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Artificial Intelligence and Optimization Computing to Lead Energy Retrofit Programs in Complex Real Estate Investments †

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Abstract: In order to plan and manage low-carbon investments in wide real estate assets, in this research, a strategic approach is developed to act on building stocks as a whole, with the aim of overcoming the single-building perspective and identifying the energy retrofit level leading to the maximum possible benefit. It is shown how artificial intelligence (AI) and optimization computing are essential to the creation of the decision-making process. In fact, energy improvement consists of an optimization problem in which conflicting objectives and constraints are balanced, and several techniques are integrated to achieve a unified result, including machine learning, economics, building energy simulation, computer programming, optimization, and risk analysis. This target is achieved by means of Artificial Neural Networks (ANNs) for energy consumption assessment, an Analytic Hierarchy Process for energy retrofit compatibility assessment, and an evolutionary optimization algorithm for the achievement of the optimal configuration of intervention on the stock, maximizing the energy and economic performance of the investment. The proposed procedure is validated on the case study of a building asset located in Northern Italy. Since the developed model relies on AI-based algorithms, it has a consequent limitation: the developed ANNs can work only for the building types, occupation profiles and climatic areas that were used in the training phase. In further development of this research, the aim will be to expand the generalization properties of the forecasting tool.

Keywords: artificial neural networks; artificial intelligence; machine learning; optimization; energy retrofit; buildings; real estate

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1. Introduction

The present research discusses the integration of **artificial intelligence** (AI) and **optimization computing** to sustain energy retrofit investments in complex real estate assets.

It is well known that, during the last few years, the efforts dedicated to achieving energy sustainability in the building sector have exponentially increased, promoting deep retrofit cycles, district approaches [1] and cost-optimal strategies [2]. A focused analysis of the state of the art highlighted that research and practice struggle to act on building portfolios as a whole, preferring to conduct tailored studies on one building at a time due to the **huge complexity** of the process and the high level of reliability of the forecasts required [3]. This, however, leads to the loss of the optimized and **strategic benefits** that could be generated by a unified programming, targeted to reach the maximum possible benefit. The single-building perspective should be overtaken, and new methodologies should be able to handle built assets as a whole in order to implement energy retrofit programs to obtain the maximum benefits in a domain of economic and technical constraints [4–7]. In this direction, artificial intelligence, machine learning and computing algorithms can be extremely useful for mass appraisal energy assessments [8–10], building energy retrofit designs [11], decisional criteria [12], optimization processes [13,14] and decision-making procedures [15–18]. Artificial Neural Networks (ANNs) have been successfully employed in this research field, obtaining very accurate results [15].

2. Materials and Methods

This paper employs an **AI-driven approach** to optimize the definition of building energy retrofitting at a district scale. The scope of going beyond the single-building perspective is to identify the set of energy retrofit actions that can provide the greatest possible benefit in terms of economic, environmental, and architectural targets [19]. For this purpose, it is necessary to collect a huge amount of data on buildings' energy profiles, produce an energy demand AI-based simulation tool, suggest and test several energy retrofit interventions, assess the associated retrofit costs and the respective energy savings, define the domini of feasibility of the analysis, perform iterative project simulations on the given building asset in tandem with an optimization tool, and identify the most convenient energy retrofit configuration for each building of the given asset. Specifically, the AI-based procedure applied in this paper can be split into the following phases:

- The first problem the research faces is the assessment of energy uses and energy-efficiency potentials for a building asset counting a plethora of premises, which ends up being a problem of **mass appraisal** [20] and **screening evaluation** [21]. To address this first issue, 100,000 parametric simulations are run in **Energy Plus** and validated on real case studies. Such simulations associate the varying building characteristics (envelope, installations, dimension, etc.) with the corresponding primary energy consumption. As illustrated in Figure 1, this allows the planner to harness the availability of a detailed database to train a set of **ANNs to forecast the building energy consumption** as a function of the building's features. In particular, the ANNs produced calculate the yearly primary energy demand for heating, cooling, hot water, and electricity in residential buildings, depending on building size, envelope properties and several energy plants parameters.

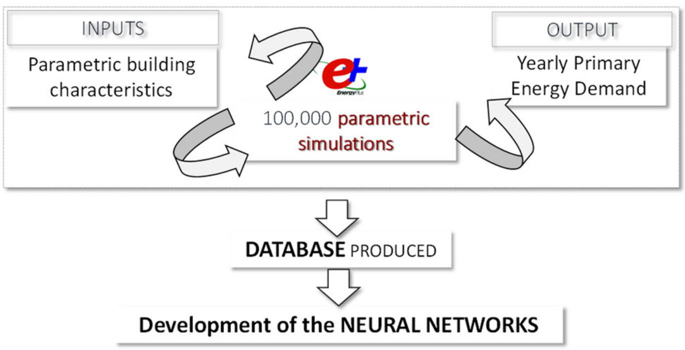

Figure 1. From building energy simulations to Neural Networks development.

- The second phase of the research is dedicated to the definition of different **energy retrofit options** that can be differently implemented on the built asset [11]. Among them are the installation of thermostatic valves, mechanical ventilation, heat recovery systems, condensing boiler, low-emission windows, high-efficiency illumination systems, and internal/external wall/roof insulation. In particular, every possible combination of the retrofit options on the buildings of the stock represents an **alternative scenario** of intervention.
- In order to understand which could be the best retrofit scenario to be implemented on every building of a stock, three **performance indexes** are introduced [12]. The three indexes measure the impact produced in terms of energy, monetary and architectural aspects. The energy savings (ES) are assessed using the neural networks, comparing the energy consumption before and after the retrofit. The net monetary savings (NS) are estimated based on a Life Cycle Costing approach. The architectural compatibility

of the retrofit measure on the building is assessed by means of an Analytic Hierarchy Process (AHP), presented in Figure 2, developed by interviewing a commission of ten experts in the fields of energy retrofit, architecture, restoration, technology, and economics. The AHP allows us to quantify the architectural compatibility of the interventions through the assessment of a restoration score (RS).

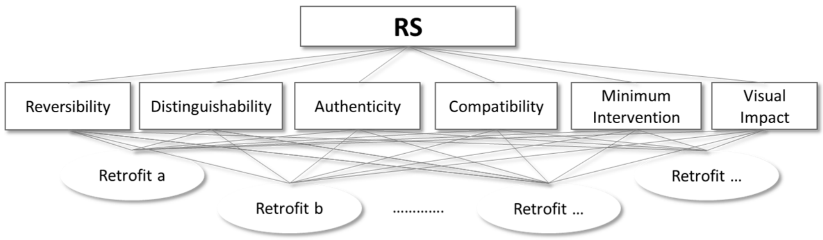

Figure 2. AHP structure.

- After the three decisional indexes, ES, NS, and RS, have been established, an **evolutionary algorithm** is launched to test out the overall benefits produced by every scenario if applied to the buildings of a stock and select the best scenario. As in Figure 3, the algorithm iteratively calculates the indexes for every scenario of intervention inside the feasibility domain, as a sum of the benefits/costs for each building. The target is the **optimal configuration** of interventions over the stock, i.e., the one that simultaneously maximizes the three indexes within the declared constraints [13,14].

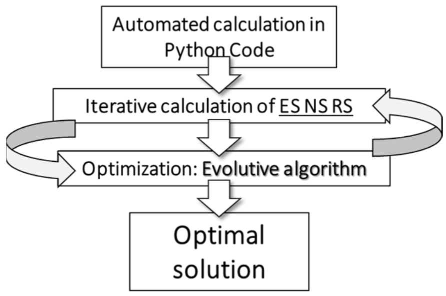

Figure 3. Optimization process.

- In the final part of the research, a **risk analysis** studies how the uncertainty factors may impact the results of the chosen configuration of interventions [22].

The overall methodology is finally resumed in Figure 4. The procedure described above is supported by a tailored **calculation tool** made of the following components: (I) Input file construction. (II) Tool for the assessment of yearly energy consumption by means of the Artificial Neural Networks, of the costs of investment for the energy retrofit intervention, and of the restoration score. Such parameters are iteratively assessed using the calculation tool for each building and each retrofit configuration. (III) Optimization process aimed at identifying the most convenient combination of energy retrofit scenarios for the entire asset of buildings, based on the simultaneous maximization of ES, NS, RS. It consists of a single-objective evolutionary algorithm, namely an algorithm where the cost function is equal to the sum of normalized ES, NS and RS, for each combination of energy retrofit configurations. (IV) A risk analysis tool investigating how uncertainty factors may vary the results of the chosen configuration of interventions, defining the most probable outcome, the worst-case scenario, and the optimal case scenario.

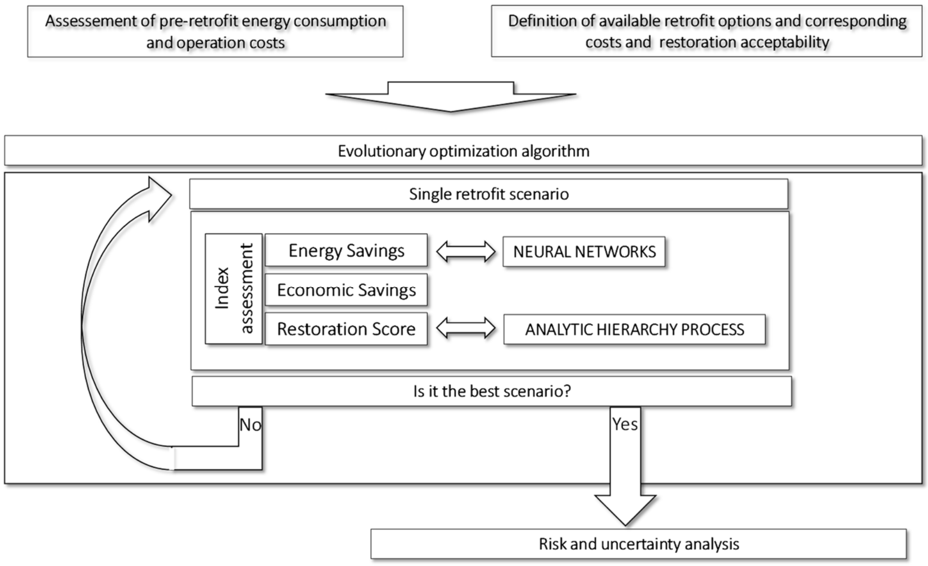

Figure 4. Complete decisional model.

3. Results Discussion and Conclusions

The procedure proposed by the authors was tested in an exemplary **case study** to test the feasibility of the procedure itself, as well as the consistency of the results. For this purpose, a building asset placed in Bologna was considered to verify the reliability of the ANNs forecasts, as well as the ES, NS and RS parameters assessments, and the effectiveness of the optimization algorithm in the identification of the most convenient combination of energy retrofit configurations. A **residential building stock** of a total of 34,411 sqm was considered, and the primary energy consumption before retrofit was assessed by the ANNs to be 1808.55 kWh/sqm. After the implementation of the model, the optimal configuration of intervention led to a total primary energy consumption of 1169.88 kWh/sqm. The total investment brought a net benefit of EUR 967,140 after 20 years.

In conclusion, the proposed procedure takes advantage of AI in a way that is able to automate complex calculations and decision-making processes. In fact:

- The developed Artificial Neural Networks can calculate the yearly primary energy, gas and electricity consumption in about 1/1000th of the time needed by usual building energy simulation software.
- The introduction of AHP automates compatibility decisions.
- The optimization algorithm automatically seeks the best solution, being able to launch and guide the search for the optimum solution among millions of available combinations of energy retrofit configurations on a large building stock.

Finally, the authors recall the purpose of the proposed calculation tool: it is aimed at assessing the best combination of energy retrofit configurations at a stock level, i.e., when there are too many options available for a manual trial-and-error approach and a guide to the most convenient scenario can greatly increase the speed and reliability in the further design refinements of the energy retrofit interventions. As such, the main contribution of this study is the attempt to fill the lack in the research and practice in the application of a methodology for energy retrofit assessment to wide building stocks, thus overcoming the single-building perspective. The model shows high flexibility when comparing multiple scenarios, **thanks to the use of AI**-integrated tools. This approach can be useful for real estate investors and stakeholders, helping to determine the optimal set of interventions for a multiplicity of buildings supported by this decisional model. The methodology produced allows the planner to pursue multiple targets at once, in agreement with recent EU Directives: maximum energy savings, economic savings and compatibility, within a domino of feasibility constraints like budget availability, technical incompatibilities, timings, and pre-set energy/monetary minimum benchmarks.

On the other hand, algorithms which, like this one, are based on a highly numerical procedure might be difficult to check and control. For this purpose, the authors plan to assist the user by means of a series of intermediate output diagrams to control the results. Moreover, the developed ANNs can be used only for assessing the energy demand of residential buildings with occupancy profiles similar to the ones used for the training. Therefore, in future releases, more refined algorithms will be used, in order to implement additional features and make the tool more flexible for other building typologies.

The research will be also improved by the Authors by testing it on other building stocks and enlarging the domains of building energy simulations, thus increasing the interventions options covered and the building characteristics considered. Moreover, the Authors are also working on the collection of a large database of building market values in Italy, paying special attention to the energy class of the premises. This database will be integrated in the model developed here in order to assess the market value of buildings after their energy refurbishment.

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References

1. European Parliament Directive (EU). 2018/844 of the European Parliament and of the council of 30th May 2018 amending Directive 2010/31/EU on the energy performance of buildings and Directive 2012/27/EU on energy efficiency. *Off. J. Eur. Union* **2018**, *2018*, 75–91.
2. European Parliament Directive. 2012/27/EU of the European Parliament and of the Council of 25 October 2012 on energy efficiency, amending Directives 2009/125/EC and 2010/30/EU and repealing Directives 2004/8/EC and 2006/32/EC. *Off. J. Eur. Union* **2012**, *55*, 1–56. [CrossRef]
3. Ruggeri, A.G.; Gabrielli, L.; Scarpa, M. Energy retrofit in european building portfolios: A review of five key aspects. *Sustainability* **2020**, *12*, 7465. [CrossRef]
4. Dirutigliano, D.; Delmastro, C.; Torabi Moghadam, S. A multi-criteria application to select energy retrofit measures at the building and district scale. *Therm. Sci. Eng. Prog.* **2018**, *6*, 457–464. [CrossRef]
5. Ascione, F.; Bianco, N.; Mauro, G.M.; Napolitano, D.F.; Vanoli, G.P. A multi-criteria approach to achieve constrained cost-optimal energy retrofits of buildings by mitigating climate change and urban overheating. *Climate* **2018**, *6*, 37. [CrossRef]
6. Civic, A.; Vucijak, B. Multi-criteria optimization of insulation options for warmth of buildings to increase energy efficiency. *Procedia Eng.* **2014**, *69*, 911–920. [CrossRef]
7. Donnarumma, G.; Fiore, P. A multi-criteria model for the comparison of building envelope energy retrofits. *AIP Conf. Proc.* **2017**, *1814*, 020024.
8. Ahmad, T.; Chen, H.; Guo, Y.; Wang, J. A comprehensive overview on the data driven and large scale based approaches for forecasting of building energy demand: A review. *Energy Build.* **2018**, *165*, 301–320. [CrossRef]
9. Swan, L.G.; Ugursal, V.I. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renew. Sustain. Energy Rev.* **2009**, *13*, 1819–1835. [CrossRef]
10. Li, W.; Zhou, Y.; Cetin, K.; Eom, J.; Wang, Y.; Chen, G.; Zhang, X. Modeling urban building energy use: A review of modeling approaches and procedures. *Energy* **2017**, *141*, 2445–2457. [CrossRef]
11. Ma, Z.; Cooper, P.; Daly, D.; Ledo, L. Existing building retrofits: Methodology and state-of-the-art. *Energy Build.* **2012**, *55*, 889–902. [CrossRef]
12. Pombo, O.; Rivela, B.; Neila, J. The challenge of sustainable building renovation: Assessment of current criteria and future outlook. *J. Clean. Prod.* **2016**, *123*, 88–100. [CrossRef]
13. Kheiri, F. A review on optimization methods applied in energy-efficient building geometry and envelope design. *Renew. Sustain. Energy Rev.* **2018**, *92*, 897–920. [CrossRef]

14. Nguyen, A.-T.; Reiter, S.; Rigo, P. A review on simulation-based optimization methods applied to building performance analysis. *Appl. Energy* **2014**, *113*, 1043–1058. [CrossRef]
15. Beccali, M.; Ciulla, G.; Lo Brano, V.; Galatioto, A.; Bonomolo, M. Artificial neural network decision support tool for assessment of the energy performance and the refurbishment actions for the non-residential building stock in Southern Italy. *Energy* **2017**, *137*, 1201–1218. [CrossRef]
16. Aydinalp-Koksal, M.; Ugursal, V.I. Comparison of neural network, conditional demand analysis, and engineering approaches for modeling end-use energy consumption in the residential sector. *Appl. Energy* **2008**, *85*, 271–296. [CrossRef]
17. Aydinalp, M.; Ugursal, V.I.; Fung, A.S. Modeling of the appliance, lighting and space-cooling energy consumption in the residential sector using neural networks. *Appl. Energy* **2002**, *71*, 87–110. [CrossRef]
18. Ascione, F.; Bianco, N.; De Stasio, C.; Mauro, G.M.; Vanoli, G.P. Artificial neural networks to predict energy performance and retrofit scenarios for any member of a building category: A novel approach. *Energy* **2017**, *118*, 999–1017. [CrossRef]
19. Nägeli, C.; Jakob, M.; Sunarjo, B.; Catenazzi, G. A Building Specific, Economic Building Stock Model to Evaluate Energy Efficiency and Renewable Energy. *Proc. CISBAT* **2015**, *2015*, 877–882.
20. Guardigli, L.; Bragadin, M.A.; Della Fornace, F.; Mazzoli, C.; Prati, D. Energy retrofit alternatives and cost-optimal analysis for large public housing stocks. *Energy Build.* **2018**, *166*, 48–59. [CrossRef]
21. Luddeni, G.; Krarti, M.; Pernigotto, G.; Gasparella, A. An analysis methodology for large-scale deep energy retrofits of existing building stocks: Case study of the Italian office building. *Sustain. Cities Soc.* **2018**, *41*, 296–311. [CrossRef]
22. Tian, W.; Heo, Y.; de Wilde, P.; Li, Z.; Yan, D.; Park, C.S.; Feng, X.; Augenbroe, G. A review of uncertainty analysis in building energy assessment. Renew. *Sustain. Energy Rev.* **2018**, *93*, 285–301. [CrossRef]