

Multi-objective optimization algorithm for building energy optimization based on MOEA/D

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Article Info	Abstract
Article History: Received 07 Aug 2026 Accepted 14 Sep 2026 Keywords: Building energy-saving; MOO; MOEA/D; Thermal comfort; Energy consumption control	Building energy-saving design needs to consider energy consumption and thermal comfort. The research aims to propose an efficient Multi-Objective Optimization (MOO) method adapted to building energy-saving design. The research first constructs an MOO model that minimizes the annual total energy consumption and maximizes indoor thermal comfort, and clarifies the decision-making elements and constraint boundaries. According to the decomposition idea of the multi-objective evolutionary algorithm, the weight vector generation, neighborhood update and mutation strategy are improved, and an improved MOO is constructed. The method is verified by residential building data in four typical climate zones in China. When this algorithm iterates for 500 generations, the Generational Distance (GD) is only 0.025, and the inverted GD reaches 0.045. The convergence and solution set distribution uniformity are significantly better than those of the comparison algorithm. The energy consumption of the solutions produced by this algorithm is 29.5%-38.6% lower than those of the comparison algorithm, with Guangzhou as low as 31.2kWh/m²·year and Harbin 42.3kWh/m²·year. Carbon emissions are reduced by 30.1%-39.8%, with Guangzhou down to 20.5kgCO₂/m²·year. The thermal comfort compliance time accounts for more than 92% with Guangzhou reaching a maximum of 96.8%. The initial investment costs are reduced by 11.7%-16.4%. This algorithm is superior to existing algorithms in convergence and uniformity of solution set distribution, which can adapt to the energy-saving design across climate zones, provide practical technical support for energy-saving and cost control throughout the building's life cycle, and has important engineering application value.

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1. Introduction

Affected by the green transformation of the construction industry, energy consumption control and thermal comfort guarantee throughout the building life cycle have become core issues in the industry. Building energy-saving design needs to balance multiple objectives, covering multiple dimensions such as envelope optimization, energy system regulation, and cost control. It faces practical challenges such as differences in different climate zones and complex engineering constraints [1-2]. However, current industry practice still generally adopts single-objective or experience-oriented design methods, which are difficult to effectively handle the inherent conflicts between multiple objectives. As a result, design solutions often suffer from problems such as high energy consumption, insufficient comfort, or excessive initial investment in actual operation [3-4].

Currently, MOO technology has been widely used in the field of building energy-saving design. To solve the high uncertainty in building life cycle environmental impact assessment, Kiss B et al. used a MOO method that combined dynamic energy consumption simulation and life cycle assessment,

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using building envelope parameters as variables. The optimized building envelopes under the current power structure could reduce life cycle greenhouse gas emissions by an average of 18% [5]. To address the multi-objective, multi-constraint, and time-consuming issues in the renovation design of historical buildings, the study employs energy simulation and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to achieve energy savings, carbon reduction, and net present value optimization. Wei H et al. combined the logarithmic additive decomposition method for optimization, and then obtained the optimal solution for multiple scenarios through the weighted sum method. When this method was applied to a courtyard building in Nanjing, energy consumption was reduced to 63.62%, net present value increased by 151.84%, and carbon emission reduction rate reached 60.48%, achieving MOO balance [6]. To balance energy efficiency, life cycle costs and thermal comfort in densely populated countries, Elsheikh A et al. proposed a MOO model for Egypt's three main climate types. Wall and roof types were design variables, incorporating local sustainable materials to optimize building envelope and HVAC system parameters. The optimal solutions in each climate zone achieved a balance between energy consumption and life cycle costs, but the proportion of discomfort time reduction in Mediterranean and semi-arid climate zones was lower than that in arid climate zones [7]. In response to the problem that the building energy efficiency certificate policy is difficult to promote stakeholder participation in renovation and the process is complicated, Araújo G R et al. used the building energy efficiency certificate database to integrate machine learning and MOO technology to provide optimal renovation plans, costs and investment returns. The coefficients of determination of energy consumption and energy efficiency certificate prediction models reached 0.84 and 0.79, respectively. The energy consumption was reduced to 60%. The return on investment in three years could be up to 7 times [8].

There are numerous studies that have developed various variants of Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D) to enhance the Multi-Objective Optimization (MOO) capabilities, but customized improvements for building optimization problems are still relatively limited. Agent-assisted optimization is often used to reduce the high computational cost of EnergyPlus simulations, but relevant practices of deep coupling between agent models and MOEA/D are still insufficient. A large number of works have combined meta-heuristic algorithms with EnergyPlus for building performance optimization, but most studies are limited to a single climate and building case. In the field of building renovation, there have been many studies on the trade-offs of energy consumption, cost, and thermal comfort, but the collaborative optimization of building envelope parameters for new residential buildings still needs to be supplemented. Uncertainty-aware optimization has gradually gained attention, but the existing solutions generally have high computational costs, and there is still a research gap for efficient frameworks suitable for residential scenarios. Therefore, the research focuses on multi-objective collaborative optimization of building energy-saving design to propose an improved optimization method based on MOEA/D to solve the performance defects and scene adaptation limitations of the existing algorithm. It is expected to provide optimization solutions that take into account energy-saving and carbon reduction, comfort experience and cost control for residential buildings, upgrade building energy-saving design technology, and implement projects. The improvement strategies of the research have clear differences in mathematical construction from the existing MOEA/D variants. In terms of weight vector generation, the existing methods mostly rely on uniform sampling or density feedback. This study proposes that the weight adjustment amplitude is directly coupled with the curvature estimation value of the Pareto front, rather than solely relying on the neighborhood density statistics. In terms of neighborhood update, traditional methods mostly adopt linear decreasing rules. This study constructs an adaptive criterion for neighborhood size based on the relative change rate of the aggregation function. In terms of mutation strategies, this study dynamically determines the combination coefficient of polynomial mutation and Gaussian mutation based on the non-dominated rank and aggregation density. The above improvements respectively address the limitations of traditional MOEA/D in building energy optimization, such as the difficulty of fixed weights in covering the real trade-off surface in different climate zones, insufficient diversity in the early stage of the neighborhood and decreased convergence accuracy in the later stage, and the tendency of single mutation to get stuck in local optima when dealing with high non-linear building parameter spaces. Its applicability is reflected in the significantly

different curvatures of the Pareto front for building energy and thermal comfort targets in different climate zones, and the adaptive weights can effectively cope with this. The thermal parameters have a clear engineering feasible domain and the calculation cost of the objective function is high. The neighborhood adaptation and mixed mutation significantly improve the search efficiency within a limited evaluation. Theoretically, the three strategies work together. The adaptive weights ensure the search direction covers the range, the dynamic neighborhood update controls the information transmission of sub-problems, the mixed mutation maintains the population diversity, and the algorithm's convergence and solution set uniformity are superior to the MOEA/D variants that adopt single or partial improvement strategies. The study systematically applies the aforementioned improved algorithm to the multi-objective energy-saving optimization of residential buildings in four typical climate zones in China, and establishes a complete optimization-simulation collaborative computing framework. The main scientific contributions are as follows: It revealed the collaborative mechanism of the three improvement strategies in the building energy optimization problem, and proved the complementary effectiveness of adaptive weight generation, dynamic neighborhood update and hybrid mutation in the trade-off between energy consumption and comfort. Moreover, it quantified the independent contributions of each strategy through ablation experiments, providing methodological support for the engineering application of MOEA/D type algorithms in building performance optimization.

2. Proposed Methodology

2.1 Construction of MOO Model for Building Energy-Saving Design

The study first deconstructs the building energy-saving design. The core lies in clarifying the internal logic of the target system, decision-making elements and constraint boundaries, and analyzing the core contradiction between energy consumption control and thermal comfort guarantee, while considering the engineering feasibility of the design plan, as shown in Figure 1.

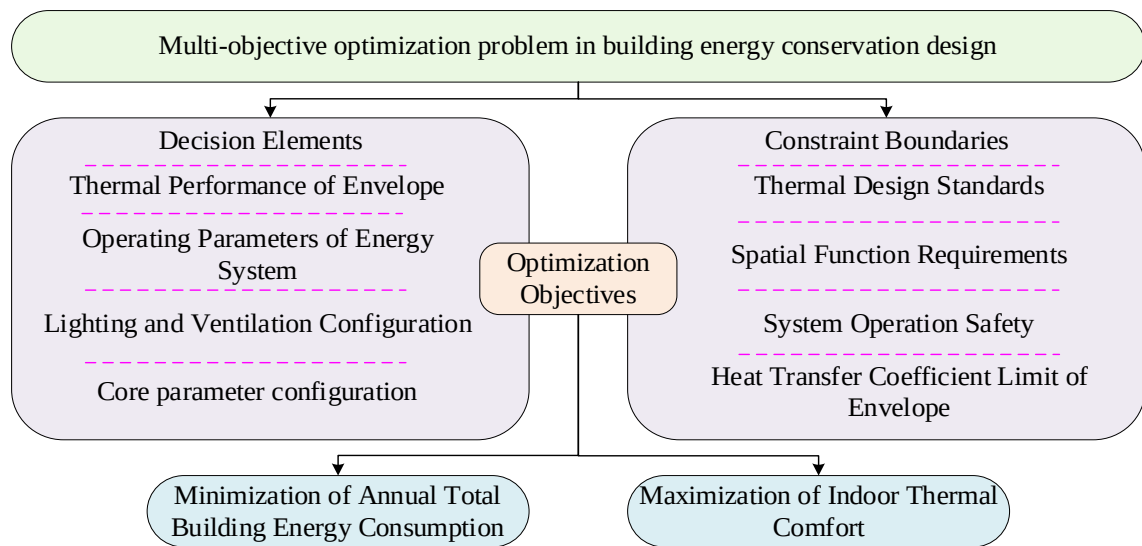


Fig. 1. MOO problem of building energy-saving design

In Figure 1, the decision-making elements are selected around three key dimensions: thermal performance of the building envelope, operating parameters of the energy system, and lighting and ventilation configuration. Core parameters that have obvious impacts on energy-saving effects and comfort experience are selected, including parameters related to the insulation layer, thermal performance parameters of doors and windows, air-conditioning system operation control parameters, and lighting system configuration parameters. All parameter values are based on current specifications to ensure the rationality of engineering applications. The constraint boundaries are formulated based on three core criteria: thermal design standards, space functional requirements and system operation safety. They cover key contents such as envelope heat transfer coefficient limits, door and window area ratio requirements, equipment operating parameter

intervals, etc., forming effective limitations on decision-making elements and ensuring that the optimization plan meets the basic requirements of architectural design [9-10]. The primary optimization goal is to minimize the total annual energy consumption. This goal comprehensively covers heating, cooling, ventilation and lighting. It takes into account the dynamic changes in climate conditions in different seasons and the time distribution characteristics of the building usage pattern, and uses the dynamic energy consumption calculation method to quantify it, given in equation (1).

$$f_1 = \sum_{t=1}^T (Q_h(t) + Q_c(t) + Q_v(t) + Q_l(t)) \cdot \Delta t \quad (1)$$

In equation (1), f_1 is the total annual energy consumption target of the building. T is the total number of calculation periods throughout the year. Δt is the time step (h) of each calculation period. $Q_h(t)$ is the heating load power (kW) in period t , which is determined by the heat transfer loss, the difference between heat transfer and radiation heat gain through doors and windows, and indoor heat load demand. $Q_c(t)$ is the cooling load power (kW) in period t , which is related to the indoor and outdoor temperature difference, solar radiation intensity, and the heat released by the indoor heat source. $Q_v(t)$ represents the ventilation energy consumption (kW) in period t , which depends on the ventilation volume and energy loss in the air treatment process. $Q_l(t)$ signifies the lighting energy consumption power (kW) in period t , which is affected by the power configuration and the efficiency of natural lighting utilization.

The second optimization goal is to maximize indoor thermal comfort. The predicted dissatisfaction percentage is used as a quantitative index. This index is based on the internationally accepted thermal comfort evaluation standard and comprehensively considers the synergistic effect of the four thermal environment parameters of indoor temperature, relative humidity, air flow velocity, and average radiant temperature. It comprehensively reflects the human body's subjective feelings, given in equation (2).

$$f_2 = 100 - 95 \cdot \exp(-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2) \quad (2)$$

In equation (2), f_2 signifies the indoor thermal comfort evaluation target. PMV signifies the predicted average voting value, which is calculated through indoor thermal environment parameters, human metabolic rate, clothing thermal resistance, and other factors. The value range is [-3,3]. The closer the value is to 0, the better the thermal comfort state. The value of the objective function is [5,100]. The smaller the value, the better the overall comfort performance of the indoor thermal environment. When the value does not exceed 10%, it is determined to meet the basic requirements for human thermal comfort [11-12]. The actual optimization objective of this model is Predicted Percentage of Dissatisfied (PPD). ITCI is merely a derived evaluation indicator used in the experiment for result comparison and is not the algorithm optimization target. The fixed assumptions used in the calculation of thermal comfort are set as a metabolic rate of 1.0 met, a clothing thermal resistance of 0.5 clo, an indoor air velocity of 0.1 m/s, an indoor relative humidity of 50%, an average radiant temperature consistent with the indoor air temperature, and a personnel occupancy schedule following the typical daily routine of a residence. The personnel are present in the room from 8:00 to 22:00 each day, and the remaining time periods are considered as unoccupied. Based on building thermal engineering principles and energy balance equations, a coupled calculation model of building thermal environment and energy consumption is constructed to clarify the impact mechanism of decision-making elements on the two objective functions, as shown in Figure 2.

In Figure 2, the decision-making element input module covers parameters related to the envelope structure, energy system, and lighting and ventilation. The coupled calculation module realizes parameter transformation through the heat conduction equation, energy balance equation, and thermal comfort evaluation model. The objective function output module outputs the energy consumption and thermal comfort quantification results, respectively [13-14]. To collaboratively optimize the two conflicting goals, the MOO model is constructed, given in equation (3).

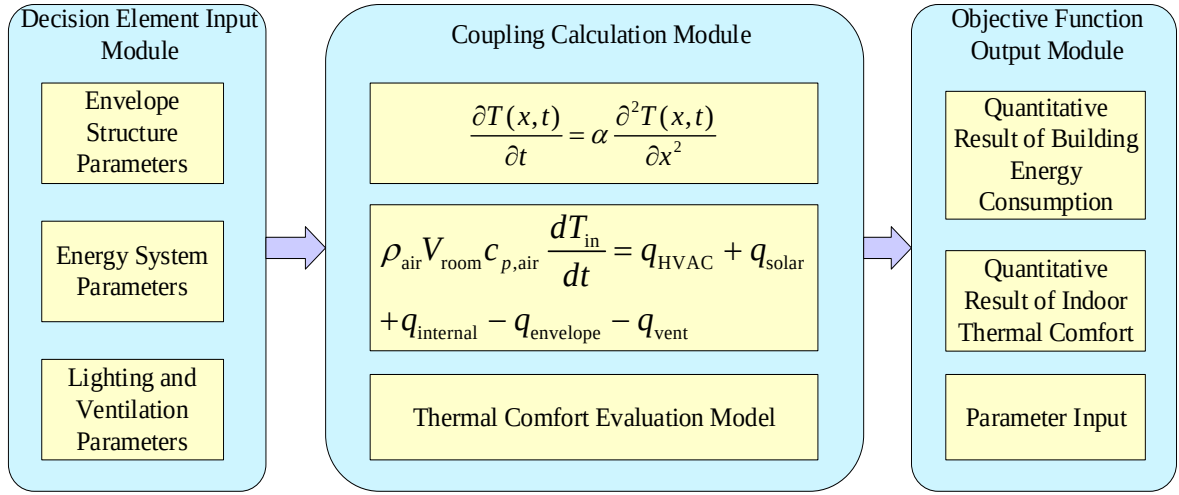


Fig. 2. Coupled calculation model of building thermal environment and energy consumption

$$\begin{cases} \min & F = [f_1, f_2]^T \\ \text{s.t.} & G_k \leq 0 \quad (k = 1, 2, \dots, K) \\ & a_j \leq x_j \leq b_j \quad (j = 1, 2, \dots, J) \end{cases} \quad (3)$$

In equation (3), F is a multi-objective function vector. There is a significant conflict between f_1 and f_2 , that is, the ultimate optimization of a single goal will degrade the performance of the other goal. G_k signifies the k -th constraint. K signifies the total constraints. x_j signifies the j -th decision parameter. J signifies the total decision parameters. a_j and b_j signify the lower limit and upper limit of the j , and jointly define the feasible region of the decision parameter. In this optimization model, the decision variables include the thermal parameters of the building envelope, the performance parameters of doors and windows, the operation control parameters of the air conditioning system, and the configuration parameters of the lighting system.

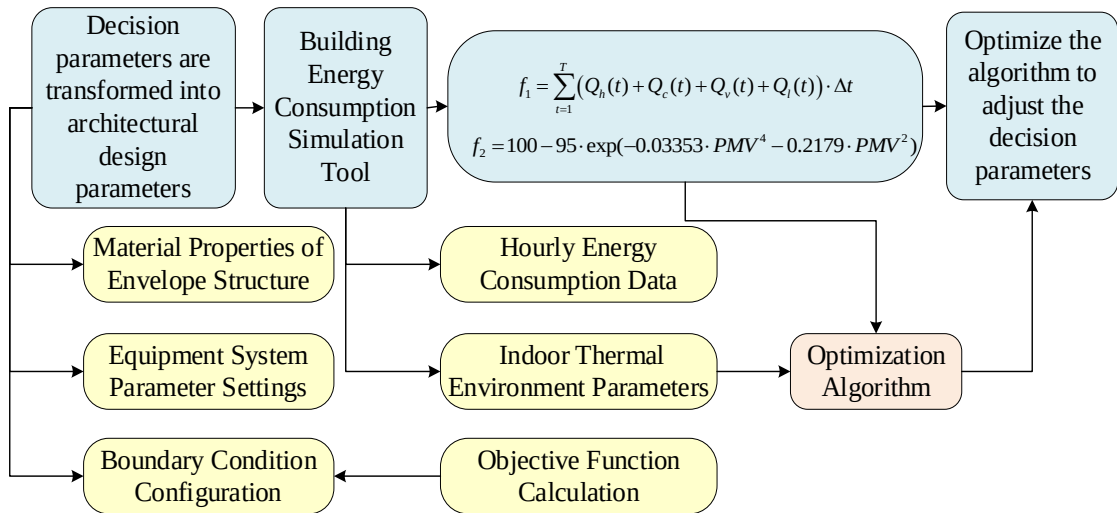


Fig. 3. Collaborative calculation mechanism of optimization model and building energy consumption simulation tool

The constraints include the limit values of the heat transfer coefficient of the building envelope, the requirements for the window-to-wall area ratio, and the parameter ranges for equipment operation. Carbon emissions, initial investment costs, and lighting satisfaction are not the optimization objectives or constraints. Instead, they are post-evaluation indicators for the optimization solution, used to comprehensively evaluate the engineering applicability of the obtained Pareto solutions from the economic and environmental perspectives. Among these, carbon emissions are calculated by multiplying the energy consumption values obtained from the optimization by the corresponding grid carbon emission factors for each climate zone. The initial

investment cost is estimated based on the market prices of building envelope and equipment selection. Moreover, lighting satisfaction is evaluated by combining natural lighting simulation and the power density of artificial lighting. These indicators do not participate in the calculation of the objective function or individual selection during the optimization iteration process. They are only used for multi-dimensional post-evaluation of the Pareto solution set after the optimization is completed.

To ensure the accuracy of model calculations and engineering applicability, a collaborative calculation mechanism between the optimization model and building energy consumption simulation tools is established, as shown in Figure 3.

From Figure 3, the decision-making parameters are first converted into building design parameters that can be identified by the simulation tool, including envelope material properties, equipment system parameter settings, boundary condition configuration, etc. Then, the building hourly energy consumption data and indoor thermal environment parameters are solved through the simulation tool. Two objective function values are calculated based on the simulation output results. Finally, the objective function value is fed back to the optimization algorithm to ensure that the objective function calculation can truly reflect the actual operating status of the building.

2.2 Design of Improved MOO Algorithm Based on MOEA/D

Based on the constructed MOO model of building energy-saving design, taking into account the conflict between energy consumption and thermal comfort goals and the engineering constraint characteristics of decision-making parameters, the study adopts the core decomposition idea of MOEA/D to design a MOO algorithm. It adapts to building energy-saving design by improving weight vector generation, neighborhood update, and mutation strategies to achieve efficient search for Pareto optimal solution sets. The core logic is to decompose the building energy-saving MOO problem into several single-objective sub-problems to be solved in parallel. Information collaboration between sub-problems improves the convergence and distribution uniformity of the solution set, ensuring that the optimization results are both consistent with engineering reality and have diverse trade-off solutions [15-16]. The study first designs an adaptive weight vector generation strategy based on the trade-off preferences of building energy-saving goals. The uniformly distributed weight vector corresponds to the trade-off ratio of different energy-saving and comfort goals. The weight vector satisfies the non-negativity and normalization conditions, given in equation (4).

$$\sum_{m=1}^M \lambda_{i,m} = 1, \quad \lambda_{i,m} \geq 0 \quad (4)$$

In equation (4), $\lambda_{i,m}$ signifies the component of the i -th weight vector on the m -th target. M signifies the number of objective functions. The initial weight vector is uniformly generated in the target space using the systematic method of Das and Dennis. The weight adaptive adjustment is triggered every 50 generations. The adjustment is based on the Euclidean distance distribution of the optimal solutions corresponding to adjacent weight vectors in the target space for the current population. If the standard deviation of the distance in a certain area exceeds 1.2 times the global standard deviation mean, it is determined that the representativeness of that area is insufficient. The weight modification adopts the redistribution strategy, transferring the weights from dense areas to areas with insufficient representativeness. The migration amplitude is proportional to the distance deviation between the regions, while maintaining all weights non-negative and normalized. This mechanism enables areas with larger front curvature to obtain more weights to refine the search, and areas with flat fronts to reduce the weight density to avoid redundant computations. Each weight vector corresponds to a potential optimization direction on the Pareto front. For example, when the weight of the energy consumption target increases, the search is more inclined to low energy consumption solutions. When the weight of the thermal comfort target increases, the search highlights improving comfort performance [17]. The overall framework of the improved MOO algorithm depending on MOEA/D is shown in Figure 4.

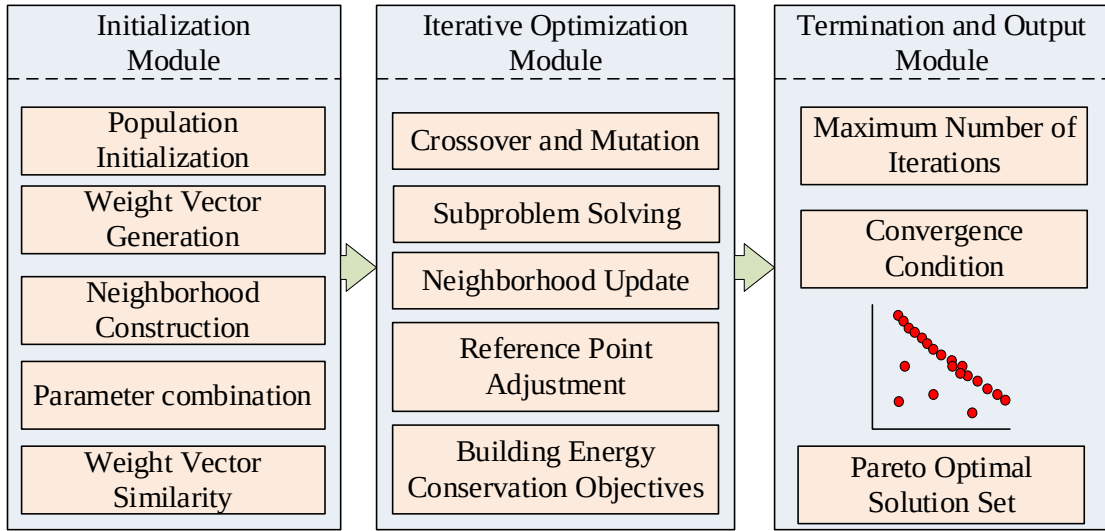


Fig. 4. Overall framework of improved MOO based on MOEA/D

In Figure 4, the initialization module includes population initialization, weight vector generation, and neighborhood construction. Population individuals correspond to building energy-saving design parameter combinations, and neighborhoods are determined based on weight vector similarity. The iterative optimization module covers cross-mutation, sub-problem solving, neighborhood update, and reference point adjustment. Each step of the operation is designed around the optimization needs of building energy-saving goals. Termination and output module: When the maximum number of iterations or convergence conditions are met, the Pareto optimal solution set is output. To efficiently decompose the building energy-saving MOO problem, the improved Chebyshev aggregation function is used in this study, fully considering the dimensional differences and project priorities of the building energy-saving goals, and converting each sub-problem into a single-objective optimization, given in equation (5).

$$g^t(X|\lambda_i, z^*) = \max_{1 \leq m \leq M} \lambda_{i,m} \cdot \frac{|f_m(X) - z_m^*|}{\Delta f_m} \quad (5)$$

In equation (5), $g^t(X|\lambda_i, z^*)$ is the aggregate function value of the i -th sub-problem. X is the building energy-saving design decision-making parameter vector. z^* is the ideal reference point. z_m^* is the current optimal value of the m -th target. Δf_m is the difference in the value range of the m -th target, which is used to eliminate the dimensional influence. This aggregation function balances the optimization priorities of different goals through the weight vector λ_i , so that the optimal solution to the sub-problem accurately corresponds to the trade-off requirements of the building energy-saving goals. In view of the continuity and engineering constraint characteristics of building energy-saving design parameters, a hybrid mutation strategy is designed, which combines polynomial mutation and adaptive Gaussian mutation to ensure population diversity and improve local search efficiency. The mutation operation is shown in equation (6).

$$x'_j = \begin{cases} x_j + \delta_j \cdot (b_j - a_j), & r < p_m \\ x_j, & r \geq p_m \end{cases} \quad (6)$$

In equation (6), x'_j signifies the j -th decision parameter after mutation. x_j is the parameter value before mutation. a_j and b_j are respectively the upper and lower boundaries of the engineering value of this parameter. δ_j signifies the variation step size, which is determined by the sensitivity of building parameters. Parameters that have obvious impacts on energy consumption are set with smaller step sizes to ensure search accuracy, and parameters that are sensitive to comfort impact are set with adaptive step sizes. r signifies a random number in $[0,1]$. p_m signifies the mutation probability (taken as 0.02). The distribution index for polynomial mutation is set to 20. The adaptive Gaussian mutation expression is as shown in equation (7).

$$\Delta_j = N(0, \sigma_j^2) \quad (7)$$

In equation (7), σ_j represents the standard deviation of the j -th decision parameter, and the variance σ_j^2 is dynamically adjusted according to the parameter sensitivity. Parameter sensitivity is defined as the amplitude of the local partial derivative of the objective function with respect to the decision parameters. It is calculated through finite difference method sampling. The higher the parameter sensitivity, the smaller the standard deviation of Gaussian variation. This is used to constrain the variation amplitude. The algorithm selects between polynomial variation and adaptive Gaussian variation with an equal probability of 0.5. Before the variation operation, the decision variables are normalized and mapped to the [0,1] interval. After the variation is completed, they are mapped back to the original physical interval. If the parameters after variation exceed the engineering upper and lower limits, the out-of-bound variables are directly truncated to the corresponding boundary values.

To improve the collaboration efficiency between sub-problems and the uniformity of solution set distribution, a dynamic neighborhood update mechanism is constructed to dynamically adjust the neighborhood size relying on the optimization progress. The neighborhood update mechanism is shown in Figure 5.

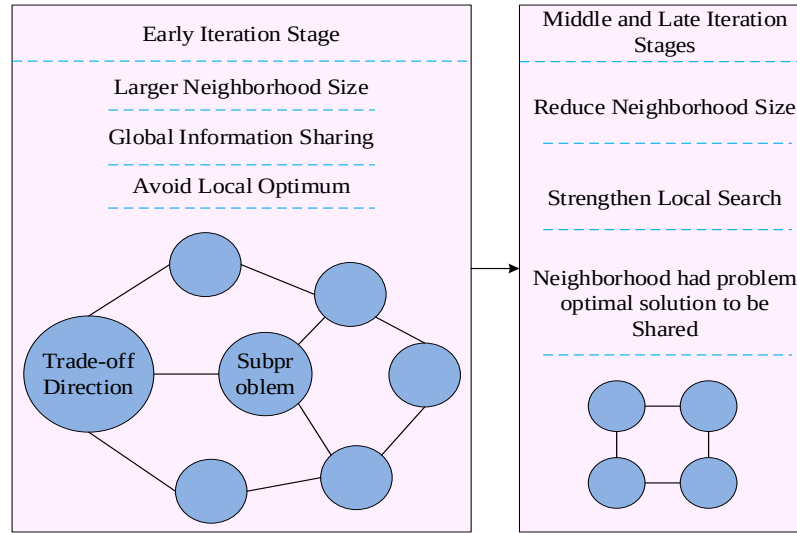


Fig. 5. Neighborhood update mechanism

In Figure 5, each node represents a sub-problem, corresponding to a certain trade-off direction of building energy-saving design. The connecting lines represent the neighborhood correlation between sub-problems. In the early stage of the iteration, a larger neighborhood size is used to promote global information sharing and avoid local optimality. In the middle and later stages, the neighborhood size is reduced to strengthen local search and enhance the convergence accuracy of the solution set. Through the sharing of optimal solutions to sub-problems in the neighborhood, the building design parameter combination with better performance can be quickly transferred and the search efficiency of the overall algorithm is improved. This mechanism sets the initial neighborhood size to 20, the minimum neighborhood size to 8, and the neighborhood size changes in a discrete stepwise manner. The update frequency is executed once every 50 generations, and the neighborhood update function is shown in equation (8).

$$T_{cur} = T - \frac{gen}{Gen_{max}min_{max_{max}}} \quad (8)$$

In equation (8), T_{cur} represents the current neighborhood size, T_{max} indicates the initial neighborhood size, T_{min} denotes the minimum neighborhood size, gen represents the current iteration number, and Gen_{max} is the maximum number of iterations. After each update of the neighborhood size, the neighborhood relationship between sub-problems will be recalculated based on the weight vector similarity. During the iteration process, if the neighborhood size does

not trigger an update, the original neighborhood association will be retained without any modification.

To efficiently update population and retain high-quality individuals, a selection strategy based on the priority of building energy-saving goals is designed, combining non-dominated sorting and aggregation function value sorting to screen the parent and offspring populations. The mathematical description of the selection strategy is shown in equation (9).

$$\text{select}(X) = \text{argmin}\{\alpha \cdot g^t(X|\lambda_i, z^*) + (1 - \alpha) \cdot \text{rank}(X)\} \quad (9)$$

In equation (9), $\text{select}(X)$ is the selected optimal individual, corresponding to the optimal parameter combination of building energy-saving design. α is the balance coefficient (taken as 0.6). $\text{rank}(X)$ signifies the non-dominated ranking. This strategy considers both the aggregation function value of the sub-problem and the non-dominated level, ensuring that the retained individuals not only meet the trade-off requirements of the building energy-saving goals, but also have good non-dominated characteristics [18-19]. The coupling and data interaction between the algorithm and the building energy-saving optimization model are shown in Figure 6.

In Figure 6, the algorithm first generates an initial building design parameter combination, and imports the parameters into the energy consumption simulation tool to calculate the objective function value. Then, the algorithm performs cross mutation, neighborhood update and other operations based on the target value to generate a new parameter combination. The new parameters are again imported into the simulation tool to calculate the target value, and the iterative cycle continues until the termination condition is satisfied. The algorithm is responsible for searching for the optimal parameter combination, and the simulation tool is responsible for accurately calculating the building energy-saving target value. The two work together to efficiently optimize building energy-saving design. The algorithm pseudocode is shown in Table 1.

Table 1. Algorithm pseudocode

Input: population size N, maximum iterations Gmax, neighborhood size T, mutation probability pm
Output: Pareto optimal solution set
1: Generate N uniform weight vectors, compute Euclidean distances among them, determine T neighbors for each subproblem
2: Initialize population randomly, evaluate objective function values, initialize ideal reference point z^*
3: for $g = 1$ to Gmax do
4: for $i = 1$ to N do
5: Randomly select two individuals from the neighborhood of the i -th subproblem, perform simulated binary crossover and hybrid mutation to generate new individual y
6: Evaluate objective function values of y , update reference point z^*
7: if y has better aggregation function value than individuals in the neighborhood then replace
8: end for
9: if $g \bmod 50 == 0$ then
10: Compute Euclidean distance distribution of optimal solutions corresponding to adjacent weights in objective space
11: Identify regions where distance standard deviation exceeds 1.2 times the global mean, mark them as underrepresented
12: Migrate weights from dense regions to underrepresented regions while maintaining non-negativity and normalization
13: end if
14: end for
15: Output non-dominated individuals in current population as Pareto optimal solution set

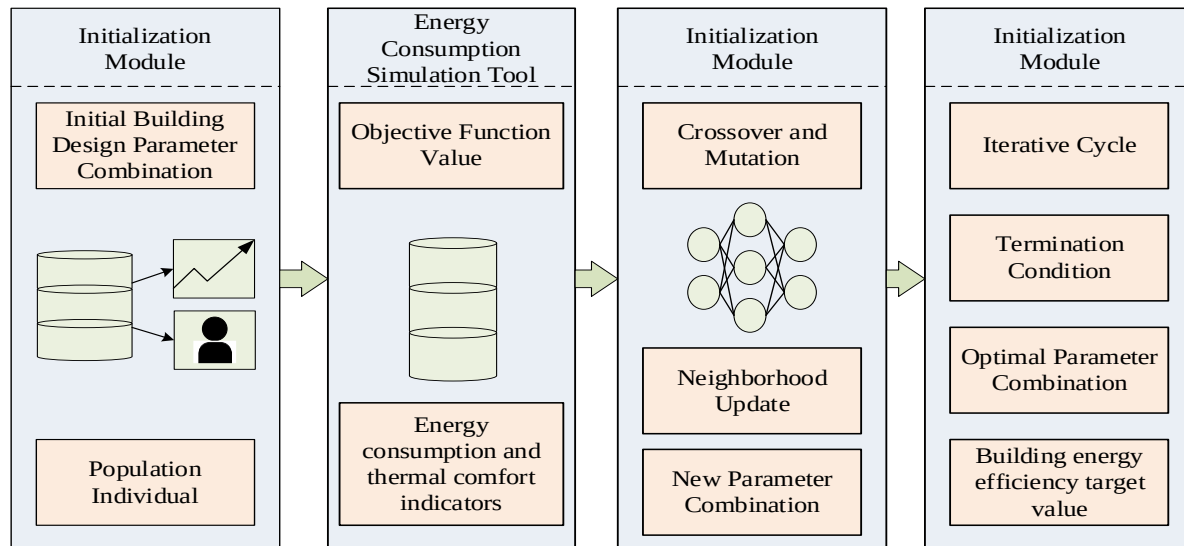


Fig. 6. Coupling and data interaction between algorithm and building energy-saving optimization model

3. Experiment Setup and Analysis

3.1 Datasets and Experiment Setup

The study utilized two types of data sources: (1) Self-made simulation data set: Based on the prototype of residential buildings in typical climate zones of China (Harbin, Beijing, Shanghai, Guangzhou), the parameters of the enclosure structure were set according to the "Code for Thermal Design of Civil Buildings" (GB 50176-2016) and the "Technical Standard for Near-Zero Energy Buildings" (GB/T 51350-2019). (2) Open-source meteorological data were taken from the typical meteorological year TMY data set provided by EnergyPlus, including hourly dry bulb temperature, relative humidity, solar radiation, wind speed, etc. This study did not conduct on-site measurement work; all building data were obtained through EnergyPlus simulation. The experimental hardware platform configuration is presented in Table 2.

Table 2. Experimental hardware platform configuration

Component category	Specific model/ specification
CPU	Intel Core i9-13900K (24 cores, 32 threads, maximum 5.8 GHz) 64 GB
Memory	DDR5 5600 MHz
Storage	2 TB NVMe PCIe 4.0 SSD
Operating System	Ubuntu 22.04 LTS (open source)
Energy consumption simulation engine	EnergyPlus v23.1.0 (open source)
Meteorological data source	Self-made: Four types of typical residential models constructed based on the "Energy Efficiency Design Standards for Residential Buildings" of China
Building prototype data	Specific model/ specification

The adopted residential prototype was a three-story rectangular slab-style house, with a total building area of 288 m². The building faces south, and the window-to-wall ratio was uniformly set at 0.45. The walls consisted of an exterior finish, insulation layer, concrete base, and internal plastering. The roof was equipped with an external insulation structure. The floor used a contact-ground reinforced concrete structure. The heat transfer coefficient of the exterior window glass ranged from 2.0 to 2.8 W/(m²·K), the building air infiltration rate was set at 0.5 air-change per hour, the personnel density was set at 0.04 people per square meter, the indoor lighting power density was 5 W/m², and the equipment power density was 3.5 W/m².

Table 3. Key input parameters of EnergyPlus building prototypes for four climate zones

Parameter category	Parameter name	Harbin (Severe cold)	Beijing (Cold)	Shanghai (Hot-summer cold-winter)	Guangzhou (Hot-summer warm-winter)
Building geometry	Building form	Three-story rectangular slab residential building	Three-story rectangular slab residential building	Three-story rectangular slab residential building	Three-story rectangular slab residential building
	Total floor area, m ²	288	288	288	288
	Building orientation	Due south	Due south	Due south	Due south
	Window-to-wall ratio	0.45	0.45	0.45	0.45
Envelope thermal performance	Wall heat transfer coefficient, W/(m ² ·K)	0.20~0.45	0.25~0.60	0.30~0.80	0.40~1.00
	Roof heat transfer coefficient, W/(m ² ·K)	0.18~0.40	0.22~0.50	0.28~0.65	0.35~0.75
	Exterior window heat transfer coefficient, W/(m ² ·K)	2.00~2.20	2.20~2.40	2.40~2.60	2.60~2.80
	Exterior window shading coefficient	0.30~0.80	0.30~0.80	0.30~0.80	0.30~0.80
Ventilation & infiltration	Air infiltration air change rate (ACH)	0.5	0.5	0.5	0.5
Internal loads	Occupancy density, person/m ²	0.04	0.04	0.04	0.04
	Lighting power density, W/m ²	5.0	5.0	5.0	5.0
	Equipment power density, W/m ²	3.5	3.5	3.5	3.5
HVAC system	Air-conditioning type	Split-type air conditioner	Split-type air conditioner	Split-type air conditioner	Split-type air conditioner
	Heating COP	2.8	2.8	2.8	2.8
	Cooling COP	3.0	3.0	3.0	3.0
	Heating set-point temperature, °C	20	20	20	20
	Cooling set-point temperature, °C	26	26	26	26
Simulation assumptions	Occupancy & load schedule	Activated: 8:00-22:00, inactive for remaining hours	Activated: 8:00-22:00, inactive for remaining hours	Activated: 8:00-22:00, inactive for remaining hours	Activated: 8:00-22:00, inactive for remaining hours
	Meteorological data source	EnergyPlus TMY3	EnergyPlus TMY3	EnergyPlus TMY3	EnergyPlus TMY3
	Simulation duration, h	8760	8760	8760	8760

The HVAC system adopted a split air conditioning system. The heating and cooling energy efficiency ratios were 2.8 and 3.0, respectively. The heating set temperature was 20 °C, and the cooling set temperature was 26 °C. The loads of people, lighting, and equipment followed the residential occupancy schedule. The indoor loads were enabled from 8:00 to 22:00, and the loads were turned

off during other periods. All models used the corresponding city TMY3 hourly meteorological files to conduct 8760-hour annual simulations. The key EnergyPlus input parameters for the residential prototypes corresponding to the four climate zones are summarized in Table 3.

3.2 Performance Verification of Improved MOO Algorithm Based On MOEA/D

To comprehensively verify the comprehensive performance of the Improved MOEA/D (IMOE/D), three comparison algorithms that were widely used and had excellent performance in the current MOO field were selected, namely: NSGA-II, Improved Firefly Algorithm (IFA), Hybrid-Integer MOO Algorithm (HIMO). The parameter settings for each comparison algorithm were uniformly listed in Table 4. The running environment and hardware configuration of all algorithms were kept consistent. Each algorithm was run independently 30 times, and the average values of each indicator were used for performance comparison.

Table 4. Parameter settings of each comparative algorithm

Algorithm	Parameter Name	Set value
IMOE/D	Population Size	100
	Maximum Iteration Number	500
	Initial Neighborhood Size	20
	Minimum Neighborhood Size	5
	Number of Weight Vectors	100
	Mutation Probability	0.02
	Polynomial Mutation Distribution Index	20
	Weight Adaptive Trigger Interval	50 generations
NSGA-II	Population Size	100
	Maximum Iteration Number	500
	Crossing Distribution Index	20
	Mutation Distribution Index	20
	Crossing Probability	0.9
	Mutation Probability	0.1
IFA	Population Size	100
	Maximum Iteration Number	500
	Absorption Coefficient of Light	1.0
	Step Size Factor	0.25
HIMO	Maximum Attractiveness	1.0
	Population Size	100
	Maximum Iteration Number	500
	Crossing Probability	0.85
	Mutation Probability	0.15
	Number of Local Search Iterations	20

The population size of the algorithm was uniformly set to 100, and the maximum number of iterations was 500. The complete operation of a single optimization run included 50,000 EnergyPlus simulation calls. The average time consumed for a single annual hourly simulation of EnergyPlus under the hardware configuration (Intel Core i9-13900K, 64GB DDR5 memory) was approximately 4.2 seconds. The total computing time for a single complete optimization run was approximately 238 seconds (including the internal operation overhead of the algorithm). Under the same population size and iteration conditions, the total optimization time of NSGA-II, IFA, and HIMO was approximately 215 seconds, 267 seconds, and 241 seconds respectively, which were at the same order of magnitude as IMOE/D. The Pareto frontier solutions of different algorithms are shown in Figure 7. X-axis: f_1 (Normalized total annual operating energy consumption, dimensionless, value range [0, 1], obtained by dividing the actual energy consumption of each solution by the maximum energy consumption value obtained by the algorithm). Y-axis: f_2 (Normalized indoor thermal comfort index ITCI, dimensionless, value range [0, 1], obtained by dividing the actual ITCI value of each solution by the maximum ITCI value obtained by the algorithm. Here, the ITCI value is numerically equal to PPD).

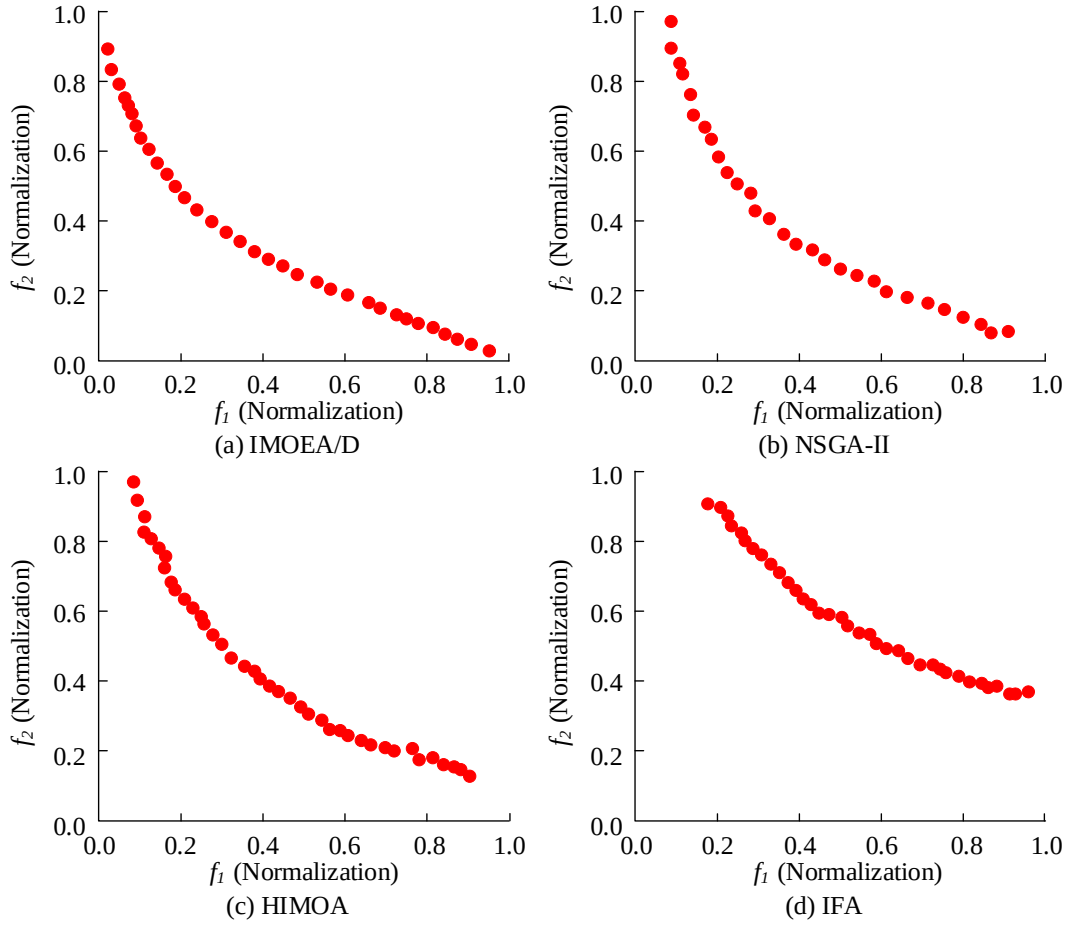


Fig. 7. Pareto front solutions of different algorithms

Figure 7(a) shows the Pareto front curve of IMOEA/D. f_2 continued to decrease from about 0.95 to below 0.02 as f_1 increased, and all solution points were distributed continuously and uniformly without obvious aggregation or empty areas. The solution set of this algorithm not only covered the full trade-off interval of f_1 and f_2 , but also ensured that the distribution density of different trade-off points was consistent. Figure 7(b) is the Pareto front of NSGA-II. The solution points were slightly clustered near $f_1=0.8$, and the distribution uniformity was weaker than IMOEA/D. Figure 7(c) shows the Pareto front of HIMOEA. The solution points were obviously clustered near $f_1=0.75$, and the solution point density in some trade-off intervals was low. Figure 7(d) is the Pareto front of IFA. The solution points were densely clustered in the $f_1=0.4\sim 0.6$ interval, and the solution points in the $f_1>0.8$ interval are sparsely distributed. The distribution uniformity and continuity of the solution set were also better than NSGA-II, HIMOEA and IFA, indicating that this algorithm had significant advantages in the trade-off ability. Figure 8 presents the convergence.

In Figure 8(a), after 200 iterations, the average objective function value of IMOEA/D stabilized below 0.10 ± 0.009 , and there was no obvious decrease in subsequent iterations, indicating that IMOEA/D could quickly reduce the average objective function value, and the convergence speed was significantly faster than other algorithms. In Figure 8(b), after 200 iterations, the optimal objective function value of IMOEA/D remained below 0.10 ± 0.007 , and the optimal objective function values of NSGA-II, HIMOEA, and IFA were stable at around 0.19 ± 0.018 , 0.28 ± 0.025 , and 0.32 ± 0.028 , respectively. IMOEA/D not only had fast convergence speed and low final objective function value, but also had more uniform solution quality within the population. It was better than NSGA-II, HIMOEA and IFA in convergence performance and solution set stability of MOO. The comprehensive comparison of the solution quality of different algorithms is shown in Figure 9. GD evaluated the closeness of the algorithm solution set to the real Pareto front. The smaller the GD, the better the convergence of the solution set. The Inverted Generational Distance (IGD) reflected the convergence and distribution uniformity of the solution set. The smaller the IGD, the solution set was both close to the Pareto front and evenly distributed.

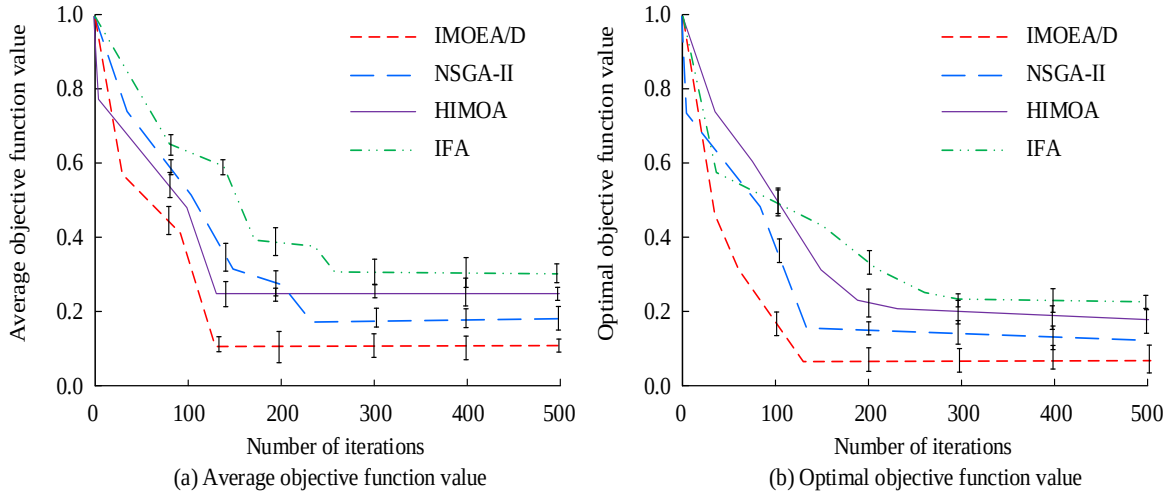


Fig. 8. Convergence of different algorithms

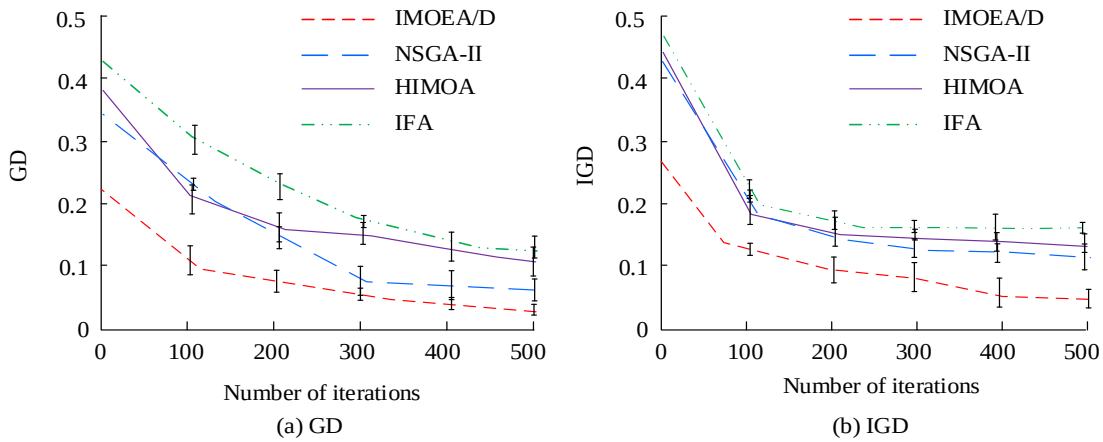


Fig. 9. Comprehensive comparison of solution quality of different algorithms

In Figure 9(a), when iteration reached 300 generations, the GD value of IMOEA/D dropped to 0.078 ± 0.012 , which was close to the ideal convergence state. At this time, the GD values of NSGA-II, IFA, and HIMOAA were still as high as 0.169 ± 0.015 , 0.215 ± 0.021 , and 0.198 ± 0.019 , respectively. After 500 iterations, the GD value of IMOEA/D was only 0.025 ± 0.004 . The improved Chebyshev aggregation function and dynamic neighborhood update mechanism adopted by IMOEA/D could more accurately guide the population to converge, effectively improving the convergence performance. In Figure 9(b), after 300 iterations, the IMOEA/D IGD value was 0.103 ± 0.014 , reflecting its significant advantage in the uniformity of solution set distribution. The adaptive weight vector generation strategy designed by IMOEA/D could ensure the uniformity of weight distribution. Combined with the mixed mutation strategy, the population diversity was maintained, allowing the algorithm to maintain a uniform distribution of solution sets during the convergence process and avoid local aggregation.

The MOO algorithm had inherent randomness. The result of a single run was not sufficient to fully demonstrate its superior performance. Therefore, all comparative experiments were independently repeated 30 times. The evaluation indicators were compared among the algorithms based on the average values of the 30 runs, and the standard deviation, minimum value, and maximum value were also recorded. When the iteration reached 500 generations, the GD mean of IMOEA/D was 0.025 (standard deviation 0.004, minimum 0.019, maximum 0.032), the IGD mean was 0.045 (standard deviation 0.006, minimum 0.037, maximum 0.055), the GD mean of NSGA-II was 0.169 (standard deviation 0.015, minimum 0.148, maximum 0.191), and the IGD mean was 0.187 (standard deviation 0.018, minimum 0.162, maximum 0.215). The mean values of all indicators of IFA and HIMOAA were between those of NSGA-II and IMOEA/D. The Wilcoxon signed-rank test was used to statistically test the differences in each indicator between IMOEA/D and each comparison algorithm at a significance level of 0.05. The results showed that all p -values were less

than 0.05, indicating that IMOEAD was significantly superior to NSGA-II, IFA, and HIMOEA in the GD, IGD, and Hypervolume (HV) indicators.

3.3 Validation of MOO Algorithms in Different Scenarios

To verify the adaptability and optimization effect of the IMOEAD algorithm proposed in the study in actual building scenarios, residential buildings were selected as the research object, with building energy consumption and living comfort as the core optimization objectives. Building Comprehensive Energy Consumption (BCEC) covers all-dimensional energy consumption such as heating, cooling, lighting, and ventilation. A lower value signifies the better energy consumption optimization effect. The Indoor Thermal Comfort Index (ITCI) adopts the Predicted Mean Vote (PMV) evaluation system. The value range is -3 (extremely cold) to +3 (extremely hot). The closer to 0, the higher the living comfort. In the experiment, $|ITCI|$ is used as the measurement standard. A lower value signifies the better comfort. Figure 10 presents the optimization effects.

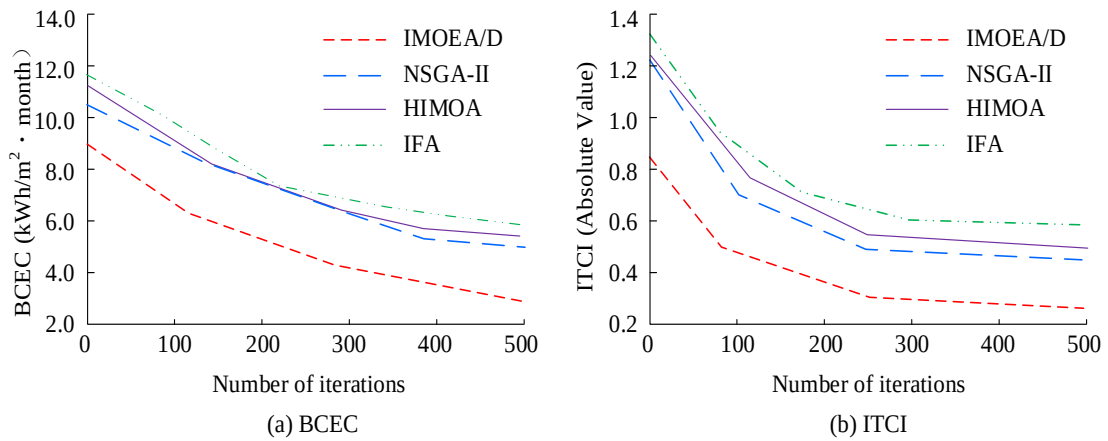


Fig. 10. Optimization effects of energy consumption and comfort of residential buildings using different algorithms

In Figure 10(a), after 100 iterations, the BCEC of IMOEAD was 6.4kWh/m²·month, which initially reflected the advantages of energy consumption optimization. After 300 iterations, the BCEC of IMOEAD dropped to 4.3kWh/m²·month, and the range of energy consumption optimization was further expanded. After 500 iterations, the BCEC of IMOEAD reached 3.2kWh/m²·month, which was 38.5% lower than that of NSGA-II. In Figure 10(b), IMOEAD also showed significant advantages in comfort optimization. After 500 iterations, the $|ITCI|$ of IMOEAD was only 0.22, and it always remained within the optimal comfort zone. IMOEAD could effectively reduce building energy consumption and significantly improve living comfort simultaneously. The optimization effect was far better than the comparison algorithm, and it had the feasibility of being applied in actual residential building energy-saving design. There were complex trade-off relationships among various optimization indicators.

Reducing annual operating energy consumption usually brought the potential risk of decreased thermal comfort, while improving the rate of meeting thermal comfort standards often led to an increase in energy consumption and initial investment costs. Carbon emissions were positively correlated with building operating energy consumption. Although high-performance selection of the enclosure structure was beneficial for energy conservation and thermal comfort, it would increase the initial investment. IMOEAD optimized and screened parameter combinations through Pareto solution sets. It coordinated the parameters of the enclosure and air conditioning system within the constraints of the construction project, avoiding over-compressing the indoor thermal environment conditions in pursuit of energy conservation. Therefore, it could achieve energy consumption reduction while maintaining a thermal comfort rate of over 92%. Some candidate solutions could balance lower carbon emissions and controllable initial investment. Different Pareto solutions corresponded to different trade-offs in each indicator. The multi-dimensional optimization effects are presented in Table 5.

Table 5. Comprehensive comparison of multi-dimensional optimization effects

Climate zone	Optimization indicators	Unit	IMOEA/D	NSGA- II	IFA	HIMOA
Cold climate zone (Harbin)	Annual operational energy consumption	kWh/m ² ·year	42.3	65.7	72.1	68.9
	Carbon emissions	kgCO ₂ /m ² ·year	28.6	43.2	47.5	45.1
	Initial investment cost	Yuan/square meter	1280.0	1450.0	1520.0	1480.0
	Proportion of thermal comfort compliance time	%	92.7	81.5	78.3	80.2
	Lighting satisfaction	%	89.4	82.6	79.8	81.3
Cold climate zone (Beijing)	Annual operational energy consumption	kWh/m ² ·year	38.6	57.9	63.4	60.5
	Carbon emissions	kgCO ₂ /m ² ·year	25.3	37.8	41.2	39.4
	Initial investment cost	Yuan/square meter	1150.0	1320.0	1380.0	1340.0
	Proportion of thermal comfort compliance time	%	94.2	83.8	80.5	82.6
	Lighting satisfaction	%	91.6	84.3	81.7	83.5
Hot summer and cold winter climate zone (Shanghai)	Annual operational energy consumption	kWh/m ² ·year	35.7	52.4	57.8	54.6
	Carbon emissions	kgCO ₂ /m ² ·year	23.1	34.5	37.6	35.8
	Initial investment cost	Yuan/square meter	1080.0	1240.0	1290.0	1260.0
	Proportion of thermal comfort compliance time	%	95.5	85.3	82.1	84.4
	Lighting satisfaction	%	93.2	86.7	83.9	85.8
Hot summer and warm winter climate zone (Guangzhou)	Annual operational energy consumption	kWh/m ² ·year	31.2	46.8	51.3	48.7
	Carbon emissions	kgCO ₂ /m ² ·year	20.5	30.7	33.4	31.9
	Initial investment cost	Yuan/square meter	1020.0	1180.0	1230.0	1200.0
	Proportion of thermal comfort compliance time	%	96.8	87.6	84.2	86.5
	Lighting satisfaction	%	94.7	88.5	85.6	87.4

In Table 5, after IMOE/D optimization, the energy consumption of the whole life cycle of the building was reduced by 29.5% to 38.6%, and the carbon emission was reduced by 30.1% to 39.8% compared with the comparison algorithm in each climate zone. The energy consumption and carbon emission reduction advantages in the severe cold climate zone were the most significant. The initial investment cost of IMOE/D was 11.7%~16.4% lower than that of the comparison algorithm. The proportion of thermal comfort compliance time after IMOE/D optimization exceeded 92%, up to 96.8%, and lighting satisfaction exceeded 89%. Although it faced higher energy consumption control pressure in severe cold climate zones, it still maintained significant optimization advantages. It proved that it had wide adaptability across climate zones and could meet the MOO needs.

3.4 Ablation Experiment

To quantify the independent contributions of each improvement strategy, additional ablation experiments were conducted under the same experimental conditions. The comparison groups included traditional MOEA/D, MOEA/D with only adaptive weight vectors (MOEA/D-AW), MOEA/D with only dynamic neighborhood (MOEA/D-DN), MOEA/D with only mixed mutation (MOEA/D-HM), and the complete IMOE/D. The evaluation results are shown in Table 6.

Table 6. Performance comparison of various algorithms in ablation experiments

Algorithm	GD	IGD	HV	Convergence rate (%)	Calculation time (s)	Diversity index (Δ)
MOEA/D	0.112	0.168	0.742	62.4	186	0.387
MOEA/D-AW	0.071	0.102	0.803	74.1	201	0.215
MOEA/D-DN	0.065	0.098	0.812	76.8	209	0.228
MOEA/D-HM	0.083	0.121	0.785	69.5	194	0.251
IMOE/D	0.025	0.045	0.892	91.3	238	0.163

The results in Table 6 show that the dynamic neighborhood had the most significant improvement on GD (a reduction of 42.0%), the adaptive weights had the most obvious enhancement on the diversity index (a reduction of 44.4%), and the hybrid mutation contributed the middle to the convergence rate (an increase of 7.1 percentage points). When all three strategies were enabled simultaneously, the GD and IGD of IMOE/D dropped to 0.025 and 0.045 respectively, while HV reached 0.892 and the convergence rate increased to 91.3%. All these indicators were superior to any single improvement strategy, indicating that the three mechanisms had a synergistic effect. In terms of computational time, the complete IMOE/D took 238 seconds, which was 28.0% more than traditional MOEA/D, but the performance improvement obtained was within the acceptable range for engineering.

4. Conclusions

This study addressed the multi-objective conflicts in building energy-saving design regarding energy consumption and thermal comfort, as well as the uneven distribution of solution sets and slow convergence speed of existing MOO algorithms. A MOO scheme based on the IMOE/D was proposed. Based on the residential building prototypes of four typical climate zones in China (extremely cold, cold, hot summer cold winter, and hot summer warm winter), the EnergyPlus simulation model was established. The IMOE/D was used to conduct collaborative optimization of the thermal parameters of the envelope structure and the equipment operation parameters for each climate zone. The experimental results showed that under 500 iterations, the GD index of IMOE/D was 0.025, and the IGD index was 0.045. The convergence performance and the uniformity of the solution set distribution were significantly better than those of NSGA-II, IFA, and HIMO. In the residential building scenarios of the four climate zones, the annual operating energy consumption after optimization by IMOE/D was 42.3, 38.6, 35.7, and 31.2 kWh/m²-year, respectively, and the corresponding carbon emissions were 28.6, 25.3, 23.1, and 20.5 kgCO₂/m²-year, which were reduced by 30.1% to 39.8% compared to the comparison algorithms. The time for thermal comfort to be met was over 92%, with the highest reaching 96.8%. The initial investment cost was reduced by 11.7% to 16.4%. These results were attributed to the performance

of the IMOEA/D algorithm in residential buildings, the four climate zones, and the set parameter range. The conclusion was limited to the multi-story residential building prototype and the corresponding climate conditions, and its applicability could not be extrapolated without adjustment to public buildings, high-rise residences, or industrial buildings and other types. In addition, the thermal comfort evaluation in this study adopted a deterministic occupancy mode assumption and did not consider the random factors such as residents' opening windows behavior, shading adjustment, and air conditioning usage habits on the dynamic impact on actual energy consumption and comfort. Further research can introduce a random simulation module for human behavior based on proxy models and couple it with the MOO framework to enhance the algorithm's robustness in real living scenarios.

References

- [1] Nasouri M, Delgarm N. Efficiency-based Pareto optimization of building energy consumption and thermal comfort: A case study of a residential building in Bushehr, Iran. *J Therm Sci.* 2024;33(3):1037-1054. <https://doi.org/10.1007/s11630-023-1933-5>
- [2] Chaturvedi PK, Kumar N, Lamba R. Multi-objective optimization for visual, thermal, and cooling energy performance of building envelope design in the composite climate of Jaipur (India). *Energy Environ.* 2025;36(7):3545-3569. <https://doi.org/10.1177/0958305X241228513>
- [3] Zhou X, Yu J, Zhang W, Zhao A, Zhou M. A multi-objective optimization operation strategy for ice-storage air-conditioning system based on improved firefly algorithm. *Build Serv Eng Res Technol.* 2022;43(2):161-178. <https://doi.org/10.1177/01436244211045570>
- [4] Benaddi FZ, Boukhattem L, Ait Nouh F, Tabares-Velasco PC, Benhamou B. Energy-saving potential assessment of a classroom building envelope through sensitivity analysis and multi-objective optimization under different climate types. *Build Serv Eng Res Technol.* 2023;44(3):309-332. <https://doi.org/10.1177/01436244231161944>
- [5] Kiss B, Szalay Z. Sensitivity of buildings' carbon footprint to electricity decarbonization: a life cycle-based multi-objective optimization approach. *Int J Life Cycle Assess.* 2023;28(7):933-952. <https://doi.org/10.1007/s11367-022-02043-y>
- [6] Wei H, Jiao Y, Wang Z, Wang W, Zhang T. Optimal retrofitting scenarios of multi-objective energy-efficient historic building under different national goals integrating energy simulation, reduced order modelling and NSGA-II algorithm. *Building Simulation.* 2024;17(6):933-954. <https://doi.org/10.1007/s12273-024-1122-9>
- [7] Elsheikh A, Motawa I, Diab E. Multi-objective genetic algorithm optimization model for energy efficiency of residential building envelope under different climatic conditions in Egypt. *Int J Constr Manag.* 2023;23(7):1244-1253. <https://doi.org/10.1080/15623599.2021.1966709>
- [8] Araújo GR, Gomes R, Ferrão P, Gomes MG. Optimizing building retrofit through data analytics: A study of multi-objective optimization and surrogate models derived from energy performance certificates. *Energy Build Environ.* 2024;5(6):889-899. <https://doi.org/10.1016/j.enbenv.2023.07.002>
- [9] Gheouany S, Ouadi H, El Bakali S. Hybrid-integer algorithm for a multi-objective optimal home energy management system. *Clean Energy.* 2023;7(2):375-388. <https://doi.org/10.1093/ce/zkac082>
- [10] Ma H, Zhang Y, Sun S, Liu T, Shan Y. A comprehensive survey on NSGA-II for multi-objective optimization and applications. *Artif Intell Rev.* 2023;56(12):15217-15270. <https://doi.org/10.1007/s10462-023-10526-z>
- [11] Singh Rajput T, Thomas A. Optimizing passive design strategies for energy efficient buildings using hybrid artificial neural network (ANN) and multi-objective evolutionary algorithm through a case study approach. *Int J Constr Manag.* 2023;23(13):2320-2332. <https://doi.org/10.1080/15623599.2022.2056409>
- [12] Yu CR, Liu X, Wang QC, Yang D. Solving the comfort-retrofit conundrum through post-occupancy evaluation and multi-objective optimisation. *Build Serv Eng Res Technol.* 2023;44(4):381-403. <https://doi.org/10.1177/01436244231174354>
- [13] Padala SPS, Skanda PM. BIM-based multi-objective optimization framework for volumetric analysis of building projects. *J Eng Des Technol.* 2025;23(5):1326-1347. <https://doi.org/10.1108/JEDT-07-2023-0309>
- [14] Wagiri F, Shih SG, Harsono K, Wijaya DC. Multi-objective optimization of kinetic facade aperture ratios for daylight and solar radiation control. *J Build Phys.* 2024;47(4):355-385. <https://doi.org/10.1177/17442591231219793>
- [15] Long F, Jin B, Xu H, Wang J, Bhola J, Shavkatovich SN. Research on multi-objective optimization of smart grid based on particle swarm optimization. *Electrica.* 2023;23(2):222-230. <https://doi.org/10.5152/electrica.2022.22047>

- [16] Liu K, Xu X, Zhang R, Kong L, Wang X, Lin D. An integrated framework utilizing machine learning to accelerate the optimization of energy-efficient urban block forms. *Building Simulation*. 2024;17(11):2017-2042. <https://doi.org/10.1007/s12273-024-1174-x>
- [17] Zhang F. Constructing a multi-objective optimization model for engineering projects based on NSGA-II algorithm under the background of green construction. *Decis Mak Appl Manag Eng*. 2024;7(1):37-53. <https://doi.org/10.31181/dmame712024895>
- [18] Liu Q, Lanfermann F, Rodemann T, Olhofer M, Jin Y. Surrogate-assisted many-objective optimization of building energy management. *IEEE Comput Intell Mag*. 2023;18(4):14-28. <https://doi.org/10.1109/MCI.2023.3304073>
- [19] Agal S, Raulji K, Shekokar K, Bhavsar N. Optimizing impact investment portfolios with reinforcement learning: A data-driven framework for balancing financial returns and SDG alignment. *FinTech Sustain Innov*. 2025:1-15. <https://doi.org/10.47852/bonviewFSI52027409>