interior air conditioning has a PMV close to zero. PPD predicts the percentage of occupants that are unhappy with the air conditioning. PPD drops as PMV approaches zero, where PPD values vary from 0% to 100%.
- Following this stage (the blue area in Figure 1), MATLAB® was used for the optimization process, using a multi-objective optimization algorithm (MOGA).
- Finally, the data output of the optimization is pushed back using the Revit plug-in developed to update the design of the building envelope with the optimized option automatically.

2.1. Building descriptions

The I4Helse office building (i4Helse, 2022) in Grimstad, Norway, has been chosen to model the thermal comfort and energy performance of the HVAC system (Figure 2). Approximately 1900 m^2 of conditioned space is available in the building. The building is four stories tall, and it is divided into zones for meetings and work. The building envelope features, the HVAC system, and setpoints follow the Norwegian building code TEK10 (Direktoratet for byggkvalitet, 2010). Table 2 summarizes the features of the primary HVAC system in the reference building. The meteorological data for this study was obtained from the ASHRAE IWEC 2 database for the climate of Kjevik, Kristiansand, Norway. The ASHRAE classification (Ashrae 90.1, 2013) provides further information about this city's climatic conditions.

2.2. HVAC system

A chiller and a heater are installed in the building utilized in this study to provide chilled and hot water for variable air volume (VAV) systems. Using the air handling unit (AHU), the fresh air is circulated and leaves through the exhaust system. The cooling and heating load automatically controls the VAV system. Figure 3 depicts a schematic representation of HVAC. This schematic depicts the proposed artificial neural network (ANN) models and their interactions with the rest of the system. The HVAC system is composed of the following components: return and supply fans, outside, discharge, and recirculation dampers, an air handling unit (AHU) with filter and cooling and heating coils, pressure-independent VAV terminal boxes, and local-loop controllers.

Numerous sensors have been used to collect the necessary data through the building management system (BMS) and by building a restful API. Supply-air temperature for each

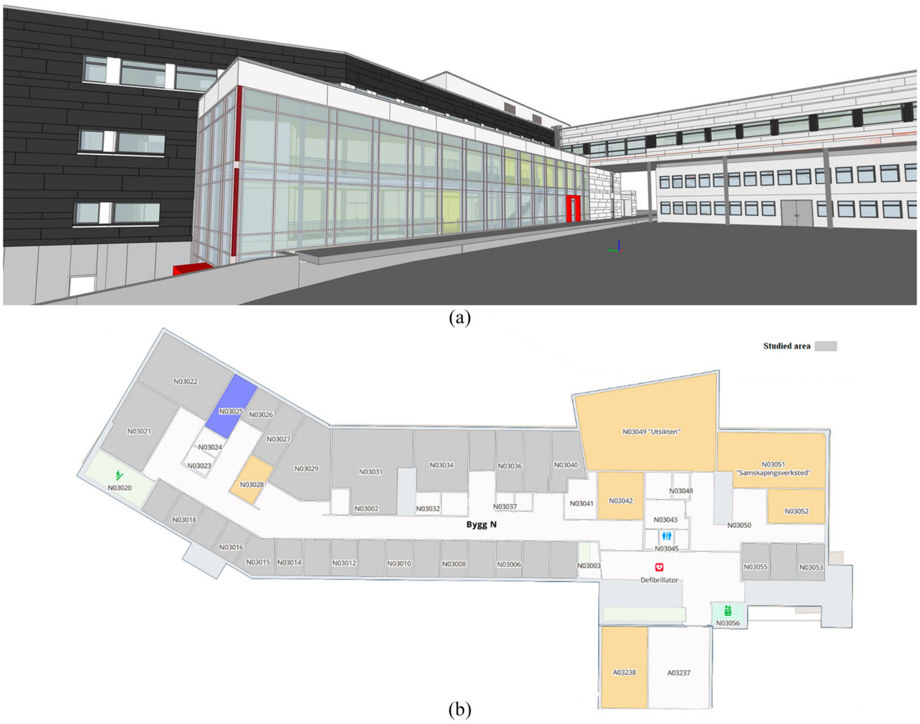


Figure 2. BIM model of I4Helse building that located in Grimstad, Norway (a), and the plan of zones at third floor in I4Hhelse building (b).

Table 2. The main features of the reference office building's HVAC systems.

Operation	Features
Strategy for the ventilation system	Mechanical balanced ventilation system with a 80% efficient rotating heat recovery system.
Ventilation system operating schedules	Monday-Friday: 12 h/day (from 06.00 to 18.00)
Cooling system	A centrally located water cooling system is used to chill the supply air in the AHU.
Heating system	A centrally located water heating system is used to heat the supply air in the AHU.
Control method	Water temperature for space heating is supplied as a function of the outside temperature. The temperature of the supply air is controlled in relation to the temperature of the return air to the AHUs (air handling units).
Room temperature set point for heating and cooling	21°C for heating and 24°C for cooling

thermal zone (Tui), the supply-air static pressure (SAP), the supply-airflow rate (Mai), the supply-water flow rate in summer (Mcw), the supply-water flow rate in winter (Mhw), the return air temperature (Tuo), the supply cooling water temperature (Twi), the return cooling water temperature (Two), the supply heating water temperature (Thi), the return heating water temperature (Tho), ambient temperature (Tai) and temperature after rotary heat exchanger (Ti) sensors are used as input to the feedback control loop.

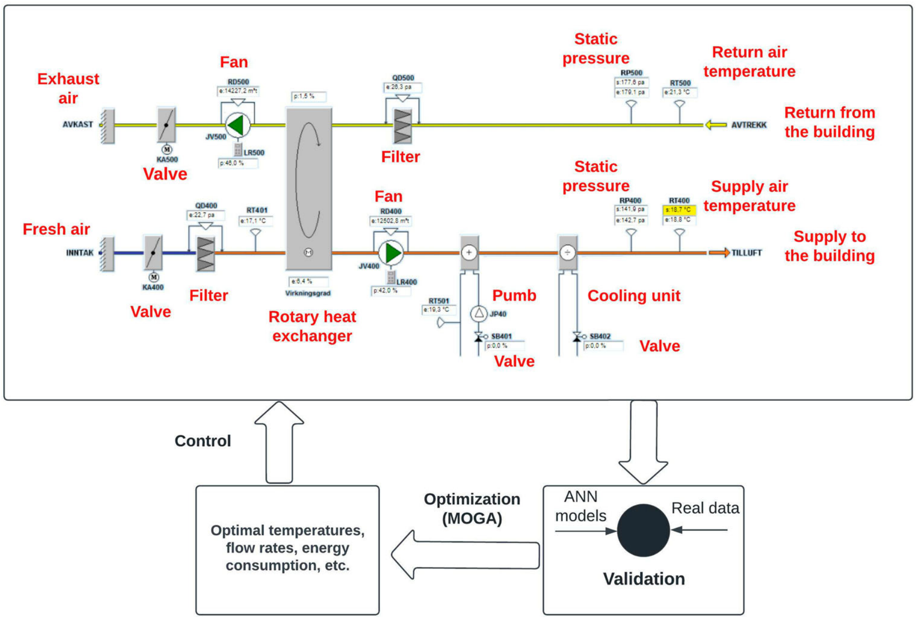


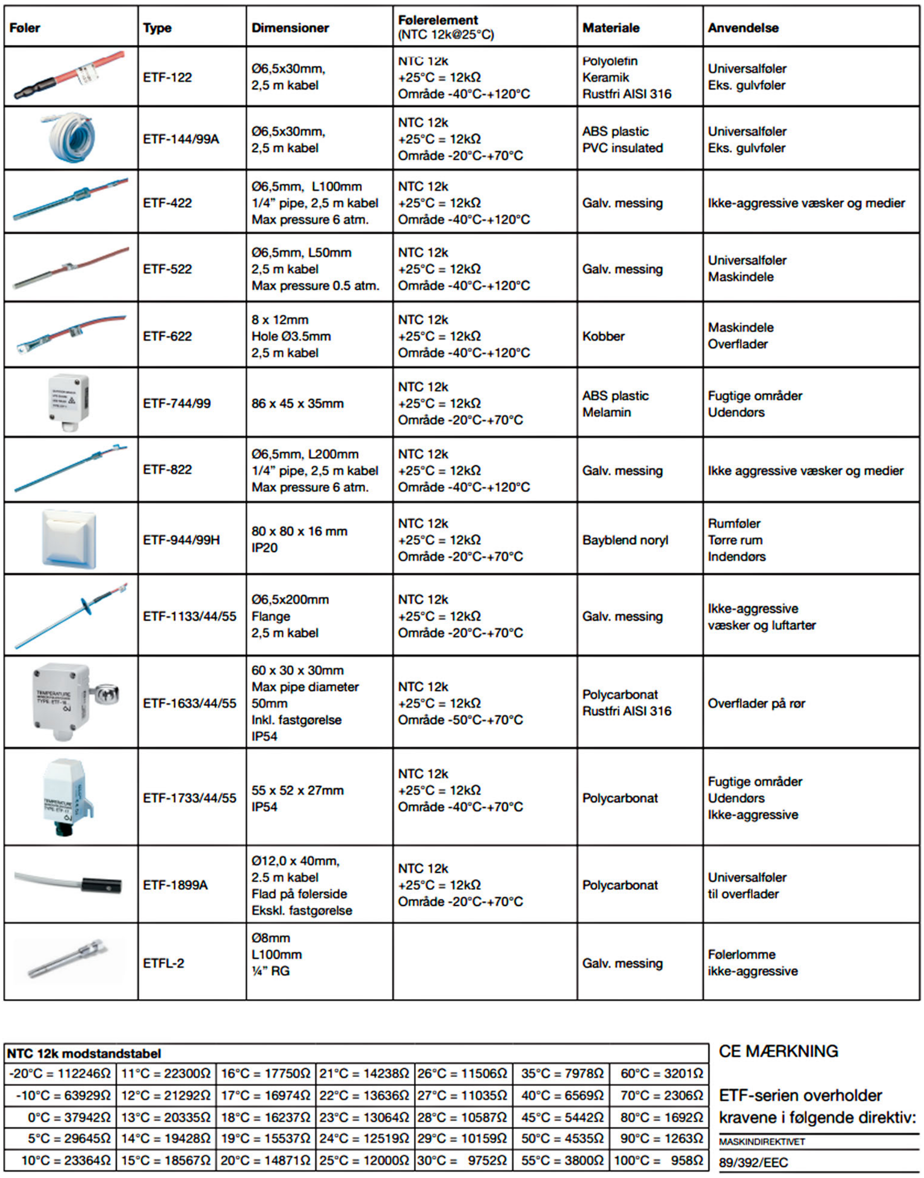
Figure 3. A Schematic diagram of the proposed HVAC with the proposed ANN models and optimization process.

The rest of the sensors are used to monitor operating conditions. Figure 4 depicts the data sheet for the sensors. In addition, Regio controllers have been utilized to manage a wide variety of variables, including but not limited to temperature, lighting, humidity, CO2 levels, and even blinds. In addition, Regio offers services related to the Internet and online interaction. It is possible to control the temperature and other functions of a room using a personal computer that is connected to the network at the office. The application system is depicted in Figure 5, and the controllers are shown in Figure 6.

Figure 7 depicts the HVAC system's local loop controllers (M1, M2, and M3), as well as the BMS's integrated optimization process. The controller regulates the supplied air temperature (M1). The controller regulates the static duct pressure (M2). The controller (M3 (n)) controls the zone air temperature in every given zone n. The BMS collects measured data (actual data) from components or subsystems. The ANN models are constantly trained using real data to fit better the real behavior of the subsystems and overall system. The ANN models give optimal total system performance by finding optimal set points and operation sequences at each time interval, as supported in this study for optimal control strategy (every 10 min).

2.3. BIM model data

In this paper, the BIM model will be utilized in two ways: as input for the Simulink model (supply parameters for building performance) and to visualize the findings. A BIM model's geometric and semantic aspects (non-geometric), including component size, materials, and installation year, will help facility managers during the optimization process. In



Føler	Type	Dimensioner	Følerelement (NTC 12k@25°C)	Materiale	Anvendelse
	ETF-122	Ø6,5x30mm, 2,5 m kabel	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Polyolefin Keramik Rustfri AISI 316	Universalføler Eks. gulvføler
	ETF-144/99A	Ø6,5x30mm, 2,5 m kabel	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	ABS plastic PVC insulated	Universalføler Eks. gulvføler
	ETF-422	Ø6,5mm, L100mm 1/4" pipe, 2,5 m kabel Max pressure 6 atm.	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Galv. messing	Ikke-aggressive væsker og medier
	ETF-522	Ø6,5mm, L50mm 2,5 m kabel Max pressure 0.5 atm.	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Galv. messing	Universalføler Maskindele
	ETF-622	8 x 12mm Hole Ø3.5mm 2,5 m kabel	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Kobber	Maskindele Overflader
	ETF-744/99	86 x 45 x 35mm	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	ABS plastic Melamin	Fugtige områder Udendørs
	ETF-822	Ø6,5mm, L200mm 1/4" pipe, 2,5 m kabel Max pressure 6 atm.	NTC 12k +25°C = 12kΩ Område -40°C-+120°C	Galv. messing	Ikke aggressive væsker og medier
	ETF-944/99H	80 x 80 x 16 mm IP20	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	Bayblend noryl	Rumføler Tørre rum Indendørs
	ETF-1133/44/55	Ø6,5x200mm Flange 2,5 m kabel	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	Galv. messing	Ikke-aggressive væsker og luftarter
	ETF-1633/44/55	60 x 30 x 30mm Max pipe diameter 50mm Inkl. fastgørelse IP54	NTC 12k +25°C = 12kΩ Område -50°C-+70°C	Polycarbonat Rustfri AISI 316	Overflader på rør
	ETF-1733/44/55	55 x 52 x 27mm IP54	NTC 12k +25°C = 12kΩ Område -40°C-+70°C	Polycarbonat	Fugtige områder Udendørs Ikke-aggressive
	ETF-1899A	Ø12,0 x 40mm, 2.5 m kabel Flad på følerside Ekskl. fastgørelse	NTC 12k +25°C = 12kΩ Område -20°C-+70°C	Polycarbonat	Universalføler til overflader
	ETFL-2	Ø8mm L100mm ¼" RG		Galv. messing	Følerlomme ikke-aggressive

NTC 12k modstandstabel						
-20°C = 112246Ω	11°C = 22300Ω	16°C = 17750Ω	21°C = 14238Ω	26°C = 11506Ω	35°C = 7978Ω	60°C = 3201Ω
-10°C = 63929Ω	12°C = 21292Ω	17°C = 16974Ω	22°C = 13636Ω	27°C = 11035Ω	40°C = 6569Ω	70°C = 2306Ω
0°C = 37942Ω	13°C = 20335Ω	18°C = 16237Ω	23°C = 13064Ω	28°C = 10587Ω	45°C = 5442Ω	80°C = 1692Ω
5°C = 29645Ω	14°C = 19428Ω	19°C = 15537Ω	24°C = 12519Ω	29°C = 10159Ω	50°C = 4535Ω	90°C = 1263Ω
10°C = 23364Ω	15°C = 18567Ω	20°C = 14871Ω	25°C = 12000Ω	30°C = 9752Ω	55°C = 3800Ω	100°C = 958Ω

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Figure 4. AHU sensors datasheet.

addition, a Restful API (Application Programming Interface) has been developed as a layer over a traditional Building Management System (BMS). The API allows collecting data from any device in the building by using a unique URL (Uniform Resource Locator). The procedure begins with HVAC sensors for control and visualization, linked to the BMS, which regulates the unit.

Moreover, with Microsoft Visual Studio Community 2019, a Plugin is embedded into the BIM model, enabling the viewing and storing of real-time sensor data directly

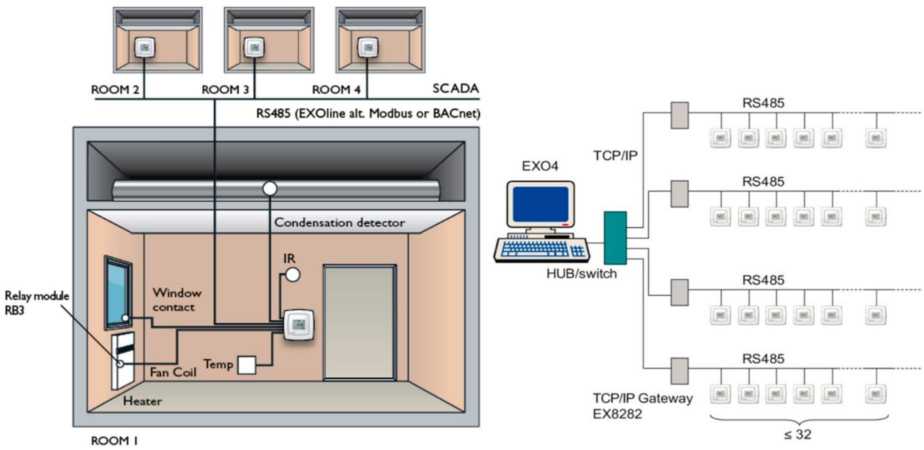


Figure 5. An example of the application system (Regio Midi, 2013).

in the BIM model. To construct the tab, ribbon, and plugin buttons, the Application base class implements an external application interface. This feature-rich plugin is ideal for facility managers since it enables them to obtain real-time sensor data and record it in the relevant condition database while keeping BIM up to date. The 'Sensor Data' option allows FM managers to check the maximum and lowest values of current sensor data and previous sensor data. The condition database also allows facility managers' management to confirm the average and historical values of the sensor. The sensor data is saved in real-time by clicking the 'Store' button, as shown in Figure 8(a). Figure 8(b) is a schematic illustration of the overall system's principle.

The BIM authoring tool utilized in this study was Autodesk Revit® 2022 (Autodesk, 2022). Autodesk Revit® is a widely used BIM-related program in research and practice (Lim et al., 2021). Additionally, several earlier studies (La Russa & Santagati, 2021) utilized Autodesk Revit® because of its accessibility to academics and interaction with text-based programming.

When utilizing the HVACDT system, data pushback is critical to the optimization process. In contrast to the data extraction process, the data pushback procedure imports data from MATLAB® to the BIM model for the optimum design choice. The Revit plugin selects the best temperatures, air flows, and pressures from the Excel template using sensor blocks (See Figure 8(c)). This method results in the production of optimal solutions that consume less energy and produce less pollution.

2.4. Post-occupancy evaluation (POE)

One of the most frequent methods to evaluate a building's inhabitants' satisfaction is a questionnaire survey known as a post-occupancy evaluation (POE). In this work, SurveyXact forms were used to create a user satisfaction survey based on comfort considerations (e.g. thermal comfort, acoustic comfort, indoor air quality, visual comfort, and space adequacy) (Bluyssen et al., 2011; de Bakker et al., 2017).

Figure 6. System controllers (Regio Midi, 2013).

This research included both physical and non-physical comfort. The questionnaire survey was designed to obtain occupant feedback as follows: Occupants have to choose their workplace by building, floor, and room. In addition, occupants have to answer questions about thermal comfort in winter and summer, indoor air quality in winter and summer, visual comfort, acoustical comfort, and workplace space adequacy.

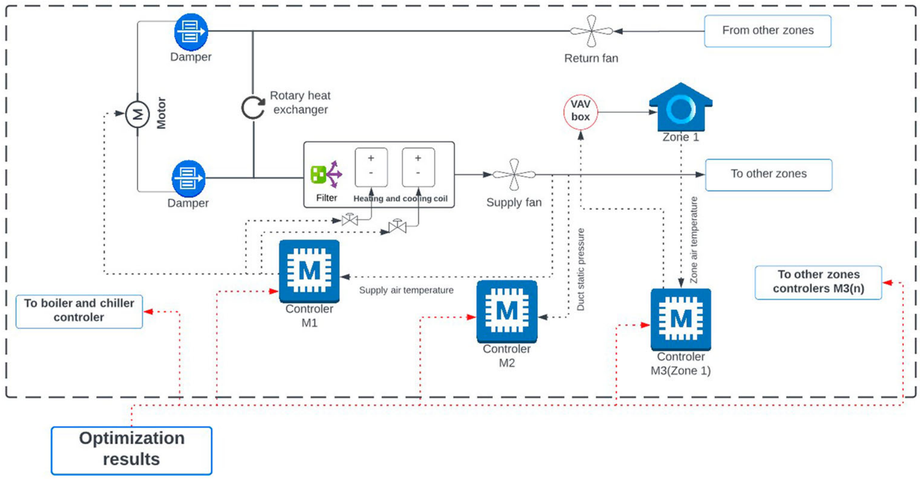


Figure 7. HVAC system controllers along with the optimization process.

The questionnaire also featured a text entry field for responders to offer additional reasons for dissatisfaction. Finally, occupants were also asked to score their happiness with thermal, auditory, visual, and spatial characteristics of the building's common areas (e.g. corridors, conference rooms, toilets, and dining rooms). The survey results were statistically analyzed to identify the cause-effect of some variables.

Rooms in BIM were used to organize the spatial data collected for this investigation. However, there was no complete BIM model of the rooms in the building; therefore, it was necessary to use a laser scanner (Topcon GLS-2000, 2016) to scan the building and then export the point clouds model (Figure 9(a)) to ReCap pro (ReCap, 2019) and finally to Revit (ReCap, 2019) to make a correct model as possible to receive the occupants' feedback.

The sensor block in rooms was a suitable host for the user satisfaction survey using the plugin in Revit since the spaces provided occupant feedback. The results can be seen in Figure 9(b), where the blue colour refers to a good indoor environment.

All I4Helse building spaces were surveyed for user satisfaction, including office spaces, hallways, kitchens, and labs. Before being put into the machine learning model, each room's occupancy density (measured in m2/person), movable windows (yes/no), and ventilation type were all incorporated into the BIM model.

Now, to calculate the thermal sensation values, Equations (1)–(4) offer the mathematical formulas for Fanger's PMV-PPD model:

$$PMV = (0.303 \cdot e^{0.036 \cdot M} + 0.028) \cdot L \tag{1}$$

$$\begin{aligned} L = M &- 0.00305 \cdot (5733 - 6.99 \cdot (M - W) - Pa) - 0.42(M - W - 58.15) \\ &- 0.0017(5867 - Pa) - 0.0014 \cdot M \cdot (34 - Ta) - 3.96 \cdot 10^{-8} \cdot Fcl \cdot ((Tcl + 273)^4 \\ &- (Tr + 273)^4) - Fcl \cdot hc \cdot (Tcl - Ta) \end{aligned} \tag{2}$$

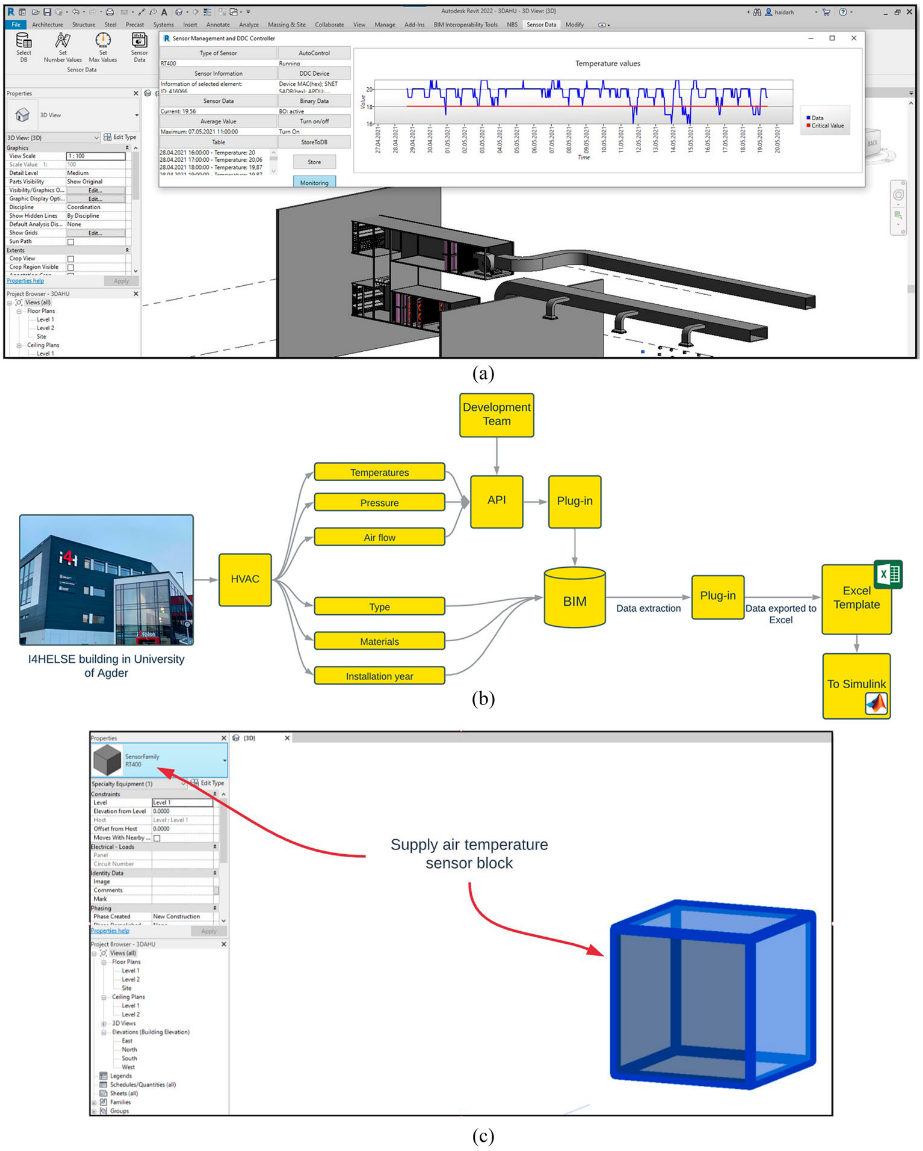
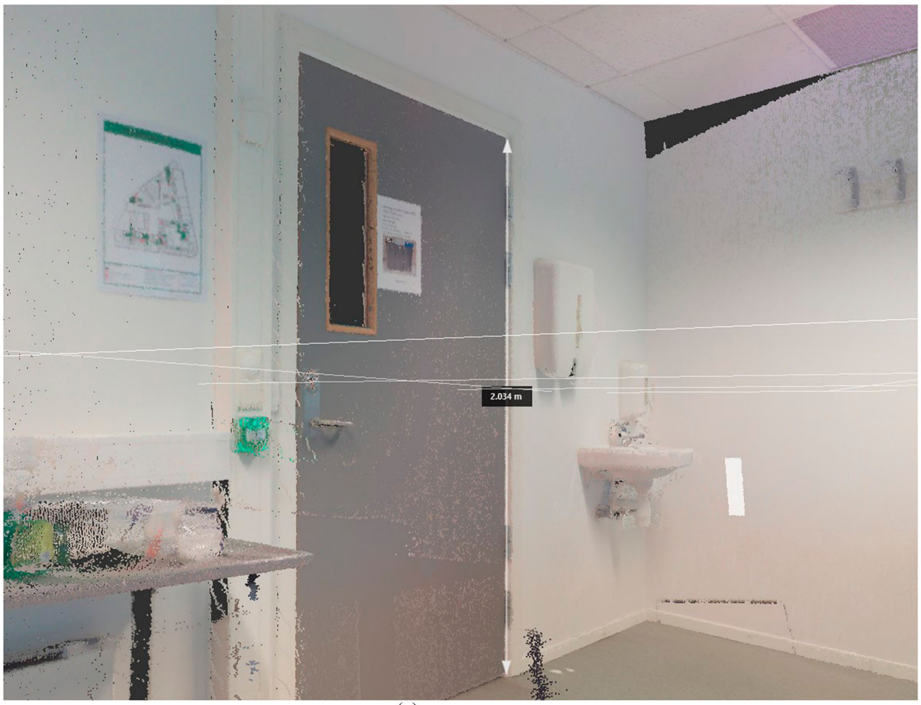


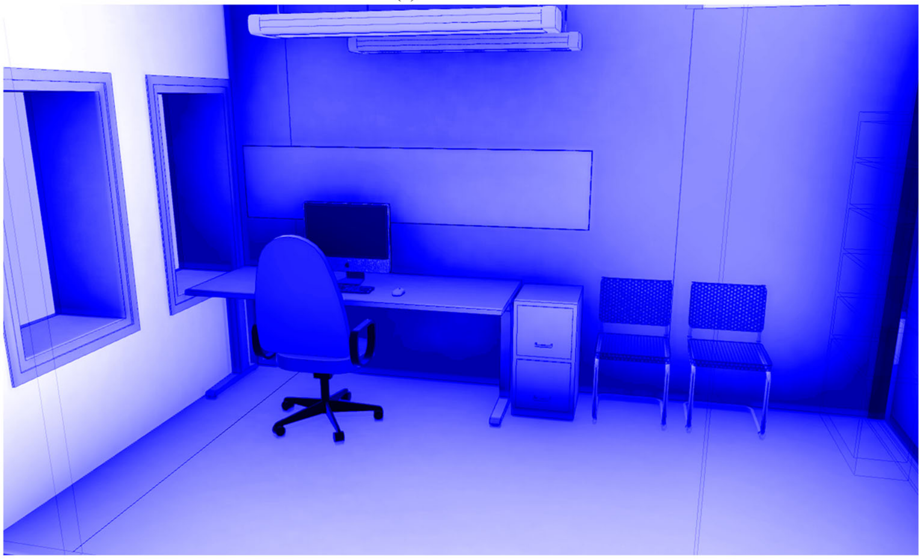
Figure 8. Plugin for sensor management (a), main data extraction components (b), and supply air temperature sensor block (c).

$$
\begin{aligned}
Tcl = 35.7 - 0.028 \cdot (M - W) - 0.155 \cdot Icl \cdot (3.96 \cdot 10^{-8} \cdot Fcl((Tcl + 273)^4 \\
- (Tr + 273)^4) + Fcl \cdot hc \cdot (Tcl - Ta))
\end{aligned} \tag{3}
$$

$$
PPD = 100 - 95 \cdot e^{-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2} \tag{4}
$$



(a)



(b)

Figure 9. A part of the point clouds model and measurements (a), and An example of BIM visualization of occupant comfort (b).

Where: *M* stands for metabolic rate, *L* for body thermal load, *W* (Wm^{-2}) stands for external work, *Ta* (°C) is the average indoor temperature, *Tcl* (°C) is the clothing's temperature, *Pa* (kPa) is the partial vapour pressure, and *fcl*(–) is the body's surface area when fully clothed to its surface area while bare. In addition, *Tr* (°C) represents the average radiant temperature, *Icl* ((m^2)°C W^{-1}) represents the thermal resistance of clothing, *var* (ms^{-1}) represents the relative air velocity to the human body, and *va* (ms^{-1}) represents the air velocity.

All the necessary calculations to find the thermal sensation were made based on Norwegian construction details 421.501 (Aage et al., 2015; Byggforskserien, 2017). During the survey, we register the occupants' answers, and we take measurements at the same time. The air velocity was measured at 1.1 m (the height of the sitting occupant's head). Figures 10, 11, 12 show the survey and measurements results.

2.5. HVACDT components

Simulink models of HVAC components based on artificial neural networks with self-learning capabilities are developed and used to conduct sophisticated, intelligent operations and to depict the HVAC system's Digital Twin model (Figure 13). An endless number of network topologies may be utilized for this purpose, but the simplest structure should be chosen to conserve computing time.

The following are the key equations for the mathematical modelling utilized in Simulink based on Byggforskserien (2017) and Aage et al. (2015), where Table 3 shows the general information regarding the reference case building:

Cooling load (kW):

$$Q_{cooling} = (Mcw \times Cpwater \times (Two - Twi)) \tag{5}$$

Heating load (kW):

$$Q_{heating} = (Mhw \times Cpwater \times (Thi - Tho)) \tag{6}$$

In summer (kW):

$$Q_{air} = (Mai \times Cpair \times (Tui - Tai)) \tag{7}$$

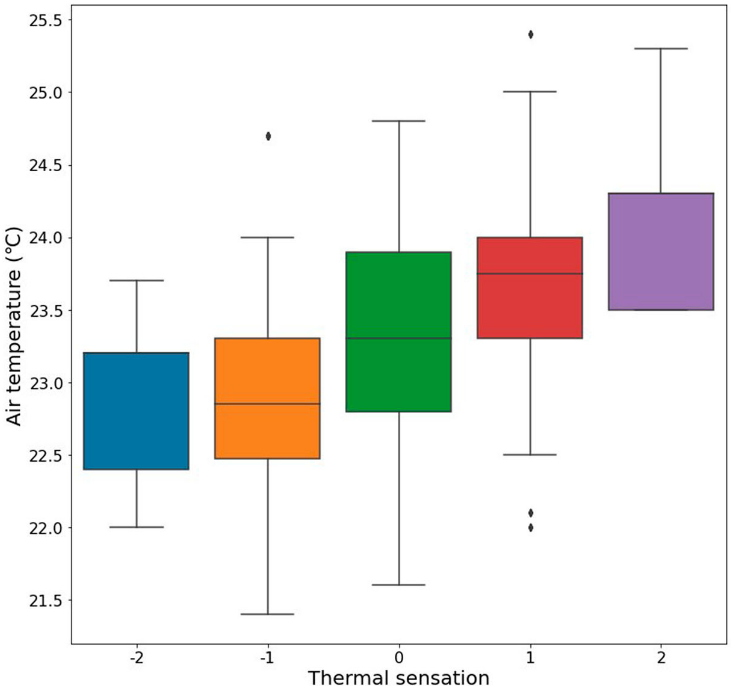
In winter (kW):

$$Q_{air} = (Mai \times Cpair \times (Tui - Ti)) \tag{8}$$

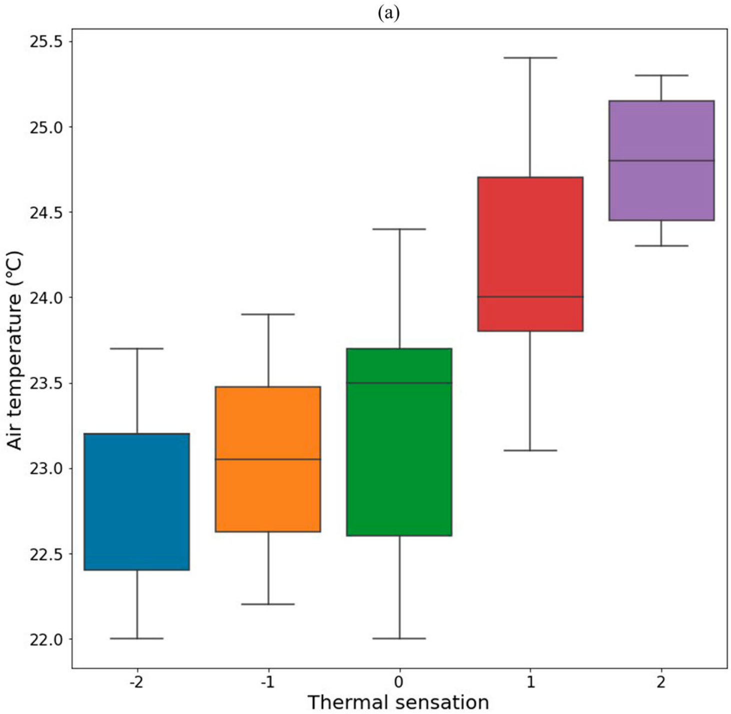
$$\eta = \frac{Q_{cooling/heating}}{Q_{air}} \tag{9}$$

$$Q_{power} = \frac{Q_{cooling/heating}}{COP} \tag{10}$$

$$\begin{aligned} C_{pwatersummer} = {} & (4.218103) + [(-0.0050041 \times (Two - Twi)) + (0.000827196(Two - Twi)^{1.5}) \\ & + (-7.44273{*}10^{-6} \times (Two - Twi)^{2.5}) \\ & + (4.15557 \times 10^{-7} \times (Two - Twi)^{3})] \end{aligned} \tag{11}$$



(a)



(b)

Figure 10. Air temperature (°C) vs. thermal sensation in winter (a), Air temperature (°C) vs. thermal sensation in summer.

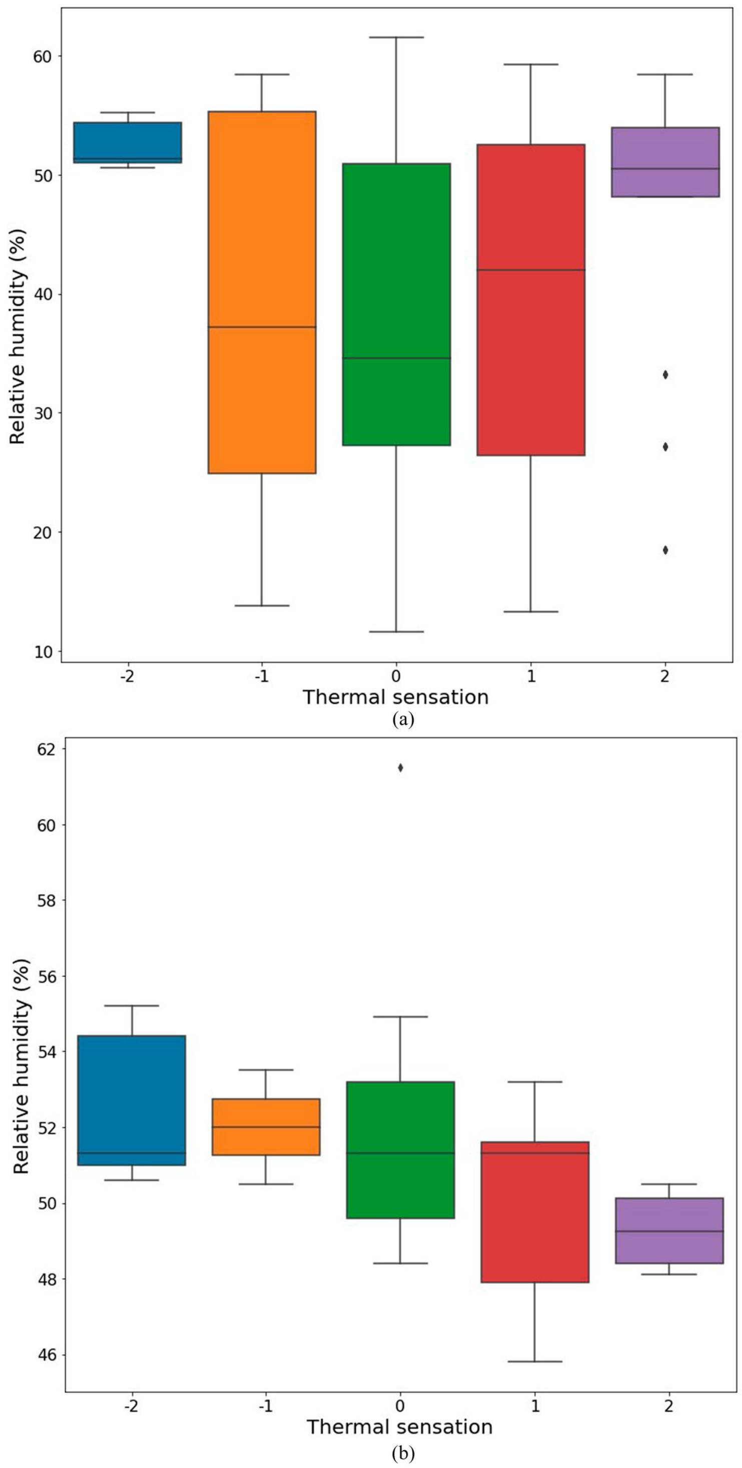
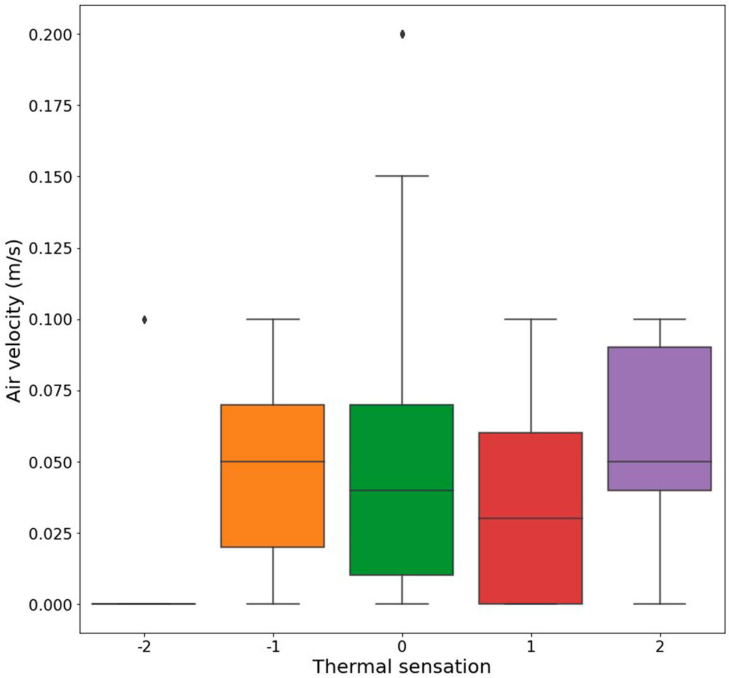
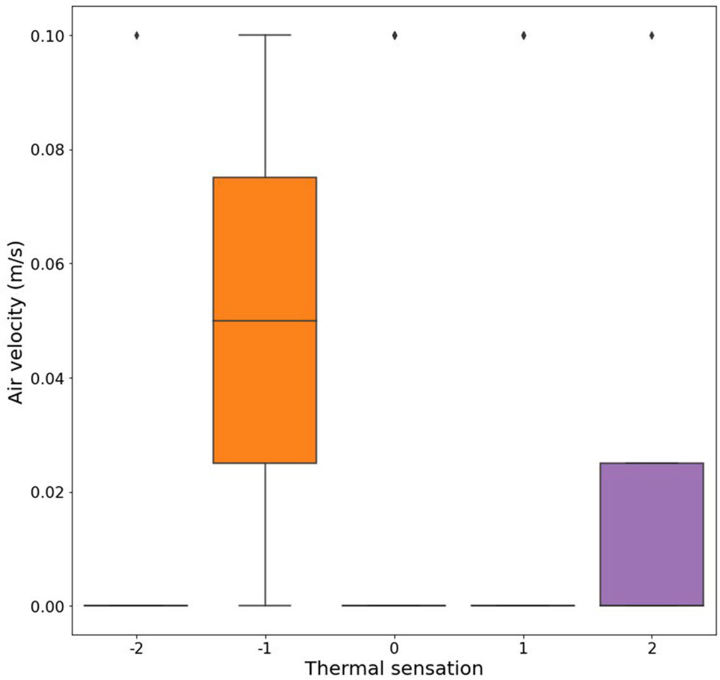


Figure 11. RH(%) vs. thermal sensation in winter (a), RH(%) vs. thermal sensation in summer.



(a)



(b)

Figure 12. Air velocity (m/s) vs. thermal sensation in winter (a), Air velocity (m/s) vs. thermal sensation in summer.

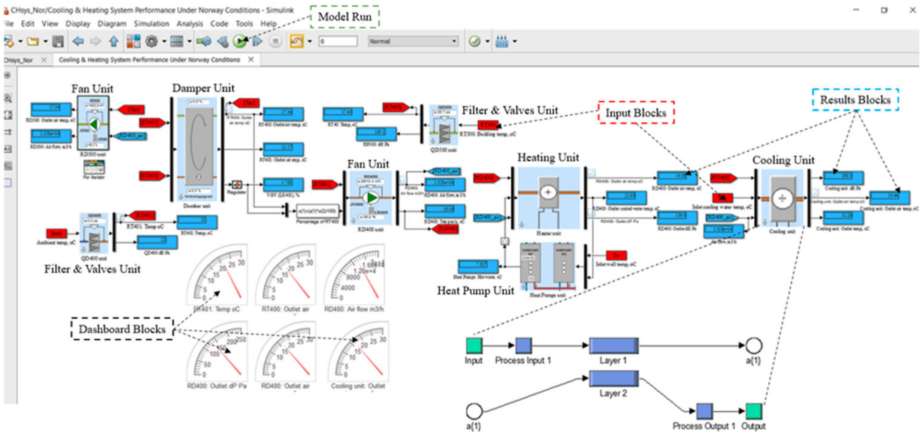


Figure 13. The developed AHU model browser under Simulink toolbox.

Table 3. The values of building envelope data and specific heat capacity.

Parameter	Initial value
External wall U-value (W/(m^2·K))	0.22
Roof U-value (W/(m^2·K))	0.18
External window, doors and glass U-value (W/(m^2·K))	1.6
Ground floor U-value, W/(m^2·K)	0.06
Normalized thermal bridge (W/(m^2·K))	0.03
Airtightness n_{50} (1/h)	0.35
External shading strategy	Qsol (klux) $>$ 40
Internal wall U-value, (W/(m^2·K))	0.62
C_{Pair} (kJ/kgK)	1.018
C_{Pwater} (kJ/kgK) at 20°C	4.186

$$
\begin{aligned}
C_{pwaterwinter} = {} & (4.218103) + [(-0.0050041 \times (Thi - Tho)) + (0.000827196(Thi - Tho)^{1.5}) \\
& + (-7.44273*10^{-6} \times (Thi - Tho)^{2.5}) \\
& + (4.15557 \times 10^{-7} \times (Thi - Tho)^{3})]
\end{aligned} \tag{12}
$$

$$C_{Pair} = 1.005 + (x \times 1.82) \tag{13}$$

$$x = RH \times \theta_s \tag{14}$$

Where: C_{Pair} in kJ/kgK, x is kg per kg dry air. By using measurement data from Landvik station (LMT, 2022), we can calculate monthly averages for temperature and relative humidity, which are converted to x-values using saturated air table. Also, 1.005 in Equation (13) is the dry air heat capacity in kJ/kgK.

The outside dry bulb and wet bulb temperatures affect the load component caused by ventilation or infiltration. This load is computed for the summer, winter, occupied, and unoccupied periods based on the following formulas:

$$q_{inf,s} = \frac{\rho_a \times C_{Pair} \times V^0_{air} \times (T_0 - T_r)}{A_{room}} \tag{15}$$

While the latent component of infiltration is computed by the following:

$$q_{inf,lat} = \frac{\rho_a \times h_{fg} \times V_{air}^0 \times (\omega_0 - \omega_r)}{A_{room}} \tag{16}$$

$$Q_{Fan} = \frac{d_p \times V_{air}}{\nu_{Fan}} \tag{17}$$

Where, ν_{Fan} is fan efficiency, d_p is total pressure (Pa), V_{air} is air volume delivered by the fan, Q_{Fan} power used by the fan (kW).

Each model contains 20 neurons in each of its two hidden layers. The output layer has two neurons and an activation function (tanch) that sums the weighted neurons in the hidden layer (see Section 2.6).

Each component in the HVAC system (e.g. rotary heat exchanger, filters, etc.) had to be validated in Simulink to produce a proper and accurate model. The most energy-intensive components are the fans, cooling units, and heaters, all of which are the subject of this study. Those models may be utilized for various purposes, but the inputs and outputs must first be defined. The models given in Figure 14 are required for such a procedure.

Fans, chilled water supply temperature, dry-bulb temperature (supply air temperature setpoint), and airflow rate are all inputs to the model of a cooling unit, whereas cooling load is the result. System airflow rate and static pressure (duct static pressure setpoint) are inputs to the fan model, which returns fan power. The inputs to the heating unit model are the same as those for the cooling unit: fan airflow rate, heated water supply temperature, entering air dry-bulb temperature, supply air dry bulb temperature (supply air temperature setpoint), and the output is the heating load. Section 2.6 explains how the Simulink model processed and treated sensor data.

Moreover, the minimum airflow rate required by NS 3701:2012 (2012) is considered during the optimization process. Adding the minimal outdoor standard technique in the overall optimization process reduces energy consumption while still meeting the current standard's ventilation requirements. The outside air is determined using a multi-zone approach based on real zone airflow rates in Norwegian standard. The standard specifies two ventilation rates, one to dilute pollutants created by occupants (R_p) and the other to dilute contaminants generated by building-related sources (R_a). The number of zone occupants P_z and the zone floor space A_z determines the needed minimum breathing zone outside air rate. When the economizer is turned off, the following is the minimal outside airflow rate V_{ot}:

$$V_{ot} = \frac{V_{ou}}{E_v} \tag{21}$$

The following are the uncorrected outside air intake flow V_{ou} and the system ventilation efficiency E_v:

$$V_{ou} = \sum((R_{pi} \times P_{zi}) + (R_{ai} \times A_{zi})) \tag{22}$$

$$E_v = \min\left(1 + \frac{V_{ou}}{V_s} - \frac{((R_{pi} \times P_{zi}) + (R_{ai} \times A_{zi}))}{V_{zi}}\right) \tag{23}$$

The optimization technique finds the best zone airflow rates V_{zi} and fan airflow rates V_s in

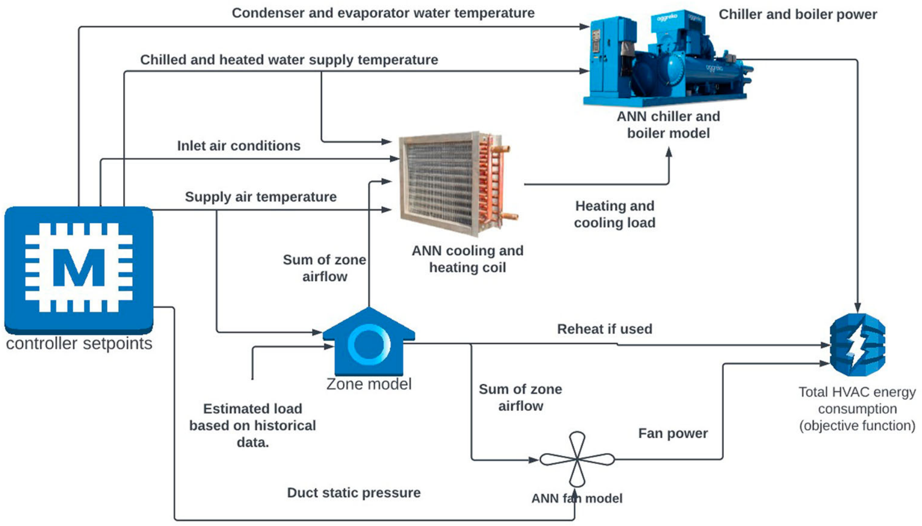


Figure 14. Component model flow chart, Nassif et al. (2005).

Equation (23). For each zone i, the term inside the parentheses is computed, and the E_v is equal to the minimal value.

2.6. ANN modelling

In order to anticipate yearly HVAC energy consumption and the building PPD values, a multilayer perceptron network (MLP) is constructed. As can be seen in Figures 15 and 16, all inputs are connected to the neurons, and all neurons are connected to the output of the MLP network, which is displayed as a three-layer structure (input layer, hidden layer, and output layer).

In the MLP network, the correlation between the input u(k) and output y(k) may be expressed mathematically as follows:

$$y(k) = f_2(w^2 x(k)) + b_2) \tag{24}$$

$$x(k) = f_1(w^1 u(k)) + b_1) \tag{25}$$

Where $x(k)$ is the hidden layer's output. w^2 and w^1 are the weight matrices for the connections between the hidden layer, the output layer, and the input layer. To denote input and output bias, the symbols b_1 and b_2 are used (Ren et al., 2009). f_1 and f_2 indicate the transfer functions of the hidden and output layers, respectively.

This study employs a tangent sigmoid transfer function, which can be represented as:

$$f(z) = \frac{(1 - e^{-2z})}{(1 + e^{-2z})} \tag{26}$$

A mathematical expression for z is $z = f(\sum w_i x_i)$ where i is the neuron's input index, x_i is the input to the neuron, w_i is the weighted factor attached to the input, z is the weighted input (Mohanraj et al., 2012).

The correlation coefficient (R) has been used to measure the correlation between outputs and targets. An R-value of 1 means a close relationship, while a value of 0 signifies a random relationship. The R is defined as Cadenas and Rivera (2009) and X. Xue (2017):

$$R = \frac{\sum_1^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_1^n ((x_i - \bar{x})^2) \sum_1^n ((y_i - \bar{y})^2)}} \tag{27}$$

Where x_i and y_i are the predicted and desired output values from model data, respectively. $\bar{x}$ and $\bar{y}$ are the mean of the predicted and desired output values, respectively. n is the number of data samples (95,000 samples). The Levenberg-Marquardt backpropagation technique will be used to train the network.

Performance of the chosen ANN configuration is assessed by completing training, validation, and testing on various data sets and comparing the results. The data sets were separated into three groups randomly: 80% for training, 10% for validation, and 10% for testing. Throughout the training, a Levenberg-Marquardt optimization technique is used to modify the network in response to the error it generates. Figures 17, 18 and 19 depict the results of the study's training, validation, and testing phases, respectively. The model's energy consumption and PPD estimated and forecasted are very consistent with the results. The PPD value ranges from 5% to 62.44%, while the energy consumption for the heating unit ranges from 3.12 kW to 60.93 kW, and for the cooling unit, it ranges from 1.84 to 62.05%, respectively. One fan consumes between 0.27 and 3.65 kW of energy, depending on its size. The straight lines in the the above mentioned figures represent a one-to-one relationship, suggesting that the measured (target) and simulated (output) fan power are in accord. This demonstrates that the intended network arrangement is practical and can accurately forecast the performance of the building under a variety of scenarios. Figure 20(a) shows the results of the total energy consumption of the HVAC system using ANN compared to the real measurements from sensors (with 88.67% accuracy). Data normalization is used to reduce the size discrepancy between each data collection. Using the StandardScaler approach (Brownlee, 2020), the data is translated into a range of 0 to 1. Finally, the occupants' thermal sensation prediction results are displayed using the confusion matrix approach (MathWorks Nordic, 2022) in Figure 20(b). The algorithm could correctly predict the thermal sensation in most situations (with 92.58% accuracy), as shown in Figure 20(b). By that, our algorithm can predict the total system's energy consumption and thermal sensation with high accuracy.

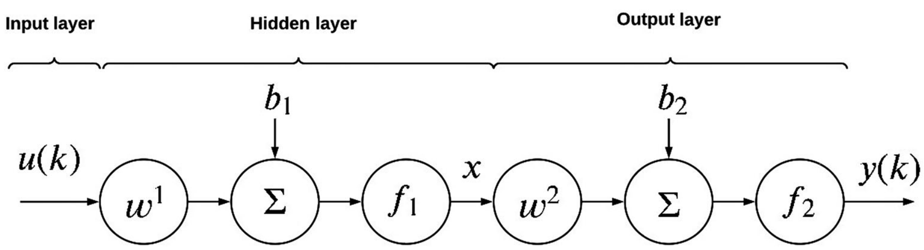


Figure 15. The inputs and outputs in the ANN's structure.

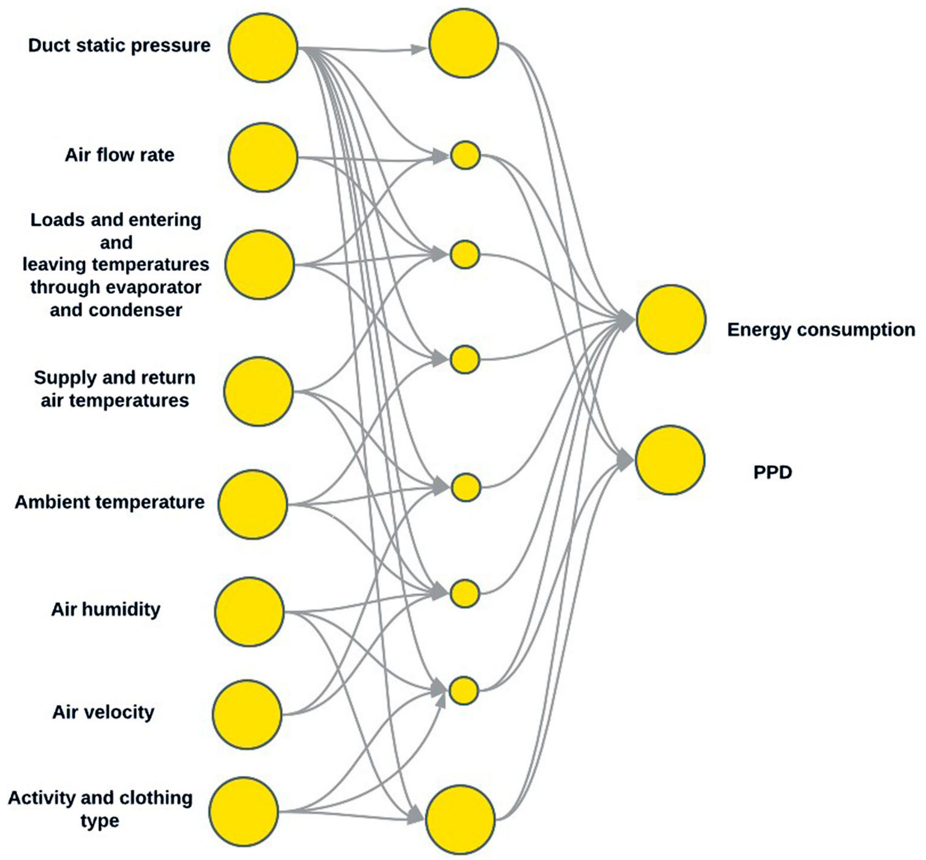


Figure 16. The multilayer perceptron network (MLP).

Additionally, the wavelet neural network (WNN), random forest (RF), and support vector machine (SVM) forecasting models' accuracies have been compared to those of the ANN model using R^2 and Root Mean Square Error (RMSE) to confirm ANN correctness. Figure 21 shows the learning curve of ANN where the training time was 36.27 s. Figure 22 comparative results lead us to conclude the following conclusions;

- The R^2 for the ANN model is the greatest. The SVM, RF, and WNN models have R^2 values of 0.93, 0.88, and 0.83, respectively, showing that the ANN model has the best prediction fitting outcomes.
- The RMSE of the ANN model is the least. The RMSEs of the ANN, WNN, SVM, and RF models are 0.027, 0.282, 0.084, and 0.153, respectively, in Figure 22, demonstrating that the ANN model has the lowest forecast fitting error.

As the ANN energy consumption prediction model has the most significant prediction accuracy and best forecast outcomes, its relationship may be employed as the fitness function of multi-objective optimization, conducive to better achievement of optimization objectives.

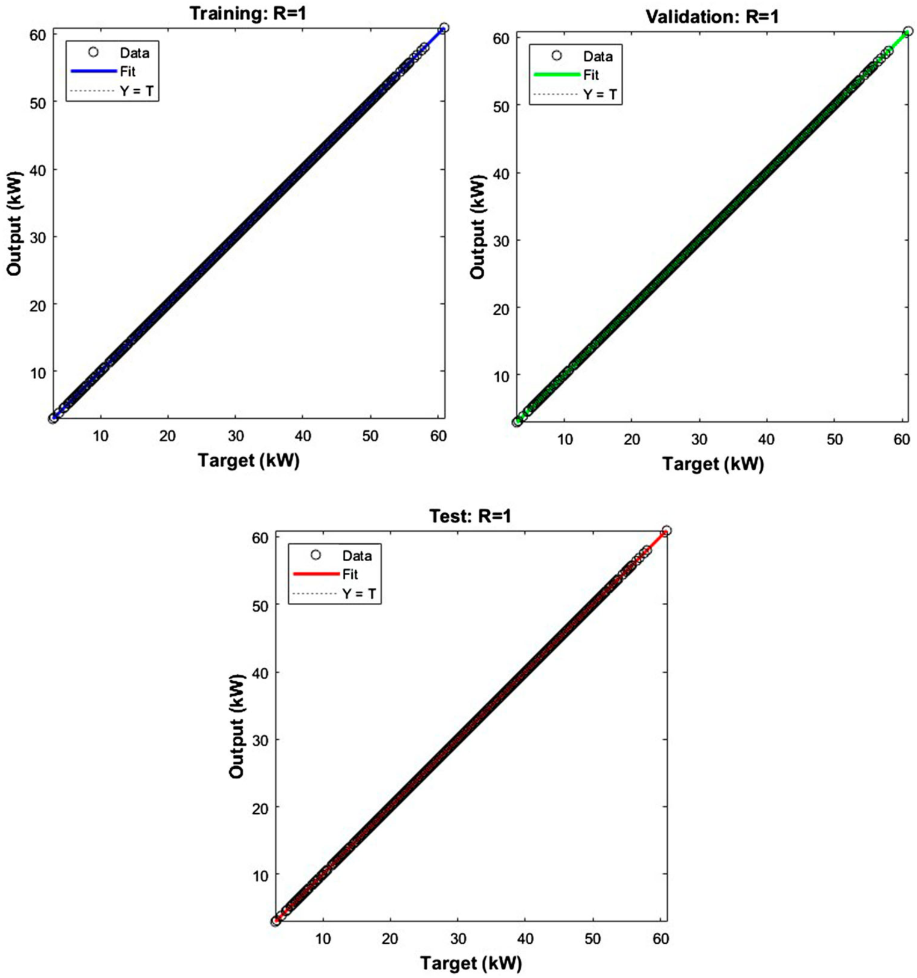


Figure 17. The power consumption results of ANN heating unit model.

2.7. Algorithm and strategy for optimization

The optimization procedure forecasts system performance over a 10-min timeframe (optimization period). As shown in Figure 2, the optimization process is assessed using data from an existing VAV system servicing offices with a total of 30 zones. The loads and external air conditions are considered constant during this short optimization phase and are calculated using the measured data gathered during the prior time. The energy consumed by each component and subsequently the overall energy used in response to the controller setpoints and operating modes are calculated using ANN models. The ANN model for each zone was trained to replicate the real case during the real-time optimization accurately. The ANN training data set of the zones were realistic with a different heating setpoint schedule in zones that will allow the ANN to produce reasonably accurate results throughout the range of possible setpoint schedules.

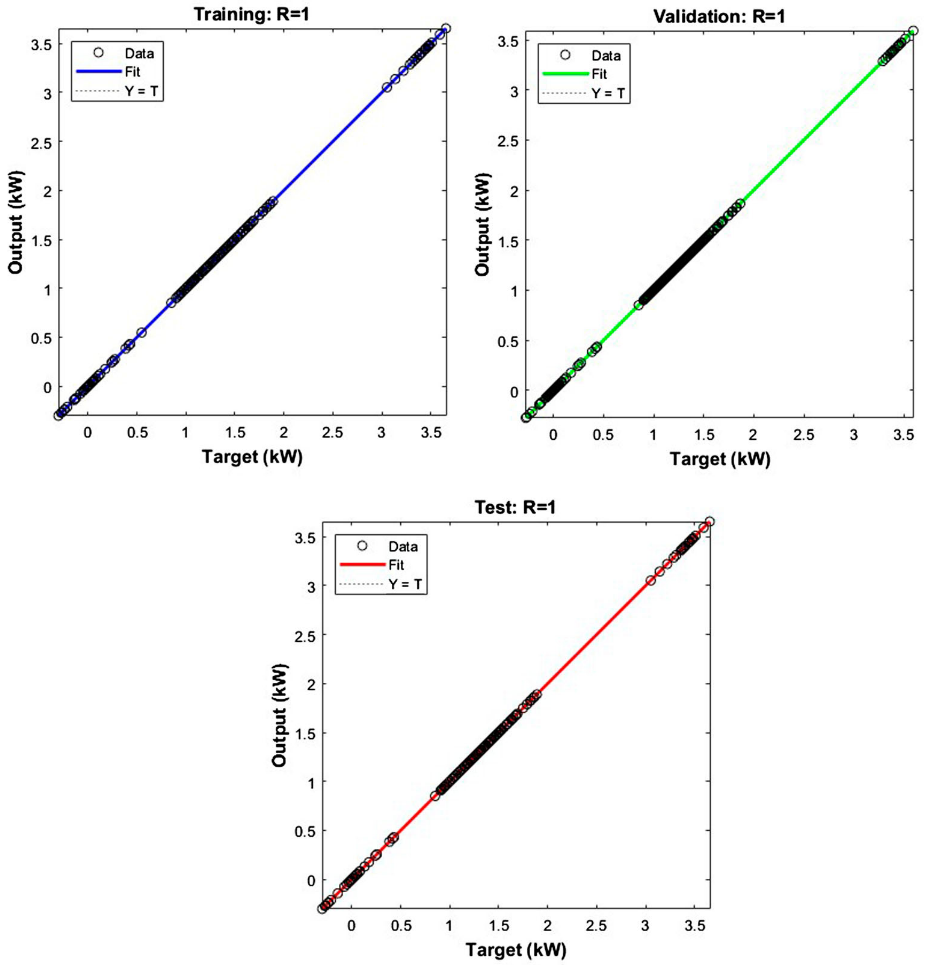


Figure 18. The power consumption results of ANN fan model.

There are two basic types of optimization algorithms: traditional gradient-based methods and gradient-free direct methods (Zhou & Haghighat, 2009). The performance of the gradient-based approach is heavily reliant on the given starting values. This approach cannot be used in the building since the interaction between the building parameters is nonlinear, resulting in discontinuous functions (Wetter & Wright, 2004). Hence, most gradient-based approaches cannot handle discontinuous functions properly.

On the other hand, the gradient-free direct technique is suitable for optimization in construction applications (Zhou & Haghighat, 2009). This is useful for solving complex issues to tackle with gradient-based approaches. The genetic algorithm, which is one of the gradient-free direct approaches, has been used effectively to optimize buildings components (M. Hosamo, 2018, july; Huang & Lam, 1997; W. Wang et al., 2005).

A genetic algorithm (GA) solves both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. GAs search

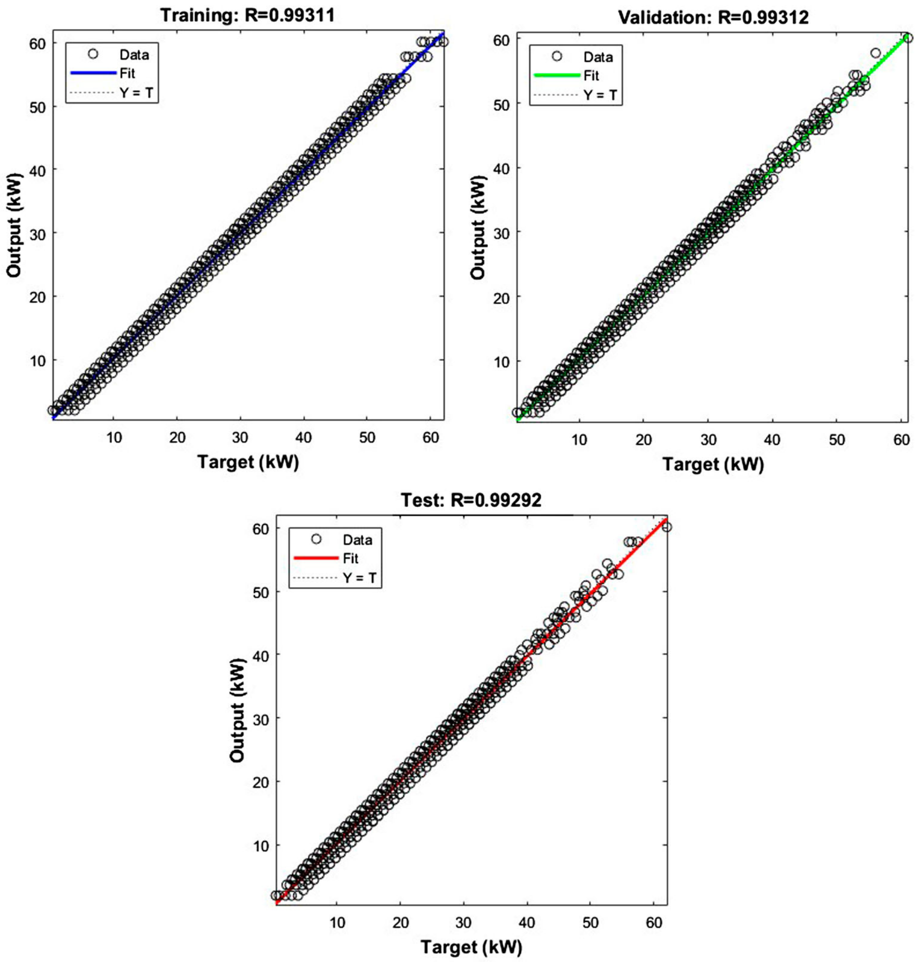


Figure 19. The power consumption results of ANN cooling unit model.

for the optimum solution from one set of possible solutions with various decision-variable values (Goldberg, 1989). This set of potential solutions is called a population. There are several populations in a GA run, and each of these populations is called a generation. Generally, better solutions (i.e. decision-variable values) closer to the optimum solution than the previous generation are created at each new generation (Rajasekar et al., 2015). In the GA context, the set of possible solutions (array of decision-variable values) is defined as a chromosome, while each decision-variable value present in the chromosome is formed by genes (Wardlaw & Sharif, 1999). Population size is the number of chromosomes in a population. The fundamental procedure of the genetic algorithm for the optimization process is shown in Figure 23.

Analysis of Variance (ANOVA) and Support Vector Machine (SVM) are used together in this work (Megantara & Ahmad, 2021; SVM-Anova, 2021) to demonstrate the most critical variables of the optimization process (Table 4). Hence, the ideal point value of optimal

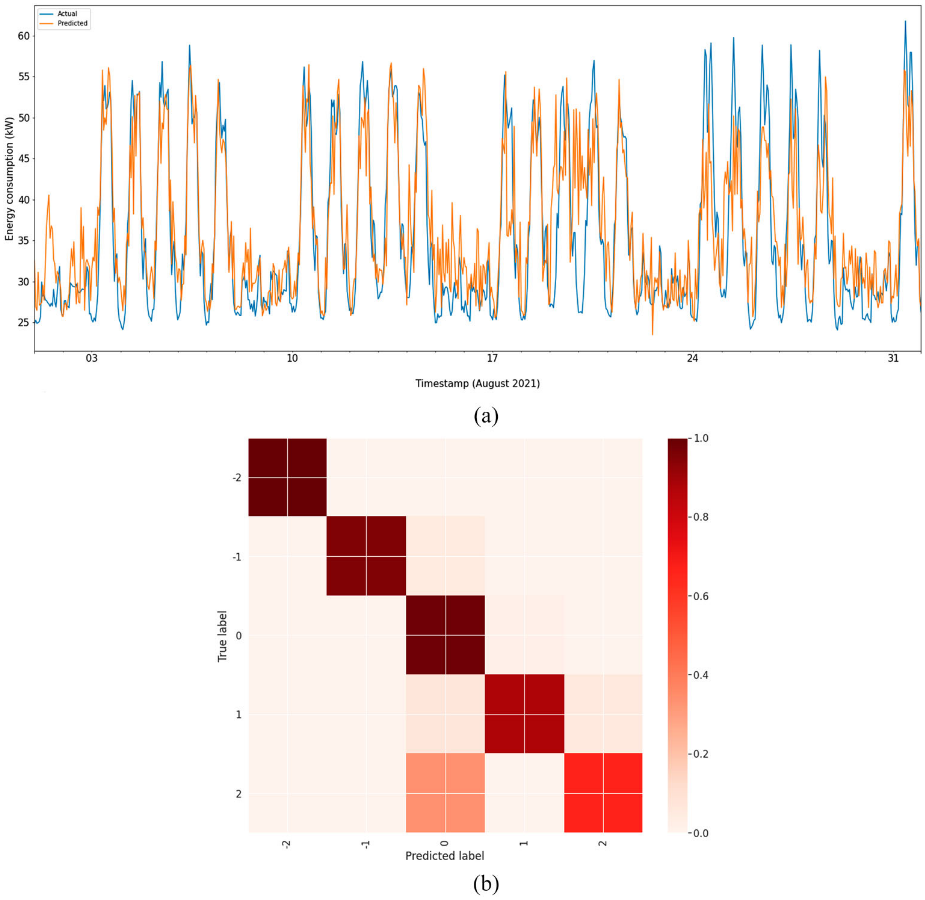


Figure 20. Comparison of total energy consumption of HVAC system between the optimal ANN model and measurements from sensors (a), and confusion matrix of thermal sensation prediction (b).

variables obtained from the multi-objective optimization approach, which can be controlled, is shown in Table 6. Based on the current requirement for the Norwegian building code TEK17 (TEK17, 2017), a good PPD should be less than 10% for optimal thermal comfort. It is, therefore, possible to increase thermal comfort while ensuring low energy usage by using the method presented in this paper.

In this work, multi-objective optimization using two objective functions is used. The first and second goal functions are building energy consumption and PPD. As seen in Figure 16, many factors are chosen as decision variables because they influence energy consumption and PPD when the HVAC system is running. Table 5 shows the range of choice factors created based on the behavior of the current HVAC system in the selected building. The value ranges are based on the Building Management System's measured parameters (BMS) that comes through the BIM model using the previously mentioned plugin.

In Figure 24, the optimization approach used in this work is briefly presented. The method starts with gathering the essential data sets for energy consumption and PPD

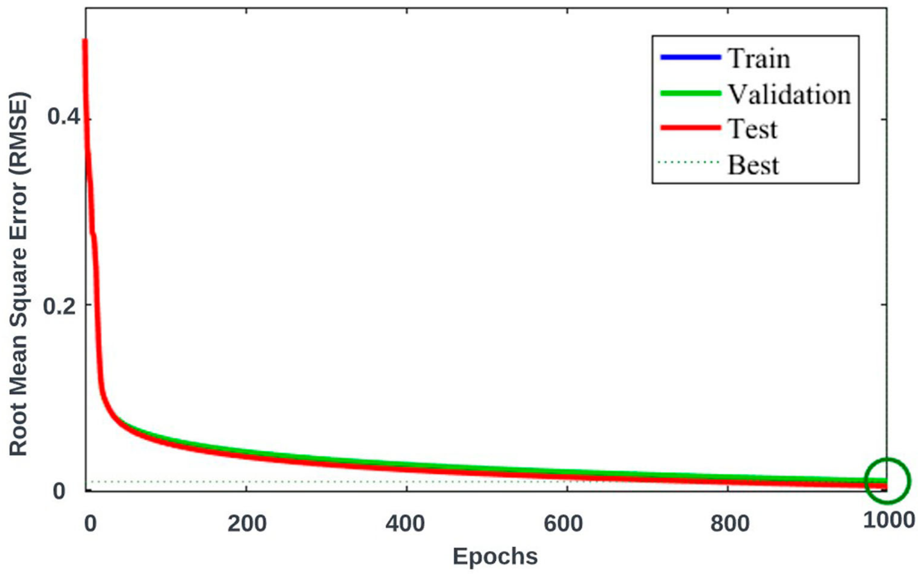


Figure 21. ANN learning curve.

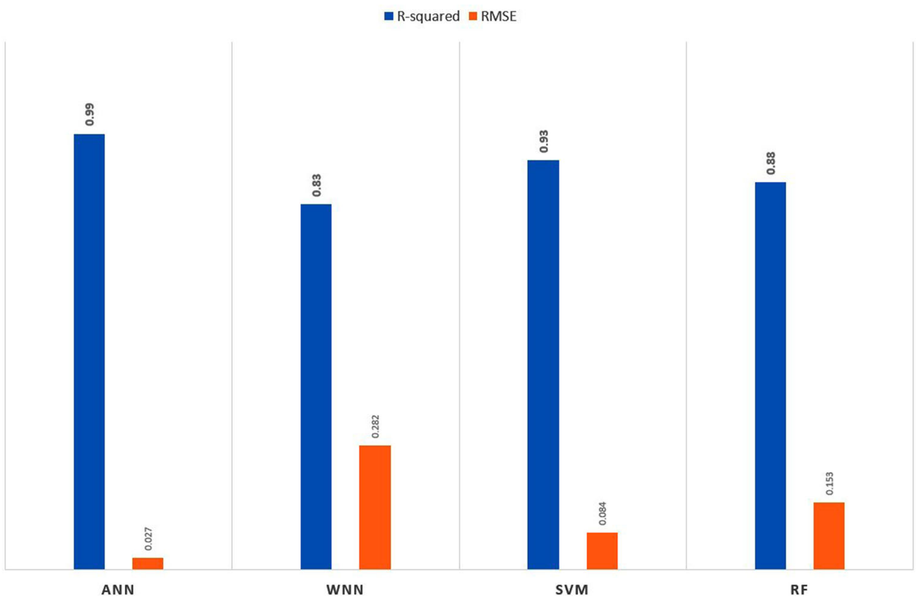


Figure 22. Comparison of the model's accuracy.

utilizing real-world sensor measurements through API via the BMS and surveying the comfort of the building's inhabitants. The optimization issue is then solved using a combination of ANN and MOGA. ANN was used to correlate the data sets between variables and two objectives. Using the new input combination formed by iteration

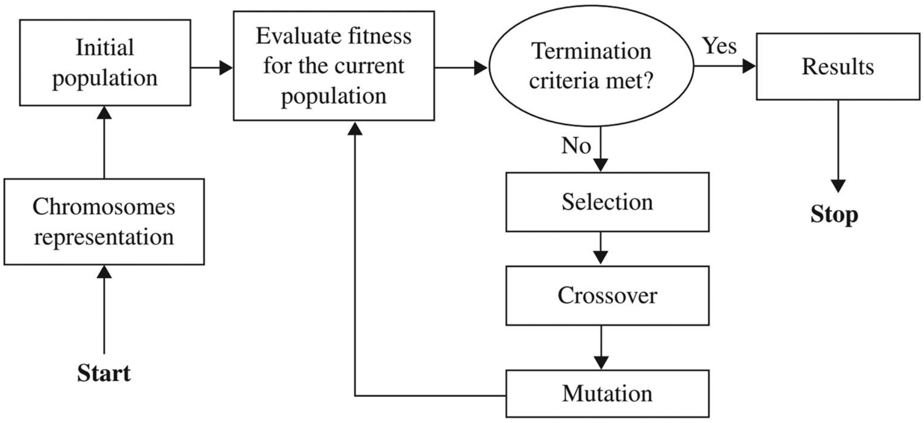


Figure 23. The Overall GA operational process.

Table 4. Top important variables in the optimization process based on the ANOVA-SVM method.

Ranking	Variable	Importance (%)
1	Relative humidity (%)	23.66
2	Air temperature (°C)	21.82
3	Clo	21.42
4	Air velocity (m/sec)	11.67
5	Met	8.18
6	Air flow (l/sec)	3.25
7	Season_Summer	2.71
8	Year	2.65
9	Sex_Female	2.13
10	Sex_Male	2
11	Season_Winter	0.51

Table 5. Input data ranges for optimization that can be controlled by the BMS system (see Figure 7).

	Range		
Variables	Summer	Winter	Unit
Supply air temperature	20–25	20–25	°C
Supply cooling water temperature	10–14	–	°C
Supply heating water temperature	–	22–45	°C
Duct static pressure setpoint	100–250	100–250	Pa
Air humidity	40–60	30–60	%
Outside airflow rate	According to Equations (21), (22), and (23)		

of decision variables in the specified range, the network obtained from the initial training predicts PPD and HVAC energy usage. The lower and upper bounds of optimization are determined by each decision variable's minimum and maximum values. In addition, the evolutionary algorithm will determine the best option for minimizing PPD and HVAC energy usage.

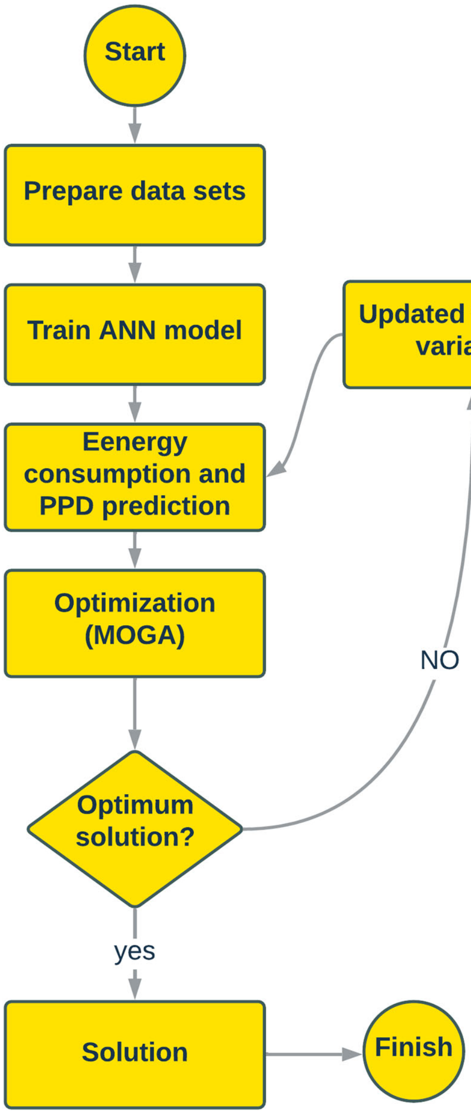


Figure 24. The framework for optimization.

The following equation can be used to define a multi-objective problem (Shirazi et al., 2012):

Find

$$x = (x_i)\Lambda_i = 1, 2, \ldots .N_{par} \tag{28}$$

Minimizing

$$f_i(x)\Lambda_i = 1, 2, \ldots .N_{obj} \tag{29}$$

$$g_j(x) = 0, \quad \Lambda_j = 1, 2, \ldots .m \tag{30}$$

$$h_k(x) = 0, \quad \Lambda_k = 1, 2, \ldots .n \tag{31}$$

where x denotes the vectors of the decision variables, N_{par} determines the number of decision variables, $f_i(x)$ is objective function, N_{obj} is number of objective functions, $g_j(x)$ and $h_k(x)$ outline equality and inequality constraints, while m and n display the number of equality and inequality restrictions, respectively.

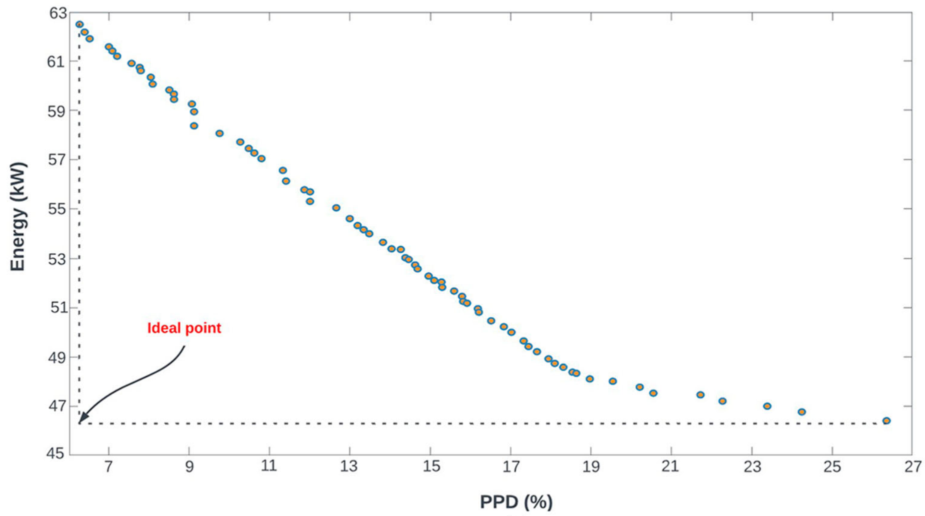
3. Results

The Pareto optimum solution for minimizing energy consumption and PPD in the referenced building is shown in Figure 25, where the optimization process took around 7.055 h. It denotes the incompatibility of the two objective functions. The decrease in energy consumption ranging from 62.8 kW to 46.4 kW led to a rise in PPD from 6.2% to 27% in winter, and ranging from 59 kW to 42.9 kW led to a rise in PPD from 3.4% to 22.4% in summer. The minimum PPD is 6.2% for winter and 3.4% for summer, representing the maximum thermal comfort. However, this is associated with the highest energy consumption, 62.8 kW in winter and 59 kW in summer. The lowest energy consumption is 46.4 kW in winter and 42.9 kW in summer but with high PPD (27% for winter and 22.4% in summer). The best solution to choose depends if energy, thermal comfort, or both were considered the main priority.

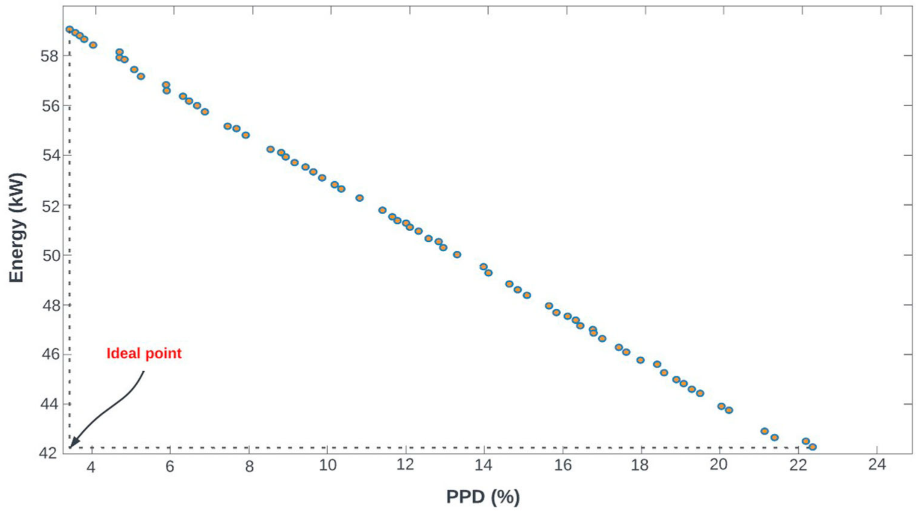
The results of the Pareto front are non-dominated in the multi-objective optimization approach (Aminyavari et al., 2014). A practical approach would be to choose a solution that corresponds to the intended operating point. To select the optimal solution, the approach for order preference by similarity to an ideal solution (TOPSIS) has been selected (Abdo-Allah et al., 2018; Ahmadi et al., 2013). As a result, the shortest distance to the ideal solution and the longest distance to the non-ideal solution may be used to determine the best option (Yue, 2011).

In Figure 25 and Table 6, the best solution (ideal point) between the two objectives is when the energy consumption and a PPD of 42.9 kW and a PPD of 3.4%, respectively, for summer, and when the energy consumption and a PPD of 46.4 kW and a PPD of 6.2%, respectively for winter. This means a reduction in energy consumption of around 22% in summer and 15.6% in winter compared to the average energy consumption of 55 kW. The same for PPD, where the original value is 15.7% in winter and 10.6% in summer, which means a reduction of 6.05% in winter and 6.7% in summer.

As previously indicated, the dynamic ANN models used in the optimization process use information from an existing VAV system that serves workplaces with 30 zones. In response to the controller setpoints and operating modes, the ANN models calculate the energy consumed by each component before calculating the overall energy consumption. The optimization procedure forecasts system performance over a 10-min timeframe (optimization period). The loads and outside air quality during this brief optimization phase are approximated from the last measured data and are presumed to be constant. The models estimate the goal function (total energy use) and transmit it back to the MOGA to be eliminated, evolved, and passed on to the next generation. The MOGA delivers a series of



(a)



(b)

Figure 25. Optimization results for (a) winter and (b) summer.

Table 6. Optimal variables related to the optimal solution (ideal point) in summer and winter (considering the most important variables that affect the results significantly and can be controlled).

	Optimized scenario		
Variable	Summer	Winter	Unit
Relative humidity	49.4	34.6	%
Supply air temperature	20.6	22.4	°C
Supply heating water temperature	–	32	°C
Supply cooling water temperature	12	–	°C
Duct static pressure setpoint	120	120	Pa
Outside airflow rate	2500	2400	l/s
PPD	3.4	6.2	%
Energy	42.9	46.4	kW

individual solutions comprising trial controller setpoints. This procedure is repeated until near-optimal or optimum solutions are found where the non-optimal setpoints are gathered from the system's real functioning.

The sum of the fan, electric reheat, and chiller powers equals the total energy used. As a consequence of the optimization procedure, the average cooling energy savings for those four days is roughly 13.2%, and 10.8% for the three summer months (June, July, and August), keeping the PPD under 10%.

Three restrictions on the static duct pressure are applied during the optimization process: (1) the maximum static duct pressure based on the design condition; (2) the minimum static duct pressure based on the fan performance specifications to avoid the instability region; and (3) the zone airflow rate is limited to be less than the maximum available zone airflow rate as determined by Equation (23).

Due to the operation at the low duct static pressure setpoint, the fan may save much energy. Furthermore, increased supply air temperature raises chilled water return temperature, improving chiller efficiency. The whole-system optimization method identifies the solution that uses the least amount of total energy. Furthermore, based on a constant minimum damper setting, the recommended outside airflow rate is lower than the actual outdoor airflow rate (150 l/s). The multi-zone ventilation approach of Equations (21), (22), and (23) are used to determine the appropriate outside airflow rate.

3.1. Stream the results to the BIM model

In the optimization process, data pushback is critical. In contrast to the data extraction process, the data pushback procedure imports the data from the optimum design option from MATLAB into the BIM model (Figure 26). The optimal sensor data variables from the Excel template are selected using a plugin, and the design loop is closed using the whole framework shown in the Figure 1.

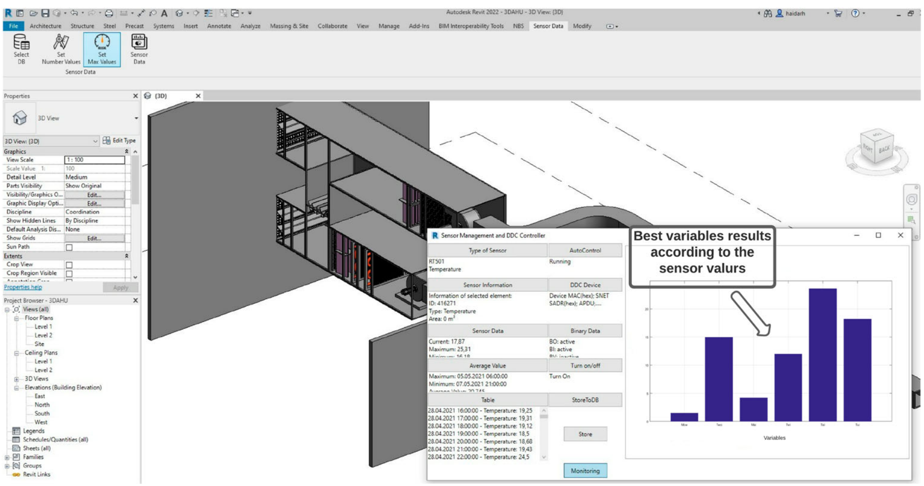


Figure 26. Stream the results from the optimization process to BIM.

4. Discussion

A Pareto-optimal front may be generated using MOGA for multi-objective building energy consumption optimization and the ideal point approach to arrive at the optimum solution for building energy consumption and thermal comfort.

Several previous studies have been conducted on building energy consumption and thermal comfort optimization (Ascione et al., 2020; Chang et al., 2020; Chaturvedi et al., 2022; B. Chen et al., 2021; R. Chen et al., 2022; Delač et al., 2022; Himmetoğlu et al., 2022; H. Li & Wang, 2019; Lu et al., 2020; Rabani et al., 2021; Rosso et al., 2020; Seghier et al., 2022; Q. Xue et al., 2022; J. Zhao & Du, 2020). Those studies focussed on specific parameters that affect building energy consumption. However, non of these studies conducted a comprehensive HVAC system optimization. In addition, our study used real data from sensors and developed a real-time optimization process in a Digital Twin framework. Furthermore, in this study, a huge database has been used to cover various possible solutions for the optimization process. Also, the suggested HVACDT framework in this research can be applied to any building system, including VAV systems, radiant cooling systems, all-air systems, etc. This is because the HVACDT has been built to import the data from any API system and integrate the results exported from the BIM with the BMS systems. Furthermore, this study implemented all the results in the BIM environment so that it can interact with the BIM environment immediately and stream the best solution in both directions (to and from BIM). As a result, the optimization technique suggested in this study gives valuable insights into the value of various control methods of HVAC set-points change in enhancing building energy performance and thermal comfort.

The enhancement of building performance with an all-air system in terms of energy usage as well as thermal and visual comfort criteria might be explored in future work on the optimization process. Additionally, it is crucial to utilize a dynamic visual comfort measure, such as usable daylight illuminance or daylight autonomy, to position the shade device.

Speaking about the building's cost-effectiveness in light of the information related to energy savings is equally noteworthy. The building's energy usage was much lower due to the optimization process than it was for the reference building. Eventually, the facility's overall life cycle costs may be most significantly influenced by lower operational expenses brought on by enhanced building energy performance. Parallel to that, it's critical to research other machine learning and optimization techniques for forecasting and improving energy consumption in buildings, such as particle swarm optimization (PSO), GLSSVM, ANN-SVM, and non-domination-based genetic algorithms (NSGA II, NSGA III).

Additionally, establishing ways for integrating BIM data into the building energy system has grown crucial as open data standards such as COBie (2021) and Industry Foundation Classes (IFC) (2021) emerge. A possible approach is to use suitable semantic web standards, which control the creation of ontologies and provide a more lightweight solution than monolithic data interchange techniques (Rezgui et al., 2011). For instance, the BrickSchema adds a semantic framework to describe physical, logical, and virtual assets (BrickSchema, 2021). Sensors are defined in the Semantic Sensor Network (SSN) ontology as components of a system deployed in a building with specified measurement capability (Dibowski et al., 2018). The Building Topology Ontology (BOT) enables the representation of any building's topology (Rasmussen et al., 2017). However, there is a lack of research on using ontology techniques to integrate BIM, energy management, and thermal comfort data in one framework.

5. Conclusions

This study provides an HVACDT framework for an office building designed and examined to assess energy consumption and thermal comfort. The HVACDT prototype system was created to address the need for an integrated BIM-based system by merging C# programming and multi-objective algorithm optimization into a single workflow to make the HVAC system more efficient.

The HVACDT system's development includes creating and preparing the BIM model for data extraction, MATLAB programming which focuses on customizing ANN and MOGA to suit the case study and generate optimization solutions, and pushing back the optimized solution to the BIM model.

The current research methods can tackle complicated optimization challenges in HVAC systems and building designs. A multi-objective optimization approach that combines ANN and MOGA has been effectively employed in Matlab to define the ideal building operation. For energy usage and PPD, the suggested ANN configuration has a high forecast accuracy. According to the optimization results, compared to the actual design, the multi-objective optimization significantly improves HVAC operation for thermal comfort while maintaining low energy usage. The Pareto front's spreading solution generates a plethora of design possibilities. The findings of this study can assist facility managers in designing and selecting a control strategy for efficiently operating HVAC systems.

Integrating BIM, C# programming, and multi-objective optimization techniques into HVACDT's design process allowed for a more thorough examination of HVAC design configurations and improved support for designers' decisions. In addition. A new data management process based on Application Programming Interfaces (Revit API) in a programming environment (C# and Windows Presentation Foundation (WPF) instead of utilizing the existing exchange data format, such as IFC, is provided in this study.

According to the findings, the average cooling energy savings for four summer days is around 13.2%, 10.8% for the three summer months (June, July, and August), helping to maintain the PPD below 10%. The minimum PPD is 6.2% for winter and 3.4% for summer, corresponding to 46.4 and 42.9 kW, respectively.

In this research, the HVACDT focussed on the HVAC system exclusively. The decision-making process can be improved in the future by including more variables, such as the energy usage index (EUI), daylighting, life cycle costs, and the efficiency of natural ventilation.

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Disclosure statement

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Appendix D

Paper 4- Multiobjective optimization of building energy consumption and thermal comfort based on integrated BIM framework with machine learning-NSGA II

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Multiobjective optimization of building energy consumption and thermal comfort based on integrated BIM framework with machine learning-NSGA II

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Detailed parametric analysis and measurements are required to reduce building energy usage while maintaining acceptable thermal conditions. This research suggested a system that combines Building Information Modeling (BIM), machine learning, and the non-dominated sorting genetic algorithm-II (NSGA II) to investigate the impact of building factors on energy usage and find the optimal design. A plugin is developed to receive sensor data and export all necessary information from BIM to MSSQL and Excel. The BIM model was imported to IDA Indoor Climate and Energy (IDA ICE) to execute an energy consumption simulation and then a pairwise test to produce the sample data set. To study the data set and develop a prediction model between building factors and energy usage, 11 machine learning algorithms are used. The best algorithm was Group Least Square Support Vector Machine (GLSSVM), later employed in NSGA II as the building energy consumption fitness function using Dynamo software. An NSGA II multi-objective optimization model is designed to reduce building energy consumption and optimize interior thermal comfort (measured by the predicted percentage of dissatisfied (PPD)). The Pareto front is calculated, and the optimum point approach is used to find the best combination of building envelope characteristics, HVAC setpoints, shading parameters, lighting, and air infiltration. The feasibility and effectiveness of the developed framework are demonstrated using a case study of an upper secondary school building in Norway; the results show that: (1) The GLSSVM has a unique capacity to forecast building energy use with high accuracy: R^2 of 0.99, an RMSE of 1.2, MSE of 1.44, and MAE of 0.89; (2) Building energy consumption and thermal comfort may be successfully improved by the GLSSVM-NSGA II hybrid technique, which reduces energy consumption by 37.5% and increases thermal comfort by 33.5%, respectively.

1. Introduction

There is no doubt that buildings play a substantial role in the overall energy use and consequently the rate of global warming. The construction industry accounts for 40% of the EU's total energy consumption and 40% of the EU's total emissions of greenhouse gases (GHG) [1,2]. Non-residential buildings (including holiday houses), for example, account for about 62% of the total building stock in Norway [3], and 40% of the total energy use in buildings (where residential and non-residential buildings account for 40% of the Norwegian total energy use) [4]. In addition, energy usage in Norway's non-residential sector has increased by around 31% since 1990, whereas residential building energy use has increased by about 9% [4], highlighting the critical need to improve the energy performance of this building type. Building energy efficiency is considerably more difficult in cold climate nations due to harsh temperature conditions and high heating demands, contributing 40% to 60% of total national energy usage [5]. Hence, energy efficiency techniques should be explored in various sectors to achieve comprehensive sustainable development, including the construction sector [6].

The location climate, building layout, building scale, building envelope and ventilation impact how much energy a building con-

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Nomenclature

AE	Actual energy value
ANN	Artificial neural network
ANOVA	Analysis of variance
API	Application Programming Interface
ASHRAE	American society of heating, refrigerating and air-conditioning engineers
BACnet	Building automation and control networks
BEM	Building energy management
BIM	Building information modeling
BMS	Building management system
BOT	Building ontology topology
COBie	Construction operations building information exchange
DNN	Deep neural network
DT	Decision tree
ELN	Elastic net
FFNN	Feed forward neural network
FM	Facility management
GA	Genetic algorithm
GB	Gradient boosting
GBDT	Gradient boosted decision trees
GBM	Gradient boosting machines
GLSSVM	Group least square support vector machine
GMDH	Group method of data handling
GMM	Gaussian mixture modelling
GPR	Gaussian process regression
HVAC	Heating, ventilation, and air conditioning
IFC	Industry foundation classes
IoT	Internet of things
KNN	K-nearest neighbors
LR	Linear regression
LSSVM	Least squares support vector machine
LSTM	Long short-term memory
MARS	Multivariate adaptive regression splines
ML	Machine learning
MLR	Multiple linear regression
n,i,j	Numbers
NN	Neural network
NSGA	Non-dominated Sorting Genetic Algorithm
OLS	Ordinary least squares
PE	Predicted energy value
PMV	Predicted mean vote
PPD	Predicted percentage of dissatisfied
RF	Random forest
RMSE	Root Mean Square Error
RNN	Recurrent neural networks
SSN	Semantic sensor network
SVM	Support vector machine
SVR	Support vector regression
URL	Uniform resource locator
VAV	Variable air volume
XGB	Extreme gradient boosting
y	Output, number

sumes [7]. Most essential among them is the building envelope since its design defines how a building will respond to external conditions [8]. For building performance optimization, building shape, facade form, and facade construction are the three main factors to consider during the early optimization stages. All of these factors are included in a building's form: its orientation, its shape, the layout of its rooms, as well as its controllable characteristics in digital building form. The window-wall layout [9,10], single-window size [11], and shading component size [12] comprise the facade form variables. Glazing insulation, light transmission, and opaque envelope insulation are some of the factors in facade construction [13–15]. In addition, building envelope heat transfer accounts for over half of the energy utilized by non-residential buildings' heating, ventilation and air conditioning systems (HVAC) during the year [16]. Therefore, building envelope characteristics integrated with HVAC setpoints must be optimized in light of the acute energy scarcity to decrease energy consumption in future building operations.

On the other hand, when examining the energy efficiency of buildings, the thermal comfort and well-being of inhabitants are essential factors to consider, especially in educational and office buildings where indoor climate affects students' and employees' performance. It becomes considerably more difficult when the goal is to increase the energy performance of the building towards zero energy buildings (ZEB) while still providing thermal comfort [17]. However, improved interior climatic conditions may increase energy use. For this reason, an extensive number of studies have examined the influence of various building parameters on the energy performance of buildings using a variety of methodologies, including data-driven methods [18], optimization techniques [19], and a mix of both approaches [20,21]. According to [22], optimization approaches may employ machine learning techniques and algorithms, such as genetic algorithms, to identify the ideal parameters for a given building, which is the focus of this paper.

Eventually, utilizing building products as optimization variables to conduct building performance optimization procedures might improve the accuracy of performance evaluation and speed up the implementation of the results. However, a significant challenge with the optimization process is the disagreement between the optimization outcomes and the project's basic modulus. Uncertainty about building performance and variables might lead to considerable discrepancies between possible solutions and results from optimizations. As a result, this study will use the IDA ICE software to simulate the imported Building Information Modeling (BIM) model and create a batch of energy consumption data, therefore presenting a way for obtaining a sufficient data set on building energy usage. To get energy consumption data, however, the usage of BIM + IDA ICE requires that parameters be defined, and the data is calculated using a simulation, which is wasteful when the data sample size is increased for design optimization. As a result, more complex and efficient algorithms are required to accurately anticipate energy consumption under various combinations of characteristics in a building's envelope design parameters, which are obviously missing.

2. Literature review

The literature review in this paper focuses on building energy simulation in combination with BIM, Machine learning (ML), multi-objective optimization, and visual programming, which are the methodologies utilized to design the integrated system presented in this paper.

2.1. Visual programming

BIM is the process of creating and managing digital representations of a building's physical and functional attributes [23]. An integrated database of coordinated information may be utilized to examine different performance criteria in a BIM model, such as architectural, structural, energy, acoustical, and lighting [24]. Furthermore, performance-based design using BIM is becoming more common in the building design disciplines [24,25].

The currently available research on building energy performance analysis uses BIM as the central data model for various energy simulation tools such as EnergyPlus [26–28], TRANSYS [28], and IDA ICE [29]. Using Industry Foundation Classes (IFC) to solve interoperability concerns is a frequent strategy in this sort of studies. However, performance-based design is more successful when BIM and parametric modeling are combined. For example, [25] developed ThemalOpt, a thermal simulation and optimization tool based on BIM. To improve previous studies, designers require a simple visual way to set up building parameters using robust open-source Multi-objective optimization (MOO) algorithms.

Visual programming interfaces can replace complex conventional coding with a visual metaphor of connecting small blocks of independent functionalities into a whole system or procedure, which designers can use to implement their sophisticated design intent (e.g., through the use of conditional statements in parametric BIM) [30]. Thanks to visual programming, it is possible to build computer programs visually instead of textually, where non-programmers or inexperienced programmers may find a more visual style of programming more straightforward to comprehend. McNeel Rhinoceros® and Autodesk Revit® both include visual programming tools called Grasshopper and Dynamo, respectively.

According to the studies above, this research was conducted using Revit and Dynamo, which differ from Grasshopper in that designers have used them for a more extended period. Many new possibilities open up for designers working in Rhino or Revit thanks to Grasshopper and Dynamo, built on Python's visual programming language. Using Dynamo, Revit users do not have to master the Revit API to construct automation routines for the software [31]. As a result, the learning curve for new users of Revit is much shorter, which means more customization options for them. In contrast to typical Revit tools, Dynamo allows designers to explore iterative frameworks in the context of a BIM tool by allowing users to construct systematic linkages to alter model elements and parameters. In addition, Dynamo can be connected with extra libraries like MOO that can be used for the optimization process.

2.2. Integration of building performance data with BIM

In the construction industry, building information modeling (BIM) is a shared knowledge resource for information about a facility that serves as a solid foundation for choices throughout its life cycle, defined as the period from its inception until its end of life phase. The advancement of BIM technology and its ever-increasing use in the construction sector have resulted in the progressive expansion of various types of information linked to buildings carried by BIM during the past few decades [32]. Researchers and practitioners have also sought to apply BIM in the context of building life-cycle analysis [33,34], among other things. When it comes to energy efficiency and environmental optimization design, there is a significant difficulty; namely, the BIM framework was not designed to integrate building performance information and data as rapidly as is necessary. These difficulties include data loss during an encounter, a lack of appropriate data standards, and highly severe technological challenges [35,36]. The absence of performance data (such as energy consumption and occupant comfort) integration capabilities has significantly hampered building information modeling (BIM) adoption in sustainable building design. As a result, a BIM-based data management and application framework for sustainable buildings must be established urgently.

The consequences of a lack of such framework are noticed throughout the whole life of the buildings. In the Architecture, Engineering, and Construction (AEC) industry, where data is often constrained to heterogeneous silos and seldom accessed beyond their native area [37], significant difficulties surround data integration. Increased operating costs and eventually poor building performance are two of the problems that may result [37].

The methodology of Building Information Modelling (BIM) has facilitated the flow of information during the design and construction phases. However, during the operating phase, this interchange remains a difficulty. BIM may be thought of as a central store for building data accessible to all project stakeholders throughout the project's lifecycle. However, BIM is simply one silo of information within the larger context of the business, and other pertinent data must also be exploited to improve both the building and the organization [38]. As a result, a system is required that can support a variety of building schemes, dimensions, purposes, configurations, and communication protocols such as BACnet that originate from disparate hardware installed throughout the building and owned by disparate supplier firms [39,40].

Additionally, establishing ways for integrating BIM data into the building energy system has grown crucial as open data standards such as COBie [41] and IFC (Industry Foundation Classes) [42] emerge. A possible approach is to use suitable semantic web standards, which control the creation of ontologies and provide a more lightweight solution than monolithic data interchange techniques [43]. For instance, the BrickSchema adds a semantic framework to the description of physical, logical, and virtual assets [44]. Sensors are defined in the Semantic Sensor Network (SSN) ontology as components of a system deployed in a building with specified measurement capability [45]. The Building Topology Ontology (BOT), which enables the representation of any building's topology [46]. However, there is a lack of research on using ontology techniques to integrate BIM, energy management, and thermal comfort data in one framework.

In this work, a plug-into integrate sensors data in BIM is developed. In addition, BRICK, BOT, and SSN ontologies are used based on COBie data to help retrieve information from an IFC model, transfer data into the COBie data standard, and provide BIM data into energy systems to address data exchange and interoperability challenges.

2.3. Artificial intelligence of building energy consumption

With the development of computer technology, artificial intelligence (AI) has attracted increasing attention as a flexible and accurate data-driven method. Machine learning (ML) technology is widely used in building analysis, modeling, and prediction [47]. ML algorithms have self-learning capabilities and can rapidly search for optimal solutions, making them suitable for solving complex nonlinear problems [48,49]. Several studies have used machine learning for building energy consumption predictions [50,51]. Other researchers developed new ML models to overcome the inequality constraints of the conventional ML models; for example, the least-squares support vector machine (LSSVM) has been used to overcome the abnormal regression in Support vector machine (SVM) [52,53].

Table 1 summarizes a few studies that used machine learning to predict building energy consumption, including some of the most used Regression methods like SVR, LR, and DT. Out from the Table 1, it is obvious that investigating the best energy use prediction remains a complex task, as there is no general agreement on the most suitable algorithm for energy prediction. Hence, in this research, the selected ML algorithms combine the most utilized algorithms and hybrid algorithms that are yet to receive much attention in energy prediction. This paper will use 11 machine

Table 1
Summary of machine learning approaches used in literature to predict the energy consumption of buildings.

Reference	Algorithm type	Description
[54]	ANN, SVM, LR	This paper focuses on applying new models to solve prediction challenges and improving model parameters or input samples for improved performance. Other factors of load prediction are broken down into meteorological conditions, building attributes, and occupancy behavior in the study.
[55]	SVM, ANN, Decision trees, Data driven models	This study examines the scopes of prediction, data attributes, and pre-processing data methods, including machine learning algorithms for prediction and performance metrics for assessment.
[56]	ANN, SVM, Hybrid ANN, Hybrid SVM	According to this study, artificial intelligence is the most appropriate strategy for managing nonlinear elements since it can deliver higher predicting performance. A hybrid of two forecasting methods, as opposed to a single forecasting approach might potentially produce more exact findings than a single forecasting method.
[57]	ANN, SVM, Ensemble model, LR	The authors evaluate AI-based building energy prediction approaches, focusing on ensemble models. The ideas and applications of multiple linear regression, artificial neural networks, support vector regression, and ensemble prediction models have been covered. This paper also discusses the benefits and drawbacks of each model type.
[58]	LR, FFNN, SVR, LS-SVM and others	Seven machine learning approaches were evaluated on two different data sets. The authors evaluated each approach's pros, drawbacks, and technical advantages. The results indicate that LS-SVM is the optimal approach for estimating the future energy usage of each home.
[59]	RNN, LSTM	Models for medium- to long-term projections of power consumption patterns in commercial and residential buildings are proposed in this work using two innovative deep RNN with LSTM models. Compared to a 3-layer multi-layered perceptron (MLP) model, the suggested RNN model fails to estimate aggregate load profiles over a 1-year time horizon.
[60]	Hybrid NN-SVM	A unique method for forecasting hourly energy load in a short time, as well as forecasting the daily consumption for the upcoming months, is presented in this paper. The technique is based on the NN-SVM with RGA optimization. Based on the findings, this new technique thoroughly depicts daily and weekly load changes and a reliable prediction of upcoming month consumption with high accuracy.
[53]	ANN, SVR, LS-SVM, GPR, GMM	This paper aims to provide an innovative hybrid modeling technique for estimating residential building energy use. This study combines data-driven techniques with forward physics-based models. The analysis described here predicts power consumption using five-minute interval data. The results of the final data analysis suggest that hybrid modeling is marginally superior to conventional data-driven methods for hourly forecasting.
[61]	DNN, RF, SVR, GBM, XGB, MLR, ELN	The potential of deep learning in building cooling load prediction is investigated using seven different algorithms. The results demonstrate that the extreme gradient boosting (XGB) technique demonstrates superior prediction to other methods.
[62]	DNN, ANN, GB, SVM, KNN, DT, LR	The accuracy of nine machine learning approaches for forecasting yearly energy usagewas examined in this study. DNN outperformed other models in predicting energy usage. ANN, GB, and SVM are also consideredefficient prediction methods in this study.
[52]	SVM, ANN, LSSVM,GMDH, GLSSVM	This study demonstrates that NN and SVM are the most often employed artificial intelligence models in building energy use prediction. A GMDH-LSSVM hybrid model was suggested in this research, and it was discovered to have a promising forecasting potential when applied to different time series forecasting areas.
[63]	OLS,RF, SVR, GPR,NN, MARS	This study puts a variety of machine learning algorithms to the test in the context of "building performance simulations." the results show that GPR generated the most accurate models in general, followed by NN and MARS.

learning algorithms, including LR, ANN, SVM, GPR, DNN, RF, XGB, NN-SVM, LSSVM, GMDH, and GLSSVM. The results from those algorithms will be compared, and the most accurate one will be used for the optimization process.

2.4. Optimization algorithm

In general, reducing energy usage is not enough to optimize building design. The ideal design option must also suit indoor climate criteria [64]. However, in building design, energy consumption and indoor climate are important but opposing goals. Considering that, determining the ideal design becomes challenging due to the various parameters and tactics involved in the optimization process [65]. Therefore, this study obtains the ideal design parameters for a building envelope using a multi-objective optimization approach with energy consumption and thermal comfort as objective functions. The genetic algorithm (GA), invented by Holland [66], is one of the most extensively used multi-objective optimization algorithms [67]. However, The GA can not preserve population variety while keeping exceptional individuals from the parent generation [68]. Srinivas and Deb devised a nondominated sorting genetic algorithm (NSGA) in 1994 to solve the GA's disadvantages and minimize the overproduction of offspring [69]. Due to the computational complexity of NSGA, the optimization outcomes are not significantly improved compared to GA. Debra et al. proposed, therefore, an NSGA II [70]. NSGA II can quickly find the optimal solution, perform selective sorting, and retain the superior individuals from the parent generation in the offspring to form a set of nondominated Pareto optimal solutions [71]. Thus, NSGA II is implemented in this study as the multi-objective optimization of building energy usage. NSGA II will be implemented through visual programming (Dynamo) using Optimo, which is a multi-objective optimization tool that allows Dynamo users to apply evolutionary algorithms to solve issues with single and multiple objectives [72].

2.5. Combine machine learning with a multi-objective optimization algorithm

An appropriate fitness function for NSGA II is required to speed convergence and locate the optimum solution. Empirical formulae or computer simulations are usually used to determine the fitness functions. Zhang constructed mathematical models that serve as a fitness function for a genetic algorithm based on empirical formulae to optimize the parameters [73]. Naderi et al. used EnergyPlus to improve the design and control characteristics of a smart shading blind [74]. Bruno et al. utilized the minor yearly energy usage and minimum construction cost from EnergyPlus as fitness functions [75]. However, the empirical equations cannot be changed to unique building circumstances, and calculating the fitness values of several individuals using simulation software is computationally costly while reducing optimization efficiency. In order to overcome the restrictions of the previously utilized fitness functions, it was recommended that ML be used to develop a surrogate model of simulation software as the fitness function of the optimization method [63]. Lin et al. employed neural networks to generate thermal comfort and overall energy consumption metamodels [76]. Nasruddin et al. used an artificial neural network and a multi-objective GA to optimize the operation of a two-chiller system in a building [77]. Wang et al. used Gradient Boosting Decision Trees (GBDT) to generate building performance metamodels [78]. In conclusion, intelligent algorithms as fitness functions can increase optimization algorithms' adaptability and efficiency [79]. The current work provides a multi-objective optimization approach for building energy consumption that combines machine learning and NSGA II.

Out from that, following are the primary research questions: (1) How to use simulation tools to simulate the BIM model and acquire energy consumption data for the ML model? (2) How to create an ML model that connects the building's energy usage to the primary influencing elements of the building envelope? (3) In terms of building energy consumption and thermal comfort, how can the ideal solution be established using NSGA II in visual programming (Dynamo)?.

The current work proposes a multi-objective optimization approach that integrates machine learning with NSGA II via Dynamo to enable intelligent prediction and optimization of building energy usage. The ML model is trained and validated to create a fast estimating building energy use model based on IDA ICE simulation data. The optimization target is then set to the surrogate model for energy consumption and the empirical formula for thermal comfort. Finally, multi-objective optimization is performed using the NSGA II through Dynamo. 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 the optimization process, which was previously unexplored in literature. The novel aspects of this research are as follows: (1) Develop a plug-in in Revit that can receive sensor data (temperature, pressure etc.) from the equipment in a school building in Norway and use this data to validate the IDA ICE model. (2) Developing a multi-objective optimization framework for concurrently improving a building's energy performance and indoor comfort, which can increase the viability of energy consumption optimization solutions. (3) Using machine learning as the fitness function to alleviate the difficulties of traditional prediction methods in terms of accuracy and efficiency. (4) Using visual programming to create a hybrid technique for predicting and optimizing a building's energy performance and other functions, which make it easier to feedback the optimization results in BIM model as well as the building's management system to increase its sustainability.

3. The proposed framework

This paper provides a novel multi-objective optimization strategy for reducing energy consumption in buildings while simultaneously increasing occupant comfort. The framework to enhance the building energy consumption data generated by IDA ICE was developed using eleven machine learning algorithms and the NSGA II technique. The flow chart for the suggested framework is depicted in Fig. 1. This framework comprises five stages, which will be discussed in further detail in the following sections.

3.1. Data collection for optimization process

This stage represents the blue box in Fig. (1). The initial stage of the proposed framework consists of preparing the BIM model for data extraction as well as the development of a plug-in that streams sensor data from the HVAC system and rooms in buildings into the BIM model, transforming the BIM model into a database that contains all of the information required to carry out the optimization process. It is necessary to confirm that the BIM model has all the geometric and thermal characteristics required for the computation as part of the preparation procedure. An accurate BIM model of the structure in issue should be accessible to facilitate data extraction throughout the data extraction procedure. For buildings without a BIM model, laser scanning [80] or 2D drawings can be used to create the building envelope elements.

3.1.1. Data gleaned from the BIM model

In this paper, the BIM model will be used in two different ways: as input for the simulation process and as a way of visualizing the outcomes of the simulation. A database of BIM models from which all of the relevant data is retrieved is required for the optimization framework to function correctly. As a result, it must be carefully modeled, and all of the required thermal and geometric characteristics of the building envelope elements must be correctly allocated to the different elements. According to the definition of the level of development (LOD) [81], it is advised to have a BIM model with a LOD of 300 or above in order to extract both the thermal and geometric data associated with the proposed framework. Autodesk Revit® 2022 [41] will be used in this study as a BIM authorizing tool because of its accessibility to researchers and its incorporation into an open-source visual programming environment (Dynamo) [82,83].

IFC (Industrial Foundation Classes (Fig. 2)) and COBie (Construction Operations Building Information Exchange are information exchange specifications for the lifetime capture [84,85] in the energy management and optimization process. The IFC file structure includes geometric information as well as object classes, relations, and resources. IFC may contain various semantic data, such as construction component costs and timelines [86]. COBie can also give information on the functioning and administration of projects [41] in real-time. As a result, whereas IFC may give geometric and semantic information in BIM models, COBie should include more information, such as location data, asset details, documentation, and graphical data, among other things.

COBie needs spatial information (space characteristics) for two reasons: (1) Space objects are critical for managing space, occupants, and energy. (2) Spaces are necessary for equipment location. Additionally, the BIM model's element ID (included in COBie) will be used as a differentiating characteristic for extracting elements for optimization and when pushing optimization findings back into the BIM model and replacing the original element with the optimized one.

As a result, this paper used a COBie extension for Revit to extract the necessary information from BIM models for optimization and transmit it to the building's energy management system. A semantic approach will then transform heterogeneous building data sources into semantically enhanced knowledge.

3.1.2. Integrate sensor data in BIM model

Several sensors have been installed in various rooms and HVAC systems across the building. Air and water supply and return temperatures, flow rates, energy consumption, control system set-

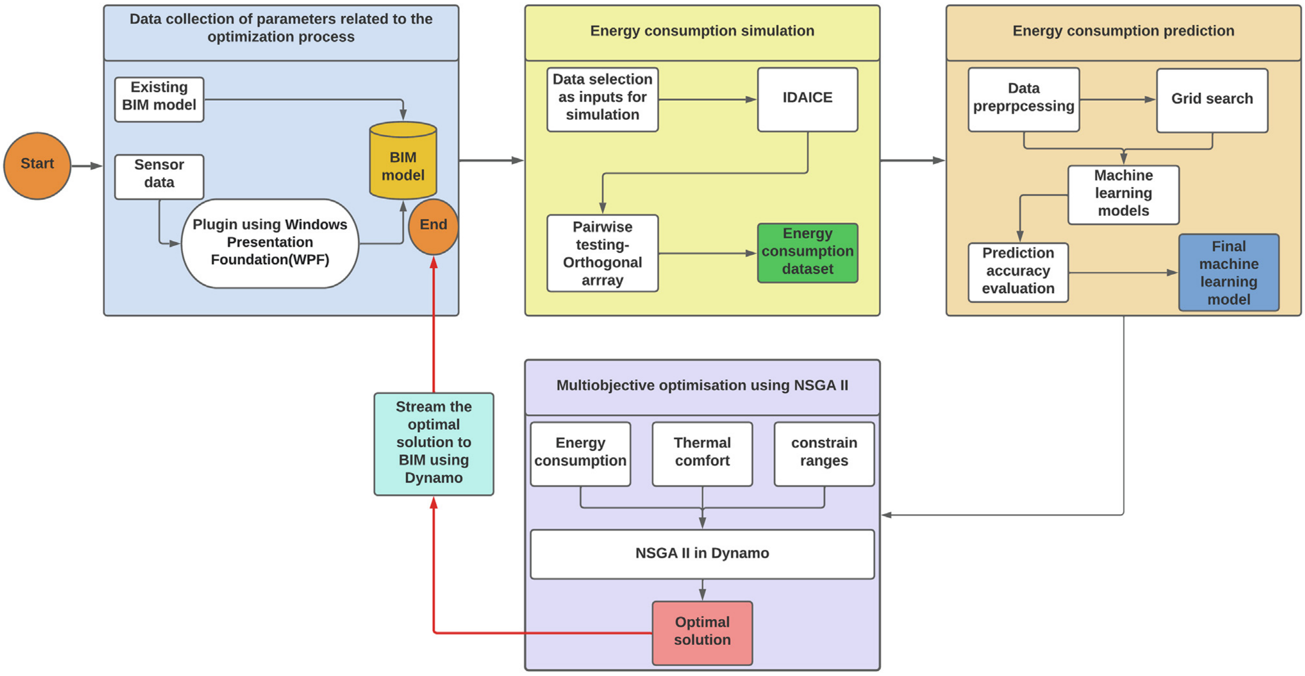


Fig. 1. Overview of the multi-objective optimization process.

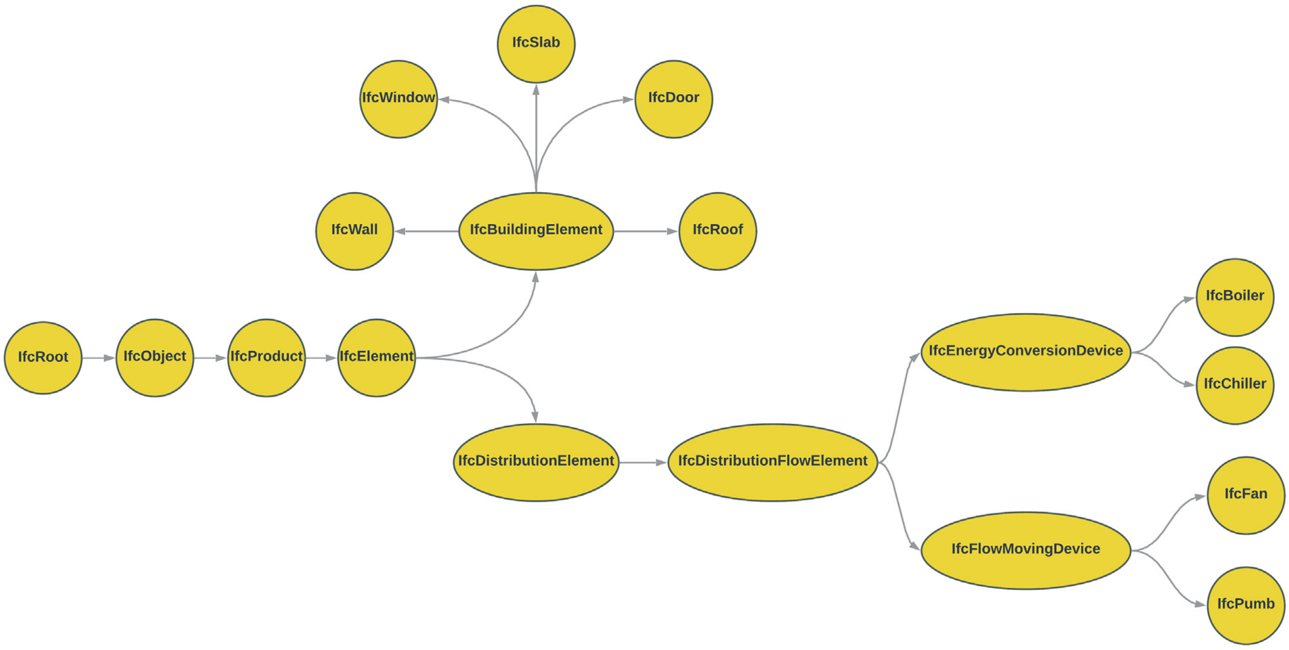


Fig. 2. Part of IFC schema that describes the correlations between energy simulation parameters..

points, humidity, CO2, and outdoor air temperature are all measured using these sensors. Access to these sensors required first gaining access to the BMS, which enabled us to monitor and record all of the essential data. However, it was not feasible to immediately extract the BMS system's data. As a result, with the assistance of a development team, it was required to implement a BACnet Restful API [87] on top of a standard BMS. In this work, Postman software [88] has been used to obtain JSON files [89] from BMS using the API built and then convert them to Excel using Python programming language. Hence, we have an automated procedure to retrieve real-time data and update the excel file continually. Additionally, the Regio controller governs the temperature of a room and the functioning of other systems in the space. Fig. 3 shows the control system.

As a next step, Windows Presentation Foundation (WPF) programming [91] in Microsoft Visual Studio Community 2019 was used to develop a Revit plugin to read the real-time sensor data and save them to MSSQL database while keeping BIM up to date. In addition, a threshold was added to the plugin to give colors of the room based on occupant comfort conditions in the building.

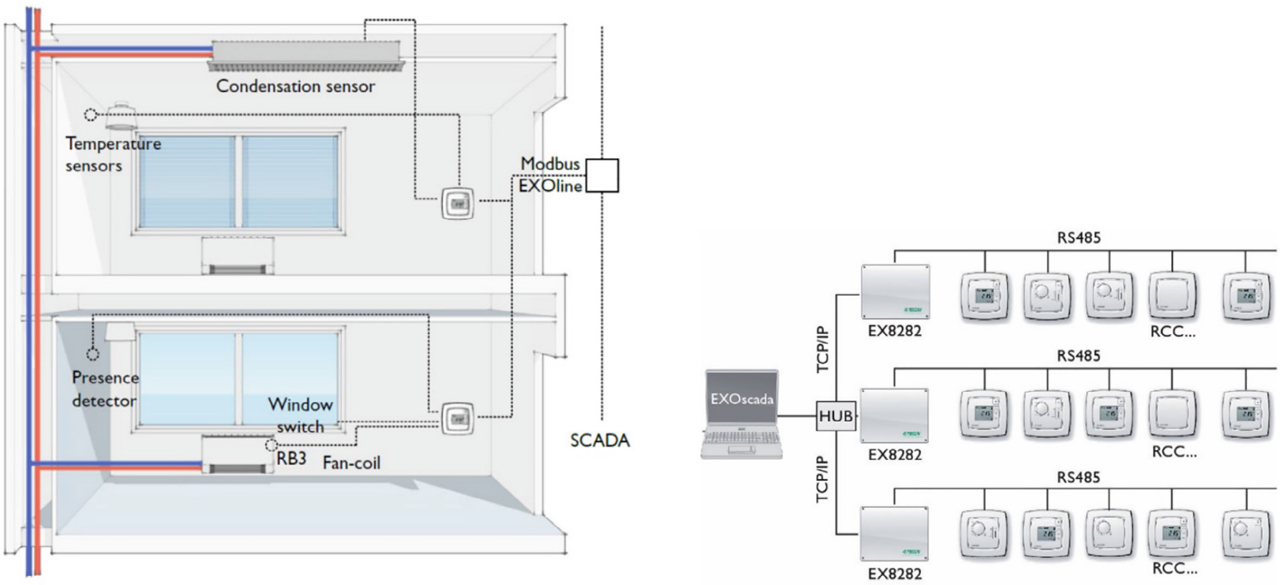


Fig. 3. An illustration of the control system [90].

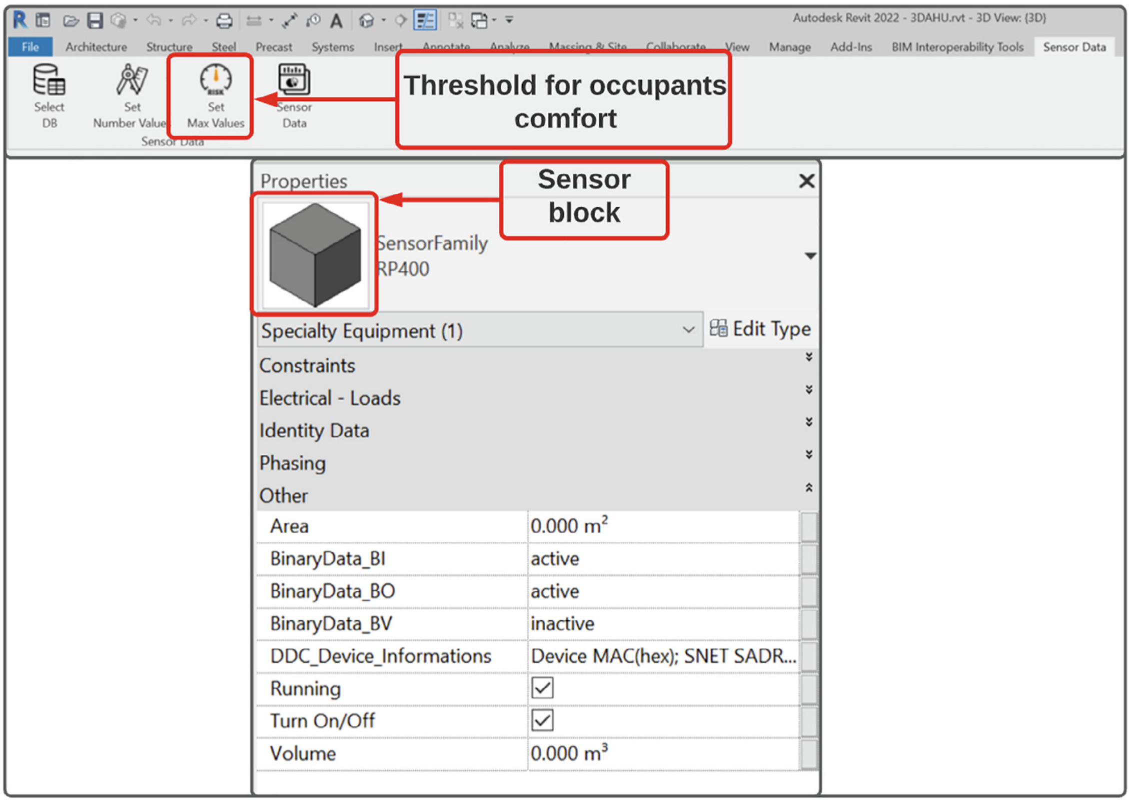


Fig. 4. Sensor management in Revit using the developed plugin.

Several sensors blocks were used in BIM to receive the sensor data and visualize them. Fig. 4 shows the sensor block.

In this study, we chose to utilize a laser scanner to scan certain zones in order to appropriately represent them in Revit because the available BIM model does not have all of the necessary information. In order to do this, we employ (TOP GLS2000 [92]), and the point clouds that are extracted have been treated in Autodesk ReCap before being sent to Autodesk Revit.

3.2. Energy consumption simulation

This stage represents the yellow box in Fig. (1).

3.2.1. Building energy consumption simulation using IDA ICE

Several building energy performance tools, such as EnergyPlus [93], TRNSYS [65,94], and IDA ICE [95,96], are commonly used in literature for building performance and optimization.

According to the research stated above, building envelope and HVAC system characteristics need to be taken into account when optimizing a building for energy efficiency and thermal comfort simultaneously. Despite this, optimizations in the literature did not consider various envelope components, control techniques, and HVAC setpoints.

As a result, the novelty of our paper is to investigate the interaction of building envelope factors with HVAC systems and parameters with other essential design variables through the optimization process, which was missing in the literature. This was accomplished by integrating the IDA ICE software with machine learning algorithms and optimization techniques to improve energy performance considering occupants' comfort conditions.

In this study, nineteen variables are taken into account, including window size, temperature, U-values, airflow, and other elements vital to a building's performance but challenging to analyze and pinpoint in the early phases of design [97,98]. The annual energy demand delivered to the building for heating, cooling, ventilation, and lighting is considered an output measured in kWh/m^2 floor space for each simulation. The district heating network system was used for heating while electricity was used for cooling where both have a daily profile. The Revit BIM model is imported into SimpleBim to preprocess it and then to IDA ICE once the primary impact parameters have been determined. According to the project's real scenario, building specifications and ambient variables are configured to simulate the energy consumption.

3.2.2. Pairwise testing for obtaining energy data set

The great potential for energy savings is made possible in large part by the work of building designers. Engineers and architects utilize a variety of metrics to evaluate a building's environmental effect while also ensuring that it meets standards for indoor climate, including energy demand, CO2 footprint, thermal comfort, daylight, and expenses [99]. Building geometry, insulation thickness, glazing qualities, and HVAC systems may all be varied to identify viable solutions by the design team. Because of the vast number of possible configurations for these factors, it is difficult and time-consuming to thoroughly examine the design options and come up with solutions that are both rational and able to satisfy all criteria. Aside from that, the majority of energy simulation software is computationally intensive. Because a single simulation might take minutes to perform, executing dozens or millions of simulations impedes widespread design analysis and optimization adoption [63].

Although supercomputers and cloud computing may be able to solve the computational problem of simulation, the cost of supercomputers is prohibitive, and the time it takes to complete thousands of simulations is still considerable in cloud computing [100]. This study will thus employ an orthogonal experiment from pairs testing to generate a batch of energy consumption data [101]. This paper uses the pairwise tool to build an orthogonal experiment based on the specified value range of design requirements to get energy consumption data sets. The machine learning model is then trained on various distinct building energy consumption data sets, each based on a particular design.

3.3. Energy consumption prediction

This stage represents the brown box in Fig. (1). Eleven machine learning algorithms will be examined to predict building energy consumption, as specified in Section 2.3, based on their popularity and recommendations in the researched literature (Table 1). We compare these algorithms on the same dataset in this work because all of the methods we choose have not been explicitly compared on a single dataset in previous research. We did not include all of the techniques shown in the Table 1 because it would be too overwhelming; instead, we picked the algorithms that show better performance than those included in the same table. Each approach has several options that impact accuracy as well as computing effort. Fitting methods, tuning parameters, and convergence criteria are examples. We attempt to find the most significant settings based on the theoretical foundation and program documentation. Furthermore, the energy consumption prediction framework will consist of four main stages as follows: (1) Data preprocessing, (2) Feature Selection, (3) Model development (training, validation and testing), and (4) Model evaluation, as shown in Fig. 5.

3.3.1. Data preprocessing

Although data preparation is time-consuming and computationally costly, it is the first step in machine learning [102]. It is necessary to perform this step to ensure that the preparation will not result in inaccurate data throughout analysis [55]. The dataset must be cleaned and normalized as part of the data preparation procedure. Outliers and missing data are removed during the data cleaning procedure. The mean value of each column is used to fill in the gaps in the data. However, to minimize confusion and complication in the model development process, all occurrences of missing values in the building dataset (due to faulty equipment or inadequate technicality during the recording of the values) were removed from the database. The data pretreatment practice of data normalization also reduces the impact of dimensions, as many features have unrelated dimensions. For example, one input variable may have values from 0.5 to 1, whereas another may have values from 1000 to 10,000. Scale discrepancies between the numbers in a model might cause issues. To prevent issues with model building, samples are normalized to a unit norm. The sklearn python module normalizer normalized the building and meteorological datasets [103]. The use of the StandardScaler approach ensures that separate samples' eigenvalue dimensions have no bearing on the prediction efficiency and accuracy [104,105].

3.3.2. Feature selection

Feature selection is crucial when employing machine learning techniques because it filters out redundant and noisy data during the training process. The noisy data was found in numerous condition indicators, including (1) energy usage, (2) supply air temperatures, (3) chiller and heater water temperature sensors, and so on. This data from sensors will help us to confirm the outcomes of our IDA ICE simulation model and to define the correct ranges for optimization process that reflect the real building as accurate as possible.

Data reduction minimizes redundant information, whereas feature selection eliminates undesired features from a dataset. When the data is cleaned, the low-variance and noisy elements are removed, and the use of data normalization reduces the size disparity between the different data sets. SVM and Analysis of Variance (ANOVA) will be combined in this study to select the feature importance [106]. ANOVA-SVM is used to improve the classifier's performance by analyzing the variance of each feature. Each subgroup test's accuracy score and the distance between each data point and its decision boundary are calculated using the ANOVA-SVM technique. The ANOVA-SVM method generates data for each feature's distance to its decision boundary, and the closer each feature is to the barrier, the more crucial it is.

3.3.3. Model development

According to Section 2.3, eleven supervised machine learning algorithms based on regression are used to forecast annual energy consumption., namely, LR, ANN, SVM, GPR, DNN, RF, XGB, ANN-SVM, LSSVM, GMDH, and GLSSVM. The Deep Neural Network (DNN) is a feed-forward neural network with three hidden layers

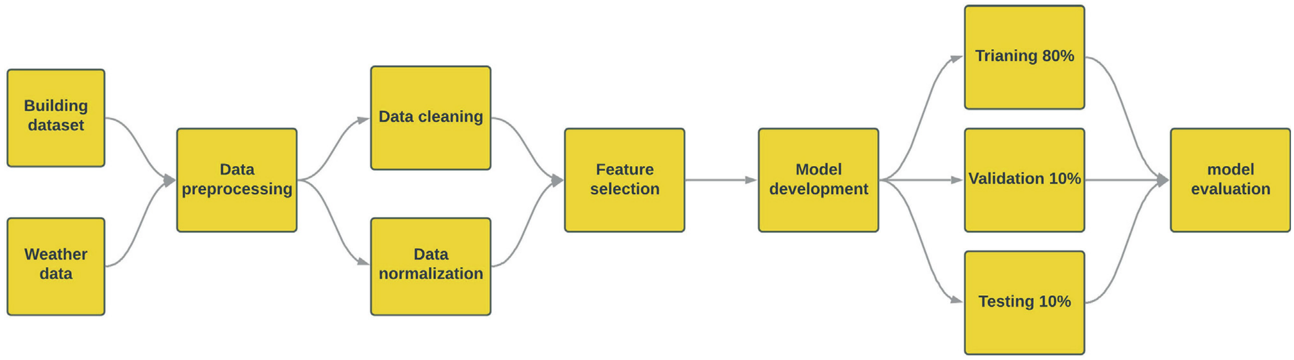


Fig. 5. Prediction framework flowchart.

and 10 neurons in each layer with lambda = 0.1, whereas the ANN has just one hidden layer and 10 and 100 neurons. The activation 'ReLU' and the optimizer 'Adam' were used. Furthermore, SVM was built with the following parameters: 1.0 value of C (a hypermeter in SVM used to manage error, where a low C indicates a low error), 1.6 value of Epsilon (defines a margin of tolerance). The kernel function substantially impacts the SVM's prediction accuracy; it should be chosen suitably for different prediction models based on the study's features. The Gaussian kernel is a radial basis kernel with outstanding anti-interference properties. As a result, the prediction model in this work is based on the Gaussian kernel function, which is expressed as follows [107]:

$$K(x_i, x) = e^{\left(-\frac{\|x_i - y\|^2}{2\sigma^2}\right)} \tag{1}$$

Where x_i is the input variable, y is the output variable, and σ^2 is the width parameter.

Grid search was used to find γ and σ^2 [108]. GLSSVM has the exact parameters of LSSVM and GMDH since it is a hybrid model of both. Furthermore, the least square regression loss function, 0.1 learning rate, and 100 estimators were also used to create the XGB model. With 30 estimators, a random forest (RF) was created.

Following data preparation, the learning algorithms are fed the selected variables based on feature importance ranking. Eighteen factors are fed into this forecasting algorithm from three different systems, including BIM models, BMS systems, and IoT sensor networks, and based on pairwise testing. A combination of data from the IoT sensors, the BMS system's data, and BIM data will be employed in the prediction process to determine the ranges for pairwise testing and extend it to include more possible combinations. The machine learning models' inputs will consist of nineteen variables as they have the most impact on the energy consumption in buildings (out from the literature review and the ANOVA-SVM method in Section 3.3.2 to choose the most critical factors): (1) U-value, external wal, (2) U-value, windows, (3) U-value, ground floor, (4) U-value, roof, (5) air supply, (6) window to wall ratio, (7) solar Heat Gain Coefficient (SHGC), (8) load (people and equipment), (9) load (lighting), (10) activate shading, (11) reflectance, (12) night ventilation, (13) shading factor, (14) air Infiltration, (15) supply air temperature setpoints, (16) supply water temperature setpoints, (17) supply water temperature to radiators, (18) return water temperature from radiators, (19) Heat exchanger Efficiency. The output of this prediction process is the annual energy consumption of the building.

Well-trained models can be used to forecast future energy usage and will be used as objective function for the optimization process. Machine learning models are trained using datasets for the required variables (input datasets from sensor data and pairwise testing (Section 3.2.2)), which result in prediction models. The input datasets are divided into three groups using a random distribution: (1) 80 percent for model training, (2) 10% for validation, and (3) 10% for testing the models.

3.3.4. Model evaluation

The following indicators are used to assess each model's performance: R-Squared (R^2), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Squared Error (MSE). The MSE and RMSE are the most commonly used assessment methods for energy consumption prediction among all the methodologies given [109,110]. The difference between expected and actual values at each point in a scatter plot is calculated using Mean Absolute Error (MAE). The mean squared error (MSE) measures the squared difference between the estimated and actual values. The Root Mean Squared Error (RMSE) is a statistic for calculating the disparities between an estimated value and the model's perceived value. R-Squared (R^2) checks the degree of fit between anticipated and actual values; however, R^2 produces the best results when close to 1.0. The closer the score is to zero, the better the performance, and the higher the value, the poorer the performance for MAE, MSE, and RMSE.

Eqs. (2)–(5) produce MAE, MSE, RMSE, and R-squared, respectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|AE_i - PE_i| \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(AE_i - PE_i)^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(AE_i - PE_i)^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{predict,i} - y_{data,i})^2}{\sum_{i=1}^{n}(y_{data,i} - y_{data})^2} \tag{5}$$

3.4. Multi-objective optimization based on NSGA II

This stage represents the purple box in Fig. 1.

3.4.1. Objective functions

In this work, the conventional mathematical functions, usually used as an objective function for optimization algorithms, are replaced by the energy consumption regression prediction methods in Section 3.3.3. These methods can resolve that a specific formula cannot express the complex nonlinear relationship between the input variables and the output objectives.

The second object function considered in this work is indoor thermal comfort, which expresses how pleased most occupants are when they are in a controlled indoor environment. PMV and PPD are two significant indices of thermal comfort in this area, representing the degree to which indoor occupants perceive the ambient temperature according to the human body thermal reaction [111]. In the PMV, there are seven assessment levels, ranging from −3 to + 3, with positive and negative values denoting hot and cold temperatures accordingly, with values closer to zero representing higher degrees of thermal comfort. As soon as the PMV is established, the PPD may be calculated to estimate the percentage of thermally unsatisfied occupants in a building. Overall, PPD identifies the proportion of persons expected to have local discomfort (0 to 100 percent).

The Eqs. ()()()()(6)–(9) for the thermal comfort indicators (PMV and PPD) are developed according to ISO 7730 [112].

$$PMV = (0.303 \cdot e^{0.036 \cdot M} + 0.028) \cdot L \tag{6}$$

$$\begin{aligned} L &= (M-W) - 0.00305 \cdot (5733 - 6.99 \cdot (M-W) - Pa) - 0.42(M - W - 58.15) \\ &\quad - 0.000017(5867 - Pa) - 0.0014 \cdot M \cdot (34 - Ta) - 3.96 \cdot 10^{-8} \cdot Fcl \cdot ((Tcl + 273)^4 \\ &\quad - (Tr + 273)^4) - Fcl \cdot hc \cdot (Tcl - Ta) \end{aligned} \tag{7}$$

$$\begin{aligned} Tcl &= 35.7 - 0.028 \cdot (M-W) - 0.155 \cdot Icl \cdot (3.96 \cdot 10^{-8} \cdot Fcl((Tcl + 273)^4 \\ &\quad - (Tr + 273)^4) + Fcl \cdot hc \cdot (Tcl - Ta)) \end{aligned} \tag{8}$$

$$PPD = 100 - 95 \cdot e^{-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2} \tag{9}$$

Where: M stands for metabolic rate (W/m^2), L for body thermal load, W (W/m^2) stands for external work, Ta (°C) is the indoor air temperature, Tcl (°C) is the clothing surface temperature, Pa (kPa) is the partial vapor pressure, and fcl(-) is the clothing surface area factor. In addition, Tr (°C) represents the average radiation temperature of envelope, Icl (m^2K/W) represents the thermal resistance of clothing. EN 15251 [113], and Norwegian building details 421.501 [114], which are based on a human body heat balance equation and subjective thermal feeling, have also been used to find the parameters of PPD and PMV.

A further relation exists between the mean radiant temperature of the building envelope (Tr) in Eq. (8) and the thermal performance of the building envelope, which can be expressed as in Eqs. (10), and (11) based on [112,115]:

$$Tr = \frac{T_1 \cdot A_1 + T_2 \cdot A_2 + \cdots + T_N \cdot A_N}{A_1 + A_2 + \cdots + A_N} = \frac{\sum_1^k (A_{nj} \cdot T_{nj})}{\sum_1^k A_{nj}} \tag{10}$$

Where: A_{nj} and T_{nj} are the building envelope's surface area and temperature, respectively.

$$T = Ta \cdot k \cdot \frac{Ta - Tout}{\alpha} \tag{11}$$

Where: Ta is the indoor air temperature, Tout is the outdoor temperature, k is the heat transfer coefficient of the envelope, and α is the heat transfer coefficient of the inner surface of the envelope.

The mean radiant temperature can then be written as follows:

$$Tr = \frac{[A_{walls} \cdot Ta \cdot U_{walls} \cdot \frac{(Ta - Tout)}{\alpha}] + [A_{windows} \cdot Ta \cdot U_{windows} \cdot \frac{(Ta - Tout)}{\alpha}] + [A_{roof} \cdot Ta \cdot U_{roof} \cdot \frac{(Ta - Tout)}{\alpha}]}{A_{walls} + A_{windows} + A_{roof}} \tag{12}$$

To include window to wall ratio, A_{walls}, and $A_{windows}$ can be written as follows:

$$A_{walls} = \frac{A_{walls} + A_{windows}}{\frac{A_{walls} + A_{windows}}{A_{walls}}} = \frac{A_{walls} + A_{windows}}{1 + \frac{A_{windows}}{A_{walls}}} \tag{13}$$

$$A_{windows} = \frac{\frac{(A_{walls} + A_{windows})}{A_{walls}} \times A_{windows}}{\frac{(A_{walls} + A_{windows})}{A_{walls}}} = \frac{(A_{walls} + A_{windows}) \cdot \frac{A_{windows}}{A_{walls}}}{1 + \frac{A_{windows}}{A_{walls}}} \tag{14}$$

By replacing the Eqs. (12)–(14) in the PMV Eq. (6), and considering Tr = f ($U_{wall}, U_{roof}, U_{windows}, U_{windows/walls}$), the final equation of PMV and building envelope can be expressed as follows:

$$\begin{aligned} PMV &= (0.303 \cdot e^{0.036 \cdot M} + 0.028) \cdot [(M-W) - 0.00305 \cdot (5733 - 6.99 \cdot (M-W) - Pa) \\ &\quad - 0.42(M - W - 58.15) - 0.000017(5867 - Pa) - 0.0014 \cdot M \cdot (34 - Ta) \\ &\quad - 3.96 \cdot 10^{-8} \cdot Fcl \cdot ((Tcl + 273)^4 - (f(U_{wall}, U_{roof}, U_{windows}, U_{windows/walls}) + 273)^4) \\ &\quad - Fcl \cdot hc \cdot (Tcl - Ta)] \end{aligned} \tag{15}$$

3.4.2. Pareto front solution using NSGA II in Dynamo

In this section, the first step is to transmit real-time sensor data from the building to the BIM model in Autodesk Revit using the previously described plugin that relies on virtual sensor blocks with the following characteristics: Date, Temperature, Humidity, Energy, and PMV attributes. Real-time streaming from IoT devices keeps these characteristics' values current in the BIM model.

Dynamo's optimization technique uses NSGA II in the Optimo package to compute the best Pareto solution in the second phase (Fig. 6). The objective (fitness) functions from the machine learning model (Section 3.4.1.), and PMV are mapped to Dynamo using a python script because the Dynamo API allows for python nodes. In order to make the dynamic PMV output more understandable, a color range function was used.

For the NSGA II, the typical binary tournament selection, crossover, and mutation operators are used. The starting population list is sorted using non-dominance fitness values in the optimization process nodes. The offspring population list's fitness values are allocated the same way as the original population list's. The current offspring population list is coupled with previously established best non-dominated solutions to ensure elitism. The best non-dominated solutions are chosen for the following iteration. The Generation Loop runs until the designer's limit is reached. The Pareto Optimal Set is constructed as an output of the optimization loop (Fig. 8), and the initial solution lists and population lists formed during the optimization process are exported as CSV files. The user can utilize the exported data for further processing.The method for obtaining a Pareto front using the NSGA II is shown in Fig. 7.

In the third phase, the optimal results from NSGA II are used to replace Revit elements (using their ID in the COBie file) and control the indoor climate to keep PMV between −0.1 and + 0.1.

3.5. Data integration

COBie is an information exchange specification used to gather and distribute data throughout its lifecycle. Despite this, there is still a difficulty with compatibility between IFC and COBie because their data structures differ from the data syntax of BIM models. COBie spreadsheets are used to import data from BIM models that have been pre-selected based on user-defined parameters into a spreadsheet program. The names of characteristics in COBie spreadsheets are typically different from the names of characteristics found in FM and BEM system data, which might cause confusion.

Currently, RDF may represent a variety of different types of building data. Much of this information is first provided in native

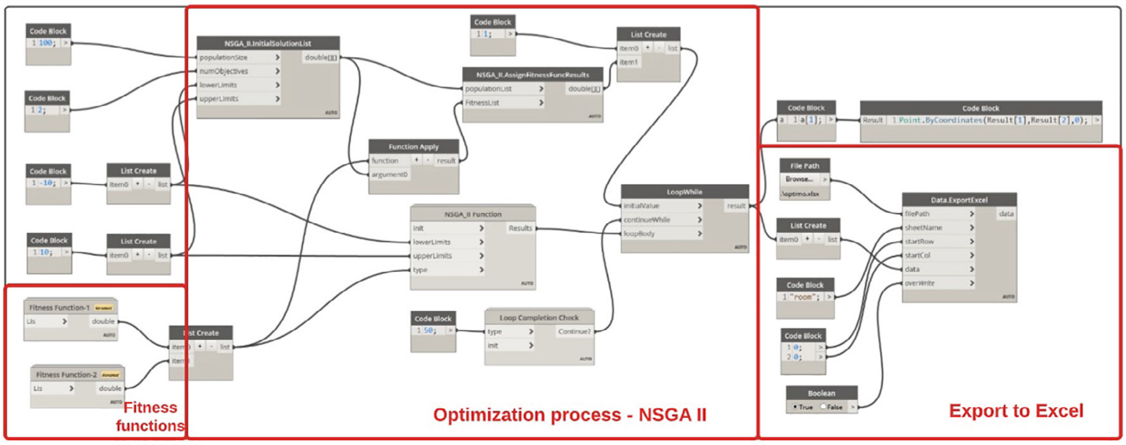


Fig. 6. An overview of NSGA II method in Dynamo.

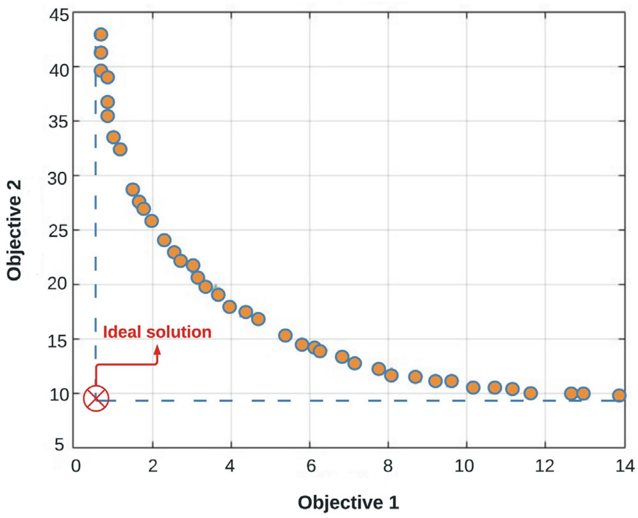


Fig. 8. The Pareto front's ideal solution.

data formats, which may then be transformed to RDF using a variety of data converters now available on the market. For the sake of this research, we do not want to use the integration of BIM, BEM, and FM for evaluation purposes, but rather to make our framework as generic as feasible; we concentrate on three essential ontologies: Brick, BOT, and SSN, which are based on COBie and IFC data respectively.

Using these ontologies, it is possible to characterize building components and relate them to sensors as system elements with specialized measurement capabilities. Using a modular approach, the sensors and domain may be split down into readily digestible information, with obvious connections to other ontologies that are accessible to enable network definition, measurement, and other functions. Python was utilized in this project to automate the mapped method.

4. Case study

4.1. Building description

Tvedestrand secondary school (a case study model illustrating the configuration of Norway's secondary school building) was considered. The building consists of a three-story structure with a total construction area of 9759.2 m^2 and a total building volume of 33746.7 m^3. The school has approximately 130 employees and 500 students; however, the building is designed for 690 students and 140 employees. Each person occupies around 11 m^2 of floor area. Most students are 16–19 years old, while the staff is between 22–67 years old. In this study, students and employees were treated equally regarding thermal comfort.

The building envelope features, the lighting system, the HVAC system, and the setpoints were selected for an educational facility that complied with the Norwegian building code TEK10 [116]. In order to acquire the building energy consumption simulation model, the BIM model of the educational building is generated in Revit and SimpleBim and then imported into IDA ICE to be used in the simulation (Fig. 9). The zone multiplier function in IDA ICE is used to shorten the computational simulation time by simplifying redundant zones in the building.

Table 2 shows the general information regarding the reference case building. The building has a total of 144 zones. This building has a total external wall area of 2103.0 m^2 and a total window area of 670 m^2. Furthermore, the shading system for the windows was made out of vertical fins. The building windows have vertical fins with a thickness of 10 mm, and a depth of 250 mm. The spacing between those fins is 500 mm. For larger window areas, a lower window U-value should be used to comply with National Building Code (TEK 10) requirements to minimize excessive building energy consumption for space heating and cooling. All properties were selected using TEK 10. So, all the initial values in Table 2 come from TEK 10 standard and have been confirmed with the facility manager. However, since we used the pairwise test to generate the inputs for the optimization process (within the boundary conditions), the initial values do not affect the optimization results. According to the standard NS 3031 [117], domestic hot water (DHW) usage was chosen based on the standardized value for educational buildings. Table 3 shows the central HVAC system's features in the reference building.

Table 4 illustrates the internal heat gain values and profiles (Occupancy, illumination, and equipment) implemented in IDA ICE based on the NS 3031 Norwegian standard. Climate data were obtained from the ASHRAE IWEC 2 database [118] for Kjevik, Kristiansand, where the average yearly outdoor temperature was roughly 9.2 °C. In this study, the PPD was calculated by taking into account the occupancy patterns in the building (07.00–19.00), room type (office, classroom, group room, labs, and lunchroom), and holiday weeks (Week 26–32 and week 52). Usage pattern in rooms with several people is based on NS3031 with some adjustments concerning room function.

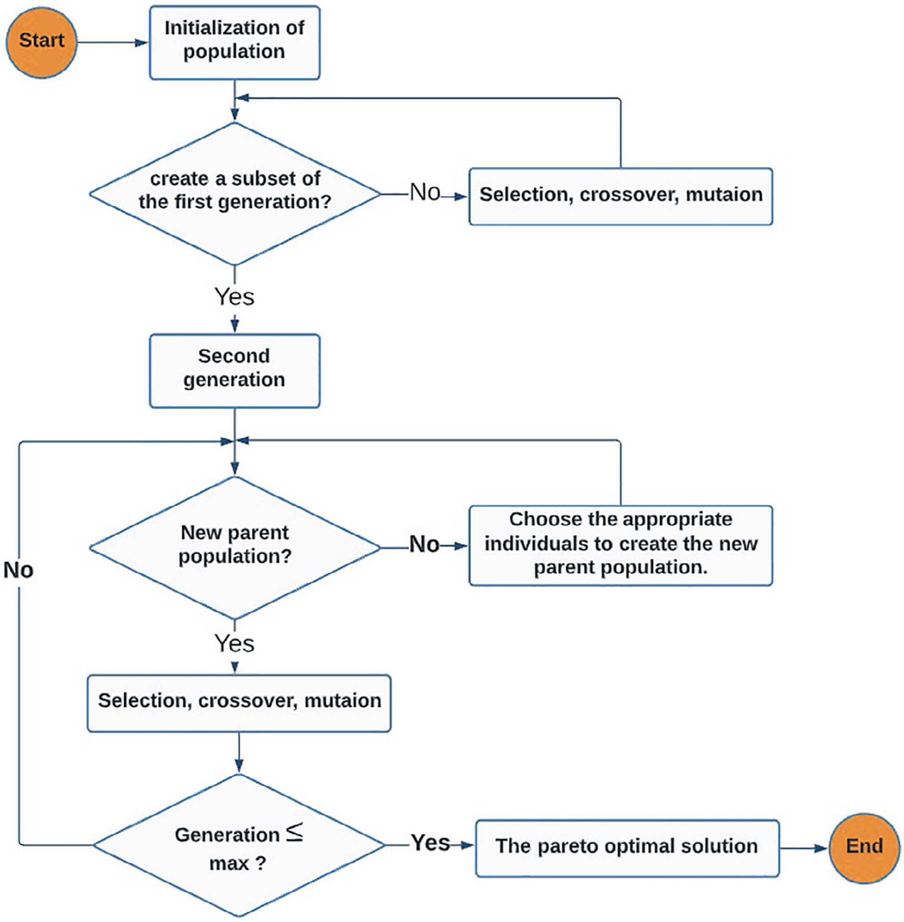


Fig. 7. The NSGA II flowchart.

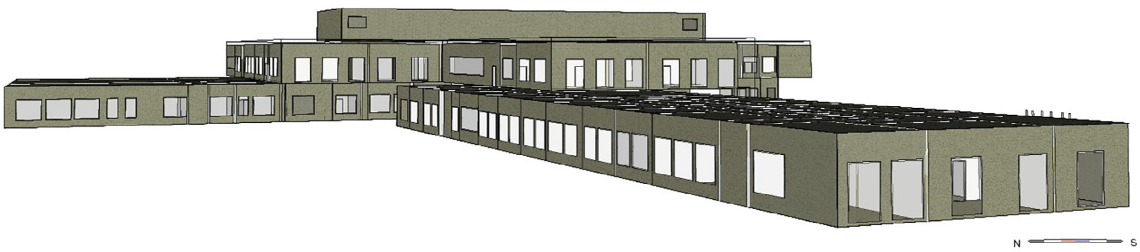


Fig. 9. Simulating the energy consumption of Tvedestrand secondary school in Norway using IDA ICE.

Table 2
Original values of building envelope data used as input values in IDA-ICE.

Parameter	Initial value
External wall U-value (W/(m^2.K))	0.15
Roof U-value (W/(m^2.K))	0.11
External window, doors and glass U-value (W/(m^2.K))	0.8
Ground floor U-value, W/(m^2.K)	0.06
Normalized thermal bridge (W/(m^2.K))	0.03
Airtightness n_{50} (1/h)	0.35
External shading strategy	Qsol (klux) >40
Internal wall U-value, W/(m^2.K)	0.62
g_t, Solar Heat Gain Coefficient (SHGC)	0.34 (3 layers glass)
Shading factor	0.2
Reflectance	0.55

Based on the parameters given in the above tables, the building net energy consumption of the original design solution is calculated using IDA ICE to be as the Table 5.

4.2. Sensor data and interoperability

In this case study, several sensors were placed to monitor the building's rooms and HVAC systems. These sensors include NTC-12 K-sensors for temperatures, PTH-3202-DR for pressure, TTH-6040–0 for outdoor temperature, and the IVL10 temperature-sensitive airflow transmitters. In addition to sensors that monitor air and water supply and return temperatures, energy usage, con-

Table 3
The reference educational building's HVAC systems.

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	District 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
DHW use	5 kWh/(m^2.year)
Night ventilation	0.36 l/((m^2.s)

Table 4
Internal heat gains values of occupants, lighting, and equipment.

Internal heat gain	Comment
Occupants: the building is occupied from 07.00 to 19.00	Activity level is considered to be 1.2 met which is 108 W/person. The usage then depends on the room type (office, classroom, group room, labs and lunchroom). Usage pattern in rooms with several people is based on NS3031 with some adjustments with regard to room function. Holiday weeks are also based on NS3031 and during the holiday week there are no heat loads are present. Holiday weeks are: week 26–32 (summer holiday), week 52 (Christmas).
Lightning during the occupied period [W/m^2]	3
Equipments during the occupied period considering no load in unoccupied zones [W/m^2]	4

Table 5
Total net energy demand calculated for the studied building (the initial case). The mechanical ventilation system cooled the zones because there was no local space cooling system.

Energy	Energy consumption (kWh/year)	Energy consumption (kWh/m^2.year)
Room heating	87080	8.92
Ventilation heat	43680	4.47
Hot water	116760	11.96
Fans	101360	10.39
Pumps	25760	2.63
Lighting	86240	8.84
Technical equipment	111720	11.45
Room cooling	–	–
Ventilation cooling	23520	2.41
Net energy consumption	**596120**	**61.07**

trol system setpoints, humidity, and CO2. Regio controllers have also been used to regulate blinds, lighting, humidity, CO2 levels, etc. The major goal of the sensor data is to validate the outputs of the original IDA ICE model and to establish the boundary conditions for the optimization process's input variables. The proposed framework in this study operates for any building based on the ontologies used in this paper. BRICK, BOT, and SSN ontologies are created based on COBie data and used to get information from an IFC model, transfer data into the COBie data standard, and offer BIM data to energy systems to handle data exchange and interoperability issues (see Section 3.5. Data integration). Modeling framework between sensor data and simulation technique is depicted in Fig. 10,11.

4.3. Inputs for the optimization process

The optimization process took a wide range of input variables into account, divided into two groups, as indicated in Table 6. The most significant characteristics in the literature guided the selection of the initial set of variables related to the building envelope and shading. The HVAC parameters and setpoints were in the second category of variables. The optimization of the latter variables in combination was absent from the literature, and no research investigated the combined control of these two types of variables for the optimization process. There were more than 40 variables that can be included in this optimization process based on the literature; however, by using the ANOVA-SVM method (Section 3.3.2), the most important variables have been taken into consideration, as can be seen in Table 6.

4.4. Dynamo for the machine learning and optimization

We first generate all the possible combinations of the decision variables, ending with 1,236,912 combinations. However, using the pairwise test, the combinations were reduced to 8000 and covered all possible solutions more effectively. We use every combination as input for IDA ICE and run one simulation based on that combination to get the annual energy consumption. It took around 16 days to finish all simulations. The final database, which includes the 8000 combinations and the corresponding energy consumption (Fig. 12), is fed into the machine learning algorithms using visual programming.

The visual programming environment enables the design space to be described rapidly, interactively, and correctly. The Dynamo process for this case study can be shown in Fig. 13. Table 6 and its ranges are used to define the decision variables in this workflow. The python script node will take the decision variables as inputs for the machine learning model and NSGA II process. So, rather than installing Python on its own, it can now be utilized as a part of Dynamo (embedded). It will be much easier to incorporate the optimization findings straight into a BIM model. TensorFlow and Sci-kit libraries must be loaded correctly for the python scripts node to function effectively. Figure shows a portion of the python script node's code. The second stage uses Optimo nodes (Fitness Function Results, Generation Algorithm, etc.) to transfer the best machine learning model to the NSGA II nodes for the optimization process. Packages of nodes are used to implement parametric performance analysis using BIM to optimize thermal comfort and energy analysis. When the run iteration number surpasses the designer's specified limit, the generation loop continues to perform the generating and sorting operations in a loop. Then, the results can be saved to an Excel file or MSSQL database

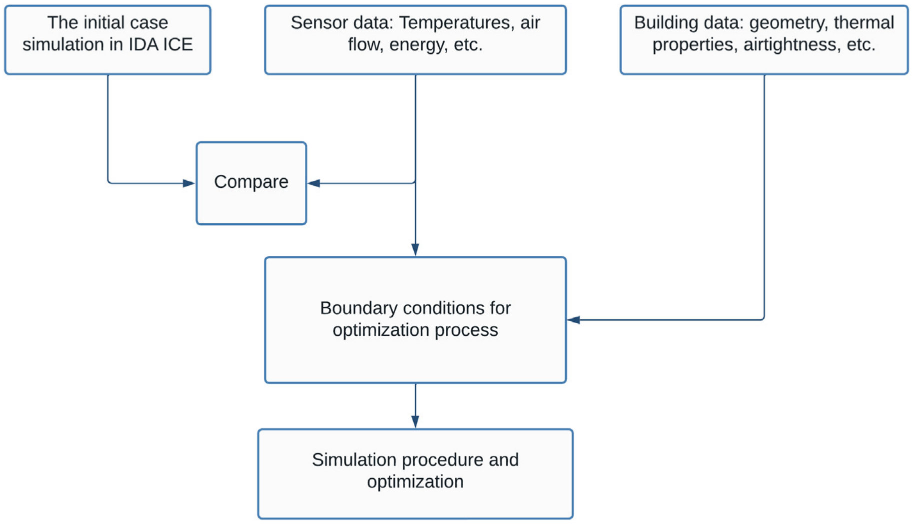


Fig. 10. The process from data input to the simulation procedure.

containing all of the optimization variables and their performance analysis findings. The next step is to replace the existed elements in the BIM model with the optimized one and visualize the thermal comfort results of each room in the BIM model using the clockwork library. The last step is to build a user interface (Fig. 13) that the final user can use to easily control the decision variables ranges and constraints using the Data-Shapes library.

4.5. Annual energy consumption prediction results

The outcome analysis revealed significant findings between the selected models in this research. In Section 3.3.4, it is mentioned that models with values closer to zero for MAE, MSE, and RMSE are good predictive models, while values closer to one for R-squared generated the most outstanding results. In this study, GLSSVM was the best effective model for forecasting annual energy consumption. LSSVM and GMDH, which has not received much attention in energy prediction, emerged as two and the third-best predictive model. The hybrid algorithm ANN-SVM comes in fourth place, outperforming the other algorithms. Even though it takes a longer time for training, GPR surpasses ANN, SVM, DNN, XGB, LR, and RF. The XGB and LR-based models have the worst performance but take the least time to train. Table 7 shows the prediction models in terms of performance indexes and time. Fig. 14 shows the results based on Table 7 algorithms, where the x-axis is the true values while the y-axis is the predicted values. The blue points in Fig. 14 are the observations, and the black lines are the predictions. The proposed GLSSVM energy consumption prediction model has the highest accuracy and the best prediction results of all existing models. This is due to its hybrid model's technique compared to other methods that mostly depend on one model only. The GLSSVM combines the GMDH with the LS-SVM [52,119]. The LS-SVM model forecasts the output signal using the input data of the innovative hybrid forecasting model, which the GMDH model chooses. Every pair of the two input variables is considered in every layer, and the polynomial function does the regression for each pair [120]. Together with the input variables, the output data of the GMDH model (which has the lowest error) is utilized as input for the LS-SVM model. The GLSSVM method is run through three to five iterations or until the output data has the least amount of error [121]. The GLSSVM model also performs better than the ANN-SVM hybrid model. This is obviously because GLSSVM depends on LSSVM, an improved version of SVM that makes the prediction faster, and the GMDH neural network, which selects an optimal structure of model or network until it finds the best one compared to ANN, which has a fixed structure. As a result, the its regression relationship can be used as the fitness function of multi-objective optimization, resulting in better achievement of optimization objectives.

4.6. Multi-objective optimization using NSGA-II

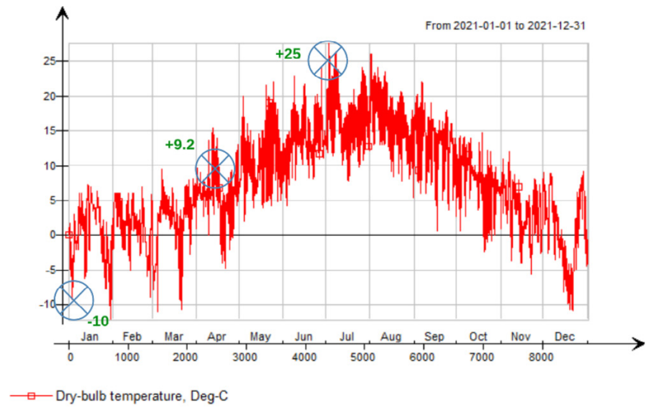
Building energy consumption reduction and improved thermal comfort are two of the optimization goals for NSGA-II. In this work, the NSGA-II adaptive mutation feature improves the variety of the GA solutions and widens the GA's search space by setting the population type as a double vector. As the population size and number of iterations are critical to the convergence of NSGA-II optimizations, the values of these parameters are presented in Table 8. According to Fig. 15, the NSGA-II optimization is carried out, and the Pareto optimum front, which comprises 37 optimal solutions, is obtained, from which we can find the following:

According to Fig. 15, thermal comfort is inversely proportional to a building's energy use. The predicted percentage of dissatisfied (PPD) improves slowly with a rapid decrease in building energy usage. However, when the building's energy usage is further reduced, the PPD rises dramatically, making it impossible to achieve both objectives simultaneously.

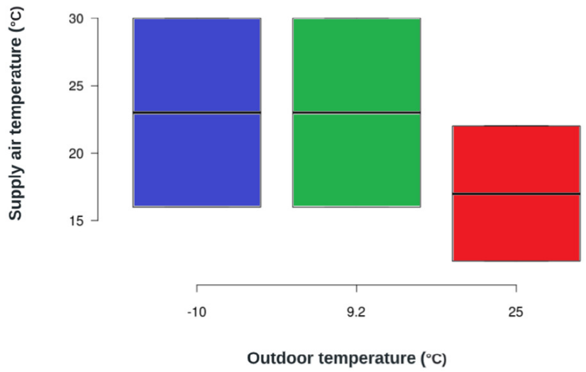
To put it another way: The results show that the Pareto optimum solutions' energy consumption and PPD are often less than 50 kWh/m^2.year and 9%, respectively, compared to the original design solution's 61.17 kWh/m^2 and 18.5%. According to these findings, NSGA-II solutions can simultaneously reduce the building's energy consumption and enhance thermal comfort.

It is shown in Table 9 that the optimal set of input parameters was found following optimization. There is a wide range of building envelope parameters in the best options. There are 3 points in Fig. 15 where the building envelope parameters and objective function values are shown in Table 9. According to the table, all options on the Pareto optimum front have different values for the building envelope parameters. By looking at the table below, several characteristics, such as roof U-value, exterior window U-value, and window-to-wall ratio, have varying values that influence energy usage and indoor thermal comfort.

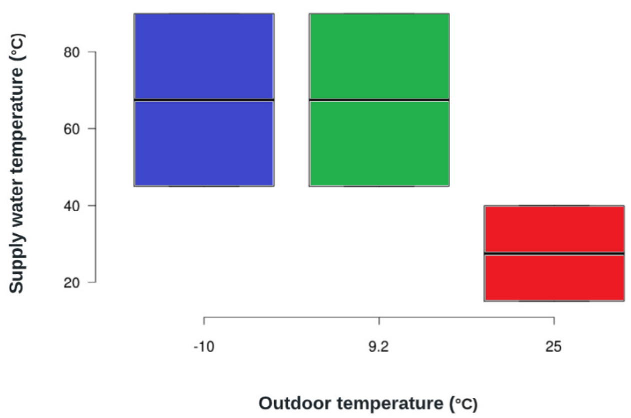
The lighting load was maintained to a minimum during the optimization phase, while the heat exchanger efficiency was max-



(a)



(b)



(c)

Fig. 11. Weather data (a), Supply air temperature ranges between 16 to 30 (°C) for −10 and 9.2 (°C), and between 13 to 22 (°C) for 25 (°C) (b), and supply water temperature ranges between 45 and 90 (°C) for −10 and 9.2 (°C), and between 15 and 40 (°C) for 25 (°C) (c).

imized. This was because improving the lighting system and heat exchanger efficiency reduced building energy consumption while having a minor impact on thermal comfort.

A modest window to wall ratio was selected for the minimum energy usage and the most significant thermal comfort situations, suggesting that this parameter was a competing element for optimizing thermal comfort and lowering energy consumption simultaneously. Building exterior walls with low U-values was favored in all cases. The highest thermal comfort satisfaction scenarios preferred the roof with the lowest U-value.

Table 6
Input parameters for the optimization procedure.

Input parameters	Value	Note
U-value, external wall [W/m^2.K]	0.12, 0.14, 0.16, 0.18, 0.2	
U-value, windows [W/m^2.K]	0.75, 0.8, 0.85, 0.9	
U-value, ground floor [W/m^2.K]	0.08, 0.10, 0.13, 0.16	
U-value, roof [W/m^2.K]	0.08, 0.10, 0.13, 0.16	
Minimum air supply (l/m^2.s)	0.5–2	min–max
Window-wall-ratio (WWR %)	30–90	min–max
g_t, Solar Heat Gain Coefficient (SHGC)	0.25, 0.32, 0.43, 0.5	
Load (lighting) (W/m^2)	2, 4, 6, 8	
Activate shading (klux)	38, 45, 52, 61, 70, 100	
Reflectance	0.4, 0.55, 0.65, 0.78	
Night ventilation (l/m^2.s)	0.3–4	min–max
Shading factor	0.2, 0.3, 0.4, 0.5, 0.6, 0.8	
Air Infiltration	0.06, 0.07, 0.1	
	HVAC	
Supply air temperature setpoints in AHU (?)	Fig. 11a and Fig. 11b	Three outside air temperature values were considered: −10, 9.2 (the average value), and 25
Supply water temperature setpoints from the central heating system (?)	Fig. 11c	Three outside air temperature values were considered: −10, 9.2 (the average value), and 25
Supply water temperature to radiators (?)	(45, 55,65, 70)	
Heat exchanger Efficiency in AHU	(0.55, 0.75, 0.85)	

Fig. 16 depicts the AHU's ideal supply air temperatures and airflow rates, as well as the central heating system's supply water temperatures. As a result of the reference building's optimization, comparable variations in supply air temperature and supply water temperature were selected for various instances (Figs. 16a, 16b,16c, and 16d) in order to reduce energy consumption and increase thermal comfort.

In addition, the best solution is found using the ideal point approach. The ideal point coordinates created by the optimal values of building energy consumption and PPD are shown in Fig. 17 at (6.2, 22.9).

Out of the results we reached in our case study, The following can be found:

1. After NSGA-II optimization, the building's energy consumption is much reduced. There is a 37.5% decrease in overall building energy consumption after optimization from 61.07 kWh/m^2.year with the original case to 22.9 kWh/m^2.year, proving that multi-objective optimization favorably reduces building energy consumption.
2. After NSGA-II optimization, the building's thermal comfort is increased. As an indicator of how well a building's thermal comfort has been improved by multi-objective optimization, the PPD went from 18.5%, with the original values of the building, to 6.2%, which is a drop of 33.5%.

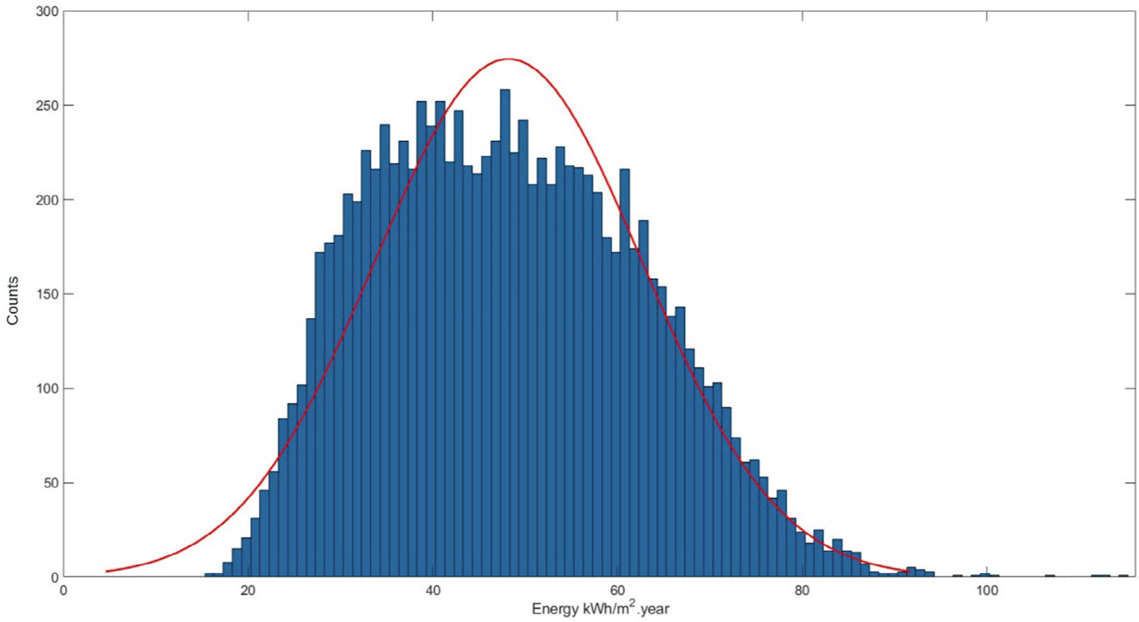


Fig. 12. Output annual energy consumption distribution from IDA ICE based on pairwise combinations..

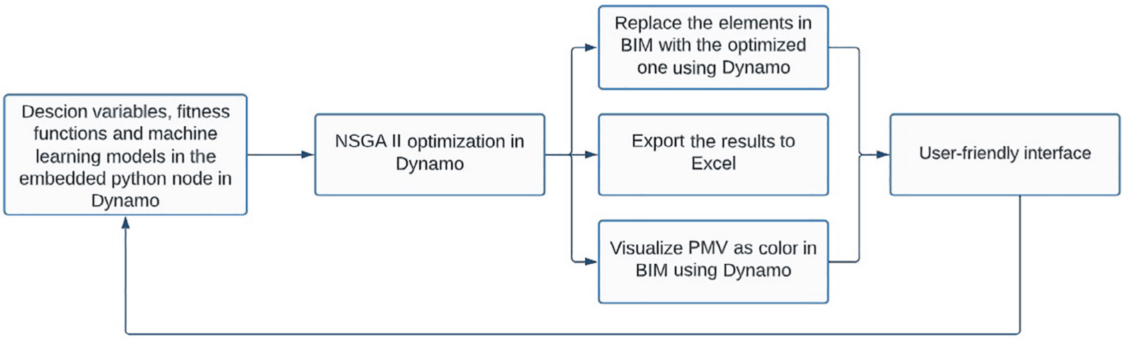


Fig. 13. The steps taken to develop optimization and machine learning models in Dynamo..

Table 7
Energy consumption prediction results based on several machine learning models.

Model	RMSE	R-Squared	MSE	MAE	Training time (seconds)
LR	5.65	0.84	31.94	4.06	4.77
ANN (one layer 10 neurons)	3.19	0.95	10.23	2.30	8.10
ANN (one layer 100 neurons)	1.88	0.98	3.54	1.41	38.10
SVM	2.35	0.97	5.56	1.79	13.01
GPR	1.94	0.98	3.80	1.46	92.83
DNN	2.05	0.98	4.23	1.57	9.26
RF	3.93	0.92	15.47	2.87	**2.06**
XGB	5.33	0.86	28.43	3.79	2.52
ANN-SVM	1.29	0.99	1.67	0.95	25.34
LSSVM	1.25	0.99	1.56	0.91	5.22
GMDH	1.27	0.99	1.62	0.95	22.68
GLSSVM	1.20	0.99	1.44	0.89	14.03

3. A comparison of building envelope characteristics before and after optimization shows that the thermal performance of envelopes, notably the wall, windows, and roofs, is critical to energy-saving and thermal comfort.

5. Discussion

A Pareto-optimal front may be generated using NSGA II for multi-objective building energy consumption optimization and the ideal point approach to arrive at the optimum solution for building energy consumption and thermal comfort. When we compare the optimal solution of building's parameter values to the original solution, we discovered that each parameter's value changes, albeit to varying degrees.

Several previous studies have been conducted on building energy consumption and thermal comfort optimization [124–126,111,127,129,129–135,71]. Those studies focused on specific parameters that affect building energy consumption. However,

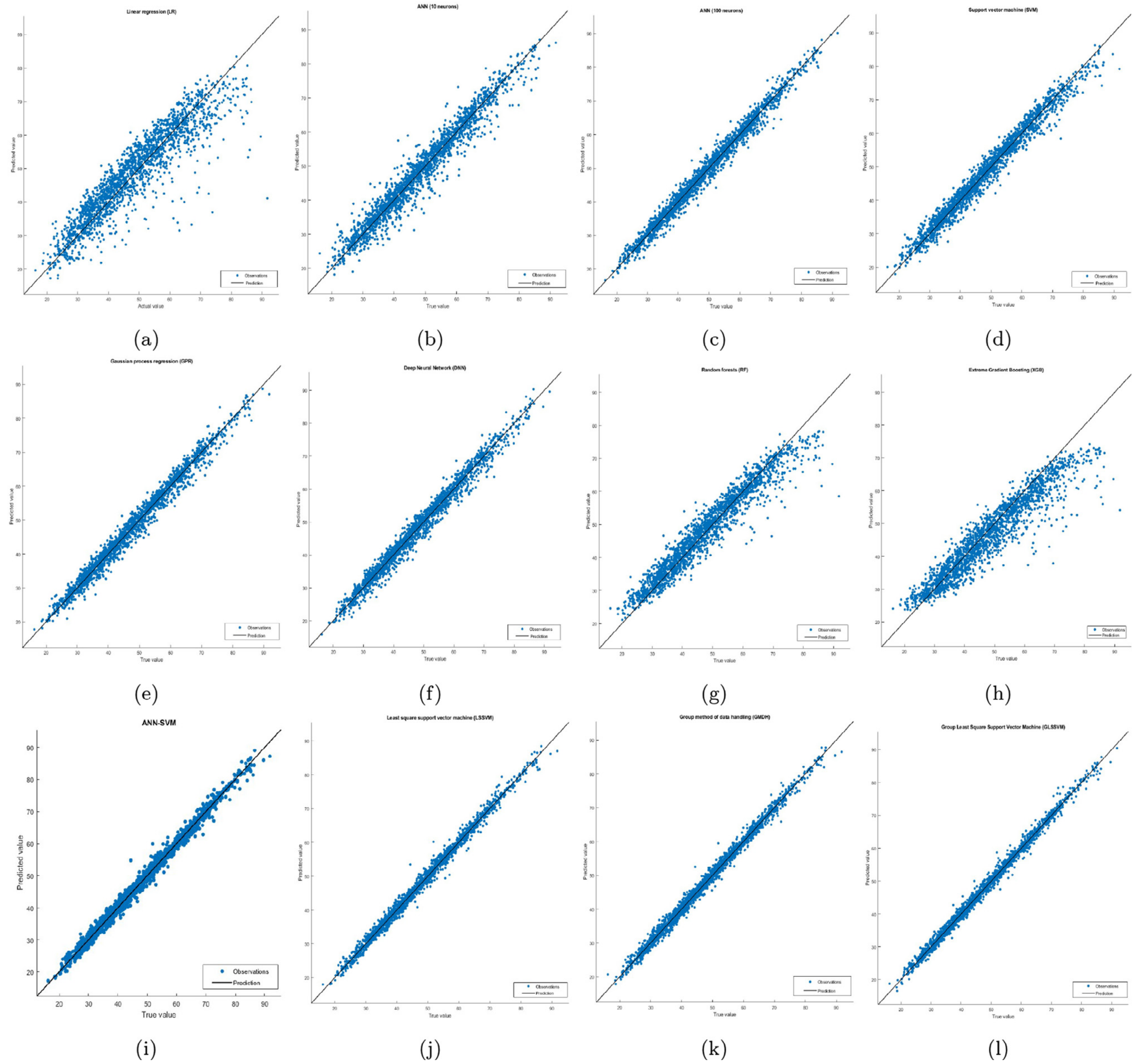


Fig. 14. Machine learning models results based on Table (7) algorithms, where the blue points represent the observations from the simulation results, and the black line represents the prediction. Also, the vertical axis represents the predicted value while the horizontal axis represents the true value: (a) Linear Regression (LR), (b) Artificial Neural Network (ANN) with one layer and 10 neurons, (c) Artificial Neural Network (ANN) with one layer and 100 neurons, (d) Support Vector Machine (SVM), (e) Gaussian Process Regression (GPR), (f) Deep Neural Network (DNN), (g) Random Forest (RF), (h) Extreme Gradient Boosting (XGB), (i) Artificial Neural Network-Support Vector Machine (ANN-SVM), (j) Least Square Support Vector Machine (LSSVM), (k) Group Method of Data Handling (GMDH), (l) Group Least Square Support Vector Machine (GLSSVM)..

Table 8
Multi-objective NSGA-II optimization parameters.

Parameter	Value
Population type	Double vector
Population size	40
Mutation function	0.8
Crossover function	0.02
Stopping criteria	Generations = 400

non of these studies conducted a comprehensive system of factors influencing the building energy consumption and thermal comfort. Our research combined 19 variables from the building envelope and HVAC system, including shading factor, SHGC, reflectance, and air infiltration. In addition, in this study, we validate the simulation results with real sensor data from the building, which is seldom done in the literature. Furthermore, in this study, a huge database has been generated to cover various possible solutions for the optimization process. We have also developed an ontology framework so that the suggested framework in this research can be applied to any building. What is unique in this study is that it implemented all the frameworks in the BIM environment so that it can interact with the BIM environment immediately and stream the best solution in both directions (to and from BIM).

Regarding the results of our research, the GLSSVM has a unique capacity to forecast building energy use with high accuracy, which has not been investigated on such a database with many variables or compared to this number of machine learning algorithms. Other studies focus most on ANN, SVM, and other ordinary methods that can not reach the accuracy of GLSSVM when it comes to such a database using a reasonable time to run the model compared to

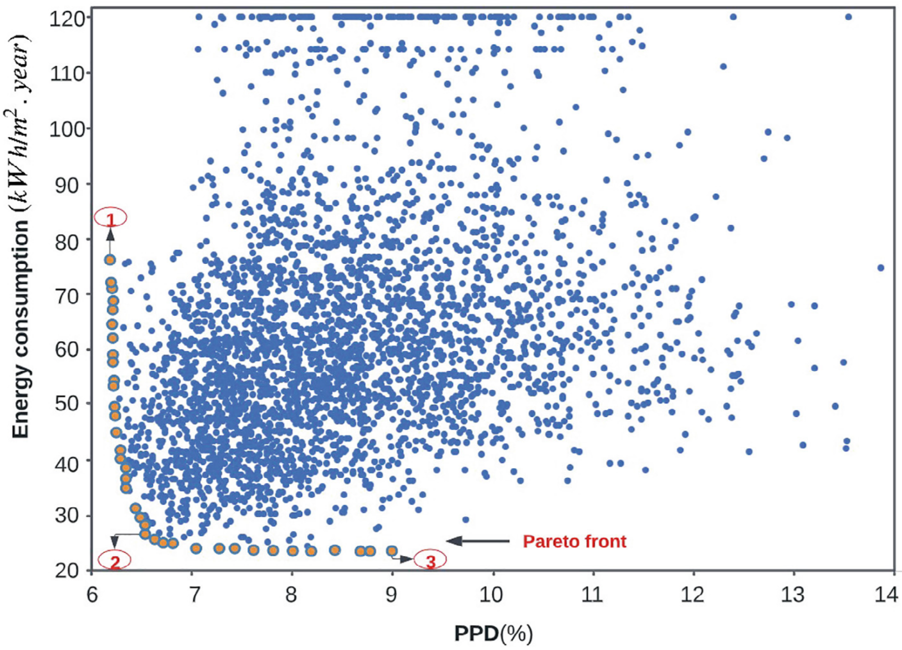


Fig. 15. The Pareto front of energy consumption optimization, where points (1) and (3) represent the anchor points that refer to the optimal points of the individual objective functions and the worst value for the other objective function in multi-objective optimization [122]. Point (2) refers to the knee point, which indicates the most satisfactory solution but not the ideal one [123]. Every blue point in the figure represents a possible solution..

Table 9
Optimized parameters from points 1,2,3 in Fig. 15, except HVAC setpoints.

Parameter	1	2	3
U-value external wall [W/m^2.K]	0.12	0.12	0.12
U-value window [W/m^2.K]	0.75	0.9	0.9
U-value roof [W/m^2.K]	0.08	0.08	0.16
WWR (%)	36.82	31.94	59.89
SHGC	0.43	0.25	0.25
Lightning [W/m^2]	8	8	8
Activate shading (klux)	70	70	61
Night ventelation [l/m^2.s]	0.7	0.7	0.5
Heat exchanger efficiency	0.85	0.85	0.85
Shading factor	0.5	0.3	0.3
Air infiltration	0.07	0.06	0.06
Reflectance	0.65	0.4	0.4
PPD (%)	6.2	6.5	9
Energy (kWh/m^2.year)	77.8	26.2	22.9

other hybrid methods (e.g., ANN-SVN). Using GLSSVM, we could replace the 16 days of simulations with 14 s of prediction, which is not stated in any similar research.

The results also show that the GLSSVM-NSGA II hybrid technique can reduce energy consumption by 37.5% and increase thermal comfort by 33.5%, respectively. Chen et al. [134] have used a similar approach using the hybrid machine learning model and NSGA II. However, they use only 54 combinations of variables compared to 8000 in our case. Their research was also limited to 6 variables related to building envelope. In addition, the BIM model in this study was only used to import the 3D model to the simulation software. However, our results agree with [134] that the external wall U value is the most important factor in the optimization. Seghier et al. [133] developed a framework using Dynamo to extract data from the BIM model, apply NSGA II in MATLAB and stream the results back to the BIM model. Even if the idea of using visual programming is similar in both research, we first used a more user-friendly interface integrated with the BIM authoring tools (plug-in in Revit®) to extract all the necessary information from the BIM model and apply all the processes inside Dynamo without needing to use MATLAB. We also included more variables and used machine learning to simplify the simulation process and understand the building performance. Rahmani et al. [72] developed a new optimization library inside Dynamo so that the optimization process can happen inside Dynamo, the same as we did in our research; however, no machine learning was applied in Dynamo as a fitness function in addition to the limited variables that been taken into account. They also did not integrate real-time sensor data with BIM in their study. All of the above studies have not used Brick, SSN, and BOT ontologies to generalize their framework so that it can be applied to several buildings.

As a result, the optimization technique suggested in this study gives valuable insights into the value of various control methods of HVAC setpoints change in enhancing building energy performance.

In addition, the operating temperature is enhanced throughout winter and summer operations, saving a significant amount of energy following the optimization. We have attempted to follow the Norwegian building regulation TEK10 and the standard NS-EN 15251:2007 by taking the solutions that fulfill the PPD criterion of less than 10%. Using Table 9, it can be shown that the most remarkable results were achieved when shading factors, air infiltration, reflectance, SHGC, and interior temperature setpoints were taken into consideration.

It is also fascinating to talk about the building's cost-effectiveness in light of the data linked to energy savings. As a result of the optimization procedure, the building's energy consumption was reduced significantly compared to the reference building. Eventually, the decrease in operational costs due to improved building energy performance may be the most significant factor in the facility's total life cycle costs. If the cost-effectiveness of other systems and materials were also taken into account, this substantial energy-saving might not be achieved. We recommended a wide range of solutions, including shading devices and HVAC setpoint adjustments, that may enhance building energy performance at a minimal investment cost.

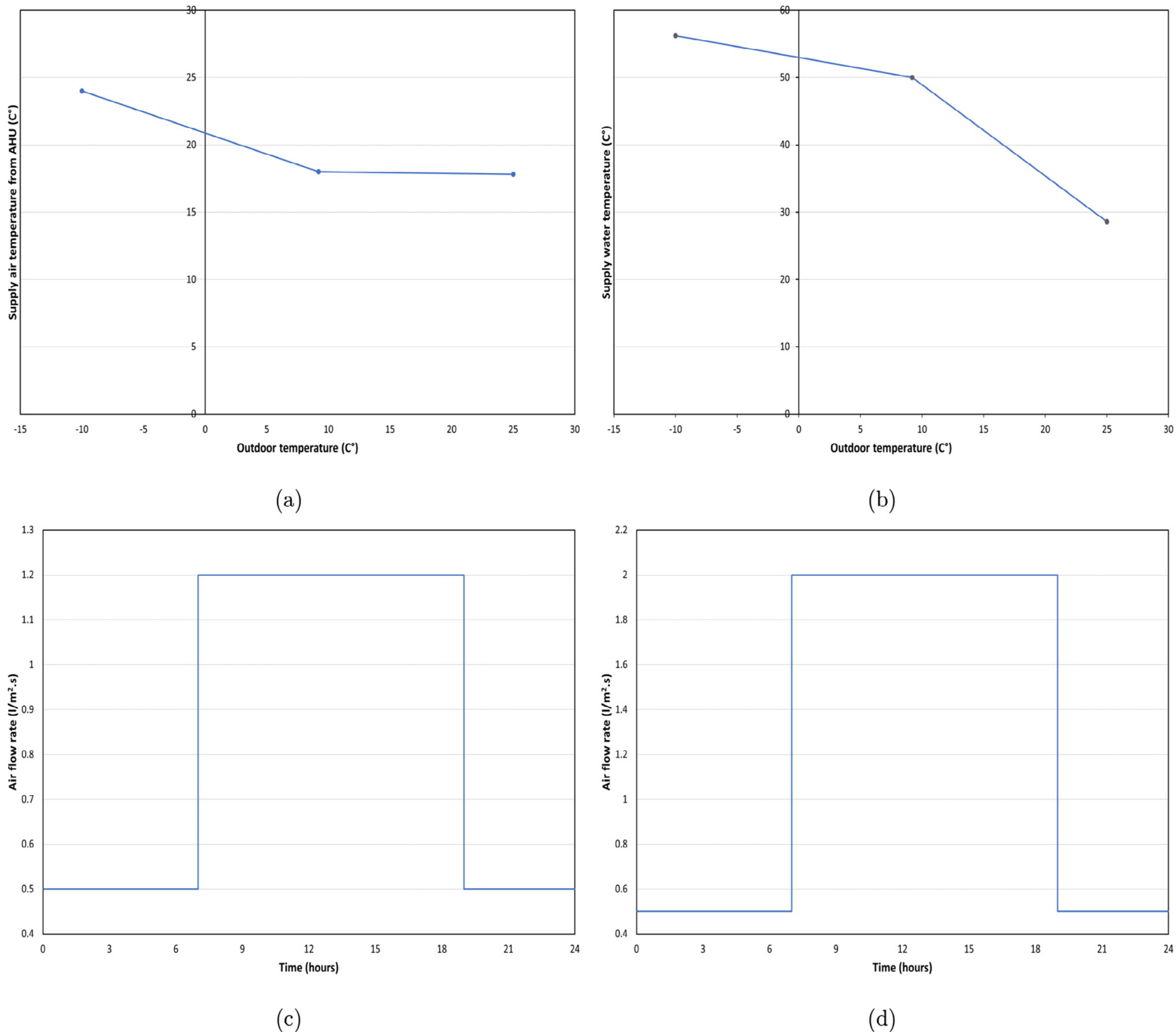


Fig. 16. (a) optimal supply air temperature from AHU, (b) optimal supply water temperature, (c) optimal ventilation supply airflow rate during the cooling season, and (d) optimal ventilation supply airflow rate during the heating season..

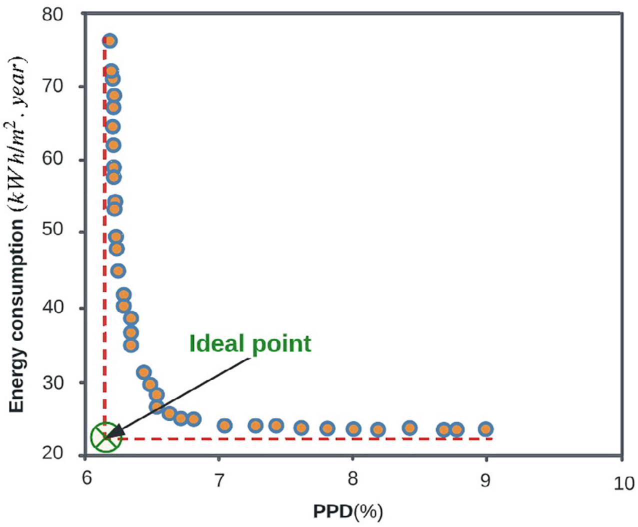


Fig. 17. The optimal solution based on the ideal point.

Another point is that our case study is a secondary school serving older students (16–20 years). However, the important question is, can the PMV formulas ((6), (7), (8), and (9)) be used in other educational settings where the occupants are younger?

The PMV model's relationships between metabolic rate, skin temperature, and thermal comfort may not be the same for children. Fanger's original study on thermal comfort did not include any children. For this reason, Fanger stated that further research was needed to see if these equations could be applied to children [136]. In the same line, several research shows that children are less sensitive to temperature changes than adults [137–139]. The high level of exercise can explain these findings among children and the wide range of activity levels during education.

The clothing insulation and metabolic heat production can be estimated, but practical methods are not accurate and affect the uncertainty in the final thermal sensation prediction to a large extent. Improving the methods to determine clothing insulation and metabolism can improve the accuracy and quality of PMV-based predictions for children [140–142].

Out from that, there is no evidence that the PMV approach can be used to predict the thermal sensation of children in a classroom accurately. Hence, to estimate PMV accurately, more data and details are required.

6. Conclusions

This study provided a multi-objective optimization framework based on BIM and machine learning-NSGAII intelligent algorithms, as well as a related application to minimize building energy consumption and increase thermal comfort by examining various building factors. An integrative optimization technique incorporating the building envelope, glazing parameters, HVAC setpoints, shading variables, and air infiltration was used for this aim.

This paper proposes a framework with four primary steps: (1) Receive all building sensor data in the BIM model using a Revit plugin and export this information to MSSQL and Excel to be used in validation of the simulation model in IDA ICE and have a good insight into actual sensor values. BIM data have also been extracted as a COBie and integrated with the building management system using several ontologies. (2) The established BIM model is imported into the IDA ICE, and a pairwise test is conducted to obtain an adequate sample dataset of building energy consumption through simulation; (3) Several machine learning models are trained on the sample dataset to establish a nonlinear mapping between the energy consumption and influencing factors; GLSSVM was the best algorithm in terms of $R2$, RMSE, MSE, and MAE; and (4) A GLSSVM-NSGAII multi-objective optimizing algorithm The effectiveness of the suggested technique was ultimately confirmed using a case study of a secondary school building in Tvedestrand, Norway, which was modeled in accordance with the Norwegian building standard TEK10. Given the circumstances, the hybrid GLSSVM-NSGA-II has proven to be the better method for enhancing the building's environmental protection and indoor comfort.

Several significant conclusions can be drawn: (1) The GLSSVM approach can accurately estimate building energy consumption based on the thermal characteristics of the building, with a $R2$ of 0.99, RMSE of 1.20, MSE of 1.44, and MAE of 0.89, compared to other models. (2) The GLSSVM-NSGAII model is very efficient for multi-objective optimization in reducing building energy consumption and enhancing interior thermal comfort. The ideal design approach reduces energy consumption by 37.5% and enhances thermal comfort by 33.5% compared to the initial design solution. (3) The exterior wall U-value should be in focus throughout the energy-efficient design of the building envelope, followed by the U-values of roofs, windows, and the window-to-wall ratio. On the basis of the novel GLSSVM-NSGAII multi-objective technique, building energy consumption and thermal comfort performance can be enhanced by implementing design modifications prior to construction. It is supposed to aid in the selection of building materials and designs. (4) The appropriate shading factor, SHGC, reflectance, and activation were determined by solar radiation and air infiltration on the outer side of the windows. Other input parameters acquired for the optimal solution included the best envelope settings and the most efficient heat exchanger in the AHU. The next step was to alter the ventilation supply air temperature and flow rate in the AHU, as well as the supply water temperature from the central heating plant to the local radiators.

Efforts to increase building efficiency and thermal and visual comfort can be pursued in the future. After the simulations have been run, post-processing daylight and Computational Fluid Dynamics (CFD) simulations may be used to examine additional aspects of thermal and visual comfort. The best location for the shade device must be determined using dynamic visual comfort criteria, such as daylight autonomy or usable daylight illuminance. Instead of comparing the average value of thermal and visual comfort indices before and after optimization, this is an intriguing situation to analyze the spatial distribution of these characteristics. For on-site power production, it is required to examine the impact of photovoltaic panel (PV) panels at the construction site. A closer look at shading and window opening controls, as well as the effects of interior air temperature, CO2, direct sunlight, and wind velocity setpoints, will be necessary to understand the control model of windows and shading in greater depth. As part of the optimization process, visual comfort must be considered. This necessitates the inclusion of additional factors, such as the window-to-floor area ratio.

CRediT authorship contribution statement

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

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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Appendix E

Paper 5- A review of the Digital Twin technology for fault detection in buildings

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A review of the Digital Twin technology for fault detection in buildings

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This study aims to evaluate the utilization of technology known as Digital Twin for fault detection in buildings. The strategy consisted of studying existing applications, difficulties, and possibilities that come with it. The Digital Twin technology is one of the most intriguing newly discovered technologies rapidly evolving; however, some problems still need to be addressed. First, using Digital Twins to detect building faults to prevent future failures and cutting overall costs by improving building maintenance is still ambiguous. Second, how Digital Twin technology may be applied to discover inefficiencies inside the building to optimize energy usage is not well defined. To address these issues, we reviewed 326 documents related to Digital Twin, BIM, and fault detection in civil engineering. Then out of the 326 documents, we reviewed 115 documents related to Digital Twin for fault detection in detail. This study used a qualitative assessment to uncover Digital Twin technology's full fault detection capabilities. Our research concludes that Digital Twins need more development in areas such as scanner hardware and software, detection and prediction algorithms, modeling, and twinning programs before they will be convincing enough for fault detection and prediction. In addition, more building owners, architects, and engineers need substantial financial incentives to invest in condition monitoring before many of the strategies discussed in the reviewed papers will be used in the construction industry. For future investigation, more research needs to be devoted to exploring how machine learning may be integrated with other Digital Twin components to develop new fault detection methods.

KEYWORDS

BIM, fault detection, predictive maintenance, IoT, Digital Twin

1 Introduction

The concept "Digital Twin" has emerged during the last decade in manufacturing, production, and operation as a computerized model that replicates the actual system (Jones et al., 2020; Sacks et al., 2020). This technology was first used in 2002 in aerospace production and product lifecycle management by NASA for the moon exploration mission Apollo 13 (Augustine, 2020).

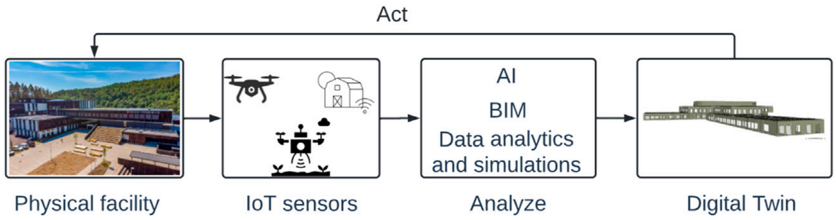

FIGURE 1
Digital Twin technology concept.

The Digital Twin represents the physical and functional properties of a complex system such as a construction project. The Digital Twin has three main elements: a physical object, a virtual model, and the connection that binds these two together. This connection is an exchange of data, information, and knowledge made possible by advanced senses such as computer vision, the Internet of things, high-speed networks, and advanced analysis technologies. All data are collected from sensors located on the physical object, which is used to establish a virtual object (Sacks et al., 2020; Jiang et al., 2021).

The Digital Twin is later used for visualization, modeling, simulation, analysis, and further planning. For constructions, this means that you always have access to models that are constantly synchronized in real-time. This allows companies to monitor progress in a 4D BIM model at any time. In addition, it can be used to analyze different courses of action and estimate their probabilities to choose the most optimal solution (Hosamo et al., 2022a). The major components of the Digital Twin may be depicted in Figure 1, where the simulation model must be confirmed utilizing technologies such as laser scanners, drones, sensor data, and so on. Once the model has been verified, it may be used to make better decisions, streamline processes, and make predictions by providing insight into how the real thing behaves in various simulated settings.

1.1 Operation and maintenance

More than 50 years of an facility asset's overall life cycle is spent in the "Operation and Maintenance" (O&M) phase, which is typical for buildings and other types of civil infrastructure (National Research Council, 2007). During the O&M phase, one of the most difficult challenges is to achieve smart building management. It is necessary to save detailed information (such as historical records, performances of facilities, correct locations, *etc.*), and various technologies would be required to do so (e.g., sensors, cameras, *etc.*). During O&M management, one of the most important challenges is overcoming and maintaining the data's integrity, validity, and interoperability (Wetzel and Thabet, 2015). As a consequence of this, it is necessary to have an O&M management system that is both efficient and intelligent to sustain dynamic information, support a variety of activities, and contribute to a healthy environment (Lu et al., 2018).

There is no integrated platform currently available to handle information scattered across many databases or support actions occurring throughout the O&M stages. Computerized Maintenance Management Systems (CMMS), Computer-Aided Facility Management (CAFM) systems, Building Automation Systems (BAS), and Integrated Workplace Management Systems (IWMS) are just some of the tools and systems that have been developed to improve O&M management (Keller, 2012). For example, CMMS is a computerized system for O&M management that may store daily work orders, historical data, service requests, and maintenance information. CMMS also can track service requests (Nojedehi et al., 2022). However, to extract the various O&M information that facilities management (FM) experts require (for example, data from CMMS and 3D models), they still have to put in a substantial amount of work and spend much time doing so (Wetzel and Thabet, 2015).

It is anticipated that building information modeling (BIM) developments would cut by 98% the time needed to update databases throughout the operation and maintenance phases (Ding et al., 2009). By modifying BIM and establishing technologies to increase data interoperability and integration, several integrated and complete solutions for O&M management have been presented. For instance, the team that worked on restoring the Sydney Opera House built a unified central data repository to enable efficient O&M management. This repository integrated a variety of various resources. However, on the whole, research is still being done to develop a complete and practical method for data integration based on BIM. This approach must be maintained and updated through the O&M phase (Ding et al., 2009; Parsanezhad and Dimyadi, 2013). An integrated, intelligent strategy or system is still necessary for ongoing development and improvement. This approach or system should be able to aid in the monitoring, updating, communicating, and integrating of O&M management concerns.

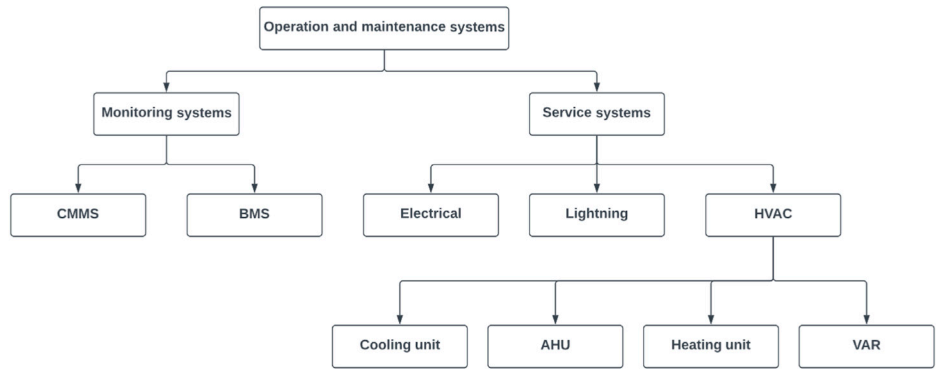

FIGURE 2
Main buildings systems that have been included in this study.

1.2 Anomaly detection for building assets

Anomaly detection for building assets is regarded as the procedure that requires the most human resources, takes the most time, and has the biggest impact throughout the operation and maintenance phase (Shi and O'Brien, 2019). Extensive research shows that prompt anomaly detection may significantly improve the safety, effectiveness, and quality of the processes involved in building operations (Shi and O'Brien, 2019). In its most basic form, it is a preventative and proactive action that ensures the assets continue to perform the original purpose they were designed throughout their lifecycle. However, one of the most critical issues is that the loads these assets are expected to carry are always shifting because of human needs. As a result, the assets' performance, such as the pump's vibration during the daily O&M, is not stationary. Conventional point-based anomaly detection algorithms cannot handle this situation very effectively, particularly in the constructed environments that are being targeted, since it is normal to be a lack of data that has been properly tagged (Qiuchen Lu et al., 2019). Digital Twin are regarded as an all-encompassing solution. Digital Twin originated as an all-encompassing method for managing, planning, predicting, and demonstrating the state of a building's infrastructure assets (Fjeld, 2020; Chen et al., 2021; Deng et al., 2021).

1.3 The scope of this study

This research explores the possibility of utilizing Digital Twin technology in the fault detection of service and monitoring systems, including:

- Data management and integration in facility maintenance.
- Real-time intelligent facility asset maintenance and monitoring.

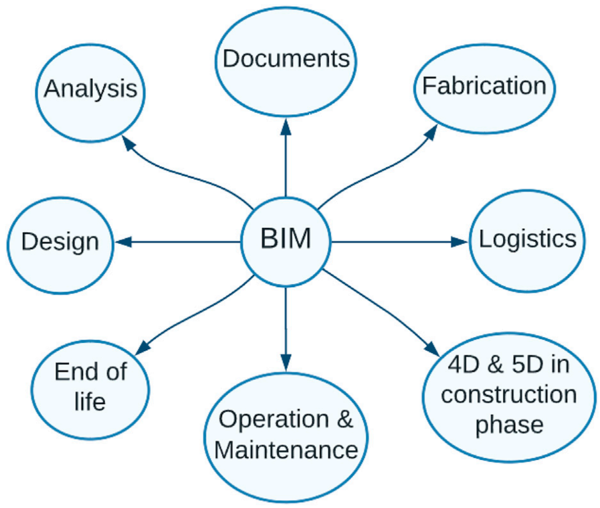

FIGURE 3
Visual explanation of a BIM project.

- A well-established machine learning data analysis technique in fault diagnosis.

The following are the questions this study aims to address:

- What is the current use of Digital Twin?
- Can Digital Twin technology enhance the current fault detection in building practices?
- What are the challenges of Digital Twin technology implementation?

Figure 2 shows the service and monitoring systems.

2 Background theory

2.1 Building information modeling

Building information modeling (BIM) was introduced some time ago and is now essential in construction, architecture, and engineering (Seyis, 2019). It was mainly introduced to differentiate between architectural 3D modeling (BIM) with a lot of information and the established 2D drawings. BIM has been praised by its users because of its ability to detect errors in early stages, making the process more efficient (Pour Rahimian et al., 2020).

BIM allows the construction of virtual models with a lot of information. Digital models contain clear-cut geometry and appropriate data to aid in the construction, production, and acquisitions necessary to finalize the project as optimal as possible (Marzouk et al., 2018).

BIM covers every aspect of the building industry. The figure below (Figure 3) visually explains the process a BIM project will go through. The example below considers a project from restoration and every step on the way through the design phase, production phase, the operational phase, and finally demolition at the end of the building's lifetime (Mijic et al., 2017).

In practice, BIM will be used by a group of engineers, architects, and contractors. They will use their chosen software to create a virtual model of the structure and share the model. This model will mainly be a 3D model of the structure, existing details and include drawings and specifications. By using this model, the group can share, identify and solve issues regarding the design and construction before the construction phase is ongoing. In addition, the model will also be used in the construction phase when new cases occur by using the model to find new alternative solutions (Eastman et al., 2011).

2.2 Internet of Things

The Internet of things (IoT) connects physical objects to the Internet through sensing technologies and different types of communication (Yuan et al., 2016). These tools gather a lot of information to form connections between objects, as well as between things and people. IoT contains various technologies, but some are more central, such as:

- Sensing technology.
- Wireless communication technology.
- Cloud computing technology.
- Radio-frequency identification (RFID) intelligent identification technology.
- Internet Protocol version 6 (IPv6) technology.

RFID technology is the one that has been implemented the most so far, at least when we are looking into BIM and IoT together. This is because they are easily connectable, and RFID technology can be used in several different ways where BIM is already implemented (Chin et al., 2012; Srewil and Scherer, 2013).

One purpose of RFID technology is to use RFID tags in the helmet of construction workers so that they can be "traced" in BIM; this is beneficial for the construction workers' safety as they can be monitored in real-time; however, a balance between workers safety and privacy should be considered. The same can be done on objects as they can be observed in transportation for logistic benefits, and in the case of a vast construction area, things can be found within the BIM model.

IoT sensors can also be a valuable tool in construction and operation since they provide construction data in fields such as temperature, humidity, stress, and strain. These values can prevent construction failure since they can give an early warning if critical values are reached (Plageras et al., 2018).

Devices that are involved with IoT are everywhere; even the simplest devices today may communicate in some ways. The technology is evolving and getting more familiar with time; this success is due to the availability of information to move around (Garramone et al., 2020).

2.3 Digital twin

The concept of Digital Twin technology is one of the segments in Industry 4.0 which is expanding the most (Boje et al., 2020; Opoku et al., 2021). A Digital Twin is a replica of the BIM model or a model from a 3D laser scan equipped with wireless sensors. The significant difference between the BIM model and the Digital Twin is that the BIM model is not dependent on real-time data to fulfill its function. The BIM model is mainly used to avoid any errors during the design and construction of a building. The digital model updates when the digital model of a physical object is changed; this is achieved through cloud-based software and the expanding diversity of IoT (Lu et al., 2020b). Figure 4 displays the process of completing a Digital Twin and highlights some positive uses: predictive maintenance, building operations improvement, and data analysis.

The importance of a Digital Twin can be described as follows: "Digital Twins will facilitate the means to monitor, understand, and optimize the functions of all physical entities, living as well as nonliving, by enabling the seamless transmission of data between the physical and virtual world." (Fuller et al., 2020).

If the Digital Twin is applied in today's architectural, construction, and engineering projects, some of the benefits one can expect are the following:

- The overall efficiency will increase throughout the entire life cycle of the service system (electrical, lighting, and HVAC systems) and monitoring system (CMMS, sensor system, AMS, and BMS systems).

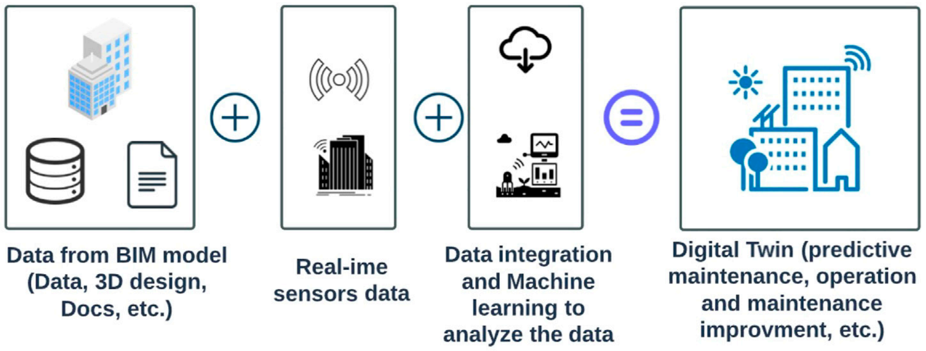

FIGURE 4
The components required to make a Digital Twin of a building and the distinction with BIM.

- Real-time updates from the physical assets make it possible to predict the failure and required maintenance of the service and monitoring systems.
- Problems can be solved without having to visit the physical object. This means determining if the problem is related to indoor air quality, acoustic comfort quality, visual comfort quality, thermal comfort quality, envelope insulation quality, and HVAC capacity to meet the thermal load.
- The Digital Twin may also provide the possibility to provide insight into occupants' behavior based on real-time data, which will result in further improvements as it is returned to the 3D simulations.

Digital Twin collect the real-time data transferred by sensors and utilize it to forecast how the process of a structure will perform during its lifetime. This can help detect eventual faults in the buildings. The detected defects could be minor errors that would only require small repairs, and potentially be more economical because it was seen in an early stage, compared to what would have been if Digital Twin were not used. It could also help detect numerous errors that could be crucial in terms of failure or total collapse. A Digital Twin is helpful for both small and bigger fault detection and will be more economical. One might avoid fatal outcomes by detecting structural issues before they appear. Digital Twin technology might be essential in areas with extreme weather and where it is familiar with natural disasters. These damages are harder to foresee since these damages are due to fatigue and will not be visible. It will be possible to predict the building's process and development using Digital Twin technology, which will help prevent a potential building collapse.

3 Research method

A mixed review technique was used to assess the applications of Digital Twin in fault detection in buildings to comprehend the topic expertise completely. This approach entails the following steps:

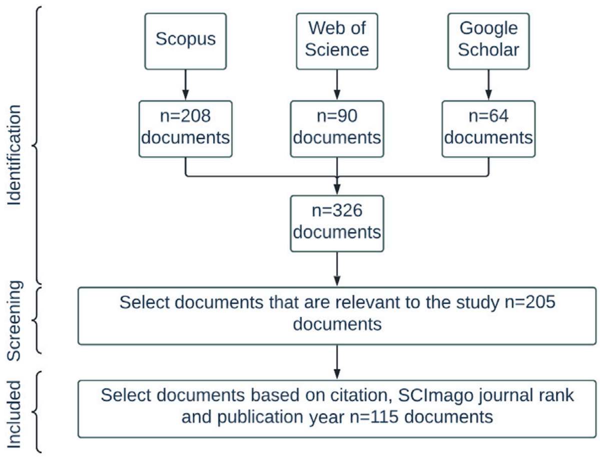

FIGURE 5
Systematic literature review flowchart.

- Choosing databases and keywords.
- Gathering and screening pertinent papers.
- Qualitative analysis.
- Identifying research gaps and future directions.

3.1 Determine the databases and keywords

The Recommended Reporting Items for Systematic Reviews (PRISMA) standard was followed during the data collection and selection phase (Page et al., 2021). The method and important procedures used in the literature review are illustrated in Figure 5.

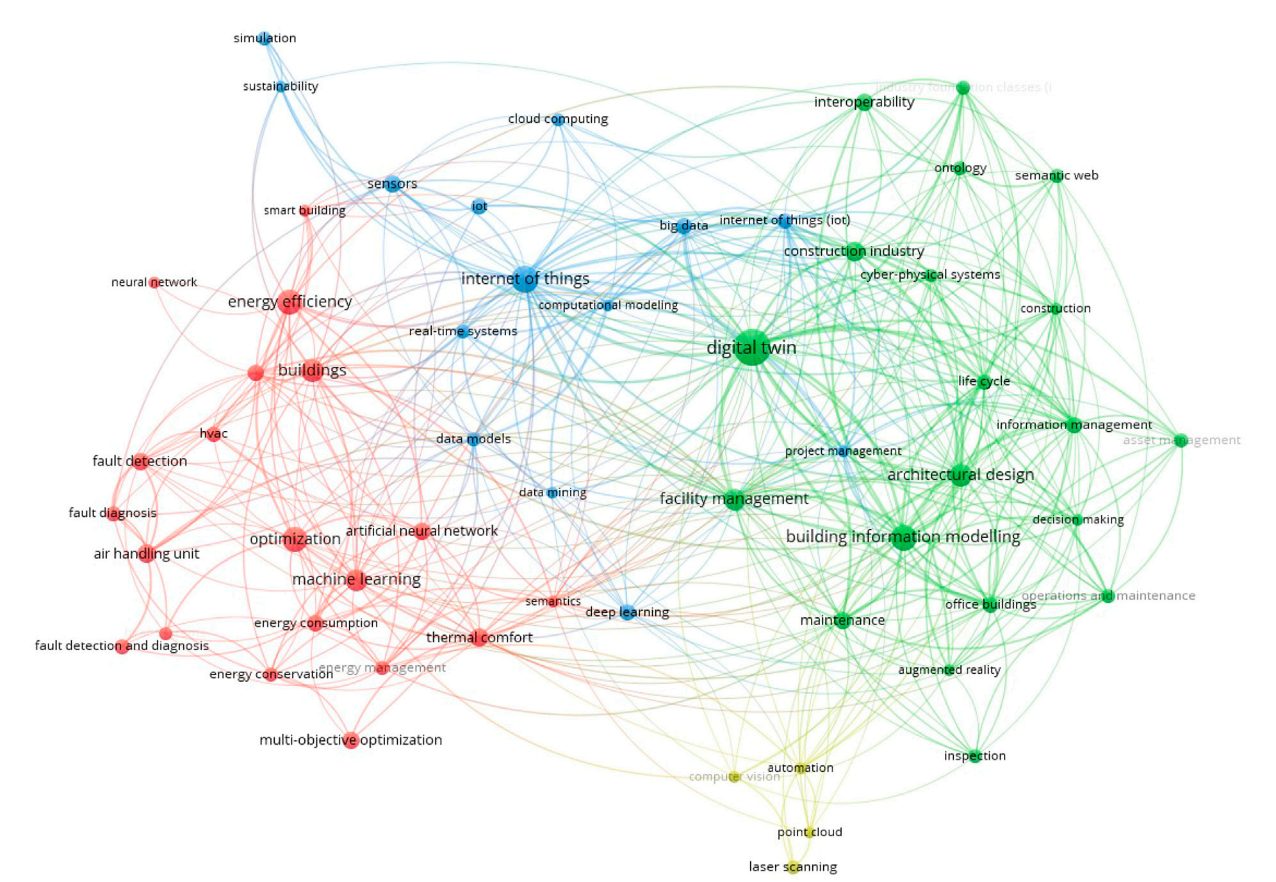

FIGURE 6
Network of keywords.

To prevent omission, a search for the most pertinent papers was conducted in three different literature databases, including Scopus, Web of Science (WoS), and Google Scholar. Reference and citation monitoring was also done to lessen the possible bias from the chosen literature databases. Search principles were developed to find papers regarding Digital Twin uses in facility maintenance. The search covered all documents, including journal articles, conference papers, and proceedings. Without specifying a publication year range, a search on the "Title/Abstract/Keyword" of the literature was carried out in July 2022.

The keywords of the existing knowledge domain in the Digital Twin for fault detection in buildings are shown using VOSviewer in Figure 6. The VOSviewer shows a distance-based representation of the keywords network. In this network, each keyword is a node, and the linkages that connect them are known as links. A connection's strength and weakness depending on the distance between two nodes. A weaker relationship between two keywords or nodes is shown by a larger distance, while a smaller distance indicates a stronger link (Perianes-Rodriguez et al., 2016). The connection strengths connected to a single node are added to the total link strength. Various colors denote different research years, and the size of the supplied nodes corresponds to the number of articles in which the phrase was first used (Oraee et al., 2017).

3.2 Collect and filter items that are of interest

After deleting duplicates, the search returned 326 items. As part of the screening process, each article's title and abstract were scrutinized for relevance to the scope of this study. Consequently, a total of 205 studies were included in the final assessment. The next stage was to determine whether or not these 205 studies could be included in the qualitative analysis. The number of citations, the year of publication, and the SCImago Journal Rank (SJR) were used to choose which articles could be used in the qualitative analysis. As a result, 115 articles were considered for inclusion in the qualitative study. Figure 7 depicts the literature trends in this study.

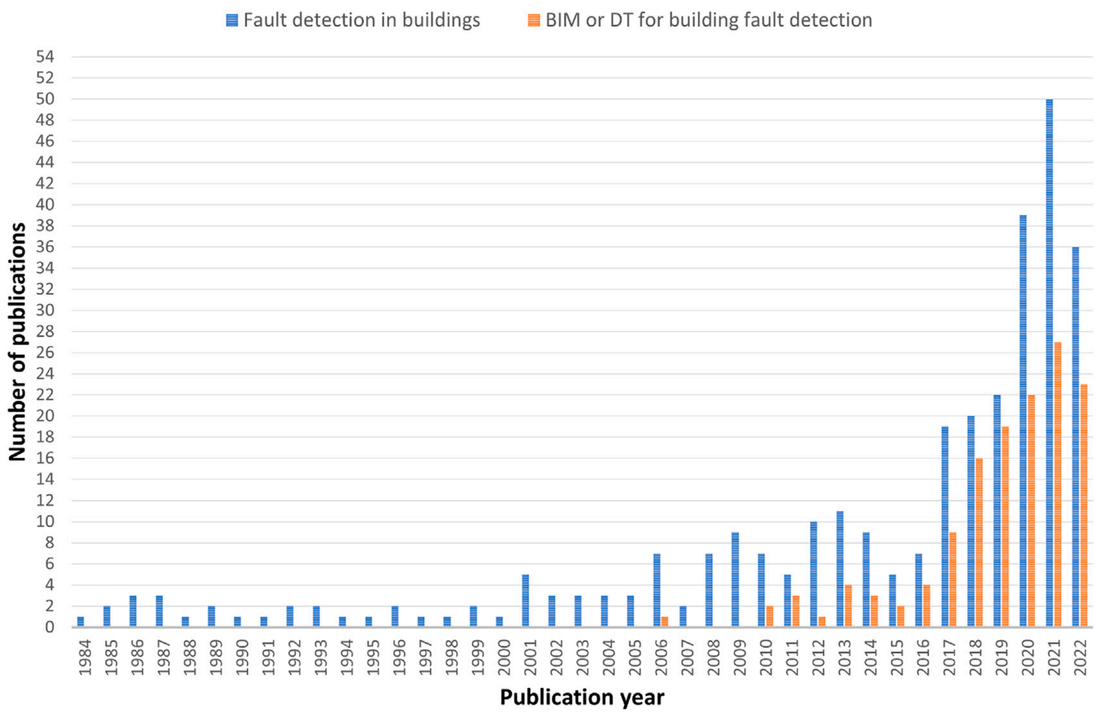

FIGURE 7
Publication distribution of literature (data as of 25 July 2022).

3.3 Qualitative analysis and future directions

In order to assess the chosen papers, identify research issues, and offer suggestions for future study paths in the examined areas, qualitative analysis is used (Onwuegbuzie et al., 2012; Baldini, 2022). To fully automate fault detection and prediction, a comprehensive framework must be made available to reduce reliance on human knowledge and intervention while increasing productivity, dependability, and timeliness. Following this, we propose BIM and machine learning as fundamental pillars of a Digital Twin-enabled framework for charting a course toward automated fault detection and prediction in buildings. Results include a qualitative analysis of factors that have the potential to improve fault detection and prediction in buildings. Using the study's findings, a road toward fault detection in buildings is drawn. In the following section, the results of this study will highlight significant applications and practical difficulties as well as potential future research areas.

4 Results

A crucial part of answering the research questions of this paper is determining the feasibility of Digital Twin technology use for fault detection. Thus the following topics have been extracted from the literature review to reflect the benefits from Digital Twin in fault detection in buildings.

4.1 Classification of faults found in the literature

Several faults have been recognized based on the literature review (Zhao et al., 2015, 2017; Bortolini and Forcada, 2019; Cheng et al., 2020; Alavi et al., 2021; Nehasil et al., 2021; Hosamo et al., 2022b). For example, heating and cooling at the same time, risk of discomfort, heat unexpected on, faulty supply fan, envelope thermal insulation, widows to wall ratio, acoustic attenuator, *etc.* Dealing with those faults and showing the potential of Digital Twin to solve these issues is our focus in this study. The Digital Twin technology has huge potential in detecting faults in real-time that typical systems cannot detect. In addition, some researchers could accurately predict the faults using the Digital Twin (Hosamo et al., 2022b), making it easier for the facility managers to make the right decision and act before the failure happens. Moreover, using Digital Twin, one can address other buildings that may make occupants uncomfortable, like visual and acoustic issues leading to less energy consumption and making people feel comfortable in

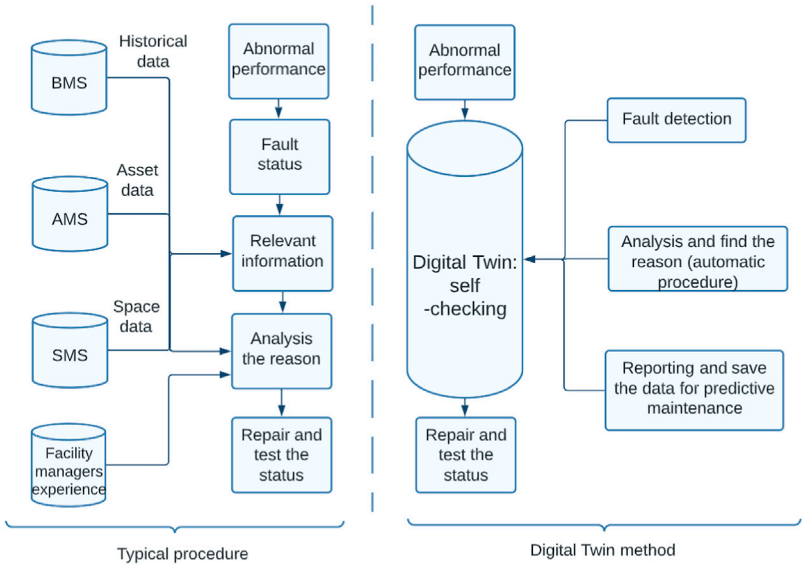

FIGURE 8
Typical procedure *versus* Digital Twin-based method.

buildings. In this sense, the next building may be learned from the detected faults by Digital Twin to be considered in the following design.

4.2 Process flow for detecting anomalies using digital twin

The level of service a facility gives its inhabitants is determined by the assets within the building that is responsible for performing the building's service functions. Consequently, building activities in the O&M phase are optimized by closely monitoring asset performance and quickly reporting abnormalities that arise. It is complicated to discover anomalies for asset monitoring because of the high degree of system complexity, the size of the integrated system, and the number of components. A frequent technique is looking for asset performance anomalies that depart from the anticipated patterns (Chandola et al., 2009; Hosamo et al., 2022b).

Digital Twin-based and traditional process flow scenarios are examined in literature studies (Lu et al., 2020a; Lu et al., 2020c; Motawa and Almarshad, 2013). There are two major flaws in the old procedure compared to Digital Twin-based anomaly identification: dispersed information and human query operations. It still takes a long time to search, query, verify and analyze the corresponding facility information from heterogeneous data sources, even though some data on maintenance and operation are managed in some facility information systems (e.g., BMS, AMS). As soon as the call service system (Figure 8) notifies facility management experts of a requirement for maintenance, they must first look for relevant asset management system information (such as historical or manufacturer information) before verifying the space management system's location information. It could be required to query the BMS or use other methods if more details are needed.

As a result of this procedure, there may be mistakes and variances. In the typical method, there is much repetition of information searches. Overlapping data, such as historical records, locations, and the associated contractors' information, can be stored in many databases (Lu et al., 2020a). In specific systems, such as AMS, BMS, and SMS, data sets of sites, buildings, and floors are saved repeatedly and redundantly. Manual query operations, in addition to the dispersed data, significantly contribute to the delay in anomaly identification. In a traditional procedure, as shown in Figure 8, the facility manager often serves as a central coordinator and makes decisions based on relevant data and expert expertise.

An intelligent and comprehensive platform is needed to efficiently search information and support semi-automated or automated operations to address these issues of the traditional approach. In light of the ease with which a DT-based system can be used to look up and validate facility information and automate anomaly detection, these issues can be alleviated.

4.3 Building data for anomaly detection

Multi-domain and multi-layer information storage, manipulation, sharing, and interaction are required in the

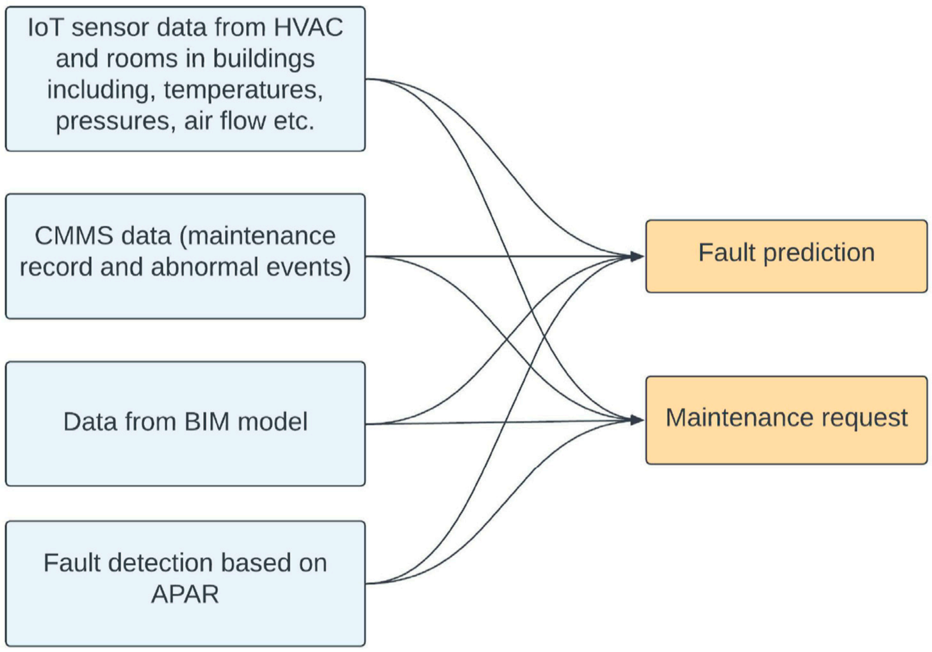

FIGURE 9
The necessary inputs for fault detection and prediction based on Digital Twin technology in existing buildings.

O&M phase to detect abnormalities in building assets. Through information sharing, effective anomaly detection may be achieved by eliminating change points induced by normal operating conditions to eliminate false alarms. Detection of anomalies in building O&M research relies on various data sources, including those discussed in previous section (such as building automation systems and building management systems, or BAS and CMMS). New O&M data sources remain within well-established communication protocols for storing and exchanging building data. Unusual operating behavior in a building's HVAC system may be detected quickly using the BAS data generated by sensors and actuators (which may be Building Management Systems (BMS) for other scenarios) (Costa et al., 2013). Building sensing data (e.g., access control system and security camera for occupancy monitoring) should be incorporated to identify if a dramatic change in external temperature is the source of the supply air temperature drop of an AHU in heating mode. Anytime the AHU heating coil valve temperature falls below its mixed air temperature, an abnormality is likely to occur. The tenants' service requests and work order issues are documented in the CMMS database (Motamedi et al., 2014). A CMMS's inspection and maintenance data might give valuable information about the building, such as fault trees and linkages between components. A building's root-cause detection capabilities can be bolstered by acquiring field expert rules. As a result, it is not easy to establish an effective anomaly detection strategy because of the fragmented nature of constructing data sources. The following section explains the Digital Twin approach for anomaly detection by integrating several data sources. Figure 9 shows the data that should be collected for building fault detection and prediction.

4.4 Integration of digital twin data

According to Digital Twin definitions, Digital Twins combine their components (e.g., AI, machine learning, and data analytics) to produce digital models that can learn and update from many sources, and to represent and forecast current and future conditions of their physical counterparts (Boje et al., 2020).

Every day, various O&M systems and databases are used (e.g., BMS and SMS) (Krämer and Beseny, 2018). In most cases, the O&M data are stored in multiple formats. As a result, gathering the diverse and dispersed O&M data necessitates significant time and effort from FM employees. In the O&M phase, data integration and intelligent asset management require a consistent and uniform data structure. The IFC data schema are the most appropriate and essential for BIM deployment and information integration because of its flexibility and consistency throughout the construction lifecycle. As a result, the present IFC must be expanded to meet O&M management needs (Cheng et al., 2020).

Furthermore, the O&M phase's asset information is not static. When it comes to sensor data, for example, it is constantly changing, and maintenance events are logged one at a time. A single IFC file would be useless for decision-making because existing IFC files may only provide basic geometric information. In this regard, a centralized data model linking to dispersed data resources in day-to-day O&M management are a suitable and realistic approach for modeling the IFC schema and integrating information (Wetzel and Thabet, 2015; Burak Gunay et al., 2019).

As a result, the data structure used in building Digital Twins' data integration layer are intended to exchange and interoperate external data connected to each BIM object on a semantic level, enabling IFC-based interoperability between BIM and other data sources. IFC is the primary data model, while other data resources are preserved in their original storage places, which are saved in several formats.

Recent studies show that FM is paying more and more attention to BIM development (Costa et al., 2013; Pärn and Edwards, 2017; Pärn et al., 2017; Pärn et al., 2018; Dixit et al., 2019). There is, however, several studies into IFC's role in operations and maintenance. O&M-related information and actions are not represented in the current IFC4 schema (Chen et al., 2018). The Digital Twin data structure construction process should include additional subclass data entities, types, and parameters necessary for FM, where a broader range of data types and O&M tasks are required (Patacas et al., 2015; Wong et al., 2018). Additional FM-related attributes and relationships must be included in a data structure for the inspection process (Costa et al., 2013; Wong et al., 2018; Dixit et al., 2019). Maintenance and inspection procedures must be incorporated into the IFC schema, inspection events, activities required for maintenance, specification, regulation, cost schedule, and other requirements are all examples of control, which is an extension of the control or constraint concept. Even while IfcControl can partially represent the information necessary for the maintenance plan, schedule, and cost, these entities are not explicitly designed for O&M management and cannot be linked totally with O&M operations.

The asset's historical record is also critical for O&M, but neither IfcOwnerHistory nor IfcPerformanceHistory includes all of the necessary information for FM. Example: IfcChangeActionEnum lacks an enumeration for the function "FM". The asset register criteria may be matched using IFC4 entities and the COBie spreadsheet. Some conditions in IFC4 cannot be tied to entities. Data gaps (such as costs, sources of components and spare parts, and consumption) and incompleteness are widespread in operations and maintenance (such as records of previous maintenance costs, pricing, and operations).

One of the most widely used national standards in the US, United Kingdom, and other nations is COBie, the most significant specification for integrating BIM and O&M systems (East, 2013). However, COBie can offer part of the O&M data that are required and still have several technical concerns that need to be addressed; for example, after the information transmission, model validation is required.

4.5 Artificial intelligence for optimization and fault prediction

"Prediction" and "optimization" are frequently vague, imprecise terms. There are several sub-disciplines under the umbrella term "artificial intelligence," such as "machine learning," "data analytics," and "logical" forms of "artificial intelligence."

Artificial Intelligence (AI) has long been considered an essential component of Digital Twins to cope with the Internet of Things (IoT) (sensing and actuation). Several studies have found that artificial intelligence (AI) is crucial to the Digital Twin's ability to forecast and optimize dynamically. There is still debate over how high a Digital Twin maturity level should be before it can accurately predict and issue warnings about the physical asset's performance (Madni et al., 2019).

A typical requirement for Digital Twins is the ability to forecast future asset behavior or health condition. Predictions must be able to anticipate subsequent environmental states throughout time using measured input and output values, as well as beginning circumstances, in contrast to simulations, which can accurately duplicate the physical conditions utilizing input data and initial conditions (Kuster et al., 2017; Tongal and Booij, 2018)). Prediction should be employed for instant physical actuation as a reaction, according to phrases like "predictive modeling" and "structural life prediction" (Patterson et al., 2016; Qi and Tao, 2018; Madni et al., 2019; Hosamo et al., 2022b).

A common perspective of exploiting IoT utilization is "Big Data" fed prediction (Qi and Tao, 2018; Yusen et al., 2018). The phrase "Big Data" itself is vague, including not just quantity but also diversity, and stages of existence, ranging from unstructured to semi-structured to organized data (Gobble, 2013). As a result, managing vast volumes of data can significantly benefit the adoption of the Digital Twin (Qi and Tao, 2018). Big data prediction strategies frequently involve machine learning or data mining, with the former emphasizing finding new patterns and implicitly understanding the data itself, while the latter focuses on replicating general knowledge. Comparing data analysis to Digital Twins in-depth, Qi and Tao (Qi and Tao, 2018) emphasize the necessity for a future fusion between the two to increase Digital Twin self-reliance and provide general interoperability. The procedures used for acquiring, scrubbing, and organizing the data combined for greater significance and employed for processing intelligent tasks present a concern.

Concern should also be expressed about the validity of the data's sources. Predictions based on real sensor data should be distinguished from forecasts based on simulated sensor data or a hybrid technique. Consideration must be given to confirming the accuracy of the prediction and its implications for actuating the physical component. In other words, can that judgment be made using existing AI techniques that are sufficiently "clever" to do so?

Like the preceding approaches that utilized AI, the term "optimization" is often used in the Digital Twin industry. Optimizing the Physical Twin's production and operational expenses appears to be the joint driving force. When it comes to manufacturing, the essential use case is to ensure that resources are allocated in the most efficient way possible, like in the case of experimental testbeds that aim to optimize assembly algorithms (Schluse et al., 2018). For example, Alam and Saddik (Alam and El Saddik, 2017) employ Bayesian networks to describe the decision model in engineering systems design. Costs scale up dramatically during operation in the built environment and energy sector (Howell et al., 2017), where balancing consumption against the demand for energy and resources is the fundamental difficulty. Infrastructure and building construction has a significant influence on operating expenses throughout the course of their lifespan. Unfortunately, there are times when the aims of construction optimization diverge from those of operation optimization during the lifecycle.

4.6 Deep learning applications in facilities management and maintenance

Using deep learning to help facility managers make better decisions and perform more efficient maintenance has significantly impacted building facilities management. Usually, there are five basic forms of maintenance: corrective, preventive, predetermined, condition-based, and predictive (Sagnier, 2018). Depending on the nature of their business, several organizations employ various maintenance strategies; however, facility managers often handle building maintenance in one of two ways: preventative or reactive. These strategies have certain drawbacks since they cannot be used for prediction and cannot avoid breakdowns when mechanical, electrical, and plumbing (MEP) components need to be repaired in advance. Predictive maintenance solutions, including cutting-edge technologies like IoT, have become the go-to solution where deep learning technologies are more commonly seen to enhance facilities management and maintenance efficiency (Cheng et al., 2020; Hong et al., 2020). Python with TensorFlow (Abadi, 2016), Keras (Ketkar, 2017), and PyTorch (Paszke et al., 2019) are common tools for creating deep learning models, as are MATLAB with Deep Learning Toolbox (Teza et al., 2022) and R (Ciaburro and Venkateswaran, 2017). Figure 10 depicts the location of FM in the BIM domain of the construction sector.

4.6.1 Classification of images

The goal of predictive maintenance is to forecast equipment breakdowns to schedule advanced corrective maintenance and avoid unplanned downtime and raise service levels. To help with facility management and maintenance, Marzouk and Zaher (Marzouk and Zaher, 2020) suggested a proactive maintenance application to maintain, improve, and run the assets of three fire protection systems cost-effectively with a deep-learning pre-trained model. The suggested deep learning model could categorize Mechanical, electrical and plumbing (MEP) components in the fire prevention systems using supervised learning and a deep CNN utilizing image classification (Marzouk and Zaher, 2020). According to the following study, a computerized decision-support system incorporating CNNs for image recognition can quickly spot fractures or other signs of deterioration in three-dimensional (3D) models (Czerniawski and Leite, 2018). Analyzing many criteria in diverse settings, an automated decision support system using 3D geometry might help facility managers make the right interventions.

Images may be categorized into millions of predetermined categories using deep learning and computer vision algorithms (Marzouk and Zaher, 2020). To improve asset management, it is also feasible to interpret printed and handwritten text, read picture information, and build useful metadata for smart image catalogs (Czerniawski and Leite, 2018). Deep learning can automatically separate Red Green Blue-Depth (RGB-D) photos into different construction parts (Deng and Chen, 2020). A shared convolutional neural network (CNN) is used for feature extraction from pictures in a vision and learning-based indoor localization framework (Wei and Akinci, 2019). Instead of requiring the deployment of RFID tags, this system concurrently conducted localization and object recognition for facility management (Wei and Akinci, 2019).

4.6.2 Detection and prediction of occupancy and energy management

Poor management of building resources, such as the HVAC and lighting systems, results from inaccurate occupancy estimation. Occupancy prediction models are created with the information gathered by occupancy sensors throughout the occupancy monitoring period. Due to the potential for very dynamic and contextual occupancy levels, these models are crucial for occupancy prediction. Advanced occupancy prediction methods employ assumption-free ANN algorithms to uncover hidden patterns in the sensor data gathered, increasing the accuracy of their predictions (Li et al., 2017). Assumptions regarding data distributions are often not made by ANN models before learning, which is consistent with their suitability for occupancy prediction.

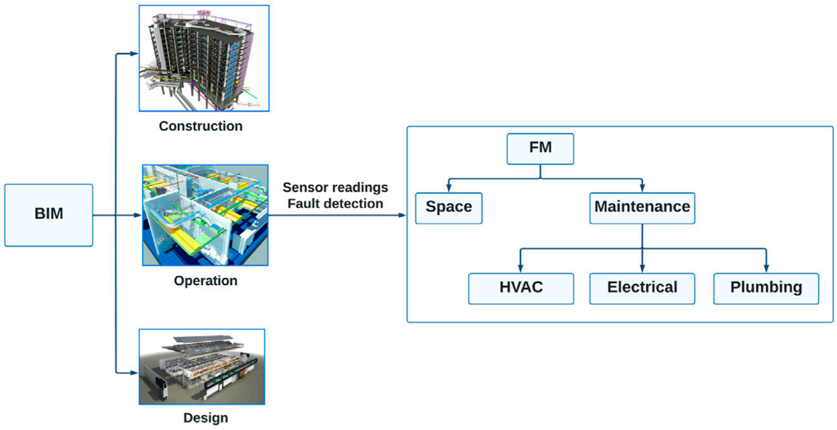

FIGURE 10
The domain of building information modeling (BIM).

The You Only Look Once (YOLO) deep CNN for multiple item identification and the multi-stream deep neural network are used by Mutis et al. (Mutis et al., 2020) to estimate occupancy counts in a room. The investigation had a positive result since using the technology for precise occupancy identification led to 10 and 15 percent energy savings, improving FM (Agarwal et al., 2010). Martani et al. (Martani et al., 2012) reported using Wi-Fi connections as a stand-in for occupancy level to analyze occupancy and measure occupant activities for energy consumption patterns (electricity, steam, and chilled water). Although just a small portion of power usage was connected to occupancy, the research findings also showed that the operation of HVAC systems depended on variables like the outside temperature and human occupancy (Martani et al., 2012). (Amato et al., 2017) presented a good CNN architecture for visual parking occupancy detection. The solution was then compacted for smart camera operation. Deep learning is recommended by Sonetti et al. (Sonetti et al., 2018) to study human behavior for intelligent and sustainable surroundings to reduce energy usage.

Occupancy prediction is critical since it influences energy use in real buildings, not just those under construction. Using IoT data, Kim et al. (Kim et al., 2019) developed a machine learning framework for HVAC that tested the performance of three occupancy estimate techniques, namely, decision trees, support vector machines, and ANNs. The study found that ANNs were more accurate in predicting occupancy than the other methods.

In order to construct the next generation of occupancy models that can reliably anticipate occupants' behavior, new DL approaches are being employed. Hammad (Hammad, 2019) presented a strategy for reducing the difference between expected and real energy consumption rates by merging BIM with an ANN model. A deep neural network training to predict occupant behavior results in accurate BIM representations, further confirmed by energy simulations. On-site thermal cameras and deep learning were used by Lee et al. (Lee et al., 2019) to construct an adaptive comfort model. Because it considers the dynamic interactions between people and their surroundings, an adaptive comfort model could be employed to operate an air conditioning system successfully. Maintaining the temperature and humidity levels in commercial spaces is essential. Data gathered from various IoT sensors shows that manual work results in wasteful energy use. Customers are more satisfied, and the energy consumption is reduced by smart supermarkets that control the HVAC and refrigeration systems themselves. A building's energy consumption is reduced as a result of maximizing the use of resources. As a result of this study, a firefly-based optimized Long short-term memory (FOLSTM) model for a supermarket was presented (Karthikeyan and Raghu, 2020). Forecasting crucial factors, such as temperature, was key to making the most available resources (Karthikeyan and Raghu, 2020).

Occupancy prediction is more important if occupant crowdedness can be forecast a day before to better facility management. Research thus far has focused on estimating the present population of a certain place, but this information might also help enhance decision-making processes in the future (Kumar et al., 2013; Zou et al., 2020). Schedule repair when foot traffic is low, i.e., during off-peak hours, to minimize disruption *via* deep learning-based time-series crowd prediction (Poon et al., 2022). For example (Poon et al., 2022), address the two fundamental restrictions where prediction accuracy drops as prediction time grows, and only the most recent input data are used by adopting a Long-Time Gap Two-Dimensional technique (LT2D). Predictions may be extended to 1 day with good accuracy using the LT2D technique, which uses long-time gap prediction with 2D inputs to leverage temporal trends from previous days. Adding the suggested LT2D approach to baseline models like Long short-term memory (LSTM), BiLSTM, and Gated recurrent units (GRUs) improves accuracy by about 22% (Poon et al., 2022).

4.7 Digital twin for "automated" fault detection and diagnostics

Although the topic of fault detection is extensive, automated fault detection and diagnosis (FDD) is the one that concentrates on data processing and maintenance decision-making assistance. However, the language used in the FDD research is a little hazy. While some authors prefer the term "fault detection and diagnostics" (FDD) ((Yu et al., 2014)), others prefer the term "automated fault detection and diagnostics" (AFDD), emphasizing the methods' automatic nature (While the processes are somewhat automated, they frequently depend on a human to perform the final verification of detected faults and to decide what maintenance measures to take) ((Kim and Katipamula, 2018)). Prognostics is also a component of specific research, which is referred to as "fault detection, diagnostics, and prognostics" (FDD&P) ((Yang et al., 2018)). Apart from the terminology aspects, specific analytical techniques are frequently used to extract characteristics from the given data and use those data for prognostics and diagnostics. This section examines the techniques used in Digital Twin-based automated fault detection, diagnostics, and prognostics.

4.7.1 Data-driven methods

Models for fault detection and diagnosis are created using data-driven techniques using previous data from BMS. Data-driven approaches can be classified as black-box depending on the models employed and their parameters; examples include polynomial regression, logistic regression, autoregressive (A.R.) models, and principal component analysis (PCA) (Cui and Wang, 2005; Radhakrishnan et al., 2006; Fisera and Stluka, 2012; Ploennigs et al., 2013; Yuwono et al., 2015) and gray-box methods (Nassif et al., 2008; Yu et al., 2011; Sun et al., 2014). The distinction between gray-box and black-box models is that gray-box models employ parameters that have a physical meaning, whereas black-box models do not.

The parameters of data-driven approaches must be tuned using non-trivial quantities of historical data, particularly in the case of artificial neural networks. Additionally, due to the operational variations, such a customized fault detection and diagnostic system cannot often be transferred to another comparable system. As a result, the techniques are not ideal for new structures or other locations without access to historical data. Additionally, even with gray box approaches, the extrapolation is restricted, and black-box methods often cannot extrapolate to find or diagnose errors in the data employed.

The majority of research on FDD for AHU either employ simulation-generated datasets (Padilla and Choinière, 2015; Allen et al., 2016; Granderson et al., 2016; Yan et al., 2016a) or datasets with manually added faults (Wang et al., 2012; Dong et al., 2014; Narayanaswamy et al., 2014; O'Neill et al., 2014; Dey and Dong, 2016). Such synthetic datasets indicate various constraints and difficulties. First, problems in buildings sometimes take arbitrary values on a scale rather than being binary, happening as defective or ordinary. A valve may allow various flows to leak, for instance, or a damper may be stuck halfway between fully open and fully closed (Li and Wen, 2014; Mulumba et al., 2015; Dey and Dong, 2016; Yan et al., 2016b). Secondly, artificial datasets typically oversimplify and make assumptions to be more practical, failing to adequately represent the range of errors that can exist in the real world. These details are required by particular FDD techniques that rely on *a priori* probability of different errors and prognostics. However, so-called natural occurrence datasets (Qin and Wang, 2005; Narayanaswamy et al., 2014), that were collected from the field have inherent limits. First, it takes time and effort to choose such datasets where the errors occur in statistically significant amounts. Furthermore, there is no assurance that all naturally occurring faults will be included in the information acquired during an observation period, regardless of how lengthy it is. Furthermore, it is challenging to confirm whether data from "regular" operations are faulty or not when data are collected from the field. There is always a chance that some faults are present; however, commissioning and other similar procedures can reduce the likelihood of concealed faults.

4.7.2 Quantitative methods

The steady and transient states of a system can be described in explicit mathematical models using quantitative model-based approaches (Weimer et al., 2012; O'Neill et al., 2014) A robust engineering design foundation is essential for quantitative methods since these methods demand vast and deep system understanding. The construction industry has seen a recent trend toward bridging the knowledge gap between design and usage by creating sophisticated simulation models throughout the design process. Data generated during the system's design might lead to the high similarity between the system dynamics and diagnostic models. A precise understanding of the system's physical workings and linkages can lead to sophisticated physical models (Kim and Katipamula, 2018). Partially differential equations based on mass and energy balances and the specific characteristics of the observed system can be used to construct such models (Katipamula and Brambley, 2005).

The ability to accurately simulate a system's transient behavior is enhanced by using comprehensive physical models (Katipamula and Brambley, 2005). Instead of explaining the development of the system, physical models require only a few assumptions to mimic differential and algebraic equations with lumped parameters (Kim and Katipamula, 2018). Even

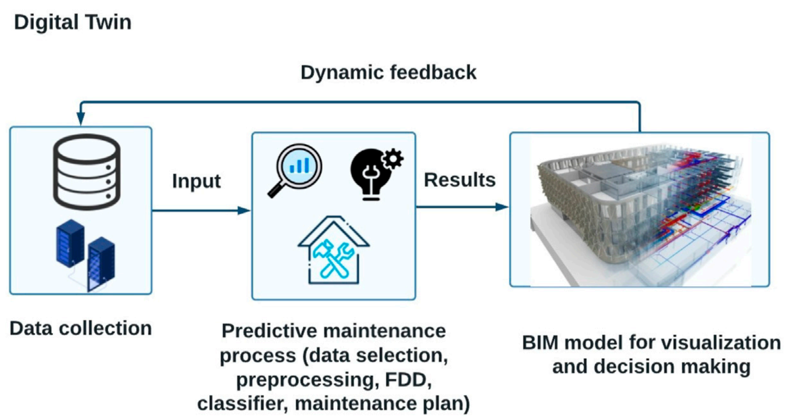

FIGURE 11
Digital Twin predictive maintenance framework.

simple physical models, need a great deal of expertise and time to develop (Kim and Katipamula, 2018).

Building models of both normal and abnormal behavior and comparing them with the measured features can help determine which model more correctly depicts the current behavior. This can be done by using either detailed or simplified models. There are more ways that employ residuals in the same way as previous methods. It is not uncommon for quantitative model-based approaches to necessitate a large amount of computer resources in order to simulate complicated systems correctly. In addition, the models are difficult to adapt to similar systems and need system characteristics that may not be readily available in the field. Another problem with such precisely calibrated models is their sensitivity to measurement or process noise.

4.7.3 Recent research

The identification of many faults at the same time has become an increasingly important area of attention in current FDD technique research (Kim and Katipamula, 2018). In the past, the primary focus has been on identifying a single error when it occurs. However, in more recent research, the emphasis has been placed squarely on the identification of several errors simultaneously. This is a difficult task, and it becomes considerably more difficult when applied to the context of building systems because the symptoms of faults and the repercussions of those faults are typically not well understood or measured. Recent research has shown an increased interest in the utilization of 'virtual sensors,' which provide estimations of values that are not directly quantifiable (Ferretti et al., 2015; Mattera et al., 2018; Nehasil et al., 2021; Zhang et al., 2021; Chen J. et al., 2022; Zhang and Leach, 2022). Even though it can be challenging or expensive to measure specific parameters and values directly, indirect measurements and analytical approaches have made it possible to develop tools that are more effective in terms of their cost-effectiveness in estimating degradation signals and current conditions.

Even new approaches are constantly being considered and researched, it appears that more and more emphasis is being placed on the technology of Digital Twins (Chen K. et al., 2022; Halmetoja, 2022; Hosamo et al., 2022b; Xia et al., 2022). It is easy to comprehend why this would be the case, given that utilizing various approaches has the potential to assist mitigate the drawbacks of any one approach. In addition, using any historical, real-time, quantitative, or qualitative models that are now accessible makes it theoretically possible to combine expert knowledge with information from the past (Figure 11). It is generally agreed that Digital Twins offer a comprehensive solution (Batty, 2018; Haag and Anderl, 2018; Qi and Tao, 2018; Tao et al., 2019; Zheng et al., 2019). The idea of Digital Twins originated as an all-encompassing method for maintaining, forecasting, and proving the state of a building's assets, allowing for improved services and FDD techniques.

4.8 Proposed digital twin structure

Figure 12 depicts the Digital Twin-based fault detection structure, which is divided into two words, virtual and physical. Operational data, such as FM systems data for operation and servicing, is transmitted from the physical world to the Digital Twin. The Digital Twin is composed of three elements in the virtual world:

1) Data mapping between three systems, including BIM, BMS, and CMMS, so we have all the necessary information in one place. Data from sensors (temperatures from buildings rooms and HVAC systems, pressure, *etc.*), maintenance logs, and FM systems for facility operation and servicing are only a few

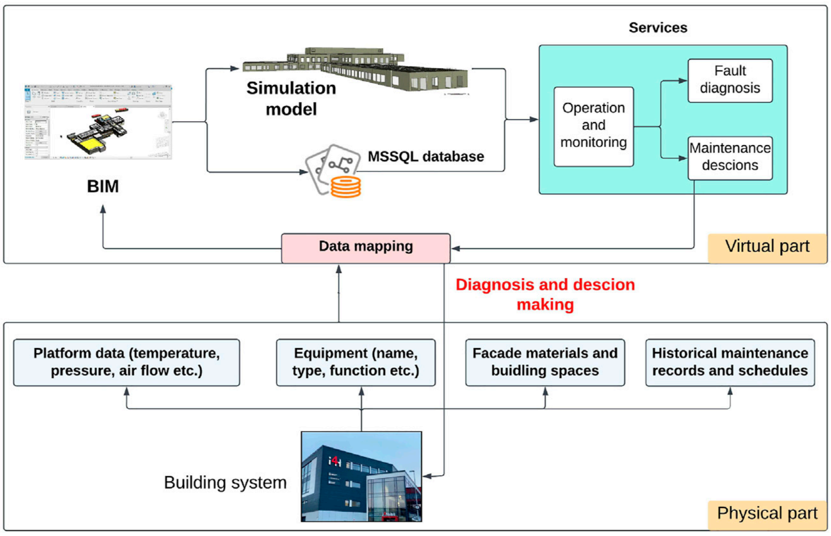

FIGURE 12
Digital Twin-based fault detection structure.

examples of the operational information delivered from the real world to the Digital Twin *via* BIM. This can happen by building an application programming interface (API) over the sensor data system to transfer all the information using C# to BIM. Also, using COBie to integrate BIM data with BMS and CMMS. In this case, we have sensor data, maintenance records, space information, equipment information, and building material information in BIM. This information can be extracted from BIM using COBie to the MSSQL database, which can be updated every 5 min.

2) Simulation model. The simulation of the complete building based on the BIM model is the major purpose of this system component. By that, it would be possible to run thousands of simulations in combination to find the best design and operation for the building. The data from the MSSQL database and the simulation (which also can be stored in MSSQL) can be used as input for classification and regression models for fault prediction.
3) Services. This module is used to assist in building operations and maintenance. Services include fault diagnosis, real-time monitoring, and maintenance decision-making.

4.9 Digital twin implementation challenges for fault detection in buildings

Even though it is mainly focused on the literature on the benefits of Digital Twin technology, some challenges must be addressed. Digital Twin runs parallel with artificial intelligence (AI) and the Internet of Things (IoT), which means they also have shared challenges. Some significant challenges of implementing Digital Twin for fault detection are listed below.

4.9.1 IT infrastructure

The first challenge is IT infrastructure. The significant growth of AI must be met with a well-utilized infrastructure for updated software and hardware to execute the algorithms. One of the biggest challenges within the infrastructure is the cost of installing and using these systems. For example, a Digital Twin for an office building of approx. 60,000 m^2 can cost anywhere between 1.2 million and 1.7 million USD (Tao et al., 2019). For this technology to succeed and for companies to benefit from it, it is essential to have an IT infrastructure that is well connected and runs smoothly (Grieves, 2015; Magomadov, 2020).

4.9.2 Standardization

The next challenge is the actual modeling of a Digital Twin, as there is no standardized approach to the procedure. Standardized methods create user understanding while ensuring the flow of information between each stage in developing and implementing a Digital Twin. Digital Twin also depends on IoT technologies regarding receiving data from smart devices. However, standards in the area of IoT require a lot of improvement, affecting the standardization of Digital Twin technology (Tuegel et al., 2011; Al-Qaseemi et al., 2016; Qi and Tao, 2018).

4.9.3 Real-time modeling

The success of Digital Twin technology depends on a real-time, two-way connection between the actual building and its Digital Twin. The challenges this entails are related to the resolution of sensor data, large data capacity, speed, *etc.* (Wu et al., 2022).

4.9.4 Data sharing

One of the most significant barriers to a Digital Twin is data sharing. This is because it is based on people's attitudes towards this, which in turn impacts the company's guidelines for what can be shared. The complexity of data sharing leads to developers being prevented from finding more integrated ideas (Magomadov, 2020).

4.10 BIM challenges as a core part of digital twin in maintenance and facility management

Usually, BIM models utilized during the design phase are not appropriate for usage during the maintenance phase (Korpela et al., 2015). The problem starts when the person who places the order is frequently unaware of the appropriate use of the BIM models and the degree to which they should require modeling. Because of this, models can sometimes be too precise or leave out necessary information entirely.

The second issue with maintenance modeling is updating BIM models during maintenance. It is unknown who would be responsible for updating the model following major renovations or additions to the building (Quach and Wenström, 2022). No one who could keep the model and its data up to date is available. In addition, the upkeep of the model would need the expertise of the maintenance staff, which is typically unavailable.

The fact that no program can use the modeled information is the third obstacle to adopting BIM in maintenance. The FM software used in the process's maintenance phase cannot yet read the information directly from the BIM models (Chen et al., 2018).

Finally, a model encompassing all the information required for fire safety, electro-technical repairs, and regulating potentially damaging situations would be too complicated for most users to implement effectively (Durdyev et al., 2022). The various maintenance models should be assigned to individual jobs, containing only the relevant data for that job.

5 Discussion

The industry has to acknowledge all the advantages and overcome the obstacles for Digital Twins to realize their full potential. This must begin with the project owners and project managers at the top of the supply chain. Stakeholders must also make the required changes.

Information sharing is significantly hampered by the absence of universal standards for data exchange. Project management teams lose important data when they do not streamline procedures and hide data. Instead, everyone might have had access to this information. This hesitancy obstructs the two-way information exchange needed to create a Digital Twin. Digital twins are increasing in number and importance in the construction sector. However, improvements to this strategy must be made as quickly as possible if it is to ever succeed in large-scale enterprises.

This may be used to identify energy waste in a building and defect identification from the construction perspective. This can identify many inefficiencies in a building since these defects are also identified by IoT sensors and the deployment of Digital Twins. This indicates that reducing energy usage will be extremely important from an environmental standpoint. Reduced operational effects result in reduced potential emissions that might benefit the environment by reducing global warming.

There are more applications for the Digital Twin technology and advantages over those already stated. The Internet of Things and the real-time data gathered can be used to track building-related faults. Buildings may employ Digital Twin technology to detect faults since it has been used in numerous projects involving other structures. One can only anticipate considerable growth in the applications of the technology in construction as Digital Twins become increasingly sophisticated.

Our findings show that Digital Twin technology is frequently used for problem detection and maintenance savings despite a relatively new concept. Numerous successful cases in industries including manufacturing, shipping, mechatronic development, and offshore wind power generation, not to mention in the field of civil engineering itself, demonstrate the great potential of digital twinning processes for improving fault prediction and detection accuracy while also lowering cost and risk to human life. Being able to act on faults at the very earliest stages or even before they happen holds enormous potential and will be crucial to preventing further tragic losses of infrastructure and life. The successful development of algorithms to predict faults and errors in the maritime field with Trailing Suction Hopper Dredgers has already provided proof of concept.

There are difficulties in creating these technologies, despite the apparent promise and the necessity. First, inaccuracies in equipment constitute a substantial obstacle. While current laser measuring and scanning technology and software are pretty advanced, intrinsic imperfections are inescapable and play a considerable role in the correctness of a Digital Twin compared to the actual as-built object. As a result of our review, it is generally acknowledged that additional improvement of scanner hardware and software, detection and prediction algorithms, modeling, and twinning programs is required for Digital Twins to be compelling enough for fault detection (and other applications). Even though these are significant obstacles, it is essential to note that the idea of Digital Twins is now a heavily explored and investigated subject in several businesses. Development, case studies, testing, and subject improvement consume many resources. It is anticipated that the application of Digital Twins in several industries will develop quickly.

Second, a lot of condition-based maintenance research comes from industrial contexts and frequently makes the implicit assumption that equipment and context are not typically present in building systems. As a result, many of the techniques described in the reviewed articles could not be helpful in the construction sector until building owners and, by extension, designers have strong enough incentives to spend money on condition monitoring.

Many failures in building operations are not life-threatening. Consequently, the symptoms might not be obvious, or the residents could fail to address the problem with facility managers. People could respond by opening windows or putting on additional clothing without informing facility managers, for instance if the air conditioning malfunctions and cannot maintain a steady temperature within. This makes it challenging to gather and identify failure signs systematically.

The commissioning of building systems, including automation systems, often occurs when the facility is close to turn over to the owners or tenants. The sensors are often calibrated and verified only in the early stages of their lifetime, despite the trend of continual commissioning appearing to gain popularity. As a result, sensor readings may become less trustworthy over time, making it more challenging to operate systems and correctly gather reliable data for condition monitoring. While a flaw in, say, the air conditioning system is likely to have evident negative impacts, the flaw may go undetected for years. Consequently, it is challenging to relate known defects to BAS measurements. Contrarily, it may be difficult to ascertain the typical operating conditions because there may or may not have been an issue observed at any given time.

Additionally, data from BMS may be lost due to network, sensor, and power outages. Given that AHU systems vary throughout facilities, this is a concern. In reality, most research either employs recordings of manually caused errors in lab settings or databases of simulated failures. It can be challenging to simulate complex systems, such as air handling units with various controllable quantities and air flow mechanics, and it can be challenging to make decisions solely based on simulated data. Typically, a model developed using data from one system cannot readily apply to another. For instance, a machine learning model trained on sensor readings from normal operations and readings from various defects is unlikely to be an excellent match to identify and fix errors in a different environment. Assessing fault costs, including energy consumed and harm to indoor air quality, is made more difficult by a lack of understanding of the failure mechanism and its associated impacts. Evaluating the probable costs of failures vs the cost of preventative replacements would be extremely helpful in predictive maintenance of non-critical systems such as air handling units.

Another issue is that, even though buildings lose energy due to poor maintenance and operation, building owners lack strong incentives to invest in preventative maintenance. Monitoring and prognostics must be carried out with no additional expense or an articulated return on investment.

The inherent division of interests in the building sector presents another, less technical difficulty. A typical scenario is where one company owns the building, the occupants from a second company, and the facility mangers from a third company. Making money is the main goal for the building owner because the structure is often just one investment among many others. Maintenance may concentrate on keeping the systems functional to reduce future maintenance expenses and maximize energy expenditures while reducing maintenance costs. The building's proper operation and the purity of the inside air are, nevertheless, what the residents care about. Maintenance companies are not compelled to provide services beyond what their clients, or building owners, want and pay for. In conclusion, building systems typically do not install sensors with condition monitoring in mind, and the current sensors may have only undergone a single calibration and verification after installation. Differentiating between normal operating conditions and malfunctioning operation is further complicated by the absence of historical data for both the particular system being monitored and other systems similar to it.

The Internet of Things system's real-time monitoring data will be combined with the maintenance and operation management systems. By simulating all system-level operational components, fault detection enabled by Digital Twins in buildings can make confident predictions about how assets in facilities will behave in dynamic operational contexts. By formally documenting a building's features and supplying important contextual information about an asset, BIM can promote data integration in a Digital Twin.

In addition, two of the many benefits of employing deep learning techniques are significant analytical powers in large data situations and the ability to identify complex defects in critical facilities in dynamic environments. There need to be more deep learning applications in predictive maintenance in civil infrastructure. IoT advancements hinder current predictive maintenance because conventional machine learning-based approaches require assistance evaluating HVAC large condition monitoring data. As a result, further work is needed to incorporate deep learning techniques into the field of HVAC predictive maintenance. Thus, it is crucial to create algorithms that require as little human involvement as possible in the pre-processing and analysis of HVAC condition monitoring data. Specifically, a CNN-based system can reliably detect faults without human knowledge by first transforming raw time-domain condition monitoring data into pictures. There is a need for greater study in this area due to high processing complexity, lengthy training times, and the possibility of reaching a local minimum.

More attention has to be paid to machine learning implementations in creating fault detection algorithms, which is a shortcoming of our study. Machine learning should be employed properly to forecast and select the best maintenance action by utilizing mathematical programming (e.g., mixed-integer), evolutionary computations, simulations, and logic-based models. As a result, routine maintenance may be automated even further. Predictive maintenance is a necessity, but it faces significant obstacles. These include the inability to accurately predict the behavior of building systems (such as faults and failures) in dynamic operational environments and the failure to account for system-level impacts in fault diagnosis analyses for real-world applications. Moreover, additional research is needed to improve interoperability across various data and information sources in BIM model operation and maintenance stages. IFC and COBie will be crucial in improving the integration of Internet of Things data with building maintenance and operation management systems in the BIM setting.

6 Conclusion

For fault detection, we used an analysis of 115 papers linked to the Digital Twin concept, and we found that an accurate description of the Digital Twin focuses on physical components, virtual models, connections between them, and a twin relationship between the two. From a physical standpoint, a Digital Twin may be used to model the physical aspects of a building or infrastructure. A wide range of modeling, simulation, calculation, and analytic tools, as well as complex algorithms, are used in digital twinning from the viewpoint of the virtual portion. Virtual and physical parts can be connected by using various technologies, such as laser scans and sensors to update geometric and non-geometric information on virtual parts to reflect the physical parts in time *via* the use of point cloud data and other data obtained from various sources such as sensors. Various Digital Twin applications for building failure detection are comprehensively covered in this paper. In light of the current study, this article provides some thoughts and ideas linked to Digital Twins in the building sector. Regarding defect identification and asset monitoring, the Digital Twin may play a significant role, and how to connect physical and virtual parts utilizing sophisticated connection technologies should be researched. It is also essential that the Digital Twin is used extensively in computation, analysis, optimization, and decision-making while employing a wide range of technologies. Finally, a Digital Twin is an effective tool for detecting and correcting faults. Civil engineering's digital twinning will soon be elevated to a new level thanks to advances in AI, sensors, the Internet of Things (IoT), software, and hardware development.

Author contributions

HH: Conceptualization, Methodology, Software, Data curation, Formal analysis, Visualization, Writing—original draft, Writing—review and editing. HN: Supervision, Methodology, Resources, Writing—review and editing. AA: Conceptualization, Methodology, Visualization. PS: Supervision, Writing—review and editing. KS: Supervision, Writing—review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Nomenclature

AHU Air handeling unit

AMS Advanced measurement systems

ANN Artificial neural network

APAR AHU performance assessment rule

API Application Programming Interface

BIM Building information modeling

BMS Building management system

CMMS Computerized maintenance management system

CNN Convolutional neural network

COBie Construction operations building information exchange

DL Deep learning

FM Facility management

HVAC Heating, ventilation, and air conditioning

IFC Industry foundation classes

IoT Internet of things

LR Linear regression

ML Machine learning

RF Random forest

SMS Smarter metering services

VAV Variable air volume

Appendix F

Paper 6- Digital Twin framework for automated fault source detection and prediction for comfort performance evaluation of existing non-residential Norwegian buildings

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

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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].

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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.

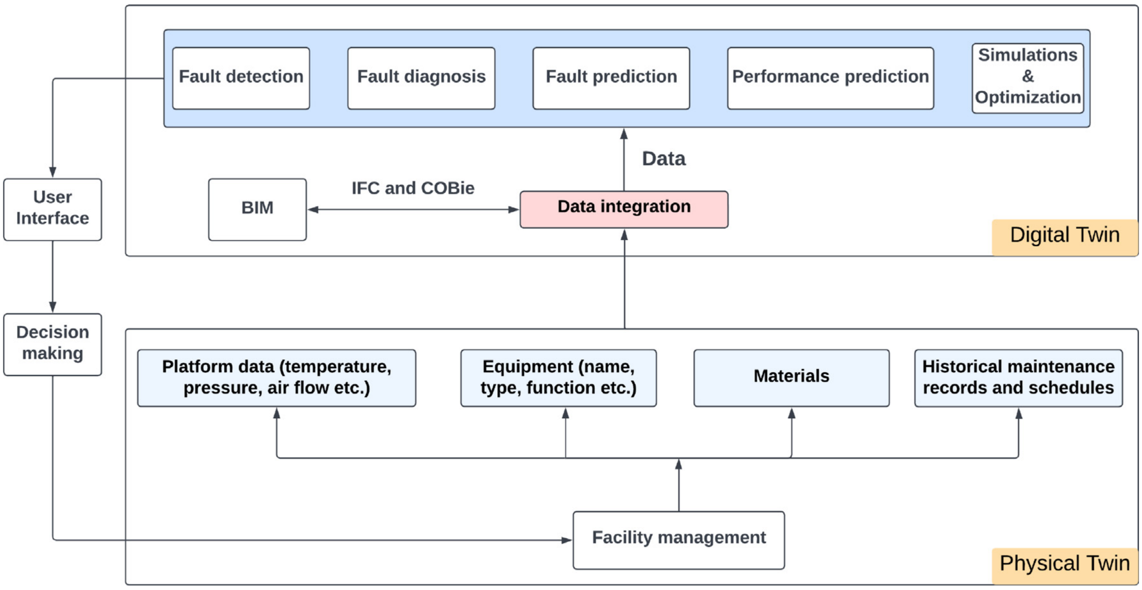

Fig. 1. Digital Twin concept for building operation to prevent future failures, reduce energy consumption and increase occupants' comfort.

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-

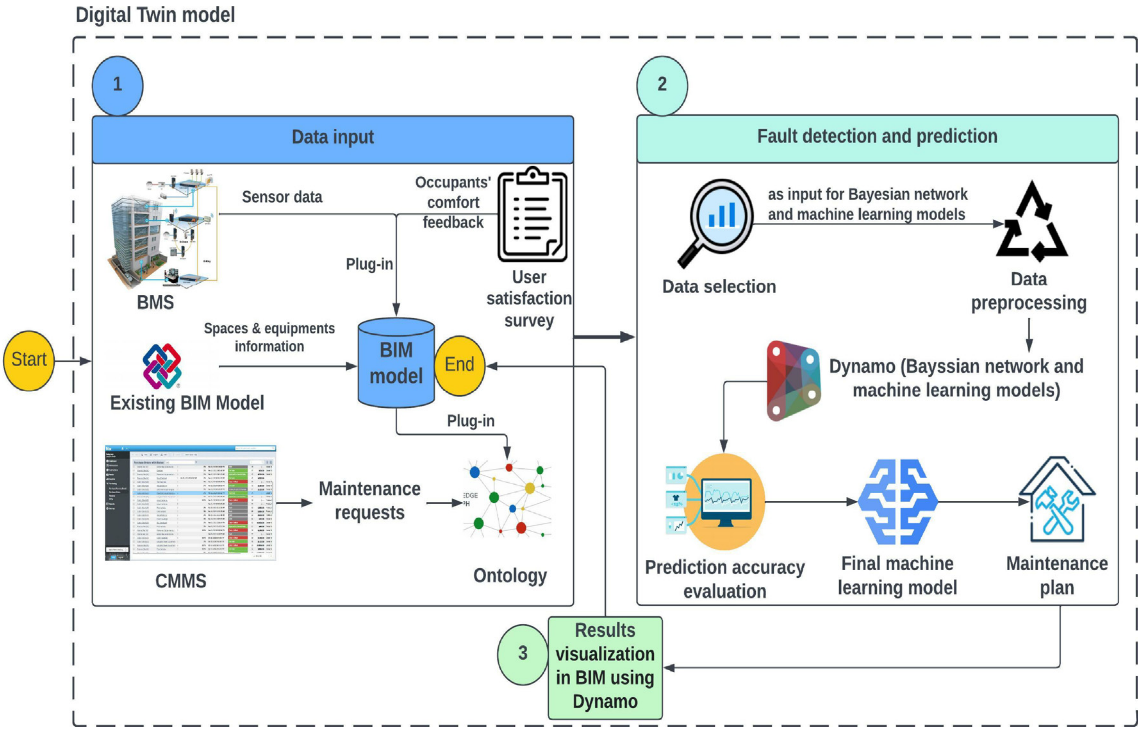

Fig. 2. The proposed Digital Twin framework for fault detection, prediction and data visualization.

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.

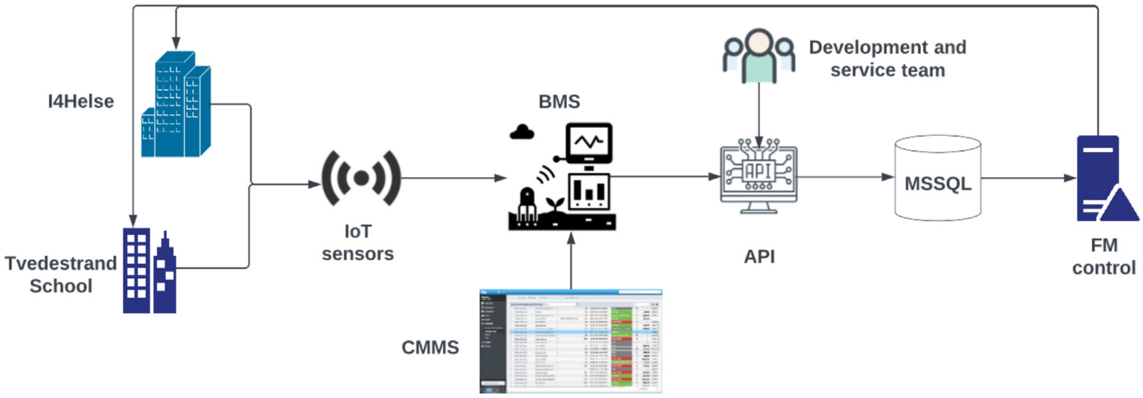

Fig. 3. IoT data gathering system including of API established by both the service and development teams.

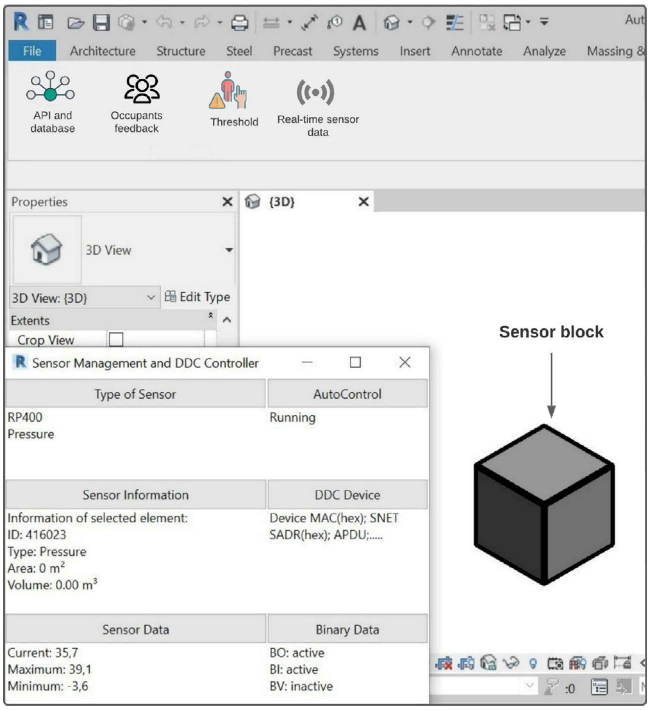

Fig. 4. Built-in sensor and occupants feedback management in Revit with the help of the developed plug-in.

(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)

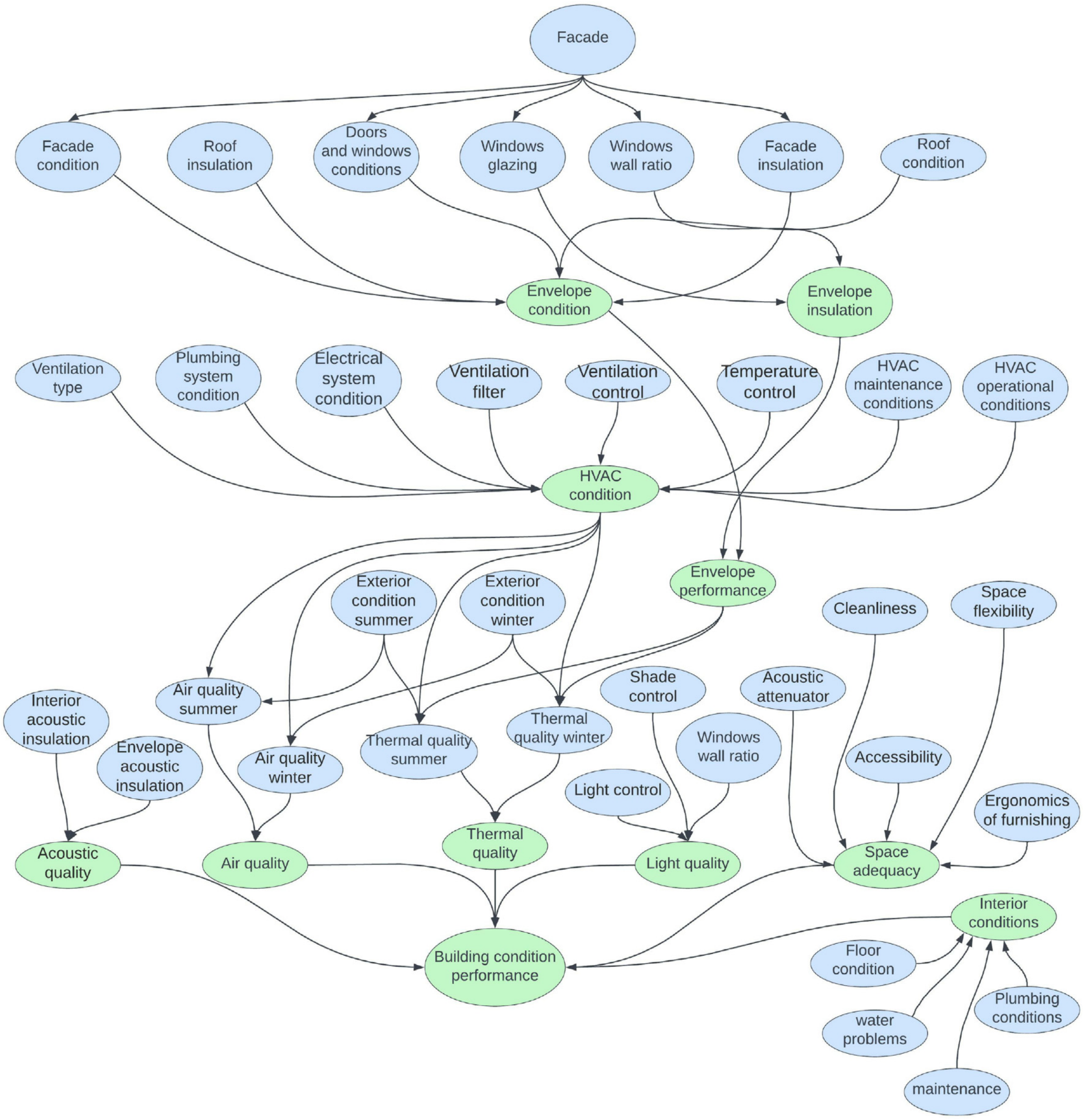

Fig. 5. The BN model for evaluating comfort performance in buildings.

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-

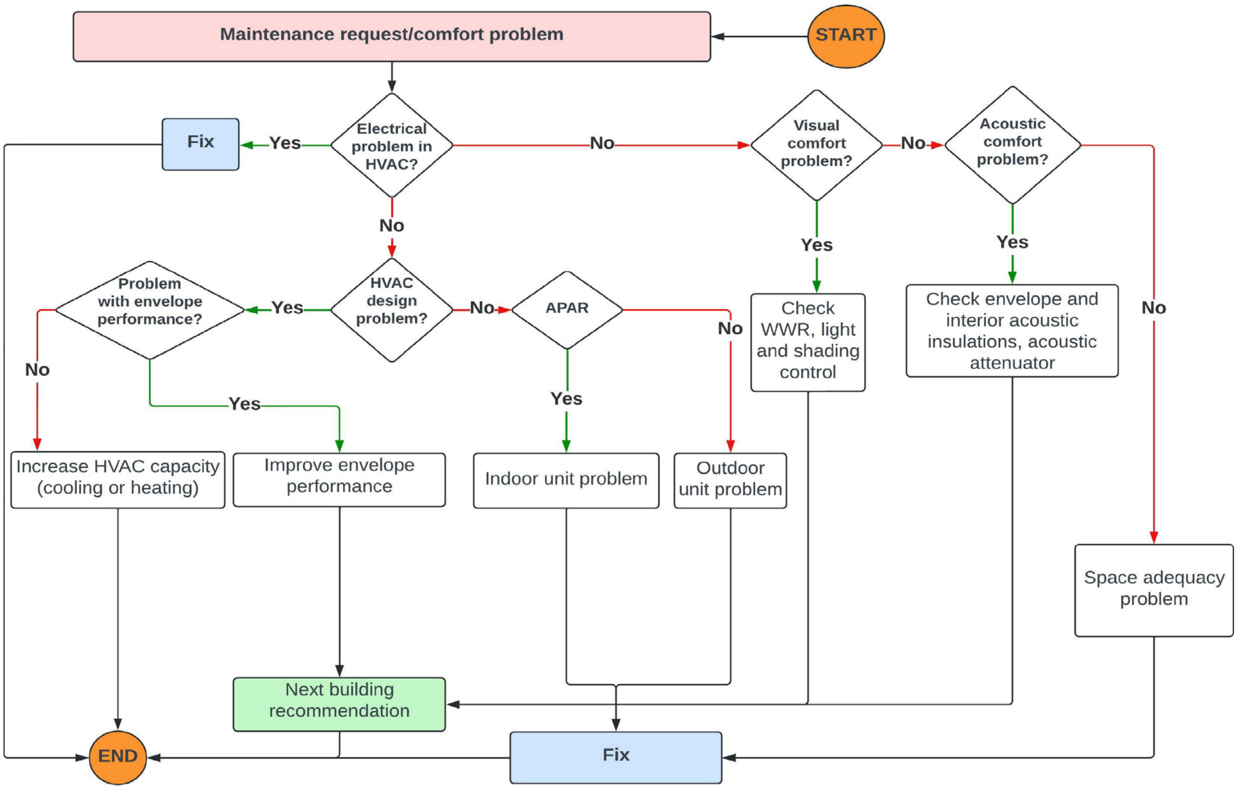

Fig. 6. The decision-making approach and framework to help facility managers detect building faults.

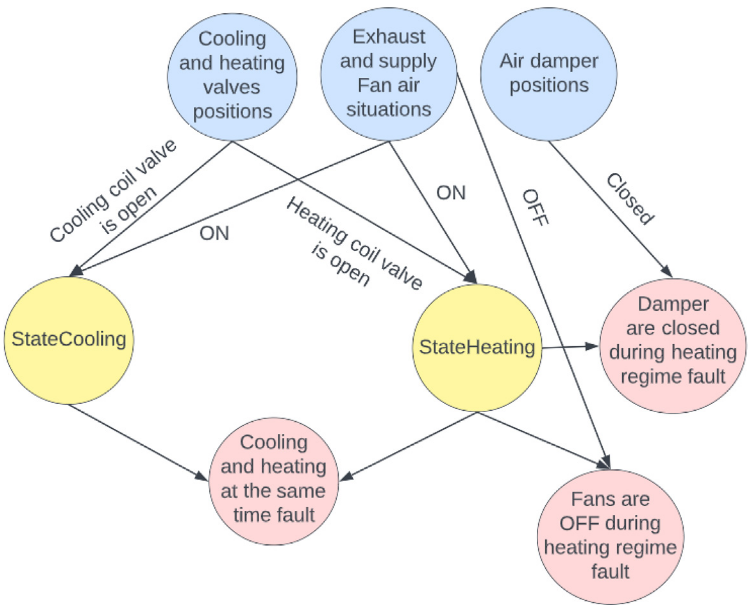

Fig. 7. An example of how the BN applies the APAR rules to check if there are any faults in the units inside the buildings. The blue nodes are the BMS data, the yellow nodes are the state nodes, and the red ones are the faults.

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.

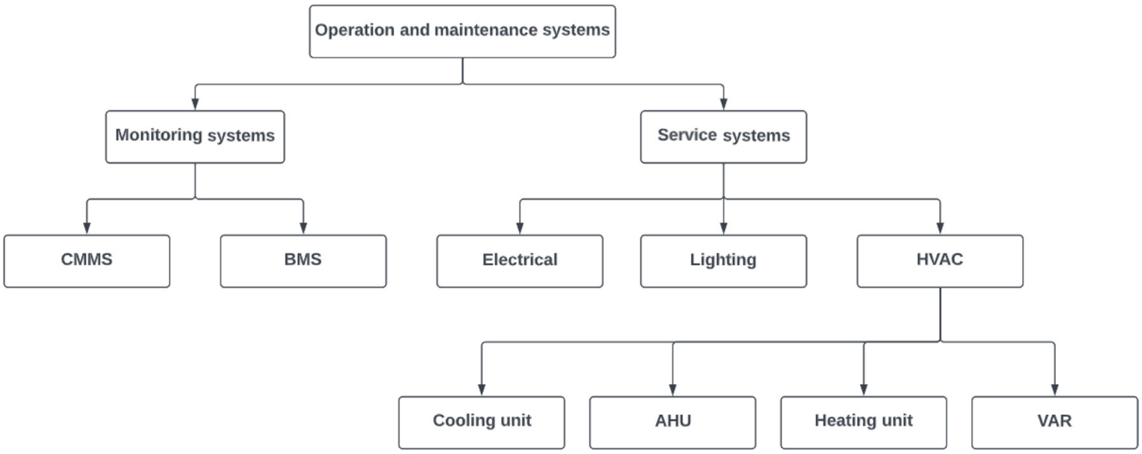

Fig. 8. Main buildings systems that have been included in this study.

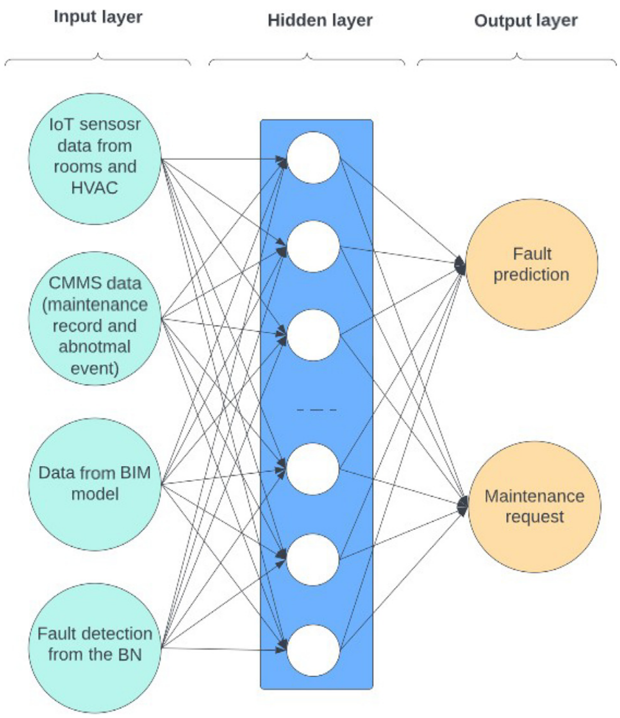

Fig. 9. The procedure of the prediction algorithm.

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

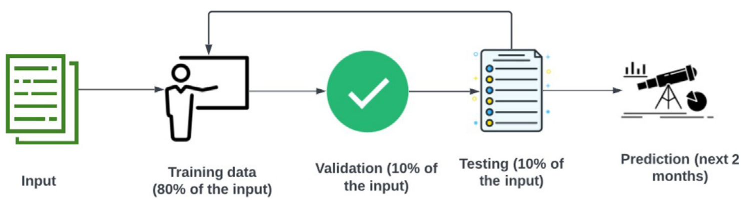

Fig. 10. The data-flow and implementation process for fault prediction.

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.

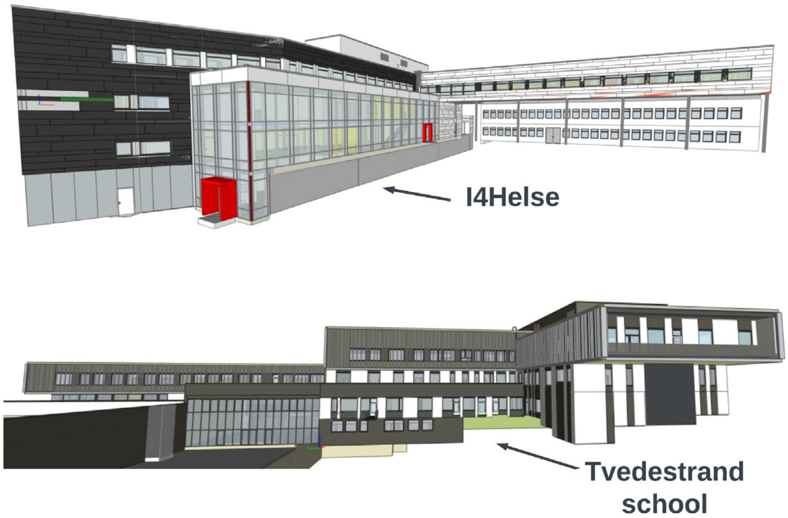

Fig. 11. I4Helse and Tvedestrand school as case studies in this paper.

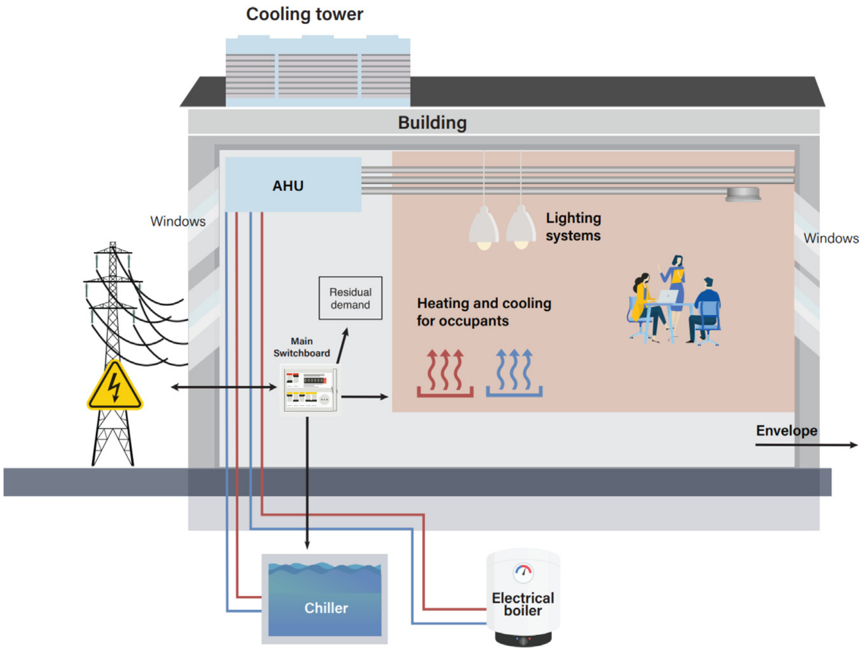

Fig. 12. The systems that are included in the Digital Twin framework through fault detection and prediction process to find occupants' discomfort reasons in buildings.

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-

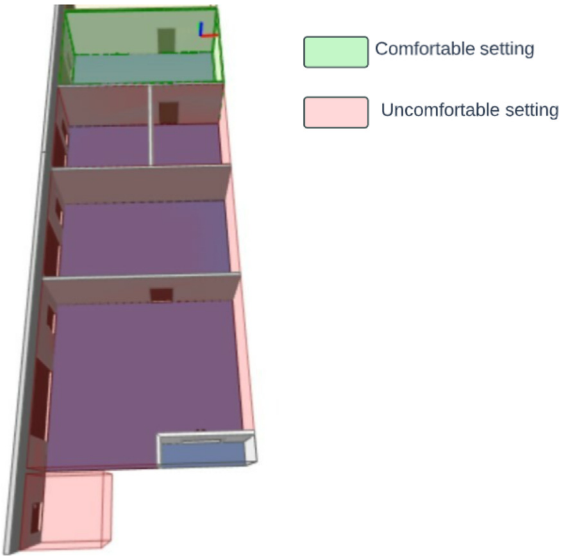

Fig. 13. Occupants' feedback of summertime indoor air quality in a part of Tvedestrand school.

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.

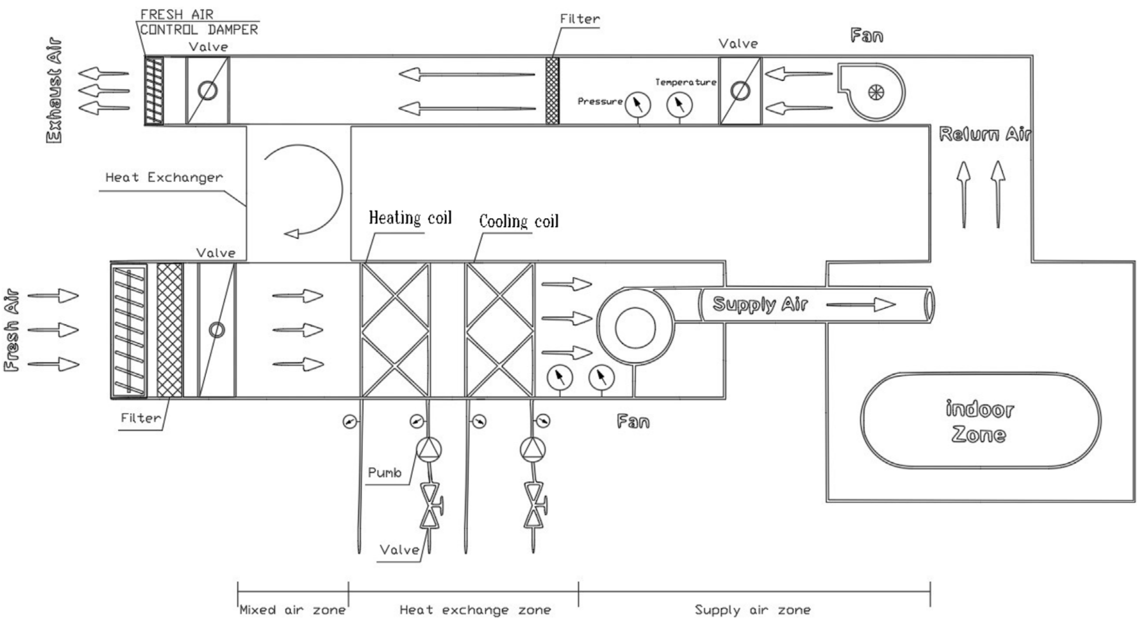

Fig. 14. Schematic illustration of HVAC from our case studies.

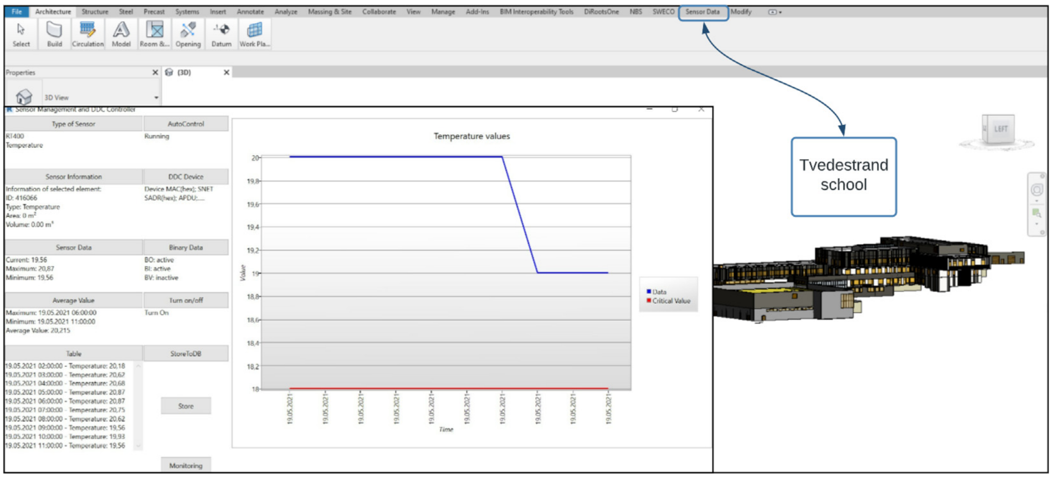

Fig. 15. The information about the building obtained via sensor data and the BIM model.

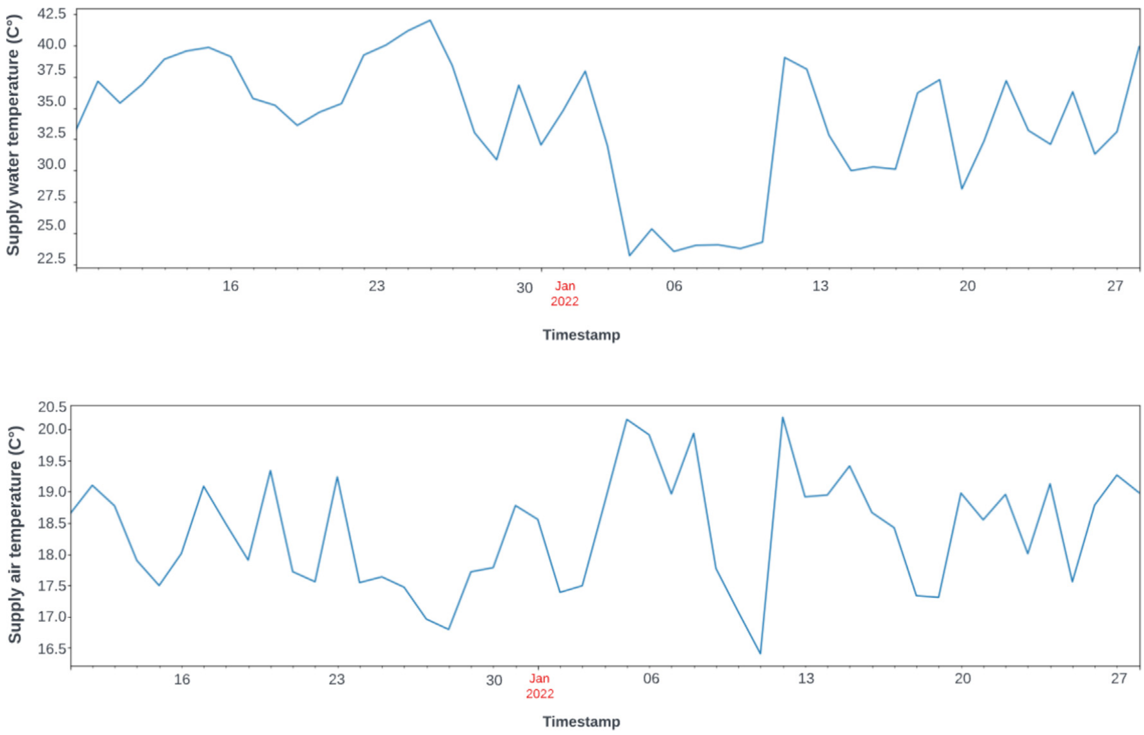

Fig. 16. A sample of the supply air temperature and supply water temperature for AHU at the Tvedestrand school during the months of December 2021 and January 2022.

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.

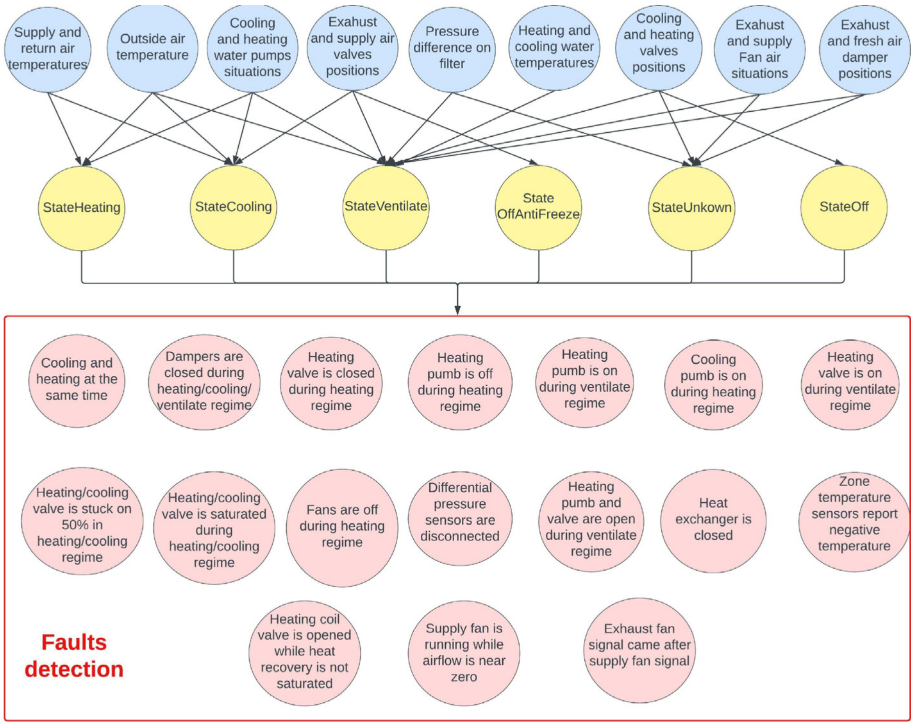

Fig. 17. The detected faults in our case studies.

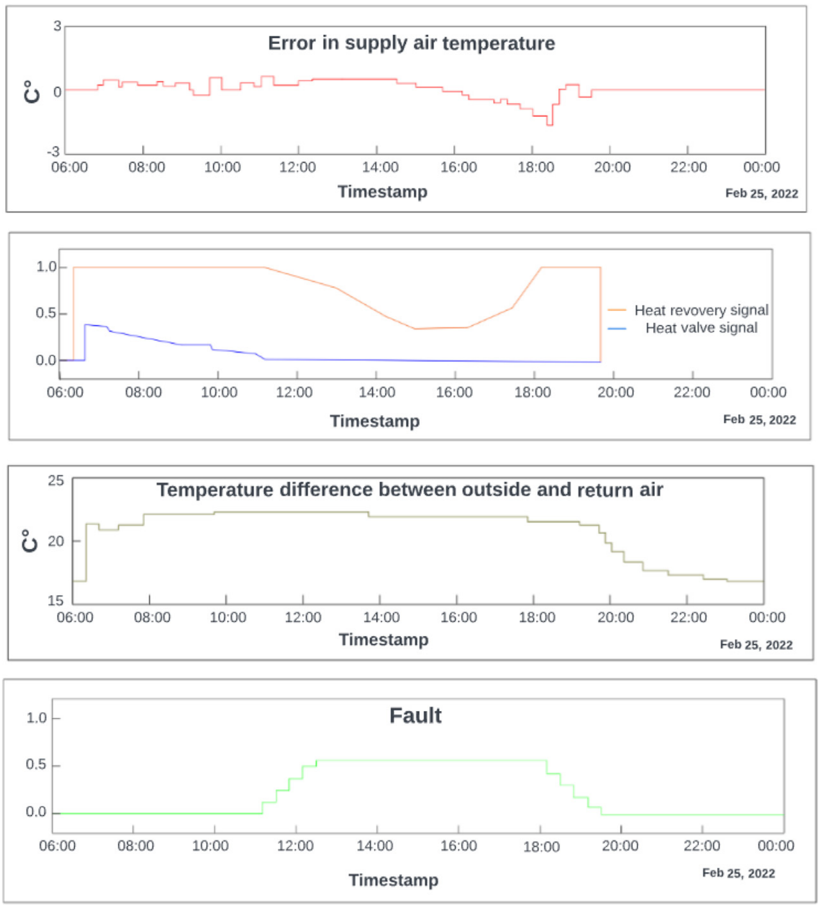

Fig. 18. Heat recover not saturated during one day in February. The fault is detected based on temperature setpoint, heat recovery signal and temperature difference between outside and returned air.

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

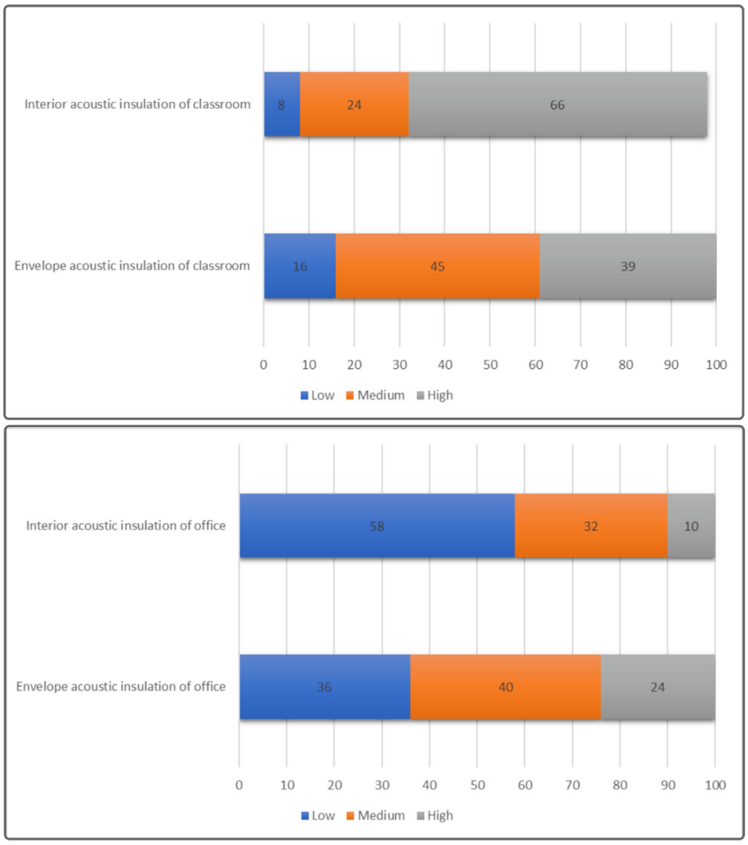

Fig. 19. acoustic comfort analysis of an office and classroom in Tvedestrand school.

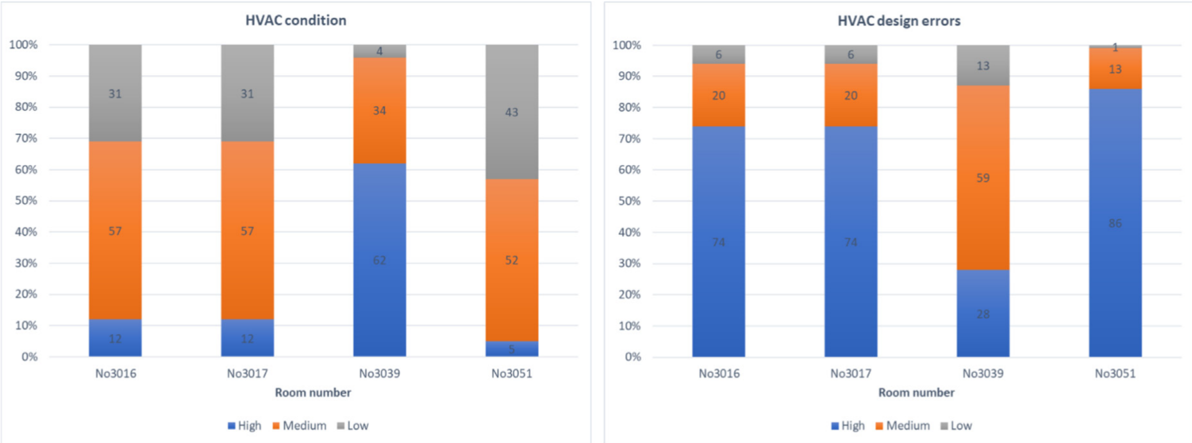

Fig. 20. The probability that each room has poor HVAC design or unsatisfactory HVAC conditions.

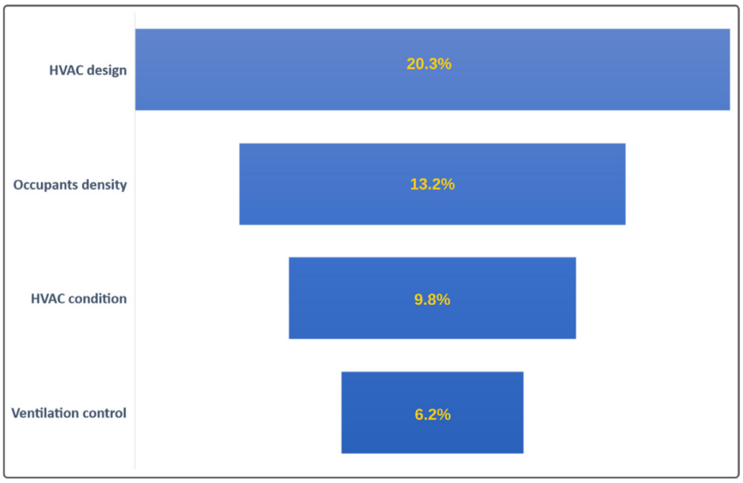

Fig. 21. The sensitive analysis of indoor air quality for rooms No3016, No3017, and No3051 in winter.

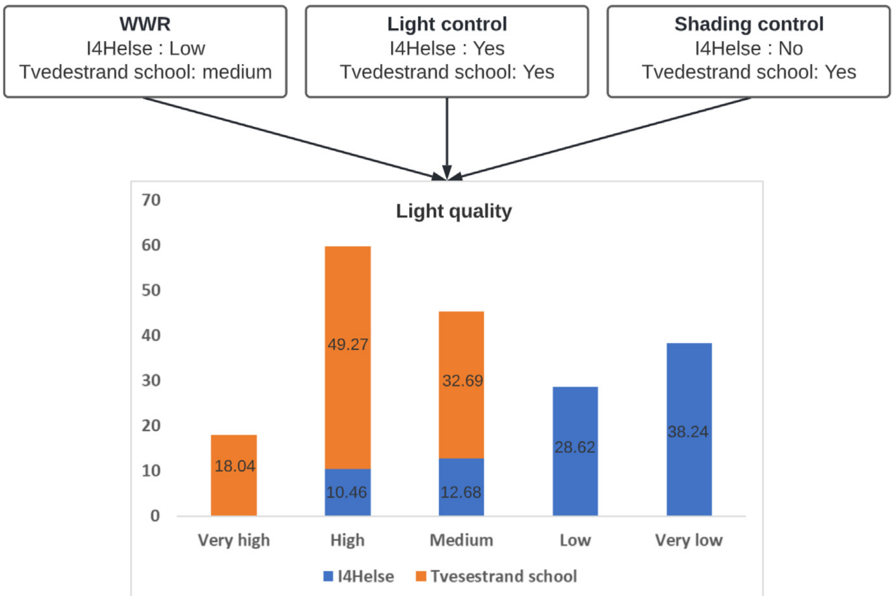

Fig. 22. Light quality probability percentage of I4Helse and Tvedestrand school.

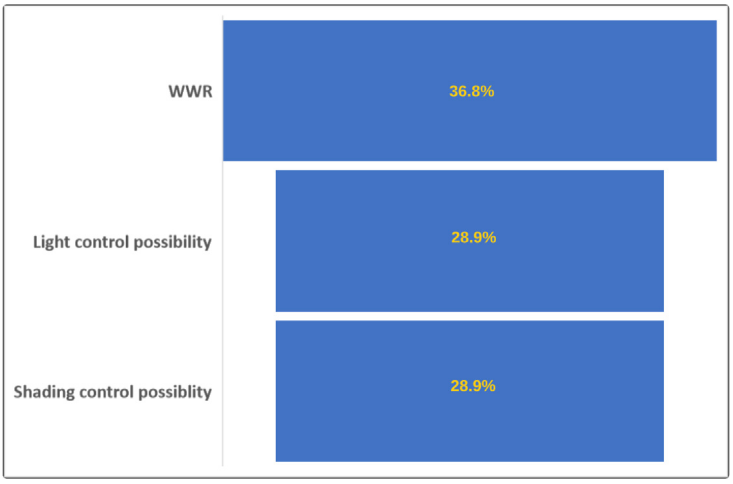

Fig. 23. Light quality sensitive analysis.

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.

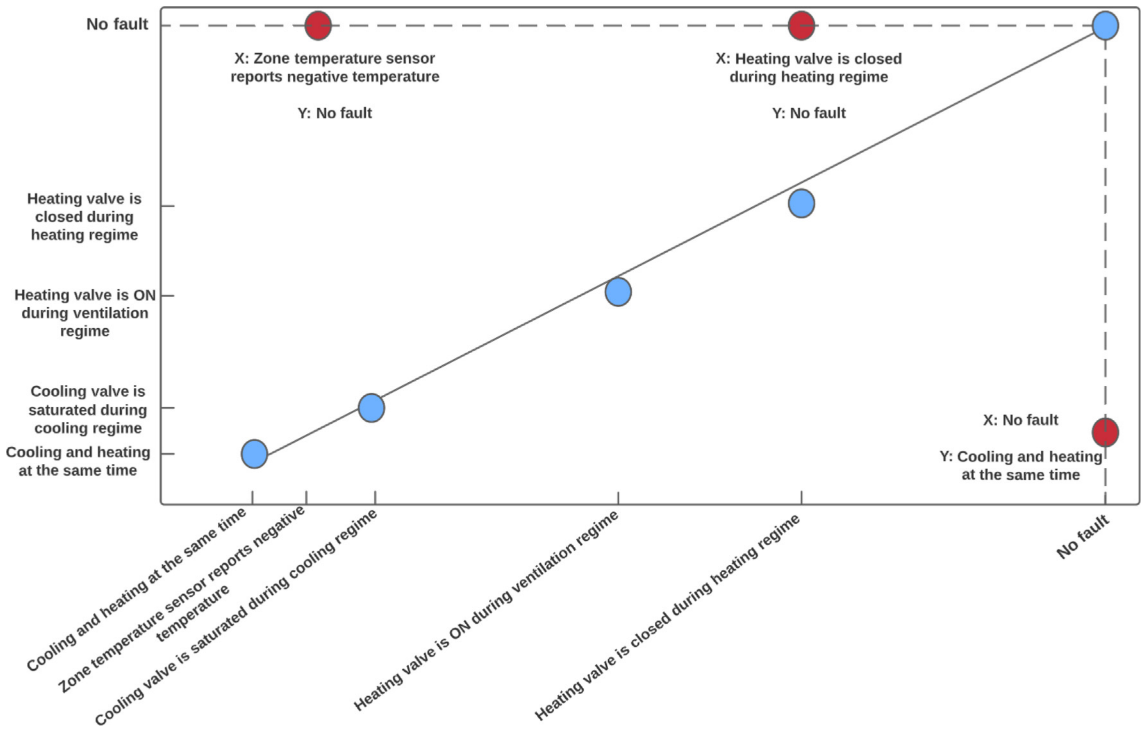

Fig. 24. Comparison between the actual and predicted faults for August and 2022 using ANN model (2 months ahead from the data that used for training and validation in Tvedestrand school) where x refers to the actual fault and y to the predicted fault.

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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Appendix G

Paper 7- Improving Building Occupant Comfort through a Digital Twin Approach: A Bayesian Network Model and Predictive Maintenance Method

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Predictive maintenance
Facility management
Decision-making

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-

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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

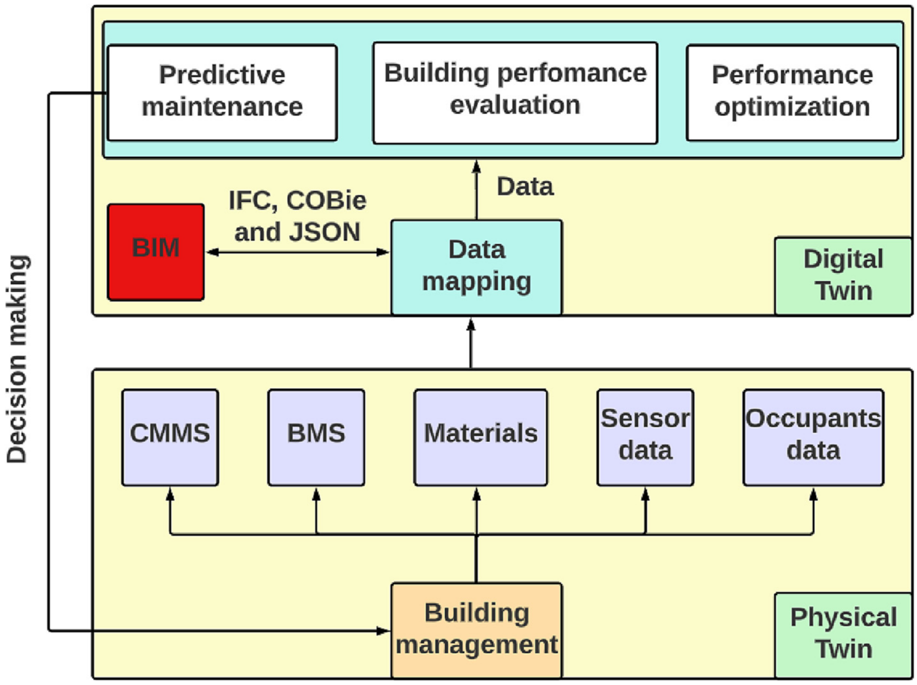

Fig. 1. Digital Twin Concept: Integrating BIM with Real-time Sensor Data and Occupant Feedback for Predictive Maintenance and Occupant Comfort.

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-

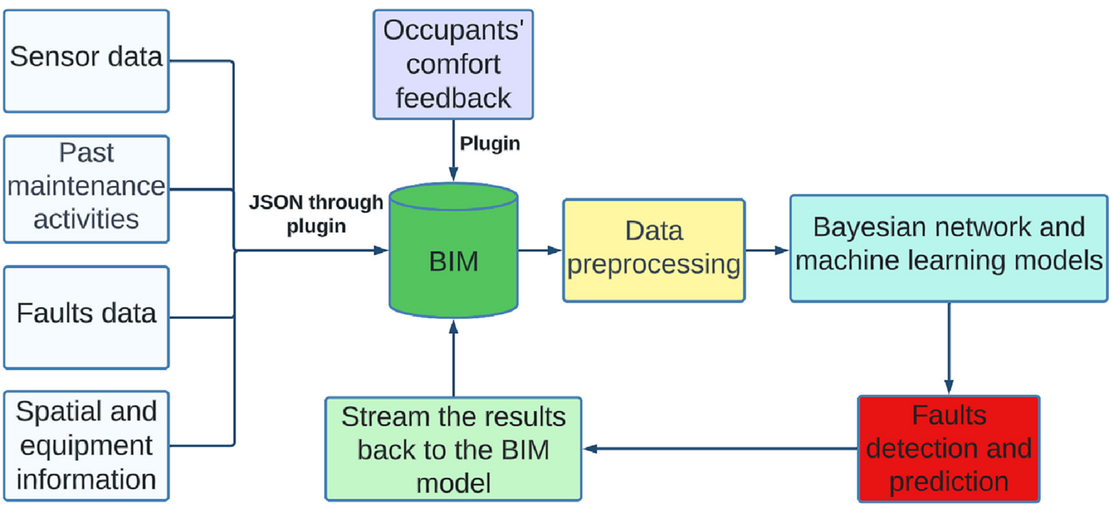

Fig. 2. The proposed Digital Twin framework for fault detection, prediction, and data visualization in building management systems.

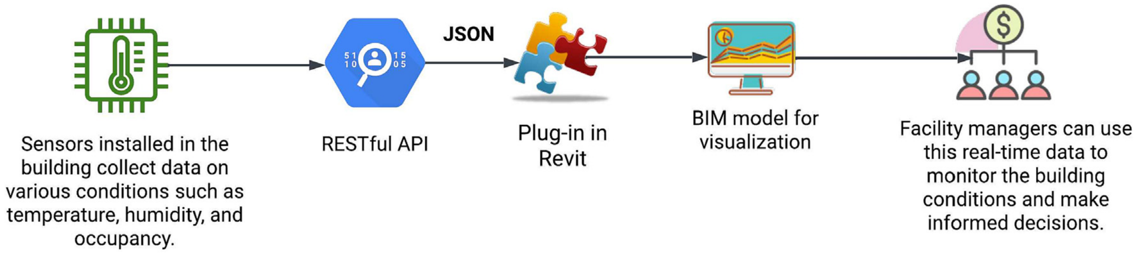

Fig. 3. Real-time monitoring and decision making through the integration of sensor data into BIM framework.

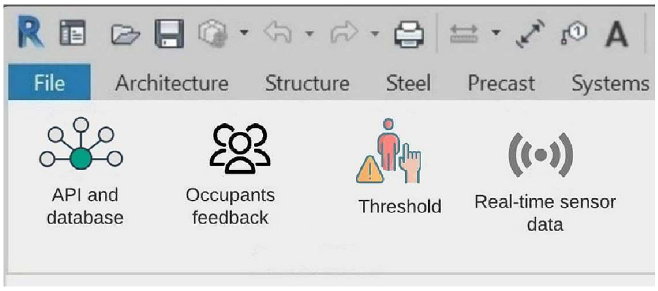

Fig. 4. Managing sensor data and occupant feedback within Revit using a custom-developed plug-in.

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

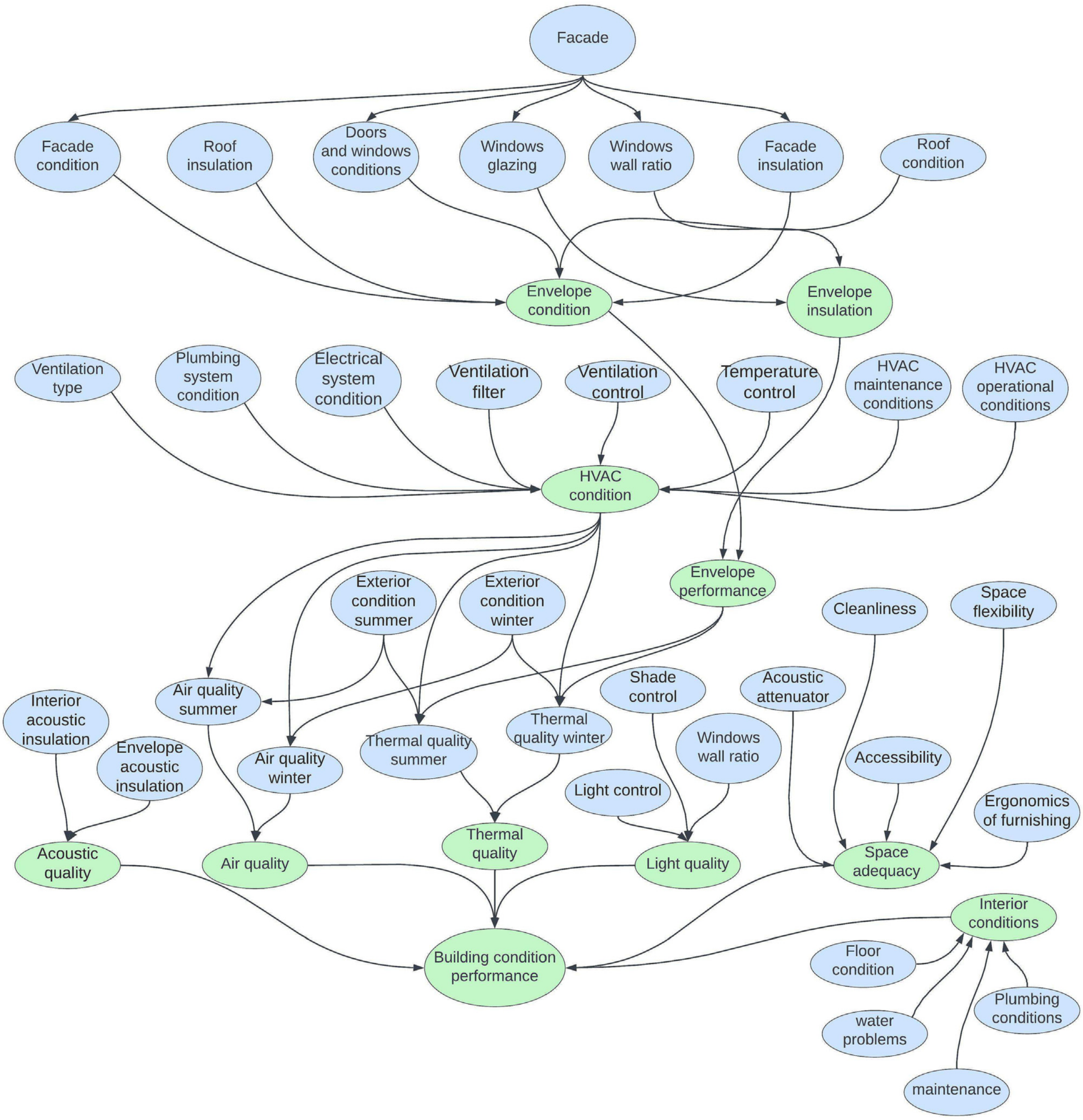

Fig. 5. Graphical representation of the Bayesian Network model for probabilistic evaluation of building comfort performance, after [16].

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.

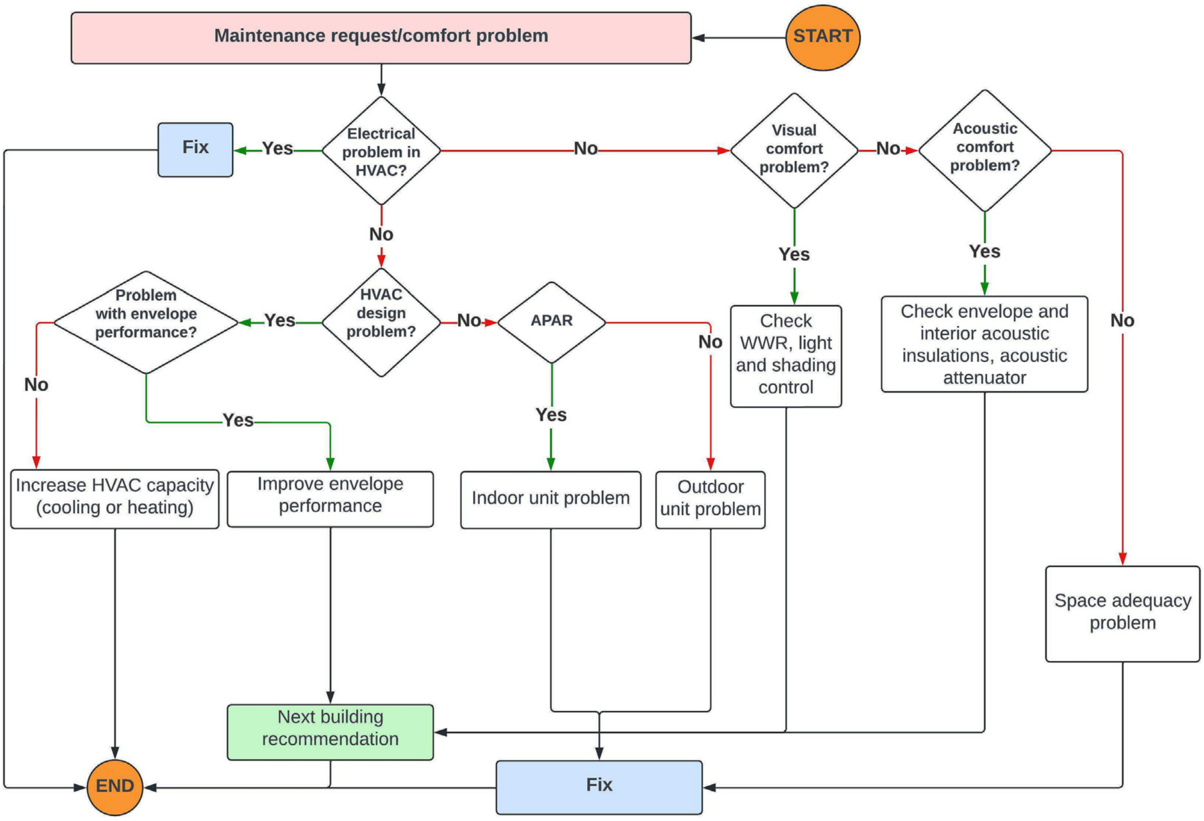

Fig. 6. The proposed framework for utilizing BIM and BN models to improve decision-making in facility management through identifying building faults and addressing occupant needs, after [97].

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.

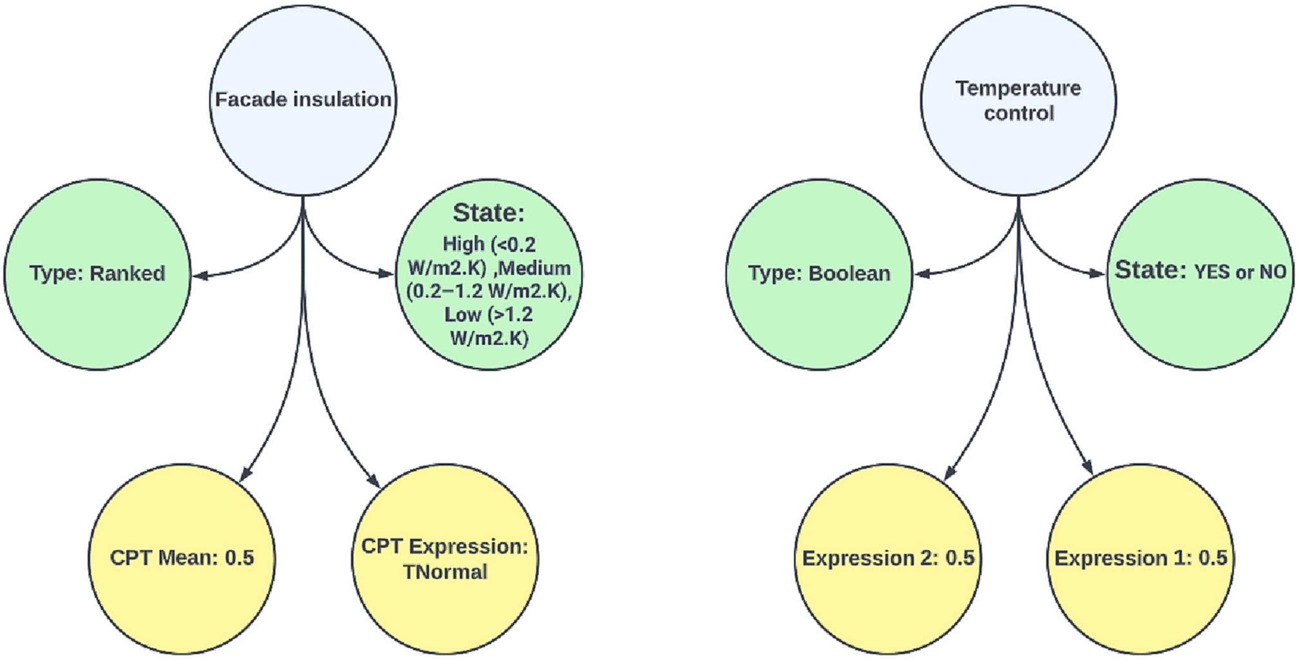

Fig. 7. Bayesian Network Model of Building Comfort Performance: CPT Representation, after [16].

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

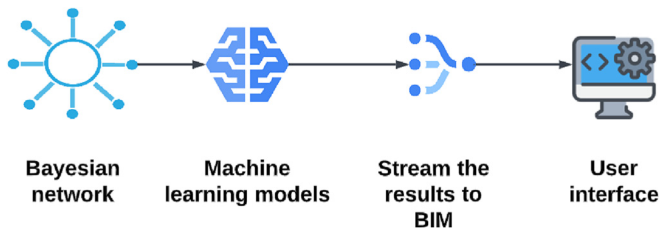

Fig. 8. The flow process of visualizing the causal analysis of rooms and HVAC data using Python scripts in Dynamo.

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)

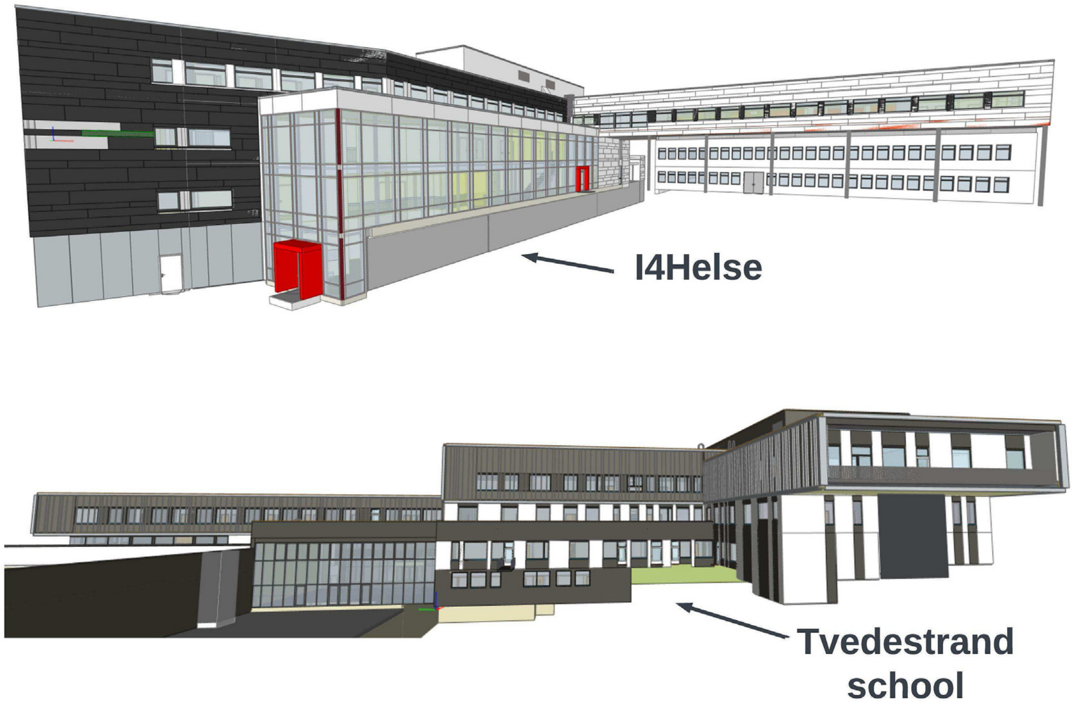

Fig. 9. BIM model of I4Helse and Tvedestrand School Buildings as Case Studies for the Digital Twin Framework Analysis.

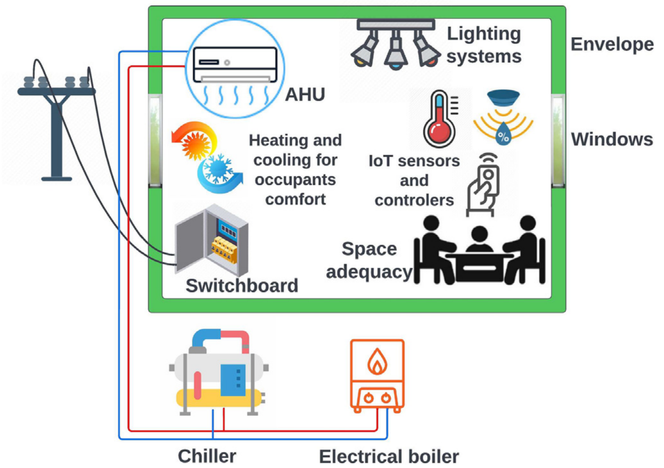

Fig. 10. Components and Systems of the Digital Twin Framework for Identifying Occupants' Discomfort in Buildings through Fault Detection and Prediction, after [84].

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

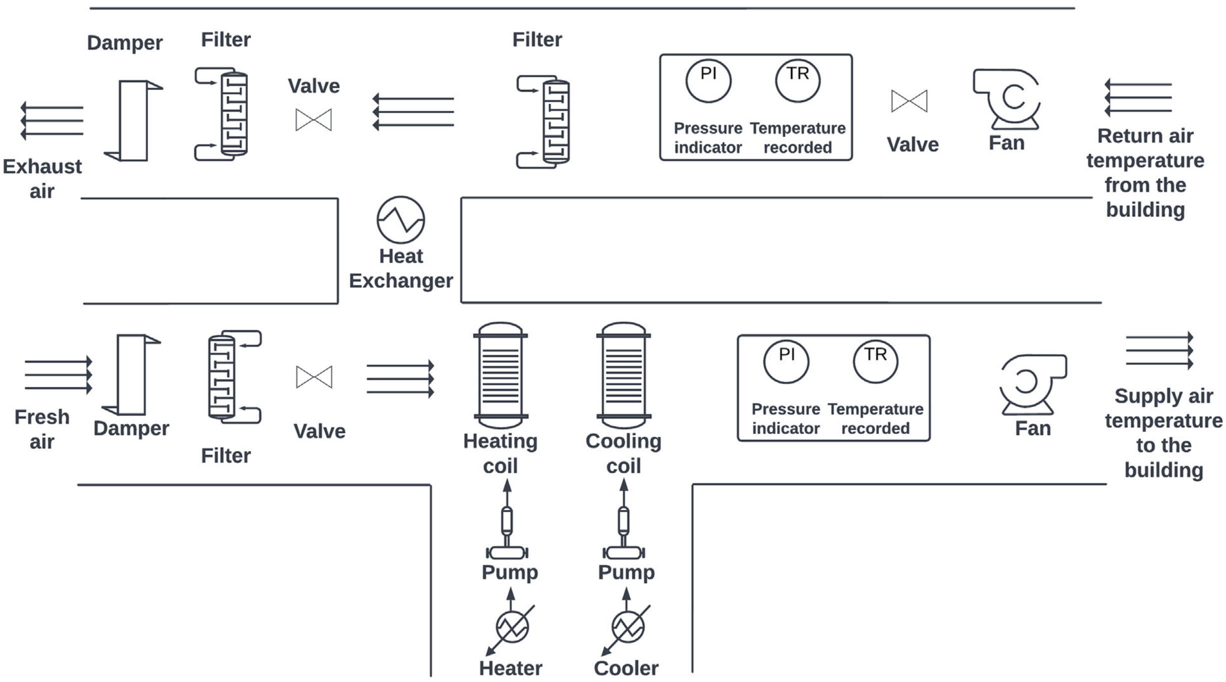

Fig. 11. Graphical Representation of the HVAC Systems in the I4Helse and Tvedestrand School.

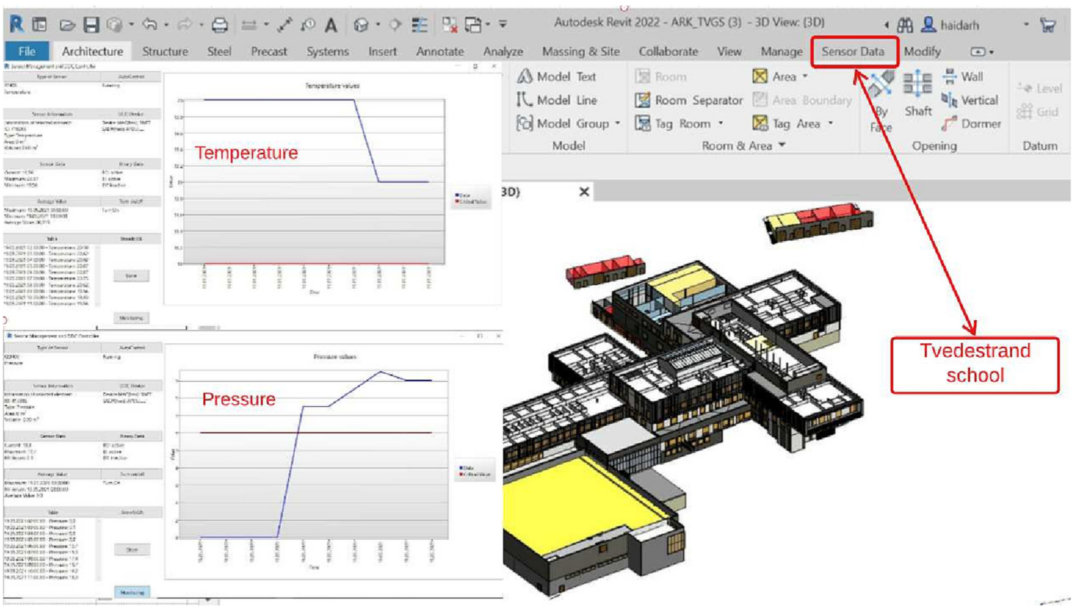

Fig. 12. The information about the building obtained via sensor data and the BIM model.

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

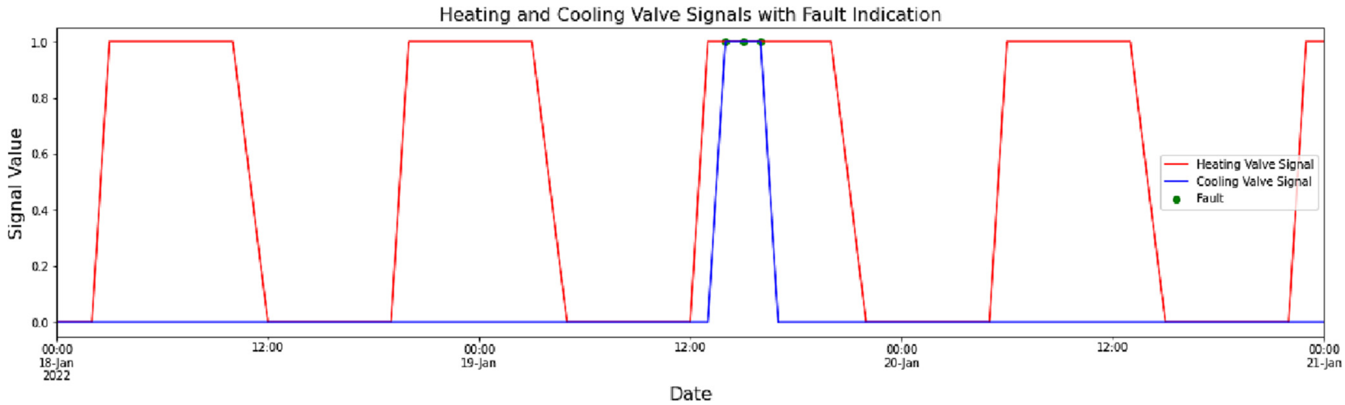

Fig. 13. Time series plot of heating and cooling valve signals for the HVAC system. The heating valve signal is active between 6 AM and 11 PM while cooling valve signal is inactive because of winter. The green points indicate heating and cooling fault, which occurred for three hours.

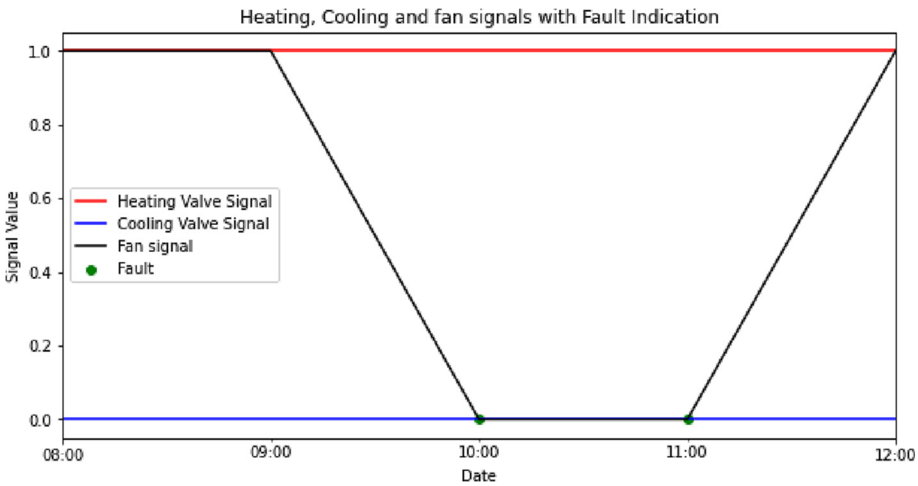

Fig. 14. Heating, cooling, and fan signals for the HVAC system during a fault occurrence. The red line shows the heating valve signal, the blue line shows the cooling valve signal, the black line shows the fan signal, and the green points indicate the fault, which occurred when the fan signal was off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

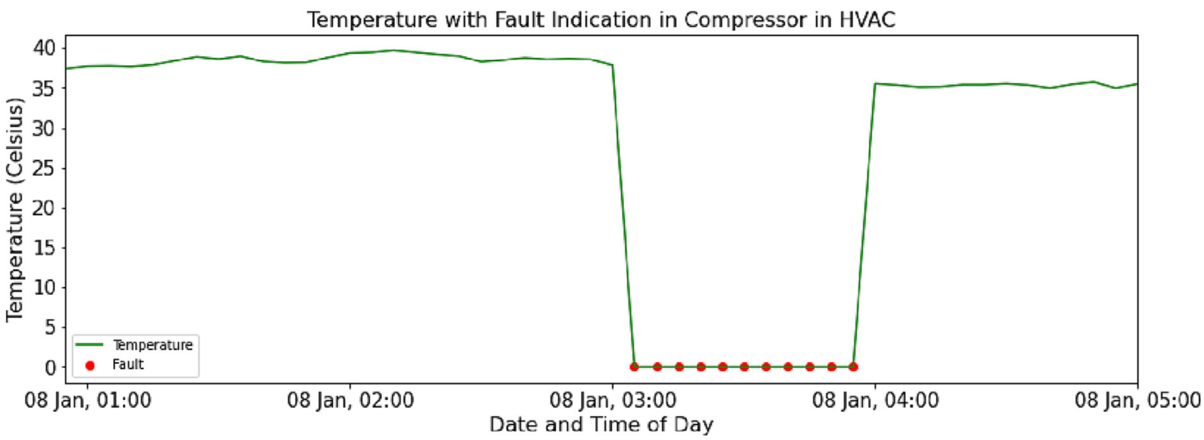

Fig. 15. Temperature of the HVAC system over a 15-day period with a fault indicated on the 10th day. The rolling average of 24 h is shown and the y-axis represents temperature in Celsius. The red scatter plot indicates the fault point. The x-axis shows the date and time of day. The plot is limited to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

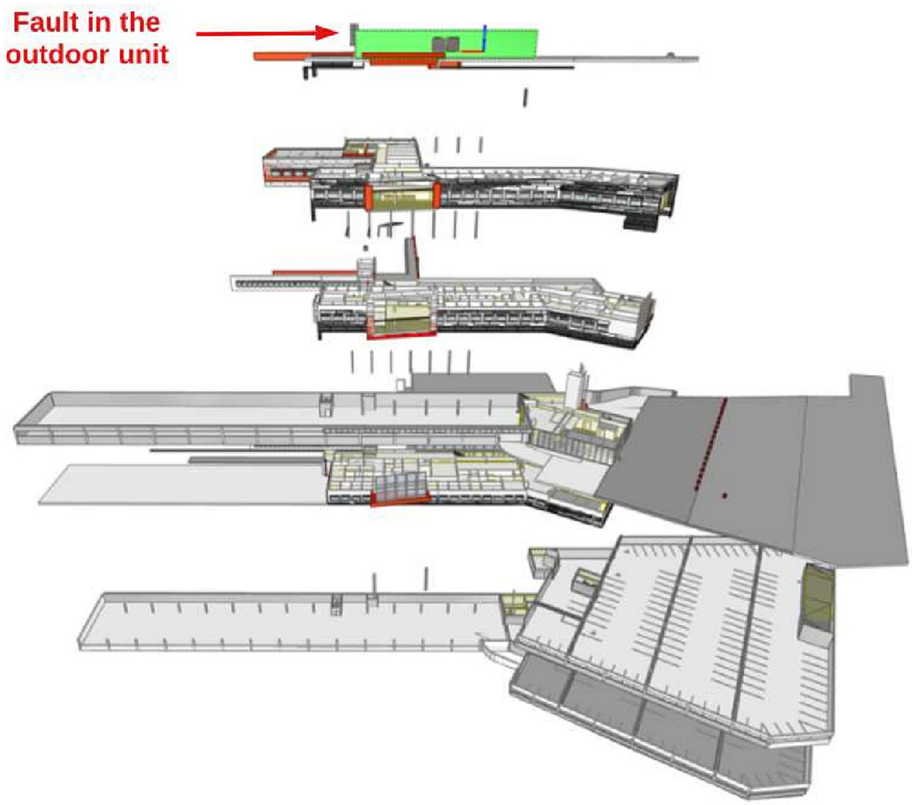

Fig. 16. BIM problem-cause analysis visualization.

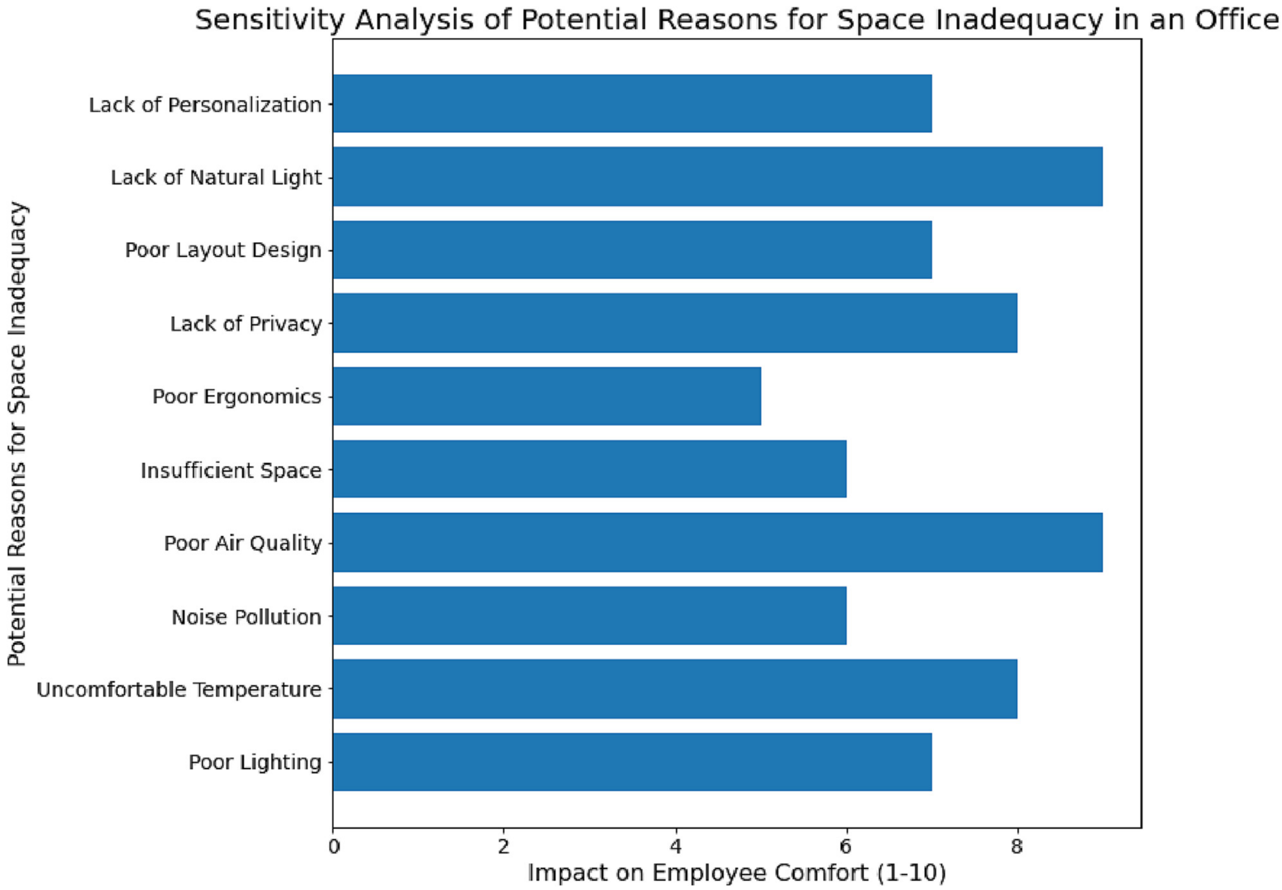

Fig. 17. Sensitivity analysis of potential reasons for space inadequacy in an office in Tvedestrand school. The horizontal bars represent the impact measured on employee comfort (1–10) for each potential reason, with higher values indicating greater impact on employee comfort. The reasons are listed 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.

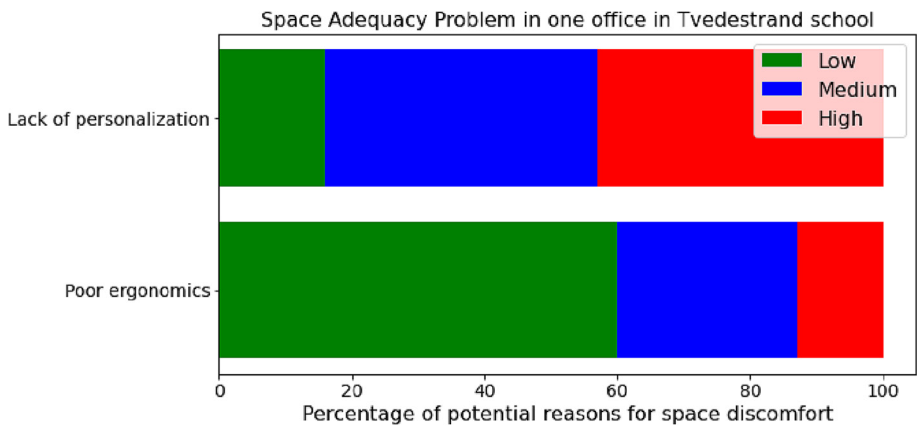

Fig. 18. Potential impact of different reasons for space inadequacy on employee comfort. The horizontal bars represent the potential impact (low, medium, high) of each reason on employee comfort, with the reasons listed on the y-axis and the potential impact shown on the x-axis. This graph is based on 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

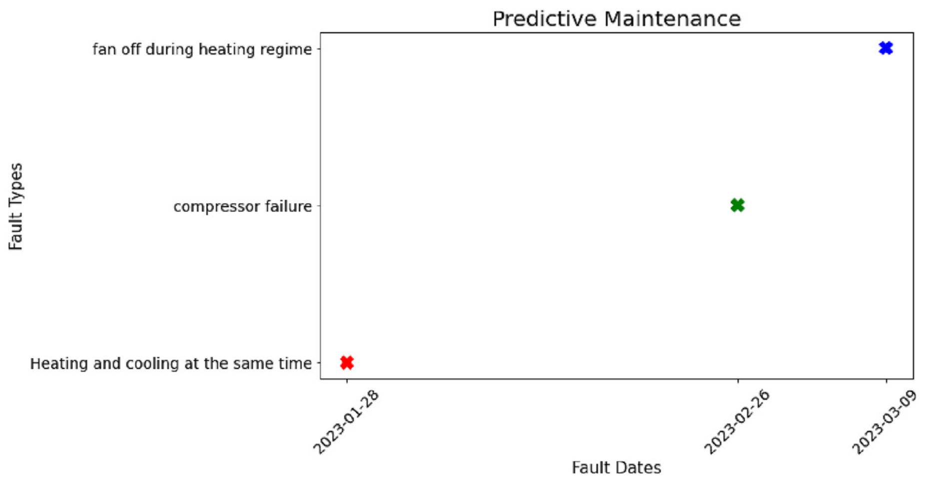

Fig. 19. A scatter plot showing the predicted dates and types of the next three faults in an HVAC system based on data from Tvedestrand school using the XGB algorithm. The plot illustrates that the model can predict the faults with different types and dates. The X-axis represents the predicted dates 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.

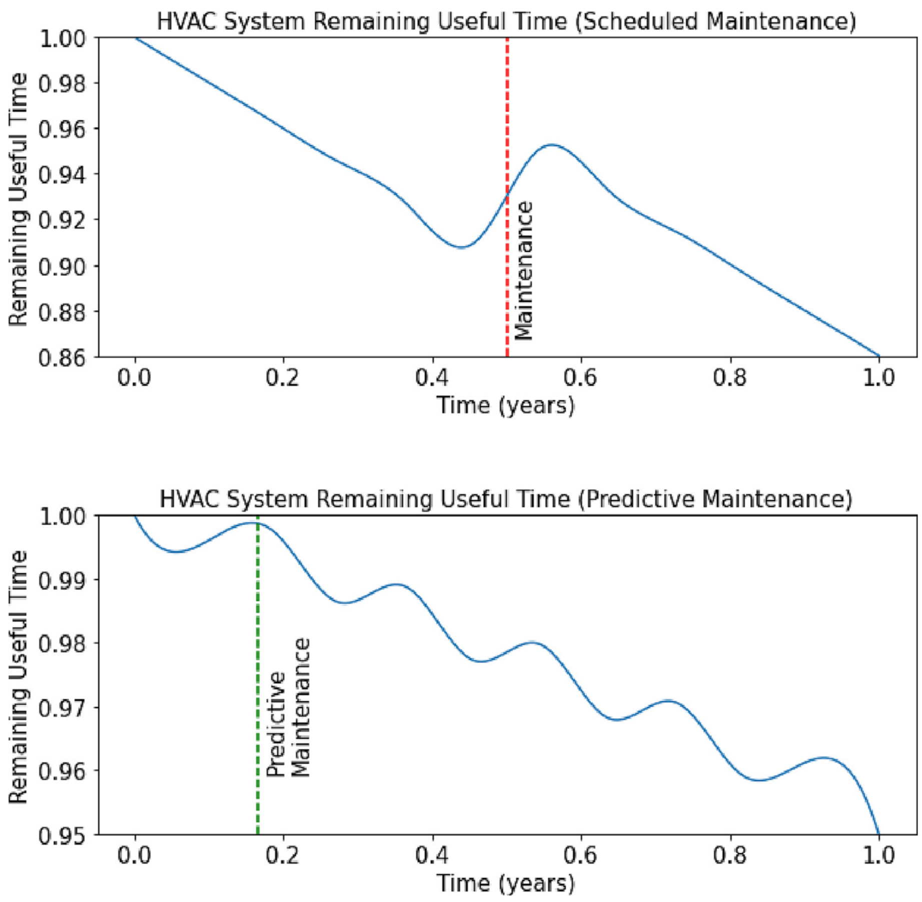

Fig. 20. Comparison of the impact of scheduled maintenance every 6 months and predictive maintenance on the remaining useful life of an HVAC system. The above plot shows the impact of scheduled maintenance, while the below plot shows the impact of predictive maintenance that can predict faults 2 months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

Measuring Occupant Comfort in Buildings: A Questionnaire Approach

Vil du delta i forskningsprosjektet
"BIM og IoT integrasjon til støtte beslutningstaking for å forbedre bygningens ytelse og energibruk"?

NB: Vi anbefaler å bruke PC versjon
Hei, takk for din deltagelse i vår undersøkelse angående menneskelig komfort i bygninger. Formålet med denne undersøkelse er å utvikle ny metode for å oppnå best mulig komfort for bygningsbrukere.

Dette er en del av min doktorgrad ved Universitetet i Agder, i studieretning fornybarenergi.

Dette vil ta ca. 10 minutter. Vi setter stor pris på om du gjennomfører hele undersøkelsen. Svarene dine fra spørreskjemaundersøkelsen blir registrert elektronisk og undersøkelsen er helt anonymt. **Begrepsforklaring:**
BIM: Building Information Modeling (3D Modell av bygning).
IoT: Internet of Things (Data fra sensorene i bygning, for eks. Temperatur, Fuktighet, CO2 OSV.)

Det er frivillig å delta
Det er frivillig å delta i prosjektet. Selv om du velger å delta i undersøkelsen så kan du når som helst trekke ditt samtykke uten å oppgi årsak. Alle dine opplysninger vil da bli slettet. Det vil ikke ha noen negative konsekvenser for deg hvis du ikke ønsker delta i undersøkelsen eller senere velger å trekke deg.

Hvor kan jeg finne ut mer
Hvis du har spørsmål til studien, eller ønsker å benytte deg av dine rettigheter, ta kontakt med: Haidar Hosamo, haidar.hosamo@uia.no, Tlf. +47 91220309 and Henrik Kofoed Nielsen, henrik.kofoed.nielsen@uia.no, +47 37233030 NSD – The Norwegian Centre for Research Data AS, by email: (personverntjenester@nsd.no) or by telephone: +47 55 58 21 17. Med vennlig hilsen
Haidar Hosamo-Hosamo

Jeg har lest samtykkeskjema og ønsker å delta I spørreundersøkelsen

(1) ❍ Ja, jeg samtykker

(2) ❍ Nei

Avsnitt 1. Detaljer om arbeidsplassen:

1.1. I hvilken etasje ligger ditt kontor?

(1) ❍ Null etasje

(2) ❍ Første etasje

(4) ❍ Andre etasje

(3) ❍ Tredje etasje

1.2. Vennligst skriv romnummeret der du jobber (Dersom du ikke husker romnummeret ditt, vennligst bruk Mazemap på denne linken for å finne frem: https://use.mazemap.com/#v=1&center=8.578000,58.334663&zoom=18.9&zlevel=3&campusid=225):

_____

1.3. Vennligst velg mellom følgende

(1) ❍ Jeg har kontor alene

(2) ❍ Jeg jobber i kontorlandskap

1.4. Vennligst spesifiser antall personer som jobber i samme kontorlandskap (under pandemien):

_____

1.5. Vennligst spesifiser antall personer som jobber i samme kontorlandskap (uten pandemien):

_____

1.6. Hvor lenge har du jobbet i denne bygningen?

(1) ❍ Mindre enn 1 år

(2) ❍ Mellom 1 og 2 år

1.7. Hvilket av følgende har du mulighet til å regulere manuelt i ditt rom? (kryss av for alle relevante)

(1) ❑ Temperatur i rom

(6) ❑ Åpne vindu

(9) ❑ Lysnivå

(10) ❑ Gardiner

(11) ❑ solskjerming

(8) ❑ Annet: ______

1.8. Bekledning og varmetap
Vennligst sjekk med klær du bruker mest (dette er en indikasjon på komfortnivået på ditt rom):

(1) ❑ Vanlig innetøy

(9) ❑ Behov for ekstra jakke eller genser

(8) ❑ Annet ______

1.9. Aktivitetsnivå og varmeproduksjon
Hvordan vil du beskrive aktivitetsnivået ditt i løpet av arbeidsdagen?

(2) ❑ Stillesittende aktiviteter

(3) ❑ Stående, lett aktivitet

(4) ❑ Stående, middels aktivitet

(5) ❑ Høy aktivitet

(6) ❑ Annet ______

Avsnitt 2. Tilfredshet med arbeidsplassen:

2.1. Angi graden av tilfredshet i forhold til de forskjellige aspektene ved arbeidsplassen din:

	Veldig misfornøyd	Misfornøyd	Nøytral	Fornøyd	Veldig fornøyd	Ikke aktuelt
Temperaturkomfort om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Temperaturkomfort om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

Innendørs luftkvalitet om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Innendørs luftkvalitet om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Visuell komfort (lysnivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Akustisk komfort (støynivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Romstørrelse	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

2.2 Hvis du er misfornøyd, hvilket av følgende bidrar til ubehag med hensyn til:

A- "Temperaturkomfort" (kryss av for alle relevante)

(1) ❑ Alltid for varmt

(2) ❑ Ofte for varmt

(3) ❑ Noen ganger for varmt

(4) ❑ Noen ganger for kaldt

(5) ❑ Ofte for kaldt

(6) ❑ Alltid for kaldt

(7) ❑ Annet: ______

2.2 Hvis du er misfornøyd, hvilket av følgende bidrar til ubehag med hensyn til:

B- "Innendørs luftkvalitet" (kryss av for alle relevante)

(1) ❑ Innestengt luft (for lite luftgjennomstrømning)

(2) ❑ Luften er tørr

(3) ❑ Luften er fuktig

(4) ❑ Forstyrrende lukt

(5) ❑ Annet: _____

2.2 Hvis du er misfornøyd, hvilket av følgende bidrar til ubehag med hensyn til:

C- "Lysnivå" (kryss av for alle relevante)

(1) ❑ Blending av sollys

(2) ❑ Mangel på dagslys

(4) ❑ Ikke mulig å kontrollere lys

(5) ❑ Lavt nivå av kunstig lys

(6) ❑ Høyt nivå av kunstig lys

(7) ❑ Annet: _____

2.2 Hvis du er misfornøyd, hvilket av følgende bidrar til ubehag med hensyn til:

D- "Romstørrelse" (kryss av for alle relevante)

(1) ❑ Mengde plass (kvm)

(2) ❑ Mulighet for å bevege seg i rommet

(3) ❑ Personvern

(4) ❑ Ergonomi av stol og bord

(5) ❑ Tilgjengelighet av utstyr (møbler, skriver osv.)

(6) ❑ Mangel på fleksibilitet

(7) ❑ Annet: _____

2.2 Hvis du er misfornøyd, hvilket av følgende bidrar til ubehag med hensyn til:

E- "Støynivå" (kryss av for alle relevante)

(1) ❑ Støy fra klimaanlegget

(2) ❑ Støy fra lys

(3) ❑ Støy fra utvendige maskiner

(4) ❑ Folk snakker høyt i korridoren

(5) ❑ Støy fra heis

(6) ❑ Dårlig lydisolasjon mellom rommene

(8) ❑ Støy fra vanndispenser i kaffekrok i 3. etg

(7) ❑ Annet: ______

Avsnitt 3. Tilfredshet med fellesarealene:

3.1. For de følgende spørsmålene, hvis du ikke bruker noen fellesområder, vennligst velg som ikke aktuelt. I de følgende spørsmålene, vennligst oppgi graden av tilfredshet i forhold til de forskjellige aspektene ved lobby, korridorer, trapper:

	Veldig misfornøyd	Misfornøyd	Nøytral	Fornøyd	Veldig fornøyd	Ikke aktuelt
Temperaturkomfort om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Temperaturkomfort om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Innendørs luftkvalitet om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

Innendørs luftkvalitet om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Visuell komfort (lysnivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Akustisk komfort (støynivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Romstørrelse	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

3.2.A. Vennligst angi laboratorie (navn og etasje) du bruker mest

_____

3.2.B. Vennligst oppgi graden av tilfredshet i forhold til de forskjellige aspektene ved laboratoriet angående

	Veldig misfornøyd	Misfornøyd	Nøytral	Fornøyd	Veldig fornøyd	Ikke aktuelt
Temperaturkomfort om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Temperaturkomfort om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Innendørs luftkvalitet om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

Innendørs luftkvalitet om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Visuell komfort (lysnivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Akustisk komfort (støynivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Romstørrelse	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

3.3.A. Vennligst angi møterom navn/nummeret og etasje du bruker mest

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3.3.B. Vennligst oppgi graden av tilfredshet i forhold til de forskjellige aspektene av møterom nummeret angående

	Veldig misfornøyd	Misfornøyd	Nøytral	Fornøyd	Veldig fornøyd	Ikke aktuelt
Temperaturkomfort om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Temperaturkomfort om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Innendørs luftkvalitet om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

Innendørs luftkvalitet om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Visuell komfort (lysnivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Akustisk komfort (støynivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Romstørrelse	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

3.4.A. Du vil normalt ha en rekke forskjellige pauser fra jobben, som lunsjpauser, te pauser og andre korte pauser i løpet av dagen, vennligst spesifiser hvor du vanligvis bruker pausetiden din (for eksempel kjøkken ved siden av arbeidsplassen min, stort møterom i 3. etasje osv.)

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3.4.B. Vennligst oppgi graden av tilfredshet i forhold til de forskjellige aspektene av sted du vanligvis bruker for pausetiden angående

	Veldig misfornøyd	Misfornøyd	Nøytral	Fornøyd	Veldig fornøyd	Ikke aktuelt
Temperaturkomfort om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Temperaturkomfort om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

Innendørs luftkvalitet om sommeren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Innendørs luftkvalitet om vinteren	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Visuell komfort (lysnivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Akustisk komfort (støynivå)	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍
Romstørrelse	(1) ❍	(2) ❍	(3) ❍	(4) ❍	(5) ❍	(6) ❍

Du er velkommen til å supplere med ytterligere informasjon som du tror kan være nyttig for dette forskningsprosjektet

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Tusen takk for at du tok deg tid til å svare på undersøkelse.
Det setter jeg veldig stor pris på.