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PERFORMANCE INDICES OF SOFT COMPUTING MODELS TO PREDICT THE HEAT LOAD OF BUILDINGS IN TERMS OF ARCHITECTURAL INDICATORS

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ABSTRACT

This study estimates the heat load of buildings in Izmir/Turkey by three soft computing (SC) methods; Artificial Neural Networks (ANNs), Fuzzy Logic (FL) and Adaptive Neuro-based Fuzzy Inference System (ANFIS) and compares their prediction indices. Obtaining knowledge about what the heat load of buildings would be in architectural design stage is necessary to forecast the building performance and take precautions against any possible failure. The best accuracy and prediction power of novel soft computing techniques would assist the practical way of this process. For this purpose, four inputs, namely, wall overall heat transfer coefficient, building area/ volume ratio, total external surface area and total window area/total external surface area ratio were employed in each model of this study. The predicted heat load is evaluated comparatively using simulation outputs. The ANN model estimated the heat load of the case apartments with a rate of 97.7% and the MAPE of 5.06%; while these ratios are 98.6% and 3.56% in Mamdani fuzzy inference systems (FL); 99.0% and 2.43% in ANFIS. When these values were compared, it was found that the ANFIS model has become the best learning technique among the others and can be applicable in building energy performance studies.

Keywords: *Heat Load, Residential Buildings, ANN, Fuzzy Logic, ANFIS, Soft Computing*

INTRODUCTION AND REVIEW

A wide variety of modelling techniques provide possibilities to predict energy consumption and the heat load of the buildings in recent years, such as simple regression techniques [1-3], dynamic simulation tools [4-6], artificial neural networks (ANNs) [7-10], adaptive-network based fuzzy inference systems (ANFIS) [11,12], the hybrid optimization algorithm [13,14] and fuzzy logic (FL) approaches [15-18]. The significance is based on their applicability and accuracy; that is their ability on how they achieve the outputs and in what kind of precision they would correspond to the reality. Regression models predict well with more homogeneous data sets but it is difficult or impossible to produce useful results for real-world problems. The performances of these algorithms are not powerful when the problem becomes complex. Dynamic simulation tools are based on physical methods which require certain guidelines and over-detailed modelling. Besides, these simulation tools are expensive and complicated, making it difficult to use. Therefore, soft modelling (SC) methods including ANNs, FL and ANFIS have become the novel tools to overcome any deficiencies observed in any other techniques by reducing one of the total error indices which are mean absolute percentage error (MAPE), mean squared error (MSE) or mean squared deviation (MSD) and root mean square error (RMSE). These models also use the statistical criteria such as correlation coefficient (R) and multiple correlation coefficient (R^2) for goodness of fit. The error indices are expected to close to zero whilst the R and R^2 should be as close as to 1 for the best performance [11, 16-18].

The building sector represents the second-largest energy consumer accounting for 37 % of the total final energy consumption (18 % in residential buildings, 19 % in non-residential buildings) in terms of final energy consumption in Turkey. However, this sector presents significant energy saving opportunities for the cost-effective energy, estimated at almost 30-50 % of the current energy consumption [19]. Heating energy consumption has the highest share in total energy consumption of buildings [20]. Consequently, the heat load is the basic numerical quantity to evaluate the energy consumption of buildings [7, 21]. The estimation of heat load is necessary, both for the new existing buildings which might be renovated to improve their energy consumption. Foreseeing early inaccuracies regarding the heat load might be avoided by designing appropriate wall overall heat transfer coefficient, building area to volume ratio, total external surface area and total window area to total

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external surface area ratio. Thus, the heat load and energy consumption might be evaluated simply and rapidly in the early design stage.

Considering the existing buildings, it might not be possible to obtain the architectural or mechanical drawings where the above mentioned parameters can be taken. If this is the case, the parameters can be obtained by field measurements. While renovating the existing buildings, the estimation of heat loads would guide professionals about what type of precautions or what type of renovation strategies might be taken into consideration.

To evaluate the heat load, ANNs are recently accepted alternative artificial intelligence methods offering a way to tackle non-linear and complex problems. Turhan et al. [7] and Ekici and Aksoy [22] succeeded to predict the heat load of existing buildings implementing a back propagation ANN model with a multiple correlation coefficient of 0.9774 and 0.948-0.985 (comparing with building energy simulation model results), respectively. Another study employed 8 input parameters (relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area and glazing distribution) in the ANN model to estimate the heating and cooling load of buildings [23]. One issue which needs to be discussed is that ANNs are black box models which make them more challenging to interpret. The model offers a weight matrix which is optimized after thousands of iterations. Furthermore, limited or noisy training data result in an illogical and meaningless output.

Fuzzy logic (FL) is an evolving method which has the ability to describe the knowledge in a descriptive human-like manner in the form of simple rules using linguistic variables [24]. The fuzzy system contains a set of rules which were developed from qualitative descriptions which makes it user friendly. During last decades, a few studies have published on predicting energy consumption of buildings. Chibattoni et al. [16] conducted a fuzzy logic energy consumption model for Italian residential buildings using the occupancy activity and typical domestic habits. The model was validated with electricity demand data recorded over the period of one year. The mean error of the model was found as 0.52% which was acceptable as quite successful prediction. Kabak et al. [17], implemented fuzzy multi-criteria decision making approach in order to analyse BEP-TR [25] energy simulation tool. The study applied an approach to categorize alternative buildings according to their overall energy performance. The criterion such as location and climate data, geometrical shape, building envelope, mechanical systems, lighting system, hot water system and renewable energy and cogeneration was used for the model. The impact of each criterion on energy consumption of buildings was analysed. Kajl et al. [26] created a fuzzy logic model to correct the outputs by post-processing the results of neural networks. The fuzzy assistant allows the user to determine the impact of eleven building parameters including length and width of buildings, number of floors, R-value of exterior wall, fenestration and U-value of windows on the annual and monthly energy consumption. The model was compared with DOE-2 [27] simulation tool results with a RMSE of 0.35.

Apart from these promising machine learning techniques, the combination of them is called ANFIS in which the benefit of self-learning procedure of ANNs and simple structure of FL are apparent. The ANFIS model was effective in forecasting the building energy consumption in cold regions, with a 0.965 prediction rate, when transparency ratios, azimuth angles, building form factors and insulation thicknesses were used as the model inputs [11]. Another study supported its performance and high accuracy similarly; however, the model had a time consuming performance with different parameter configuration [28].

The question is whether gathering the strongest characterization of each technique (ANNs and FL) and combining them in ANFIS would result in a higher prediction power or not? Goyal et al. (2014) compared ANNs, FL and ANFIS and figured out that FL had the highest estimation rate, when the prediction of daily pan evaporation was the case [29]. Applications and comparison of the SC methods are apparent in several research areas apart from energy studies [30-33]. Islam [32] developed a number of AI techniques varying from ANNs to FL to estimate electrical load in a company. The study showed that ANNs was principally attractive, as they were capable of handling the nonlinear relationships between load and the factors affecting them directly from historical data. Wang et al. [33] compared the performances of ANNs, autoregressive moving-average (ARMA), ANFIS, support vector machine (SVR) and genetic programming (GP) models on forecasting monthly discharge time series. The evaluation criteria contained the MAPE and the R. The ANFIS model was the best performed technique with an R of 0.9322. A further study resulted in the highest estimation performance of neuro-fuzzy systems to figure out the thermal diffusivity of building materials when compared to ANNs and inverse methods [34].

This paper presents the comparison of three SC models, namely, ANNs, FL and ANFIS in the field of predicting heat load of buildings. For the validation, the results are compared with a building simulation tool which is called The Standard Assessment Procedure for Energy Rating of Dwellings software (KEP-IYTE-ESS) [35]. The study also shows which SC method performs better on prediction of the heat load of buildings.

OVERVIEW OF SC TECHNIQUES

The SC methods which are used for the study are described in this section.

ANNs

ANNs are data-driven mathematical models which resemble the biological nervous system [36]. Being capable of capturing non-linear relationships among the parameters is ANNs' superiority. The structure of the ANNs is composed of parallel element units called neurons. A schematic representation of an ANN model is shown in Figure 1.

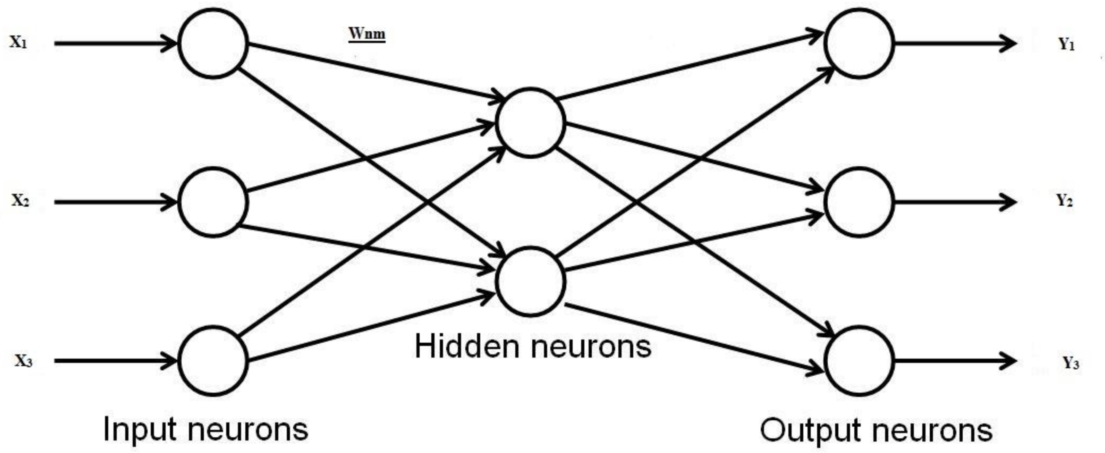


Figure 1. Schematic representation of a feed forward ANN

ANNs have three layers-the input, hidden and output layers. Each layer is composed of a high number of interconnected- and weighted- neurons transmitting the signals in the entire structure to produce the output. Input layer is the incoming signals whilst output layer is the desired ones. Hidden layer is the connection between input and output layers which stores the net information and transfer functions. The target output at each output neuron is minimized by adjusting the weights and biases through some training algorithm. Scalar input x_1,x_2 and x_3 are multiplied by weight w_{nm} and the weighted values are fed to the summing confluence. The neuron has a bias bi that is summed with the weighted inputs in order to form the net input netj given in Eq. (1).

$$(net_j) = x_1\, w_{1j} + x_2\, w_{2j} + \ldots\ldots + x_n w_{nj} + b_i \tag{1}$$

The sigmoid function is usually employed as an activation function in the training step of the network. The sigmoid function is expressed as Eq. (2):

$$y = 1/(1+ e - netj) \tag{2}$$

The objective of the model is to decrease error to an acceptable value that is called epoch or training cycle. The error is expressed by the root-mean-squared error value (RMSE), which can be calculated with following equation (3):

$$E=½[p\Sigma_i\Sigma|t_{ip}- o_{ip}|]\ ½ \tag{3}$$

where (E) is the RMSE, t the network output, and o the desired output vectors over all the pattern (p).

FL Approach

FL is a logical system which aims at a formulation of approximate reasoning. First, the approach was proposed by Loutfi A. Zadeh in 1965 with the work “Fuzzy Theory” [37]. Zadeh defined the concept of Fuzzy Sets as a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function which assigns to each object a grade of membership ranging between zero and one. After 1974, this technique was applied in many areas such as controlling of physical or chemical parameters like temperature, electric current, flow of fluid and motion of machines [38]. The general structure of the FL modelling is presented in Figure 2.

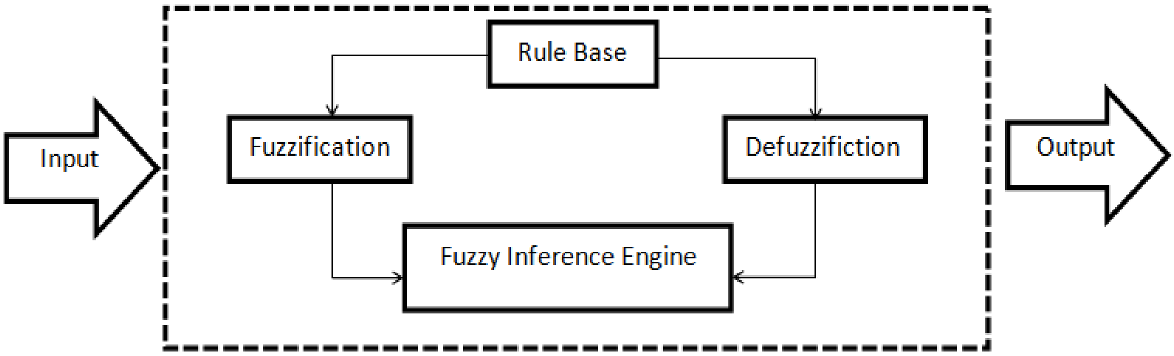


Figure 2. The structure of Fuzzy logic modelling

A fuzzy set is a generalization of an ordinary set by allowing a degree (or grade) of membership for each element. Many degrees of membership are allowed in fuzzy sets. The degree of membership is indicated by a number between 0 and 1. In extreme cases, if the degree is 0, the element does not belong to the set, and if 1, the element belongs 100% to the set.

In a set, every element is associated with a degree of membership. This means that the membership function (MF) of a set represents each element to its degree. The membership function assists the partial belongings mathematically which have values between 0 and 1. It is formally written as Eq. 4.

$$\mu A\ (x): X \rightarrow [0,\ 1] \tag{4}$$

Basic relations for fuzzy sets are specified like in the ordinary sets. Fuzzy operations include union, intersection, complement, binary relations and composition of relations as classical operations.

Fuzzy logic rules are called as contingent statements that describe the dependence of one or more linguistic variable on another. The simple form of the basic lingual If-Then rule is shown as;

If “α” is A and “β” is B, then “λ” is C.

Here, the corresponding linguistic values are A, B and C while α, β and λ are the inputs. For example “if temperature is HIGH the humidity is ZERO” is a fuzzy implication.

The model basically includes four components: fuzzification, fuzzy rule base, fuzzy output engine, and fuzzification [38,39]. For each input and output variable selected is converted to degrees of membership by fuzzification. It includes definition of fuzzy sets, determination of the degree of membership of crisp inputs in appropriate fuzzy sets. All fuzzy variables are theoretically represented as a number between 0 and 1.In order to obtain the fuzzy output, Fuzzy rule base form the basis for the fuzzy logic. It contains rules that cover all suitable fuzzy relations between inputs and outputs. The fuzzy rule-based system uses IF-THEN rule based system given by IF ascendant, THEN consequent [40]. Following rules are constituted for the example [41].

R1 : If x_1 is LOW and x_2 is SHORT then y is VILLAGE
R2 : If x_1 is LOW and x_2 is LONG then y is TOWN
R3 : If x_1 is HIGH and x_2 is SHORT then y is TOWN
R4 : If x_1 is HIGH and x_2 is LONG then y is TOWN

For the fourth rule; it is assumed as if the population of the settlement (x_1) is high and the distance to the furthest municipality (x_2) is high then the rate of being municipality (y) is high.

Each fuzzy rule gives a single number that represents the truth value of that rule. All fuzzy rules are taken into account by fuzzy inference engine in the fuzzy rule base. The fuzzy inference system is a framework based on concepts of fuzzy set theorem, fuzzy if-then rules, and fuzzy reasoning. Conventional fuzzy inference systems are typically built by domain experts and have been used in automatic control, decision analysis, and expert systems. Optimization and adaptive techniques expand the applications of fuzzy inference systems to fields such as adaptive control, adaptive signal processing, nonlinear regression, and pattern recognition. Fuzzy inference system can take either fuzzy inputs or crisp inputs, but the outputs it produces are almost always fuzzy sets. Sometimes it is necessary to have a crisp output, especially in a situation where a fuzzy inference system is used as a controller. Therefore, a method of defuzzification is required to extract a crisp value that best represents the fuzzy set. With crisp inputs and outputs, a fuzzy inference system implements a nonlinear mapping from its input space to output space. This mapping is accomplished by a number of fuzzy if-then rules, each of which describes the local behaviour of the mapping [42]. There are two methods widely used; the minimum and the product operation methods. If "°" is the operator that indicates rule of inference, Eq. 5 can be written in terms of membership function for minimum operator.

$$oB(y) = MAX\,[\,MIN\,(\,oA(x),\, oR(x,y)\,)]\; x \in E1 \tag{5}$$

Similarly, Eq. 6 can be written in terms of membership function for prod operator.

$$oB(y) = MAX\,[\,oA(x),\, oR(x,y)]\; x \in E1 \tag{6}$$

Defuzzification converts fuzzy output set to crisp. It is necessary to convert the fuzzy quantities into crisp quantities because generated fuzzy results cannot be used as such to the applications. Defuzzification can also be called as "rounding off" method [39]. There are many defuzzification methods named as (COG) (centroid), bisector of area (BOA), mean of maxima (MOM), leftmost maximum (LM), rightmost maximum (RM), centre of sums and weighted average method [39]. Centroid method is the most widely used method as expressed in Eq.7;

$$K_x^* = \frac{\sum_i \mu(Kix)Kix}{\sum_i \mu(Kix)} \tag{7}$$

K_x^* is the defuzzified output value,K_{ix} is the output value in the ith subset, and $\mu(K_{ix})$ is the membership value of the output value in the i^{th} subset.

ANFIS

ANFIS is the combination of ANNs and FL approaches which has adaptive nodes and directional links [43]. With the ability of a fuzzy system and with the numeric power of a neural system adaptive network, ANFIS has been shown to be powerful on prediction studies. Figure 3 shows the schematic representation of a typical ANFIS model.

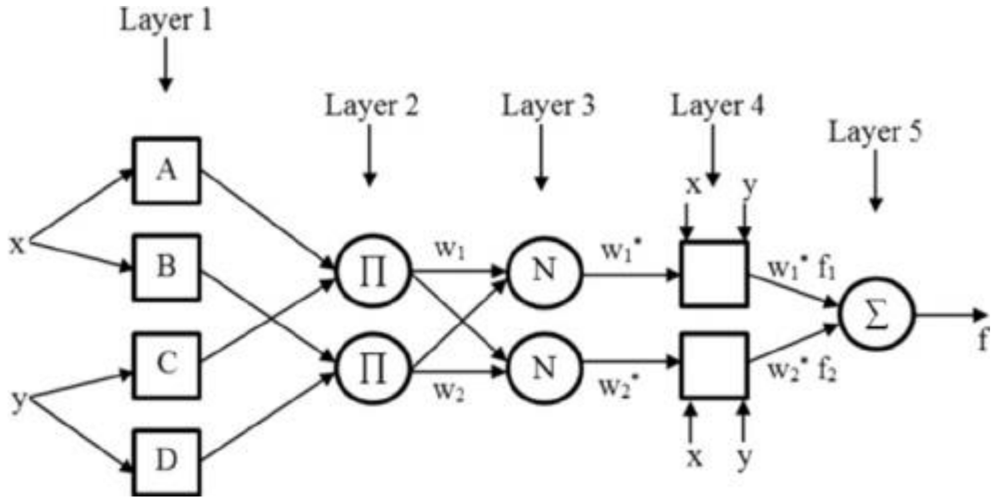


Figure 3. Architecture of ANFIS [43]

Figure 3 has two inputs (x and y) and one output (f). The model implements Sugeno-Takagi fuzzy inference systems and if-then rules:
R1: IF x is A1 and y is B1 THEN f1= p1x + q1y+r1
R2: IF x is A2 and y is B2 THEN f2= p2x + q2y+r2
Here, Ai and Bi are the fuzzy sets, fi is the output and pi,qi and ri are the design parameters in training phases. The nodes in ANFIS can be summarized as follows;
Layer 1: The layer that input variables are introduced to the system. The membership functions are used as node functions.
Layer 2: The layer that the rules are constructed with the strength of corresponding layer.This layer generates output.
Layer 3: The layer is an average layer that optimizes firing strength.
Layer 4: Consequent nodes that act as a defuzzifier.
Layer 5: Output nodes. The layer generates an output from the sum of each rule.

ANFIS uses training algorithm to optimize the design parameters to predict the desired output. When the optimum parameters are found, the gradient descent method starts to adjust parameters corresponding to the fuzzy sets in the input layer. Similarly, the output is calculated by applying the forward pass.

MODELLING THE HEAT LOAD OF BUILDINGS USING SC METHODS

Gathering the data

The subject matter is the residential building stock in İzmir (38.25 N, 27.08 E), Turkey, while the study material itself included the apartments' floor plans, sections and drawings of mechanical installation as obtained from the Municipalities of the city. To allow the broadness and randomness of the problem definition and overall findings, a total of 148 buildings with a variety of zoning, floor plans, heights and orientation are chosen as they are distributed in scattered regions of the city. Figure 4 illustrates the schematic elevation and plan drawings of a building which is four-storey high involving two separate apartments on each floor. The number of floors ranged from 5 to 11, which directly provides information about the building form and its volume; while the orientation covers every direction due to the city plan. Their zoning status which influences their total external wall area, is either detached or attached on two sides. The data, on the other hand, correspond to the values of overall heat transfer coefficient of the walls (U value), area-to-volume ratio (A/V), total external surface area (TESA), total window area-to-total external surface area ratio (TWA/TESA) which are calculated and obtained the above mentioned drawings. These are the most notable architectural parameters when the heat load has been calculated. An example is summarized in Table 1.

The heat load values are gathered through simulations. The software named KEP-IYTE-ESS runs the heat load calculations for each apartment, as explained in detail in previous studies [7 , 35, 44]. This monthly static method including degree-day correction is based on the European standard EN ISO 13790 (2008) and the Turkish standard TS 825. Its calculation process is validated and supported by BESTEST [45, 46]. The performance of ANNs, FL and ANFIS depends on the comparison of soft computing findings with the ones obtained from the software KEP-IYTE-ESS.

Development of SC methods

Three SC models were developed by employing original data from architectural projects. . In this study, taking the data into consideration, the wall overall heat transfer coefficient (U), area/volume ratio (A/V), total external surface area (TESA), total window area/total external surface area ratio (TWA/TESA). Although there are several more parameters to obtain heat load of buildings, the parameters were chosen in this study are easily measurable ones in case of architectural drawings of the buildings are not available which is the case for the

Table 1. Heating load characterization of one apartment

	U value of the wall (W/m^2K)	TESA (m^2)	A/V (1/m)	TWA/TESA (-)	Heat Load (kW/m^2)
Apartment 1	1.43	213.66	0.4134	0.1636	0.0266
Apartment 2	1.37	1324.04	0.4001	0.1048	0.0425
Apartment 3	1.64	736.56	0.391	0.3016	0.0907

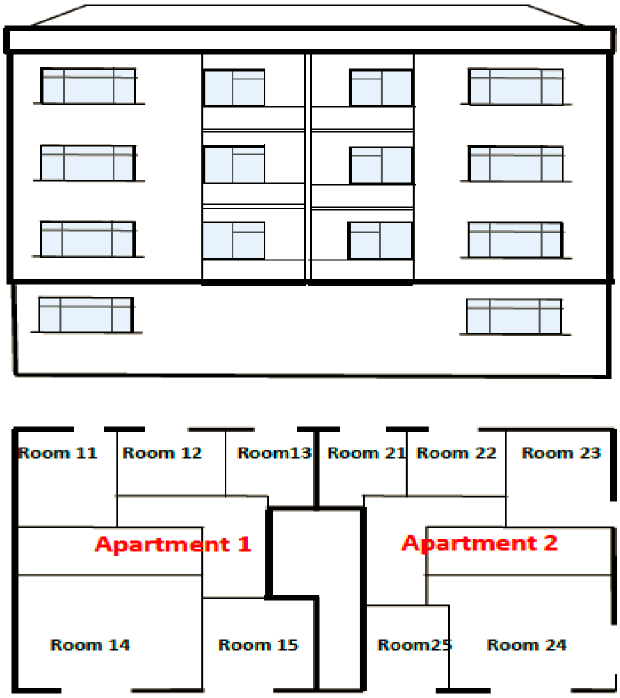


Figure 4. Schematic drawings of one residential building with two apartments on one floor

most existing buildings. Since these parameters are related with the geometry of the buildings, the architects would obtain easy and quick insight on the heat load of new buildings in the very early design stage. The maximum and minimum values of input parameters are listed in Table 2.

Table 2. Input and output parameters used in three SC models

Code	Input parameters	Data used in three SC models	
		Minimum	**Maximum**
x_1	U (W/m^{2}K)	0.43	1.83
x_2	A/V (1/m)	0.0579	0.6404
x_3	TESA (m^2)	208.44	2655.82
x_4	TWA/TESA (-)	0.1048	0.6348
y_1	HL (kW/m^2)	0.0019	0.0918

The information about the input parameters is given in ref. [7, 47, 48].

Some standard procedures should be used to prepare the data for modelling like data filtering and standardization [39,49]. For this purpose, following data-standardization equation were used and is given as:

$$x\ i= 0.1 + 0.8\ (xi - xmin\ i)/\ (xmax\ i - xmin\ i) \tag{8}$$

where xmax i and xmax i are the minimum and maximum values of ith node in the input data for all feed vectors, respectively. Moreover, the data was split into a training set (80% of the total data) for learning purposes of SC models and a test set (20% of the total data) for the evaluation process. Performance of models were characterized by multiple correlation coefficient (R2) and mean absolute percentage error (MAPE) which are given as:

$$R^2 = 1 - (\ \Sigma_j \mid t_j\text{-}o_j \mid 2\ /\ \Sigma_j\ (oj)^2\ ) \tag{9}$$

$$MAPE = 1/p\ \Sigma j\ [|\ (t_j - o_j)\ /\ t_j|]*100 \quad (10)$$

t is the target value, o is the output value and p is the number of input-output pairs [50]. Here, the R^2 is expected to be close to 1, while the MAPE should be as close as to zero for the best performance.

ANN model

ANN models were developed for the case buildings and published earlier in Ref [7]. The Levenberg–Marquardt (LM) algorithm were used for the models with an iteration number of 20,000. The optimum structure of the best ANN models was found to be 4-7-5-1 neuron in each layers. Learning rate was constant during the prediction process and equal to 0.02. Log-sigmoid transfer function which is widely used for transfer function was selected in the hidden layer and output layer. For further detail of ANN model structure please see Ref. [7].

FL model

FL approach is particularly useful in prediction problems due to its simplicity and natural structure. To generate a simpler model, FL model was established including four inputs (U, A/V, TESA and TWA/TESA) and an output (HL). Both Mamdani and Sugeno fuzzy inference systems (FIS) were developed for the study. The fuzzy subsets of the variables were considered to have triangular and trapezoid membership functions. The inference operator and defuzzification methods were selected as "the min" and "centroid" methods, respectively. Three subdivisions of inputs and parameters namely were set as low (L), medium (M) and high (H) as represented in Figure 5.

In the model, the fuzzy rules were expressed as "IF-THEN" format. Table 3 shows an example of 20 fuzzy rules set randomly from the total 81 rules.

Table 3. 20 fuzzy rules selected from the total of 81 sets

U value of the wall (W/m^2K)	A/V ratio (m^2/m^3)	TESA (m^2)	TWA/TESA (-)	HL (kW/m^2)
L	L	L	L	VL
L	L	L	H	L
M	L	L	L	L
H	L	L	L	M
L	L	M	M	M
L	M	H	L	M
L	L	H	H	H
L	L	H	L	M
L	M	L	L	VL
L	L	H	L	L
L	L	H	M	M
H	H	M	H	VH
H	L	H	M	VH
H	L	L	H	H
M	L	L	H	H
M	L	M	H	H
H	L	M	M	VH
H	M	M	H	VH
H	H	L	H	H
H	H	H	H	VH

Let us assume that the U value of the wall is 0.8 W/m^2K, A/V ratio is 0.30 m^2/m^3, TESA is 250 m^2 and TWA/TESA is 0.2. We want to find out the fuzzy output of the heat load of the building under these variables would be. As seen in Figure 5, 0.8 W/m^2K is a part of "low" and "medium" subsets of the U value of the wall with $\mu(U)=0.95$ and $\mu(U)=0.05$ membership degrees, respectively. Similarly, 0.3 of A/V ratio is a part of "low" and "medium" subsets with membership degrees of $\mu(A/V)=0.05$ and $\mu(A/V)=0.95$, respectively. The fuzzy inference engine would consider the following rules from the fuzzy rule base related to the above example and

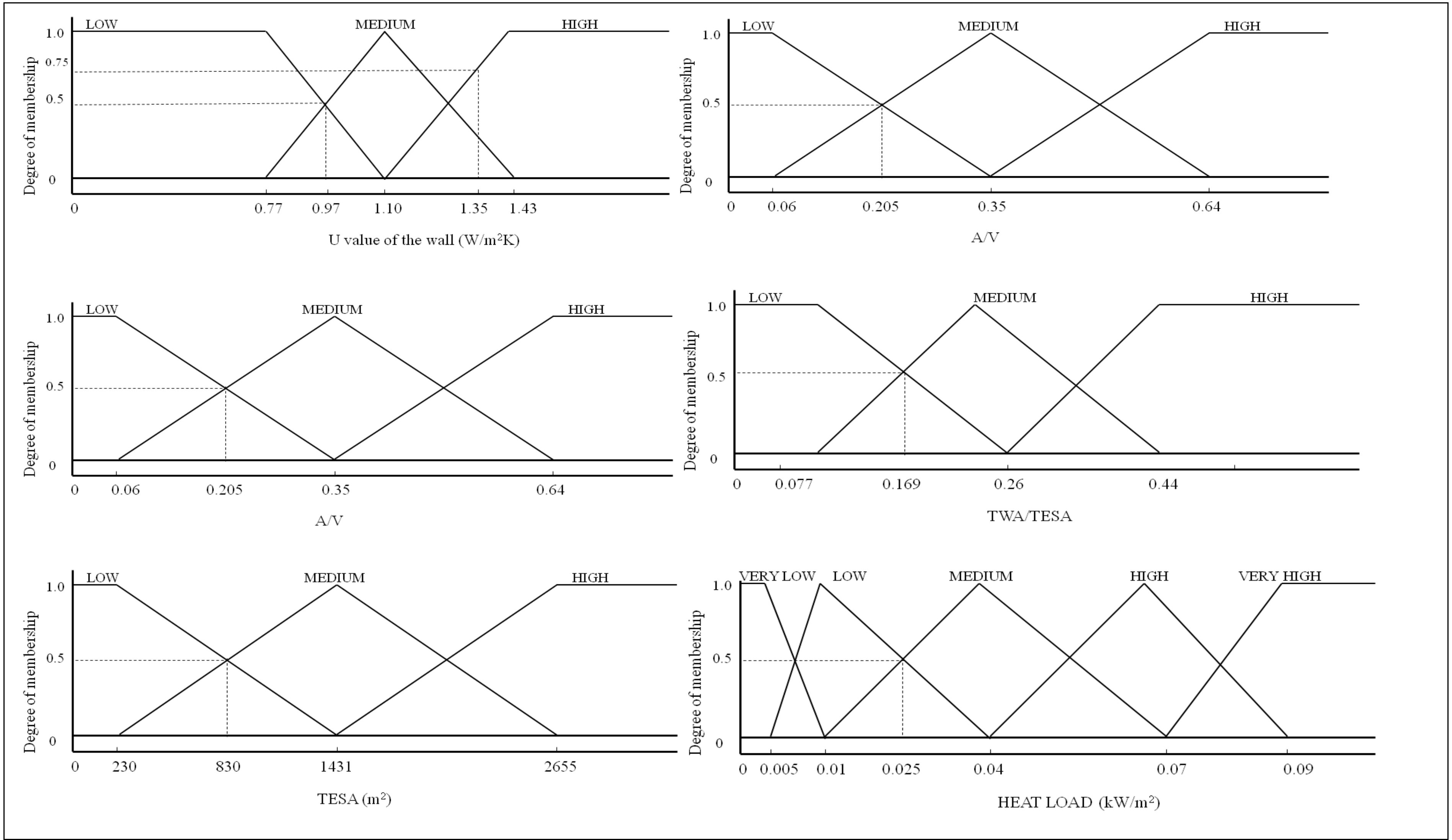


Figure 5. Block diagram used for fuzzy modeling

IF U value of the wall is "low" (μ(U)=0.90), A/V ratio is "medium" (μ(A/V)=0.83), TESA is "low" (μ(TESA)=0.98) and TWA/TESA is "low" (μ(TWA/TESA)=0.32) **THEN** the heat load of the building is "very low" (μ(HL)= **min** (0.90, 0.83, 0.98,0.32)= 0.32.
IF U value of the wall is "low" (μ(U)=0.90), A/V ratio is "low" (μ(A/V)=0.17), TESA is "medium" (μ(TESA)=0.02) and TWA/TESA is "medium" (μ(TWA/TESA)=0.68) **THEN** the heat load of the building is "medium" (μ(HL)= **min** (0.90, 0.17, 0.02,0.68)= 0.02.

Figure 5 shows the output value of 0.0084 kW/m^2 corresponding to 0.32 degree of membership in the "very low" subset of the heat load of building and the output values of 0.0106 and 0.069 kW/m^2 corresponding to 0.02 degree of membership in the "medium" subset of the heat load of building.
When one employs Eq. (7) for the above example, the following output value would be obtained by weighted-average defuzzification;

heat load**= [0.32*(0.0084) + 0.02*(0.0106+0.095)/2]/ (0.32+0.02)*
heat load= 0.0102 kW/m*^{2}

ANFIS Model

ANFIS approach have many benefits since it is the combination of ANN and FL approaches. To this aim, an ANFIS model was developed with 300 epoch, 3-3-3 number of neurons and 81 fuzzy rules. Sugeno-type ANFIS model with four inputs and an output was selected as the best performed model. The input membership function was 'gaussmf' and the output membership function was 'linear'. Table 4 depicts the used training parameters in the ANFIS model for the heat load of buildings prediction.

Table 4. Training parameters of the ANFIS for the heat load

Parameters	Heat load of buildings
Number of nodes	193
Number of linear parameters	405
Number of nonlinear parameters	24
Number of fuzzy rules	81
Membership function	Gaussmf
Epoch	300
Output MF type	Linear
Number of MF (input)	3-3-3

RESULTS AND DISCUSSION

Three SC models of existing residential buildings were developed for 4 input parameters which were U value of the wall, A/V ratio, TESA and TWA/TESA ratio. The output parameter was the heat load of the buildings. The input data was compiled from a total number of 148 residential building including 2136 apartments situated in Izmir. The developed models were applied to predict the heat load of buildings and compare with the KEP-IYTE-ESS results. The commonly used statistical criteria mean absolute percentage error (MAPE) and the multiple correlation coefficient (R^2) were calculated to evaluate the performance of the models. The comparison of KEP-IYTE-ESS and the best ANN model results of building heat load set is given in Figure 6a. The figures indicate that the model is able to give a successful prediction of 97.7% the MAPE of 5.06. Figure 6b depicts the comparison of KEP-IYTE-ESS and FL model results of building heat load set. From the figures, it is evident that the FL model illustrates a reasonably good performance with R^2 of 98.6%.
Mamdani method is widely accepted for capturing expert knowledge that allows us to describe the expertise in more intuitive, more human-like manner. On the contrary, Sugeno method is computationally efficient and works well with optimization and adaptive techniques, makes it very attractive in control problems, particularly for dynamic non-linear systems. The most fundamental difference between Mamdani-type FIS and Sugeno-type FIS is the way the crisp output is generated from the fuzzy inputs. Mamdani FIS has output membership functions whereas Sugeno FIS has no output membership functions [51, 52]. Table 5 shows the comparison of two FIS performances. The highest R^2 of 98.6% and the lowest MAPE of 3.56% were obtained with Mamdani fuzzy inference systems.

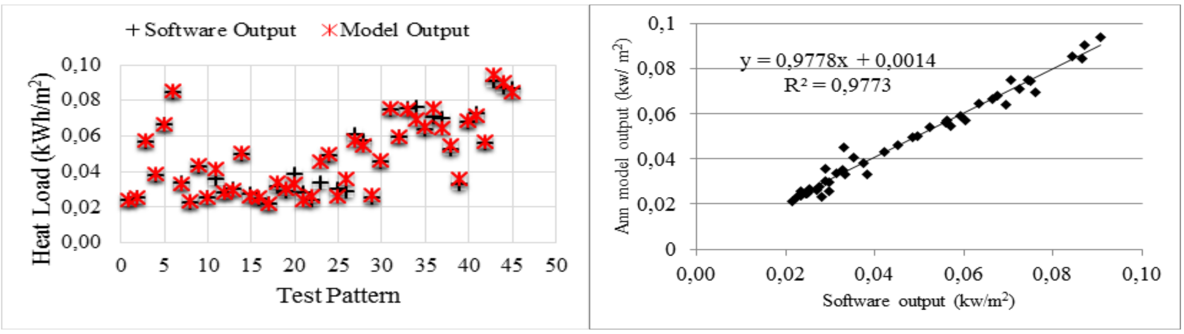
Figure 6c shows the comparison of ANFIS model and simulation results. The figures indicate that the predicted values of the model had close match with the simulation software outputs (R^2 of 99%). The comparison of all SC methods developed in this paper are shown in Figure 7. Analysing the results, it is worth to say that ANFIS model outperforms the other SC models.

Table 5. Performance measurement of different fuzzy models

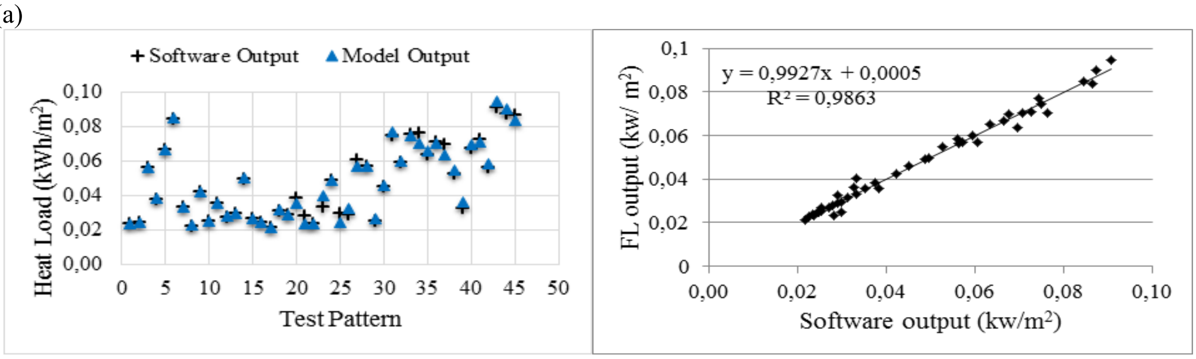
The type of FIS	MAPE	R^2
Mamdani	3.56	0.986
Sugeno	4.64	0.979

Figure 8 and 9 represent the comparison of three SC methods in terms of statistical criteria both training and testing phases. Considering the empirical models, the multiple correlation coefficient was 0.985, 0.991, and 0.994, while the MAPE was 4, 4.12 and 3.21 during training phase, respectively as computed by the ANN, FL and ANFIS models. Similarly, the multiple correlation coefficient was 0.977, 0.986, and 0.990, respectively while the MAPE was 5.06, 3.56 and 2.43 during testing phase, respectively, as computed by the ANN, FL and ANFIS models.

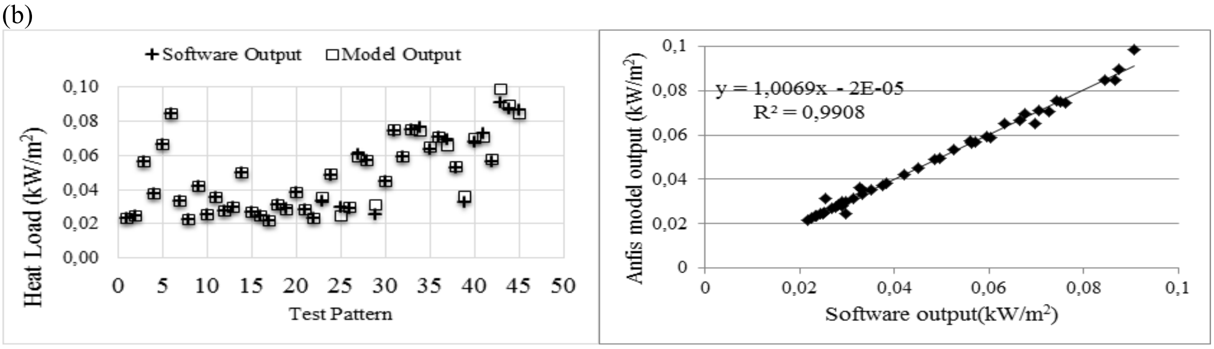
From performance indices, it can be concluded that ANFIS model gives the best results on predicting the heat load of buildings. Some final comments can be drawn in this part. ANN models are black-box models and it is difficult to interrupt the model and change the parameters. FL model uses verbal rules which need experience and time. However, ANFIS model is a self-organization model without requirements of programming. On the other hand, ANFIS model integrates both neural networks and fuzzy logic principles that has the benefits of two SC methods.



(a)



(b)



(c)

Figure 6. (a) ANN model (b) FL model and (c) ANFIS model results and their comparison with the simulated values (left); and their statistical evaluations (right).

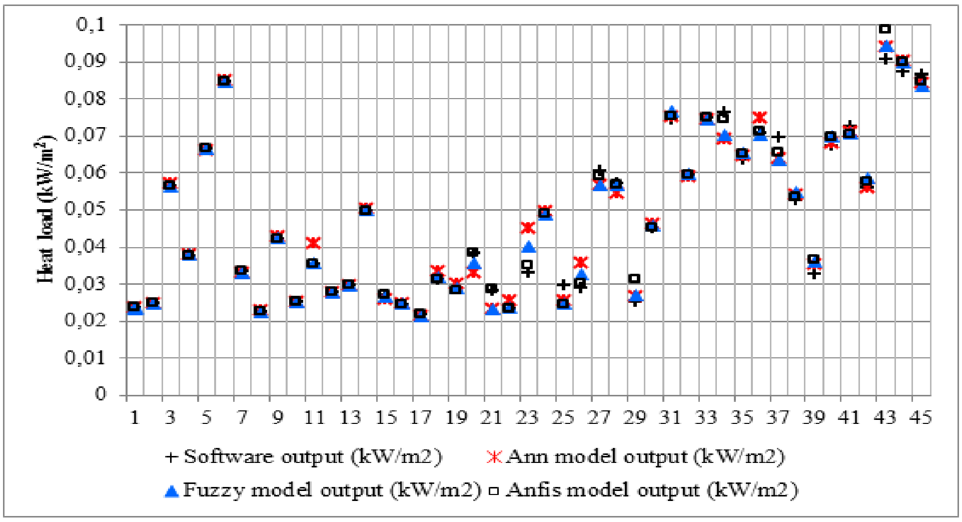


Figure 7. The comparison of three SC models with simulated data

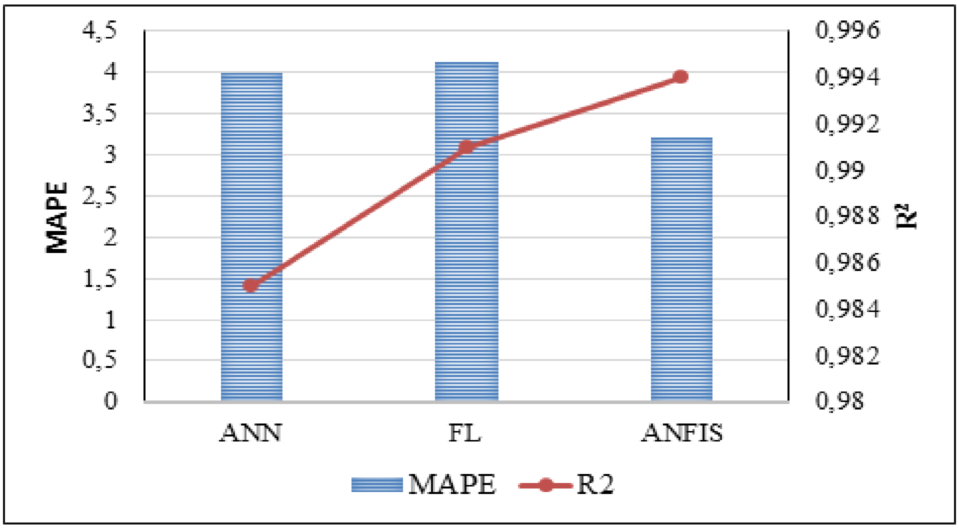


Figure 8. The comparison of three SC models for training phase in terms of statistical criteria

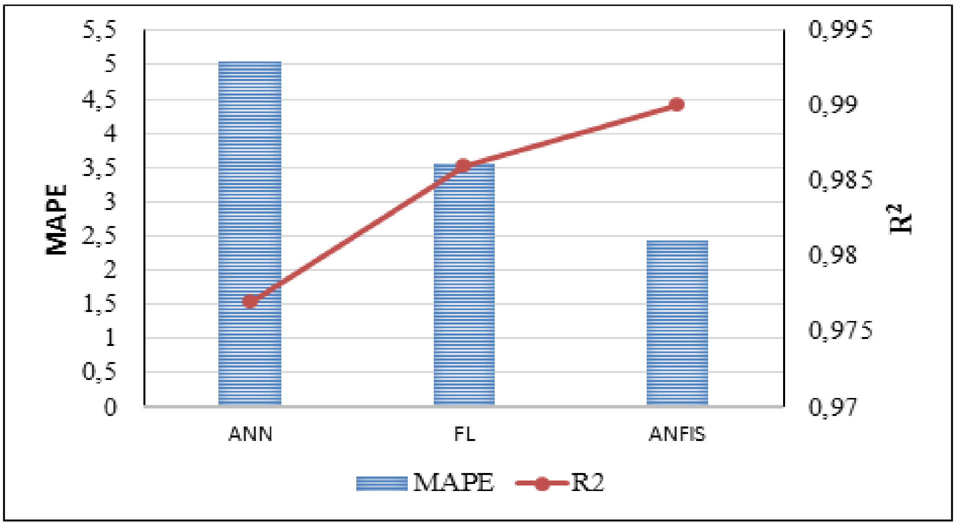


Figure 9. The comparison of three SC models for testing phase in terms of statistical criteria

CONCLUSIONS

This paper explores the potential of the ANN, FL and ANFIS modelling techniques on the estimation of the heat load of buildings. The input data are composed of basic architectural parameters, U value of the wall, A/V ratio, TWA/TESA ratio and TESA, which are gathered from drawings of 2136 apartments located in Izmir-Turkey. In general, the prediction of the heat load of building requires data on many input parameters. Further, it involves non-linear equations whose solution is complex. The dynamic building energy simulation software require detailed building and environmental parameters as input data which is possible only for the buildings whose architectural projects are accessible and valid. As expected, existing input data, however, will lead to a low accurate simulation. In addition, operating the simulation tools is difficult to perform and they normally require expert users. Regression models generally use homogenous data sets and predictions are often done with statistical software which are based on conventional algorithms such as curve fitting, the least square method and time series. However, the flexibility of these models is limited by the formulation of the building parameters that have non-linear relationships among each other. ANNs can solve non-linear and complex problems but they are black box models. Besides, limited or noisy training data may result in an inconsistent and meaningless output in some models. Fuzzy logic models are useful tools in the prediction of heat load of buildings where the building and environmental parameters are unknown. Comparing the number of input data required for simulation software, fuzzy logic models suggest a simple model with a high accuracy using limited input parameters. However, the FL technique requires a significant time and experienced users to construct the verbal rules. ANFIS model has the advantage of being significantly faster and more accurate than many ANN and FL models. The results indicated that the SC models are powerful tools to estimate the heat load of buildings. Considering statistical parameters, ANFIS model was the best model both in training and testing phases

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NOMENCLATURE

ANFIS	adaptive neuro-fuzzy inference system
AI	artificial intelligence
ANNs	artificial neural networks
ARMA	autoregressive moving-average
A/V	area/volume ratio (1/m)
b_i	Bias
CO_2	carbon dioxide
FIS	fuzzy inference system
FL	fuzzy logic
GP	genetic programming
HL	heat load (kW/m^2)
K_{x*}	defuzzified output value
K_{ix}	output value in the ith subset
LM	levenberg-marquardt
MAPE	mean absolute percentage error
MF	membership function
MSE	mean squared error
MSD	mean squared deviation
net_j	net inputs
o	desired output
p	Pattern
R	correlation coefficient
R^2	multiple correlation coefficient
RMSE	root mean squared error

SC	soft computing
SVR	support vector machine
t	network output
TESA	total external surface area (m^2)
TWA/TESA	total window area/ total external surface area
$\mu(K_{ix})$	membership value of the output value in the i^{th} subset
U	wall overall heat transfer coefficient (W/m^2K)
$x_1, x_2, \ldots, x_n$	scaler inputs
$w_{1j}, w_{2j}, \ldots w_{nj}$	Weights
y	Output

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