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Analysis of the Building Envelope Materials, Climate, and Earthquake Zones in Energy-efficient Building Designs

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Abstract. Energy-saving has become one of the basic strategies for developing countries like Turkey that need energy imports. One of these strategies is energy-efficient building designs. The energy-efficient building envelope, which is one of the most important components of energy-efficient building designs, is of great importance in terms of insulation, indoor comfort, and environmental effects. In addition, the climatic and seismic characteristics of the regions where the buildings will be built are a matter of curiosity for building designers. It is an important problem to determine the effect of climate and earthquake zones on the building envelope. In this study, the effects of climate and earthquake zones on the costs in the building life cycle, together with the building envelope properties, are investigated. Life cycle cost assessment (LCA) analysis is applied by considering the parameters of building envelope material cost, heating energy consumption cost, cooling energy consumption cost, CO_2 emission cost, embodied carbon cost, and earthquake-based repair cost. Fourteen different decision variables are taken into account, including exterior plaster, wall, and roof insulation material, wall, interior plaster, the thickness of these materials, window type, and window/wall ratio. Significance levels of decision variables for heating energy consumption, cooling energy consumption and CO_2 emission are calculated. It is determined that five decision variables for heating energy consumption, four for cooling energy consumption, and seven for CO_2 emission are more important. It is an interesting pattern that earthquake zones have 28%, 46%, and 13% importance for heating energy consumption, cooling energy consumption, and CO_2 emission. It has been observed that the EnergyPlus-based ANN approach proposed for LCA analysis provides over 95% accuracy on the sample data set.

Keywords: Energy-efficient building, building envelope, LCA, climate zones, seismic zones.

INTRODUCTION

An energy-efficient building is called a structure that provides minimum carbon emission by using energy effectively consumed for heating, cooling, air conditioning, and lighting. The most important stage in the construction processes of energy-efficient buildings is the design step. The building needs less energy through the measures taken and the decisions made during the design phase.

The most basic strategy for less energy consumption and carbon emissions is to design an energy-efficient building envelope. The energy-efficient building envelope consists of components that provide thermal insulation and indoor comfort. However, thermal insulation systems are not preferred in developing countries such as Turkey because of the higher cost of purchase and installation of insulation [1]. Therefore, the building (residential/commercial) sectors in Turkey need to spend a lot of money on heat suppression every year [2]. In addition, the most basic factor affecting the choice of materials and equipment in energy-efficient buildings is the feature of the region where the building will be built. Since it is not appropriate to use the same building envelope designs in different climatic zones, climatic characteristics also have an impact on the heating and cooling energy consumption and carbon emissions of buildings. In addition to the climatic characteristics, the earthquake characteristics of the regions where the buildings will be constructed should also be taken into account in the thermal energy consumption. Since depending on the specific geographical region where it is situated, a building can potentially be attacked by being exposed to natural hazards such as earthquakes it may suffer from different levels of structural deformation [3]. This situation may cause the thermal balance of the indoor environment to be lost due to deterioration in the building envelope. Naturally, more energy consumption and more carbon emissions will be required in order to restore the thermal balance. In order to prevent more energy consumption, possible repair costs of the building envelope should also be considered, taking into account the possibility of an earthquake.

Countries that are developing and in need of energy imports, such as Turkey, must make different laws and regulations to reduce their energy consumption. Moreover, in a country with different climate and earthquake zones such as Turkey again, heating and cooling energy consumption cannot be the same in every zone. Therefore, in recent years, energy-efficient building designs have become one of the most important strategic activities of governments that need energy import.

Once the studies in the literature are reviewed, the life cycle cost assessment (LCA) is generally used for energy-efficient building designs. The cost parameters that occur during the economic life of the buildings are taken into account through the LCA approach. Accordingly, different parameters including energy consumption, material cost, and environmental impacts are included in LCA. In addition, numerical calculations, simulation programs, or artificial intelligence approaches are preferred to obtain LCA parameters.

Caglayan et al. [4] analyzed the heating energy consumption and material cost for four different climate zones in Turkey, taking into account the window type, wall insulation, ceiling insulation, and basement floor insulation material thicknesses. They developed an optimization tool by using numerical calculation formulas in genetic algorithm (GA). In addition, they performed a sensitivity analysis for window, wall, ceiling, and basement insulation materials. Himmetoğlu et al. [5] applied the attribute reduction to obtain the climate characteristics affecting the heating and cooling energy consumption of a public building for two different climate zones in Turkey. They also proposed a structure called PSACONN mining to determine the most suitable building envelopes that give the minimum heating and cooling energy consumption. Acar et al. [6] took into account the orientation, wall insulation material, roof insulation material, glazing type, and window thickness for the residential buildings in Turkey. They used the EnergyPlus simulation program and non-dominated sorting genetic algorithm-II (NSGA-II) together to analyze building envelope alternatives that minimize the total thermal energy demand and investment cost. Delgarm et al. [7] analyzed envelope alternatives that minimize heating, cooling, and lighting energy consumption for four different climate zones, by considering shading specifications, window size, glazing, and wall material. They aimed to scan the entire solution space in a shorter time by developing an EnergyPlus-based particle swarm optimization (PSO) algorithm. Chantrelle et al. [8] considered exterior wall type, roof type, ground floor type, intermediate floor type, partition wall type, and window type as decision variables. They analyzed energy consumption, thermal comfort, investment cost, and environmental impacts using the TRNSYS simulation program and the NSGA-II approach together. Karmellos et al. [9] aimed to determine the most suitable building envelope combination that minimizes annual energy consumption and investment cost for two different climate zones. They have developed a MATLAB-based tool for decision-makers, taking into account door type, window type, wall type, energy systems, lighting systems, and electrical appliances. Echenagucia et al. [10] aimed to minimize the heating, cooling, and lighting energy demands for different climatic regions by considering the number of windows, window position, window shape, window type, wall thickness, and glazing. They used EnergyPlus and NSGA-II together. Gossard et al. [11] analyzed the annual energy consumption and comfort levels for two different climate zones, taking into account the thermophysical properties of the external wall. They proposed an approach including TRNSYS and NSGA-II approaches, taking into account thermal conductivity and volumetric specific heat for the wall and the roof as decision variables. Ascione et al. [12] proposed an approach that minimizes the percentage of heating/cooling energy demand and thermal discomfort hours for two cities with the same climate features. They considered window type, insulation thickness, wall density, solar absorptance, and thermal emissivity by using the EnergyPlus simulation program integrated into the NSGA-II approach. Wang and Wei [13] analyzed building envelope designs that minimize building energy loads and construction costs for tropical and subtropical climate zones. By integrating numerical calculations into quantum GA, they used the wall material, roof material, window sizes, glazing, window shading, orientation, and the number of windows as decision variables. Albatayneh [14] aimed to minimize heating and cooling loads to provide thermal comfort by using EnergyPlus and GA together for a climate zone. A sensitivity analysis was performed by using regression analysis for the decision variables of orientation, wall insulation thickness, roof insulation material, partition construction, window/wall ratio, window type, window shading, glazing type, infiltration rate, and natural ventilation rate. Chegari et al. [15] aimed to minimize heating and cooling energy consumption by using TRNSYS, NSGA-II, and ANN approaches together. They considered exterior wall materials, roof materials, window materials, glazing, shading, and air changing as the decision variables. Bre et al. [16] analyzed heating and cooling performances for decision variables of roof type, exterior wall type, interior wall type, solar orientation, solar absorptance, window size, window type, window shading, and infiltration rate by using EnergyPlus, the artificial neural network (ANN), and NSGA-II together. Huang et al. [17] analyzed the heating energy consumption by proposing a mathematical model using numerical formulations. Insulation thicknesses, orientation, window/wall ratio, and window type were taken into account as decision variables. Lu et al. [18] applied LCA through EnergyPlus by considering heating energy consumption, cooling energy consumption, CO_2 emission, material cost, and heat transfer coefficient. Window type, wall insulation type, roof insulation type, and insulation thickness were used as decision variables. Yuan et al. [19] proposed an LCA approach to minimize material cost, heating energy consumption, and cooling energy consumption using numerical calculations. They considered door, window, exterior walls, partition walls, and roof materials as decision variables. Lin et al. [20] used the NSGA-II approach to minimize the building envelope cost and CO_2 emissions. They considered wall material, roof material, glass curtain material, window size, number of windows, number of glasses, window sunshade shape, window sunshade type, and six different air conditioning parameters as the decision variable. Kim et al. [21] applied feature subset selection with the C4.5 decision tree method, taking into account parameters such as material type, insulation thickness, and air gap for walls and roofs. For more detailed literature on envelope design and material analysis in energy-efficient buildings, the review paper published by Kheiri [22] may be reviewed. To the author's knowledge, there is only one study evaluating the effects of earthquakes on energy-efficient building envelope materials. In the study presented by Liu and Mi [23], damages that occur only on the windows due to earthquakes (drift rate) are taken into account along with the thermal energy consumption of the building, CO_2 emission, and material cost.

This study has a wider perspective than the above studies in terms of its scope. The most important contribution of this study is to consider the effects of climate and earthquake zones in energy-efficient building designs, as well as the importance levels of the window, exterior plaster, insulation (wall and roof), wall, and interior plaster materials used in the building envelope. The second important contribution is to take into account the heating energy consumption, cooling energy consumption, building carbon emissions, embodied carbon, material costs, and repair costs caused by the earthquake effect. Accordingly, in the first step of the study, the parameters that most affect heating, cooling, and CO_2 emissions from the climate and earthquake zone parameters along with the building envelope attributes are determined. In the second step of the study, an LCA analysis including heating energy consumption, cooling energy consumption, CO_2 emission, embodied carbon, material cost, and earthquake repair cost is proposed. ANN models based on the EnergyPlus simulation program are developed to predict heating, cooling, and CO_2 emissions. The proposed approach is performed in a small-sized case study.

This paper is organized as follows. In Section "Research Elaborations", the approaches used for the proposed methodology are presented. In Section "Results and Findings for a Case Study", a case study is presented. Conclusions are given in Section "Conclusions".

RESEARCH ELABORATIONS

The proposed methodology consists of three main steps. In the first step, the feature subset selection is performed in order to analyze the features affecting the heating energy consumption, cooling energy consumption, and CO_2 emission. In the second step, the predictive models are developed in order to separately forecast heating energy consumption, cooling energy consumption, and CO_2 emission according to the features obtained in Step-1. In the last step, an LCA analysis including the material cost, embodied carbon, and seismic repair cost along with the parameter values estimated in Step-2 is performed.

Feature Subset Selection

The proposed approach analyzes the effects of building envelope material features and regional characteristics on heating energy consumption, cooling energy consumption, and CO_2 emission. The importance and effect of regional characteristics and material characteristics may not be the same for the mentioned parameters. Therefore, the decision variables affecting each parameter should be evaluated separately.

In this step, 'the correlation-based feature subset selection algorithm for machine learning' (CfsSubsetEval) approach proposed by Hall [24] was preferred for the feature selection process. The CfsSubsetEval is an approach that evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them [24]. The random forest algorithm presented by Breiman [25] was used to analyze the accuracy of the CfsSubsetEval approach. The random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest [25].

In the proposed approach, applying the feature subset selection to the decision variables for heating energy consumption, cooling energy consumption, and CO_2 emission parameters aims to make the estimation structure work better. In addition, it will enable the discovery of hidden patterns between the mentioned parameters and decision variables.

The Predictive Modeling

Energy simulation programs are useful for the energy analysis of buildings in the design phase [5]. A wide variety of building simulation programs have been developed [26]. Examples of these programs are BLAST, EnergyPlus, eQUEST, TRACE, DOE2, and ECOTECT [21]. Crawley [27], Sadineni [28], and Mirsadeghi [29] present a detailed review of building simulation programs used in the literature.

EnergyPlus is a well-known, free software program developed by the U.S. Department of Energy that can be used to perform whole-building energy analysis [26]. It has two main libraries that are component and template libraries. It also has the ability to analyze many features from material alternatives to hourly air values, from metabolic rates to storage. It provides convenience to decision-makers in the design processes in every region through the detailed climate files of almost every region of the world. However, no single energy simulation program offers sufficient capabilities and flexibilities to analyze integrated building systems and to enable rapid prototyping of innovative building and system technologies [30]. Once the number of alternatives increases in the building design processes, the time to enter data into EnergyPlus and the time to evaluate the results increases. Therefore, there is a need for effective and practical approaches that mimic the working mechanism of EnergyPlus. Using simulation programs along with artificial intelligence techniques will increase the efficiency of building design processes. In this study, ANN models, which learn the working structure of the EnergyPlus simulation program, are developed.

ANN models consist of six basic elements. These are layers, weights, neurons, network structure, training algorithm, and transfer functions. ANN models generally consist of three layers: input, hidden, and output layers. There are neurons that hold information in each layer. Each neuron in each layer has a certain weight value. According to this weight value, the values of the output neurons vary. Determining the neuron weights is the most important step in ANN models. Weight calculation processes are carried out through training algorithms. Information transmission between the layers is provided by transfer functions. The network structure of ANN models determines the form of information transmission. Detailed technical information and the basic concept of an ANN can be found in Refs. [31–33].

In order to obtain EnergyPlus-based ANN models, a sample input data set representing the whole alternative solution space is generated by considering the different values of the decision variables. According to this data set, heating, cooling energy consumptions, and CO_2 emissions are calculated with the EnergyPlus program, and a sample output data set is obtained. ANN models are developed separately for heating energy consumption, cooling energy consumption, and CO_2 emission by using input and output sample data sets. In the study, EnergyPlus-based ANN models are proposed for cases where there are intensive calculations and many alternatives.

Life Cycle Cost Assessment (LCA) Analysis

LCA is an economic analysis technique that takes into account the investment cost and the periodic (e.g., monthly, annual) costs that will occur during the economic life of the building for the project management processes. It is very effective in making the most appropriate decision, especially for energy-efficient building designs, taking into account the investment costs and annual costs.

In this study, heating energy consumption, cooling energy consumption, CO_2 emission, embodied carbon, material cost, and earthquake repair cost are considered as parameters of the LCA. Although prediction models are created for heating energy consumption, cooling energy consumption, and CO_2 emissions, there is no need to create prediction models for embodied carbon, material cost, and earthquake repair cost. Since the embodied carbon, material cost and earthquake repair cost are material-oriented, there is no need for estimation since the related parameter values can be calculated directly with a simple calculation.

RESULTS AND FINDINGS FOR A CASE STUDY

Building Definition

In this section, the proposed methodology was applied to a small-sized case study. A one-story structure was designed with residential building features for the case study. The building has an area of 25×25 m^2. It also has four flats, two elevators, two warehouses, a staircase, and a fire escape. The flats are symmetrical. Each flat consists of four living rooms, a bathroom, a kitchen, a toilet, and a hall. The materials used on the floor are sand-cement plaster (12.5 mm), polystyrene rigid foam (20 mm), reinforced concrete (150 mm), screed (50 mm), and ceramic (20 mm). Partition walls are in the form of brick (105 mm) and both-side plaster (12 mm). The building height is 3 meters.

The building model designed in DesignBuilder, which is an interface program that provides data entry to EnergyPlus, is shown in Figure 1. The case study building was designed to be cooled to 24°C when the temperature rises above 28°C, and to be heated to 22°C when the temperature drops below 18°C.

In the proposed approach, applying the feature subset selection to the decision variables for heating energy consumption, cooling energy consumption, and CO_2 emission

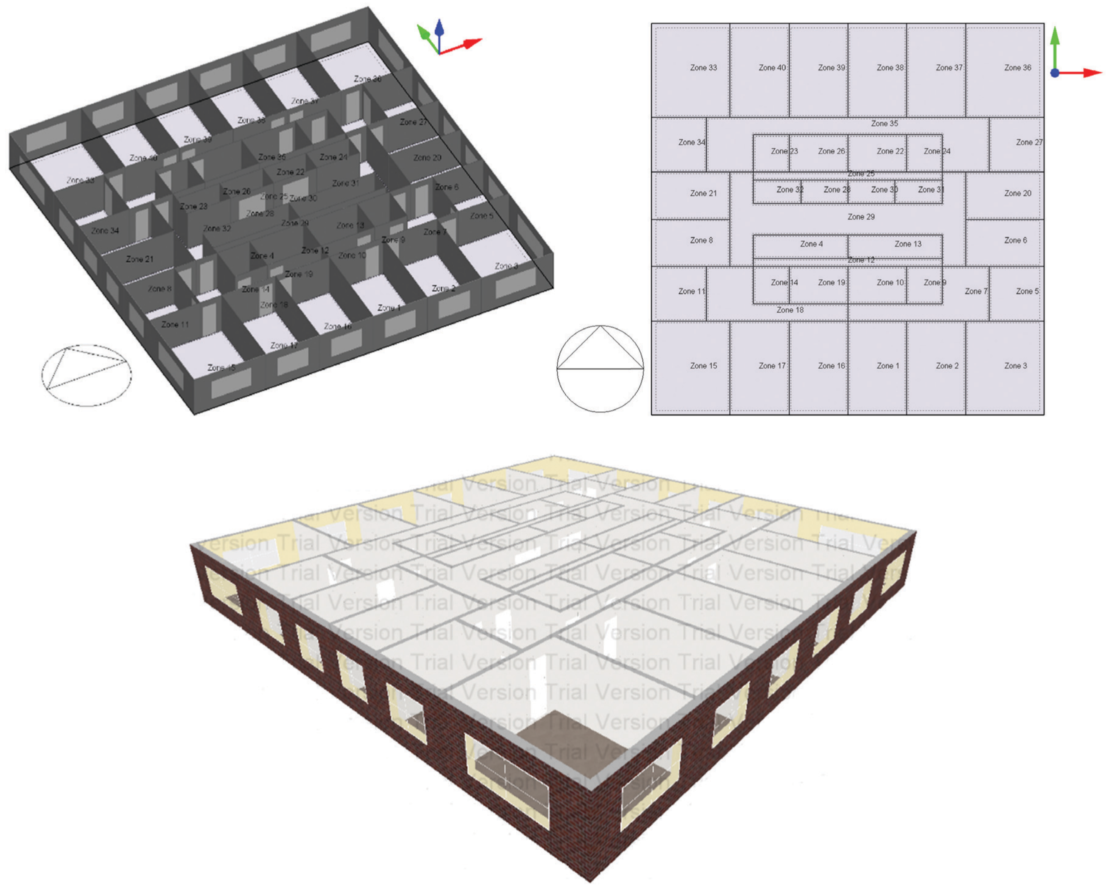

Figure 1. DesignBuilder single-story building model (not scaled).

parameters aims to make the estimation structure work better. In addition, it will enable the discovery of hidden patterns between the mentioned parameters and decision variables.

Feature Subset Selection

In the case study, two main input attributes are taken into account. These are building envelope variables and regional decision variables. The building envelope decision variables are interior plaster, masonry material, masonry insulation material, exterior plaster, roof insulation material, the thickness of these materials, window type, and window/wall rate. For regional decision variables, climatic zones and earthquake zones are taken into account. The effects of these decision variables on heating energy consumption, cooling energy consumption, and CO_2 emission are analyzed and hidden patterns are investigated. The alternatives used for the building envelope decision variables are presented in Table 1. For regional decision variables, four different climate and earthquake zones in Turkey are taken into account. Four different regions are selected to represent each climate and earthquake zone in Turkey. General information about the pilot regions is given in Table 2.

It is applied to the building in the case study by generating a hundred different combinations covering each alternative in each decision variable. That is, heating energy consumption, cooling energy consumption, and CO_2 emission values are obtained through EnergyPlus according to a hundred different combinations, considering the alternatives and pilot regions selected from the building envelope decision variables. There are more than ten million alternative combinations in total, including pilot regions. While determining a hundred different combinations, alternatives representing all spaces should be determined, taking into account the worst and best scenarios. Once the number of alternatives is increased, the time spent on EnergyPlus will increase. Therefore, its number should be kept at a reasonable level.

According to the results obtained with EnergyPlus, the most appropriate input decision variables are determined for each related parameter by applying the CfsSubsetEval approach. A comparison of results with and without CfsSubsetEval is shown in Table 3. Random Forest is applied to compare the results. The decision variables determined as a result of the tree structures obtained are shown in Table 4. Decision variables obtained as a result of feature subset selection will be used to develop ANN models.

Table 1. Building envelope decision variables for the case study.

Materials and Thickness [mm]	Material Features		Materials and Thickness [mm]	Material Features	
External Plaster [10-20-25]	Cost ($/m^2)	λ (W/mK)	Internal Plaster [10-20-25]	Cost ($/m^2)	λ (W/mK)
Lightweight aggregate plaster	15	0.23	Lightweight aggregate plaster	15	0.23
Sand-cement mortar	10	0.72	Sand-cement mortar	10	0.72
Perlite-plaster	20	0.08	**Roofing finishes [10-15-20]**	**Cost ($/m^2)**	**λ (W/mK)**
Insulation material [20-30-50-70]	**Cost ($/m^2)**	**λ (W/mK)**	Glass-wool	30	0.036
Glass-wool	30	0.036	Stone-wool	25	0.038
Polyurethane-rigid foam	40	0.026	**Glazing type**	**Cost ($/m^2)**	**λ (W/mK)**
Stone-wool	25	0.038	PVC joinery 3-chambered double glazed 6mm/6mm	35	2.4
Wood-fibred	10	0.043	PVC joinery 5-chambered double-glazed 3mm/13mm	50	1.798
Wall material [100-200-300]	**Cost ($/m^2)**	**λ (W/mK)**	PVC joinery 5-chambered double-glazed 6mm/13mm	65	1.772
Aerated concrete	100	0.15	window/wall ratio (0.30)		
Block-bims	75	0.2	window/wall ratio (0.35)		
Hollow brick	60	0.45	window/wall ratio (0.40)		

Table 2. The feature of the pilot regions.

Parameters	Units	Attributes			
Pilot Regions	–	1	2	3	4
Climate Zone No	–	1	2	3	4
Seismic Zone No	–	1	3	4	2
SRM	%	0.8	0.2	0.05	0.5
Latitude	(°)	38.3949	40.9113	39.9727	39.9058
Longitude	(°)	27.0819	29.1558	32.8637	41.2544
Altitude	(m)	29	18	891	1860
PGA	(m/sec^2)	$PGA \geq 4$	$0.3 > PGA \geq 0.2$	$0.2 > PGA \geq 0.1$	$0.4 > PGA \geq 0.3$
# of Earthquake $(\mathbf{4 \leq M_x < 5})$	earthquake/50 years	69	38	14	34
# of Earthquake $(\mathbf{5 \leq M_x < 6})$	earthquake/50 years	38	13	10	37
# of Earthquake $(\mathbf{6 \leq M_x < 7})$	earthquake/50 years	3	0	0	4
# of Earthquake $(\mathbf{7 \leq M_x})$	earthquake/50 years	0	1	0	1
# of Earthquake $(\mathbf{4 \leq M_x})$	earthquake/50 years	110	52	24	76

Table 3. The feature of the pilot regions.

		With CfsSubsetEval	Without CfsSubsetEval
Heating	**R**	0.964	0.961
energy	**MAE**	2566.600	3493.791
consumption	**RMSE**	4203.605	4910.223
Cooling	**R**	0.995	0.955
energy	**MAE**	2566.600	2418.435
consumption	**RMSE**	4203.605	3321.873
CO_2 emission	**R**	0.956	0.928
	MAE	405.367	526.524
	RMSE	510.462	675.785

Table 4. Reduced decision variables with feature subset selection.

Heating Energy Consumption	Cooling Energy Consumption	CO_2 Emission
Climate zone	Climate zone	Masonry material
Insulation material	Insulation material	Masonry thickness
Seismic zone	Seismic zone	Roof insulation material thickness
Roof insulation material thickness	Window type	Seismic zone
Window type		Insulation thickness
		Window type
		Window/wall ratio

EnergyPlus-based ANN Modeling

The number of attributes is reduced by means of the feature subset selection. Thus, it is possible to generate simpler models with fewer inputs for ANN models. Note that, since the effect of the decision variable on each input parameter may not be the same, the same input decision

Table 5. The features of ANN models.

ANN Parameters	Heating Energy Consumption	Cooling Energy Consumption	CO_2 Emission
Network type	Feedforward MLP	Feedforward MLP	Feedforward MLP
Training algorithm	BFGS algorithm	BFGS algorithm	BFGS algorithm
Number of hidden layers	One hidden layer	One hidden layer	One hidden layer
Number of input neurons	Five input neurons	Four input neurons	Seven input neurons
Number of hidden neurons	Nine hidden neurons	Eight hidden neurons	Seven hidden neurons
Number of output neurons	One output neuron	One output neuron	One output neuron
Rate of training data	70%	70%	70%
Rate of testing data set	30%	30%	30%
Hidden layer transfer function	Tanh	Logistic	Exponential
Output layer transfer function	Tanh	Tanh	Linear
Training correlation	0.991878	0.976179	0.987460
Testing correlation	0.992607	0.974807	0.978744

variables are not taken into account in ANN models. Therefore, instead of generating a single ANN model, three different models are produced for heating energy consumption, cooling energy consumption, and CO_2 emission.

The Model Structures

According to Table 4, five, four, and seven input neurons are used for heating energy consumption, cooling energy consumption, and CO_2 emission, respectively. For the ANN training processes, a hundred-data set determined in the previous step is used. For each ANN model, feedforward MLP is used as the network structure. As the training algorithm, the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm is preferred. A single hidden layer is used. *Linear*, *logistic*, *tanh*, and *exponential* functions are considered for the transfer functions. The number of neurons in the hidden layer is relaxed between 3–11, 3–10, and 4–12 for heating energy consumption, cooling energy consumption, and CO_2 emission, respectively. In order to determine the best ANN model for each output parameter, the training algorithm is run 1000 times using the STATISTICA64® package program. The properties of the ANN models generated by obtaining the most appropriate weights are shown in Table 5.

Sensitivity Analysis

The significance levels of the decision variables for each ANN model are analyzed and given in Table 6. Here, it is observed that earthquake zones are as important as climatic zones. In fact, it is interesting to see that earthquake zones are more important than insulation criteria.

Table 6a. The sensitivity analysis results of the decision variables for the heating energy consumption.

Heating Energy Consumption			
Decision Variables	Importance Levels	Weights	Rank
Climate zone	48.125	0.533	1
Insulation material	5.458	0.060	4
Seismic zone	25.592	0.283	2
Roof insulation material thickness	6.161	0.068	3
Window type	4.937	0.055	5

Table 6b. The sensitivity analysis results of the decision variables for the cooling energy consumption.

Cooling Energy Consumption			
Decision Variables	Importance Levels	Weights	Rank
Climate zone	20.431	0.379	2
Insulation material	2.278	0.042	4
Seismic zone	24.891	0.461	1
Window type	6.352	0.118	3

Table 6c. The sensitivity analysis results of the decision variables for the CO_2 emission.

CO_2 Emission			
Decision Variables	Importance Levels	Weights	Rank
Masonry material	1.075	0.030	7
Masonry thickness	13.669	0.377	1
Roof insulation material thickness	8.743	0.241	2
Seismic zone	4.586	0.127	4
Insulation thickness	2.215	0.061	5
Window type	1.188	0.033	6
Window/wall ratio	4.770	0.132	3

The Building Envelope LCA Analysis

In this step of the study, LCA approach is applied for energy-efficient building envelope designs. The LCA parameters are the cost of materials used in the building envelope, earthquake-based repair cost, embodied carbon, heating energy consumption, cooling energy consumption, and CO_2 emission for the case study. Since the analysis of many alternatives and criteria with energy simulation programs is time-consuming, ANN models are developed. On the other hand, since the cost of materials, earthquake-based repair cost, and embodied carbon values are material-oriented and can be easily calculated, there is no need to develop an estimation model. The material cost consists of building envelope and window costs. Exterior plaster, insulation, masonry, and interior plaster materials affect the cost of the building envelope. Since window/wall is a decision variable, the building envelope and window surface area are not constant (Table 1). For 30%, 35%, and 40% window/wall ratios, the building envelope surface area is 210 m^2, 195 m^2, and 180 m^2, and window surface area is 90 m^2, 105 m^2, and 120 m^2, respectively. Building envelope and window costs are investment costs. Other LCA parameters are costs incurred over the economic life cycle of the building. Since the LCA approach is cost-based, each parameter must be converted to cost. The embodied carbon is carbon emissions that occur during the entire life cycle of materials (from production to consumption). The earthquake-based repair cost depends on the material cost, the magnitude of the earthquake, and the probability of earthquakes that could damage the building envelope. If we take into account the risk of earthquakes for each year during the lifespan of the building, the earthquake-based repair cost should also be converted to present value. In addition, the costs of energy consumption, CO_2 emissions, and embodied carbon are also converted to present value. Therefore, the present worth factor (PWF) should be calculated. Eqs. (1) and (2) are used to calculate the PWF. The LCA equation is given in Eq. (3). The parameters used for the LCA approach are shown in Table 7.

$$PWF = \frac{(1+i^*)^N - 1}{i^* \cdot (1+i^*)^N} \tag{1}$$

$$i^* = f(x) = \begin{cases} \dfrac{i-g}{1+g}, & i > g \\ \dfrac{g-i}{1+i}, & i < g \end{cases} \tag{2}$$

where, i^* is the interest rate adapted for inflation, N is the lifespan, i is the interest rate, and g is the inflation rate.

$$\begin{aligned} LCC_i = {} & \sum_{k=1}^{4} (ESA \cdot EC + WSA \cdot WC) \cdot SRM_k \cdot PoE_{ik} \\ & + ESA \cdot EC + WSA \cdot WC + (HEC \cdot AHEC \\ & + CEC \cdot ACEC + CC \cdot ACC + ECA \cdot ECAC) \\ & \cdot PWF \quad \text{for } i = 1, \ldots, 4. \end{aligned} \tag{3}$$

For the earthquake-based cost, four different earthquake zones are determined in Turkey. The earthquake zones are defined on the expected peak ground acceleration (PGA) for a return period of 475 years (10% exceedance in 50 years) [34]. In 2018, Turkey's earthquake zones map was renewed by Turkey Disaster and Emergency Management Authority (AFAD) [35]. In the new map, the earthquake zones are separated according to the PGA values. In this study, for the PoE, the number of earthquakes with $M_x \geq 4$ between 1970 and 2020 (50 years) is taken into account in each region. Since it has been observed that earthquakes whose magnitudes are 4 and greater than 4 have damaged the buildings in Turkey, $M_x \geq 4$ has been considered. The SRM is assumed as 20%, 50%, 80%, and 100% for significant local damages of many components ($4 \leq M_x < 5$), extensive damages of many components ($5 \leq M_x < 6$), extensive widespread damages ($6 \leq M_x < 7$), and complete widespread damages ($7 \leq M_x$); respectively [81]. For the application, the probability of at least one earthquake occurring in a year is calculated. Since earthquakes commonly follow Poisson distribution [36], the earthquake probability for the magnitude j in each region is calculated with Eq. (4). Accordingly, for instance, the probability of at least one earthquake is $1 - PoE_{1,M_x \geq 4}(X = 0) = 0.8892$ for region-1.

Table 7. LCA parameters.

Symbols	Definitions	Symbols	Definitions
LCC_i	Life cycle cost for pilot region-i (i = 1,…,4)	HEC	Heating energy unit cost
ESA	Envelope surface area	AHEC	Annual heating energy consumption
EC	Envelope unit cost	CEC	Cooling energy unit cost
WSA	Window surface area	ACEC	Annual cooling energy consumption
WC	Window unit cost	CC	Carbon emission unit cost
SRM_k	The seismic repair multiplier for the earthquake magnitude-k (k = 1, … ,4)	PoE_{ik}	The probability of the earthquakes with a magnitude of k in region i
ACC	Annual cooling emission	ECA	Embodied carbon amount
PWF	Present worth factor	ECAC	Embodied carbon amount unit cost

$$PoE(x) = \frac{e^{-\lambda} \cdot \lambda^x}{x!} \tag{4}$$

where, e is Euler's number. λ represents the average (expected) number of earthquakes in unit period. x is the number of earthquakes occurring in unit period.

As a result, a thousand different alternatives were generated to calculate the accuracy of the results obtained with the LCA approach. A thousand different combinations were applied manually in EnergyPlus. Since it is almost impossible to manually enter all combinations into EnergyPlus, randomly selected a thousand different combinations

Table 8. Summary table.

	EnergyPlus	Proposed Methodology	Error (%)	Accuracy (%)
Maximum ($)	14523.19	14002.19	0.0359	0.9641
Minimum ($)	10023.21	10481.01	0.0457	0.9543
Mean ($)	12102.38	12472.26	0.0306	0.9694

were evaluated. A summary of the results obtained is presented in Table 8.

CONCLUSIONS

Energy-efficient building designs have an important strategic position for developing countries such as Turkey that need energy imports. The most important component of energy-efficient building designs is energy-efficient building envelopes. A broad perspective is presented that takes into account energy consumption, indoor comfort, and environmental effects. By applying LCA analysis, heating, cooling energy consumption, CO_2 emission, material cost as well as embodied carbon, and earthquake-based cost are also taken into account. Interior plaster, wall insulation, roof insulation, wall, exterior plaster, material thicknesses, window, window/wall, climate, and earthquake zones are considered for the decision variables. Significance levels of decision variables for heating energy consumption, cooling energy consumption and CO_2 emissions were determined. According to the results obtained, it is observed that the earthquake zones have a remarkable effect. In future studies, the scope of the study can be expanded by using metaheuristic approaches such as GA and PSO, which can scan the entire alternative solution space.

CONFLICT OF INTEREST

All financial, commercial or other relationships that might be perceived by the academic community as representing a potential conflict of interest must be disclosed. If no such relationship exists, authors will be asked to confirm the following statement:

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

A standard statement.

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