

A REVIEW ON THE OPTIMIZATION METHODS APPLIED TO SIMULATION-BASED BUILDING PERFORMANCE ANALYSIS

Mariana Chaves Reis

Instituto Tecnológico de Aeronáutica
Praça Marechal Eduardo Gomes, 50 - Vila das Acacias, São José dos Campos - SP, 12228-900
maricivil12@gmail.com

Paulo Ivo Braga de Queiroz

Instituto Tecnológico de Aeronáutica
Praça Marechal Eduardo Gomes, 50 - Vila das Acacias, São José dos Campos - SP, 12228-900
pi@ita.br

ABSTRACT

The built environment is a major contributor to global energy consumption and CO₂ emissions, necessitating a focus on building energy efficiency. This study reviews the evolution of optimization techniques in improving building performance, emphasizing computational simulations, machine learning, and multi-objective optimization. Despite their proven benefits, practical application remains limited due to barriers like high computational demands, specialized knowledge, and software integration issues. This review identifies key obstacles and proposes strategies to enhance usability and efficiency. Addressing these challenges requires integrated workflows, industry-academia collaboration, and standardized guidelines. By overcoming these hurdles, the building sector can significantly advance in energy efficiency, sustainability, and climate resilience. This work highlights the importance of bridging the gap between research and practice to fully leverage optimization methods in building design.

KEYWORDS. Optimization Methods. Building Performance Simulation. Energy Efficiency.

Paper topics: 8 – EN&PG – PO na Área de Energia, Petróleo e Gás. 4 – AG&MA – PO na Agricultura e Meio Ambiente.

1. Introduction

The building sector plays a significant role in global energy consumption and greenhouse gas emissions, accounting for approximately 44% of final energy use and 40% of CO₂ emissions split between construction and operation phases [Kistelegdi et al. 2022]. Given its significant environmental impact, especially in terms of energy usage, there is a pressing need for improvement. Energy-efficient buildings not only help mitigate these impacts but also enhance energy security by reducing dependence on non-renewable energy sources and lowering the risks associated with energy price volatility [Ascione et al. 2019], [Berg and Fuglseth 2018].

As urbanization continues to rise, alongside the effects of climate change, the demand for energy—particularly for heating, cooling, and other resources—is increasing [Chapman et al. 2017]. This makes the development of energy-efficient buildings more critical than ever. As a result, modern building design has become more complex, requiring a focus on climate resiliency, adherence to stringent energy standards, and a careful balance of objectives such as reducing energy consumption, maintaining occupant thermal comfort, and minimizing the overall environmental impact [Li et al. 2021].

Meeting these demands necessitates the integration of advanced technologies and renewable energy sources, high-performance building envelopes, energy-efficient HVAC systems, and smart building technologies. This holistic approach ensures that buildings are not only efficient but also resilient and adaptable to changing conditions.

Optimization techniques have emerged as useful tools for improving building energy efficiency, enabling the identification of optimal design parameters, operational strategies, and retrofit solutions that can significantly enhance a building's energy performance [Shi et al. 2016]. Techniques such as computational simulations, machine learning algorithms, and multi-objective optimization have proven particularly effective in modeling and improving building systems, identifying the most effective design choices, material selections, and operational strategies [Fumo 2014], [Evins 2013].

Despite the advancements in optimization techniques, their application in real-world building projects remains limited. The building industry continues to rely on traditional design and construction methods due to various barriers, including the complexity of optimization tools, the need for specialized expertise, upfront costs, and regulatory challenges. Additionally, resistance to adopting new technologies and methodologies within the sector hinders the broader use of optimization techniques [Attia et al. 2021]. This gap between research and practical application calls for further investigation into how optimization techniques can be better integrated into the industry's standard practices.

To bridge this gap, it is essential to map recent studies to provide insights into the evolution of optimization methods in building energy efficiency and identify potential future research areas. Through a critical literature review, this study intends to address the following topics:

1 - How has the use of optimization methods in building energy efficiency evolved over the years;

2 - What are the main obstacles hindering the adoption of optimization methods in the building industry;

3 - What strategies can be employed to improve the usability and computational efficiency of optimization methods in building design?

By exploring these questions, this study seeks to contribute to the advancement of knowledge in building performance optimization, facilitating the development of more sustainable and energy-efficient buildings.

This work is divided into four sections. Following a brief introduction in Section 1, the methods adopted for selecting the works considered in this literature review are presented in Section 2. Section 3 discusses the evolution of optimization in the building sector literature, and

Section 4 presents obstacles for a more widespread adoption of optimization methods in the building industry. Finally, Section 5 brings conclusions and suggestions for future research.

2. Methods

A systematic literature review was conducted to assess the current research on the application of optimization techniques to building energy efficiency. The Scopus and ScienceDirect databases were selected for this review due to their relevance and comprehensive coverage in engineering and operations research. The search included keywords such as “building performance simulation” AND “optimi?ation” to account for both British and American spellings.

To focus on recent developments, a time filter was applied to include works published from 2010 onwards. Additionally, only peer-reviewed articles written in English were considered, ensuring both the quality of the research and accessibility to a broader audience. Table 1 outlines the search process.

Table 1: Search Procedure

Database	Search Terms	Results
Scopus	“building performance simulation” AND optimi?ation	153
Science Direct	“building performance simulation” AND optimi?ation	80
Science Direct	“building energy efficiency” AND optimi?ation	68

Source: Author's own work

After the initial search, the results were manually filtered to remove duplicates and exclude papers that did not align with the research focus. This filtering process ensured that only the most relevant studies were selected.

The review process involved extracting and synthesizing key information from the remaining studies, focusing on:

- 1) Relevance to the optimization of building energy efficiency,
- 2) Detailed description of the optimization methods and their application, and
- 3) Quantitative analysis of the optimization results and their impact on energy efficiency improvement.

This approach ensured a thorough understanding of the topic and a focus on the most significant advancements in building energy efficiency optimization techniques.

3. Evolution of the Optimization Applied to Building Energy Efficiency

The optimization of building energy efficiency has gone through extensive evolution, employing various methods over time. Early approaches, constrained by limited computational power, primarily targeted single-objective optimization, such as minimizing energy consumption or cost [Longo et al. 2019]. Among these, analytical optimization techniques were particularly noteworthy for their use of mathematical models to derive optimal solutions [Kramer et al. 2012].

One notable application of early analytical methods was optimizing building geometry to minimize direct solar irradiation, leveraging the Calculus of Variations to derive theoretically optimal building forms [Caruso et al. 2013]. Despite simplifying assumptions about building materials and a focus on rectangular shapes, this research provided practical guidelines for enhancing energy efficiency. Additionally, other studies focused on optimizing building components, like window size and envelope materials, demonstrating the practical benefits of analytical methods despite their inherent assumptions [Pisello et al. 2017], [Nassar and Aly 2013].

With advances in computational power, Building Performance Simulation (BPS) tools saw advancements. Researchers began integrating analytical methods with these simulation tools, using linear and nonlinear programming to optimize building performance based on simulation

outputs. This integration led to more energy-efficient designs capable of meeting multiple objectives [Touloupaki and Theodosiou 2017]. Building Performance Simulation tools such as EnergyPlus, TRNSYS, and IDA ICE became standard for modeling and evaluating building energy performance, providing insights for various optimization algorithms [Samaan et al. 2018], [Pan et al. 2023].

The field then shifted towards multi-objective optimization techniques, which allow for the simultaneous consideration of multiple, often conflicting objectives [Tsala and Koronaki, 2021], [Machairas et al. 2014], [Kheiri 2018]. This approach recognizes the complexity of building design, where decisions must balance a range of stakeholder needs, such as energy efficiency, cost, and environmental impact [Shao et al. 2014]. These techniques are crucial because objectives like minimizing energy use, ensuring thermal comfort, and managing construction costs often conflict [Sun et al. 2020], [Rosso et al. 2020]. Multi-objective optimization requires a careful evaluation of design alternatives, accounting for multiple goals and stakeholder preferences [Hamdy and Mauro 2017], [Nadkarni and Puthuvayi 2020]. However, balancing these competing objectives can increase complexity and lead to inefficiencies, as noted by Allmendinger et al. [2021].

Heuristic optimization methods, such as genetic algorithms and particle swarm optimization, emerged as useful tools for addressing the complexity of building energy optimization [Abdallah and El-Rayes 2015], [Motlagh et al. 2021]. These algorithms, which mimic natural selection processes, iteratively improve design solutions based on their fitness. For example, genetic algorithms coupled with EnergyPlus have reduced life-cycle costs and energy demand in building designs [Ferdyn-Grygierek and Grygierek 2017].

Integrating evolutionary algorithms with simulation tools can be computationally expensive, especially for large-scale models. Parameter settings are critical to avoid converging to local optima and require expertise for effective application. The population-based search strategy of evolutionary algorithms leads to high computational complexity, particularly in contexts where detailed simulations are needed [Calcerano & Martinelli 2016]. The extensive search spaces of these problems demand evaluating many potential solutions, increasing computational demands further.

Achieving high-quality solutions near the Pareto front necessitates numerous generations and evaluations. Handling multiple objectives adds effort by maintaining and comparing diverse solution sets. Balancing exploration and exploitation in high-dimensional problems extends run times for satisfactory convergence and precision [Wright et al. 2013]. Additionally, stochastic simulations increase computational needs due to variability and uncertainty; although parallel computing can accelerate evaluations, practical limits exist based on hardware and algorithm efficiency.

In recent years, artificial intelligence (AI) techniques, such as reinforcement learning and generative adversarial networks (GANs), have been applied to building energy optimization, further advancing the field. Reinforcement learning enables agents to learn optimal decision-making strategies by interacting with simulated environments through trial and error. Meanwhile, GANs have the potential to automatically generate high-performing building designs, offering a new dimension to optimization. Integrating these innovative AI-driven approaches with traditional simulation-based methods presents promising opportunities for addressing the increasing complexity of building energy optimization [Zemero et al. 2019], [Carlucci et al. 2015], [Wortmann 2017], [Olatunde et al. 2024].

To mitigate these computational challenges, researchers have explored meta-modeling techniques like the Distance-Weighted Gradient-Network (DWGN) method [Brunetti 2020]. This method reduces the sampling size needed for design space exploration by using near-neighbor gradients to interpolate unknown points. It outperforms traditional methods like kriging, particularly in handling sparse data and unsmooth performance landscapes, significantly lowering computational burdens while maintaining high predictive accuracy and improving optimization efficiency.

Beyond evolutionary algorithms, robust optimization methods have been developed to identify solutions resilient to uncertainties in input parameters and operating conditions, such as weather and occupant behavior [Shao et al. 2014], [Tsala and Koronaki 2021]. Additionally, machine learning-based optimization leverages data-driven models, such as surrogate models, to explore design spaces and identify optimal solutions efficiently. These models predict performance based on initial simulations, enabling real-time feedback during the design process and enhancing the quality and diversity of generated designs [Brown 2020].

4. Challenges in Widespread Adoption and Future Perspectives

Despite significant progress, several challenges hinder the widespread adoption of optimization techniques in building energy efficiency. These challenges include high computational demand, software integration issues, the steep learning curve associated with advanced optimization methods, and a disconnect between research and industry. The key challenges include:

4.1. High Computational Demand

Optimization methods such as evolutionary algorithms and multi-objective optimization are computationally intensive, requiring substantial resources and time for large-scale projects or complex building designs [Piotrowski et al. 2017], [Yi 2020]. These methods often necessitate numerous iterations, simulations, and evaluations to converge on optimal solutions, which can lead to prohibitively long processing times [Calcerano & Martinelli 2016], [Wright et al. 2013].

4.2. Steep Learning Curve

Advanced optimization techniques demand a high level of expertise to set up simulations, configure optimization parameters, and interpret results. This complexity can present a barrier for professionals without advanced training in these areas, such as architects and engineers [Raj et al. 2021]. Additionally, the challenge of parameter settings in evolutionary algorithms makes it difficult to avoid local optima and achieve effective outcomes [Ferdyn-Grygierek and Grygierek 2017].

4.3. Cost and Resource Constraints

Acquiring and implementing advanced BPS tools and optimization software is costly, and continuous investment is required for software updates, hardware maintenance, and staff training [Raj et al. 2021]. For smaller firms or projects, these costs can be prohibitive, limiting access to these technologies.

4.4. Software Compatibility and Integration

Ensuring seamless integration between different simulation and optimization tools can be challenging due to differences in data formats, user interfaces, and processing capabilities [Østergård et al. 2016]. This creates bottlenecks in workflow and increases the complexity of applying optimization methods in practical settings.

4.5 Disconnect Between Research and Industry

While academic researchers focus on developing novel optimization methods, these innovations are often not aligned with the practical constraints of real-world projects [Nguyen et al. 2014]. Industry practitioners may face challenges in applying research-based methods that have not been tested or adapted for large-scale, real-world use.

4.6. Proposed Solutions and Future Research Directions

To address these challenges, several strategies can be implemented. First, meta-modeling techniques like the Distance-Weighted Gradient-Network (DWGN) method can reduce computational demands by optimizing the sampling size needed for design exploration [Brunetti 2020]. Machine learning-based optimization, which uses surrogate models to predict performance, is another promising avenue that allows for real-time feedback during the design process, reducing computational overhead [Brown 2020].

Second, improving accessibility through the development of user-friendly interfaces for optimization tools is essential. These tools should combine ease of use with computational

efficiency, reducing the expertise required to apply advanced methods. For example, automating parameter tuning and simplifying the setup process could lower barriers to entry for industry professionals. Additionally, collaboration between academia and industry is crucial to ensure that optimization techniques are both innovative and practical. Joint efforts, such as co-developing tools and conducting case studies, can bridge the gap between research and practice, accelerating the adoption of these methods [Huang and Niu 2016], [Mei and Wang 2021].

Lastly, establishing standardized guidelines and benchmarks for applying optimization in building design is important to support broader adoption. Comprehensive standards can promote consistency and encourage best practices, making it easier for industry stakeholders to implement these methods [Aste et al. 2017]. By addressing these challenges through a focused research agenda and collaboration between academia and industry, the full potential of optimization techniques can be realized in creating energy-efficient and sustainable buildings.

5. Conclusions

This review contributes to addressing a research gap in understanding and implementing of optimization methods within the building sector, while also shedding light on the evolution of their integration. By critically reviewing recent literature and aiming to answer key research questions, including how the utilization of optimization methods in building energy efficiency has evolved over time, what obstacles hinder their widespread adoption in the industry, and what strategies can enhance their usability and computational efficiency in building design, this study offers valuable insights.

There is a lot of potential for improving energy efficiency and overall sustainability in the building sector through optimization. Additionally, there is a growing need for improving energy efficiency and other goals such as resiliency to climate change and occupant thermal comfort. Techniques such as evolutionary algorithms, robust optimization, and machine learning-based methods have shown promise in improving building energy performance, occupant comfort, and environmental impact.

However, some challenges persist, underscoring the need for closer collaborations between the research community and industry to develop user-friendly tools and establish clear guidelines and benchmarks. Addressing these challenges is crucial for unlocking the full potential of optimization methods in enhancing energy efficiency, sustainability, and resilience to climate change in the building sector, while ensuring occupant thermal comfort.

References

- Abdallah, M., & El-Rayes, K. (2015). Optimizing the selection of building upgrade measures to minimize the operational negative environmental impacts of existing buildings. *Building and Environment*, 84, p.32-43.
- Allmendinger, R., Jaszkievicz, A., Liefoghe, A., Tammer, C., (2021). What if we Increase the Number of Objectives? Theoretical and Empirical Implications for Many-objective Optimization. <https://arxiv.org/abs/2106.03275>. Acessado: 2024-05-28.
- Ascione, F., Bianco, N., Masi, R F D., Mastellone, M., Vanoli, G P. (2019). Phase Change Materials for Reducing Cooling Energy Demand and Improving Indoor Comfort: A Step-by-Step Retrofit of a Mediterranean Educational Building. *Buildings*, 12(19), p.3661.
- Aste, N., Manfren, M., Marenzi, G. (2017). Building Automation and Control Systems and performance optimization: A framework for analysis. *Renewable and Sustainable Energy Reviews*, 75, p.313-330.

Attia, S., Hamdy, M., O'Brien, W., & Carlucci, S. (2021). Assessing gaps and needs for integrating building performance optimization tools in the design process." *Energy and Buildings*, 250, 111273.

Berg, F., Fuglseth, M. (2018). Life cycle assessment and historic buildings: energy-efficiency refurbishment versus new construction in Norway. *Journal of Architectural Conservation*, 24, p. 152–167.

Brown, N C. (2020). Design performance and designer preference in an interactive, data-driven conceptual building design scenario. *Design Studies*, 68, p. 1-33.

Brunetti, G L. (2020). Grafting of design-space models onto models of different scope or resolution. *Journal of Building Performance Simulation* 13:3, pages 227-246.

Calcerano, F., & Martinelli, L. (2016). Numerical optimisation through dynamic simulation of the position of trees around a stand-alone building to reduce cooling energy consumption. *Energy and Buildings*, 112, p. 234-243.

Carlucci, S., Cattarin, G., Causone, F., & Pagliano, L. (2015). Multi-objective optimization of a nearly zero-energy building based on thermal and visual discomfort minimization using a non-dominated sorting genetic algorithm (NSGA-II). *Energy and Buildings*, 104, 378-394.

Caruso, G., Fantozzi, F., Leccese, F. (2013). Optimal theoretical building form to minimize direct solar irradiation. *Solar Energy*, 97, p. 128-137.

Chapman, S., Watson, J. E. M., Salazar, Á., Thatcher, M., & McAlpine, C. (2017). The impact of urbanization and climate change on urban temperatures: A systematic review. *Landscape Ecology*, 32(10), 1921-1935

Evins, R. (2013): "A review of computational optimisation methods applied to sustainable building design." *Renewable and Sustainable Energy Reviews*, 22, 230-245

Ferdyn-Grygierek, J., Grygierek, K. (2017). Multi-Variable Optimization of Building Thermal Design Using Genetic Algorithms. *Energies*, 10, p. 1570-1570.

Fumo, N. (2014): "A review on the basics of building energy estimation." *Renewable and Sustainable Energy Reviews*, 31, 53-60

Hamdy, M., & Mauro, G M. (2017). Multi-Objective Optimization of Building Energy Design to Reconcile Collective and Private Perspectives: CO2-eq vs. Discounted Payback Time. *Energies*, 10, p. 1016.

Huang, Y., Niu, J. (2016). Optimal building envelope design based on simulated performance: History, current status and new potentials. *Energy and Buildings*, 117, p.387-398.

Kheiri, F. (2018). A review on optimization methods applied in energy-efficient building geometry and envelope design. *Renewable and Sustainable Energy Reviews*, 92, p. 897-920.

Kisteleghi, I., Horváth, K R., Storcz, T., Ercsey, Z. (2022). Building Geometry as a Variable in Energy, Comfort, and Environmental Design Optimization—A Review from the Perspective of Architects. *Buildings*, 12, p. 69-69.

- Kramer, R., Schijndel, J V., Schellen, H. (2012). Simplified thermal and hygric building models: A literature review. *Frontiers of Architectural Research*, 1, p. 318-325.
- Li, Q., Zhang, L., Zhang, L., & Wu, X. (2021). Optimizing energy efficiency and thermal comfort in building green retrofit. *Energy*, 237, 121509.
- Longo, S., Montana, F., Sanseverino, E R. (2019). A review on optimization and cost-optimal methodologies in low-energy buildings design and environmental considerations. *Sustainable Cities and Society*, 45, p. 87-104.
- Machairas, V., Tsangrassoulis, A., & Axarli, K. (2014). Algorithms for optimization of building design: A review. *Renewable and Sustainable Energy Reviews*, 31, p. 101-112
- Mei, L., Wang, Q. (2021). Structural Optimization in Civil Engineering: A Literature Review. *Buildings*, 11, p. 66-66.
- Motlagh, S F M., Sohani, A., Saghafi, M D., Sayyaadi, H., & Nastasi, B. (2021). The Road to Developing Economically Feasible Plans for Green, Comfortable and Energy Efficient Buildings. *Energies*, 14, p. 636.
- Nadkarni, R R., & Puthuvayi, B. (2020). A comprehensive literature review of Multi-Criteria Decision Making methods in heritage buildings. *Journal of Building Engineering*, 32, p. 101814.
- Nassar, K., Aly, M. (2013). Analytical optimization of simple roof shading devices. Conference Paper. In *Proceedings of BS2013:13th Conference of International Building Performance Simulation Association*, 419-425, Chambéry. IBPSA.
- Nguyen, A T., Reiter, S., Rigo, P. (2014). A review on simulation-based optimization methods applied to building performance analysis. *Applied Energy*, 113, p. 1043-1058.
- Olatunde, T. M., Okwandu, A. C., Akande, D. O., & Sikhakhane, Z. Q. (2024). Reviewing the role of artificial intelligence in energy efficiency optimization. *Engineering Science and Technology, an International Journal*, 5(4), 1243-1256.
- Østergård, T., Jensen, R L., & Maagaard, S. (2016). Building simulations supporting decision making in early design – A review. *Renewable and Sustainable Energy Reviews*, 61, p.187-201.
- Pan, Y., Zhu, M., Liu, Y., Yang, Y., Liang, Y., Yin, R., Yang, Y., Jia, X., Wang, X., Zeng, F., Huang, S., Hou, D., Xu, L., Yin, R., & Yuan, X. (2023). Building energy simulation and its application for building performance optimization: A review of methods, tools, and case studies. *Advances in Applied Energy*, 10, p.100135.
- Piotrowski, A., Napiórkowski, M., Napiórkowski, J., Rowiński, P M. (2017). Swarm Intelligence and Evolutionary Algorithms: Performance versus speed. *Information Science*, 384, p.34-85.
- Pisello, A L., Castaldo, V L., Piselli, C., Fabiani, C., Cotana, F. (2017, December 1). Thermal performance of coupled cool roof and cool façade: Experimental monitoring and analytical optimization procedure. *Energy and Buildings*, 157, p. 35-52.

- Raj, B P., Meena, C S., Agarwal, N., Saini, L., Khahro, S H., Subramaniam, U., & Ghosh, A. (2021). A Review on Numerical Approach to Achieve Building Energy Efficiency for Energy, Economy and Environment (3E) Benefit. *Energies*, 14, p.4487.
- Rosso, F., Ciancio, V., Dell'Olmo, J., & Salata, F. (2020). Multi-objective optimization of building retrofit in the Mediterranean climate by means of genetic algorithm application. *Energy and Buildings*, 216, 109945.
- Samaan, M M., Farag, O., & Khalil, M E. (2018). Using simulation tools for optimizing cooling loads and daylighting levels in Egyptian campus buildings. *HBRC Journal*, 14, p. 79-92.
- Shao, Y., Geyer, P., & Lang, W. (2014). Integrating requirement analysis and multi-objective optimization for office building energy retrofit strategies. *Energy and Buildings*, 82, 356-368.
- Shi, X., Tian, Z., Chen, W., Si, B., Jin, X. (2016). A review on building energy efficient design optimization from the perspective of architects. *Renewable and Sustainable Energy Reviews*, 65, p. 872-884.
- Sun, C., Liu, Q., Han, Y. (2020). Many-Objective Optimization Design of a Public Building for Energy, Daylighting and Cost Performance Improvement. *Applied Sciences*, 10, p.2435.
- Touloupaki, E., Theodosiou, T. (2017). Energy Performance Optimization as a Generative Design Tool for Nearly Zero Energy Buildings. *Procedia Engineering*, 180, p. 1178- 1185.
- Tsala, S., & Koronaki, I. (2021). Optimization Algorithms for Energy Building Applications. *IOP Conf Ser: Materials Science and Engineering*, 1037, p.01204.
- Wortmann, T. (2017). Model-based optimization for architectural design: Optimizing daylight and glare in Grasshopper. *Journal of Architectural Design*, 1(2), 176-185.
- Wright, J A., Brownlee, A E I., Mourshed, M., & Wang, M. (2013). Multi-objective optimization of cellular fenestration by an evolutionary algorithm. *Journal of Building Performance*, 7, p-33-51.
- Yi, H. (2020). Visualized Co-Simulation of Adaptive Human Behavior and Dynamic Building Performance: An Agent-Based Model (ABM) and Artificial Intelligence (AI) Approach for Smart Architectural Design. *Sustainability*, 12, p.6672.
- Zemero, B. R., Tostes, M. E. D. L., Bezerra, U. H., Batista, V. D. S., & Carvalho, C. (2019). Methodology for preliminary design of buildings using multi-objective optimization based on performance simulation. *Journal of Building Performance*, 141(4).