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Research Article

Evaluation of Thermal Insulation Performance of Building Exterior Wall Based on Multiobjective Optimization Algorithm

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A complete evaluation of conflicting and nonlinear multiperformance is referred to as an evaluation system. Therefore, multiobjective optimization research for building performance is of great importance. Considering the above problems, this paper proposes a multiobjective performance optimization platform at the architectural design stage. The optimization research is combined with the basic algorithms. It is based on Grasshopper software. It aims to provide a fast and effective method for the optimization design of sustainable buildings. It is important to note that this workflow has no restrictions on what to optimize for or what to target, and can be determined on a case-by-case basis. To evaluate the use of the work platform and make the research results more extensive, the standard model of the inner corridor space building in office buildings in cold areas was extracted. The extracted standard model was taken as the final research object. At the same time, the convergence, distribution, and comprehensive evaluation indexes of the simulation results were analyzed. The quantitative influence parameter system of window parameters on the total building energy consumption, lighting uniformity, and glare probability was established. A series of parametric design models based on the comprehensive optimal solution of building energy consumption and lighting quality was obtained. The main purpose of this paper is to design a green building design method based on the principle of goal-oriented design. This paper, combined with the group search function of nondominated genetic algorithm (NSGA-II), the energy consumption of the building, and the evaluation function of indoor thermal and humid environment, is obtained and linked with MATLAB. The energy consumption of residential buildings and indoor thermal comfort were taken as the optimization objectives of the design scheme. The automatic optimization model of the architectural design scheme was established. Finally, the Pareto solution set of the architectural design scheme is obtained, and the designer can select the appropriate design scheme of the Pareto solution set according to the actual situation of the project, to meet the requirements of green building design. The design scheme optimized by this method can effectively reduce building energy consumption and improve indoor thermal comfort.

1. Introduction

The construction industry, along with transportation and industry, has been the top energy consumer in China. According to China Energy Statistical Yearbook 2016, the construction industry consumed around 910 million tons of standard coal, accounting for 26 percent of total end energy consumption in China. The enormous usage of energy products has resulted in a slew of societal issues. Various climatic disasters caused by the greenhouse effect have occurred on a regular basis in recent years, and environmental concerns have been placed on the agendas of all

countries and have become critical issues that must be tackled immediately. Our government has proposed a sustainable development strategy that calls for the simultaneous growth of the environment and the economy. As the concept of sustainable development is introduced, building energy conservation begins to transform into green buildings. A green building is a building that follows the concept of sustainable development in the whole life cycle. It saves resources to the greatest extent, protects the environment, and reduces pollution. It also provides a healthy, comfortable, and efficient living environment for people. It adapts to the surrounding environment harmoniously. For the past

two years, China's green building has entered a stage of rapid development, showing a trend of rapid growth. At the same time, the domestic academic research on green building has mushroomed after the rain.

There is now a wide spectrum of green building research in the academic community, but it primarily focuses on the development of a green building evaluation index system, the selection of assessment techniques, and the economic evaluation of the entire life cycle. Most research on economic assessment begins with a macro perspective and builds the overall evaluation model based on different perspectives. There is no relevant standard for the economic evaluation of green buildings. Building energy conservation is an important component of green building evaluation. Because of the complexity of the green building itself, it is very difficult to make an overall economic evaluation of it. As a result, this research chooses an energy-saving green building project to investigate its local economic influence on green building. On this premise, the study article performs energy-saving optimization in order to obtain the best cost performance of the energy-saving green building project.

Green building development in China has been limited as a new idea in the construction sector owing to implementation costs and advantages. The uncertainty of additional cost and incremental value, in particular, causes developers to adopt a conservative approach to the creation of green buildings. Because energy-saving projects make up a substantial amount of green building projects, the choice of energy-saving solutions will have a direct impact on the size of additional costs and incremental benefits. The ability of developers to make scientific decisions determines whether the economy of green building energy-saving solutions can be adequately analyzed. Therefore, it is of great significance to select and optimize energy-saving schemes based on the focal degree of minimizing incremental cost and maximizing incremental benefit. Specific performance is given in the following aspects:

(1) Provide Evaluation Tools for Decision-Makers: Based on the composition analysis and measurement of incremental cost and the incremental benefit of energy conservation projects, this paper establishes an incremental comprehensive benefit evaluation model, which is convenient for participants to have a clear and profound understanding of incremental cost and the incremental benefit of energy conservation of green buildings, to make a scientific evaluation of the design scheme.

(2) Provide Optimization Tools for Decision-Makers: Through the energy conservation optimization model, the best energy conservation scheme is selected to provide decision-making reference for the participants of green construction, to achieve the construction goal of minimizing incremental cost and maximizing energy conservation benefit.

(3) Provide Supplements for Deficiencies: To provide some supplements for the deficiencies of the existing

theoretical research and pave the way for further in-depth research in the future, the existing theoretical research is insufficient in the optimization of green building energy conservation projects, and the multiobjective optimization model proposed in this paper makes up for this defect to some extent. Although the research depth is insufficient, it provides a reference for further research by scholars.

Initially, Caldas and Norford et al. combined the energy consumption simulation software DOE2.1 E with a genetic algorithm, set the minimum annual building total energy consumption as the objective function, and conducted optimization studies with the position and size of windows in different orientations of office buildings as independent variables [1]. Coley and Schukat also adopted the form of energy consumption simulation software combined with a genetic algorithm, set the minimum annual total building energy consumption as the objective function, and optimized the research by taking the thermal conductivity and heat capacity of the model as the design variables [2].

In terms of building energy consumption, the data statistics show that the thermal insulation and thermal insulation performance of the transparent envelope and the traditional wall are very different. The performance of the traditional wall varies only from 1/6 to 1/5 in the building running energy consumption. The proportion of the transparent envelope is about 40% to 50%. During refrigeration, the heating energy consumption for two square sides results in poor heat prevention and poor effect of heat insulation. This poor heat prevention is the result of the transparent envelope structure that consumes the heating load from 30% to 50% and summer refrigeration load from 20% to 30%, respectively. A transparent enclosure structure, on the other hand, brings natural light within, decreases lighting energy consumption, and reduces the usage of lighting equipment at the same time. It may also minimize lighting equipment for interior heat and reduce air conditioning load. In terms of architectural lighting, the window of a place, size, area, types of glass, and other important parameters directly affect the quantity and quality of the indoor lighting environment. This includes uniform luminance value whether it meets the requirements from multiple aspects, such as day-lighting or glare in office buildings. The comfortable indoor light environment has an extremely important role on the members of the building. The impact of windows on building lighting should be given priority.

After the introduction, the literature review of the paper has been discussed. After that, the building performance evaluation index has been discussed in which the building energy consumption and the importance of lightning have been explained deeply, following that the simulation methods and optimization results have been discussed. Lastly, the research paper has been concluded.

2. Related Work

In this paper, the influence of building energy consumption considering thermal insulation, thermal insulation

performance, energy utilization characteristics, and building lighting considering lighting characteristics performance is the key research part. This section further explains the literary analysis of the study.

2.1. Research on Thermal Insulation.

At the end of the 1980s, the research of intelligent optimization algorithms entered its heyday, and it has been successfully applied in many fields, such as optimal control, data mining, mechanical design, shop scheduling, logistics, and distribution because intelligent optimization algorithm has outstanding ability in dealing with complexity and constraint. It also has the ability to deal with nonlinear, multiminimum, large-scale, and other problems. It attracts architects to apply it to building performance optimization, solving the problem of the cumbersome optimization process. In the past, single optimization results have saved a lot of simulation work and time. There are many types of intelligent optimization algorithms, such as artificial neural networks, genetic algorithms, particle swarm optimization (PSO), simulated annealing, tabu search, and hybrid optimization strategy. These algorithms are focused on the single objective optimization, and then the multiobjective optimization algorithm, to a large extent. It solves the building performance multiobjective optimization problems, and the diversity of optimization schemes has been greatly improved at the same time.

In many cases, there is more than one target in the simulation optimization research of building performance. At this time, there are two main solutions. The first one is to use the weight coefficient method to transform multiple targets into single targets by setting different weight coefficients for different objective functions. The second is the multiobjective evolutionary algorithm, which is capable of dealing with complicated difficulties that are difficult to solve with traditional optimization methods. Palonen and Hasan et al. used Hooke–Jeeves and PSO hybrid algorithm to optimize the insulation layer of the envelope to minimize energy consumption in the whole life cycle [3]. Radiance and Sakamoto combined radiance with the genetic algorithm to optimize 21 parameters, including window size, position, shadow, and reflectivity and made maximum use of natural light [4]. Holst adopts the Hooke–Jeeves algorithm to minimize the dissatisfaction ratio of the building's annual total energy consumption and thermal environmental comfort, adopts the weight coefficient method to change the two objectives into one, and optimizes parameters such as window-wall ratio, glass type, and transmission coefficient [5].

Mahdavi used hill climbing, SA, and stage optimization algorithms to optimize the structural form and thickness of the building envelope. The algorithm aims at indoor temperature, building energy consumption, and light environment comfort. The weight system method integrates multiple objectives into one, which greatly reduces the trouble of optimization. The problem is that the optimal solution obtained by optimization is relatively single. It is also an important factor that the weight coefficient method is increasingly rejected by people. In addition, the weight coefficient does take a lot of time. From the perspective of optimization efficiency, the weight coefficient method is not the best solution for resolving multiobjective optimization [6]. The multiobjective optimization algorithm is another method to solve the optimal solution problems. The optimal solution set is also called Pareto front. By using the structured multiobjective genetic algorithm (MOGA), Wang et al., this algorithm aims to minimize the cost consumption and energy consumption of waste disposal in the whole life cycle. It optimizes the structure orientation, wall structure, roof structure, length-width ratio, glass type, and window-wall ratio as design variables [7]. Through the comparison of multiobjective optimization algorithms, Talbourdet et al. presented the most suitable NSGA-II algorithm according to the actual situation. Taking the building energy consumption and cost minimization as the objective function in the whole life cycle, the construction form, construction thickness, and cost of the building envelope are optimized. Moreover, the parameters such as the location and window-wall ratio of the building transparent envelope were optimized [8].

For the two objective functions of minimum energy consumption and minimum total cost, Wright et al. used the NSGA-II optimization algorithm to optimize window design parameters, including window-wall ratio and window height [9]. Magnier and Haghighat combined the multiobjective optimization algorithm NSGA-II with artificial neural network ANN. Taking HAVC system parameters and window parameters as design variables, we consider comfort as much as possible. By building energy consumption as the optimization objective, a widely distributed Pareto front was obtained [10]. Vignesh et al. set the maximum solar penetration for the entire day. By setting the minimum solar penetration time in the afternoon and the minimum building cost as the optimization objectives and by changing the geometric form of the building façade and the interior space of the building, he adopted the Dexen evolution method to obtain the optimal solution. The optimal solutions are compared and evaluated by meeting the above parameters [11]. Lee et al. combined the building energy consumption simulation software TRNSYS and the building natural lighting simulation software Daysim with the intelligent optimization algorithm ModeFRONTIER. The method was used to minimize the building energy consumption. According to the design goal, the algorithm optimized the thickness, form, area, and angle of the PV board of the envelope [12]. In China, one after another scholar has carried out building performance simulation research since the 1990s [13]. The research on building performance optimization has developed rapidly in recent years; although the architectural design stage started late, Chen Fei [14], Su Jianming [14], and Xia Chunhai [15] et al. studied the optimization method of building performance in the architectural design stage.

Li Ziwei selected the commonly used 3D modeling software for architectural design as the platform. He proposed the interface flow of forwarding calculation and reverse optimization of embedded performance simulation plug-in. He has also verified the feasibility of the two

methods with architectural examples [16]. Shan Jie proposed a green building analysis method based on Grasshopper and completed the optimization design of the wind environment of building clusters. He also proposed plane energy-saving for individual buildings and exterior shading components [17]. Han Yunsong also proposed the method of building form generation under the influence of the environment. He proposed this method by using Ecotect and WinAir as performance simulation platforms, Rhinoceros as a geometric modeling platform, and Grasshopper as a parameter programming platform. And the architectural information modeling platform of Autodesk Revit Architecture is also used to evaluate the results. It is verified by an example in light of sunshine and wind environment by the cultural and educational building in an urban college in a cold area [18]. In domestic research, the number of research objectives is not limited to a single study, and many researchers carry out multiobjective studies. In addition, Hou Dan proposed the simulation process of building performance based on an intelligent optimization algorithm. Taking the waiting hall of the railway station as an example, he established a set of energy consumption and lighting simulation optimization platform based on Grasshopper. By taking the total building energy consumption, the total cost of envelope structure, and UDI100-2000 as the target, the geometric variable design method of envelope structure is proposed [19].

3. Building Performance Evaluation Index

Building performance related to energy-saving includes building thermal performance, natural ventilation, and natural lighting. The topic of this study is light environment comfort when combined with the interior physical environment explored in this article, and the indicator that may directly represent whether a building is energy-saving is building energy consumption. Therefore, this section introduces the indicators of natural lighting and building energy consumption in detail.

3.1. Building Energy Consumption.
There are two ways to define building energy consumption: one is the generalized building energy consumption, which refers to the energy consumption in the process of the building life cycle from the production and construction of building materials to the operation, transformation, and disassembly. The other way is the narrow sense of building energy consumption, that is, building operating energy consumption. This method includes heating, air conditioning, lighting, and some other daily life activities generated by energy consumption. In the past, most of the research on building performance mainly uses energy consumption during building operation. The process can better reflect the influence of the building envelope on the building performance index.

The building envelope is divided into two kinds of structures. One is the opaque envelope structure, and the other is the transparent envelope structure. The opaque envelope structure includes a wall, roof, ground, etc., and the transparent envelope structure includes a window, glass curtain wall, glass day-lighting top, transparent glass door, etc. Because of its special role, the window occupies the largest area in the transparent envelope and has the greatest impact on the indoor physical environment. Therefore, it is regarded as the main transparent envelope, and the effect of another transparent envelope on the indoor physical environment can be ignored.

When evaluating the energy consumption performance of buildings during operation, the most commonly used indicators are the annual total energy consumption of buildings, air conditioning energy consumption, heating energy consumption, and artificial lighting energy consumption. The latter is also the three types with the largest proportion of the annual total energy consumption of buildings. Combining the research goal of this paper is to find a window design method to meet the visual comfort and energy-saving. Therefore, the selection of building annual total energy consumption as the optimization target is the overall evaluation of building energy consumption performance. The optimization of this process has the most direct and practical significance.

3.2. Natural Lighting.
The lighting situation is greatly affected by weather factors. With the development of a series of dynamic lighting indexes, existing lighting indexes may be used to better assess the interior lighting environment. Therefore, in addition to meeting the requirements of day-lighting coefficient and day-lighting uniformity in GB 50033–2013, a series of dynamic light environment evaluation indexes are also used in the quality research of the existing light environment. The commonly used parameters in the research are as follows:

3.2.1. Lighting Coefficient (C).
It is defined as "the ratio of the illumination produced by the diffuse light from the overcast sky at a point on a given indoor plane to the illumination produced by the diffuse light from the overcast sky at the same time and the same place on an open outdoor horizontal plane." According to GB 50033–2013, the day-lighting coefficient of office space side window lighting should not be less than 3.0%.

3.2.2. Day-Lighting Uniformity.
It is defined as "the ratio of the lowest value of the day-lighting coefficient on the reference plane to the average value (it can also be expressed as the ratio of the lowest illumination value on the reference plane to the average value)." According to GB 50033–2013, when lighting from the top, the lighting uniformity of office space is required to be no less than 0.7.

3.2.3. Daylight Autonomy (DA).
It is defined as "the proportion of the time when the illumination value of the working face is greater than the critical value of artificial lighting to the total time of the year." DA indicates the efficiency of a building's use of natural light. It was first defined in the Swiss day-lighting design standard in 1989 and then redefined by Reinhart and Walkenhorst. On the

working face, the ratio of the minimum lighting value to the total time of the year to meet the natural lighting standard.

3.2.4. Continuous Daylight Autonomy (CDA).
Based on the research on natural lighting in educational buildings, Professor Rogers first proposed the CDA parameter. In addition to the original DA parameter, the impact of illumination values lower than the artificial opening critical value on the indoor lighting condition has been considered in the computation of the CDA parameter. By calculating the proportion between the illumination value and the critical illumination value, the proportion value is defined as the influence degree of illumination value on the indoor light environment. For example, take the third light climate region as an example. The indoor critical luminance value is 450lx, when the measurement point luminance value is 300lx. It can be concluded that the contribution of natural light to the indoor light environment in this period is 300lx/450lx = 0.67. This parameter indicates that even partial natural light if it is not changed has several benefits for the indoor light environment.

3.2.5. Useful Daylight Illuminance (UDI).
It is defined as "the ratio of the total time of the working surface by a certain range of illumination value to the total time of the whole year." This parameter was first proposed by Mardaljevic and Nabil in 2005. The natural illuminance is divided into three segments. The indicator obtained by it is UDI2000. UDI100-2000, the most extensively used in the study, indicates that the light level may fulfill the usual visual work demands of employees at this time.

3.2.6. Daylight Probability (DGP).
It is defined as "the degree of disturbance caused by glare." It was proposed by Jan Wienold and Jens Christoffersen in 2006. The value of daylight probability ranges from 0 to 1. A larger value indicates a greater degree of interference. Therefore, it can directly reflect people's subjective feelings. Compared with other glare parameters, such as daylight index (DGI) and unified glare rating (UGR), DGP results are more intuitive to evaluate glare interference. On the other hand, the DGP evaluation system solves the defects of glare value in the nonuniform lighting environment that other glare parameters cannot evaluate. Finally, the previous development of the glare parameter equation is used to evaluate the small artificial light source. DGP also solves the defect that other glare parameters are not applicable to evaluate the large light source. In conclusion, the DGP glare parameter is more suitable for building natural lighting environment evaluation than other glare parameters.

Among the above indicators, day-lighting coefficient and day-lighting uniformity are hard indicators, which must be met in the design of natural lighting of buildings. Therefore, in this chapter, they are used as evaluation indicators. The remaining three indexes were taken as evaluation indexes of indoor lighting conditions. Better indoor lighting conditions can be obtained if the DA and UDI100-2000 indexes are large and the DGP indexes are smaller.

4. Simulation Method of Joint Optimization of Building Performance

Because the established optimization model is intended to be performed on areas comprised of hundreds of buildings, the optimum design scheme of this method can efficiently reduce building energy consumption while increasing indoor thermal comfort. Some of the simulation methods that have been performed to evaluate the building performance using multiobjective optimization are discussed below.

4.1. Theoretical Basis of Multiobjective Evolutionary Algorithm.
An evolutionary algorithm is a global optimization algorithm based on the theory of biological evolution with high robustness and wide practicability. It is also highly nonlinear, easy to modify, and parallel. It is capable of dealing with complex issues that are difficult to address using typical optimization algorithms without regard to problem attributes. Regardless of the complexity of the problems, this algorithm has no limitations to be solved by traditional optimization methods. In real life, most numbers are composed of multiple small goals, and these goals are likely to conflict with each other. To achieve the optimal overall goal, subgoals are usually considered comprehensively. The most commonly used method is to compromise the subgoals. Therefore, to solve the problem of multiobjective optimization, the multiobjective optimization algorithm is proposed.

Firstly, the general description of the multiobjective optimization problem is given.

Given the decision vector $X = (x1, x2, \ldots xn)$, it satisfies the following constraints:

$$g_i(X) \geq 0, \quad (i = 1, 2, \ldots, k), \tag{1}$$

$$h_i(X) = 0, \quad (i = 1, 2, \ldots, l). \tag{2}$$

There are "r" optimization objectives, and these "r" optimization objectives are conflicting. The optimization objectives can be expressed as

$$f(X) = (f_1(X), f_2(X), \ldots, f_r(X)). \tag{3}$$

Seek $X^* = (x^*1, 2^*x \ldots xn^*)$, and make $f(X^*)$ in meeting the constraints of (1) and (2) at the same time.

In multiobjective optimization, the optimal solution is usually called Pareto optimal solution, which was proposed by Vilfredo Pareto in 1896. For example, given a multiobjective optimization problem min, its optimal solution set is defined as

$$P^* = \{X^*\} = \left\{ X \in \Omega | \exists X' \in \Omega, f_j(X') \leq f_j(X), (j = 1, 2, \ldots, r) \right\}. \tag{4}$$

Figure 1 shows the general flow of a class of Pareto-based multi-objective evolutionary algorithms. Among them, the nondominant set consists of nondominant solutions, which

refer to the current optimal solution of each generation of the evolutionary population. The nondominated set is constantly approaching the real optimal solution set, and finally the optimal is achieved. The multiobjective evolutionary algorithm is run through the selective algebraic control method, and the nondominated solution set acquired by the last generation is also the ultimate Pareto optimum solution set obtained.

According to different selection mechanisms, multiobjective optimization algorithms can be divided into aggregation function, population-based method, and Pareto-based method. When the aggregation function is linear, it is difficult to find the final optimal solution. In the "speciation" stage based on the population method, there may be some species that are particularly prominent in the population, while others are ignored. Moreover, for some species, all subgoals are considered comprehensively, but the single sub-goal is not the optimal solution. It is likely to be "abandoned" in the selection process. The Pareto-based method integrates the concept of the Pareto optimal solution, which makes the final solution infinitely close to the real optimal solution. After comprehensive consideration of the three methods, the Pareto-based method is finally selected as the basis of the multiobjective algorithm in this paper. The research in recent years is mainly focused on this method.

According to the construction design method of buildings in cold regions, the specific process of annual energy consumption simulation calculation by using the external wall mathematical model with variable building factors described in E2 is as follows:

(1) E2.1: The heating heat consumption per building unit is calculated according to the heating heat consumption model of the building unit in inhabited conditions. In occupied conditions, the heating heat consumption model of the building unit is as follows:

$$q_{km} = \frac{Q_{km}}{A_0} \bullet \frac{t_i - t_e}{t_{ia} - t_{ea}} \bullet \frac{278}{H_r} + \left(\frac{t_i - t_e}{t_{ia} - t_{ea}} - 1 \right) \bullet q_{IH}. \quad (5)$$

(2) E2.2: Calculate the heating heat consumption per building unit under unoccupied conditions using the heating heat consumption model of the building unit. The heating heat consumption model of the building unit under uninhabited conditions is as follows:

$$q_{km} = \frac{Q_{km}}{A_0} \bullet \frac{t_i - t_e}{t_{ia} - t_{ea}} \bullet \frac{278}{H_r} - q_{IH}. \quad (6)$$

QHM is building unit heating heat consumption, W/m²; Qhm is the total amount of heating measured at the thermal entrance of the building during the test duration MJ; QIH is building internal heat per unit floor area, W/m²; Ti is single room average indoor calculated temperature.

According to the design method of building structures in cold regions, the simulation calculation process of carbon

emissions at the stage of building construction, building use, and building demolition as described in E3 is as follows:

(1) E3-1: Create a carbon emission model during the building stage and compute the carbon emissions during this stage using the carbon emission model created during the construction stage. The carbon emission model at the construction stage is as follows:

$$E_{con} = E_{con,1} + E_{con,2} + E_{con,3}. \quad (7)$$

(2) E3.2: Establish the carbon emission model of the building use stage, and calculate the carbon emission of this stage using the carbon emission model of the building usage stage, which is as follows:

$$E_{opr} = E_{opr,1} + E_{opr,2}, \quad (8)$$

where $E_{opr,1}$ is the CO_{2eq} emission generated by the energy consumption of air conditioning and lighting equipment, in a unit of kg, and $E_{opr,2}$ is the CO_{2eq} emission of refrigerant escaping in the construction use stage, in the unit of kg.

(3) E3.3: Establish the carbon emission model of the building demolition stage, and calculate the carbon emission of this stage according to the carbon emission model of the building demolition stage; the carbon emission model of the building demolition stage is

$$E_{dis} = E_{dis,1} + E_{dis,2} + E_{dis,3}. \quad (9)$$

5. Optimization Results and Analysis

Figures 2 and 3 show the distribution of Pareto optimal solutions in all evolutionary algebras. To have an intuitive understanding of the change of objective function value, a box is used to show the change in data. As can be seen from the figure, in the evolution process, the floating range of minimum value of Pareto optimal solution is very small, but the variation range of maximum value is large. The distribution of the solution set of each generation of all objective functions also fluctuates greatly, especially the change of objective function related to lighting uniformity. First of all, from the changing trend of the minimum value of the Pareto optimal solution, with the advancement of evolution, the minimum values of the three objective functions all show a downward trend, which indicates that the distribution range of this index is also gradually expanding. Secondly, in terms of distribution, the median line (mean value) of the three objective functions is in the middle and the distribution range is wide at the later stage of optimization, indicating that the distribution tends to be good.

As shown in Figure 2, the maximum and minimum values of the Pareto optimal solution of each generation vary within 2000 KWh, with a small variation range. In the beginning, the distribution was tilted toward the highest value,
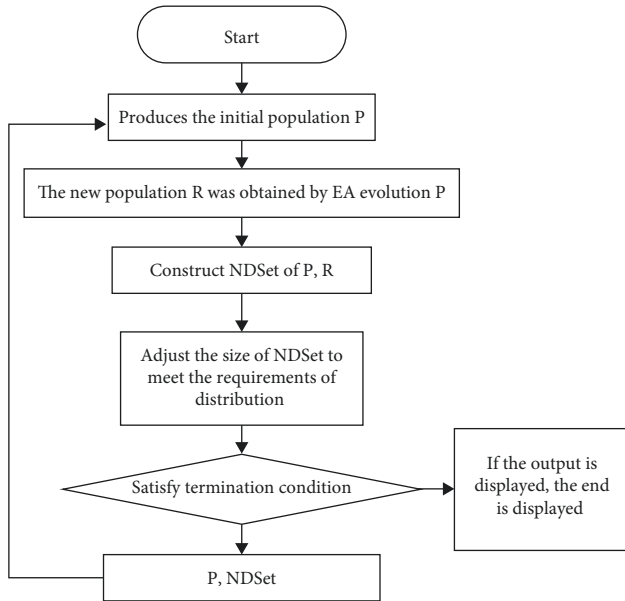
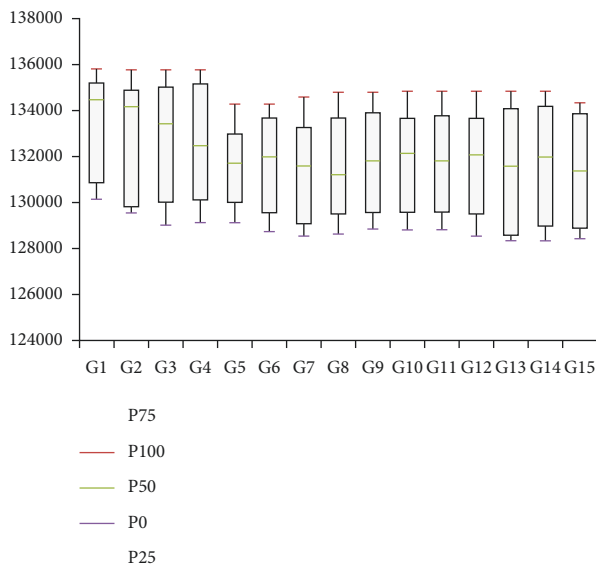FIGURE 1: Operation flow of a class of MOEA algorithms.

FIGURE 2: Distribution of Pareto optimal solution set of each generation of building energy consumption objective function value.
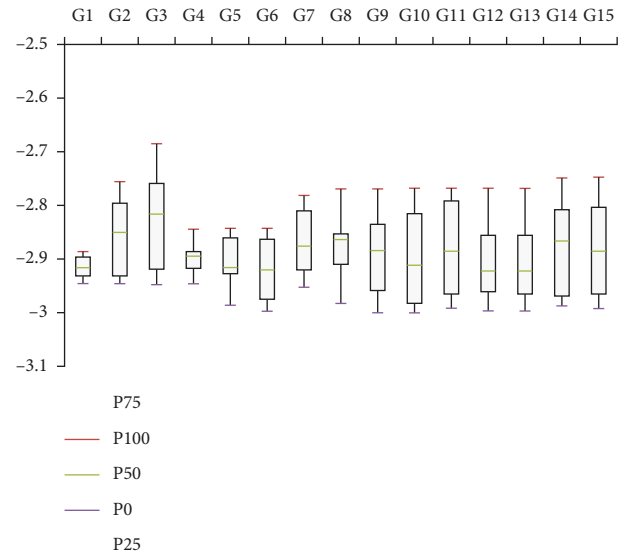

FIGURE 3: Distribution of Pareto optimal solution set of lighting uniformity objective function value of each generation.
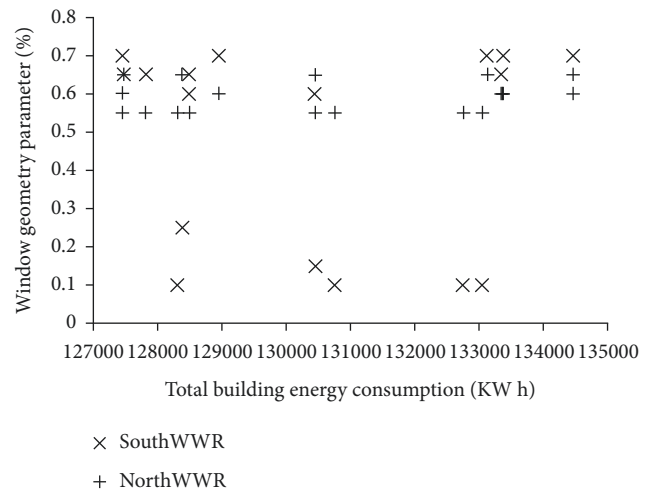

FIGURE 4: Relationship between the objective function value of building energy consumption of Pareto optimal solution and window geometric parameters.

followed by a rather uniform condition with a slight variation, suggesting that the distribution was good.

It can be seen from Figure 3 that no matter the maximum and minimum value and distribution status, the objective function related to lighting uniformity is the one with the most drastic changes among the three objective functions. However, from the ninth generation onward, the maximum and minimum values showed a stable trend and the distribution was getting better and better.

Figure 4 shows the relationship between window parameters (including window-wall ratio, window height, window sill height, and window centerline distance) and the values of the three objective functions in the optimization process under the composition of different variables. In addition, the impact of glass-type factors on the objective function value is not investigated. The fundamental problem is that glass type has four properties, making it impossible to do correlation analysis on just one of them.

As can be seen from Figure 4, there is no specific positive and negative correlation between the objective function values in almost all of the parameters at the same time. To eliminate the causes of this phenomenon is not a single design variable parameter, and there is no correlation between the objective function values. Figure 4 shows only the window-wall than one independent variable parameter changing, and the rest of the parameters are the same. Under the condition that can be seen from the figure, the total energy consumption of the building is positively correlated with the parameters of the

window-wall ratio. On the other hand, considering the three objective functions of building energy consumption, lighting uniformity, and glare occurrence probability, the results of the independent variable parameters obtained in the Pareto optimal solution are comprehensive. Therefore, there are two main reasons for no obvious correlation between the parameters of the independent variable and the objective function value in the Pareto optimal solution set. First, most of the design parameters of the independent variable are in a discrete state. Second, there is no correlation between the three objective function values.

6. Conclusion

This study is aimed at building the design phase of the multi-objective joint simulation optimization. Considering the cold zone gallery board office building as the research object, the standard model of multiobjective joint simulation optimization work platform and flow process are verified. Finally, it aims to get to optimize the building energy consumption and indoor day-lighting quality window design reference number. Due to its special structural form, the transparent envelope has an important influence on many properties of the building, such as building energy consumption, lighting, ventilation, and solar energy utilization. Taking the standard model of a corridor office building in a cold area as the research object, this paper establishes the simulation optimization workflow of building performance based on a multiobjective optimization algorithm. Based on the established joint simulation optimization platform, the building window parameters were optimized to minimize the total energy consumption, increase the lighting uniformity, and reduce the occurrence probability of glare. The workflow has no restriction on the optimization object and optimization target, but can be determined according to the specific situation. In addition, the selection of optimal solutions greatly increased human subjective judgment so that architects can choose according to their design characteristics. This can obtain good architectural performance in the architectural design stage. It will greatly improve the efficiency of architectural design [19].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References

[1] R. Evins, "A review of computational optimisation methods applied to sustainable building design," *Renewable and Sustainable Energy Reviews*, vol. 22, pp. 230–245, 2013.

[2] F. Moore, *Concepts and Practice of Architectural Daylighting*, John Wiley & Sons Incorporated, Hoboken, NY, U.S.A, 1991.

[3] R. Debbarma, S. Kundu, and V. Vineet, "An investigation of daylight performance and energy saving in foundry shed and staircase building," *Int. J. Eng. Innovative Technol.(IJEIT)*, vol. 3, no. 3, 2013.

[4] T. Miyazaki, A. Akisawa, and T. Kashiwagi, "Energy savings of office buildings by the use of semi-transparent solar cells for windows," *Renewable Energy*, vol. 30, no. 3, pp. 281–304, 2005.

[5] C. Wangkadilok, W. Sriratana, N. Tammarugwattana, and L. Tanachaikhan, "An experimental study of natural lighting for energy conservation using top-up control method," in *Proceedings of the 2008 SICE Annual Conference*, pp. 2196–2199, IEEE, Japan, August 2008.

[6] B. T. Griffith, H. Goudey, and D. Arasteh, "Surface temperatures of window specimens: infrared thermography laboratory measurements," *ASHRAE Transactions*, vol. 108, p. 525, 2002.

[7] A. Offiong and A. U. Ukpoho, "External window shading treatment effects on internal environmental temperature of buildings," *Renewable Energy*, vol. 29, no. 14, pp. 2153–2165, 2004.

[8] L. G. Caldas and L. K. Norford, "A design optimization tool based on a genetic algorithm," *Automation in Construction*, vol. 11, no. 2, pp. 173–184, 2002.

[9] D. A. Coley and S. Schukat, "Low-energy design: combining computer-based optimisation and human judgement," *Building and Environment*, vol. 37, no. 12, pp. 1241–1247, 2002.

[10] M. Palonen, A. Hasan, and K. Siren, "A genetic algorithm for optimization of building envelope and HVAC system parameters," *Proc. IBPSA'09*, vol. 11, pp. 159–166, 2009.

[11] F. Trubiano, M. S. Roudsari, and A. Ozkan, "Building simulation and evolutionary optimization in the conceptual design of a high-performance office building," in *Proceedings of the Conference of International Building Performance Simulation Association*, vol. 13, pp. 1306–1314, France, August 2013.

[12] J. N. Holst, "Using whole building simulation models and optimizing procedures to optimize building envelope design with respect to energy consumption and indoor environment," in *Proceedings of the Eigth International Conference*, Netherlands, August 2003.

[13] A. Mahdavi and P. Mahattanatawe, *Enclosure Systems Design and Control Support via Dynamic Simulation-Assisted Optimization*, Beijing University, Sanya, China, 2003.

[14] W. Wang, R. Zmeureanu, and H. Rivard, "Applying multi-objective genetic algorithms in green building design optimization," *Building and Environment*, vol. 40, no. 11, pp. 1512–1525, 2005.

[15] J. A. Wright, A. Brownlee, M. M. Mourshed, and M. Wang, "Multi-objective optimization of cellular fenestration by an evolutionary algorithm," *Journal of Building Performance Simulation*, vol. 7, no. 1, pp. 33–51, 2014.

[16] L. Magnier and F. Haghighat, "Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network," *Building and Environment*, vol. 45, no. 3, pp. 739–746, 2010.

[17] V. S. Kaushik and P. Janssen, "Multi-criteria Evolutionary Optimisation of Building Enveloped during Conceptual Stages of Design," in *Proceedings of the 17th International Conference on Computer Aided Architectural Design Research in Asia*, January 2012.

[18] B. Lee and J. L. Hensen, "Towards zero energy industrial halls–simulation and optimization with integrated design approach," in *Proceedings of the thirteenth international IBPSA conference*, India, 2013.

[19] C. Ye, L. Chen, S. Ni, and J. Zhou, "Evaluation model of forest eco economic benefits based on discrete particle swarm optimization," *Environmental Technology & Innovation*, vol. 22, Article ID 101426, 2021.