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Green building envelope designs in different climate and seismic zones: Multi-objective ANN-based genetic algorithm

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A R T I C L E I N F O

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A B S T R A C T

In recent years, the major component of green building designs adopted by governments in order to reduce CO_2 emissions as well as energy consumption is the green building envelope. The green envelope has the most important share in terms of thermal energy consumption, environment, and indoor comfort criteria. Determining the most suitable building envelope combination in the building life cycle is an important problem for designers. This study presents a new multi-objective approach that determines the most suitable green envelope designs for the buildings in different climate and earthquake zones, taking into account CO_2 emissions, heating/cooling energy consumption, and material cost in terms of life cycle cost analysis. To this end, EnergyPlus building performance simulation program, artificial neural network (ANN), and genetic algorithm are used together. After the heating and cooling energy consumption, CO_2 emissions, and material cost values are obtained for a certain number of the envelope alternatives with the EnergyPlus, ANN models that learn the working mechanism of EnergyPlus are trained according to these values. An ANN-based genetic algorithm procedure is developed to search the whole envelope alternative space by using the trained ANN models with EnergyPlus. The proposed approach allows searching in a very short time the whole alternative space, which is almost impossible to scan with EnergyPlus by reducing the time spent and the number of alternatives required for the design and simulation processes of the green building envelope. The proposed approach is performed for a design-stage city hospital structure in Turkey. Window type, the internal/external plaster, wall, and insulation materials along with the thicknesses of these materials, which consist of 46 different variables, are determined as envelope attributes for four different climate and seismic zones. The green building envelope designs obtained with the proposed approach are entered into EnergyPlus and the consistency of the results is compared. ANN models with an average accuracy of over 97% are developed. Without the CO_2 emission cost in the life cycle cost, the mean absolute percent error (MAPE) values for each region are 0.67%, 0.6%, 0.58%, and 1.78%, respectively. With the CO_2 emission cost in life cycle cost, the MAPE values for each region are 0.96%, 0.88%, 0.86%, and 0.43%, respectively. According to the obtained results, there is a consistency of over 99% between EnergyPlus and the proposed approach.

Introduction

Building construction and operations accounted for 36 % of global final energy consumption and 39 % of global energy-related CO_2 emissions in 2017 according to the research of the International Energy Agency (IEA) [1]. It is projected that these values will increase even more in the future. Therefore, green or sustainable buildings have become one of the most essential policies in terms of thermal (heating/cooling) energy consumption and CO_2 emission for the governments. A green building is a practice of constructing the building providing more resource efficiency and leading to fewer environmental effects during the life cycle of the buildings [2]. Green buildings consider main issues such as efficient use of water and energy, renewable energy, pollution, reducing CO_2 emission, indoor comfort, and use of materials that are non-toxic [2,3]. One of the most basic components of green buildings is the green design of the building envelope. The green envelope designs have the most important share in terms of heating/cooling energy

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Nomenclature

Abbreviation

ANN	Artificial neural network
BFGS	Broyden-Fletcher-Goldfarb-Shanno
CO_2	Carbon dioxide
eps	Expanded polystyrene foam
ETS	Emission trading system
GA	Genetic algorithm
HVAC	Heating, ventilating and air conditioning
lacb	Lightweight aggregate concrete block
LCC	Life cycle cost
LCCA	Life cycle cost assessment
MAPE	Mean absolute percentage error
MLP	Multi-layer perceptron
nacb	Normal aggregate concrete block
PGA	Peak ground acceleration
pur	Polyurethane-rigid foam
pvc	Polyvinyl chloride
SRM	Seismic repair multiplier
TS 825	Thermal Insulation Requirements for Buildings
xps	Extruded polystyrene foam

Symbols

U	Thermal transmittance coefficient (W/m^{2}k)
A_i	Total surface areas of the external wall (1) and window (2) (i=1, 2) (m^2)
B_i	Unit costs of the building envelope (1) and window (2) (i=1, 2) (m^2)
C	Unit price of energy consumption ($/kwh)
D	Annual heating and cooling energy consumption (kwh)
d	Thickness of the material
E	Unit price of the ETS ($/kgco$_2$)
F	Annual CO_2 emission (kgco$_2$)
g	Inflation rate
I	Input gene
i	Interest rate
i^*	Interest rate adapted for inflation
N	Lifespan
O	Output gene
PWF	Present worth factor (year)
R	Thermal transmittance resistance
r	Correlation coefficient
U_d	Envelope thermal transmittance limit (W/m^{2}k)
U_w	Window thermal transmittance limit (W/m^{2}k)
Y_{ANN}	ANN output value
Y_{sim}	EnergyPlus output value

Greek symbol

λ_h	Thermal conductivity coefficient (W/mK)

Subscript

$\mathscr{F}$	Transfer function
hn	Hidden neuron
in	Input neuron
ip	Input parameter
on	Output neuron
op	Output parameter
Wih	Input-hidden weight
Wno	Hidden-output weight

consumption, CO_2 emission, pollution, and indoor comfort criteria. Thus, the green envelopes of the buildings can provide important benefits in terms of environmental, economic, and social.

Governments have recently attached importance to environmental policies and initiatives such as the Paris Agreement and the Kyoto Protocol to control carbon emissions besides their energy consumption [4]. One of these policy tools is the carbon emission trading system (ETS) allowance price widely preferred as a carbon pricing initiative. ETS has been recently used by many countries such as Germany [5], the USA (California), Switzerland, and South Korea [6] to price the carbon emissions caused by the heating and cooling energy consumption of buildings. Considering these situations, it will become an essential requirement in the future to design insulation systems for sustainable buildings by including CO_2 pricing, building envelope material, and thermal energy consumption costs in the life cycle cost assessment (LCCA).

The most important input attributes for designing a green building in terms of thermal insulation are the climate characteristics of the region and the building envelope. It would not be the proper approach to apply the same thermal insulation policy to all climate zones. One of the most basic thermal strategies according to the climate characteristics is building envelope. The building envelope, which separates the building from the external environment, generally consists of plaster, wall, and insulation material. The thickness and thermal conductivity (λ_h) value of the building envelope are the primary criteria ensuring thermal balance in the building according to each climate zone and affecting energy consumption as well as CO_2 emission. In fact, although another input attribute while determining the building envelope materials for the LCCA is seismic zones, the seismic zone where the building will be built is often neglected in energy-efficient and green building envelope designs. Depending on the specific geographic area in which it is located, a building may be subject to different levels of structural deformation as it can potentially be attacked by exposure to natural hazards such as earthquakes [7]. These deformations adversely affect the energy efficiency of the building envelope. Accordingly, this paper presents a perspective that simultaneously considers CO_2 emission, heating/cooling energy consumption, and material cost in designing the green building envelopes according to the different climate and seismic zones.

There are three main categories in building energy analysis [8]: Engineering calculations, numerical simulations, and machine learning. The engineering calculation approach calculates the heating and cooling energy consumption by using physics laws and formulae. Since the mathematical solution process is quite intense in large and complex buildings, the approach is too difficult to implement. There are comprehensive literature studies that consider engineering calculations of the building envelope [9–15].

The numerical simulation approach is a detailed methodology in which physical rules are applied by computer programs in order to simulate the building energy consumption. It allows detailed analyses of complex buildings for energy consumption. It has advantages for limited building envelope designs determined by the decision-maker(s). Crawley et al., [16], Sadineni et al., [17], and Mirsadeghi [18] presented a detailed review that considers many building energy performance simulation programs used in the literature. In the literature, there are many studies about the energy simulation for the building envelope [19–24].

With the development of technology, however, the range and properties of the materials to be used for the building envelope have considerably diversified. In terms of simulation programs, it is almost impossible to choose the most suitable building envelope configuration among the many building envelope alternatives to design a green and energy-efficient building within a reasonable time frame. Therefore, advanced approaches are required because simulation programs are insufficient to evaluate many building envelope combinations. The machine learning approach can make many analyses, which is difficult for conventional approaches in terms of building energy consumption, more easily and in a shorter time. Machine learning techniques have been widely used in building energy analysis to predict energy demand by analyzing weekly, daily, or even hourly consumption data such as the heating, cooling, and lighting according to information such as weather conditions, population, and usage density. Supervised classification, regression, and optimization-based techniques are widely preferred [25–33]. In particular, in building energy analysis problems that have big-volume data, it may be almost impossible to obtain output manually according to many input attributes. However, a certain amount of data is properly trained using machine learning approaches in order to perform these analyses. As a result of the training, the tendency of building energy consumption, the characteristics affecting the building energy consumption, and different previously unknown patterns are determined. The outputs obtained with the trained data are compared with the actual outputs and the performance of the method is analyzed. Thus, a mechanism is generated that can give an idea about the energy consumption analysis of the building. Recently, among many machine learning techniques, artificial neural network (ANN) has been widely used in optimizing the design of an energy-efficient building [8]. It can help decision-makers such as architects and engineers make a preliminary estimation of building energy performances by using several simple input attributes for selecting the building envelope in the early stage of design. ANN can be adopted to predict the whole solution space, calculated by means of time-consuming simulations [34]. It saves modeling time by increasing the efficiency of the architectural design, and eliminates the disadvantages of simulation programs, especially when used with simulation programs. Thus, thermal insulation outputs for climate and building envelope inputs can be produced in a reasonable time. In the literature, there are a number of ANN and metaheuristic studies that analyze the impacts of building envelope materials on the thermal performance of buildings. Sambou et al., [35] presented a method aiming to optimize both thermal insulation and thermal inertia. They applied the genetic algorithm (GA) code developed by Leyland [36] and Molyneaux [37] and used the quadrupoles method in order to calculate the thermal capacitance as a way to quantify the inertia of the wall. Ahmad et al., [38] proposed supervised data mining models that forecast the short and medium-term horizon cooling loads for building energy optimization and management. Zemella et al., [34] proposed an evolutionary neural network model considering carbon emission, cooling, and artificial lighting for an energy-efficient building façade. They considered visual area, horizontal overhang, vertical fins, and glass type as façade variables. Although they decreased the space to be scanned, they calculated 1,500 different alternatives by using EnergyPlus among 193,500 alternatives, which is too many numbers for large and complex buildings. Ahmad et al., [39] compared random tree and ANN for high-resolution prediction of building energy consumption. They estimated the hourly heating, cooling, and air conditioning (HVAC) energy consumption of a hotel in Spain by incorporating social attributes such as the number of guests. Devi and Manonmani [40] developed fuzzy back propagation neural network consisting of fifty-one inputs and twenty-four outputs for forecasting short-term electricity prices. The fuzzy-BPNN model presented a better solution compared to Multi-Layer Perceptron (MLP). Hawkins et al., [41] generated an ANN model using energy data of buildings located at London University. Son et al., [42] predicted the energy consumption of government-owned buildings by generating an ANN model. They analyzed and validated 175 sets of data derived from the 2003 ‘Commercial Building Energy Consumption Survey’ database by considering 26 different variables. Mishra and Singh [43] proposed an ANN structure based on Windowed Momentum Algorithm in order to forecast monthly energy consumption using previous three-year monthly weather information and energy data. Deb et al., [44] compared an ANN and a multi-layer regression model to estimate HVAC-related energy consumption for pre- and post-retrofitted office buildings. They assessed 14 building and system level variables for 56 office buildings. Dong et al., [45] evaluated the energy consumption and cost of an office building in a severely cold region by coupling the EnergyPlus, Grasshopper, and ANN toolbox of MATLAB. They considered eleven variables consisting of façade window to wall ratio and wall insulation materials as input attributes. Caglayan et al., [46] utilized the GA in order to determine the most suitable thickness of insulation material and window type according to the climate regions. They aimed to minimize material costs and heating energy consumption. Just one type of insulation material was used for the ceiling, basement, and exterior walls. Nine window types were analyzed. Fifteen different thicknesses of expanded polystyrene for exterior walls, twenty different thicknesses of stone wool for the ceiling, and twenty different thicknesses of extruded polystyrene for the basement floor were analyzed. Wu et al., [47] proposed a process-based LCCA structure for office buildings in China. They conducted the LCCA by defining and quantifying both energy consumption and CO_2 emissions according to The Environmental Protection Agency, the International Organization for Standardization, and The Society of Environmental Toxicology. Tuhus-Dubrow and Krarti [48] presented a simulation–optimization tool by using a GA and a building energy simulation engine together in order to optimize building envelope design in residential buildings. They considered the building envelope features and building shapes. Nejat et al., [49] presented a global review of energy consumption, CO_2 emissions, and policies for the residential building sector. Ahmad et al., [50], D'Amico et al., [51], Mohandes et al., [52], and Kheiri [53] presented a detailed and comprehensive review of applications of ANN in order to forecast and analyze building energy consumption. In the literature, however, the sole paper that considers the earthquake effect on the life cycle cost (LCC) of energy-efficient buildings was published by Liu and Mi [54]. They analyzed the LCC for two different window types by taking into account a single seismic zone. They used EnergyPlus, one of the numerical simulation approaches.

In recent years, thermal energy storage methods have become quite popular as well as building envelope designs for energy-efficient building designs. In the literature, there are many studies on methods such as liquid storage, solid storage, seasonal storage, chemical storage, and storage in phase change materials [77–81]. In particular, methods using phase change materials may be useful for engineering applications of the building envelope.

Although the aforementioned studies show that determining building envelope design is common in the literature, the scope of this study is different. To the best of our knowledge, there is no multi-objective study that takes into account CO_2 emissions, heating and cooling energy consumption, and material cost to design a green building envelope according to different climate and seismic zones.

This paper proposes a multi-objective and holistic approach in terms of the LCCA of the green building envelope by focusing on energy efficiency, environmental pollution, indoor comfort, and material usage in green buildings. For the LCCA of the building envelope, heating and cooling energy consumption, CO_2 production caused by energy consumption, and building envelope material cost are considered together. It is aimed to determine the most suitable green building envelope in order to ensure thermal comfort and structural sustainability of the buildings to be built in different climatic (thermal insulation) and seismic zones. First, the heating and cooling energy consumption, CO_2 emission, and the building envelope material cost values are obtained for a certain number of building envelope alternatives with the EnergyPlus simulation program. Then, three separate ANN models are trained according to heating/cooling energy consumption, CO_2 emission, and material cost values calculated for a certain number of building envelope alternatives by the EnergyPlus in order to analyze all building envelope combinations. Finally, the most suitable building envelope configurations giving the minimum building envelope LCC for each region are determined by using the ANN-based GA model. This proposed approach enables the determination of the most suitable envelope combinations by easily scanning alternative combinations that are

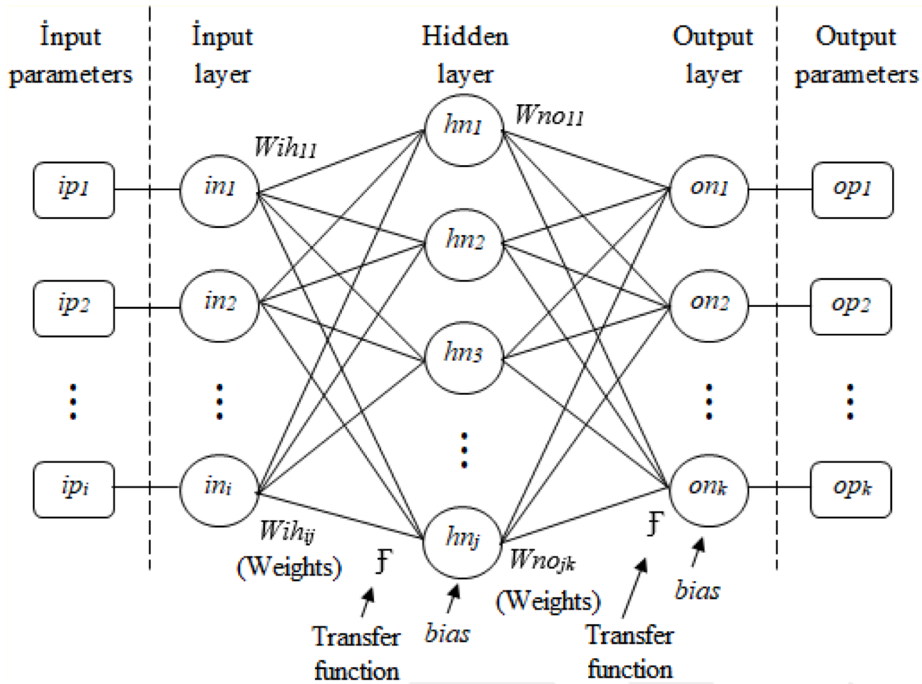


Fig. 1. A general ANN structure.

almost impossible with EnergyPlus. The proposed approach is performed for pilot regions in a case study. It is observed that there is an average of over 97 % correlation between inputs and outputs for the three separate ANN models. Moreover, without the CO_2 emission cost in the life cycle cost, the mean absolute percent error (MAPE) values for four regions are 0.67 %, 0.6 %, 0.58 %, and 1.78 %, respectively. In addition, with the CO_2 emission cost in life cycle cost, the MAPE values for each region are 0.96 %, 0.88 %, 0.86, and 0.43 %, respectively. According to the obtained results, there is a consistency of over 99 % between EnergyPlus and the proposed approach.

The remainder of the paper is as follows: Section 2 includes materials and methods to be utilized in the study. In Section 3, the proposed model is defined in detail. An application of the proposed approach is presented for a public building in Section 4. Finally, Section 5 includes the conclusion and future work.

Materials and methods

Artificial neural network

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use [55]. The basic structure of ANN is inspired by the transmission of information in nerve cells called neurons. According to Haykin [55], the ANN structure resembles the brain in two respects. First, knowledge is obtained by a network by means of a learning procedure. Second, the connection among the neurons is provided through synaptic weights which are used to store the knowledge. ANN models mostly have three different layers; input, hidden, and output layers. The input layer consists of input neurons representing the independent input variables. The output layer consists of output neuron(s) representing the dependent output variables. The number of hidden layers and the number of neurons in the hidden layer may vary according to the characteristics of each model and data set. The information transmission between layers is provided by network structures such as feedforward and feedback. Transfer functions are used to transfer information between neurons. There are many transfer functions such as exponential, gaussian, hyperbolic-tangent, linear, logistic (sigmoid), polynomial, and radial basis functions. The most important step for ANNs is the learning process of the ANN structure. Training algorithms are used to accurately model the patterns between the available inputs and outputs. The weight value of each neuron is determined by the training algorithm. The more consistently the training algorithm calculates these weights, the better the model will perform in terms of output(s). Many training algorithms have been used in the literature [82]. Detailed technical information and the basic concept of an ANN can be found in Refs. [8,83,84]. A general ANN structure is shown in Fig. 1.

The simulation program is run hundreds or even thousands of times to obtain appropriate results with an optimization method integrated with the simulation program. Running the simulation for each result is computationally time-consuming. For this reason, it is an effective approach to create structures that learn the working mechanism of the simulation in order to obtain faster results and make optimization methods work faster. The ANN is one of the most suitable methods to recognize the complex patterns between inputs (building envelope and climate attributes) and outputs (material cost, CO_2 emission, and heating/cooling energy consumption) by integrated into EnergyPlus' working structure. The ANN provides effective solutions to linear and nonlinear complex problems for which traditional mathematics and methodologies cannot find an acceptable solution. The ANN, which enables a mathematical relationship between input and output values by using a series of real numbers called weights and bias, is widely used in nonlinear pattern recognition processes and offers successful results. Therefore, the ANN can be adopted to predict the whole solution space, calculated by means of time-consuming simulations [34]. In particular, it provides the advantages such as time-saving and simplicity for decision-makers, when used with simulation programs. Thus, thermal insulation outputs for climate and building envelope inputs can be produced in a reasonable time.

Classic Genetic Algorithm

GA is a *meta*-heuristic search algorithm that mimics the evolution theory. It is based on the process of natural selection among individuals. It is based on the principle of producing the fittest individuals by transferring good genes from a generation to the next generation. The

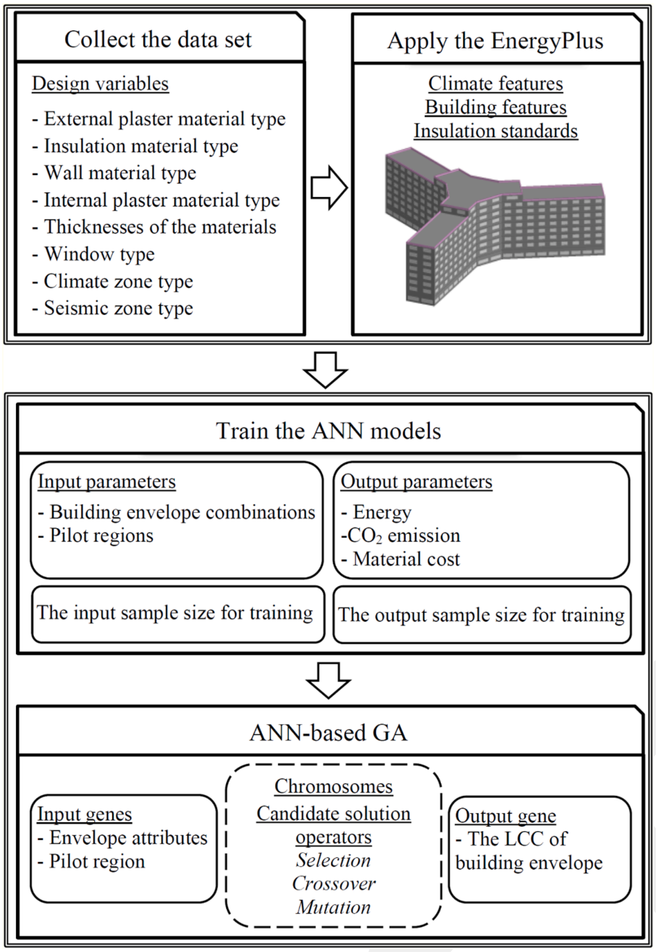


Fig. 2. Flowchart of the proposed approach.

GA simulates the process of determining the chromosome structure made up of the best genes to produce the fittest individuals. It is utilized in order to optimize a specific fitness function in both unconstrained and constrained optimization problems.

The main characteristics of a GA are as follows [56]:

- The GA uses probabilistic transition rules, not deterministic ones.
- For the search, the GA focuses on a solution space, not a single solution.
- The GA works with the coding of the parameter set, not the parameters themselves.
- The GA uses payoff information, not derivatives.

The GA utilizes operators such as crossover and mutation to generate new chromosomes that optimize the fitness function. Crossover is the most significant phase in the GA. For each pair of parents to be mated, a crossover point is randomly chosen among the genes. The mutation is the occasional (with a small probability) random alteration of the value of a strong position. In fact, the mutation is a process of a random walk through the coded parameter space. Its purpose is to ensure that important information contained within strings may not be lost prematurely [56]. The operators are repeated until both stop criteria and constraints are ensured to optimize the fitness function.

The GA is an important search procedure designed to solve multivariable functions such as the fitness function in this study. In the proposed model, by using ANN and GA together, the strengths of both solution structures were combined and an effective approach was presented. The problem was modeled mathematically using ANN, and then the most suitable solutions for this model were obtained with GA. The high accuracy results obtained showed that the ANN-based GA approach is very suitable for the problem addressed.

Energy simulation modeling

Energy simulation software programs are quite important in terms of decision-makers for buildings in the design phase. Decisions made in the design step for a project have a strong effect on the LCCAs of a building [57,58]. Since obtaining the heating and cooling energy consumption by trying alternative configurations is almost impossible in time and cost respects, building energy simulation programs can be effectively and efficiently utilized for analyzing alternative building systems in terms of building heating and cooling demand/consumption. Building energy simulation programs consist of mainly-three tools: modeling, designing, and analysis [59]. Simulation programs that simultaneously include these three tools are very useful for evaluating the performance-based designs of buildings. In order to obtain consistent and efficient results from simulation programs, the climatic characteristics of the region, and the materials to be used in the building should be introduced to the simulation program in detail. Although they have advantages in evaluating a limited number of alternative configurations, evaluating a large number of alternatives is very difficult in terms of data entry and time.

In this study, the EnergyPlus simulation program, which is widely preferred in the literature, was used. The DesignBuilder interface was used to design the building and enter the data into EnergyPlus. It is a whole building energy simulation program, which can be used in order to model building energy consumption and CO_2 production. It is an open-source and no charge program funded by the U.S. Department of Energy's Building Technologies Office. It has a detailed climate and material library. Moreover, in terms of thermal comfort, it provides a detailed analysis by taking into account the human density and metabolism in the buildings.

Proposed approach

The proposed approach presents a holistic structure in terms of LCC to design a green building envelope. Considering heating and cooling energy consumption, building envelope cost, and CO_2 production cost caused by energy consumption, it is aimed to choose the most suitable envelope configuration for different seismic and climate zones in terms of building sustainability and thermal comfort. The proposed approach consists of two main stages with sub-stages. These are 'Stage 1: Simulation Modeling' and 'Stage 2: ANN-based GA Modeling'. In the simulation modeling stage, the heating and cooling energy consumption, CO_2 emission, and material cost values are obtained for a certain number of building envelope alternatives with the EnergyPlus simulation program. The ANN modeling stage presents a GA model based on three separate ANN models in order to determine the best building envelopes for pilot regions according to the data set obtained in the first main stage. The flowchart of the proposed approach is shown in Fig. 2. I_i is input gene in Fig. 2 ($i = 1, \ldots, 10$). I_1, I_2, I_3, I_4, I_5, I_6, I_7, I_8, I_9, and I_{10} represent external plaster, the thickness of the external plaster, insulation material, the thickness of the insulation material, wall material, the thickness of the wall material, internal plaster, the thickness of the internal plaster, window type, and the pilot region, respectively. O represents the output gene. It is the fitness function minimizing the LCC of the building envelope according to related ten input genes.

The first stage includes data collection and EnergyPlus simulation. The second stage consists of training the ANN models and determining the most suitable building envelope for each pilot region with the ANN-based GA model. In this section, each step of the proposed approach will be described in detail.

Stage 1: The simulation modeling stage

Step-1 Collect the dataset: This step consists of two main sets of design variables: building envelope attributes and pilot regions. The building envelope attributes will be the input attribute for the ANN models along with the pilot regions. The pilot regions include two main features. These are climate and seismic zone features. The building envelope attributes consist of the window type, external plaster material, insulation material, wall material, internal plaster material, and these materials' thicknesses. There is a direct relationship in terms of building energy consumption between the thermal transmittance (U) of the building envelope and climate zones. For each climate zone, the building envelope to be used in the building must be below a certain U value. The λ_h value and unit cost of each material are considered while the building envelope is determined for each climate zone. Furthermore, the material seismic repair multiplier (*SRM*) is taken into account for potential material damage according to seismic zones. This multiplier can change according to the danger in the seismic zone. The *SRM* is multiplied by the material cost and added as the material repair cost.

The content of the data set to be used for the input attributes depends on the decision-maker(s). However, it is important to determine the data set for each design, taking into account the market, standards, and rules in the related region. For instance, the building envelope materials have a wide range of products in the world. According to related regions, the availability and supply of materials may differ. In addition, in real applications, a data set should be generated according to the limits and materials allowed by the local governments and global organizations. The use of each material may not be suitable for each climate and seismic zone. Therefore, it is an important requirement to collect an appropriate input dataset. The proposed approach is flexible in terms of attribute selection and data volume. In Section 4.1.1, the attributes of climate, seismic, and building envelope will be described in detail for an application study.

Step-2 Apply the EnergyPlus: The main aim of this step is to obtain energy consumption, CO_2 production, and building envelope cost data using the EnergyPlus program in order to generate good ANN models. In this step, first, the building was designed on DesignBuilder. Building features were entered into the program in detail. Second, the pilot regions were selected among the climate zones determined in Step-1. Then, m different building envelope combinations were generated according to the building envelope attributes for each pilot region-i ($i = 1, \ldots, n$). Finally, these combinations were simulated for obtaining CO_2 production, envelope material cost, and heating/cooling energy consumption. Note that, the number of envelope combinations to be used for simulation is decided by the designer(s) and decision-maker(s). The ANN model may not represent the whole space to be scanned well if m is kept low. On the other hand, if m is kept too high, more time is spent on the simulation process.

Thermal comfort in buildings is highly related to human health as well as productivity. Thermal comfort is the condition of the mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation [60]. Thermal comfort should be equally provided in every zone of the building. Thermal comfort levels differ for residences, office buildings, and hospitals. EnergyPlus presents the heat balance-based solution that performs condensation calculations in order to ensure indoor thermal comfort. Therefore, occupancy density, metabolic evaluations, and heating–cooling set-points required for the thermal comfort of the building are performed in EnergyPlus.

Stage 2: ANN-based GA modeling stage

Step-1 Train ANN Models: This step aims to generate a prediction structure that considers the simulation model. As the material alternatives that can be used in the building envelope diversify, it becomes difficult to determine the most suitable building envelope combination through simulation. Since the number of envelope configurations to be simulated will increase, analyzing whole envelope combinations in simulation programs will require time-consuming and detailed data entry. Therefore, the ANN structures, which can easily scan the entire alternatives within a reasonable time, are modeled. ANN models are trained separately for each output dataset (heating/cooling energy consumption, CO_2 emissions, and material cost) obtained in the previous step according to the input dataset. Note that, each climate zone has a thermal transmittance limit (U_d). Therefore, any building envelope combination in the input dataset cannot be preferred for any climate zone. However, while training the ANN models for the data set generated, the U_d values of the thermal insulation zones were not considered. The U value of the building envelopes was relaxed throughout each ANN training so that the ANN models could learn the structure of the problem and all possibilities in detail.

Step-2 Determine the Most Suitable Building Envelopes: In this step, the GA is used to determine the most suitable building envelope combination in each pilot region according to the ANN models obtained in the previous step. The most suitable building envelope is defined as the envelope combination that gives the minimum LCC for the pilot regions in the proposed approach. For the GA, each building envelope attribute and climate zone represents one gene. That is, the fitness function is optimized according to a chromosome structure consisting of ten genes. The fitness function is to minimize the LCC of the building envelope including CO_2 pricing along with building envelope material cost, and heating/cooling energy consumption cost. Recently, governments have imposed a "carbon pricing" policy to control carbon emissions. Carbon pricing is usually applied in two different ways in the world: carbon tax and ETS [4]. For the buildings, it would be both a more realistic and more environmentally friendly approach to take into account material and energy costs, as well as CO_2 costs. The material cost is the capital cost that occurs during the construction phase of the building. Since the heating and cooling energy consumption costs along with CO_2 costs occur during the economic life cycle of the building, they are the long-run cost criteria. Therefore, CO_2 cost and energy consumption cost should be converted into the present worth. The fitness function ($) giving LCC of the building envelope is formulated in Eq. (1).

$$LCC = \sum_{k=1}^{2}(A_k{}^*(1+SRM)^*B_k) + C^*D^*PWF + E^*F^*PWF \tag{1}$$

where, A_1 and A_2 (m^2) are the total surface areas of the external wall and window, respectively. B_1 and B_2 ($/$m^2$) are the unit costs of the building envelope and window. *SRM* is the seismic repair multiplier. C ($/kWh) is the unit price of energy consumption, and D (kWh) is the annual heating and cooling energy consumption. E ($/kg$CO_2$) is the unit price of the ETS, and F (kgCO_2) is the annual CO_2 emission. *PWF*(year) is the present worth factor. *PWF* is formulated in Eq. (2) [46].

$$PWF = \frac{(1+i^*)^N - 1}{i^*(1+i^*)^N} \tag{2}$$

where, i^* is the interest rate adapted for inflation, and N is the lifespan. i^* is formulated in Eq. (3) [46].

$$i^* = f(x) = \begin{cases} \dfrac{i-g}{1+g}, i > g \\ \dfrac{g-i}{1+i}, i < g \end{cases} \tag{3}$$

where, i is the interest rate, and g is the inflation rate.

In this step, while a suitable building envelope was determined for each pilot region with the ANN-based GA, U_d values of climate zones were taken into account as the feasibility constraint. If the U value of a building envelope configuration is bigger than the U_d value of the climate zone containing the pilot region, the related building envelope cannot be considered for that pilot region. The proposed approach was prepared in this direction. The U value of a building envelope was formulated in Eqs. (4) and (5) [61].

Table 1
Pilot Regions.

Pilot Regions	Climate Zone No	Seismic Zone No	U_d (W/m^{2}K)	U_w (W/m^{2}K)	*SRM*	Latitude (°)	Longitude (°)	Altitude (m)	Population
1	1	1	0.7	2.4	0.80	38.3949	27.0819	29	4,320,519
2	2	3	0.6	2.4	0.20	40.9113	29.1558	18	15,067,724
3	3	4	0.5	2.4	0.05	39.9727	32.8637	891	5,503,985
4	4	2	0.4	2.4	0.50	39.9058	41.2544	1860	767,848

Table 2
The basic features and DesignBuilder model of the city hospital model.

Elements	Features
The area of each floor	2800 m^2
The area of the loft	1000 m^2
The surface area of the building	10200 m^2
The window-wall ratio	30 %
Ground floor height	4 m
Height of each floor	3 m
The roof features	20 mm gypsum plaster, 100 mm cast concrete, 20 mm wood wool, 13 mm roof screed, 19 mm asphalt
The floor features	20 mm ceramic, 50 mm screed, 150 mm reinforced concrete,
	20 mm polystyrene rigid foam, 12.5 mm cement-gypsum plaster
Internal wall features	Double-sided 13 mm gypsum, 105 mm brick

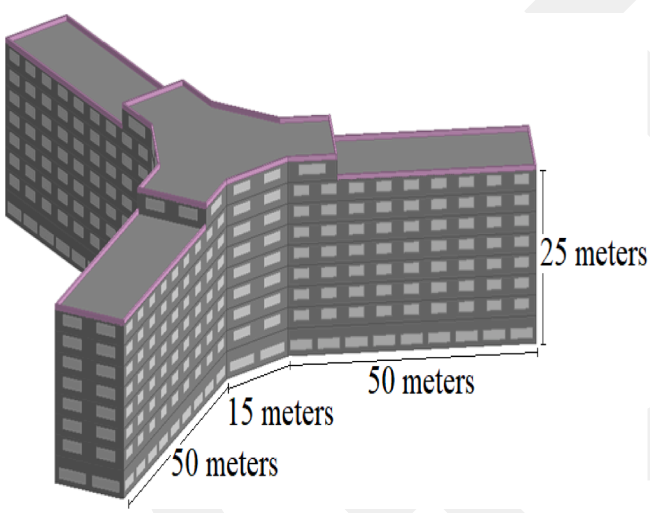


Fig. 3. DesignBuilder Model of the city hospital.

$$R = \frac{d}{\lambda_h} \tag{4}$$

$$U = \frac{1}{R_1 + \cdots + R_n} \tag{5}$$

where, d represents the thickness of the material. R is the thermal transmittance resistance of the material, λ_h is the thermal conductivity coefficient of the material, and U is the thermal transmittance coefficient of the building envelope.

An application for proposed approach

A green envelope for the buildings should have features such as reducing environmental pollution, increasing energy efficiency, providing indoor comfort, and using appropriate materials. Accordingly, the application study is focused on the relationships between the climate, building envelope, carbon emission, and heating/cooling energy consumption for 'the city hospitals project' in Turkey.

The simulation modeling stage

Collecting the data set

The materials in the Turkish market, climate, and seismic characteristics are taken into account while generating the data set for the city hospital project. Local insulation standards called "Thermal Insulation Requirements for Buildings" (TS 825) [61] are used for thermal insulation systems in Turkey. The building envelope attributes, as mentioned before, are determined as external plaster material, insulation material, wall material, internal plaster material, the thickness of these materials, and window type. The alternative materials, which can be used for the building envelope at the city hospital, are shown in Appendix-A Table A1. The alternative materials are determined by taking into account TS 825. The material types and thicknesses were determined from TS 825 material catalog by considering market research and the materials used in Turkey. The proposed approach is compatible in order to analyze different building attributes influencing the thermal energy consumption and CO_2 emission, and the materials preferred for different countries.

Turkey is divided into four different climate zones according to TS 825 [61]. The degree-day method is used to determine the climatic zones. The thermal transmittance limit of the window (U_w) and the U_d values for each climate zone are specified in TS 825. Four pilot regions are chosen to represent each thermal climate zone. In addition, each region represents a seismic zone in Turkey. Turkey Earthquake Zones Map, which entered into force in 1996, was renewed by Turkey Disaster and Emergency Management Authority (AFAD) and published in the Official Gazette dated 18 March 2018 [62]. In the new map, the seismic zones are separated according to the peak ground acceleration (PGA) values. The seismic zones are defined on the expected PGA for a return period of 475 years (10 % exceedance in 50 years) [63]. In order to analyze potential material damage caused by the earthquake, the number and magnitude of earthquakes in the past years are considered for each seismic zone where the building will be constructed. The *SRM* is assumed as 5 %, 20 %, 50 %, and 80 % for significant local damages of some components (zone-4), significant local damages of many components (zone-3), extensive damages of many components (zone-2), and extensive widespread damages (zone-1); respectively [54]. The city hospitals in the design stage have the capacity to serve not only the region where it is built but also the surrounding regions. These regions selected from climate and seismic zones, taking into account the location, population density, and demographic characteristics, are shown in Table 1.

EnergyPlus application

Designing of city hospital building. The building design defined in this study is a member of 'the city hospitals project' that will serve certain regions in Turkey. The city hospital, which has eight-story and a loft, consists of many offices, clinics, resting rooms, operating rooms, intensive care units, and laboratories. DesignBuilder model and the basic features of the building are given in Table 2 and Fig. 3, respectively.

Table 3
The ANN parameters.

Network type	Feedforward MLP
Training algorithm	BFGS algorithm
Number of hidden layers	One hidden layer
Number of input neurons	Ten input neurons
Number of output neurons	One output neuron (for each ANN)
Rate of training data	70 %
Rate of testing data set	15 %
Rate of validation data set	15 %
Hidden layer transfer function	Hyperbolic-tangent
Output layer transfer function	Logistic

Energy simulation modeling. In terms of thermal comfort, the hospital was designed to be heated up to 22 °C when the temperature drops below 19 °C and to be cooled up to 24 °C when the temperature rises above 27 °C. The density of hospital use was accepted as 0.2125 people / m^2 by considering the EnergyPlus database.

In this study, twenty-five different materials were considered for four basic building envelope layers. Once the thicknesses of materials were taken into account, the number of total building envelope combinations is 1,600,000. If these combinations are applied to each pilot region, the number of models to be simulated will be 6,400,000. It is impossible to evaluate the entire combinations by using EnergyPlus or any simulation programs in a reasonable time. In this step, the purpose of energy simulation is to obtain output data in order to train the ANN models.

In the application, a data set consisting of 200 different building envelope configurations is designed for training the ANN models. Therefore, considering each pilot region, these configurations were simulated to determine heating/cooling energy consumptions, CO_2 production caused by energy consumption, and the building envelope cost by means of the EnergyPlus simulation program. Approximately-three to five minutes were spent on each combination including data entry and simulation process. Building envelope materials and thicknesses are chosen randomly for building envelopes to be used in the simulation. However, it should be noted here that the generated data set should be a sample representing the whole solution space. Therefore, in this sample data set containing 200 different combinations, each type of material is used at least once so that the ANN structures could recognize all materials. Note that, the sample data set is only used to train three separate ANN models. Moreover, while ensuring the randomness for the building envelope attributes, the materials were used as uniformly as possible to prevent density in the use of some materials. The number of envelope combinations to be used for simulation is decided by the designer(s) and decision-maker(s). The ANN model may not represent the whole space to be scanned well if the sample data set is kept low. On the other hand, if the sample data set is kept too high, more time is spent on the simulation process. Since detailed and large buildings are taken into account in real-life problems, it is too difficult to evaluate all possibilities for decision-makers. In particular, such as in this case study, it is almost impossible to evaluate 6,400,000 different alternatives. Therefore, they want to simulate as few combinations as possible by reducing the time spent with simulation programs. The proposed approach may be a suitable decision support system for decision-makers.

The ANN-based GA modeling stage

Training ANN models

The most important contribution of the ANN structures in this study is that they obtain the results in a reasonable time by mimicking the working structure of the EnergyPlus simulation program. Accordingly, generating a good ANN structure that is suitable for the problem is very critical in order to generate consistent and robust results. Therefore, the parameters used for ANN structure should be determined appropriately. The related ANN parameters are determined by researching the ANN parameters utilized on “energy subjects” in the literature. In this study, separate ANN structures were generated for total energy consumption, CO_2 emission, and building envelope cost. Feedforward MLP [64–66] was chosen as the network type for each ANN structure. The most important step in ANN models is to calculate the weights of each neuron with the training algorithm. The weight values are calculated by coding the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm [39,67,68] in the Delphi programming language. One hidden layer was preferred for each ANN model [69–71]. 70 %, 15 %, and 15 % of the data set were used for training, testing, and verification, respectively, which are the ratios preferred in the literature [72,73]. Moreover, the hyperbolic tangent function and logistic function preferred in building envelope studies [8,52,74] were selected for the hidden layer and the output layer as transfer functions, respectively. Each step in the ANN models is coded originally by the authors. The parameters used for the ANN structures are shown in Table 3.

The input attributes in the data set include the building envelope attributes and pilot regions (Table 5). The building envelope attributes are external plaster material, external plaster thickness, insulation material, insulation material thickness, wall material, wall thickness, internal plaster, internal plaster thickness, and window type. That is, each ANN model has ten input neurons in the input layer. The output data set consists of thermal energy consumption, CO_2 production, and building envelope cost. As a result of the trials, 4, 10, and 9 hidden neurons were determined in the hidden layers for CO_2 emission, heating/cooling energy consumption, and the envelope material cost, respectively. According to the ANN training models, the input-hidden layer and hidden-output layer weights along with related bias weights were achieved for ANN structures of CO_2 emission, energy consumption, and building envelope cost. The efficiency of ANN models is analyzed with the correlation coefficient and MAPE. The correlation coefficient is used to show the ability of the generated ANN models to represent relationships between inputs and outputs. The MAPE is used to show error values between the results obtained by the ANN models and the simulation. The correlation coefficient and MAPE are formulated in Eqs. (6) and (7), respectively. All results of the energy consumption, CO_2 emission, and material cost obtained through the ANN models and the EnergyPlus are presented in the supplementary file. ANN performance for CO_2 emission, energy consumption, and envelope material cost are summarized in Table 4.

$$r = \frac{n \bullet \left(\sum x \bullet y\right) - \left(\sum x\right) \bullet \left(\sum y\right)}{\sqrt{\left[n \bullet \left(\sum x^2\right) - \left(\sum x\right)^2\right] \bullet \left[n \bullet \left(\sum y^2\right) - \left(\sum y\right)^2\right]}} \tag{6}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{\left|Y_{sim,i} - Y_{ANN,i}\right|}{Y_{sim,i}} \tag{7}$$

where, r represents the correlation coefficient, n is the number of instances (row), x is the independent variable, and y represents the dependent variable. $Y_{sim,i}$ is the output value calculated by EnergyPlus. $Y_{ANN,i}$ represents the output value predicted by the ANN models.

In the proposed approach, instead of generating a single ANN structure for CO_2 emission, energy consumption, and material cost, a separate ANN structure is generated for each one of them. It is aimed to provide flexibility for the decision-maker by generating different ANN models for each output attribute. That is, the proposed approach is flexible whether the CO2 emission, energy consumption, and material cost are taken into account separately in the fitness function. There is no need to design a new ANN model when one of the output attributes is removed from the fitness function according to the decision maker's preference. In addition, once a different output attribute is taken into account in the fitness function, instead of generating an ANN model again for all output attributes, an ANN model is only generated for the added output attribute. There is no guarantee that the new single ANN model to be generated will give a good result due to the added new output. A generated single ANN structure is not guaranteed to perform

Table 4
Performance of ANN models for CO_2 emission, energy consumption, and material cost.

Outputs	Network name	Training correlation	Training MAPE (%)	Testing correlation	Testing MAPE (%)	Validation correlation	Validation MAPE (%)
CO_2 emission	MLP-10–4-1	0.975428	0.429601	0.963566	0.711523	0.963566	0.817975
Energy consumption	MLP-10–10-1	0.971014	1.149453	0.974448	1.245021	0.967380	1.860698
Envelope cost	MLP-10–9-1	0.988769	4.579023	0.982340	4.775788	0.989567	5.407138

Table 5
Input attributes and LCC output (chromosome structure).

Input Genes	***Building envelope attributes***	I_1	External plaster
		I_2	Thickness of the external plaster
		I_3	Insulation material
		I_4	Thickness of the insulation material
		I_5	Wall material
		I_6	Thickness of the wall material
		I_7	Internal plaster
		I_8	Thickness of the internal plaster
		I_9	Window type
	Region	I_{10}	Region No
Output Gene	***Total cost***	O	LCC of building envelope

Table 6
The GA parameters.

Number of generations	100 generations
Population size	100 chromosomes
Operators	Crossover operator Mutation operator
Crossover rate	0.8
Mutation rate	0.2

well for every output since one-to-one relationships and patterns between inputs and outputs could be prevented. There are also some studies in the literature that consider heating energy consumption, cooling energy consumption, and indoor comfort with different ANN models [75,76].

As an example, by considering the number of the hidden neurons determined for each ANN model in Table 4, models that consider three outputs in a single ANN are developed. That is, the performances of the networks MLP-10–4-1, MLP-10–10-1, and MLP-10–9-1 are compared with the performances of the networks MLP-10–4-3, MLP-10–10-3, and MLP-10–9-3. Moreover, a three-output ANN model is developed by changing the number of neurons in the hidden layer by the trial-and-error method. A comparison of the developed models is shown in Appendix-A Table A2. It seems more appropriate to consider the output sets in separate ANN models.

Determining the most suitable building envelopes using ANN-Based GA procedure

In the study, the LCCA method is used to determine the most suitable building envelope alternative for each region. The fitness function for the ANN-based GA procedure is the LCC of the building envelope in Eq. (1), which is the sum of the heating/cooling energy consumption cost, the CO_2 emission cost, and the building envelope material cost. In the European Union, the ETS allowance price was 0.027 \$/kgCO_2 in 2019 [4]. The heating/cooling energy unit price is determined as 0.03 \$/kWh. Unit cost and λ_h value of building envelope attributes are given in Appendix-A Table A1. The building lifespan is 20 years, the interest rate is 12 % and the inflation rate is 10 %.

In the proposed ANN-based GA procedure, the fitness function value of each candidate chromosome is obtained by using weights and bias values determined by the ANN. Input genes of each chromosome in the proposed GA structure consist of eight building envelope attributes (I_1, …, I_8), one window attribute (I_9), and one pilot region (I_{10}). The output gene includes the LCCA value of the building envelope (O) representing cost value, which belongs to input genes in the related chromosome. Here, the input genes and output gene are kept together in each chromosome structure. In the proposed GA procedure, a new candidate chromosome is generated by using the input genes in the existing chromosome through the GA operators. The output gene of the new candidate chromosome is kept empty. The sequencing of input genes in a chromosome generated with operators in the GA is used as input attributes for ANN models. The LCC value is calculated by using the fitness function for the results obtained with the ANN models. This LCC value is saved in the output gene of the same candidate chromosome. Thus, the input genes and the output gene obtained with these genes are represented by the same chromosome. This procedure is also applied to the next candidate chromosome. It should be noted that operators in the GA can only be applied to input genes representing the building material attributes. The input gene representing the pilot region and the output gene are not included in the operator processes. The pilot region gene is not affected by the mutation, crossover, or selection operators since a separate building envelope combination is searched for each region. However, the pilot region gene is kept in the chromosome structure since it is an input attribute for ANN models. An example chromosome structure is shown in Table 5.

In the first step, the proposed ANN-based GA procedure starts the search process through initial chromosomes which are produced with random values within the allowable range. In fact, the input gene values of any chromosome serve as input values of the ANN structures. The cost values of CO_2 emission, energy consumption, and building envelope material are determined by passing through the necessary procedures with the weight and bias values obtained by the ANN training. Here, different weight and bias values are used for each cost. These three cost values, which are calculated through the ANN parameters (i.e., weights and bias values) and input values of each chromosome, are added by using Eq. (1). The sum value is the fitness value of the related chromosome. This value represents the solution quality of the related chromosome. It has an essential responsibility in order to transfer to the next generation of good solutions.

In the proposed approach, the search process was applied during 100 generations (number of generations) with 100 chromosomes (population size). The population size should not be confused with the sample data set used for ANN. There is no relationship between the population size in GA and the size of the sample data set used in ANN. The sample data set is only used to train three separate ANN models. This data set is not the whole solution space, but the sample representing the whole solution space. It is not used for GA's operating procedures. On the other hand, population size is a parameter required for the GA procedure. The population size is a parameter used to scan the whole solution space through the GA. The best solution in each generation during the algorithm is directly transferred to the next generation. Thus, the best solution is preserved. After the first step, as it is known, alternative candidate solutions of GA are obtained through selection, crossover, and

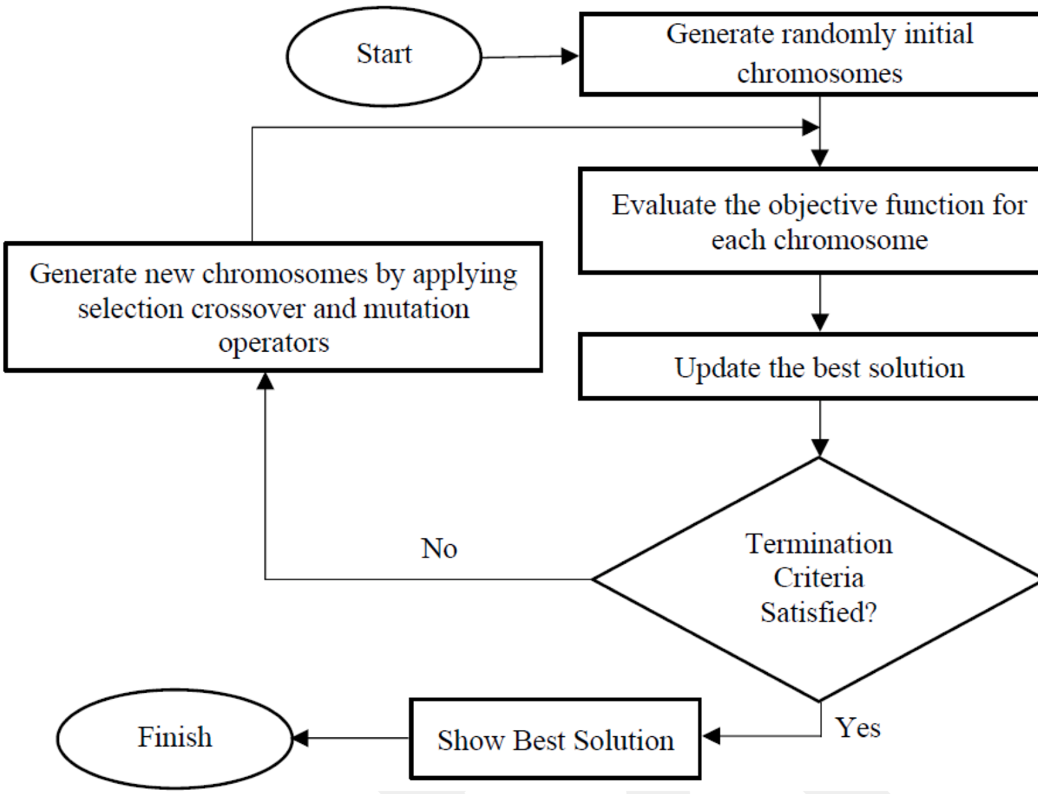


Fig. 4. ANN-based GA process.

Table 7
The building envelope configurations for the minimum LCC without ETS allowance cost.

Building envelope materials	Region-1		Region-2		Region-3		Region-4	
	Type	*Thickness*	*Type*	*Thickness*	*Type*	*Thickness*	*Type*	*Thickness*
External plaster	Lap	2.5 cm	Perlite-plaster	2.5 cm	Lap	1 cm	Lap	1 cm
Insulation	Wood-fibred	7 cm	Wood-fibred	7 cm	Wood-fibred	7 cm	Wood-fibred	7 cm
Wall material	Perforated brick	10 cm	Perforated brick	30 cm	Perforated brick	25 cm	Perforated brick	30 cm
Internal plaster	Gypsum plaster	2.5 cm	Gypsum plaster	1 cm	Gypsum plaster	1 cm	Gypsum plaster	1 cm
Window type	3-chambered	6 mm/6 mm	3-chambered	6 mm/6 mm	3-chambered	6 mm/6 mm	3-chambered	6 mm/6 mm

mutation operators. For this, the roulette wheel method, which is widely used in the literature and the constant values of GA, was used in the proposed algorithm (0.8 for crossover and 0.2 for mutation). Here, in the process of obtaining new individuals with the effect of the roulette wheel and the selection operator, it is ensured that not only solutions with better fitness value are selected with a higher probability, but also worse solutions. The GA parameters are shown in Table 6. The process of the ANN-based GA is shown in Fig. 4.

The U values of the candidate solutions considered as the feasibility constraint are also calculated in each step. As aforementioned, due to the U value, not every envelope combination can be used for every pilot region. After the ANN models were decided, the U_d value was used in order to determine the most suitable configuration for each pilot region. For any pilot region, the building envelope combination with a U value above the U_d value of the climate zone was not considered. Thus, the space that should be scanned was reduced for each pilot region.

Results and discussion

In this study, the problem is modeled mathematically by using ANN, and then the most suitable envelope solutions according to this model are obtained with GA. The most suitable configurations obtained for each region with the proposed approach are entered in the DesignBuilder in order to compare the building envelope LCC results of the proposed approach and the EnergyPlus for each region. The annual energy consumption values, building envelope unit material costs, and CO_2 emissions are calculated by EnergyPlus for each combination. Then, the LCCs of the building envelope for each region are calculated by using the fitness function (Eq. (1)) for the EnergyPlus. Finally, the building envelope LCC results of the proposed approach and the EnergyPlus are compared. Comparing the results is very important to measure the consistency of the proposed approach. The proposed ANN-based GA structure that has learned the working mechanism of EnergyPlus well allows us to scan the entire alternative space. The proposed approach aims to determine the most suitable building envelope configuration for each climate zone by considering the EnergyPlus. MAPE is used to compare the results obtained with EnergyPlus and the proposed approach and to determine their differences (error rates). A low MAPE means that the accuracy of the result obtained with the proposed approach is high. Without including the ETS, the proposed approach provided 99.09 % mean accuracy for the LCC of the building envelope. The proposed approach provided 99.22 % accuracy for the LCC of the building envelope by including the ETS. The LCC values of the building envelope calculated by the proposed approach without including ETS were obtained between 1.48 and 1.74 million dollars for each region. The LCC values of the building envelope calculated with the proposed

Table 8
The building envelope configurations for the minimum LCC with ETS allowance cost.

Building envelope materials	Region-1		Region-2		Region-3		Region-4	
	Type	*Thickness*	*Type*	*Thickness*	*Type*	*Thickness*	*Type*	*Thickness*
External plaster	Lap	2.5 cm	Perlite-plaster	2.5 cm	Lap	1 cm	Lap	1 cm
Insulation	Wood-fibred	7 cm	Wood-fibred	7 cm	Wood-fibred	7 cm	Wood-fibred	7 cm
Wall material	Perforated brick	15 cm	Perforated brick	30 cm	Hollow brick	30 cm	Perforated brick	30 cm
Internal plaster	Gypsum plaster	2.5 cm	Gypsum plaster	1 cm	Gypsum plaster	1 cm	Gypsum plaster	1 cm
Window type	3-chambered	6 mm/6 mm	3-chambered	6 mm/6 mm	3-chambered	6 mm/6 mm	3-chambered	3 mm/13 mm

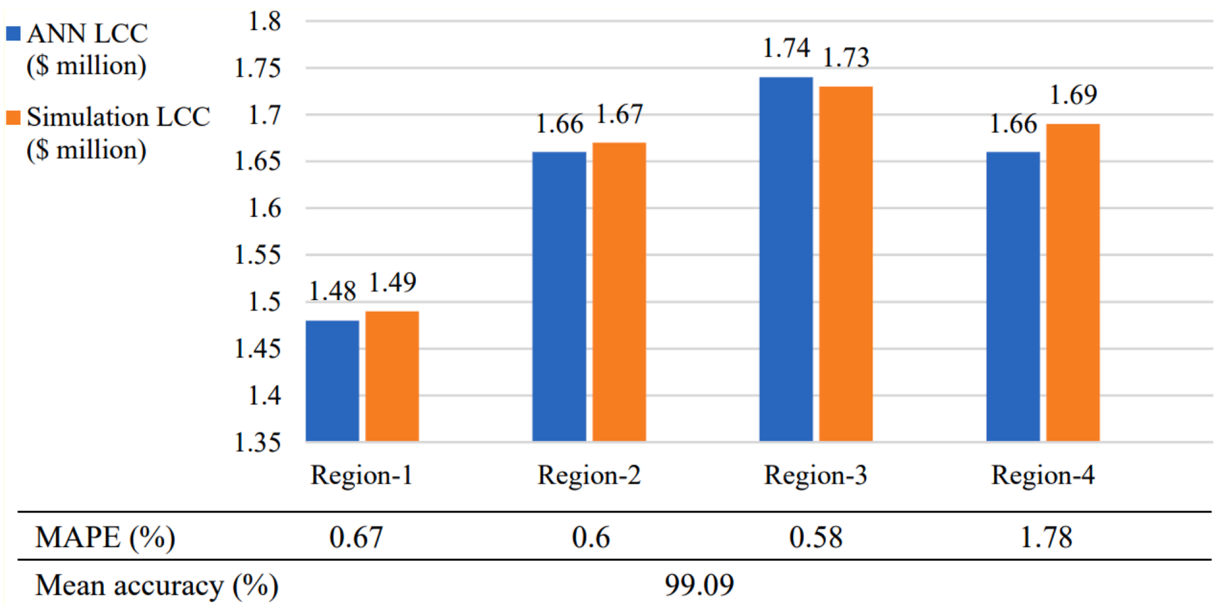


Fig. 5. LCC values without ETS allowance cost.

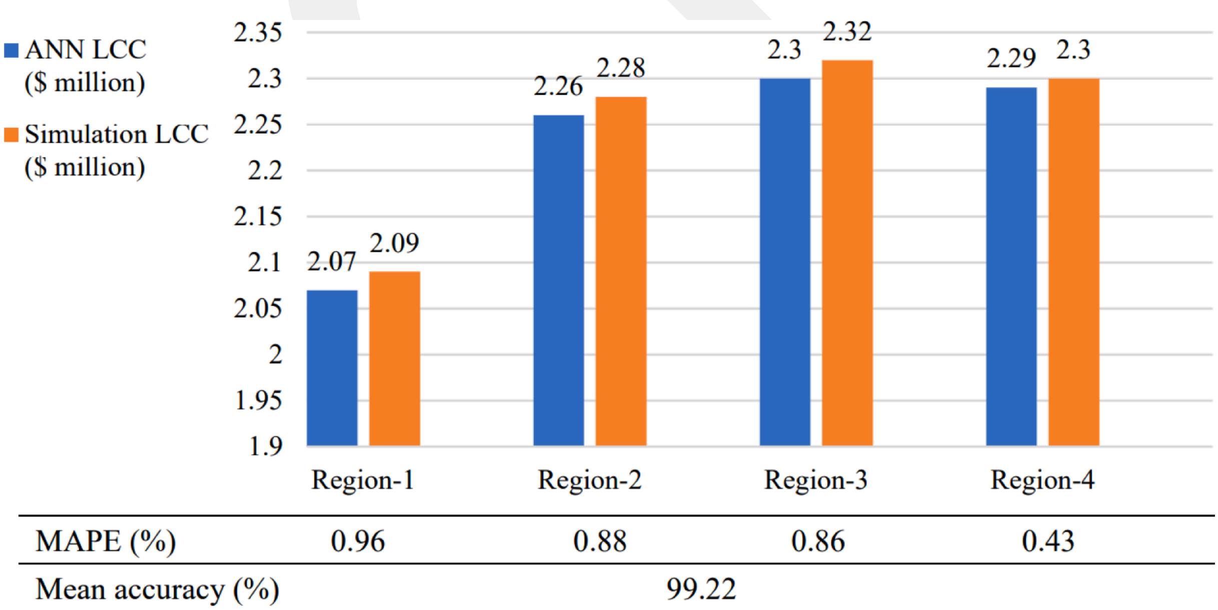


Fig. 6. LCC values with ETS allowance cost.

approach by including the ETS were obtained between 2.07 and 2.3 million dollars for each region. It was observed that the ETS allowance price affected the LCC of the building envelope by around 35 %-40 %. The building envelope combinations determined by the proposed approach for each pilot region without and with the ETS are shown in Tables 7 and 8, respectively. The LCC values without and with ETS calculated by the proposed approach and EnergyPlus are shown in Figs. 5 and 6, respectively. In addition, the CO_2 emission cost, thermal energy consumption cost, and material cost values calculated by the proposed approach and EnergyPlus for the most suitable building

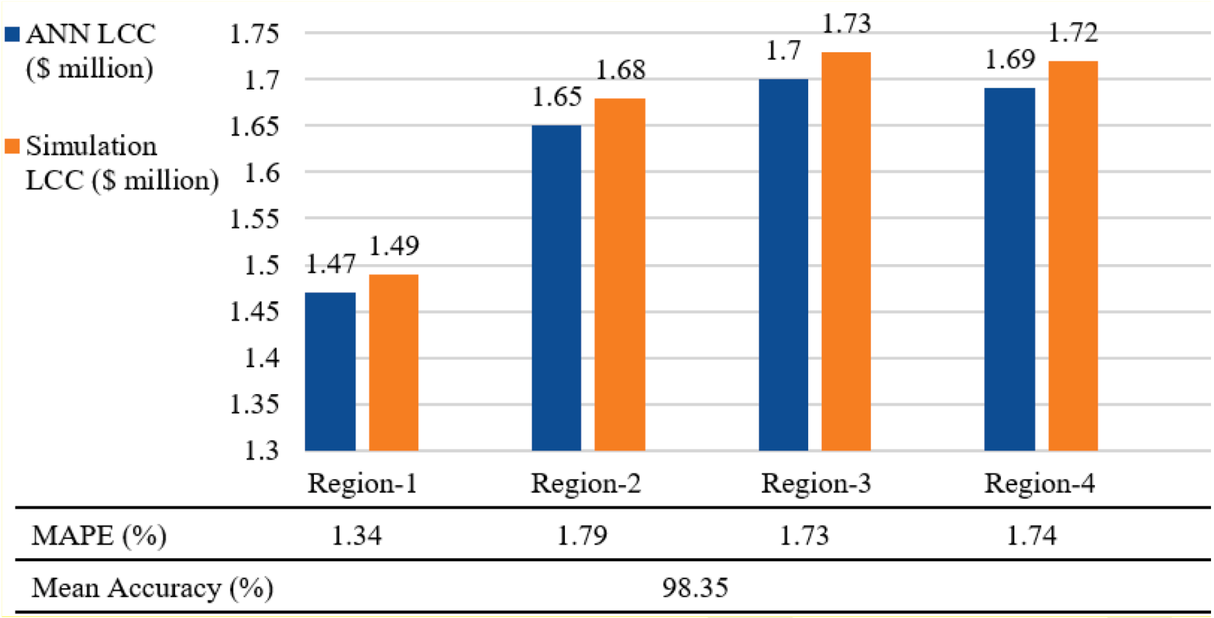


Fig. 7. LCC values without ETS allowance cost considering the fire safety.

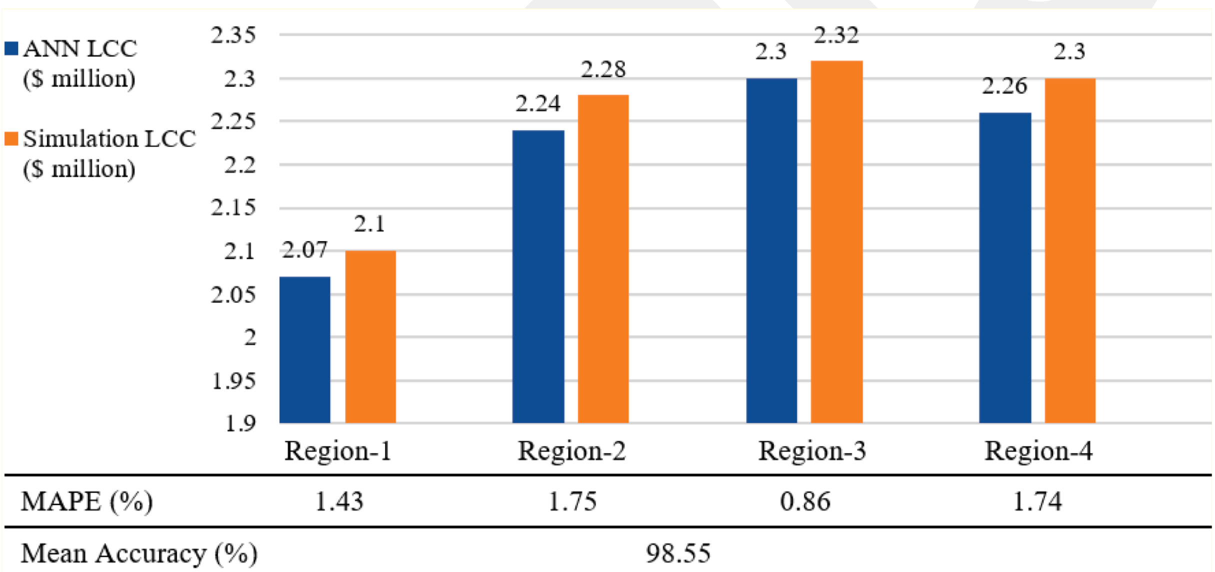


Fig. 8. LCC values with ETS allowance cost considering the fire safety.

Table 9
The building envelope configurations for the minimum LCC without ETS allowance cost considering the fire safety.

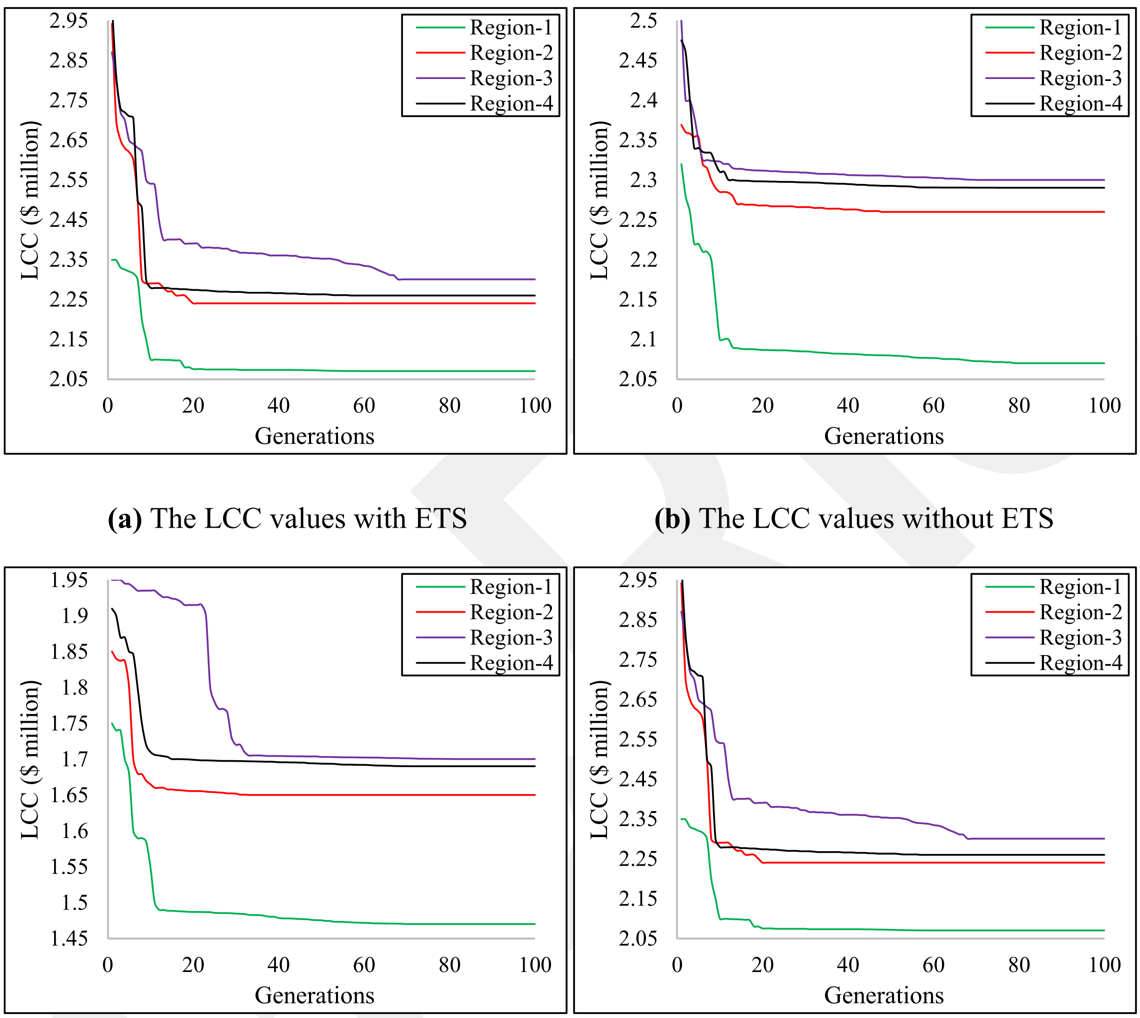
Building envelope materials	Region-1		Region-2		Region-3		Region-4	
	Type	*Thickness*	*Type*	*Thickness*	*Type*	*Thickness*	*Type*	*Thickness*
External plaster	Lap	2.5 cm	Lap	2.5 cm	Lap	1 cm	Lap	1 cm
Insulation	Glass-wool	7 cm	Glass-wool	7 cm	Glass-wool	7 cm	Glass-wool	7 cm
Wall material	Perforated brick	10 cm	Gas concrete	15 cm	Perforated brick	25 cm	Perforated brick	30 cm
Internal plaster	Gypsum plaster	2.5 cm	Gypsum plaster	2.5 cm	Gypsum plaster	1 cm	Gypsum plaster	1 cm
Window type	3-chambered	6 mm/6 mm	3-chambered	3 mm/13 mm	3-chambered	6 mm/6 mm	3-chambered	6 mm/6 mm

envelope alternatives are given in Appendix-A Tables A3 and A4. According to the MAPE values, accuracy of above 99 % was achieved for each LCC. The obtained results show that the proposed approach is effective in order to obtain the building envelope configurations that minimize the LCC of the green building envelope in the different climate and seismic zones.

Although some building envelope materials are cheaper and quite effective for insulation, they may not be satisfactory in terms of fire safety. In recent years, it has become important to design a building envelope considering fire safety. Therefore, wood-fibred, eps, pvc, and xps materials with low fire resistance were excluded and building envelope alternatives were reevaluated for fire safety. Accordingly, the

Table 10
The building envelope configurations for the LCC of building envelope with ETS allowance cost considering the fire safety.

Building envelope materials	Region-1		Region-2		Region-3		Region-4	
	Type	*Thickness*	*Type*	*Thickness*	*Type*	*Thickness*	*Type*	*Thickness*
External plaster	Lap	2.5 cm	Perlite-plaster	2.5 cm	Lap	1 cm	Lap	1 cm
Insulation	Glass-wool	7 cm	Glass-wool	7 cm	Glass-wool	7 cm	Glass-wool	7 cm
Wall material	Perforated brick	15 cm	Perforated brick	30 cm	Hollow brick	30 cm	Perforated brick	30 cm
Internal plaster	Gypsum plaster	2.5 cm	Gypsum plaster	1 cm	Gypsum plaster	1 cm	Gypsum plaster	1 cm
Window type	3-chambered	6 mm/6 mm	3-chambered	6 mm/6 mm	3-chambered	6 mm/6 mm	3-chambered	3 mm/13 mm



(a) The LCC values with ETS

(b) The LCC values without ETS

(c) The LCC values with ETS considering the fire safety

(d) The convergence diagram without ETS considering the fire safety

Fig. 9. The convergence diagrams of the proposed GA procedure.

building envelope combinations determined by the proposed approach for each pilot region without and with the ETS are shown in, respectively. The LCC values with and without ETS calculated by the proposed approach and EnergyPlus are shown in Figs. 7 and 8, respectively. It was observed that fire safety could be achieved with LCC values similar to the ones in Figs. 5 and 6 including the results for the case of fire safety ignored. In addition, the CO_2 emission cost, thermal energy consumption cost, and material cost values calculated by the proposed approach and EnergyPlus for the most suitable building envelope alternatives are given in Appendix-A Tables A5 and A6.

Once Tables 7 and 8 are analyzed, it is observed that the inclusion of ETS could affect the material type and thickness for the most suitable green building envelope design. For example, while 10 cm of perforated brick is selected for wall material in the pilot region-1 for the building envelope design without ETS, 15 cm of perforated brick is selected for the design with ETS. Whereas 25 cm of perforated brick was preferred for wall material in the pilot region-3 without the ETS, 30 cm of hollow brick is selected for the design with ETS. For the window type, 6 mm/6mm and 3 mm/13 mm of 3-chambered are determined for designs without ETS and with ETS in the pilot region-4, respectively. On the other hand, insulation materials have the most impact on heating and cooling energy consumption it is interesting to determine that the ETS does not change the type and thickness of insulation material.

Once Tables 9 and 10 are analyzed, it is observed that the inclusion of

ETS could affect the material type and thickness for the most suitable green building envelope design. For instance, while 15 cm of gas concrete is selected for wall material in the pilot region-2 for the building envelope design without ETS, 30 cm of perforated brick is selected for the design with ETS. In addition, whereas 2.5 cm of gypsum plaster was preferred for internal plaster in the pilot region-2 without the ETS, 1 cm of gypsum plaster is selected for the design with ETS.

The proposed algorithm was coded in the Delphi programming language. It was run 5 times for each region and the best values were presented. Each solution was obtained in less than 10 s on average. There was no specific parameter optimization for the algorithm. According to ETS and fire safety situations, convergence diagrams of the proposed GA procedure are shown in Fig. 9.

Conclusion and future work

Energy consumption in buildings has become very important for states in terms of national energy-saving policies. Especially for the past 50 years, energy-efficient building designs have become quite popular in order to reduce energy consumption and carbon emissions in the buildings. In green and energy-efficient building design, it cannot be ignored that thermal energy consumption and carbon production are mostly affected by the building envelope and climate. It is not difficult at all to reduce the thermal energy consumption and CO_2 emission by considering the thermal climate zones and choosing the building envelope materials according to these climatic and seismic zones. This paper presents a holistic approach, which determines the building envelope configuration, by providing a perspective to decision-makers throughout the building design phase. It is aimed to discover patterns amongst the huge volume of data consisting of climate, thermal energy consumption, CO_2 production, and the building envelope materials by using data mining and machine learning techniques.

The proposed approach has a multi-objective structure considering energy (heating/cooling), cost, and environment (CO_2 production) criteria. It is aimed to determine the most suitable green building envelope alternative that provides indoor thermal comfort and environmental sustainability in buildings to be built in different climatic and seismic zones. The proposed approach is applied for the city hospital project according to the pilot regions chosen from four climate zones in Turkey.

Note that, the combinations obtained do not guarantee minimum energy consumption, cost, or CO_2 production. However, the algorithm provides decision-makers with highly consistent ideas across all combinations. The attributes and values used in the study may vary. It is flexible for different qualities and structures. Without including the ETS, the proposed approach provided 99.18 % (MAPE) accuracy for the LCC of the building envelope. The proposed approach provided 99.13 % (MAPE) accuracy for the LCC of the building envelope by including the ETS. As a result, the proposed approach has an accuracy of more than 99 % according to the MAPE values.

No parameter optimization is performed for the proposed approaches in this study. Parameter optimization is an important step in order to obtain more accurate results on forecasting and optimization methods. For future studies, parameter optimization may be applied to the ANN and GA parameters.

In recent years, thermal energy storage methods have become quite popular as well as building envelope designs for energy-efficient building designs. Considering thermal energy storage methods together with green building envelope designs can yield successful results. The parameters such as temperature distribution and melting fraction in building envelope materials may present a remarkable and different perspective for the LCC of the building envelope. In particular, once phase change materials, one of the thermal energy storage methods, are considered for building envelope materials, they may have a significant effect on reducing building energy consumption, CO_2 emissions, and material cost in the long run. In addition, embodied carbon has recently become very important in green building designs. The CO_2 emission, which occurs in the process from the production to consumption of the material, called embodied carbon, is not taken into account in the building life cycle for this study. For future studies, a different perspective can be provided for CO_2 emission and green building by considering both operational and production parameters. Moreover, roof systems can be included in energy consumption and good results can be obtained according to the proposed approach.

Providing a sustainable LCCA by considering social policies as well as energy and environmental factors in terms of the building life cycle will become very important for green building designs in the future.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

An Application for Proposed Framework.

Table A1
Building envelope materials for the application.

Materials and thickness [cm]	**Material features**	
External plaster [1–1.5–2-2.5]	**Cost ($/m²)**	**λ(W/mK)**
Lightweight aggregate plaster (lap)	12	0.23
Lime-cement mortar	20	0.8
Lime-sand mortar	10	0.9
Sand-cement mortar	17	0.72
Perlite-plaster	25	0.08
Insulation [2–3–5–7]	**Cost ($/m²)**	**λ(W/mK)**
Wood-fibred	10	0.043
Glass-wool	30	0.036
Expanded polystyrene foam (eps)	7	0.04
Phenol foam	5	0.04
Expanded-perlite	25	0.055
Cork	35	0.044
Polyurethane-rigid foam (pur)	40	0.026
Polyvinyl chloride (pvc)	4	0.16
Stone-wool	10	0.038
Extruded polystyrene foam (xps)	5	0.03
Wall material [10–15–20–25–30]	**Cost ($/m²)**	**λ(W/mK)**
Hollow brick	55	0.28
Perforated brick	45	0.45
Gas concrete	50	0.2
Lightweight aggregate concrete block (lacb)	60	0.19
Normal aggregate concrete block (nacb)	65	0.51
Internal plaster [1–1.5–2-2.5]	**Cost ($/m²)**	**λ(W/mK)**
Gypsum-plaster	20	0.18
Lime-gypsum mortar	15	0.45
Lime-cement mortar	20	0.8
Lime-sand mortar	10	0.9
Sand-cement mortar	17	0.72
Glazing type	**Cost ($/m²)**	***U* (W/m2K)**
PVC joinery 3-chambered double glazed 6 mm/6mm	35	2.4
PVC joinery 3-chambered double glazed 3 mm/13 mm	40	1.978
PVC joinery 5-chambered double-glazed 3 mm/13 mm	50	1.798
PVC joinery 5-chambered double-glazed 6 mm/13 mm	65	1.772

Table A2
Training, testing, and validation results for single-output and three-output ANN models.

Outputs	Network name	Training correlation	Testing correlation	Validation correlation
CO_2 emission	MLP-10–4-1	**0.975428***	**0.963566***	**0.963566***
Energy consumption	MLP-10–10-1	**0.971014***	**0.974448***	0.96738
Envelope cost	MLP-10–9-1	**0.988769***	0.982340	0.989567
CO_2 emission	MLP-10–4-3	0.972632	0.961362	0.960352
Energy consumption	MLP-10–4-3	0.943915	0.938127	0.937252
Envelope cost	MLP-10–4-3	0.959367	0.959582	0.958631
CO_2 emission	MLP-10–10-3	0.941645	0.938921	0.938862
Energy consumption	MLP-10–10-3	0.970463	0.973642	**0.970162***
Envelope cost	MLP-10–10-3	0.932396	0.923544	0.927536
CO_2 emission	MLP-10–9-3	0.937853	0.934512	0.936472
Energy consumption	MLP-10–9-3	0.923264	0.926817	0.929871
Envelope cost	MLP-10–9-3	0.960239	0.961731	**0.989706***
CO_2 emission	MLP-10–11-3	0.975122	0.96156	0.959201
Energy consumption	MLP-10–11-3	0.970354	0.970023	0.953256
Envelope cost	MLP-10–11-3	0.979233	**0.983362***	0.964872
*The best value"				

Table A3
Energy consumption and material costs for the minimum LCC without ETS allowance cost.

Results		Region-1	Region-2	Region-3	Region-4
Energy consumption	**ANN-based GA results (GWh)**	2.64	2.9	3.1	2.91
	Simulation results (GWh)	2.66	2.92	3.08	2.97
	MAPE (%)	0.75	0.68	0.65	2.02
Material cost	**ANN results ($/m^2)**	8.59	15.36	12.21	14.2
	Simulation results ($/m^2)	8.25	15.03	12.27	14.52
	MAPE (%)	4.12	2.20	0.49	2.20
Results	**ANN LCC ($ million)**	1.48	1.66	1.74	1.66
	Simulation LCC ($ million)	1.49	1.67	1.73	1.69
	MAPE (%)	0.67	0.60	0.58	1.78
	Accuracy (%)	99.09			

Table A4
CO_2 emission, energy consumption and material costs for the minimum LCC without ETS allowance cost.

Results		Region-1	Region-2	Region-3	Region-4
CO_2 emission	**ANN results (tCO_2)**	1322.55	1330.08	1285.5	1306.96
	Simulation results (tCO_2)	1339.45	1343.46	1275.62	1313.63
	MAPE (%)	1.26	1.00	0.77	0.51
Energy consumption	**ANN results (GWh)**	2.61	2.9	3.01	2.95
	Simulation results (GWh)	2.66	2.92	3.03	2.98
	MAPE (%)	1.88	0.68	0.66	1.01
Material cost	**ANN results ($/m^2)**	8.59	15.36	15.7	14.25
	Simulation results ($/m^2)	8.25	15.03	17.52	14.52
	MAPE (%)	4.12	2.20	10.39	1.86
Results	**ANN LCC ($ million)**	2.07	2.26	2.3	2.29
	Simulation LCC ($ million)	2.09	2.28	2.32	2.3
	MAPE (%)	0.96	0.88	0.86	0.43
	Accuracy (%)	99.22			

Table A5
Energy consumption and material costs for the minimum LCC without ETS allowance cost considering the fire safety.

Results		Region-1	Region-2	Region-3	Region-4
Energy consumption	**ANN results (GWh)**	2.64	2.92	3	2.96
	Simulation results (GWh)	2.67	2.97	3.06	3.01
	MAPE (%)	1.12	1.68	1.96	1.66
Material cost	**ANN results ($/m^2)**	6.99	9.87	12.87	14.97
	Simulation results ($/m^2)	7.4	10.4	13.67	15.92
	MAPE (%)	5.54	5.10	5.85	5.97
Results	**ANN LCC ($ million)**	1.47	1.65	1.7	1.69
	Simulation LCC ($ million)	1.49	1.68	1.73	1.72
	MAPE (%)	1.34	1.79	1.73	1.74
	Accuracy (%)	98.35			

Table A6
CO_2 emission, energy consumption and material costs for the minimum LCC with ETS allowance cost considering the fire safety.

Results		Region-1	Region-2	Region-3	Region-4
CO_2 emission	**ANN results (tCO_2)**	1322.72	1331.37	1285.58	1286.74
	Simulation results (tCO_2)	1337.48	1341.78	1272.51	1309.95
	MAPE (%)	1.10	0.78	1.03	1.77
Energy consumption	**ANN results (GWh)**	2.62	2.86	2.97	2.9
	Simulation results (GWh)	2.65	2.91	3.02	2.96
	MAPE (%)	1.13	1.72	1.66	2.03
Material cost	**ANN results ($/m^2)**	9	15.57	17.9	15
	Simulation results ($/m^2)	9.65	16.43	18.92	15.92
	MAPE (%)	6.74	5.23	5.39	5.78
Results	**ANN LCC ($ million)**	2.07	2.24	2.3	2.26
	Simulation LCC ($ million)	2.1	2.28	2.32	2.3
	MAPE (%)	1.43	1.75	0.86	1.74
	Accuracy (%)	98.55			

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seta.2022.102505.

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