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

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ABSTRACT

Detailed parametric analysis and measurements are required to reduce building energy usage while maintaining acceptable thermal conditions. This research suggested a system that combines Building Information Modeling (BIM), machine learning, and the non-dominated sorting genetic algorithm-II (NSGA II) to investigate the impact of building factors on energy usage and find the optimal design. A plugin is developed to receive sensor data and export all necessary information from BIM to MSSQL and Excel. The BIM model was imported to IDA Indoor Climate and Energy (IDA ICE) to execute an energy consumption simulation and then a pairwise test to produce the sample data set. To study the data set and develop a prediction model between building factors and energy usage, 11 machine learning algorithms are used. The best algorithm was Group Least Square Support Vector Machine (GLSSVM), later employed in NSGA II as the building energy consumption fitness function using Dynamo software. An NSGA II multi-objective optimization model is designed to reduce building energy consumption and optimize interior thermal comfort (measured by the predicted percentage of dissatisfied (PPD)). The Pareto front is calculated, and the optimum point approach is used to find the best combination of building envelope characteristics, HVAC setpoints, shading parameters, lighting, and air infiltration. The feasibility and effectiveness of the developed framework are demonstrated using a case study of an upper secondary school building in Norway; the results show that: (1) The GLSSVM has a unique capacity to forecast building energy use with high accuracy: R^2 of 0.99, an RMSE of 1.2, MSE of 1.44, and MAE of 0.89; (2) Building energy consumption and thermal comfort may be successfully improved by the GLSSVM-NSGA II hybrid technique, which reduces energy consumption by 37.5% and increases thermal comfort by 33.5%, respectively.

1. Introduction

There is no doubt that buildings play a substantial role in the overall energy use and consequently the rate of global warming. The construction industry accounts for 40% of the EU's total energy consumption and 40% of the EU's total emissions of greenhouse gases (GHG) [1,2]. Non-residential buildings (including holiday houses), for example, account for about 62% of the total building stock in Norway [3], and 40% of the total energy use in buildings (where residential and non-residential buildings account for 40% of the Norwegian total energy use) [4]. In addition, energy usage in Norway's non-residential sector has increased by around 31% since 1990, whereas residential building energy use has increased by about 9% [4], highlighting the critical need to improve the energy performance of this building type. Building energy efficiency is considerably more difficult in cold climate nations due to harsh temperature conditions and high heating demands, contributing 40% to 60% of total national energy usage [5]. Hence, energy efficiency techniques should be explored in various sectors to achieve comprehensive sustainable development, including the construction sector [6].

The location climate, building layout, building scale, building envelope and ventilation impact how much energy a building con-

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Nomenclature

AE	Actual energy value
ANN	Artificial neural network
ANOVA	Analysis of variance
API	Application Programming Interface
ASHRAE	American society of heating, refrigerating and air-conditioning engineers
BACnet	Building automation and control networks
BEM	Building energy management
BIM	Building information modeling
BMS	Building management system
BOT	Building ontology topology
COBie	Construction operations building information exchange
DNN	Deep neural network
DT	Decision tree
ELN	Elastic net
FFNN	Feed forward neural network
FM	Facility management
GA	Genetic algorithm
GB	Gradient boosting
GBDT	Gradient boosted decision trees
GBM	Gradient boosting machines
GLSSVM	Group least square support vector machine
GMDH	Group method of data handling
GMM	Gaussian mixture modelling
GPR	Gaussian process regression
HVAC	Heating, ventilation, and air conditioning
IFC	Industry foundation classes
IoT	Internet of things
KNN	K-nearest neighbors
LR	Linear regression
LSSVM	Least squares support vector machine
LSTM	Long short-term memory
MARS	Multivariate adaptive regression splines
ML	Machine learning
MLR	Multiple linear regression
n,i,j	Numbers
NN	Neural network
NSGA	Non-dominated Sorting Genetic Algorithm
OLS	Ordinary least squares
PE	Predicted energy value
PMV	Predicted mean vote
PPD	Predicted percentage of dissatisfied
RF	Random forest
RMSE	Root Mean Square Error
RNN	Recurrent neural networks
SSN	Semantic sensor network
SVM	Support vector machine
SVR	Support vector regression
URL	Uniform resource locator
VAV	Variable air volume
XGB	Extreme gradient boosting
y	Output, number

sumes [7]. Most essential among them is the building envelope since its design defines how a building will respond to external conditions [8]. For building performance optimization, building shape, facade form, and facade construction are the three main factors to consider during the early optimization stages. All of these factors are included in a building's form: its orientation, its shape, the layout of its rooms, as well as its controllable characteristics in digital building form. The window-wall layout [9,10], single-window size [11], and shading component size [12] comprise the facade form variables. Glazing insulation, light transmission, and opaque envelope insulation are some of the factors in facade construction [13–15]. In addition, building envelope heat transfer accounts for over half of the energy utilized by non-residential buildings' heating, ventilation and air conditioning systems (HVAC) during the year [16]. Therefore, building envelope characteristics integrated with HVAC setpoints must be optimized in light of the acute energy scarcity to decrease energy consumption in future building operations.

On the other hand, when examining the energy efficiency of buildings, the thermal comfort and well-being of inhabitants are essential factors to consider, especially in educational and office buildings where indoor climate affects students' and employees' performance. It becomes considerably more difficult when the goal is to increase the energy performance of the building towards zero energy buildings (ZEB) while still providing thermal comfort [17]. However, improved interior climatic conditions may increase energy use. For this reason, an extensive number of studies have examined the influence of various building parameters on the energy performance of buildings using a variety of methodologies, including data-driven methods [18], optimization techniques [19], and a mix of both approaches [20,21]. According to [22], optimization approaches may employ machine learning techniques and algorithms, such as genetic algorithms, to identify the ideal parameters for a given building, which is the focus of this paper.

Eventually, utilizing building products as optimization variables to conduct building performance optimization procedures might improve the accuracy of performance evaluation and speed up the implementation of the results. However, a significant challenge with the optimization process is the disagreement between the optimization outcomes and the project's basic modulus. Uncertainty about building performance and variables might lead to considerable discrepancies between possible solutions and results from optimizations. As a result, this study will use the IDA ICE software to simulate the imported Building Information Modeling (BIM) model and create a batch of energy consumption data, therefore presenting a way for obtaining a sufficient data set on building energy usage. To get energy consumption data, however, the usage of BIM + IDA ICE requires that parameters be defined, and the data is calculated using a simulation, which is wasteful when the data sample size is increased for design optimization. As a result, more complex and efficient algorithms are required to accurately anticipate energy consumption under various combinations of characteristics in a building's envelope design parameters, which are obviously missing.

2. Literature review

The literature review in this paper focuses on building energy simulation in combination with BIM, Machine learning (ML), multi-objective optimization, and visual programming, which are the methodologies utilized to design the integrated system presented in this paper.

2.1. Visual programming

BIM is the process of creating and managing digital representations of a building's physical and functional attributes [23]. An integrated database of coordinated information may be utilized to examine different performance criteria in a BIM model, such as architectural, structural, energy, acoustical, and lighting [24]. Furthermore, performance-based design using BIM is becoming more common in the building design disciplines [24,25].

The currently available research on building energy performance analysis uses BIM as the central data model for various energy simulation tools such as EnergyPlus [26–28], TRANSYS [28], and IDA ICE [29]. Using Industry Foundation Classes (IFC) to solve interoperability concerns is a frequent strategy in this sort of studies. However, performance-based design is more successful when BIM and parametric modeling are combined. For example, [25] developed ThemalOpt, a thermal simulation and optimization tool based on BIM. To improve previous studies, designers require a simple visual way to set up building parameters using robust open-source Multi-objective optimization (MOO) algorithms.

Visual programming interfaces can replace complex conventional coding with a visual metaphor of connecting small blocks of independent functionalities into a whole system or procedure, which designers can use to implement their sophisticated design intent (e.g., through the use of conditional statements in parametric BIM) [30]. Thanks to visual programming, it is possible to build computer programs visually instead of textually, where non-programmers or inexperienced programmers may find a more visual style of programming more straightforward to comprehend. McNeel Rhinoceros® and Autodesk Revit® both include visual programming tools called Grasshopper and Dynamo, respectively.

According to the studies above, this research was conducted using Revit and Dynamo, which differ from Grasshopper in that designers have used them for a more extended period. Many new possibilities open up for designers working in Rhino or Revit thanks to Grasshopper and Dynamo, built on Python's visual programming language. Using Dynamo, Revit users do not have to master the Revit API to construct automation routines for the software [31]. As a result, the learning curve for new users of Revit is much shorter, which means more customization options for them. In contrast to typical Revit tools, Dynamo allows designers to explore iterative frameworks in the context of a BIM tool by allowing users to construct systematic linkages to alter model elements and parameters. In addition, Dynamo can be connected with extra libraries like MOO that can be used for the optimization process.

2.2. Integration of building performance data with BIM

In the construction industry, building information modeling (BIM) is a shared knowledge resource for information about a facility that serves as a solid foundation for choices throughout its life cycle, defined as the period from its inception until its end of life phase. The advancement of BIM technology and its ever-increasing use in the construction sector have resulted in the progressive expansion of various types of information linked to buildings carried by BIM during the past few decades [32]. Researchers and practitioners have also sought to apply BIM in the context of building life-cycle analysis [33,34], among other things. When it comes to energy efficiency and environmental optimization design, there is a significant difficulty; namely, the BIM framework was not designed to integrate building performance information and data as rapidly as is necessary. These difficulties include data loss during an encounter, a lack of appropriate data standards, and highly severe technological challenges [35,36]. The absence of performance data (such as energy consumption and occupant comfort) integration capabilities has significantly hampered building information modeling (BIM) adoption in sustainable building design. As a result, a BIM-based data management and application framework for sustainable buildings must be established urgently.

The consequences of a lack of such framework are noticed throughout the whole life of the buildings. In the Architecture, Engineering, and Construction (AEC) industry, where data is often constrained to heterogeneous silos and seldom accessed beyond their native area [37], significant difficulties surround data integration. Increased operating costs and eventually poor building performance are two of the problems that may result [37].

The methodology of Building Information Modelling (BIM) has facilitated the flow of information during the design and construction phases. However, during the operating phase, this interchange remains a difficulty. BIM may be thought of as a central store for building data accessible to all project stakeholders throughout the project's lifecycle. However, BIM is simply one silo of information within the larger context of the business, and other pertinent data must also be exploited to improve both the building and the organization [38]. As a result, a system is required that can support a variety of building schemes, dimensions, purposes, configurations, and communication protocols such as BACnet that originate from disparate hardware installed throughout the building and owned by disparate supplier firms [39,40].

Additionally, establishing ways for integrating BIM data into the building energy system has grown crucial as open data standards such as COBie [41] and IFC (Industry Foundation Classes) [42] emerge. A possible approach is to use suitable semantic web standards, which control the creation of ontologies and provide a more lightweight solution than monolithic data interchange techniques [43]. For instance, the BrickSchema adds a semantic framework to the description of physical, logical, and virtual assets [44]. Sensors are defined in the Semantic Sensor Network (SSN) ontology as components of a system deployed in a building with specified measurement capability [45]. The Building Topology Ontology (BOT), which enables the representation of any building's topology [46]. However, there is a lack of research on using ontology techniques to integrate BIM, energy management, and thermal comfort data in one framework.

In this work, a plug-into integrate sensors data in BIM is developed. In addition, BRICK, BOT, and SSN ontologies are used based on COBie data to help retrieve information from an IFC model, transfer data into the COBie data standard, and provide BIM data into energy systems to address data exchange and interoperability challenges.

2.3. Artificial intelligence of building energy consumption

With the development of computer technology, artificial intelligence (AI) has attracted increasing attention as a flexible and accurate data-driven method. Machine learning (ML) technology is widely used in building analysis, modeling, and prediction [47]. ML algorithms have self-learning capabilities and can rapidly search for optimal solutions, making them suitable for solving complex nonlinear problems [48,49]. Several studies have used machine learning for building energy consumption predictions [50,51]. Other researchers developed new ML models to overcome the inequality constraints of the conventional ML models; for example, the least-squares support vector machine (LSSVM) has been used to overcome the abnormal regression in Support vector machine (SVM) [52,53].

Table 1 summarizes a few studies that used machine learning to predict building energy consumption, including some of the most used Regression methods like SVR, LR, and DT. Out from the Table 1, it is obvious that investigating the best energy use prediction remains a complex task, as there is no general agreement on the most suitable algorithm for energy prediction. Hence, in this research, the selected ML algorithms combine the most utilized algorithms and hybrid algorithms that are yet to receive much attention in energy prediction. This paper will use 11 machine

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

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

learning algorithms, including LR, ANN, SVM, GPR, DNN, RF, XGB, NN-SVM, LSSVM, GMDH, and GLSSVM. The results from those algorithms will be compared, and the most accurate one will be used for the optimization process.

2.4. Optimization algorithm

In general, reducing energy usage is not enough to optimize building design. The ideal design option must also suit indoor climate criteria [64]. However, in building design, energy consumption and indoor climate are important but opposing goals. Considering that, determining the ideal design becomes challenging due to the various parameters and tactics involved in the optimization process [65]. Therefore, this study obtains the ideal design parameters for a building envelope using a multi-objective optimization approach with energy consumption and thermal comfort as objective functions. The genetic algorithm (GA), invented by Holland [66], is one of the most extensively used multi-objective optimization algorithms [67]. However, The GA can not preserve population variety while keeping exceptional individuals from the parent generation [68]. Srinivas and Deb devised a nondominated sorting genetic algorithm (NSGA) in 1994 to solve the GA's disadvantages and minimize the overproduction of offspring [69]. Due to the computational complexity of NSGA, the optimization outcomes are not significantly improved compared to GA. Debra et al. proposed, therefore, an NSGA II [70]. NSGA II can quickly find the optimal solution, perform selective sorting, and retain the superior individuals from the parent generation in the offspring to form a set of nondominated Pareto optimal solutions [71]. Thus, NSGA II is implemented in this study as the multi-objective optimization of building energy usage. NSGA II will be implemented through visual programming (Dynamo) using Optimo, which is a multi-objective optimization tool that allows Dynamo users to apply evolutionary algorithms to solve issues with single and multiple objectives [72].

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

An appropriate fitness function for NSGA II is required to speed convergence and locate the optimum solution. Empirical formulae or computer simulations are usually used to determine the fitness functions. Zhang constructed mathematical models that serve as a fitness function for a genetic algorithm based on empirical formulae to optimize the parameters [73]. Naderi et al. used EnergyPlus to improve the design and control characteristics of a smart shading blind [74]. Bruno et al. utilized the minor yearly energy usage and minimum construction cost from EnergyPlus as fitness functions [75]. However, the empirical equations cannot be changed to unique building circumstances, and calculating the fitness values of several individuals using simulation software is computationally costly while reducing optimization efficiency. In order to overcome the restrictions of the previously utilized fitness functions, it was recommended that ML be used to develop a surrogate model of simulation software as the fitness function of the optimization method [63]. Lin et al. employed neural networks to generate thermal comfort and overall energy consumption metamodels [76]. Nasruddin et al. used an artificial neural network and a multi-objective GA to optimize the operation of a two-chiller system in a building [77]. Wang et al. used Gradient Boosting Decision Trees (GBDT) to generate building performance metamodels [78]. In conclusion, intelligent algorithms as fitness functions can increase optimization algorithms' adaptability and efficiency [79]. The current work provides a multi-objective optimization approach for building energy consumption that combines machine learning and NSGA II.

Out from that, following are the primary research questions: (1) How to use simulation tools to simulate the BIM model and acquire energy consumption data for the ML model? (2) How to create an ML model that connects the building's energy usage to the primary influencing elements of the building envelope? (3) In terms of building energy consumption and thermal comfort, how can the ideal solution be established using NSGA II in visual programming (Dynamo)?.

The current work proposes a multi-objective optimization approach that integrates machine learning with NSGA II via Dynamo to enable intelligent prediction and optimization of building energy usage. The ML model is trained and validated to create a fast estimating building energy use model based on IDA ICE simulation data. The optimization target is then set to the surrogate model for energy consumption and the empirical formula for thermal comfort. Finally, multi-objective optimization is performed using the NSGA II through Dynamo. Thus, the originality of our work comes from the fact that it investigates the interaction of building envelope elements with HVAC systems and parameters with other critical design variables through the optimization process, which was previously unexplored in literature. The novel aspects of this research are as follows: (1) Develop a plug-in in Revit that can receive sensor data (temperature, pressure etc.) from the equipment in a school building in Norway and use this data to validate the IDA ICE model. (2) Developing a multi-objective optimization framework for concurrently improving a building's energy performance and indoor comfort, which can increase the viability of energy consumption optimization solutions. (3) Using machine learning as the fitness function to alleviate the difficulties of traditional prediction methods in terms of accuracy and efficiency. (4) Using visual programming to create a hybrid technique for predicting and optimizing a building's energy performance and other functions, which make it easier to feedback the optimization results in BIM model as well as the building's management system to increase its sustainability.

3. The proposed framework

This paper provides a novel multi-objective optimization strategy for reducing energy consumption in buildings while simultaneously increasing occupant comfort. The framework to enhance the building energy consumption data generated by IDA ICE was developed using eleven machine learning algorithms and the NSGA II technique. The flow chart for the suggested framework is depicted in Fig. 1. This framework comprises five stages, which will be discussed in further detail in the following sections.

3.1. Data collection for optimization process

This stage represents the blue box in Fig. (1). The initial stage of the proposed framework consists of preparing the BIM model for data extraction as well as the development of a plug-in that streams sensor data from the HVAC system and rooms in buildings into the BIM model, transforming the BIM model into a database that contains all of the information required to carry out the optimization process. It is necessary to confirm that the BIM model has all the geometric and thermal characteristics required for the computation as part of the preparation procedure. An accurate BIM model of the structure in issue should be accessible to facilitate data extraction throughout the data extraction procedure. For buildings without a BIM model, laser scanning [80] or 2D drawings can be used to create the building envelope elements.

3.1.1. Data gleaned from the BIM model

In this paper, the BIM model will be used in two different ways: as input for the simulation process and as a way of visualizing the outcomes of the simulation. A database of BIM models from which all of the relevant data is retrieved is required for the optimization framework to function correctly. As a result, it must be carefully modeled, and all of the required thermal and geometric characteristics of the building envelope elements must be correctly allocated to the different elements. According to the definition of the level of development (LOD) [81], it is advised to have a BIM model with a LOD of 300 or above in order to extract both the thermal and geometric data associated with the proposed framework. Autodesk Revit® 2022 [41] will be used in this study as a BIM authorizing tool because of its accessibility to researchers and its incorporation into an open-source visual programming environment (Dynamo) [82,83].

IFC (Industrial Foundation Classes (Fig. 2)) and COBie (Construction Operations Building Information Exchange are information exchange specifications for the lifetime capture [84,85] in the energy management and optimization process. The IFC file structure includes geometric information as well as object classes, relations, and resources. IFC may contain various semantic data, such as construction component costs and timelines [86]. COBie can also give information on the functioning and administration of projects [41] in real-time. As a result, whereas IFC may give geometric and semantic information in BIM models, COBie should include more information, such as location data, asset details, documentation, and graphical data, among other things.

COBie needs spatial information (space characteristics) for two reasons: (1) Space objects are critical for managing space, occupants, and energy. (2) Spaces are necessary for equipment location. Additionally, the BIM model's element ID (included in COBie) will be used as a differentiating characteristic for extracting elements for optimization and when pushing optimization findings back into the BIM model and replacing the original element with the optimized one.

As a result, this paper used a COBie extension for Revit to extract the necessary information from BIM models for optimization and transmit it to the building's energy management system. A semantic approach will then transform heterogeneous building data sources into semantically enhanced knowledge.

3.1.2. Integrate sensor data in BIM model

Several sensors have been installed in various rooms and HVAC systems across the building. Air and water supply and return temperatures, flow rates, energy consumption, control system set-

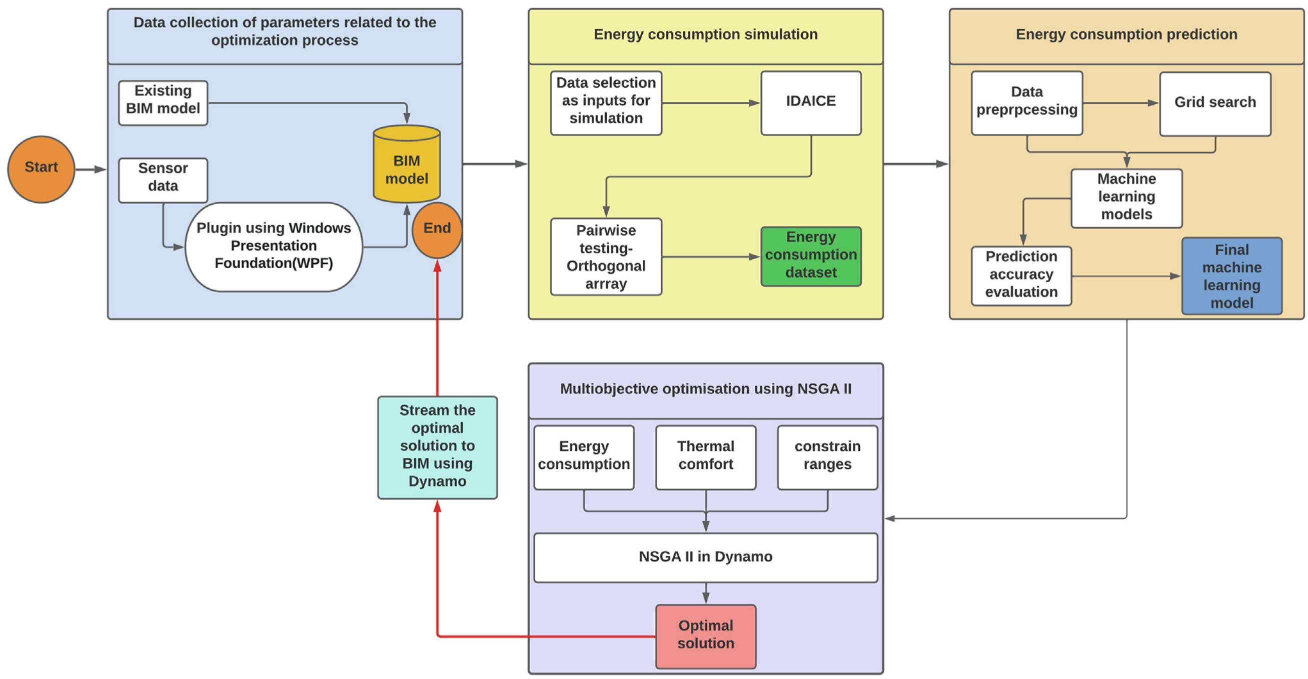


Fig. 1. Overview of the multi-objective optimization process.

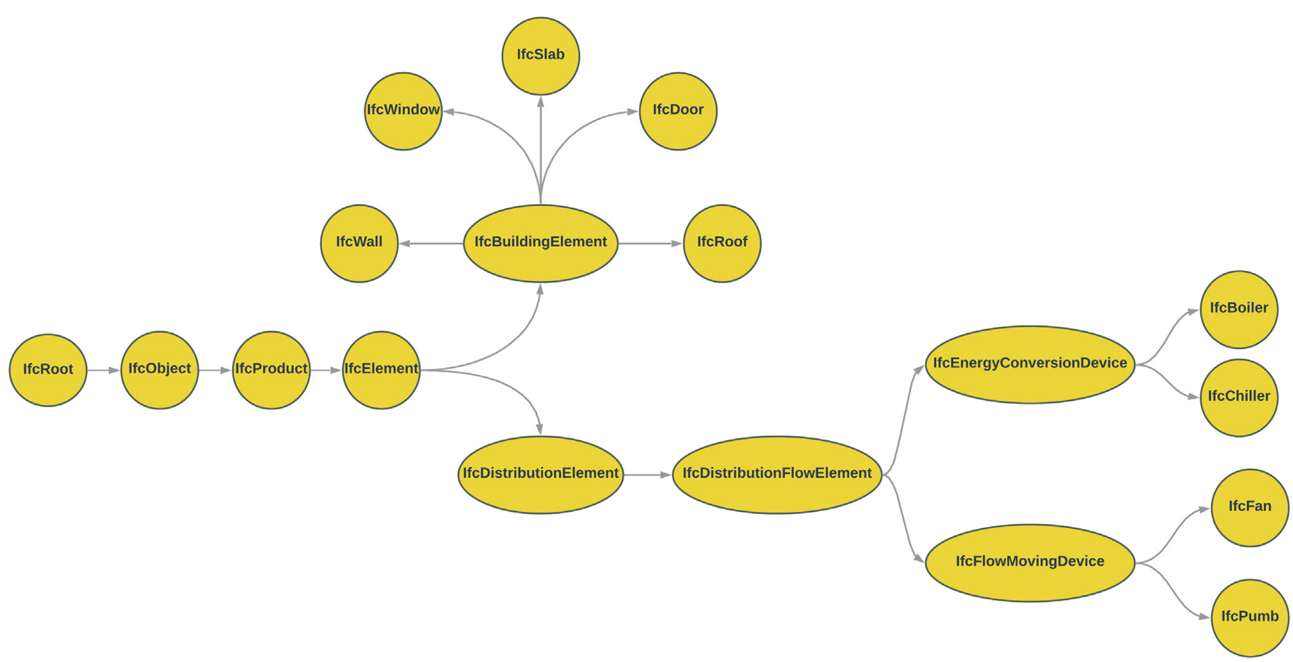


Fig. 2. Part of IFC schema that describes the correlations between energy simulation parameters..

points, humidity, CO2, and outdoor air temperature are all measured using these sensors. Access to these sensors required first gaining access to the BMS, which enabled us to monitor and record all of the essential data. However, it was not feasible to immediately extract the BMS system's data. As a result, with the assistance of a development team, it was required to implement a BACnet Restful API [87] on top of a standard BMS. In this work, Postman software [88] has been used to obtain JSON files [89] from BMS using the API built and then convert them to Excel using Python programming language. Hence, we have an automated procedure to retrieve real-time data and update the excel file continually. Additionally, the Regio controller governs the temperature of a room and the functioning of other systems in the space. Fig. 3 shows the control system.

As a next step, Windows Presentation Foundation (WPF) programming [91] in Microsoft Visual Studio Community 2019 was used to develop a Revit plugin to read the real-time sensor data and save them to MSSQL database while keeping BIM up to date. In addition, a threshold was added to the plugin to give colors of the room based on occupant comfort conditions in the building.

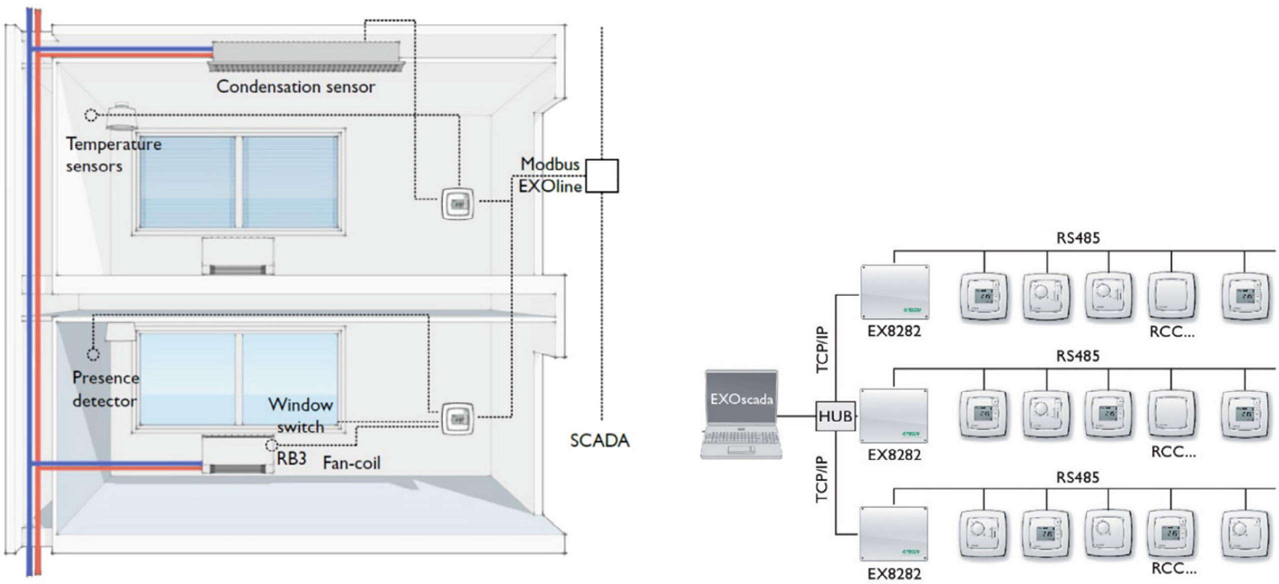


Fig. 3. An illustration of the control system [90].

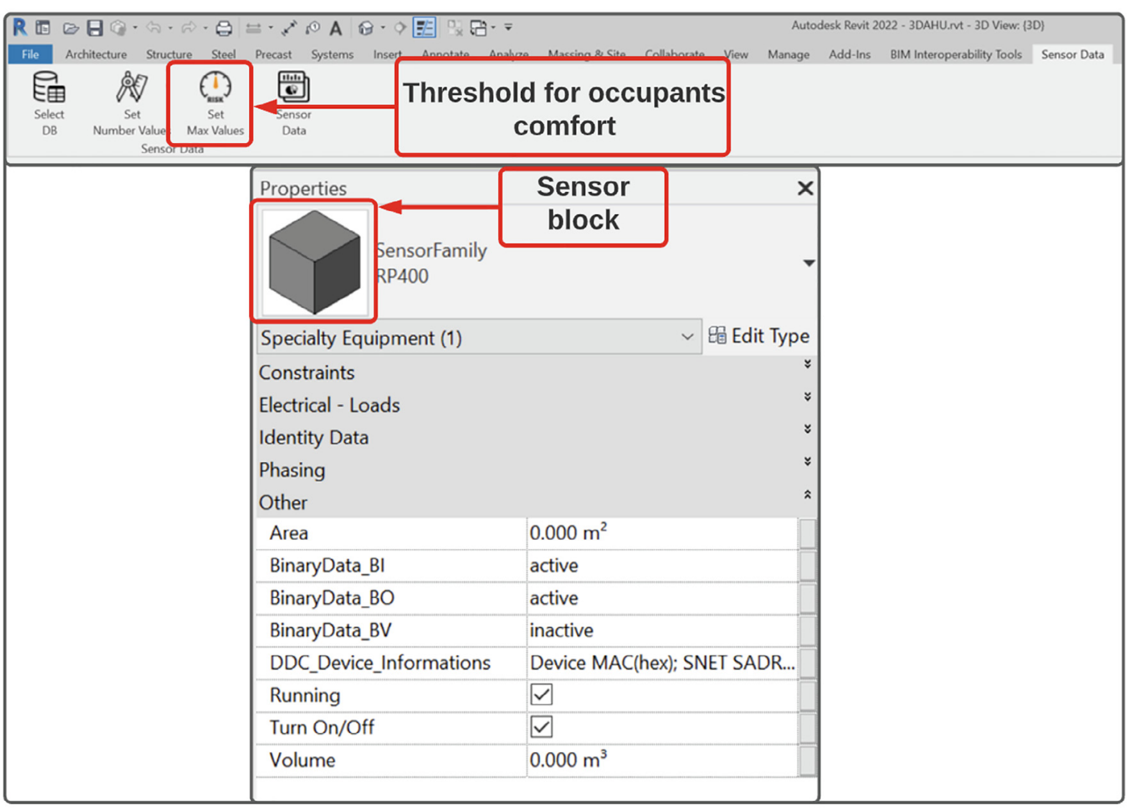


Fig. 4. Sensor management in Revit using the developed plugin.

Several sensors blocks were used in BIM to receive the sensor data and visualize them. Fig. 4 shows the sensor block.

In this study, we chose to utilize a laser scanner to scan certain zones in order to appropriately represent them in Revit because the available BIM model does not have all of the necessary information. In order to do this, we employ (TOP GLS2000 [92]), and the point clouds that are extracted have been treated in Autodesk ReCap before being sent to Autodesk Revit.

3.2. Energy consumption simulation

This stage represents the yellow box in Fig. (1).

3.2.1. Building energy consumption simulation using IDA ICE

Several building energy performance tools, such as EnergyPlus [93], TRNSYS [65,94], and IDA ICE [95,96], are commonly used in literature for building performance and optimization.

According to the research stated above, building envelope and HVAC system characteristics need to be taken into account when optimizing a building for energy efficiency and thermal comfort simultaneously. Despite this, optimizations in the literature did not consider various envelope components, control techniques, and HVAC setpoints.

As a result, the novelty of our paper is to investigate the interaction of building envelope factors with HVAC systems and parameters with other essential design variables through the optimization process, which was missing in the literature. This was accomplished by integrating the IDA ICE software with machine learning algorithms and optimization techniques to improve energy performance considering occupants' comfort conditions.

In this study, nineteen variables are taken into account, including window size, temperature, U-values, airflow, and other elements vital to a building's performance but challenging to analyze and pinpoint in the early phases of design [97,98]. The annual energy demand delivered to the building for heating, cooling, ventilation, and lighting is considered an output measured in kWh/m^2 floor space for each simulation. The district heating network system was used for heating while electricity was used for cooling where both have a daily profile. The Revit BIM model is imported into SimpleBim to preprocess it and then to IDA ICE once the primary impact parameters have been determined. According to the project's real scenario, building specifications and ambient variables are configured to simulate the energy consumption.

3.2.2. Pairwise testing for obtaining energy data set

The great potential for energy savings is made possible in large part by the work of building designers. Engineers and architects utilize a variety of metrics to evaluate a building's environmental effect while also ensuring that it meets standards for indoor climate, including energy demand, CO2 footprint, thermal comfort, daylight, and expenses [99]. Building geometry, insulation thickness, glazing qualities, and HVAC systems may all be varied to identify viable solutions by the design team. Because of the vast number of possible configurations for these factors, it is difficult and time-consuming to thoroughly examine the design options and come up with solutions that are both rational and able to satisfy all criteria. Aside from that, the majority of energy simulation software is computationally intensive. Because a single simulation might take minutes to perform, executing dozens or millions of simulations impedes widespread design analysis and optimization adoption [63].

Although supercomputers and cloud computing may be able to solve the computational problem of simulation, the cost of supercomputers is prohibitive, and the time it takes to complete thousands of simulations is still considerable in cloud computing [100]. This study will thus employ an orthogonal experiment from pairs testing to generate a batch of energy consumption data [101]. This paper uses the pairwise tool to build an orthogonal experiment based on the specified value range of design requirements to get energy consumption data sets. The machine learning model is then trained on various distinct building energy consumption data sets, each based on a particular design.

3.3. Energy consumption prediction

This stage represents the brown box in Fig. (1). Eleven machine learning algorithms will be examined to predict building energy consumption, as specified in Section 2.3, based on their popularity and recommendations in the researched literature (Table 1). We compare these algorithms on the same dataset in this work because all of the methods we choose have not been explicitly compared on a single dataset in previous research. We did not include all of the techniques shown in the Table 1 because it would be too overwhelming; instead, we picked the algorithms that show better performance than those included in the same table. Each approach has several options that impact accuracy as well as computing effort. Fitting methods, tuning parameters, and convergence criteria are examples. We attempt to find the most significant settings based on the theoretical foundation and program documentation. Furthermore, the energy consumption prediction framework will consist of four main stages as follows: (1) Data preprocessing, (2) Feature Selection, (3) Model development (training, validation and testing), and (4) Model evaluation, as shown in Fig. 5.

3.3.1. Data preprocessing

Although data preparation is time-consuming and computationally costly, it is the first step in machine learning [102]. It is necessary to perform this step to ensure that the preparation will not result in inaccurate data throughout analysis [55]. The dataset must be cleaned and normalized as part of the data preparation procedure. Outliers and missing data are removed during the data cleaning procedure. The mean value of each column is used to fill in the gaps in the data. However, to minimize confusion and complication in the model development process, all occurrences of missing values in the building dataset (due to faulty equipment or inadequate technicality during the recording of the values) were removed from the database. The data pretreatment practice of data normalization also reduces the impact of dimensions, as many features have unrelated dimensions. For example, one input variable may have values from 0.5 to 1, whereas another may have values from 1000 to 10,000. Scale discrepancies between the numbers in a model might cause issues. To prevent issues with model building, samples are normalized to a unit norm. The sklearn python module normalizer normalized the building and meteorological datasets [103]. The use of the StandardScaler approach ensures that separate samples' eigenvalue dimensions have no bearing on the prediction efficiency and accuracy [104,105].

3.3.2. Feature selection

Feature selection is crucial when employing machine learning techniques because it filters out redundant and noisy data during the training process. The noisy data was found in numerous condition indicators, including (1) energy usage, (2) supply air temperatures, (3) chiller and heater water temperature sensors, and so on. This data from sensors will help us to confirm the outcomes of our IDA ICE simulation model and to define the correct ranges for optimization process that reflect the real building as accurate as possible.

Data reduction minimizes redundant information, whereas feature selection eliminates undesired features from a dataset. When the data is cleaned, the low-variance and noisy elements are removed, and the use of data normalization reduces the size disparity between the different data sets. SVM and Analysis of Variance (ANOVA) will be combined in this study to select the feature importance [106]. ANOVA-SVM is used to improve the classifier's performance by analyzing the variance of each feature. Each subgroup test's accuracy score and the distance between each data point and its decision boundary are calculated using the ANOVA-SVM technique. The ANOVA-SVM method generates data for each feature's distance to its decision boundary, and the closer each feature is to the barrier, the more crucial it is.

3.3.3. Model development

According to Section 2.3, eleven supervised machine learning algorithms based on regression are used to forecast annual energy consumption., namely, LR, ANN, SVM, GPR, DNN, RF, XGB, ANN-SVM, LSSVM, GMDH, and GLSSVM. The Deep Neural Network (DNN) is a feed-forward neural network with three hidden layers

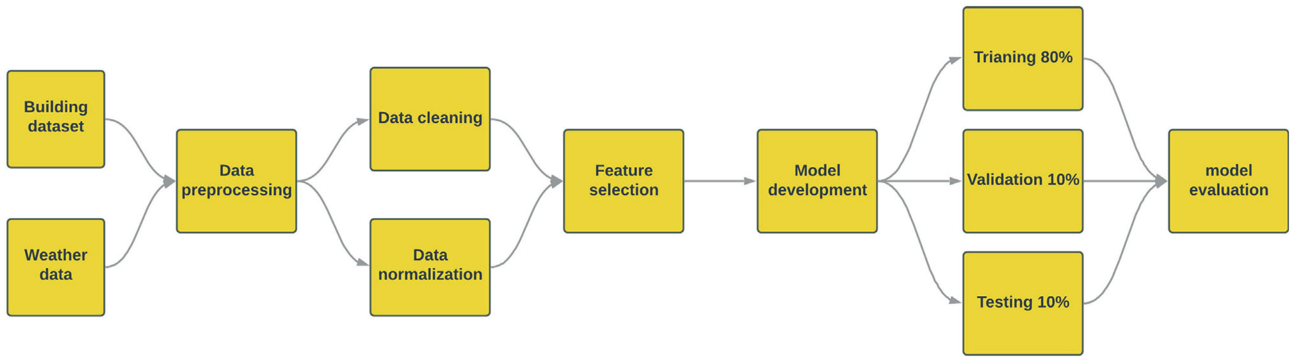


Fig. 5. Prediction framework flowchart.

and 10 neurons in each layer with lambda = 0.1, whereas the ANN has just one hidden layer and 10 and 100 neurons. The activation 'ReLU' and the optimizer 'Adam' were used. Furthermore, SVM was built with the following parameters: 1.0 value of C (a hyper-meter in SVM used to manage error, where a low C indicates a low error), 1.6 value of Epsilon (defines a margin of tolerance). The kernel function substantially impacts the SVM's prediction accuracy; it should be chosen suitably for different prediction models based on the study's features. The Gaussian kernel is a radial basis kernel with outstanding anti-interference properties. As a result, the prediction model in this work is based on the Gaussian kernel function, which is expressed as follows [107]:

$$K(x_i, x) = e^{\left(-\frac{\|x_i - y\|^2}{2\sigma^2}\right)} \tag{1}$$

Where x_i is the input variable, y is the output variable, and σ^2 is the width parameter.

Grid search was used to find γ and σ^2 [108]. GLSSVM has the exact parameters of LSSVM and GMDH since it is a hybrid model of both. Furthermore, the least square regression loss function, 0.1 learning rate, and 100 estimators were also used to create the XGB model. With 30 estimators, a random forest (RF) was created.

Following data preparation, the learning algorithms are fed the selected variables based on feature importance ranking. Eighteen factors are fed into this forecasting algorithm from three different systems, including BIM models, BMS systems, and IoT sensor networks, and based on pairwise testing. A combination of data from the IoT sensors, the BMS system's data, and BIM data will be employed in the prediction process to determine the ranges for pairwise testing and extend it to include more possible combinations. The machine learning models' inputs will consist of nineteen variables as they have the most impact on the energy consumption in buildings (out from the literature review and the ANOVA-SVM method in Section 3.3.2 to choose the most critical factors): (1) U-value, external wal, (2) U-value, windows, (3) U-value, ground floor, (4) U-value, roof, (5) air supply, (6) window to wall ratio, (7) solar Heat Gain Coefficient (SHGC), (8) load (people and equipment), (9) load (lighting), (10) activate shading, (11) reflectance, (12) night ventilation, (13) shading factor, (14) air Infiltration, (15) supply air temperature setpoints, (16) supply water temperature setpoints, (17) supply water temperature to radiators, (18) return water temperature from radiators, (19) Heat exchanger Efficiency. The output of this prediction process is the annual energy consumption of the building.

Well-trained models can be used to forecast future energy usage and will be used as objective function for the optimization process. Machine learning models are trained using datasets for the required variables (input datasets from sensor data and pairwise testing (Section 3.2.2)), which result in prediction models. The input datasets are divided into three groups using a random distribution: (1) 80 percent for model training, (2) 10% for validation, and (3) 10% for testing the models.

3.3.4. Model evaluation

The following indicators are used to assess each model's performance: R-Squared (R^2), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Squared Error (MSE). The MSE and RMSE are the most commonly used assessment methods for energy consumption prediction among all the methodologies given [109,110]. The difference between expected and actual values at each point in a scatter plot is calculated using Mean Absolute Error (MAE). The mean squared error (MSE) measures the squared difference between the estimated and actual values. The Root Mean Squared Error (RMSE) is a statistic for calculating the disparities between an estimated value and the model's perceived value. R-Squared (R^2) checks the degree of fit between anticipated and actual values; however, R^2 produces the best results when close to 1.0. The closer the score is to zero, the better the performance, and the higher the value, the poorer the performance for MAE, MSE, and RMSE.

Eqs. (2)–(5) produce MAE, MSE, RMSE, and R-squared, respectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|AE_i - PE_i| \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(AE_i - PE_i)^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(AE_i - PE_i)^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{predict,i} - y_{data,i})^2}{\sum_{i=1}^{n}(y_{data,i} - y_{data})^2} \tag{5}$$

3.4. Multi-objective optimization based on NSGA II

This stage represents the purple box in Fig. 1.

3.4.1. Objective functions

In this work, the conventional mathematical functions, usually used as an objective function for optimization algorithms, are replaced by the energy consumption regression prediction methods in Section 3.3.3. These methods can resolve that a specific formula cannot express the complex nonlinear relationship between the input variables and the output objectives.

The second object function considered in this work is indoor thermal comfort, which expresses how pleased most occupants are when they are in a controlled indoor environment. PMV and PPD are two significant indices of thermal comfort in this area, representing the degree to which indoor occupants perceive the ambient temperature according to the human body thermal reaction [111]. In the PMV, there are seven assessment levels, ranging from -3 to $+3$, with positive and negative values denoting hot and cold temperatures accordingly, with values closer to zero representing higher degrees of thermal comfort. As soon as the PMV is established, the PPD may be calculated to estimate the percentage of thermally unsatisfied occupants in a building. Overall, PPD identifies the proportion of persons expected to have local discomfort (0 to 100 percent).

The Eqs. ()()()()(6)–(9) for the thermal comfort indicators (PMV and PPD) are developed according to ISO 7730 [112].

$$PMV = (0.303 \cdot e^{0.036 \cdot M} + 0.028) \cdot L \tag{6}$$

$$\begin{aligned} L =\ & (M - W) - 0.00305 \cdot (5733 - 6.99 \cdot (M - W) - Pa) - 0.42(M - W - 58.15) \\ & - 0.000017(5867 - Pa) - 0.0014 \cdot M \cdot (34 - Ta) - 3.96 \cdot 10^{-8} \cdot Fcl \cdot ((Tcl + 273)^4 \\ & - (Tr + 273)^4) - Fcl \cdot hc \cdot (Tcl - Ta) \end{aligned} \tag{7}$$

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

$$PPD = 100 - 95 \cdot e^{-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2} \tag{9}$$

Where: M stands for metabolic rate (W/m^2), L for body thermal load, W (W/m^2) stands for external work, Ta (°C) is the indoor air temperature, Tcl (°C) is the clothing surface temperature, Pa (kPa) is the partial vapor pressure, and fcl(-) is the clothing surface area factor. In addition, Tr (°C) represents the average radiation temperature of envelope, Icl (m^2K/W) represents the thermal resistance of clothing. EN 15251 [113], and Norwegian building details 421.501 [114], which are based on a human body heat balance equation and subjective thermal feeling, have also been used to find the parameters of PPD and PMV.

A further relation exists between the mean radiant temperature of the building envelope (Tr) in Eq. (8) and the thermal performance of the building envelope, which can be expressed as in Eqs. (10), and (11) based on [112,115]:

$$Tr = \frac{T_1 \cdot A_1 + T_2 \cdot A_2 + \cdots + T_N \cdot A_N}{A_1 + A_2 + \cdots + A_N} = \frac{\sum_1^k (A_{nj} \cdot T_{nj})}{\sum_1^k A_{nj}} \tag{10}$$

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

$$T = Ta \cdot k \cdot \frac{Ta - Tout}{\alpha} \tag{11}$$

Where: Ta is the indoor air temperature, Tout is the outdoor temperature, k is the heat transfer coefficient of the envelope, and α is the heat transfer coefficient of the inner surface of the envelope.

The mean radiant temperature can then be written as follows:

$$Tr = \frac{[A_{walls} \cdot Ta \cdot U_{walls} \cdot \frac{(Ta - Tout)}{\alpha}] + [A_{windows} \cdot Ta \cdot U_{windows} \cdot \frac{(Ta - Tout)}{\alpha}] + [A_{roof} \cdot Ta \cdot U_{roof} \cdot \frac{(Ta - Tout)}{\alpha}]}{A_{walls} + A_{windows} + A_{roof}} \tag{12}$$

To include window to wall ratio, A_{walls}, and $A_{windows}$ can be written as follows:

$$A_{walls} = \frac{A_{walls} + A_{windows}}{\frac{A_{walls} + A_{windows}}{A_{walls}}} = \frac{A_{walls} + A_{windows}}{1 + \frac{A_{windows}}{A_{walls}}} \tag{13}$$

$$A_{windows} = \frac{\frac{(A_{walls} + A_{windows})}{A_{walls}} \times A_{windows}}{\frac{(A_{walls} + A_{windows})}{A_{walls}}} = \frac{(A_{walls} + A_{windows}) \cdot \frac{A_{windows}}{A_{walls}}}{1 + \frac{A_{windows}}{A_{walls}}} \tag{14}$$

By replacing the Eqs. (12)–(14) in the PMV Eq. (6), and considering Tr = f ($U_{wall}, U_{roof}, U_{windows}, U_{windows/walls}$), the final equation of PMV and building envelope can be expressed as follows:

$$\begin{aligned} PMV =\ & (0.303 \cdot e^{0.036 \cdot M} + 0.028) \cdot [(M - W) - 0.00305 \cdot (5733 - 6.99 \cdot (M - W) - Pa) \\ & - 0.42(M - W - 58.15) - 0.000017(5867 - Pa) - 0.0014 \cdot M \cdot (34 - Ta) \\ & - 3.96 \cdot 10^{-8} \cdot Fcl \cdot ((Tcl + 273)^4 - (f(U_{wall}, U_{roof}, U_{windows}, U_{windows/walls}) + 273)^4) \\ & - Fcl \cdot hc \cdot (Tcl - Ta)] \end{aligned} \tag{15}$$

3.4.2. Pareto front solution using NSGA II in Dynamo

In this section, the first step is to transmit real-time sensor data from the building to the BIM model in Autodesk Revit using the previously described plugin that relies on virtual sensor blocks with the following characteristics: Date, Temperature, Humidity, Energy, and PMV attributes. Real-time streaming from IoT devices keeps these characteristics' values current in the BIM model.

Dynamo's optimization technique uses NSGA II in the Optimo package to compute the best Pareto solution in the second phase (Fig. 6). The objective (fitness) functions from the machine learning model (Section 3.4.1.), and PMV are mapped to Dynamo using a python script because the Dynamo API allows for python nodes. In order to make the dynamic PMV output more understandable, a color range function was used.

For the NSGA II, the typical binary tournament selection, crossover, and mutation operators are used. The starting population list is sorted using non-dominance fitness values in the optimization process nodes. The offspring population list's fitness values are allocated the same way as the original population list's. The current offspring population list is coupled with previously established best non-dominated solutions to ensure elitism. The best non-dominated solutions are chosen for the following iteration. The Generation Loop runs until the designer's limit is reached. The Pareto Optimal Set is constructed as an output of the optimization loop (Fig. 8), and the initial solution lists and population lists formed during the optimization process are exported as CSV files. The user can utilize the exported data for further processing.The method for obtaining a Pareto front using the NSGA II is shown in Fig. 7.

In the third phase, the optimal results from NSGA II are used to replace Revit elements (using their ID in the COBie file) and control the indoor climate to keep PMV between -0.1 and $+0.1$.

3.5. Data integration

COBie is an information exchange specification used to gather and distribute data throughout its lifecycle. Despite this, there is still a difficulty with compatibility between IFC and COBie because their data structures differ from the data syntax of BIM models. COBie spreadsheets are used to import data from BIM models that have been pre-selected based on user-defined parameters into a spreadsheet program. The names of characteristics in COBie spreadsheets are typically different from the names of characteristics found in FM and BEM system data, which might cause confusion.

Currently, RDF may represent a variety of different types of building data. Much of this information is first provided in native

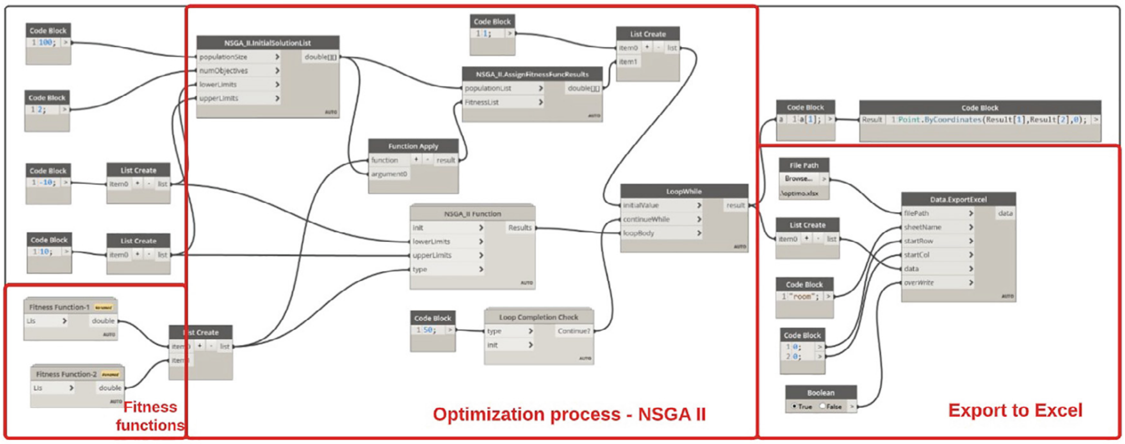


Fig. 6. An overview of NSGA II method in Dynamo.

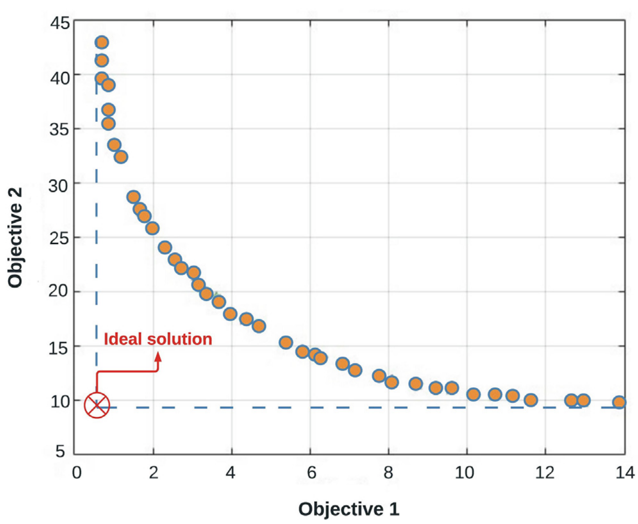


Fig. 8. The Pareto front's ideal solution.

data formats, which may then be transformed to RDF using a variety of data converters now available on the market. For the sake of this research, we do not want to use the integration of BIM, BEM, and FM for evaluation purposes, but rather to make our framework as generic as feasible; we concentrate on three essential ontologies: Brick, BOT, and SSN, which are based on COBie and IFC data respectively.

Using these ontologies, it is possible to characterize building components and relate them to sensors as system elements with specialized measurement capabilities. Using a modular approach, the sensors and domain may be split down into readily digestible information, with obvious connections to other ontologies that are accessible to enable network definition, measurement, and other functions. Python was utilized in this project to automate the mapped method.

4. Case study

4.1. Building description

Tvedestrand secondary school (a case study model illustrating the configuration of Norway's secondary school building) was considered. The building consists of a three-story structure with a total construction area of 9759.2 m^2 and a total building volume of 33746.7 m^3. The school has approximately 130 employees and 500 students; however, the building is designed for 690 students and 140 employees. Each person occupies around 11 m^2 of floor area. Most students are 16–19 years old, while the staff is between 22–67 years old. In this study, students and employees were treated equally regarding thermal comfort.

The building envelope features, the lighting system, the HVAC system, and the setpoints were selected for an educational facility that complied with the Norwegian building code TEK10 [116]. In order to acquire the building energy consumption simulation model, the BIM model of the educational building is generated in Revit and SimpleBim and then imported into IDA ICE to be used in the simulation (Fig. 9). The zone multiplier function in IDA ICE is used to shorten the computational simulation time by simplifying redundant zones in the building.

Table 2 shows the general information regarding the reference case building. The building has a total of 144 zones. This building has a total external wall area of 2103.0 m^2 and a total window area of 670 m^2. Furthermore, the shading system for the windows was made out of vertical fins. The building windows have vertical fins with a thickness of 10 mm, and a depth of 250 mm. The spacing between those fins is 500 mm. For larger window areas, a lower window U-value should be used to comply with National Building Code (TEK 10) requirements to minimize excessive building energy consumption for space heating and cooling. All properties were selected using TEK 10. So, all the initial values in Table 2 come from TEK 10 standard and have been confirmed with the facility manager. However, since we used the pairwise test to generate the inputs for the optimization process (within the boundary conditions), the initial values do not affect the optimization results. According to the standard NS 3031 [117], domestic hot water (DHW) usage was chosen based on the standardized value for educational buildings. Table 3 shows the central HVAC system's features in the reference building.

Table 4 illustrates the internal heat gain values and profiles (Occupancy, illumination, and equipment) implemented in IDA ICE based on the NS 3031 Norwegian standard. Climate data were obtained from the ASHRAE IWEC 2 database [118] for Kjevik, Kristiansand, where the average yearly outdoor temperature was roughly 9.2 °C. In this study, the PPD was calculated by taking into account the occupancy patterns in the building (07.00–19.00), room type (office, classroom, group room, labs, and lunchroom), and holiday weeks (Week 26–32 and week 52). Usage pattern in rooms with several people is based on NS3031 with some adjustments concerning room function.

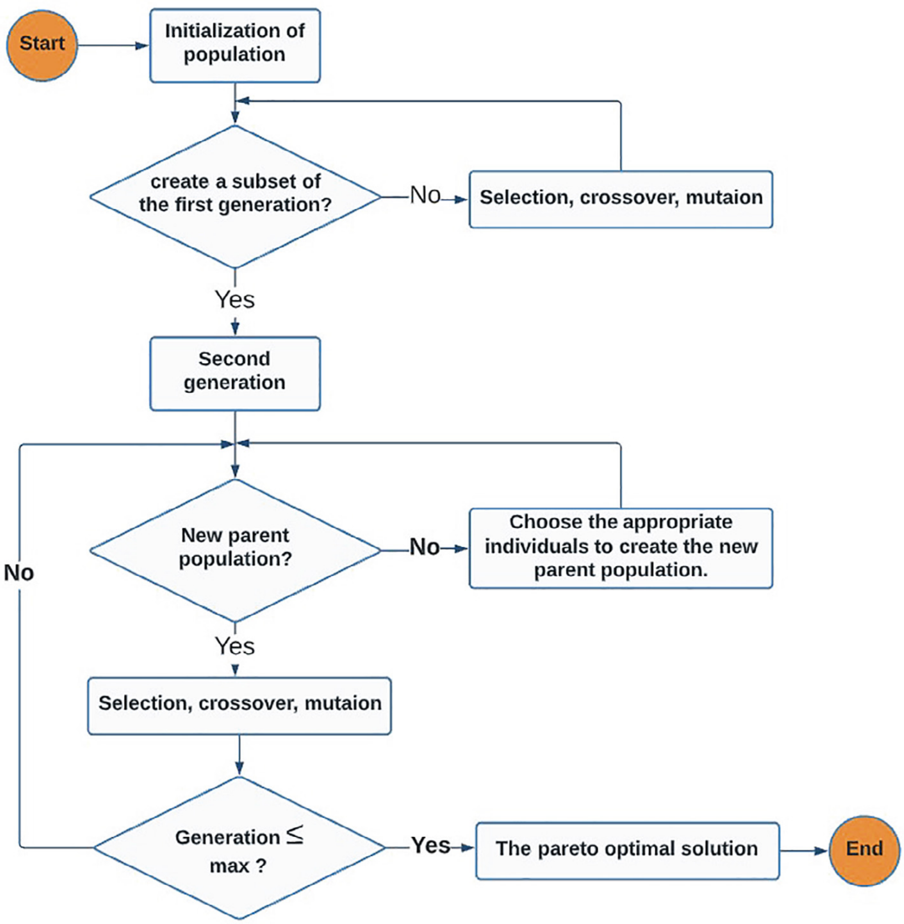


Fig. 7. The NSGA II flowchart.

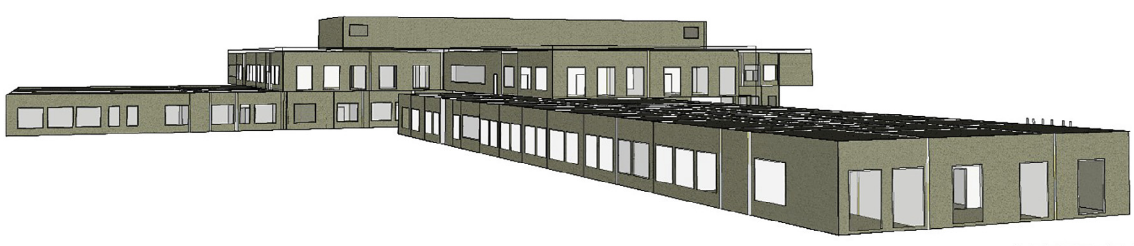


Fig. 9. Simulating the energy consumption of Tvedestrand secondary school in Norway using IDA ICE.

Table 2
Original values of building envelope data used as input values in IDA-ICE.

Parameter	Initial value
External wall U-value (W/(m^2.K))	0.15
Roof U-value (W/(m^2.K))	0.11
External window, doors and glass U-value (W/(m^2.K))	0.8
Ground floor U-value, W/(m^2.K)	0.06
Normalized thermal bridge (W/(m^2.K))	0.03
Airtightness n_{50} (1/h)	0.35
External shading strategy	Qsol (klux) >40
Internal wall U-value, W/(m^2.K)	0.62
g_t, Solar Heat Gain Coefficient (SHGC)	0.34 (3 layers glass)
Shading factor	0.2
Reflectance	0.55

Based on the parameters given in the above tables, the building net energy consumption of the original design solution is calculated using IDA ICE to be as the Table 5.

4.2. Sensor data and interoperability

In this case study, several sensors were placed to monitor the building's rooms and HVAC systems. These sensors include NTC-12 K-sensors for temperatures, PTH-3202-DR for pressure, TTH-6040–0 for outdoor temperature, and the IVL10 temperature-sensitive airflow transmitters. In addition to sensors that monitor air and water supply and return temperatures, energy usage, con-

Table 3
The reference educational building's HVAC systems.

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

Table 4
Internal heat gains values of occupants, lighting, and equipment.

Internal heat gain	Comment
Occupants: the building is occupied from 07.00 to 19.00	Activity level is considered to be 1.2 met which is 108 W/person. The usage then depends on the room type (office, classroom, group room, labs and lunchroom). Usage pattern in rooms with several people is based on NS3031 with some adjustments with regard to room function. Holiday weeks are also based on NS3031 and during the holiday week there are no heat loads are present. Holiday weeks are: week 26–32 (summer holiday), week 52 (Christmas).
Lightning during the occupied period [W/m^2]	3
Equipments during the occupied period considering no load in unoccupied zones [W/m^2]	4

Table 5
Total net energy demand calculated for the studied building (the initial case). The mechanical ventilation system cooled the zones because there was no local space cooling system.

Energy	**Energy consumption (kWh/year)**	**Energy consumption (kWh/m^2.year)**
Room heating	87080	8.92
Ventilation heat	43680	4.47
Hot water	116760	11.96
Fans	101360	10.39
Pumps	25760	2.63
Lighting	86240	8.84
Technical equipment	111720	11.45
Room cooling	–	–
Ventilation cooling	23520	2.41
Net energy consumption	**596120**	**61.07**

trol system setpoints, humidity, and CO2. Regio controllers have also been used to regulate blinds, lighting, humidity, CO2 levels, etc. The major goal of the sensor data is to validate the outputs of the original IDA ICE model and to establish the boundary conditions for the optimization process's input variables. The proposed framework in this study operates for any building based on the ontologies used in this paper. BRICK, BOT, and SSN ontologies are created based on COBie data and used to get information from an IFC model, transfer data into the COBie data standard, and offer BIM data to energy systems to handle data exchange and interoperability issues (see Section 3.5. Data integration). Modeling framework between sensor data and simulation technique is depicted in Fig. 10,11.

4.3. Inputs for the optimization process

The optimization process took a wide range of input variables into account, divided into two groups, as indicated in Table 6. The most significant characteristics in the literature guided the selection of the initial set of variables related to the building envelope and shading. The HVAC parameters and setpoints were in the second category of variables. The optimization of the latter variables in combination was absent from the literature, and no research investigated the combined control of these two types of variables for the optimization process. There were more than 40 variables that can be included in this optimization process based on the literature; however, by using the ANOVA-SVM method (Section 3.3.2), the most important variables have been taken into consideration, as can be seen in Table 6.

4.4. Dynamo for the machine learning and optimization

We first generate all the possible combinations of the decision variables, ending with 1,236,912 combinations. However, using the pairwise test, the combinations were reduced to 8000 and covered all possible solutions more effectively. We use every combination as input for IDA ICE and run one simulation based on that combination to get the annual energy consumption. It took around 16 days to finish all simulations. The final database, which includes the 8000 combinations and the corresponding energy consumption (Fig. 12), is fed into the machine learning algorithms using visual programming.

The visual programming environment enables the design space to be described rapidly, interactively, and correctly. The Dynamo process for this case study can be shown in Fig. 13. Table 6 and its ranges are used to define the decision variables in this workflow. The python script node will take the decision variables as inputs for the machine learning model and NSGA II process. So, rather than installing Python on its own, it can now be utilized as a part of Dynamo (embedded). It will be much easier to incorporate the optimization findings straight into a BIM model. TensorFlow and Sci-kit libraries must be loaded correctly for the python scripts node to function effectively. Figure shows a portion of the python script node's code. The second stage uses Optimo nodes (Fitness Function Results, Generation Algorithm, etc.) to transfer the best machine learning model to the NSGA II nodes for the optimization process. Packages of nodes are used to implement parametric performance analysis using BIM to optimize thermal comfort and energy analysis. When the run iteration number surpasses the designer's specified limit, the generation loop continues to perform the generating and sorting operations in a loop. Then, the results can be saved to an Excel file or MSSQL database

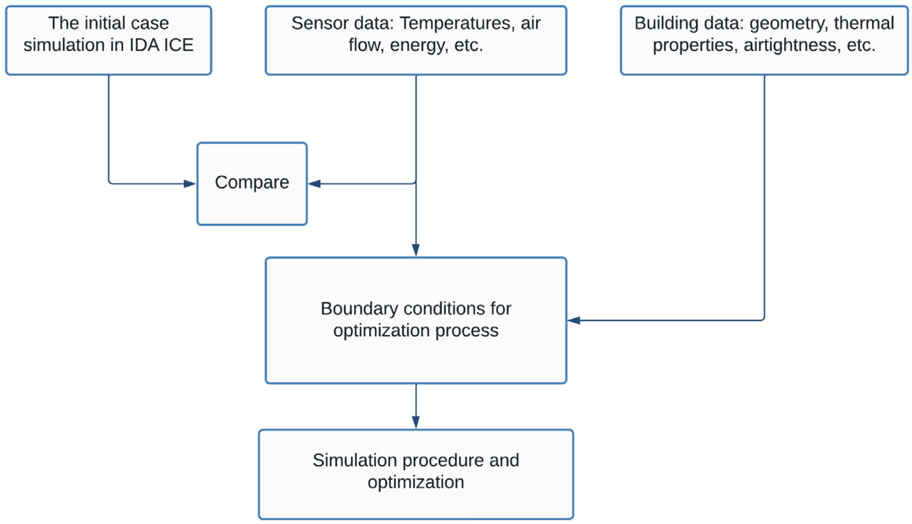


Fig. 10. The process from data input to the simulation procedure.

containing all of the optimization variables and their performance analysis findings. The next step is to replace the existed elements in the BIM model with the optimized one and visualize the thermal comfort results of each room in the BIM model using the clockwork library. The last step is to build a user interface (Fig. 13) that the final user can use to easily control the decision variables ranges and constraints using the Data-Shapes library.

4.5. Annual energy consumption prediction results

The outcome analysis revealed significant findings between the selected models in this research. In Section 3.3.4, it is mentioned that models with values closer to zero for MAE, MSE, and RMSE are good predictive models, while values closer to one for R-squared generated the most outstanding results. In this study, GLSSVM was the best effective model for forecasting annual energy consumption. LSSVM and GMDH, which has not received much attention in energy prediction, emerged as two and the third-best predictive model. The hybrid algorithm ANN-SVM comes in fourth place, outperforming the other algorithms. Even though it takes a longer time for training, GPR surpasses ANN, SVM, DNN, XGB, LR, and RF. The XGB and LR-based models have the worst performance but take the least time to train. Table 7 shows the prediction models in terms of performance indexes and time. Fig. 14 shows the results based on Table 7 algorithms, where the x-axis is the true values while the y-axis is the predicted values. The blue points in Fig. 14 are the observations, and the black lines are the predictions. The proposed GLSSVM energy consumption prediction model has the highest accuracy and the best prediction results of all existing models. This is due to its hybrid model's technique compared to other methods that mostly depend on one model only. The GLSSVM combines the GMDH with the LS-SVM [52,119]. The LS-SVM model forecasts the output signal using the input data of the innovative hybrid forecasting model, which the GMDH model chooses. Every pair of the two input variables is considered in every layer, and the polynomial function does the regression for each pair [120]. Together with the input variables, the output data of the GMDH model (which has the lowest error) is utilized as input for the LS-SVM model. The GLSSVM method is run through three to five iterations or until the output data has the least amount of error [121]. The GLSSVM model also performs better than the ANN-SVM hybrid model. This is obviously because GLSSVM depends on LSSVM, an improved version of SVM that makes the prediction faster, and the GMDH neural network, which selects an optimal structure of model or network until it finds the best one compared to ANN, which has a fixed structure. As a result, the its regression relationship can be used as the fitness function of multi-objective optimization, resulting in better achievement of optimization objectives.

4.6. Multi-objective optimization using NSGA-II

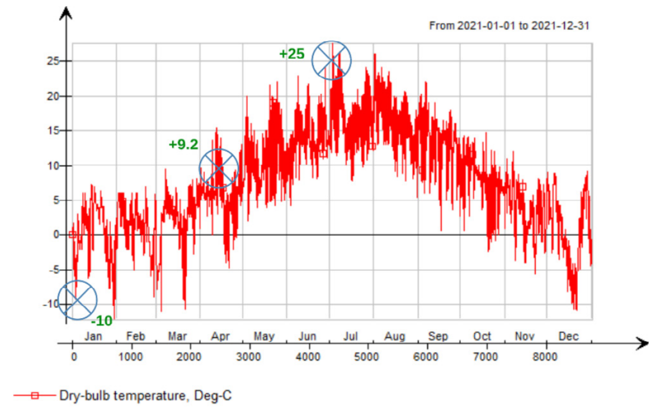
Building energy consumption reduction and improved thermal comfort are two of the optimization goals for NSGA-II. In this work, the NSGA-II adaptive mutation feature improves the variety of the GA solutions and widens the GA's search space by setting the population type as a double vector. As the population size and number of iterations are critical to the convergence of NSGA-II optimizations, the values of these parameters are presented in Table 8. According to Fig. 15, the NSGA-II optimization is carried out, and the Pareto optimum front, which comprises 37 optimal solutions, is obtained, from which we can find the following:

According to Fig. 15, thermal comfort is inversely proportional to a building's energy use. The predicted percentage of dissatisfied (PPD) improves slowly with a rapid decrease in building energy usage. However, when the building's energy usage is further reduced, the PPD rises dramatically, making it impossible to achieve both objectives simultaneously.

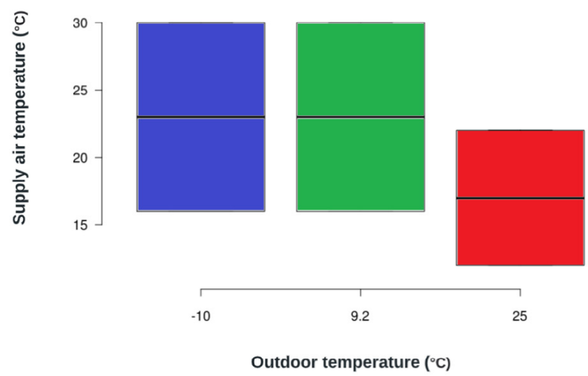
To put it another way: The results show that the Pareto optimum solutions' energy consumption and PPD are often less than 50 kWh/m^2.year and 9%, respectively, compared to the original design solution's 61.17 kWh/m^2 and 18.5%. According to these findings, NSGA-II solutions can simultaneously reduce the building's energy consumption and enhance thermal comfort.

It is shown in Table 9 that the optimal set of input parameters was found following optimization. There is a wide range of building envelope parameters in the best options. There are 3 points in Fig. 15 where the building envelope parameters and objective function values are shown in Table 9. According to the table, all options on the Pareto optimum front have different values for the building envelope parameters. By looking at the table below, several characteristics, such as roof U-value, exterior window U-value, and window-to-wall ratio, have varying values that influence energy usage and indoor thermal comfort.

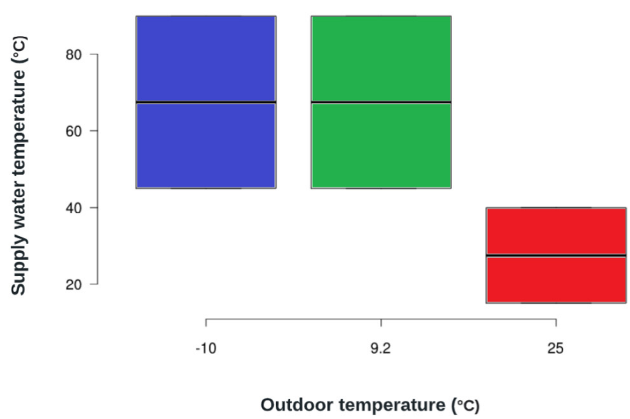
The lighting load was maintained to a minimum during the optimization phase, while the heat exchanger efficiency was max-



(a)



(b)



(c)

Fig. 11. Weather data (a), Supply air temperature ranges between 16 to 30 (°C) for −10 and 9.2 (°C), and between 13 to 22 (°C) for 25 (°C) (b), and supply water temperature ranges between 45 and 90 (°C) for −10 and 9.2 (°C), and between 15 and 40 (°C) for 25 (°C) (c).

imized. This was because improving the lighting system and heat exchanger efficiency reduced building energy consumption while having a minor impact on thermal comfort.

A modest window to wall ratio was selected for the minimum energy usage and the most significant thermal comfort situations, suggesting that this parameter was a competing element for optimizing thermal comfort and lowering energy consumption simultaneously. Building exterior walls with low U-values was favored in all cases. The highest thermal comfort satisfaction scenarios preferred the roof with the lowest U-value.

Table 6
Input parameters for the optimization procedure.

Input parameters	Value	Note
U-value, external wall [W/m^2.K]	0.12, 0.14, 0.16, 0.18, 0.2	
U-value, windows [W/m^2.K]	0.75, 0.8, 0.85, 0.9	
U-value, ground floor [W/m^2.K]	0.08, 0.10, 0.13, 0.16	
U-value, roof [W/m^2.K]	0.08, 0.10, 0.13, 0.16	
Minimum air supply (l/m^2.s)	0.5–2	min–max
Window-wall-ratio (WWR %)	30–90	min–max
g_t, Solar Heat Gain Coefficient (SHGC)	0.25, 0.32, 0.43, 0.5	
Load (lighting) (W/m^2)	2, 4, 6, 8	
Activate shading (klux)	38, 45, 52, 61, 70, 100	
Reflectance	0.4, 0.55, 0.65, 0.78	
Night ventilation (l/m^2.s)	0.3–4	min–max
Shading factor	0.2, 0.3, 0.4, 0.5, 0.6, 0.8	
Air Infiltration	0.06, 0.07, 0.1	
	HVAC	
Supply air temperature setpoints in AHU (?)	Fig. 11a and Fig. 11b	Three outside air temperature values were considered: −10, 9.2 (the average value), and 25
Supply water temperature setpoints from the central heating system (?)	Fig. 11c	Three outside air temperature values were considered: −10, 9.2 (the average value), and 25
Supply water temperature to radiators (?)	(45, 55,65, 70)	
Heat exchanger Efficiency in AHU	(0.55, 0.75, 0.85)	

Fig. 16 depicts the AHU's ideal supply air temperatures and airflow rates, as well as the central heating system's supply water temperatures. As a result of the reference building's optimization, comparable variations in supply air temperature and supply water temperature were selected for various instances (Figs. 16a, 16b,16c, and 16d) in order to reduce energy consumption and increase thermal comfort.

In addition, the best solution is found using the ideal point approach. The ideal point coordinates created by the optimal values of building energy consumption and PPD are shown in Fig. 17 at (6.2, 22.9).

Out of the results we reached in our case study, The following can be found:

1. After NSGA-II optimization, the building's energy consumption is much reduced. There is a 37.5% decrease in overall building energy consumption after optimization from 61.07 kWh/m^2.year with the original case to 22.9 kWh/m^2.year, proving that multi-objective optimization favorably reduces building energy consumption.
2. After NSGA-II optimization, the building's thermal comfort is increased. As an indicator of how well a building's thermal comfort has been improved by multi-objective optimization, the PPD went from 18.5%, with the original values of the building, to 6.2%, which is a drop of 33.5%.

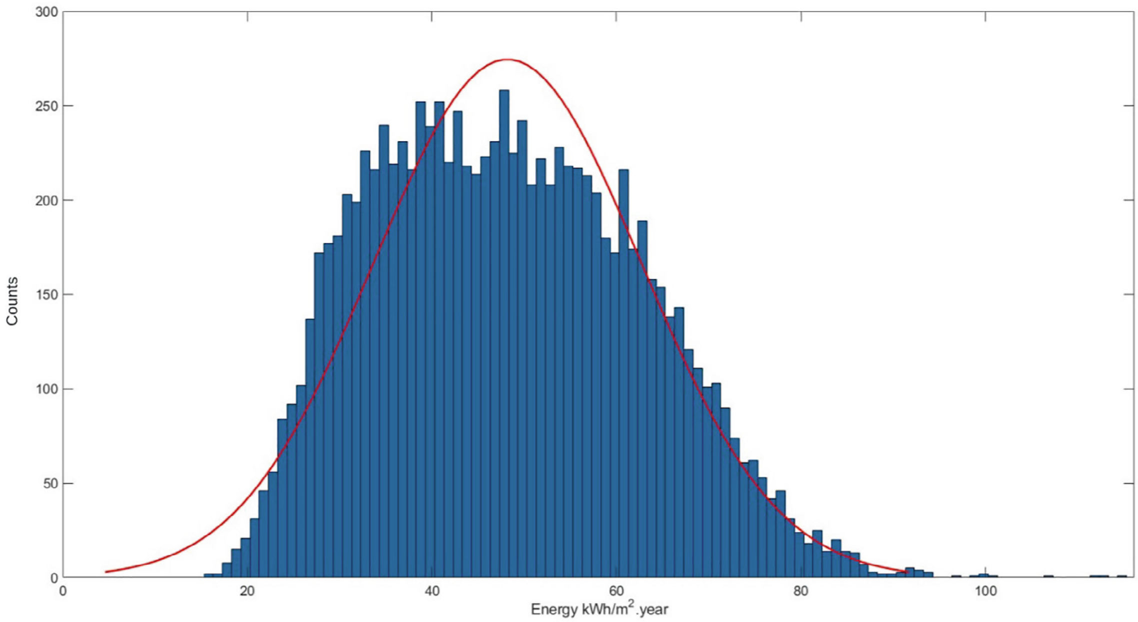


Fig. 12. Output annual energy consumption distribution from IDA ICE based on pairwise combinations..

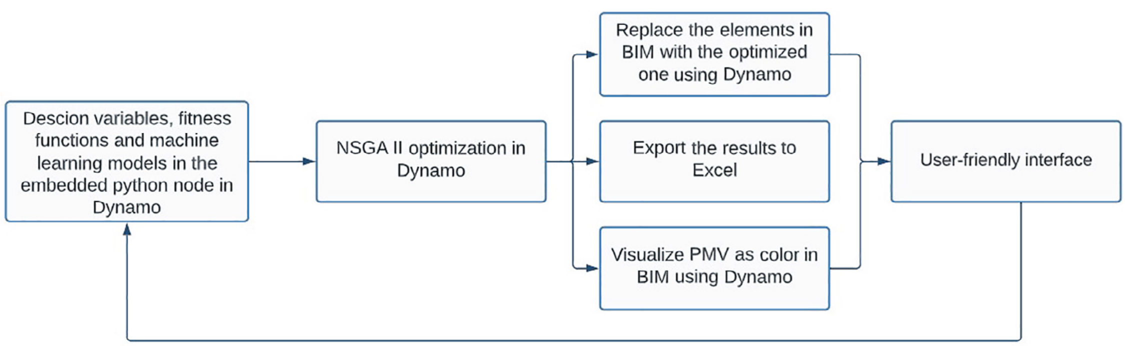


Fig. 13. The steps taken to develop optimization and machine learning models in Dynamo..

Table 7
Energy consumption prediction results based on several machine learning models.

Model	RMSE	R-Squared	MSE	MAE	Training time (seconds)
LR	5.65	0.84	31.94	4.06	4.77
ANN (one layer 10 neurons)	3.19	0.95	10.23	2.30	8.10
ANN (one layer 100 neurons)	1.88	0.98	3.54	1.41	38.10
SVM	2.35	0.97	5.56	1.79	13.01
GPR	1.94	0.98	3.80	1.46	92.83
DNN	2.05	0.98	4.23	1.57	9.26
RF	3.93	0.92	15.47	2.87	**2.06**
XGB	5.33	0.86	28.43	3.79	2.52
ANN-SVM	1.29	0.99	1.67	0.95	25.34
LSSVM	1.25	0.99	1.56	0.91	5.22
GMDH	1.27	0.99	1.62	0.95	22.68
GLSSVM	1.20	0.99	1.44	0.89	14.03

3. A comparison of building envelope characteristics before and after optimization shows that the thermal performance of envelopes, notably the wall, windows, and roofs, is critical to energy-saving and thermal comfort.

5. Discussion

A Pareto-optimal front may be generated using NSGA II for multi-objective building energy consumption optimization and the ideal point approach to arrive at the optimum solution for building energy consumption and thermal comfort. When we compare the optimal solution of building's parameter values to the original solution, we discovered that each parameter's value changes, albeit to varying degrees.

Several previous studies have been conducted on building energy consumption and thermal comfort optimization [124–126,111,127,129,129–135,71]. Those studies focused on specific parameters that affect building energy consumption. However,

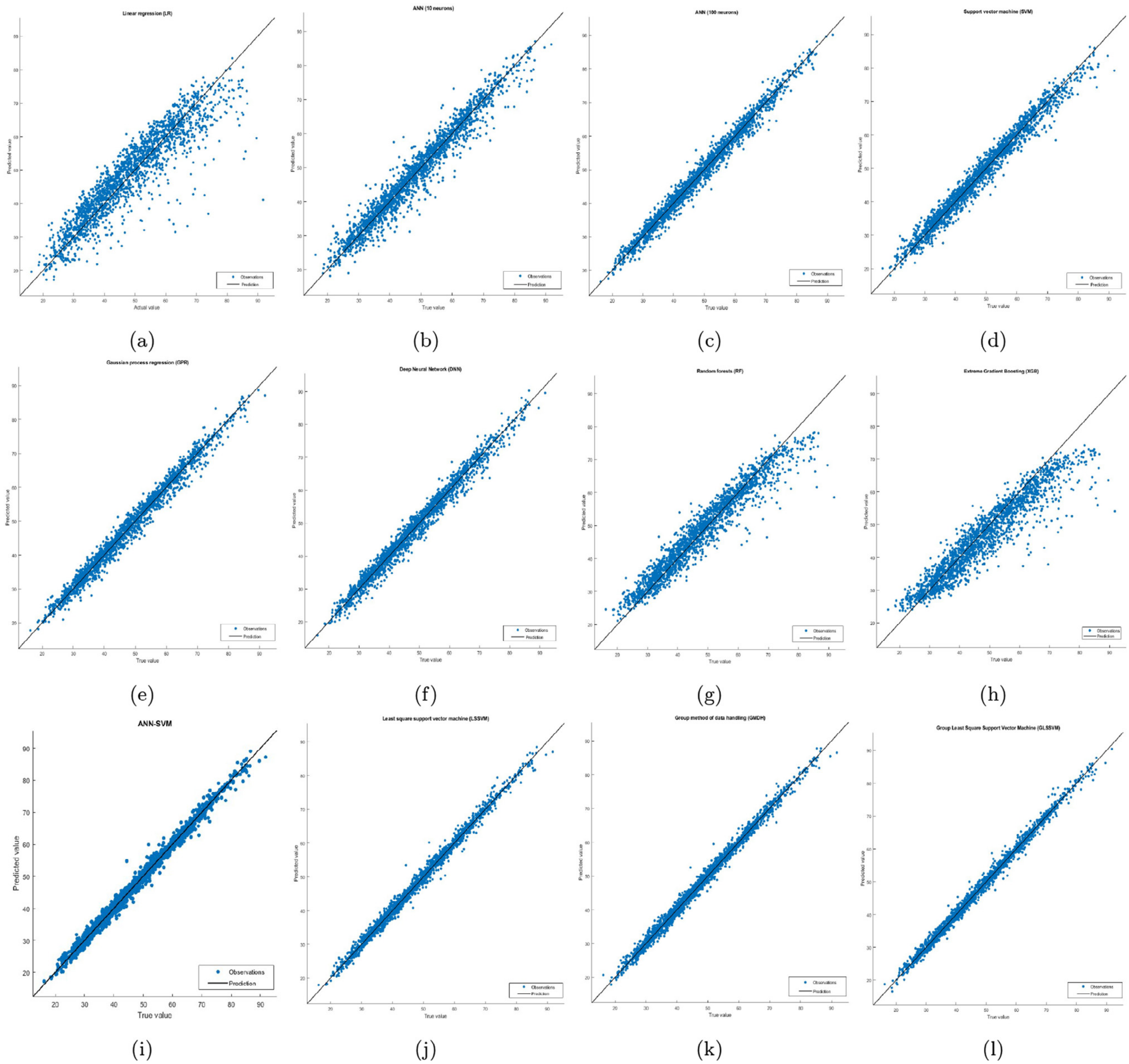


Fig. 14. Machine learning models results based on Table (7) algorithms, where the blue points represent the observations from the simulation results, and the black line represents the prediction. Also, the vertical axis represents the predicted value while the horizontal axis represents the true value: (a) Linear Regression (LR), (b) Artificial Neural Network (ANN) with one layer and 10 neurons, (c) Artificial Neural Network (ANN) with one layer and 100 neurons, (d) Support Vector Machine (SVM), (e) Gaussian Process Regression (GPR), (f) Deep Neural Network (DNN), (g) Random Forest (RF), (h) Extreme Gradient Boosting (XGB), (i) Artificial Neural Network-Support Vector Machine (ANN-SVM), (j) Least Square Support Vector Machine (LSSVM), (k) Group Method of Data Handling (GMDH), (l) Group Least Square Support Vector Machine (GLSSVM)..

Table 8
Multi-objective NSGA-II optimization parameters.

Parameter	Value
Population type	Double vector
Population size	40
Mutation function	0.8
Crossover function	0.02
Stopping criteria	Generations = 400

non of these studies conducted a comprehensive system of factors influencing the building energy consumption and thermal comfort. Our research combined 19 variables from the building envelope and HVAC system, including shading factor, SHGC, reflectance, and air infiltration. In addition, in this study, we validate the simulation results with real sensor data from the building, which is seldom done in the literature. Furthermore, in this study, a huge database has been generated to cover various possible solutions for the optimization process. We have also developed an ontology framework so that the suggested framework in this research can be applied to any building. What is unique in this study is that it implemented all the frameworks in the BIM environment so that it can interact with the BIM environment immediately and stream the best solution in both directions (to and from BIM).

Regarding the results of our research, the GLSSVM has a unique capacity to forecast building energy use with high accuracy, which has not been investigated on such a database with many variables or compared to this number of machine learning algorithms. Other studies focus most on ANN, SVM, and other ordinary methods that can not reach the accuracy of GLSSVM when it comes to such a database using a reasonable time to run the model compared to

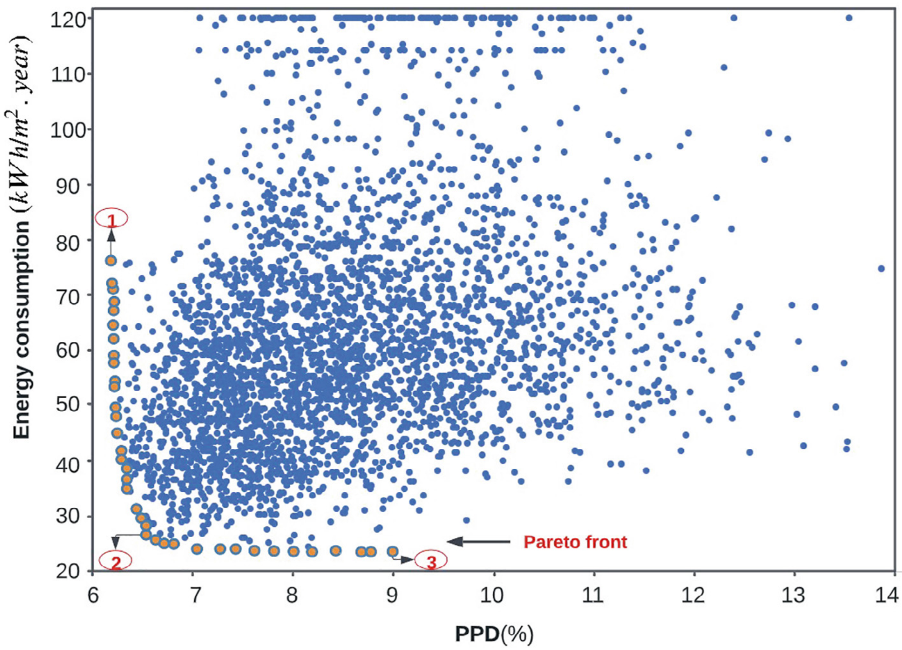


Fig. 15. The Pareto front of energy consumption optimization, where points (1) and (3) represent the anchor points that refer to the optimal points of the individual objective functions and the worst value for the other objective function in multi-objective optimization [122]. Point (2) refers to the knee point, which indicates the most satisfactory solution but not the ideal one [123]. Every blue point in the figure represents a possible solution..

Table 9
Optimized parameters from points 1,2,3 in Fig. 15, except HVAC setpoints.

Parameter	1	2	3
U-value external wall [W/m^2.K]	0.12	0.12	0.12
U-value window [W/m^2.K]	0.75	0.9	0.9
U-value roof [W/m^2.K]	0.08	0.08	0.16
WWR (%)	36.82	31.94	59.89
SHGC	0.43	0.25	0.25
Lightning [W/m^2]	8	8	8
Activate shading (klux)	70	70	61
Night ventelation [l/m^2.s]	0.7	0.7	0.5
Heat exchanger efficiency	0.85	0.85	0.85
Shading factor	0.5	0.3	0.3
Air infiltration	0.07	0.06	0.06
Reflectance	0.65	0.4	0.4
PPD (%)	6.2	6.5	9
Energy (kWh/m^2.year)	77.8	26.2	22.9

other hybrid methods (e.g., ANN-SVN). Using GLSSVM, we could replace the 16 days of simulations with 14 s of prediction, which is not stated in any similar research.

The results also show that the GLSSVM-NSGA II hybrid technique can reduce energy consumption by 37.5% and increase thermal comfort by 33.5%, respectively. Chen et al. [134] have used a similar approach using the hybrid machine learning model and NSGA II. However, they use only 54 combinations of variables compared to 8000 in our case. Their research was also limited to 6 variables related to building envelope. In addition, the BIM model in this study was only used to import the 3D model to the simulation software. However, our results agree with [134] that the external wall U value is the most important factor in the optimization. Seghier et al. [133] developed a framework using Dynamo to extract data from the BIM model, apply NSGA II in MATLAB and stream the results back to the BIM model. Even if the idea of using visual programming is similar in both research, we first used a more user-friendly interface integrated with the BIM authoring tools (plug-in in Revit®) to extract all the necessary information from the BIM model and apply all the processes inside Dynamo without needing to use MATLAB. We also included more variables and used machine learning to simplify the simulation process and understand the building performance. Rahmani et al. [72] developed a new optimization library inside Dynamo so that the optimization process can happen inside Dynamo, the same as we did in our research; however, no machine learning was applied in Dynamo as a fitness function in addition to the limited variables that been taken into account. They also did not integrate real-time sensor data with BIM in their study. All of the above studies have not used Brick, SSN, and BOT ontologies to generalize their framework so that it can be applied to several buildings.

As a result, the optimization technique suggested in this study gives valuable insights into the value of various control methods of HVAC setpoints change in enhancing building energy performance.

In addition, the operating temperature is enhanced throughout winter and summer operations, saving a significant amount of energy following the optimization. We have attempted to follow the Norwegian building regulation TEK10 and the standard NS-EN 15251:2007 by taking the solutions that fulfill the PPD criterion of less than 10%. Using Table 9, it can be shown that the most remarkable results were achieved when shading factors, air infiltration, reflectance, SHGC, and interior temperature setpoints were taken into consideration.

It is also fascinating to talk about the building's cost-effectiveness in light of the data linked to energy savings. As a result of the optimization procedure, the building's energy consumption was reduced significantly compared to the reference building. Eventually, the decrease in operational costs due to improved building energy performance may be the most significant factor in the facility's total life cycle costs. If the cost-effectiveness of other systems and materials were also taken into account, this substantial energy-saving might not be achieved. We recommended a wide range of solutions, including shading devices and HVAC setpoint adjustments, that may enhance building energy performance at a minimal investment cost.

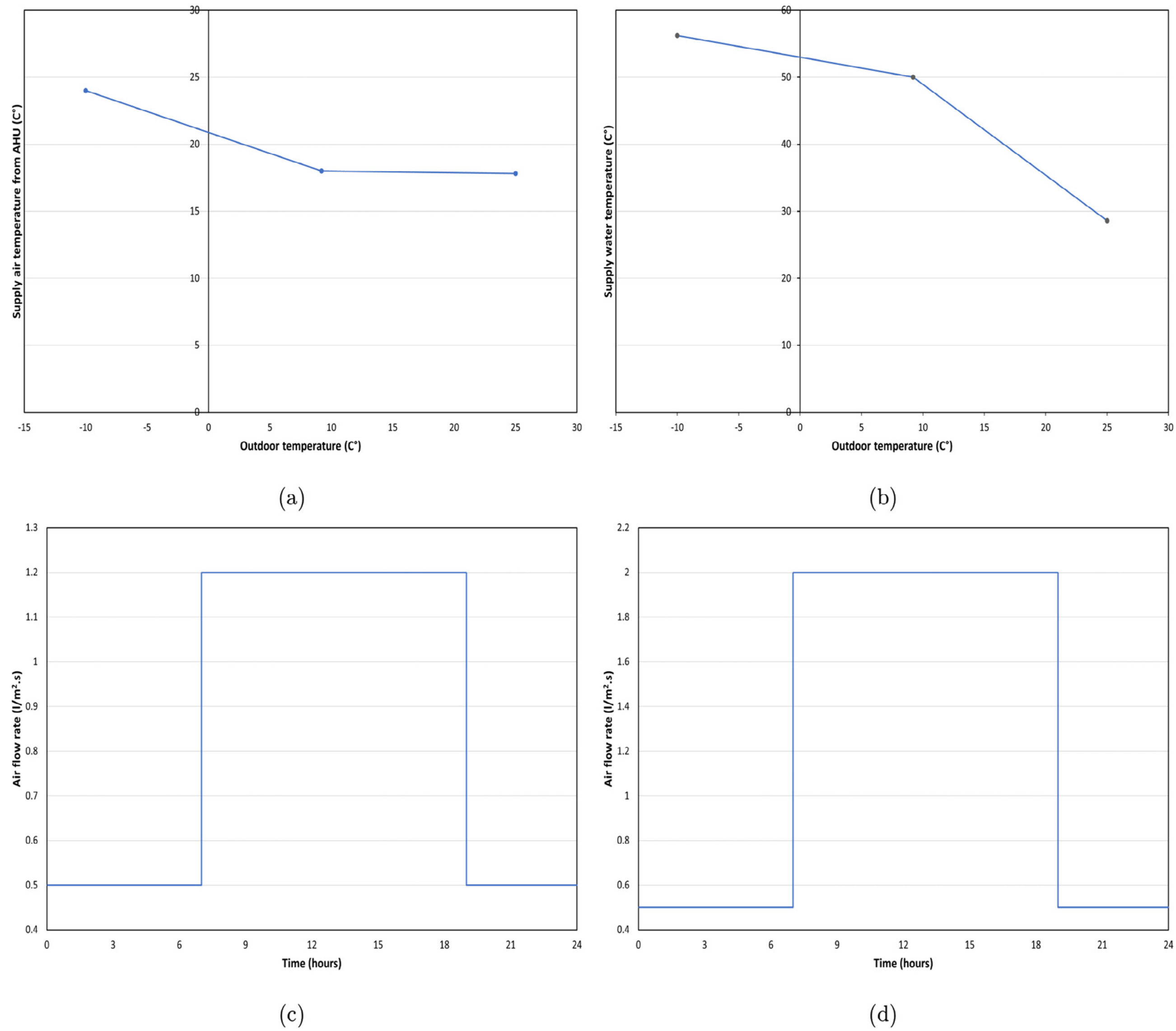


Fig. 16. (a) optimal supply air temperature from AHU, (b) optimal supply water temperature, (c) optimal ventilation supply airflow rate during the cooling season, and (d) optimal ventilation supply airflow rate during the heating season..

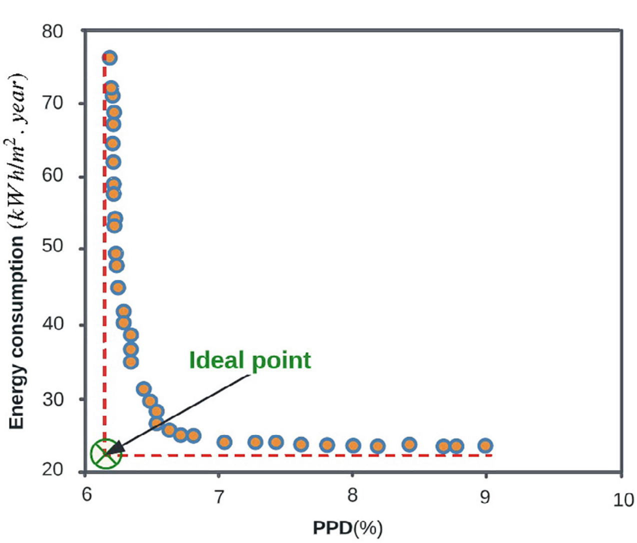


Fig. 17. The optimal solution based on the ideal point.

Another point is that our case study is a secondary school serving older students (16–20 years). However, the important question is, can the PMV formulas ((6), (7), (8), and (9)) be used in other educational settings where the occupants are younger?

The PMV model's relationships between metabolic rate, skin temperature, and thermal comfort may not be the same for children. Fanger's original study on thermal comfort did not include any children. For this reason, Fanger stated that further research was needed to see if these equations could be applied to children [136]. In the same line, several research shows that children are less sensitive to temperature changes than adults [137–139]. The high level of exercise can explain these findings among children and the wide range of activity levels during education.

The clothing insulation and metabolic heat production can be estimated, but practical methods are not accurate and affect the uncertainty in the final thermal sensation prediction to a large extent. Improving the methods to determine clothing insulation and metabolism can improve the accuracy and quality of PMV-based predictions for children [140–142].

Out from that, there is no evidence that the PMV approach can be used to predict the thermal sensation of children in a classroom accurately. Hence, to estimate PMV accurately, more data and details are required.

6. Conclusions

This study provided a multi-objective optimization framework based on BIM and machine learning-NSGAII intelligent algorithms, as well as a related application to minimize building energy consumption and increase thermal comfort by examining various building factors. An integrative optimization technique incorporating the building envelope, glazing parameters, HVAC setpoints, shading variables, and air infiltration was used for this aim.

This paper proposes a framework with four primary steps: (1) Receive all building sensor data in the BIM model using a Revit plugin and export this information to MSSQL and Excel to be used in validation of the simulation model in IDA ICE and have a good insight into actual sensor values. BIM data have also been extracted as a COBie and integrated with the building management system using several ontologies. (2) The established BIM model is imported into the IDA ICE, and a pairwise test is conducted to obtain an adequate sample dataset of building energy consumption through simulation; (3) Several machine learning models are trained on the sample dataset to establish a nonlinear mapping between the energy consumption and influencing factors; GLSSVM was the best algorithm in terms of $R2$, RMSE, MSE, and MAE; and (4) A GLSSVM-NSGAII multi-objective optimizing algorithm The effectiveness of the suggested technique was ultimately confirmed using a case study of a secondary school building in Tvedestrand, Norway, which was modeled in accordance with the Norwegian building standard TEK10. Given the circumstances, the hybrid GLSSVM-NSGA-II has proven to be the better method for enhancing the building's environmental protection and indoor comfort.

Several significant conclusions can be drawn: (1) The GLSSVM approach can accurately estimate building energy consumption based on the thermal characteristics of the building, with a $R2$ of 0.99, RMSE of 1.20, MSE of 1.44, and MAE of 0.89, compared to other models. (2) The GLSSVM-NSGAII model is very efficient for multi-objective optimization in reducing building energy consumption and enhancing interior thermal comfort. The ideal design approach reduces energy consumption by 37.5% and enhances thermal comfort by 33.5% compared to the initial design solution. (3) The exterior wall U-value should be in focus throughout the energy-efficient design of the building envelope, followed by the U-values of roofs, windows, and the window-to-wall ratio. On the basis of the novel GLSSVM-NSGAII multi-objective technique, building energy consumption and thermal comfort performance can be enhanced by implementing design modifications prior to construction. It is supposed to aid in the selection of building materials and designs. (4) The appropriate shading factor, SHGC, reflectance, and activation were determined by solar radiation and air infiltration on the outer side of the windows. Other input parameters acquired for the optimal solution included the best envelope settings and the most efficient heat exchanger in the AHU. The next step was to alter the ventilation supply air temperature and flow rate in the AHU, as well as the supply water temperature from the central heating plant to the local radiators.

Efforts to increase building efficiency and thermal and visual comfort can be pursued in the future. After the simulations have been run, post-processing daylight and Computational Fluid Dynamics (CFD) simulations may be used to examine additional aspects of thermal and visual comfort. The best location for the shade device must be determined using dynamic visual comfort criteria, such as daylight autonomy or usable daylight illuminance. Instead of comparing the average value of thermal and visual comfort indices before and after optimization, this is an intriguing situation to analyze the spatial distribution of these characteristics. For on-site power production, it is required to examine the impact of photovoltaic panel (PV) panels at the construction site. A closer look at shading and window opening controls, as well as the effects of interior air temperature, CO2, direct sunlight, and wind velocity setpoints, will be necessary to understand the control model of windows and shading in greater depth. As part of the optimization process, visual comfort must be considered. This necessitates the inclusion of additional factors, such as the window-to-floor area ratio.

CRediT authorship contribution statement

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

Declaration of Competing Interest

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

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