Rule-Based Mamdani-Type Fuzzy Modelling of Buildings Annual Heating Energy Need in Design of Industrial Buildings in Konya-Turkey

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ABSTRACT
In this study, it is aimed to present a model in which measures can be taken to improve the energy performance of buildings while designing industrial areas. Within the context of the study, it was investigated in the workplace buildings in the Eski Industry and Karatay Industry in Konya. As a result of the research conducted in the workplaces in the area, 128 different building alternatives emerged in terms of design parameters such as building size, orientation, and exterior wall material properties. Annual heating energy needs of these alternatives are calculated by the calculation method in TSE 825. A fuzzy logic (FL) model, an artificial intelligence method, was created by using some of the calculated values. The rest of the calculated heating energy need values and the values obtained from the FL model were compared with the multiple coefficients of determination (R-squared). As a result of the comparison, it was revealed that the FL model created predicted the annual heating energy need of the buildings by 98.1%. This shows that the FL model created can be used to estimate the annual heating energy need at an accuracy rate of 98.1% of the single volume industrial buildings to be designed.
Keywords: Building Energy Performance; Fuzzy Logic; Architecture and Artificial Intelligence; Industrial Buildings; Architecture and Machine Learning.

1 INTRODUCTION

Energy-saving and environmental protection are among the most critical issues facing societies (Li et. al. 2018). Especially the energy need of the building sector constitutes a large part of the total energy consumption in many countries (Yıldız and Arsan 2011). The energy used in buildings constitutes more than 40% of the total energy used in the world (EC D Directive 2002). The reasons for the high energy consumption of the construction sector can be shown as uncontrolled urbanization, energy spent during building construction activities, and inadequate energy-saving measures in buildings (Yıldız and Arsan 2011). The loss of fossil fuels and climate change make it very important to reduce energy consumption in the construction industry (Lee et. al. 2013). To reduce building energy use, zero / low energy buildings are becoming more and more important (Li et. al. 2018). Various policies have been developed all over the world to reduce energy consumption. In 2002, the European Union (EU) adopted the Energy Performance of Buildings Directive, which sets the best efficiency standards for both commercial and residential buildings (EPBD 2002). This directive is aimed to ensure that all buildings built in all EU Member States as of 2020 are Zero Energy Buildings (NZEB) (EPBD 2010). The U.S. California Public Facilities Commission plans to reach zero energy buildings (NZEB) for all new commercial construction by 2030 (CPUCD 2007).

Designers are looking for solutions that will increase the energy efficiency of their buildings while providing comfort and quality conditions (Alireza and Coelho 2015). Kavgic et. al. (2015) introduced the Monte Carlo (MC) model, which estimates the heating energy consumption of residential stocks. Andarini et al. (2018) have defined parameters to reduce

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cooling energy requirements in small office buildings. Salvati et al. have developed a strategy that reveals the annual energy need according to urban climate characteristics by doing 10 field studies in Italy and Chile (Salvati et. al. 2020). Wetter and Polak aimed to minimize the annual energy consumption of an office building and used an algorithm to optimize the building design (Wetter and Polak 2004). Jia et al. developed a machine learning-based 30-neuron ANN model to predict the cooling load of high-rise residential buildings (Jia et al. 2021). Attia et al. (2013) investigated the existing Building Performance Optimization tools for zero energy building design. Heiselberg et al. found important parameters to design sustainable buildings and to reduce the energy consumption of selected buildings (Heiselberg et. al. 2009). Magnier and Haghighat have performed multi-purpose optimization of building design using artificial neural networks and genetic algorithms (Magnier and Haghighat 2010). Choudhary et al. (2003) have developed a hierarchical design framework to optimize building performance. Wright and Mourshed (2009) have been optimized with the genetic algorithm in terms of energy efficiency, for the size of the windows directed to the south, the size, number, and location of the windows. Wang et al. (2005) applied genetic algorithms for green building design optimization. It was determined by De Wit (2001) that there are parameters that have an effect on thermal comfort in naturally ventilated office buildings. To be able to design the building passive solar by Stevanovic (2013); work has been done on optimization of parameters such as building form, opaque envelope components, glass, and shading elements. Badescu et al. (2010) worked on the passive office building. Dominguez-Munoz et al. (2010) conducted a sensitivity analysis to find key factors in calculating peak cooling loads in buildings. Koo et al. (2014) used algorithms and algorithmic models in conjunction with energy simulation software to determine optimal configurations of building components such as building envelopes. Many studies conducted so far have demonstrated that improving energy performance in buildings can be achieved by focusing on building design parameters (de Wilde et. al. 2002). In some studies, it has been revealed that the building orientation parameter has an important effect on the energy gain of buildings (Morrissey et. al. 2011). In some studies, the effect of window sizes has been investigated (Giovannini et. al. 2019; Obrecht et. al. 2019) . At the same time, the changes in the shape and position of the window and the effects of the height/length ratios of the windows and their location along the building facades on the energy gain of the buildings were investigated (Mechri et. al. 2010; Mendez et. al. 2015). In addition, the most suitable window-to-wall ratio (WWR) configurations have been studied (Wright and Mourshed 2009; Goia et. al. 2013). Some researchers have shown that solar energy gain is not independent of the window shape (Cascone et. al. 2013). In some studies, thermo-physical properties (Gossard et. al. 2013; Jiang et. al. 2012) or insulation thickness (Lollini et. al. 2006; Axaopoulos et. al. 2014) of the opaque envelope have been optimized.

The construction sector in Turkey has been the second-largest energy consumer in the year 2001 25.793 million tons of energy consumption (Oğulata 2002). Research has been done; if the amount of energy used in buildings in Turkey is reduced to the level of the European Union countries, it shows that an average of 30 to 40% energy savings is possible (ÇBS 2015). Therefore, reducing the need for energy in buildings located in Turkey is an important issue. It is clear that previous studies have generally concentrated on residential areas or office buildings. Thus, there is a need for research that focuses on parameters that affect the energy performance of industrial areas. Industrial areas constitute a large part of the city after the residential areas in the city. Reducing the need for energy in industrial areas in the cities will contribute significantly to energy conservation. While using buildings, air conditioning such as heating and cooling are made in order to provide indoor comfort conditions. The biggest energy expenditure is used to provide the heating energy needs while these air conditioners are made. While designing industrial buildings, the energy problem can be solved by reducing the annual heating energy need. Konya city where the research is located in the Central Anatolia region of Turkey and is the fifth-largest city in the country. The city is in a position that affects the region in which it is located both economically and socially. Industrial areas constitute 8.5% of the total settlement area in the city of Konya. This rate shows that industrial areas play an important role in air and environmental pollution as well as energy consumption in the city.

In this study, an FL model has been developed to estimate the energy needs while designing industrial buildings. In the literature, it is seen that the FL model is used in studies related to Energy. Chekired et al. present a new energy management strategy for a house in the coastal region of Algeria. The proposed energy management algorithm is based on the FL technique. In the study, a strategy has been developed to meet the energy needs and comfort of the user, depending on the energy supplied from the PV system (Chekired et. al. 2017). Zhang et al. proposed a fuzzy expert system for efficient energy smart home management systems. The framework of the proposed fuzzy expert system is used to simplify designing smart microgrids with storage systems, renewable resources, and controllable loads on resources. Moreover, the fuzzy expert framework improves energy and storage to harness renewable energy and maximize the financial gain of the microgrid (Zhang et. al. 2020). Based on these studies, the idea has emerged that the FL model can also be used in modeling the energy gains that can be obtained by passive design methods of buildings. The FL system is easy and understandable. It has features that can help produce effective solutions to complex problems. The system can be easily modified to improve performance. It helps to deal with uncertain situations. FL; structurally, it consists of blurring, rule-based inference mechanism, and defuzzification units. Membership functions and inference methods used in the FL controller are important factors that directly affect the performance of the controller.

While calculating the heating energy requirement values used while creating the model, the calculation method in TSE 825 was used. TSE 825 standard; It aims to determine the standard calculation method and values in order to limit the amount of energy to be constructed or to be used in existing buildings in Turkey, to save energy, and to calculate the net energy need. Therefore, the research area; The data in this calculation method was used for Karatay Industry and Eski Industry campuses in Konya. The province of Konya, where the study was conducted, is in the 3rd climate zone according to TSE 825 and the average air temperatures of this climate region are determined by the standard. Calculations were made using this calculation method for the heating period in this climate type and the heating energy requirement was determined. At the same time, according to TSE 825, indoor temperatures must be 16 degrees in order to provide thermal comfort conditions in workshops. Calculations were made for the months when the air temperature was below 16 degrees.

In the industrial buildings, the TSE 825 suggests that the temperature level of the interior space of the industrial buildings should be at least 16 °C to provide the thermal comfort conditions of the working area. Therefore, the calculations done in the current study were considered in the case of a temperature of less than 16 °C. In this context, the Konya province is regarded as the 3rd climate/day region according to the TSE 825 and also, it has been reported that the monthly average temperature of all months except June, July, August, and September of the 3rd region cities are less than 16 °C. For this reason, that can be also applied to Konya province.

2 RESEARCH SIGNIFICANCE

In this study, a machine learning model study was conducted that can help reduce the heating energy need of buildings by experimenting during the design phase. In the present research, field studies were carried out at workplaces located in Karatay Industry and Eski Industry campuses in Konya, and data was collected from these areas. 128 different building alternatives have been presented with the data obtained from the area. Annual heating energy needs of these building alternatives are calculated using the calculation method in TSE 825. Using the calculation results, a fuzzy logic (FL) model has been developed that estimates the annual heating energy need of the buildings. As a result of the parametric study carried out with this model, it was deduced that the developed model correctly estimates the annual heating energy need of the buildings by 98.1%. Using the

FL model achieved in the current study, it will be possible to obtain optimum results by trying the designs to be made. After determining that the model gives mostly correct results, new building alternatives were created in different combinations. The material heat transmission account values and annual solar energy gain values of these building alternatives are defined to the system as the input parameters. With these values entered into the system, the annual heating energy needs for new building alternatives were obtained from the developed FL model. The situations that give the best results according to orientation, size, and material properties are presented with these values. On the other hand, considering TSE 825 to determine the heat energy need of such buildings makes the calculations more complex. Moreover, ISO 13790 propose a calculation methodology for the estimation of heat energy need of such buildings; however, this methodology is also very complex and hard to follow. But the model that was developed in the current study offers a very simple and easy model to estimate the heating energy need of industrial buildings.

3 EXISTING CODE FORMULATION

In order to make calculations in the study, the heating energy requirement calculation method was used in single-volume buildings in TSE 825 Building Thermal Insulation Rules Standard. TSE 825 Thermal Insulation Rules Standard in Buildings was published in 1999 and subsequently updated. In this study, the last version published in 2013 is used. One of the purposes of the TSE 825 Standard, the heating energy of buildings in Turkey reveals calculation methods can be used in the calculation of need (TSE 825 2013). In the calculation method specified in the standard; heat losses through conduction, convection, radiation and ventilation, internal heat gains, and solar energy gains are taken into consideration. Other factors are considered constant. In order to calculate the annual heating energy need, monthly earnings must be calculated (1). Then monthly energy needs can be collected and annual energy needs can be found (2).

$$Q_{Year} = \sum Q_{month} \tag{1}$$

$$Q_{month} = \left[H(\Theta_i - \Theta_e) - \eta_{month}\left(\phi_{i,month} + \phi_{s,month}\right)\right].t \tag{2}$$

where

Q_{year} is annual heating energy requirement,
Q_{month} is monthly heating energy requirement,
H is specific heat loss of the building,
Θ_i is monthly indoor temperature,
Θ_e is monthly outdoor temperature,
η_{month} is average monthly usage factor for gain
$\phi_{i,month}$ is monthly average internal gains (can be taken as constant),
$\phi_{s,month}$ is monthly average solar energy gain, and
t is time (s) (TSE 825 2013; Aydın and Bıyıklı 2020).

While calculating the monthly heating energy need, it is necessary to calculate some intermediate values. Calculations are made in the following order. This is because some values are used at another calculated value.

- Calculation of thermal transmittance coefficient (U)
- Calculation of specific Heat Loss (H)
- Calculation of monthly average earnings ($\phi_{s,month}$)
- Calculation of the gain usage factor (η_{month})

After calculating these intermediate values, the annual heating energy need of the buildings could be calculated.

4 OVERVIEW OF THE FL METHOD

There are many fuzzy logic membership functions and inference methods in different structures in the literature (Ünsal and Alışkan 2016). Mamdani is a widely used fuzzy inference method. The main reasons for this are; Mamdani inference is more appealing to human perception, its design is relatively easy, and it is more interpretable. In Mamdani inference, the inputs and outputs are fuzzy values. Membership values are calculated according to the rules triggered by the input values. Then the calculated values are given to the max or min operator according to the rules and/or their logical connectors. If the facts in the rule are connected with 'and', the calculated membership values are given to the min operator; If it is connected with 'or', it is given to the max operator. These operators, as their names suggest, return the smallest or largest of the multiple values they receive (Ünsal and Alışkan 2016).

FL is a form of human thought and reasoning ability and applies this model to problems in line with needs (Zadeh and Kacprzyk 1992). The application areas of fuzzy sets, also called human simulation, have a close relationship with the human thinking system and behavior. Therefore, it is very important to examine human beings in order to get good results. The biggest target for FL; is to take the good sides of people and reinforce the areas they are inadequate (Sugeno and Kank 1986). The FL approach is based on the assumption that logical values can take values between 'true' and 'false' (0 or 1) (Mamdani and Gaines 1987). According to classical logic theory, there are black and white, there are no tones in between. In the fuzzy set logic, all shades of grey between black and white are accepted (Vrusias 2005). Mamdani-based fuzzy models work with input and output parameters (Equations 3 and 4). In the Mamdani fuzzy model, both the input functions and the outcome functions are fuzzy propositions (Bojadziev and Bojadziev 1991).

$$x = [\, x_1, \ldots, x_2]^T \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ \cdot & \cdot \\ \cdot & \cdot \\ x_{n1} & x_{n2} \end{bmatrix} \qquad (3)$$

$$g = [g_{1,\ldots,}g_{n,}] \qquad (4)$$

In Mamdani-based fuzzy models, rules are used to enable the system to learn. A general fuzzy model is created with an if-then rule base (Equation 5) (Zadeh and Kacprzyk 1992).

$$R_i :\ if \ \ x\ is\ A_i \ \ then\ y\ is\ B_i\,, \quad i = 1,2,\ldots,K \qquad (5)$$

where

R_i is the rule number,
x is the system's input variable,
y is the output variable, and
A_i and B_i are fuzzy sets.

The membership function μ_a (x) is defined as the FL subset, while this structure is called the triangle membership function equation (see *Figure 1*) (Bojadziev and Bojadziev 1991).

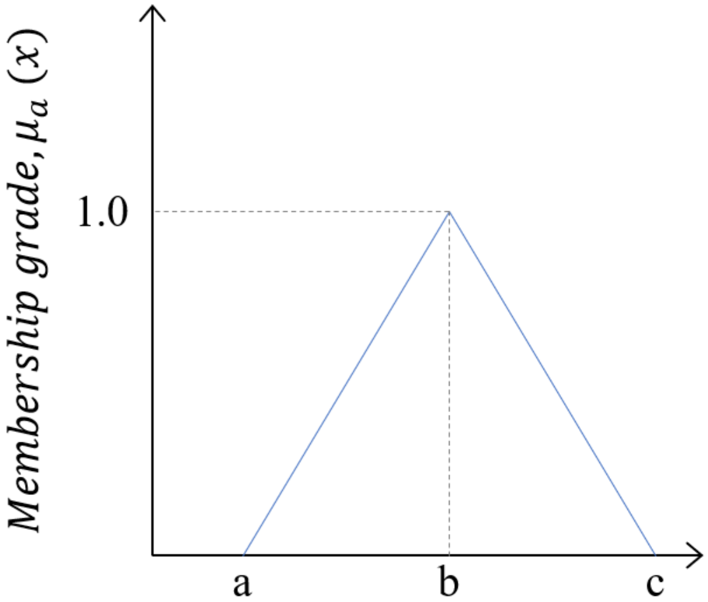


Figure 1. The structure of the triangle membership function

In FL models, triangular membership functions are defined by a, b and c.
where
a and c are minimum and maximum value, and
b represents the most probable value (Bai and Wang 2006).

The equation for the triangular membership functions is expressed by the following expression:

$$\mu a\ (x) = \begin{pmatrix} (x-a)/(b-a) & if & a \leq x \leq b \\ (x-c)/(b-c) & if & b \leq x \leq c \\ 0; & & otherwise \end{pmatrix} \quad (6)$$

As a result, the creation of the FL system consists of three stages. The first is to make the input and output parameters suitable for the FL system, the second is to create and define the rules, and the third stage is to compare the results with the available data (Bai and Wang 2006; Sivanandam et. al. 2007).

5 DEVELOPMENT OF THE FL-BASED MODEL

In the study, firstly, field research was carried out. Building alternatives were created using the data obtained from the field research and the annual heating energy needs of these building alternatives were calculated. The annual heating energy need calculation method of the buildings in TSE 825 was used in these calculations. The FL model, which calculates the annual heating energy need of the buildings, was created by using the calculated values.

5.1 DESIGN PARAMETERS

Designers have to make some decisions when designing buildings. While making these decisions, it is possible to make designs by considering the energy performance. When designing buildings in industrial areas, as design parameters to be considered in terms of energy performance;

- Building geometry (size features),
- Building orientation,
- Building shell wall material properties are determined.

When the dimensional properties of the buildings in the Karatay Industry and Eski Industry campus where the industrial buildings are located are examined, the usage of the spaces in different dimensions was determined. In the construction phase, workplaces, which are considered in one dimension, were divided or merged as needed and three different dimensions of spaces were obtained (see *Table 1*).

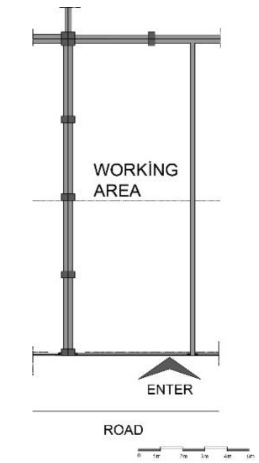
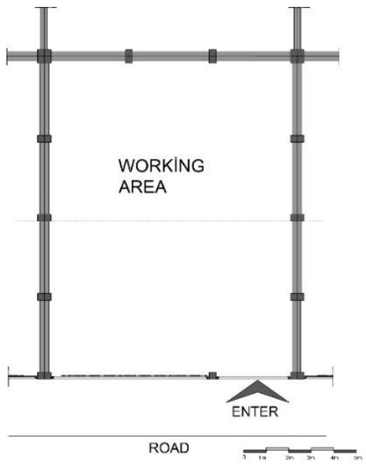
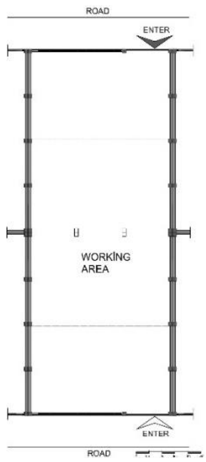
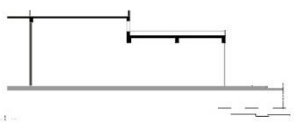
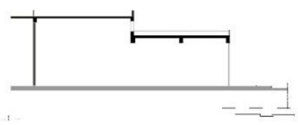
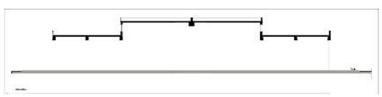
The first is called a small-sized workplace, the second is a medium-sized workplace, and the third is called a large-sized workplace. The area of a small-sized workplace is 74 m^2, a medium-sized workplace is 150m^2 and a large-sized workplace is 300 m^2.

The external wall material properties of the buildings were examined and it was revealed that there are three types of materials commonly used in the buildings (see *Table 1*).

Exterior wall material properties of buildings; It has been obtained as a result of research that it can be reinforced concrete, pumice block, and perforated brick. The alternative orientation of the buildings and windows size is presented in *Table 2*.

Orientation alternatives of the small-sized workplace; south, north, east/west oriented window is defined as an alternative and the window size is 21.42 m^2. Orientation alternatives of the medium-sized workplace; the south, north, east/west oriented window is defined as an alternative and the window size is 38.15 m^2. Orientation alternatives of the large-sized workplace; south/north, east/west oriented window is defined as an alternative and the window size is 76.3 m^2. 128 different building alternatives were created with combinations obtained from all these alternatives. The 82 (about 65%) different building alternatives of the total dataset were used to train the FL model. On the other hand, the remained part was employed to test the developed model.

Table 1 Workplace size and wall material properties

	Workplace size properties		
Area	Small-sized workplace Workplace area: 74 m^2	Medium-sized workplace Workplace area: 150 m^2	Large-sized workplace Workplace area: 300 m^2
Floor Plan			
Section			
	Wall material properties		
	Wall material alternative I	Wall material alternative II	Wall material alternative III

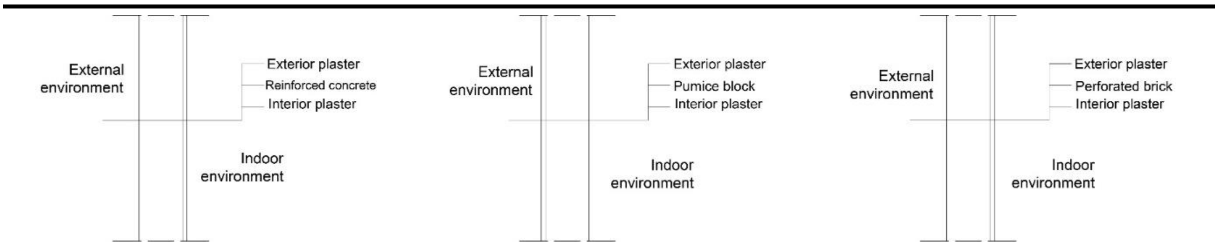


Table 2 Windows Size and Building Orientation Properties

Building Size	***Window Size, m²***	***Building Orientation***
Small-sized workplace	21.42	South, north, east/west
Medium-sized workplace	38.15	South, north, east/west
Large-sized workplace	76.30	south/north, east/west

5.2 DESIGN MODEL

The annual heating energy requirement of building alternatives has been calculated to create the FL model. Input and output parameters are created by taking into account the calculation values. Membership functions consisting of two input and output parameters are defined to the system. Membership functions of the system are defined by using the values of these input and output parameters. Then, the rules were created and defined to the system and the system was learned. Then, the accuracy of the model was tested by comparing the calculated values and the values obtained from the FL model.

Defining membership functions

Determining membership functions is an FL process and converts a numerical value to an FL value. In the study of FL modeling of energy efficiency of industrial buildings, the input-output parameters of the system, that is, the membership functions of the system should be determined. In order for the system to work properly, the input and output parameters must be defined correctly. This model consists of two inputs and one output system. Appropriate values within the design parameters that affect the energy performance of the buildings have been defined and defined as entrance parameters. As the output parameter, the expected result from the model is taken into consideration (see *Figure 2*).

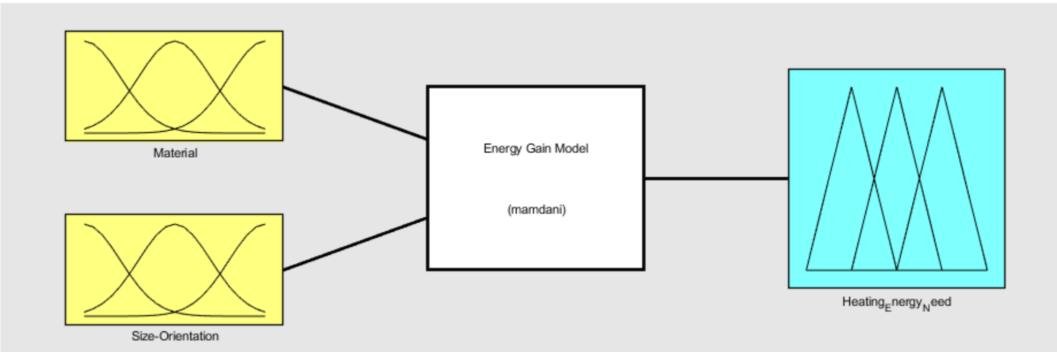


Figure 2. Designed model structure

The first of the input parameters is the heat conduction calculation values of the type of material called 'M'. Membership functions of the material alternative have been created by defining these values as input parameters to the FL system. Triangular membership functions are used in the system. Variable degrees of membership of material are shown as follows (see *Figure 3*).

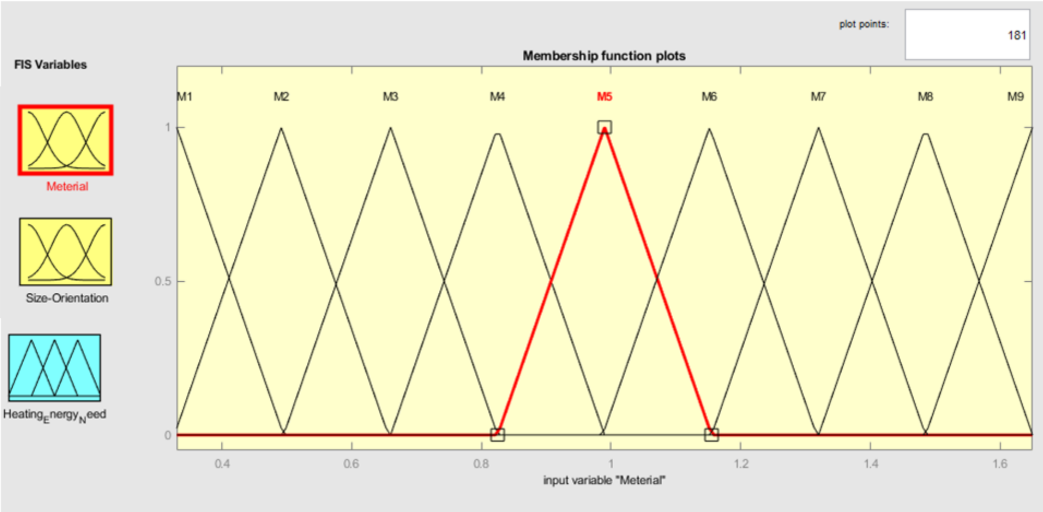


Figure 3. The degree of membership of building exterior wall material values

As mentioned in the previous sections, building sizes and building orientation parameters are important factors in reducing the annual heating energy need of the buildings. Transparent surfaces of buildings, such as windows, directly affect the amount of solar energy gain. At the same time, these surfaces cause heat losses as the heat permeability resistance is weak. The annual heating energy need values of the buildings change according to the orientation feature of the buildings. The sun rays coming in the north direction and the sun rays coming in the south direction differ. Based on this information, solar energy gain values were calculated according to the size of the buildings and the orientation of the building window openings. These values calculated are defined as the second input parameter, which is called SO, to the FL system. Using triangular membership functions in the system, the membership functions orientation factors were established. Membership degrees of the orientation variables are shown in the figure below (see *Figure 4*).

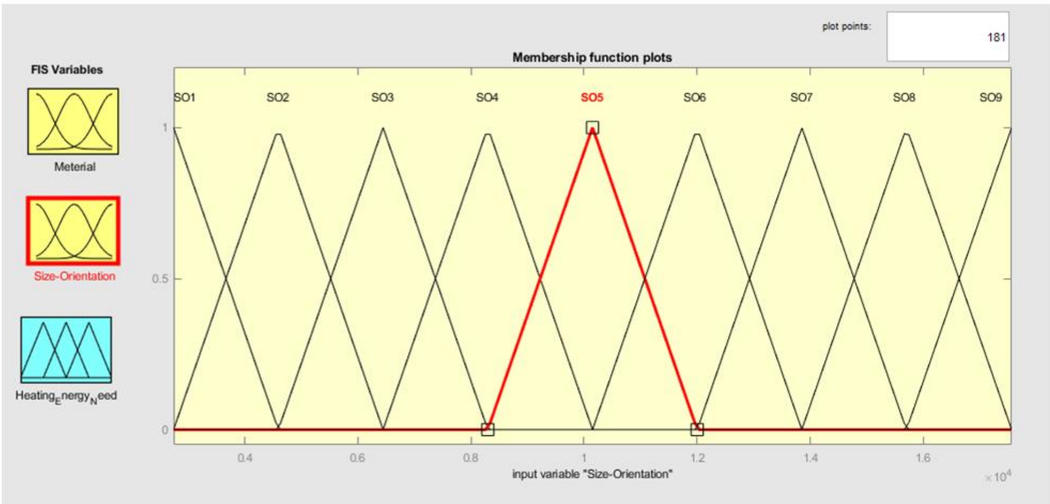


Figure 4. Membership graph of building annual solar energy gain values

When the values of the M input parameter are defined to the system, the system has assigned 9 triangular membership functions and a range value is defined for each function. For example, the range value of the M6 membership function; consists of values in the range of 0.9869 – 1.317. When the values of the SO input parameter are defined to the system, the system has assigned 9 triangular membership functions and defined a range value for each function. For example, the interval value of the SO3 membership function; consists of the values in the range of $4.6x10^3$ – $8.31x10^3$.

Annual heating energy need (Q) values calculated depending on the orientation, size, and material parameters of the building alternatives created are defined as the output parameters of the FL system and membership functions of the heating energy need values entered into the system are created. Triangular membership functions are used in the system. Membership degrees of the annual heating energy need variables are shown in the figure below (see *Figure 5*).

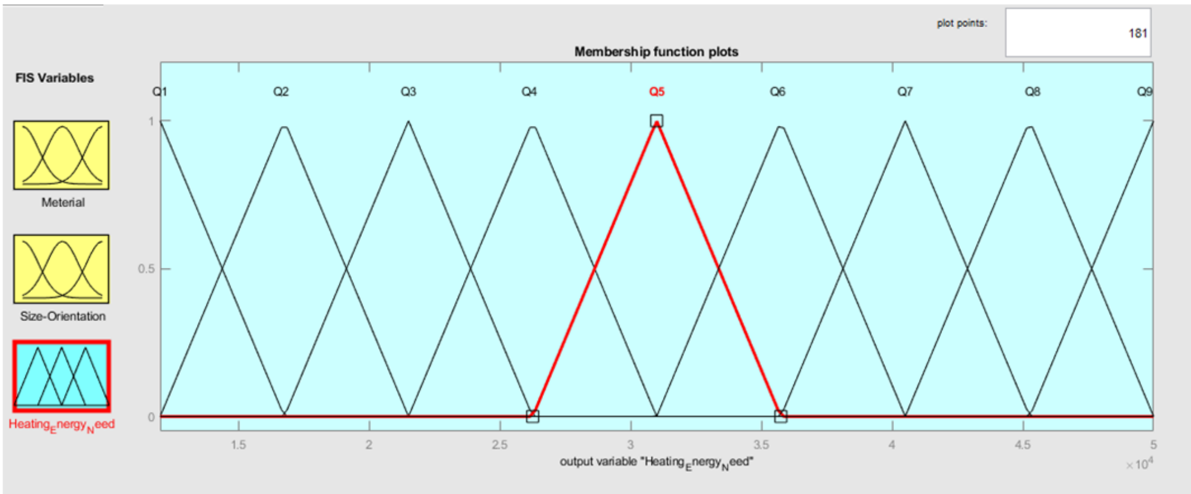


Figure 5. Graph of membership degree of building annual heating energy need values

When the values of the output parameter of the Q (annual heating energy need of buildings) are defined to the system, the system has assigned 9 triangular membership functions and a range value is defined for each function. For example, the interval value of the Q8 membership function; consists of values between 4.058 x10^4-5.009 x10^4.

Fuzzy membership functions in analytical form; M, SO, and Q values are expressed by the following Equations 7, 8, and 9.

$$f_{m,3}(x) = \begin{cases} 0 & ; \quad x \leq 0.495 \\ (x-0.495)/(0.165) & if \quad 0.495 \leq x \leq 0.660 \\ (0.825-x)/(0.165) & if \quad 0.660 \leq x \leq 0.825 \\ 0 & ; \quad x \geq 0.825 \end{cases} \tag{7}$$

$$f_{so,3}(x) = \begin{cases} 0 & ; \quad x \leq 4595 \\ (x-4595)/(1851) & if \quad 4595 \leq x \leq 6446 \\ (8298-x)/(1851) & if \quad 6446 \leq x \leq 8298 \\ 0 & ; \quad x \geq 8298 \end{cases} \tag{8}$$

$$f_{Q,3}(x) = \begin{cases} 0 & ; \quad x \leq 1675 \\ (x-1675)/(475) & if \quad 1675 \leq x \leq 2150 \\ (2625-x)/(475) & if \quad 2150 \leq x \leq 2625 \\ 0 & ; \quad x \geq 2625 \end{cases} \tag{9}$$

Creating Fuzzy Sets Of Parameters And Creating Rules

When the membership functions are defined in the system, the fuzzy set of each input and output parameter occurs. Triangular membership functions represent the value ranges determined by the system. Each of the input and output parameters defined in the system consists of 9 triangular functions. Numerical input and output values have been converted into verbal variables. These can be expressed as L1-very very low, L2-very low, L3-low, L4-negative medium, L5-medium, L6-positive medium, L7-high, L8-very high, L9-very very high. The numerical value ranges of these functions are given in the table below (see *Table 3*).

Table 3 Fuzzy sets of input and output parameters

Membership name	***Very very low***	***Very low***	***Low***	***Negative medium***	***Medium***	***Positive medium***	***High***	***Very high***	***Very very high***
	L1	L2	L3	L4	L5	L6	L7	L8	L9
Material, W/m.K	M1 0.167-0.495	M2 0.3265-0.6565	M3 0.495-0.825	M4 0.660-0.990	M5 0.825-1.155	M6 0.9869-1.317	M7 1.155-1.485	M8 1.32-1.65	M9 1.485-1.815
Sizes and orientation, W	SO1 891.9-4595	SO2 2743-6446	SO3 $4.6x10^3$ - $8.31x10^3$	SO4 6446-$1.01x10^4$	SO5 8298-$1.2x10^4$	SO6 $1.015x10^4$-$1.385x10^4$	SO7 $1.2x10^4$ - $1.57x10^4$	SO8 $1.385x10^4$ - $1.756x10^4$	SO9 $1.57x10^4$ - $1.941x10^4$
Annual heating energy need, kW.h	Q1 $7.251x10^3$-$1.675x10^4$	Q2 $1.208x10^4$-$2.158x10^4$	Q3 $1.675x10^4$-$2.625x10^4$	Q4 $2.158x10^4$-$3.099x10^4$	Q5 $2.625x10^4$-$3.570x10^4$	Q6 $3.099x10^4$-$4.058x10^4$	Q7 $3.570x10^4$-$4.526x10^4$	Q8 $4.058x10^4$-$5.009x10^4$	Q9 $4.526x10^4$-$5.476x10^4$

Through the defined membership functions, it is provided to convert the precisely defined values into fuzzy expressions. After determining the membership functions, the stage of creating FL rule tables comes. The rules include input/output relationships that enable defining the control strategy. The fuzzy rule base consists of two parts separated by the words "if-than". The premise is composed of verbal information such as input variables in the 'if' section, and the output value in the 'then' section. The Mamdani method has been adopted as the inference system. This method provides inference using verbal rules determined by the expert. 57 rules have been defined in the system. Examples of the rules are given in *Table 4*.

Table 4 Rule table considered in the development of the fuzzy logic-based model

RULE NO		***M***		***SO***		***Q***	***RULE NO***		***M***		***SO***		***Q***
1	*if*	*M=M1*	*and*	*SO=SO2*	*then*	*Q=Q2*	**30**	*if*	*M=M6*	*and*	*SO=SO5*	*then*	*Q=Q4*
2	*if*	*M=M1*	*and*	*SO=SO1*	*then*	*Q=Q2*	**31**	*if*	*M=M5*	*and*	*SO=SO4*	*then*	*Q=Q4*
3	*if*	*M=M2*	*and*	*SO=SO1*	*then*	*Q=Q2*	**32**	*if*	*M=M6*	*and*	*SO=SO4*	*then*	*Q=Q4*
4	*if*	*M=M2*	*and*	*SO=SO2*	*then*	*Q=Q2*	**33**	*if*	*M=M5*	*and*	*SO=SO3*	*then*	*Q=Q4*
5	*if*	*M=M3*	*and*	*SO=SO2*	*then*	*Q=Q2*	**34**	*if*	*M=M7*	*and*	*SO=SO5*	*then*	*Q=Q4*
6	*if*	*M=M3*	*and*	*SO=SO1*	*then*	*Q=Q2*	**35**	*if*	*M=M6*	*and*	*SO=SO3*	*then*	*Q=Q4*
7	*if*	*M=M4*	*and*	*SO=SO2*	*then*	*Q=Q2*	**36**	*if*	*M=M7*	*and*	*SO=SO4*	*then*	*Q=Q4*
8	*if*	*M=M4*	*and*	*SO=SO1*	*then*	*Q=Q2*	**37**	*if*	*M=M9*	*and*	*SO=SO5*	*then*	*Q=Q4*
9	*if*	*M=M5*	*and*	*SO=SO2*	*then*	*Q=Q2*	**38**	*if*	*M=M7*	*and*	*SO=SO3*	*then*	*Q=Q4*
10	*if*	*M=M5*	*and*	*SO=SO1*	*then*	*Q=Q2*	**39**	*if*	*M=M9*	*and*	*SO=SO4*	*then*	*Q=Q5*
11	*if*	*M=M6*	*and*	*SO=SO2*	*then*	*Q=Q2*	**40**	*if*	*M=M9*	*and*	*SO=SO3*	*then*	*Q=Q6*

12	*if*	*M=M6*	*and*	*SO=SO1*	*then*	*Q=Q2*	**41**	*if*	*M=M1*	*and*	*SO=SO9*	*then*	*Q=Q7*
13	*if*	*M=M7*	*and*	*SO=SO2*	*then*	*Q=Q2*	**42**	*if*	*M=M1*	*and*	*SO=SO8*	*then*	*Q=Q7*
14	*if*	*M=M7*	*and*	*SO=SO1*	*then*	*Q=Q2*	**43**	*if*	*M=M2*	*and*	*SO=SO9*	*then*	*Q=Q7*
15	*if*	*M=M9*	*and*	*SO=SO2*	*then*	*Q=Q2*	**44**	*if*	*M=M2*	*and*	*SO=SO8*	*then*	*Q=Q7*
16	*if*	*M=M9*	*and*	*SO=SO1*	*then*	*Q=Q2*	**45**	*if*	*M=M3*	*and*	*SO=SO8*	*then*	*Q=Q7*
17	*if*	*M=M1*	*and*	*SO=SO5*	*then*	*Q=Q3*	**46**	*if*	*M=M3*	*and*	*SO=SO9*	*then*	*Q=Q7*
18	*if*	*M=M1*	*and*	*SO=SO4*	*then*	*Q=Q3*	**47**	*if*	*M=M3*	*and*	*SO=SO8*	*then*	*Q=Q8*
19	*if*	*M=M2*	*and*	*SO=SO5*	*then*	*Q=Q3*	**48**	*if*	*M=M4*	*and*	*SO=SO9*	*then*	*Q=Q8*
20	*if*	*M=M2*	*and*	*SO=SO4*	*then*	*Q=Q3*	**49**	*if*	*M=M4*	*and*	*SO=SO8*	*then*	*Q=Q8*
21	*if*	*M=M1*	*and*	*SO=SO3*	*then*	*Q=Q3*	**50**	*if*	*M=M5*	*and*	*SO=SO9*	*then*	*Q=Q8*
22	*if*	*M=M2*	*and*	*SO=SO3*	*then*	*Q=Q3*	**51**	*if*	*M=M5*	*and*	*SO=SO8*	*then*	*Q=Q8*
23	*if*	*M=M3*	*and*	*SO=SO5*	*then*	*Q=Q3*	**52**	*if*	*M=M6*	*and*	*SO=SO9*	*then*	*Q=Q8*
24	*if*	*M=M3*	*and*	*SO=SO4*	*then*	*Q=Q3*	**53**	*if*	*M=M6*	*and*	*SO=SO8*	*then*	*Q=Q9*
25	*if*	*M=M3*	*and*	*SO=SO3*	*then*	*Q=Q3*	**54**	*if*	*M=M7*	*and*	*SO=SO8*	*then*	*Q=Q9*
26	*if*	*M=M4*	*and*	*SO=SO5*	*then*	*Q=Q3*	**55**	*if*	*M=M7*	*and*	*SO=SO9*	*then*	*Q=Q9*
27	*if*	*M=M4*	*and*	*SO=SO4*	*then*	*Q=Q3*	**56**	*if*	*M=M9*	*and*	*SO=SO9*	*then*	*Q=Q9*
28	*if*	*M=M4*	*and*	*SO=SO3*	*then*	*Q=Q4*	**57**	*if*	*M=M9*	*and*	*SO=SO8*	*then*	*Q=Q9*
29	*if*	*M=M5*	*and*	*SO=SO5*	*then*	*Q=Q4*							

These rules will enable the system to learn to calculate. Rules must be defined by the system. The image of the entry of rule 1 into the system is shown in the figure below (see *Figure 6*).

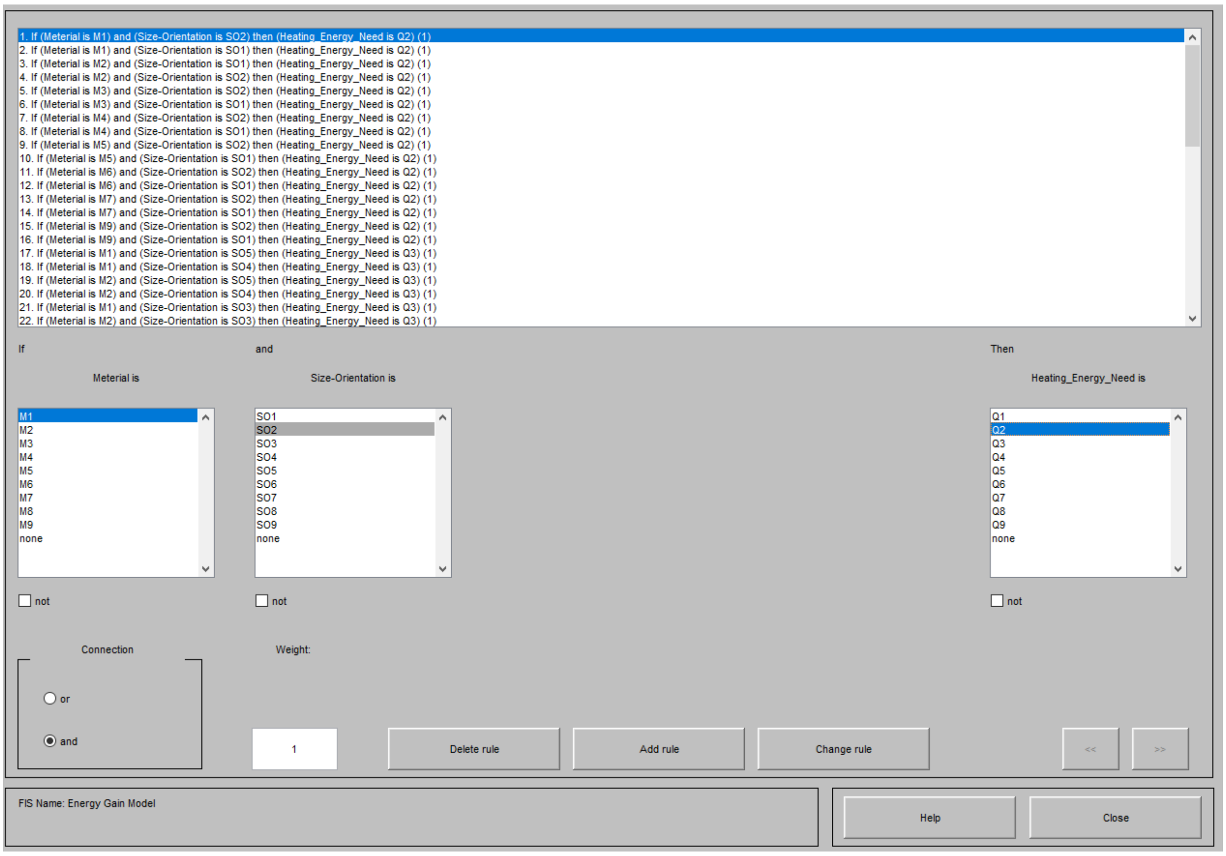


Figure 6. Entering the rules into the software

In *Figure 6*, rule-1 entry to the system is also seen. As such, 57 rules are defined to the system so that the system learns. In order for the system to be used by the readers, the setup of the system can be created by entering the input and output values given in *Table 4* into an FL interface on any software, as shown in *Figures 2-5*. By defining the rules in *Table 5* to the system as seen in *Figure 6*, an FL model that estimates the annual energy need in workshops can be created. By entering the thermal conductivity values of the building envelope material properties and the energy gain according to the size and orientation characteristics of the buildings into this system, the annual energy need can be easily estimated and designs can be shaped according to the results.

6 RESULTS AND DISCUSSION

The FL model system, which provides the estimation of the annual heating energy of the buildings during the design phase, is learned. In this learning process, rules are defined for the FL system. These rules have been determined according to the values previously calculated according to different alternatives. At the next stage, after learning is provided, it is necessary to test whether the system predicts correctly according to the new design situations. To check whether the system is working correctly, newly calculated values are entered into the system. To test the accuracy of the results of the FL system, 46 different alternatives were calculated. The input values of these calculated alternatives were entered into the system and the results were obtained from the system. The values obtained by the calculations are compared with the values estimated on the FL model and the degree of accuracy is checked. In other words, the results obtained from the FL model are tested. Below is an image of the interface used to estimate the value (see *Figure 7*).

Figure 7. Testing the rule 26

Estimation results of the FL model are given in the graphic in *Figure 8*. These graphs show the relationship between the annual heating energy requirement of the buildings with output parameters and the input parameters, namely material, orientation-size parameters. Computed data are compared with the data obtained from the FL model, and if there is an error, the stages of creating FL sets and determining the membership function are returned (Ata and Dincer 2017; Dincer et. al. 2013) 46 different alternatives were tried to compare the calculated values with the results of the FL system. These values were compared with the multiple determination coefficient methods. The comparison graph is given as follows (see *Figure 9*).

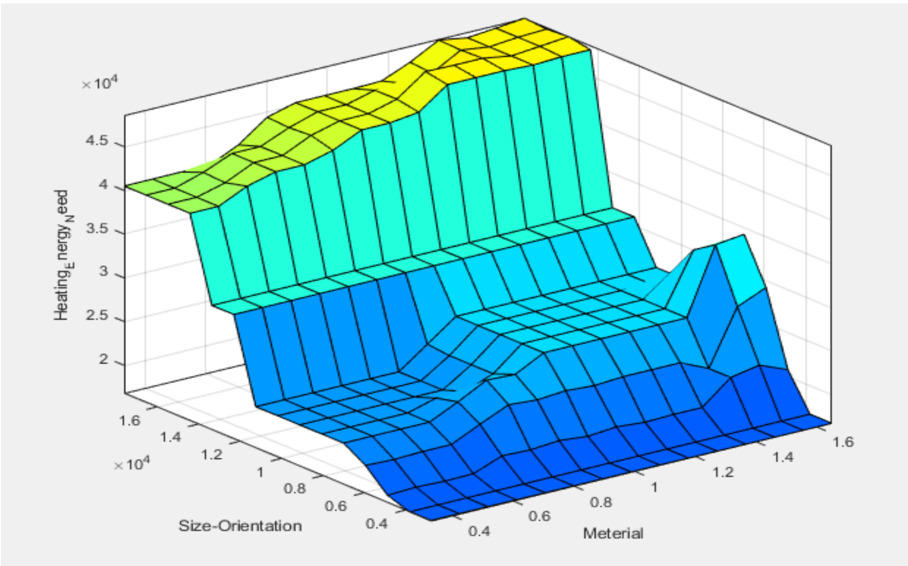
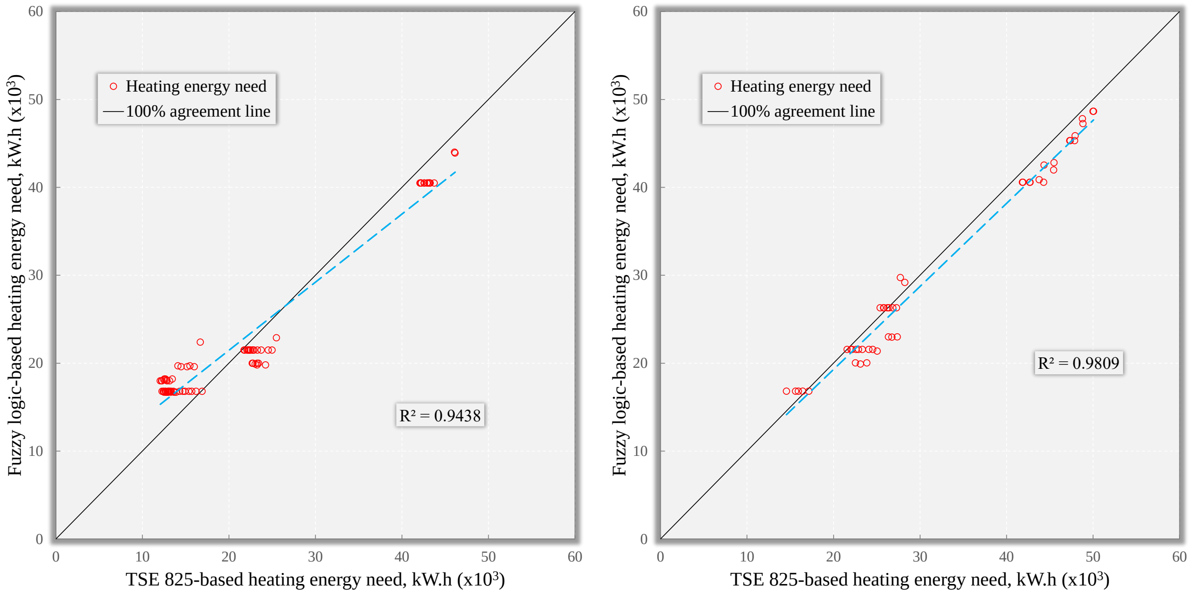


Figure 8 The relationship between the input and output variables of the FL model



(a) (b)

Figure 9. Comparison of TSE 825-based heating energy needs with FL-based ones: (a) training and (b) testing datasets

The FL model created according to the information in this graph accurately predicts the annual heating energy need of the buildings by 98.1%. This result shows that the model can be successfully used in estimating the annual heating energy need of the buildings during the design phase.

The comparison of the calculated values of the annual heating energy need of the industrial buildings with the values obtained from the FL model results in terms of the sized-orientation properties parameter and the comparison of the values obtained from the FL model results in terms of the material parameter are shown in *Figures 10* and *11*.

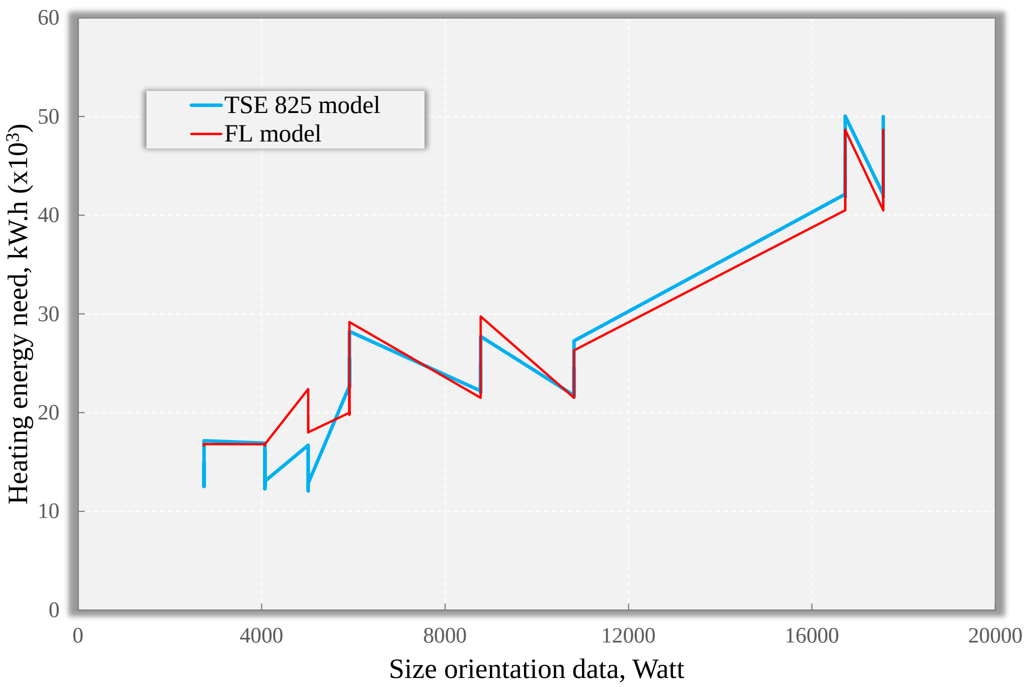


Figure 10. Comparison of calculated values with FL values according to SO input parameter

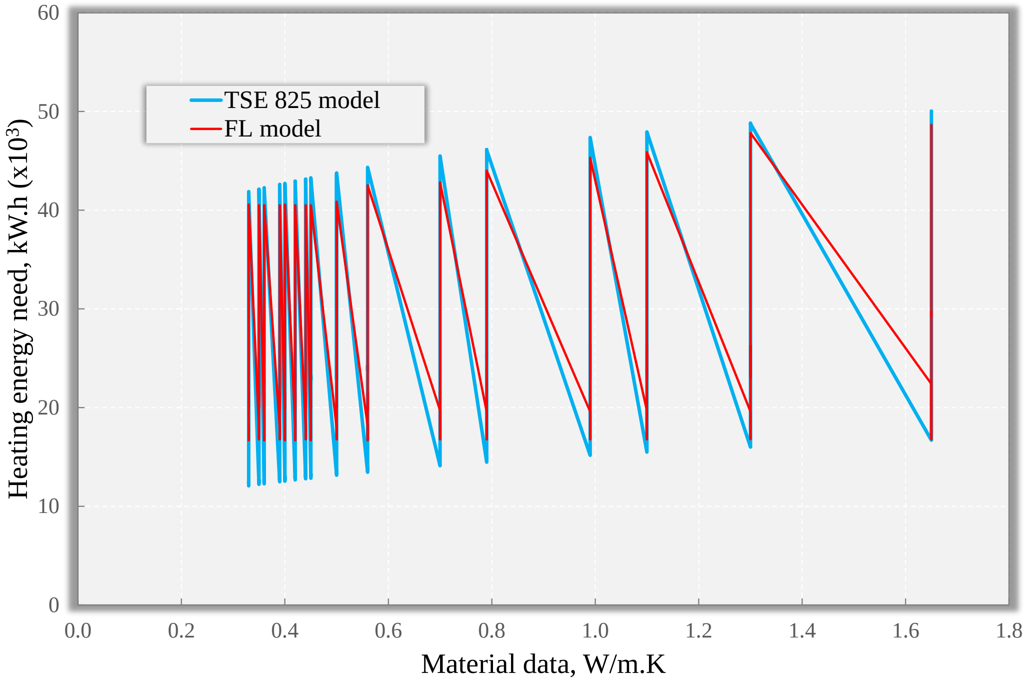


Figure 11. Comparison of calculated values with FL values according to M input parameter

As seen in the graph, the calculated values of the annual heating energy need of the industrial buildings and the values obtained from the FL model results gave parallel results in terms of the orientation parameter. The calculated values of the annual heating energy need of the industrial buildings and the values obtained from the FL model results gave parallel results in terms of the material parameter. This shows that the system is working correctly. By looking at the curves in the graph in *Figure 11*, it is concluded that the values of the FL model and calculated values show similar results. This graph shows that the FL model predicts the results correctly.

After determining the correct prediction of the model, new building alternatives were created in different combinations. The material heat transmission calculation values and annual solar energy gain values of these building alternatives are defined to the system as input parameters. With these values entered into the system, the annual heating energy need for new building alternatives was obtained from the FL model. These values are given in the table below (see *Table 5*).

Table 5 Annual heating energy need table of buildings created according to new alternatives

No	Material values (W/m.K)	Building orientation	Window size (m^2)	Solar energy gain (W)	Annual heating energy need (kWh)
1	0.34	North	25	4746.40	17347.2
2	0.62	North	25	4746.40	17375
3	0.41	North	25	4746.40	17486.2
4	1.00	North	25	4746.40	18097.8
5	0.81	North	25	4746.40	18125.6
6	1.20	North	25	4746.40	18209
7	0.92	North	25	4746.40	18348
8	0.72	North	25	4746.40	18292.4
9	0.41	East/West	20	5635.84	19348.8
10	0.52	East/West	20	5635.84	19432.2

11	1.60	North	25	4746.40	19626.8
12	0.72	East/West	20	5635.84	21322.6
13	1.40	East/West	20	5635.84	21823
14	1.20	East/West	20	5635.84	21962
15	0.72	North	35	6644.96	23407.6
16	0.72	East/West	25	7044.80	23407.6
17	0.81	North	40	7594.24	23463.2
18	0.92	East/West	40	11271.68	23935.8
19	0.92	South	25	8676.80	24213.8
20	0.92	East/West	25	7044.80	24519.6
21	0.81	East/West	25	7044.80	24630.8
22	0.92	South	20	6941.44	24714.2
23	0.81	South	20	6941.44	24853.2
24	0.92	North	35	6644.96	25520.4
25	0.81	North	35	6644.96	25631.6
26	1.60	East/West	35	9862.72	27299.6
27	1.60	North	50	9492.80	28078
28	1.60	South	25	8676.80	29746
29	0.41	South	35	12147.52	31136
30	1.60	South	20	6941.44	34194
31	1.60	North	35	6644.96	35028
32	0.52	East/West	55	15498.56	41422
33	0.52	South	50	17353.60	41144
34	0.62	South	50	17353.60	41422
35	0.81	East/West	50	14089.60	43368
36	0.81	South	45	15618.24	17347.2
37	1.00	South	40	13882.88	17375
38	1.40	East/West	55	15498.56	17486.2

In this table, the data obtained as a result of estimating the annual heating energy need of the building alternatives created according to different orientations, window sizes, and material properties are calculated. According to the information in this table, while the window size and orientation feature are constant, the annual heating energy need values of the buildings increase as the heat transfer calculation value of the building shell wall material increases. As the transparent surface ratios of the buildings increase depending on the size, their annual heating energy needs to increase. The effect of the orientation factor on the annual heating energy need decreases the heating energy need of the buildings when the window is directed to the south. In the north direction, the heating energy need of the buildings increases.

The exterior wall material of the building alternative, which has the lowest annual heating energy requirement among the new building alternatives, has a heat transmission calculation value of 0.34 W/m.K. The window size of this building alternative is 25 m^2 and the building windows are oriented to the north. The building alternative that needs the highest heating energy is the building alternative with a window area of 55 m^2. The outer wall material of this alternative has a heat transmission calculation value of 1.4 W/m.K. According to the information in *Table 6*, while the window size and orientation feature is fixed, the annual heating energy requirement values of the buildings increase as the heat transmission calculation value of the building exterior wall material increases. In cases where building windows are oriented to the south, the heating energy need of the buildings decreases. In cases where windows are oriented to the north, the heating energy need of the buildings increases. As the window size of the buildings increases, annual heating energy needs to increase.

In addition, some statistical parameters, indicating the error that occurred during the prediction, are presented in *Table 6*. In order to indicate the reliability and accuracy of the developed FL model, mean absolute percent error (MAPE), mean square error (MSE), and root mean square error (RMSE) were respectively determined by the following expressions.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{m_i - p_i}{m_i}\right| x100 \quad (10)$$

$$MSE = \frac{\sum_{i=1}^{n}(m_i - p_i)^2}{n} \quad (11)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(m_i - p_i)^2}{n}} \quad (12)$$

When the values given in this table are investigated, it will be seen that the developed FL model has a reliable prediction performance. The errors occurring during the prediction show that the developed FL model yields a relatively low estimation difference. Besides, the mean, minimum, maximum, and standard deviation values of normalized heating energy needs are presented in this table. Regarding these values, it can be stated the sub-datasets, training and testing, relatively reflects the whole dataset.

Table 6 Statistical parameters and normalized values of the developed FL model

	Statistical parameters				Normalized values			
	MAPE	MSE	RMSE	R-squared	Mean	Min	Max	SD
Training dataset	18.87	11.59	3.41	0.944	1.121	0.817	1.491	0.205
Testing dataset	6.05	4.54	2.13	0.981	0.961	0.840	1.155	0.065
All data	14.26	9.06	3.01	0.957	1.06	0.817	1.491	0.185

7 CONCLUSIONS

Energy consumption has to be taken into account when designing or using buildings due to reasons such as increased environmental pollution, depletion of energy resources, and increasing costs of these resources. Within the context of the study, the data were obtained from this area by examining the Auto Industry and Eski Industry campuses in Konya city. The annual heating energy need of industrial buildings was calculated with the data obtained from the examinations and modeled by the FL modeling technique. In the developed system, the output parameter is Q (annual heating energy need of the buildings). The input parameters are SO (solar gain based on orientation and size characteristics) and 'M' (external wall material heat transmission calculation values). Rules have been created to determine the system behavior of the FL model. Based on the aforementioned findings, the following conclusions can be drawn:

- With the precautions to be taken while designing the buildings, the energy need of the buildings can be significantly reduced. The FL values were compared with the calculated method and the multiple regression analysis statistical method. R-squared values of 0.957 for all data, and 0.944 and 0.981 respectively for training and testing sub-datasets were achieved. These values show that the FL model developed in the current study can successfully predict the annual heating energy need of such buildings. It can be employed in the design stage of such buildings that are to be constructed next.
- The statistical evaluation of the FL model generated in this study revealed that there is a small amount of error occurring during the prediction of the heating energy need of industrial buildings by the FL model.

- In addition, the developed FL model requires less effort to be employed in the determination of the heating energy need of such buildings than the proposed design provisions such as TSE 825 and ISO 13790.
- The results demonstrated that the developed FL model has a material and size-orientation sensitivity.
- Finally, it can be stated that the FL model developed in the present study can be operated on any software that contains a fuzzy logic tool.

Recommendations For Future Works

The study herein deals with the application of FL to develop a model for estimation of the heating energy need of the industrial buildings. The results achieved within the scope of the current study revealed that the model has a good and reliable estimation performance. However, we recommend to the other researchers who may also study this topic that another soft-computing technique like support vector machine, artificial neural network, ant colony, gene expression programming, machine learning, response surface methodology, etc., to develop a model for the estimation of the heating energy need of the industrial buildings as well as residential and commercial buildings, hospital, etc.

Apart from those considered in this study, there are design parameters that affect the annual heating energy need of the building. For example, it is evaluated in terms of urban design, criteria such as building ranges and the location of buildings relative to each other, and their effect on energy gain is also among the subjects that can be studied. The study evaluated the annual heating need of the building, but cooling is an issue that can be worked on different energy loads such as lighting loads. In the study, single-room auto industry structures were examined and alternatives were created. Heating and cooling loads can also be operated for buildings with more than one volume. In addition, the energy load of the buildings can be reduced by modeling with the FL method in buildings with functions other than industrial buildings.

Additionally, the authors suggest to the researchers who may study in this field that any simulation software such as EnergyPlus and Trnsys can be employed in their research to compare the heating energy need-based performance of the buildings as well as the FL model developed in the current study.

Nomenclature

Q_{Year}	annual heating energy requirement (kW.h)
Q_{month}	monthly heating energy requirement (kW.h)
H	specific heat loss of building (W/K)
Θ_i	Monthly indoor temperature (°C)
Θ_e	Monthly outdoor temperature (°C)
η_{month}	Average monthly usage factor for gain (without unit)
$\phi_{i,month}$	Monthly average internal gains (can be fixed) (W)
$\phi_{s,month}$	Monthly average solar gain (W)
t	Time (s)
U	Thermal transmittance coefficient (W/m^2K)
TSE 825	Turkish Standard (Building thermal insulation rules standard)
$\mu_a(x)$	Membership function
M	Material membership function
SO	Size and orientation function
Q	Heating energy need membership function

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