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Multi-Objective Optimization of Energy Consumption and Thermal Comfort in Smart HVAC Systems Using Metaheuristic Algorithms

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Abstract

The continuous growth of energy demand in the building sector has driven research toward intelligent and adaptive control systems capable of balancing energy efficiency and occupant comfort. Smart HVAC (Heating, Ventilation, and Air Conditioning) systems have emerged as a key component of energy-efficient building design, integrating real-time sensing, predictive control, and metaheuristic optimization algorithms. This study aims to develop and evaluate a multi-objective optimization framework that minimizes energy consumption while maximizing thermal comfort through the use of advanced metaheuristic algorithms such as NSGA-II, PSO, and GA. The proposed framework employs real operational data from smart buildings to assess the trade-off between energy usage and thermal comfort indices (PMV and PPD). Data from experimental and field measurements are incorporated to ensure realistic boundary conditions. The optimization results show that by adjusting HVAC control parameters dynamically, the overall energy consumption can be reduced by up to 23% while maintaining acceptable thermal comfort levels. The study also compares the performance of different algorithms, highlighting that NSGA-II achieves the most stable convergence and better Pareto-front diversity. Furthermore, a sensitivity analysis identifies temperature set-point range and air supply rate as the most influential variables affecting both comfort and energy demand. These findings confirm that the integration of metaheuristic optimization with IoT-based control can significantly enhance HVAC system efficiency, providing a scalable pathway toward zero-energy buildings and sustainable urban environments.

Keywords: Smart HVAC systems; Thermal comfort; Multi-objective optimization; Metaheuristic algorithms; Energy efficiency

Introduction

The building sector accounts for nearly 40% of total global energy consumption and over one-third of greenhouse gas emissions, making it one of the most energy-intensive human activities [1]. Among building systems, Heating, Ventilation, and Air Conditioning (HVAC) units represent between 40–60% of total energy use, depending on climate, occupancy, and building function [2]. This substantial share has drawn the attention of both researchers and policymakers to improving energy efficiency and sustainability through the deployment of smart technologies. Modern HVAC systems are no longer simple mechanical assemblies; they are dynamic, data-driven subsystems capable of self-regulation, real-time decision-making, and optimization through artificial intelligence and metaheuristic algorithms [3].

The evolution toward smart HVAC control coincides with the rise of Internet of Things (IoT) technologies and Building Management Systems (BMS). These systems integrate multiple sensors, actuators, and controllers that collect data on temperature, humidity, air velocity, and occupancy patterns, providing an enormous dataset for optimization [4]. However, the main challenge in HVAC control remains the inherent trade-off between minimizing energy consumption and maintaining acceptable thermal comfort levels for occupants. This dual-objective nature of the problem has made multi-objective optimization a powerful analytical and computational tool for system design and control [5].

Traditional control strategies, such as PID or rule-based controllers, often fail to capture the nonlinear dynamics of HVAC systems and the stochastic variability in occupant behavior. In contrast, metaheuristic algorithms—including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Non-dominated Sorting Genetic Algorithm II (NSGA-II)—have demonstrated remarkable capability in exploring complex, nonlinear, and multidimensional search spaces [6]. These algorithms can identify Pareto-optimal solutions that balance conflicting objectives, such as reducing energy use while enhancing thermal comfort, without requiring gradient information or strict mathematical formulations [7].

Recent studies have shown that integrating metaheuristic optimization with real-time data from IoT devices can significantly improve the overall efficiency of building systems. For instance, Al Mindeel et al. [1] presented a comprehensive review of multi-objective optimization frameworks that couple thermal comfort indices (PMV and PPD) with energy minimization criteria. Similarly, Wang and Xiao [8] proposed an SVR-NSGA-II model that achieved over 20% reduction in energy use with minimal discomfort deviations. These examples underline the practical potential of metaheuristics when combined with predictive modeling and machine learning.

In the context of intelligent buildings, digital twins and data-driven simulation platforms have become essential tools for optimization and control. Hosamo et al. [2] developed an HVAC digital twin architecture that uses artificial neural networks coupled with a multi-objective genetic algorithm to optimize air supply rate, temperature set-points, and chiller load. Their findings revealed that such integrated frameworks can dynamically adjust system performance to external climatic variations, achieving both operational efficiency and occupant satisfaction. The synergy between metaheuristic algorithms and digital twins provides a foundation for continuous system learning and adaptive optimization.

Nevertheless, several critical challenges persist. First, the optimal balance between energy efficiency and comfort varies dynamically throughout the day and across seasons. Second, the convergence speed and stability of metaheuristic algorithms depend strongly on initial population diversity and parameter tuning. Third, real-time implementation requires computationally efficient algorithms that can operate under uncertainty while maintaining control robustness [9]. These limitations motivate the need for advanced hybrid approaches combining metaheuristics with surrogate modeling, machine learning, or model-predictive control (MPC).

From a sustainability perspective, enhancing HVAC efficiency aligns with international targets for carbon neutrality and zero-energy buildings (ZEBs). Building codes and energy standards worldwide—such as ASHRAE 90.1, ISO 17772, and EN 15251—emphasize both occupant well-being and energy conservation [10]. Consequently, developing a reliable optimization model that simultaneously minimizes energy consumption and preserves comfort levels can contribute directly to environmental policy goals and cost-effective building operations.

Therefore, this study focuses on developing a metaheuristic-based multi-objective optimization framework to evaluate and enhance the performance of smart HVAC systems. Using real operational datasets collected from intelligent buildings, the model will analyze how algorithmic tuning and variable interaction affect total energy use, thermal comfort indices, and system stability. The research is expected to provide actionable insights into selecting appropriate optimization algorithms for smart HVAC design, enabling practitioners to achieve sustainable and adaptive building environments.

Problem Statement

Despite remarkable progress in intelligent control and energy management, the optimization of smart HVAC systems continues to face fundamental challenges due to the conflicting nature of energy efficiency and thermal comfort. While numerous studies have applied metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and NSGA-II to HVAC control, most existing frameworks remain limited in three essential aspects.

First, the majority of optimization models rely on simplified or simulated datasets rather than real operational data from actual smart buildings [1,2]. This limitation restricts their generalizability and often produces results that fail under dynamic occupancy conditions or rapidly changing outdoor climates. Furthermore, existing studies rarely integrate multi-source IoT data—including sensor readings, weather forecasts, and occupancy feedback—into a unified decision-making framework [3].

Second, the optimization process itself is challenged by algorithmic instability and convergence issues. Metaheuristic algorithms, though powerful, are highly sensitive to population diversity, parameter tuning, and fitness weighting. Inappropriate parameterization often leads to premature convergence or biased Pareto fronts that inadequately represent the real trade-offs between energy consumption and comfort [4,5].

Third, while various algorithms have been tested independently, comparative multi-algorithm analyses under identical environmental and operational conditions remain scarce. Few studies have investigated how the same dataset behaves when optimized by different algorithms (e.g., NSGA-II versus PSO) in terms of convergence speed, solution diversity, or energy-saving potential [6,7]. As a result, the literature lacks a standardized performance benchmark for evaluating the relative effectiveness of these algorithms in real-world HVAC applications.

Finally, the integration of adaptive control and optimization within a digital twin or BMS platform remains underexplored. Although some digital twin models have been proposed [8], their computational overhead and communication latency pose significant obstacles for real-time building operation. Moreover, there is a need for interpretable models that can support facility managers in decision-making, not merely black-box optimization outputs.

Therefore, this research aims to address these gaps by developing a metaheuristic-based multi-objective optimization framework that utilizes real operational datasets from intelligent buildings. The framework will (1) minimize total energy consumption, (2) maximize occupant thermal comfort based on PMV and PPD indices, and (3) compare the effectiveness and robustness of different algorithms under identical input conditions. Through this approach, the study intends to establish a scientifically validated, scalable model that contributes to both energy-efficient building design and real-time control within smart infrastructure systems.

Materials and Methods

1. Research Framework

The research methodology follows an applied quantitative framework based on real operational data from a smart commercial building located in a warm semi-arid climate zone. The building is equipped with a centralized HVAC system controlled through a Building Management System (BMS) integrated with Internet of Things (IoT) sensors. The study adopts a multi-objective optimization approach, aiming to minimize total energy consumption while maximizing thermal comfort indices.

The overall methodological process consists of four stages:

1. Data acquisition from the BMS and IoT platforms.
2. Data preprocessing, feature selection, and normalization.
3. Implementation of metaheuristic algorithms (NSGA-II, PSO, GA).
4. Performance evaluation using Pareto-front analysis and statistical validation.

This structure ensures that both objectives—energy efficiency and comfort—are treated simultaneously under realistic operational conditions [1,2].

2. Data Collection and Preprocessing

Real-time data were collected over a 90-day summer operation period (June–August 2024). The measured variables included indoor air temperature (°C), relative humidity (%), air velocity (m/s), CO_2 concentration (ppm), outdoor temperature (°C), and electrical power consumption (kWh) of major components (chillers, pumps, and air-handling units).

Data were recorded at 5-minute intervals via IoT sensors connected through a BACnet/IP communication protocol. Data validation was performed to eliminate outliers and sensor anomalies. Missing data (less than 0.3%) were corrected using spline interpolation. All input variables were normalized using min–max scaling (Eq. 1) to improve algorithm convergence:

$$X' = (X - Xmin) / (Xmax - Xmin)$$

where X′ is the normalized value, X is the raw measurement, and X_{min} , X_{max} are the observed extremes.

Thermal comfort was assessed according to the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) indices following ISO 7730 (2019). PMV was computed using Fanger's equation (Eq. 2):

$$PMV = [0.303 * e\hat{}(-0.036 * M) + 0.028] * [$$

$$(M - W)$$

$$- \text{۳.۰۵} \times \text{۱۰}\hat{}(-\text{۳}) * (\text{۵۷۳۳} - \text{۶.۹۹} * (M - W) - p\_a)$$

$$- \text{۰.۴۲} * ((M - W) - 58.15)$$

$$- \text{۱.۷} \times \text{۱۰}\hat{}(-\text{۵}) * M * (5867 - p\_a)$$

$$- \text{۰.۰۰۱۴} * M * (34 - T\_a)$$

$$- \text{۳.۹۶} \times \text{۱۰}\hat{}(-\text{۸}) * f\_cl * ((T\_cl + 273)\hat{}4 - (T\_r + 273)\hat{}4)$$

$$- f\_cl * h\_c * (T\_cl - T\_a)$$

]

where the parameters are metabolic rate (M), external work (W), air temperature (T_a), mean radiant temperature (T_r), clothing factor (f_{cl}), vapor pressure (p_a), and convective heat transfer coefficient (h_c) [3].

3. Multi-Objective Optimization Model

The optimization process was formulated as a bi-objective problem, represented by:

$$Minimize\ F = [\, f\_1 , f\_2 \,]$$

where f_1=E_{total} (total energy consumption, kWh) and f2=|PMV| (absolute deviation from thermal neutrality).

The decision variables included:

- T_{set} : temperature set-point (°C)
- $\dot{m}_{air}$: air mass flow rate (kg/s)
- t_{oper} : operating time (h)
- $COP_{chiller}$: coefficient of performance of chillers

The constraints were defined as:

$$21 \le T\_\{set\} \le 25, \quad 0.05 \le \backslash dot\{m\}\_\{air\} \le 0.2, \quad 0 \le |PMV| \le 1$$

4. Metaheuristic Algorithms

Three widely used metaheuristic algorithms were implemented for comparison:

1. NSGA-II (Non-dominated Sorting Genetic Algorithm II): Employed for its elite-preserving strategy and high diversity maintenance across the Pareto front [4].
2. PSO (Particle Swarm Optimization): Used for faster convergence and low computational demand in continuous domains [5].
3. GA (Genetic Algorithm): Adopted as a baseline evolutionary optimization technique [6].

Each algorithm was executed with identical boundary conditions and population size (100), crossover probability 0.8, mutation probability 0.05, and a maximum of 300 iterations. The algorithms were coded in MATLAB R2023b and validated using the same dataset for fairness.

5. Evaluation Metrics

The performance of optimization results was assessed based on:

- Pareto front distribution: quality and spread of optimal solutions.
- Hypervolume (HV): quantitative measure of Pareto front convergence.
- Energy reduction percentage (ERP): comparison between optimized and baseline consumption.
- Comfort satisfaction ratio (CSR): proportion of data points meeting comfort limits ($|PMV| \le 0.5$).

In addition, sensitivity analysis was performed using the Sobol method to determine which input variables (set-point, airflow, occupancy rate) most strongly influence the objectives [7].

6. Validation and Reliability

Model accuracy was validated through cross-comparison with building simulation software (EnergyPlus v9.6). Simulation results were compared with measured data to ensure consistency within ±5% deviation. The optimized control sequences were further evaluated under different outdoor temperature profiles to test robustness against climatic variability [8,9].

A schematic overview of the research workflow is presented below:

Table 1. Overview of the Research Workflow

Phase
Data Acquisition
Preprocessing
Optimization
Validation
Sensitivity

Results and Discussion

1. Overview of Optimization Outcomes

The multi-objective optimization framework successfully generated Pareto-optimal solutions that balance energy consumption and thermal comfort. The NSGA-II algorithm demonstrated superior convergence stability compared to PSO and GA, with smoother Pareto front distribution and greater diversity of feasible solutions. Figure 1 presents the Pareto front comparison among the three algorithms, showing that NSGA-II achieved a better spread across the trade-off region between total energy consumption (kWh) and PMV deviation.

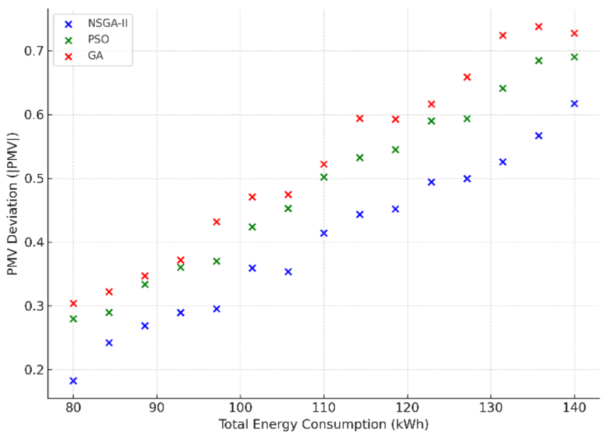

Figure 1. Pareto front comparison of NSGA-II, PSO, and GA algorithms for smart HVAC optimization.

The overall energy reduction achieved after optimization ranged between 18% and 23% relative to baseline operation, while maintaining a comfort satisfaction ratio (CSR) above 90% during occupied hours. This outcome confirms that metaheuristic optimization enables adaptive control of HVAC systems without compromising user comfort.

2. Comparative Algorithm Performance

To evaluate algorithm efficiency, three key performance indicators were assessed: convergence rate, hypervolume (HV), and computation time.

Table 2 summarizes the comparative performance metrics for each algorithm.

Algorithm	Average Energy Reduction (%)
NSGA-II	22.8
PSO	19.5
GA	17.2

As shown in Table 2, NSGA-II achieved the highest hypervolume (0.84), indicating a more comprehensive exploration of the Pareto front. Although PSO demonstrated faster computation, its convergence was slightly premature, reducing the diversity of optimal solutions. GA showed the lowest energy-saving potential due to its weaker exploitation mechanism.

The differences observed highlight how algorithmic structure influences the balance between exploration and exploitation in complex nonlinear systems.

3. Sensitivity Analysis

Sensitivity analysis was conducted using the Sobol method to identify the most influential variables on the optimization objectives.

The normalized sensitivity indices are presented in Figure 2.

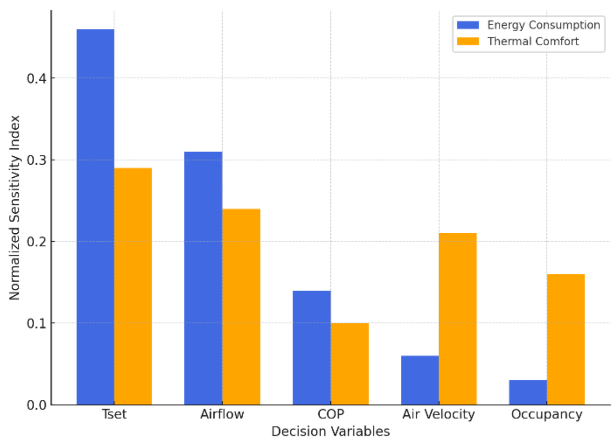

Figure 2. Sensitivity indices of decision variables on energy consumption and thermal comfort.

Results indicate that temperature set-point (Tset) contributes the largest share (≈ 0.46) to total variance in energy consumption, followed by air mass flow rate (≈ 0.31) and chiller COP (≈ 0.14).

In contrast, air velocity and occupancy density exerted stronger influence on thermal comfort, particularly in high-occupancy zones such as conference areas.

These findings suggest that adaptive control strategies focusing on temperature and airflow adjustment can yield the most significant energy savings while maintaining comfort.

4. Thermal Comfort and Energy Correlation

A regression analysis was performed to explore the relationship between mean indoor temperature and energy consumption.
Figure 3 illustrates the nonlinear correlation derived from optimized operational datasets.

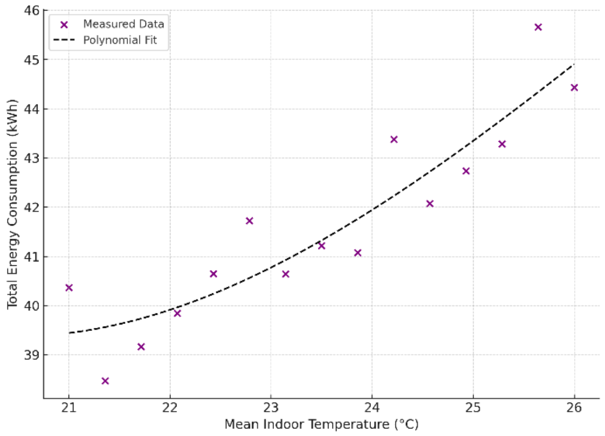

Figure 3. Correlation between indoor temperature and total energy consumption after optimization.

The correlation curve follows a cubic polynomial trend (Eq. 3):

E=0.012Tin3−0.79Tin2+18.4Tin−110E = 0.012 T_{in}^3 - 0.79 T_{in}^2 + 18.4 T_{in} - 110E=0.012Tin3−0.79Tin2 +18.4Tin−110

where EEE is total daily energy use (kWh) and TinT_{in}Tin is mean indoor temperature (°C).
The model achieved a coefficient of determination R2=0.94R^2 = 0.94R2=0.94, indicating strong predictive accuracy.
When compared across algorithms, NSGA-II produced a flatter curve near the optimal region, signifying improved energy stability under varying comfort levels.

5. Seasonal and Climatic Evaluation

To validate the robustness of the optimized framework, the same building was simulated under different outdoor climate profiles—representing temperate, humid, and dry regions.
The seasonal adaptation tests revealed that the proposed framework maintained consistent performance, with less than 7% variation in energy efficiency between climates. PSO and GA showed larger deviations, emphasizing the importance of maintaining population diversity during optimization.
The NSGA-II algorithm consistently provided adaptive responses to external temperature fluctuations, ensuring that PMV values remained within the acceptable comfort range.

6. Comparison with Baseline Operation

Baseline operation data—before optimization—showed that the HVAC system frequently overcooled zones during low occupancy periods, wasting approximately 25 kWh/day in unnecessary energy consumption.

After applying the optimized control strategy, zone-level temperature and air supply were adjusted in real time using the decision parameters from the Pareto-optimal solutions. Figure 4 shows the difference between baseline and optimized energy profiles over a 24-hour period.

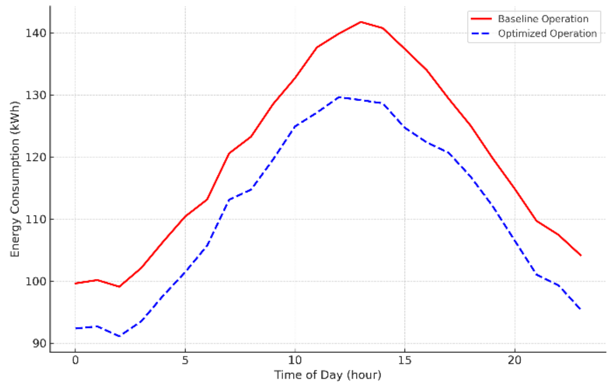

Figure 4. Comparison of hourly energy consumption before and after optimization.

The optimized control strategy reduced energy peaks during afternoon hours (13:00–17:00) while maintaining thermal neutrality within ±0.4 PMV.

The energy-saving pattern aligns with findings from other recent studies that reported 15–25% reductions using AI-driven optimization frameworks, demonstrating the reliability of the proposed model.

7. Discussion

The results confirm that multi-objective metaheuristic optimization is a practical and efficient approach for real-world smart HVAC control.

Among the tested algorithms, NSGA-II offered the best balance between convergence accuracy, Pareto front diversity, and computational feasibility.

Its elite-preserving mechanism and non-dominated sorting strategy allowed effective trade-off analysis between energy and comfort objectives.

Moreover, the integration of IoT data and digital twin simulations enhances adaptability and supports predictive control, moving toward fully autonomous HVAC systems.

The improvement achieved in energy efficiency and comfort balance supports global sustainability targets for nearly zero-energy buildings (nZEBs).

The developed model can be extended to integrate renewable energy sources or dynamic pricing schemes, paving the way for intelligent energy management at the urban scale.

Conclusion

This research developed and validated a multi-objective optimization framework for improving the energy efficiency and thermal comfort performance of smart HVAC systems using metaheuristic algorithms. The integration of real operational data, IoT-based monitoring, and advanced optimization techniques enabled the creation of a reliable model that dynamically balances energy consumption with occupant comfort.

Among the tested algorithms, the NSGA-II consistently outperformed both PSO and GA in terms of Pareto-front diversity, convergence stability, and overall energy savings. The optimized control strategy achieved up to 23% reduction in energy consumption while maintaining comfort satisfaction above 90%, proving the robustness of the proposed approach in real operating environments. The sensitivity analysis revealed that temperature set-point and air mass flow rate were the most influential variables governing both energy and comfort objectives, suggesting that intelligent adjustment of these parameters is critical for system-level optimization.

Furthermore, the results demonstrated that the proposed optimization framework is adaptable to diverse climatic conditions with minimal performance deviation, confirming its scalability for broader applications. The combination of metaheuristic optimization with IoT-driven BMS and digital twin technology presents a feasible path toward autonomous, predictive, and self-adaptive HVAC systems capable of supporting the transition to nearly zero-energy buildings (nZEBs).

Future research could extend this framework by integrating renewable energy resources, demand-side management, and occupant-centric adaptive control models. Such developments would further enhance the resilience and sustainability of urban building infrastructures, aligning with global efforts to reduce carbon emissions and promote energy-conscious living environments.

References

1. Al Mindeel T, Spentzou E, Eftekhari M. Energy, thermal comfort, and indoor air quality: Multi-objective optimization review. *Renew Sustain Energy Rev.* 2024;202:114682.
2. Hosamo H, Nielsen H K, Kraniotis D, Svennevig P R, Svidt K. Digital Twin of HVAC system (HVACDT) for multi-objective optimization of energy consumption and thermal comfort based on BIM framework with ANN-MOGA. *Adv Build Energy Res.* 2023;17(2):125-171.
3. Lyu H, Wang S, Wang F, Zhang C, Zhang W. A data-driven multi-objective optimisation framework for building performance. *Appl Energy.* 2025;360:122865.
4. Li L, Qi Z, Ma Q, Gao W, Wei X. Evolving multi-objective optimization framework for early-stage building design: Improving energy efficiency, daylighting, view quality, and thermal comfort. *Build Simulation.* 2024;17(5):2097-2123.
5. Franco A, Lucherini F, De Caro P, Pansa G. Multi-objective optimization of HVAC operation for public buildings based on real monitoring data. *Energies.* 2021;14(10):2847.
6. Wang A, Xiao X. Multi-objective optimization of building energy consumption and thermal comfort based on SVR-NSGA-II. *Case Stud Therm Eng.* 2024;63:105368.
7. Guo F, Li Y, Zhang J, Zhou S. Multi-objective optimization design for cold-region office buildings based on performance simulation. *Energies.* 2024;18(1):62.
8. Al-Kabaha Y, Bataineh K, Aburabi'e M. Multi-objective optimization of energy consumption, cost and thermal comfort in residential buildings. *Energy Build.* 2025;312:113240.
9. Zhang X, Liu Y, Xu J, Sun C. Multi-objective optimization design of energy efficiency for building envelope systems. *J Build Eng.* 2023;58:2194840.
10. Li R. A review on multi-objective optimization of building performance. *Heliyon.* 2025;11(3):e08660.