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Energy

Effect of passive energy retrofitting strategies by using ANN: a case of a hospital building

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This study aims to examine the effect of frequently used energy strategies, such as insulation of external walls and roof, glazing type, shading devices, and indoor air temperature of the building, by using the artificial neural networks (ANN) of the Balikesir University Hospital building. The different energy-efficient strategies were simulated after modelling and calibrating the building by way of DesignBuilder. The five other insulation materials and window types were selected, and the overhang and louvre were applied with different lengths as a shading device. Based on the strategies, ANN produced 6250 data points eligible for building construction mode and hospital building use. As a result, when comparing the model output values, ANN gives the results with a satisfactory accuracy of 99% for the estimation and test data. After analysing ANN results, when the current indoor temperature results are set, the maximum saving rate is 18.66% and 72.48% for the heating and cooling periods, respectively.

Keywords: artificial intelligence/building information modelling (BIM)/buildings/energy/statistical analysis/structures and design

Notation

C_e	electricity cost ($/kWh)
C_{fuel}	fuel cost ($/m^3)
C_{ins}	insulation material cost ($/m^3)
EW	external wall insulation thickness (cm)
g	inflation rate
H_u	heating value of the fuel (J/m^3)
i	interest rate
k	thermal conductivity of insulation material (W/m·K)
M_p	average of the actual measured values
N	year
N_p	number of data points
R	coefficient of regression
Roof	roof insulation thickness (cm)
SD	shading device length (m)
T_b	balance temperature (°C)
T_i	indoor air temperature (°C)
T_o	outdoor air temperature (°C)
η	heating system efficiency

1. Introduction

In buildings, calculating energy consumption improves energy demands, decreasing energy consumption and reducing the effect on the indoor environment. In Turkey, the energy-efficient building needs have increased in the past decades (Kurekci, 2016). Based on the energy-efficient building design, examination of the heating (HL) and cooling (CL) load is necessary to specify the heating, ventilating, and air conditioning (HVAC) system to sustain the high-quality indoor environment. If combined adequately at the conceptual design stage, passive design strategies are buildings' most practicable and economical energy and thermal environment management methods (Alhuwayil *et al*., 2018).

Various strategies exist for energy management in buildings, and the most viable way is passive design methods. In this method, all available designs of building forms are considered at the design stage to minimise energy consumption and improve thermal, acoustic, and visual comfort levels. Passive design strategies for energy management in buildings could be categorised depending on their focus on different aspects of a building, such as daylighting, ventilation type, orientation, insulation materials, shading devices (SD), structural materials and properties, glazing, and so on (Mujeebu and Alshamrani, 2016).

Healthcare facilities have higher energy demands than all other buildings for heating, cooling, and electricity because of their 7/24 operation times; many different facilities such as operation rooms, patient rooms, clinics, and so on; and use of a wide variety of medical equipment. Moreover, the need for thermal comfort to provide a better environment has recently resulted in significant energy demand growth. Besides, the conventional HVAC systems make these buildings' heating and cooling loads expensive. Thus, the healthcare sector needs energy-efficient solutions at minimum cost to decrease energy use (Vanhoudt *et al*., 2011). Hospital energy consumption mainly occurs from using electricity for lighting, HVAC systems, and natural gas or fuel for boilers and domestic hot water. Also, these buildings have high potential in terms of energy savings, ranging from 21% to 45% worldwide (Li and Yao, 2021). Thus, hospitals must have an energy-efficiency programme to examine energy demand.

Few researchers have studied this subject; nevertheless, there are so few studies on calculating energy consumption for both seasons (heating and cooling), containing the effect of optimum insulation of external wall and roof, glazing types, SDs, and thermal comfort temperatures. For this purpose, the influence of external wall and roof insulation, SD, and glazing type on energy consumption is numerically investigated for different parameters, according to recommended indoor air temperature values by TS 825 (Maaß *et al*., 2008) and ASHRAE 14 (ASHRAE, 2017). As can be seen from the literature, cooling seasons were ignored due to the low number of cooling degree days. One of the novelties of this study is to investigate the effectiveness of the artificial neural network (ANN) model in predicting energy consumption for both seasons, considering different performance improvement parameters, and to reveal the impact of these parameters on energy consumption. Therefore, this research is a case study of Turkey's Balikesir University Hospital building aimed at improving energy demand and performance using the ANN model.

This study analyses energy use and savings by applying different passive retrofitting scenarios to the hospital building. Then, reveal the optimal strategies using ANN for the heating and cooling period. There are three research questions for this study:

1. How to improve the energy efficiency of large-scale hospital buildings?
2. What are the main parameters that affect building energy consumption?
3. Is it practical to analyse the building energy use using an ANN?

To answer the above research questions, the defined strategies are (objectives): (*a*) data collection of selected hospital buildings (electricity and gas consumptions), (*b*) modelling and calibration of a building with DesignBuilder, (*c*) specifying the parameters that affect the energy use for both periods, and (*d*) creating an ANN model using MATLAB and training the data set.

Moreover, this paper contributes significantly to the literature from a different aspect. The study is particularly helpful for heating-dominated cities, such as Balikesir, Rome, Rabat, and Portland (Figure 1). The study's results provide an essential prediction for high-performance healthcare facilities regarding heating and cooling loads. Thus, these results may help to resemble and analyse energy consumption, efficiency, and savings. The goal is to analyse the effect of passive design strategies that can benefit design makers, architects and energy management firms (Attia, Shadmanfar and Ricci, 2020).

This study advances the current body of knowledge by simultaneously addressing both heating and cooling seasons in a large-scale healthcare facility through the integration of calibrated building simulations and ANNs. Previous works in the literature have primarily concentrated on heating loads in residential or office buildings, often neglecting cooling loads due to their relatively lower contribution in certain climates. However, in hospital buildings, cooling demand can be significant because of the 24/7 operation schedules, high internal loads, and strict thermal comfort requirements. By modelling and calibrating a hospital building and then applying an ANN to explore thousands of retrofitting scenarios, this study demonstrates a novel methodology that enables reliable predictions for both seasonal conditions with reduced computational effort.

Furthermore, the research introduces a systematic approach by combining passive design parameters, insulation thickness,

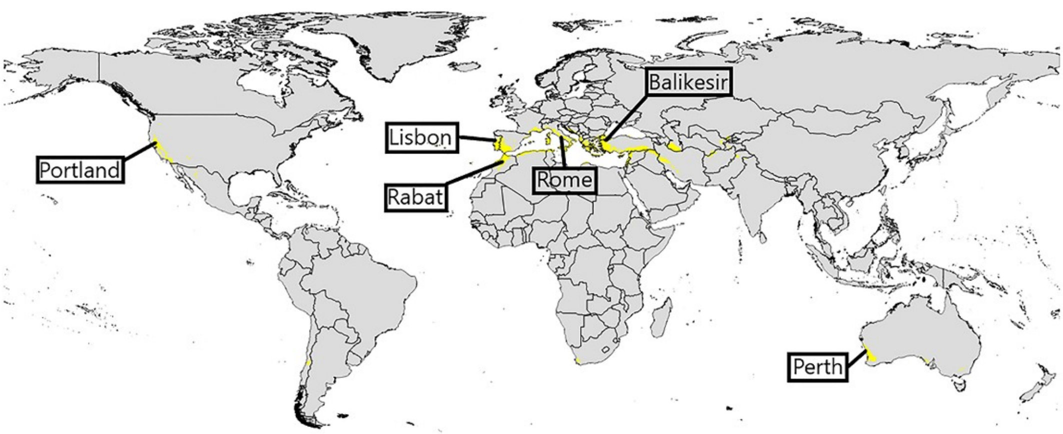


Figure 1. The climate zone is similar to that of Turkey worldwide (hot-summer Mediterranean climate)

glazing type, SDs, and indoor air temperature settings within the ANN framework. This allows for the identification of optimal retrofitting strategies that can maximise energy savings for heating and cooling simultaneously. Thus, the proposed methodology fills a gap in the literature by extending the scope of ANN-based prediction models beyond heating-only analyses and providing a holistic framework applicable to healthcare facilities and other high-energy-intensity building types.

2. Methodology

The methodology is based on modelling and validating a hospital building according to current climate conditions. Then the second phase is defining performance improvement parameters for energy use. These parameters are used to create an ANN model. After validating the ANN model, all combination results can be generated without simulations. The analyses enable the determination of energy consumption for both seasons and for each scenario. As a result, the optimum strategies are revealed according to ANN results. The research methodology is given in Figure 2.

2.1 Literature review

A literature review was conducted to reveal the use of passive design strategies. The publications mainly focused on building insulation, glazing, and SDs. Many studies are about calculating optimum insulation thickness under different climate conditions, insulation materials and fuels (Çomaklı and Yüksel, 2003; Kon, 2018). Kaynakli (2012) observed that the optimal insulation thickness depends on many parameters (building type, climate conditions, energy source, heating system efficiency, materials, etc.). As is known, when the thickness of insulation material is increased, the heat gains and losses will be notably reduced. However, insulation costs will also increase. In this case, the insulation thicknesses should be calculated and applied by cost analysis (Çomaklı and Yüksel, 2003). The degree-day (DD) method is

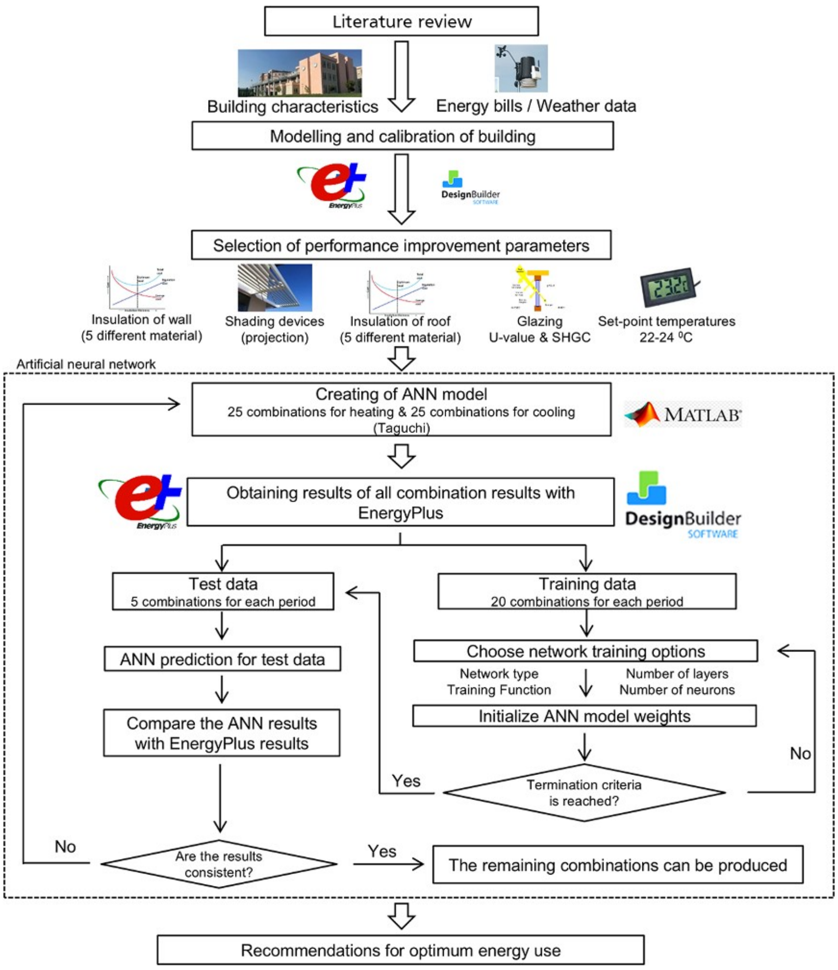


Figure 2. Conceptual framework of the study

commonly preferred on this theme (Kurekci, 2016), especially in studies performed in steady-state conditions (Daouas, 2010; Ucar and Balo, 2009; Yildiz *et al*., 2008).

Açıkkalp and Kandemir (2019) developed a new method to calculate the optimum insulation thickness, known as the Combined Economic and Environmental Method, which considers both environmental and economic effects. Analyses were conducted for the external walls of Bilecik, Turkey, where rock wool and glass wool were selected as insulation materials. Optimal insulation thicknesses were found to range between 2 and 20 cm, and payback periods were calculated to be between 1.3 and 5.1 years. Ozel (2012) investigated the optimum insulation thickness to decrease building heat load. According to the results, the optimum insulation thicknesses changed between 5.4 and 19.2 cm, and payback periods were found between 3.56 and 8.85 years for different insulation materials for twenty 20-year lifetime. Lee *et al*. (2012) optimised the annual heating, cooling and lighting energy consumption values by applying other glazing systems. Besides, they examined the effect of *U*-value, solar heat gain coefficient (SHGC), window-to-wall ratio, and orientation. Their results recommended the optimal configurations for the window system type, size, and orientation. Ozel (2018) examined the effect of the window-to-wall ratio on optimum insulation thickness. For this purpose, annual heating and cooling transmission loads were reviewed according to the window-to-wall ratio. Calculations were performed for different wall orientations and single-layer versus double-layer glazing by varying the window-to-wall ratio from 0% to 100%. As a result, the effects of window area in the wall, the type of window and wall orientations were analysed. Kirimtat *et al*. (2019) suggested novel design strategies for energy-efficient SDs by parametric modelling and performance evaluation-based optimisation. According to the annual energy consumption results, they reach significant energy savings of up to 14% while keeping the daylight feasibility above 50%.

Dombaycı and Gölcü (2008) enhanced an ANN model to observe daily mean ambient temperatures in Denizli, Turkey. The temperature values were measured over three years (2003–2005) and were used to train the model, and the 2006 values were used as a test sample. The network was trained using Levenberg–Marquardt feed-forward backpropagation algorithms. Skiba *et al*. (2016) examined the potential energy savings for Zielona Gora (Poland) markets. They offered an ANN model to estimate the investment costs to reduce the energy consumption in buildings and allowed using this model for cities in Poland and worldwide. The energy consumption is modelled by using an ANN, allowing massive systems to be analysed and increasing the practicability of measurement and verification. A biomedical facility is used to show the ANNs' ability to evaluate energy savings under actual conditions accurately. As a result, Gallagher *et al*. (2018) found a 604 527 kWh energy savings potential with 57% uncertainty at a confidence interval of 68%. Bagnasco *et al*. (2015) investigated the hospital building electricity consumption using an ANN. They suggested that their model can be easily integrated into a Building Management System or a real-time monitoring system.

2.1 The study building and area

Turkey has many different climate areas according to the Köppen–Geiger classification. Most of the country falls almost entirely within a Mediterranean climate (Csa), humid continental climate (Dsa), and cold semi-arid climates (BSk) (Beck *et al*., 2020). A part of the west side falls in the (Dfb) cold weather. Thus, Turkey is a heating-dominated country (Kurekci, 2016). Köppen–Geiger is the widely used classification method for building energy demands.

In Balikesir, winter periods generally have cold and rainy weather; summer periods are hot. The building's area is ≈38 000 square metres and has six floors, including seven blocks. Electricity is used for the cooling, and natural gas is used for the heating. A thermostat controls the HVAC system. Besides, the hospital has 200 beds and includes different facilities such as surgery, laboratories, staff rooms, and so on. Patient rooms are oriented to the northeast and south-west and have large windows (Caner and Ilten, 2020). The weather data were obtained from a weather station close to the building. Figure 3 shows the general view of the building, and Figure 4 shows the investigated façades. Detailed information for the hospital building is presented in Table 1. Indoor air temperatures were recorded with a hobo data logger (Caner and Ilten, 2020).

Figure 5 illustrates the monthly outdoor and indoor average air temperatures of the Balikesir University Hospital building, as obtained from the weather station and the HOBO data logger. It can be observed that heating is done from 15 September to 15 May, and cooling is done from 15 May to 15 September.

2.2 The structure of the hospital building

Heating and cooling energy consumption of buildings usually arises from the building envelope, such as, external walls, windows, roofs, and floors. This study calculates the optimum insulation thicknesses, considering the heat losses and gains through the external walls, roof, floor, and glazing (Table 2).

2.3 Creation of building energy model

DesignBuilder (EnergyPlus-based) was selected as the simulation tool because it provides a robust and widely validated environment for analysing complex buildings such as hospitals, enabling detailed modelling of HVAC systems and calibration with actual energy consumption data. Nevertheless, DesignBuilder also has certain limitations, including high computational demand and simplified assumptions regarding occupant behaviour. To ensure reliability, the model was calibrated using measured energy

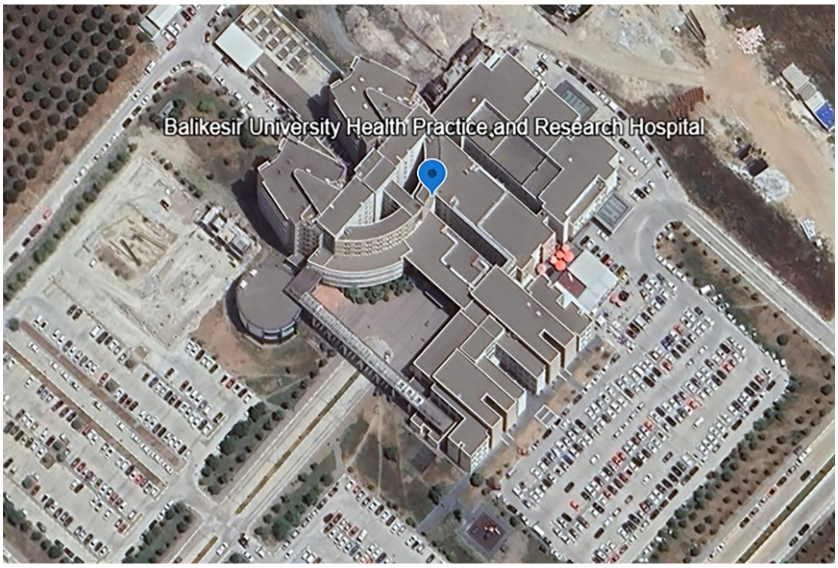


Figure 3. A general view of the selected building

Figure 4. Balikesir University hospital façades: (a) South, (b) North-West, and (c) South-West

consumption and validated according to ASHRAE Guideline 14 criteria. In parallel, an ANN framework was developed, where training and testing data sets were created based on the Taguchi L25 orthogonal design. The purpose of this approach is not to directly apply the same ANN model to other buildings, but rather to demonstrate how such a framework can be adapted for analysing energy consumption in different building contexts. Since heating and cooling periods involve different influencing parameters, developing a unified ANN applicable across multiple building types would require a separate study and potentially different artificial intelligence methods, which falls beyond the scope of this work. Using the occupation ratio, lighting system, type of HVAC system (Figure 6), indoor temperature set values, glazing types, and insulation materials, a model was developed close to the absolute consumption values on Energy Plus.

The details to model the building are given below:

- Occupancy density: Hospital building is mainly used in the winter period between 8:00 a.m. and 09:00 p.m. and the summer period between 08:00 a.m. and 05:00 p.m. According to these data, occupancy density is calculated as 0.13/m^2.
- Lightning: The whole building is illuminated chiefly between 10:00–12:00 a.m. and 4:00–9:00 p.m. Also, from 9:00 p.m. to 07:00 a.m., it is accepted as only corridors, intensive care units, and operation rooms are illuminated. Thus, the lightning density is accepted as 3.5 W/m^2.

Table 1. Description of the investigated hospital building (Figure 4)

Floor area: m^2	Number of floors/blocks	Investigated floor/block	Shading device	Building envelope	Material used
37 000	6/7	6/3	Painted glass	South façade: wall	Andesite (3 mm)
	—	—	—	—	Expanded polystyrene (3 cm)
	—	—	—	—	External plaster (3 cm)
	—	—	—	—	Concrete wall (30 cm)
	—	—	—	—	Internal plaster (2 cm)
	—	—	—	North-West façade: floor window	Double glazed
	—	—	—	—	4–12–4 (mm)
	—	—	—	—	Green painted
	—	—	—	North-East façade: wall	Laminate covering (orange colour/8 mm)
	—	—	—	—	Expanded polystyrene (3 cm)
	—	—	—	—	External plaster (3 cm)
	—	—	—	—	Gas concrete (33 cm)
	—	—	—	—	Internal plaster (2 cm)

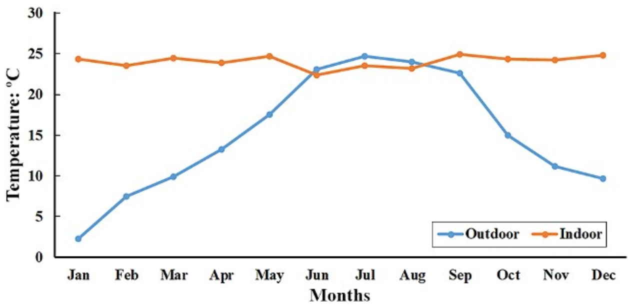


Figure 5. Mean outdoor and indoor air temperatures of Balikesir University hospital building according to months (2017)

- Computers and office equipment: According to data taken from hospital administration, due to the equipment's high electricity usage, such as magnetic resonance imaging, tomography, and roentgen, the consumption is accepted as 2.4 W/m^2.
- Air infiltration is accepted as 0.7 ac/m^3 according to ASHRAE HVAC Design Manuel (Edition, no date).
- The indoor air temperatures are measured for 2 years, and average temperatures entered the programme as 24.4°C for the heating season and 25.78°C for the cooling season (Caner and Ilten, 2020).
- As an HVAC system, fan coil units with four pipes for heating and an air-cooled chiller for cooling are defined. Also, there is a domestic hot water unit. Besides, the bathrooms have only radiators for heating. Also, the ground floor has an unoccupied zone, so neither is heated or cooled for both seasons.

The view of the hospital building model is given in Figure 7.

2.3.1 Calibration of building energy model

After applying the essential building information in the DesignBuilder programme, the model is calibrated based on the energy consumption values for 2017. Actual consumption values were taken from the university accounting unit by checking the monthly natural gas and electricity bills. For natural gas, the unit of measure was m^3. These values are given in Figure 8. According to the figure, 1 m^3 of natural gas is equivalent to 10.64 kWh of electricity (Huang *et al*., 2019). The results were contrasted with the electricity consumption of the selected building to evaluate any energy-efficiency strategy.

Firstly, mean bias error (MBE) (Equation 1) was calculated based on the difference between the measured energy consumption data and the simulation result for each month (Coakley *et al*., 2014). MBE can be calculated with the below formula:

1. $$MBE(\%) = \frac{\sum_{i=1}^{N_p} (m_i - s_i)}{\sum_{i=1}^{N_p} (m_i)}$$

Root mean square error (RMSE) represents the root of the mean of the error frames. The differences between energy consumption data are squared monthly to calculate the RMSE and it is formulated as follows:

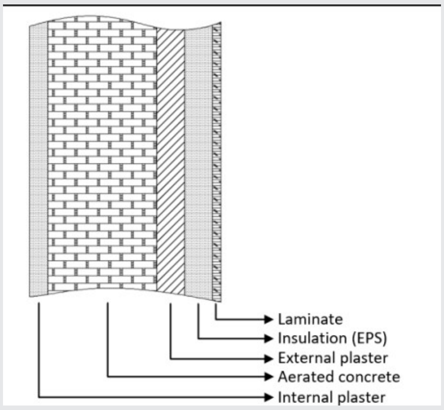
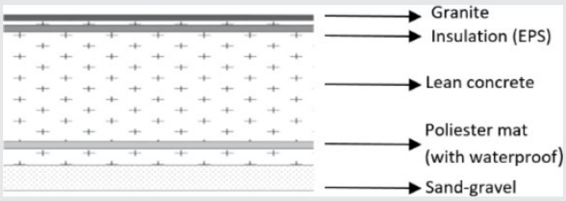
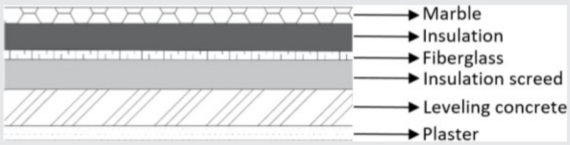
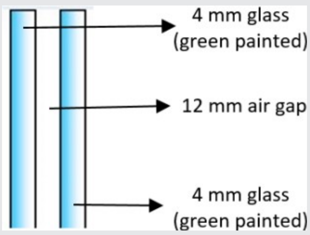
2. $$RMSE = \sqrt{\sum_{i=1}^{N_p} ((m_i - s_i)^2 / N_P)}$$

Here, RMSE is divided by the actual energy consumption, and the cumulative variation of the root mean squared error (CVRMSE) value can be calculated as follows:

3. $$CVRMSE = \frac{\sqrt{\sum_{i=1}^{N_p} ((m_i - s_i)^2 / N_P)}}{-M_P}$$

M_p (the average of the actual values measured) is also calculated with the equation below:

Table 2. Properties of the building structure and *U*-values

Structure elements	Structure properties	*U*–value: W/m^{2}K
External wall		0.763
Roof		0.574
Floor		0.332
Glazing		1.978

4. $$\overline{M_P} = \frac{\sum_{i=1}^{N_p} m_i}{N_P}$$

N_p is the data numbers in the range ‘p’ (N monthly = 12). The MBE and CVRMSE values examined to calibrate the building model depend on the various standards (Coakley *et al*., 2014). The EnergyPlus simulation model is considered reliable if the results meet the criteria outlined in Table 3.

2.4 Selection of performance improvement parameters

Many strategies can be developed to save energy by using buildings more efficiently. Reducing the fossil energy needs of the building is possible through architectural changes, the more efficient use of HVAC systems (Zhang *et al*., 2019), the improvement of the existing insulation material or the production of energy from renewable energy sources (Li and Hong, 2019). It is necessary to decrease the heat load in winter and heat gains in summer to minimise energy consumption in buildings. Applying thermal insulation to the hospital building has been proposed to prevent heat losses and gains without sacrificing thermal comfort. TS 825 entered force in 2013, and Turkey is divided into five zones according to DD values (Maaß *et al*., 2008). The province of Balikesir is in the second region (Figure 9).

Total thermal transmittance values of zones according to DD are given in Table 4.

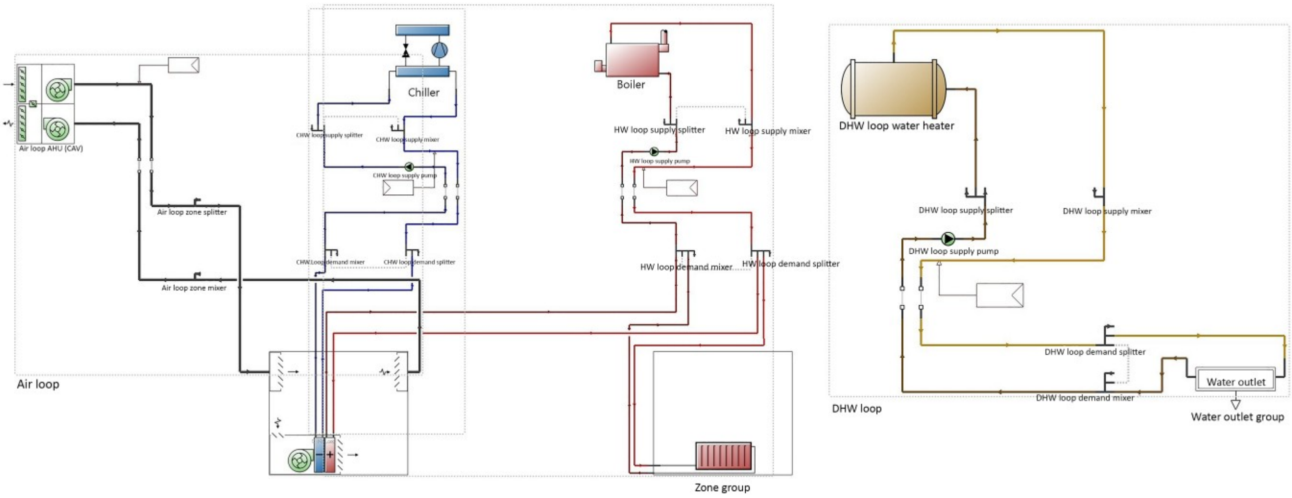


Figure 6. Schematic representation of the HVAC system of Balikesir University hospital building

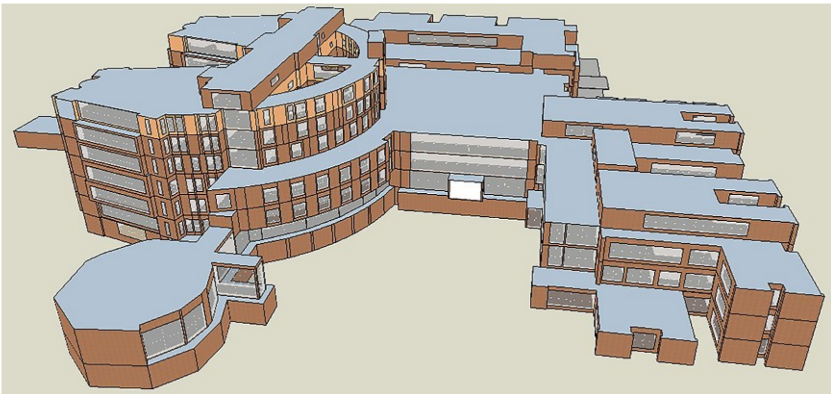


Figure 7. A view of the Balikesir University hospital building model

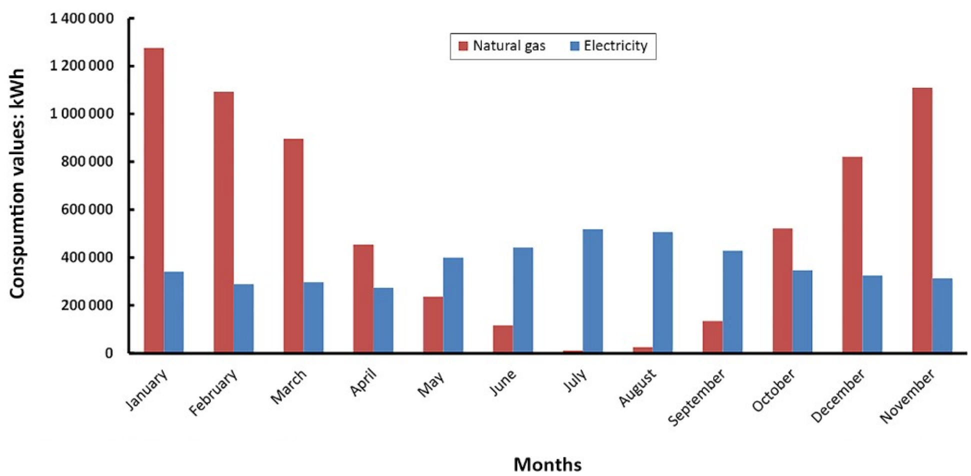


Figure 8. The current energy consumption values of the building (2017)

Table 3. Calibration criteria for an energy simulation model of the building (ASHRAE, 2017)

	Monthly criteria: %		Hourly criteria: %	
Standard	MBE	CVRMSE (monthly)	MBE	CVRMSE (hourly)
ASHRAE	5	15	10	30

The Izoder programme was used to determine the recommended insulation thicknesses for walls and roofs according to TS 825. The heat transfer coefficients and thicknesses of the building elements and insulation materials used for the walls and roof of the buildings have been entered into the programme, and the *U*-values were calculated. The *U*-values given in Table 4 for the second zone were used to compare the results. Based on these values, minimum thermal insulation thicknesses were calculated. Since the floor *U*-value (0.52 $W/m^2.K$) for the existing building is sufficient according to TS 825, which was revised in December 2013 (TS 825, 2013), there is no need to change the floor insulation. However, increasing the insulation thickness for the external walls and roof is necessary. Moreover, the current window *U*-value was found as 1.978, and it was thought that the recommended minimum window (1.8) should be provided according to TS 825.

2.4.1 Calculation of optimum insulation thicknesses

In calculating the optimum insulation thickness for the external walls, roofs, and floors of buildings, the DD) values should be calculated regarding the outdoor air temperatures (Kaynakli, 2013). DD values fundamentally depend on the equilibrium temperature (T_b). T_b is the temperature at which the building does not require heating or cooling at that time, and can vary from one building to another due to differences in building structural

Table 4. Recommended *U*-values for each zone (TS 825)

Zone	*U* wall: W/m^2K	*U* roof: W/m^2K	*U* floor: W/m^2K	*U* window: W/m^2K
First	0.66	0.43	0.66	1.8
Second	0.57	0.38	0.57	1.8
Third	0.48	0.28	0.43	1.8
Fourth	0.38	0.23	0.38	1.8
Fifth	0.36	0.21	0.36	1.8

properties. A DD value is used to calculate optimum insulation thickness and to predict energy consumption and demand. The indoor and outdoor temperature differences are used here (Kaynakli, 2012). The TS 825 (Maaß *et al.*, 2008) standard states that heating is required when there is a 3°C temperature difference between indoor and outdoor environments. It considers the monthly average temperature data for the outdoor temperature DD value. This difference is due to solar energy and internal gains (Kaynaklı and Yamankaradeniz, 2007). Thus, T_b can be expressed as follows depending on the indoor air temperature (T_i) of the building (Atmaca *et al.*, 2006):

5. $$T_b = T_i - 3$$
$$T_b = T_i - 3$$

The heating DD values according to TS 825 can be calculated for the outdoor monthly average air temperature as below (Equation 6), where T_o is the daily average outdoor air temperature;

6. $$\text{If } (T_o \le T_b),\ \text{HDD} = 30\sum_{1}^{12}(T_i - T_0)$$

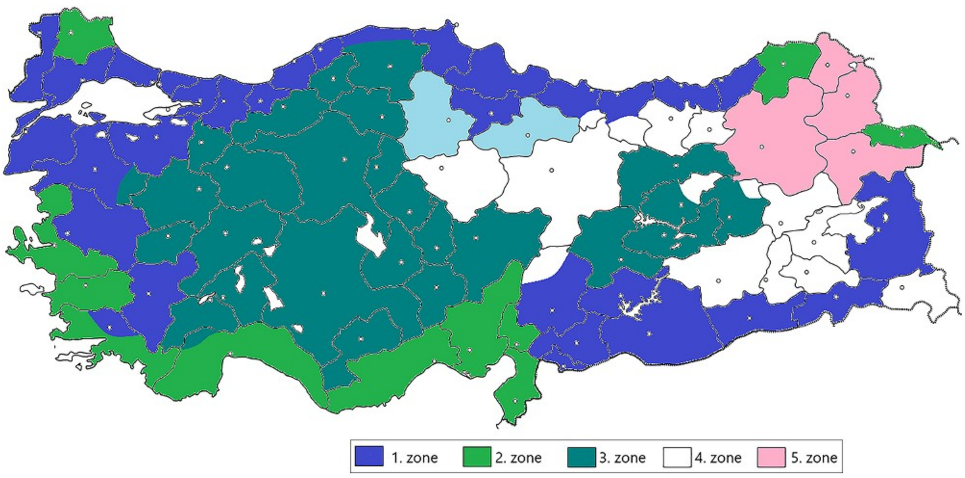


Figure 9. Five climate zones according to degree-day values in Turkey (TS 825)

The cooling DD values according to TS 825 can be calculated for outdoor monthly average air temperature as below (Equation 7) (Kon and Yüksel, 2013):

7. $$\text{If } (T_o \leq T_b)\text{CDD} = 30\sum_{1}^{12}(T_b - T_0)$$

Life cycle cost analysis determines the optimum insulation thickness. The total heating cost is calculated with the present worth factor (PWF) (Equation 10) for *N* years of life (Dombaycı *et al*., 2005; Kurekci, 2016). Life cost analysis is the economic assessment technique which calculates the price of the part or system (Kaynakli and Kilic, 2005). Lifetime, interest rate, and inflation rates affect the life cost analysis, and optimum insulation thickness affects the present worth factor. The interest rate and inflation rates are not constant. With the change in interest and inflation rates, PWF and, thus, the optimum insulation thickness also change (Dombaycı *et al*., 2006). The present worth is calculated as follows;

8. $$\text{If } i > g \text{ real interest rate; } r = \frac{i - g}{1 + g}$$

9. $$\text{If } i > g;\ r = \frac{g - i}{1 + i}$$

10. $$\text{So; } PWF = \frac{(1 + r)^N - 1}{r\,.\,(1 + r)^N}$$

11. $$\text{If } i = g;\ PWF = \frac{N}{1 + i}$$

If the equation is derived according to the thickness of insulation and is equal to zero, the optimum insulation thickness, which is the thickness at which the insulation cost and fuel cost are most appropriate (Kurekci, 2016).

The thickness that minimises the total heating cost is optimum insulation, and it is determined with the following equation (Equation 12) (Kurekci, 2016):

12. $$x_{opt,H} = 293.94\,.\left(\frac{HDD\,.\,C_{fuel}\,.\,k\,.\,PWF}{H_u\,.\,C_{ins}\,.\,\eta}\right)^{\frac{1}{2}} - k\,.\,R_{t,w}$$

The thickness that minimises the total cooling cost is optimum insulation, and it is determined with the following equation (Equation 13) (Kurekci, 2016):

13. $$x_{opt,H} = 293.94\,.\left(\frac{CDD\,.\,C_e\,.\,k\,.\,PWF}{C_{ins}\,.\,COP}\right)^{\frac{1}{2}} - k\,.\,R_{t,w}$$

Here, CDD is cooling degree-day and HDD is heating degree-day, PWF is the present worth factor, $R_{t,w}$ is the uninsulated walls' thermal resistance. H_u is the heating value of the fuel, and η is the heating system efficiency. C_{fuel} is the cost of fuel, C_e is the cost of electricity, C_{ins} is the cost of insulation material, k is the thermal conductivity of the insulating material, and the COP (Čongradac *et al*., 2012) is the cooling system coefficient of performance (Table 5) (Kurekci, 2016).

The thickness that is minimising the total cooling and heating cost is optimum insulation, and it is determined with the following equation (Equation 14):

14. $$x_{opt,H} = 293.94\,.\left(\frac{HDD\,.\,C_{fuel}\,.\,k\,.\,PWF}{H_u\,.\,C_{ins}\,.\,\eta} + \frac{CDD\,.\,C_e\,.\,\text{k}\,.\,PWF}{C_{ins}\,.\,COP}\right)^{\frac{1}{2}} - k\,.\,R_{t,w}$$

Insulation materials' properties are shown in Table 6.

The properties of fuels used in the study are shown in Table 7.

2.4.2 Properties of external shading

Louvre and overhang SDs are selected for the study. The length of shadings is 0.5 m and 1 m for each type, and four different SDs are used. The details of the louvre and its overhang are presented in Figure 10.

2.4.3 Glazing types and set-point temperatures

The hospital building has 4–12–4 mm green painted glass with filled air, and its *U*-value is 1.978 W/m^2.K (Table 2). The building was constructed in 2013 before the Turkish Standards renovation

Table 5. The parameters used in calculation and values (Kon, 2017; Kurekci, 2016)

Parameter	Value
Natural gas price, Cfuel	0.385 \$/m^3
Efficiency, η	0.92
Low heat value, Hu *J*/m^3	34.485*106
Electricity price	0.107 \$/kWh
Interest rate, (*i*)	7.25%
The inflation rate, (*g*)	11.13%
Lifetime, *N*	10 years
PWF	8.27
COP (Čongradac *et al*., 2012)	2.5

Table 6. Properties of the insulation materials

Insulation material	K: W/m.K	Price: $/m^3
Extruded polystyrene (XPS)	0.031	180
Expanded polystyrene (EPS)	0.039	120
Glass wool (GW)	0.040	75
Rock wool (RW)	0.040	80
Polyurethane (PUR)	0.024	260

Table 7. Properties of fuels (Huang *et al.*, 2019; Kurekci, 2016)

Fuel	Low heat value: Hu	Efficiency	Price	Equivalent: kWh
Natural gas	34 485 kJ/m^3	0.92	0.385 $/m^3	10.64
Electricity	3596 kJ/kWh	0.99	0.107 $/kWh	1

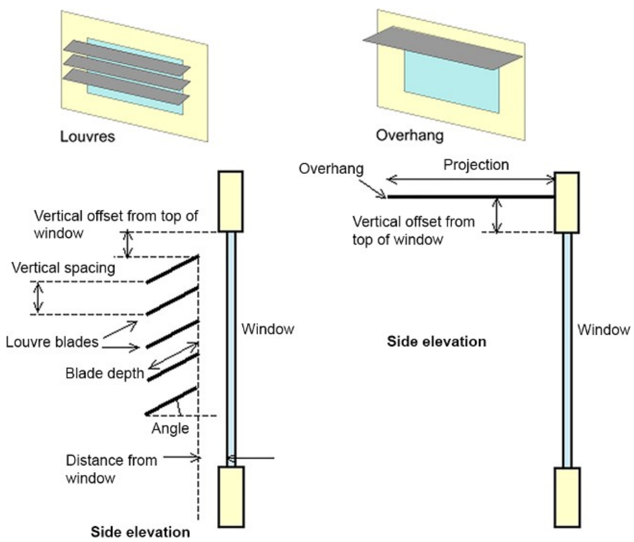


Figure 10. Properties of shading devices

(Pilechiha *et al.*, 2021). Thus, the building envelope did not meet the recommended *U*-values in TS 825, 2013 (Table 4). For this purpose, four different types of glazing were selected for the study. The *U*-values of selected glazing types are given in Table 8 (ISO, 2003). The comfort range was taken from ASHRAE Standard [28] for the buildings' indoor temperatures as 22°C–24°C (Table 8).

2.5 Artificial neural networks

Solving complicated problems can be improved by using ANNs. These algorithms rely on the connection between a large amount of data to identify the correlation between input and output data, which can be challenging to analyse in all situations (Ciulla *et al.*, 2019). Thus, it efficiently estimates the complex correlations of networks to answer complicated problems (Neto and Fiorelli, 2008). Thus, exact results are preserved, while the computational time becomes unimportant (Sharif and Hammad, 2019). ANN models the correlation between input and output data trained by measured data with different network types. The critical parameter in an ANN is the neurons, vital units for the ANN. The data is transferred from previous neurons to the following neurons (Ahmad *et al.*, 2017). The learning process, 'network training', is the capability to learn the system based on previous relationships and use them to generalise the consequences for new forecasts (Neto and Fiorelli, 2008). A transfer function operates on these data and compounds them to produce output data sent to the following layers of neurons. Each neuron has a related weight and bias that trains the network with ensured inputs and outputs, using different strategies (Reynolds *et al.*, 2018). The iteration period stops when the goal is achieved. It is defined as epochs obtained at maximum iterations by minimising certain factors, such as the RMSE (Afram *et al.*, 2017Asadi *et al.*, 2014) or the SSE (Ascione *et al.*, 2016).

ANNs are used in different fields, including energy heating or cooling load prediction, electricity consumption (Bagnasco *et al.*, 2015) and energy savings, predicting energy consumption and thermal comfort (Ascione *et al.*, 2017a) and potential retrofit scenarios (Yu *et al.*, 2014). Several studies evaluated the reduction of building energy consumption by way of ANN (Garnier *et al.*, 2015; Huang *et al.*, 2015) and maximised the thermal comfort hours (Ning and Zaheeruddin, 2009). ANNs

Table 8. Selected design strategies for the winter and summer periods

Period	Window *U*-value: W/m^2.K	SHGC value of window	SD: m	Type	Temperature: °C
Winter period	1.978	0.687	0	—	24.4
	1.8	0.641	0.5	Louvre	24
	1.3	0.47	1	Louvre	23.5
	1.1	0.30	0.5	Overhang	23
	0.7	0.135	1	Overhang	22
Summer period	1.978	0.687	0	—	25.78
	1.8	0.641	0.5	Louvre	24
	1.3	0.47	1	Louvre	23.5
	1.1	0.30	0.5	Overhang	23
	0.7	0.135	1	Overhang	22

can be programmed in many programmes, such as MATLAB®, and these tools' efficiency has been revealed in several building studies. ANN is the most widely used model in building energy estimation (Asadi *et al*., 2014). Melo *et al*. (2014) clarified the abilities of ANN models and recommended them as a surrogate approximation of the energy demand evaluation tool. Mean square error (MSE) values define the performance of tools, and these are calculated according to the differences between the predictions and the targets of the network (Equation 15):

$$\text{15.}\quad \text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(X_i - X_{i,\text{target}})^2$$

Here, N is the data number; and X_i and $X_{i,\ targets}$ are the outputs and targets of the network for training and test processes, respectively (Bui *et al*., 2019).

2.5.1 Training and testing of the network

The training set size must be appropriately created based on the ANN's frame. Concerning this, the minimum reliable size is accepted as five inputs and outputs. The second group data checks the network's accuracy by way of the coefficient of regression (R). The ratio of the training and testing set sizes is generally 9/1 and taken as 5/1 in this study. The critical thing in ANNs is determining the learning set that best illustrates the problem. Based on the orthogonal sequences developed from the Taguchi analysis, the samples represent the problem space. Different energy strategies (combinations) were investigated for both seasons according to parameters that affect energy consumption. The critical point here is that the SDs are defined as 0 and 1 in the MATLAB programme, and their length is displayed in a separate column because MATLAB treats the same values for different elements as similar. In the SD column (Table 9), 0 represents 'no SD', 0.5 represents '0.5 m SD', and 1 represents '1 m SD'. The other values on the table represent the optimum insulation thicknesses. According to these strategies, 6250 (2 × 55) simulations for heating and cooling periods are required.

In the ANN, simulations based on the L25 orthogonal sequence designed for this example were taken as a learning set. According to this series, 25 experiments are required. In this case, the factors placed in the L25 orthogonal array and the results of the EnergyPlus will be used to create an ANN training model. Thus, the energy consumption for each combination for 50 experiments will be presented (25 for heating and 25 for the cooling period) (Gadhave and Ragit, 2017). Minitab determines the learning set number; thus, it is accepted as reliable.

The number of factors affecting the energy consumption for the heating and cooling period is taken as 5 in this study. Thus, five input units and one output unit are estimated. However, three different columns were used to define the SD. As a result, seven input units and one output unit are used (Figure 11).

The parameters for network training are given in Table 10. The network training was carried out according to the mentioned learning rules. The simulation results were compared with the network results to determine whether the network was learning. In the learning set, 25 analyses were performed; 20 were used for training the network, and five were used for testing the network. All input/output data should be scaled to the [0,1] range before training the ANN to improve the training efficiency. It is called data normalisation, giving weight to all variables and suppressing them. The data set details were given in Section 3 without normalisation to understand values and results better; however, for the ANN prediction, all results were used as normalised in the background (Aydinalp *et al*., 2004).

3. Results

3.1 The comparison of energy consumption

A 1-year simulation of the model was analysed to calibrate the hospital building. The monthly natural gas consumption values were obtained by way of simulation and compared with the

Table 9. Used energy strategies and levels

EW: cm	Roof: cm	Window *U*-value: W/m^2.K	SHGC value of window	SD: m	SD louvre	SD overhang	Temperature: °C
Heating period							
EPSopt	EPSopt	1.978	0.687	0	0	0	24.4
XPSopt	XPSopt	1.8	0.641	0.5	1	0	24
GWopt	GWopt	1.3	0.47	1	1	0	23.5
RWopt	RWopt	1.1	0.30	0.5	0	1	23
PURopt	PURopt	0.7	0.135	1	0	1	22
Cooling period							
EPSopt	EPSopt	1.978	0.687	0	0	0	25.78
XPSopt	XPSopt	1.8	0.641	0.5	1	0	24
GWopt	GWopt	1.3	0.47	1	1	0	23.5
RWopt	RWopt	1.1	0.30	0.5	0	1	23
PURopt	PURopt	0.7	0.135	1	0	1	22

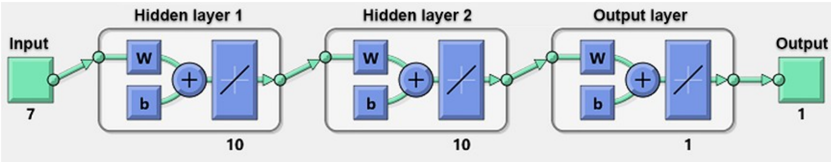


Figure 11. Artificial neural network model of design parameters

Table 10. Network training parameters for heating and cooling period

	Heating period	Cooling period
Network type	Feed-forward back prop	
Training function	TRAINLM	TRAINSCG
Adaptation learning function	LEARNGDM	LEARNGDM
Performance function	MSE	MSE
Number of layers	3	3
Number of neurons	10 / 10 / 1	10 / 10 / 1
Transfer function	PURELIN	PURELIN

building natural gas bills in Figure 12. Actual consumption values (the bills) were taken from the university accounting unit. To address this, the modelling process explicitly incorporated the main end-use categories: lighting, equipment, and cooling, based on measured operational schedules and data provided by the hospital administration. For equipment loads, a constant intensity of 2.4 W/m^2 was assumed, as reported in the manuscript, reflecting medical and office equipment usage (e.g. MR, tomography, roentgen devices, computers), which was confirmed by the facility management. Lighting loads were modelled with a density of 3.5 W/m^2, following the measured schedules of operating hours (daytime, evening, and night). Cooling electricity demand was then isolated in the simulation by subtracting the estimated lighting and equipment electricity consumption from the total electricity use, in accordance with the EnergyPlus calibration procedure.

The MBE value (Equations 1 and 2) was found to be 3.28%, and the CVRMSE value was 4.70%. Since MBE is 3.28% <5% and CVRMSE is 4.70% <15%, the model is reliable for heating load (Equation 16).

16. $5\% \leq MBE_{monthly} \leq 5\% \, ve \, CVRMSE_{monthly} \leq 15\%$

The monthly data gathered from the building model and obtained from the university accounting service were compared in Figure 13.

MBE and CVRMSE values were figured out based on this data. The MBE value was 3.25%, and the CVRMSE value was 4.36%. MBE was 3.25% <5%, and CVRMSE was 4.36% <15%; thus, the model is reliable for cooling load.

3.2 Calculation of optimum insulation thicknesses

For the external wall, with the help of Equations 12, 13, and 14, insulation costs, fuel costs, and total costs calculated for five

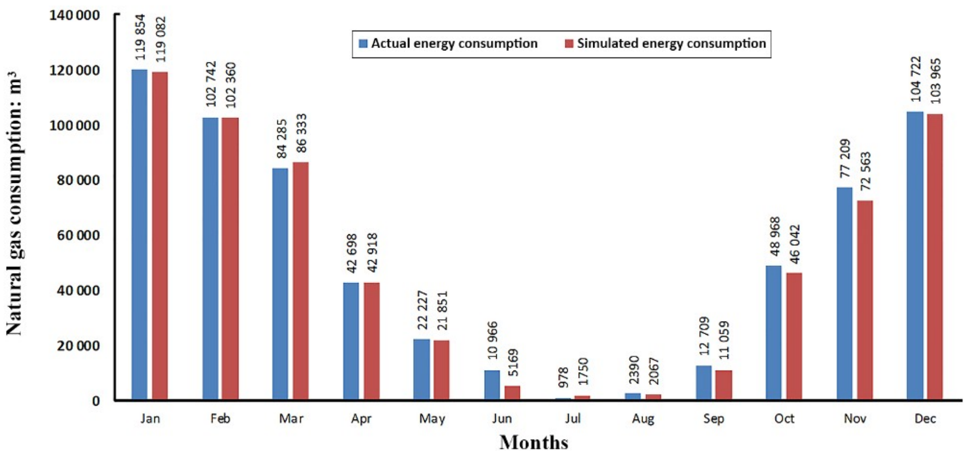


Figure 12. Actual and simulated natural gas consumption of the building

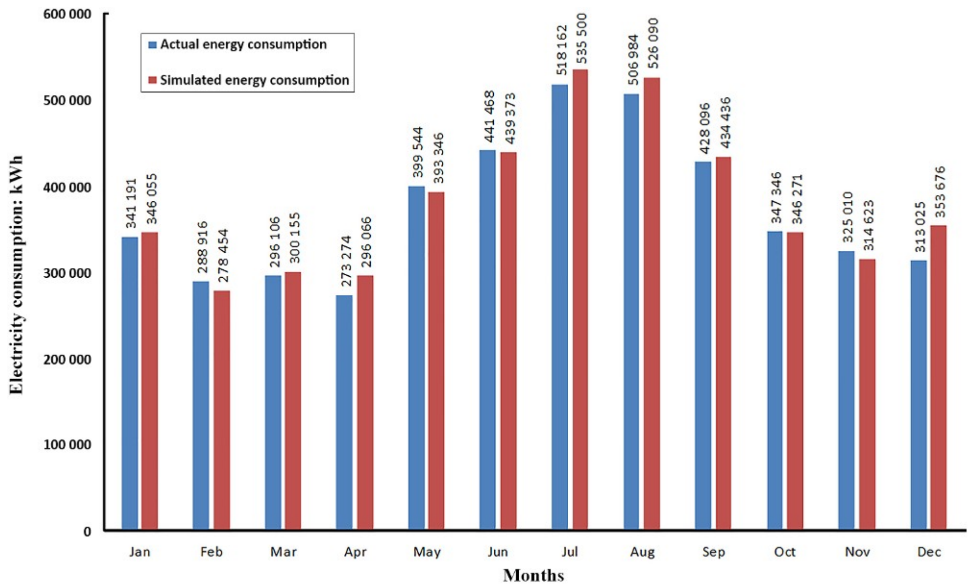


Figure 13. Actual and simulated electricity consumption of the building

different insulation materials were given in Figure 14. The points that minimise the total cost (insulation cost + fuel cost) are the optimum insulation thicknesses of that insulation material. The energy savings resulting from changing the external wall insulation material of the hospital building were simulated. Therefore, only natural gas consumption has been considered in the analyses performed, and no other analysis has been carried out considering that other fuel types are not cost-effective.

For the roof, with the help of Equations 12, 13, and 14, insulation costs, fuel costs, and total costs were estimated for five different insulation materials, as shown in Figure 15. The energy savings obtained by internal insulation and the existing 4 cm expanded polystyrene (EPS) material were calculated using the optimum insulation thicknesses in simulations.

The optimum insulation thicknesses according to measurement results for the external wall, roof, and floor were given in Table 11. For GW and RW, both materials have the same thermal properties. However, optimum insulation thickness is the thickness that results in the minimum energy cost and total insulation cost. The differences in their thicknesses occurred due to the material prices. Also, the material layers of the walls and roofs are quite different. Thus, the differences between optimum insulation thicknesses of roofs and walls are remarkable. In addition, there was no need for insulation for the floor for EPS, extruded polystyrene (XPS), and polyurethane (PUR) insulation materials. It is because the current insulation thickness is sufficient. For GW and RW, the thicknesses were too low; thus, they can be accepted as sufficient for the floor.

3.3 The effect of performance improvement parameters

In Tables 12 and 13, regression analyses were performed to see the effect of external wall insulation, roof insulation, window type, solar shading, and indoor air temperature conditions on the energy consumption obtained from the simulations. According to the analysis results, the R^2 value for the heating period was 0.99 (Table 12). There is a high correlation between energy consumption and the factors examined (Indoor air temperature, shading, glazing type, roof insulation, and external wall insulation). Table 13 shows the effect of external wall insulation, roof insulation, window type, solar shading, and indoor air temperature change on energy consumption for the heating period. Indoor air temperature values were taken from our previous study, calculating the thermal comfort temperature for hospital buildings (Caner and Ilten, 2020).

According to the analysis results for the cooling period, the R^2 value was found as 0.450 (Table 14). There is a low correlation between energy consumption and the factors examined. When the significance levels are examined in Table 15, the effect of glazing type, shading type, and change of the indoor air temperature (sig. <0.05) on the energy consumption for the cooling period is seen. However, external wall insulation and roof insulation do not significantly affect energy consumption (sig.> 0.05).

3.4 The ANN combination results

In the ANN model, the L25 orthogonal sequence designed for this example was taken as a learning set. EnergyPlus performed 50 simulations (25 for cooling and 25 for heating); the results are in Table 16. In Table 16, for the EW column, 2.15 represents PUR,

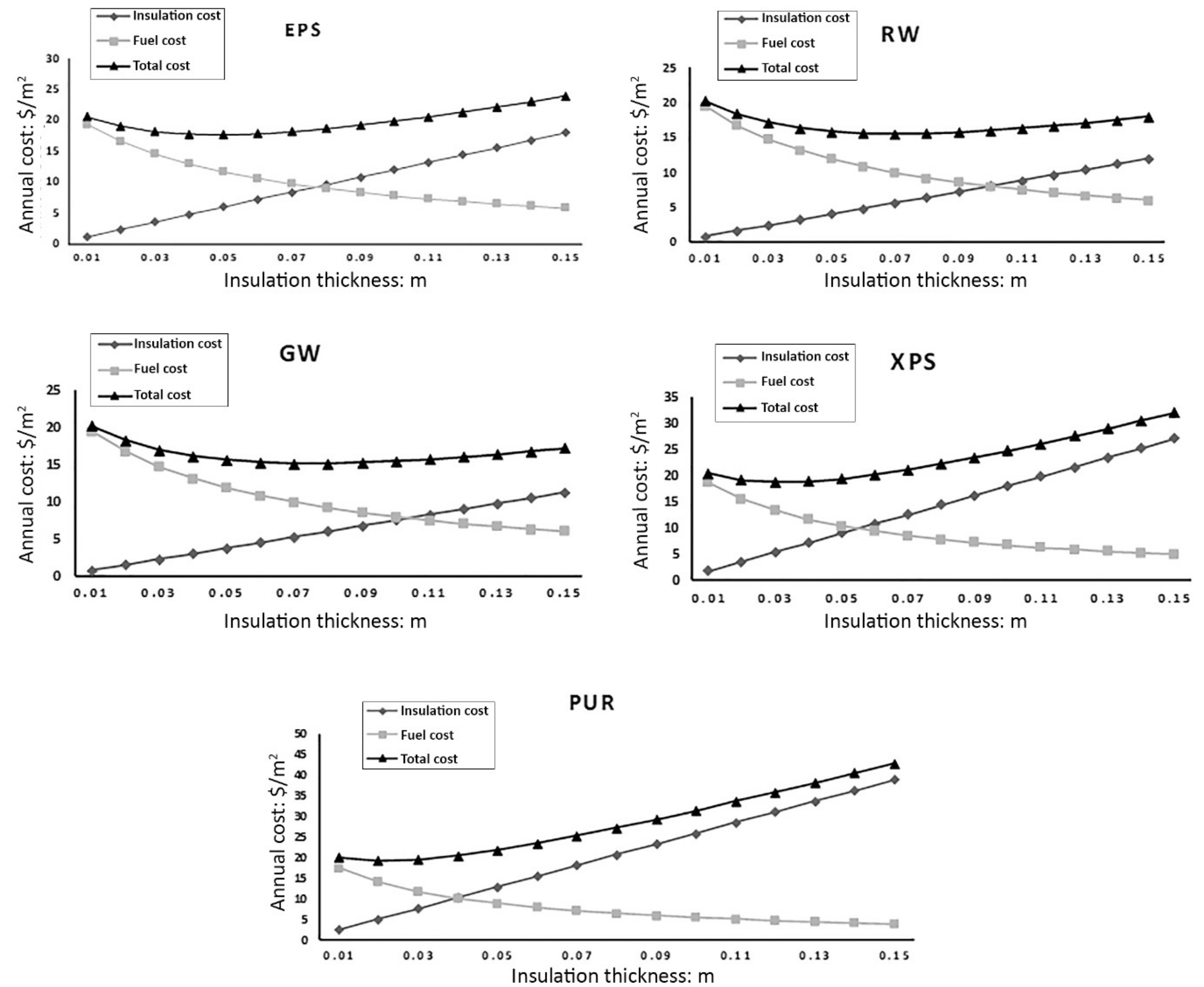


Figure 14. Optimum insulation thickness values for external walls for five different insulation materials

3.17 represents XPS, 4.78 represents EPS, 7.07 represents RW, and 7.78 represents GW. For the Roof column, 1.11 represents PUR, 1.82 represents XPS, 3.13 represents EPS, 5.34 represents RW, and 5.74 represents GW.

Here, 20 of the 25 simulations were used as network training data, and five were used as test data. Tables 17 and 18 show the data used for training and testing.

By comparison of the results of the analysis and network, error rates (Table 19), and regression coefficients were calculated.

The regression coefficients obtained from the network training for both periods can be seen in Figure 16. According to these results, it can be said that the test results of the network meet the analysis results made with the DesignBuilder programme at a perfect rate of R = 0.99 for heating and R = 0.96–0.99 for the cooling period.

According to these results, the remaining 3100 values of the 3125 combinations were created separately for both periods. Table 20 shows the combinations that give the minimum energy consumption according to the 22°C, 24°C, and measured indoor temperature values (24.4°C for heating and 25.78°C for the cooling period).

When the saving rates are examined, if the measured indoor air temperatures are applied, the saving rate is 18.66% for the heating period and 72.48% for the cooling period. It is important to note

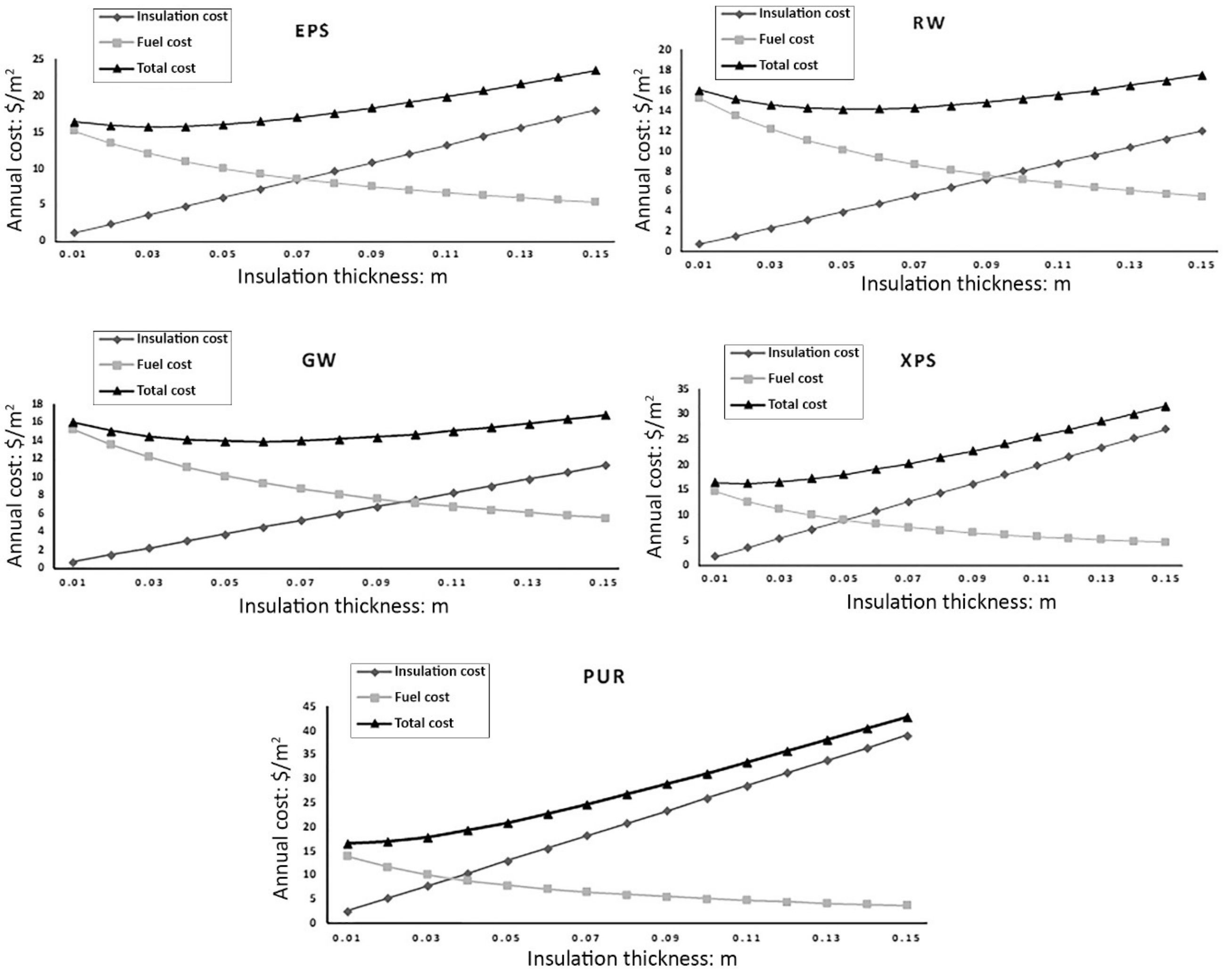


Figure 15. Optimum insulation thickness values for the roof for five different insulation materials

Table 11. Optimum insulation thickness values for different materials

According to measurements: cm	EPS	XPS	GW	RW	PUR
EW	4.78	3.17	7.48	7.07	2.15
Floor	—	—	0.68	0.27	—
Roof	3.13	1.82	5.74	5.34	1.11

Table 12. The regression coefficients of the heating period

Model	R	R^2	Standard error
Energy consumption	0.996	0.990	34 483.13725

Dependent variable: Indoor air temperature, shading, glazing type, roof insulation, and external wall insulation

that the optimum combinations for the heating and cooling periods are different. As seen in Table 20, while the SD is not used for the heating period, a 1-m overhang shading is provided for the cooling period. It can be said that maximum energy savings for the cooling period can be achieved using a 1-m louvre. Thus, using the SD in summer will avoid excessive heat gain through solar radiation (Ameur *et al.*, 2020). However, during the heating season, SDs will increase energy consumption due to reduced solar heat gain (Liu *et al.*, 2019; Shi *et al.*, 2019). Therefore, it can be said that the steady SD is not suitable for the selected hospital building. The selection of glazing type is considered; the best results in all combinations are in the glazing type with a *U*-value of 0.7 W/m²K.

4. Discussion

In this section, we will review the significant findings of this study, detailing its strengths and limitations, before analysing the

Table 13. The effect of selected parameters on energy consumption

	Unstandardised coefficients		Standardised coefficients		
Model	B	Standard error	Beta	T	Sig.
Constant	3 511 588.82	195 898.14	—	17.926	0.000
EW	−31 339.721	3293.036	−0.194	−9.517	0.000
Roof	−35 105.488	3734.878	−0.191	−9.399	0.000
Glazing	667 442.125	14 856.384	0.914	44.926	0.000
Shading	58 531.500	4876.652	0.244	12.002	0.000
Temp.	61 303.305	8257.214	0.151	7.424	0.000

Dependent variable: Energy consumption

Table 14. The regression coefficients of the cooling period

Model	R	R^2	Standard error
Energy consumption	0.752	0.450	13 340.03443

Dependent variable: Indoor air temperature, shading, glazing type, roof insulation, and external wall insulation

study in the context of practice and research. The main concepts of building energy efficiency mainly relate to insulation, shading, glazing type, and thermal comfort (Qu *et al*., 2020). Therefore, proposing a specific definition of energy efficiency for buildings is a complex idea (Attia *et al*., 2021). Thus, each building should take into consideration the usage type. The following sections discuss possible questions that we answered in this study.

- What are the main parameters that affect the energy efficiency of hospital buildings?
- What are the capabilities of ANN for building energy use?

4.1 Findings and recommendations

For this study, we defined optimum configurations for heating and cooling seasons for hospital buildings and developed a framework used by designers, architects, and future occupants (Açıkkalp and Kandemir, 2019). The following recommendations can be helpful for designers to reach the low-energy-use buildings:

- The proposed methodology in the study can significantly support building performance optimisation studies. Most importantly, these approaches explore multiple retrofit scenarios (such as envelope types, glazing, thermal comfort, etc.), requiring multiple energy simulations that provide reliable building performance estimations. Thus, time-consuming building performance simulation tools are required due to their accuracy, which can be applied to many existing buildings. This problem can be solved with advanced ANNs, which provide good reliability and significantly reduce the required computational load (≈98%). This study's reliability values are 99% and 96% for the heating and cooling periods, respectively.
- Considering the savings rates, when measured indoor air temperatures were applied, 18.66% savings were achieved in the heating period and 72.48% in the cooling period. It is essential to note that the optimal combinations for the heating and cooling periods differ (Table 20).
- It can be said that maximum energy savings can be achieved for the cooling period by using a 1-m louvre. Thus, using an SD in summer will prevent excessive heat gain through solar radiation (Ameur *et al*., 2020). However, using an SD for the heating season will increase energy consumption as it will reduce solar heat gain. Therefore, it can be said that the fixed SD is not suitable for the selected hospital building (Liu *et al*., 2019).

As is known, insulation materials' payback periods are usually concise when applied to buildings. Energy-efficiency investments support lightening the countries' dependency on fossil fuel sources. Especially today, when energy demands and costs are seriously increasing, this situation plays a significant role in energy

Table 15. The effect of parameters on energy consumption

	Unstandardised coefficients		Standardised coefficients		
Model	B	Standard error	Beta	T	Sig.
Constant	−41 968.852	52 060.891	—	−0.806	0.430
EW	−570.394	1273.933	−0.068	−0.448	0.659
Roof	−302.925	1444.863	−0.032	−0.210	0.836
Glazing	−12 531.452	5747.293	−0330	−2.180	0.042
Shading	−5700.260	1886.566	−0.457	−3.022	0.007
Temp.	6918.945	2132.466	0.491	3.245	0.004

Dependent variable: Energy consumption

Table 16. Data obtained for the heating period as a result of simulations

EW: cm	Roof: cm	Glazing: W/m^2.K	SD: m	Temp.: °C	Natural gas consumption: kWh	Electricity consumption for cooling: kWh
2.15	3.13	0.7	0.5	23.5	5 409 749	44 985
2.15	1.82	1.978	1	23	6 410 220	105 497
2.15	5.74	1.8	0	22	5 855 765	77 624
2.15	5.34	1.3	0.5	24.4/25.78	5 754 899	84 805
2.15	1.11	1.1	1	24	5 796 435	59 000
3.17	3.13	1.8	1	23	6 105 658	70 304
3.17	5.74	1.1	1	24.4/25.78	5 776 047	43 007
3.17	5.34	0.7	0	24	5 205 337	96 210
3.17	1.11	1.978	0.5	23.5	6 247 407	89 373
3.17	1.82	1.3	0.5	22	5 756 926	84 527
4.78	1.82	1.8	0.5	24	6 104 875	81 417
4.78	5.74	1.3	1	23.5	5 678 519	43 069
4.78	5.34	1.1	0.5	23	5 519 443	61 026
4.78	1.11	0.7	1	22	5 462 065	101 767
4.78	3.13	1.978	0	24.4/25.78	6 130 635	88 222
7.07	3.13	1.1	0.5	22	5 394 975	96 123
7.07	1.82	0.7	1	24.4/25.78	5 366 659	95 542
7.07	5.74	1.978	0.5	24	6 034 100	37 600
7.07	1.11	1.3	0	23	5 594 335	69 481
7.07	5.34	1.8	1	23.5	6 067 101	76 236
7.48	3.13	1.3	1	24	5 835 462	62 923
7.48	5.74	0.7	0.5	23	5 065 533	62 331
7.48	5.34	1.978	1	22	5 934 463	105 852
7.48	1.11	1.8	0.5	24.4/25.78	6 132 746	76 542
7.48	1.82	1.1	0	23.5	5 444 173	79 140

Table 17. Network training and testing data for the heating period

EW: cm	Roof: cm	Window *U*-value: W/m^2.K	SD: m	SD louvre	SD overhang	Temperature: °C	Natural gas consumption: kWh
Training data							
4.78	1.82	1.8	0.5	1	0	24	6 104 875
4.78	5.74	1.3	1	1	0	23.5	5 678 519
4.78	5.34	1.1	0.5	0	1	23	5 519 443
4.78	1.11	0.7	1	0	1	22	5 462 065
3.17	3.13	1.8	1	1	0	23	6 105 658
7.48	3.13	1.3	1	0	1	24	5 835 462
3.17	5.74	1.1	1	0	1	24.4	5 776 047
3.17	5.34	0.7	0	0	0	24	5 205 337
3.17	1.11	1.978	0.5	1	0	23.5	6 247 407
7.48	5.74	0.7	0.5	1	0	23	5 065 533
7.48	5.34	1.978	1	1	0	22	5 934 463
7.48	1.11	1.8	0.5	0	1	24.4	6 132 746
7.07	3.13	1.1	0.5	1	0	22	5 394 975
7.07	1.82	0.7	1	1	0	24.4	5 366 659
7.07	5.74	1.978	0.5	0	1	24	6 034 100
7.07	1.11	1.3	0	0	0	23	5 594 335
2.15	3.13	0.7	0.5	0	1	23.5	5 409 749
2.15	1.82	1.978	1	0	1	23	6 410 220
2.15	5.74	1.8	0	0	0	22	5 855 765
2.15	5.34	1.3	0.5	1	0	24.4	5 754 899
Test data							
4.78	3.13	1.978	0	0	0	24.4	6 130 635
7.48	1.82	1.1	0	0	0	23.5	5 444 173
3.17	1.82	1.3	0.5	0	1	22	5 756 926
7.07	5.34	1.8	1	0	1	23.5	6 067 101
2.15	1.11	1.1	1	1	0	24	5 796 435

Table 18. Network training and testing data for the cooling period

EW: cm	Roof: cm	Window *U*-value: W/m^2.K	SD: m	SD louvre	SD overhang	Temperature: °C	Electricity consumption: kWh
Training data							
2.15	3.13	0.7	0.5	0	1	23.5	44 985
2.15	5.74	1.8	0	0	0	22	105 497
2.15	5.34	1.3	0.5	1	0	25.78	77 624
2.15	1.82	1.978	1	0	1	23	84 805
3.17	5.34	0.7	0	0	0	24	70 304
3.17	5.74	1.1	1	0	1	25.78	43 007
3.17	1.11	1.978	0.5	1	0	23.5	96 210
3.17	1.82	1.3	0.5	0	1	22	89 373
4.78	5.74	1.3	1	1	0	23.5	81 417
4.78	1.11	0.7	1	0	1	22	43 069
4.78	5.34	1.1	0.5	0	1	23	61 026
4.78	3.13	1.978	0	0	0	25.78	101 767
7.07	1.11	1.3	0	0	0	23	96 123
7.07	5.74	1.978	0.5	0	1	24	95 542
7.07	1.82	0.7	1	1	0	25.78	37 600
7.07	5.34	1.8	1	0	1	23.5	69 481
7.48	5.74	0.7	0.5	1	0	23	62 923
7.48	3.13	1.3	1	0	1	24	62 331
7.48	5.34	1.978	1	1	0	22	105 852
7.48	1.11	1.8	0.5	0	1	25.78	76 542
Test data							
7.48	1.82	1.1	0	0	0	23.5	79 140
4.78	1.82	1.8	0.5	1	0	24	88 222
3.17	3.13	1.8	1	1	0	23	84 527
2.15	1.11	1.1	1	1	0	24	59 000
7.07	3.13	1.1	0.5	1	0	22	76 236

Table 19. Analysis and comparison of network test values

Heating period			Cooling		
Analyses value	Network test value	Error: %	Analyses value	Network test value	Error: %
6 130 635	6 177 593	−0.77%	79 140	83 714	−5.78%
5 444 173	5 534 381	−1.66%	88 222	91 153	−3.32%
5 756 926	5 765 091	−0.14%	84 527	80 038	5.31%
6 067 101	6 022 528	0.73%	59 000	57 506	2.53%
5 796 435	5 880 560	−1.45%	76 236	78 677	−3.20%

consumption policies. Considering the optimum insulation thickness calculated depending on the various fuel types and pollution caused by fossil fuel wastes, natural gas is the optimum fuel type. At the same time, the optimum insulation thickness is lower when compared to other fuels for natural gas; also, initially, the investment costs will be lower.

As an implementation of the results, the saving rate is 18.66% and 72.48% for the heating and cooling periods, respectively. The highest saving was obtained when the results were compared between the TS 825 and ASHRAE 14. Notably, the saving rates for the cooling period are excessively high, as TS 825 offers **22°C** indoor air temperatures for the heating period and overlooks the cooling season. Similarly, ASHRAE 14 offers **22°C–24°C** indoor air temperature for both seasons.

A notable outcome of this study is the difference in ANN prediction accuracy between the heating and cooling periods. While the regression coefficient for the heating season was consistently very high ($R = 0.99$), the cooling season showed slightly lower but still robust accuracy ($R = 0.96–0.99$). The inherent variability of cooling loads in hospital buildings can explain this discrepancy. During the summer, internal gains from medical equipment, lighting, and occupant activity fluctuate more dynamically compared to the relatively stable heating season. In addition, cooling demand is more sensitive to external factors such as solar radiation intensity, diurnal variations, and SD performance, which are more difficult to represent with constant input assumptions. These factors introduce additional uncertainty into the ANN model, leading to a marginally lower accuracy for cooling predictions.

Nevertheless, the achieved accuracy remains within acceptable limits for practical applications, demonstrating that the ANN model can reliably capture the complex relationships governing hospital energy consumption across both seasons. This observation also underscores the importance of incorporating more detailed operational data, particularly regarding equipment and lighting usage, into future models to further enhance prediction performance in cooling-dominated conditions.

4.2 Strengths and limitations

Implementing performance improvement parameters on buildings offers many opportunities to decrease energy consumption. Thus, simulations are crucial for building assessments regarding energy loads to reduce loads. Using calibrated building simulation examines the effect of new design strategies or renovations. Moreover, the detailed characterisation of the building's performance allows the closing of the performance gap. However, the model of the complex buildings will require much time to simulate all the different performance improvement parameters. As in this study, the total combined number is 6250 (2×5^5) for the cooling and heating seasons, and these cases will take ≈520 days to complete using an Intel Kaby Lake Core i7-7700 K 4.2 GHz processor. In this study, to overcome this problem, the ANN model is used. The ANN model requires a small training group to create a suitable model for further simulations. In this study, 50 (25 for heating and 5 for cooling) combinations of the 6250 combinations are sufficient to create a valid model for both periods, and these cases took four days.

The study's sample size is created using the Taguchi design in Minitab. In total, 20 of 25 simulations are used as training data, and 5 of 25 simulations are used as test data. The strength of this method (Taguchi) lies in its minimal sample size requirement. When comparing the literature, Asadi *et al*. (2014) used 950 simulation samples to validate their model. However, their building model is 15 times smaller and has fewer features than the building used in this study, which employed the Latin hypercube sampling (LHS) method in MATLAB. Ninety-five of these data are used for testing.

Similarly, Ascione *et al*. (2017a) used the LHS method and obtained 500 simulation results to validate their model, and 50 were used for testing. Beccali *et al*. (2017) used 116 training and 17 test data to validate their ANN model. Reynolds *et al*. (2018) used 27 training data to validate their model and examined Cardiff's small, simple office building. Naji *et al*. (2016) used 32 simulation data to train their model, using 22 of these as a training set. Bagnasco *et al*. (2015) trained their ANN model by using 2.5 months of data out of 12 months to predict the electricity consumption of hospital buildings. Neto and Fiorelli (2008) used 15 months of weather data for training and three months to test and validate their university building model. Also, they suggest that after proper calibration, the simulation tool and the ANN model would become helpful tools for forecasting the building energy demands and loads. Jovanović *et al*. (2015) predicted the heating energy consumption of a university campus by using three different ANN models, and they used different input parameters for each model. They validated their network using 318 data for training and 100 data for testing. It can be said that all proposed neural network models can predict heating consumption with great accuracy. The outcomes of those studies show excellent results and satisfactory ANNs' reliability. They are comparable to previous studies on using ANNs to predict building energy performance. Accordingly, it is easy to say that the model used in our study is suitable for checking ANN's natural strength and accuracy and will be a good reference for further studies.

Another strength of the ANN method is its high accuracy and speed. The number of neurons and layers, and the network training function options of the method allow high accuracy to be obtained. In addition, ANN can yield the same results in seconds, rather than requiring hundreds of hours of simulation. When the literature is examined, almost all studies have more than 90% accuracy rates, and this accuracy rate is accepted as suitable to predict the rest of the data. After the validation of the model for both seasons (Figure 16), the other simulations were produced by way of ANN within seconds. Also, ANNs can provide good reliability and substantially reduce the required computational workload (around 98%) (Ascione *et al*., 2017b).

ANN has the limitation of being too rigid on the training data set. It leads to problems in creating a flexible model (Deb *et al*., 2018). Especially in Taguchi design, there are limited input parameters and levels. For example, in this study, we used a 5 × 5 design due to its rigid structure. When we selected five different insulation materials for the roof and external wall, primarily used in the market, there were no other options to select five levels for the other parameters. In our study, the parameters are flexible; thus, we quickly adapted them to this Taguchi design. A challenge here is to develop a relatively flexible model with a high accuracy rate that learns from the training data and performs well on the testing data. The other limitations of our study can be explained as follows;

- The validation of the building model is crucial to analyse energy consumption. Thus, all data belonging to the buildings should have been appropriately gathered, such as building project and building properties, occupancy density, heating and cooling set-point temperature (if it is possible, it will be measured for at least a year), equipment, and activity levels of occupants (Caner and Ilten, 2020).

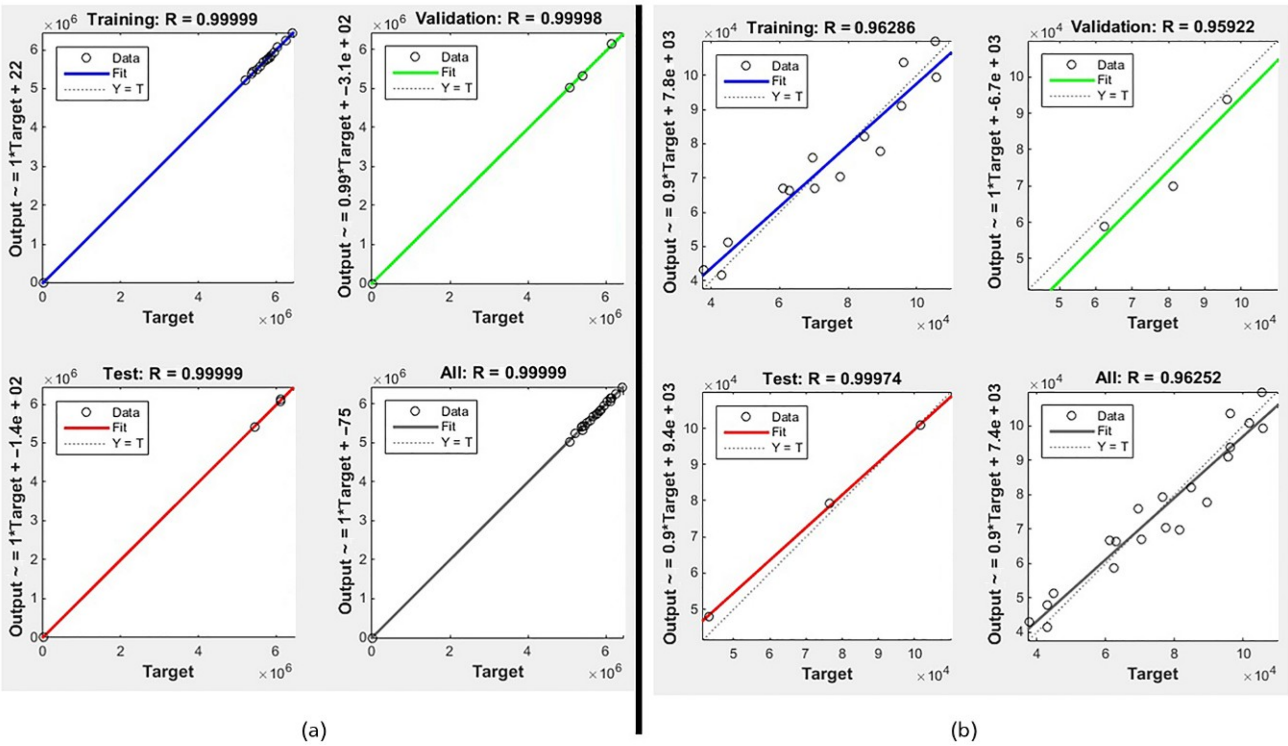


Figure 16. Regression coefficients for heating (a) and cooling (b) period

Table 20. Optimum combinations for heating and cooling periods

EW: cm	Roof: cm	Window *U*-value: W/m^2.K	SD: m	SD louvre	SD overhang	Temperature: °C	Natural gas consumption: kWh
7.48	5.74	0.7	0	0	0	24.4	5 190 359
7.48	5.74	0.7	0	0	0	22	5 006 476
7.48	5.74	0.7	0	0	0	24	5 159 712

EW: cm	Roof: cm	Window *U*-value: W/m^2.K	SD: m	SD louvre	SD overhang	Temperature: °C	Electricity gas consumption: kWh
2.15	5.74	0.7	1	0	1	25.78	27 621.5
4.78	1.11	0.7	1	0	1	22	43 069
2.15	5.74	0.7	1	0	1	24	35 600.5

- The climate zones must be analysed according to the climate type (cooling- or heating-dominated). When we examine the optimum combinations for heating and cooling periods (Table 20), it changes explicitly (Bai and Wang, 2018).
- Optimum insulation thicknesses are essential to decrease the total cost (Kaynakli, 2012). Especially for the external wall and roof, a suitable insulation type must be selected. Also, the fire class of these materials should be taken into consideration.
- For heating-dominated zones, a constant SD should be avoided; it is better for cooling-dominated zones; however, it must be examined before implementation. In addition, movable SDs are preferable if possible (Harkouss *et al.*, 2018).

4.3 Implications for the practice and future research

The use of ANN in building energy forecasts is crucial due to its high accuracy, speed, and reliability. The model used in this study is one of the most accessible prediction models that can be easily created by anyone who has very little information, and without the need for long-term training in MATLAB. In the study, we select the parameters mainly used in the market and practice; thus, anyone from the market can quickly adapt this network to their study and predict the effect of different parameters on energy consumption. We selected a 5-5 Taguchi design model with five performance improvement parameters and five levels for each. However, this model is rigid, and there are limited design models in Taguchi, restricting their users. Thus, according to Taguchi design models, the users should pay attention to the parameter numbers and levels.

The Balikesir University administration primarily considers this study, and it is important to take the necessary steps as soon as possible to optimise energy consumption. In line with the data obtained, energy saving of around 20% is critical for only one building belonging to the university. Moreover, considering that the University of Balikesir has more than ten buildings similar to the hospital building, the total energy use of the university can be decreased quickly.

Balıkesir province, where the study was conducted, has a climate that can be found throughout Turkey. When examined in this direction, the building contains design parameters that can spread throughout the country, starting from the public buildings in Balıkesir. The parameters used in the study can be applied quite easily due to the selection of parameters that are mostly used in practice. In cases where it cannot be applied regionally due to the lack of material, the model has the opportunity to be revised rapidly. Thus, an improvement in energy consumption can be achieved with the building's construction.

While designing a hospital building, the occupants' energy consumption and thermal comfort needs should be considered. The indoor temperatures obtained in this study were taken from our previous study (Caner and Ilten, 2020). For this reason, the study is critical in shedding light on future studies, as it considers the temperatures determined by the standards and user preferences. However, completing this and similar studies requires a significant amount of work due to modelling and measurement. Also, this study can be implemented in different building types, and the revision of the TS 825 can be made according to these data and different climate zones.

5. Conclusions

In this study, the energy consumption of the hospital building located in Balikesir, Turkey, is estimated, and a reference model was calibrated using EnergyPlus. The results showed that the model validates building energy performance in both the cooling and heating seasons. Energy modellers and experts for other hospital buildings can use the reliable and consistent model. The model was calibrated according to ASHRAE 14.

The ANN model forecasts energy consumption according to previous measurements and weather data. Thus, examining new design strategies to reduce energy consumption can only be utilised after they are performed. However, after suitable building model calibration, the ANN model can become a valuable tool for estimating building energy consumption. In the ANN, an accurate simulation result was compared with the network results to determine whether the network was learning and whether the test results of the network met the analysis results made with the DesignBuilder programme at a perfect rate.

The different climate zones required different insulation methods, SDs and glazing types. This study provides insights into healthcare buildings. Besides, the results confirm the gap between the early design performance assumptions and the actual performance. Moreover, it is suggested that the workflow described in this study could be adopted for the Turkish standards. It is a crucial attempt at energy-efficient design strategies for Turkish hospital buildings. Future studies will focus on the other building types, different locations, window-to-wall ratios, weather conditions, and comparing movable SDs, and so on. It is a pre-study, and many others will be developed to enhance the strategies to examine the air-conditioned buildings' energy consumption to predict it much better.

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