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A Lightweight AIGC-Based Multi-Objective Architectural Space Generation Method: Collaborative Optimization of Thermal Comfort and Ventilation Performance

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ABSTRACT

Driven by the global push for green building and sustainable development, the collaborative optimization of thermal comfort and ventilation performance has become a key requirement for improving the quality of the built environment. Traditional architectural design methods often face challenges such as long design cycles, low efficiency, and high energy consumption when balancing multiple performance objectives. Existing Artificial Intelligence Generated Content (AIGC) technologies, though promising, tend to involve complex models and high computational costs, and most focus solely on optimizing single performance aspects, lacking consideration of thermal-ventilation synergy. To address these limitations, this study proposes a lightweight AIGC-based method for multi-objective architectural space generation, focusing on two key areas: (1) constructing a collaborative optimization model for thermal comfort and ventilation by analyzing their coupling relationships and integrating key elements such as spatial layout, envelope design, and ventilation systems to develop performance-enhancing strategies; and (2) developing a lightweight AIGC algorithmic framework that reduces computational resource dependency while enabling efficient generation of architectural spaces with simultaneous optimization of thermal and ventilation performance. The outcomes of this research aim to overcome the limitations of conventional design paradigms and provide an intelligent tool that is both efficient and sustainable for early-stage architectural design, thereby advancing the digital and green transformation of the building design industry.

1. INTRODUCTION

Against the global background of advocating green buildings and sustainable development [1-3], the environmental performance of architectural spaces has attracted increasing attention. Thermal comfort [4, 5] and ventilation performance [6, 7], as core indicators for evaluating the quality of the built environment, directly affect people's living and working experiences as well as physical and mental health within buildings. With the acceleration of urbanization and the increasing complexity of building functions [8, 9], traditional architectural design methods face many challenges in balancing thermal comfort and ventilation performance, such as long design cycles, high energy consumption, and low optimization efficiency [10-13]. In recent years, the rapid development of AIGC technology [14, 15] has provided new ideas and methods for architectural space generation. Lightweight AIGC technology, with its advantages of high efficiency, intelligence, and low computational cost, has shown great application potential in the field of architectural design. It can help achieve multi-objective architectural space generation and meet the demand for high-quality built environments.

Research on the collaborative optimization of thermal comfort and ventilation performance in buildings, as well as the lightweight AIGC-based multi-objective architectural space generation method based on thermal comfort and ventilation performance, has important theoretical and practical significance. This research can enrich the theoretical system of environmental performance optimization in buildings, explore new theories and methods for deep integration of AIGC technology and architectural design, and provide theoretical support for multi-objective architectural space generation. Through the collaborative optimization of thermal comfort and ventilation performance, the environmental quality of architectural spaces can be significantly improved, and building energy consumption can be reduced, which aligns with the concepts of green buildings and sustainable development. Meanwhile, the application of lightweight AIGC technology can improve the efficiency and quality of architectural design, reduce manual intervention, provide more efficient and intelligent design tools for architects, and promote the digital transformation of the architectural design industry.

At present, there are already many research results on thermal comfort and ventilation performance in buildings, but some deficiencies and shortcomings still exist. Some studies only consider thermal comfort or ventilation performance individually, lacking the collaborative optimization of both. For example, Literature [16] focuses only on the simulation and optimization of thermal comfort in buildings, ignoring the impact of ventilation performance on thermal comfort, resulting in optimization schemes that are difficult to meet both performance requirements in practical applications. In terms of architectural space generation methods, traditional methods rely on manual experience and trial-and-error, which are inefficient and difficult to cover complex multi-objective optimization problems [17, 18]. Although some studies have attempted to apply AIGC technology in architectural design, most adopt complex models and algorithms with high computational costs. For example, the AIGC model used in literature [19] requires a large amount of computational resources and time, making it difficult to achieve a lightweight and efficient implementation, thus limiting its application in real projects.

The main content of this paper includes two parts. The first part is the collaborative optimization scheme of thermal comfort and ventilation performance in buildings. By analyzing the relationship between thermal comfort and ventilation performance, a collaborative optimization model is established. Considering factors such as spatial layout, envelope structure, and ventilation system of buildings, a set of optimization strategies is proposed to improve both thermal comfort and ventilation performance. The second part is the lightweight AIGC-based multi-objective architectural space generation method based on thermal comfort and ventilation performance. Combined with lightweight AIGC technology, an efficient architectural space generation model is constructed to realize rapid generation and multi-objective optimization of architectural spaces, reducing computational cost while ensuring generation quality. The value of this research lies in filling the gap in current studies regarding the collaborative optimization of thermal comfort and ventilation performance and the lightweight AIGC-based architectural space generation method, providing an efficient, intelligent, and sustainable solution for architectural design. Through this method, spatial schemes that meet multi-objective requirements can be quickly generated in the early stage of architectural design, providing strong support for subsequent detailed design and engineering practice, and promoting the development of the architectural industry toward a greener, smarter, and more efficient direction.

2. COLLABORATIVE OPTIMIZATION SCHEME FOR BUILDING THERMAL COMFORT AND VENTILATION PERFORMANCE

The collaborative optimization scheme for building thermal comfort and ventilation performance proposed in this paper addresses the limitations of static clothing models in traditional studies for evaluating thermal comfort and the complexity of the influence of operating parameters, and constructs a multi-factor collaborative optimization framework from a dynamic coupling perspective. First, breaking through the traditional model of isolated optimization for a single performance, the spatial layout of the building, envelope structure characteristics, ventilation system parameters, and dynamically changing clothing thermal resistance of the human body are integrated into a unified analysis system. The interaction mechanism between thermal comfort and ventilation airflow organization is precisely captured by Computational Fluid Dynamics (CFD) numerical simulation technology. Second, the Taguchi method is introduced to quantitatively evaluate the influence degree of supply air parameters and outdoor weather conditions on thermal comfort under different clothing thermal resistance levels, identifying key influencing factors. Furthermore, combined with the response surface method of central composite design, a response surface model covering temperature distribution, airflow velocity, and thermal comfort indicators is established to reveal the synergistic evolution law of thermal comfort and ventilation efficiency under multi-parameter coupling. Finally, based on the above analysis, a collaborative optimization model is constructed to integrate spatial design parameters and equipment operation parameters, forming an integrated optimization strategy that considers both the dynamic demand of thermal comfort and the energy efficiency of the ventilation system.

2.1 Influence analysis of operating parameters on thermal comfort

This paper adopts the Taguchi method to explore the basic principle of the influence degree of operating parameters on thermal comfort under different clothing thermal resistance levels, based on the unique advantage of the method in quantifying factor influences and optimizing parameter combinations in multi-factor complex systems. In the building environment, the human clothing state dynamically changes with seasons, activity types, etc., and differences in clothing thermal resistance directly affect the heat exchange efficiency between the human body and the environment, thereby changing the demand for ventilation parameters. The Taguchi method systematically organizes multi-factor experiments, converting a complex parameter space into a quantifiable statistical model, which can not only identify dominant operating parameters for thermal comfort under different clothing thermal resistance levels, but also evaluate the stability of parameter combinations through error factor analysis, avoiding evaluation deviations caused by static model assumptions. The Taguchi method, through orthogonal experiment design, sets supply air temperature, supply air velocity, supply air angle, and outdoor weather conditions as controllable factors, and treats different levels of clothing thermal resistance as noise factors, constructing an orthogonal table covering multi-factor level combinations with minimal experimental runs. This method takes the thermal comfort index as the quality characteristic, and evaluates the robustness of thermal comfort to clothing thermal resistance changes under different parameter combinations by calculating the signal-to-noise ratio, identifying the main effects and interactions of operating parameters that significantly affect thermal comfort, and quantifying the influence weight of each factor under different clothing thermal resistance scenarios.

Considering that the absolute value of the Predicted Mean Vote (PMV) index for thermal comfort evaluation is better when smaller, it is converted into the Predicted Percentage of Dissatisfied (PPD) index, which does not take negative values and also aims for "smaller is better" as the optimization objective. The target characteristic is clarified as the smaller-the-better characteristic, and the corresponding signal-to-noise ratio calculation formula is used to quantify thermal comfort performance. This method converts the experimental results of different combinations of operating parameters and clothing thermal resistance levels into signal-to-noise ratios, using the magnitude to represent the robustness of thermal comfort against parameter fluctuations: the larger the signal-to-noise ratio, the smaller and more stable the PPD value under that parameter combination, indicating better and more ideal thermal comfort performance. Assuming the signal-to-noise ratio is represented by *SN*, the number of experiments by *l*, and the target value of the *u*-th experiment by *b*(*u*), then the calculation formula is:

$$SN = -10\log_{uv}\left(\frac{1}{l}\sum_{u=1}^{l} b^2(u)\right) \quad (1)$$

By systematically calculating the signal-to-noise ratio of each parameter combination, it is possible to effectively identify key control factors that significantly affect thermal comfort, quantify their main effects and interactions, and provide data support for selecting optimal parameter combinations that both reduce PPD values and minimize performance fluctuations in multi-parameter coupling scenarios, thereby serving the core objective of dynamically matching human clothing differences and ventilation system parameters in the "collaborative optimization scheme for building thermal comfort and ventilation performance."

2.2 Construction of ventilation performance response surface model

The basic principle of constructing a ventilation performance response surface model in this paper using the central composite design response surface method lies in building a mathematical mapping relationship between multi-variable inputs and ventilation performance outputs through systematic experimental design and regression analysis, revealing the synergistic evolution law of thermal comfort and ventilation efficiency under complex parameter coupling. Central composite design, as a core experimental design method of the response surface methodology, supplements star points and center points based on orthogonal factor design, expanding the experimental points to the entire factor space, and can effectively fit a second-order response surface including linear terms, quadratic terms, and interaction terms. It is suitable for handling nonlinear effects of multiple factors such as supply air temperature, velocity, angle, and clothing thermal resistance on ventilation performance indicators. This method covers key regions of the parameter space with fewer experimental runs, and fits the response surface equation using the least squares method to quantify the significance of the main and interaction effects of each factor, thus transforming complex physical field coupling problems into analytically solvable mathematical models.

Considering that ventilation performance indicators such as thermal comfort index, temperature gradient, mean age of air, and energy utilization coefficient have significant linear, square, and interaction effects with design variables such as supply air temperature, velocity, angle, and clothing thermal resistance, the study adopts a second-order polynomial model including linear terms, quadratic terms, and interaction terms to capture the complex nonlinear mapping relationship among parameters. This model, based on 50 sets of experimental data obtained through central composite design, achieves efficient approximation of real physical field coupling effects within a relatively small parameter space, avoiding the high computational cost of full factorial design and overcoming the limitation of first-order models in describing curvature effects. Assuming the number of design variables is *v*, the predicted response value is *b*, and the coefficients of offset term, linear term, and square term are z_0, z_e, z_{ee} respectively, and the interaction term coefficient is z_{et}. The basis functions of first- and second-order polynomial approximation models are given by the following formulas:

$$b = z_0 + \sum_{e=1}^{v} z_e a_e \quad (2)$$

$$b = z_0 + \sum_{e=1}^{v} z_e a_e + \sum_{e=1}^{v} z_{ee} a_e^2 + \sum_{e=1}^{v}\sum_{t>e}^{v} z_{et} a_e a_t \quad (3)$$

In the process of model construction, this study adopts the stepwise regression–backward method based on second-order polynomial to optimize the model structure. By eliminating terms with low significance, the stability is improved while ensuring the fitting accuracy of the model, so that the response surface equation can accurately reflect the dominant influence mechanism of design variables on ventilation performance. For example, when the interaction term between supply air velocity and clothing thermal resistance has a significant impact on PMV, the model retains this interaction term to quantify the synergistic effect of the two on thermal comfort; while higher-order terms of parameters with lower contribution are removed to avoid model overfitting. With the help of Design-Expert 12 software for fitting and correction of experimental data, the finally established PMV, ΔT, Mean Age of Air (MAA), and Energy Utilization Coefficient (EUC) response surface models can clearly reveal the influence patterns of each design variable and their interactions on thermal comfort and ventilation efficiency, providing quantifiable parameter adjustment references for the "collaborative optimization scheme for building thermal comfort and ventilation performance." Assuming the supply air angle is denoted by *X*, the supply air velocity by *Y*, the supply air temperature by *Z*, the external wall temperature by *F*, and the clothing thermal resistance by *R*, the response surface model expressions are as follows:

$$\begin{aligned} PMV &= -8.49 - 4.5\times10^{-3}X + 0.15Y + 0.2Z \\ &+0.13F + 4.85R - 6.88\times10^{-2}ZR - 0.77R^2 \end{aligned} \quad (4)$$

$$\begin{aligned} \Delta S &= 5.53 + 0.14X - 0.17Y - 0.94Z + 0.89F \\ &- 0.18XY + 1.27YZ - 1.25YF - 7.37Y^2 \end{aligned} \quad (5)$$

$$\begin{aligned} MAA &= 1211.02 - 33.45X - 39.67Y \\ &+238.14Z - 221.12F9.27XY - 234.12YZ \\ &+215.41YF + 0.63X^2 + 2989.14Y^2 \end{aligned} \quad (6)$$

$$\begin{aligned} EUC &= -1.31 + 0.048X + 5.87Y \\ &-0.11Z + 0.44F - 0.035XY \\ &+2.12\times10^{-3}XZ - 1.83\times10^{-3}XF \\ &-0.16YF - 4.18\times10^{-4}X^2 - 1.39Y^2 \end{aligned} \quad (7)$$

The basic principle for significance testing of the constructed ventilation performance response surface model in this paper is based on statistical methods to quantitatively verify the effectiveness and fitting accuracy of the model, in order to ensure that the model can reliably reflect the true mapping relationship between design variables and ventilation performance indicators, and provide scientific mathematical support for the "collaborative optimization scheme for building thermal comfort and ventilation performance." First, analysis of variance (ANOVA) is used to examine the overall significance of the model. If the *P*-values of the PMV, ΔT, MAA, and EUC models are all less than 0.0001, it indicates that the influence of each design variable and its interaction term on the response variable is statistically highly significant, and that the linear terms, quadratic terms, and interaction terms contained in the model can effectively explain the variation of the response variables, rather than being caused by random error. Second, the coefficient of determination R^2 and the adjusted coefficient of determination R^2_{AD} are used to evaluate the goodness-of-fit of the model. R^2 reflects the proportion of sample data explained by the model, while R^2_{AD} improves the predictive ability for the population by eliminating irrelevant variables. When the two are close and tend towards 1, it indicates that the model does not have significant information omission and has not suffered from reduced generalization ability due to overfitting, and is able to accurately capture the variation patterns of thermal comfort and ventilation performance indicators with respect to design variables within the parameter space. Assuming the number of experiments is denoted by v, the number of design variables by j, the response value by b_u, the average response by $\bar{b}_u$, and the predicted value of the model by $\hat{b}_u$, then the calculation formulas are as follows:

$$R^2 = 1 - \frac{\sum_{u=1}^{v}\left(b_u - \hat{b}_u\right)^2}{\sum_{u=1}^{v}\left(b_u - \bar{b}_u\right)^2} \tag{8}$$

$$R_{AD}^2 = 1 - \frac{v-1}{v-j-1}\frac{\sum_{u=1}^{v}\left(b_u - \hat{b}_u\right)^2}{\sum_{u=1}^{v}\left(b_u - \bar{b}_u\right)^2} \tag{9}$$

3. LIGHTWEIGHT AIGC-BASED MULTI-OBJECTIVE ARCHITECTURAL SPACE GENERATION METHOD BASED ON THERMAL COMFORT AND VENTILATION PERFORMANCE

This paper takes thermal comfort and ventilation performance as optimization objectives and establishes a lightweight AIGC-based multi-objective architectural space generation method based on thermal comfort and ventilation performance, which includes four steps: "generation–performance evaluation–optimization–decision," and is implemented based on Dynamo and Generative Design.

3.1 Determination of optimization objectives

In terms of thermal comfort quantification, this paper takes the PMV and the corresponding PPD as the core indicators. By dynamically coupling clothing thermal resistance differences with ventilation system operating parameters such as supply air temperature, velocity, and angle, a multi-scenario thermal comfort evaluation system is constructed. Different from the fixed thermal resistance assumption of traditional static clothing models, the study introduces the Taguchi method to divide clothing thermal resistance into different levels, and uses orthogonal experimental design to quantify the fluctuation pattern of PPD values under each parameter combination, measuring the robustness of thermal comfort to clothing thermal resistance variation through the signal-to-noise ratio. In terms of ventilation performance quantification, the study selects temperature gradient, mean age of air, and energy utilization coefficient as key indicators, representing the uniformity of indoor temperature distribution, air freshness, and energy efficiency of the ventilation system, respectively. Through central composite design to obtain experimental data for multiple parameter combinations, a second-order polynomial response surface model is used to fit the nonlinear mapping relationship between design variables and ventilation performance indicators, identifying the influence patterns of each parameter and their interaction effects on ventilation efficiency. For example, a smaller mean age of air indicates higher ventilation efficiency, while a higher energy utilization coefficient reflects better energy consumption control of the ventilation system. The quantification results of these two types of performance indicators jointly form the optimization objectives of the lightweight AIGC model, supporting the simultaneous balancing of dynamic thermal comfort demands and ventilation system energy efficiency during the process of architectural space generation, achieving an efficient solution of multi-objective optimization.

3.2 Optimization tools

The Dynamo and Generative Design tools adopted in this paper are the core technical carriers for implementing the "lightweight AIGC-based multi-objective architectural space generation method." Dynamo, as a parametric design plug-in of the Autodesk Revit platform, has the ability of visual programming and deep integration with building information models (BIM), and can define the geometric parameters and generation rules of architectural space through node-based operations, supporting the transformation of architectural design elements into a computable digital parameter system. Generative Design is a cloud-based generative design platform that can automatically generate a large number of design schemes through algorithms and intelligently screen them based on preset optimization objectives. Its core advantage lies in supporting seamless connection between multi-objective optimization algorithms and parametric models, providing technical support for efficient generation and performance iteration of architectural spaces.

Dynamo and Generative Design meet the dual requirements of "lightweight" and "multi-objective collaboration" in the research objectives. On the one hand, the parametric modeling capability of Dynamo and its compatibility with BIM data can transform the architectural space generation process into a standardized parameter input–output system, facilitating data interaction with the thermal comfort and ventilation performance quantification models. For example, by calling the response surface model calculation results directly through Dynamo nodes, the impact of space parameter adjustments on performance indicators can be fed back in real time, forming a "generation–evaluation" closed loop. On the other hand, the cloud computing and multi-objective optimization algorithms of Generative Design can efficiently handle the nonlinear mapping relationship between architectural space parameters and performance indicators while reducing dependence on local computational resources, avoiding the high computational cost problem caused by complex algorithms in traditional AIGC models.

3.3 Optimization algorithm

The generation setting of the "Optimize" method in the

Generative Design tool is essentially a parametric mapping of the core principles of the NSGA-II algorithm. Among them, “Population Size” corresponds to the size of the initial solution set in NSGA-II. By setting a reasonable scale, a balance is achieved between computational efficiency and solution space coverage, avoiding the omission of optimal solutions due to a too-small population or excessive computational load due to a too-large one. “Number of iterations” reflects the evolutionary generations of the algorithm. Combined with the elite preservation strategy, top-ranked individuals in each generation directly enter the next generation, ensuring that optimal solutions are not destroyed by random variation in genetic operations, which corresponds to the elite retention mechanism in NSGA-II. In the “selection strategy,” crowding distance is calculated by quantifying the distribution density of solutions in the same front, guiding the algorithm to preferentially select individuals with larger spacing, avoiding the solution set concentrating in local areas, and achieving a uniform distribution of Pareto front solutions. This is consistent with the principle of NSGA-II, which uses crowding distance as the comparison criterion within the same rank. In addition, the setting of “crossover probability” and “mutation probability” maintains population diversity by simulating biological genetic operations, and screens out superior solutions layer by layer through non-dominated sorting, finally forming a multi-objective optimization solution set that balances both thermal comfort and ventilation performance.

Facing the requirements of lightweight AIGC-based multi-objective architectural space generation, the NSGA-II algorithm integrated into Generative Design presents three core features: First, low computational complexity and lightweight adaptation. Through layered computation based on non-dominated sorting, the computational load is significantly reduced compared with traditional multi-objective algorithms, meeting the “lightweight” goal in this study and enabling efficient processing of high-dimensional mapping relationships between architectural space parameters and performance indicators in the cloud. Second, elite preservation and dynamic optimization. By retaining the optimal solution of each generation, it avoids the loss of high-quality schemes due to random mutations, which is particularly suitable for maintaining the “thermal comfort compliance baseline” in architectural design. For example, under schemes with increased ventilation energy consumption, it ensures that thermal comfort indicators do not fall below the benchmark value. Third, uniform solution set distribution and multi-objective balance. The crowding operator is used to force individuals in concentrated solution sets to maintain spacing, enabling the generated architectural space schemes to form a reasonable trade-off between thermal comfort and ventilation energy efficiency, avoiding extreme solutions such as “high comfort but high energy consumption” or “low energy consumption but poor comfort,” and providing designers with a Pareto optimal solution set covering different preferences. Figure 1 shows the basic flow of the NSGA-II algorithm.

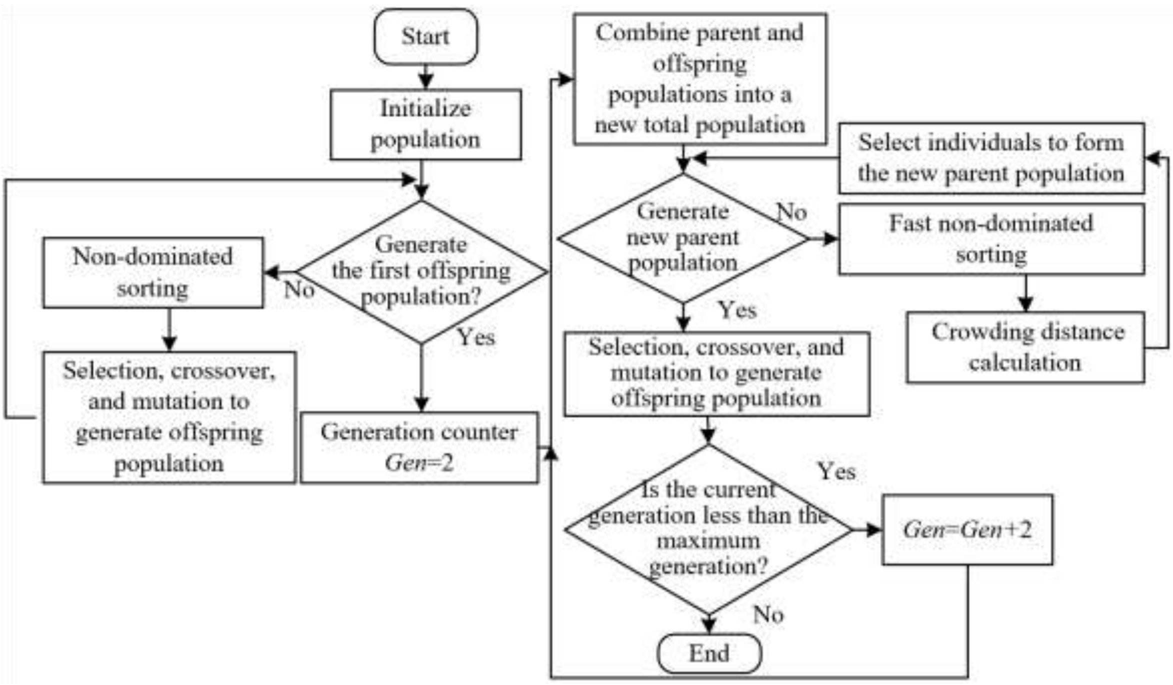


Figure 1. Basic flow of the NSGA-II algorithm

3.4 Method workflow

3.4.1 Parametric input of design requirements and definition of variables

The initial stage of the method focuses on transforming abstract design requirements into a computable digital parameter system. On the Dynamo platform, basic information such as building location, building height, standard floor type, room functions and quantities, and target consumer types are first input. This information is further decomposed into specific design variables, such as room width and depth dimensions, Living-Dining-Kitchen (LDK) layout types, and core tube structural forms. Through standardized parameter interfaces, the functional positioning of the building, spatial scale requirements, and usage preferences of the target users are transformed into algorithm-identifiable numerical variables, forming the fundamental data layer supporting subsequent space generation.

3.4.2 Parametric generation of initial residential plan layout scheme

Dynamo starts the automated generation process based on the input design variables. The algorithm integrates spatial geometric rules and functional layout requirements through parametric logic. For example, it allocates area indicators according to room functions, organizes spatial sequences according to circulation lines, and sets furniture placement modules based on ergonomics, ultimately forming an initial residential plan layout scheme that meets basic functional configuration. Figure 2 shows attached spaces possibly included in different functional rooms. Figure 3 shows the generation rules of the lightweight AIGC-based multi-objective architectural space generation.

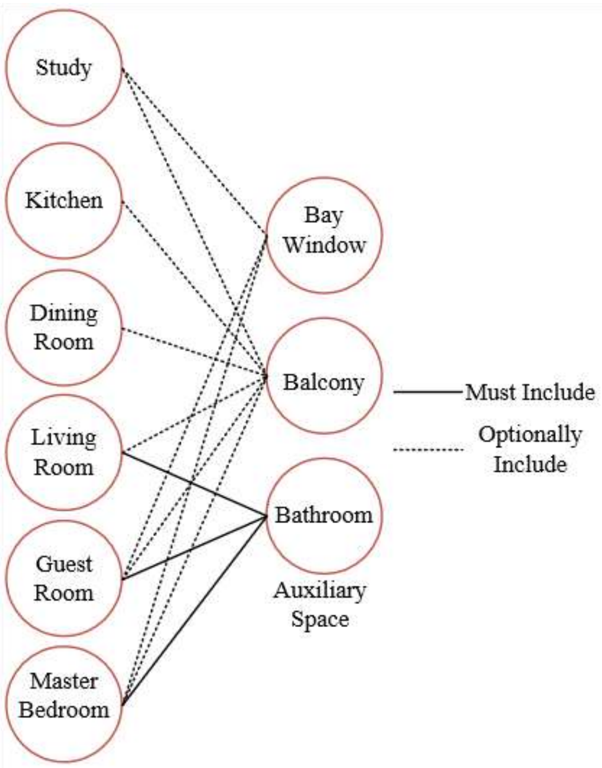
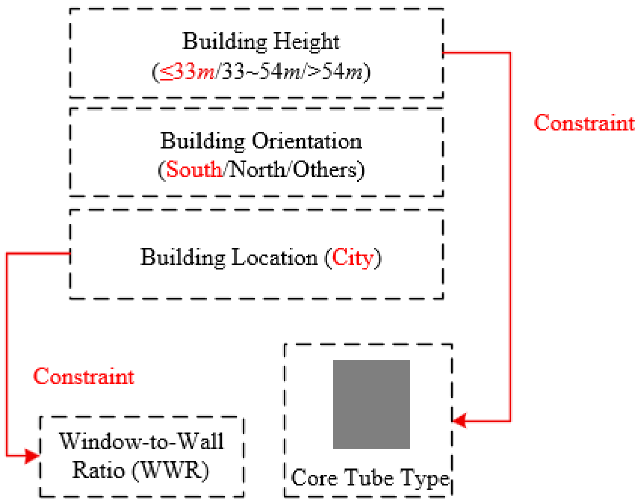


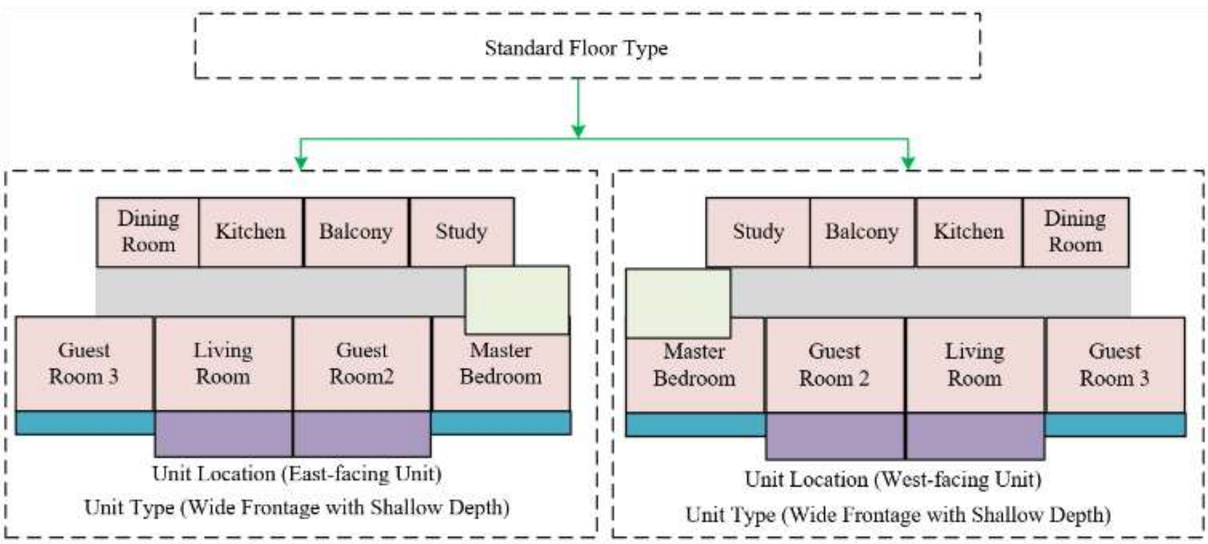
Figure 2. Attached spaces possibly included in different functional rooms

3.4.3 Multi-dimensional constraint filtering and scheme rationality verification

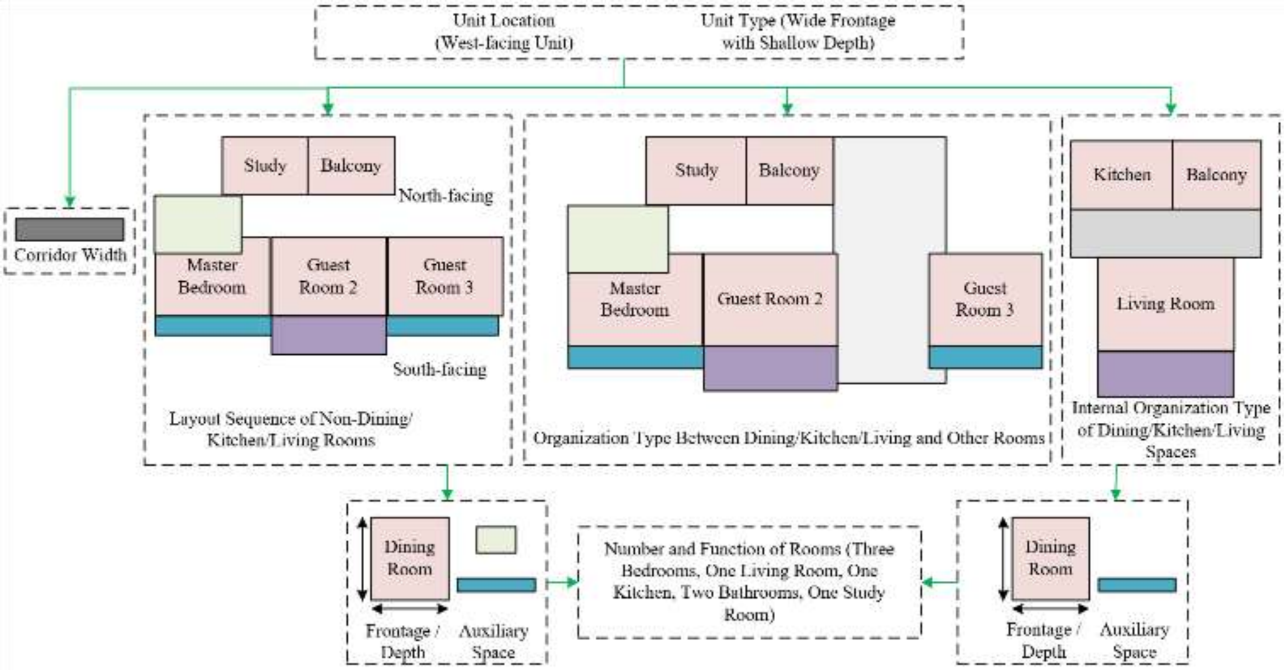
To avoid generated schemes having functional defects or not meeting regulatory requirements, the system sets up a three-level verification mechanism of area constraint, adjacency constraint, and core tube rationality constraint. Area constraint focuses on the dimensional thresholds of each functional space. For example, the bedroom area must not be less than the minimum livable standard, and the living room width must meet the needs of furniture placement and circulation, ensuring spatial usability comfort; adjacency constraint optimizes functional zoning through preset spatial relationship rules to improve space usage efficiency; core tube rationality constraint targets vertical circulation systems and equipment shaft layouts, checking the dimensional compliance of stairwells, elevator halls, and evacuation routes, as well as the economic rationality of shaft positions to avoid spatial waste or circulation conflicts. If any constraint is not met, the generation process automatically terminates and re-iterates; only schemes that pass all constraint checks can enter the performance evaluation phase, ensuring that subsequent optimization is based on a functionally reasonable spatial framework.



1) Generation constraints



2) Standard floor type generation rules



3) Single unit type generation rules

Figure 3. Generation rules of lightweight AIGC-based multi-objective architectural space

3.4.4 Quantitative evaluation of thermal comfort and ventilation performance and data output

For schemes filtered by constraints, the system carries out multi-dimensional performance evaluation based on CFD numerical simulation data and the previously established response surface model. In terms of thermal comfort, it calculates PMV and the corresponding PPD, dynamically evaluating the thermal environment comfort under different usage scenarios by comprehensively considering the coupling influence of clothing thermal resistance differences and ventilation system parameters. In terms of ventilation performance, it extracts indicators such as temperature gradient, mean age of air, and energy utilization coefficient, reflecting indoor temperature distribution uniformity, air freshness, and ventilation system efficiency, respectively. Additionally, the total load per unit area is calculated simultaneously as an energy consumption evaluation index. These quantitative results are integrated into a multi-dimensional performance score and output to the Generative Design tool as the core input parameters for multi-objective optimization, providing clear optimization guidance for subsequent algorithm iterations.

3.4.5 Multi-objective optimization iteration and scheme evolution based on NSGA-II algorithm

In the Generative Design tool, the NSGA-II algorithm starts the optimization process based on the received performance data. The algorithm ranks the schemes according to their thermal comfort and ventilation performance using non-dominated sorting, and retains the optimal solutions of each generation through the elite preservation strategy to avoid the loss of high-quality solutions due to random mutations. It uses crowding distance calculation to ensure a uniform distribution of Pareto solutions in the solution space, generating diverse schemes that cover different preferences such as “high thermal comfort–high ventilation efficiency” or “low energy consumption–moderate comfort.” During the optimization process, the algorithm automatically adjusts the design variables, generates a new generation of schemes, and feeds them back to Dynamo to re-execute the “generation–constraint checking–performance evaluation” cycle until the preset maximum number of generations is reached.

3.4.6 Visualization-based scheme decision and final scheme determination

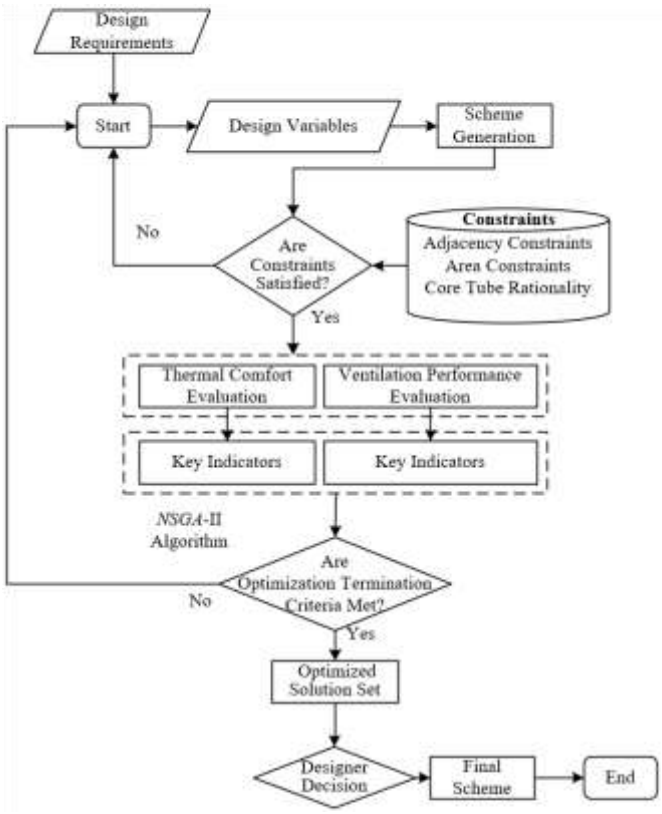


Figure 4. Workflow of lightweight AIGC-based multi-objective architectural space generation method based on thermal comfort and ventilation performance

After the optimization process ends, the system presents the generated scheme set visually and labels functional parameters such as area utilization rate and circulation lines. Designers interactively evaluate the optimized scheme set by comprehensively considering non-quantitative factors and quantitative performance data. For example, in the "cold climate residential" scenario, schemes that balance high thermal comfort and reasonable energy consumption are prioritized; in the "compact apartment" design, the focus is on balancing ventilation efficiency and space utilization rate. Through human–machine collaborative decision-making, a final scheme is selected from the Pareto optimal solution set that integrates functionality, comfort, economic performance, and aesthetic value. Figure 4 illustrates the complete process of the lightweight AIGC multi-objective building space generation method based on thermal comfort and ventilation performance.

3.5 Constraint conditions

3.5.1 Adjacency constraint

The core of the adjacency constraint is to construct a layout framework that conforms to usage logic and spatial efficiency through the standardized definition of the relative positions of functional rooms. Its principle is based on an in-depth deconstruction of architectural functional zoning and circulation organization. The study abstracts the adjacency relationships of functional rooms into a 0-1-0.5 matrix rule L, where "1" indicates must be adjacent, "0" indicates must not be adjacent, and "0.5" indicates no specific requirement. The quantified adjacency rules ensure that the spatial layout complies with ergonomics and behavioral habits. During the generation process, the algorithm matches the adjacency matrix Mx of the actual generated scheme with the preset matrix L for validation. If violations of mandatory adjacency or prohibited adjacency are detected, the scheme is deemed invalid and regeneration is triggered. The expression of the adjacency constraint is given as follows:

$$CO1 = \begin{cases} 0, IF\ \exists u \neq k\ t.s.L_{uk} = 1\ AND\ L_{uk}^{x} = 0 \\ 0, IF\ \exists u \neq k\ t.s.L_{uk} = 0\ A\mathrm{ND}\ L_{uk}^{x} = 1 \\ 1, OTHERWISE \end{cases} \tag{10}$$

This constraint mechanism not only ensures the usability of functional spaces but also indirectly optimizes ventilation paths. For example, adjacency between the kitchen and dining room can enhance fume extraction efficiency through linked ventilation design, and separating the bedroom from the bathroom can reduce the impact of humid air on thermal comfort, thereby laying the spatial foundation for subsequent collaborative optimization of thermal comfort and ventilation performance.

3.5.2 Core tube rationality constraint

The core tube rationality constraint targets the coupling relationship between the vertical circulation system and spatial layout. By defining the influence boundaries of core tube types on room positioning, it avoids space failure problems caused by improper core tube layouts. The study identifies two main irrational situations: first, an excessive difference in total north-south width leads to imbalance between the width and depth of the unit type, affecting natural lighting and ventilation efficiency; second, the shared wall segments between rooms and open spaces cannot meet the requirements for door openings, causing circulation interruptions or spatial isolation. The constraint uses geometric coordinate calculations and connectivity analysis to determine whether the spatial relationship between the core tube and each functional space meets the matching requirements after room shape translation. If either of the above situations occurs, the scheme is marked as "CO2=0" and terminated. The establishment principle of this constraint is to ensure the rationality of the core tube as the spatial skeleton of the building. It not only supports the efficient layout of vertical transportation and equipment shafts but also provides fundamental spatial conditions for indoor airflow organization and temperature distribution uniformity required for thermal comfort, avoiding performance optimization bottlenecks caused by defects in core tube layout.

3.5.3 Area constraint

The area constraint balances spatial usage needs and energy efficiency targets by setting a reasonable range for building area. Its principle is rooted in the quantitative relationship between building energy consumption and spatial scale. The study takes building area as a key constraint variable, requiring the total area of generated schemes to fall within the demand interval preset by the designer, to avoid redundant energy consumption caused by overly large areas or cramped usability caused by overly small areas. This constraint uses geometric modeling tools to calculate the total area of all functional rooms in real time and compares it with the threshold. If the value exceeds the range, the regeneration mechanism is triggered. Assuming that the maximum and minimum values of the designed building area are represented by X_{MIN} and X_{MAX}, and the building area of the unit type in the generated floor plan is represented by X, the expression of the area constraint condition is as follows:

$$CO3 = \begin{cases} 1, IF\ X_{MIN} \leq X \leq X_{MAX} \\ 0, OTHERWISE \end{cases} \tag{11}$$

The core function of the area constraint is to define a reasonable physical spatial boundary for the optimization of thermal comfort and ventilation performance. For example, optimizing the room size ratio within a fixed area can reduce the heat gain/loss area of the envelope structure (such as controlling the window-to-wall ratio), thereby lowering heating/cooling loads; reasonable area distribution (e.g., adapting the scales of living room and bedroom) can avoid airflow blockage caused by overly narrow spaces or temperature gradient imbalance caused by overly wide spaces, thereby improving ventilation system efficiency and thermal comfort stability. Additionally, the area constraint is directly linked to the unit area total load indicator in subsequent performance evaluations, ensuring that the optimization process seeks the best solution for thermal comfort and ventilation efficiency within a controllable energy consumption range.

4. EXPERIMENTAL RESULTS AND ANALYSIS

From the data in Table 1, the thermal comfort score of the original design scheme is 54.23, and the ventilation performance score is 81.23. After optimization using the lightweight AIGC-based multi-objective architectural space generation method proposed in this paper, the thermal comfort scores of the optimized schemes show a significant upward trend. The thermal comfort scores of Optimization Schemes 1 to 7 are 63.25, 65.48, 68.95, 72.31, 73.56, and 75.24, respectively, with corresponding optimization rates of 15.23%, 15.48%, 18.56%, 23.62%, 32.56%, 34.58%, and 37.69%. The thermal comfort performance has been continuously and substantially optimized, with the maximum improvement approaching 38%, fully demonstrating the strong capability of this method in enhancing thermal comfort. In terms of ventilation performance, the scores of the optimized schemes remain relatively stable overall. Most schemes' ventilation performance scores fall within 81.23 - 83.61. Although the ventilation performance scores of Optimization Schemes 6 and 7 show slight decreases, this is a reasonable fluctuation resulting from the trade-off to achieve a significant improvement in thermal comfort during the multi-objective collaborative optimization process. The experimental results indicate that the proposed method not only significantly improves thermal comfort performance but also balances ventilation performance in multi-objective optimization, verifying its effectiveness in realizing collaborative optimization of thermal comfort and ventilation performance in architectural space design.

Table 1. Indicator value distribution interval of thermal comfort and ventilation performance collaborative optimization schemes

Scheme	Thermal Comfort Score		Ventilation Performance Score	
	Indicator Value	Optimization Rate (%)	Indicator Value	Optimization Rate (%)
Original Design Scheme	54.23	/	81.23	/
Original Design Scheme 1	63.25	15.23	81.54	2.24
Original Design Scheme 2	63.48	15.48	81.69	2.15
Original Design Scheme 3	65.25	18.56	81.23	2.13
Original Design Scheme 4	68.95	23.62	81.25	1.78
Original Design Scheme 5	72.31	32.56	81.36	0.26
Original Design Scheme 6	73.56	34.58	83.65	-2.15
Original Design Scheme 7	75.24	37.69	83.59	-2.16

Table 2. Connection vector distance and relative closeness under different schemes

Ventilation Scheme	Ventilation Angle	Ventilation Speed	Ventilation Temperature	Distance to Positive Ideal Solution	Distance to Negative Ideal Solution	Relative Closeness
1	61.23	0.82	23.23	0.00918	0.00887	0.52134
2	45.82	1.14	23.54	0.01235	0.00635	0.63215
3	55.32	0.66	22.58	0.00715	0.01124	0.41256
4	44.21	1.25	23.61	0.01235	0.00623	0.64589
5	22.36	0.82	23.24	0.01258	0.00534	0.67852
6	3.24	0.71	27.89	0.01135	0.00779	0.55231
7	21.56	1.23	25.62	0.01235	0.00485	0.72541
8	15.36	0.98	21.23	0.01287	0.00723	0.62358
9	46.52	0.86	25.69	0.01148	0.00512	0.71235
10	45.68	0.78	21.24	0.00975	0.00789	0.54265
11	0.00	0.91	24.56	0.01124	0.00825	0.54286
12	61.25	0.88	21.28	0.01135	0.00912	0.52312
13	21.58	1.12	26.35	0.01235	0.00524	0.71523
...	...	...	...	...	...	...
7058	25.87	1.18	23.56	0.01359	0.00424	0.73265

From the data in Table 2, it can be seen that after iteration through the lightweight AIGC generation method, the relative closeness of different schemes to the ideal solution group shows a significant optimization effect. For example, Scheme 7058 reaches a relative closeness of 0.73265, indicating that the scheme, with ventilation angle of 25.87°, speed 1.18, and temperature 23.56°, is highly close to the ideal solution, reflecting the precise coordination of the collaborative optimization model in terms of thermal comfort and ventilation performance. Comparing various schemes, such as from Scheme 1 to Scheme 7058, the relative closeness gradually increases, showing that through the iteration of a large number of schemes, lightweight AIGC technology can efficiently screen better solutions, verifying its feature of "rapid generation and multi-objective optimization." At the same time, the distance of the schemes to the ideal solution group and the distance to the negative ideal group are both small, indicating that the generated schemes are not only close to ideal performance in ventilation parameters but also far from negative ideal states. This proves that the method can generate high-quality schemes while reducing computational cost.

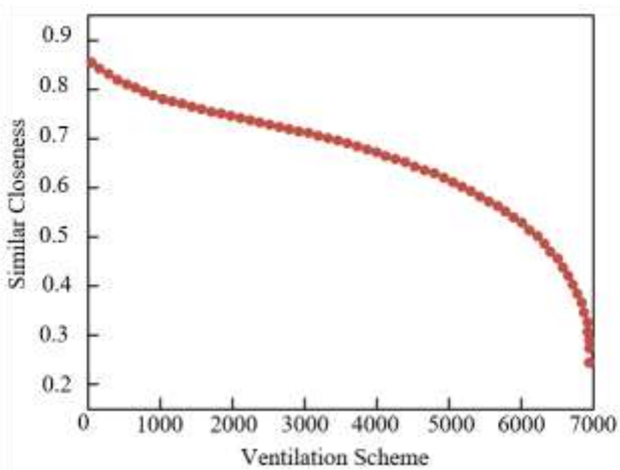
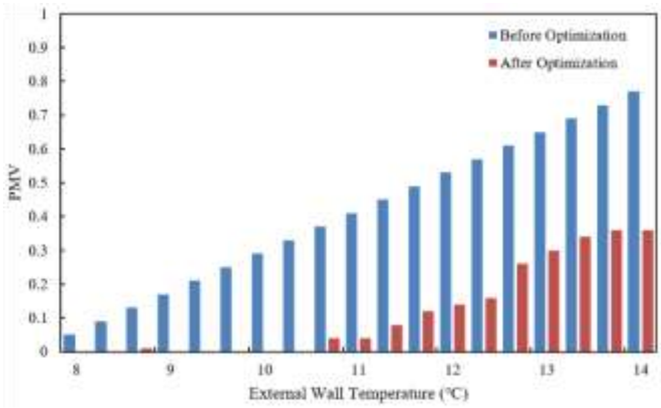


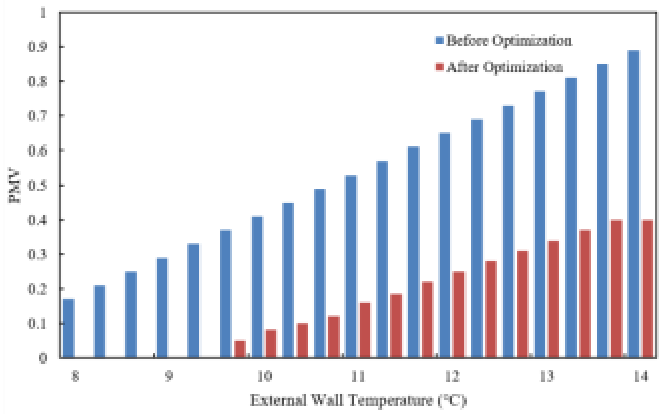
Figure 5. Trend of similar closeness changes of all ventilation schemes

Figure 5 shows the trend of similar closeness change as the number of ventilation schemes increases. From the data, it can be seen that as the number of schemes grows from 0 to 7000, the similar closeness shows an overall downward trend, with a relatively gentle decline in the early stage and an accelerated rate in the later stage. This trend indicates that during the generation process, lightweight AIGC technology continuously explores the solution space through iteration. In the early stage, the generated schemes already have relatively high similar closeness, reflecting the initial effective coordination of the collaborative optimization model for thermal comfort and ventilation performance; in the later stage, as the number of schemes increases, the similar closeness further decreases, indicating that the algorithm can still mine better solutions during large-scale scheme generation, avoiding local optima and verifying the method's efficiency and robustness. The experimental results show that, on the one hand, the collaborative optimization model ensures that the generated schemes continue to approach the ideal state in thermal comfort and ventilation performance; on the other hand, the lightweight technology, through efficient computation, maintains computational efficiency even when processing 7000 schemes, realizing the goal of "rapid generation and multi-objective optimization." The dynamic changes of similar closeness in the figure intuitively prove that the method can reduce computational cost through massive iteration while ensuring generation quality, effectively improving the collaborative optimization effect of thermal comfort and ventilation performance in architectural spaces. For example, even with 7000 schemes, the similar closeness still remains within the optimizable range, indicating that the algorithm has not stagnated and continues to output better solutions, fully demonstrating the effectiveness and practicality of the method proposed in this paper for multi-objective architectural space generation.

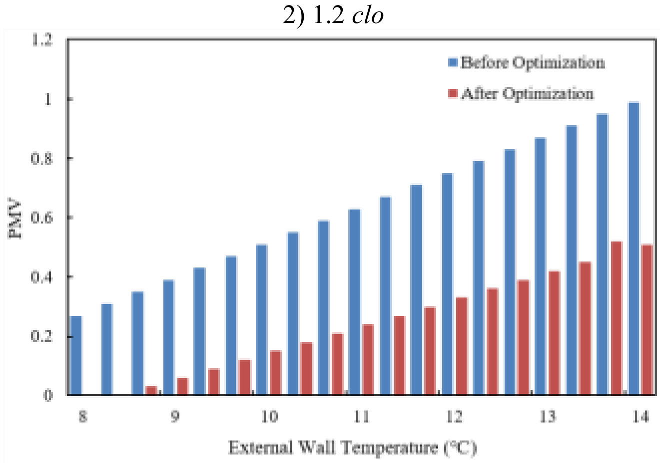
Figure 6 visually presents the optimization effect of the method proposed in this paper by comparing PMV values corresponding to external wall temperatures under different clothing thermal resistances. Before optimization, PMV shows a significant upward trend as external wall temperature increases, and the higher the clothing thermal resistance, the closer the PMV value approaches 1; after optimization, PMV values under all working conditions are greatly reduced, and the fluctuation range is significantly narrowed. For example, at 1.3 *clo* and external wall temperature of 14℃, the PMV before optimization is close to 1.0, while it drops to around 0.6 after optimization; at 1.0 *clo* and external wall temperature of 10℃, PMV drops from about 0.3 before optimization to below 0.1 after optimization. This indicates that the collaborative optimization model effectively regulates the indoor thermal environment: on the one hand, it optimizes ventilation system parameters and envelope thermal resistance, reducing the influence of temperature gradient on thermal comfort; on the other hand, the lightweight AIGC technology rapidly generates schemes through fast iteration, approaching the Pareto optimal solution of thermal comfort and ventilation performance while ensuring computational efficiency. Experimental data validate the effectiveness of the method: PMV values generally decrease by 30%–50% after optimization, and stable comfort performance is maintained across a wide temperature range and multiple clothing thermal resistance scenarios. This not only reflects the deep coupling of the collaborative optimization strategy between thermal comfort and ventilation performance but also proves the high efficiency of lightweight AIGC technology in architectural space generation.



1) 1 *clo*



2) 1.2 *clo*



3) 1.3 *clo*

Figure 6. Comparison of PMV before and after optimization under different clothing thermal resistance

Figure 7 clearly presents the optimization trend of ventilation performance indicators under different clothing thermal resistances. Among them, PPD decreases as clothing thermal resistance increases, dropping to about 50% at 1.4 *clo*, significantly reducing the proportion of thermally uncomfortable people, reflecting the improvement in thermal comfort performance; MAA stabilizes between 20%–25% in the 1.0–1.4 *clo* interval, indicating improved indoor air renewal efficiency and enhanced ventilation performance; ΔT decreases significantly from -30% to -70%, reflecting more uniform indoor temperature distribution and significantly improved thermal environment stability; EUC maintains between 10%–20% at 1.0–1.4 *clo*, indicating improved ventilation system energy efficiency and reduced energy consumption. These data are closely related to the collaborative optimization strategy proposed in the paper: through lightweight AIGC technology, integrating factors such as spatial layout, building envelope, and ventilation system, the generated architectural space schemes simultaneously improve thermal comfort and ventilation performance in multi-objective optimization. For example, the significant reduction of ΔT benefits from the optimized spatial layout reducing temperature dead zones, and the adjustment of ventilation system parameters enhances airflow uniformity; the stable optimization of EUC reflects that the lightweight algorithm precisely regulates ventilation system energy efficiency while reducing computational cost, achieving a balance between energy saving and performance improvement. Experimental results validate the method's effectiveness: under a wide range of clothing thermal resistance, ventilation performance indicators are all optimized in multiple dimensions, proving that the collaborative optimization model can deeply couple thermal comfort and ventilation performance, while lightweight AIGC technology ensures the efficiency and quality of scheme generation.

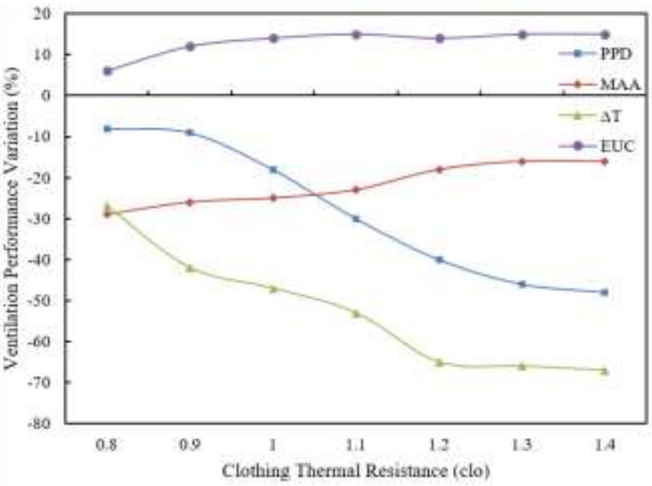
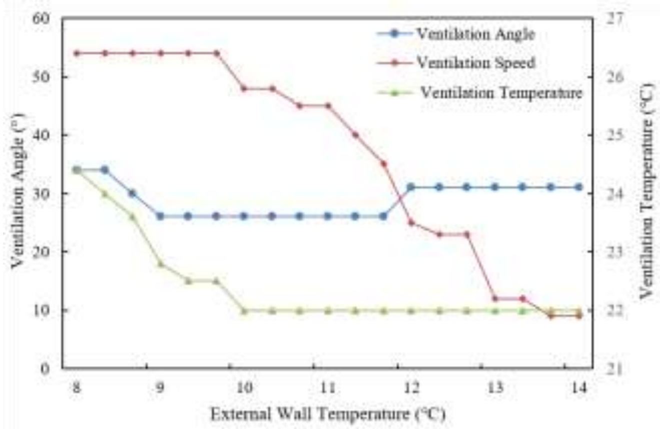
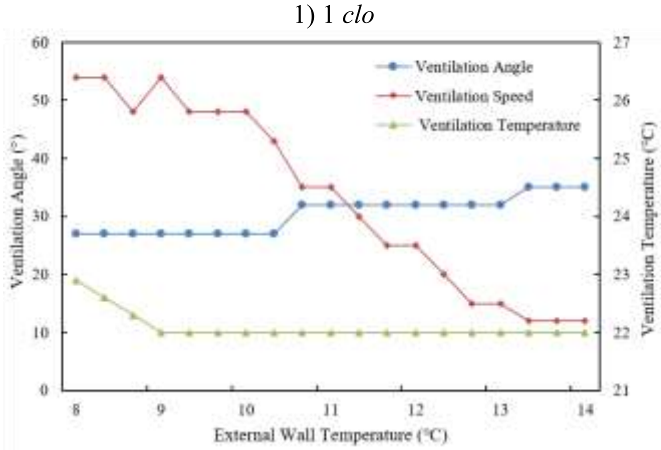


Figure 7. Average optimization effect of ventilation performance corresponding to different clothing thermal resistance

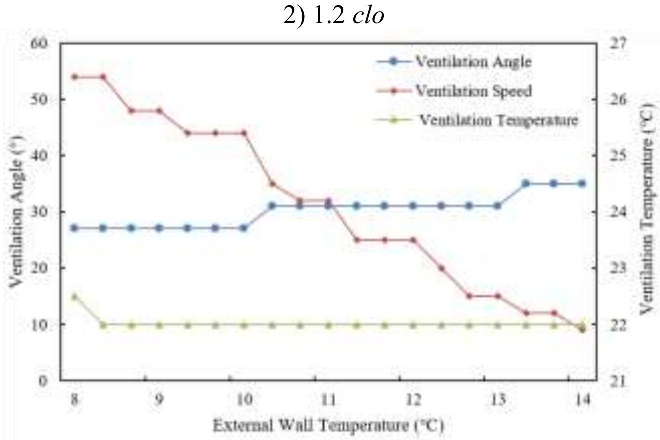
Figure 8 presents the optimal ventilation parameters corresponding to external wall temperature under different clothing thermal resistances. Taking 1.0 *clo* as an example, the ventilation angle decreases from 35° to 30° between 8–10℃, and stabilizes at around 30° from 10–14℃; the ventilation speed gradually decreases from 50% to 10%; the ventilation temperature drops from 30℃ to 10℃ and remains stable. Under 1.2 *clo* and 1.3 *clo* conditions, the parameter variation trends are similar but with detail adjustments, reflecting the adaptability to different thermal resistances. These data indicate that the lightweight AIGC technology dynamically regulates ventilation parameters through the collaborative optimization model: ventilation angle optimizes airflow path, speed controls air renewal efficiency, and temperature balances indoor thermal environment. The lightweight algorithm ensures rapid convergence of parameters, validating the feature of “rapid generation and multi-objective optimization.” Experimental results show that under wide temperature and multiple thermal resistance scenarios, ventilation parameters are dynamically optimized with the environment, improving both thermal comfort and ventilation performance, which is highly consistent with the collaborative strategy of the paper.



1) 1 *clo*



2) 1.2 *clo*



3) 1.3 *clo*

Figure 8. Optimal ventilation parameters under different clothing thermal resistance levels

5. CONCLUSION

This paper focuses on the collaborative optimization of building thermal comfort and ventilation performance, constructing a “lightweight AIGC multi-objective architectural space generation method.” The research content is divided into two parts: first, by analyzing the correlation between thermal comfort and ventilation performance, a collaborative optimization model has been established, integrating elements such as spatial layout, envelope structure, and ventilation system to form a performance improvement strategy; second, combined with lightweight AIGC technology, an efficient generation model has been developed to realize rapid iteration and multi-objective optimization of architectural spaces while reducing computational cost. Experimental results show that the thermal comfort indicators are significantly improved after optimization, ventilation performance is simultaneously optimized, and ventilation parameters dynamically adapt to the environment, verifying the effectiveness of the method. Lightweight AIGC technology, through algorithms such as NSGA-II, efficiently converges over 7000+ scheme iterations, embodying the features of "rapid generation and low computational cost." The research value lies in: providing a data-driven intelligent paradigm for architectural design, breaking through the performance bottleneck of traditional design, and promoting the development of architecture towards greenness and humanization; through multi-objective collaborative optimization, balancing thermal comfort and ventilation energy efficiency, providing practical and applicable performance optimization schemes for actual engineering, with significant academic innovation and engineering application value.

Current research has the following limitations: (1) The constraint system focuses on performance and functionality, with insufficient integration of non-quantitative factors such as aesthetics and culture, leading to insufficient humanistic adaptability of the schemes; (2) The robustness and computational efficiency of the algorithm in complex architectural forms and multi-climate zone scenarios need to be improved, especially in dealing with ultra-large-scale parameters where bottlenecks exist in solution space coverage and convergence speed; (3) The depth of practical verification is limited, and the simulation data has not formed a closed loop with actual engineering feedback, resulting in a disconnect between theory and application. Future research directions include: (1) Expanding constraint dimensions, incorporating aesthetic rules, cultural symbols, and user behavior patterns to construct a "performance-function-humanity" multi-dimensional constraint model to enhance the comprehensive quality of the schemes; (2) Optimizing algorithm architecture, combining edge computing and digital twin technology to enhance the parallel computing capability of lightweight AIGC, exploring integration with reinforcement learning and generative adversarial networks to improve solution space diversity and convergence efficiency, adapting to complex scenarios; (3) Strengthening the engineering closed loop, establishing actual case libraries, collecting measured data through IoT sensors to iteratively optimize the model, and developing scenario-based generation strategies for severe cold and hot-humid climate zones to enhance the universality of the method.

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