Journal of Soft Computing in Civil Engineering 5-4 (2021) 41-56

Contents lists available at SCCE

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Effects of Window-to-Wall Ratio on Energy Consumption: Application of Numerical and ANN Approaches

Aniseh Saber[1*]

1. M.Sc., Department of Engineering, Civil, Construction and Architecture, Marche Polytechnic University, Ancona, Italy

Corresponding author: *s1091787@studenti.univpm.it*

https://doi.org/10.22115/SCCE.2021.281977.1299

ARTICLE INFO

Article history:
Received: 18 April 2021
Revised: 13 October 2021
Accepted: 29 October 2021

Keywords:
Wall-to-window ratio;
Energy consumption;
Design builder;
Recycled panels;
Artificial neural networks.

ABSTRACT

Buildings account for a major part of Total Energy Consumption (TEC) in comparison to that of industry and other sections. The opening and envelope material can affect their TEC. Accordingly, this paper aims to study the effects of the window to external wall ratio (WWR) and the application of recycled panels as the building envelope on the total energy consumption in a one-floor residential building located in Iran and characterized by a semi-arid climate. To follow the sustainability criterion, we designed two concrete panels for the external walls' envelope including a porous concrete panel and recycled ash concrete panel. The WWR varies between 5% to 95% and the optimal WWRs are separately presented for all the months. To develop the models, we used Design Builder software which its simulations are validated via field observations. For all the panels, the least energy consumption is obtained when the WWR is 5%. However, due to lighting issues, the most optimal WWR is calculated as 45-55% based on the results of the numerical simulations. Further, it is proved that the recycled ash concrete panel outperforms the porous concrete panel in terms of minimum energy consumption. Hence, it is recommended to use eco-friendly material as the external walls envelop with the WWR below 50%. The numerical simulations provided 240 data points for each panel which is exploited to develop an ANN model. The results suggested that the ANN models predict the TEC based on the month and WWR with high accuracy.

How to cite this article: Saber A. Effects of window-to-wall ratio on energy consumption: application of numerical and ANN approaches. J Soft Comput Civ Eng 2021;5(4):41–56. https://doi.org/10.22115/scce.2021.281977.1299

1. Introduction

Energy consumption and sustainable designs of buildings are among the most prominent issues that are of interest by many architectures and engineers in recent decades. This is due to the crucial role of buildings in global energy requirements. That's why building energy efficiency can be assumed as a main solution to reduce unfavorable effects of buildings on the environment and human being [1]. Although, several methodologies have been applied to reduce the energy consumption from buildings, the building energy end-uses are projected to increase in the future due to several factors such as: increasing population, economic growth, and climate change. The buildings consume a considerable portion of energy and as a consequence, they are a major source of climate change [2]. In the European Union (E.U.), 40% of total energy consumption is related to buildings and made them the largest end-use sector in 2012 [3]. Fig. 1 illustrates the total energy consumption by various sectors in Iran. As indicated, the buildings' energy consumption is more evident than other sectors. As a consequence, the CO_2 emissions from the residential building sector stand in 3rd place as illustrated in Fig. 2. Therefore, it is fundamental to decrease energy consumption and use eco-friendly sustainable designs in the residential buildings of Iran.

Based on the data presented by world energy balances and statistics (IEA, 2020a, 2020b), the residential sector stands in the third rank in terms of TEC around the world. Therefore, it is fundamental to decrease energy consumption and use eco-friendly sustainable strategies in residential buildings. Energy-saving approaches in buildings can be classified into active and passive strategies [4]. Active methods deal with mechanical and electrical systems such as photovoltaic systems [5]. However, passive strategies focus on the optimization of building configuration and material such as geometry, orientation, glazing, shading, and insulation. Besides the advantages, the implementation of active systems may be time-consuming and costly. Nevertheless, the application of passive systems can lead to eco-friendly and energy-efficient designs. Among the components of the passive system, the building envelope material proved to be a more dominant parameter that influences the amount of energy consumption and thermal comfort of the residents [6].

It is shown that on average, 50% of TEC used for heating public places is transferred via the building envelope [7]. Keeping this in mind and following the sustainability targets, one can wonder about the application of waste and recycled material as the building components which guarantee significant advantages regarding the economic, energetic, and environmental points of view. Recently, the rate of municipal and construction waste produced during construction, operation, and demolition of buildings is increasing. Their reprocessing and reusing as the building material satisfy the sustainability targets. That is why many researchers have focused on the properties of various recycled-waste materials as the building envelope.

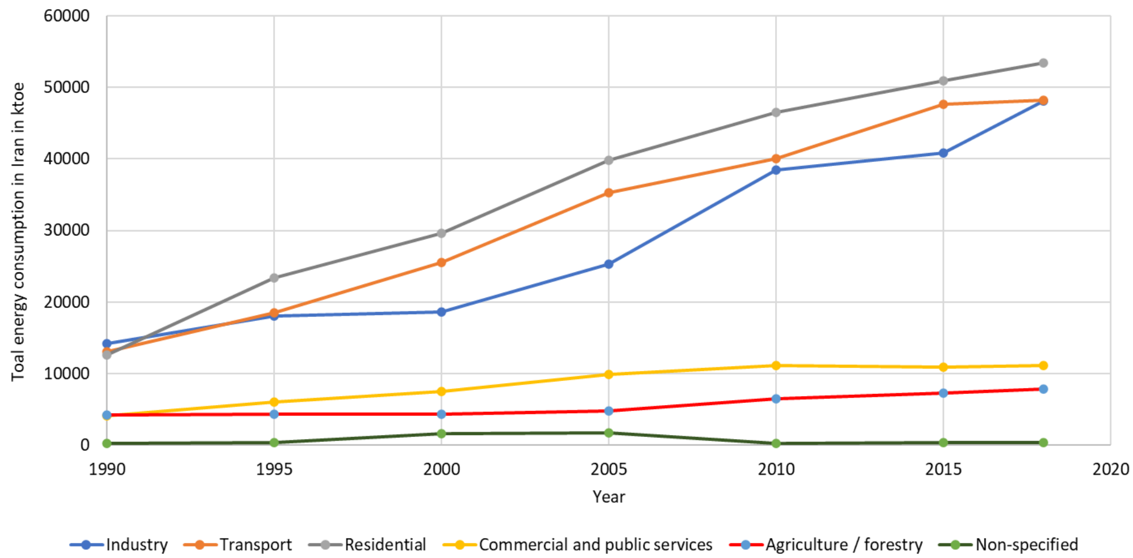

Fig. 1. Total final energy consumption (TFC) by sector, Islamic Republic of Iran 1990-2018 [5].

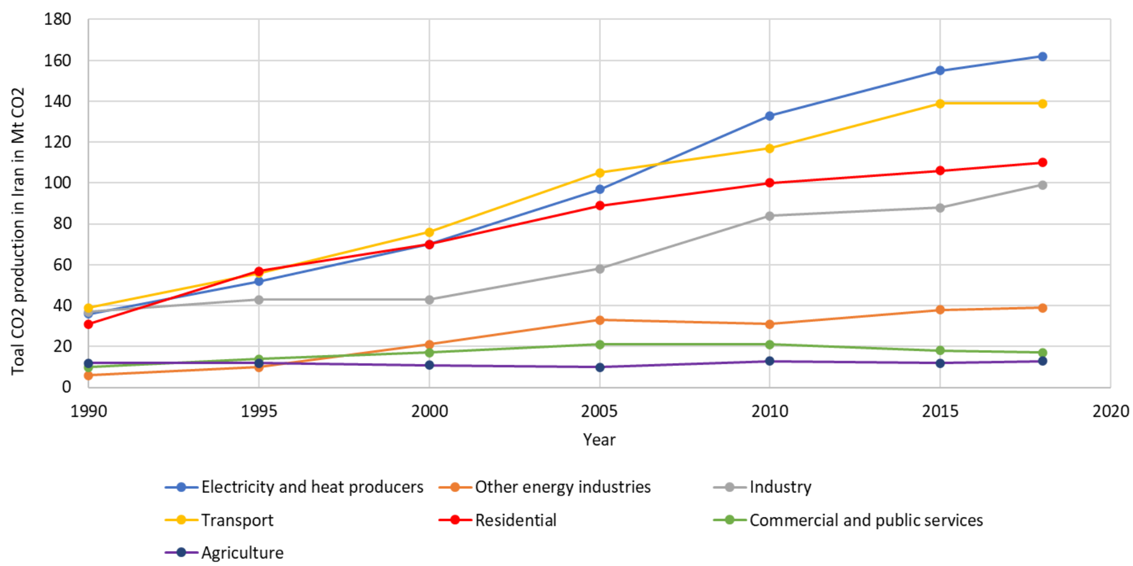

Fig. 2. Total CO2 emissions by sector, Islamic Republic of Iran 1990-2018 [6].

The implementation of recycled aggregates as the exterior envelope of the buildings, as well as the optimal ratio of windows to external wall size, can enhance the building performance regarding energy efficiency. The optimal WWR considers the effects of total energy consumption for cooling and heating and lighting. The impact of the window-to-wall ratio (hereafter WWR) on energy consumption is reported in several contributions [8–10]. The methodologies exploited in these contributions are categorized into numerical, field, experimental studies.

Afsarian et al. [2] investigated the performance of recycled aggregate panels as the external walls in energy conservation in a residential building. They proved that the energy consumption in the building is made with recycled ash concrete panels is significantly less than that of the buildings with porous concrete as the exterior envelope. Alibaba [9] optimized the window to external walls proportion in a university office based on the predicted mean vote (PMV) and a predicted percentage of dissatisfied (PPD). The results suggested that the optimal conditions are obtained when the WWR is 10%. Shaeri et al. [8] studied the optimum WWR of various façades of an office building in the three cities of Bushehr, Shiraz, and Tabriz (located in Iran, but they have utterly different climate conditions). The results suggested that for all the investigated climates the optimal WWR for the northern facade of the building ranges between 20%-30%. However, in the case of the southern façade, the optimal WWRs are 20%-30% for Bushehr, 10%-30% for Shiraz, and 20%-30% for Tabriz. Application of the extreme ranges of the optimal WWR in different cities leads to a 16%-25% difference in the energy consumption in Tabriz while this difference is 20%-100% for other cities. Fallah [11] studied the impacts of WWR on the energy efficiency of traditional residential and educational buildings in Iran employing fields survey and software simulations. The field observations showed that the investigated samples have WWR between 5%-15%. However, the numerical simulations proved that the optimal WWR is 30% for the southern façades when they are equipped with double-glazed windows but 15% while using single-glazed windows. To determine the optimal value of contributing parameters, recently, many studies exploited the capabilities of machine learning and optimization algorithms to predict and determine the most optimum values of input parameters [12–17].

The above-mentioned studies provided valuable information regarding the optimal WWR in different buildings. However, to our best knowledge, there is not any study in which the optimal WWR is determined for different recycled panels as the external walls' envelope. Accordingly, we aim to investigate the effects of WWR on the energy efficiency of various concrete panels (porous and recycled concrete panels) in a residential building located in Tabriz, Iran. Further, the optimal WWR is predicted for different walls envelope in all the months.

The structure of the paper is as follows: Section 2 gives detailed information about the building of interest, modeling procedure, and PSO approach. The results of this paper are presented in Section 3 and finally, Section 4 contains the summary and conclusions.

2. Material and method

2.1. Reference building

The building of interest contains 100 m^2 area and is built into a 10 m long, 10 m high, and 10 m wide. Fig. 3 illustrates the real (left panel) and 3Ds (right panel) representation of the building of interest. On each external wall, there is a window with variable dimensions which varies between 5% to 95%. Since the main goal of this study is to investigate the effects of the WWR on the TEC, we neglected the details of the internal plan in the modeling procedure. Table 1 summarizes the detailed information of the building which is exploited to develop numerical and data-driven models. The building is aimed to be occupied by two persons and it is assumed that the HVAC system is on during the occupied period.

Fig. 3. The real and 3Ds representation of the building of interest [1].

2.2. Envelope material

The reference building is located in Tabriz which is characterized by semi-arid cold climate conditions. In cold regions, the thermal conduction through the building envelope is more evident in comparison to the other climate conditions. It is proved that on average the 50% of TEC used for heating of the public places is transferred via the building envelope [7]. Two dominant factors which have a significant effect on the TEC through the envelope are envelope material and WWR. To assess the impact of the WWR, we developed various numerical and data-driven models using the different values of WWR ranging from 55 to 95%. Further, to evaluate the energy efficiency of recycled aggregate materials, we implemented three different recycled panels as the building envelope. The application of these renewable materials is completely in line with the sustainability targets highlighted in Agenda 21 for sustainable construction. One of the most widely used materials for building envelope is concrete which has a major impact on the environment and sustainable designs. Hence, in this study, three concrete panels including conventional concrete panels and concrete with recycled ash aggregates are implemented as the building envelope. Table 2 summarizes the information of these panels.

Table 1
Geographical, HVAC, and envelope Information of the building of interest.

Design factor		Value
Building location (Tabriz)	Coordinates	38°04′N 46°18′E
	Building type	Residential building
	Floor area (m^2)	100
	Elevation (m)	1351
	Time zone (h)	UTC+03:30
	Site ground temperature (ºC)	19
Windows glazing and frame	U-factor (W/m^2K)	1.6
	Solar heat gain coefficient	0.44
	Frame conductance (W/m^2K)	4.5
	Frame solar absorptance	0.7
	Frame thermal hemispherical emissivity	0.7
Lightning	Watts per zone area	12
	Fraction radiant	0.32
Electric equipment	Watts per zone floor area	10
	Fraction radiant	0.3
HVAC template	type	Fan-coil
	Constant heating setpoint (ºC)	21
	Constant cooling setpoint (ºC)	26

Table 2
The components of the various reference panels.

Reference panel	Components	proportion
Conventional or porous concrete	Recycled concrete aggregates (%)	40
	Cement (kg/m3)	400
	Water/cement	0.42
	Air entraining plasticizer (%) (per weight of cement)	
Concrete with 36% recycled solid incinerator bottom ash aggregate	Bottom ash (%)	36
	Cement (%)	24
	Vermiculite (%)	20
	Sand (%)	20

3. Modeling procedure

In this paper, to developing the numerical models, Design Builder software is employed. Since this software is user-friendly and has an easy-to-use interface, it is very convenient to import all the required information for the energy simulation models such as the building geometry, thermal properties of the components, windows to wall ratio, HVAC characteristics, the information of the building location, among others. Fig. 4 illustrates the steps that must be accomplished for developing a model using Design-Builder software.

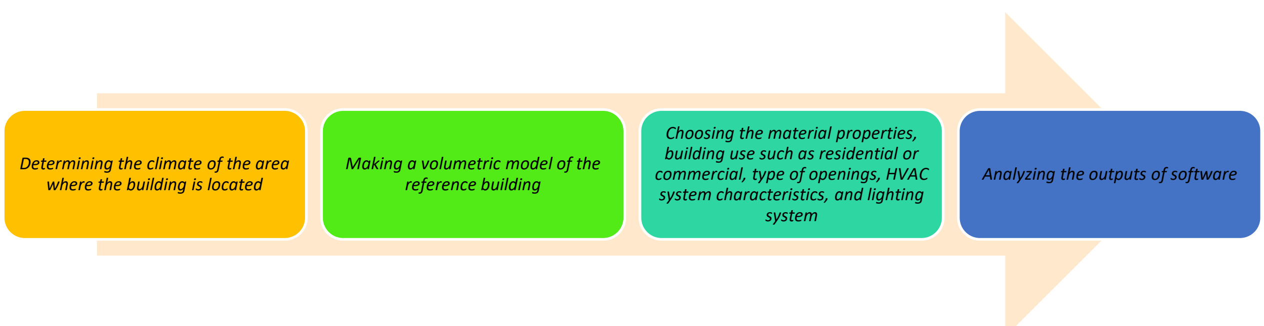

Fig. 4. Four preparatory steps must be accomplished to develop a model using Design-Builder software.

Based on the available literature openings account for a big amount of energy loss in buildings which should be design and operate properly. Besides, It is shown that one of the influential parameters concerning energy consumption of buildings are envelope material WWR [2]. On the other hand, climate condition due to the diversity of seasons and the angle of sun affect the energy balance of buildings in terms of heating and cooling. These logics can be addressed as the main reason behind the selection of WWR during various months as the input parameter. To develop a relationship between the input (WWR) and output (TEC) parameters, we exploited the capabilities of artificial neural networks. Recently, it is proved that this method is very robust and accurate in the prediction of the relationship between various parameters [12]. Hence, in the current study, we first developed the results of TEC based on various values of WWR at the different months (raging from January to December) for different envelope materials. Then, the developed datasets are imported into the ANNs to generate a relationship between the TEC and WWR during the year for panels.

3.1. Artificial neural networks (ANNs)

ANNs is an innovative technology inspired by the human brain and nervous system. To generate a relationship between the input and output parameters, they emulate a biological neural network[18]. Recently, it is proved that ANNs are capable to be implemented for dynamic modeling of nonlinear systems, classification, identification, and prediction, among others [19]. Like the human brain configuration, ANN contains a set of neurons, the fundamental processing element of a neural network, which is arranged in different layers, such as input, hidden, and output layers. The input layer (only one layer) is responsible to receive the external data to execute the pattern recognition. The output layer (only one layer) produces the problem solution and the hidden layers (one or more layers) perform as the intermediate components [20]. The multiplayer perceptron (MLP) is a popularly applied neural network structure [21]. Fig. 5 (left panel) illustrates a neuron and a three-layer perceptron neural network. The inputs and output of the neuron are defined using $\vec{X}$ and y, respectively. The output component of a neuron is produced via multiplying each input component multiplied by its estimated weight (assume that $\vec{W}$ stands for the weights vector) and importing the summation of these values into the activation function. Equation 1 indicates the mathematical expression between the inputs and output values in a neuron.

$$y = \mathcal{F}\left(\sum_{i=1}^{N} \vec{W}\ \vec{X}\right) \tag{1}$$

In which N stands for the number of input vector components.

The structure of a four-layer perceptron neural network is illustrated in Fig. 5 (right panel). As shown, the input layer contains the various parameters used to predict the outputs in the output layer. To predict the output vector, the ANN assigns a weight to each connection from the input parameter to the consecutive neuron in the next layer. For example, in the presented network, the weight matrix between input and first hidden layer is represented by $\vec{w}$. Bypassing the summed values of all the nodes entering the neuron through the activation function, the outcome of the neuron is produced which is the input of the consecutive layer.

The number of neurons in the input and output layers depends on the input and output parameters. However, the number of hidden layers and neurons at each hidden layer is challenging. In general, the more complicated the nonlinear behavior is, the more hidden layers and neurons will be added [22]. The optimal configuration of the employed ANN can be determined using an optimization algorithm. However, Rogers and Dowla [23] suggested the following criteria for the determination of hidden layer neurons number:

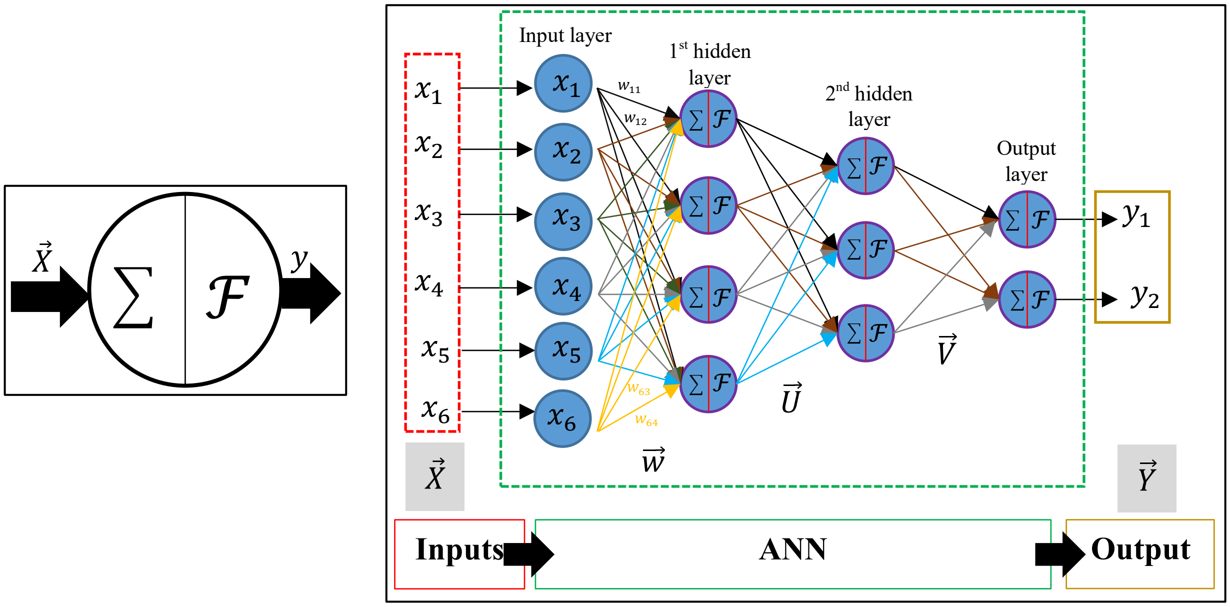

Fig. 5. A schematic representation of a neuron (left panel); A Four-layer perceptron neural network (right panel).

$$H_{Num} \leq 2INP_{Num} + 1$$
$$H_{Num} \leq \frac{TR_{Num}}{INP_{Num} + 1} \qquad (2)$$

where H_{Num} is the number of neurons in the hidden layers, INP_{Num} stands for the number of input parameters, and TR_{Num} refers to the number of training data points. In the current study, INP_{Num} equals to one and $TR_{Num} = 168$; hence, using Eq. (2) one can obtain the maximum number of neurons in the hidden layers as three neurons. The number of hidden layers and activation function, as well as the training algorithm, is determined based on the trial-and-error process. Table 3 summarizes the results of the optimal configuration of the employed ANN in the current study. The full dataset for each panel comprises 240 data points (12 months and for each month we developed 20 data points using the various percentage of WWR) which are divided into a training dataset (70% of the full dataset) and a testing dataset (30% of the whole data points). The statistical indices including the minimum (Min), Mean, maximum (Max), and standard deviation (Std) of the input and output parameters for all the panels are presented in table 3.

3.1.1. Evaluation of the developed ANN models

To evaluate the performance of the ANN developed models in the prediction of TEC in terms of WWR, four statistical parameters including Correlation Coefficient (CC), Root Mean Square Error (RMSE), Scatter Index (SI), and BIAS (as given in Eq. (3)) are exploited. The CC measures the strength of the linear relationship between two parameters. In our case, these parameters are the simulated TEC and the predicted TEC by the ANN. The value of the CC varies between -1 to +1 which, respectively, shows the completely negative and positive correlation between the parameters of interest. The RMSE measures the error of prediction based on the simulated values and it has the dimension of the parameters of interest. The more is the RMSE is, the weaker is the predictions of the developed models. The SI indicates the percentage of root mean square error concerning mean observations. Hence, it is not affected by the parameters scale since it does not have any dimension. To recognize that the models' predictions are overestimated or underestimated, the BIAS can be implemented. The positive values of BIAS refer to the predictions' overestimation while the negative values of the BIAS stand for the predictions' underestimation.

Table 3
Detailed information of the employed ANN, and training and testing data sets for different recycled panels

Network type	**A three-layer feed-forward network**			
Training algorithm	Levenberg-Marquardt back propagation			
Learning rate and iteration	0.01 and 1500, respectively			
Activation function	Log Sigmoid			
Number of layers	Three layers (input layer, hidden layer, and output layer)			
Number of neurons in each layer	Input layer	1 (the input parameter: WWR)		
	Hidden layer	3		
	Output layer	1 (the output parameter: TEC)		
Number of data points	Training data points	168		
	Testing data points	72		
	Full data points	240		
Input parameter	Window-to-Wall Ratio (WWR) in percent		Porous concrete panel	Recycled ash concrete panel
		Min	5.00	5.00
		Mean	50.00	50.00
		Max	95.00	95.00
		Std	27.45	27.45
Output parameter	Total Energy Consumption (TEC) in kWh/m^2		Porous concrete panel	Recycled ash concrete panel
		Min	2.01	0.17
		Mean	6.64	4.55
		Max	14.71	13.10
		Std	3.28	3.20

$$CC = \frac{\sum_{i=1}^{N}(O_i - \overline{O_m})(P_i - \overline{P_m})}{\sqrt{\sum_{i=1}^{N}(O_i - \overline{O_m})^2 \times \sum_{i=1}^{N}(P_i - \overline{P_m})^2}}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{N}} \tag{3}$$

$$SI = \frac{RMSE}{\overline{O_m}} \times 100\%$$

$$BIAS = \frac{\sum_{i=1}^{N}(P_i - O_i)}{N}$$

in which the subscript i and m refer to the counter of data points and mean values, respectively. N stands for the total number of data points, and O and P denote the observed (simulated by design-builder) and predicted (by developed ANN models), respectively. $\overline{O_m}$ is the mean value of the observed values while $\overline{P_m}$ is the mean value of the predicted values.

4. Results and discussion

It is evident that the variations of TEC with the WWR in the various panels depend on the month of interest. Although for most months, the TEC is directly proportional to the WWR, in some months (particularly in cold weather conditions and winter) the minimum TEC occurs when WWR is around 50-55%. In contrary to this fact, since the WWR is constant during the year, for different panels we are seeking to evolve various ANN models in which the TEC is predicted based on the WWR. The results of the developed model will use for the determination of the optimal WWR for each panel.

4.1. Porous concrete panel

4.1.1. Optimal WWR

Fig. 6 illustrates the TEC against WWR in different months for the porous concrete panel. In many cases (such as January, May, June, July, August, September, October, and December), the least TEC is obtained when WWR is 5%. However, the optimal WWR is 50% in February and March, 20% in April and November. The least TEC (ranges between 2-4 kWh/m^2) occurs in October while the most TEC ranges 12-15 kWh/m^2 and occurs in January. Since the low values of the WWR may evoke lightning problems, it is recommended that the optimal WWR be assumed as 45-55% in the case of porous concrete panels as the building envelop.

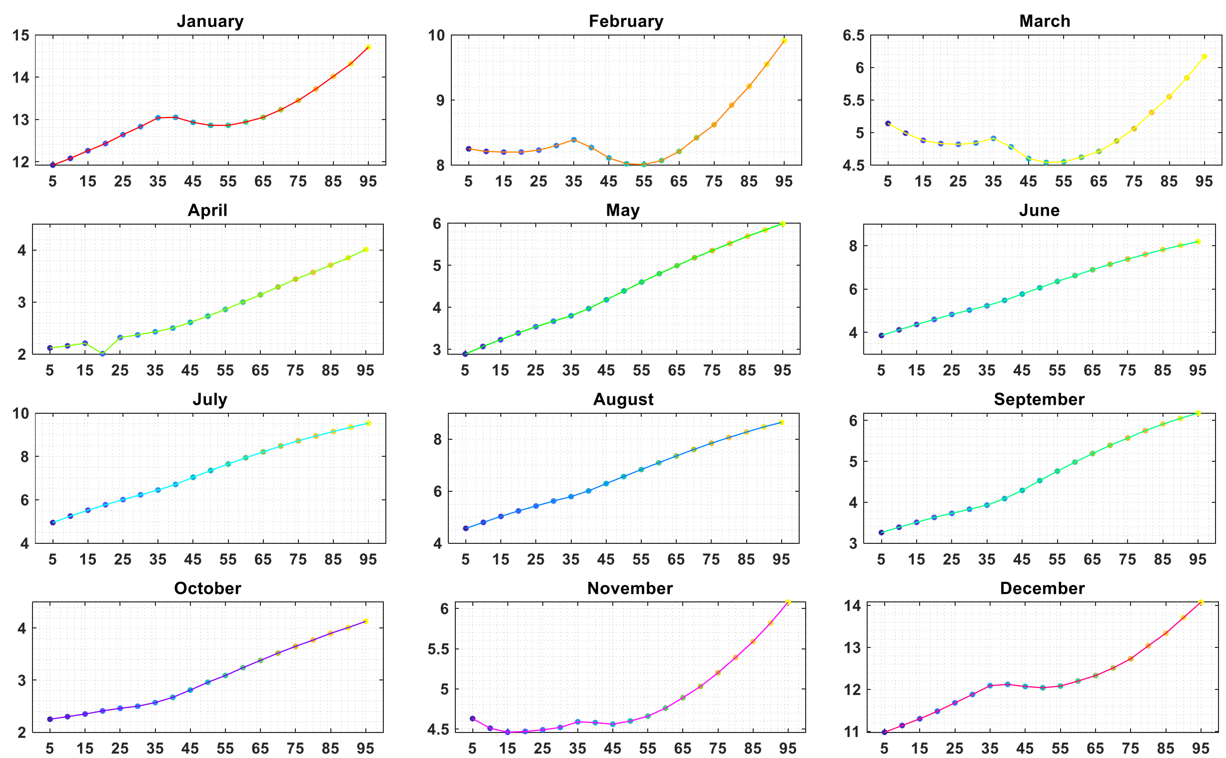

Fig. 6. TEC (horizontal axis) against WWR (vertical axis) in various months for porous concrete panel.

4.1.2. ANN results in the prediction of TEC in terms of the WWR

Using the collected data points (240 data points) extracted from the simulations conducted via design builder software, the ANN model is developed. In the developed ANN model, the input parameters are WWR and the month of interest. Table 5 summarizes the performance of the developed model for the training and full data points. The CC of various data sets is close to one which is indicative of this model's accuracy. The test data points are selected by random and that is why the developed model underestimates the training dataset while overestimates the testing and full datasets (the BIAS of the training dataset is -3.464 but it is 5.986 for the testing dataset and 2.522 for the full dataset). Inspection of Fig. 7 reveals that the developed model predicts the simulated data points with high accuracy. As indicated, all the data points are in the vicinity of the fit line which is indicative of a high correlation between the simulated and predicted TEC values.

Table 5
Comparison of the developed ANN model in the prediction of training, testing, and full data sets (porous concrete panel).

	CC	$RMSE$	$SI(\%)$	$BIAS$
Training dataset	0.988	0.508	7.601	-3.464
Testing dataset	0.978	0.564	8.521	5.986
Full dataset	0.984	0.525	7.908	2.522

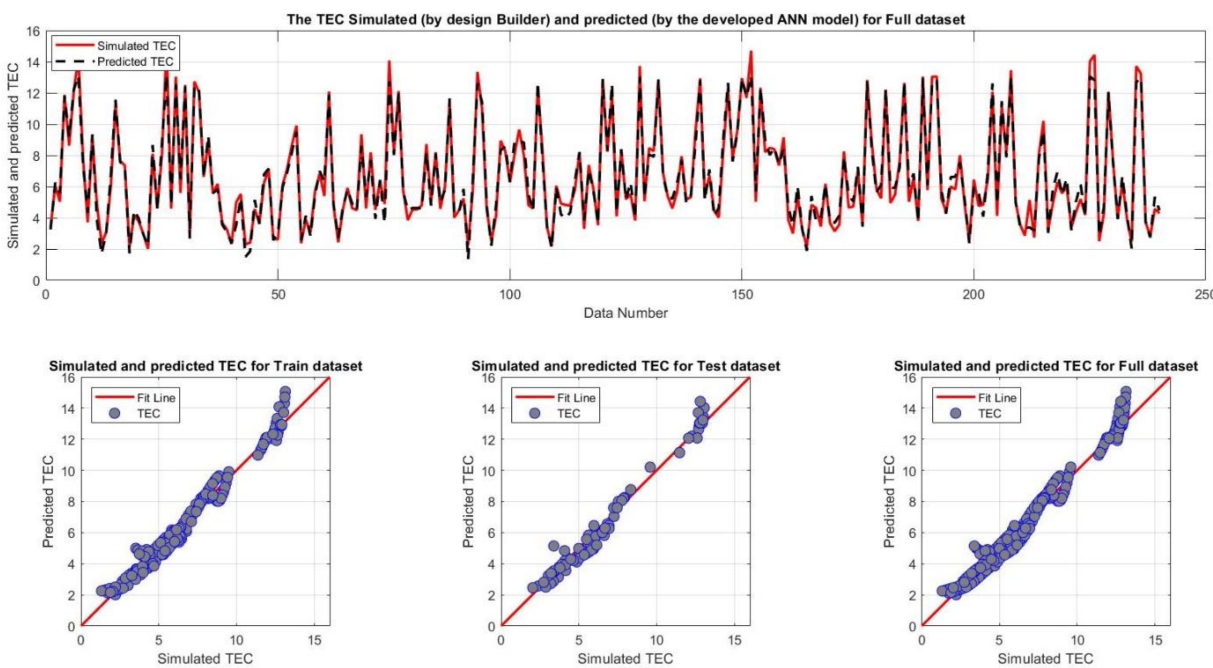

Fig. 7. Performance of the ANN developed model in predicting the TEC in terms of WWR for all the months.

4.2. Recycled ash concrete panel

4.2.1. Optimal WWR

Fig. 8 illustrates the TEC against WWR in different months for the recycled ash concrete panel. Like the porous concrete panels, the least total energy consumption is achieved when the WWR is 5%. However, this is not practically feasible due to various reasons such as lightning problems. An increase in WWR increases TEC. However, in cold seasons (such as November, December, January, February, and March) the TEC decreases when the WWR is between 45-55%. The least TEC (ranges between 0.2-0.5 kWh/m^2) occurs in April and October while the most TEC ranges 12-13 kWh/m^2 and occurs in December and January.

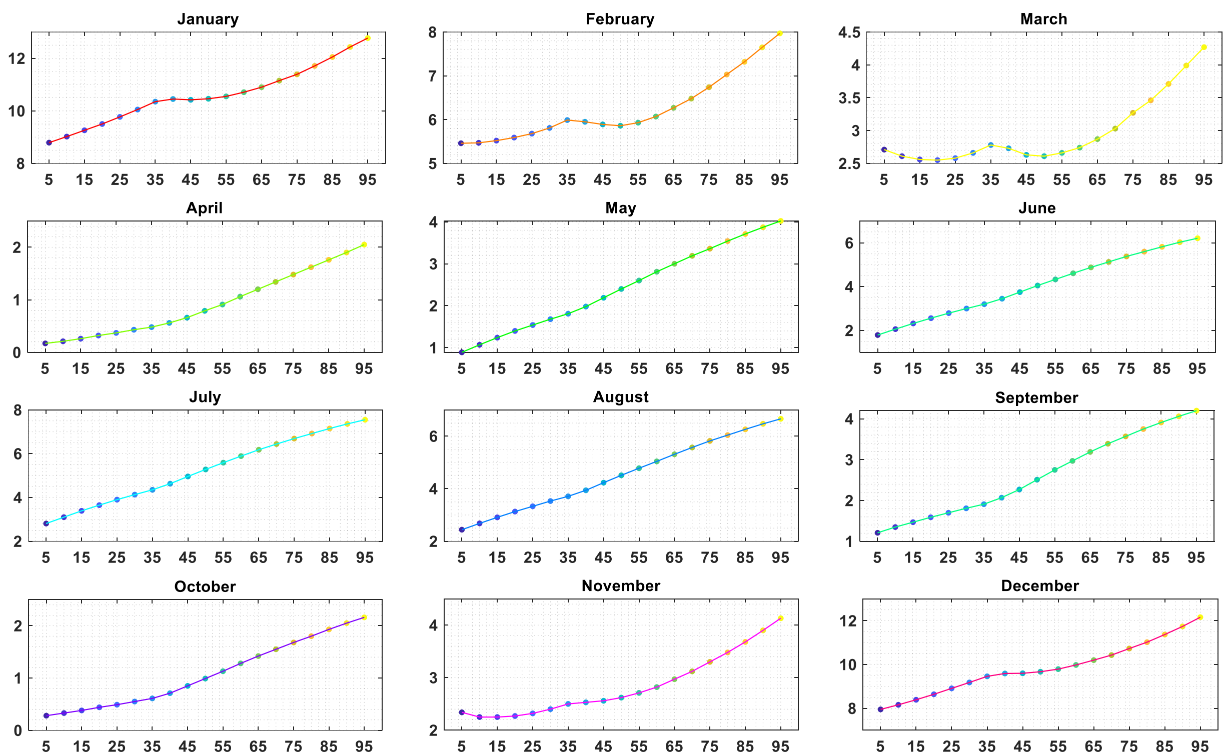

Fig. 8. TEC (horizontal axis) against WWR (vertical axis) in various months for recycled ash concrete panel (porous concrete panel).

4.2.2. ANN results in the prediction of TEC in terms of the WWR

The trial-and-error process of various ANN configurations proved that the most optimal ANN model is achieved using the four neurons in the hidden layer. Table 6 summarizes the performance of the developed model for the training and full data points. For all the data sets the correlation coefficient approaches one which is indicative of an excellent correlation between the predicted and simulated TEC values. The CC of various data sets is close to one which is indicative of this model's accuracy. The test data points are selected by random and that is why the developed model underestimates the training dataset while overestimates the testing and full datasets (the BIAS of the training dataset is -3.464 but it is 5.986 for the testing dataset and 2.522 for the full dataset). Inspection of Fig. 7 reveals that the developed model predicts the simulated data points with high accuracy. As indicated, all the data points are in the vicinity of the fit line which is indicative of a high correlation between the simulated and predicted TEC values. Considering the range of TEC which ranges from 2 kWh/m^2 to 14 kWh/m^2 (see table 3), the model accurately predicts the simulated TEC in terms of $RMSE$. Please note the $RMSE$ has the same unit as the TEC. The scatter index which is the non-dimensional form of $RMSE$ also proves that the model performs accurately. Finally, the BIAS reveals that the predictions of the developed model are underestimated; however, the underestimation is very low and negligible. All in all, the developed ANN model can predict the TEC of the recycled ash concrete panel with high accuracy. Fig. 9 illustrates the above-mentioned explanations schematically.

Table 6
Comparison of the developed ANN model in the prediction of training, testing, and full data sets (recycled ash concrete panel).

	CC	$RMSE$	$SI(\%)$	$BIAS$
Training dataset	0.995	0.291	6.391	-0.758
Testing dataset	0.993	0.417	9.126	-4.316
Full dataset	0.994	0.333	7.329	-5.074

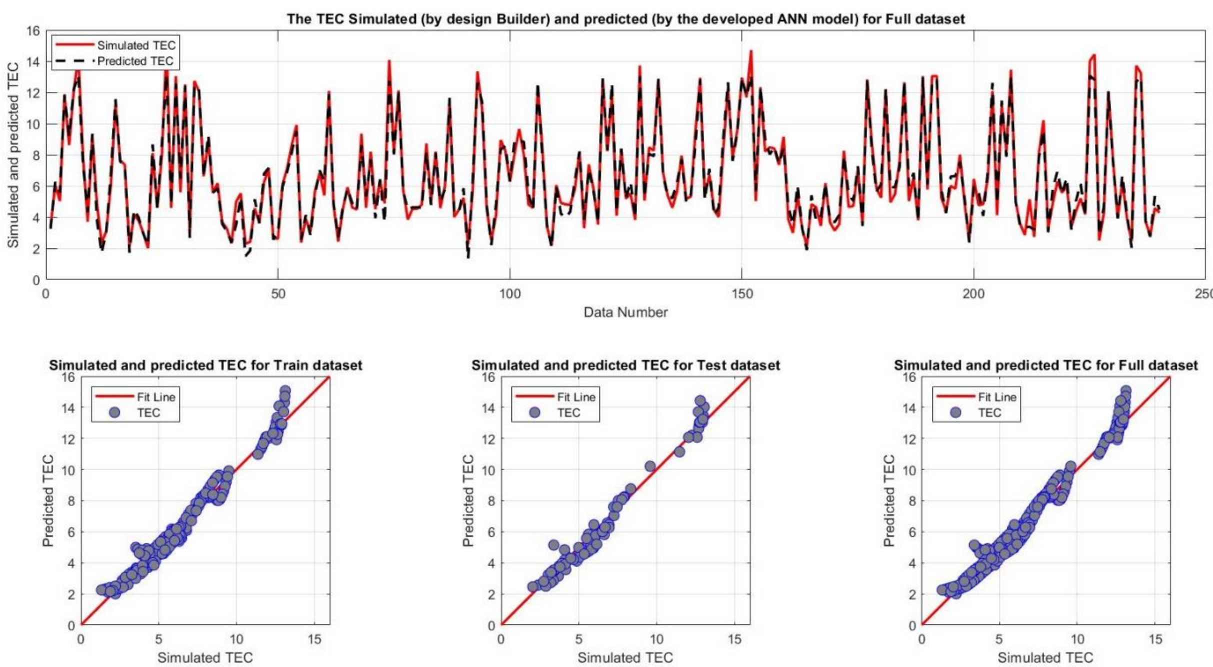

Fig. 9. Performance of the ANN developed model in predicting the TEC in terms of WWR for all the months (recycled ash concrete panel).

5. Conclusions

In this paper, the effects of recycled concrete panels application in the total energy consumption of a residential building located in Tabriz is investigated. Further, the most optimal value of the window-to-wall ratio is determined based on the results of the numerical simulations. To do this, we implemented two panels including normal porous concrete panel and recycled ash concrete panel as the building envelope. The numerical simulations are done using the design-builder software. The model of interest is a one-floor residential building in which the external walls are made of porous concrete or recycled ash concrete panels, as well as one opening (window), which is available on each external wall. We changed the window-to-wall ratio from 5% to 95% for both the panels and generate datasets. The simulation results are exploited for the determination of the optimal WWR for each panel and the development of ANN models.

The numerical simulations with design builder software proved that the recycled ash concrete panel outperforms the porous concrete regarding the total energy consumption. However, the optimal WWR was revealed to be 45-55% in both cases. It means that using recycled ash concrete material in the exterior facades makes the building more energy efficient; however, WWR does not change drastically considering these two materials.

To be most specific, the variation range of TEC in the case of the recycled ash concrete is less than that of porous concrete. For instance, in January, TEC varies between 8 to 13 for recycled ash concrete although this range is 12-15 in the case of porous concrete. Such trend is observed for all the months. In warm seasons, an increase in WWR increases the TEC. However, in cold seasons such as November, December, January and February, TEC is directly proportional to WWR when its value is less than 15 or larger than 55. Out of these ranges, TEC decreases with an increase in opening percentage.

The ANN models have one input layer (two input parameters including month and WWR), one hidden layer (in which there are 3 and 4 neurons for the porous concrete and recycled ash concrete panels, respectively), and the output layer contains the TEC of the building. We have 240 data points for each panel that 70% of them used for the model training and 30% used for testing the developed model accuracy. The statistical indices of the developed model revealed that the ANN is capable to predict the TEC in building with high accuracy. However, the ANN model developed for the recycled ash concrete panel outperforms the ANN model developed for the porous concrete panel. Regarding the correlation coefficient, both the models have the best performance in a way that the CC index approaches one. In terms of root mean square error and scatter index, the models reveal to predict the simulation results accurately. Inspection of the BIAS parameter of the models proved that the ANN model of porous concrete overestimates the simulations while the ANN model of recycled panel underestimates it. However, the overestimation and underestimation values are very low and negligible.

Acknowledgments

The authors are thankful for the journal editor and anonymous reviewers.

Funding

This research received no external funding.

Conflicts of interest

The authors declare no conflict of interest.

Authors contribution statement

Aniseh Saber: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Roles/Writing – original draft.

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