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AN ESTIMATE OF ENERGY CONSUMPTION FOR HOUSING BUILDINGS IN HOT CLIMATIC ZONES THROUGH ARTIFICAL INTELLIGENCE METHODS: CASE OF ANTALYA

ABSTRACT

Buildings use about one-third of total energy consumed in order to meet their heating and cooling needs. The building envelope that enables to protect it from physical factors in the outer environment is quite effective upon the amount of energy consumed. For the energy efficient solutions, it is necessary to enhance the heating and cooling performance of the building envelope. With this aim, in the study, the energy loads were calculated, which were consumed for heating and cooling by a building established as a reference through a simulation program in the province of Antalya, which respects a hot climatic zone, and the shifts in yearly heating and cooling loads of the alternative models were examined, which were developed by changing the thermal insulation thickness and the window-to-wall area ratio. In the study, the modern, effective artificial intelligence methods were used to enhance the energy performance of multi-dimensional buildings. Of the models for which heating and cooling load calculation had not been made before, the estimates for the thermal loads were made using an energy simulation program, and it has been reached that thermal insulation thickness and window-to-wall area ratio have effect on both loads.

Keywords: Thermal Performance, Heating Load, Cooling Load, Thermal Insulation, Artificial Intelligence

1. INTRODUCTION

Thanks to economic and social developments, a higher quality of life is offered to building users. The increase in quality of life brings with it more energy consumption. Energy consumption is at the core of today's growth and development plans. According to studies, energy consumption mostly occurs in housing, industry, transportation and agriculture. Energy consumption in housing, in particular, has the biggest share in Turkey as it is in many countries [1]. According to regulations on energy consumption in buildings, it is possible to improve the thermal performance of buildings. It is possible to reduce the energy used in houses by 25-45% with only a few design measures taken [2]. Most of the energy used is consumed for heating and cooling buildings. The amount of energy consumed for thermal requirements can

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be greatly reduced by changing the heat insulation applied to exterior walls and window-to-wall ratios [3].

Cheung, Fuller and Luther, in a study conducted in 2005, studied the parameters such as heat insulation thickness, color of exterior walls, window system, window area and addition of shading element to ensure efficient use of energy in high-rise buildings. The energy savings provided by the change of these parameters are calculated with the help of the TRNSYS building energy simulation software [4]. In 2014, Baykal investigated the effect of the change in thermal insulation thickness on the energy loads on the facades in different directions, and determined the optimum thermal insulation thickness by carrying out cost analysis [5]. In 2011, Daouas worked numerically with the CFFT analytical method to determine the optimum thermal insulation thicknesses of structures and has reached the conclusion that thermal insulation thickness must be different in different directions [6]. Tsanas and Xifara used statistical machine learning tools in 2012 to estimate the energy performance of houses. In their study, changes in heating and cooling load that occurred due to changes in parameters such as building form, surface area, wall area, total height, direction, window area and window position were investigated. The results of the building energy simulation software were compared with an artificial intelligence based algorithm for calculating the heating and cooling load [7]. Maçka, Yaşar and Pehlevan, in their study in 2011, made calculations with different wall types and different window-wall ratios with the help of EnergyPlus building energy simulation software for a building considered to be in the province of Trabzon. They have identified appropriate alternatives in terms of energy usage and cost [8].

In this study, the thermal loads of models without any heating and cooling load calculations are estimated by using artificial intelligence techniques to improve energy performance of houses. With this study, the effect of heat insulation thickness and window-to-wall ratio on these two loads was determined. The study concludes that energy consumption can be reduced during the design phase of buildings.

2. RESEARCH SIGNIFICANCE

The parameters which affect the energy performance of buildings is not necessary to individually calculate the intermediate values thanks to this study. Some of the values used in calculations can be learned by artificial intelligence and the effect of intermediate values can be obtained. At the same time, in order to determine which of the parameters affecting the energy performance of the building is more effective, weighed by artificial intelligence techniques. With this method, the energy performance can be calculated without having to use building energy simulation program.

3. METHODS

The study was carried out in four steps: creating the reference building; calculating the heating and cooling loads; estimating the energy using artificial intelligence techniques; and weighting the effects of insulation thickness according to different directions, and window-to-wall ratio. Using a DesignBuilder building energy simulation program, a residential building, which was considered to be in Antalya, a city that has the hottest climate of Turkey, was modeled. The reference building was modeled with width, depth and height dimensions of 10x10x3m respectively, and selected by taking into account the U (Heat Transmission Coefficient) values determined for walls, ceilings, floors, and windows in TS 825 Standard of Thermal Insulation Rules in Buildings.

All characteristics of the reference building designed in the study were kept the same, and the heating and cooling load calculation was initially performed by changing the thermal insulation thickness to 3, 5, and 7cm. Then, in order to investigate the effects of insulation thickness in different directions, insulation thickness of one side was increased by increments of 1cm in the range of 3-10cm, while the other three sides were kept at 3cm initially in the first calculation, 5cm in the second calculation, and 7cm in the third calculation. In order to investigate the influence of window-to-wall ratio on heating and cooling load in the study, the calculation was made by changing window-to-wall ratio between 10%, 20%, 30%, 40%, 50%, 60%, 70%, and 80%. Afterwards, the window-to-wall ratio was changed in one direction and kept constant in other directions in order to study the effect of window-to-wall ratio in different directions. With the data sets of thermal loads obtained, estimations of heating and cooling loads were made using artificial intelligence techniques for insulation thickness and window-to-wall ratios that were not provided to the software. Then the weight ratios of window-to-wall ratio in different directions and heat insulation thickness on heating and cooling loads were determined.

3.1. Building Model

For the study, a single-story building was modeled with width, depth and height dimensions of 10x10x3m respectively. Four sides of the building with a low inclined roof were designed to have the same material, insulation thickness and window ratio. Since the effect of thermal insulation thickness and window-to-wall ratio with regard to different directions was investigated, the building was designed as an empty space and the function of the building was housing (Figure 1).

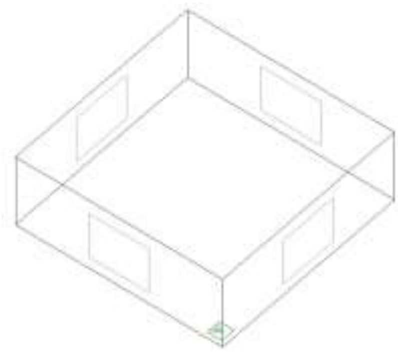


Figure 1. Building Model

3.2. Meteorological Data

In TS 825 Standard of Thermal Insulation Rules in Buildings, Turkey is divided into 4-degree day zones. Antalya (30:42°E 36:53°N) is located in the 1st degree day zone and is influenced by the Mediterranean climate, which displays a hot-temperate climate characteristic. In winter, there is more precipitation than in summer months. The months with highest temperature and longest sunshine are July and August (Table 1) [9]. For the calculation of thermal loads, climatic data of Antalya province were obtained from Meteonorm and loaded into DesignBuilder building energy simulation software [10].

Table 1. Meteorological data for Antalya

Months	Jan.	Febr	Mar.	Apr.	May	June	July	Aug.	Sem.	Oct.	Nov.	Dec.
Average Temperature (C^0)	9.9	10.4	12.7	16.2	20.5	25.4	28.4	28.2	24.8	20	14.9	11.4
Average sun. Time (Hours)	5.2	5.6	6.6	8.1	10.6	11.4	12.1	11.4	10	8.1	6.3	5

3.3. DesignBuilder Energy Simulation Software

DesignBuilder is an EnergyPlus-based software tool designed to measure buildings' performance in terms of energy, carbon emissions, lighting and comfort. The building can be simulated in this software by defining data such as materials used in the building, building users, heating, and cooling and ventilation systems. Among the objectives of the software are; the evaluation of building facades in terms of energy consumption and shading factors, the use of sun rays in buildings, the evaluation of the effect of lighting systems on energy loads, the investigation of the effect of shading with respect to surrounding buildings and sunshine, ventilation of buildings, and design and identification of heating and cooling systems [11].

3.4. Artificial Neural Network (YSA) Based Forecast Model

A multi-layered, forward-feed and back-propagation network model was used as an ANN-based estimation model in the study. The designed ANN estimation model is given in Figure 2. The network with a three-layered structure has 8 input and 2 output parameters. A total of three data sets are used for this model created with a supervised learning model; two data sets for training the network, and one data set for testing. The data sets used in the training phase are called the "training" and "verification" data sets. From these data sets, the purpose of using the training set is to discover optimal network weights and bias values. The function of the verification set is to evaluate the progress of the training, to determine the realization of learning, and to decide whether or not to terminate the training period. Data samples used in the verification set are not used in the training process and in the generation of weights. After the training phase in ANN, the test phase is commenced. The goal of the test phase is to measure the success of the network created during the training phase over previously untested data samples [12].

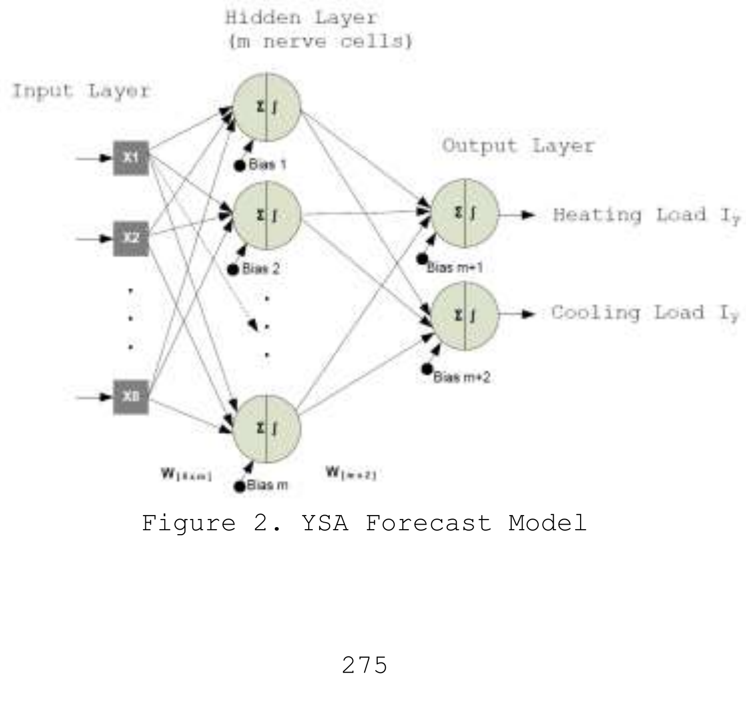


Figure 2. YSA Forecast Model

The ANN estimation model generated after training, verification and testing requires only the values of the input parameters to estimate the heating and cooling load.

3.5. Genetic k-NN Based Estimation and Weighting Model

The prepared model estimates the heating and cooling load and explores the optimum weights of the parameters that are effective on these loads. The estimation task is performed with k-nn [13], while the weighting task is performed with a genetic algorithm [14]. The weighting model represents the effect of the attributes of a problem on the target outputs with the optimal value in the range (0.1). The expression 'optimal' here corresponds to the weight values that maximize the prediction performance of k-nn. In the study, a total of eight input attributes have been defined as <x1, x2, …, x8> that corresponds respectively to change in window-to-wall ratio in north, south, east, west directions, and the change of heat insulation thickness in north, south, east, west directions; and two target outputs <Iy, Sy> have been defined respectively for annual heating and cooling load (Table 2). Table 3 gives the pseudocode of the genetic k-nn based estimation and weighting algorithm.

Table 2. Input parameter by variables

	Window to Wall Ratio				Insulation Thickness			
Wall Direction	North	South	East	West	North	South	East	West
Input Parameter	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8

Table 3. Pseudocode of genetic k-NN algorithm

(i)	Defining Training and Test Data
(ii)	Defining Training and Test Data
(iii)	Creating the k-nn Estimation Model (Fitness Function f(k-nn)) a. Distance correlation b. Number of Neighbors
(iv)	Creating the Genetic Weighing Unit a. Chromosome design b. Population creation c. Operator selections (crossover, mutation) d. Calculation of fitness value
(v)	Weighting Process Cycle (i=1:n), i-cycle variable, n-maximum number of cycles a. Parent selection b. Crossover c. Mutation d. Updating
(vi)	Recording Optimal Weights

- **Defining Problem Parameters:** The information on four different directions and for different insulations, which are the independent variables of the problem, and the annual heating/cooling loads, the dependent variables of the problem, are defined at this stage. The problem has 8 inputs and 2 outputs.
- **Defining Training and Test Data:** The training data set is used in the weighting process. After optimal values of the weights are discovered, the estimation performance of the model is measured using the test data set.
- **Creating the k-nn Estimation Model:** This model is defined as a function. The parameters of the function are; "a distance correlation such as Manhattan, Minkowski, Euclidean", "a

neighbor number such as 3, 5, 7 determined according to the problem, distance relation, and number of data samples", "a data set consisting of sample observations" and "a query observation for which the target parameter value will be estimated". The reference study [12] can be examined with regard to the determination of k-nn parameters.

- **Creating the Genetic Weighing Unit:** The design of this unit is based on the problem definition. This unit, which weights the independent variables for the Iy and Sy target outputs, will ultimately form these two vectors <Wx1Iy, Wx2Iy, …, Wx8Iy> and <Wx1Sy, Wx2Sy, …, Wx8Sy> both with eight dimensions. Accordingly, a chromosome representing a candidate for solution in the genetic algorithm has a structure consisting of eight genes, one for each dependent variable. Therefore, the mathematical expression of a population of solutions (population P consisting of m-number of solution candidates) to be created by the genetic algorithm for both cooling and heating load can then be represented as given in equation 1 [13,15]:

$$P \equiv \begin{bmatrix} W_{X_{11}} & \cdots & W_{X_{18}} \\ \vdots & \ddots & \vdots \\ W_{X_{m1}} & \cdots & W_{X_{m8}} \end{bmatrix}, \begin{bmatrix} U_1 \\ \vdots \\ U_m \end{bmatrix} \qquad (1)$$

  In Equation 1, population P is defined with [mx8] dimensions. Here, each row represents a solution candidate, whereas each row of the m-dimensional vector on the right side represents the fitness of each solution candidate to the problem. The k-nn function is used to calculate the fitness value of a solution candidate. The k-nn estimator, which takes the weights of the solution candidate as a parameter, returns the prediction performance based on these weights as a fitness value.
- **Weighting Process Cycle:** In this process, optimum weight values of independent variables are searched. Process termination is based on the maximum number of cycles and the k-nn estimator performance. This process, summarized in four steps in Algorithm 1, ends with storing the most successful solution candidate among the P-solution candidates given in Equation 1 as the solution. In this process, "parent selection", "crossover", "mutation" and "update" operations are performed iteratively within the population consisting of m solution candidates until the termination criteria are met.
- **Recording Optimal Weights:** When the iterative process described in the fifth step ends, the most successful solution candidate (which has the highest fitness value or which makes the performance of the k-nn estimator maximum) within the P-solution candidates population is recorded.

4. RESULTS AND DISCUSSION

This section was studied under two headings; firstly the annual heating and cooling load values were obtained for the models with changed thermal insulation thickness and window-to-wall ratio with regard to the reference building prepared in the scope of the study. Then, by using artificial intelligence techniques, the thermal loads of models without heating and cooling load calculations were estimated and the weights of the parameters in these loads were determined.

4.1. Simulation Results

Within the scope of the study, in addition to the reference building modeled with 3cm heat insulation thickness and 30% window ratio model, a total of 171 simulation results with different heat insulation thicknesses in different directions and different window-to-wall ratios were obtained. The effect of different thermal insulation thicknesses and window-to-wall ratio changes on energy consumption with regard to the reference building was separately examined.

4.1.1. Impact of Insulation Thickness Change on Energy Consumption

At this stage of the study, a total of 3 different models were established with 5cm heat insulation thickness in all directions and 10% window-to-wall ratio, and 7cm heat insulation thickness in all directions and 50% window-to-wall ratio, in addition to the reference building with 3cm heat insulation thickness and 30% window-to-wall ratio. In order to investigate the effects of thermal insulation thickness in different directions on these three models, different models were established by changing heat insulation thickness on one facade of the building between 3cm and 10cm in increments of 1cm, while keeping heat insulation thickness constant in the other three facades of the building.

4.1.2. Effect of Window-to-Wall Ratio Change on Energy Consumption

At this stage of the study, a total of 3 different models were established with 10% window-to-wall ratio and 5cm heat insulation thickness in all directions, and 50% window-to-wall ratio and 7cm heat insulation thickness in all directions, in addition to the reference building with 30% window-to-wall ratio and 3cm heat insulation thickness. In order to investigate the effect of window-to-wall ratio in different directions on these three models, different models were established by changing the window-to-wall ratio on one facade of the building between 10%, 20%, 30%, 40%, 50%, 60%, 70% and 80%, while keeping the window-to-wall ratio constant on the other three facades of the building.

4.2. Energy Consumption Estimation Using Artificial Intelligence Techniques

A total of 171 data samples were used in the study. 60% of these data samples (103 samples) were randomly selected to generate the training set, 20% to generate verification and 20% to generate test data sets (34 samples each). Figure 3 shows the ANN network model. The network obtained after different combinations were tried has a single hidden layer, while the number of nerve cells in the hidden layer is six.

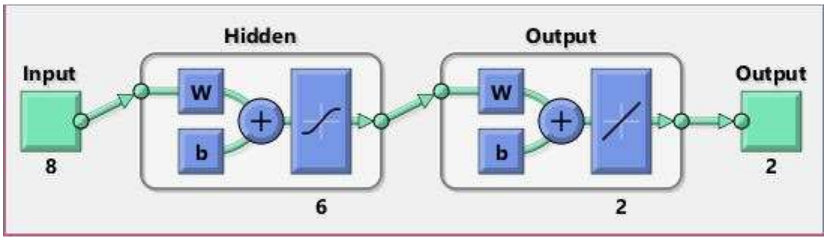


Figure 3. Developed YSA model for implementation

4.2.1. Artificial Neural Network (YSA) Forecast Model Results

The error values obtained for training (blue color) and test (red color) samples in the developed ANN model are given in Figure 3. In the graph, while the orange line indicates the center point where the error is zero, the error grows as we move from this center point towards positive and negative directions. Accordingly, the numbers on the horizontal axis are error values. The vertical axis of the graph shows the number of data samples. An ideal error graph is expected to have the error values for all data samples to be zero, in other words, to converge on the orange line. However, in real systems, this graph is interpreted as a successful error graph if it is in the form of a bell under the best conditions. As it can be seen from the graph, as we move in the positive and negative direction of the horizontal axis, very few data samples are encountered, which indicates that the number of data samples with big errors is extremely low. Since there is no graph of the verification data set in Figure 4, it is understood that the error is zero for the samples in the corresponding data set.

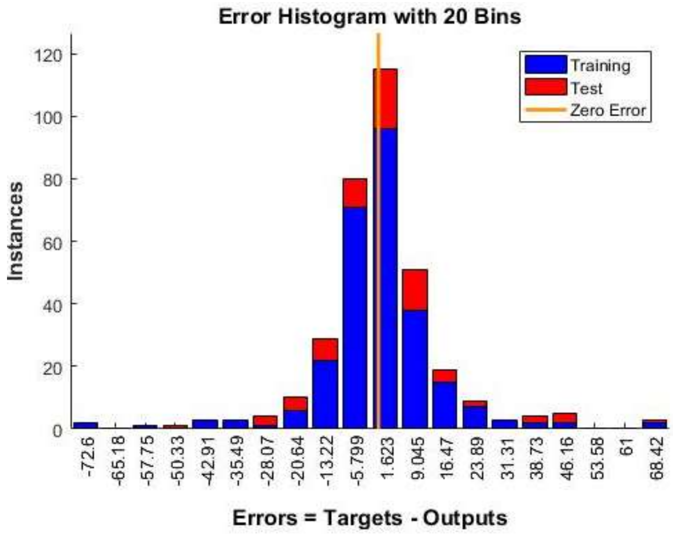
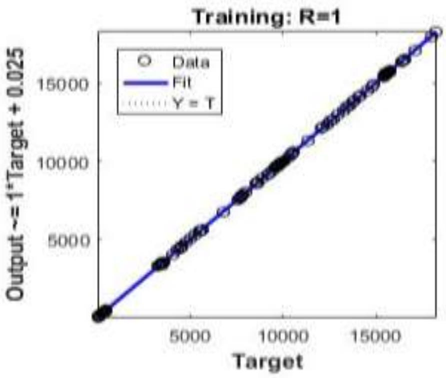
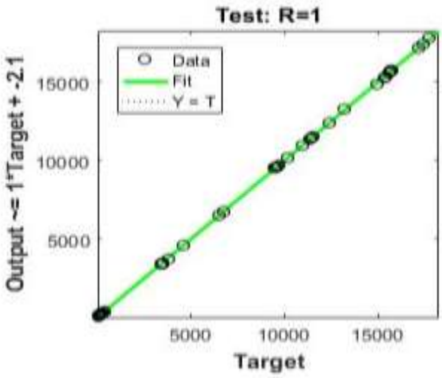


Figure 4. Error graph

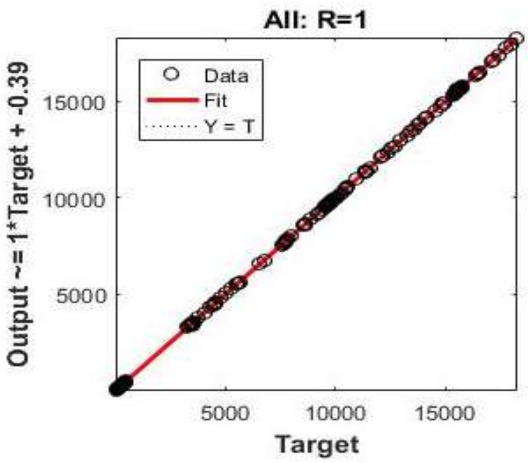
Figures 5 a, b, and c show the estimation performance of the ANN model in training, testing, and all data sets, respectively. The horizontal axis is the actual values of the heating and cooling loads of the data samples, while the vertical axis is the predicted value of the ANN. The 'R' given in Figure 3 takes values between [0, 1] depending on the overlap of the output and actual values. If both values overlap for all data samples, an angle of 45 degrees occurs in the graph, and R=1 in this case. This means that the error is approximately zero. In other words, this figure is the regression graph showing the results of training. The line that is drawn closest to the results here is the regression line of the ANN.



(a)



(b)



(c)

Figure 5. (a) Training, (b) test ve (c) regression curves regarding all data sets

4.2.2. Genetic k-NN Predictive Model Results

Experimental results of the genetic k-nn estimation model unit, different distance metrics, and k-neighborhoods are given in Table 3.1. The fact that the estimation of heating load is made with an error of 6% and cooling load is estimated with an error of 2% according to Table 4 indicates the accuracy of the data set as well as the strength of the developed models.

Table 4. Errors percentage obtained from genetic k-nn estimation model

k-nn Parameters		Percent Error in Test Data Mean	
Distance Relation	Number of Neighbors	Heating Load	Cooling Load
Oklit	3	6.95	2.35
	5	8.15	1.95
	7	11.45	2.33
Manhattan	3	5.69	2.41
	5	8.7	2.46
	7	11.86	2.33

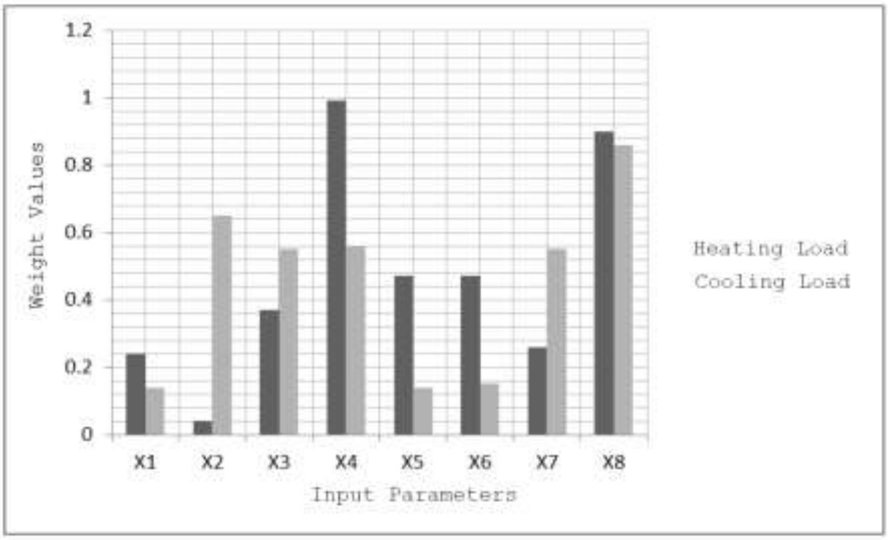
Table 5 gives the optimal weight values for the independent variables on heating and cooling loads. These values were discovered by the genetic weighting unit. The values getting closer to 1 in the range of 0-1 indicates that they are more effective. Accordingly, the conditions for obtaining the optimal weight values for the heating load are the Manhattan distance metric and a neighbor number of 3. The conditions under which optimal weight values are obtained for the cooling load are the Euclidean distance metric and a neighbor number of 5.

Table 5. Weight values of impact of independent variables on Iy and Sy

Target Output	Independent variable weight values							
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Heating Load Iy	0.24	0.04	0.37	0.99	0.47	0.47	0.26	0.9
Cooling Load Sy	0.14	0.65	0.55	0.56	0.14	0.15	0.55	0.86

5. CONCLUSIONS

In this study, the effects of the changes in thermal insulation thickness and window-to-wall ratio on the thermal loads of the reference building considered to be in the province of Antalya were examined. A total of 3 different models were established with 5cm heat insulation thickness in all directions and 10% window-to-wall ratio, and 7cm heat insulation thickness in all directions and 50% window-to-wall ratio, in addition to the reference building with 3cm heat insulation thickness and 30% window-to-wall ratio. In order to investigate the effects of thermal insulation thickness and window-to-wall ratio in different directions on these three models, 171 models were simulated by using a total of 8 input parameters with different thermal insulation thickness and window-to-wall ratio figures on one facade of the building, while thermal insulation thickness and window-to-wall ratio was kept constant on the other three facades. The two output parameters obtained by using the DesignBuilder software are annual heating and cooling loads. Of the total 171 data samples used, 60% were randomly selected for generating the training data set, 20% for the verification data set, and 20% for the test data set. Using the designed ANN-based estimation model, heating and cooling load estimates were made for different inputs other than the 171 samples and not included in the 8 input parameters. For example, the annual heating and cooling loads of a building with a window-wall ratio of 40% and a thermal insulation thickness of 5cm on all facades can be estimated by the trained program, although this building is not included in the datasets. Based on the results of the genetic k-NN estimation model, more effective input parameters on annual heating and cooling loads among the input parameters defined in Table 2 were identified (Graphic 1). According to this, x4 is more effective than other input parameters on heating load, followed by x8, x5, x6, x3, x7, x1 respectively, while the least effective parameter is x2. The most effective input parameter on cooling load is x8, followed by x2, x4, x3, x7, x6. The least effective parameters on cooling load are x1 and x5, which have the same weight.



Graphic 1. Graph showing influence of independent variables on Iy and Sy

When all the parameters studied are considered, it is possible to transform buildings into buildings that consume less energy by taking simple design measures while the buildings are still in the design phase. In this direction, searching for energy efficient solutions with just building energy simulation software packages has become a time-consuming effort today. Instead, more results can be obtained from less data by using modern and effective artificial intelligence techniques. The results of this study reveal which of the 8 input parameters should be focused on more or less. In this context, it will be a much faster and more energy efficient solution to make estimations with the trained software by making changes on the x4 parameter, the most effective parameter on heating load, instead of the x2 parameter, the least effective parameter, and to find the x4 parameter value at which the building consumes the least amount of energy.

NOTICE

This study was presented as an oral presentation at the International Conference on Advanced Engineering Technologies (ICADET) in Bayburt between 21-23 September 2017.

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