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Prediction and optimization of energy consumption in an office building using artificial neural network and a genetic algorithm

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ABSTRACT

The aim of this study is to propose a reliable method to optimize the energy consumption of buildings. Also, the most effective input parameters are defined which are used in the energy consumption of a research center building located in Iran as a case study. Accordingly, EnergyPlus software is implemented to evaluate energy consumption and scrutinize the crucial factors numerically. Afterward, a robust artificial neural network (ANN) using multi-layer perceptron model (MLP) is created, trained, and tested to simulate energy consumption in the building. Furthermore, energy optimization is performed by Galapagos plugin based on a Genetic Algorithm considering the critical variables. The main results show that the optimization of the system can mitigate energy consumption by about 35 %. In addition, the outcomes of the sensitivity analysis demonstrate that the number of occupants has the highest influence on the energy consumption of the edifice followed by wall U-value which is related to wall insulation. Finally, the results of computations showed that the trained MLP model proposed in this study can accurately predict energy consumption in the building. To sum up, the proposed model may be applied to similar buildings to predict and optimize energy consumption.

1. Introduction

Nowadays, due to the growing intensity of energy consumption, researchers are on the brink of making significant advances in minimizing and optimizing energy consumption, particularly in buildings (Esmaeilzadeh, Zakerzadeh, & Koma, 2018). Considering the increased energy consumption and high dependence on fossil fuels, our planet suffers from climate change (Habibollahzade, Gholamian, Ahmadi, & Behzadi, 2018; Habibollahzade, Houshfar et al., 2018). Therefore, environment protection and energy saving are recognized as essential issues currently. According to the last published report on the management level of the Iranian's energy consumption in 2012, households and commercial buildings accounted for 40.7 % of the total energy consumption (Hakiminejad, Fu, & Titkanlou, 2015). Furthermore, CO_2 emissions are increased sharply showing the importance of energy consumption strategies (Habibollahzade, Gholamian et al., 2018; Habibollahzade, Houshfar et al., 2018). Energy renovation methods are important not only to develop the buildings' energy performance, but also to reduce climate changes' effects (Farahani, Wallbaum, & Dalenbäck, 2018). Accordingly, developing some new methods and or technologies would be a decent choice to utilize the energy sources in a more efficient manner. In this regard, extensive studies have focused on ASHRAE standards in order to evaluate energy management. Besides, several simulation tools, such as Dest, EnergyPlus, DOE-2, and TRNSYS package, have been utilized to simulate architectural forms based on the available environmental/meteorological data (Lu, Zheng, & Kong, 2016). It should be noted that different methods have been used to estimate energy consumption e.g. statistical, multivariate, and cluster analysis, stepwise selection, support vector regression (SVR), and artificial neural network (ANNs) (Amber et al., 2018). ANN is a potent tool for evaluation of multi-faceted practical problems. One of the most important benefits of ANNs is the capability to estimate the continuous nonlinear function with predefined accuracy (Lewicki & Marino, 2003). Meanwhile, ANNs are widely used for predicting energy consumption in various buildings (Lartigue, Lasternas, & Loftness, 2014).

1.1. ANN applications in buildings

In last three decades, with the advent of soft computing methods such as artificial neural networks (ANNs) and fuzzy systems, several architectural and civil engineering problems have been efficiently solved (e.g., (Amiri, Dehghanbanadaki, & Nazir, 2020; Bui, Nguyen,

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Ngo, & Nguyen-Xuan, 2020; Dehghanbanadaki, Sotoudeh, Golpazir, Keshtkarbanaeemoghadam, & Ilbeigi, 2018; Ali Dehghanbanadaki, Khari, Arefnia, Ahmad, & Motamedi, 2019; Mustapa, Dahlan, Yassin, & Buildings, 2020; Walker, Khan, Katic, Maassen, & Buildings, 2020; Zhang & Pan, 2020). But, considering the application of the ANN in buildings, Mohandes, Zhang, and Mahdiyar (2019)) reviewed the potential of ANN in buildings due to its abilities in cultivating the modeling and prediction of buildings energy consumption. The results revealed that using ANN in building energy analysis provides some advantages e.g. accurate prediction, ease of use, fault tolerance, adaptive learning, and self-organization. Of important, the electricity demand of 47 commercial buildings were estimated using various soft computing methods such as boosted-tree, random forest, SVM-linear, quadratic, cubic, fine Gaussian and ANN. Two years of data were used in training the model and the prediction was performed using another year of untrained data. The final results indicated the acceptable accuracy of the ANN model. Besides, Beccali, Ciulla, Lo Brano, Galatioto, and Bonomolo (2017)) showed that ANN might be considered as a useful tool in order to renovate the building`s energy consuming. According to the relevant studies performed by Olofsson and Andersson (2002), ANN has a superior performance compared to the other methods for estimating energy consumption in the buildings. Moreover, Wong, Wan, and Lam (2010)) developed different ANNs for office buildings in sub-tropical climates. For this purpose, the office buildings were simulated by EnergyPlus software, afterward, three types of input parameters (9 inputs), weather conditions, building envelope, and day type, were considered. Some inputs include the average of daily dry-bulb and wet-bulb temperatures, daily global solar radiation and aperture, and daylight and overhang. Furthermore, the researchers evaluated electric lighting and the entire building electricity as well as heating and cooling systems based on the given inputs. The results reported an average of 0.98 for the Nash–Sutcliffe efficiency coefficient (NSE) of the output parameters proving the acceptable performance of ANN.

Bu, Shao, Wang, Chen, and Wang (2020)) estimated the energy consumption of hotel buildings using a support vector machine (SVR) model. In their study, the RBF kernel function was chosen as the kernel function of the SVR, and the accuracy of the model prediction was improved by optimizing the kernel parameters. The inputs of the model were considered as the weather parameters and operating parameters of the hotel air-conditioning system. Their results indicated that with low MSE and high regression indices of the best SVR model could estimate the real energy consumption with an average 6 % difference.

In the other study, Kim, Jung, and Kang (2019)) utilized ANN-based residential energy consumption prediction models. In the modeling, residential building information and user features in South Korea were considered. Their study discussed about the share of influencing parameters namely the number of exterior walls, housing direction, housing area, number of years occupied, number of household members, and the occupation of the household head on the energy estimation. Their results revealed the high accuracy of the ANN model in the prediction of energy consumption.

In a similar work, Bui, Nguyen, Ngo, and Nguyen-Xuan (2020)), the energy consumptions of a building including the heating and cooling load were estimated using hybridization of ANN model with firefly algorithm (EFA). In addition, the performance of EFA-ANN was validated by comparing the obtained results with other methods. Their results showed that EFA-ANN model with acceptable performance indices could assist civil engineers and construction managers in the early designs of energy-efficient buildings.

1.2. Effective parameters in energy consumption

Regarding to finding effective parameters on energy-use reduction, Martínez, Pacheco, and Ordó (2012)) revealed that buildings orientation, shape, envelope system, passive heating, and cooling mechanisms, and shading and glazing were the most useful parameters from energy consumption viewpoint. In addition, the impact of the building shape on building's life cycle was concluded as the most significant influencing factor besides compactness indicant, shape factor, and climate. Moreover, the building orientation, shape, and the ratio between the external building and building volume were determined to affect energy consumption considerably. Aiming to find the other useful parameters in energy consumption, Boyano, Hernandez, and Wolf (2013)) investigated the energy-conserving potential of a rectangular office building in three locations (in Europe) considering different climate zones i.e., Tallinn, Madrid, and London. Accordingly, the effects of lighting, window insulation, external walls (U-valued), and building orientation were investigated. The results revealed that lighting was the most effective factor in the total energy demand due to its considerable operation time. Besides, they proved that the correlation between insulation and energy consumption varies in cold, mild, and warm climate species. In a later study, Li, Hong, and Yan (2014)) investigated The effect of climate circumstance, building envelope, equipment, and size, besides indoor environmental conditions on the reduction of energy consumption. For this purpose, 51 high-performance office buildings in the U.S., Europe, China, and other parts of Asia were chosen and simulated. Furthermore, the effects of the residents' manners, operation, and conservation were investigated via two case studies. Accordingly, energy demand reduction was considered. Therefore, they concluded that both parameters would affect energy saving substantially. Moreover, Evin, Ucar, and Ucar (2019)) compared four insulation materials for 20 buildings in four cities with different climates. Hemsath and Hosseini (2015) performed energy and sensitivity analysis to investigate the impact of the crucial factors on energy consumption. Accordingly, energy consumption is considered to be depended on location, climate, and building size, so they solely considered building form, geometric differences, and material through two different cases of sensitivity analysis. The results indicated that the outer zone could significantly impact energy consumption, while horizontal and vertical geometries may affect the results equally and similarly to use materials.

1.3. Energy optimization

It is worth bearing in mind that, combining energy consumption simulation with various optimization manners such as computational optimization, simulation-based optimization, building performance optimization, and performance-driven design, may be worthy of investigation to reduce the energy consumption in the buildings (Nguyen, Reiter, & Rigo, 2014). Obviously, implementing the high-performance techniques can definitely help the researchers to optimize the building energy consumption, as studied in the previous studies (Griego, Krarti, & Hernandez-Guerrero, 2015). Foucquier, Robert, Suard, Stéphan, and Jay (2013)) evaluated three different optimization techniques such as "white box", "black box" and "grey box". However, Magnier and Haghighat (2010) studied an office building for optimizing thermal comfort and energy consumption with different technique by using TRNSYS and ANN. Accordingly, variables related to the HVAC systems and passive solar design were assumed for simulation purpose. The corresponding results revealed that implementing a Genetic Algorithm as the optimization tool can effectively reduce the energy consumption in the buildings. Ferrara, Filippi, Sirombo, and Cravino (2015)) examined a school classroom as a case study to decrease energy demand for heating, cooling, and lighting by TRNSYS package. Subsequently, the energy demand was optimized by dynamic optimization software via Genetic Algorithm integrated with TRNSYS software. Lu et al. (2016) showed that renewable energy systems could significantly contribute to designing and establishing zero-carbon buildings. In the corresponding study, renewable energy systems were optimized by multi-objective optimization manner and Genetic Algorithm technique to be used for three buildings. Results indicated that the Genetic Algorithm concluded to be the most reliable method, while sufficient data

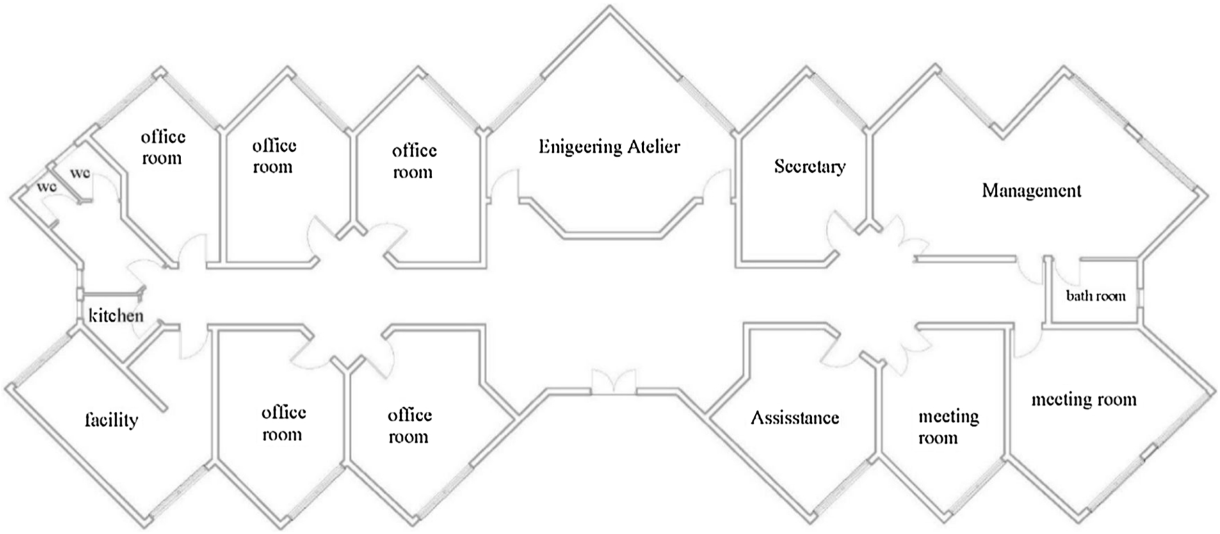

Fig. 1. The studied research center plan.

Table 1
Properties of the materials used in this study.

Section	Parameter	Value
Floor		
Layer 1	Thickness [m]	0.02
	Conductivity [S/m]	1.5
	Density [kg/m^3]	2100
	Specific Heat [kJ/kg K]	1000
Layer 2	Thickness [m]	0.02
	Conductivity [S/m]	0.35
	Density [kg/m^3]	1400
	Specific Heat [kJ/kg K]	840
Layer 3	Thickness[m]	0.35
	Conductivity [S/m]	2.5
	Density[kg/m^3]	2500
	Specific Heat [kJ/kg K]	750
Walls		
Layer 1	Thickness [m]	0.02
	Conductivity [S/m]	0.35
	Density [kg/m^3]	1400
	Specific Heat [kJ/kg K]	840
Layer 2	Thickness [m]	0.35
	Conductivity [S/m]	2.5
	Density [kg/m^3]	2500
	Specific Heat [kJ/kg K]	750
Layer 3	Thickness [m]	0.03
	Conductivity [S/m]	0.57
	Density [kg/m^3]	1200
	Specific Heat [kJ/kg K]	1090
Roof		
Layer 1	Thickness [m]	0.0015
	Conductivity [S/m]	45.006
	Density [kg/m^3]	7680
	Specific Heat [kJ/kg K]	418.4
Layer 2	Thickness [m]	0.01
	Conductivity [S/m]	0.048
	Density [kg/m^3]	200
	Specific Heat [kJ/kg K]	1000
Layer 3	Thickness [m]	0.3
	Conductivity [S/m]	52
	Density [kg/m^3]	7780
	Specific Heat [kJ/kg K]	460.54
Windows		
Layer 1	U-factor	3.69
	Solar Heat Gain Coefficient	0.25
Layer 2	U-factor	3.69
	Solar Heat Gain Coefficient	0.25

can be obtained through the use of multi-objective optimization by comparing the architectural patterns. Mattoni, Gori, and Bisegna (2017)) optimized indoor lighting of an office by Genetic Algorithm technique. The results indicated that at the optimum condition, uniformity of illuminance increased considering a reduction in the number of luminaires and maximum UGR values (Unified Glare Rating). In a recent study, Delgarm, Sajadi, Kowsary, and Delgarm (2016)) tried to combine EnergyPlus with the multi-objective particle swarm optimization method to enhance energy utilization presuming four climate regions in Iran. They selected the building orientation, shading, window size, glazing, and wall material properties as the variable and effective parameters. Eventually, they showed that using a reliable simulation may significantly reduce the cooling, heating, lighting electricity, and total energy consumption.

Salvalai, Malighetti, Luchini, and Girola (2017)) performed a comprehensive investigation of energy renovation for a 30 years old school. In addition, 38 different buildings with different ages and typical designs had been optimized by the authors. Accordingly, external and internal insulation, windows replacement and new plan installation had been considered. Gustafsson et al. (2017) studied office buildings renovation for increasing energy efficiency. Subsequently, windows, envelope insulation, heating and cooling system, ventilation and solar photovoltaics were chosen as the crucial parameters for renovating the edifices in European climates. The results indicated that the energy cost would be decreased to 77 %. In another study, researchers revealed a new optimization method for energy-use of buildings using and evolving the Ant Colony Optimization algorithm. The results showed that internal loads and infiltration rate could decrease energy consumption by 4.8 % in an office building (Bamdad, Cholette, Guan, & Bell, 2018). The renovation of buildings has been developed to achieve Nearly Zero Energy Building (Brambilla, Salvalai, Imperadori, & Sesana, 2018) or even presuming the strategies about the renovation of building construction (Dotzler, Botzler, Kierdorf, & Lang, 2018). Yigit and Ozorhon (2018) conducted a method for optimizing the energy consumption of a building by genetic algorithm. The simulations were performed based on building size, location and occupation schedule by which optimal building configuration was concluded. Dermentzis et al. (2019) evaluated heating and cooling consumption of three types of buildings (single-, multi-family house, and office) before and after renovation. Results showed that the presented method could reduce the heating and cooling energy by 8 % and 15 %, respectively. The considered parameters for renovating purpose included roof and wall insulations, windows and stairs insulations. In another research, the type of building, the number of occupants, the income level of the occupants

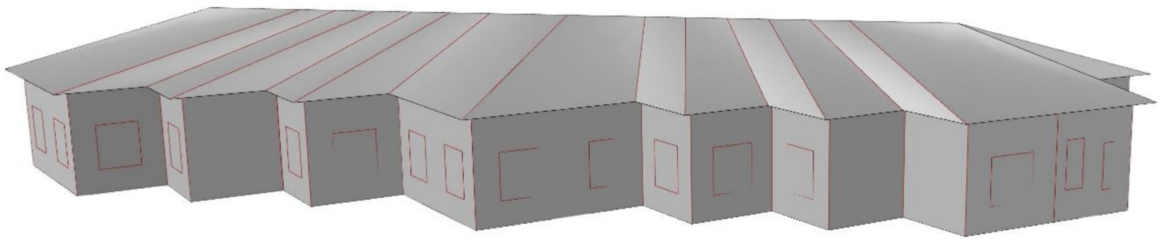

Fig. 2. A 3D schematic of the investigated research center.

Table 2
Mean annual meteorological data of Tehran's climate region used in this study ("National & Local Weather Radar, 2020 n.d.).

Parameter	Value
Dry-bulb temperature	18.35 °C
Dew point temperature	3.19 °C
Relative humidity	40.38 %
Wind speed	2.78 m/s
Wind direction	233.03°
Radiation	232.05 Wh/m^2
Barometric pressure	889085.44 Pa

Table 3
Input factors and their corresponding chosen range based on ASHRAE standard.

Item	Name	Minimum	Maximum	Average
1	Wall U-value [W/m^{2}k]	0.35	0.8	0.5
2	Equipment load rate [W/m^2]	2	15	8.5
3	Infiltration rate [m^3/s-m^2]	0.0001	0.0006	0.00035
4	Lighting intensity [W/m^2]	3	15	9
5	Number of occupants [PPL/m^2]	0.02	0.5	0.225
6	Roof U-value [W/m^{2}k]	0.2	0.5	0.35

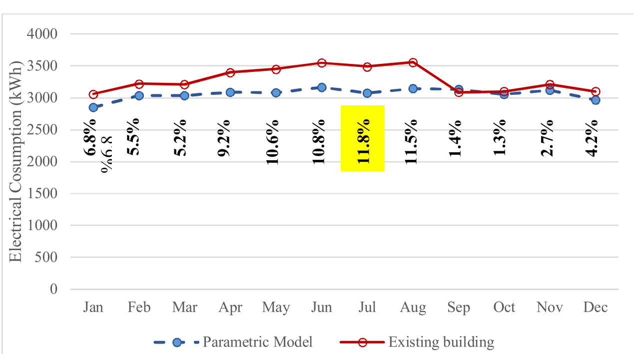

Fig. 3. A comparison between electrical use bills of the studied building and the results of numerical simulation.

and the occupancy time on the actual energy savings were chosen as the critical factors in energy-saving and building renovation (van den Brom, Meijer, & Visscher, 2019). Ascione, Bianco, Maria Mauro, and Napolitano (2019)) optimized energy consumption, energy-related global cost and discomfort hours by considering temperatures, building orientation, radiative and thermos-physical properties in four different climates. Gil-Baez, Padura, and Huelva (2019)) renovated school buildings with saving up to 17.7 % for heating and up to 15.9 % for cooling. Besides, Harkouss, Fardoun, and Biwole (2018)) saved cooling demands up to 54 %, 87 % and 52 % by passive solutions.

All the aforementioned studies proved the significance of optimizing the energy-use of the buildings which must be considered for all the construed buildings. This research aims to optimize the energy-use of studied building using Genetic Algorithm with the help of ANN. Furthermore, the studied method may be implemented to further analyze similar buildings. Accordingly, the crucial parameters are ascertained for reducing the energy consumption which is essential for the optimization purpose. This study provides the following information: (i) the diverse steps to gather all appropriate data and features of the research center, (ii) prioritize the inputs and analyze essential data concerning the building's energy performance supplied by the software and (iii) The way of scrutinizing the results for optimizing the buildings' energy consumption. It should be declared that the method could be generalized and adapted to assess other buildings' energy consumption.

To sum up, the main novelties and objectives of this study may be summarized as:

- Creating, training and employing various ANN models to quantify the required energy of the existing building.
- Conducting a comprehensive sensitivity analysis to assess the effect of the input parameters on energy consumption.
- Finding the most effective parameters on the reduction and prediction of energy consumption through the ANN, respectively.
- Ascertaining the highly effective parameters on reducing the energy consumption of the studied and similar buildings.
- Introducing the Multi-Layer Perceptron (MLP) networks as a potent tool for sensitivity analysis.
- Using Genetic Algorithm to optimize the energy consumption of a building located in Tehran and the energy consumption cost as well.
- Implementing Grasshopper platform by EnergyPlus engine, subsequently generating an energy database considering the most effective factors.
- Implementing Genetic algorithm method to minimize the energy consumption by optimizing the effective parameters using Galapagos plugin.

In this regard, this research highly contributes to the knowledge gap and undertakes a longitudinal assessment for determining the useful parameters to reduce the energy consumption in the buildings with similar weather condition.

2. Modeling and optimization

2.1. Case study and data set

In this research, a Sustainable Research Center in North of Tehran, Iran (Latitude 51 21`, longitude 35 44`) was selected as a case study. As shown in Fig. 1, the building has one floor with a total surface of approximately 500 m^2, eight office rooms, one laboratory, meeting room and kitchen, besides two bathrooms. The wide side of the building faces north-south orientation along with one main entrance door located on the west side. Allegedly, about 25 occupants present in the building as referred from 7 AM to 6 PM, five days a week. Table 1 demonstrates the properties of the materials used in the building. It is noteworthy, for numerical modeling using EnergyPlus, the wall U-value is calculated as a coherent material, while different materials in the wall section are considered.

The building considering is simulated and modeled the extracted data based on the reliable reports and the corresponding procedure is

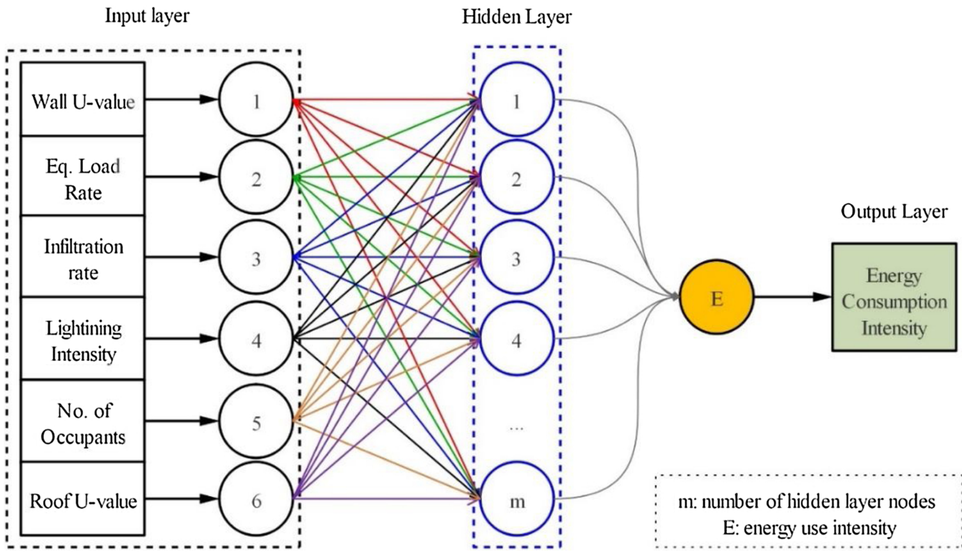

Fig. 4. Topology of the ANN for this study.

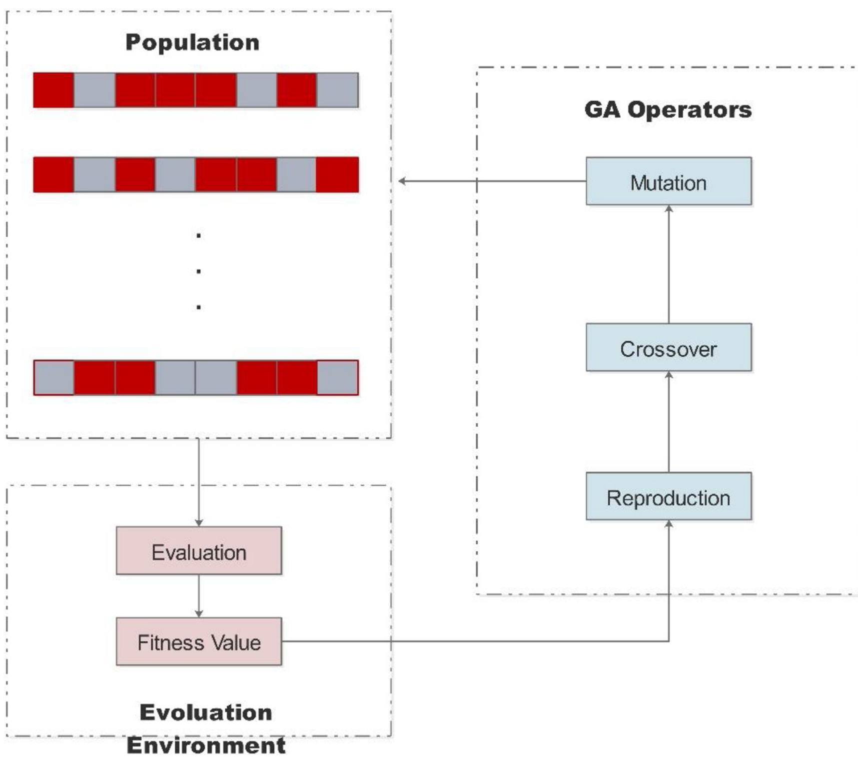

Fig. 5. The procedure taken by the Genetic algorithm.

described in detail. Accordingly, energy consumption database is generated, weather data is extracted and implemented, details of the case study are presented, input parameters are chosen and described, and eventually, the optimization procedure is explained clearly.

Input parameters of this research were selected considering solid building envelope and mechanical systems, namely wall U-value, equipment load rate, lighting density, infiltration rate, number of people, and roof U-value. Apparently, the solid building envelope and mechanical systems may significantly impact the amount of energy consumption. In addition, three concepts are proposed for designing purpose based on the capability to perform any possible changes for the studied building to reduce energy consumption. Infiltration rate can be expressed as the desired rate of outside air infiltration into the zone per square meter of the exterior facade. Values of infiltration rate should be in m^3/s-m^2. Also, equipment load rate is desired equipment load per square meter of floor. Values here should be in W/m^2. Typical values can range from 2 W/m^2 (for just a laptop or two in the zone) to 15 W/m^2 for an office filled with computers and appliances. The other parameter, lighting density is lighting load per square meter of floor. Values of lighting should be in W/m^2. Usual values can range from 3 W/m^2 for efficient LED bulbs to 15 W/m^2 for incandescent heat lamps. Furthermore, a number of people can be explained as The desired number of per square meter of floor at peak occupancy. Moreover, wall U-value and roof U-value.

2.1.1. Database generation

In this study, Grasshopper plugins, e.g. Ladybug and Honeybee, were used for energy simulation and predicting energy consumption.

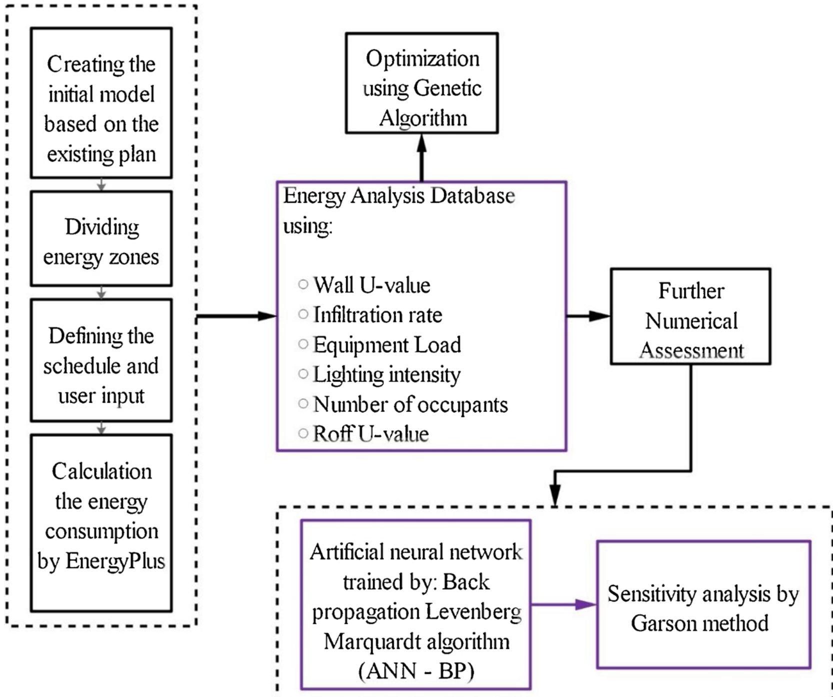

Fig. 6. A Flowchart describing the whole numerical modeling and optimization procedure.

These plugins benefit the advantages of the EnergyPlus engine. Accordingly, characterized by high precision and other significant advantages, EnergyPlus may be the most suitable engine for energy simulation of the building among DOE-2, TRNSYS, ESP-r, and IDAICE (Evins, Pointer, & Vaidyanathan, 2010). Therefore, EnergyPlus software is implemented for predicting energy consumption and for further analyzing the system from an energy assessment viewpoint. For this purpose, a 3d model of an existing research center was created in Rhino software; thereafter the energy zones were generated in grasshopper plugin as it can be seen in Fig. 2. After defining the zones including, wall, roof and floor materials, windows and the minimum and maximum of parameters rate; the energy consumption of the building was calculated by honeybee plugin using EnergyPlus engine.

2.1.2. Weather data

Weather data were collected ("National & Local Weather Radar, 2020 n.d.) and then imported to Metronome software. Thus, created weather data were imported into an EPW file format to fulfill the simulation program and having a climate-based and accurate simulation. Based on ASHRAE Standard 90, 1–2010, Tehran's climate is classified as 3B. Mean annual meteorological data of Tehran's climate region are listed in Table 2.

For conducting the building energy simulations, the correlative relation (and the reasons for) between inputs and their influence on the selected outputs needs to be recognized (Hemsath & Hosseini, 2015). Altering the inputs of the building can significantly affect the outputs values regarding energy consumption. Therefore, operating range of inputs, the inputs themselves beside the outputs should be cautiously selected. To achieve perfect results and simulation accurately reflect the outcomes, various inputs are considered to be variable factors: climate location, geometry, materials, lighting, equipment, zone loads, and occupancy along with zone programs. Accordingly, 1602 simulations were cautiously conducted considering different values for the input variables.

2.2. Methods

2.2.1. Artificial neural network

To have a satisfactory ANN model, employing a sufficient number of data is necessary to enable the model to estimate a continuous function. In this research, 1602 computer simulations were performed by Grasshopper plugins by different input values since creating the ANN models is essential to conduct the sensitivity analysis. Afterward, various ANN modes were created, trained, and tested based on the results of the performed simulations. Neural Network Toolbox in MATLAB software was employed to simulate ANN models, and for learning the related algorithm, back propagation Levenberg Marquardt was used. Therefore, in this paper, the effect of several neurons was evaluated in the hidden layer, and the model concluding the prime performance was selected as the best and most suitable ANN model to estimate the energy of the studied building. The correlation between the inputs (u(k)) and output (y(k)) in the MLP network can be summarized as follows

$$y(k) = f_2(w^2x(k) + b^2) \quad (1)$$

$$x(k) = f_1(w^1u(k) + b_1) \quad (2)$$

where x(k) demonstrates the output vector from the hidden layer. The connection weight matrix from input layers to hidden layer and from hidden layer to output layer are shown by w^1 and w^2. The bias numbers in input and output layers are indicated by b_1 and b_2. The transfer functions of the hidden layer and output layer can be used as follow:

$$f(z) = \frac{(1 - e^{-2z})}{(1 + e^{-2z})} \quad (3)$$

Z shows a function of

$$Z = f(\sum w_i x_i) \quad (4)$$

In this study, the considered data divided based on the suggested method by Shahin et al. (2004): 70 % of data for training, 15 % for validation, and 15 % for testing were selected. Finally, to determine the adequate ANN model, the effect of different numbers of hidden neurons was evaluated on the performance criterion of the models. Table 3 shows the chosen range of input factors based on ASHRAE standard.

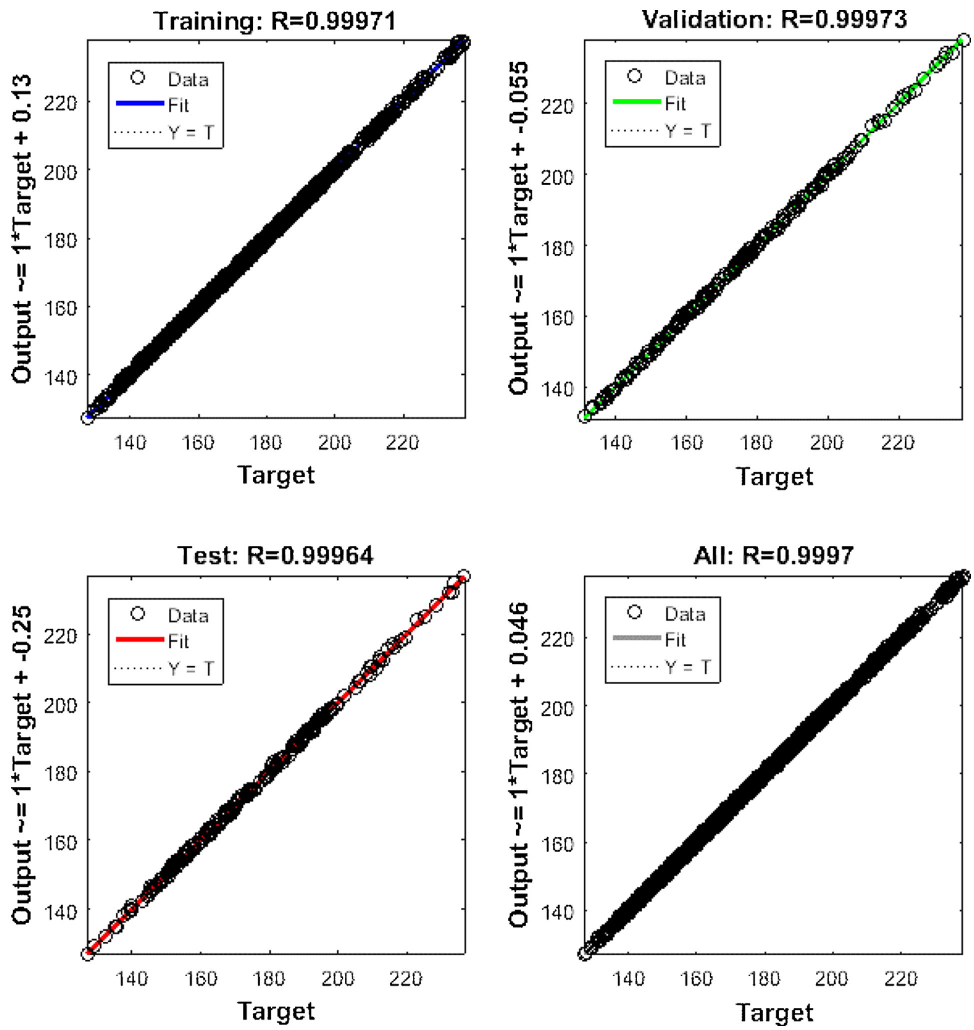

Fig. 7. Regression analysis.

Table 4
Weights of the input layer and hidden layer.

Items	Input – 1	Input – 2	Input – 3	Input – 4	Input – 5	Input – 6
N- 1	0.0877	0.0163	0.0387	0.073	0.0113	0.0018
N- 2	0.5185	0.7388	−0.9424	−1.353	−0.5923	0.178
N- 3	−1.616	5.9335	0.4889	3.3652	1.159	3.2628
N-4	0.9887	0.1492	1.6615	−1.154	0.2685	−0.1767
N- 5	0.3561	0.902	0.4987	−1.2395	−0.8453	−1.0827
N- 6	−1.4951	−0.995	0.712	0.5202	−0.1096	0.0795
N- 7	0.6238	0.6728	1.3258	1.4014	−0.373	1.0739
N- 8	0.4729	1.683	−0.3543	−0.8924	0.7914	−0.8996
N- 9	0.0423	−0.006	0.0116	−0.1164	2.6745	0.0059
N- 10	−0.059	0.0376	−0.0433	−0.4531	0.0501	0.0023

Note: N = neuron.

Table 5
Performance indices of the best model.

Items	Samples	MSE (kWh/m^2)	R
Training	945	3.18684e^{-1}	9.99711e^{-1}
Validation	203	3.27709e^{-1}	9.99728e^{-1}
Testing	203	3.93728e^{-1}	9.99638e^{-1}

Furthermore, Fig. 4 demonstrates the topology and details of the used model.

Besides, the coefficient of correlation (R) and mean square error

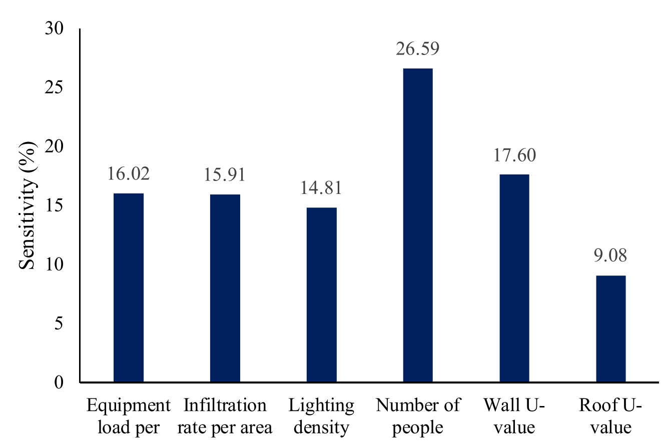

Fig. 8. Sensitivity analysis by Garson method (6 inputs).

(MSE) were chosen as the performance indicants of the ANNs (Eqs. (5) and (6)):

$$R = \frac{n(\sum_{i=1}^{n} x_i x'_i) - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} x'_i)}{\sqrt{[n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x'_i)^2]}\sqrt{n\sum_{i=1}^{n} x_i'^2 - (\sum_{i=1}^{n} x'_i)^2}} \quad (5)$$

$$MSE = \frac{\sum_{i=1}^{n} |(x_i - x'_i)^2|}{n} \quad (6)$$

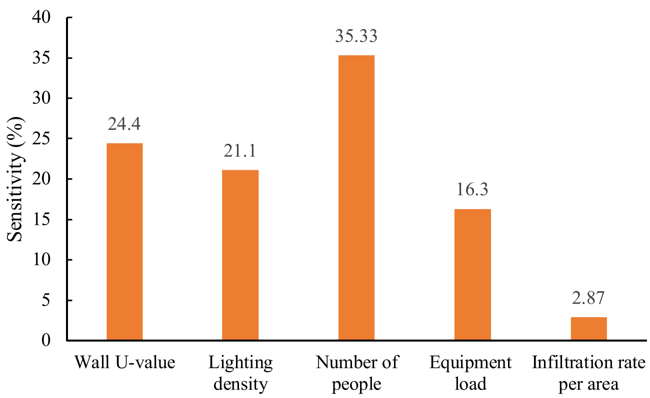

Fig. 9. Sensitivity analysis by Garson method (5 inputs).

where x_i denotes measured energy and x'_i represents predicted energy.

2.2.2. Genetic algorithm

Genetic Algorithm (GA), known as one of the foremost optimization algorithms, is evolved based on the Darwinian evolution of population (Dincer, Rosen, & Ahmadi, 2017). The initial operators of GA are based on selection, crossover, and mutation (Habibollahzade, Gholamian, & Behzadi, 2019). The benefits of this algorithm can be seen when a large group of parameters is considered for optimization (Erdinc & Uzunoglu, 2012). It is notably, it has been proven that GA is a suitable method for optimizing building energy, especially for envelope, Shape, HVAC, and renewable energy systems (Evins et al., 2010). Furthermore, GA assesses multiple performance indicants to ascertain a set of optimum solutions within a short amount of time. However, implementing GA for practical problems require extensive mathematical and computer programming knowledge. On the other hand, David Rutten (Rutten, 2013) created Galapagos to overcome correlative problems and conveniently implement the algorithm. Thanks to the development of software products such as Galapagos Evolutionary Solver, GA is widely used by architects and engineers. Noteworthy, Galapagos is an evolutionary solver plugin in Grasshopper, which uses GA to fulfill the optimization. Essentially, Galapagos is a solution that confirms acceptable environmental performance and controls trial time and error processes (González & Fiorito, 2015). In this method, the changes in the simulation can be implemented routinely, and the results can be saved and systematized based on their performance. Therefore, in this study, the primary goal of each optimization is to determine input parameters' value to minimize energy consumption. Accordingly, a Rhino component, named Galapagos, was used in this research to achieve optimum fitness. It is worth bearing in mind that, the concept of Galapagos optimization is based on GA. The population is chosen by three operators: selection, crossover and mutation. "Each of the individuals in population undergoes fitness evaluation, that is, evaluation of the objective function"(Ali, Emary, & Abd El-Kareem, 2009). Considering selection, individuals are chosen based on Eq. (7) where f (parent i) denotes the fitness of the ith parent.

$$P_{Selection} = F(parent_i) \Big/ \sum F(parent_i) \tag{7}$$

Randomly combining of good portions of each genome is called crossover. Afterward, random **P** is generated and if **P** < $\mathbf{P_{mut}}$, the random **P** is counted as allele. Fig. 5 shows the GA algorithm process.

In the optimization process, genetic parameters were set as follows: stagnant 50, population 50, maintenance 5%, and inbreeding 75 %. It should be noted that the number of 50 for the population means that after 50 simulations, a new generation is reproduced and on the other hand, algorithm parameters have a substantial impact on the performance of the algorithm. To have a satisfactory accuracy, the aforementioned algorithm parameters' values are considered according to the scientific literature reports. However, the parameters used in the algorithm should be modified if the accuracy of the outcomes would not be satisfactory. Generally, the optimization process associated with GA might stop regarding two ways which are considered in this study: (1) setting a time duration for it to stop automatically; (2) setting certain pre-definitions to stop the process in the case of unsuccessful iterations.

Fig. 6 shows the whole numerical simulation procedure including optimization algorithm.

3. Results and discussion

The ANN results, sensitivity outcomes along with optimization results are presented and discussed in detail.

3.1. Validation

To validate the energy results of the building simulation by EnergyPlus software, a comparison between electrical consumption bills of the existing building and the results of the simulation one is presented in Fig. 3. The bills of electrical consumption have been gathered monthly, duration of one year in standard situation from existing research center. Other part of the study such as ANN and Genetic algorithm were toolbox of the MATLAB software and a plugin of the Grasshopper software which were validated. As can be seen in the figure, there is a decent agreement between the outcomes of this study and available empirical data where a maximum error of 11.8 % concluded.

3.2. Artificial neural network results

To have a satisfactorily accurate ANN model, 1602 simulation tests were performed, and for the data division, 70 % of the data were used for the training, 15 % for the validation, and 15 % for the testing. Accordingly, to fulfill the simulation, different ANN models were created and thereafter simulated with only one hidden layer and many hidden neurons. The selection process of hidden layer neurons was performed based on the trial-and-error test, indicating that the best performer model is associated with the ANN model with 10 hidden neurons (Topology: 6 × 10 × 1). Fig. 7 shows the details of the ANN model highlighting the fact that *MSE* values ranged from 3.18e-1 to 3.93e-1 kWh/m^2, while R value (average for all data) was concluded to be 0.9997. Considering the concluded indicants, the high-performance level for the best ANN model can be proven in this study. MSE demonstrates the distance between the model's estimate of test values and the actual test value. The result shows that continuing after Epoch 10, the performance of the ANN remained constant; however, the best *MSE* was determined in Epoch 25. Furthermore, a sensitivity analysis of the

Table 6
Details of simulation (1), simulation (151), and simulation (301).

Iteration number	Wall U-value [W/m^2.k]	Equipment load rate [W/m^2]	Infiltration rate [m^3/s-m^2]	Lighting density [W/m^2]	Number of occupants [PPL/m^2]	Roof U-value [W/m^2.k]
1	0.513	2	0.0001	3	0.02	0.32
151	0.384316	5	0.0001	9	0.37	0.283158
301	0.77	5	0.0001	8	0.21	0.283158

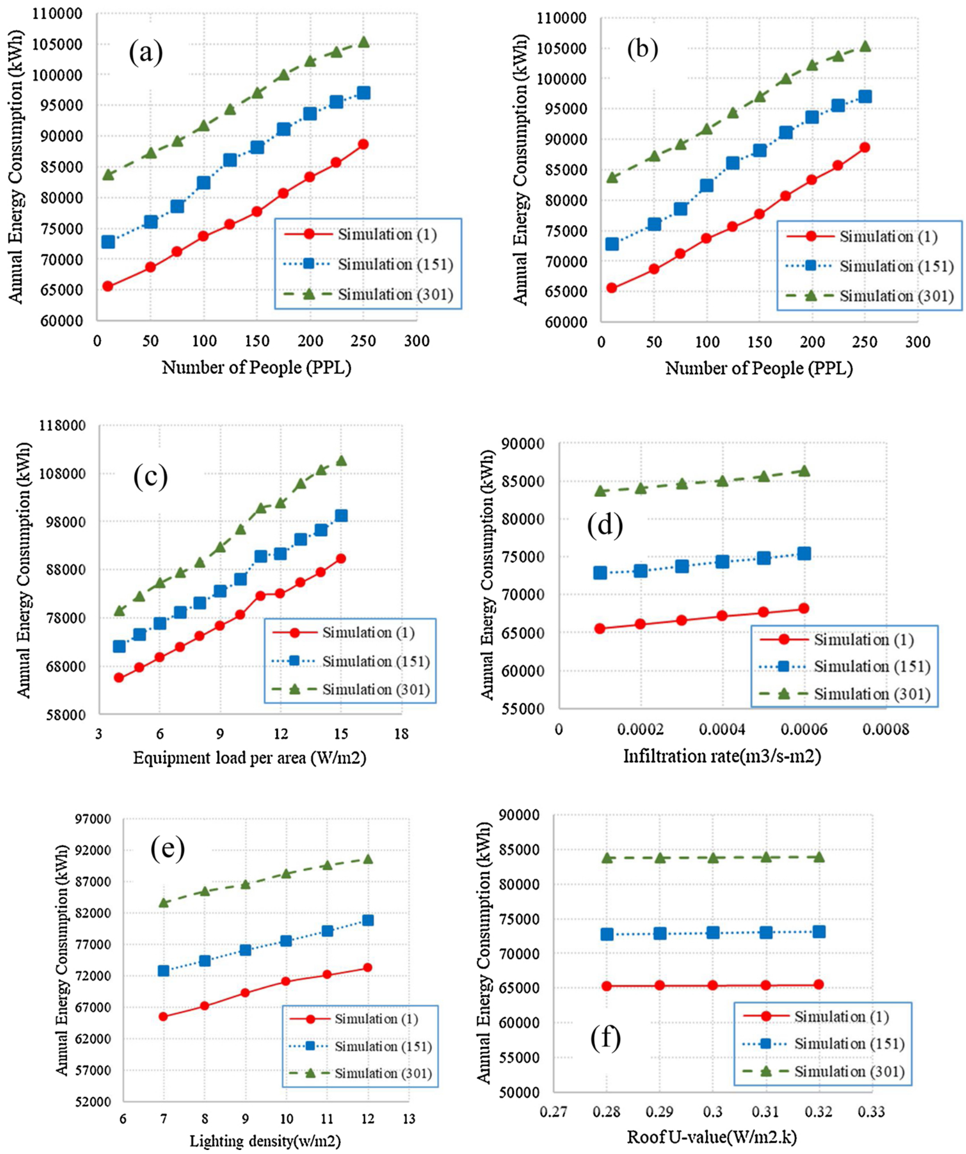

Fig. 10. (a) Effect of “Number of people” parameter on energy consumption (b) Effect of “Wall U-Value” parameter on energy consumption (c) Effect of “Equipment load per area” parameter on energy consumption (d) Effect of “Infiltration rate” parameter on energy consumption (e) Effect of “Lighting density” parameter on energy consumption (f) Effect of “Roof U-value” parameter on energy consumption.

best ANN model was conducted using *Garson’s* algorithm (Garson, 1991), and the details of the algorithm are provided in Fig. A1 in Appendix A. On the other hand, the weights of the best ANN model were extracted from pre-defined commands in MATLAB software. For a sample, Table 4 shows the details of the weights of input and hidden layers of the best ANN model, while Table 5 indicates the performance indices of the favorable model.

3.3. Sensitivity analysis

After ascertaining the ideal ANN, the weights and biases of the network were extracted, as shown in Table 4 and the outputs were utilized for the sensitivity analysis. Fig. 8 quantitatively demonstrates the importance of each input parameter for predicting the energy consumption of the studied Research Center. The inference from the figure is that the number of occupant’s influences more significantly on the energy consumption compared to the other parameters. Accordingly, the increment of the occupants can potentially increase energy consumption as the energy demand increases. On the other hand, wall U-value, equipment load, and infiltration rate may affect energy consumption somewhat equally. Wall U-value with the contribution of 17.60 % was ascertained to be the second most effective parameter according to the conducted sensitivity analysis. The figure further shows that the effect of equipment load rate (16.02 %) is comparable with the infiltration rate per area (15.91 %). Naturally, roof U-value was found to be the least influencing factor (9.08 %) for the simulation. Hence, the main aim of this study is to evaluate and compare the effects of crucial parameters on the target of ANN. Furthermore, for comparison purposes, another sensitivity analysis was conducted considering five inputs regardless of roof U-value, as shown in Fig. 9. However, similar outcomes were obtained, and the number of occupants was determined as the most effective parameter. Additionally, once more, the wall U-value was ranked second with a value of 24.4 %. Therefore, the authors believe that based on the results of sensitivity analysis of the models, to decrease the energy consumption, controlling attending of the people to the research center and the used-material in walls can have significant impact.

To determine variations of energy use and effective parameters, first, three ANN simulation tests were selected for comparison purposes, and then energy consumption was evaluated. The details of these three

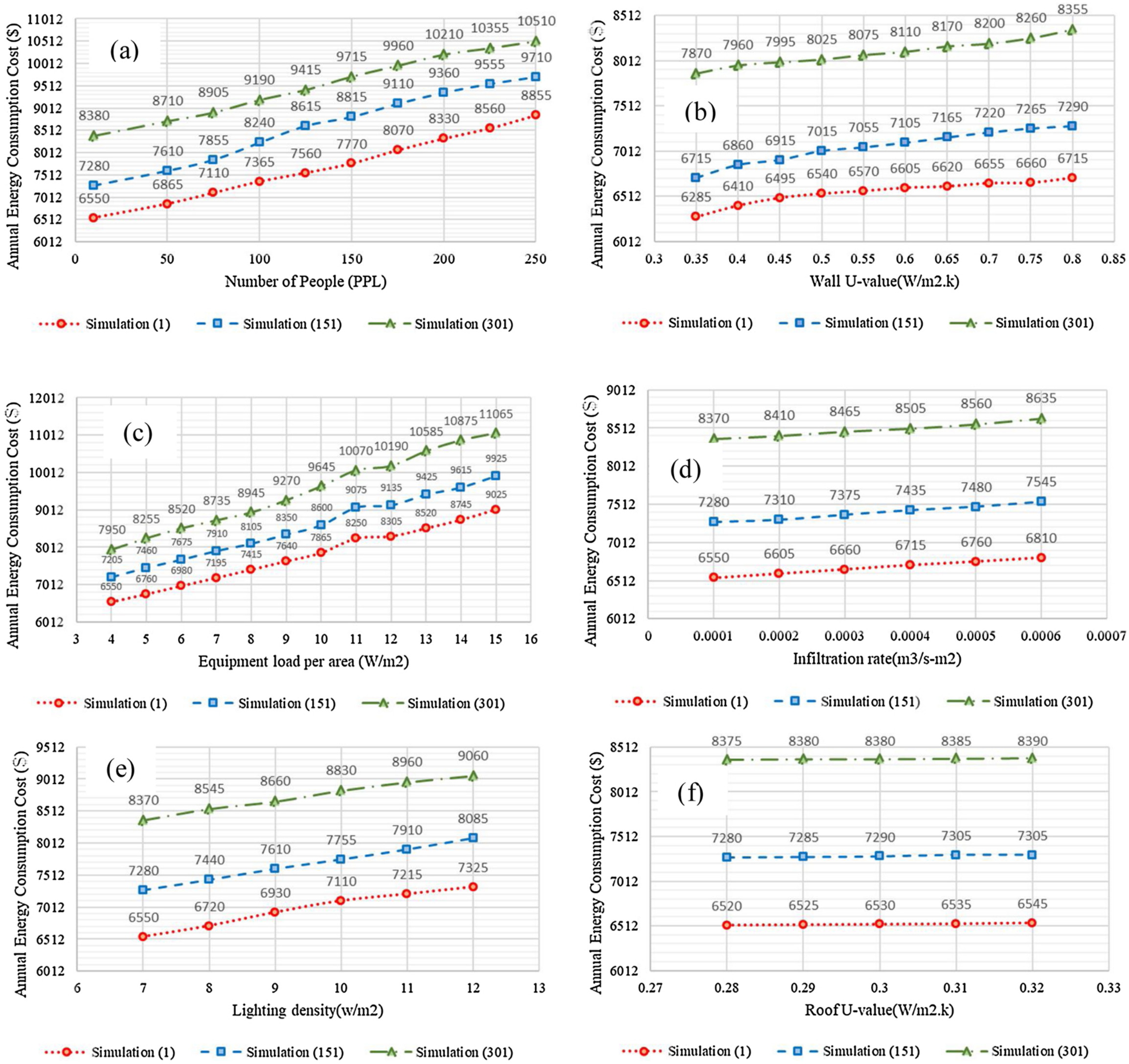

Fig. 11. (a) Effect of "Number of people" parameter on energy Cost (b) Effect of "Wall U-Value" parameter on energy Cost (c) Effect of "Equipment load per area" parameter on energy Cost (d) Effect of "Infiltration rate" parameter on energy Cost (e) Effect of "Lighting density" parameter on energy Cost (f) Effect of "Roof U-value" parameter on energy Cost.

ANN simulation tests are provided in Table 6. In the next step, different ranges of initial six parameters were inserted into the ANN model in MATLAB software, and the results of the predicted energy consumption were recorded. The calculated variations of energy consumption are presented in Fig. 10a–f based on the effective input parameters and also the calculated annual energy cost are shown in Fig. 11a–f as well. According to the comparison results of the mentioned sensitivity analyses, it can be observed that the rate of variation of energy consumption based on the input parameters mostly confirms the sensitivity results. For a better understanding, Fig. 12 shows the effect of the number of occupants and wall U-value on energy consumption over 1602 simulation tests. As can be seen in the 3D chart, as the number of occupants in the case study grows, the energy consumption increases sharply. Also, when the wall U-value raises, the energy consumption increases, yet not as high as the case with the high number of occupants. This statement again confirms the results of the sensitivity analysis.

As mentioned before, the number of occupants had the highest effect on energy consumption, and equipment load per area ranked third among the effective parameters. In contrast, different outcomes were achieved considering the concluded trends. The difference between the slopes and sensitivity analysis results is rooted in the fact that they are non-comparable. Thus, the trends can be compared with respect to the simulation number of each parameter with decent accuracy.

3.4. Optimization results

The optimization process proposed in the methodology section was implemented for the case of a Research Center to reach the minimum amount of energy consumption. To ascertain the optimum amount of energy consumption, 1243 iterations were evaluated. The results of 20 optimum energy consumption rates are characterized in Table 6. Besides, the variability ranges of each optimized variable were selected following the particularities of the case study, authors' expertise, and similar previous optimization studies. Based on the best 20 iterations energy-use percent, founded by GA, shown in Fig. 13. The energy-use percent from 20 minimum iterations decreased from 31.4%–35% (111.14–106.9). Concerning the overall optimum results, annual energy consumption decreased by 35 %; from 163 kW h/m^2 to 106.9 kW h/m^2 by changing the factors values. Creating the ANN models not only does ascertain the relation among inputs and outputs, but it can also determine the effective parameters in energy consumption. Considering the linear relationship between all inputs and outputs, the lowest value is the best option while this is valid only for iteration 20. For finding the other lowest iterations, the ANN model is required.

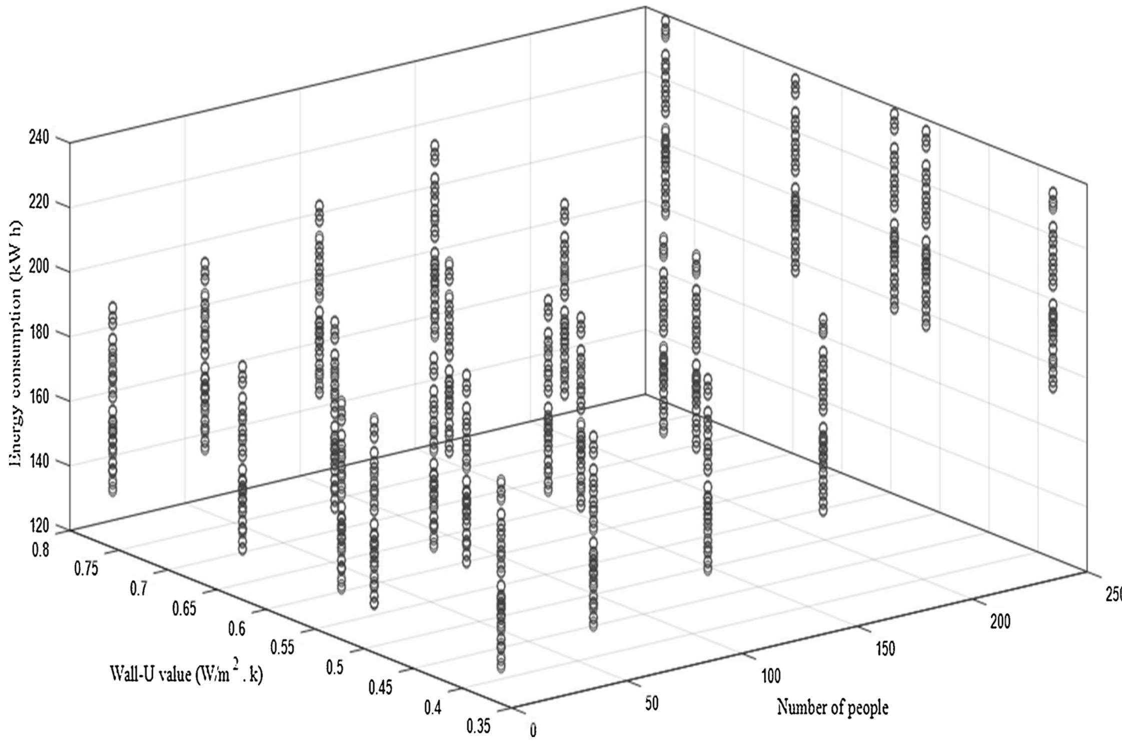

Fig. 12. Effect of the number of occupants and wall U-value on energy consumption (1602 simulations).

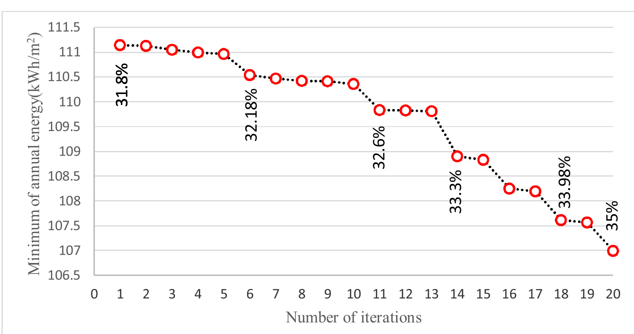

Fig. 13. Optimization percent of the energy consumption in the last 20 iterations.

According to Table 7, the iteration number (20) has the minimum energy consumption rate of 0.384316 for Wall U-value. In ASHRAE Standard 90.1–2010, the mentioned value is obtained for the external wall steel-frame, which is appropriate for the relevant climate zone of the case study. For the roof U-value, number 0.283158 indicates the external roof IEAD material. Also, other materials with the same wall U-value and roof U-value can be used for the minimum energy consumption. Since equipment load rate is the sum value of the number of computers and applications per meter on the floor, number 2 indicates that 1–2 laptops are enough for each zone based on current occupants needed. To carry out some detailed simulations, every room is divided into two zones. Therefore, 2–4 laptops are suggested to be enough for each room. Finally, infiltration rates showed that the building was considered as a compact building, and number 3 for lighting density indicated that all light bulbs should be replaced by efficient LED bulbs. Fig. 14 shows the energy consumption value for different parts of the buildings when the solutions are converged. Considering the Fig. 15, As energy consumption decreased, the energy Cost has been declined as well. Based on the energy price, the average of 241 $ will be saved monthly by decreasing 35 % of energy consumption.

Findings can be applied to other buildings in a similar approach. The proposed method can be performed for different climate zones. Moreover, the result of sensitive analysis can be considered for deciding the start point of renovating of the current buildings. For the future studies, an examination of the other renovation parameters such as material of windows and other insulation is suggested. Other recommendations would be investigating the role of interior design in reducing the energy consumption and conducting the building renovation by linking ANN other innovative optimization algorithms.

4. Comparison to the literature

To find the impact rates of parameters on energy consumption, Lu, Li, and Lin (2020)) considered Wall-U value, occupant density and occupant schedule as parameters of optimization. The results showed that energy consumption decreased up to 13 %. Comparing their result and this paper's findings, findings confirmed the result of the mentioned paper. Although, in this paper, infiltration rate, lighting density, roof U-value and equipment load rate were considered additionally as the input parameters. Likewise, in other studies, wall construction, WWR, angel and width of windows were deliberated as input parameters and energy consumption decreased 21.3 % (Toutou, Fikry, & Mohamed, 2018). As can be seen, wall construction counts as an important parameter for energy optimizing. Comparing the mentioned papers and our findings, the results of this paper confirmed the other studies and add several important parameters and rating the impact of parameters on energy reduction. In one of the related work, Keshtkarbanaeemoghadam, Dehghanbanadaki, and Kaboli (2018)) simulated, estimated, and then optimized the heating energy demand of a shelter located in mountainous areas (Damavand mountain) in Iran. For improving the performance indices of the ANNs, metaheuristic algorithms of particle swarm optimization (PSO) and gray wolf optimization (GWO) were utilized. The basic ANN was trained based on conventional back-propagation algorithm (BP). In addition, two different optimizer engines, i.e., Galapagos and Silvereye, were employed to minimize the heating energy demand in the proposed models. Sensitivity analysis was also performed in their study and the results demonstrated that a number of people or occupant density was recognized as the most

Table 7
Details of Galapagos results.

Iteration number	Wall U-value [W/m^{2}k]	Equipment load rate [W/m^2]	Infiltration rate [m^3/s-m^2]	Lighting density [W/m^2]	Number of occupants [PPL/m^2]	Roof U-value [W/m^{2}k]	Energy consumption [kWh/m^2]
20	0.384316	2	0.0001	3	0.02	0.283158	106.993465
19	0.384316	2	0.0001	3	0.02	0.326303	107.56526
18	0.384316	2	0.0001	3	0.03	0.283158	107.614932
17	0.384316	2	0.0001	3	0.03	0.326303	108.193744
16	0.384316	2	0.0001	3	0.04	0.283158	108.252708
15	0.384316	2	0.0001	3	0.04	0.326303	108.833355
14	0.384316	2	0.0001	3	0.05	0.283158	108.901906
13	0.384316	2	0.0003	3	0.02	0.326303	109.813901
12	0.384316	2	0.0003	3	0.03	0.283158	109.826615
11	0.384316	2	0.0001	4	0.02	0.283158	109.837642
10	0.513649	2	0.0001	3	0.02	0.283158	110.358919
9	0.384316	2	0.0001	4	0.02	0.326303	110.41745
8	0.384316	2	0.0003	3	0.03	0.326303	110.422601
7	0.384316	2	0.0001	4	0.03	0.283158	110.475342
6	0.513649	2	0.0001	3	0.02	0.283158	110.544136
5	0.513649	2	0.0001	3	0.02	0.326303	110.963747
4	0.384316	3	0.0001	3	0.02	0.283158	111.001368
3	0.384316	2	0.0001	4	0.03	0.326303	111.053236
2	0.384316	2	0.0001	4	0.04	0.283158	111.127653
1	0.513649	2	0.0001	3	0.02	0.326303	111.149996

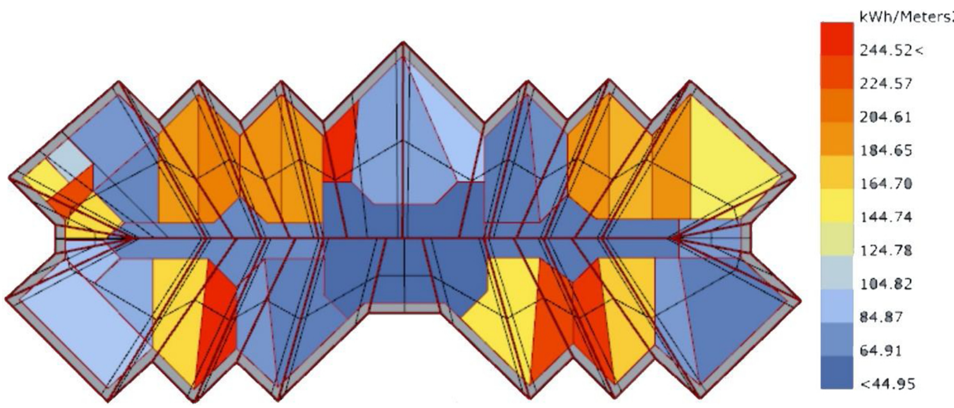

Fig. 14. Energy consumption value for different parts of the studied building.

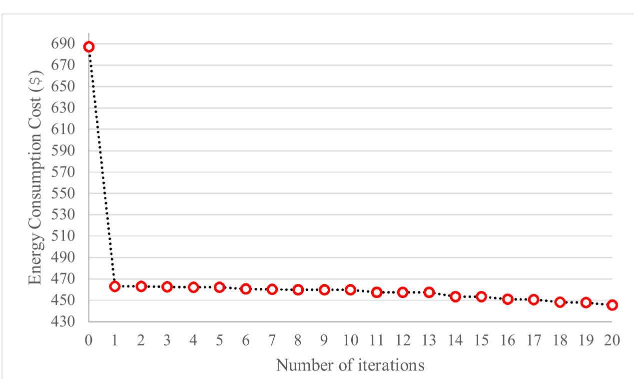

Fig. 15. Energy consumption Cost of the studied building.

important factor for decreasing of the energy consumption (Keshtkarbanaeemoghadam et al., 2018). Their finding was as similar as our finding in sensitivity analysis. Furthermore, the mentioned research used the same optimization and software as well as this paper.

5. Conclusion

Reducing the energy consumption of the buildings located in Iran was the main objective of this research. Creating, training and employing numerous ANN models to compute the required energy of the current edifice, conducting a comprehensive sensitivity analysis to evaluate the effect of the input factors on energy-use and finding the most effective factors on energy consumption through the use of ANN are the novelties of this study. In addition, the simulations of energy analysis of the building were performed using grasshopper and EnegyPlus calculation engine. Subsequently, an Artificial Neural Network (ANN) was trained by propagation Levenberg-Marquardt to estimate the most effective parameters of the building on energy consumption. Six critical parameters, namely the number of occupants, wall U-value, roof U-value, equipment load rate, infiltration rate, and lighting density, were considered as the input of the ANN, and the energy consumption was selected as the objective function. Furthermore, two different sensitivity analyses were accomplished to evaluate the effect of important parameters on energy consumption considering the case study. Eventually, the energy consumption of the studied edifice was optimized by Genetic Algorithm method via Galapagos plugin. The results demonstrated that the average energy consumption decreased by 35 % through the optimization process of the energy use in the case study by Genetic Algorithm. Architectural parameters have a significant and critical role in determining the building's energy performance, which can be vastly reduced by choosing suitable design parameters. Other main important results of this study are classified as:

1 The results demonstrated that the best ANN model had MSE = 0.39 e^{-2} MWh and the average regression index of around one (0.9971, 0.9972 and 0.9963 for training, validation, and testing, correspondingly), presentation high performance of the model. Consequently, this ANN model is promising and can be used to forecast energy consumption.
2 *Garson's* algorithm shows the high accuracy for ANN model regarding the renovating by 99.9 %.
3 By considering the input parameters of the sensitivity analysis, the most useful parameter in renovating the building is the number of occupants and in the second level, wall U-value by 26.59 % and 17.60 %.
4 In a sensitivity analysis, equipment load rate and infiltration rate have been similar effect on energy-use rate (16.02 % and 15.91 %).
5 Optimizing the proposed models by Galapagos plugs-in indicated a substantial decline in the energy consumption. Meanwhile, the Galapagos plug-in determined the averages 106.90 kW h for energy-use of the research center.
6 The 241$ will be saved monthly by conducting the energy optimization as the paper proposed
7 Considering the GA, based on ASHRAE Standard 90.1–2010, the external wall steel-frame is a proposed material for the relevant climate zone of the case study.
8 The proposed model can be considered for renovating the buildings as innovative method for energy consumption reduction by considering the proposed parameters for other existing building renovation.

It should be mentioned that the most important parameters were selected to optimize the energy consumption of the studied Research Center. However, more input parameters may be explored and applied to evaluate more complexed and complicated buildings. Accordingly, considering the other parameters not only does moderate the energy consumption, but they also optimize other critical elements of building performance, e.g. heating and cooling in particular, thermal comfort, and environmental impacts. Thus, new design parameters can be taken into account in order to include and extend the mentioned objectives for future research studies.

Declaration of Competing Interest

We have no conflicts of interest to disclose.

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Appendix A

Fig. A1

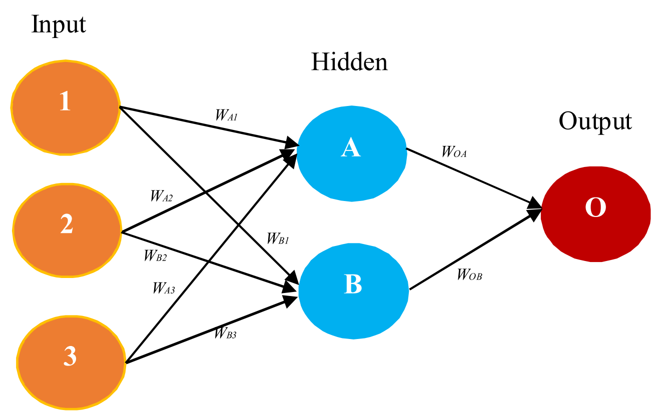

Fig. A1. Garson Algorithm Process (Example for 3 inputs and 2 hidden layers).

Determination of connection weights.

Item	Hidden A	Hidden B
IN 1	W_{A1}	W_{B1}
IN 2	W_{A2}	W_{B2}
IN 3	W_{A3}	W_{B3}
Output	W_{AO}	W_{BO}

$C_{A1} = (W_{A1})\,(W_{OA})$.

Item	Hidden A	Hidden B
IN 1	C_{A1}	C_{B1}
IN 2	C_{A2}	C_{B2}
IN 3	C_{A3}	C_{B3}

$r_{A1} = |C_{A1}| / (|C_{A1}| + |C_{A2}| + |C_{A3}|)$.

Item	Hidden A	Hidden B	Sum
Input 1	r_{A1}	r_{B1}	S_1
Input 2	r_{A2}	r_{B1}	S_2
Input 3	r_{A3}	r_{B1}	S_3

$$R_{A1} = [S_1 / (S_1 + S_2 + S_3)] \ (100\ \%).$$

Item	Relative importance
Input 1	R_{A1}
Input 2	R_{A2}
Input 3	R_{A3}

References

Ali, A. D., Emary, I. M. M. E., & Abd El-Kareem, M. M. (2009). Application of genetic algorithm in solving linear equation systems. *MASAUM Journal of Basic and Applied Science, 1*(2), 179–185. Retrieved from https://pdfs.semanticscholar.org/a62e/d1bea684947fce63f527d7b5388867022607.pdf.

Amber, K. P., Ahmad, R., Aslam, M. W., Kousar, A., Usman, M., & Khan, M. S. (2018). Intelligent techniques for forecasting electricity consumption of buildings. *Energy, 157*, 886–893. https://doi.org/10.1016/j.energy.2018.05.155.

Amiri, S., Dehghanbanadaki, A., ... Nazir, R. (2020). *Unit composite friction coefficient of model pile floated in kaolin clay reinforced by recycled crushed glass under uplift loading.* undefined. (n.d.). Retrieved fromElsevierhttps://www.sciencedirect.com/science/article/pii/S2214391219303885.

Ascione, F., Bianco, N., Maria Mauro, G., & Napolitano, D. F. (2019). Building envelope design: Multi-objective optimization to minimize energy consumption, global cost and thermal discomfort. Application to different Italian climatic zones. *Energy*. https://doi.org/10.1016/J.ENERGY.2019.02.182.

Bamdad, K., Cholette, M. E., Guan, L., & Bell, J. (2018). Building energy optimisation under uncertainty using ACOMV algorithm. *Energy and Buildings, 167*, 322–333. https://doi.org/10.1016/j.enbuild.2018.02.053.

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

Boyano, A., Hernandez, P., & Wolf, O. (2013). Energy demands and potential savings in European office buildings: Case studies based on EnergyPlus simulations. *Energy and Buildings, 65*, 19–28. https://doi.org/10.1016/j.enbuild.2013.05.039.

Brambilla, A., Salvalai, G., Imperadori, M., & Sesana, M. M. (2018). Nearly zero energy building renovation: From energy efficiency to environmental efficiency, a pilot case study. *Energy and Buildings, 166*, 271–283. https://doi.org/10.1016/j.enbuild.2018.02.002.

Bu, Z., Shao, M., Wang, X., Chen, X., & Wang, Y. (2020). *Prediction of energy consumption in hotel buildings via support vector machines Building Sub-metering Data Application view project Prediction of energy consumption in hotel buildings via support vector machines.* Elsevierhttps://doi.org/10.1016/j.scs.2020.102128.

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

Bui, D. K., Nguyen, T. N., Ngo, T. D., & Nguyen-Xuan, H. (2020b). An artificial neural network (ANN) expert system enhanced with the electromagnetism-based firefly algorithm (EFA) for predicting the energy consumption in buildings. *Energy, 190*(October 2019), https://doi.org/10.1016/j.energy.2019.116370.

Dehghanbanadaki, A., Sotoudeh, M. A., Golpazir, I., Keshtkarbanaeemoghadam, A., & Ilbeigi, M. (2018). Prediction of geotechnical properties of treated fibrous peat by artificial neural networks. *Bulletin of Engineering Geology and the Environment*. https://doi.org/10.1007/s10064-017-1213-2.

Dehghanbanadaki, A., Khari, M., Arefnia, A., Ahmad, K., & Motamedi, S. (2019). A study on UCS of stabilized peat with natural filler: A computational estimation approach. *KSCE Journal of Civil Engineering, 23*(4), 1560–1572. https://doi.org/10.1007/s12205-019-0343-4.

Delgarm, N., Sajadi, B., Kowsary, F., & Delgarm, S. (2016). Multi-objective optimization of the building energy performance: A simulation-based approach by means of particle swarm optimization (PSO). *Applied Energy, 170*, 293–303. https://doi.org/10.1016/j.apenergy.2016.02.141.

Dermentzis, G., Ochs, F., Gustafsson, M., Calabrese, T., Siegele, D., Feist, W., ... Bales, C. (2019). A comprehensive evaluation of a monthly-based energy auditing tool through dynamic simulations, and monitoring in a renovation case study. *Energy and Buildings, 183*, 713–726. https://doi.org/10.1016/j.enbuild.2018.11.046.

Dincer, I., Rosen, M. A., & Ahmadi, P. (2017). *Optimization of energy systems.* https://doi.org/10.1002/9781118894484.

Dotzler, C., Botzler, S., Kierdorf, D., & Lang, W. (2018). Methods for optimising energy efficiency and renovation processes of complex public properties. *Energy and Buildings, 164*, 254–265. https://doi.org/10.1016/j.enbuild.2017.12.060.

Erdinc, O., & Uzunoglu, M. (2012). Optimum design of hybrid renewable energy systems: Overview of different approaches. *Renewable and Sustainable Energy Reviews, 16*(3), 1412–1425. https://doi.org/10.1016/j.rser.2011.11.011.

Esmaeilzadeh, A., Zakerzadeh, M. R., & Koma, A. Y. (2018). The comparison of some advanced control methods for energy optimization and comfort management in buildings. *Sustainable Cities and Society, 43*, 601–623. https://doi.org/10.1016/J.SCS.2018.08.038.

Evin, D., Ucar, A., & Ucar, A. (2019). *Accepted manuscript.* https://doi.org/10.1016/j.applthermaleng.2019.03.102.

Evins, R., Pointer, P., & Vaidyanathan, R. (2010). Configuration of a genetic algorithm for multi-objective optimisation of solar gain to buildings. *Proceedings of the 12th Annual Conference on Genetic and Evolutionary Computation - GECCO' 10*, 1327. https://doi.org/10.1145/1830483.1830726.

Farahani, A., Wallbaum, H., & Dalenbäck, J. (2018). SC. *Sustainable Cities and Society*. https://doi.org/10.1016/j.scs.2018.10.033.

Ferrara, M., Filippi, M., Sirombo, E., & Cravino, V. (2015). A simulation-based optimization method for the integrative design of the building envelope. *Energy Procedia, 78*, 2608–2613. https://doi.org/10.1016/j.egypro.2015.11.309.

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

Garson, G. (1991). Interpreting neural-network connections. *Artificial Intelligence Expert, 6*. Retrieved from https://dl.acm.org/citation.cfm?id=129452.

Gil-Baez, M., Padura, Á. B., & Huelva, M. M. (2019). Passive actions in the building envelope to enhance sustainability of schools in a Mediterranean climate. *Energy*, 144–158. https://doi.org/10.1016/j.energy.2018.10.094.

González, J., & Fiorito, F. (2015). Daylight design of office buildings: Optimisation of external solar shadings by using combined simulation methods. *Buildings, 5*(2), 560–580. https://doi.org/10.3390/buildings5020560.

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

Gustafsson, M., Dipasquale, C., Poppi, S., Bellini, A., Fedrizzi, R., Bales, C., ... Holmberg, S. (2017). Economic and environmental analysis of energy renovation packages for European office buildings. *Energy and Buildings, 148*, 155–165. https://doi.org/10.1016/j.enbuild.2017.04.079.

Habibollahzade, A., Gholamian, E., & Behzadi, A. (2019). Multi-objective optimization and comparative performance analysis of hybrid biomass-based solid oxide fuel cell/solid oxide electrolyzer cell/gas turbine using different gasification agents. *Applied Energy, 233–234*(October 2018), 985–1002. https://doi.org/10.1016/j.apenergy.2018.10.075.

Habibollahzade, A., Gholamian, E., Ahmadi, P., & Behzadi, A. (2018). Multi-criteria optimization of an integrated energy system with thermoelectric generator, parabolic trough solar collector and electrolysis for hydrogen production. *International Journal of Hydrogen Energy, 43*(31), 14140–14157. https://doi.org/10.1016/j.ijhydene.2018.05.143.

Habibollahzade, A., Houshfar, E., Ashjaee, M., Behzadi, A., Gholamian, E., & Mehdizadeh, H. (2018). Enhanced power generation through integrated renewable energy plants: Solar chimney and waste-to-energy. *Energy Conversion and Management, 166*(February), 48–63. https://doi.org/10.1016/j.enconman.2018.04.010.

Hakiminejad, A., Fu, C., & Titkanlou, H. M. (2015). A critical review of sustainable built environment development in Iran. *Proceedings of the ICE-Engineering Sustainability*, 105–119.

Harkouss, F., Fardoun, F., & Biwole, P. H. (2018). Passive design optimization of low energy buildings in different climates. *Energy, 165*, 591–613. https://doi.org/10.1016/j.energy.2018.09.019.

Hemsath, & Hosseini, B. (2015). Sensitivity analysis evaluating basic building geomtry's effect on energy use. *Renewable Energy*. Retrieved from https://www.sciencedirect.com/science/article/pii/S0960148114007599.

Keshtkarbanaeemoghadam, A., Dehghanbanadaki, A., & Kaboli, M. H. (2018). Estimation and optimization of heating energy demand of a mountain shelter by soft computing techniques. *Sustainable Cities and Society, 41*, 728–748. https://doi.org/10.1016/j.scs.2018.06.008.

Kim, M., Jung, S., & Kang, J. (2019). Artificial neural network-based residential energy consumption prediction models considering residential building information and user features in South Korea. *Sustainability, 12*(1), 109. https://doi.org/10.3390/su12010109.

Lartigue, B., Lasternas, B., & Loftness, V. (2014). Multi-objective optimization of building envelope for energy consumption and daylight. *Indoor and Built Environment, 23*(1), 70–80. https://doi.org/10.1177/1420326X13480224.

Lewicki, G., & Marino, G. (2003). Approximation by superpositions of a sigmoidal function. *Zeitschrift Fur Analysis Und Ihre Anwendung, 22*(2), 463–470. https://doi.org/10.4171/ZAA/1156.

Li, C., Hong, T., & Yan, D. (2014). An insight into actual energy use and its drivers in high-performance buildings. *Applied Energy, 131*, 394–410. https://doi.org/10.1016/j.apenergy.2014.06.032.

Lu, S., Zheng, S., & Kong, X. (2016). The performance and analysis of office building energy consumption in the west of Inner Mongolia Autonomous Region, China. *Energy and Buildings, 127*, 499–511. https://doi.org/10.1016/j.enbuild.2016.06.008.

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

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

Martínez, G., Pacheco, R., & Ordó, J. (2012). Energy efficient design of building: A review. *Renewable and Sustainable Energy Reviews, 16*, 3559–3573. https://doi.org/10.1016/j.rser.2012.03.045.

Mattoni, B., Gori, P., & Bisegna, F. (2017). A step towards the optimization of the indoor luminous environment by genetic algorithms. *Indoor and Built Environment, 26*(5), 590–607. https://doi.org/10.1177/1420326X15608229.

Mohandes, S. R., Zhang, X., & Mahdiyar, A. (2019). A comprehensive review on the application of artificial neural networks in building energy analysis. *Neurocomputing*. https://doi.org/10.1016/j.neucom.2019.02.040.

Mustapa, R., Dahlan, N., Yassin, A., & Buildings, A. N.-E. (2020). *Quantification of energy savings from an awareness program using NARX-ANN in an educational building.* undefined. (n.d.) Retrieved fromElsevierhttps://www.sciencedirect.com/science/article/pii/S0378778819331032.

National and Local Weather Radar (2020). *National and local weather radar, daily forecast, hurricane and information from the weather channel and weather.cOm.* (n.d.).

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

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

Rutten, D. (2013). Galapagos: On the logic and limitations of generic solvers. *Architectural Design, 83*(2), 132–135. https://doi.org/10.1002/ad.1568.

Salvalai, G., Malighetti, L. E., Luchini, L., & Girola, S. (2017). Analysis of different energy conservation strategies on existing school buildings in a Pre-Alpine Region. *Energy and Buildings, 145*, 92–106. https://doi.org/10.1016/j.enbuild.2017.03.058.

Shahin, M. A., Maier, H. R., & Jaksa, M. B. (2004). Data division for developing neural networks applied to geotechnical engineering. *Journal of Computing in Civil Engineering, 18*(2), 105–114. https://doi.org/10.1061/(ASCE)0887-3801(2004)18:2(105).

Toutou, A., Fikry, M., & Mohamed, W. (2018). The parametric based optimization framework daylighting and energy performance in residential buildings in hot arid zone. *Alexandria Engineering Journal, 57*(4), 3595–3608. https://doi.org/10.1016/j.aej.2018.04.006.

van den Brom, P., Meijer, A., & Visscher, H. (2019). Actual energy saving effects of thermal renovations in dwellings—Longitudinal data analysis including building and occupant characteristics. *Energy and Buildings, 182*, 251–263. https://doi.org/10.1016/j.enbuild.2018.10.025.

Walker, S., Khan, W., Katic, K., Maassen, W., & Buildings, W. Z.-E. (2020). *Accuracy of different machine learning algorithms and added-value of predicting aggregated-level energy performance of commercial buildings.* undefined. (n.d.) Retrieved fromElsevierhttps://www.sciencedirect.com/science/article/pii/S0378778819319139.

Wong, S. L., Wan, K. K. W., & Lam, T. N. T. (2010). Artificial neural networks for energy analysis of office buildings with daylighting. *Applied Energy, 87*(2), 551–557. https://doi.org/10.1016/j.apenergy.2009.06.028.

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

Zhang, L., & Pan, Y. (2020). *Data-driven estimation of building energy consumption with multi-source heterogeneous data BIM Data Analytics View project Data-driven estimation of building energy consumption with multi-source heterogeneous data.* Elsevierhttps://doi.org/10.1016/j.apenergy.2020.114965.