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A conceptual framework for multi-objective optimization of building performance: Integrating intelligent algorithms, simulation tools, and climate adaptation

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Abstract This study systematically examined recent research trends in multi-objective optimization (MOO) for building performance from 2020 to 2024 and proposed a conceptual framework integrating intelligent algorithms, simulation tools, and climate adaptation strategies. A thematic analysis of 40 peer-reviewed articles was conducted using ATLAS.ti, revealing three dominant research themes: intelligent algorithms, building performance simulation techniques, and adaptive design for climate change. Quantitative analysis highlights China's prominent contributions to the field, while the thematic analysis reveals three key findings: (1) optimization methods based on intelligent algorithms such as NSGA-II, artificial neural networks, and gradient-boosted decision trees significantly enhance computational efficiency; (2) dynamic simulation integrated with lifecycle assessment enables a more comprehensive evaluation of building performance; and (3) climate-adaptive strategies improve building resilience to future climate uncertainties. Based on these insights, the proposed framework combines these three components to achieve computational efficiency, maintain accuracy, and improve adaptability. The framework provides a systematic, data-driven approach to address trade-offs among energy efficiency, thermal comfort, and indoor air quality. Its practical value is demonstrated through applications in residential, educational, and commercial buildings across various climate zones. These case studies highlight the framework's capability to guide high-performance, sustainable, and climate-responsive building design. Furthermore, this review identifies future research priorities, including the integration of dynamic simulation with real-time optimization, and the development of lifecycle-oriented, comprehensive evaluation systems to address emerging environmental challenges. Overall, the study contributes a holistic perspective and actionable methodology for advancing intelligent, climate-adaptive building performance optimization.

Keywords: multi-objective optimization, building performance, intelligent algorithms, building performance simulation, climate-adaptive design, conceptual framework

1. Introduction

The building sector is currently facing unprecedented challenges amid global climate change and rising energy demands. As a major contributor to global energy consumption and carbon emissions, this sector is under increasing pressure to balance sustainability with optimal indoor environmental quality and occupant comfort. According to the International Energy Agency, buildings account for 36% of the global final energy consumption and nearly 40% of the total direct and indirect carbon dioxide (CO_2) emissions (International Energy Agency, 2021; Li et al., 2022). This growing concern has driven a strong focus on building performance optimization, particularly through multi-objective optimization (MOO) approaches, which can effectively address the complex trade-offs between competing performance objectives (Tabbah et al., 2024).

Building performance optimization is inherently a multi-objective problem, encompassing energy efficiency, thermal comfort, indoor environmental quality, daylighting performance, and economic feasibility. These objectives frequently conflict; for example, maximizing energy efficiency can sometimes compromise occupant comfort, whereas increasing natural daylight may inadvertently increase cooling loads. Similarly, a trade-off exists between the upfront costs of energy-efficient designs and their long-term operational savings. Traditional single-objective optimization methods often struggle to capture these complex interactions and trade-offs, reinforcing the need for MOO techniques in modern building design and operation (Sun et al., 2020).

Recent technological advancements have significantly reshaped the landscape of building performance optimization. The emergence of intelligent algorithms, particularly machine learning techniques, has provided powerful tools for addressing complex optimization problems. These innovations enable the efficient exploration of vast design spaces, facilitating the rapid

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prediction of building performance and opening new possibilities for designing high-performance, sustainable buildings. In parallel, advanced computational methods combined with sophisticated building performance simulation tools increase the efficiency and accuracy of optimization processes (Huang & Zhao, 2024; Sun et al., 2022).

In addition to computational efficiency, lifecycle assessment (LCA) approaches have expanded the scope of optimization by incorporating long-term environmental impacts and economic performance over a building's entire lifecycle (Hong et al., 2020; Kiamili et al., 2020). These advancements underscore the growing complexity of modern building performance optimization and the necessity for integrated frameworks that can holistically address multiple performance dimensions.

Despite these advancements, several research gaps remain in the literature. First, although progress has been made in developing optimization algorithms and simulation tools, the practical implementation of MOO in real-world building design continues to face efficiency challenges. A key issue is to balance the computational speed with the solution accuracy for complex building systems. Second, existing optimization frameworks tend to focus on specific aspects of building performance, such as energy efficiency or thermal comfort, without fully integrating multiple performance metrics within a unified framework that also considers climate adaptability. Third, although the importance of intelligent algorithms, simulation tools, and climate resilience is widely recognized, a limited understanding of how these components can be effectively integrated into real-world design processes remains. This is particularly critical for addressing uncertainties in future climate scenarios.

Given these gaps, this study sought to systematically examine recent trends in building performance MOO and explore how emerging insights can contribute to a comprehensive framework that integrates intelligent algorithms, simulation tools, and climate adaptability. This research is guided by the following questions: What are the current trends in MOO for building performance from 2020 to 2024, and how can these insights provide a comprehensive framework that integrates intelligent algorithms, simulation tools, and climate adaptability?

Climate change adds another layer of complexity to building performance optimization. Buildings must not only achieve optimal performance under current conditions but also adapt to future climate scenarios (Dodoo & Ayarkwa, 2019). This challenge has spurred an increased focus on climate-adaptive design strategies and the development of optimization frameworks that incorporate climate uncertainties (Lawrence et al., 2019). Consequently, the integration of dynamic simulation technique**s** and adaptive design approaches has become essential for ensuring building resilience in response to evolving environmental conditions (Dodoo, 2020).

Building performance optimization has advanced significantly in three key areas: the development of intelligent algorithms for computational efficiency, the enhancement of simulation tools for performance prediction, and the emergence of climate adaptability strategies. Although individual studies have made substantial contributions in each of these areas, the field still lacks a unified framework that systematically integrates these components. For example, Zou et al., (2021) improved computational efficiency via neural network-based optimization, Wu et al., (2024) explored the integration of Bayesian optimization with genetic algorithms, and Li et al., (2024) focused on climate adaptability in early-stage design. However, there remains a critical need for an overarching framework that synthesizes these advancements into a comprehensive approach.

To address this gap, this study proposed a conceptual framework that integrates intelligent algorithms, simulation tools, and climate adaptability. The novelty of the framework lies in its ability to holistically balance computational efficiency, predictive accuracy, and climate resilience, thereby enabling a more comprehensive and adaptable optimization process. By bridging existing knowledge gaps, the proposed framework aims to enhance both practical implementability and long-term sustainability in building performance optimization.

This study systematically analyzes recent advancements in MOO for building performance (2020--2024) and identifies key trends, challenges, and opportunities in this rapidly evolving field. It specifically examines the application of intelligent algorithms, the role of building performance simulation tools, and the development of climate-adaptive design strategies. On the basis of these findings, this study proposes a conceptual framework for building performance MOOs that integrates these elements, offering guidance for both future research and practical applications.

The remainder of this paper is organized as follows. Section 2 details the materials and methods used in this systematic review. Section 3 presents both quantitative and qualitative findings, organized around the three key themes identified in our analysis. Section 4 introduces and discusses the proposed conceptual framework, demonstrating how it integrates and builds on existing approaches. Finally, Section 5 concludes the paper with practical implications and directions for future research.

2. Methodology and Thematic Analysis

This study employed a research methodology aligned with that introduced by Zairul (2020, 2021a, 2021b) and Zairul et al., (2023), utilizing ATLAS.ti as the primary tool for conducting a thematic review. This methodology followed the thematic analysis framework outlined by Braun and Clarke (2006), which provides a structured approach for identifying patterns and constructing themes through an in-depth examination of the subject matter. Thematic analysis, as applied in this study, was carried out via a systematic five-step process.

The process begins by defining the research question (Define RQ) to establish the study's direction and scope. The second step, screening (Screen), involved an initial selection of studies relevant to the research question. This was followed by filtering (Filter), where inclusion and exclusion criteria were applied to refine the selection, ensuring that only the most relevant studies were retained. The fourth step, finalizing (Finalize), involves cleaning and validating the data to increase accuracy and completeness. Finally, synthesis (Synthesis) was conducted via ATLAS.ti to extract key themes from the selected studies through thematic analysis.

To ensure rigorous and systematic selection of literature, the study applied the following inclusion criteria: 1) publications from the last five years (2020--2024), 2) studies focusing on building performance and MOO, 3) articles written in English, and 4) peer-reviewed journal papers. The literature search was conducted on November 14, 2024, using the SCOPUS and Web of Science databases because of their extensive coverage and ability to ensure the reliability and comprehensiveness of the research findings. The search strategy, including the specific search string and the number of identified articles, is presented in Table 1.

Table 1 Search strings from scopus and WoS.

Database	Search strings	Results
SCOPUS	TITLE-ABS-KEY (("multi-objective optimisation" OR "multi-objective optimization" OR "MOO") AND ("building performance")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2022) OR LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2024))	102 results
Web of Science (WoS)	Refine results for ("multi-objective optimization" OR "multi-objective optimization" OR "MOO") AND ("building performance") (Topic) and 2020 or 2021 or 2022 or 2023 or 2024 (Publication Years) and English (Languages) and Article (Document Types)	98 results

A comprehensive search retrieved 102 records from SCOPUS and 98 records from the Web of Science, totaling 200 initial articles. These articles were subjected to a rigorous screening process to eliminate irrelevant studies. Duplicated records across both databases were identified and removed, and the remaining articles were reviewed and validated for relevance and alignment with the research focus. As a result, 40 articles met the inclusion criteria (Figure 1).

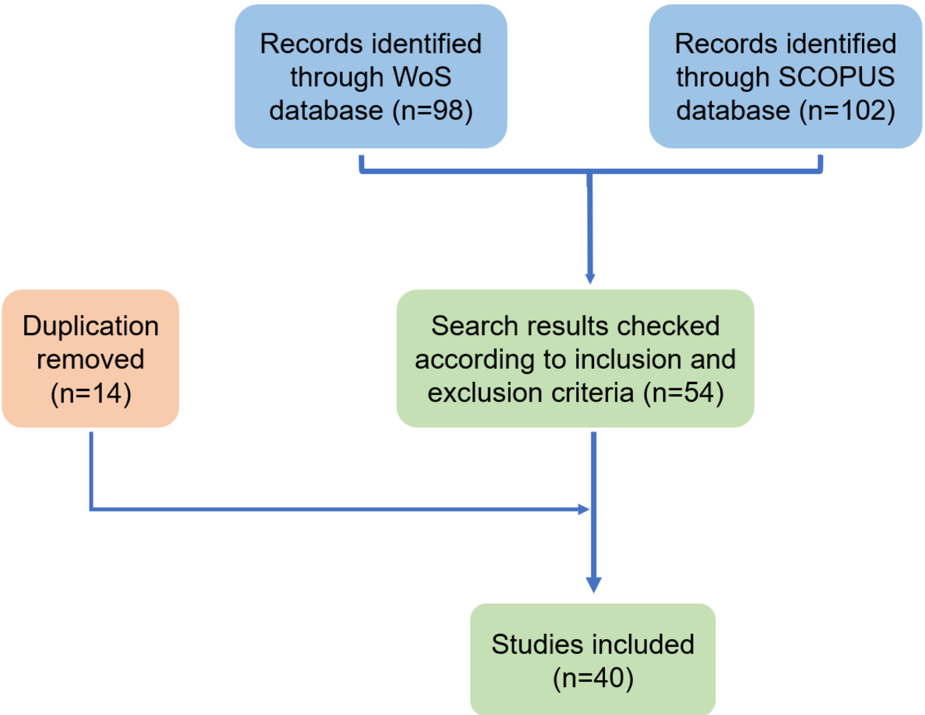

Figure 1 Inclusion and exclusion criteria flowchart

Following literature selection, thematic analysis was conducted to systematically identify and consolidate key themes. The initial coding process involved categorizing concepts on the basis of their frequency and significance in the selected literature. The coding criteria encompassed the primary research focus of each study, the methodological approaches employed, the key findings and contributions, and the future research directions suggested by the authors.

The initial stage yielded multiple preliminary themes, including optimization algorithms, simulation tools, climate considerations, energy efficiency, and thermal comfort. To enhance coherence and conceptual clarity, the preliminary themes were subjected to an iterative consolidation process. Consolidation was guided by four key criteria: 1) frequency of occurrence in the literature, 2) interconnectedness of concepts, 3) relevance to building performance optimization, and 4) alignment with current industry challenges.

For example, various optimization algorithms (e.g., nondominated sorting genetic algorithm-II (NSGA-II), NSGA-III, and multi-objective particle swarm optimization (MOPSO) and machine learning approaches (e.g., artificial neural networks (ANNs) and gradient-boosted decision trees (GBDTs) were initially coded as separate themes. However, owing to their shared focus on computational optimization methods, they were later grouped under the broader theme of “intelligent algorithms.” Similarly, different simulation tools and performance assessment methods were integrated into the theme "building performance simulation" on the basis of their common role in performance prediction and evaluation.

Through this structured thematic analysis, three primary themes emerged as the most significant: intelligent algorithms, building performance simulations, and adaptive design for climate change. These themes were selected on the basis of their prevalence in the recent literature, their fundamental role in addressing contemporary building performance challenges, and their potential for integration within a comprehensive optimization framework. Additionally, these themes are aligned with industry trends toward smart, sustainable, and climate-resilient building designs.

By capturing the most critical aspects of multi-objective building performance optimization, these themes not only represent the current state of research but also offer promising directions for future development. Their integration into a unified framework provides valuable insights for advancing both academic research and practical applications in the field.

3. Results and Discussion

The results of this thematic review are presented in two sections: (i) quantitative and (ii) qualitative. The quantitative findings focused on the analysis of word cloud visualizations, key author distributions, and publication trends by country, drawing from the metadata and content of the 40 selected articles. By concentrating on the literature published from 2020 to 2024, this analysis highlights the most recent developments in the field and provides insights into emerging research trends.

The qualitative findings offer a deeper exploration of the selected articles, which were systematically coded to extract the key research themes. This process enabled a structured discussion of the predominant thematic trends, which were subsequently analyzed in detail.

3.1. Quantitative analysis

3.1.1. Word cloud analysis

The word cloud visualization (Figure 2) provides a graphical representation of the key terms used in the selected studies, where the size of each term corresponds to its prominence in the literature. The most frequently occurring terms include "building” (5245 occurrences), "energy" (5240), "optimization" (3304), "design" (3012), "performance" (2569), and "objective" (1842). The high frequency of these terms reflects their centrality in the field, emphasizing a strong research focus on optimizing building performance through systematic design and energy efficiency strategies.

Notably, the frequencies of "building" and "energy" are nearly equal, suggesting a strong correlation between the building design and energy considerations. This trend aligns with the study’s framework, which emphasizes energy efficiency as a key optimization objective. Additionally, the prominent appearance of technical terms such as "NSGA," "algorithm," "parameters," and "model" highlights the widespread use of optimization techniques, particularly genetic algorithms and parametric modeling. The frequent appearance of words such as "solution," "climate," "Pareto," and "prediction" corresponds to the field's emphasis on MOO, climate considerations, and performance prediction. These trends strongly align with the three key themes identified in the qualitative analysis: 1) intelligent algorithms, 2) building performance simulations, and 3) adaptive design for climate change.

3.1.2. Geographical and temporal trends in research output

Figure 3 illustrates the global distribution of research on MOO in building performance, as depicted through a world map with publication counts. China leads the field with 23 publications, followed by notable contributions from various European countries, the United States, and other nations. This distribution suggests that, while the research landscape is global, China has maintained a dominant role in advancing the field.

The Sankey diagram (Figure 4) shows the temporal distribution of publications across different countries from 2020 to 2024, illustrating the evolution of research output over time. The diagram highlights China’s sustained contributions throughout the study period, with publications spanning all five years, indicating consistent research investments and interests. Moreover, research activities in other countries have fluctuated with varying levels of output across different years. An important observation is the gradual increase in the number of contributing countries over time, indicating a broadening of international participation in MOO research on building performance. This trend suggests that the field is becoming more globally recognized with increasing collaboration across regions.

The geographical and temporal trends observed in these analyses emphasize the expanding global impact of research on building performance optimization. While research priorities and contributions vary across countries, the increasing involvement of diverse nations suggests a growing internationalization of knowledge exchange in this field. Future research efforts are expected to promote a greater regional balance, ensuring a more equitable contribution of advancements in MOO technologies for sustainable building design.

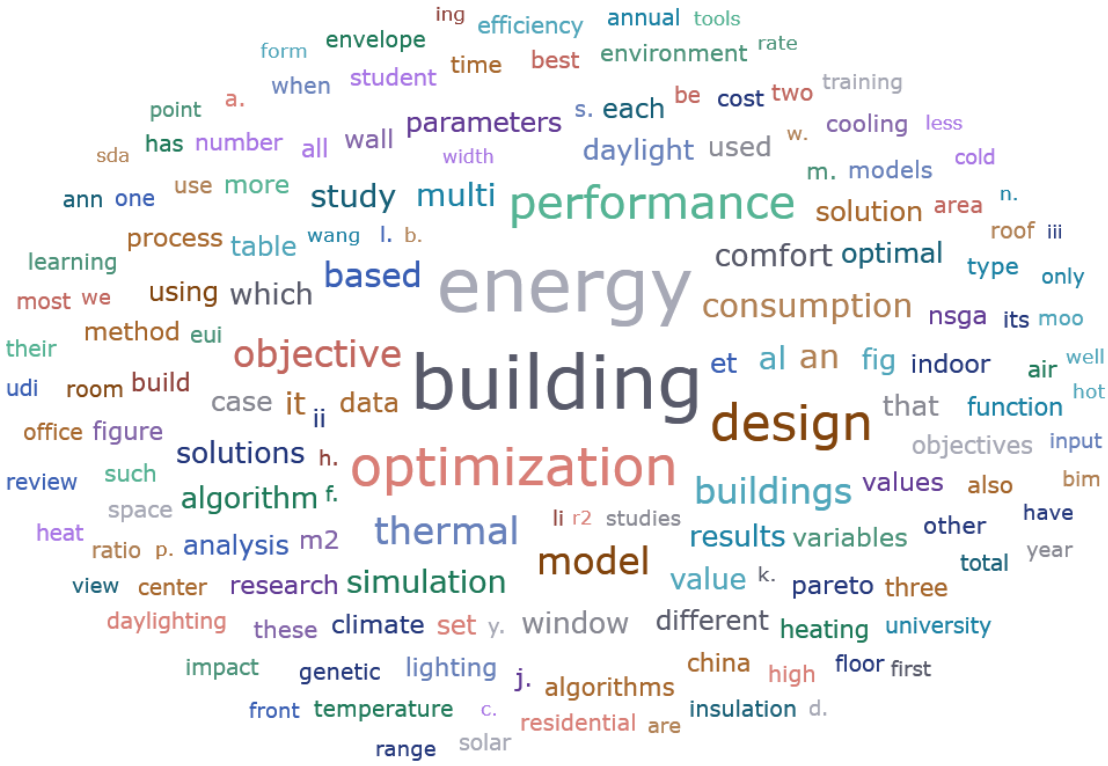

Figure 2 Word cloud generated from 40 articles.

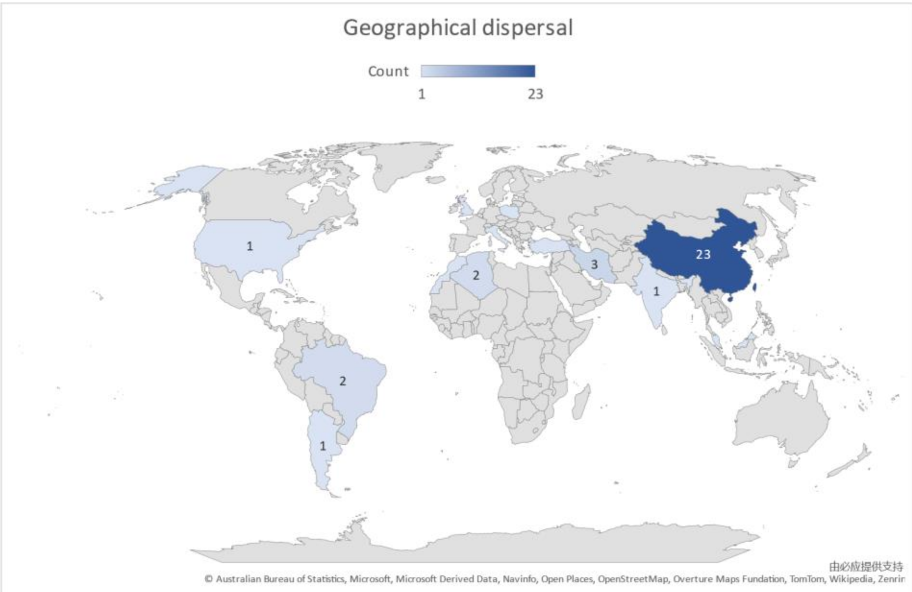

Figure 3 Geographic distribution map.

3.2. Qualitative analysis

3.2.1. Thematic analysis and coding framework

Thematic analysis of the selected literature identified major trends and patterns, as summarized in Table 2. Following an iterative coding process, the initial ten attributes were consolidated into three dominant themes (Figure 5): 1) intelligent algorithms, 2) building performance simulation, and 3) adaptive design for climate change. These themes are not mutually exclusive; several articles were coded under multiple themes, reflecting the interconnected nature of these research areas.

• "Intelligent algorithms" involve optimization techniques, such as genetic algorithms and machine learning, that increase the computational efficiency in building performance optimization.

• "Building performance simulation" provides the analytical foundation for optimization algorithms by evaluating design alternatives across multiple objective functions.

• "Adaptive design for climate change" focuses on climate-responsive strategies, ensuring that buildings remain resilient under future climate uncertainties.

Despite stemming from different research directions, these themes together support a more integrated strategy for optimizing building performance.

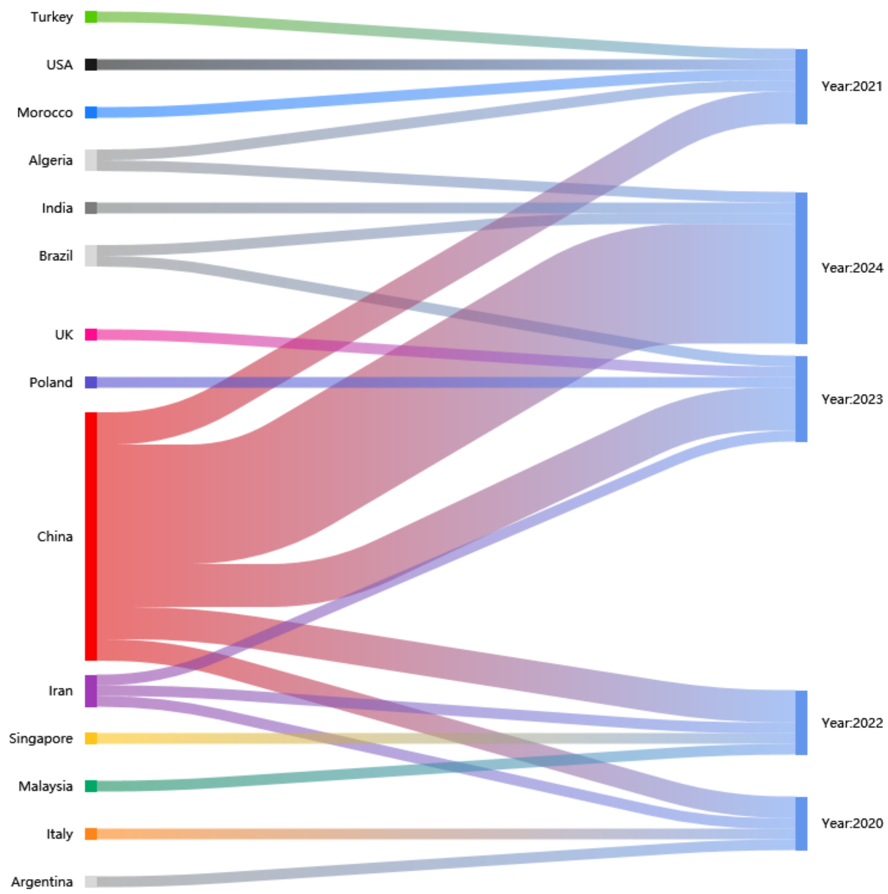

Figure 4 Sankey diagram of countries and publication years.

3.2.2. Intelligent algorithms in building performance optimization

MOO has become a critical research focus in green building design, particularly for enhancing energy efficiency, thermal comfort, and daylighting. The emergence of intelligent algorithms has significantly revolutionized this field by integrating optimization techniques with data-driven machine-learning models, enabling rapid and precise optimization.

Intelligent algorithms include a wide range of methods, such as:

• Evolutionary optimization techniques, e.g., NSGA-II, NSGA-III, the hypervolume estimation algorithm (HypE), and MOPSO);

• Machine learning models, e.g., ANNs, GBDT, and deep reinforcement learning (DRL);

• Surrogate models for accelerating computational simulations;

Although these methods have demonstrated significant advantages, their development and application remain an active research focus owing to challenges such as data dependency, adaptability to complex nonlinear problems, and control of model errors. The network visualization in Figure 6 presents the theme of the intelligent algorithms.

Among the optimization algorithms, the NSGA-II has gained the most widespread application in building performance optimization (Lu et al., 2023). It effectively balances multiple objectives, such as energy consumption, thermal comfort, and daylighting. Zou et al., (2021) incorporated NSGA-II within a multistage optimization framework combined with ANNs, achieving a 2,570-fold improvement in computational efficiency compared with traditional methods. Similarly, Yue et al., (2021) employed NSGA-II in combination with surrogate modeling to improve thermal comfort and enhance energy performance in the design of a campus sports facility, reducing the optimization time from 10 months to just 2 days.

Table 2 Documents according to themes.

	Intelligent algorithms	Building performance simulation	Adaptive design for climate change
(Abd Salam & Lannon, 2023)	√	-	√
(Bahdad et al., 2022)	√	√	-
(Bre et al., 2020)	√	√	-
(Chegari et al., 2021)	√	√	-
(Chen et al., 2024)	√	-	√
(da Silva et al., 2024)	√	-	-
(Fan et al., 2024)	√	-	-
(Jun & Fei, 2024)	√	√	-
(Lakhdari et al., 2021)	√	-	-
(Z. Li et al., 2023)	√	-	√
(L. Li et al., 2023)	-	√	-
(M. Li et al., 2024)	√	-	-
(L. Li et al., 2024)	-	-	√
(Liang & Jing, 2022)	√	-	-
(M. Liu et al., 2024)	√	√	-
(R. Liu et al., 2024)	√	-	√
(Y. Lu et al., 2022)	√	-	-
(Markarian et al., 2024)	√	-	-
(Nazari et al., 2023)	√	-	-
(Ouanes & Sriti, 2024)	√	-	-
(Pan et al., 2024)	√	-	-
(Pilechiha et al., 2020)	√	√	-
(Ratajczak et al., 2023)	√	√	-
(Razmi et al., 2022)	√	√	-
(Rosso et al., 2020)	√	-	√
(Shao et al., 2022)	-	√	-
(Shen & Pan, 2023)	√	√	-
(Silva et al., 2023)	√	√	-
(R. Wang et al., 2020)	√	√	-
(M. Wang et al., 2024)	√	-	-
(R. Wang et al., 2020)	√	√	√
(S. S. Wang et al., 2021)	√	-	-
(Wu et al., 2024)	√	√	-
(Xiao et al., 2023)	√	√	√
(Yi et al., 2021)	√	√	-
(Yilmaz & Yilmaz, 2021)	-	√	-
(Yu et al., 2024)	√	√	√
(Yue et al., 2021)	√	√	-
(Zhao et al., 2022)	√	-	-
(Zou et al., 2021)	√	-	-

Building on NSGA-II, NSGA-III, an extended version developed by Deb and Jain (2014), has been applied to high-dimensional objective optimization to address multiple building performance indicators (Li et al., 2024; Razmi et al., 2022). Other optimization methods have also contributed significantly to this field. For example:

• HypE enhances hypervolume metrics, making it effective for addressing complex building design problems. Pilechiha et al., (2020) applied HypE to optimize office building window designs and achieved significant improvements in balancing energy consumption, daylighting, and view quality.

• Bayesian optimization is particularly effective in addressing computationally expensive simulations, such as dynamic building performance simulations (Shen & Pan, 2023).

• Particle swarm optimization (PSO) has fast convergence rates, particularly in specific optimization tasks (Lenin, 2018). Chegari et al., (2021) successfully combined MOPSO and ANNs to optimize residential buildings in Morocco, significantly reducing heating demands and increasing thermal comfort.

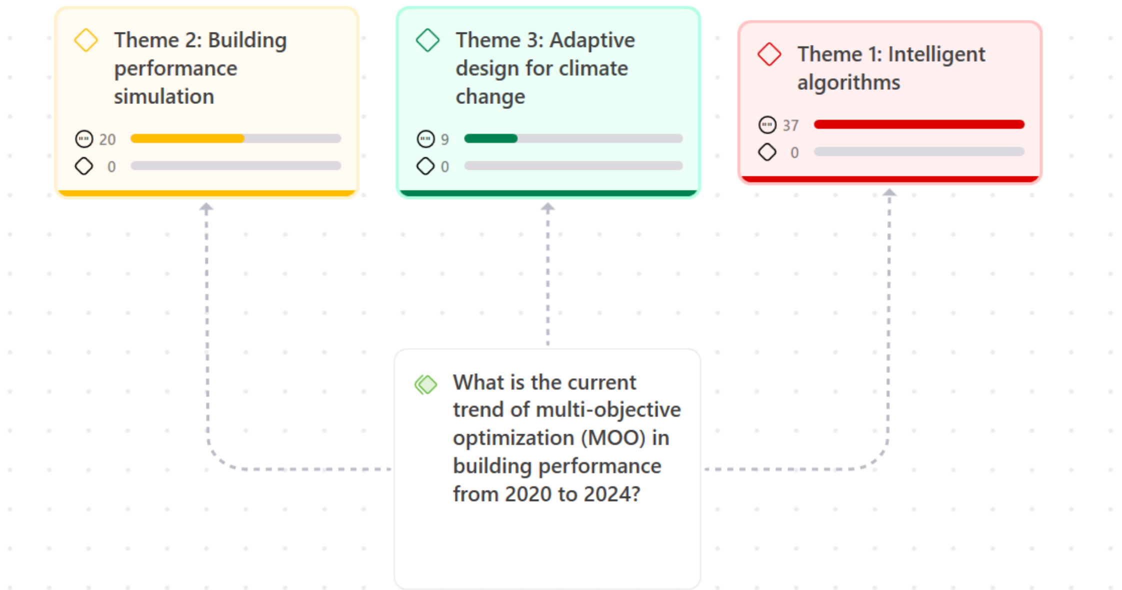

Figure 5 Three consolidated themes after integration.

Figure 6 Network on the intelligent algorithm theme.

Although genetic algorithms remain dominant, alternative methods, such as HypE, PSO, and Bayesian optimization, have demonstrated distinct advantages in certain scenarios, reinforcing the need for hybrid approaches tailored to specific optimization challenges.

The integration of machine learning has further advanced building performance optimization by improving computational efficiency and prediction accuracy. ANNs have been widely adopted as surrogate models, significantly accelerating complex performance simulations. For example, Chegari et al., (2021) combined ANNs with MOO algorithms to increase thermal comfort and energy efficiency in residential buildings, significantly reducing the simulation time. Similarly, Bre et al., (2020) employed ANNs to optimize the thermal comfort and energy efficiency of residential buildings, achieving a 75% reduction in computational time compared with traditional methods. Zou et al. (2021) demonstrated that ANN-based methods can efficiently balance multiple objectives and provide reliable Pareto-optimal solutions.

The evolution of ANNs has paved the way for deep learning techniques to further improve performance optimization. For example, Lu et al., (2022) utilized generative adversarial networks (GANs) to rapidly predict environmental performance, offering an efficient optimization tool for building design. DRL, which integrates deep learning with reinforcement learning, has been proven to be highly effective in dynamic environments. Pan et al., (2024) proposed a DRL framework using the deep deterministic policy gradient (DDPG) model to optimize design parameters in educational facilities, achieving significant improvements in energy consumption, carbon emissions, and thermal comfort.

Beyond deep learning models, the GBDT has emerged as an efficient alternative for structured data modeling in building optimization. This algorithm leverages gradient boosting strategies and tree models, making it particularly effective for structured data optimization. GBDT is also often integrated with Bayesian optimization or genetic algorithms to enhance performance. Wang et al., (2020) combined GBDT with NSGA-II to optimize building energy consumption, carbon emissions, and thermal comfort, achieving computational speeds several times faster than those of conventional methods. Wu et al., (2024) integrated Bayesian optimization with XGBoost (BO-XGBoost) and NSGA-II, leading to a 44.1% reduction in energy consumption, a 10.9% improvement in thermal comfort, and a 1.7% enhancement in daylighting performance.

These studies demonstrate the substantial potential of intelligent algorithms, particularly machine learning-based approaches, for improving building performance optimization. Their integration has led to remarkable enhancements in both computational efficiency and optimization accuracy.

Despite their advantages, intelligent algorithms have several critical limitations that warrant further investigation. First, although the application of individual algorithms has been well studied, considerable room remains for exploring the potential synergies between different algorithmic approaches. For example, although the NSGA-II and deep learning models have been individually successful, their systematic integration for real-time optimization applications remains underdeveloped. A promising avenue is the combination of the global search capabilities of evolutionary algorithms with deep learning pattern recognition strengths, which could enhance dynamic building optimization in complex building environments.

Second, current optimization approaches focus primarily on static building parameters and design-phase optimization. However, real-time adaptation to changing conditions during building operations is becoming increasingly necessary. Pan et al. (2024) explored real-time optimization via DRL; however, the integration of real-time sensor data and adaptive control strategies with traditional optimization algorithms remains a key challenge.

Third, the robustness and generalizability of intelligent algorithms in real-world applications require further attention. Although Zou et al. (2021) and Wu et al. (2024) demonstrated significant improvements in computational efficiency, their applications are limited to specific building types and operating conditions. Scaling these algorithms to more complex and diverse building systems while maintaining both computational efficiency and solution accuracy is a pressing challenge.

Several promising research directions have emerged that address these limitations.

1. Development of hybrid approaches: Integrating physics-based building energy models with data-driven optimization methods can increase the accuracy and efficiency of real-world applications. For example, integrating traditional building energy simulation tools with advanced machine learning models can better capture both the physical constraints of building systems and the complex patterns in operational data.

2. Incorporation of real-time data: Strengthening the integration of real-time optimization capabilities with building management systems can enable continuous adaptation to changing conditions.

3. Advancing AI-driven MOO: Combining reinforcement learning with genetic algorithms can offer new insights for handling high-dimensional optimization problems.

As the field continues to progress, addressing these issues is essential for effectively applying intelligent algorithms in building performance optimization. Ensuring computational efficiency, adaptability, and scalability will drive further advancements and high-performance building design.

3.2.3. Building performance simulation techniques

Recent technological advancements have significantly improved the integration of building performance simulations with optimization algorithms, enabling the development of dynamic simulations with optimization algorithms. These advancements allow for more precise evaluations by incorporating climate change, user behavior, and lifecycle factors into performance simulations. Additionally, the adoption of LCA methods has expanded the scope of simulation beyond initial energy efficiency, addressing long-term energy consumption, environmental impact, and economic performance. These innovations support flexible responses to changing environmental conditions and user demands, paving the way for smarter and more sustainable building design. The network visualization in Figure 7 shows related research on the building performance simulation theme. The figure highlights several key studies that demonstrate the application of various simulation tools to address different aspects of building performance analysis. These studies covered multiple domains ranging from energy performance and daylighting analysis to parametric modeling, reflecting the diversity and development trends in building performance simulation research.

Figure 7 Network on the building performance simulation theme.

Building performance simulation tools serve as the foundation for MOO and provide accurate performance metrics for design evaluations. EnergyPlus is widely recognized for its strengths in energy consumption analysis and thermal comfort assessment (Bre et al., 2020; Shao et al., 2022; Silva et al., 2023; Wang et al., 2020; Yılmaz & Yılmaz, 2021). Radiance specializes in precise daylight performance simulations and has been extensively applied in lighting optimization research (Li et al., 2023; Xiao et al., 2023). Honeybees and Ladybugs, which are integrated as plugins for Grasshopper's parametric design platform, further enhance simulation capabilities by allowing interactive parametric modeling and real-time evaluation (Bahdad et al., 2022; M. Liu et al., 2024; Razmi et al., 2022). DesignBuilder, a visualization tool built on EnergyPlus, offers an intuitive performance evaluation interface for designers, making it a widely adopted tool in the field (Shen & Pan, 2023). The integration of these performance simulation tools with optimization algorithms into joint simulation workflows has become a standard practice in current MOO processes, allowing researchers and designers to explore optimal solutions efficiently across a range of feasible design alternatives.

Beyond dedicated simulation platforms, MATLAB and Python have become essential computational tools for integrating simulation software with optimization algorithms. These programming environments support the execution of advanced optimization techniques such as NSGA-II, NSGA-III, and MOPSO and facilitate workflow automation for simulation tools such as EnergyPlus and Design Builder and scripting tools, offering flexibility and efficiency for the invocation of simulation software and execution of algorithms (Blank & Deb, 2020; Harris et al., 2020). Python libraries, including NumPy, SciPy, and Pymoo, have significantly enhanced computational efficiency by streamlining the integration of building performance simulations with optimization processes. MATLAB supports dynamic simulation, energy efficiency analysis, and thermal comfort assessments and is valuable in MOO studies (Jun & Fei, 2024; Liang & Jing, 2022; S. S. Wang et al., 2021; Yu et al., 2024; Yue et al., 2021). These computational tools effectively bridge the gap between building performance simulation and optimization, enabling more occurate, scalable, and efficient workflows.

With the shift from static to dynamic modeling, building performance simulation now supports real-time responses to evolving weather patterns and user interactions. Recent studies have explored potential surrogate models and parametric design tools to improve simulation speed and accuracy. Pan et al., (2024) developed a dynamic optimization framework that integrates DRL with time-dependent climate patterns, enhancing building adaptability to fluctuating environmental conditions. Similarly, Rosso et al., (2020) applied an internal genetic algorithm within Python to optimize residential buildings in Mediterranean climates and conducted hourly dynamic simulations to assess energy demand. Li et al., (2024) incorporated user interaction behaviors, such as shading device operations and windows, into simulation models, thereby developing a framework that closely aligns with real-world building performance. Their approach also includes a hybrid weighting method that combines subjective and objective evaluation techniques to increase the robustness and comprehensiveness of the decision-making process.

Building performance simulation plays a crucial role in LCA, which involves evaluating energy use, environmental impact, and economic feasibility across a building's entire lifecycle from design and construction to operation and demolition. Several recent studies have highlighted this growing research area. Wang et al., (2020) proposed an LCA-based building performance trade-off framework that optimizes lifecycle costs and environmental impacts while improving indoor thermal comfort. Chen et al., (2024) introduced a comprehensive framework that integrates future climate uncertainties, prioritizing carbon emissions, costs, and indoor comfort. Li et al., (2023) leveraged machine learning models for lifecycle performance prediction, providing insights into energy efficiency and cost optimization. Wu et al., (2024) introduced a hybrid framework that integrates Bayesian optimization and genetic algorithms, optimizing residential building performance across the entire lifecycle. Li et al., (2024) examined the economic efficiency of rural housing envelope renovations by incorporating a 20-year cost–benefit analysis (CICBR-20-year lifecycle) while also assessing improvements in daylighting and indoor comfort. These studies demonstrate how building performance simulations and LCA methods contribute to sustainable design, helping designers and engineers balance short- and long-term performance objectives.

Despite significant progress, several challenges persist in the field of building performance simulation. One fundamental challenge lies in bridging the gap between simulation capabilities and real-world building operations. Many simulation models treat buildings as isolated systems, failing to capture the complex interactions among occupant behavior, environmental conditions, and building control systems. Although Pan et al., (2024) and Li et al., (2024) have made progress in incorporating dynamic factors, real-world implementations remain challenging. Another key limitation is the computational complexity of multiscale simulations. Handling multiple temporal and spatial scales remains computationally intensive, particularly when attempting to balance detailed building physics simulations with long-term lifecycle impacts. The validation of the simulation results against real-world performance data is another major issue. Despite efforts to incorporate user interaction behavior (L. Li et al., 2024), discrepancies between simulated predictions and actual building performance continue to be observed. These gaps are particularly evident in lifecycle assessments, where long-term predictions must account for numerous uncertainties in building operations and environmental conditions.

To address these challenges, future research should focus on developing multiscale simulation frameworks that integrate component- and building-level analyses. Enhancing real-time operational data integration into simulation models is essential to achieve more accurate and adaptive predictions. Improving uncertainty quantification techniques, particularly for long-term lifecycle assessments, is also necessary to ensure reliable decision-making in sustainable building design. Additionally, advancing machine-learning-driven simulation techniques can enable faster and more precise optimization of complex building performance scenarios. By incorporating these advancements, building performance simulations can move toward a more robust, scalable, and real-world framework, supporting the continued development of high-performance, sustainable building designs.

3.2.4. Adaptive design for climate change

As global climate change intensifies, buildings must go beyond simply ensuring energy efficiency and occupant comfort under current climatic conditions. They must also be designed to adapt to evolving climatic variations. Climate-adaptive design requires strategic planning from the initial stages of architectural development to ensure that buildings are not only responsive to present-day performance demands but also resilient to long-term climate fluctuations (L. Li et al., 2024). During the design phase, buildings must be equipped to handle immediate performance challenges while maintaining their adaptability to climate change throughout their lifecycle (Z. Li et al., 2023). The integration of advanced methodologies such as LCA, dynamic simulation, and machine learning has greatly enhanced the adaptability and sustainability of architectural design.

These innovative approaches allow buildings to respond flexibly to diverse climate scenarios, meet current requirements, and proactively address future climate uncertainties. By leveraging these tools, architects and engineers can ensure optimal performance and long-term sustainability in response to environmental variability. The network visualization in Figure 8 maps these interconnected methodologies, illustrating their role in advancing adaptive design for climate change.

In recent years, MOO has emerged as a fundamental strategy in building performance simulation and design optimization, with the aim of balancing key indicators, such as energy efficiency, thermal comfort, and daylight performance. Researchers have increasingly employed advanced methodologies, including genetic algorithms, machine learning, and LCA techniques, to explore how optimized architectural design can enhance building performance under variable climate conditions. For example, Liu et al., (2024) utilized genetic algorithms and statistical analysis to develop optimal design solutions for buildings in cold regions of China, with a focus on both performance and economic efficiency. Similarly, Rosso et al., (2020) used genetic algorithms for MOO to retrofit Mediterranean climate buildings, ensuring that existing structures could efficiently adapt to regional climate challenges. Xiao et al., (2023) proposed an MOO framework that simultaneously optimized the daylighting performance, energy consumption, and thermal comfort for atrium buildings in regions of China with hot summers and cold winters. The studies highlighted in Figure 8 underscore the importance of integrating these computational approaches to improve climate adaptability in building performance optimization.

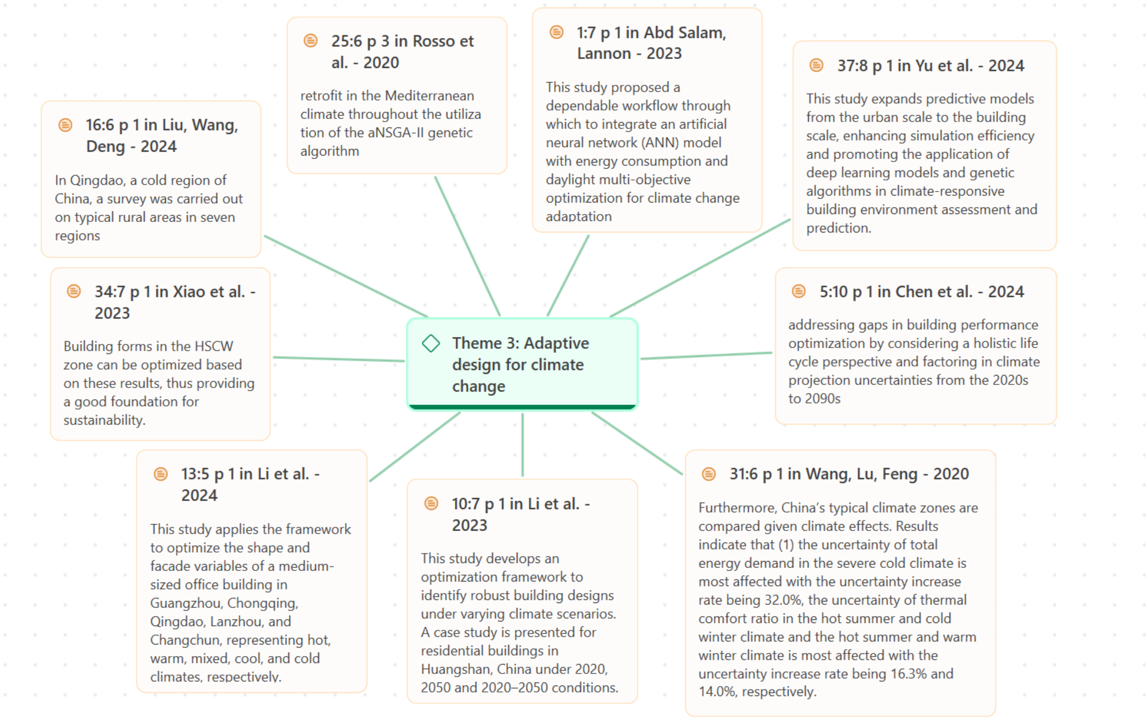

Figure 8 Network of the adaptive design for the climate change theme.

The design decisions made in the early stages of building development play a critical role in determining long-term adaptability and sustainability. Li et al., (2024) developed an MOO framework specifically for the initial design phase, enabling buildings to be preemptively adaptable to varying climate conditions. Their research featured an in-depth case study examining medium-sized office buildings across five distinct climate zones in China, showing the effectiveness of climate-responsive strategies in the early stages of architectural planning. Wang et al., (2020) expanded upon this by incorporating uncertainty and sensitivity analysis into an MOO process and investigating how adjustment strategies such as window ventilation and shading influence building performance across different climate conditions. These findings demonstrated that climate-adaptive strategies should be integrated at the earliest possible stage to ensure resilient and efficient building operations in the face of increasing climate unpredictability.

As climate-adaptive design continues to gain momentum in the field of building performance optimization, researchers have begun exploring more sophisticated methodologies for addressing future climate uncertainties. Abd Salam and Lannon (2023) trained an ANN model to predict energy consumption and daylight performance, demonstrating a novel approach to integrate predictive modeling into architectural design. Chen et al., (2024) introduced a resilient design framework based on integrated learning models and the two-archive evolutionary algorithm for constrained MOO (C-TAEA), effectively showing how future climate scenarios could impact building lifecycle performance. This study provides a new methodological foundation for enhancing lifecycle resilience to climate variability. Li et al., (2023) employed general circulation models to predict future climate conditions, utilizing MOO strategies to increase energy efficiency while reducing lifecycle costs. Their case study evaluated residential building performance in 2020 and 2050 and across the 2020–2050 period, highlighting the long-term impact of climate change on architectural design and the use of predictive tools for future-proofing buildings. Yu et al., (2024) developed an innovative MOO framework that leveraged NSGA-III and CFD-based GAN mapping predictions, thereby facilitating a climate-responsive design tailored to various climate zones. Their work demonstrated the adaptability of machine learning-enhanced optimization, extending its potential application to urban microclimate prediction at the street block scale.

Thus, climate-adaptive design has become an integral component of building performance optimization, transitioning from a passive adaptation approach to proactive innovation. By incorporating optimization algorithms and intelligent technologies, such as machine learning, buildings can dynamically adjust to evolving climate conditions and enhance long-term sustainability. Research indicates that optimized design approaches not only enhance building performance across diverse climatic regions but also provide effective strategies for mitigating future climate challenges, positioning the architectural industry toward greater resilience and adaptability. As technological advancements continue, future architectural design processes are expected to place greater emphasis on climate adaptability, utilizing sophisticated predictive models and optimization algorithms to deliver precise and effective design strategies for sustainable development. This evolution in building design represents a fundamental shift, where buildings are no longer passive recipients of external climate forces but active participants in mitigating and responding to climate change challenges.

Despite these advancements, integrating climate-adaptive design principles into practical building design and operation presents considerable challenges. Current approaches often struggle to balance immediate performance requirements with long-term climate resilience, thereby posing difficulties when translating theoretical frameworks into practical design solutions. Yu et al., (2024) successfully developed a framework for a climate-responsive design across multiple climate zones. Li et al., (2023) demonstrated methods for evaluating building performance under projected climate conditions, the implementation of which remains challenging. This difficulty arises primarily from the complex interactions among building systems, occupant behavior, and evolving environmental conditions, making it difficult to synchronize theoretical predictions with real-world applications.

Future research on climate-adaptive building design should prioritize bridging the gap between theoretical advancements and practical implementations. Efforts should focus on developing robust methods for incorporating climate uncertainties into early-stage design decision making, ensuring that adaptive strategies are embedded at the core of architectural planning. Further improvements in integrating adaptive strategies with building lifecycle assessments are necessary to provide more realistic long-term solutions. Additionally, practical tools that allow designers to evaluate and implement climate-adaptive strategies more effectively are urgently needed. Particular emphasis should be placed on devising approaches that address both immediate building performance requirements and long-term resilience simultaneously, ensuring that architectural designs remain adaptable to evolving environmental conditions while maintaining optimal functionality across their lifecycle. Addressing these challenges is essential for advancing climate-adaptive design frameworks and ensuring their widespread adoption in the next generation of sustainable architecture.

4. Conceptual Framework for Multi-Objective Optimization in Building Performance

Building on the research trends and challenges identified in the previous sections, this chapter presents a conceptual framework for the MOO of building performance. The framework was designed to integrate intelligent algorithms, simulation tools, and climate adaptation strategies to address the complex and evolving challenges in building performance optimization. By synthesizing these components, the framework provides a structured approach for balancing competing design objectives, ensuring that buildings achieve both high performance and long-term adaptability.

Figure 9 illustrates the conceptual framework structured to respond to climate change and the environmental challenges currently facing the building sector. These challenges, including the energy crisis, sustainability mandates, and user comfort requirements, are the primary motivators for research and practical applications in building performance optimization. At the core of the framework is the MOO process, which encompasses several key optimization metrics, such as energy efficiency, thermal comfort, indoor environmental quality, acoustic performance, economic feasibility, environmental impact, and operational efficiency. The MOO process involves establishing performance objectives, conducting trade-off analyses to determine Pareto-optimal solutions, and employing decision-making methods to select an optimal design scheme.

To illustrate how the framework can be applied in practice, consider a residential building located in a climate zone characterized by hot summers and cold winters, where maintaining energy efficiency and indoor comfort is essential despite significant seasonal changes. Wu et al. (2024) applied this framework in such a setting, demonstrating how simulation tools, intelligent algorithms, and climate adaptation strategies interact to optimize building performance. In the simulation phase, Grasshopper and its plugins (Ladybug and Honeybee) were used to evaluate multiple performance aspects simultaneously. In the optimization stage, the framework employs BO-XGBoost for rapid performance prediction and NSGA-II for optimization, enabling the identification of optimal design solutions while considering local building codes and construction feasibility. The ability of the framework to systematically integrate advanced computational methods with real-world design constraints underscores its effectiveness in bridging the gap between optimization theory and practical applications.

In addition to residential applications, the framework has been successfully implemented across various building types and climate contexts, thereby demonstrating its broad applicability. Xiao et al. (2023) applied a similar framework to optimize atrium buildings in hot summer and cold winter climates, achieving an 18.67% reduction in energy use intensity by optimizing key form variables, such as the roof inclination angle and north–south section aspect ratio, while maintaining balanced daylighting and thermal comfort. Similarly, M. Liu et al. (2024) demonstrated the effectiveness of the framework in optimizing university buildings, where the integration of envelope design parameters and shading strategies resulted in a 58.8% reduction in energy consumption and a 53% increase in thermal comfort hours. These examples demonstrate how the framework converts complex optimization problems into actionable design strategies, serving as a key resource for architects and engineers aiming to improve building performance through systematic, data-driven approaches.

The effectiveness of the framework is driven by the dynamic interaction among its three core components: intelligent algorithms, simulation tools, and climate adaptation strategies. The synergy between these elements is crucial for achieving real-time optimization, as they work together in an integrated feedback loop at the operational level. Various intelligent optimization algorithms, including NSGA-II, NSGA-III, MOPSO, and HypE, along with machine learning models, such as ANN, GBDT, and GAN, provide robust computational capabilities that enhance the optimization process. For example, when optimizing the envelope design of a building, simulation tools such as EnergyPlus and Radiance generate multidimensional performance data under different design scenarios. EnergyPlus evaluates energy consumption and thermal comfort, whereas radiance assesses daylighting performance. These performance data are then fed into machine learning models such as BO-XGBoost, which rapidly predicts performance outcomes for various design configurations. The NSGA-II subsequently processes these predictions to identify Pareto-optimal solutions and balance multiple competing objectives. Through this iterative process, the integration of climate adaptation strategies ensures that the optimization results remain robust across seasonal and future climate variations, forming a comprehensive and adaptive optimization loop.

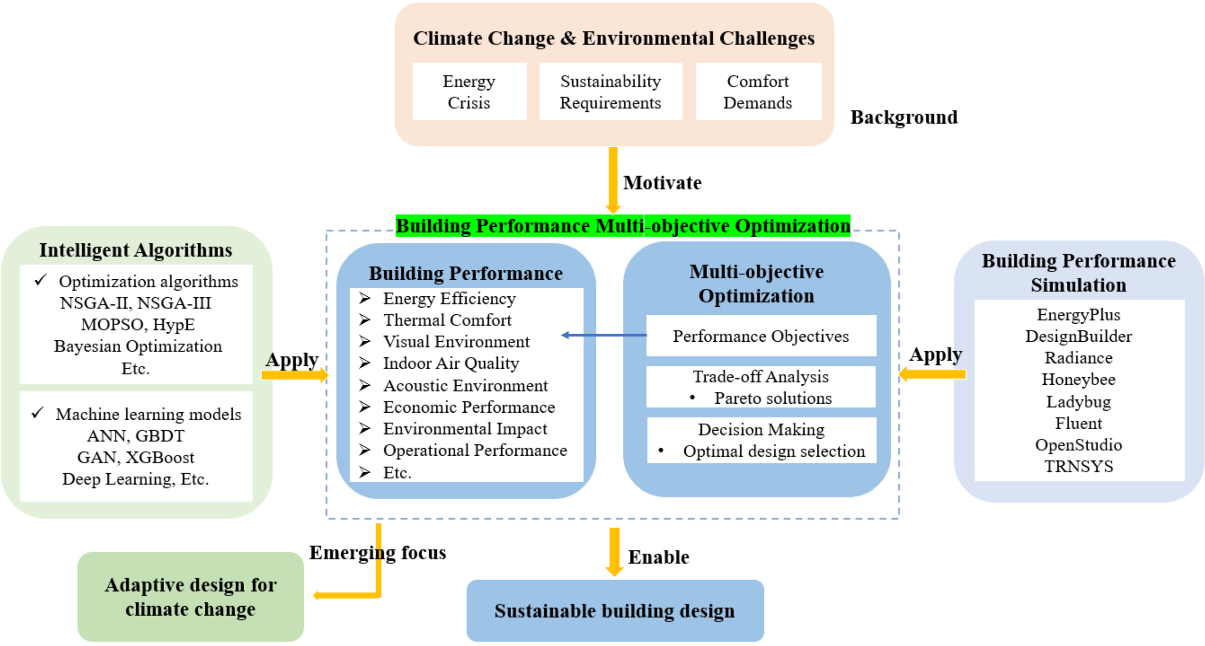

Figure 9 Conceptual framework for building performance multi-objective optimization.

Overall, the conceptual framework comprehensively articulates the core elements of multi-objective building performance optimization by integrating key dimensions such as contextual drivers, optimization objectives, algorithmic support, simulation tools, and long-term sustainability goals. In addition to just a structural representation, the framework establishes clear interconnections between these components, demonstrating how they collectively contribute to achieving a sustainable, adaptive building design. By fostering a holistic, multilayered optimization process, the framework addresses both immediate performance needs and long-term resilience, ensuring that buildings remain functional, efficient, and adaptable in the face of evolving climate and environmental conditions.

A key strength of the framework is its ability to increase computational efficiency by strategically integrating intelligent algorithms with simulation tools. Traditional optimization methods often have high computational costs, particularly when evaluating many design variables and performance constraints. However, by leveraging machine learning models, such as those employed by Wu et al. (2024), in combination with simulation-based optimization, the framework enables rapid performance evaluation without sacrificing accuracy. This data-driven approach streamlines the optimization process, allowing for the efficient handling of complex design tasks that would otherwise be computationally prohibitive via conventional methods alone.

Furthermore, the framework's emphasis on climate-adaptive design represents a crucial advancement in building performance optimization, addressing both immediate and future climate challenges. The integration of simulation tools with climate-adaptive components allows designers to evaluate and optimize performance across multiple temporal scales, ensuring that buildings not only meet current environmental requirements but are also prepared for long-term climate change. L. Li et al. (2024) applied this approach in an office building design study, where their framework evaluated performance metrics across different climate scenarios, taking lifecycle implications into account. Similarly, Yu et al. (2024) demonstrated how the framework could be adapted for specific climate zones, maintaining both energy efficiency and occupant comfort while ensuring adaptability to future climate variations. These studies illustrate how the integration of climate-adaptive strategies enhances the robustness of the framework, enabling a sustainable, future-proof building design.

Although the framework represents a comprehensive and effective approach to building performance optimization, further development is necessary to increase its scalability and applicability. One primary challenge is the need for sophisticated protocols governing data exchange between simulation tools and optimization algorithms, particularly in managing uncertainties related to climate predictions and occupant behavior patterns. These factors play a significant role in long-term building performance and must be incorporated into future iterations of the framework to improve its predictive accuracy. Additionally, expanding the scalability of the optimization process across different building types, regional climates, and urban contexts is a critical area for future research.

To further enhance the practical applicability of the framework, future research should focus on refining validation methods for optimization results and developing standardized implementation guidelines for different types of building projects. Establishing clear protocols for integrating the framework into real-world architectural practices will ensure that they can be effectively utilized by designers, engineers, and policymakers. Further studies should explore the potential of real-time optimization by leveraging advanced AI-driven techniques to dynamically adjust building performance in response to changing environmental conditions.

By addressing these areas, the framework can be further refined and expanded, ultimately providing designers with more robust tools for creating sustainable climate-adaptive buildings. As a scalable, adaptable, and computationally efficient solution, the framework represents a significant step forward in the evolution of building performance optimization, supporting the development of high-performance, resilient, and future-ready architectural designs.

5. Conclusion and Future Directions

This paper presents a comprehensive thematic review of MOO in building performance from 2020 to 2024, analyzing 40 carefully selected articles to identify current trends, challenges, and opportunities in this rapidly evolving field. Through quantitative and qualitative analyses, three major themes emerged: intelligent algorithms, building performance simulations, and adaptive design for climate change. These findings inform the development of a conceptual framework designed to effectively integrate these components, bridging the gap between theoretical research and practical applications in building performance optimization.

5.1. Summary of key findings

This study highlights intelligent algorithms as powerful tools for tackling complex building performance optimization problems. The integration of machine learning techniques, such as ANNs and GBDT, has significantly improved computational efficiency while maintaining high solution accuracy. These advancements have enabled researchers to handle intricate multi-objective problems and enhance the optimization of energy efficiency, thermal comfort, and indoor environmental quality in building design.

The evolution of building performance simulation tools has played a crucial role in advancing comprehensive and accurate performance evaluation. The integration of dynamic simulation techniques with LCA methods has facilitated a holistic approach to optimization, accounting for both initial design decisions and long-term environmental and economic impacts. This shift reflects a growing recognition of the importance of evaluating building performance across its entire lifecycle rather than limiting assessments to the design phase alone. By incorporating real-world operational conditions, simulation tools can now provide more realistic performance insights, supporting the development of high-performance, sustainable buildings.

Another significant trend is the emergence of climate-adaptive design as a critical element in building performance optimization. Research has increasingly emphasized the importance of developing optimization frameworks that can accommodate future climate uncertainties while maintaining optimal performance. This trend represents a fundamental shift from static design approaches to dynamic, flexible, and adaptable solutions that can respond to changing environmental conditions. By integrating predictive climate modeling, adaptive materials, and real-time performance monitoring, climate-adaptive design reshapes the future of sustainable architecture and positions buildings as active participants in climate resilience.

5.2. Research implications and future directions

Despite the significant progress made in MOO for building performance, several key challenges and opportunities remain, thereby providing directions for future research. One of the primary challenges is to enhance the performance of intelligent algorithms. Although machine learning and evolutionary algorithms have demonstrated strong optimization capabilities, there is still a need for greater robustness and generalizability when they are applied to cross-domain performance objectives and large-scale optimization problems. Computational efficiency remains a concern, particularly as the complexity of optimization problems increases. Additionally, improving the practical applicability and operational feasibility of these algorithms in real-world engineering projects is essential for bridging the gap between theoretical advancements and implementation in architectural and construction practices.

Another pressing research direction is the development of dynamic simulations and real-time optimization capabilities. As the demand for continuous building performance optimization extends into the operational phases of buildings, simulation technologies that support real-time dynamic optimization are needed. Future research should focus on adapting simulation models to real-time user behavior patterns and fluctuating environmental conditions. This requires the creation of more efficient surrogate models that can provide rapid and accurate performance predictions and the development of dynamic assessment methods that enable continuous performance monitoring and adjustment. Enhancing real-time optimization capabilities will allow buildings to respond dynamically to operational changes, ensuring consistently high performance throughout their lifecycle.

This study also underscores the importance of adopting a lifecycle-oriented approach for comprehensive optimization. Although many current optimization models focus primarily on energy efficiency, a more integrated, multidimensional perspective is needed. Future research should emphasize optimizing building performance from a life-cycle perspective, incorporating multiple indicators, such as energy consumption, environmental impact, economic feasibility, and user comfort. This requires the development of more sophisticated optimization strategies that balance short-term design trade-offs with long-term sustainability goals. Additionally, enhanced decision-support tools should be created to facilitate more holistic and informed decision-making by architects, engineers, and policymakers.

Therefore, addressing climate adaptability and uncertainty remains crucial research priorities. The uncertainties caused by climate change pose significant challenges for optimizing building performance, necessitating the development of more flexible and adaptive optimization methods. Future research should focus on establishing more accurate climate prediction models, enabling performance assessment methodologies to evaluate building resilience under a wide range of evolving climate scenarios. The ability to respond proactively to climate variability through adaptive design strategies is a key determinant in ensuring the long-term sustainability and resilience of buildings.

5.3. Theoretical and practical contributions

The findings and proposed framework of this study make several significant contributions to both the theoretical understanding and practical applications of building performance optimization. Whereas existing frameworks typically emphasize either computational efficiency or climate adaptation, the proposed framework uniquely integrates intelligent algorithms, simulation tools, and climate adaptation strategies into a cohesive system. This comprehensive integration allows for a more effective MOO that not only addresses immediate performance requirements but also ensures long-term climate resilience. By demonstrating how these components interact dynamically, the framework provides a systematic approach for bridging the gap between theoretical advancements and real-world applications in sustainable building design.

A key theoretical contribution of this study is the demonstration of how the strategic integration of simulation tools with optimization algorithms can significantly enhance computational efficiency without sacrificing solution accuracy. Recent studies, such as those by Wu et al. (2024) and M. Li et al. (2024), support this finding, illustrating how the combination of machine learning models with traditional simulation tools accelerates the optimization processes while maintaining high prediction accuracy. This insight reinforces the importance of hybrid optimization approaches, where AI-driven predictive models complement physics-based simulation tools, leading to more efficient and scalable building performance analysis.

The emphasis of the framework on climate adaptation represents another major advancement over traditional static optimization methods. By incorporating adaptive strategies that respond to evolving environmental conditions, the framework provides a robust and future-proof approach for building performance optimization. Conventional methods often rely on fixed climatic assumptions, which limits their long-term effectiveness. In contrast, the proposed framework dynamically integrates climate prediction models, adaptive materials, and real-time performance monitoring, ensuring that optimized designs remain resilient to changing climate conditions over time. This adaptive approach aligns with the increasing global emphasis on climate-responsive architecture, making a critical contribution to both theoretical discourse and practical implementation.

In addition to providing theoretical insights, the proposed framework offers valuable guidance for implementing MOO in real-world building projects. By clearly defining the interactions among intelligent algorithms, simulation tools, and climate adaptation strategies, the framework provides a structured methodology that can be adopted by architects, engineers, and policymakers to enhance sustainable design practices. The identified research directions further highlight opportunities for improving current optimization methodologies, particularly in the areas of climate adaptation and real-time optimization, which remain pressing challenges for practitioners striving to create resilient and energy-efficient buildings.

5.4. Future outlook and emerging technologies

The success of building performance optimization increasingly depends on interdisciplinary collaboration and technological innovation. Emerging technologies, such as digital twins, edge computing, and blockchain, have significant potential for enhancing optimization capabilities, enabling more real-time, data-driven decision-making in building operations. Digital twins, for example, can provide real-time feedback loops that allow buildings to adjust their performance continuously on the basis of operational data and environmental conditions. Blockchain technologies can enhance data transparency and security in terms of performance tracking and energy transactions. However, while these innovations present exciting possibilities, they must be balanced by practical considerations related to implementation complexity, cost, and user acceptance. Therefore, future research should not only focus on technical advancements but also prioritize the development of practical tools and frameworks that can be effectively adopted by industry professionals without excessive technological or financial barriers.

The field of building performance optimization presents significant opportunities for advancing integrated approaches that combine intelligent algorithms, simulation tools, and climate adaptation strategies. By addressing the theoretical and practical challenges outlined in this study, researchers and practitioners can develop sustainable, adaptive, and resilient building design and operation strategies. As climate change continues to exacerbate environmental and energy challenges, the pursuit of innovative, data-driven, and climate-responsive optimization methods will be essential to ensure that future buildings are not only high-performing but also capable of overcoming long-term environmental uncertainties.

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Ethical Considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

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