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# Residential Building Design and Optimization in Arid Climates using Multiple Objectives and ANN-GA

Belahya Hocine[1,*], Boubekri Abdelghani[1], Belarbi Rafik[2], Romani Zaid[3]

[1] LENREZA, UKMO, Ouargla University, Ouargla, Algeria
[2] LaSIE, Université de la Rochelle, 17042, La Rochelle, France
[3] National School of Architecture Tetouan, Tetouan, Morocco

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**ABSTRACT**

Residential buildings in arid regions, such as South Algeria, are responsible for a considerable portion of the total electrical energy consumption, surpassing 60%. To tackle this challenge, this research proposes a novel multi-objective approach aimed at designing typical residential buildings. This approach combines the utilization of a Genetic Algorithm (GA) optimization technique with an Artificial Neural Network (ANN) model, implemented using the Python programming language and integrated with TRNSYS software. The performance of the ANN model is thoroughly evaluated and validated using the TRNSYS software. The integration of Python and TRNSYS facilitates the generation of training datasets for the ANN model. This co-simulation framework provides a powerful tool for accurately estimating energy consumption and life cycle costs (LCC). The results obtained through the TOPSIS-based analysis reveal a remarkable reduction in cooling and heating energy usage, up to 51.43% and 98.97%, respectively, when compared to the basic scenario.

## 1. Introduction

In 2020, buildings were responsible for 36% of the world's energy consumption as well as 37% of $CO_2$ emissions [1,2]. Better building design, energy-efficient technologies, and decarbonization legislative incentives are needed to improve building energy efficiency, which can result in important reductions in terms of energy use and associated carbon emissions. Studies have shown that energy efficiency measures, for instance building insulation, efficient lighting and HVAC systems, and the use of energy-efficient appliances and equipment can result in energy savings of 30-80% compared to conventional buildings [3-5]. In Algeria, rapid urbanization and government incentives for urban regeneration resulting in an important growth in the amount of residential buildings being constructed. However, designing buildings that are both energy-efficient and functional can be a difficult task, as architects must balance several competing factors, including aesthetic design, budget limitations, thermal comfort, and energy performance. In the lack of regulations relating to climate,

* *Corresponding author.*
*E-mail address: belahya.hocine@univ-ouargla.dz*

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the use of the same building energy-efficient designs in new buildings to address both environmental and economic concerns in a vast climatic diversity as Algeria, which make the seasonal energy consumption in the building achieve a huge amount for system air condition (cooling and heating). It has been found that roughly half of the energy used within a building is dedicated to maintaining indoor temperature and air quality [6]. In hot regions, cooling systems can consume 65 % of energy total energy. The complexity of the design depends on several factors that can impact the energy performance of a building, including its geometric design, the thermal properties of the materials used in its construction, the energy systems it uses, the local weather conditions, and the behavior of the occupants also there is a contradiction between the cooling and heating, e. g wall windows ration in the south can reduce heating but it has bad influence in the cooling. When attempting to determine an exact estimate of the efficiency of a building's energy use, it can be difficult to take all these factors into consideration. Energy-efficient building design and retrofitting of older structures can increase comfort, lower energy use, and cut greenhouse gas emissions. To achieve this goal, it is essential to have the ability to predict a building's performance. Given the importance of sustainability and the critical role that buildings play in this regard, it is necessary to increase efforts toward finding practical and cost-effective solutions to improve energy efficiency in buildings. This will help to address the sustainability challenges we face and move towards a more sustainable future. Several approaches are suggested in this regard to determine a building's energy performance. Tools for optimizing building energy have grown in importance in both the design of new buildings and the retrofitting of current ones. However, considering the complex interactions and variables involved in estimating a building's energy performance can prove challenging. As a result, numerous methods are firmly established to assess the energy efficiency of a house. These methods include engineering calculations, numerical simulations, and data-driven simulations [7]. One of the main methods for evaluating building energy consumption is using physical laws, which is particularly important in the early stages of analysis owing to the complexity of the calculations involved. Additionally, numerical simulation techniques are used to analyze building performance and address any limitations of engineering calculation methods. To study the energy characteristics of buildings, various building energy simulation tools have been developed. These tools aid architects and engineers in identifying the energy demands for heating, cooling, and lighting within a structure. The aim of this project is to improve the forecast capability and design options for low-energy buildings by integrating high-performance computational methods with life cycle cost (LCC) analysis. This research is separated into several sections. The first section covers relevant literature on machine learning applications in building research and seasonal energy usage. Next, the case study and technique are explained. The proposed method involves combining an ANN and GA procedure with LCC analysis modelling to optimize complex ANN topologies and improve prediction performance. We used an open source Python script that was utilized to create the ANN-GA algorithm for this investigation [8]. The framework is applied using a model for social housing construction in Algeria in the section of the essay that follows. Through training and testing on data from building energy models, the framework is initially utilized to determine the optimum ANN architectures. The part also shows how well the improved ANN model performs in estimating the output targets for life cycle cost and building session energy. In the end, conclusions are reached and suggestions for further investigation are made.

## 2. Literature Review

### *2.1 Energy-saving*

Researchers working in this area of study are very interested in developing energy-saving design and optimization techniques. Depending on the constraint, the experts have concentrated on identifying the most critical factors [9]. This research study the window-to-wall ratio (WWR) of buildings in China's low-latitude zone needs to be optimized by taking daylighting performance and energy usage into account.

The optimal WWR values, which meet daylighting requirements and have low energy consumption, vary by sunshade configuration and building orientation [10]. This research presents a study that aims to determine the optimal size of window surfaces for minimizing energy consumption in a typical office building in Italy. The study considers various configurations, including climate, building envelope thermal features, and mounted lighting electric charge. The effect of a switchable protecting shading device is also evaluated. The window dimensions are assessed in terms of the window-to-wall ratio. The examines were completed using the Energy Plus simulation code. To improve the building's energy efficiency, facade design parameters are optimized, including window type, wall insulation, window-to-wall ratio, and shading devices [11]. Ma *et al.,* [12] investigated the correlation between maximum window-to-wall ratios and temperature fluctuations in thermally self-sufficient buildings, considering various levels of thermal insulation in the building envelope. Mangkuto *et al.,* [13] examined the impact of the Wall-to-Window Ratio (WWR), the reflectivity of walls, and the position of windows on various measures of daylight and the energy requirements for lighting in basic structures situated in tropical regions. Using simulation software, this study examined the energy efficiency of buildings with various forms and surface-to-volume ratios [14]. Findings indicated that optimizing design and ratio can reduce energy consumption.

### *2.2 Evolutionary Algorithms and ANN Surrogate Model*

Evolutionary algorithms, such as Genetic Algorithm (GA), are commonly used in building energy optimization due to their ability to handle nonlinear interactions between cost, energy performance, and building design characteristics. However, the simulation-based optimization approaches can be impractical for architects to integrate into their daily workflow due to the numerous simulations that must be performed. To overcome this limitation, surrogate models have been developed by researchers and incorporated into evolutionary algorithms, making it easier to apply to build energy optimization methods in the construction industry. Magnier and Haghighat [15] presents an approach for optimizing building performance using a simulation-based ANN and a multi objective Genetic Algorithm. The method was utilized to enhance thermal comfort and energy efficiency in a dwelling, resulting in significant improvements in both areas and revealing multiple potential designs with trade-offs between the two objectives [16]. In this research, an ANN and a GA are used to evaluate a multi-objective optimization model, technology choices in a building retrofit project. The model is demonstrated using a school building case study and considers energy consumption, retrofit cost, and thermal discomfort hours as conflicting objectives. The model assesses the trade-offs between these objectives. Kerdan *et al.,* [17] presents an exergy-based multi-objective optimization tool for assessing the impact of various retrofit measures in non-domestic buildings. The tool links EnergyPlus and a Genetic Algorithm optimization process using a Python add-on. The tool was tested using two UK archetype buildings and was able to achieve significant improvements in annual energy use, exergy destruction, and thermal comfort. The tool can be extended to include exergo-economic optimization. Zhang *et al.,* [18] presents a data-driven framework for evaluating and selecting optimal retrofit packages for improving the energy performance of existing residential buildings in Canada.

The framework incorporates methods for multi-criteria decision-making, multi-objective optimization, and machine learning, to predict energy performance, assess environmental and economic impacts, and identify the best retrofit packages. The approach was proven to be useful in estimating building energy efficiency and assisting decision-makers in selecting retrofit packages using data from a housing structure in British Columbia, Canada.

### *2.3 Hyperparameters Optimization*

Algorithms are critical in the construction of energy simulations because they identify the best combination of model parameters and configurations that minimize errors and improve prediction accuracy. Several studies have also combined artificial neural networks (ANNs) with Hyperparameters optimization to optimize building energy usage for both cooling and heating [19]. A technique to multi-objective optimization is suggested in this work for heating, ventilating, and air conditioning (HVAC) systems using ANNs and genetic algorithms and applies it to a building in Hong Kong. The ANN GA model of choice may identify the best architecture for ANN among several viable structures, as shown in Table 1.

**Table 1**
Hyperparameters Optimization variables and their range

| ANN Hyperparameters | GA Parameters |
|---|---|
| Number of hidden layers: from 2 to 4 | Number of generations: 20 |
| Number of neurons per layer: from 1 to 20 | Population size: 30 |
| Activation functions: | Crossover rate: 20% |
| Sigmoid, Tanh, Elu and Relu | Mutation percentage: 30% |
| Optimizers: Adam, Adagrad, RMSProp and SGD | |
| Dropout rate: 0 to 0.4 step 0.1 | |
| Epochs: 30, 50, 100, 200 | |
| Batch size: 32, 64, 128, 256, 512 | |

### *2.4 Research Gap*

A comprehensive review of the literature on building energy reveals that several studies have utilized various software tools and machine learning techniques to predict the energy performance of sustainable and efficient buildings. However, these studies often involve the use of multiple software tools, leading to complex and fragmented analysis processes. In contrast, this research proposes a novel approach that aims to streamline the analysis process and improve accuracy. The proposed method involves the development of a co-simulation framework that combines Python and a TRNSYS-based Artificial Neural Network (ANN). This integrated framework allows for a reliable estimation of energy performance, as well as other important metrics such as life cycle cost and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) technique. By leveraging the capabilities of Python and TRNSYS, the research team can achieve a more efficient and cohesive analysis process. The Python programming language provides flexibility and advanced data processing capabilities, while TRNSYS offers a powerful platform for building energy simulation. To optimize the performance of the ANN model, a genetic optimization algorithm (GA) is employed. This algorithm helps identify the optimal structure and hyperparameters for the ANN, leading to more accurate predictions. It is worth noting that despite the availability of numerous studies and simulation tools for evaluating building designs, no previous attempts have been made to combine TRNSYS, Python, and the ANN-GA modeling approach in this particular way. Therefore, this research represents a novel and promising contribution to the field of building energy analysis, offering a more integrated and efficient approach for achieving reliable predictions and facilitating sustainable building design.

Spyder is an open-source Python platform Figure 1 that offers an impressive integration of features, encompassing data exploration, deep inspection, analysis, interactive execution, debugging, and visualization. Regarding the optimization process, it is necessary to introduce the mechanism of the proposed method, which is based on the Artificial Neural Network algorithm (ANN). ANN is a method that is widely used for regression and classification problems in machine learning. ANN models consist of multiple layers of interconnected nodes, which enable them to learn and identify complex patterns in the input data. The optimization process in this study employs an ANN typical to forecast the cooling, heating, and LCC outputs based on the input parameters.

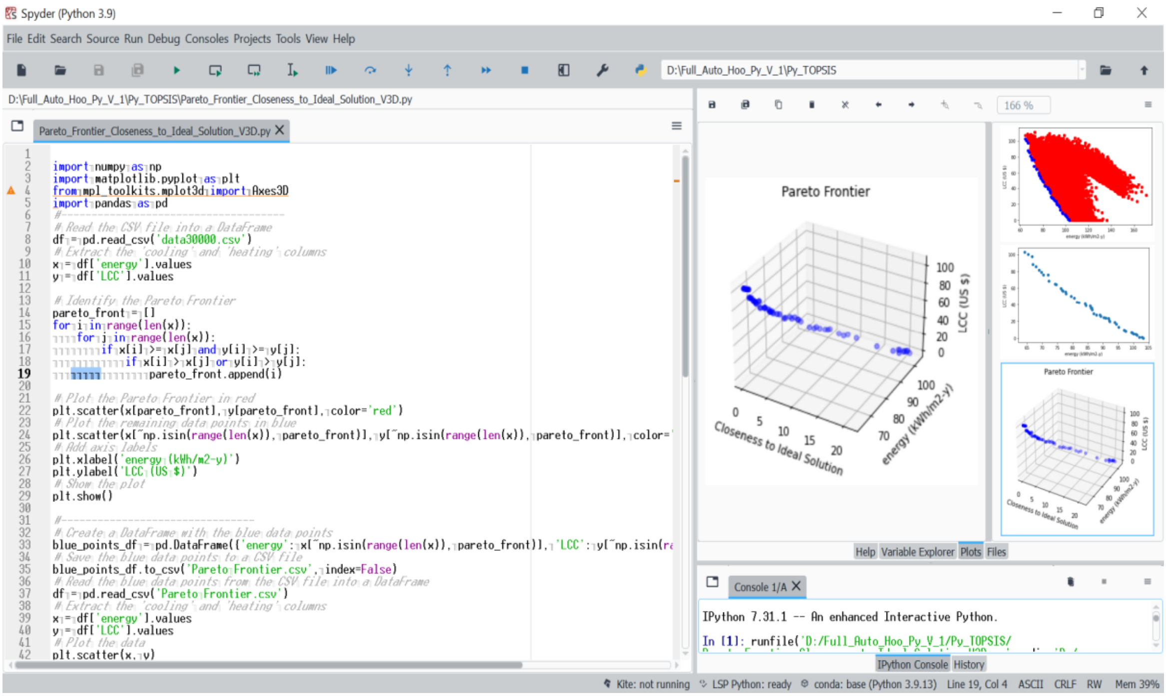

**Fig. 1.** The interface of Spyder (Python)

## 3. Methodology

### *3.1 Framework of the Study*

Meta-heuristic search algorithms such as GA and PSO are the most utilized algorithms for Building Optimization Problems (BOPs). In optimization studies involving simulation programs, GenOpt and Matlab optimization toolboxes are the two most widely used optimization engines, with TRNSYS being a popular choice. Despite the popularity of optimization techniques, the practical application of building optimization in real-world design challenges is still in its early stages of development. While there are several simulation and optimization tools available, issues such as coupling techniques, usability, adaptability, and efficiency pose challenges to their widespread use. These challenges, which include improving time and performance, limit the extensive application of optimization techniques in building design practice. In this study, a surrogate model was created to forecast the heating and cooling loads of residential structures using data from statistics and a literature analysis. The thermal design of a few representative typical buildings was optimized using the generated surrogate model. Figure 2 shows the methodology, which made use of an evolutionary optimization algorithm (GA) and a surrogate model. Because it depends on several variables, including temperature, humidity, occupant activity level, air flow, garment insulation, temperature of heat-emitting surfaces, and metabolic rate of people, measuring thermal comfort in buildings can be difficult. Hence, it is crucial to consider several parameters, including internal temperature, air circulation, humidity, and the building's thermal characteristics. In the design and operation of buildings, thermal comfort and energy efficiency are important factors to consider.

The health and productivity of those who live there depend on a suitable interior environment, and conserving energy can lower greenhouse gas emissions and lower energy costs. Buildings must utilize energy-efficient heating, cooling, and ventilation systems in addition to steps to prevent heat gain or loss, such as insulation and airtightness. Buildings that use natural light and ventilation, passive solar architecture, green infrastructure, and smart building technologies are all techniques that can improve thermal comfort and energy efficiency. Figure 2 summarizes the optimization framework. First, a TRNSYS model of the current building is made, and it is verified by contrasting it with utility billing information. LHS algorithm is then used to create demonstrative data of simulation cases based on this model. After that, it is used to train and validate the ANN. Then, a GA is run using the ANN to assess the best architecture of ANN, the last step is to find the best non-dominated solutions as shown in the Algorithm architecture used ANN-GA.

(i) The first task involves defining the variables that characterize a building and then generating nearly random building scenarios using the Latin Hypercube Sampling (LHS) algorithm.
(ii) The study involves the parametric analysis and simulation of multiple building energy approaches and measures. To accomplish this, a Python TRNSYS co-simulation is employed to simulate a nearly random sample generated through the Latin Hypercube Sampling (LHS) technique. The primary goal of this step is to construct a substantial database which can be utilized for training the Artificial Neural Network (ANN). To analyze and simulate various building energy approaches and measures, the study employs a parametric approach. The simulation is carried out using a Python TRNSYS co-simulation that utilizes the LHS technique to create a nearly arbitrary sample. The primary objective of this phase is to build significant data that can be utilized to train the Artificial Neural Network (ANN).
(iii) The ANN's framework must be optimized next. To do this, genetic optimization approaches are used to identify the ideal ANN Hyperparameters and structures while protecting the fundamental characteristics of extra complex modeling structures. The creation of a cost function using several ANN performance measures, like R2, is the first step in the optimization process.
(iv) After obtaining the results of the optimization process, one design solution is chosen and evaluated for its aesthetic appeal using the Pareto chart visualization and the TOPSIS method.

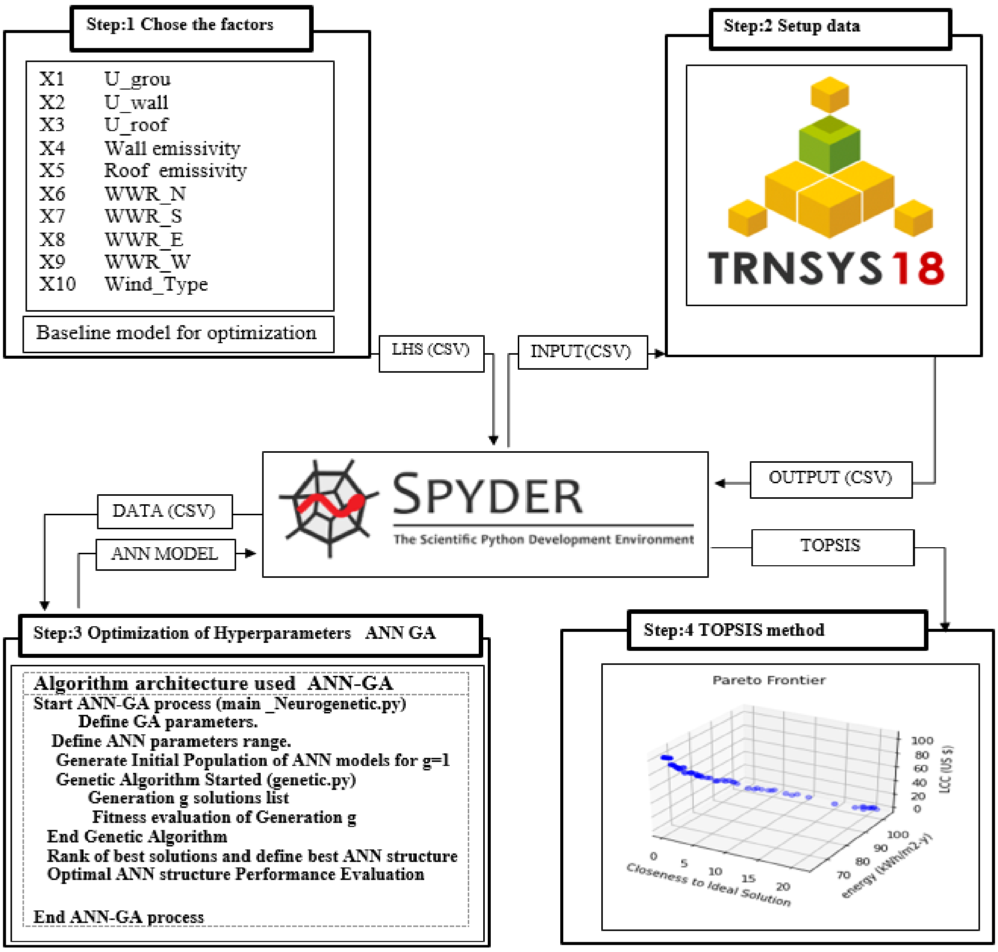


**Fig. 2.** The study's overall framework

### *3.2 Building Descriptions*

There are many different factors that can affect the performance of a building, and these factors can be grouped into several categories. Some of the main categories of factors that can impact building performance include Geometric design such as the shape, size, and orientation of a building can affect its energy performance. Thermal characteristics: The materials used in the construction of a building, as well as the insulation levels and airtightness of the building envelope, can all impact its energy performance. Building energy systems; The heating, cooling, and ventilation systems used in a building can have a significant impact on its energy consumption. Weather conditions: The local climate and weather patterns can affect a house's energy performance, as they determine the amount of heat and light that the building receives and the amount of heat that it loses to the outdoors. Occupant behavior: The actions of the people who use the building, such as turning lights on and off, adjusting the thermostat, and using appliances, can also affect its energy performance. Other factors: There are many other factors that can impact building performance, including the age and maintenance of the building, the efficiency of the appliances and equipment used in the building, and the presence of any energy-saving features such as solar panels or energy-efficient windows. The base house of this study is one of identical residential families.

Table 2 summarizes key optimization variables for a building, encompassing heat transfer coefficients for underground (Ugrou), wall (Uwall), and roof (Uroof). It includes emissivity values for walls and roofs, window-to-wall ratios for diverse facades, and windows types. The chosen insulation material is extruded polystyrene, Windows types, categorized as Simple, Double, and Triple.

**Table 2**
Optimization variables inputs used and their range

| Variables | Description | Variable range and isolated material used | | Price |
|---|---|---|---|---|
| X1 | Ugrou | [0–10] in 1 cm Steps | Extruded polystyrene | 8.28 [US $/m$^2$] |
| X2 | Uwall | [0–25] in 1 cm Steps | Extruded polystyrene | 8.28 [US $/m$^2$] |
| X3 | Uroof | [0–25] in 1 cm Steps | Extruded polystyrene | 8.28 [US $/m$^2$] |
| X4 | Wall emissivity | [0.1–0.9] in 0.1 Steps | - | [-] |
| X5 | Roof emissivity | [0.1–0.9] in 0.1 Steps | - | [-] |
| X6 | WWR_N | [1.50–7.50] in 0.01 m$^2$ Steps | - | [-] |
| X7 | WWR_S | [1.50–7.50] in 0.01 m$^2$ Steps | - | [-] |
| X8 | WWR_E | [1.50–7.50] in 0.01 m$^2$ Steps | - | [-] |
| X9 | WWR_W | [1.50–7.50] in 0.01 m$^2$ Steps | - | [-] |
| X10 | Wind_Type | Simple | - | 144.83 [US $/m$^2$] |
| | | Double | - | 365.52 [US $/m$^2$] |
| | | Triple | - | 655.17 [US $/m$^2$] |

The building's exterior structure is detailed in Table 3, providing insights into the composition and characteristics of the baseline model's wall. The wall incorporates layers of cement (2 cm), hollow brick (15 cm), air spacer (5 cm), polystyrene (with variable thickness), hollow brick (10 cm), and plaster (1.5 cm). For a more thorough explanation of the house's features, the reader is recommended to Belahya *et al.,* [6].

**Table 3**
Description of wall and parameters used in Baseline model

| Wall Materials | Cement | Hollow brick | Spacer of air | Polystyrene | Hollow brick | Plaster | $R_i$ | $R_0$ | $R_{w,t}$ |
|---|---|---|---|---|---|---|---|---|---|
| Thickness(cm) | 2 | 15 | 5 | / | 10 | 1,5 | | | |
| k (W/ m. K) | 1,16 | 0,48 | 0,31 | 0,034 | 0,48 | 0,35 | | | |
| R (m$^2$K/W) | 0,017 | 0,313 | 0,161 | / | 0,208 | 0,043 | 0,11 | 0,05 | 0,742 |

### *3.3 Mathematical Modelling*

Three primary methodologies are employed to calculate building energy performance: numerical simulations, engineering calculation methods, and data-driven simulations. Engineering calculation methods utilize engineering principles and equations to estimate a building's performance, while numerical simulations employ computer software to model and analyze a building's performance. Data-driven simulations use data to develop models of a building's performance. These methodologies can be employed individually or in combination to accurately forecast a building's energy performance. Several building energy simulation programs have been established to evaluate the energy features of buildings.

Numerous assessment metrics can be used to determine the precision of the developed model. such as the coefficient of determination ($R^2$), Relative Squared Error (RSE), Mean Absolute Error (MAE) and root Mean Squared Error (RMSE). $R^2$ is the percentage variance explained by the independent variables in the dependent variable. The following equations can be used to calculate these values:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i}^{n}(yi-\hat{y}i)^2} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i}^{n}|yi-\hat{y}i| \tag{2}$$

$$\mathrm{RSE} = \frac{\sum_{i}^{n}(yi-\hat{y}i)^2}{\sum_{i}^{n}(yi-\bar{y}i)^2} \tag{3}$$

$$\mathrm{R}^2 = 1 - \mathrm{RSE} \tag{4}$$

Here, the average response values, and actual predicted are represented by the letters $y_i$ and $\hat{y}i$ respectively. This article presented the trained model's accuracy.

### *3.4 Artificial Neural Network*

Machine learning algorithms, aided by big data, are increasingly being used for prediction in a variety of engineering-related fields. Because of the availability of large amounts of data, machine learning algorithms can investigate finer-grained trends and develop more accurate predictions [20]. Each neuron receives input data via weights and bias from neurons in the preceding layer. It then combines this data using an activation function to yield output data. that, when the relationship between input and output variables is learned, can be utilized to forecast system performance. To forecast building seasonal energy use and assess the LCC, an ANN was used in this study.

To generate data for training the ANN, parametric runs are necessary, which can be automated using TRNSYS runs. The Spyder program is linked with TRNSYS to produce building (.bui) and deck (.dck) files built on selected models, run TRNSYS using those files, save the results, and resume.

LHS is a popular method for generating an accurate representation of a population's size and distribution using a small sample. LHS is used to make the training database smaller while maintaining the representativeness of the sample. Parametric training was conducted using LHS to generate the database sample, in which 30000 different building models were simulated. The LHS sampling method was chosen because by stratifying the input probability distributions, it makes sure that the sample data points are distributed evenly throughout the search space. The resolution of the physics-based models is hourly, which means that each model simulates 8760 outputs for each desired variable. The Python script can automatically calculate and generate the design's model. Previous research has indicated that MLP neural networks, convolutional neural networks, and recurrent neural networks are among the ANN models utilized. The MLP neural network model is considered the most practical and effective for prediction when dealing with a large number of input and output variables [21,22]. As seen in Figure 3, an MLP neural network typically has one input layer, one or more hidden layers, and one or more output layers.

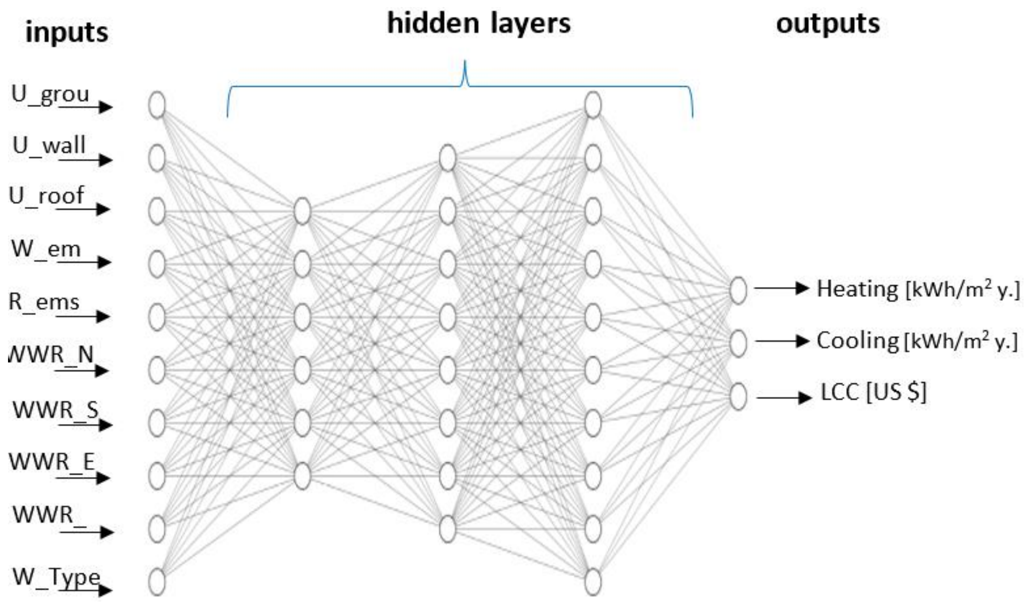


**Fig. 3.** Artificial Neural Network (ANN) architecture used

*3.5 Life Cycle Cost (LCC)*

The second output, or life cycle cost, is computed for 50 years in the manner shown below:

$$\mathrm{LCC} = \sum_{\mathrm{i=1}}^{\mathrm{n}} \frac{|\mathrm{CC_n+M_n}|+|\mathrm{CEB_n-CE_n}|}{(1+\mathrm{r_d})^{\mathrm{n}}}\ [\mathrm{US\$}] \tag{5}$$

where n is the overall evaluation period, in this case n = 50 years, CCn is the design's capital cost in US dollars, Mn is its maintenance cost, CEBn is its annual energy cost in US dollars, and rd is its discount rate. CEn is the annual energy cost for the optimize case [US$] and CEn equal heat cost plus Cooling cost, cooling cost we get it directly times the price of kWh which is 0.05 [US$], about the natural gas energy consumption Heat cost we used:

$$Heat\ cost\ [US\$] = \\ flow\ gas\ [m^3]\ x\ 11.9[cal\ /m^3]\ x\ 1.1622E-6[kWh/cal]\ x\ 0.05\ [US\$/kWh] \tag{6}$$

*3.6 TOPSIS Method*

Following the identification of Pareto optimal solutions, this article used the TOPSIS [23]. The TOPSIS compensatory aggregation multi-criteria decision-making (MCDM) method is used to evaluate the performance of the optimal solutions and determine the best range. This involves assigning weights to each measure, standardizing scores for each measure, and computing the linear parting between each estimation objective and the perfect target. By comparing a small number of evaluation objectives, the TOPSIS method aids in the selection of the best option [24]. A multi-objective optimization problem is one in which more than one objective function must be minimized or maximized. MO's goal is to find a set of solutions that are optimal in terms of all objectives. These are known as Pareto optimal solutions because it is impossible to improve the value of one objective function without diminishing the value of at least one of the other objective functions [24,25]. TOPSIS is a decision-making method that uses a set of criteria to evaluate multiple options. LCC (Life Cycle Cost) is a method for calculating the total cost of a product or system over its entire life cycle, including installation, operation, maintenance, and disposal costs. Using TOPSIS for LCC entails weighing the life cycle costs of various options for a building system or component, such as a heating or cooling system. The TOPSIS method ranks each option based on its distance from the ideal solution, which is defined as the option with the highest overall LCC. The higher an option's ranking, the closer it is to the perfect resolution. TOPSIS applied to LCC can assist building owners and managers in making informed decisions about which systems or components to select for their buildings, based on the total cost of ownership over the entire life cycle of the system. This method can also consider factors like energy efficiency, maintenance requirements, and environmental impact. Overall, TOPSIS is a useful method for evaluating LCC in building systems and components and can help building owners and managers make informed decisions that consider both economic and environmental factors. The TOPSIS is a method of multi-criteria decision-making that is used to evaluate a set of alternatives based on multiple criteria. The method involves defining an "ideal" solution, which is the best possible solution, and a "negative ideal" solution, which is the worst possible solution. The alternatives are then evaluated based on their similarity to the ideal and negative ideal solutions [24]. Consider a choice matrix X with i alternatives and j criteria. The intersection of each alternative and all criteria is represented by the expression xij, where A and C represent the criteria and the available options, respectively. TOPSIS involves numerous phases, including:

(i) Identify the decision criteria and the alternatives to be evaluated.

$$X = \begin{bmatrix} 0 & C_1 & C_2 & C_3 \\ A_1 & x_{21} & \dots & x_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ A_i & x_{i1} & \dots & x_{ij} \end{bmatrix} \tag{7}$$

(ii) Normalize the decision matrix by converting the data into relative values (i.e., between 0 and 1)

$$\mathrm{r_{ij}} = \frac{\mathrm{x_{ij}}}{\sqrt{\sum_1^{\mathrm{i}} \mathrm{x_{ij}^2}}} \tag{8}$$

(iii) Multiply each member of the standardized decision matrix by the weight of the relevant criterion to create the weighted standardized decision matrix.

$$\mathrm{v_{ij}} = \mathrm{w_{ij}}\ \mathrm{r_{ij}} \tag{9}$$

where $w_i$ is the load of ith criterion.

(iv) Identify the positive ideal solution $\mathrm{D}^+$ and the negative ideal solution $\mathrm{D}^-$.

$$D^+ = \{v_1^+ . v_2^+ . \ \dots \ v_j^+\} \tag{10}$$

$$D^- = \{v_1^- . v_2^- . \ \dots \ v_j^-\} \tag{11}$$

and

$$v_j^+ = \left[max\left(v_{ij}\right).i\epsilon\ BC\ or\ min\left(v_{ij}\right).j\ \epsilon\ CC\right] \tag{12}$$

$$v_j^- = \left[min\left(v_{ij}\right).i\epsilon\ BC\ or\ min\left(v_{ij}\right).j\ \epsilon\ CC\right] \tag{13}$$

where, respectively, BC and CC stand for cost and benefit criteria.

(v) Euclidean distance should be used to determine each alternative's distance from the $\mathrm{d}_i^+$ and $\mathrm{d}_i^-$.

$$d_i^+ = \sqrt{\sum_{j=1}^{j}\left(v_{ij} - v_j^+\right)^2} \tag{14}$$

$$d_i^- = \sqrt{\sum_{j=1}^{j}\left(v_{ij} - v_j^-\right)^2} \tag{15}$$

(vi) The alternative with the straight distance to the $\mathrm{d}_i^+$ and longest distance to the $\mathrm{d}_i^-$ is the best alternative, though the different with the longest distance to the $\mathrm{d}_i^+$ and shortest distance to the $\mathrm{d}_i^-$ is the worst alternative.

$$I_i = \frac{d_i^-}{d_i^+ - d_i^-} \tag{16}$$

## 4. Results and Discussions

This section is divided into three parts. A first has occurred. The best ANN architecture model was chosen using GA. Analysis and validation were performed on the artificial neural network (ANN) model that was used, and its results were compared to simulations carried out using TRNSYS. Finally, the study presented the results obtained using the TOPSIS approach, which included the use of an ANN model to generate the TOPSIS results, which were used for comparison purposes in decision-making.

### *4.1 Hyperparameters ANN GA Tested*

An ANN was trained on a personal computer with an i7 6600U processor, 16 GB of RAM, and a 2.6 GHz CPU. The dataset was split into training data and test data. The Python programming environment, along with Pandas, NumPy, TensorFlow, and Scikit-learn libraries, were used to optimize and train the ANN models. The trained models were then used to determine how much energy is needed for heating and cooling by combining LLC and energy consumption. The multi-objective optimization objectives were set based on these two indicators, and the Pareto optimal solutions were obtained. The TOPSIS method was used to set up the results. In this study, equal weightage was assigned to each objective, but decision-makers can modify the objective weights referring to their specific needs and financial constraints.

After testing various hyperparameters, as illustrated in Figure 4 and Figure 5, error histograms for optimal ANN-based predictions of heating, cooling, and LCC were examined. The subsequent configuration yielded the most favorable outcomes:

(i) An ANN has ten input variables and three output variables.
(ii) MLP has four hidden neuron layers.
(iii) Relu function is the activation function. Adam is the optimizer.

(iv) The dropout rate is 0.
(v) The batch size is 10.
(vi) The number of epochs is 150.

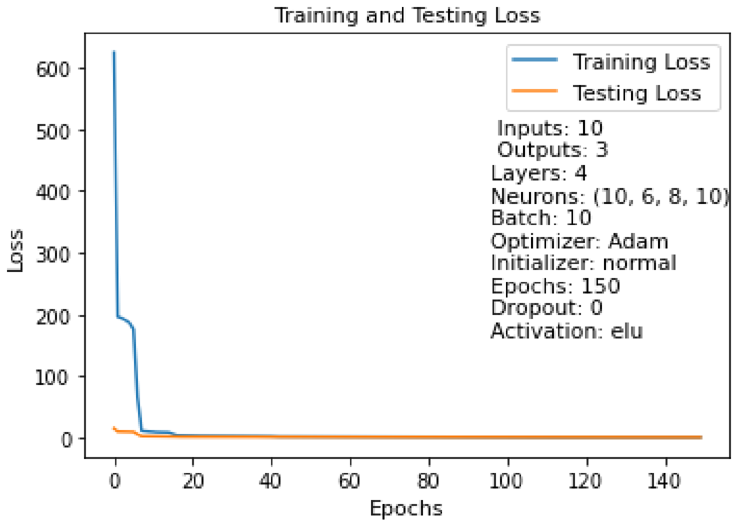


**Fig. 4.** MSE accuracy for the ideal ANN model

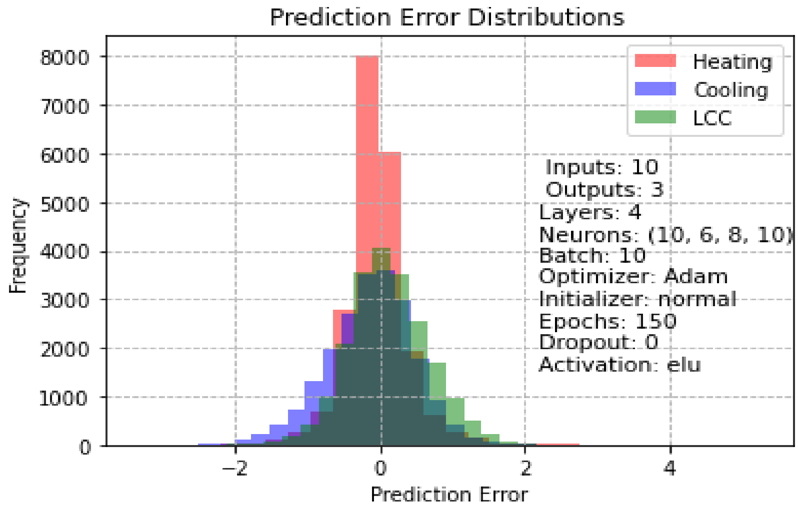


**Fig. 5.** Error histograms for optimum ANN-based predictions of heating, cooling and LCC

*4.2 Validation of ANN Model*

The sample dataset used in this analysis was divided into two main subsets: the training dataset and the test dataset. Each of these subsets served a specific purpose in the overall process of developing and evaluating the model. The training dataset and its derivative datasets played a critical role in preventing overfitting and underfitting of the model. Overfitting occurs when the model becomes overly complex and fits the training data too closely, making it difficult to generalize well to new, unseen data. Underfitting, on the other hand, happens when the model is too simplistic and fails to capture the patterns and relationships present in the training data adequately. The test dataset, separate from the training dataset, was used as an independent evaluation of the model's performance. It allowed for the assessment of the model's prediction capabilities on unseen data, providing a measure of its overall accuracy and reliability.

To evaluate the performance of the optimized ANN model, the target values obtained from physics-based models were compared to the model's predictions for seasonal energy cooling, heating, and life cycle cost (LCC). The correlation between the target values and the model's predictions was demonstrated through regression plots, as illustrated in Figure 6. The results showed high correlation coefficients (R2) between the target values and the ANN model's predictions. Specifically, for the heating case, the R2 value was 99.57%, for the cooling case, it was 99.77%, and for the LCC case, it was 99.94%. These high R2 values indicate that the ANN model was able to accurately account for the variability in the target data, despite the wide range of design models present. It is worth noting that in scenarios where there are multiple outputs, researchers often create separate ANN models to predict each outcome individually. However, the proposed optimization technique offered the advantage of identifying a single ANN model capable of accurately capturing multiple outputs with significant variability. This approach not only reduced the computational resources required for training and evaluating multiple models but also delivered comparable or even superior performance.

Overall, the analysis demonstrated that the developed ANN model, optimized through the proposed technique, exhibited strong predictive capabilities for seasonal energy cooling, heating, and LCC. The model's high accuracy and ability to handle multiple outputs make it a valuable tool for efficient and reliable prediction in the context of building design optimization.

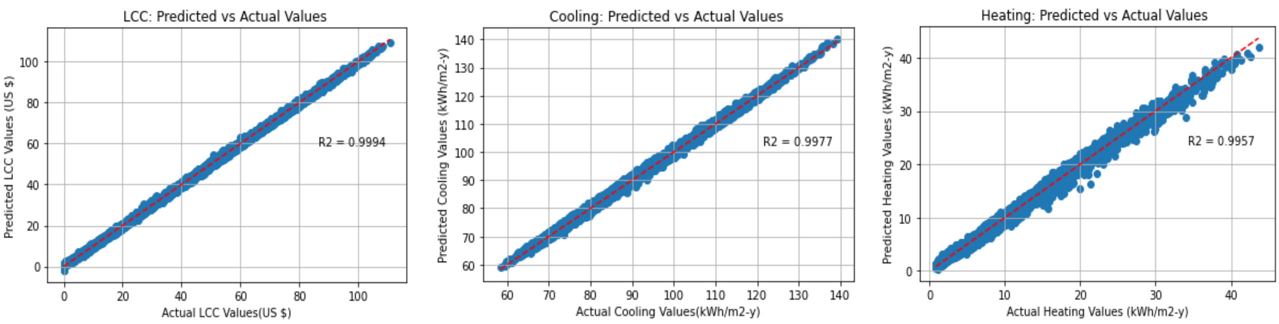

**Fig. 6.** Correlation between the best ANN output prediction's performance and simulated targets

30000 cases were used to train the ANN. If the RMSE stabilizes after a certain number of iterations, the training is said to have reached convergence. After 150 epochs, the ANN training achieved this objective adding a last RMSE of 0.0315. The correlation coefficients between the network outputs and the correctly matched TRNSYS simulation outputs for the three outputs under study were discovered to be extremely near to one, indicating an extremely strong between the desired values and the results.

### *4.3 Optimization Results*

The optimization process involved the integration of the genetic algorithm (GA) model with Python co-simulation code, enabling efficient ANN-based optimization. The objective functions considered in this study were seasonal energy consumption and life cycle cost (LCC), which are crucial factors in residential building design. To identify non-dominated optimal solutions, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) decision-making method was employed. This method allowed the determination of Pareto-front curves, representing a set of optimal solutions that strike a balance between energy consumption and cost considerations. To generate the training datasets for the ANN model, the TRNSYS software in Python was utilized, ensuring reliable and accurate modeling. Figure 7 in the paper highlights two unique Pareto solutions. The first solution, referred to as the heating-optimal solution (HOS) and denoted as point A, offers the potential for significant cost savings while minimizing cooling energy usage. On the other hand, the cooling-optimal solution (COS), represented by point B, emphasizes the reduction of cooling energy consumption. It is essential to consider the trade-off between seasonal energy requirements and cost savings to ensure a balanced approach that satisfies the needs of both private and public stakeholders. To aid decision-makers in selecting the most suitable design option based on their specific requirements, a Multi-Criteria Decision Making (MCDM) analysis was conducted. This analysis involved determining the two-dimensional Euclidean distances of each solution from the ideal solutions. The Pareto results were first normalized and weighted, and then the weighted values (vij) were calculated. Figure 7 provides a visualization of the identification process, illustrating the Pareto-front sets of positive and negative ideal solutions. To further evaluate the solutions, the Euclidean distances from each solution to the positive ideal solution $\mathrm{d}_i^+$ and the negative ideal solution $\mathrm{d}_i^-$ were calculated. These distances, along with the proximity to the ideal solution, were used to compute the TOPSIS scores. The solution with the highest TOPSIS score was deemed the best option, following the ordering of all solutions in the Pareto-front set based on their TOPSIS scores. The proximity to the ideal seasonal energy solution is depicted in Figure 8, providing valuable insights into the performance of each solution.

While conducting energy projects, particularly in government projects, financial incentives have drawn more attention due to the optimization design's higher cost and requirement for financial support. The primary financial worries of stakeholders concerning new projects, such as high upfront costs and protracted payback periods, can be alleviated by financial incentives, which will boost their readiness to renovate their facilities. On the other hand, financial incentives may ultimately place a heavy financial burden on governments. The data presented above indicates that the best design packages can offer both financial and environmental advantages. TOPSIS analysis facilitated the identification of Pareto-optimal solutions that balance seasonal energy consumption and cost considerations.

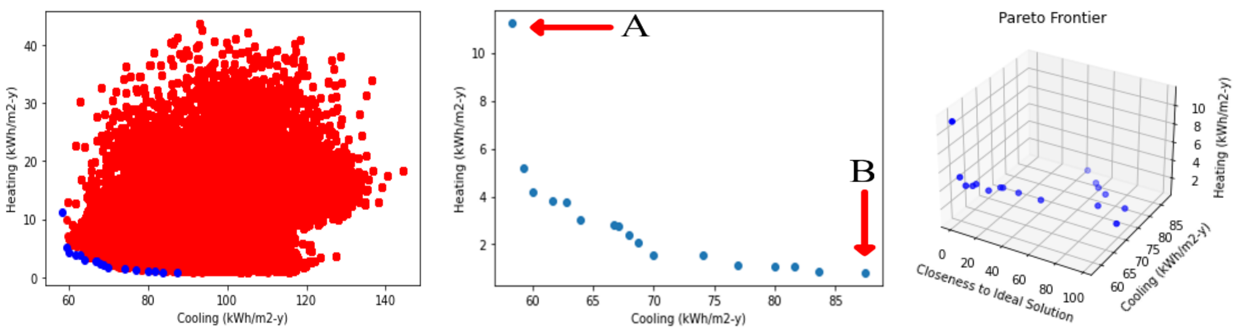

**Fig. 7.** The optimal result for Cooling and Heating energy found with the Pareto Frontier and TOPSIS

The presented methodology and findings contribute to the field of building design optimization, enabling stakeholders to make informed decisions that enhance energy efficiency and cost-effectiveness in residential buildings. To help residents, comprehend the financial advantages of a new design or retrofits and compel them to adopt them, governments can now offer more informational awareness initiatives resulted in a significant reduction in cooling and heating energy demand of up to 51.43% and 98.97.

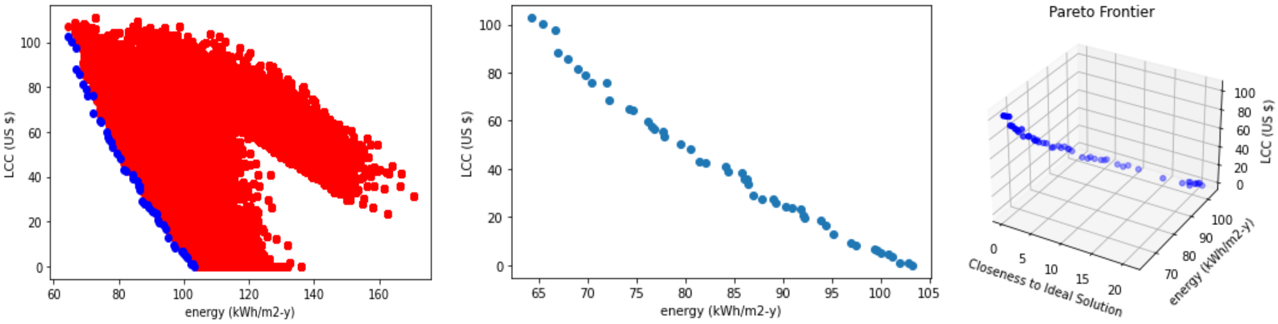


**Fig. 8.** The optimal result for energy and LCC found with the Pareto Frontier and TOPSIS

## 5. Conclusions

In this paper, a comprehensive study was conducted to optimize the design and operational parameters of buildings in arid regions, specifically South Algeria, by integrating Artificial Neural Network (ANN) modeling and Genetic Algorithm (GA) techniques. The primary objective was to enhance energy efficiency and overall performance in building design. The research employed a multi-objective optimization framework based on ANN, with a focus on seasonal energy consumption and life cycle cost (LCC) as the primary objective functions. To generate reliable and extensive datasets for training and evaluation, Latin Hypercube Sampling (LHS) techniques were utilized. The impact of sample size on the performance of the ANN model and optimization outcomes was thoroughly assessed, employing a range of sample sizes up to 30,000 tests. To understand the influence of individual input parameters on the objective functions, a sensitivity analysis was performed. A Python-based genetic algorithm code was developed and integrated with the ANN model to optimize the design variables and achieve the best possible outcomes. The resulting non-dominated optimal solutions, represented by Pareto-front curves, were evaluated using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to determine the most favorable options. The co-simulation approach was adopted, combining Python code and the TRNSYS tool, to ensure accurate modeling and training datasets. The ANN model was utilized to assess the energy efficiency of various architectural modules based on a specific case study. The training outcomes and prediction accuracy of the ANN model were meticulously analyzed using a separate test dataset.

The research findings indicated that optimizing the envelope designs of reference buildings through the integration of ANN and GA optimization systems could result in significant improvements in energy efficiency. Various thermal and geometric parameters, including window-to-wall ratio (WWR) and insulation thickness, were explored as decision parameters for building design. It was observed that cost-effective designs with remarkable energy savings could be achieved by allocating an appropriate budget for the building envelope. Cooling energy usage was reduced by up to 51.43%, while heating energy consumption showed reductions of up to 98.97%. However, it is important to note that the energy-optimal envelope designs may vary depending on factors such as material availability, cost, local standards, regulations, and specific building design characteristics. Therefore, the proposed optimization system should be tailored to the unique context of each project. Aiding in the optimization of building designs.

This research contributes to the advancement of sustainable building practices in arid regions by presenting a comprehensive multi-objective optimization framework that integrates Python programming language, ANN modeling, TRNSYS software, and the TOPSIS decision-making method. The proposed framework offers a robust methodology for designing energy-efficient residential buildings, considering various objective functions and design parameters. The insights gained from this study serve as a valuable resource for architects, engineers, and policymakers in their efforts to enhance energy efficiency and reduce energy consumption in residential constructions.

Overall, this research underscores the importance of considering multiple objectives and employing advanced optimization techniques within the Python, TRNSYS, ANN-GA and TOPSIS framework, in the pursuit of sustainable building design in arid regions. The findings highlight the potential for significant energy savings and cost reduction through the application of the suggested approach, paving the way for more environmentally conscious and economically viable residential buildings.

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