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Multi-Objective Building Retrofitting Utilizing Evolutionary Algorithms and Machine Learning Models

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Abstract: The retrofitting of existing buildings provides an enormous opportunity for increasing tenant wellbeing and comfort while lowering worldwide greenhouse gas emissions and energy usage. This is regarded as one of the primary techniques for obtaining environmental sustainability through construction at a less cost and with the highest rate of adoption. Although a large selection of retrofit methodologies is gladly accessible, strategies for identifying the most appropriate combination of retrofit operations for specific projects remain a serious technical problem. This study provides a novel Multi Evolutionary Genetic-optimized Artificial Neural Network algorithm (MEGANN) to quantitatively evaluate technological possibilities in a building retrofitting project. This research offers the speed of estimation with the power of Multi-objective evolutionary optimization and machine learning algorithms. The analysis begins with the individualized optimization of objective functions with a focus on the properties and efficiency of the building, including energy consumption and retrofit cost. We evaluate our approach by comparing it to conventional procedures. The results are superior to those obtained by any other currently available techniques.

Keywords: *Retrofitting building, energy consumption, multi evolutionary genetic-optimized artificial neural network algorithm* (MEGANN)

1. Introduction

The energy industry has severe obstacles that exacerbate daily. International Energy Agency's "three Es" are "energy security," "environmental protection," and "economic growth." The present trends in energy raise serious concerns about all three [1]. The construction industry is one of the biggest energy users, using a lot of energy and emitting a lot of greenhouse gases (GHG). Buildings in the US used 75% of the country’s electricity and 41% of all major energy in 2010. Building-related energy use accounts for around 41% of CO2 emissions, 55% of SO2 emissions, and 15% of NOx emissions generated in the United States [2]. Similar circumstances may be seen in the European Union (EU), where the construction industry is responsible for 40% of the world's total CO2 emissions and 40% of the world's ultimate energy consumption. The EU-27's dependence on imported energy has increased during the last 10 years, reaching 53.9%. In comparison to 1999, that’s a 9-point bump up, right there. Therefore, the Energy Efficiency and Performance Building Directive (EPBD) 2002/91/EC and its recasts reveal that the cornerstone of European energy policy has a clear direction toward the management and sensible usage of energy in buildings [3]. Energy efficiency has gained widespread acceptability among building owners since it has allowed the majority of European nations to reduce the energy consumption of new homes by better than 55% without raising their construction costs [4]. Only 5% of the energy is used by these structures, which make up around 20% of the total building stock. However, even if all upcoming structures were to be constructed with very low electrical and heating energy needs, the overall rise in energy demand would only be halved. The demand as it is now would not change. The most substantial impact on the overall energy needs in the building stock for many years to come will Often, very modest extra expenses are required when developing new structures to make them extremely energy-effective. On the other side, it is more challenging and expensive to make significant energy efficiency in older structures; however, it is always feasible to find several actions that are both economical and energy efficient. However, the solution utilized and the actions conducted must have solid justification and are wisely selected both when constructing new buildings and implementing measures in existing buildings [6]. That is to say, when buildings are being retrofitted, it is crucial to choose the best strategy quickly because if alternative approaches are selected and put into practice, it will only be feasible to transform the

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structure at a later time at a much highest cost [7]. The work required in retrofitting is often complicated and diverse, requiring the integration of several specialists under highly changeable circumstances. When considering the technical, technological, ecological, social, and comfort considerations, a building and its surroundings constitute a complex system. The dependency between subsystems is vital since each one affects the overall efficiency performance. For this reason, it is challenging to conduct a thorough building retrofit evaluation.

2. Related Works

The research [8] offered a fast decision-making tool that can quickly determine the best retrofitting scheme without the time-consuming characteristics of manually repeated steps. It was produced utilizing a hybrid machine-learning method. The research [9] proposed a methodology for optimizing the location and quantity of strengthening with steel jacketing to reduce the overall cost of seismic retrofitting. The suggested framework utilizes a Genetic Algorithm (GA) routine that iteratively configures reinforcements to equivalent the ideal result for a 3D RC frame fiber-section model built in Open Sees. The paper [10] aimed to facilitate multi-objective optimization of energy retrofit plans for non-residential buildings by providing a quick energy performance estimate engine. The study [11] presented a methodical framework for selecting and locating the most effective retrofit solutions for preexisting structures. We introduce the overarching problem of building retrofits and the major concerns that must be taken into account when deciding whether or not to invest in such projects. The paper [12] compared and contrasted three large-scale retrofitting interventions currently in use in three European cities (Nantes, Hamburg, and Helsinki) to identify governance recommendations for local authorities on replicating and scaling up retrofitting initiatives. The work [13] provided a proxy model for determining the appropriate methods for enhancing an existing building's thermal performance and energy efficiency. Artificial neural networks are utilized in the construction of this model to achieve a good trade-off between accuracy and computational cost. The work [14] presented a machine learning (ML)-based framework for a data-driven, economical building retrofit study that makes use of the significance of the input factors. The research [15] employed the use of infrared thermographs and temperature sensors to analyze the thermal performance of a deep retrofitted building in the UK. The estimated energy savings of a modified building are then compared to the thermal performance of a baseline building in the same region.

3. Methododolgy

In this section we discuss about the technology choices in retrofitting building using Multi Evolutionary Genetic-optimized Artificial Neural Network algorithm (MGANN).

3.1. Multi Evolutionary Genetic-optimized Artificial Neural Network algorithm (MEGANN)

An optimization algorithm called a genetic algorithm takes its cues from the principles of genetic evolution and natural selection. Natural selection is a method often employed to quantitatively assess technology choices in a building retrofit project. because the fittest people have a superior chance of surviving and passing on their genes to the next generation.

A general description of a genetic algorithms operation is given below:

Step 1 (Initialization): Make a starting population of people (possible options). Each person is represented by an x number that falls between [0, 10]. The problem dictates the population size, which may be chosen depending on the preferred exploration-exploitation trade-off.

Step 2 (Evaluation): Calculate the value of f(x) for each x value to determine the fitness of each member of the population. Since we want to maximize this function, the fitness function in this situation is just f(x) = x^2.

Step 3 (Selection): Each person's selection likelihood varies in direct proportion to how fit they are. Users may choose from several selection techniques, including rank-based selection, roulette wheel selection, and tournament selection.

Step 4 (Reproduction): To produce offspring, use genetic operators like crossover and mutation. Crossover is the process of creating a new person by fusing the genetic material of two parents. An individual's genes undergo random alterations as a result of mutation. These operators aid in the exploration of fresh areas of the search space while retaining certain traits of the fittest individuals.

Step 5 (Replacement): Replace the existing population with the next generation. Both parents and children will be part of the new population. By taking this measure, it is made sure that the fittest people have a better opportunity of passing on their genetic makeup to the next generation.

Step 6 (Termination): For a specified number of generations or until a termination requirement is satisfied, repeat steps 2 through 5. A maximum number of iterations, achieving a desirable degree of fitness, or a combination of criteria might serve as the termination criterion.

The genetic algorithm searches the search space by repeatedly repeating these stages until it finds the value of x that maximizes the function f(x) = x^2. The most physically fit person in the ultimate population will be the answer.

The ANN is a collection of neurons with unidirectional links between them that may mimic the brainpower capacity for pattern recognition and association learning in data. Each neuron j has an activated function θ_i associated with it, and each connection among neurons j,i has a weight u_{ji} given to it that regulates how much impact neuron j has on neuron i. The weighted connections between the neurons, which stand in for the fundamental processing units of an ANN, enable the modeling of complicated interactions. Normally, the neurons are arranged in layers, and each layer's neurons are connected directly to the layers above it (Figure 1). The levels in between are referred to as "hidden layers," while the first layer is known as the "input layer" and the final one is the "output layer." The initial hide layer receives the input information from the input layer, where it aggregates and transforms them as follows:

$$net_i = \sum_{j \in O_i} u_{ji} P_j \quad (1)$$

Where O_i is the collection of neurons that had linked to neuron i, P_j is the output of neuron I, and wij is the weight of the link connecting neuron j and i. The following formula is used to determine a neuron's output.

$$P_j = \phi\,(net_j) \quad (2)$$

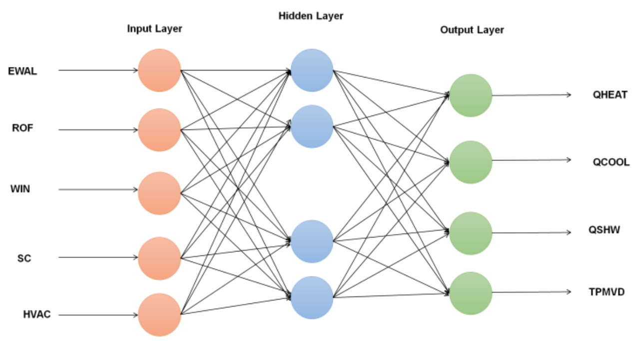

Fig.1. Three layers of ANN

Where ϕ represents neuron j is an activated function. The hyperbolic tangent function, with the formula$e(y) = \frac{f^y - f^{-y}}{f^y + f^{-y}}$, is a typical activation function. This function is very helpful since it may be both continual and distinct, which are requirements for determining the network error gradient. The neurons in the subsequent layer get each neuron's output after that. This process is continued for each additional layer until the network's output layer is reached. The output layer's output corresponds to the network's overall output.

An ANN's connection weights must be changed to simulate non-linear relations. The usual method for doing this entails two steps. Backpropagation is used to determine each neuron's error signal for a specific observation in the initial step. The error function determines the error signal. Regression's error function is written as $F = \frac{1}{2}\sum_{j=1}^{m}(s_i - P_j)^2$, where m is the overall number of goal values, P_j is the output neuron j and s_i is the goal value. The error function leads to the calculation of the error signal as follows:

$$\delta_i = \begin{cases} \phi'(net_i)(P_i - s_i) & if\ is\ an\ output\ neuron \\ \phi'(net_i)\sum_l \delta_l u_{il} & otherwise \end{cases} \quad (3)$$

where P_i is the neuron i output, s_i is the neuron j's target value, u_{il} is the weight of the link between neurons j and k, k is the neuron error signal, net_i is the input from the network system to neuron j, and ϕ' is the derived activated function

$$\Delta u_{ji} = -\eta \frac{\partial F}{\partial u_{ji}} = -\eta \delta_i P_j \quad (4)$$

The linked weights are modified by the use of the Training Algorithm in the second phase. Where u_{il} is the weight of the link between neuron j and neuron i, E stands for error function, P_j for neuron j output, and i for neuron i error signal. Continue all steps till a termination requirement is satisfied. To enhance the network's training, several gradient expansions and modifications have been suggested. To increase the training's resistance to noise, the error gradients are often added across a "mini-batch" of data. The cumulative modifications are then used to modify the connection weights. Also, utilizing an accelerated gradient while modifying the connection weights may significantly enhance training results.

$$\delta_i = \begin{cases} \phi'(net_i)(P_i - s_i) & if\ is\ an\ output\ neuron \\ \phi'(net_i)\sum_l \delta_l u_{il} & otherwise \end{cases} \quad (5)$$

Where P_i is the neuron i output, s_i is the neuron j's target value, u_{il} is the weight of the link between neurons j and k, k is the neuron error signal, net_i is the input from the network system to neuron j, and ϕ' is the derived activated function

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The Multi-objective optimization (MOO) models are intended to capture the many, competing, and incommensurate elements of evaluating the merits of prospective solutions, identify their trade-offs, and give a solid technological foundation for decision assistance. In general, there are many non-dominated (Pareto optimum) solutions to MOO because the competing goal functions prevent the existence of a single solution. We aim to simultaneously optimize energy use, retrofit costs, and hours of temperature discomfort in our model. Due to its structure and decision-making processes, this MOO model has a combinatorial character. Its nonlinearity is brought on by the calculations for building performance. The non-dominated front has so been referred to as the genetic algorithm (GA). The MGEANN as the assessment purpose in terms of both energy use and thermal discomfort estimates once it has been trained and verified. By utilizing the 'gamultiobj' function of the GA toolbox in MATLAB, the set of non-dominated solutions is found during optimization.

A regulated elitist GA is used by the 'gamultiobj' tool in MATLAB. This is based on the same genetic algorithm (GA) principles as any other GA, in that it evolves a population of people to solve an optimization problem. An individual stands in for the many retrofit technologies and interventions that might be applied to a building in this research. It is clear from looking at Figure 2 that each person is analogized by a single chromosome, the genes for which determine a wide variety of characteristics.

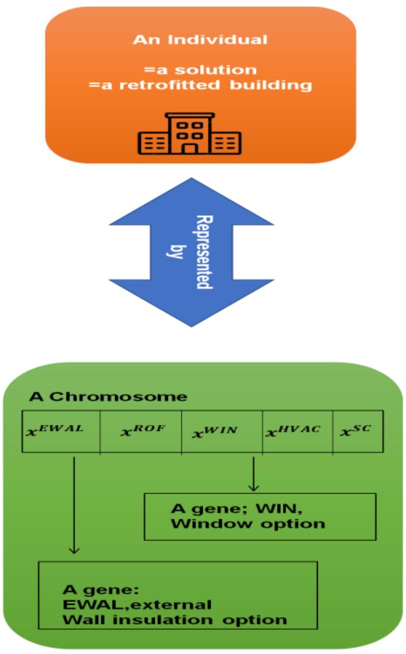

Fig.2. A chromosomal representation of an optimal retrofitting strategy.

Integer decision variables X^{EWAL},X^{ROF},X^{WIN}, X^{SC}, and X^{HVAC} are defined as follows:

X^{EWAL}: Type of external wall insulating material

X^{ROF}: Name of the kind of roofing insulation material

X^{WIN}: Identifier of the window type

X^{SC}: Type of solar collector identification

X^{HVAC}: ID of the kind of HVAC system.

4. Result and Discussion

Retrofitting a building can have a significant impact on energy consumption by implementing energy efficiency measures and upgrading systems. The specific energy consumption reduction achieved through retrofitting will depend on various factors, including the building's initial energy performance, the scope of retrofit measures, and the efficiency improvements implemented. TRNSYS does a direct evaluation of the building's energy use. Total energy consumption (EC) is the result of adding the energy requirements for sanitary hot water (QSHW), space cooling (QCOOL), and space heating (QHEAT) systems. The overall energy consumption is reduced by the SHW generated by the solar collector (QSC). In addition, energy usage for lighting is not taken into account since it is not anticipated that the execution of the contemplated retrofit operations would considerably impact this. The energy consumption is shown in Figure 3 and Table 1, and it demonstrates that our suggested approach MEGANN uses less energy than other methods that are already in use, such as DUE-S, LSTM, and RNN.

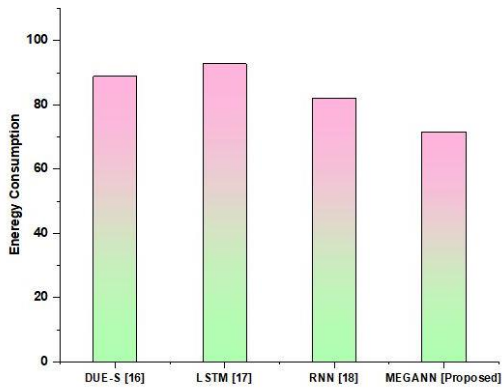

Fig.3. Comparative Analysis of Energy Consumption

We examine the aforementioned parameters and demonstrate that we derived the model cost in the Configuration Cost and Execution Cost sections below.

Table 1. Comparison of Energy Consumption

Methods	Energy Consumption
DUE-S [16]	88.85
LSTM [17]	92.72
RNN [18]	81.91
MEGANN [Proposed]	71.5

Retrofit cost refers to the expenses associated with upgrading or modifying an existing system, structure, or equipment to improve its performance, efficiency, or functionality. Retrofitting is commonly done in various industries and sectors, including building construction, energy, transportation, and manufacturing, among others. The cost of the retrofit is shown in Figure 4 and Table 2. And it demonstrates that our suggested strategy is less effective than other existing methods.

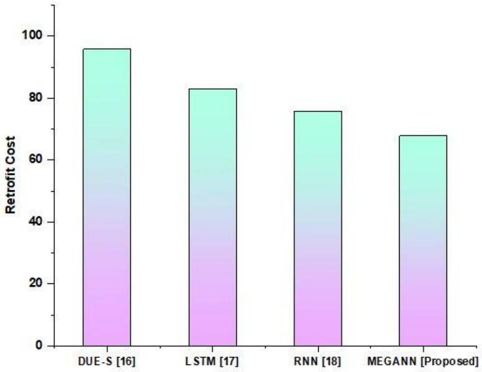

Fig.4. of Comparative Analysis of retrofit cost

Table 2. Comparison of retrofit cost

Methods	Retrofit Cost
DUE-S [16]	95.81
LSTM [17]	82.95
RNN [18]	75.78
MEGANN [Proposed]	67.85

5. Conclusion

In this work, MEGANN was used to implement a multi-objective optimization model. The graphs may also be used to calculate the retrofit costs associated with any change in energy use, whether it be increased or decreased. Thus, the ultimate choice may be based on a thorough assessment of the circumstances, including the effects of energy use and retrofit costs. The suggested method has a great deal of promise for resolving complex multi-objective building retrofitting issues, and it may be used as a tool to help with project-related decision-making. Future work would need to integrate the suggested model with a method for factoring the decision-making preference into the decision-making procedure. Additionally, Analysis of Uncertainty is necessary to give the decision-making enough due to the multiple unknown elements associated with a building retrofit, including savings calculation, weather predictions, cost data for retrofit measures, and assurance in selecting and determining the optimum retrofit options.

References

[1] Nepal, R. and Paija, N., 2019. Energy security, electricity, population, and economic growth: The case of a developing South Asian resource-rich economy. Energy policy, 132, pp.771-781.

[2] MacNaughton, P., Cao, X., Buonocore, J., Cedeno-Laurent, J., Spengler, J., Bernstein, A. and Allen, J., 2018. Energy savings, emission reductions, and health co-benefits of the green building movement. J. Expo. Sci. Environ. Epidemiol, 28(4), pp.307-318.

[3] Zgajewski, T., 2015. The Energy Performance of Buildings: Promises Still Unfulfilled. Egmont Paper No. 78, May 2015.

[4] Li, Y., Kubicki, S., Guerriero, A. and Rezgui, Y., 2019. Review of building energy performance certification schemes towards future improvement. Renewable and Sustainable Energy Reviews, 113, p.109244.

[5] Filippi, M., 2015. Remarks on the green retrofitting of historic buildings in Italy. Energy and Buildings, 95, pp.15-22.

[6] Ruparathna, R., Hewage, K. and Sadiq, R., 2016. Improving the energy efficiency of the existing building stock: A critical review of commercial and institutional buildings. Renewable and sustainable energy reviews, 53, pp.1032-1045.

[7] Karthick, S. ., Shankar, P. V. ., Jayakumar, T. ., Suba, G. M. ., Quadir, M. ., & Paul Roy, A. T. . (2023). A Novel Approach for Integrated Shortest Path Finding Algorithm (ISPSA) Using Mesh Topologies and Networks-on-Chip (NOC). International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 87–95. https://doi.org/10.17762/ijritcc.v11i2s.6032

[8] Gallo, W.W.C., Clemett, N., Gabbianelli, G., O'Reilly, G. and Monteiro, R., 2023. Influence of parameter uncertainty in multi-criteria decision-making when identifying optimal retrofitting strategies for RC buildings. Journal of Earthquake Engineering, 27(7), pp.1769-1794.

[9] Shin, J. and Park, S., 2022. The optimum retrofit strategy of FRP column jacketing system for non-ductile RC building frames using artificial neural network and genetic algorithm hybrid approach. Journal of Building Engineering, 57, p.104919.

[10] Di Trapani, F., Malavisi, M., Marano, G.C., Sberna, A.P. and Greco, R., 2020. Optimal seismic retrofitting of reinforced concrete buildings by steel-jacketing using a genetic algorithm-based framework. Engineering Structures, 219, p.110864.

[11] Seyedzadeh, S., Rahimian, F.P., Oliver, S., Rodriguez, S. and Glesk, I., 2020. Machine learning modeling for predicting non-domestic buildings energy performance: A model to support deep energy retrofit decision-making. Applied Energy, 279, p.115908.

[12] Ma, Z., Cooper, P., Daly, D. and Ledo, L., 2012. Existing building retrofits: Methodology and state-of-the-art. Energy and buildings, 55, pp.889-902.

[13] Pardo-Bosch, F., Cervera, C. and Ysa, T., 2019. Key aspects of building retrofitting: Strategizing sustainable cities. Journal of environmental management, 248, p.109247.

[14] Mondal, D., & Patil, S. S. (2022). EEG Signal Classification with Machine Learning model using PCA feature selection with Modified Hilbert transformation for Brain-Computer Interface Application. Machine Learning Applications in Engineering Education and Management, 2(1), 11–19. Retrieved from http://yashikajournals.com/index.php/mlaeem/article/view/20

[15] Thrampoulidis, E., Mavromatidis, G., Lucchi, A. and Orehounig, K., 2021. A machine learning-based surrogate model to approximate optimal building retrofit solutions. Applied Energy, 281, p.116024.

[16] Deb, C., Dai, Z. and Schlueter, A., 2021. A machine learning-based framework for cost-optimal building retrofit. Applied Energy, 294, p.116990.

[17] Al-Habaibeh, A., Sen, A. and Chilton, J., 2021. Evaluation tool for the thermal performance of retrofitted buildings using an integrated approach of deep learning artificial neural networks and infrared thermography. Energy and Built Environment, 2(4), pp.345-365.

[18] Nutkiewicz, A., Yang, Z. and Jain, R.K., 2018. Data-driven Urban Energy Simulation (DUE-S): A framework for integrating engineering simulation and machine learning methods in a multi-scale urban energy modeling workflow. Applied Energy, 225, pp.1176-1189.

[19] Deb, C., Dai, Z. and Schlueter, A., 2021. A machine learning-based framework for cost-optimal building retrofit. Applied Energy, 294, p.116990.

[20] Ma, J., Cheng, J.C., Jiang, F., Chen, W., Wang, M. and Zhai, C., 2020. A bi-directional missing data imputation scheme based on LSTM and transfer learning for building energy data. Energy and Buildings, 216, p.109941.