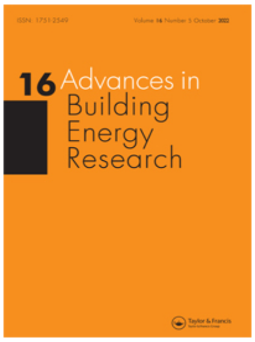


Advances in Building Energy Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/taer20

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

Haidar Hosamo, Mohsen Hosamo Hosamo, Henrik Kofoed Nielsen, Paul Ragnar Svennevig & Kjeld Svidt

To cite this article: Haidar Hosamo, Mohsen Hosamo Hosamo, Henrik Kofoed Nielsen, Paul Ragnar Svennevig & Kjeld Svidt (2022): 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, DOI: 10.1080/17512549.2022.2136240

To link to this article: https://doi.org/10.1080/17512549.2022.2136240

Published online: 26 Oct 2022.

ADVANCES IN BUILDING ENERGY RESEARCH
https://doi.org/10.1080/17512549.2022.2136240

Taylor & Francis
Taylor & Francis Group

OPEN ACCESS Check for updates

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

Haidar Hosamo[a], Mohsen Hosamo Hosamo[b], Henrik Kofoed Nielsen[a], Paul Ragnar Svennevig[a] and Kjeld Svidt[c]

[a]University of Agder, Grimstad, Norway; [b]Cyber defense center, Advania, Oslo, Norway; [c]Aalborg University, Aalborg Ø, Denmark

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.

ARTICLE HISTORY
Received 20 June 2022
Accepted 27 September 2022

KEYWORDS
Digital Twin; building information modelling; building optimization; thermal comfort; ANN; MOGA

CONTACT Haidar Hosamo Hosamo haidarh@uia.no University of Agder, Jon Lilletuns vei 9, Grimstad 4879, Norway

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. Multi-objective 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.

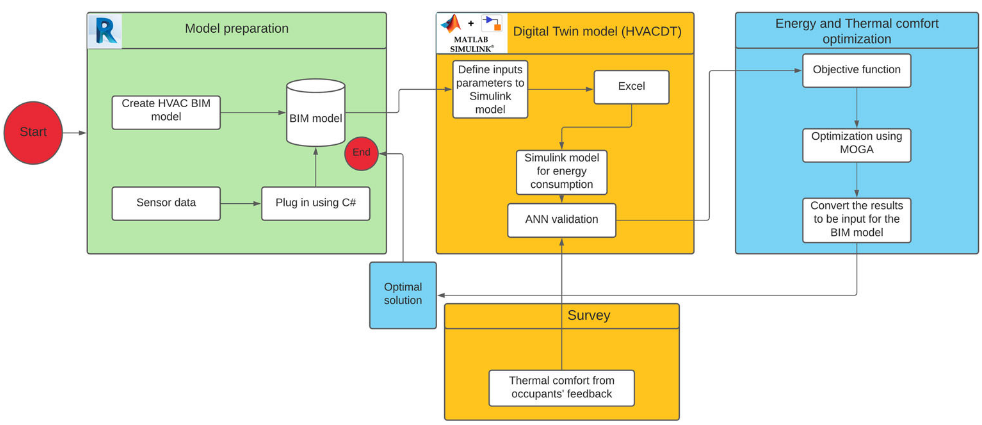


Figure 1. The Digital Twin framework for the optimization process.

- 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

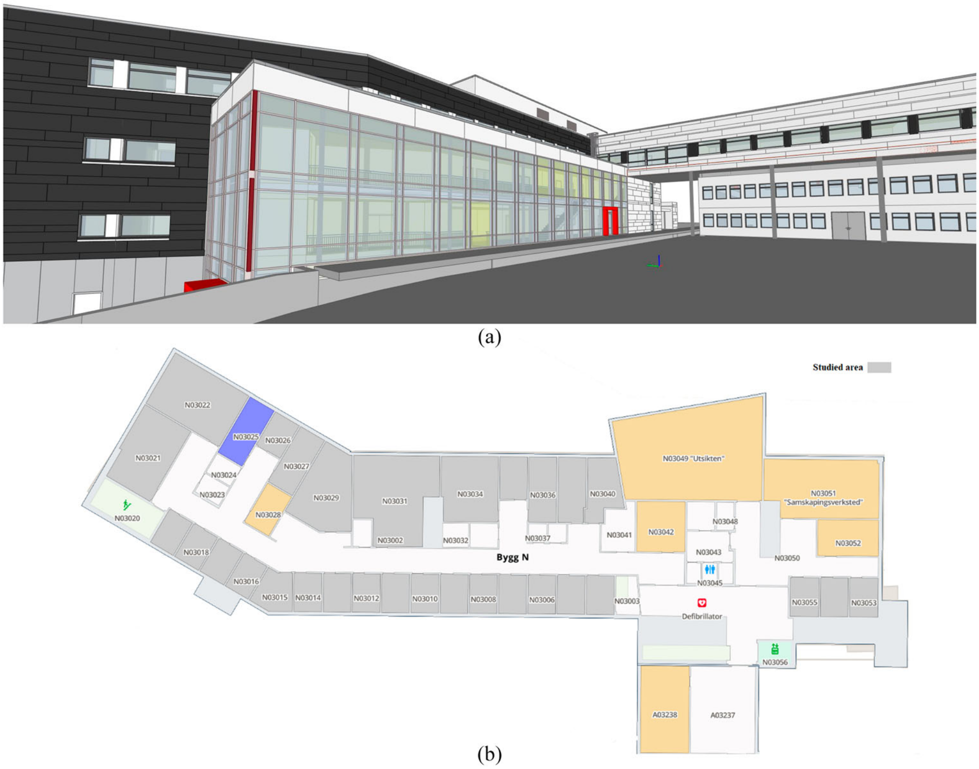


Figure 2. BIM model of I4Helse building that located in Grimstad, Norway (a), and the plan of zones at third floor in I4Hhelse building (b).

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.

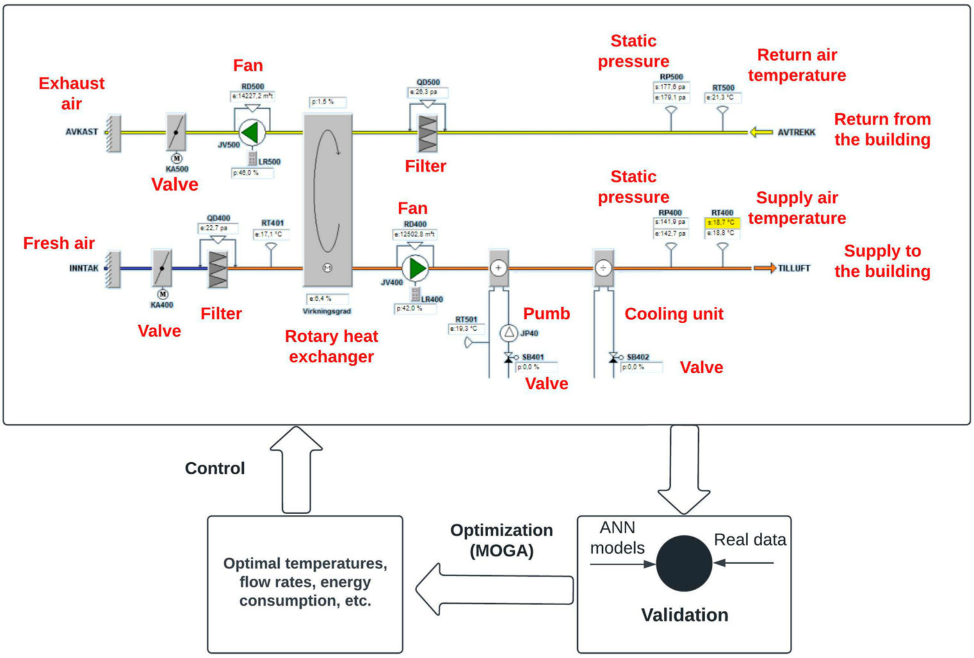


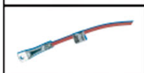
Figure 3. A Schematic diagram of the proposed HVAC with the proposed ANN models and optimization process.

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

CE MÆRKNING

ETF-serien overholder kravene i følgende direktiv:

MASKINDIREKTIVET

89/392/EEC

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

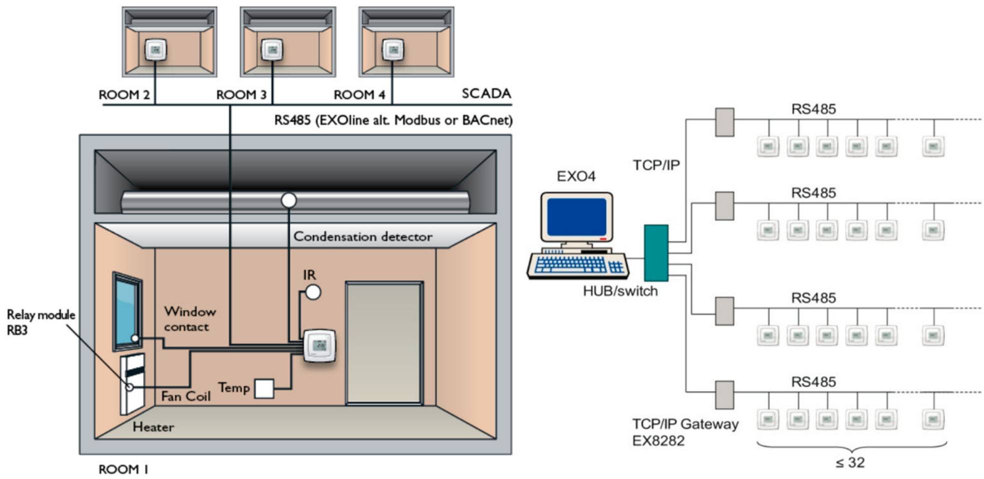


Figure 5. An example of the application system (Regio Midi, 2013).

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.

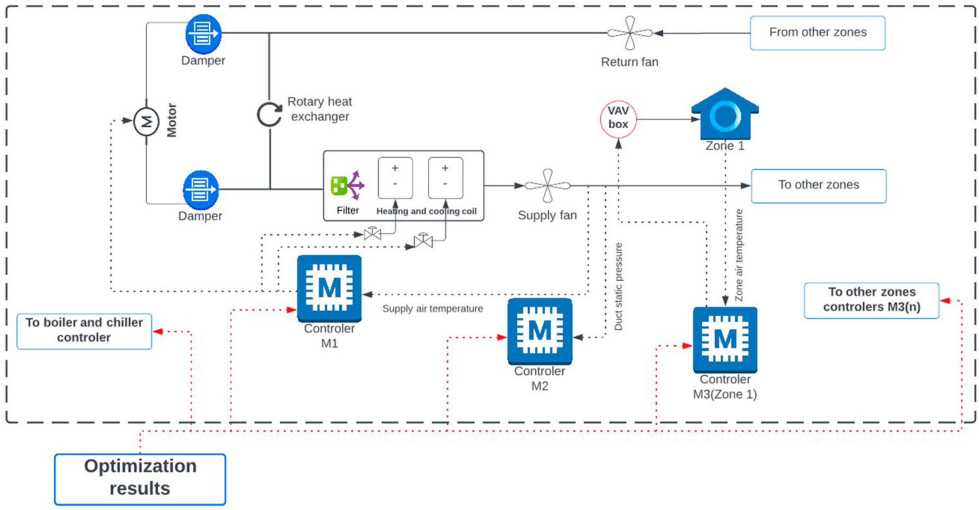


Figure 7. HVAC system controllers along with the optimization process.

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:

$$PMV = (0.303 \cdot e^{0.036 \cdot M} + 0.028) \cdot L \tag{1}$$

$$\begin{aligned} L = {} & M - 0.00305 \cdot (5733 - 6.99 \cdot (M - W) - Pa) - 0.42(M - W - 58.15) \\ & - 0.0017(5867 - Pa) - 0.0014 \cdot M \cdot (34 - Ta) - 3.96 \cdot 10^{-8} \cdot Fcl \cdot ((Tcl + 273)^4 \\ & - (Tr + 273)^4) - Fcl \cdot hc \cdot (Tcl - Ta) \end{aligned} \tag{2}$$

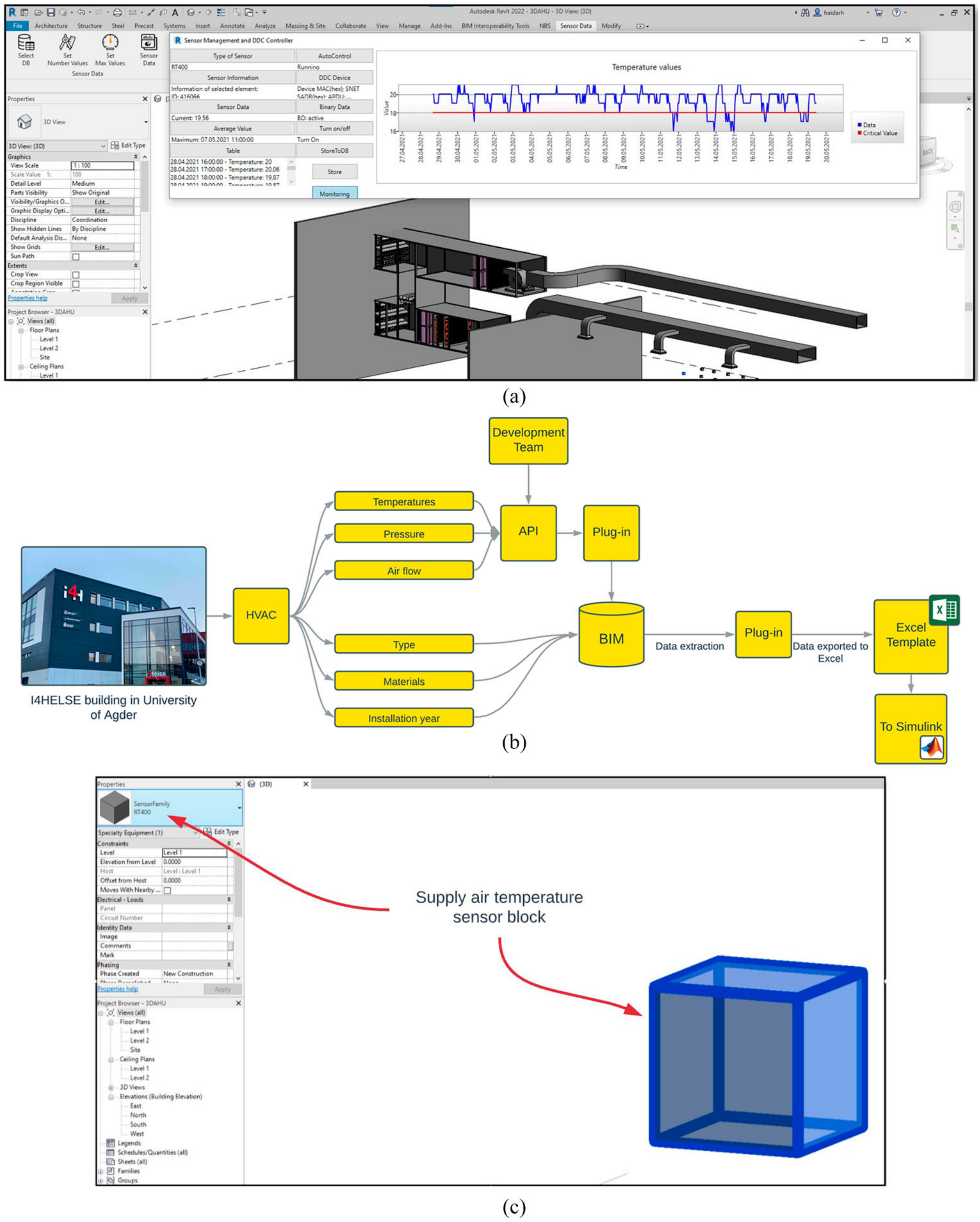


Figure 8. Plugin for sensor management (a), main data extraction components (b), and supply air temperature sensor block (c).

$$Tcl = 35.7 - 0.028 \cdot (M - W) - 0.155 \cdot Icl \cdot (3.96 \cdot 10^{-8} \cdot Fcl((Tcl + 273)^4 - (Tr + 273)^4) + Fcl \cdot hc \cdot (Tcl - Ta)) \tag{3}$$

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

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):

$$Q_{air} = (Mai \times Cpair \times (Tui - Tai)) \tag{7}$$

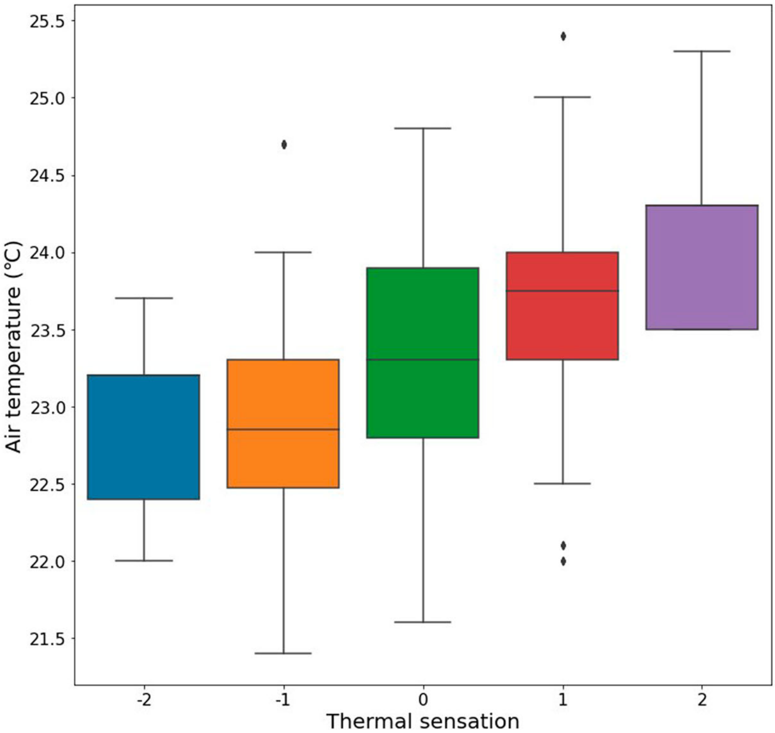
In winter (kW):

$$Q_{air} = (Mai \times Cpair \times (Tui - Ti)) \tag{8}$$

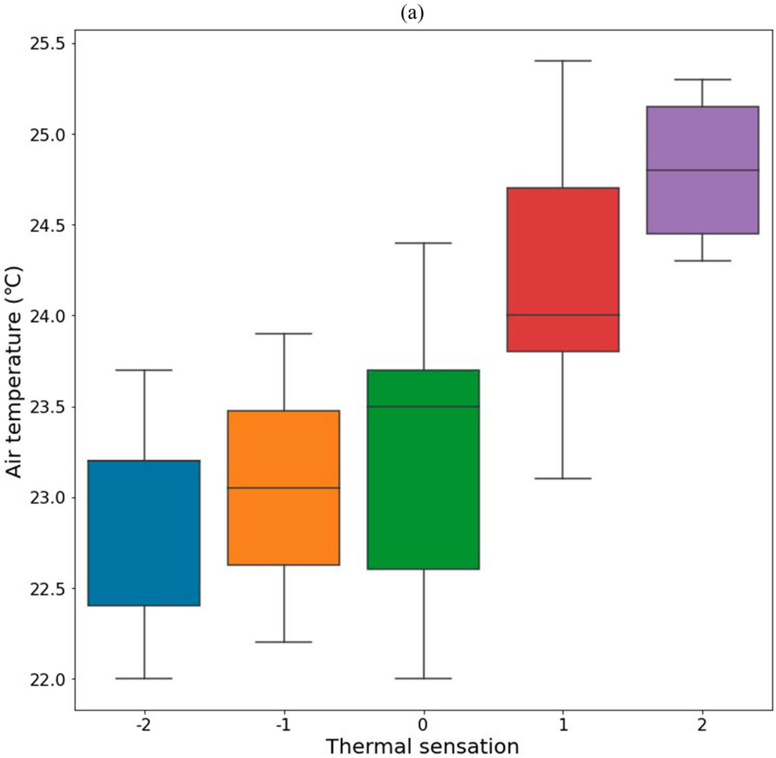
$$\eta = \frac{Q_{cooling/heating}}{Q_{air}} \tag{9}$$

$$Q_{power} = \frac{Q_{cooling/heating}}{COP} \tag{10}$$

$$\begin{aligned} C_{pwatersummer} = {} & (4.218103) + [(-0.0050041 \times (Two - Twi)) + (0.000827196(Two - Twi)^{1.5}) \\ & + (-7.44273 * 10^{-6} \times (Two - Twi)^{2.5}) \\ & + (4.15557 \times 10^{-7} \times (Two - Twi)^{3})] \end{aligned} \tag{11}$$

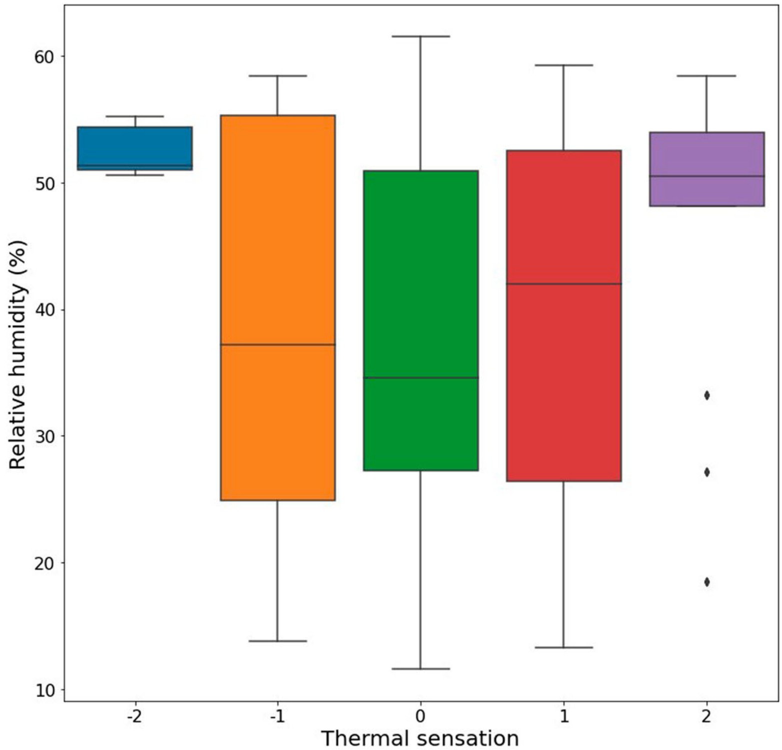


(a)

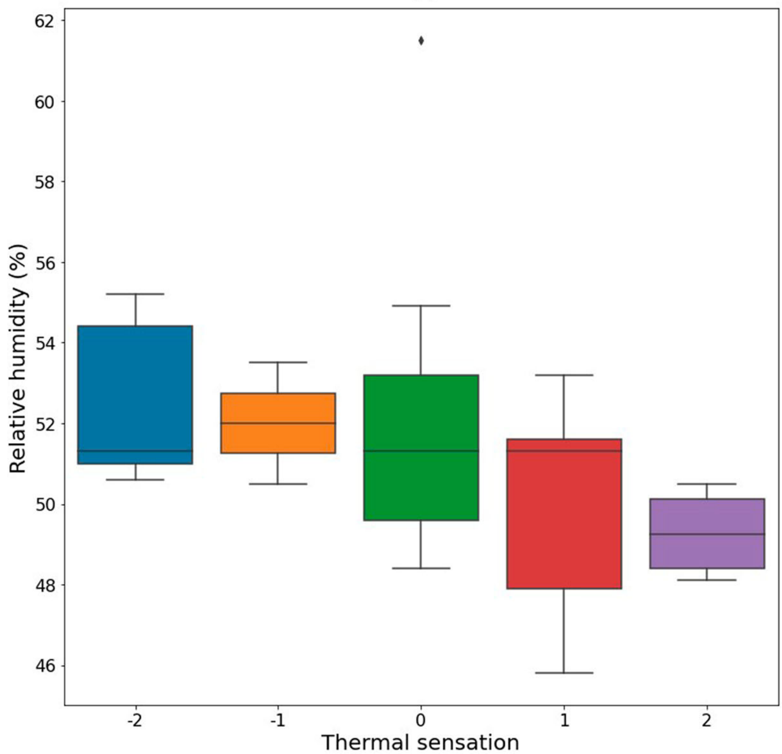


(b)

Figure 10. Air temperature (°C) vs. thermal sensation in winter (a), Air temperature (°C) vs. thermal sensation in summer.

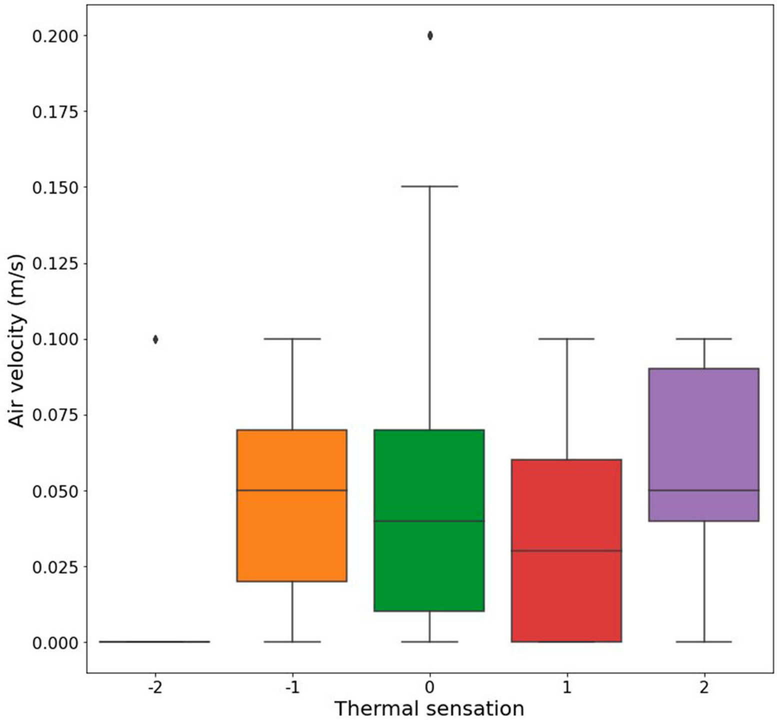


(a)

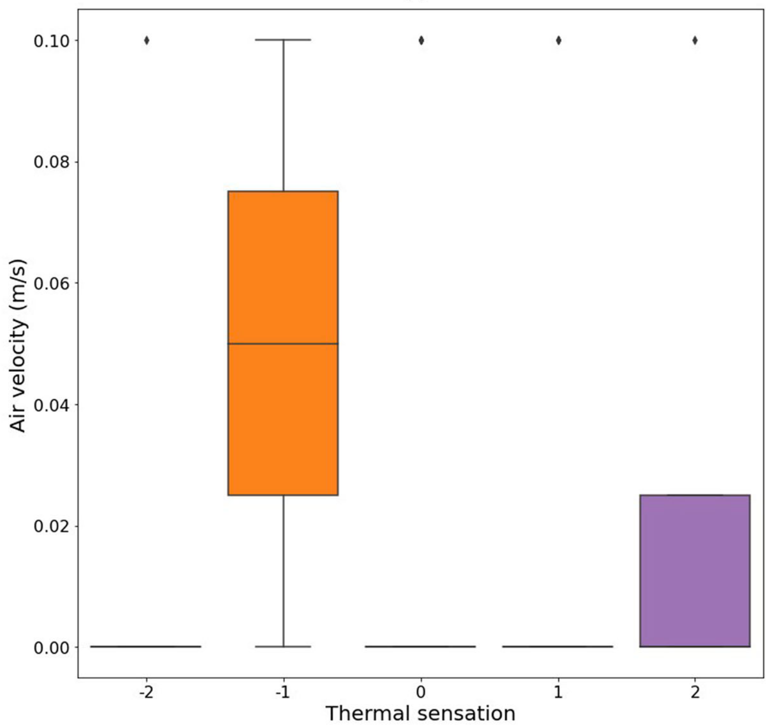


(b)

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.

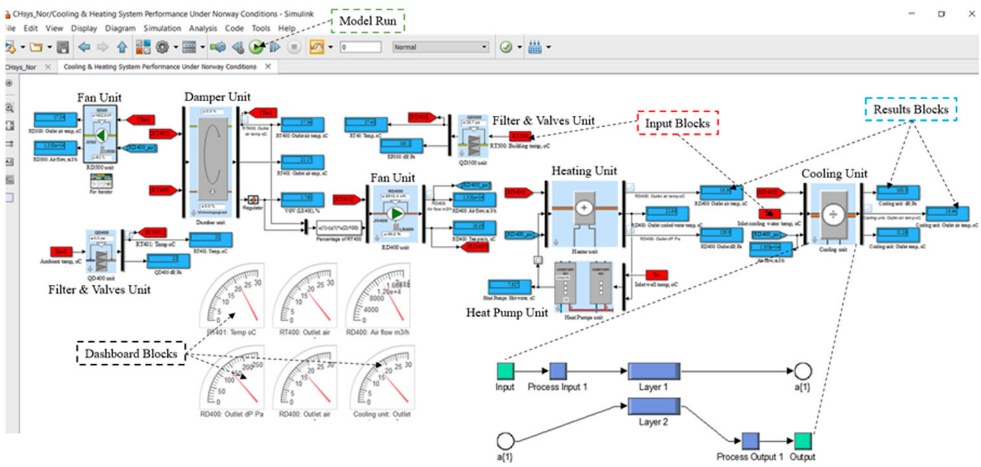


Figure 13. The developed AHU model browser under Simulink toolbox.

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:

$$q_{inf,s} = \frac{\rho_a \times C_{Pair} \times V_{air}^{0} \times (T_0 - T_r)}{A_{room}} \tag{15}$$

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)

A further relation exists between the mean radiant temperature of the building envelope (*Tr*) in and the thermal performance of the building envelope, which can be expressed as in Equations (18), and (19) based on NS-EN ISO 7730 (2006) and Osborn (1985):

$$Tr = \frac{T_1 \cdot A_1 + T_2 \cdot A_2 + \cdots + T_N \cdot A_N}{A_1 + A_2 + \cdots + A_N} = \frac{\sum_1^k (A_{nj} \cdot T_{nj})}{\sum_1^k A_{nj}} \tag{18}$$

Where: A_{nj} and T_{nj} are the building envelope's surface area and temperature, respectively.

$$T = Ta \cdot U \cdot \frac{Ta - Tout}{\alpha} \tag{19}$$

Where: Ta is the indoor air temperature, Tout is the outdoor temperature, U 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:

$$Tr = \frac{\left[A_{walls} \cdot T_a \cdot U_{walls} \cdot \frac{(Ta-Tout)}{\alpha}\right] + \left[A_{windows} \cdot T_a \cdot U_{windows} \cdot \frac{(Ta-Tout)}{\alpha}\right] + \left[A_{roof} \cdot T_a \cdot U_{roof} \cdot \frac{(Ta-Tout)}{\alpha}\right]}{A_{walls} + A_{windows} + A_{roof}} \tag{20}$$

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

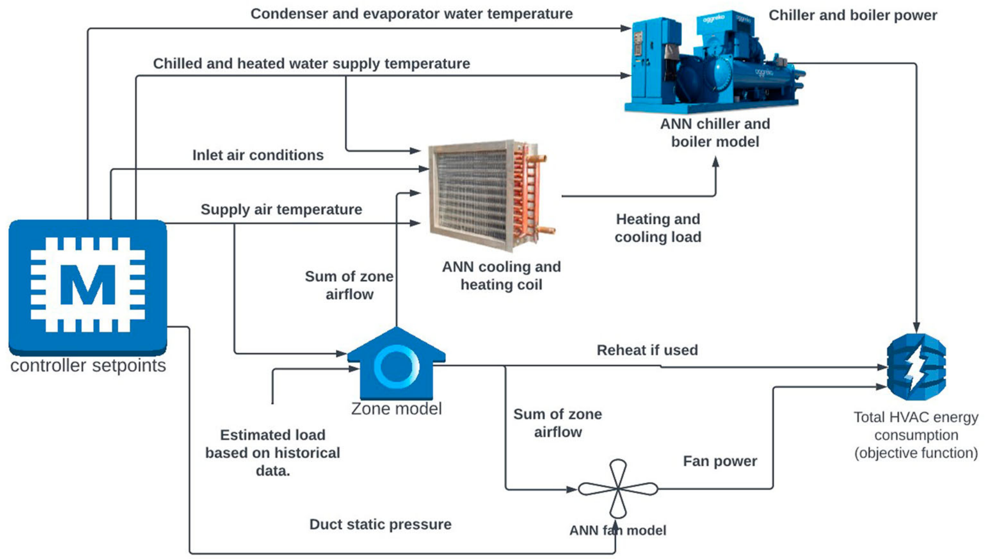


Figure 14. Component model flow chart.

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 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

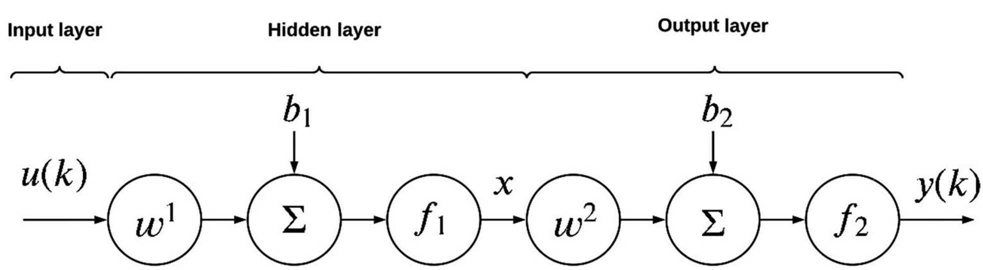


Figure 15. The inputs and outputs in the ANN's structure.

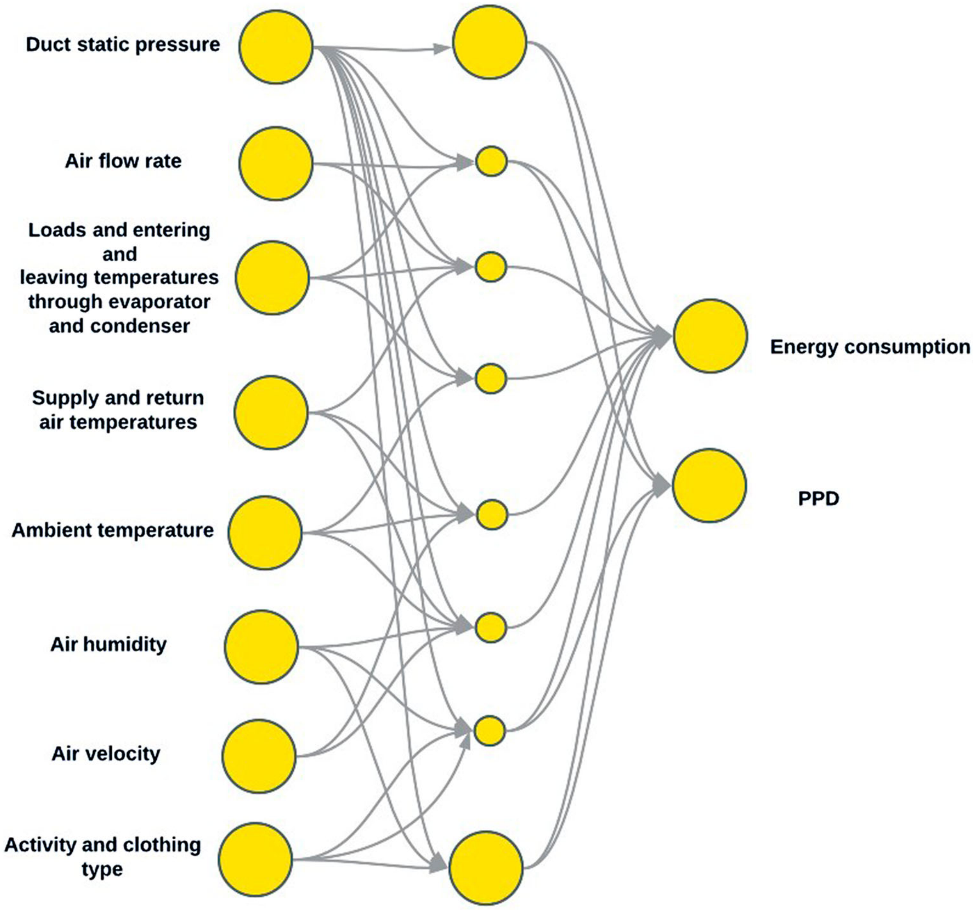


Figure 16. The multilayer perceptron network (MLP).

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

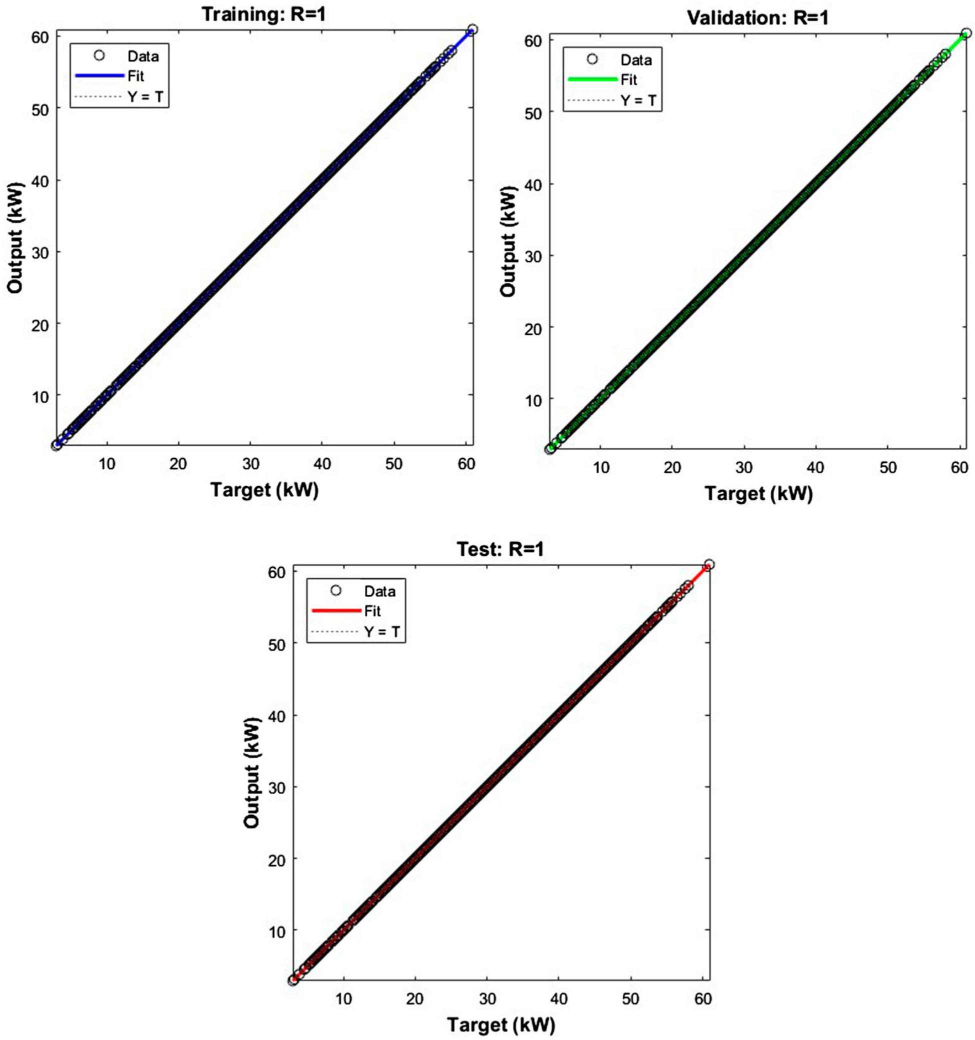


Figure 17. The power consumption results of ANN heating unit model.

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.

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.

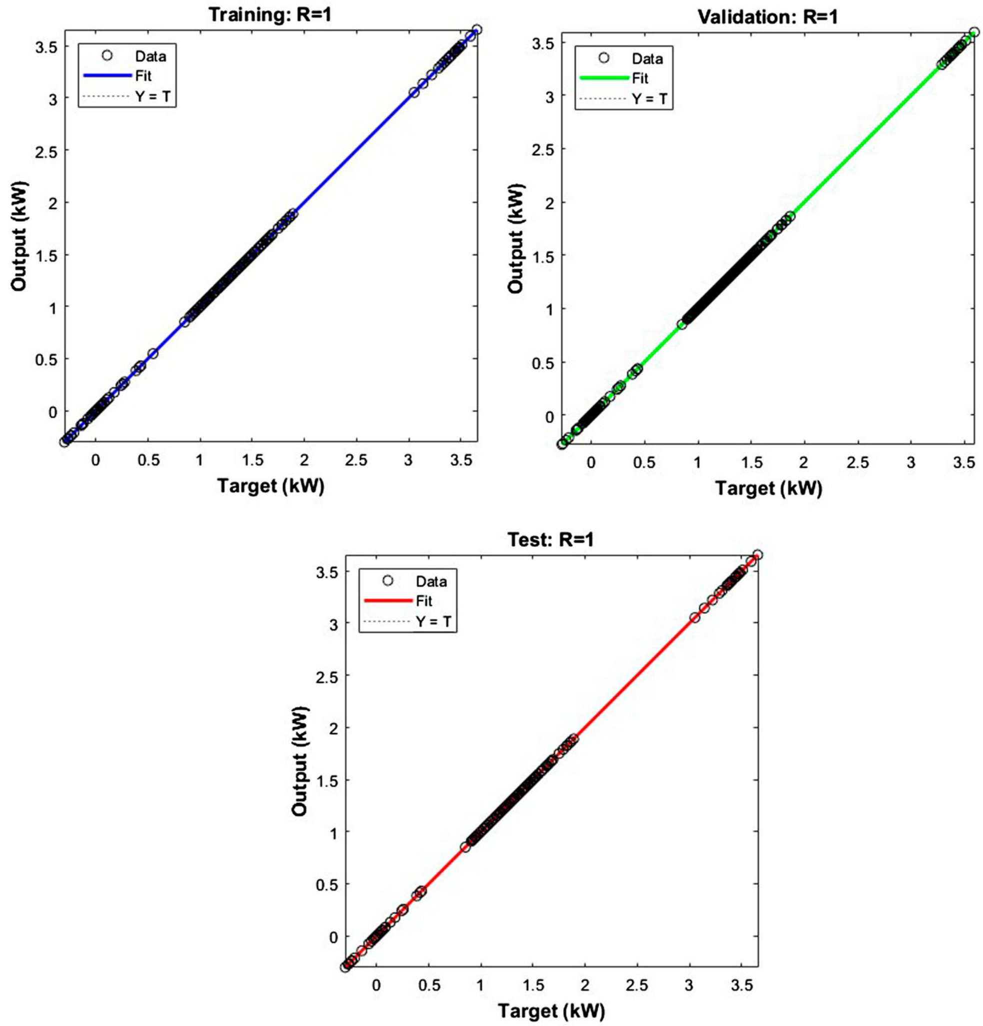


Figure 18. The power consumption results of ANN fan model.

- 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.

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

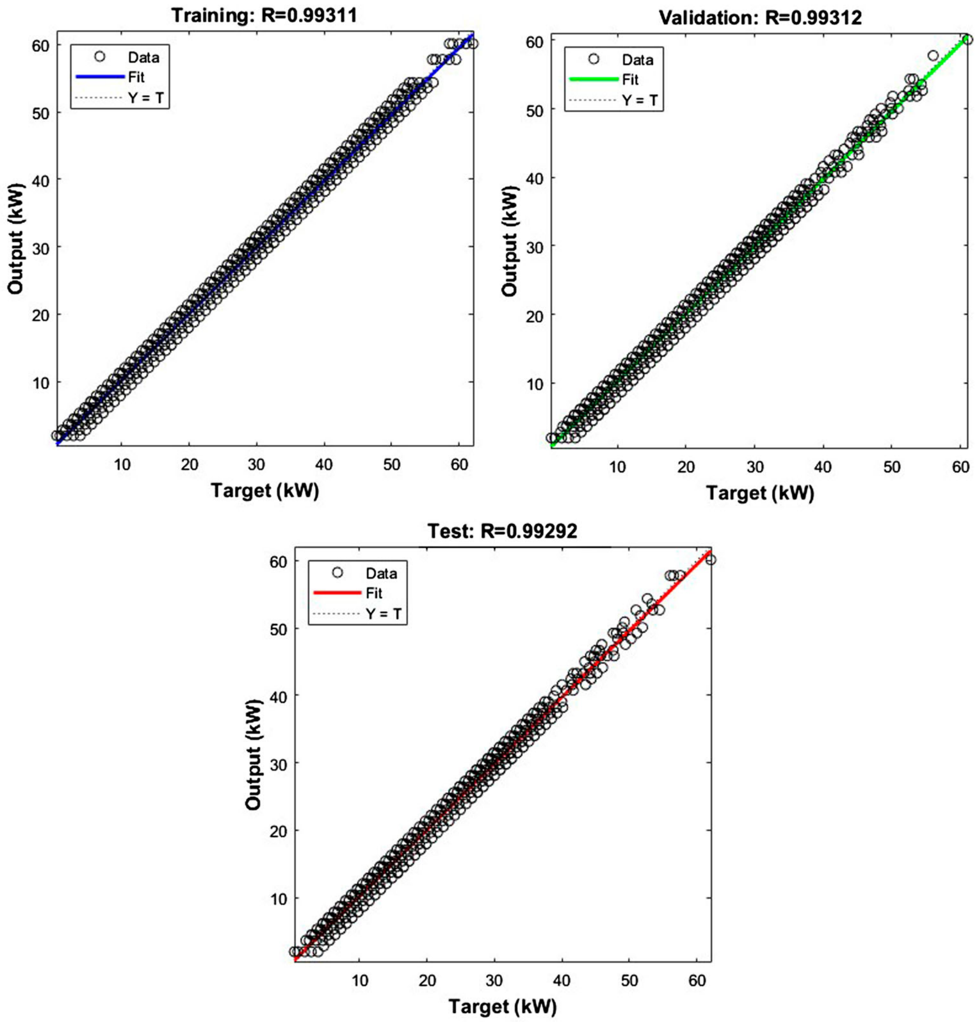
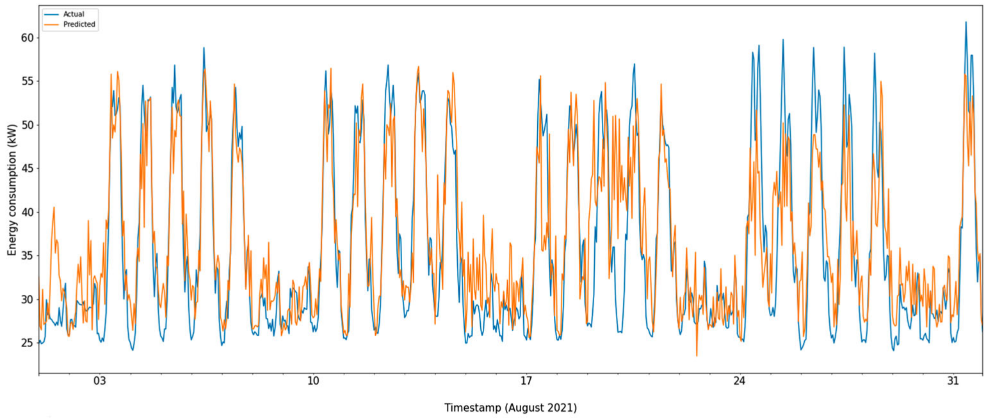


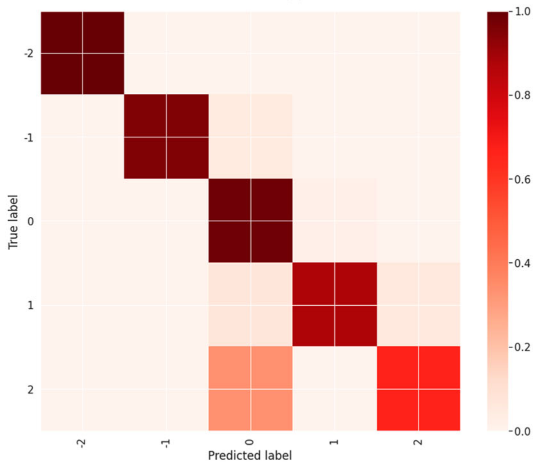
Figure 19. The power consumption results of ANN cooling unit model.

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.

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



(a)



(b)

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).

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 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

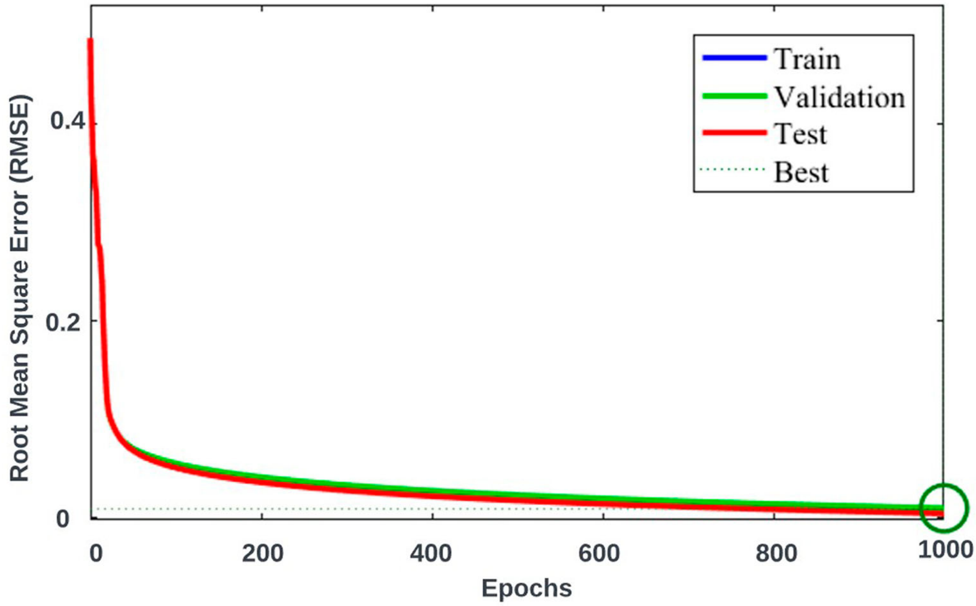


Figure 21. ANN learning curve.

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 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 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

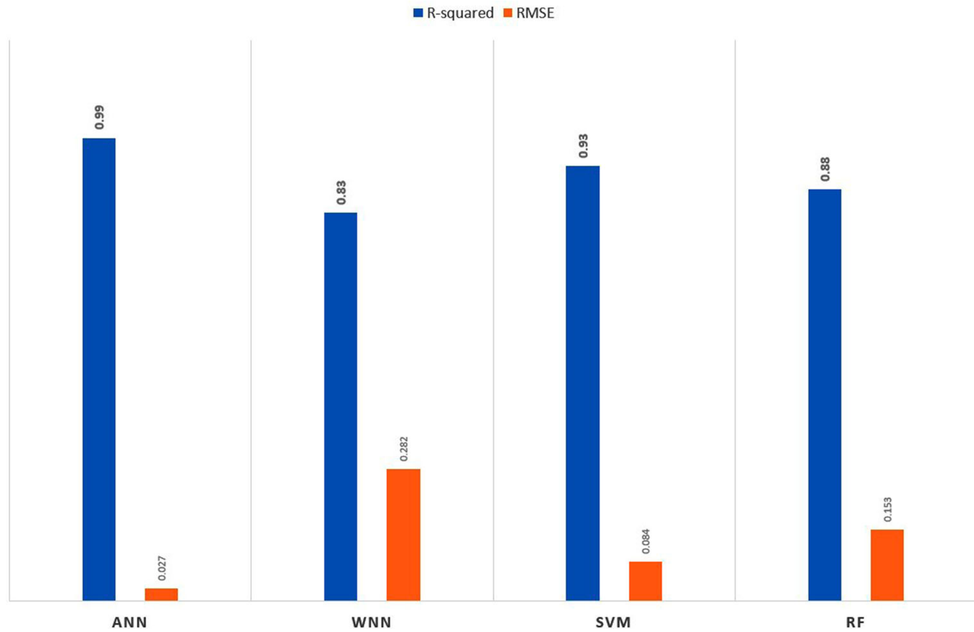


Figure 22. Comparison of the model's accuracy.

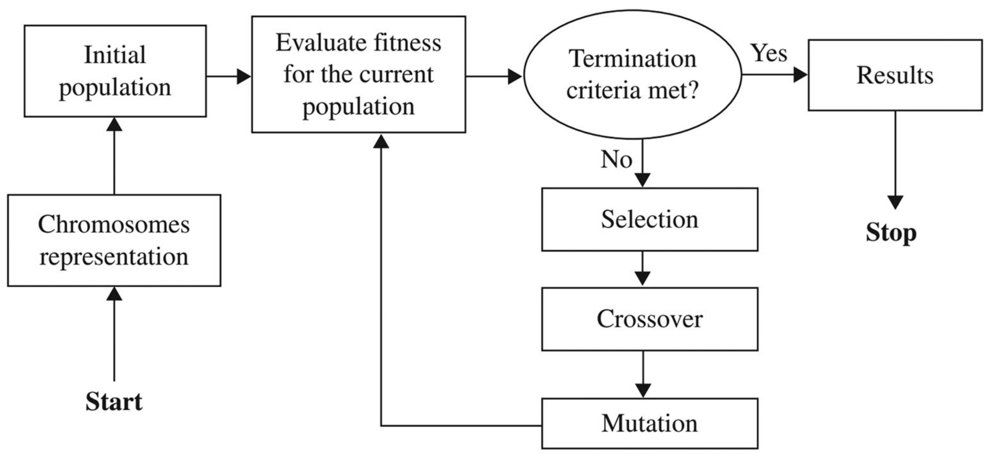


Figure 23. The Overall GA operational process.

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 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.

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)		

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

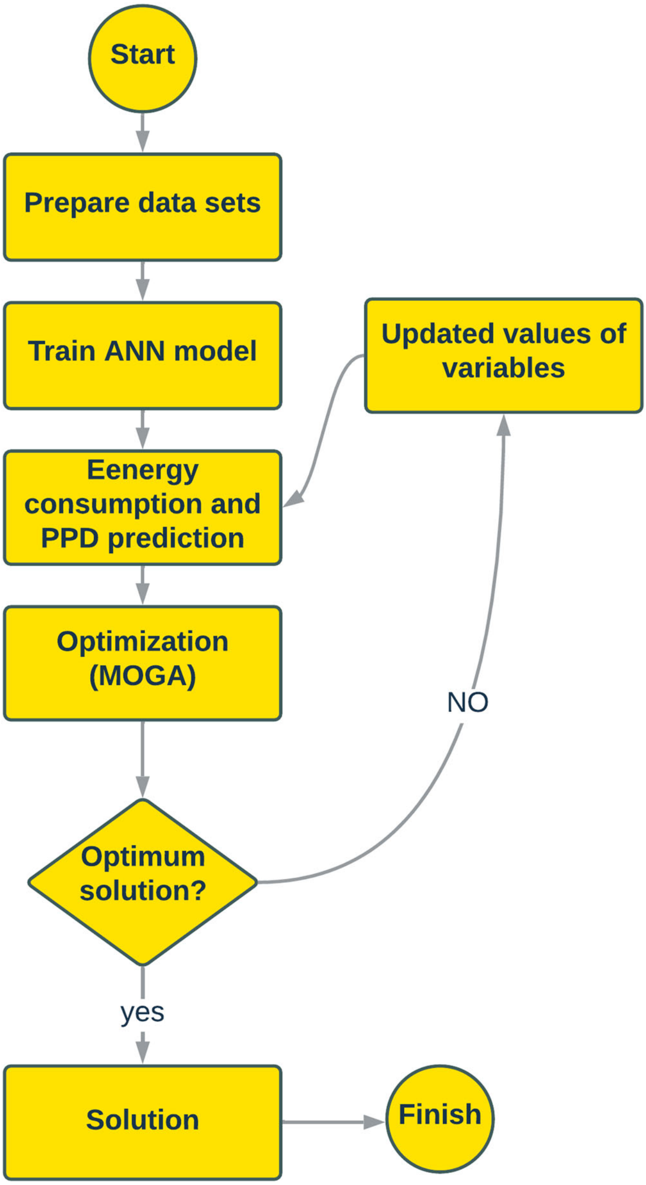


Figure 24. The framework for optimization.

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

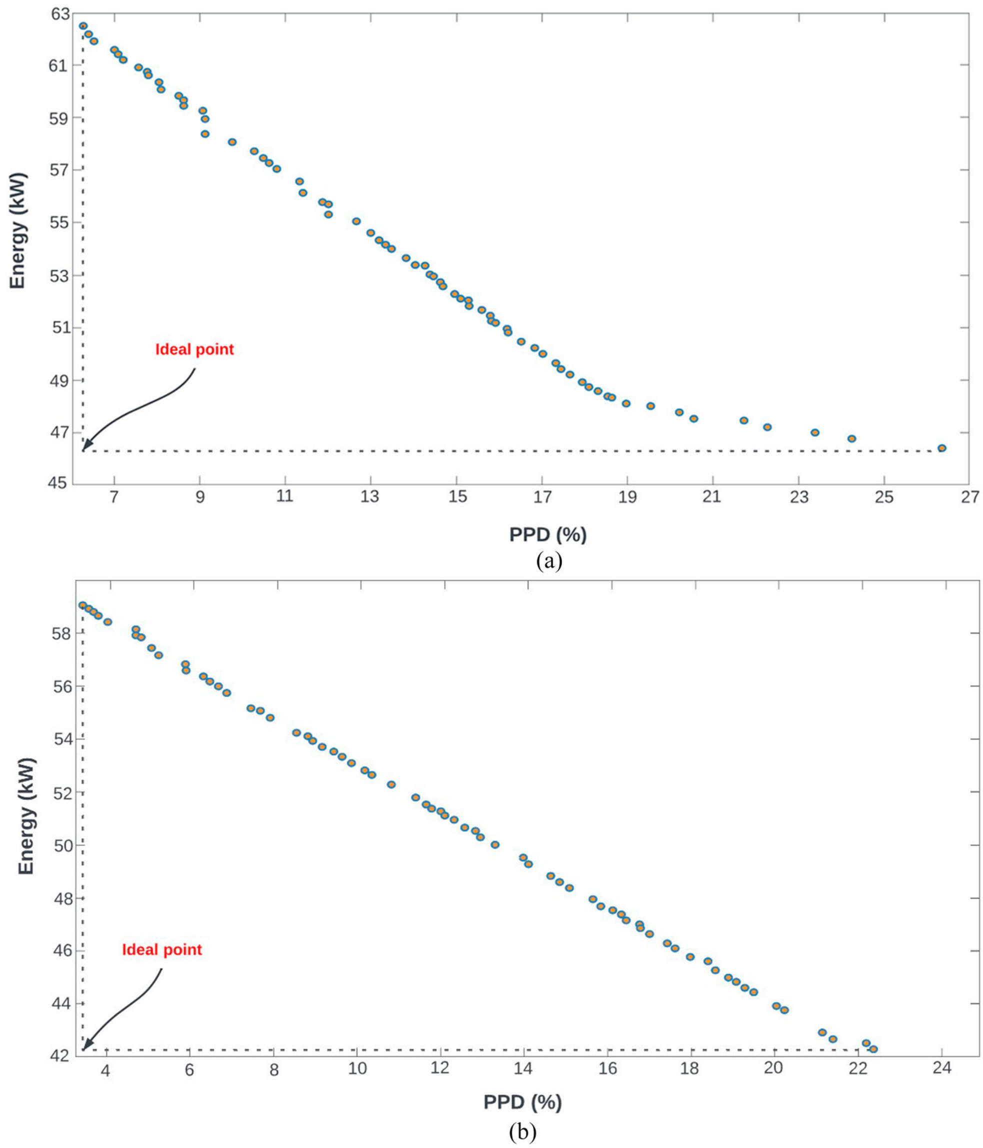


Figure 25. Optimization results for (a) winter and (b) summer.

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

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

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 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 optimal and non-optimal total energy usage for four days in summer are shown in Figure 26. 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%.

The ideal static pressure levels vary according to the operating conditions, as illustrated in Figure 27, where the system typically runs from 07:00 to 19:00. 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 (Figure 27), 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.

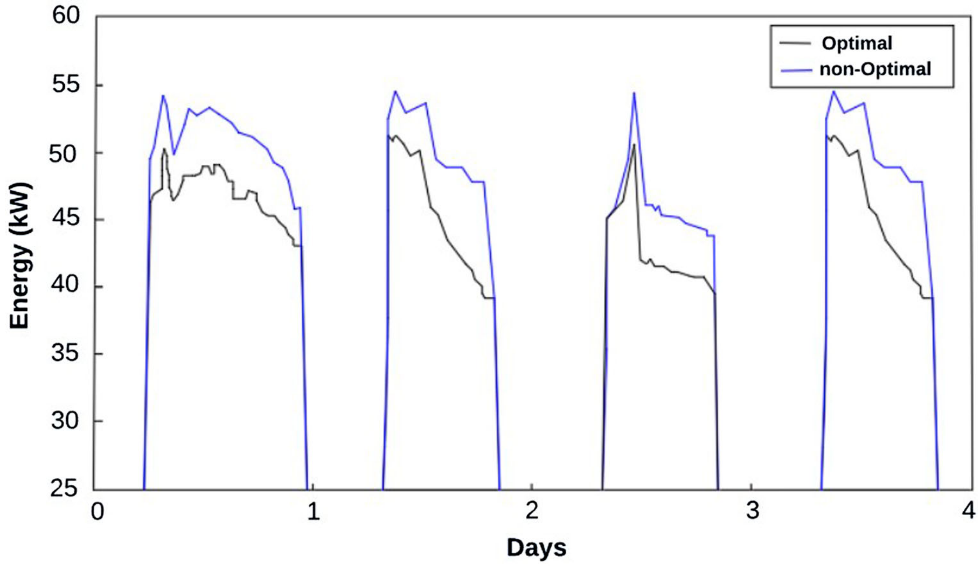


Figure 26. Energy consumption with optimization results during 4 days in summer.

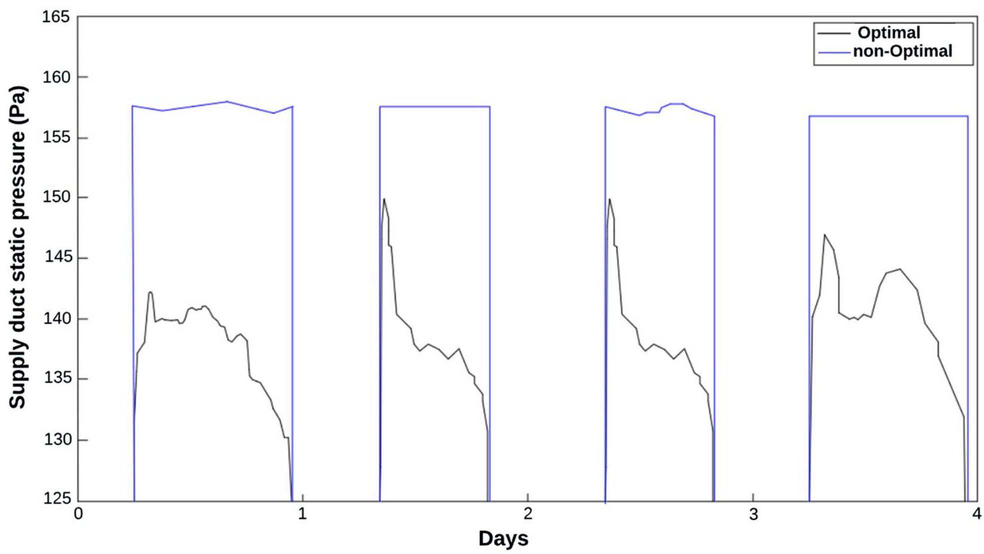


Figure 27. Supply duct static pressures with optimization results during 4 days in summer.

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 28). 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.

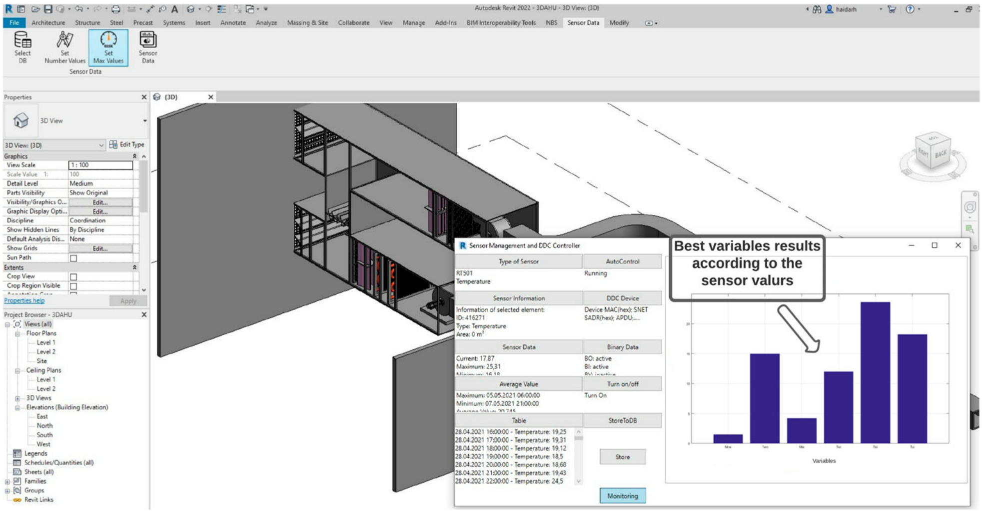


Figure 28. Stream the results from the optimization process to BIM.

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 setpoints 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.

Acknowledgments

The authors appreciate all of the contributors for their gracious support and input.

Disclosure statement

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.

Funding

The work presented in this journal paper is funded by Scandinavian Sustainable Circular Construction (S2C) and Interreg.

ORCID

Kjeld Svidt http://orcid.org/0000-0002-5078-6270

References

Aage, L., Nick, A., Bjarne, A., Christian, D., & Flemming, H. (2015). *Varme Staabi* (7th ed.). Praxis – Nyt Teknisk Forlag.

Abbasi, S., & Noorzai, E. (2021). The BIM-based multi-optimization approach in order to determine the trade-off between embodied and operation energy focused on renewable energy use. *Journal of Cleaner Production*, *281*, Article 125359. https://doi.org/10.1016/j.jclepro.2020.125359

Abdo-Allah, A., Iqbal, T., & Pope, K. (2018). Modeling, analysis, and design of a fuzzy logic controller for an AHU in the S.J. Carew building at memorial university. *Journal of Energy*, *2018*, Article e4540387. https://doi.org/10.1155/2018/4540387

Ahmad, A. S., Hassan, M. Y., Abdullah, M. P., Rahman, H. A., Hussin, F., Abdullah, H., & Saidur, R. (2014). A review on applications of ANN and SVM for building electrical energy consumption forecasting. *Renewable and Sustainable Energy Reviews*, *33*, 102–109. https://doi.org/10.1016/j.rser.2014.01.069

Ahmadi, M. H., Sayyaadi, H., Mohammadi, A. H., & Barranco-Jimenez, M. A. (2013). Thermo-economic multi-objective optimization of solar dish-Stirling engine by implementing evolutionary algorithm. *Energy Conversion and Management*, *73*, 370–380. https://doi.org/10.1016/j.enconman.2013.05.031

Alcalá, R., Benítez, J. M., Casillas, J., Cordón, O., & Pérez, R. (2003). Fuzzy control of HVAC systems optimized by genetic algorithms. *Applied Intelligence*, *18*(2), 155–177. https://doi.org/10.1023/A:1021986309149

Amasyali, K., & El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. *Renewable and Sustainable Energy Reviews*, *81*, 1192–1205. https://doi.org/10.1016/j.rser.2017.04.095

Aminyavari, M., Najafi, B., Shirazi, A., & Rinaldi, F. (2014). Exergetic, economic and environmental (3E) analyses, and multi-objective optimization of a CO2/NH3 cascade refrigeration system. *Applied Thermal Engineering*, *65*(1), 42–50. https://doi.org/10.1016/j.applthermaleng.2013.12.075

Araszkiewicz, K. (2017). Digital technologies in facility management – the state of practice and research challenges. *Procedia Engineering*, *196*, 1034–1042. https://doi.org/10.1016/j.proeng.2017.08.059

Ascione, F., Bianco, N., Iovane, T., Mauro, G. M., Napolitano, D. F., Ruggiano, A., & Viscido, L. (2020). A real industrial building: Modeling, calibration and Pareto optimization of energy retrofit. *Journal of Building Engineering*, *29*, Article 101186. https://doi.org/10.1016/j.jobe.2020.101186

Ashrae 90.1 (2013). *Normative appendix B building envelope climate criteria*.

Assaf, S., & Srour, I. (2021). Using a data driven neural network approach to forecast building occupant complaints. *Building and Environment*, *200*, Article 107972. https://doi.org/10.1016/j.buildenv.2021.107972

ATD (2010). *Aligning training with priority outcomes at NPS*. https://www.td.org/magazines/the-public-manager/aligning-training-with-priority-outcomes-at-nps

Autiosalo, J., Vepsäläinen, J., Viitala, R., & Tammi, K. (2020). A feature-based framework for structuring industrial Digital Twins. *IEEE Access*, *8*, 1193–1208. https://doi.org/10.1109/Access.6287639

Autodesk (2022). Revit software | Get prices & buy official revit | Autodesk. https://www.autodesk.com/products/revit

Azhar, S., Carlton, W. A., Olsen, D., & Ahmad, I. (2011). Building information modeling for sustainable design and LEED® rating analysis. *Automation in Construction*, *20*(2), 217–224. https://doi.org/10.1016/j.autcon.2010.09.019

Baldi, S., Korkas, C. D., Lv, M., & Kosmatopoulos, E. B. (2018). Automating occupant-building interaction via smart zoning of thermostatic loads: A switched self-tuning approach. *Applied Energy*, *231*, 1246–1258. https://doi.org/10.1016/j.apenergy.2018.09.188

Beccali, M., Ciulla, G., Lo Brano, V., Galatioto, A., & Bonomolo, M. (2017). Artificial neural network decision support tool for assessment of the energy performance and the refurbishment actions for the non-residential building stock in Southern Italy. *Energy*, *137*, 1201–1218. https://doi.org/10.1016/j.energy.2017.05.200

Bluyssen, P. M., Aries, M., & van Dommelen, P. (2011). Comfort of workers in office buildings: The European HOPE project. *Building and Environment*, *46*(1), 280–288. https://doi.org/10.1016/j.buildenv.2010.07.024

Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2020). Towards a semantic construction Digital Twin: Directions for future research. *Automation in Construction*, *114*, Article 103179. https://doi.org/10.1016/j.autcon.2020.103179

BrickSchema (2021). Home – BrickSchema. https://brickschema.org/

Brownlee, J. (2020, June). *How to use standardscaler and minmaxscaler transforms in python*. https://machinelearningmastery.com/standardscaler-and-minmaxscaler-transforms-in-python/

Bui, D.-K., Nguyen, T. N., Ngo, T. D., & Nguyen-Xuan, H. (2020). An artificial neural network (ANN) expert system enhanced with the electromagnetism-based firefly algorithm (EFA) for predicting the energy consumption in buildings. *Energy*, *190*, Article 116370. https://doi.org/10.1016/j.energy.2019.116370

Byggforskserien (2017). 421.501 Termisk inneklima. Betingelser, tilrettelegging og målinger. https://www.byggforsk.no/dokument/193/termisk_inneklima_betingelser_tilrettelegging_og_maalinger

Cadenas, E., & Rivera, W. (2009). Short term wind speed forecasting in La Venta, Oaxaca, México, using artificial neural networks. *Renewable Energy*, *34*(1), 274–278. https://doi.org/10.1016/j.renene.2008.03.014

Carvalho, J. P., Bragança, L., & Mateus, R. (2019). Optimising building sustainability assessment using BIM. *Automation in Construction*, *102*, 170–182. https://doi.org/10.1016/j.autcon.2019.02.021

Chang, S., Castro-Lacouture, D., & Yamagata, Y. (2020). Decision support for retrofitting building envelopes using multi-objective optimization under uncertainties. *Journal of Building Engineering*, *32*, Article 101413. https://doi.org/10.1016/j.jobe.2020.101413

Chaturvedi, S., Bhatt, N., Gujar, R., & Patel, D. (2022). Application of PSO and GA stochastic algorithms to select optimum building envelope and air conditioner size – A case of a residential building prototype. *Materials Today: Proceedings*, *57*, 49–56. http://doi.org/10.1016/j.matpr.2022.01.330

Chen, B., Liu, Q., Chen, H., Wang, L., Deng, T., Zhang, L., & Wu, X. (2021). Multiobjective optimization of building energy consumption based on BIM-DB and LSSVM-NSGA-II. *Journal of Cleaner Production*, *294*, Article 126153. https://doi.org/10.1016/j.jclepro.2021.126153

Chen, R., Tsay, Y.-S., & Ni, S. (2022). An integrated framework for multi-objective optimization of building performance: Carbon emissions, thermal comfort, and global cost. *Journal of Cleaner Production*, *359*, Article 131978. https://doi.org/10.1016/j.jclepro.2022.131978

Chen, Z., Hammad, A. W. A., Kamardeen, I., & Akbarnezhad, A. (2020). Optimising embodied energy and thermal performance of thermal insulation in building envelopes via an automated building information modelling (BIM) tool. *Buildings*, *10*(12), 218. https://doi.org/10.3390/buildings10120218

COBie (2021). *What is COBie*? https://www.thenbs.com/knowledge/what-is-cobie

Congradac, V., & Kulic, F. (2009). HVAC system optimization with CO2 concentration control using genetic algorithms. *Energy and Buildings*, *41*(5), 571–577. https://doi.org/10.1016/j.enbuild.2008.12.004

de Bakker, C., Aries, M., Kort, H., & Rosemann, A. (2017). Occupancy-based lighting control in open-plan office spaces: A state-of-the-art review. *Building and Environment*, *112*, 308–321. https://doi.org/10.1016/j.buildenv.2016.11.042

Delač, B., Pavković, B., Lenić, K., & Mađerić, D. (2022). Integrated optimization of the building envelope and the HVAC system in nZEB refurbishment. *Applied Thermal Engineering*, *211*, Article 118442. https://doi.org/10.1016/j.applthermaleng.2022.118442

Deshko, V., Buyak, N., Bilous, I., & Voloshchuk, V. (2020). Reference state and exergy based dynamics analysis of energy performance of the "heat source – human – building envelope" system. *Energy*, *200*, Article 117534. https://doi.org/10.1016/j.energy.2020.117534

Dhariwal, J., & Banerjee, R. (2017). An approach for building design optimization using design of experiments. *Building Simulation*, *10*(3), 323–336. https://doi.org/10.1007/s12273-016-0334-z

Dibowski, H., Ploennigs, J., & Wollschlaeger, M. (2018). Semantic device and system modeling for automation systems and sensor networks. *IEEE Transactions on Industrial Informatics*, *14*(4), 1298–1311. https://doi.org/10.1109/TII.2018.2796861

Ding, Y., Wang, Q., Kong, X., & Yang, K. (2019). Multi-objective optimisation approach for campus energy plant operation based on building heating load scenarios. *Applied Energy*, *250*, 1600–1617. https://doi.org/10.1016/j.apenergy.2019.04.164

Direktoratet for byggkvalitet (2010). https://dibk.no/regelverk/tek/3/14/14-1/

Dong, B., Li, Z., Rahman, S. M. M., & Vega, R. (2016). A hybrid model approach for forecasting future residential electricity consumption. *Energy and Buildings*, *117*, 341–351. https://doi.org/10.1016/j.enbuild.2015.09.033

Edwards, R. E., New, J., & Parker, L. E. (2012). Predicting future hourly residential electrical consumption: A machine learning case study. *Energy and Buildings*, *49*, 591–603. https://doi.org/10.1016/j.enbuild.2012.03.010

Elbeltagi, E., Hegazy, T., & Grierson, D. (2005). Comparison among five evolutionary-based optimization algorithms. *Advanced Engineering Informatics*, *19*(1), 43–53. https://doi.org/10.1016/j.aei.2005.01.004

Fan, C., Xiao, F., & Zhao, Y. (2017). A short-term building cooling load prediction method using deep learning algorithms. *Applied Energy*, *195*, 222–233. https://doi.org/10.1016/j.apenergy.2017.03.064

Fanger, P. O. (1973). Assessment of man's thermal comfort in practice. *Occupational and Environmental Medicine*, *30*(4), 313–324. https://doi.org/10.1136/oem.30.4.313

Ferdyn-Grygierek, J., & Grygierek, K. (2017). Multi-variable optimization of building thermal design using genetic algorithms. *Energies*, *10*(10), 1570. https://doi.org/10.3390/en10101570

Foucquier, A., Robert, S., Suard, F., Stéphan, L., & Jay, A. (2013). State of the art in building modelling and energy performances prediction: A review. *Renewable and Sustainable Energy Reviews*, *23*, 272–288. https://doi.org/10.1016/j.rser.2013.03.004

Freitas, J. d. S., Cronemberger, J., Soares, R. M., & Amorim, C. N. D. (2020). Modeling and assessing BIPV envelopes using parametric Rhinoceros plugins Grasshopper and Ladybug. *Renewable Energy*, *160*, 1468–1479. https://doi.org/10.1016/j.renene.2020.05.137

Goins, J., & Moezzi, M. (2013). Linking occupant complaints to building performance. *Building Research & Information*, *41*(3), 361–372. https://doi.org/10.1080/09613218.2013.763714

Goldberg, D. E. (1989). *Genetic algorithms in search, optimization and machine learning* (7th ed.). Addison-Wesley Longman Publishing Co., Inc.

Griego, D., Krarti, M., & Hernandez-Guerrero, A. (2015). Energy efficiency optimization of new and existing office buildings in Guanajuato, Mexico. *Sustainable Cities and Society*, *17*, 132–140. https://doi.org/10.1016/j.scs.2015.04.008

Grieves, M., & Vickers, J. (2017). Digital Twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In F.-J. Kahlen, S. Flumerfelt, & A. Alves, (Eds.), *Transdisciplinary perspectives on complex systems: New findings and approaches* (pp. 85–113). Springer International Publishing. https://doi.org/10.1007/978-3-319-38756-7_4

Han, D., Rolfsen, C. N., Engeland, B. D., Hosamo, H., Hjelmbrekke, H., Hu, K., Guo, T., & Ying, C. (2021). Research on BIM and virtual pre-assembly technology in construction management. In *ECPPM 2021–eWork and eBusiness in architecture, engineering and construction* (pp. 351–356). CRC Press.

Harun, M. F., Samah, A. A., Majid, H. A., Yusoff, Y., & Lim, Y. -W. (2017). Optimization of green building design to achieve green building index (GBI) using genetic algorithm (GA). In *2017 6th ICT international student project conference (ICT-ISPC)* (pp. 1–4). IEEE. https://doi.org/10.1109/ICT-ISPC.2017.8075310

Himmetoğlu, S., Delice, Y., Kızılkaya Aydoğan, E., & Uzal, B. (2022). Green building envelope designs in different climate and seismic zones: Multi-objective ANN-based genetic algorithm. *Sustainable Energy Technologies and Assessments*, *53*, Article 102505. https://doi.org/10.1016/j.seta.2022.102505

Hosamo, H., Sliteen, I., & Ding, S. (2021). Numerical analysis of bearing capacity of a ring footing on Geogrid reinforced sand. *Buildings*, *11*(2), 68. https://doi.org/10.3390/buildings11020068

Hosamo, H. H., & Hosamo, M. H. (2022). Digital Twin technology for bridge maintenance using 3D laser scanning: A review. *Advances in Civil Engineering*, *2022*, Article e2194949. http://doi.org/10.1155/2022/2194949

Hosamo, H. H., Imran, A., Cardenas-Cartagena, J., Svennevig, P. R., Svidt, K., & Nielsen, H. K. (2022). A review of the Digital Twin technology in the AEC-FM industry. *Advances in Civil Engineering*, *2022*, Article e2185170. http://doi.org/10.1155/2022/2185170

Hosamo, H. H., Svennevig, P. R., Svidt, K., Han, D., & Nielsen, H. K. (2022). A Digital Twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics. *Energy and Buildings*, *261*, Article 111988. https://doi.org/10.1016/j.enbuild.2022.111988

Hosamo, M. (2018, July). The effect of changing the weight parameter boundaries in random early detection method. *Journal of Computer Engineering & Information Technology*, *7*(1). http://doi.org/10.4172/2324-9307.1000195

Huang, W., & Lam, H. N. (1997). Using genetic algorithms to optimize controller parameters for HVAC systems. *Energy and Buildings*, *26*(3), 277–282. https://doi.org/10.1016/S0378-7788(97)00008-X

i4Helse (2022). Forside – i4Helse – bærekraftige helseteknologiske løsninger. https://www.i4helse.no/

Industry Foundation Classes (IFC) (2021). https://www.buildingsmart.org/standards/bsi-standards/industry-foundation-classes/

International Energy Agency (2013). *Transition to sustainable buildings*.

Jeong, K., Hong, T., Kim, J., & Cho, K. (2019). Development of a multi-objective optimization model for determining the optimal CO2 emissions reduction strategies for a multi-family housing complex. *Renewable and Sustainable Energy Reviews*, *110*, 118–131. https://doi.org/10.1016/j.rser.2019.04.068

Khan, M. W., Choudhry, M. A., Zeeshan, M., & Ali, A. (2015). Adaptive fuzzy multivariable controller design based on genetic algorithm for an air handling unit. *Energy*, *81*, 477–488. https://doi.org/10.1016/j.energy.2014.12.061

Kim, H., & Hong, T. (2020). Determining the optimal set-point temperature considering both labor productivity and energy saving in an office building. *Applied Energy*, *276*, Article 115429. https://doi.org/10.1016/j.apenergy.2020.115429

Korkas, C. D., Baldi, S., & Kosmatopoulos, E. B. (2018). 9 – grid-connected microgrids: Demand management via distributed control and human-in-the-loop optimization. In I. Yahyaoui (Ed.), *Advances in renewable energies and power technologies* (pp. 315–344). Elsevier. https://doi.org/10.1016/B978-0-12-813185-5.00025-5

Korkas, C. D., Baldi, S., Michailidis, I., & Kosmatopoulos, E. B. (2016). Occupancy-based demand response and thermal comfort optimization in microgrids with renewable energy sources and energy storage. *Applied Energy*, *163*, 93–104. https://doi.org/10.1016/j.apenergy.2015.10.140

Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, *51*(11), 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474

Kusiak, A., Zeng, Y., & Xu, G. (2013). Minimizing energy consumption of an air handling unit with a computational intelligence approach. *Energy and Buildings*, *60*, 355–363. https://doi.org/10.1016/j.enbuild.2013.02.006

La Russa, F. M., & Santagati, C. (2021). An AI-based DSS for preventive conservation of museum collections in historic buildings. *Journal of Archaeological Science: Reports*, *35*, Article 102735. http://doi.org/10.1016/j.jasrep.2020.102735

Lee, B., Jang, Y., & Choi, J. (2020). Multi-stage optimization and meta-model analysis with sequential parameter range adjustment for the low-energy house in Korea. *Energy and Buildings*, *214*, Article 109873. https://doi.org/10.1016/j.enbuild.2020.109873

Lee, J., Lapira, E., Bagheri, B., & Kao, H.-a. (2013). Recent advances and trends in predictive manufacturing systems in big data environment. *Manufacturing Letters*, *1*(1), 38–41. https://doi.org/10.1016/j.mfglet.2013.09.005

Li, H., & Wang, S. (2019). Coordinated optimal design of zero/low energy buildings and their energy systems based on multi-stage design optimization. *Energy*, *189*, Article 116202. https://doi.org/10.1016/j.energy.2019.116202

Li, T., Zhao, Y., Zhang, C., Luo, J., & Zhang, X. (2021). A knowledge-guided and data-driven method for building HVAC systems fault diagnosis. *Building and Environment*, *198*, Article 107850. https://doi.org/10.1016/j.buildenv.2021.107850

Lim, Y.-W., Chong, H.-Y., Ling, P. C. H., & Tan, C. S. (2021). Greening existing buildings through building information modelling: A review of the recent development. *Building and Environment*, *200*, Article 107924. https://doi.org/10.1016/j.buildenv.2021.107924

Lim, Y.-W., Seghier, T. E., Harun, M. F., Ahmad, M. H., Samah, A. A., & Majid, H. A. (2019). Computational BIM for building envelope sustainability optimization. *MATEC Web of Conferences*, *278*, Article 04001. https://doi.org/10.1051/matecconf/201927804001

Lin, C. J., Wang, K. -J., Dagne, T. B., & Woldegiorgis, B. H. (2022). Balancing thermal comfort and energy conservation – a multi-objective optimization model for controlling air-condition and mechanical ventilation systems. *Building and Environment*, *219*, Article 109237. https://doi.org/10.1016/j.buildenv.2022.109237

Lin, Y.-H., Tsai, K.-T., Lin, M.-D., & Yang, M.-D. (2016). Design optimization of office building envelope configurations for energy conservation. *Applied Energy*, *171*, 336–346. https://doi.org/10.1016/j.apenergy.2016.03.018

Liu, Y., Li, M., Wong, B. C. L., Chan, C. M., Cheng, J. C. P., & Gan, V. J. L. (2021). BIM-BVBS integration with openBIM standards for automatic prefabrication of steel reinforcement. *Automation in Construction*, *125*, Article 103654. https://doi.org/10.1016/j.autcon.2021.103654

LMT (2022). *Nedlasting av værdata – LandbruksMeteorologisk Tjeneste (LMT)*. https://lmt.nibio.no/agrometbase/getweatherdata_new.php

Lu, S., Li, J., & Lin, B. (2020). Reliability analysis of an energy-based form optimization of office buildings under uncertainties in envelope and occupant parameters. *Energy and Buildings*, *209*, Article 109707. https://doi.org/10.1016/j.enbuild.2019.109707

Mabkhot, M. M., Al-Ahmari, A. M., Salah, B., & Alkhalefah, H. (2018). Requirements of the smart factory system: A survey and perspective. *Machines*, *6*(2), 23. https://doi.org/10.3390/machines6020023

Madni, A. M., Madni, C. C., & Lucero, S. D. (2019). Leveraging Digital Twin technology in model-based systems engineering. *Systems*, *7*(1), 7. https://doi.org/10.3390/systems7010007

Magnier, L., & Haghighat, F. (2010). Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and artificial neural network. *Building and Environment*, *45*(3), 739–746. https://doi.org/10.1016/j.buildenv.2009.08.016

Mat Daut, M. A., Hassan, M. Y., Abdullah, H., Rahman, H. A., Abdullah, M. P., & Hussin, F. (2017). Building electrical energy consumption forecasting analysis using conventional and artificial intelligence methods: A review. *Renewable and Sustainable Energy Reviews*, *70*, 1108–1118. https://doi.org/10.1016/j.rser.2016.12.015

MathWorks Nordic (2022). *Compute confusion matrix for classification problem – MATLAB confusionmat – MathWorks Nordic*. https://se.mathworks.com/help/stats/confusionmat.html

Megantara, A., & Ahmad, T., & Institut Teknologi Sepuluh Nopember (2021). ANOVA-SVM for selecting subset features in encrypted internet traffic classification. *International Journal of Intelligent Engineering and Systems*, *14*(2), 536–546. https://doi.org/10.22266/ijies

Mehndi, S. M., & Chakraborty, I. (2020). Simulation for a cost-effective and energy efficient retrofits of the existing building stock in India using BIM. In *2020 International conference on contemporary computing and applications (IC3A)* (pp. 237–243). IEEE. https://doi.org/10.1109/IC3A48958.2020.233305

Mohanraj, M., Jayaraj, S., & Muraleedharan, C. (2012). Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems – A review. *Renewable and Sustainable Energy Reviews*, *16*(2), 1340–1358. https://doi.org/10.1016/j.rser.2011.10.015

Naderi, E., Sajadi, B., Behabadi, M. A., & Naderi, E. (2020). Multi-objective simulation-based optimization of controlled blind specifications to reduce energy consumption, and thermal and visual discomfort: Case studies in Iran. *Building and Environment*, *169*, Article 106570. https://doi.org/10.1016/j.buildenv.2019.106570

Nasruddin, Y., Alhamid, M. I., Daud, Y., Surachman, A., Sugiyono, A., Aditya, H. B., & Mahlia, T. M. I. (2016). Potential of geothermal energy for electricity generation in Indonesia: A review. *Renewable and Sustainable Energy Reviews*, *53*, 733–740. https://doi.org/10.1016/j.rser.2015.09.032

Nasruddin, Y., Sholahudin, S., Satrio, P., Mahlia, T. M. I., Giannetti, N., & Saito, K. (2019). Optimization of HVAC system energy consumption in a building using artificial neural network and multi-objective genetic algorithm. *Sustainable Energy Technologies and Assessments*, *35*, 48–57. https://doi.org/10.1016/j.seta.2019.06.002

Nassif, N., Kajl, S., & Sabourin, R. (2005). Optimization of HVAC control system strategy using two-objective genetic algorithm. *HVAC&R Research*, *11*(3), 459–486. https://doi.org/10.1080/10789669.2005.10391148

Natephra, W., Yabuki, N., & Fukuda, T. (2018). Optimizing the evaluation of building envelope design for thermal performance using a BIM-based overall thermal transfer value calculation. *Building and Environment*, *136*, 128–145. https://doi.org/10.1016/j.buildenv.2018.03.032

Nguyen, A.-T., Reiter, S., & Rigo, P. (2014). A review on simulation-based optimization methods applied to building performance analysis. *Applied Energy*, *113*, 1043–1058. https://doi.org/10.1016/j.apenergy.2013.08.061

NS 3701:2012 (2012). https://www.standard.no/no/Nettbutikk/produktkatalogen/Produktpresentasjon/?ProductID=587802

NS-EN ISO 7730 (2006). *Ergonomics of the thermal environment – Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria*.

Olofsson, T., & Andersson, S. (2002). Overall heat loss coefficient and domestic energy gain factor for single-family buildings. *Building and Environment*, *37*(11), 1019–1026. https://doi.org/10.1016/S0360-1323(01)00094-4

Olu-Ajayi, R., Alaka, H., Sulaimon, I., Sunmola, F., & Ajayi, S. (2022). Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. *Journal of Building Engineering*, *45*, Article 103406. https://doi.org/10.1016/j.jobe.2021.103406

Osborn, P. D. (1985). Section B – calculation and analysis procedures. In P. D. Osborn (Ed.), *Handbook of energy data and calculations* (pp. 69–228). Butterworth-Heinemann. https://doi.org/10.1016/B978-0-408-01327-7.50006-3

Østergård, T., Jensen, R. L., & Maagaard, S. E. (2018). A comparison of six metamodeling techniques applied to building performance simulations. *Applied Energy*, *211*, 89–103. https://doi.org/10.1016/j.apenergy.2017.10.102

Poel, B., van Cruchten, G., & Balaras, C. A. (2007). Energy performance assessment of existing dwellings. *Energy and Buildings*, *39*(4), 393–403. https://doi.org/10.1016/j.enbuild.2006.08.008

Pombeiro, H., Machado, M. J., & Silva, C. (2017). Dynamic programming and genetic algorithms to control an HVAC system: Maximizing thermal comfort and minimizing cost with PV production and storage. *Sustainable Cities and Society*, *34*, 228–238. https://doi.org/10.1016/j.scs.2017.05.021

Qi, Q., & Tao, F. (2018). Digital Twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE Access*, *6*, 3585–3593. https://doi.org/10.1109/ACCESS.2018.2793265

Qiao, J., Zhang, Z., & Chen, E. (2021). Optimization of IoT-based motion intelligence monitoring system. *Complexity*, *2021*, Article e9938479. http://doi.org/10.1155/2021/9938479

Rabani, M., Bayera Madessa, H., & Nord, N. (2021). Achieving zero-energy building performance with thermal and visual comfort enhancement through optimization of fenestration, envelope, shading device, and energy supply system. *Sustainable Energy Technologies and Assessments*, *44*, Article 101020. https://doi.org/10.1016/j.seta.2021.101020

Rahman, A., Srikumar, V., & Smith, A. D. (2018). Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. *Applied Energy*, *212*, 372–385. https://doi.org/10.1016/j.apenergy.2017.12.051

Rajasekar, N., Jacob, B., Balasubramanian, K., Priya, K., Sangeetha, K., & Sudhakar Babu, T. (2015). Comparative study of PEM fuel cell parameter extraction using genetic algorithm. *Ain Shams Engineering Journal*, *6*(4), 1187–1194. https://doi.org/10.1016/j.asej.2015.05.007

Rasmussen, M., Pauwels, P., Hviid, C., & Karlshøj, J. (2017). *Proposing a central AEC ontology that allows for domain specific extensions*.

ReCap (2019). Edit Point Clouds | ReCap 2019 | Autodesk Knowledge Network. https://knowledge.autodesk.com/support/recap/learn-explore/caas/CloudHelp/cloudhelp/2019/ENU/Reality-Capture/files/Reality-Capture-Edit-Point-Clouds-html-html.html

Regio Midi (2013).*Regio Midi manual*.

Ren, L., Liu, Y., Rui, Z., Li, H., & Feng, R. (2009). Application of Elman neural network and MATLAB to load forecasting. In *2009 International conference on information technology and computer science* (Vol. 1, pp. 55–59). IEEE. https://doi.org/10.1109/ITCS.2009.20

Rezgui, Y., Boddy, S., Wetherill, M., & Cooper, G. (2011). Past, present and future of information and knowledge sharing in the construction industry: Towards semantic service-based e-construction? *Computer-Aided Design*, *43*(5), 502–515. https://doi.org/10.1016/j.cad.2009.06.005

Rolfsen, C. N., Lassen, A. K., Han, D., Hosamo, H., & Ying, C. (2021). The use of the BIM-model and scanning in quality assurance of bridge constructions. In *ECPPM 2021 – eWork and eBusiness in architecture, engineering and construction* (p. 4). CRC Press.

Rosso, F., Ciancio, V., Dell'Olmo, J., & Salata, F. (2020). Multi-objective optimization of building retrofit in the Mediterranean climate by means of genetic algorithm application. *Energy and Buildings*, *216*, Article 109945. https://doi.org/10.1016/j.enbuild.2020.109945

Sagnier, C. (2018, November). *Types of maintenance: 5 must-know examples*. https://mobility-work.com/blog/5-types-maintenance-you-should-know/

Seghier, T. E., Lim, Y. -W., Harun, M. F., Ahmad, M. H., Samah, A. A., & Majid, H. A. (2022). BIM-based retrofit method (RBIM) for building envelope thermal performance optimization. *Energy and Buildings*, *256*, Article 111693. https://doi.org/10.1016/j.enbuild.2021.111693

Seo, B., Yoon, Y. B., Mun, J. H., & Cho, S. (2019). Application of artificial neural network for the optimum control of HVAC systems in double-skinned office buildings. *Energies*, *12*(24), 4754. https://doi.org/10.3390/en12244754

Seong, N.-C., Kim, J.-H., & Choi, W. (2019). Optimal control strategy for variable air volume air-conditioning systems using genetic algorithms. *Sustainability*, *11*(18), 5122. https://doi.org/10.3390/su11185122

Shabani, A., Hosamo, H., Plevris, V., & Kioumarsi, M. (2021, November). A preliminary structural survey of heritage timber log houses in Tonsberg, Norway. In *12th international conference on structural analysis of historical constructions (SAHC)*, Interdisciplinary projects and case studies. https://doi.org/10.23967/sahc.2021.012

Shirazi, A., Aminyavari, M., Najafi, B., Rinaldi, F., & Razaghi, M. (2012). Thermal–economic–environmental analysis and multi-objective optimization of an internal-reforming solid oxide fuel cell–gas turbine hybrid system. *International Journal of Hydrogen Energy*, *37*(24), 19111–19124. https://doi.org/10.1016/j.ijhydene.2012.09.143

SVM-Anova (2021). *SVM-Anova: SVM with univariate feature selection*. https://scikit-learn/stable/auto_examples/svm/plot_svm_anova.html

TEK17 (2017). *Building technical regulations (TEK17) 2017, with guidance (in Norwegian), §13-4*. Thermal indoor climate.

Topcon GLS-2000 (2016, December). *Topcon GLS-2000 compact high-speed laser scanner*. https://spatialscanners.net/topcon-gls-2000-compact-high-speed-laser-scanner/

Vachhani, V. L., Dabhi, V. K., & Prajapati, H. B. (2015). Survey of multi objective evolutionary algorithms. In *2015 International conference on circuits, power and computing technologies [ICCPCT-2015]* (pp. 1–9). https://doi.org/10.1109/ICCPCT.2015.7159422

Wang, B., Yin, C., Luo, H., Cheng, J. C. P., & Wang, Q. (2021). Fully automated generation of parametric BIM for MEP scenes based on terrestrial laser scanning data. *Automation in Construction*, *125*, Article 103615. https://doi.org/10.1016/j.autcon.2021.103615

Wang, R., Lu, S., & Feng, W. (2020). A three-stage optimization methodology for envelope design of passive house considering energy demand, thermal comfort and cost. *Energy*, *192*, Article 116723. https://doi.org/10.1016/j.energy.2019.116723

Wang, W., Zmeureanu, R., & Rivard, H. (2005). Applying multi-objective genetic algorithms in green building design optimization. *Building and Environment*, *40*(11), 1512–1525. https://doi.org/10.1016/j.buildenv.2004.11.017

Wang, Z., & Srinivasan, R. S. (2015). A review of artificial intelligence based building energy prediction with a focus on ensemble prediction models. In *2015 Winter simulation conference (WSC)* (pp. 3438–3448). https://doi.org/10.1109/WSC.2015.7408504

Wardlaw, R., & Sharif, M. (1999). Evaluation of genetic algorithms for optimal reservoir system operation. *Journal of Water Resources Planning and Management*, *125*(1), 25–33. https://doi.org/10.1061/(ASCE)0733-9496(1999)125:1(25)

Wetter, M., & Wright, J. (2004). A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization. *Building and Environment*, *39*(8), 989–999. https://doi.org/10.1016/j.buildenv.2004.01.022

Wright, J., & Alajmi, A. (2016). Efficient genetic algorithm sets for optimizing constrained building design problem. *International Journal of Sustainable Built Environment*, *5*(1), 123–131. https://doi.org/10.1016/j.ijsbe.2016.04.001

Xu, J., Lu, W., Anumba, C. J., & Niu, Y. (2020). From smart construction objects to cognitive facility management. In C. J. Anumba, & N. Roofigari-Esfahan (Eds.), *Cyber-physical systems in the built environment* (pp. 273–296). Springer International Publishing. https://doi.org/10.1007/978-3-030-41560-0_15

Xue, J., Xu, Z., & Watada, J. (2012). Building an integrated hybrid model for short-term and mid-term load forecasting with genetic optimization. *International Journal of Innovative Computing, Information & Control: IJICIC*, *8*(10(B)), 7381–7391.

Xue, Q., Wang, Z., & Chen, Q. (2022). Multi-objective optimization of building design for life cycle cost and CO2 emissions: A case study of a low-energy residential building in a severe cold climate. *Building Simulation*, *15*(1), 83–98. https://doi.org/10.1007/s12273-021-0796-5

Xue, X. (2017). Prediction of daily diffuse solar radiation using artificial neural networks. *International Journal of Hydrogen Energy*, *42*(47), 28214–28221. https://doi.org/10.1016/j.ijhydene.2017.09.150

Yigit, S., & Ozorhon, B. (2018). A simulation-based optimization method for designing energy efficient buildings. *Energy and Buildings*, *178*, 216–227. https://doi.org/10.1016/j.enbuild.2018.08.045

Yong, Z., Li-juan, Y., Qian, Z., & Xiao-yan, S. (2020). Multi-objective optimization of building energy performance using a particle swarm optimizer with less control parameters. *Journal of Building Engineering*, *32*, Article 101505. https://doi.org/10.1016/j.jobe.2020.101505

Yue, Z. (2011). A method for group decision-making based on determining weights of decision makers using TOPSIS. *Applied Mathematical Modelling*, *35*(4), 1926–1936. https://doi.org/10.1016/j.apm.2010.11.001

Zemero, B. R., Tostes, M. E. d. L., Bezerra, U. H., Batista, V. d. S., & Carvalho, C. C. M. M. (2019, January). Methodology for preliminary design of buildings using multi-objective optimization based on performance simulation. *Journal of Solar Energy Engineering*, *141*(4), Article 040801. https://doi.org/10.1115/1.4042244

Zhang, J., Xing, L., Peng, G., Yao, F., & Chen, C. (2019). A large-scale multiobjective satellite data transmission scheduling algorithm based on SVM+NSGA-II. *Swarm and Evolutionary Computation*, *50*, Article 100560. https://doi.org/10.1016/j.swevo.2019.100560

Zhang, K. (2020). Energy-saving parameterized design of buildings based on genetic algorithm. *International Journal of Building Pathology and Adaptation*, *38*(5), 785–795. https://doi.org/10.1108/IJBPA-05-2019-0050

Zhao, H.-x., & Magoulès, F. (2012). A review on the prediction of building energy consumption. *Renewable and Sustainable Energy Reviews*, *16*(6), 3586–3592. https://doi.org/10.1016/j.rser.2012.02.049

Zhao, J., & Du, Y. (2020). Multi-objective optimization design for windows and shading configuration considering energy consumption and thermal comfort: A case study for office building in different climatic regions of China. *Solar Energy*, *206*, 997–1017. https://doi.org/10.1016/j.solener.2020.05.090

Zhou, L., & Haghighat, F. (2009). Optimization of ventilation system design and operation in office environment, part I: Methodology. *Building and Environment*, *44*(4), 651–656. https://doi.org/10.1016/j.buildenv.2008.05.009