Neural Networks to Better Identify Actions and Scenarios for Improving Energy Performance of Existing Buildings

Aboudoul-Manaf Issifou[1], Smain Femmam[2,*], Nadia Femmam[3], and Samia Nefti-Meziani[4]

[1]Energy Efficient Engineering, CNAM & Engineering School ENSIATE, Paris, France
[2]Networks and Communications, Haute-Alsace University, Mulhouse, France
[3]Mohamed Khider University, Biskra Algeria
[4]Birmingham Institute for Robotics, School of Engineering, College of Engineering and Physical Sciences, University of Birmingham, Birmingham, B15 2TT, United Kingdom
aboudoul-manaf.issifou@ensiate.fr (A.-M.I.); smain.femmam@uha.fr (S.F.);
nadia.femmam@univ-biskra.dz (N.F.); s.nefti-meziani@bham.ac.uk (S.N.-M.)
*Corresponding author
Manuscript received January 20, 2025; revised February 22, 2025; accepted March 7, 2025; published May 20, 2025

***Abstract*—In a sustainable development approach focused on three pillars, reducing the ecological footprint of anthropogenic activities is a major issue. In France, the building sector, which includes the residential and tertiary sectors, is one of the most energy-intensive sectors. Natural gas (fossil energy) is the energy vector most used to meet the significant energy needs of residential buildings. To reduce the carbon footprint, the energy renovation of residential and tertiary buildings can prove to be a key pillar for meeting sustainable development indicators and thus safeguarding our environment. The use of artificial intelligence, in this case neural networks, could make it possible to achieve enormous energy savings since it can analyze the building in its smallest details, studying the performances and specificities of existing energy systems and then propose improvements and renovation scenarios that are much more adapted to the behavior and model of the building. In concrete terms, how can neural networks be used, through learning, to suggest relevant actions for improving energy performance? This article first presents the role that artificial intelligence, in this case neural networks, could play in the context of the energy renovation of existing buildings, then a neural network applied to a project in order to propose actions to improve energy performance and more efficient renovation scenarios. The authors made a combined use of neural networks and genetic algorithms allowing respectively a rapid evaluation and optimization of the data sought.**

***Keywords*—static analysis, dynamic analysis, malware detection, hybrid approach, energy performance**

I. Introduction

On a European scale, the building sector has been for around ten years and remains one of the most energy-consuming sectors. According to recent studies [1, 2], this sector represents 40% of final energy consumption and is responsible for 36% of CO_2 emissions across the European Union (EU). This led the European Union to adopt Directive 2002/91/EC on the energy performance of buildings in 2002 [3] and to redefine its performance indicators in 2010 [4].

These EU directives have translated in most member countries into measures or regulations (for example RT2005, RT2012 or RE2020 in the case of France) so that all new constructions are more efficient. These countries have succeeded in constructing new buildings that consume less energy and without significantly increasing the cost of construction and real estate costs (rent, purchase, etc.) [5].

Some studies [6] demonstrate that investing upstream in high-performance new construction is less costly compared to a renovation scenario. Although these buildings are already efficient, they could later be subject to new regulations with much more restrictive requirements. Hence the need to implement more appropriate and optimal performance improvement actions [7] during new construction in order to reduce the cost of future renovation. During a renovation, taking into account aspects such as technical, technological, ecological, social, architectural, comfort, aesthetics, etc. [8] and their interdependence is essential in order to achieve a project which fits perfectly into its environment, respects the regulations in force but also which corresponds to the aspirations of the project owner.

This article has five main parts including the introduction. The second part presents some existing models and methods to enable effective decision-making during an energy renovation while the third part presents an inventory of data essential to the use of artificial intelligence to help the renovation of the real estate portfolio. The fourth part presents a case study carried out by the authors and the last part is dedicated to the synthesis and conclusion.

II. Literature Review

Studies aimed at using artificial intelligence to improve existing frames are recent. Several models and methods have been developed to assess conditions and support building renovation decisions. These approaches fall into two broad categories. The first category includes models in which alternative renovation solutions are defined in advance, such as those proposed by Gero *et al.* [9], Jaggs and Palmer [10], Flourentzou and Roulet [11], and Rey [12]. These works have made extensive use of multi-criteria analysis (MCA) to compare the thermal performance of buildings with other criteria such as construction costs and usable space. Other researchers, such as Kaklauskas *et al.* [13], have also introduced MCA methods into renovation projects, focusing on prioritizing alternatives and selecting the optimal solution.

In 2014, Ehsan Asadi, Manuel Gameiro da Silva, Carlos Henggeler Antunes, Luís Dias, Leon Glicksman proposed a multi-objective optimization algorithm based on genetic algorithms and neural networks. This article is based on these studies. However, the algorithm in their studies is much more suited to commercial buildings, since the learning database is derived from commercial and educational buildings. In the specific context of this article, the preliminary studies aim to design an algorithm for residential buildings, since in France in particular, the share of consumption by residential buildings are not negligible.

Studies have shown that complete renovation of buildings, including the envelope, heating, ventilation and air-conditioning (HVAC) systems and lighting, can significantly optimize energy performance. For example, in [14] demonstrated that the building envelope and mechanical systems have a strong influence on total life-cycle costs (LCC). There is a close correlation between optimizing energy performance and LCC, as the choice of retrofit materials and components significantly affects life-cycle cost. However, it is more difficult to find a relationship between energy performance and environmental sustainability, a balance that remains a challenge for improving a building's overall performance.

Life cycle assessment (LCA) is a systematic approach to evaluating the environmental impacts of a product or process throughout its life cycle [15]. This can include the selection of environmentally preferable materials as well as the optimization of construction processes [16]. Some ACL studies have focused on complete building renovations [17] or material levels [18]. In fact, in [17] authors used multi-objective genetic algorithms (MOGA) to optimize the renovation of a multifunctional building, considering carbon footprint and life-cycle cost over a 60-year period. They showed that the insulation of thermal bridges and the use of different heating systems and fuels are key factors in this optimization. However, proposing a renovation strategy that maximizes the use of resources while reducing energy consumption and environmental impacts at an acceptable cost remains a complex challenge for decision-makers due to the large number of parameters to be considered.

Wang *et al.* [19] argue that building energy assessment is a valuable tool, enabling decision-makers to improve energy performance by providing comparative indices. Burman *et al.* [20] classify assessment methods into two broad categories: top-down and bottom-up approaches. The former involves designing a system without considering information on the subsystems and calculating energy rates based on general building materials. In contrast, the bottom-up approach incorporates the details of individual systems and compares them with actual performance to produce a more accurate estimate.

Borgstein *et al.* [21] reviewed model-based benchmarking methods and empirical approaches, grouping them into three broad categories: engineering calculations, simulation models and statistical modeling. Engineering methods rely on physical laws to determine energy consumption, while energy simulation uses software to assess building performance. Statistical methods, on the other hand, rely on historical data, often applying regression models to estimate building consumption. These models, also known as data-driven surrogate models, exploit existing information without requiring complex system details.

Statistical models, commonly used for benchmarking, introduce an anticipated value of energy consumption based on building characteristics. Among the most widespread approaches in this field are simple and multivariate regression models, as well as the change-point regression model, which captures the non-linear behavior of input variables. In addition, advanced techniques such as stochastic frontier analysis and data envelopment analysis can be used to calculate inefficiencies and assess relationships between variables.

The increase in exploitable databases has led to growing interest in the use of artificial intelligence, particularly Machine Learning (ML), in the construction sector.

III. Materials and Methods

This article demonstrates the use of neural networks to improve the energy performance of existing buildings. The design of artificial algorithms for improving the energy performance of existing residential buildings will begin soon. In fact, this article builds on the studies mentioned in the literature review and in the tertiary sector to also demonstrate the interest of using neural networks in the residential context and highlights the potential similarities it could have.

The building sector (residential, tertiary and industrial real estate) is the most energy-intensive sector in France. In order to reduce greenhouse gas emissions and in a process of decarbonization of the sector, energy renovation is an essential tool. As part of the energy renovation of existing buildings, energy renovation refers to all the work aimed at reducing the energy consumption of a building and improving its energy efficiency. Generally, the objectives targeted by design offices are reducing the energy consumption and greenhouse gas emissions of the building, achieving financial savings on energy bills, improving the hygrothermal comfort of the occupants. All these objectives lead to an increase in the real estate value of the building.

Traditionally, the work to be carried out on the building results from a thermal and energy study carried out by auditors or real estate diagnosticians using thermal and energy simulation tools such as Pléiades, BatiAudit, Cype, Liciel, etc. The use of this software requires varying levels of mastery of thermal energy or building energy. These tools are based on certain default values and often require estimates of other quantities such as the thermal transmission coefficients of old joinery, air tightness, the electrical consumption of ventilation motors, the power of lighting fixtures, occupancy scenarios, DHW draw-off, balancing and distribution efficiencies, etc.

The methods used to evaluate performance indicators and support decisions regarding building renovation can be categorized into two classes: methods where renovation actions or scenarios are explicitly known in advance (a priori) [22–25] and methods where renovation actions or scenarios are implicitly defined as part of an optimization [26–29].

In the first category of methods, the study manager defines his various renovation criteria and the weight that each criterion represents (weighting) among many others. The renovation scenario is a weighted sum of all the criteria, and it is therefore possible to find only one scenario which optimizes the weighted sum. Authors in [30] are among the first to have proposed a multi-criteria analysis (MCA) in the context of building renovation in order to find a compromise between the thermal performance of a building and other criteria such as cost, living space. The authors of manuscripts [31–33] propose techniques based on MCA to determine various renovation scenarios. Still in the context of building renovation, others [34] developed a multivariate and MCA-based method determining the relevance, the degree of priority of the different renovation scenarios and which deduces the most relevant scenario for the renovation.

This traditional method has some limitations since the data 'commodity' for building modeling can vary from one auditor to another depending on the level of experience and the rigor in the approach. Therefore, there is a risk that the results obtained, generally the final energy consumption, are not consistent with the factual readings. Although the invoice reconciliation makes it possible to possibly correct the differences between the recorded and calculated consumptions and to improve the reliability of the thermal model, this step is generally reduced to modifying a few parameters and estimates with the sole aim of having a difference of less than 10% between the calculated and invoiced consumptions. The reliability of the basic model, commonly called the existing state, is crucial since the decisions concerning the nature of the actions to be implemented in order to improve energy performance intrinsically arise from it.

The second category of methods is an approach based on multi-objective optimization (Multi-Objective Optimization, MOO). This approach makes it possible to search for a plethora of renovation scenarios in a large field defined by constraints. The renovation solution comes from the optimization of different objective functions. In the context of energy renovation, authors of [15] proposed a model based on MOO which makes it possible to define renovation actions or scenarios by minimizing energy consumption and the cost of renovation. They also developed an MOO model that can be combined with TRNSYS and GenOp in order to optimize the cost of renovation, energy savings and thermal comfort of a residential building. The MOO model combined with a genetic algorithm (Genetic Algorithm, GA) makes it possible to considerably reduce the simulation time.

Research has made it possible to create an MOO model combined with GA and neural networks (Artificial Neural Networks, ANN) which makes it possible to optimize energy consumption [35], the cost of renovation scenarios and the duration of discomfort in school buildings. The model makes it possible to study several building models with wall insulation (with various materials), the integration of joinery, solar thermal collectors and various climate systems.

What is the optimization model based on neural networks? A modeling of the existing building is carried out using dedicated software, here in particular using TRNSYS. The model obtained is configured and validated through a comparison of energy consumption with those of invoices (invoice reconciliation). From this model, a database consisting of several building models is generated using the hypercube sampling (LHS) algorithm. This database is used to train and validate the neural network (ANN). A Multi-Objective Genetic Algorithm (MOGA) using the neural network is then executed to obtain the different most relevant renovation scenarios.

The optimization steps based on the neural network are represented by the figure opposite.

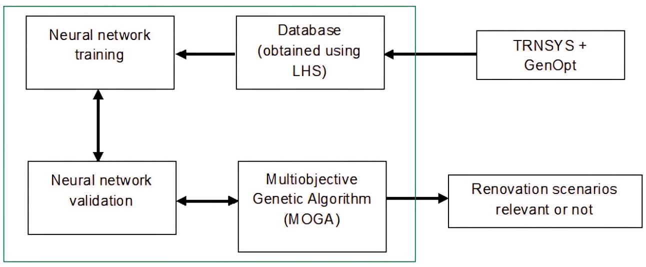

Fig. 1. Optimization steps carried out in MATLAB [1].

As for the neural network, it is made up of 3 layers including the input layer, a hidden layer and the output layer as shown in the Fig. 2 [36]. The input parameters are the wall insulation material (External wall insulation material type identifier, EWAL), the roof insulation material type identifier (ROOF), the type of joinery (window type identifier, WIN), the type of solar thermal collector (solar collector type identifier, SC) and the type of HVAC system (HVAC system type identifier, HVAC). The output data are energy consumption and total duration of thermal discomfort.

It is therefore clear that to obtain reliable results, it is important that the input data are realistic. For example, the thermal performance of a wall depends not only on its composition but also on the humidity, cracks or degradation suffered over time. Furthermore, the energy performance of an energy system such as the boiler or the exchanger will vary depending on the age due to fouling, wear of materials, etc.

In this context, we can imagine the use of artificial intelligence, in this case neural networks, which will make it possible to predict the energy performance of the different components and energy systems of the building. In order for neural networks to be reliable, the training data must also be reliable.

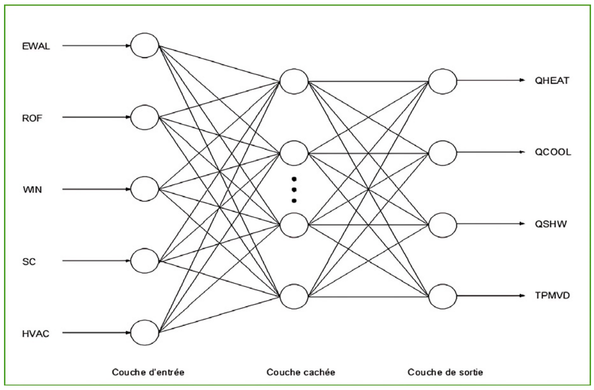

Fig. 2. Neural network architecture [1].

Improving the energy performance of existing buildings is a crucial issue for reducing the carbon footprint, decarbonizing the sector and promoting environmental sustainability. To train a neural network capable of optimizing this performance, it is essential to have a diverse, reliable and complete data set. This data must cover several aspects of the buildings, including their physical characteristics, heating and cooling systems, as well as usage habits. This data can range from general data to technical building data. For example, for HVAC systems, data should include the Type of heating (Boiler, heat pump, electric heating, etc.), the type of cooling (Central air conditioning, window units, passive cooling systems, etc.), the ventilation system (Natural, mechanical, heat recovery.), the age and efficiency of the equipment: Date of installation and energy efficiency of the devices.

For consumption and performance data, one should have the Historical energy consumption for heating, air conditioning, and ventilation, energy efficiency such as the Coefficient of Performance (COP), Energy Efficiency Ratio (EER), and fibal data on maintenance and repairs such as the history of maintenance and repairs of the HVAC systems.

It will also be necessary to have the history of energy consumption on the forms of energy used (electricity, gas, and other energy sources), peak periods (information on the hours or periods of maximum energy consumption) and energy bills including the monthly or annual costs of energy bills. It will also be necessary to have demographic information on the occupants including the occupancy rate; age groups, lifestyle (daily behaviors, hours of presence), responses to climatic conditions (Reactions to temperature variations (opening windows, adjusting thermostats).

The database will also have to make it possible to have technological innovation data. This concerns for example emerging technologies, pilot projects, feedback.

IV. Result and Discussion

This part describes the application of the previous optimization algorithm to an educational institution in Portugal [1]. The energy model of the establishment's buildings was produced using TRNSYS and validated through invoice reconciliation. A sample of 950 models of the establishment created using the LHS algorithm and simulated with TRNSYS was used for training the neural network. The neural network was developed and trained using MATLAB. The input layer is made up of 5 cells each dedicated to an energy performance improvement action. The hidden layer is a set of 15 neurons and the output layer of 4 neurons.

The neural network was trained using the 950 models generated. After 150 iterations, the mean square error reaches 0.0240. The correlation coefficient between the network output data and that of the TRNSYS software is very close to 1. The neural network thus developed was validated using 95 other projects. On these projects, the highest relative error observed on energy consumption is 1.4% while that on the duration of discomfort is 2.5%. The statistical distribution of relative errors across all these projects is shown in the table below.

Table 1. Distribution of relative errors

Relative error		**<1%**	**<2.5%**	**<5%**	**<10%**	**<25%**	**Relative error (%)**
Number of cases	QHEAT	47%	70%	89%	99%	100%	1.4
	QCOOL	92%	100%	100%	100%	100%	0.5
	QSHW	93%	100%	100%	100%	100%	0.4
	TPMVD	33%	60%	89%	98%	100%	2.5

Within the framework of the educational establishment and with a view to multi-objective optimization of energy consumption (EC), the cost of renovation (ReCost) and the percentage of discomfort duration (TPMVD), the model made it possible to obtain the different scenarios illustrated in the following figure.

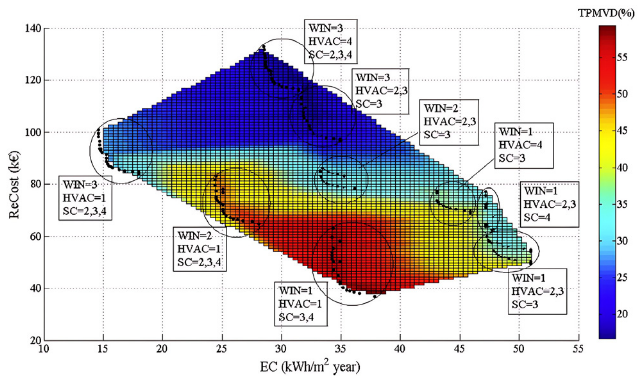

Fig. 3. Results of multi-objective optimization of energy consumption, renovation cost and discomfort duration [1].

We note that to obtain a scenario with a consumption of less than 20 kWh/m²year it is necessary to insulate the opaque walls (walls and roof), to use type 3 double-glazed joinery, a generator of heating (only without cold production). Under these conditions, thermal comfort is obtained for 70% of the time (approximately 30% of the discomfort time).

Finally, Taher *et al.* [37] authors introduced DroidDetectMW, a hybrid model that uses multi-head attention-based control flow traces and image visualization to achieve high malware detection rates while minimizing false positives [29].

Author Contributions

This article, conducted by Aboudoul-Manaf Issifou, follows his research on the implementation of neural networks in the renovation of existing residential buildings. S. Femmam and N. Femmam analyzed and improved the introduced approach and supervised the work. All authors had approved the final version.

The project will begin shortly and aims to achieve the following:

Prediction of consumption: Neural networks can analyze historical consumption data to predict future energy needs, enabling better resource management.

System optimization: They can adjust in real-time the parameters of heating, ventilation, and air conditioning systems to maximize energy efficiency while maintaining occupant comfort.

Anomaly detection: Neural networks can quickly identify malfunctions or unusual behavior in energy consumption, allowing for preventive maintenance.

Personalization: By learning the habits of the occupants, neural networks can tailor energy management to their specific needs.

Integration of renewable energies: They can optimize the use of renewable energy sources by predicting production and adjusting consumption accordingly.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

The research's topic, goals, and objectives were suggested by Aboudoul Issifou and Pr. Smain Femmam. Throughout the study, university professors Samia Nefti-Meziani, Nadia Femmam, and Smain Femmam played a crucial role. For instance, they helped to validate and enhance the research process. They helped with the article's writing as well.

Acknowledgment

I would like to thank Professor Mr. Femmam for agreeing to support me in this endeavor and for his theoretical and practical contributions, as well as for being the corresponding author.

References

[1] E. Asadi, M. Gameiro da Silva, C. H. Antunes, L. Dias, and L. Glicksman, "Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application," *Energy and Buildings*, vol. 81, pp. 444–456, 2014. http://dx.doi.org/10.1016/j.enbuild.2014.06.009

[2] *Energy Performance of Buildings: Climate Neutrality by 2050*, News, European Parliament.

[3] Directive 2002/91/EC of the European Parliament and of the Council of 16 December 2002 on the Energy Performance of Buildings, *Official Journal of the European Communities*, 2002 (Brussels, Belgium).

[4] Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings (recast), *Official Journal of the European Communities*, 2010.

[5] A. Kaklauskas, E. Zavadskas, S. Raslanas, R. Ginevicius, A. Komka, and P. Malinauskas, "Selection of low-e windows in retrofit of public buildings by applying multiple criteria method COPRAS: A Lithuanian case," *Energy and Buildings*, vol. 38, no. 5, pp. 454–462, 2006.

[6] *Advanced Energy Retrofit Guide—Practical Ways to Improve Energy Performance*, NREL, Building Technologies Office, US Department of Energy, 2013.

[7] E. Abel and A. Elmorth, "Buildings and energy—A systematic approach," *Forskningsrådet Formas*, 2007.

[8] A. Kaklauskas, E. Zavadskas, and S. Raslanas, "Multivariant design and multiple criterion analysis of building refurbishments," *Energy and Buildings*, vol. 37, no. 4, pp. 361–372, 2005.

[9] J. S. Gero, N. Dcruz, and A. D. Radford, "Energy in context—a multicriteria model for building design," *Building and Environment*, vol. 18, no. 3, pp. 99–107, 1983.

[10] M. Jaggs and J. Palmer, "Energy performance indoor environmental quality retrofit—a European diagnosis and decision-making method for building refurbishment," *Energy and Buildings*, vol. 31, pp. 97–101, 2000.

[11] F. Flourentzou and C. A. Roulet, "Elaboration of retrofit scenarios," *Energy and Buildings*, vol. 34, pp. 185–192, 2002.

[12] E. Rey, "Office building retrofitting strategies: Multicriteria approach of an architectural and technical issue," *Energy and Buildings*, vol. 36, pp. 367–372, 2004.

[13] A. Kaklauskas, E. Zavadskas, and S. Raslanas, "Multivariant design and multiple criteria analysis of building refurbishments," *Energy and Buildings*, vol. 37, no. 4, pp. 361–372, 2005.

[14] Purdy and Beausoleil-Morrison, "The significant factors in modelling residential buildings," *Building and Environment*, Part 2, 2001.

[15] Cabeza *et al.*, "Life cycle assessment (LCA) and life cycle energy analysis (LCEA) of buildings and the building sector: A review," 2014. https://doi.org/10.1016/j.rser.2013.08.037

[16] [16] Asdrubali *et al.*, "Life cycle analysis in the construction sector: guiding the optimization of conventional Italian buildings," *Energy and Buildings*, 2013.

[17] [17] Schwartz *et al.*, "Implementing multi objective genetic algorithm for life cycle carbonfootprint and life cycle cost minimisation: A building refurbishmentcase study," *Energy and Buildings*, 2016.

[18] [18] Nicolae and George-Vlad, "Life cycle analysis in refurbishment of the buildings as intervention practices in energy saving," *Energy and Buildings*, 2015.

[19] [19] Wang *et al.*, "Renewable energy consumption and economic growth in OECD countries: A nonlinear panel data analysis," *Energy and Buildings*, 2020.

[20] [20] Burman *et al.*, "Ecosystem-atmosphere carbon and water exchanges of subtropical evergreen and deciduous forests in India," *Energy and Buildings*, 2021.

[21] [21] Borgstein *et al.*, "Developing energy consumption benchmarks for buildings: Bank branches in Brazil," *Energy and Buildings*, 2014.

[22] [22] J. S. Gero, N. Dcruz, and A. D. Radford, "Energy in context—a multicriteria model for building design," *Building and Environment*, vol. 18, no. 3, pp. 99–107, 1983.

[23] [23] M. Jaggs and J. Palmer, "Energy performance indoor environmental quality retrofit—a European diagnosis and decision-making method for building refurbishment," *Energy and Buildings*, vol. 31, pp. 97–101, 2000.

[24] F. Flourentzou and C. A. Roulet, "Elaboration of retrofit scenarios," *Energy and Buildings*, vol. 34, pp. 185–192, 2002.

[25] E. Rey, "Office building retrofitting strategies: Multicriteria approach of an architectural and technical issue," *Energy and Buildings*, vol. 36, pp. 367–372, 2004.

[26] E. Asadi, M. G. da Silva, C. H. Antunes, and L. Dias, "A multi-objective optimization model for building retrofit strategies using TRNSYS simulations, GenOpt and MATLAB," *Building and Environment*, vol. 56, pp. 370–378, 2012.

[27] C. Diakaki, E. Grigoroudis, and D. Kolokotsa, "Towards a multi-objective optimization approach for improving energy efficiency in buildings," *Energy and Buildings*, vol. 40, no. 9, pp. 1747–1754, 2008.

[28] E. Asadi, M. G. da Silva, C. H. Antunes, and L. Dias, "Multi-objective optimization for building retrofit strategies: A model and an application," *Energy and Buildings*, vol. 44, pp. 81–87, 2012.

[29] C. Diakaki, E. Grigoroudis, N. Kabelis, D. Kolokotsa, K. Kalaitzakis, and G. Stavrakakis, "A multi-objective decision model for the improvement of energy efficiency in buildings," *Energy*, vol. 35, no. 12, pp. 5483–5496, 2010.

[30] J. S. Gero, N. Dcruz, and A. D. Radford, "Energy in context—a multicriteria model for building design," *Building and Environment*, vol. 18, no. 3, pp. 99–107, 1983.

[31] M. Jaggs and J. Palmer, "Energy performance indoor environmental quality retrofit—a European diagnosis and decision-making method for building refurbishment," *Energy and Buildings*, vol. 31, pp. 97–101, 2000.

[32] F. Flourentzou and C. A. Roulet, "Elaboration of retrofit scenarios," *Energy and Buildings*, vol. 34, pp. 185–192, 2002.

[33] E. Rey, "Office building retrofitting strategies: Multicriteria approach of an architectural and technical issue," *Energy and Buildings*, vol. 36, pp. 367–372, 2004.

[34] A. Kaklauskas, E. Zavadskas, and S. Raslanas, "Multivariant design and multiple criterion analysis of building refurbishments," *Energy and Buildings*, vol. 37, no. 4, pp. 361–372, 2005.

[35] O. Liouane, T. Bakir, S. Femmam, and A. Benabdelali, "On-line sequential ELM based localization process for large scale Wireless Sensors Network," in *Proc. 2021 IEEE 5th International Conference on Control, Automation and Diagnosis (ICCAD)*, Grenoble, France, Nov. 3–5, 2021. Doi:10.1109/ICCAD52417.2021.9638725.

[36] S. Femmam, M. F. Zerarka, and M. I. Benakila, "New approach construction for wireless zigbee sensor based on embedding pancake graphs," *Networks and Communication Technologies Journal*, vol. 1, no. 1, pp. 7–25, Jun. 2012. DOI:10.5539/nct.v1n1p7.

[37] F. Taher, O. AlFandi, M. Al-fairy, H. Al Hamadi, and S. Alrabaee, "DroidDetectMW: A Hybrid intelligent model for Android Malware detection," *Applied Sciences (Switzerland)*, vol. 13, no. 13, Article 772, 2023.