EAI Endorsed Transactions
on Energy Web
Research Article **EAI.EU**

Research on Energy-Efficient Building Design Using Target Function Optimization and Genetic Neural Networks

Youxiang Huan[1,*]

[1]Department of Architectural Engineering, School of Civil Engineering, Yangzhou Polytechnic College, Yangzhou, 225000, China

Abstract

OBJECTIVES: This research aims to provide data for decision-makers to achieve sustainability in building construction projects.
METHODS: A multi-objective optimization method, using the non-sorting genetic algorithm (NSGA-II), assesses energy efficiency by determining optimal wall types, insulation thickness, and insulation type. This paper utilizes the EnergyPlus API to directly call the simulation engine from within the optimization algorithm. The genetic neural network algorithm iteratively modifies design parameters (e.g., building orientation, insulation levels etc) and evaluates the resulting energy performance using EnergyPlus.
RESULTS: This reduces energy consumption and life cycle costs. The framework integrates Matlab-based approaches with traditional simulation tools like EnergyPlus. A data-driven technology compares the framework's effectiveness.
CONCLUSION: The study reveals that optimal design configurations can reduce energy consumption by 30% and life cycle costs by 20%, suggesting changes to window fenestration and envelope insulation are necessary. The framework's accuracy and simplicity make it valuable for optimizing building performance.

Keywords: Building performance, Cost performance, Life cycle cost analysis, Thermal Index, ANN, Design variables

Received on 22 07 2024, accepted on 02 01 2025, published on 21 01 2025

doi: 10.4108/ew.6709

1. Introduction

Energy is an essential resource that is essential to the modern civilization. Additionally, it is an essential component of the process of social and economic growth in nations that have undergone industrialization. The use of energy has been shown to have a positive correlation with economic growth, according to a substantial body of research (Pablo-Romero et al., 2017; Echenagucia et al., 2015). On the other hand, environmental issues that are associated with energy are a subject of significant concern on a worldwide scale. For instance, studies have shown that an increase in the amount of energy used is linked to an increase in both the gross domestic product and the amount of carbon dioxide emissions (Ghaffarianhoseini et al., 2013).

In addition to being responsible for around forty percent of the world's total energy consumption, buildings are also responsible for the majority of the greenhouse gas emissions that countries produce. Structures are responsible for about one quarter of the world's total energy consumption and seventeen percent of the emissions of greenhouse gases (Han and Pei, 2013). This is because buildings are used for residential purposes. In the process of seeking to exercise control over the use of energy and other natural resources,

*Corresponding author: huanyx081@outlook.com

governments often face a number of challenges. Both the high emissions of greenhouse gases and the depletion of energy supplies are two of the most important concerns that the power generating business is now facing on a global basis (Sadineni et al., 2011; Chauhan and Saini, 2014). Typically, fresh ways are required to solve problems.

When it comes to energy management, the majority of small island developing states (SIDS) are now too dependent on imported energy supplies (Chauhan and Saini, 2014). This is in contrast to their goal of achieving energy independence and self-sufficiency. Since the 1990s, the member states of the Caribbean Community (CARICOM) have been rapidly expanding their energy consumption, and, ever since that time, fossil fuels have been the primary source of energy for these countries (Martínez et al., 2014; Niles and Lloyd, 2013; IEA, 2013; Edwards et al., 2012). Despite the fact that buildings are an essential component of the transition toward sustainable energy, it is possible to make the buildings in the region more energy efficient without compromising on their level of comfort.

Developing countries are not making sufficient efforts to enhance the energy efficiency of their structures, and the majority of the building designs in these countries are highly inefficient when it comes to the amount of energy that they use. Several worldwide advancements in energy efficiency have made it possible to create "green" and "net zero energy" buildings. These advancements have opened the path for environmental sustainability.

Despite the fact that it is a difficult task, there is room for development in the design of buildings in order to lessen the amount of energy that is used by buildings in nations that are economically disadvantaged. Thermal envelope characteristics have the potential to have a significant impact on the amount of energy that a building consumes. A significant number of developed nations have created envelope efficiency guidelines, but a significant number of developing nations have not (IEA, 2013). If we wish to contribute to the advancement of building design standards in these regions, it is essential that we carry out research on building envelopes that are energy-efficient. When it comes to predicting consumption patterns and improving energy efficiency, designers often make use of simulators. This is because building energy systems are notoriously complicated. Through the use of an optimization strategy, it is possible to ascertain which efficiency measures would be most advantageous to put into action. In order to meet the requirements of building design, optimization approaches that are based on simulations have evolved into a strategy that is both dependable and effective. In order to achieve increased energy efficiency in building designs, it is required to make improvements to the building envelope. In the field of building design, optimization techniques have been used extensively in order to discover the most effective solutions. A variety of various domains, including building energy systems, design optimization, and building optimization, have been investigated by researchers (Yang et al., 2017; Pacheco et al., 2012; Ferrara et al., 2016; Ascione et al., 2016; Bajpai and Dash, 2012; Lu et al., 2015; Pezzini et al., 2011). There have been a multitude of creative and comprehensive approaches established for the purpose of lowering the amount of energy that is used by buildings. There have been studies that have investigated the transferability of technologies that have a broad range of applications to various designs in different climates and with varied building structures, for example (Mahdavi et al., 2021; Meng, 2022). There are studies and methodologies that may be used to solve design optimization issues; however, there is a dearth of research that Caribbean nations can utilize to quantify these solutions with data from the actual world and provide objective analysis for the creation of energy policy. Due to the fact that several of these nations are now pursuing changes in this area, this presents an extremely difficult situation. Through the use of verified data from the purpose of this project is to evaluate residential building design by producing construction envelope designs that are both energy-efficient and cost-effective. These designs will be developed using a multi-objective optimization approach. It is expected that policymakers will be able to make better judgments based on objective data, which would assist the nation in accomplishing the goals that it has set for its energy strategy.

More time is required for the optimization strategy (Futrell, 2015) due to the fact that it involves testing many sets of weight components. In order to enhance the performance design of the building, an Artificial Neural Network (ANN), which is a typical data-driven technique, was also used (Wright, 2015; Li, 2013; Magnier, 2010). It is important to take note of the fact that the accuracy of the ANN's predictions is partially dependent on the optimization performance of the ANN approach. An error rate of around five percent is thought to be associated with the ANN on average. According to the findings of this study, an online interactive optimization framework should be constructed by combining Matlab-based optimization approaches with EnergyPlus. It is not necessary to make any modifications to the code in order to make use of any of the many optimization techniques that are made available by the Matlab library.

1.1. Motivation and contribution

The global energy crisis has made it imperative, more than ever before, to reduce energy use and transition to renewable energy sources. Buildings that are designed to be energy efficient are crucial to achieving these goals. In light of the critical need to combat climate change, studies on green building practices that may reduce emissions of greenhouse gases have been accelerated. Energy efficiency measures that reduce power consumption have the potential to save a significant amount of money for both building proprietors and occupants. Energy-efficient structures may improve the welfare of their occupants by ensuring that they maintain optimal levels of temperature, illumination, and air quality. The development of advanced optimization algorithms and artificial intelligence has opened up new opportunities for the design of energy-efficient buildings.

This paper incorporates an optimization test that employs the Non-Sorting Genetic Algorithm (NSGA-II) for its execution. For the purpose of evaluating the effectiveness of the optimization, we have decided to compare the artificial neural network (ANN) method. After doing an in-depth study, it will become abundantly evident that the framework that has been offered is the most advantageous alternative that is now accessible. The basis for a paradigm that can be utilized for online interactive optimization in the design of building performance architecture is the key purpose of the study. This is the fundamental objective of the research. Based on the results of this research, it is recommended to build an online interactive optimization framework using EnergyPlus in conjunction with optimization methods developed in Matlab. To take use of any of the several optimization methods provided by the Matlab library, no changes to the code are required.

2. Approach and Methodology

One typical method used to evaluate building designs is the combination of an optimization tool and an energy simulator (Deb et al., 2000; Nguyen et al., 2014). By using a co-simulation technique, the multi-objective optimization approach may be implemented. By using this technology, it is possible to analyze the energy simulator's output in a setting tailored for optimization.

Genetic algorithms (GA) also excel when faced with difficult problems, big solution sets, and plenty of probabilistic factors (Deb et al., 2000). This is on top of the fact that they work well with both continuous and discontinuous functions, as well as non-linear functions. Throughout the process, audited data is used to create and validate a baseline model. Furthermore, it is important to note that this baseline model serves as the foundation for applying and evaluating changes to the building envelope design throughout the optimization process.

While the primary purpose of this investigation is to reduce overall energy consumption and expenditures via the use of multi-objective optimization, the primary emphasis of this investigation is on the building envelope elements. The sole kind of energy that is being evaluated in this research is electrical energy, in addition to the other forms of energy that are being investigated. During the process of conducting optimization studies, it is common practice to make assumptions about the kind of building, the local construction techniques and price, as well as the weather conditions. The term "life cycle cost analysis" is not synonymous with "life cycle analysis," which is a process that entails determining the total amount of energy that a structure has used during its entire lifespan and then examining the effects that this energy has had on the environment

3. Optimization Framework

3.1. Optimization Framework with an Interactive Configuration

The primary objective of the research is to provide the foundation for a paradigm that can be used for online interactive optimization in the design of building performance architecture. In a nutshell, the framework is comprised of two modules: Matlab, which is an optimization module, and EnergyPlus, which is a building simulation module. The initial phase in the process associated with this framework is the input file, which is responsible for supplying the related building characteristics. A set interior and exterior building design, a schedule for electrical equipment, lighting, and occupancy, and climatic data that links to changes in this configuration are some of the aspects that are included in this kind of structure. In order to facilitate the transmission of data and files between EnergyPlus and Matlab, the development of the interface module is an essential step that must be taken. The outcome of this is that two different applications will basically merge into a single interactive optimization framework. Each iteration starts with an invocation of EnergyPlus to conduct the simulation, and Matlab is the one that gets the data in order to evaluate the cost function. In the event that the optimization requirements are reached, the framework will be responsible for producing the outcomes. In the event that it does not work, the design variables are modified and stored to a new file in preparation for the input of the subsequent iteration. The following procedures are included in the optimization process:

1. The first step is to use EnergyPlus to generate a building model file (.idf) for the simulation module. It is important to take note that the output file of EnergyPlus should be set to the table format (.xls);
2. To proceed with the optimization module, the second step is to choose an acceptable optimization method by using Matlab (.m). On the basis of the design variables, cost functions and potential restrictions are generated via the process.
3. In the third step, a template input file is manually prepared in preparation for the interactive module. This file is used to recreate new control variables at each iteration. For the purpose of storing design variables that have been given from Matlab, a text file (.txt) is generated.
4. After finishing all of the preliminary work, proceed to the fourth step, which is to perform the optimization until the design variables that have been optimized are acquired in Matlab.

3.2. Non-sorting Genetic Algorithm (NSGA-II)

In accordance with the information presented in (Delgarm et al., 2016), the NSGA-II approach is often regarded as being among the most effective multi-objective evolutionary programming methods. Following the beginning of a randomized population-based search on the solution space and restrictions, the NSGA-II organizes the solutions into fronts according to the non-demonization criterion. According to the crowding distance, which is a measurement of how close a person is to their neighbor, the next step is to assign a value to each individual based on that distance. It would seem that there is a greater variety of people when the quantity is greater. For the purpose of selecting the players, a binary tournament that utilizes a packed comparison operator is used. Immediately after the mutation and crossover procedures have been finished, the parents and their offspring are brought back together in order to produce fresh generations (Deb et al., 2000). In the study situations that have been taken into consideration, the overall solution space and the encoded chromosomal length both amount to nine.

The optimization problem in this design set is discontinuous, and all of the design variables are discrete, thus finding a solution to it is not a simple task with this design set. The software known as EnergyPlus is capable of simulating the real energy use of a building. The platform takes in and output data in the form of text files (Pedersen et al., 2016; Zhang, 2012). It is self-contained and operates independently.

4. Optimisation Model and the Variables of the Design

A number of features, which are referred to as design variables, are modified as part of the optimization process in order to reduce the efficiency of the goal functions of the system. There are a total of eight factors that may be adjusted in order to get the desired results with this optimization. The many decision-making aspects that were taken into account directly resulted in the large variety of potential solutions that were evaluated. The energy efficiency of a structure is influenced by a wide number of elements, and it would need a significant amount of time and resources to take into consideration all of the aspects that have an effect on the building's energy efficiency. In an effort to make the issue easier to understand, the variables that were selected by the researchers are those that are associated with the primary features of building envelopes. Within the context of the baseline scenario, the optimization approach maintains the heating and cooling set points at the values that were initially established. This is done with the intention of separating the impacts of alterations that have been made to the outside of the structure. When determining the values of the costs, it is necessary to take into consideration the RSMeans building construction cost database (https://www.rsmeansonline.com/) as well as the RSMeans residential cost database (https://www.rsmeansonline.com/). This takes into consideration the cost of the materials for all of the variables. In order to maintain a suitable design solution space, discrete variables are used across the board for all of the parameters. Figure 1 presents the block diagram for the proposed method.

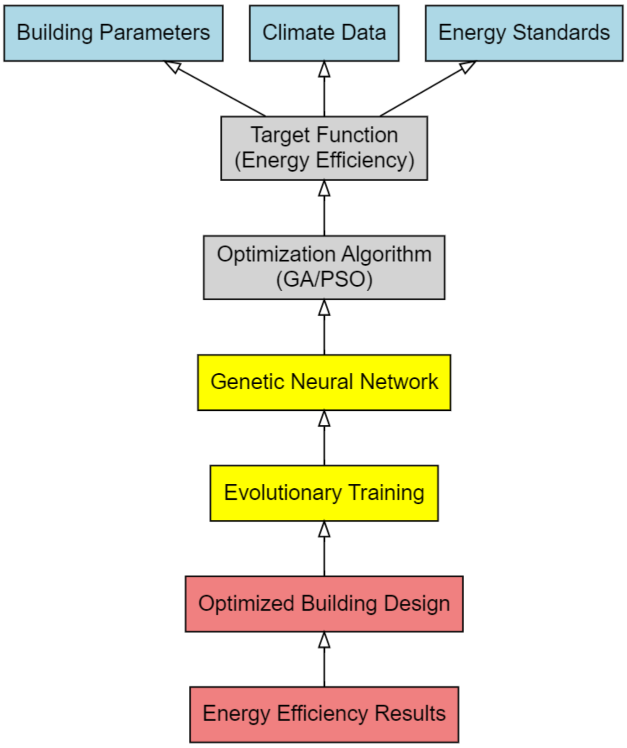


Figure 1. Block diagram for the proposed methodology

4.1. Objective Functions and Constraints

An expression that has the purpose of being minimized or maximized within the constraints of a particular set of parameters is referred to as an objective function since it is used in the field of optimization. The primary areas of focus for this investigation are the thermal index, energy performance, and economic performance of the issue under investigation. By using the aim functions and restrictions, these performances are evaluated and evaluated more thoroughly. The proportion of people who are dissatisfied with the building is the constraint, despite the fact that the total building energy consumption and the life cycle cost of the project are both objective functions. In order for the programming approach to be optimized, EnergyPlus must first identify the values of the limits and objectives that are being considered. This information was derived from EnergyPlus's calculations.

4.2. Variables in the Design

Within the scope of this study, eight design variables have been selected for optimization purposes. These variables include the building height (BH), Building width (BW), Building orientation (BO), the window-to-wall ratio (WWR), the window heat transfer coefficient (WHC_{window}), Wall heat transfer coefficient (WHC_{wall}), solar gain coefficient (SC), and the thickness of the insulation (TI). Everything that was chosen has been shown to have an effect on the amount of energy that is used (https://www.rsmeansonline.com/). Table 1 provides a summary of the distributions of the design variables with their value ranges.

Table 1. Value range for eight design variables

Type of Sampling	Value Range
Building height (BH)	3.0–6.5 m
Building width (BW)	12.9–15m
Window-to-wall ratio (WWR)	0.1–0.9
Building orientation (BO)	2–4degree
Window heat transfer coefficient (WHC_{window})	1W/m^{2}K - 6W/m^{2}K
Wall heat transfer coefficient (WHC_{wall})	~11.5W/m^{2}K
Solar gain coefficient (SC)	0.25-0.75
Thickness of the insulation (TI)	200-300mm

4.3. Functions of the Cost

We use four environmental variables, namely temperature, relative humidity, mean radiant temperature, and air velocity, to analyse thermal behaviour of the building (Ascione et al., 2016). It may range from -10 (an excessively cold temperature) to +10 (an excessively warm temperature. For the purpose of this investigation, the thermal behaviour indicator is denoted by the number of hours that occur over the whole year in which the thermal index does not fall within the range of -1 to +1.

Amount of energy used

The energy consumption of the building (E_C) is the total that is used to describe the energy consumption indication (Ascione et al., 2016).

$$E_C = \frac{H_{load}}{H_{efficiency}} + \frac{C_{Load}}{C_{efficiency}} \quad (1)$$

The terms H_{load} and $H_{efficiency}$ refer to heating load and heating efficiency of building. The terms C_{load} and $C_{efficiency}$ refer to cooling load and cooling efficiency. Within the scope of this investigation, the values of heat and cool have been established as 0.44 and 0.77, respectively.

Life-cycle costs

LCC, which stands for life-cycle cost, is a statistic that is used to evaluate the cost of a project. This metric takes into account the expenditures that are connected with ownership, operation, maintenance, and disposal. The Life Cycle Cost (LCC) method is ideal for evaluating different building design options in order to meet a certain level of performance (such as comfort, building regulations, energy requirements, etc.). The investment costs, maintenance requirements, replacement schedules, and potential lifespans of various design possibilities are all different from one another. LCC methodology may be used for any capital expenditure choice that necessitates greater initial expenses in order to lower future operational costs. In general, the cash flow total of the net present values for a particular option is what is referred to as the life cycle cost according to the equation (2) that is shown below. In the following manner, the life cycle cost (LCC) is calculated by adding the present value of cash inflows and cash outflows that occur over the course of the building's lifetime,

$$LCC = \sum_{t=0}^{N} \frac{N_{cash}}{(1+i)^t} \quad (2)$$

Here, N_{cash} is net cash flow, i is present vlaue of energy cost and t is time period of occurring cost.

Thermal Index

The state of mind in which the occupant expresses happiness with the thermal environment is what we mean when we talk about thermal index. Due to the fact that people spend the majority of their time indoors, it is essential for a structure to provide its inhabitants a safe and pleasant refuge from the elements of the surrounding environment. Several different approaches to evaluating thermal index have been developed as a result of the complexity of this topic (Fanger, 1970). The thermal index is calculated by using Fanger model (Fanger, 1970) as

$$TI = 3.03^{-0.036 H_{area}} + (0.028)(H_{internal} - H_{loss}) \quad (3)$$

Here, H_{area} is heat dissipation per unit area, $H_{internal}$ is internal heat of building and H_{loss} is heat loss from the building.

Table 2. Adaptation strategies for different construction projects

Residential Buildings	Commercial Buildings	Industrial Buildings	High-Rise Buildings	Historic or Retrofit Buildings
Window-to-wall ratio optimization	High-performance glazing systems	Energy-efficient roofing systems	Double-skin façades	Energy-efficient window retrofits
Double- or triple-glazed windows	Solar shading devices (e.g., overhangs, louvers)	Insulated metal panels	Advanced glazing systems with integrated shading	Insulation upgrades (e.g., adding insulation to existing walls)
Insulation materials (e.g., fiberglass, cellulose)	Advanced insulation materials (e.g., vacuum insulation panels)	High-performance windows with low-E coatings	High-performance insulation materials	Façade restoration with energy-efficient materials

Air-tight construction techniques	Energy-efficient façade systems	Optimized natural ventilation systems	Wind and thermal analysis for optimal envelope design	Synergistic design approaches (e.g., combining insulation and solar shading)

Table 3. Genetic Algorithm (GA) parameters and integration with building information modeling

Population size	100-500 potential solutions
Generation count	100-1000 iterations
Crossover probability	0.5-0.8
Mutation probability	0.1-0.3
Data Exchange	Import building geometry and material properties
Simulation integration	Run energy simulations using optimized designs
Results visualization	Display energy efficiency and cost savings

The particulars of the construction process include the kind of building, the weather, the location, and the materials that were used. It is important to take into consideration the second purpose, which is to take into account the cost, energy efficiency, and impact on the environment via GNN, optimize the design of the window and insulation for optimal performance via evolutionary training. Once all is said and done, the building will have windows that are both energy-efficient and have good insulation around them. During the process of optimizing the objective function, it is important to work toward streamlining the use of energy. We make certain that the costs associated with construction are effectively handled. We also ensure that the temperature is comfortable and that the air quality inside is satisfactory. Table 2 presents adaptation strategies for different construction projects. Table 3 presents the Genetic Algorithm (GA) parameters and integration with building information modeling.

5. Results and Discussion

Integrating optimization techniques with artificial neural networks (ANNs) has also been shown in many research to potentially improve building performance design (Edwards et al., 2012). In order to streamline the simulation process, each iteration of this optimization maximizes the employment of a surrogate model based on an artificial neural network (ANN). Using this method could significantly cut down on computation time. To begin, there are three primary components to the process:

1. Developing an EnergyPlus-based building model and establishing a database to store the model's input and output pairs constitute the first stage. The first step is to build a standard BP model.
2. The second is to train and validate an initial ANN model with the IO data mentioned earlier.
3. The third is to integrate the trained ANN model into the optimization framework so it can help predicted the best solutions.

The optimization search is where NSGA-II shines. Figures 2-4 show the results of the optimization framework with regard to total energy costs (E_C), life cycle cost (LCC), and thermal index (TI) in relation to sensitivity analysis, respectively. The optimization reduces life cycle costs by 20% and reduces annual building energy consumption by 30%, according to the contribution to improving the building envelope designs. To achieve a reduction in energy expenses, it is evident that thermal comfort must be compromised. To measure how well an interactive framework optimizes, a traditional Back Propagation (BP) neural network must be designed. This section applies the same architectural principle to residential structures. For the BP network, the training samples include ninety distinct sets of data, while the testing samples include ten distinct sets of data from the same dataset. The ANN is trained and verified using this database. To improve the BP network model's accuracy and convergence rate, the training and testing samples are normalized. Doing so improves the precision of the model. A BP network model with its own hidden layer and seven neurons is constructed as part of this project.

5.1. Workflow Automation

A scripting language like Python or MATLAB can be used to automate the workflow, linking the optimization algorithm with EnergyPlus. Data is exchanged between the optimization algorithm and EnergyPlus through files or databases. Tasks such as generating input files for EnergyPlus, running simulations, and extracting results are automated to streamline the process.

5.2. Parametric Modeling

EnergyPlus allows you to import design data from parametric modeling tools, which allows you to conduct simulations in the software. The optimization approach is able to repeatedly experiment with different design parameters thanks to parametric modeling, which in turn causes the blueprint of the structure to be altered. When you make use of EnergyPlus's accurate and comprehensive simulations of energy performance, you can be certain that your efforts to optimize will be well-grounded. Using EnergyPlus, you are able to experiment with a wide variety of design alternatives, including some that include complex building geometries and control approaches. Through integration with EnergyPlus, simulation may be automated, which significantly reduces the amount of time and effort required for optimization.

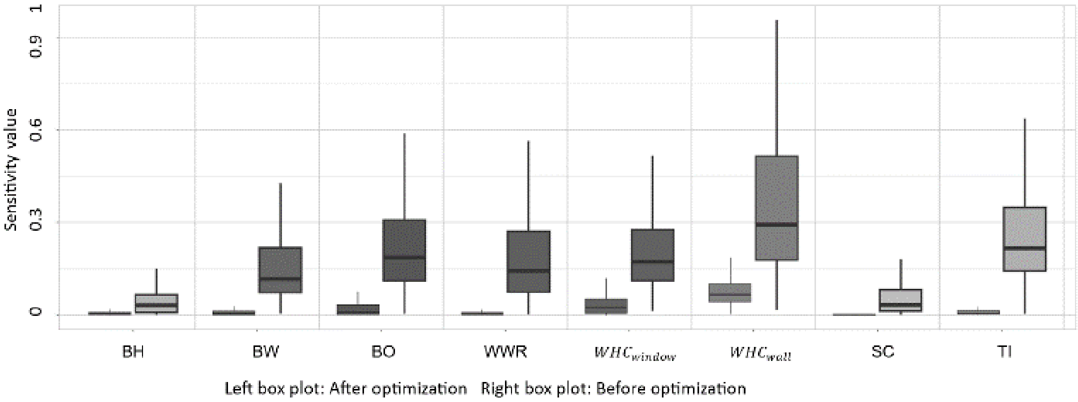


Figure 2. Box plot for eight design variables have been selected for optimization for life cycle cost (LCC) based sensitivity analysis

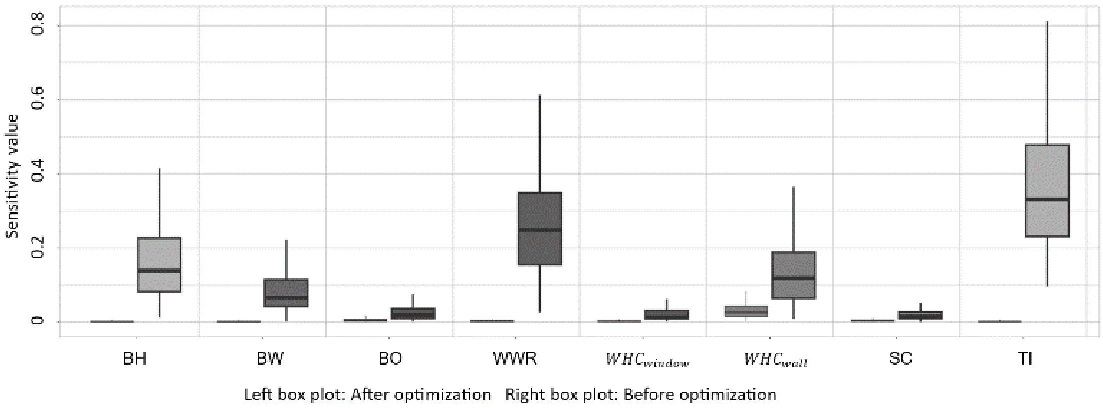


Figure 3. Box plot for eight design variables have been selected for optimization for energy performance (E_C)

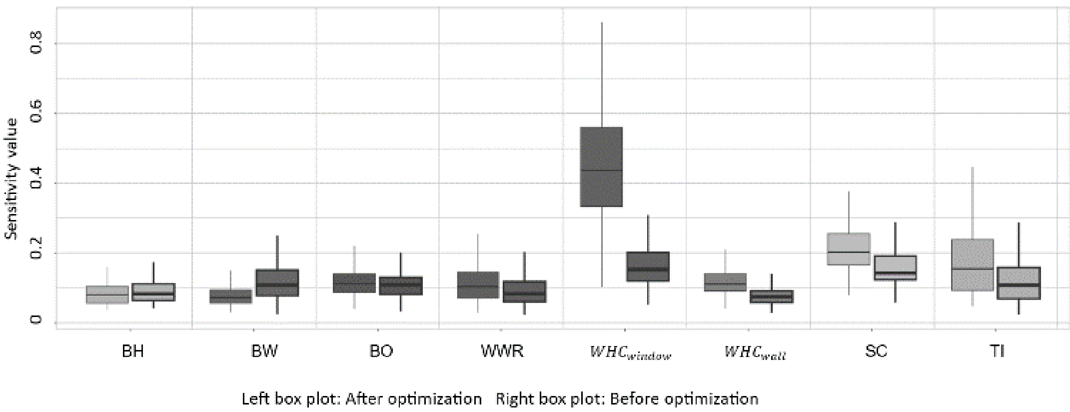
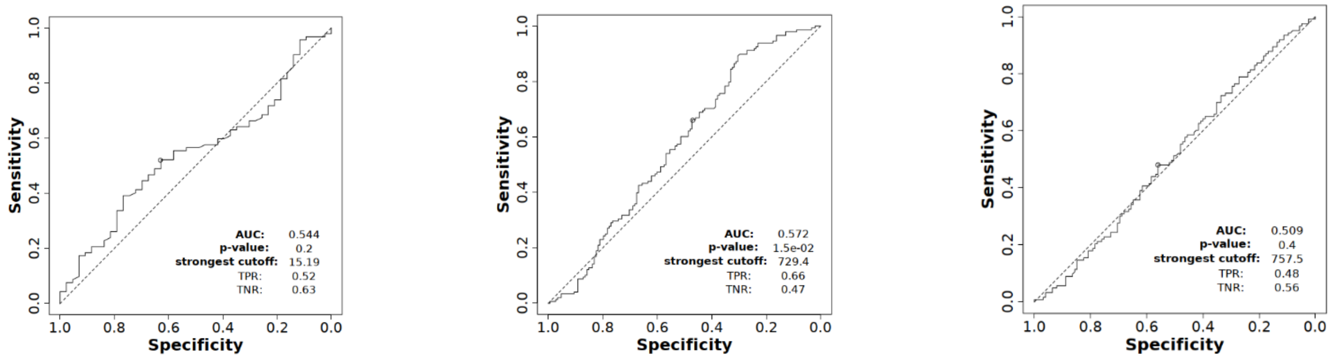


Figure 4. Box plot for eight design variables have been selected for optimization for Thermal Index (TI)

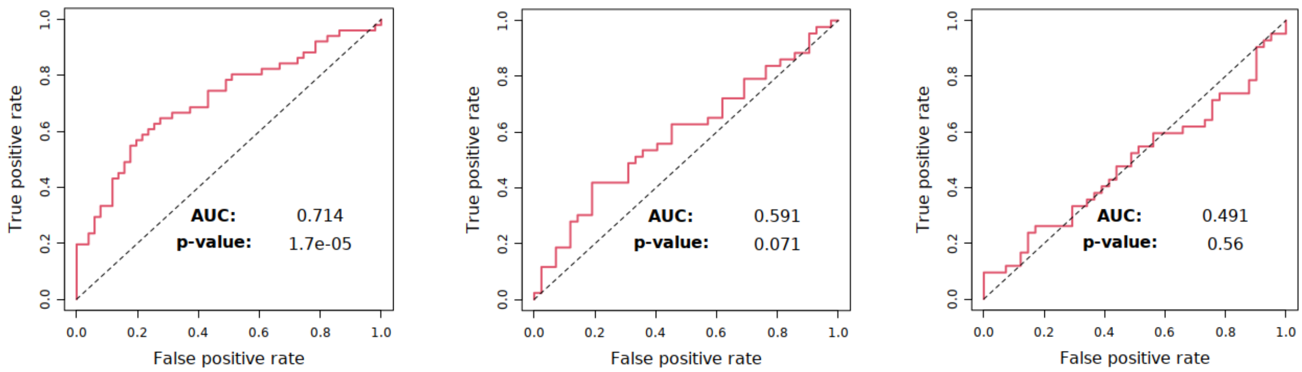
5.3. Trade-off between Sensitivity and Specificity

There can be a trade-off between Sensitivity and Specificity. Increasing one might decrease the other. The optimal balance depends on the specific application. For example, in a medical diagnosis system, a high Sensitivity for a disease might be crucial to avoid missing positive cases, even if it leads to some false positives requiring further tests. The ANN Techniques for Sensitivity and Specificity perform well for cost-sensitive learning when threshold adjustment is used. When the penalty for misclassifying a class is increased, the model may be trained to prioritize that class. Depending on your budget, this might make the test more sensitive or more specific. Total energy costs (E_C), life cycle cost (LCC), and thermal index (TI) are analyzed in Fig. 5(a-c) as sensitivity and specificity, respectively. Sensitivity and specificity analysis provide light on how well artificial neural networks (ANNs) perform on classification tasks, especially in imbalanced datasets. Now that you know how well the model detects positive and negative occurrences, you may make informed judgments according to the priorities of the application you're in charge of. When the training weight of a class's misclassifications is increased, the risk that the model would acquire bias and favor that class is increased as well. There is a possibility that cost allocation will have an effect on either the true positive rate (TPR) or the false positive rate (FPR), depending on the manner in which finances are distributed. Total energy costs (E_C), life cycle cost (LCC), and thermal index (TI) are analyzed in Fig. 6(a-c) as TPR and FPR, respectively.



(a) (b) (c)

Figure 5. Sensitivity and Specificity analysis based on ANN (a) For energy performance (E_C) (b) For life cycle cost (LCC) (c) For thermal index (TI)



(a) (b) (c)

Figure 6. True positive rate (TPR) and False positive rate (FPR) analysis based on ANN (a) For energy performance (E_C) (b) For life cycle cost (LCC) (c) For thermal index (TI)

In this paper, the most energy-efficient materials, as well as the most effective building layouts and orientations, were discovered. It is possible to create improvements in thermal comfort, insulation, and heat loss via the use of optimum design. According to the results of this research, there is a possibility that ecologically friendly building practices will be developed. It has been determined from the findings of this study that there is a need for optimization techniques that are not only more efficient but also more effective in order to tackle the difficulties that are associated with complicated building design concerns. It is likely that the potential benefits of combining objective function optimization with genetic neural networks in order to achieve more comprehensive optimization will be examined during the course of this research. This is because the goal of this study is to achieve more complete optimization

6. Conclusion

Incorporating a simulation-based multi-objective optimization strategy into home design might lead to more economical and energy-efficient construction. The goal of this research is to provide an optimization approach that has been successful in improving building performance via design. For the purpose of comparison, the interactive framework's efficacy is assessed using the artificial neural network (ANN) method. Both of these models have shown to be suitable for optimizing building performance design. This was shown by how the results turned out. Additionally, when compared to results achieved using the ANN method, those obtained using the interactive framework are superior. The provided optimization framework has the potential to be a useful tool for the design of building performance due to its simplicity and accuracy, which are desirable aspects. Reason being, the framework has been made available.

This approach is more cost effective and energy conservative than the current standards. It reduces life cycle costs by 20% and reduces annual building energy consumption by 30%, according to the contribution to improving the building envelope designs. This is in contrast to the norms that are already in effect. The effects of incorporating building envelope modifications into retrofits and new constructions into the legislative process must be carefully considered. To this end, it is possible to use practical design solutions that simultaneously decrease energy consumption.

The results of this research have led to the development of building designs that are much more energy-efficient than the conventional methods. Structures that are energy efficient not only contribute to the slowing of global warming, but they also reduce the influence that they have on the environment. Optimal design may, among other things, improve the quality of the air within the building, minimize the number of pollutants, and increase thermal comfort. Energy-efficient buildings are related with increased property values, in addition to minimizing the running expenditures that are charged by the building. This research shows how genetic neural networks and optimization may be used to develop constructable structures. The study's findings apply to a wide range of building needs and dimensions, making them beneficial to new and retrofitting projects.

References

[1] A. Chauhan and R. P. Saini, “A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control,” Renew. Sustain. Energy Rev., vol. 38, pp. 99–120, 2014.

[2] A. Ghaffarianhoseini, N. Dalilah, U. Berardi, A. Ghaffarianhoseini, N. Makaremi, and M. Ghaffarianhoseini, “Sustainable energy performances of green buildings: a review of current theories, implementations and challenges,” Renew. Sustain. Energy Rev., vol. 25, pp. 1–17, 2013.

[3] A.-T. Nguyen, S. Reiter, and P. Rigo, “A review on simulation-based optimization methods applied to building performance analysis,” Appl. Energy, vol. 113, pp. 1043–1058, 2014.

[4] B. Futrell, Bi-objective Optimization of Building Enclosure Design for Thermal and Lighting Performance. Building & Environment, 92:591-602, 2015.

[5] C. O. Pedersen, U. S. A. Cerl, and F. C. Winkelmann, “EnergyPlus: Energy Simulation Program,” ASHRAE J., vol. 42, no. 4, pp. 49–56, 2000.

[6] E. E. Edwards, O. S. Iyare, and L. L. Moseley, “Energy consumption in typical Caribbean office buildings: A potential short term solution to energy concerns,” Renew. Energy, vol. 39, no. 1, pp. 154–161, Mar. 2012.

[7] Echenagucia, T.M.; Capozzoli, A.; Cascone, Y.; Sassone, M. The early design stage of a building envelope: Multi-objective search through heating, cooling and lighting energy performance analysis. Appl. Energy, Vol.154, pp.577–591, 2015.

[8] F. Ascione, R. F. De Masi, F. de Rossi, S. Ruggiero, and G. P. Vanoli, “Optimization of building envelope design for nZEBs in Mediterranean climate: Performance analysis of residential case study,” Appl. Energy, Vol. 183, pp. 938–957, 2016.

[9] J.A. Wright. Constrained, mixed-integer and multi-objective optimization of building designs by NSGA-II with fitness approximation, Applied Soft Computing, Vol.39, pp.114-126, 2015.

[10] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan, “A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II,” in Parallel Problem Solving from Nature PPSN VI: 6th International Conference Paris, France, September 18-20, 2000 Proceedings, Berlin, Heidelberg: Springer, 2000, pp.849–858.

[11] K. Li, Optimization of ventilation system operation in office environment using POD model reduction and genetic algorithm, Energy and Buildings, Vol.67, pp.34-43, 2013.

[12] K. Niles and B. Lloyd, “Small Island Developing States (SIDS) & energy aid: Impacts on the energy sector in the Caribbean and Pacific,” Energy Sustain. Dev., vol. 17, no. 5, pp. 521–530, 2013.

[13] L. Magnier, Multi-objective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network, Building & Environment, 45(3):739-746, 2010.

[14] L.MARTÍNEZ, L. VILLARREAL UGARTE, C. MENCHACA, R. PORSEN, and M. BREMER, “State of Play

of Sustainable Building in Latin America / Situación de la Edificación Sostenible en América Latina," 2014.
[15] M. del P. Pablo-Romero, R. Pozo-Barajas, and R. Yñiguez, "Global changes in residential energy consumption," Energy Policy, vol. 101, pp. 342–352, 2017.
[16] M. Ferrara, E. Sirombo, A. Monti, E. Fabrizio, and M. Filippi, "Influence of Envelope Design in the Optimization of the Operational Energy Costs of a Multi-family Building," Energy Procedia, vol. 101, pp. 216–223, Nov. 2016.
[17] M.-D. Yang, M.-D. Lin, Y.-H. Lin, and K.-T. Tsai, "Multi-objective optimization design of green building envelope material using a nondominated sorting genetic algorithm," Appl. Therm. Eng., vol. 111, pp. 1255–1264, 2017.
[18] Mahdavi, A.; Berger, C.; Amin, H.F.; Ampatzi, E.; Andersen, R.K.; Azar, E.; Barthelmes, V.M.; Favero, M.; Hahn, J.; Khovalyg, D.; et al. The Role of Occupants in Buildings' Energy Performance Gap: Myth or Reality? Sustainability 2021, 13, 3146.
[19] Meng, Y. Research on Building Energy Efficiency Optimization Based on Sensitivity Analysis of Design Parameters. Ph.D. Thesis, Tianjin University, Tianjin, China, 2022.
[20] N. Delgarm, B. Sajadi, S. Delgarm, and F. Kowsary, "A novel approach for the simulation-based optimization of the buildings energy consumption using NSGA-II: Case study in Iran," Energy Build., vol. 127, pp. 552–560, 2016
[21] P. Bajpai and V. Dash, "Hybrid renewable energy systems for power generation in stand-alone applications: A review," Renew. Sustain. Energy Rev., vol. 16, no. 5, pp. 2926–2939, 2012.
[22] P. O. Fanger, Thermal comfort. Analysis and applications in environmental engineering. Copenhagen: Danish Technical Press., 1970.
[23] P. Pezzini, O. Gomis-Bellmunt, and A. Sudri-Andreu, "Optimization techniques to improve energy efficiency in power systems," Renew. Sustain. Energy Rev., Vol. 15, no. 4, pp. 2028–2041, 2011.
[24] R. Pacheco, J. Ordóñez, and G. Martínez, "Energy efficient design of building: A review," Renew. Sustain. Energy Rev., Vol. 16, no. 6, pp. 3559–3573, 2012.
[25] R. S. Means Engineering Department, Residential cost data, 2014, 33rd ed. Norwell, MA: R.S. Means, 2013. RSMeans Data Online. Available: https://www.rsmeansonline.com/.
[26] S. B. Sadineni, S. Madala, and R. F. Boehm, "Passive building energy savings: A review of building envelope components," Renew. Sustain. Energy Rev., Vol. 15, no. 8, pp. 3617–3631, 2011.
[27] The International Energy Agency, "Modernising Building Energy Codes to secure our Global Energy Future: Policy Pathway," Paris, 2013 https://www.undp.org/sites/g/files/zskgke326/files/migration/tr/PP7_Building_Codes_2013_WEB.pdf
[28] X. Han, J. Pei, Multi-objective building energy consumption prediction and optimization for eco-community planning, Energy & Buildings, 66(5):22-32, 2013.
[29] Y. Lu, S. Wang, and K. Shan, "Design optimization and optimal control of grid-connected and standalone nearly/net zero energy buildings," Appl. Energy, Vol. 155, pp. 463–477, Oct. 2015.
[30] Y. Zhang, "Use jEPlus as an efficient building design optimisation tool," in CIBSE ASHRAE Technical Symposium, 2012, no. April, pp. 1–12.