



Developing surrogate ANN for selecting near-optimal building energy renovation methods considering energy consumption, LCC and LCA

Sayed Amirhosain Sharif^{a,1}, Amin Hammad^{b,*}

^a Concordia University, Department of Building, Civil, and Environmental Engineering, 1455 De Maisonneuve Blvd. W., Montreal, Quebec, Canada, H3G 1M8

^b Concordia University, Concordia Institute for Information Systems Engineering, 1455 De Maisonneuve Blvd. W., Montreal, Quebec, Canada, H3G 1M8

ARTICLE INFO

Keywords:

Building energy
Energy consumption prediction
Simulation-based multi-objective optimization
Life cycle assessment
Life cycle cost
Artificial neural network
Renovation
Machine learning model

ABSTRACT

Buildings are responsible for more than 30% of the total energy consumption and an equally large amount of related greenhouse gas emissions. Improving the energy performance of buildings is a critical element of building energy conservation. Furthermore, renovating existing buildings' envelopes and systems offers significant opportunities for reducing Life Cycle Cost (LCC) and minimizing negative environmental impacts. This approach can be considered as one of the key strategies for achieving sustainable development goals at a relatively low cost, especially when compared with the demolition and reconstruction of new buildings. One of the main methodological and technical issues of this approach is selecting a desirable renovation strategy among a wide range of available options.

The main idea and motivation behind this study relies on trying to bridge the gap between Simulation-Based Multi-Objective Optimization (SBMO) and Artificial Neural Network (ANN). For a whole building simulation and optimization, current SBMOs often need thousands of simulation evaluations. Therefore, the optimization becomes unfeasible because of the computation time and complexity of the dependent parameters. To this end, one feasible technique to solve this problem is to implement surrogate models to computationally imitate expensive real building simulation models. The objective of the research focuses on developing a robust ANN to explore vast and complex data generated from the SBMO model. More specifically, this research aims to propose an accurate ANN to predict energy consumption using data from the SBMO model. The proposed model will potentially offer new venues to predict Total Energy Consumption (TEC), LCC, and Life Cycle Assessment (LCA) for different renovation scenarios, and select the optimum scenario. To illustrate the applicability of the model, a case study was developed and the accuracy of the proposed model was evaluated. Results show that models constructed using ANNs are considerably less time-consuming than the conventional Building Energy Model (BEM) while achieving acceptable accuracy.

1. Introduction

Buildings are responsible for almost 30% of the world total delivered energy consumption and for 50% of world greenhouse gas emissions; therefore, considering methods for decreasing carbon emission and energy consumption related to buildings is vital for improving sustainability [71]. On the other hand, buildings can be considered as nonlinear systems with dynamic and complex behaviors and with relatively long lifecycles [1]. There are a significant number of components and systems in buildings that strongly affect building energy performance [69]. This complexity causes difficulties in optimizing the whole building energy performance, while considering Total Energy Consumption (TEC), building Life Cycle Cost (LCC), and environmental

impacts.

New advancements in technologies relying on Artificial Neural Network (ANN) improve computational capabilities and the accuracy of models. Few studies have been conducted covering the integration of ANN and simulation or optimization. Also, the full integration between them, especially for building renovation, is still an open research problem. Besides, modeling and energy performance analysis using ANN for building renovation is not commonly used by decision-makers to perform comprehensive implementation, creating the need for a better energy analytical framework.

The integration of the simulation and optimization algorithms improves the energy performance of buildings through the selection of optimum scenarios and the fine-tuning of the desired renovation

* Corresponding author.

E-mail addresses: se_sh@encs.concordia.ca (S.A. Sharif), hammad@ciise.concordia.ca (A. Hammad).

¹ PH (514) 848-2424; ext. 7074.

methods. For a detailed model in a large project, Simulation-Based Multi-Objective Optimization (SBMO) often needs hundreds or thousands of simulation runs [2]. To achieve reliable results, the energy performance of each renovation scenario should be calculated by implementing whole building simulation tools that consider the specific characteristics of the building over the study period [3]. It is clear that this procedure also results in a prohibitive computational time, even for simple buildings, and sometimes becomes unfeasible due to the complexity of the dependent parameters. One feasible method to resolve this problem is to implement surrogate models to computationally mimic expensive, real building simulation models with a more feasible model.

This research aims to develop surrogate ANNs for selecting near-optimal building energy renovation methods. The ANN will be trained using the results of our previous research [3] focusing on Genetic Algorithms (GA) optimization of building energy renovation considering TEC, LCC, and Life Cycle Assessment (LCA) pairwise. Different scenarios can be compared in a building renovation strategy to improve energy efficiency. Each scenario considers several methods, including the improvement of the building envelopes, Heating, Ventilation and Air-Conditioning (HVAC) and lighting systems. The ANNs were developed as the surrogate models for emulating computationally expensive real building simulation models with more feasible models [66]. The proposed ANN models allow the extension of the traditional Building Energy Models (BEMs). To demonstrate the applicability of the models, a case study is developed to evaluate the accuracy of proposed ANNs. The case study of an institutional building has been investigated where different renovation methods have been processed using the SBMO model. The findings of the study demonstrate that the proposed trained network can act as an accurate and quick model for optimizing the energy performance of buildings, considering LCC and LCA.

The remainder of this paper is organized as follows. Literature review (Section 2), including the relevance of SBMO and ANN models, research methodology (Section 3), the implementation and case study (Section 4), and finally, the conclusions, limitations, and future works (Section 5).

2. Literature review

2.1. Energy-related renovation aspects

Improvement in the energy performance of existing buildings has a significant role in reducing negative environmental impacts [4]. However, most of the existing university buildings' envelopes and systems are in poor condition [5,62]. Therefore, an accurate energy predictive model is essential to facilitate better energy management systems.

Whole building renovation comprising envelope, HVAC, and lighting systems, has a notable influence on optimizing energy performance. Purdy and Beausoleil-Morrison [6] showed that building envelope and mechanical systems contribute tremendously to the total building LCC. Also, there is a strong correlation between optimizing energy performance and the LCC, as choosing different materials and components for renovation has a significant impact on the LCC. On the other hand, when it comes to improving environmental sustainability, finding a correlation between optimizing energy performance and LCC is a challenge [7]. Finding a balance between these important concepts is crucial to improving a building's energy performance.

LCA is a comprehensive and systematic approach to evaluating environmental impacts of a product or process during its entire life cycle [8]. LCA can incorporate the selection of environmentally preferable materials and the optimization and evaluation of the construction processes [9]. In the LCA of buildings, some of the impacts are currently not sufficiently studied [72]. One such impact is the results of changes that are made during renovations of a building throughout its life cycle [10]; Tabatabaee et al., 2015. LCA studies have been conducted on whole building renovation [11] or considering

refurbishments at the materials level [12] to find optimum results. Schwartz et al. [11] implemented Multi Objective Genetic Algorithms (MOGA) to find optimal designs for the renovation of a residential multi-function building, considering life cycle carbon footprint (LCCF) and LCC. The expected life cycle in their research was 60 years. By applying MOGA, the renovation LCC and LCCF can be decreased. They considered insulating thermal bridges and utilizing different heating systems and fuels as two main factors in the optimization. Renovation changes should be considered as a part of the building's recurring embodied energy. However, proposing a renovation strategy that takes full advantage of resources, while reducing the energy consumption and negative environmental impacts within an acceptable budget, is a big challenge for decision-makers, due to the complexity of the subject and the number of parameters involved.

With increasing advancements in innovative energy management technologies and methods for the renovation of existing buildings, such as efficient energy equipment, energy analysis tools, and building simulation tools, the opportunity to mitigate energy related problems and implement new optimization methods for renovation projects becomes practical. On the other hand, decision-makers, energy managers and participants in energy renovation projects, primarily tested their assumptions using BEMs, such as EnergyPlus and DesignBuilder [64], which are time-consuming.

2.2. Classification of building energy optimization

Several methods have been proposed by scholars to visualize, analyze, optimize, and predict the energy performance of buildings, implementing different mathematical, statistical and computational models [13]. These methods cover a wide range of techniques, from basic mathematics to the most complex neural networks, to improve building energy performance. However, despite the significant contribution of research on optimizing energy consumption, there is limited research focusing on a comprehensive renovation of existing buildings to minimize TEC, LCC, and their environmental impact using LCA.

The majority of optimization research focused on building envelope, building form, HVAC systems, and renewable energy. Energy, construction costs, LCC, operational costs, and comfort are among the most selected objective functions of optimization studies [14]. It is worthwhile to mention that some of the optimization methods (e.g. enumerative methods) are not frequently used in building optimization because the search space is usually too large or complex for these methods [15]. Stochastic and calculus-based optimization methods are more commonly used in complex optimization studies [16]. The MultiOpt tool, which is an integrated Non-dominated Sorting Genetic Algorithm (NSGA-II) optimization method, and the TRNSYS and COMIS simulation tools were used by Chantrelle et al. [15] to optimize energy use, comfort, and investment. Optimal façade solutions for a renovation case were considered by Jin and Overend [17] using EnergyPlus simulation and evaluating the trade-off between energy use, user productivity, and cost. Optimization procedures, such as evolutionary algorithms, can be implemented. However, building optimization, including multiple objectives, is usually a time-consuming process [18,19].

2.3. Challenges of simulation-based optimization in BEM

BEMs may be simplified [20] or comprehensive, which take significant computational time [15]. Also, several BEMs, e.g., EnergyPlus, TRNSYS, DOE-2, e-QUEST, COMIS (building performance simulation tools), and GenOpt [68] (optimization tool), are able to simulate energy consumption and calculate the cost and other related parameters, and apply different renovation scenarios based on the available building components and materials [14]. A multitude of recent studies have been conducted on the development of the SBMO models, which

integrate optimization and simulation into BEMs [21–23]. However, despite its strength, SBMOs are not able to guarantee optimal solutions from among the many possibilities of different scenarios [2].

The main obstacles in current SBMOs can be categorized in two main groups. From simulation point of view, the complexity of the dependent parameter and the computational time are the main issues. Moreover, from the optimization point of view, the uncertainty of many parameters should be considered during the optimization, including the optimization engine, the decision variables, the number of parameters to be optimized, the value of the objective functions, and constraints. Furthermore, current SBMOs are not user friendly and do not consider different parameters for a comprehensive assessment. Also, SBMOs are expensive and they need expert users to input detailed information based on the building complexity. Furthermore, for a big project, SBMO models may become infeasible because of the aforementioned problems. To solve the problem of infeasibility of SBMO, two techniques can be used. The first technique is to implement very simplified models instead of a detailed simulation model. This technique has many drawbacks, such as increasing the chance of inaccuracy, or oversimplification of the existing building, or even the inability of modeling complex building characteristics. For instance, Lee [24] used a two-step method to solve this problem. In the first step, a simple model was implemented, and then more detailed simulation models were developed considering the outcomes of the previous model. The second step reduces the number of generations or the population size of the optimization model. It is clear that these reductions also decrease the performance of the optimization algorithms significantly, or may even lead to sub-optimal solutions [25]. Another technique is to implement surrogate models (approximation models) to imitate computationally expensive, real building simulation models, with an appropriately representative model. Surrogate models (meta-models) can reduce the computational time while generating acceptable accuracy [26].

2.4. Surrogate Machine Learning Models in BEMs

Surrogate models are usually used at the preprocessing and post processing steps in simulation-based optimization studies of buildings [2]. The reliability of the surrogate model can be tested by comparing the results of the surrogate models with the original BEM [27]. Furthermore, several research studies have been conducted considering Machine Learning (ML) techniques for buildings as surrogate models [28–30]; and [31]. Also, a few studies addressing the integration of ML and simulation, or optimization, have been conducted. However, full integration between them, especially for building renovation, is still an open research problem.

Surrogate models are among the most promising solutions to improve convergence speed in optimization problems, while maintaining accuracy, as they can reduce the function evaluation computation cost and smooth noisy response functions [2] [65]. A Machine Learning Model (MLM) is a surrogate model of the original simulation model [67]. MLMs use data-driven techniques to train data from BEMs as an alternative approach [32]. Creating an MLM often involves the following three main steps: (1) Sampling input features as the dataset, which creates a dataset for training the surrogate model; (2) Applying a suitable MLM based on the dataset, training, validating, and testing before using it as a “surrogate” of the original model; (3) deploying MLM as a prediction model. In more detail, the first step includes data collection and processing, while the second step focuses on the MLMs development. During the second step, the processes of the selection and development of MLM, training, validation, and testing take place. The first and second steps may be iteratively repeated for the MLM until the convergence happens or validation achieves success. Finally, in the third step, the MLM can be utilized as a prediction model. Fig. 1 describes the stepwise procedure of the methodology.

Wei et al. [33] reviewed different data-driven methods implemented in building energy consumption. They categorized current

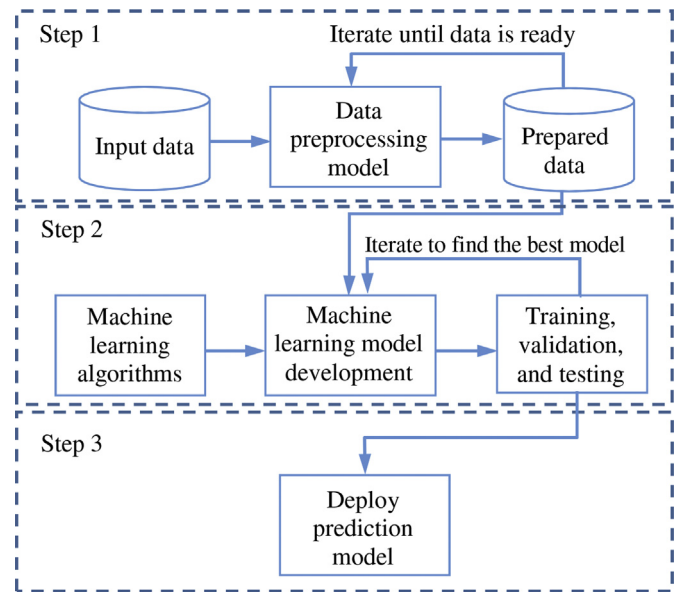


Fig. 1. Machine learning process for creating a surrogate model.

methods in two main groups, which are prediction methods (e.g. ANN, GA, SVM, statistical regression, and decision tree) and classification methods (e.g. K-mean clustering, hierarchy clustering, and self-organizing map) [70]. The number of published research papers about surrogate models related to buildings has been increased in recent years [33,34]. The study of Amasyali and El-Gohary in Ref. [35] shows that a significant number of previous ML studies (47% out of 63 studies) have used ANN to predict building energy consumption. Using ANN has a high potential for improving energy consumption modeling, analysis, and long-term forecasts for industries [36].

2.5. Artificial Neural Networks (ANNs)

ANNs are a type of Artificial Intelligence modeling method that imitates the human brain's behavior [37]. ANNs efficiently emulate the complex relationships of biological networks to answer complex non-linear problems [38]. By doing so, accurate results are maintained, while the computational time becomes insignificant. ANNs model the relationship between inputs and outputs by learning from the recorded data. Neurons are the fundamental computation units for ANN, which are connected by weighted links (synapses connections). Information transmission and manipulation occur using these networks. Input data from previous neurons is received by the following neurons. The learning process in ANN, called “network training”, is the ability to learn “rules” based on previous known relationships, and using them to control physical phenomena and generalize results for new situations [39]. A transfer function is used to manage these data and combine them to generate output data that are sent to the neurons in the next layer. Each neuron has associated weight and bias, which makes the network learn from provided inputs and outputs using training techniques. This iterative procedure continues until a stopping criterion is achieved, that can be the maximum number of iterations defined as epochs or the goals that are obtained, which properly set the weights of the synaptic connections by minimizing certain factors, for example the Root Mean Squared Error (RMSE) [40,41] or the Sum of Squared Errors (SSE) [42].

Feedforward Multi-Layer Perceptron (MLP) with linear or nonlinear neurons, Recurrent Neural Network (RNN), and Radial Basis Function neural network are among the different types of ANN structures. However, MLP feedforward algorithm is the most popular ANN [40]. Two architectures are used to improve the efficiency of the ANNs, which are Back-Propagation Neural Network (BPNN) and RNN [33].

Table 1
An overview of related ANN literature.

Reference	Method	ANN Method	Input		Output			Scope	Tool			
			Env	HVAC	Li	Comments	TEC			LCC	LCA	Comments
[40]	ANN used to design the supervisory MPC for HVAC. The MPC generated the dynamic temperature set-point profiles and BT water	SO	-	✓	-	HVAC system data for: ERV, AHU, BT, RFH and GSHP	✓	✓	-	Operating cost of the equipment and thermal comfort	Residential HVAC system	MATLAB, EnergyPlus, Measured data
[48]	Comparison between RF and ANN for high-resolution prediction	S	-	✓	-	Electricity consumption, outdoor air temperature, RH, time, social parameters	✓	-	-	Building energy consumption	Hotel in Madrid, Spain	Python, neurolab
[41]	Evaluation of ANNs with the optimization power of GA. MOO to study the interaction between the conflicting objectives and assess their trade-offs.	S	✓	✓	-	Building's characteristics and performance: EC, retrofit cost, and thermal discomfort hours, EW and R materials, W, solar collector and HVAC	✓	✓	-	EC, Retrofit cost, TPMVD	A school building Retrofit	MATLAB, TRNSYS, and GenOpt
[49]	ANN for the prediction of both average and maximum indoor air velocities	S	✓	-	-	Air velocity, Wind speed and direction for door openings, building width and length	-	-	-	Predict indoor average and maximum air velocities	New building designs in Turkey	FLUENT, MATLAB
[50]	Single-objective and MOO trained by ANN (filled with the genes of the best chromosome)	SO	✓	-	-	Insulation material, W type, W frame material, wall thermal resistance, and south and north WWR	✓	-	✓	Operational energy and environmental impacts	Low-rise office building envelope design	eQuest, ATHENA IE, Pascal
[51]	LM used to optimize the NN training. Then the prediction model based on the new algorithm was set up in terms of the main factors affecting the EC.	SO	-	-	-	Average temperature, Dew-point temperature, RH, electric consumption data	✓	-	-	Electric consumption	Public building short-term Prediction	MATLAB
[52]	NN used as the temperature identification structure to calculate the temperature of the near future accurately	O	-	-	-	Observed temperature of building equipment in an intelligent building	✓	-	-	Effective calculation of temperature	University library electronic reading room	Sensor data
[43]	The cost-optimal analysis by MOGA uses ANNs to predict building energy performance	SO	-	✓	-	Annual PEC factors, DH, global cost for energy uses over building lifecycle, TC	✓	✓	-	PEC ₁₀ , PEC ₂₀ , DH, and energy retrofit	Feasible for any building Retrofit	EnergyPlus and MATLAB
[45]	Predictive control of multi zone HVAC management (six self-growing ANN)	SO	-	✓	-	MPC and total consumption of electrical power	✓	✓	-	Thermal comfort and EC	Non-residential building	EnergyPlus, GA, and MATLAB
[46]	Hybrid Model Predictive Control (MPC) for energy and cost savings	-	-	-	-	Thermal dynamics of the building, overall thermal capacitance and heat gain from the occupants	✓	✓	-	MPC, temperature, energy and cost savings	An airport terminal building	Resistance capacitance thermal networks
[18]	Simulation-based optimization of an integrated meta-model for daylighting and HVAC	SO	-	✓	✓	Outdoor temperature, illuminance, (blind slat angle, supply air set point, AHU status, water flow, and outdoor air mixing ratio)	-	✓	-	Total power consumption, constraints indoor thermal and visual comfort	Office building	EnergyPlus and MATLAB
[53]	A simulation-based ANN to characterize building behavior, and combines this ANN with NSGA-II.	SO	✓	✓	-	HVAC system settings, thermostat programming, and passive solar design, W, WWR, RH, thermal mass	✓	-	-	Thermal comfort and EC	Residential house	TRNSYS and MATLAB
[39]	Comparison between ANN and detailed energy simulation model	S	✓	✓	✓	Building EC profile and meteorological data, (geometry, wall & W materials, Li, equipment & occupancy schedules)	✓	-	-	Predict EC (Li, Occupancy, & equipment) and weather parameters	University admin building	EnergyPlus
[54]	Adaptive ANN for unexpected pattern changes, and real-time on-line building prediction	-	-	✓	-	Data about temperatures and chiller electric demand and the temperature and electric demand measurements enclosed within the W	✓	-	-	To predict the chiller electric demand	CANMET Energy Technology Center	MATLAB
[44]	MOGA-BP network model for rapidly prediction	SO	✓	-	-	Plans, floor area, orientation, stories, shape coefficient, WWR, Wall, R, W (HTC,HII)	✓	-	-	EC and indoor thermal comfort	Residential buildings design	MATLAB

(continued on next page)

Table 1 (continued)

Reference	Method	ANN Method	Input		Output				Scope		Tool
			Env	HVAC	Li	Comments	TEC	LCC	LCA	Comments	
Current Study, 2019	Surrogate ANN for Selecting Near-Optimal Building Energy Renovation Methods	SO	NSGA-II and ANN	✓	✓	R, EW, FT, W, WWR, HVAC, COS, HOS, Li, EWO	✓	✓	✓	TEC, LCC, and LCA pairwise	Design-Builder and MATLAB

Nomenclature: Air Handling Unit (AHU); Best Network after Multiple Iterations (BNMID); Back-Propagation (BP); Buffer Tank (BT); Particle Swarm Optimization Algorithm (PSO); Percentage of Annual Discomfort Hours (PDH); Energy Consumption (EC); Energy Recovery Ventilator (ERV); Heat Transfer Coefficient (HTC); Heat Inertia Index (HII); Fixed Set-Point (FSP); Genetic Algorithm (GA); Ground Source Heat Pump (GSHP); Latin Hypercube Sampling (LHS); Levenberg-Marquardt Algorithm (LM); Life Cycle Environmental (LCE); Multi Criteria Analysis (MCA); Mean Squared Error (MSE); Model Predictive Control (MPC); Multi Objective Genetic Algorithm (MOGA); Mean Absolute Percentage Error (MAPE); Multi-Layer Perceptron (MLP); Natural Ventilation (NV); Neural Network (NN); Predicted Mean Vote (PMV); Optimization (O); Primary Energy Consumption (PEC); Radiant Floor Heating (RFH); Relative Humidity (RH); Response Surface Approximation Model (RSA); Simulation (S); Scaled Conjugate Gradient (SCG); Thermal Comfort (TC); Thermal Predicted Mean Vote Discomfort (TPMVD); Window to Wall Ratios (WWR).

BPNNs consistently propagate the computed output errors as negative feedback to neurons to modify the weight and concentration of input neurons. This method improves the accuracy of the ANN computation capability by minimizing output errors. The backward connection in RNNs enables the former layers to process their current inputs, as well as what they have learned from the inputs. RNNs have internal memory. Therefore, they are able to recall their input and accurately predict future outcomes.

ANNs have been used in various research areas, including energy performance prediction, energy and cost optimization, and energy retrofitting [43]; and [44]. Several studies have been proposed to minimize energy consumption using ANN [45,46]; and [47]. Several recent publications introducing ANN methods are categorized in Table 1. ANNs are pre-programmed in many tools, such as MATLAB®, and their efficiency is demonstrated in various building studies [33,50]. Melo et al. [55] explained different capabilities of ANN models and proposed them as a surrogate approach of energy performance assessment tool in labelling programs.

The integration of optimization and ANN initiated in early 1993. However, integrated models have been rarely used on BEMs ([35,42]. Concurred with the previous studies, this kind of integrated models can be very practical for SBMOs. Magnier and Haghighat [53] trained an ANN using TRNSYS simulation data. Then they coupled trained-validated ANN with NSGA-II to optimize energy consumption and thermal comfort considering HVAC system settings, thermostat programming, and passive solar design (called GAINN). Obviously, the time of the simulation by using TRNSYS is far greater than the time needed by the ANN. The direct coupling between TRNSYS and NSGA-II would take more than 10 years; while using the GAINN approach, this time is reduced to 3 weeks for the whole methodology, which is mainly the simulation time required to generate the dataset [53].

Asadi et al. [56] proposed a Multi Objective Optimization (MOO) considering five decision variables, i.e. insulation material for roof and external walls, windows, HVAC systems, and solar collector types for building retrofitting and three objective functions, i.e. energy consumption, thermal discomfort hours, and overall investment costs. The energy consumption for lighting is excluded from their study. Consequently, a three layer feedforward ANN with input, hidden, and output layers, was utilized to combine with the MOO to quantitatively evaluate the selection of different technologies for retrofitting of an existing school.

Among recent publications, some of them mainly focus on the improvement of the HVAC and lighting using MOO [18,19,57]. Kim et al. [18] developed an Integrated Daylighting and HVAC (IDHVAC) model using simulation-based optimization to predict building energy performance by artificial lighting regression models and ANN. Their model used the design of experiments method to generate the database that was utilized for ANN training. Integration of GA and IDHVAC system, which is based on the database that was generated using the EnergyPlus model, leads to minimizing TEC while satisfying occupants visual and thermal comfort, concurrently [18].

Minimizing the energy and cost for HVAC systems in existing commercial buildings is studied by Huang et al. in Ref. [46]. They proposed a Hybrid Model Predictive Control (HMPC) by combining a classical Model Predictive Control (MPC) with an ANN feedback linearization algorithm. The HMPC model contains a simplified physical model for control and an inverse ANN, which works independently as a nonlinear compensator for the HVAC process. They utilized both a forward ANN and an inverse model in the feedback loop. The merits of using an inverse ANN model is to determine the link between the virtual input and the actual input [46]. Wei et al. [19] proposed a data-driven method to optimize the TEC of the HVAC system in an Energy Resource Station (ERS) center, considered as a typical office facility.

Garnier et al. [45] developed a predicative method for the management of multi zone HVAC systems in non-residential buildings using EnergyPlus, GA, and a low-order ANN. Initially EnergyPlus is used for

energy simulation modeling. Consequently, GA is developed to minimize the total consumption of electrical power while achieving acceptable thermal comfort requirements utilizing Predicted Mean Vote (PMV) indicator. In more detail, GA optimizes the operation time of all of the HVAC subsystems by computing the right time to turn the HVAC subsystems on and off while meeting thermal comfort requirements. They created six self-growing ANN-based models and implemented them as internal controller models.

The study by Neto and Fiorelli [39] on comparing EnergyPlus simulation methods with ANN models has two important conclusions. Firstly, both models are suitable to estimate energy consumption, and secondly, EnergyPlus predictions have an error range of $\pm 13\%$ for 80% of the tested reference buildings. The results for the ANN models revealed a fair agreement between energy consumption predictions and Existing Situation (ES), with about 10% error, considering different networks for working days and weekends. However, they claim that utilizing a more suitable ANN can improve the results [39]. Ahmad et al. [48] showed that the performance of the BPNN is marginally better than the performance of Random Forest (RF) for predicting the hourly HVAC electricity consumption.

Reviewing the existing prediction models using ANN for energy consumption done by Amasyali and El-Gohary [35]; leads to the following observations: (1) The majority of models, (81%) focused on non-residential buildings, specifically educational and commercial buildings; (2) Almost half of the proposed models predicted TEC (47%), while 31% and 20% of the models predicted cooling and heating energy consumption, respectively. Interestingly, only 2% of the models predicted lighting energy consumption; (3) variety of features were selected by scholars, including external weather conditions, indoor environmental conditions, building attributes, related occupant behavior and occupancy, and time features. However, previous studies used ANNs to simulate or predict only few aspects of the buildings. Besides, there is limited research combining all types of features in a building simultaneously [33,35]. Furthermore, currently only a modest amount of literature is available on the energy consumption prediction through integrating ANN and BEM and none of them consider the whole building envelope, HVAC, and lighting simultaneously.

In this study, different ANNs are used to predict and model energy performance, LCC, and environmental impacts of renovating combinations of elements of an existing building (i.e., Roof Types (R), External Walls (EW), windows (W), Façade Type (FT), Window to Wall Ratio (WWR), HVAC systems, Cooling Operation Schedule (COS), Heating Operation Schedule (HOS), Lighting systems (Li), and External Window Open (EWO)).

3. Research methodology

This study focuses on ANN to achieve renovation scenarios that minimize TEC, LCC, and environmental impacts. Different ANNs were used to model the relationship between the near optimal renovation scenarios of the buildings envelope, HVAC, and lighting, and their TEC, LCC, and LCA (Fig. 2). The following paragraphs initially provide a brief introduction of the SBMO and then explains the research methodology.

Firstly, extensive data is collected on existing buildings related to several factors including TEC, outside temperature, building envelope components, HVAC and lighting systems. Then an energy model of the existing building is created in DesignBuilder and validated through the comparison with energy bills. Consequently, the SBMO model that combines TEC, LCC, and LCA, which is proposed by the authors [3], is used to propose the near optimal renovation scenarios. Subsequently, a representative dataset of renovation scenarios is created using the results of SBMO. This dataset is used to train and validate different ANN models. It is worthy to mention that the complexity of the ANN models has a significant effect on the training time and performance of the model. Furthermore, to evaluate the efficiency of the proposed model, a

comparison between the SBMO and the final results of the ANNs is performed to clarify the performance of the surrogate model.

The proposed model integrates the optimization power of SBMO with modeling capabilities of Multilayer Perceptron (MLP) ANN. The main advantage of this integration is to improve the computing time while achieving acceptable accuracy.

The proposed framework has three essential but interdependent parts, which are SBMO model development, data processing, and surrogate model development. Each part has several phases that are explained in detail. The proposed method combines the following seven phases as shown in Fig. 2: (1) SBMO for building renovation considering TEC, LCC, and LCA for some parts of the building, which was the result of a previous study [3]; (2) Data preprocessing including database development and integration; (3) Dataset preparation using the buffer list; (4) Data normalization; (5) Loading normalized data; (6) ANNs development; and (7) Training and testing of proposed ANNs, which will be used as a prediction model.

3.1. Modeling in simulation tool (SBMO model) (phase 1)

A computer model of the building under consideration is developed in the BEM. Special care should be taken in the model development. The simulation model contains information about related external factors, such as weather data and geographic location, and internal critical factors, such as building envelope components and materials, detailed HVAC system and lighting system, as well as an operational schedule for heating and cooling to investigate the performance of the Existing Situation (ES). Finally, other information is modelled, such as the functionality of each space, typical occupant activities and clothing, and appliance energy consumption, as would be expected in the real building. For validation, the simulation results should be compared with energy bills, in terms of energy consumption. Although other factors such as building occupancy, equipment, and Domestic Hot Water (DHW) have been modelled on the BEM, they remain constant for SBMO optimization. Acceptable renovation methods or ranges are defined based on the results of a previous study [3] for the building envelope, HVAC systems and lighting systems. Each renovation scenario considers several methods, including the improvement of the building envelopes, HVAC and lighting systems, and has individual labels, including TEC and LCC, or TEC and LCA.

Consequently, the second part of Phase 1 involves developing the optimization model, which is integrated with the simulation tool to shape the SBMO model. A specific category of Genetic Algorithms, named Multi-Objective Evolutionary Algorithm (MOEA), is selected. The MOEA enables the algorithm to optimize all objective functions simultaneously, based on Pareto dominance. The Non-dominated Sorting and crowding Genetic Algorithm II (NSGA-II) is chosen for this part of the study. The objective functions are calculated for each renovation method using the capability of the BEM. The optimization engine computes the objective functions, which minimize TEC, LCC, and LCA for each scenario, based on the selected values of the methods in each simulation run.

The SBMO generates near-optimal scenarios for a particular strategy. The results of the optimization are shaped into the Pareto front, which will be used to investigate the trade-off relationships among the different renovation scenarios, as well as to develop input data for Phase 2 of the data preprocessing (Fig. 2). The final goal of this phase is to simultaneously optimize all objective functions of TEC, LCC, and LCA.

To lessen the computational burden, one part of the building (i.e. one floor) that is representative of the whole building has been simulated and optimized using the SBMO model. The initial search space contains a huge number of different renovation scenarios (by the billions), which include many related factors. A small number of possible scenarios (about 5000 different renovation scenarios, including Pareto front) is generated from the SBMO model. However, calculating TEC,

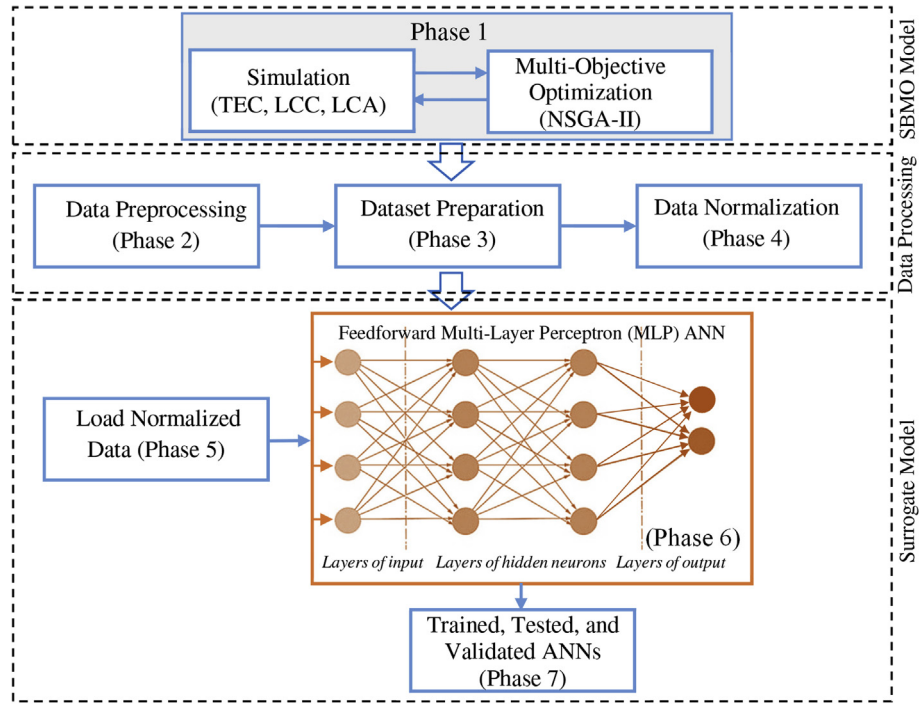


Fig. 2. Architecture of the proposed model.

LCC, and environmental impacts for these generated scenarios is a time-consuming task for simulation tools. It is worth mentioning that training a surrogate model using inaccurate data can produce misleading results.

3.2. Data preprocessing (phase 2)

Data preprocessing includes dataset development and integration. The preprocessing of the input layer data is vital, which is sometimes ignored in ANN developments. The preprocessing step is needed to eliminate missing or repeated values, and inconsistencies for different features through data transformation and integration [58]. For instance, Amasyali and El-Gohary [59] preprocessed outdoor weather-related parameters to develop possible feature pool for their MLM, which is used to predict hourly cooling energy consumption. They removed non-occupied hours data (e.g., weekend hours) from the dataset because their case study has altered operational features in these hours. They performed a stepwise regression for feature selection. The results indicated that out of 22 weather-related variables, only 14 features should be utilized for MLM. Consequently, they used mean and standard deviation to center and scale each feature of the dataset, respectively [59]. The preprocessing phase has many advantages, such as minimizing biased data, and creating a complete and clean dataset. In this study, repetitive and noisy (invalid) renovation scenarios have been removed from the dataset.

3.3. Dataset preparation using a buffer (phase 3)

Phase 3 is for selecting a buffer of acceptable scenarios (within a predefined range), in terms of TEC, LCC, and LCA using a sequential approach (Fig. 3). Initially, the Pareto Front results are identified, labeled, and excluded from the main list. Consequently, new Pareto Front results are generated from non-optimal configurations and excluded from the main list, and added to the selected list of solutions. This step is iteratively repeated until a sufficient number of solutions is selected. A schematic definition of the buffer (blue area) of acceptable renovation scenarios, considering two constraints (maximum acceptable value) for TEC and LCC is shown in Fig. 3.

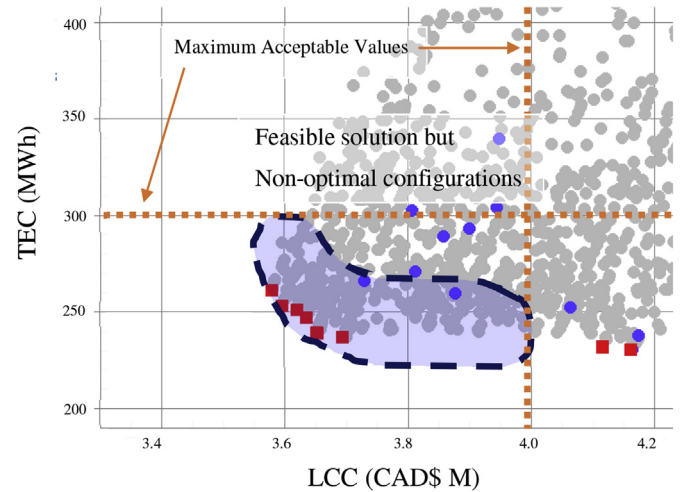


Fig. 3. A schematic definition of the proposed buffer.

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})} (x'_{max} - x'_{min}) + x'_{min} \quad (1)$$

Several studies have concluded that for a network with N number of variables, a sample size of $2 \times N$ or more is sufficient to correctly sample the search space [53,60]. It should be noted that a smaller sample dataset can reduce the representation of the search space, while selecting too many samples will increase computation cost [60].

3.4. Data normalization (phase 4)

In Phase 4, both the renovation methods (that are considered as input features) and the objective functions resulting from proposed scenarios (target features) are normalized using a linear transformation approach. The magnitude of the input values should be scaled to avoid the overflow error in the input value [61]. Furthermore, some of the features do not have units (e.g. R, EW, and W) or have percentages (e.g. WWR and EWO) or have their own units (e.g. TEC, LCC, and LCA).

Data normalization unifies features that may significantly alter the feature values, thereby affecting the quality and accuracy of the dataset and avoiding dependency on the selection of feature units. Also, data normalization can stop features with large ranges from compensating for those with relatively smaller ranges (e.g. LCC with a value range of millions can outweighs EWO with a maximum value of 70%). The contribution of different renovation methods as input features, to TEC, LCC, and LCA values, as target features, may differ substantially. A code is assigned to each method that specifies its name. Furthermore, the Number of Replications (NoR) of a method in different renovation scenarios indicates its importance, which must be considered to prevent the occurrence of the outweighing problem. Otherwise, it may force the network into depending on specific methods and outweighing the others. Although excellent outputs can be shown, the ANN's performance is tied to that particular dataset, which may result in the incapability of the ANN to perform well with new data. Therefore, the ANN cannot be generalized. After normalizing the data, each feature must be related to a weight that indicates its importance. The normalization phase is very critical to increase the range of deviance and reducing the effect of the magnitude of the input data throughout the ML training process. Min-max normalization (Eq. (1)), which is used in this research, has the ability to maintain the intrinsic interaction between the initial data because it executes a linear normalization. To achieve better training performance, all input and output data are transformed using min-max normalization [58]. For a parameter x the normalized value x' , is obtained as: where x_{min} and x_{max} are the minimal and maximal value of the variable x , and x'_{min} and x'_{max} are the minimal and maximal values of the variable x after normalization, which can be transformed to a range between -1 and $+1$.

3.5. Surrogate model training and testing (phases 5–7)

Surrogate model development has four phases: (1) Load normalized data (Phase 5), (2) ANN models development (Phase 6), and (3) Training, validation, and testing (Phase 7). The goal of Phase 5 is to divide and load input data into two subcategories, which are training and testing data, to find the optimum modeling of an ANN including weights and biases. Therefore, a random selection approach is utilized that selects 70% of the normalized data to train the ANN and optimize weights and biases, and the remaining 30% of the data is used for testing and validation. Subsequently, the definition of the ANN architecture is implemented in the Phase 6 of ANN methodology. The aim is to define the number of layers and the number of neurons within each layer and select a suitable training algorithm. Two different ANNs have been developed, i.e. ANN1 (TEC vs. LCC) and ANN2 (TEC vs. LCA) (Fig. 4).

Each MLP ANN is defined with different neurons in the input, hidden, and output layers. The number of neurons in the input layer is equal to the number of input variables. The most commonly used activation functions in the optimization of ANNs are hyperbolic tangent

sigmoid, linear transfer functions, and Logistic sigmoid [50,54]. The final phase for surrogate modeling (Phase 7) in ANN is training, validation, and testing of the network. Therefore, the Mean Squared Errors (MSEs) for both training and testing datasets should be calculated to evaluate the performance of the ANN. Weights and biases values for each neuron should be adjusted and optimized to minimize the MSEs for the training and test datasets concurrently [50]. MSE values describe the network's performance and are calculated based on the average of the summation of the differences between the network predictions and the targets (Eq. (2)):

$$MSE = \frac{1}{N} \sum_{i=1}^N (X_i - X_{i,target})^2 \quad (2)$$

where N is the number of data, X_i , and $X_{i,target}$ are the network output and target values for training and test processes, for the i th experiment, respectively.

4. Implementation and case study

The following section describes the implementation of ANN based on the results of SBMO on the last floor (containing the roof) of a multipurpose university building at Concordia University with a net floor area of 1708 m². The input data were provided by developing the Building Information Model (BIM) using Revit. 2D plans and sections, documents including building envelope and roof components and materials, were adjusted in the BIM model as shown in Fig. 5 (a and b).

DesignBuilder [64] is used in analyzing whole building energy performance calculations. It is a user-friendly tool and it has the capability of optimizing building performance. ANNs are created in MATLAB[®] using the results of the DesignBuilder as input parameters and weighting factors for networks' training and testing. The SBMO model of building energy performance considering TEC, LCC, and LCA is developed to create networks' inputs to properly select the accurate values for decision variables (i.e. to identify the near optimum renovation scenarios).

The MATLAB[®] environment is used for developing the related functions, which are employed later on for ANNs. Based on the recommendation of MATLAB, the range of $(-1, 1)$ was used to normalize all inputs and outputs before training, to improve the efficiency of the network. The complexity of an ANN model is determined by the number of hidden layers. To minimize the training dataset error, the number of hidden layer neurons should be increased, which, as a result, will compromise the generalization ability of the ANN. The back-propagation method is used for the ANN training, associated with the Levenberg-Marquardt (LM) algorithm. Two different transfer functions are used, which are the hyperbolic tangent sigmoid, used in the initial and hidden layers, and linear functions, used in the output layer. Fig. 6 shows the implementation steps and the tools used to achieve the results.

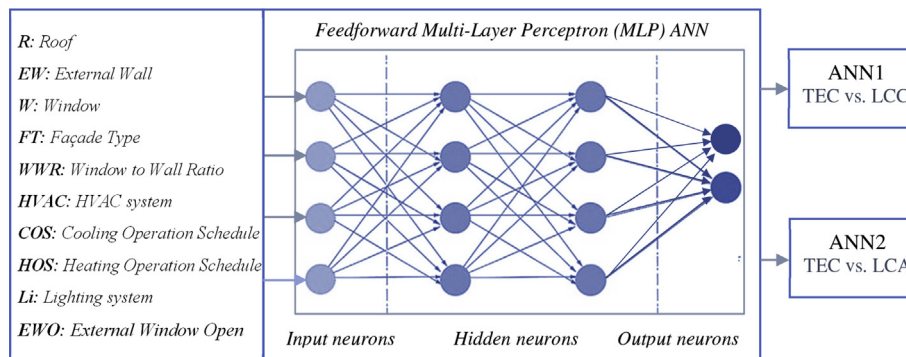
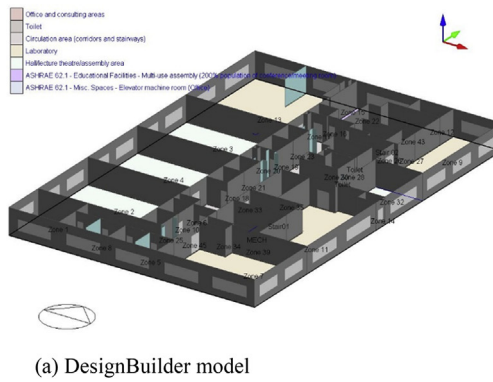


Fig. 4. Artificial neural network architecture.



(a) DesignBuilder model



(b) Front side of the University building.

Fig. 5. Case study model.

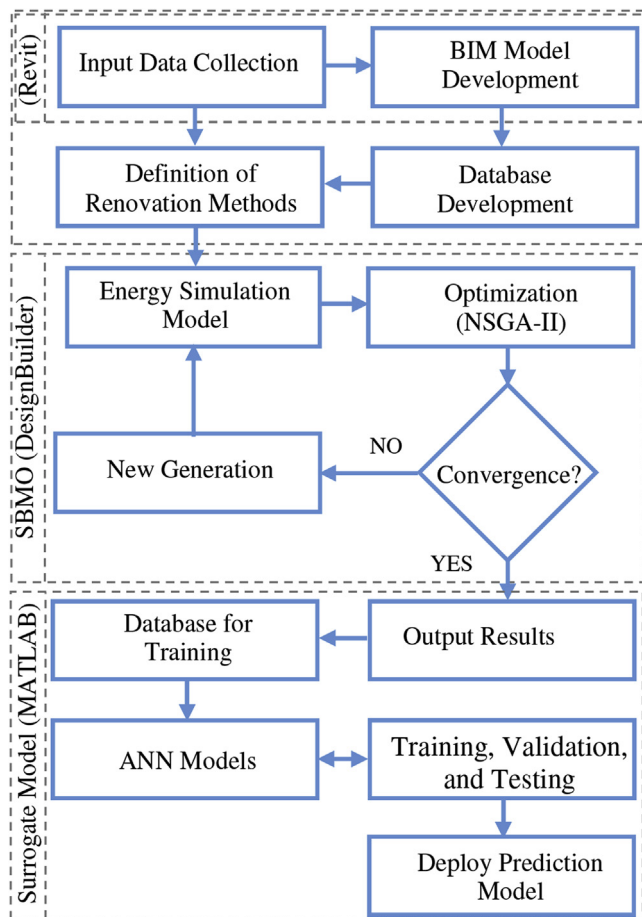


Fig. 6. Implementation steps.

4.1. Energy SBMO model

The case building is located in Montreal, Canada. The local weather data were used in the simulations. Extensive data were collected on the existing building related to several factors including TEC, outside temperature, existing building envelope components, i.e. external walls, roof, properties of windows (frame and glazing), their locations, and orientations. Also, the detailed HVAC system and lighting systems, allocation of building activities, and Domestic Hot Water (DHW) were adjusted in the BEM. Several parameters were added or modified, and different “zones” were defined in the model to obtain more accurate results (Fig. 5(a)). Sample input data of the building characteristics are shown in Table 2. Simulations are performed for the cold-climate city of

Table 2

Sample input data of the building characteristics.

Description	Characteristics
Roof Surfaces	U-value = 0.25 W/m ² K.
Exterior Walls	Brick/block exterior finishing
Windows	WWR: 30% clear 6 mm glass, Double glazing in some parts, Frame: Steel and Aluminum
Airtightness	0.3 ACH constant rate, ON 24/7
Operation Schedule	7:00–23:00 Mon-Fri
Space Allocation	Study spaces, office, mechanical and electrical room, restrooms, storage, and corridors.
Activity	Educational Facilities (multi use), Occupancy density: 1.0764 (people/m ²)
HVAC System	Fan coil unit, Air cooled chiller, Boilers and chillers: on 24/7, Air systems shut off: 11:00–7:00 a.m.
Temperature Setting	22 °C cooling, 28 °C cooling set back, 20 °C heating, and 15 °C heating set back
Heating	Natural Gas, Max: 45 °C
Cooling	Electricity from grid, Min: 12 °C
DHW	Electricity from grid, Dedicated hot water boiler

Table 3

Cross-checking of the results.

TEC of Existing Situation (ES) (kWh/m ²)		Differences (%)
Energy Bills (Metering)	358	–
DesignBuilder (Energy Simulation Tool) [64]	381	6.1
ATHENA (LCA Simulation Tool) [63]	391	9.2

Montreal (Climate Zone 5). The obtained results show that the controlled temperature is 20.09 °C, radiant temperature is 15.84 °C, operative temperature is 17.97 °C and the outside dry-bulb temperature is –23.20 °C. In this climate zone, the energy consumption in buildings is mainly used for heating.

The data collected were then validated by other methods such as a semi-structured interview, site visit, and analyzing the plans and sections of the building. The result of the TEC for ES, which is calculated by the BEM, is validated through comparison with energy bills, and ATHENA LCA simulation tool [63] (Table 3). The total site energy consumption is about 651,485 kWh, which is equal to 381 kWh/m². The actual energy consumption based on the energy bills was 611,479 kWh for the years 2014–2015, which reflects 6.1% difference in the values (DesignBuilder). This difference is considered acceptable (Table 3). The specific collected data are then added to the extensible database, which includes a wide range of different renovation methods of the buildings envelope, HVAC, and lighting. The extensible database also contains other information, i.e. LCC and environmental impacts related to each method. The next step involves defining the renovation

Table 4
Building systems renovation codes and number of replications (NoR).

ID	HVAC- Heating, Ventilation and Air-Conditioning (25)	Code	NoR
HVAC01	Air to Water Heat Pump (ASHP) Hybrid with Gas Boiler, NV	15,350	53
HVAC01	Air to Water Heat Pump (ASHP), Convectors, NV	15,400	191
HVAC02	Fan Coil Unit (4-Pipe) with District Heating + Cooling	15,450	175
HVAC02	Fan Coil Unit (4-Pipe), Air cooled Chiller	15,500	5
HVAC02	Fan Coil Unit (4-Pipe), Air cooled Chiller, DOAS	15,550	24
HVAC02	Fan Coil Unit (4-Pipe), Water cooled Chiller, Water-side economizer	15,600	72
HVAC03	PTAC Electric Heating	15,650	174
HVAC03	PTAC HW Heating	15,700	57
HVAC04	PTHP	15,750	28
HVAC05	Radiator heating, Boiler HW, Mech vent Supply + Extract	15,800	84
HVAC05	Radiator heating, Boiler HW, Mixed mode NV, Local comfort cooling	15,850	8
HVAC05	Radiator heating, Boiler HW, NV	15,900	78
HVAC07	Radiators Electric, NV	15,950	2992
HVAC06	Split + Separate Mechanical Ventilation	16,000	71
HVAC06	Split no fresh air	16,050	19
HVAC08	VAV, Air-cooled Chiller, Fan-assisted Reheat (Parallel PIU)	16,100	149
HVAC08	VAV, Air-cooled Chiller, HR, Outdoor air reset	16,150	14
HVAC08	VAV, Air-cooled Chiller, HR, Outdoor air reset + mixed mode	16,200	32
HVAC08	VAV, Air-cooled Chiller, Outdoor air reset	16,250	45
HVAC08	VAV, Air-cooled Chiller, Reheat	16,300	75
HVAC08	VAV, Air-cooled Chiller, Steam humidifier, Air-side HR, Outdoor air	16,350	18
HVAC09	VAV, Dual duct, Air-cooled Chiller	16,400	16
HVAC09	VAV, Dual duct, Water-cooled Chiller	16,450	225
HVAC10	VAV, Water-cooled Chiller, Air-side HR, Outdoor air reset	16,500	5
HVAC10	VAV, Water-cooled Chiller, Full Humidity Control	16,550	9
ID	HOS- Heating Operation Schedule (7)	Code	NoR
HOS04	7:00–23:00 Mon - Fri	2,050,250	1030
HOS05	6:00–18:00 Mon - Fri	2,050,750	575
HOS02	Max Indoor temp for NV: Always 100	2,051,250	1583
HOS02	Max Outdoor temp for NV: Always 100	2,051,750	795
HOS02	Mixed mode temperature control	2,052,250	182
HOS01	On 24/7	2,052,750	167
HOS03	Two season schedule (Northern Hemisphere)	2,053,250	287
ID	COS- Cooling Operation Schedule (7)	Code	NoR
COS04	7:00–23:00 Mon - Fri	450,900	263
COS05	6:00–18:00 Mon - Fri	451,500	2844
COS02	Max Indoor temp for NV: Always 100	452,100	230
COS02	Max Outdoor temp for NV: Always 100	452,700	258
COS02	Mixed mode temperature control	453,300	636
COS01	On 24/7	453,900	148
COS03	Two season schedule (Northern Hemisphere)	454,500	140
ID	Li- Lighting (8)	Code	NoR
Li02	Canadian energy code	90,000	378
Li04	Fluorescent, compact (CFL)	91,500	97
Li05	High-pressure Mercury	93,000	238
Li06	High-pressure sodium	94,500	99
Li03	LED with linear control	96,000	491
Li03	LED	97,500	2992
Li04	T5 (16 mm) Fluorescent, HF, LINEAR daylighting	99,000	67
Li04	T5 (16 mm) Fluorescent, HF	100,500	257

goals, methods, and tasks for each renovation scenario based on available methods, which are embedded in the databases. The goal is to develop renovation scenarios based on a set of methods. Each scenario consists of several renovation methods within the applicable strategy.

Two separate optimizations are performed using the NSGA-II algorithm, which is integrated in the simulation tool. Simulation is carried out for each renovation scenario generated by the NSGA-II optimization process, and TEC, LCC, and LCA values obtained from the simulations are calculated pairwise. The SBMO process is iteratively repeated until the convergence criteria are achieved. Afterwards, optimum renovation scenarios (non-dominated) and dominated scenarios along with detailed information about the selected methods for each scenario are stored in the database (Phase 1). In this study, the results of SBMO are used to generate the lists of acceptable renovation scenarios. A more

detailed, step-by-step description of the SBMO methodology is available in Ref. [3].

Subsequently, in Phase 2, datasets are collected, and noisy or repeated scenarios are identified with significant variations in the TEC, LCC, or LCA. These noisy (e.g., invalid scenarios) or repeated scenarios should be removed from the final dataset through data transformation and integration. The output of the SBMO model is summarized in two different Excel files containing 4720 results. It is worthwhile to mention that the contribution of different renovation methods to the TEC, LCC and LCA may differ significantly, which is defined by the number of replications of that method in different renovation scenarios (NoR) (Table 4 and Table 5). Consequently in Phase 3, the results of previous phases were filtered to remove the infeasible scenarios using the buffering approach. Among the different renovation scenarios, only 463

Table 5
Building envelope renovation codes and number of replications (NoR).

ID	EW- External wall (22)	Code	NoR
EW04	Lightweight curtain wall (insulated to 1995 regs)	100	92
EW04	Lightweight curtain wall insulated to 2000 regs	140	150
EW09	Innovative wall	180	57
EW08	Advanced Insulation	220	14
EW03	Cavity wall (E&W) Part L	260	34
EW08	Advanced Insulation	300	8
EW01	Brick air, concrete block-Uninsulated - MW	340	28
EW03	Cavity wall (E&W) Part L	380	63
EW05	Semi-exposed wall Energy code - HW	420	21
EW05	Semi-exposed wall Energy code - LW	460	142
EW05	Semi-exposed wall Energy code - MW	500	71
EW05	Semi-exposed wall Typical reference - HW	540	49
EW05	Semi-exposed wall Typical reference - LW	580	90
EW05	Semi-exposed wall Typical reference - MW	620	155
EW06	Wall - Energy code standard - HW	660	243
EW06	Wall - Energy code standard - LW	700	53
EW06	Wall - Energy code standard - MW	740	197
EW07	Wall - State-of-the-art - MW	780	2669
EW02	Brick cavity with insulation - HW	820	335
EW02	Brick cavity with insulation -LW	860	19
EW02	Brick cavity with insulation -MW	900	69
EW01	Brick air, concrete block	940	60
ID	R- Roof (16)	Code	NoR
R02	Combined flat roof - Energy code - HW	5000	83
R02	Combined flat roof - Energy code -LW	5250	63
R02	Combined flat roof - Energy code -MW	5500	184
R03	Combined flat roof - 19 mm asphalt - HW	5750	265
R03	Combined flat roof - 19 mm asphalt -LW	6000	22
R03	Combined flat roof - 19 mm asphalt - MW	6250	91
R04	Combined flat roof - Typical reference - HW	6500	32
R04	Combined flat roof - Typical reference - LW	6750	29
R04	Combined flat roof - Typical reference -MW	7000	72
R05	Combined semi-exposed roof - Energy code - HW	7250	17
R05	Combined semi-exposed roof - Energy code - MW	7500	20
R00	Project flat roof	7750	3114
R07	Innovative	8000	299
R01	R-19 + 10 (3.3 + 1.8), U-0.041 (0.232)	8250	184
R01	R-19 + 19 (3.3 + 3.3), U-0.046 (0.261)	8500	62
R05	Combined semi-exposed roof - Energy code - LW	8750	82
ID	FT- Facade type (22)	Code	NoR
FT01	100% fitted glazing	1350	36
FT02	40% Vertical Glazing ASHRAE 90.1 Appx G	1400	72
FT04	Curtain wall, 85% glazed	1450	36
FT03	Fixed height 1.5 m, 30% glazed	1500	42
FT03	Fixed height 1 m, 20% glazed	1550	62
FT03	Fixed windows - height:1.0 m, width:0.5	1600	3093
FT03	Fixed windows - height:1.0 m, width:1.0	1650	113
FT03	Fixed windows - height:1.5 m, width:1.0	1700	128
FT05	Horizontal strip, 50% glazed	1750	33
FT05	Horizontal strip, 60% glazed	1800	108
FT05	Horizontal strip, 70% glazed	1850	76
FT05	Horizontal strip, 80% glazed	1900	69
FT05	Horizontal strip, 90% glazed	1950	133
FT05	Horizontal strip, 100% glazed	2000	93
FT06	Preferred height 1.5 m, 10% glazed	2050	305
FT06	Preferred height 1.5 m, 20% glazed	2100	38
FT06	Preferred height 1.5 m, 30% glazed	2150	35
FT06	Preferred height 1.5 m, 40% glazed	2200	34
FT06	Preferred height 1.5 m, 50% glazed	2250	33
FT06	Preferred height 1.5 m, 60% glazed	2300	25
FT06	Preferred height 1.5 m, 70% glazed	2350	18
FT06	Preferred height 1.5 m, 80% glazed	2400	21
FT06	Preferred height 1.5 m, 90% glazed	2450	4
FT06	Preferred height 1.5 m, 100% glazed	2500	10
ID	W- Window frame types (6)	Code	NoR
W01	Aluminum window frame (no break)	1,105,000	57
W01	Aluminum window frame (with thermal break)	1,106,000	143
W02	Painted Wooden window frame	1,107,000	167

(continued on next page)

Table 5 (continued)

W04	BIPV	1,108,000	3453
W03	UPVC window frame	1,109,000	329
W02	Wooden window frame	1,110,000	470

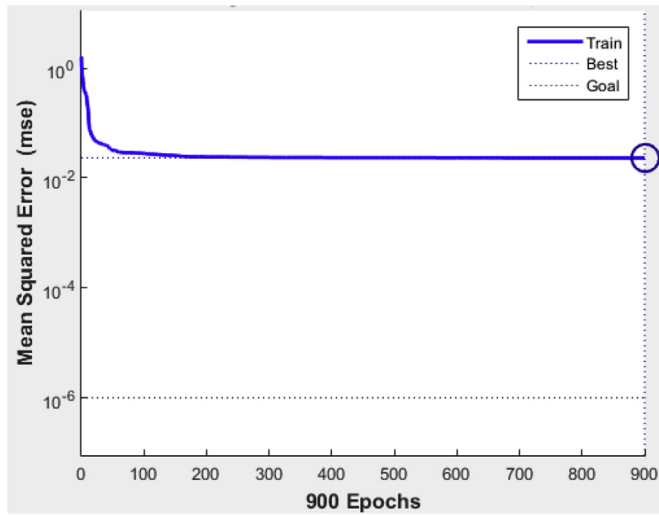


Fig. 7. The performance of ANN training (TEC vs. LCC).

Table 6

Statistical details of the ANN model training and testing.

Response	TEC vs LCC	TEC vs LCA
Training dataset	325	325
Testing dataset	138	138
Dataset (Total)	463	463
Number of epochs	900	900
Training MSE	0.016	0.056
Test MSE	0.088	0.124

were selected due to their acceptable results in terms of TEC, LCC, and LCA.

The next phase is the normalization of data (Phase 4), which can prevent the occurrence of the outweighing problem between large-scale results (e.g. LCC and LCA) and those with relatively small ranges (e.g. WWR and EWO). Therefore, a code is assigned to each method that specifies its name and its importance while avoiding the occurrence of the outweighing problem.

4.2. Architecture of Artificial Neural Network models

Two datasets of 463 renovation scenarios, including ten renovation methods (results of SBMO) and the values of two objective functions for each scenario (i.e. TEC, LCC, and LCA pairwise), were used for ANN training and testing. As previously mentioned (Section 3.3) there is no general rule for choosing the number of hidden layer neurons. It is essential to develop ANNs that are able to predict TEC, LCC, and LCA of a renovation scenario with reliable accuracy. However, an increase in the number of neurons in hidden layers may result in overfitting/overtraining problem. In this case the generalization accuracy of ANNs may be impaired because of fitting some 'noise' in the dataset. Concurrently, another problem that also effects the ANNs performance is the underfitting, which occurs in shallow ANNs with too few neurons in hidden layers. Underfitting can result in large errors in the ANN [48].

In this study, initially five-layer ANNs were defined with 10 neurons in the input layer, three neurons in the hidden layers, and two neurons in the output layer. Then a gradually searching method was used to reach the optimal values. It was found that in this model, the higher number of layers and neurons significantly improves the accuracy of the ANN. Finally, a five-layer ANN was defined with 10-5-6-4-2 neurons in input, hidden (three layers), and output layers. The number of neurons in the input layer is equal to the number of input variables, i.e. $R, EW, W, FT, WWR, HVAC, COS, HOS, Li$, and EWO as illustrated in Fig. 4. The numbers of hidden neurons in the respective layers are defined based on the try and error approach to achieve the best MSE on the test data. The most commonly used *Tansig* activation function was used for the hidden and output layers to measure outputs of each neuron within the normalization range of -1 to $+1$. ANNs were trained, implementing the Levenberg–Marquardt and Bayesian regularization algorithms. Convergence for the training is achieved if MSE is stabilized over certain iterations or if the maximum number of epochs is reached (e.g. 900) (Fig. 7).

4.3. Results and discussion

A sample of 138 renovation scenarios, different from the previous cases, was used to test each network. A random selection approach was utilized that selected 70% of the normalized data to train the ANN and optimize weights and biases, and the remaining 30% of the data is used for the validation and testing process. ANN outputs were assessed with the equivalent SBMO outputs. It is worthwhile to mention that both

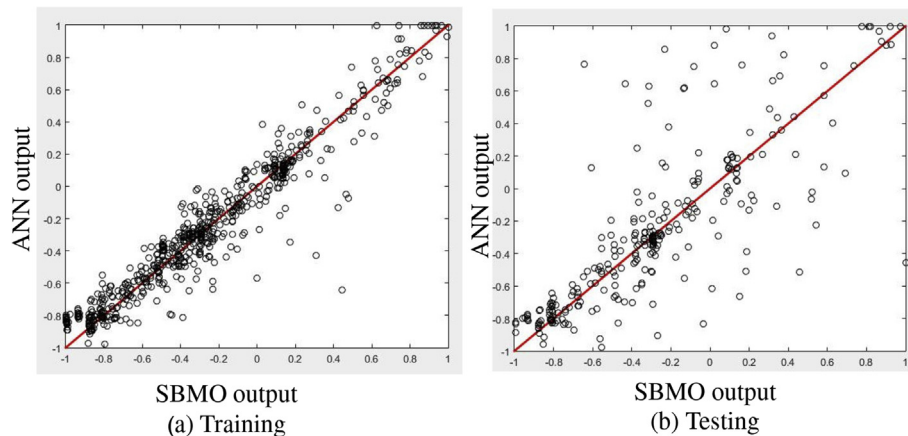


Fig. 8. Regression plots of ANNs vs. SBMO outputs.

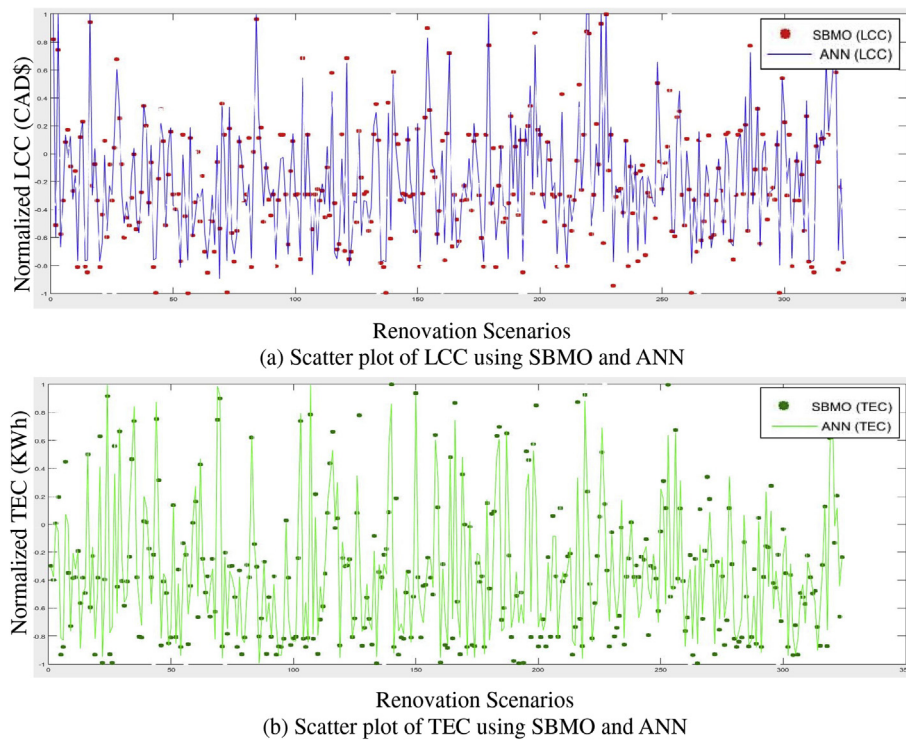


Fig. 9. Scatter plots of training output.

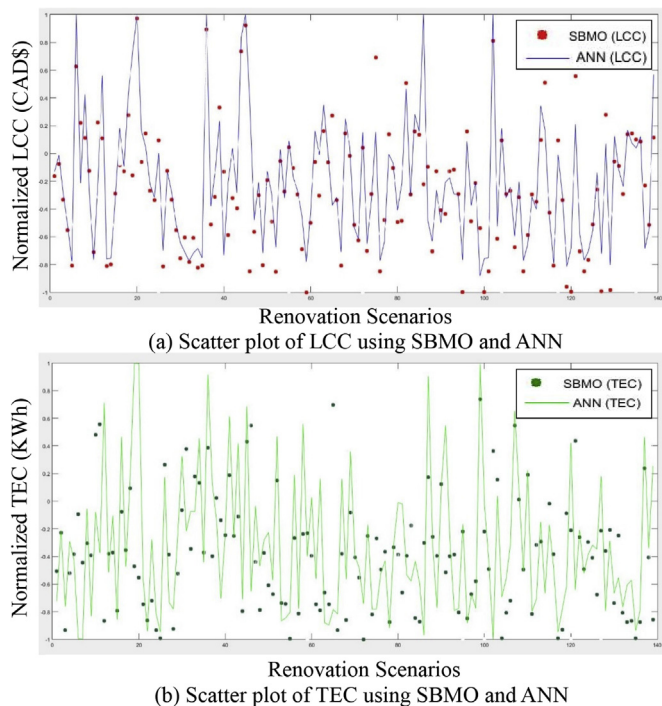


Fig. 10. Scatter plots of testing outputs.

ANNs were trained and tested using the same datasets. In this paper, only the results of the ANN1, which is considering TEC and LCC are discussed. The same procedure was implemented for TEC and LCA (ANN2), and the results are shown in Table 6.

Regression correlation coefficients, between the network outputs and the corresponding SBMO model outputs, were found to be very close to 1 for the two outputs studied, thus demonstrating a very good correlation between outputs and target values, Fig. 8 (a and b). The

normalized LCC and TEC results for SBMO and the predicted values of the ANN training (325 points) and testing (138 points) outputs were compared in Figs. 9 and 10, respectively. Each point in the scatter plot in Figs. 9 and 10 corresponds to a renovation scenario obtained from SBMO, and each line corresponds to ANN prediction model. The predicted values for each ANN models enjoy high levels of accuracy, since the amounts of underestimated or overestimated values predicted by the network are negligible. A careful observation of SBMO points shows that the majority of them fall along the ANN prediction line. Therefore, it indicates that prediction results are in very good agreement with the SBMO.

4.3.1. Performance evaluation of the proposed ANN model

In this section, performance results of the ANN prediction model for TEC and LCC vs LCA are reported. The training is considered to have 900 epochs. However, the MSE stabilized after a certain number of iterations. The training goal was achieved after 170 epochs (Fig. 7). The results predicted by the ANNs (LCC and TEC) presented in Fig. 8 (a and b) show high accuracy because the MSE of the predicted TEC vs LCC is 0.016, while MSE of the predicted TEC vs LCA is 0.056, respectively (Table 6). Consequently, the fact that the ANNs provide suitable approximations with an acceptable deviation has been proven.

4.3.2. Computational time considerations

Simulations were performed for the SBMO model with the total time of 170 h using an Intel® Core™ i7-3770 CPU@ 3.40 GHz processor and 8.00 GB RAM. The total computation time for the training, validation, and testing of the ANN model was about 150 s using the same computer. It is worthy to mention that each simulation takes about 180 s using the SBMO model, while the proposed ANNs can provide results in less than 1 s. The ANNs were developed as surrogate models for emulating computationally expensive, real building simulation models. It is clear that using energy simulation tools results in a prohibitive computational time. The computational time saving associated with the proposed surrogate models is significant.

5. Conclusions, limitations, and future works

This research focuses on developing new and robust ANNs for use as surrogate models for simulation by using data generated from the SBMO model developed in our previous research [3]. The outcome of this study shows that the proposed ANN models can efficiently predict the TEC, LCC, and LCA for the whole building renovation scenarios considering the building envelope, HVAC, and lighting systems.

In the first phase, the optimization process, coupled with the energy simulation tool, forecasts the building TEC, LCC, and LCA. The proposed ANNs can work as a building simulation tool to predict TEC, LCC, and LCA; thereby significantly decreasing computational time and effort.

The case study was implemented based on the results of the SBMO. Different ANNs are generated in MATLAB® by using the outcomes of DesignBuilder energy simulations for network training and testing. The regressions between the ANN predictions and target SBMO outputs plots show an acceptable agreement between the predictions and the SBMO, with regression coefficients close to 1. The ANNs provide satisfactory approximation to the SBMO, with the MSE for TEC vs. LCC and TEC vs. LCA of 0.016 and 0.056, respectively. Therefore, ANNs are acceptable to implement as surrogate models for simulation in SBMO to allow fast evaluations.

This study outlines several limitations of the current SBMO models, mainly due to the large number of simulations required for the evolution process. To increase the level of accuracy, the number of simulations should be increased, which leads to higher computational time. Another limitation of the BEMs is that both DesignBuilder and ATHENA [63] do not capture all aspects of renovation projects. For instance, the impact of the components that have been removed in the renovation process is not included in the calculation. Additionally, one dataset of an institutional building was used for training, testing and validation of the ANNs. Therefore, the trained ANN models are only suitable for similar buildings.

Future development involves training and fine-tuning of the ANN for feature extraction and prediction, improving algorithms, and generalization. Although the authors are fairly confident in the results, other models (e.g., Deep learning models) should be implemented to improve the performance. In future work, the authors will propose a novel deep learning model to generate more generalized building prediction models while improving the computational efficiency and accuracy.

Acknowledgment

This research was made possible by “Fonds de recherche du Québec Nature et technologies” (FRQNT) award from the Quebec Government and a scholarship from the “Pierre Arbour Foundation”.

References

- [1] U.S. Department of Energy, Annual Energy Outlook 2012 with Projections to 2035, (2012) Retrieved 5, 1, 2016, from the EIA website at www.eia.gov/forecasts/aeo.
- [2] A.-T. Nguyen, S. Reiter, P. Rigo, A review on simulation-based optimization methods applied to building performance analysis, *Appl. Energy* 113 (2014) 1043–1058 Elsevier Ltd.
- [3] S.A. Sharif, A. Hammad, Simulation-based multi-objective optimization of institutional building renovation considering energy consumption, life-cycle cost and life-cycle assessment, *J. Build. Eng.* 21 (November 2018) (2018) 429–445 Elsevier Ltd.
- [4] Z. Ma, P. Cooper, D. Daly, L. Ledo, Existing building retrofits: methodology and state-of-the-art, *Energy Build.* 55 (2012) 889–902.
- [5] CBC News, CBC News, 10 5 (2016) Retrieved 2, 14, 2017, from: <http://www.cbc.ca/news/canada/montreal/mcgill-concordia-quebec-buildings-university-1.3793180>.
- [6] J. Purdy, I. Beausoleil-Morrison, The significant factors in modelling residential buildings, *Canmet Center for Technology*, 7th International IBPSA Conf., Rio de Janeiro, 2001.
- [7] S.A. Sharif, A. Hammad, Simulation-based Optimization of Building Renovation Considering Energy Consumption and Life Cycle Assessment. *International Workshop on Computing in Civil Engineering (IWCCE 2017)*, University of Washington, Seattle, 2017.
- [8] L. Cabeza, L. Rincón, i. Vilarinho, G. Pérez, A. Castell, Life cycle assessment (LCA) and life cycle energy analysis (LCEA) of buildings and the building sector: a review, *Renew. Sustain. Energy Rev.* 29 (2014) 394–416.
- [9] F. Asdrubali, C. Baldassarri, V. Fthenakis, Life Cycle Analysis in the construction sector: guiding the optimization of conventional Italian buildings, *Energy Build.* 64 (2013) 73–89.
- [10] C. Anand, B. Amor, Recent developments, future challenges and new research directions in LCA of buildings: a critical review, *Renew. Sustain. Energy Rev.* 67 (2017) 408–416.
- [11] Y. Schwartz, R. Raslan, D. Mumovic, Implementing multi objective genetic algorithm for life cycle carbon footprint and life cycle cost minimisation: a building refurbishment case study, *Energy* 97 (2016) 58–68 Elsevier Ltd.
- [12] B. Nicolae, B. George-Vlad, Life cycle analysis in refurbishment of the buildings as intervention practices in energy saving, *Energy Build.* 86 (2015) 74–85 Elsevier B.V..
- [13] M. Abdallah, Optimizing the Selection of Sustainability Measures for Existing, University of Illinois, Illinois at Urbana-Champaign, 2014.
- [14] R. Evins, A review of computational optimisation methods applied to sustainable building design, *Renew. Sustain. Energy Rev.* 22 (2013) 230–245 Elsevier.
- [15] F.P. Chantrelle, H. Lahmidi, W. Keilholz, M. El Mankibi, P. Michel, Development of a multicriteria tool for optimizing the renovation of buildings, *Appl. Energy* 88 (4) (2011) 1386–1394 Elsevier Ltd.
- [16] U. Diwekar, *Introduction to Applied Optimization*, Springer Science and Business Media, 2013 e-QUEST, Retrieved 11, 1, 2015, from <http://doe2.com/equest/>.
- [17] Q. Jin, M. Overend, Facade renovation for a public building based on a whole-life value approach, *First Building Simulation and Optimization Conference*, 2012, pp. 417–424 September.
- [18] W. Kim, Y. Jeon, Y. Kim, Simulation-based optimization of an integrated day-lighting and HVAC system using the design of experiments method, *Appl. Energy* 162 (2016) 666–674 Elsevier Ltd.
- [19] X. Wei, A. Kuskiak, M. Li, F. Tang, Y. Zeng, Multi-objective optimization of the HVAC (heating, ventilation, and air conditioning) system performance, *Energy* 83 (2015) 294–306 Elsevier Ltd.
- [20] X. Xu, S. Wang, A mixed-mode building energy model for performance evaluation and diagnosis of existing buildings, *Build. Serv. Eng. Technol.* 29 (1) (2008) 73–83.
- [21] N. Delgarm, B. Sajadi, F. Kowsary, S. Delgarm, Multi-objective optimization of the building energy performance: a simulation-based approach by means of particle swarm optimization (PSO), *Appl. Energy* 170 (2016) 293–303 Elsevier Ltd.
- [22] A. Gosavi, *Simulation-Based Optimization: Parametric Optimization Techniques and Reinforcement Learning*, (2014).
- [23] V. Machairas, A. Tsangrassoulis, K. Axarli, Algorithms for optimization of building design: a review, *Renew. Sustain. Energy Rev.* 31 (1364) (2014) 101–112.
- [24] J.H. Lee, Optimization of indoor climate conditioning with passive and active methods using GA and CFD, *Build. Environ.* 42 (9) (2007) 3333–3340.
- [25] W. Wang, H. Rivard, R. Zmeureanu, An object-oriented framework for simulation-based green building design optimization with genetic algorithms, *Adv. Eng. Inf.* 19 (2005) 5–23.
- [26] J.P.C. Kleijnen, *Statistical Tools for Simulation Practitioners*, Marcel Dekker, New York, 1987.
- [27] B. Eisenhower, Z. O'Neill, S. Narayanan, V.A. Fonoberov, I. Mezić, A methodology for meta-model based optimization in building energy models, *Energy Build.* 47 (2012) 292–301.
- [28] F. Ascione, N. Bianco, R.F. De Masi, C. De Stasio, G.M. Mauro, G.P. Vanoli, Artificial Neural Networks for Predicting the Energy Behavior of a Building Category: A Powerful Tool for Cost-Optimal Analysis. *Cost-Effective Energy Efficient Building Retrofitting: Materials, Technologies, Optimization and Case Studies*, Elsevier Ltd, 2017.
- [29] F. Chollet, *Deep Learning with Python*, Manning Publications Co., United States of America, 2013.
- [30] D.E. Marasco, C.E. Kontokosta, Applications of machine learning methods to identifying and predicting building retrofit opportunities, *Energy Build.* 128 (2016) 431–441 Elsevier B.V..
- [31] H. Naganathan, W.O. Chong, X. Chen, Building energy modeling (BEM) using clustering algorithms and semi-supervised machine learning approaches, *Autom. Construct.* 72 (2016) 187–194 Elsevier B.V..
- [32] C.V. Gallagher, K. Bruton, K. Leahy, D.T.J. O'Sullivan, The suitability of machine learning to minimise uncertainty in the measurement and verification of energy savings, *Energy Build.* 158 (2018) 647–655 Elsevier B.V..
- [33] Y. Wei, X. Zhang, Y. Shi, L. Xia, S. Pan, J. Wu, M. Han, X. Zhao, A review of data-driven approaches for prediction and classification of building energy consumption, *Renew. Sustain. Energy Rev.* 82 (September 2017) (2018) 1027–1047 Elsevier Ltd.
- [34] A.S. Ahmad, M.Y. Hassan, M.P. Abdullah, H.A. Rahman, F. Hussin, H. Abdullah, R. Saidur, A review on applications of ANN and SVM for building electrical energy consumption forecasting, *Renew. Sustain. Energy Rev.* 33 (2014) 102–109 Elsevier.
- [35] K. Amasyali, N.M. El-Gohary, A review of data-driven building energy consumption prediction studies, *Renew. Sustain. Energy Rev.* 81 (2018) 1192–1205 Elsevier Ltd.
- [36] M.A. Azadeh, S.F. Ghaderi, S. Sohrabkhani, Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors, *Energy Convers. Manag.* 49 (8) (2008) 2272–2278.
- [37] J. Yang, H. Rivard, R. Zmeureanu, Building energy prediction with adaptive artificial neural networks, *Ninth International IBPSA Conference*, 2005, pp. 1401–1408.
- [38] K. Gurney, *An Introduction to Neural Networks*, [Book] Taylor & Francis, London, UK, 2005 2005.
- [39] A.H. Neto, F.A.S. Fiorelli, Comparison between detailed model simulation and

- artificial neural network for forecasting building energy consumption, *Energy Build.* 40 (12) (2008) 2169–2176.
- [40] A. Afram, F. Janabi-Sharifi, A.S. Fung, K. Raahemifar, Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems: a state of the art review and case study of a residential HVAC system, *Energy Build.* 141 (2017) 96–113 Elsevier B.V..
- [41] E. Asadi, M. G. da Silva, C.H. Antunes, L. Dias, L. Glicksman, Multi-objective optimization for building retrofit: a model using genetic algorithm and artificial neural network and an application, *Energy Build.* 81 (2014) 444–456 Elsevier.
- [42] L. Magnier, Multiobjective Optimization of Building Design Using Artificial Neural Network and Multiobjective Evolutionary Algorithms, (2008).
- [43] F. Ascione, N. Bianco, C. De Stasio, G.M. Mauro, G.P. Vanoli, CASA, cost-optimal analysis by multi-objective optimisation and artificial neural networks: a new framework for the robust assessment of cost-optimal energy retrofit, feasible for any building, *Energy Build.* 146 (2017) 200–219 Elsevier B.V..
- [44] W. Yu, B. Li, H. Jia, M. Zhang, D. Wang, Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design, *Energy Build.* 88 (2015) 135–143 Elsevier B.V..
- [45] A. Garnier, J. Eynard, M. Caussanel, S. Grieu, Predictive control of multizone heating, ventilation and air-conditioning systems in non-residential buildings, *Appl. Soft Comput.* J. 37 (2015) 847–862 Elsevier B.V..
- [46] H. Huang, L. Chen, E. Hu, A new model predictive control scheme for energy and cost savings in commercial buildings: an airport terminal building case study, *Build. Environ.* 89 (2015) 203–216 Elsevier Ltd.
- [47] M. Ning, M. Zaheeruddin, Neuro-optimal operation of a variable air volume HVAC&R system, *Appl. Therm. Eng.* 30 (5) (2010) 385–399 Elsevier Ltd.
- [48] M.W. Ahmad, M. Mourshed, Y. Rezgui, Trees vs Neurons : comparison between random forest and ANN for high-resolution prediction of building energy consumption, *Energy Build.* 147 (2017) 77–89 Elsevier B.V..
- [49] T. Ayata, E. Arcaklioğlu, O. Yildiz, Application of ANN to explore the potential use of natural ventilation in buildings in Turkey, *Appl. Therm. Eng.* 27 (1) (2007) 12–20.
- [50] R. Azari, S. Garshasbi, P. Amini, H. Rashed-Ali, Y. Mohammadi, Multi-objective optimization of building envelope design for life cycle environmental performance, *Energy Build.* 126 (2016) 524–534 Elsevier B.V..
- [51] Z. Bocheng, L.U. Kuo, L.V. Dinghao, L.U.O. Jing, F. Xuan, Short-term Prediction of Building Energy Consumption Based on GALM Neural Network, *Ameii*, 2015, pp. 867–871.
- [52] L. Chen, Q. Fang, Z. Zhang, Research on the identification of temperature in intelligent building based on feedforward neural network and particle swarm optimization algorithm, 2010 6th International Conference on Computer Science and Information Technology, 2010, pp. 286–290.
- [53] L. Magnier, F. Haghighat, Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network, *Build. Environ.* 45 (3) (2010) 739–746 Elsevier Ltd.
- [54] J. Yang, H. Rivard, R. Zmeureanu, On-line building energy prediction using adaptive artificial neural networks, *Energy Build.* 37 (12) (2005) 1250–1259.
- [55] A.P. Melo, D. Cóstola, R. Lamberts, J.L.M. Hensen, Development of surrogate models using artificial neural network for building shell energy labelling, *Energy Policy* 69 (2014) 457–466 Elsevier.
- [56] E. Asadi, M.G. Silva, C.H. Antunes, L. Dias, State of the art on retrofit strategies selection using multi-objective optimization and genetic algorithms, *Nearly Zero Energy Building Refurbishment*, Springer, London, 2013, pp. 279–297.
- [57] P.M. Ferreira, A.E. Ruano, S. Silva, E.Z.E. Conceição, Neural networks based predictive control for thermal comfort and energy savings in public buildings, *Energy Build.* 55 (2012) 238–251.
- [58] Z.J. Yu, Mining Hidden Knowledge from Measured Data for Improving Building Energy Performance, (2012).
- [59] K. Amasyali, N. El-Gohary, Deep Learning for Building Energy Consumption Prediction. Leadership in Sustainable Infrastructure, CSCE, 2018.
- [60] J. Conraud-bianchi, A Methodology for the Optimization of Building Energy, Thermal, and Visual Performance, Thesis in the Department of Building, Building, Civil and Environmental Engineering, Concordia University, 2008.
- [61] J.A. Freeman, D.M. Skapura, Neural Networks: Algorithms, Applications, and Programming Techniques, Loral Space Information Systems and Adjunct Faculty, School of Natural and Applied Sciences University of Houston at Clear Lake, Addison-Wesley Publishing Company, 1991.
- [62] ASHRAE Design Guide, Advanced Energy Design Guide for Small to Medium Office Buildings, Book. Atlanta, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc, 2014.
- [63] ATHENA Impact Estimator, Athena Impact Estimator for Buildings V4.2 Software and Database Overview, (2017) Retrieved 10, 14, 2017, from <https://calculatelca.com/software/impact-estimator/user-manual/>.
- [64] DesignBuilder Software Ltd, DesignBuilder, (2016) Retrieved 1, 1, 2016, from <https://www.designbuilder.co.uk/>.
- [65] A. Graves, M. Liwicki, S. Fernández, R. Bertolami, H. Bunke, J. Schmidhuber, A novel connectionist system for unconstrained handwriting recognition, *IEEE Trans. Pattern Anal. Mach. Intell.* 31 (5) (2009) 855–868.
- [66] S.A. Kalogirou, M. Bojic, Artificial neural networks for the prediction of the energy consumption of a passive solar building, *Energy* 25 (5) (2000) 479–491.
- [67] X. Li, X. Wu, Constructing long short-term memory based deep recurrent neural networks for large vocabulary speech recognition, *Acoustics, Speech and Signal Processing (ICASSP)*, 2015 IEEE International Conference on. IEEE, 2015, 2015, pp. 4520–4524.
- [68] GenOpt, Retrieved 20, 1, 2018, from <https://simulationresearch.lbl.gov/GO/>.
- [69] Institute for Building Environment and Energy Conservation, Total Energy Use in Buildings Analysis and Evaluation Methods, Programme on Energy in Buildings and Communities, 2013, p. 132.
- [70] C. Li, Z. Ding, D. Zhao, J. Yi, G. Zhang, Building energy consumption prediction: an extreme deep learning approach, *Energies* 10 (10) (2017) 1–20.
- [71] Natural Resources Canada, Survey of Commercial and Institutional Energy Use (SCIEU), Buildings, Retrieved from Natural Resources Canada, (2015) Retrieved 1, 8, 2016, from https://oee.nrcan.gc.ca/corporate/statistics/neud/dpa/data_e/databases.cfm.
- [72] W. Wang, R. Zmeureanu, H. Rivard, Applying multi-objective genetic algorithms in green building design optimization, *Build. Environ.* 40 (11) (2005) 1512–1525.