Construction of Sustainable Building Performance Optimization Design Model Based on Sensitive Multi-objective Decision-making

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In view of the frequent changes in the building performance scheme and the many factors affecting the indicators, it is difficult to achieve better application accuracy and optimization effect only based on the experience of architects. Moreover, due to the limitation of professional ability, it is difficult to analyze the architectural design process directly with the help of intelligent algorithms, and the interactivity is poor. Based on this, the study proposes an optimization design scheme based on sensitivity multi-objective decision-making, which takes the sensitivity factor into consideration, optimizes the design scheme based on the relationship between architectural variables, and achieves the calculation of the fitness function of the multi-objective problem with the help of intelligent optimization algorithms. The results indicated that the improved algorithm has better convergence and effectiveness when carrying out the selection of program indicators, and it can obtain the average number of performance-attained design solutions is 5.58. After the improvement of the building program, it was found that the influence weight of the glass heat transfer coefficient accounted for a larger proportion, and the error value of the indicator results was smaller, which effectively improved the optimization efficiency of the building. In addition, in the optimized design of the scheme, the number of modifications were less than 12 times, which was much smaller than the number before optimization. The proposed method can effectively provide reference value for architects to carry out program optimization.

Povzetek: Prispevek predlaga model za optimizacijo trajnostne gradbene zmogljivosti, ki temelji na občutljivem večciljnem odločanju. Uporaba inteligentnih algoritmov izboljša natančnost in učinkovitost zasnove ter zmanjša število potrebnih sprememb.

1 Introduction

The development of the global concept of sustainable development and the worsening energy crisis have made sustainable building (SB) has gradually become the mainstream selection. SB emphasizes on minimizing the negative impact on the environment during the whole cycle of building design, construction, operation and demolition, while ensuring the building function, comfort and economy, which has the characteristics and advantages of green environment protection, energy saving and emission reduction [1]. Existing SB design methods have made some progress in improving energy efficiency, utilizing renewable energy, and reducing resource consumption, but there are still limitations. For example, traditional methods often do not consider comprehensively enough when dealing with the optimization of multiple aspects of building performance (BP), or are inefficient in achieving the optimal design solution, and the multi-objective nature of BP optimization design makes the design process complex and difficult to achieve the optimal balance of various indicators [2]. In the construction process, the impact of the physical and chemical environments on the building should be taken into account, analyzed comprehensively, and the relationship between different factors should be grasped in order to effectively realize the embodiment of BP advantages [3]. Therefore, the study proposes a sensitivity-based multi-criteria decision-making algorithm (SMDA) for the SB design model in order to ensure the balance between multiple performance objectives, aiming to provide building designers with an effective decision support tool. The sensitivity measurements of the relevant parameters of the design solution are generally measured mostly by direct or indirect methods, and the specific methods involved are local sensitivity analysis (LSA), labeled regression coefficient ordering, Fourier amplitude sensitivity experiments, and Sobol global sensitivity analysis. LSA is computationally simple, easy to understand and can be applied to most evaluation models. The innovation of the study is to identify and quantify the key factors affecting BP through sensitivity analysis, and the application of multi-criteria decision-making (MCDM) method and improved algorithms can also be used to optimize the building scheme by considering multiple performance indicators, thus ensuring the environmental and economic performance of the building.

2 Related works

MCDM is widely used in various industries as a scheme for evaluating and selecting decision objectives using multiple criteria. To extensively study the sensitivity of multi-criteria decision-making methods, scholars such as Nabavi and Wang proposed a method that uses eight multi-criteria decision-making methods fused with entropy methods and correlation between criteria. The experimental results indicated that for some of the multi-criteria decision-making methods such as gray relational analysis and example-based portfolio evaluation method and simple phase weighting method are not sensitive to three of the alternative decision-making schemes [4]. Scholars such as Basten developed a model for MCDM in order to minimize product maintenance time and repair cost. This model analyzed the total maintenance cost and total maintenance time after generating Pareto bounds using the ε-constraint method [5]. To develop the ratio analysis of Pythagorean fuzzy multi-objective optimization with the addition of a full multiple-form approach to solve multi-criteria decision problems with completely unknown information about the criterion weights, Sarkar and Biswas devised a new distance metric model by combining the Hamming distance and the Hausdorff metric. The model verified the sensitivity of the proposed model by varying the criterion weights affecting the strategy hierarchy [6]. In the field of disposable device technology for biopharmaceuticals, Zurcher et al. proposed a multi-stage decision support method with the objective of reducing the process risk in the pharmaceutical process. This method was experimentally verified by the researchers, who systematically explored and researched the uncertainty in each stage of the pharmaceutical process using the proposed method [7]. In order to study the safe water, use in various places under the global warming environment, Deshbhushan and Rajiv proposed a centralized rainwater harvesting model integrating GIS and multi-criteria decision making. The study compared various predefined criteria by using criterion importance and entropy of inter-criteria correlation and verified in subsequent experiments that the proposed model is informative for practical application assessment [8].

In terms of BP, a large number of current examples show that multi-objective optimization methods can significantly improve BP. To enhance the interaction between the optimization process and the architectural process, Lin et al. proposed a preference-based MCDM method to realize the designer's decision-making preferences during the optimization process, which makes the objective more reliable and improves the optimization efficiency at the same time. Experimental results demonstrated that the constructed method has better convergence and higher preference satisfaction, which is more applicable to the objective decision-making process in the early design stage [9]. To ensure the coexistence between different analysis methods used in the building process, Utkucu and Sozer proposed an approach using building information modeling and integrating the MCDM method and multi-criteria eugenic evaluation. Experimental data demonstrated that the proposed method is able to achieve energy savings of more than 75% and accurately categorize the energy performance of different buildings based on a detailed energy analysis [10]. Xie and Wang used a hybrid MCDM approach to propose a multi-objective lightweighting and crashworthiness optimization design method for complex cross-sectional shapes and sizes of S-rails to determine the set of optimal solutions to weigh the optimal points. The experimental results showed that the total mass of the optimized model is reduced by 25.62% and the performance is improved compared to the initial optimized model [11]. In terms of the configuration of buildings, Seyed et al. proposed a robust clustering multi-objective method based on MCDM to address the uncertainty in the input variables of the pipeline maintenance distribution network. This method incorporated hydraulic simulation, pipeline failure rate prediction, nonlinear interval planning, and multi-criteria decision making. It was important to note that pipeline maintenance is costly and must be carried out on a regular basis. The method was experimentally demonstrated to be able to improve the physical performance of the network by 56% and the hydraulic performance by 35% when implementing optimal instructions, and reduce the annual deficit in node demand to 69% [12]. The study organized the content of past literature and obtained Table 1.

Table 1: Compilation of past literature ideas

References	Methods	Key findings	Limitations
[4]	Using eight multi-criteria decision-making methods to integrate entropy method and inter criteria correlation for scheme selection	Grey relational analysis and case analysis show poor sensitivity	Lack of further definition of the application of limited methods in decision-making problems of different natures
[5]	Established a multi-criteria decision management (MCDM) model for	This method can reduce maintenance time to a certain	The application scope of the model may be limited to

	products to ε- constraint method for generating Pareto boundaries	extent	specific maintenance optimization problems, and constraint methods may be difficult to consider the multidimensional factors of product management
[6]	A metric model combining Hamming distance and Hausdorff metric to solve multi criteria decision-making problems	This model verifies the sensitivity of the proposed model by changing the standard weights that affect the policy hierarchy	The complexity of the model may face difficulties in determining parameters in practical applications, and weight adjustments may overlook the consideration of expert knowledge and experience
[7]	Research on technical issues of disposable biopharmaceutical equipment using multi stage decision support method	Reduced pharmaceutical process risks and validated the uncertainty of each stage in the pharmaceutical process through experiments	This technology needs to be validated in different environments and technologies
[8]	A centralized rainwater collection model integrating geographic information systems and multi standard decision-making was proposed, which compares predefined standards based on the importance of standards and the correlation entropy between standards	This method has reference value for the practical application evaluation of safe water use	The applicability and accuracy of the model may be limited by data quality and availability.
[9]	A preference based architectural MCDM method was proposed to optimize the decision preferences of designers	This method has better convergence and preference satisfaction, improved optimization efficiency, and is more suitable for the target decision-making process in the early design stage	There may be an excessive reliance on designer preference information
[10]	Integrating MCDM method and multi standard eugenics evaluation method through building information modeling	This method can achieve energy-saving effects of over 75% and can be classified based on detailed energy analysis	The complexity of the method is high, and the scope of promotion and application will be limited to a certain extent
[11]	A multi-objective lightweight and crashworthiness optimization design method is proposed for S-shaped guide rails using a hybrid MCDM method	The total mass of the optimized model has been reduced by 25.62%, and the performance has been improved	The specificity between determining the optimal solution and setting conditions makes the method difficult to generalize
[12]	A robust clustering multi-objective method based on MCDM was proposed to solve the uncertainty problem of input variables in pipeline maintenance distribution networks.	The physical performance of the pipeline network has been improved by 56%, the hydraulic performance has been improved by 35%, and the annual deficit of node demand has been reduced to 69%	The specificity between determining the optimal solution and setting conditions makes the method difficult to generalize
Research method	Propose an optimization design scheme based on sensitivity multi-objective decision-making, and use intelligent optimization algorithms to calculate the fitness	This improved algorithm has good convergence and effectiveness, with an average of 5.58 design schemes achieving performance	Research on different types of buildings is an important aspect of improving and optimizing design indicators

	function for multi-objective problems.	standards and less than 12 modifications	

In summary, the research related to MCDM method has been maturely developed and widely applied in various industries, but in terms of building optimization performance, MCDM still has a large space for progress research, based on this, the study proposes the SB characteristic, introduces the sensitivity to analyze the variables affecting the building and improves the design of its design scheme.

3 Construction of SMDA-based performance optimization model for sustainable building

The MCDM algorithm, also known as the multi-criteria algorithm, is developed in the mid-1970s. As a decision analysis method, it can be useful in the phases of system planning, design and manufacturing, focusing on solving problems that may occur in the present or future. Conventional MCDM methods generally include two kinds of MCDM and multi-attribute decision making, which have more mature development in both theory and practice, and therefore the MCDM method has been more widely used. The study is based on the sensitivity multi-objective analysis to optimize the analysis of SB, and to explore its influence variable indicators.

3.1 Construction based on the SMDA algorithm

As in the real situation, architects in the construction industry need to coordinate the variables between different design objectives according to the actual needs in order to solve the conflict of objectives between multiple performances. The process is not a simple comparison and selection, but requires trade-offs between multiple objectives and related parameter adjustments. A SMDA is employed to investigate the design solution and to adjust the performance of the solution and the values of each parameter. The modification of the overall solution is carried out by comparing the values of each parameter's influence weight in the longitudinal direction of the design solution. Multi-objective performance design generally contains more and more complex attribute relationships, should be considered to use a higher degree of adaptation and broader sensitivity analysis method to optimize the BP model, considering the Fourier amplitude sensitivity experiments are relatively higher cost budget, the study uses the Sobol global sensitivity analysis method to calculate the sensitivity of the input values [13-15]. The sensitivity index of Sobol method is calculated as shown in Equation (1).

$$\begin{cases} TS(i) = s_i + \sum_{j=1}^{m} s_{ij} + \ldots + s_{1,2,\ldots,m} \\ \sum_{i=1}^{m} s_i + \sum_{1 \le i \le j \le m} s_{ij} + \ldots + s_{1,2,\ldots,m} = 1 \end{cases} \tag{1}$$

In Equation (1), $TS(i)$ is the total sensitivity index of the input variable x_i and s_i is the first order sensitivity index of the input variable. m is the total number of input variables and s_{ij} is the sensitivity index between the i th input variable and the j th input variable. $s_{1,2,\ldots,m}$ is the sum of the first-order sensitivity values of the input variables. The study modifies specific functional relationships in accordance with the variable relationship between the design objectives and design variables, thereby enhancing the optimization of the functional relationship between the input and output values. The comprehensive performance of the design scheme is identified as the entry point for analysis, with the various factors affecting the BP design scheme serving as the base point. Hierarchical analysis is used to calculate and analyze the sensitivity matrix values of each design variable in terms of the performance of the design objectives and to calculate the weight values of the performance of each parameter of the original solution under this condition. The computational flow of the hierarchical analysis method is shown in Figure 1.

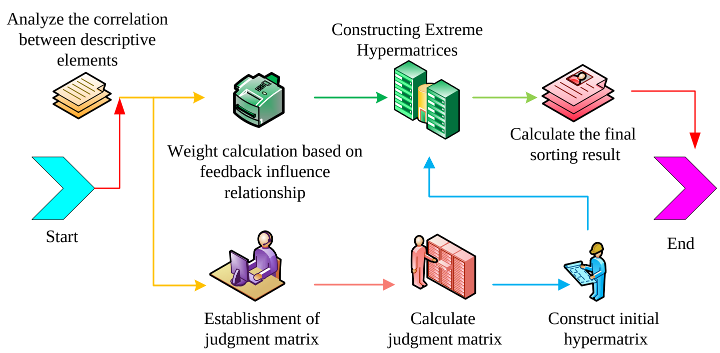


Figure 1: The calculation process of ANP

In Figure 1, hierarchical analysis is required to analyze the decision-making problem in the calculation process and to analyze the correlation of the relevant factors involved, and to judge the independence or correlation between the elements. In the model construction process, the development of a network layer design containing the interrelationships of elements is realized based on the objectives and guidelines for setting up a control layer. The important feature vectors of the quasi-measurement layer to the target layer under a single scenario are calculated using the hierarchical analysis method, and the calculation formula is shown in Equation (2) [16].

$$c_{fi} = k_i (f_i - f_{i,s}) / (f_{i,\max} - f_{i,\min}) \qquad (2)$$

In Equation (2), c_{fi} is the importance feature vector and k_i is the penalty function. k_i takes the value of 1 when the selected performance metrics do not meet the requirements of the adjustment. k_i takes the value of -0.001 when the selected performance metrics meet the requirements of the desired adjustment. f_i is the value assigned to the performance under the scenario, and $f_{i,s}$ is the criterion value of the i th performance under the individual scenario. $f_{i,\min}$ is the minimum value for the i th performance in the database. $f_{i,\max}$ is the maximum value of the i th performance in the database. The hierarchical analysis method is employed to identify the importance eigenvectors of each variable in the scheme layer. Subsequently, the importance eigenmatrix of each parameter under a specific number of parameters is constructed. The resulting importance eigenvectors of the criterion layer and the importance matrix of the scheme layer are calculated to determine the comprehensive impact weights of all the variables on the original scheme. This process yields Equation (3).

$$w = [c_{f1}, c_{f2}, ..., c_{fn}] \begin{bmatrix} c_1^{f_1} & c_2^{f_1} & \cdots & c_n^{f_1} \\ c_1^{f_2} & c_2^{f_2} & \cdots & c_n^{f_2} \\ \vdots & \vdots & \ddots & \vdots \\ c_1^{f_n} & c_2^{f_n} & \cdots & c_n^{f_n} \end{bmatrix} \qquad (3)$$

In Equation (3), w is the comprehensive impact weight of all variables on the original program, $\begin{bmatrix} c_1^{f_1} & c_2^{f_1} & \cdots & c_n^{f_1} \\ c_1^{f_2} & c_2^{f_2} & \cdots & c_n^{f_2} \\ \vdots & \vdots & \ddots & \vdots \\ c_1^{f_n} & c_2^{f_n} & \cdots & c_n^{f_n} \end{bmatrix}$ is the importance matrix under the program level, and the rest of the explanation is consistent with the meaning of the previous section. For the degree of contribution of the first design variable to the current target program, the formula is shown in Equation (4).

$$w_j = c_{f_1} * c_j^{f_1} + c_{f_2} * c_j^{f_2} + ... + c_{f_m} * c_j^{f_m} \qquad (4)$$

In Equation (4), w_j is the contribution value of the design variables to the degree of comprehensive performance improvement of the current target program, and the rest of the parameters are interpreted in the same way as before. According to the size of the obtained contribution value can further determine the improvement ability and enhancement effect on the comprehensive performance of the current research program when the reference variable changes. If the w_j value is >0, the value of the variable should be reduced accordingly, and vice versa, the value of the variable should be increased accordingly.

3.2 Construction of SMDA-based performance optimization algorithm for sustainable building

After constructing the completed SMDA algorithm, the study has been able to calculate the weighting effects of the parameter factors in the original scheme on the scheme, but this does not directly provide the architect with a certain performance-attainment design solution. Therefore, the study weighs each objective on the basis of multi-objective optimization problem decision making, fuses the SMGA algorithm with genetic algorithm (GA), and proposes a method of sensitivity multi objective decision fusion genetic algorithm (SMGA) an intelligent optimization algorithm that will use the objective expectations instead of subjective weights weighting to the computation of the fitness function. Since the GA fused with SMGA algorithm is capable of solving the involved problems at runtime by imitating the relevant principles and phenomena and using heuristics to optimize the problem without prior knowledge of the mathematical characteristics of the solution of the problem to be optimized, its high robustness and practicability have led to a wide range of applications of the GA in the design of building solutions, operation and maintenance of equipment and energy. The functional expression defining the multi-objective adaptation function $G(x)$ is shown in Equation (5).

$$\max G(x) = \sum_{i=1}^{m} k_i * g_i \qquad (5)$$

In Equation (5), g_i is the normalized fitness value of the i th performance objective, and k_i is the penalty function of each performance objective. When i fails, k_i takes the value of 10000, and vice versa k_i takes the value of 1. At a later stage, the normalized fitness values g_i of all the performance objectives are summed to obtain the fitness function of the multi-objective problem. At the same time, the operator is selected for the unqualified performance i and the sifting out of the solutions of the infeasible solution scheme is carried out. In the GA variation session, for the design scheme $x = [x_1, x_2, ..., x_n]$ constructed by the n dimensional decision variables, the weight vector $w=[w_1, w_2, ..., w_n]$ of the influence of each variable on the current scheme is calculated using the SDMA algorithm previously used in the study, by changing the evolution. The maximum variable of lucidity in the process, which in turn improves the objective function. Roulette is performed on the merged population R thus determining the operator, selecting the number of individuals N_p to perform variation and crossover operations on R, calculating the fitness function $F(x_j)$ and normalizing it as shown in Equation (6).

$$F'(x_j) = \frac{F(x_j) - f_{\min}}{f_{\max} - f_{\min}} \quad (6)$$

In Equation (6), $F'(x_j)$ is the normalized fitness function of the interpretation scheme and $F(x_j)$ is the fitness function. $f_{\min}$ is the performance minimum of the explained solution and $f_{\max}$ is the performance maximum of the explained solution. After obtaining the normalized fitness function of the solution, the selection probability of each solution is further calculated and its functional expression is shown in Equation (7).

$$p(x_j) = \frac{F'(x_j)}{\sum_{j=1}^{2Np} F'(x_j)} \quad (7)$$

In Equation (7), N_p is the number of selected individuals. Using the same idea to solve the cumulative probability, the functional expression is shown in Equation (8).

$$q(x_j) = \sum_{r=1}^{j} p(x_r) \quad (8)$$

In Equation (8), r is a member in population R and $p(x_r)$ is the selection probability of the selected member r. Based on the N_p explanatory schemes obtained from the selection operator, further mutation operations are carried out, and in order to prevent the SMGA proposed by the study from over-controlling the individual's best solution scheme and thus falling into a local optimal solution situation, the study stratifies the N_p explanatory schemes obtained. This is formulated as follows: 2/3 of the N_p explanation scheme is used for the previously constructed SMDA algorithm for the mutation operation, and the remaining 1/3 N_p explanation scheme is used for the regular mutation operation. In the variation operation of SMDA, for the j th solution of the scheme $x_j = [x_j^1, x_j^2, ..., x_j^n]$, the weight $w_j = [w_j^1, w_j^2, ..., w_j^n]$ is calculated according to Equation (4) mentioned earlier in the study, which in turn calculates the normalized influence weight of the k th design variable x_j^k. The calculation formula is shown in Equation (9).

$$w_j^k{}' = (w_j^k - w_{\min}) / (w_{\max} - w_{\min}) \quad (9)$$

In Equation (9), $w_j^k{}'$ is the normalized impact weight of the design variables and w_j^k is the weight of the design variables before variance crossover. $w_{\max}$ is the maximum value of the impact weights of all design variables and $w_{\min}$ is the minimum value of the impact weights of all design variables. A random number d is generated for comparison for any design variable x_j^k in the closed interval from 0 to 1. If the randomly generated value d is less than or equal to the normalized weights, the associated k th actual variable is variant. When the normalized weights are greater than 0, the corresponding design variables should be reduced in value accordingly and a new design variable is randomly generated at the $[d_{\min}, x_j^k]$ as a new design variable participating in the mutation crossover. The conventional variation operation is to use a fixed rate of variation instead of normalized weights when performing variation operation on a single design solution [17]. When the value of the selected random number of values in the selected interval is less than the fixed rate of variation, the same randomly generates a new design variable in $[k_{\min}, k_{\max}]$ for the variation operation [18, 19]. The flow of the SMGA algorithm proposed in the study is shown in Figure 2.

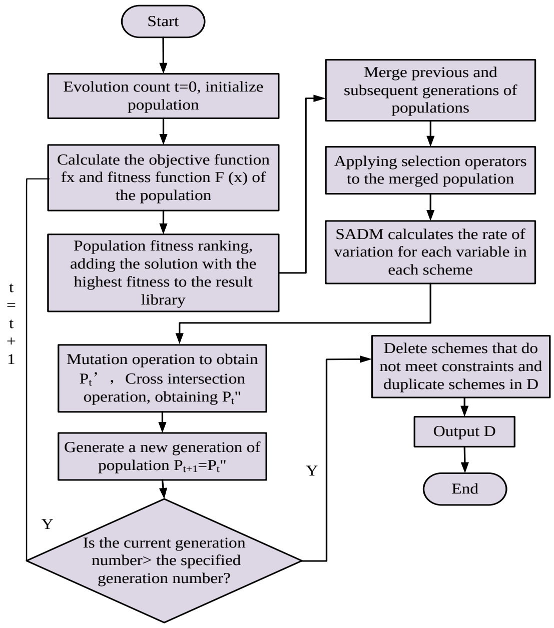


Figure 2: Schematic diagram of SMGA algorithm flow

In Figure 2, after the mutation operation and part of the regular operation using the SDMA algorithm, it is necessary to carry out the corresponding population crossover operation on the population after the end of the mutation operation. For the j th solution $x_j = [x_j^1, x_j^2, ..., x_j^n]$ obtained using the SDMA algorithm a number c is randomly generated in the interval [0,1]. if the selected value c is smaller than its corresponding selection probability p_c, a crossover operation needs to be carried out on it, and the parent generated by the crossover operation for the c_1 th solution is $x_{c1} = [x_{c1}^1, x_{c1}^2, ..., x_{c1}^n]$. subsequently, an indexed value c_2 is randomly generated in $[1, N_p]$ and another crossover parent is generated $x_{c2} = [x_{c2}^1, x_{c2}^2, ..., x_{c2}^n]$, and a randomly generated bit value v_c in [1,n] is used to confirm the position of the selected parent scheme at crossover. In turn, a new scheme x_{c1}' is obtained, whose functional expression is shown in Equation (10).

$$x_{c1}' = [x_{c1}^1, x_{c1}^2, ..., x_{c1}^{vc}, x_{c2}^{vc+1}, ..., x_{c2}^n] \tag{10}$$

Perform crossover operation for each solution in the population to get a new generation of population. Set the number of iterations to loop from computing the objective function and fitness function to the crossover operation. Determine whether the number of iterations has reached the maximum number of iterations, and thus determine whether to stop the optimization to output the optimal solution set. Finally output the optimal solution set and process the result database to remove the solutions and performances in the database that do not meet the set expectation and output the optimal solution set of the remaining solutions.

4 Examination of the effectiveness of the application of sustainable building performance optimization design

In the method design section, the research first constructs a multi-objective decision-making algorithm based on sensitivity, and calculates the matrix values and weight values of the target performance under the variables in the architectural scheme design. Concurrently, research is conducted on the balancing of various objectives based on multi-objective optimization problem decision-making, integrating the SMGA algorithm with the GA, and using an intelligent optimization algorithm to adjust weight values, thereby avoiding the influence of subjective settings on the results. To validate the efficacy of the proposed algorithm, a case study is conducted on a building in a cold climate to optimize its energy consumption, lighting, and other multi-objective issues. The requisite parameters for the algorithm are then defined. The study set the population size and the number of iterations to be 50, the variation rate to be 0.1, and the crossover rate to be 0.9. The algorithm is optimized for the population on the basis of the initial scheme in the same experimental environment, and the number of experiments is 20. During the experiment, the performance metrics of the GA before and after the improvement are collected and the results are shown in Table 2.

Table 2: Performance results of GA before and after optimization

Number of experiments	Convergence speed		Optimal solution size		The diversity of decision space		Effectiveness	
1	11	4	8	14	0.057	0.071	8.874	9.053
2	12	7	7	7	0.057	0.055	4.516	7.535
3	22	6	5	9	0.06	0.073	7.144	9.748
4	12	6	5	11	0.05	0.054	3.962	8.741
5	7	2	6	12	0.066	0.063	4.823	9.721
6	13	9	6	11	0.062	0.061	7.203	10.208
7	17	6	9	9	0.065	0.065	8.203	9.57
8	16	6	5	8	0.06	0.055	7.027	8.128
9	6	2	7	10	0.054	0.066	7.701	10.174
10	2	7	10	5	0.061	0.049	5.627	7.475
11	15	2	4	8	0.04	0.068	5.8	9.102
12	10	3	8	11	0.057	0.071	8.086	9.065
13	34	4	4	10	0.064	0.068	2.678	10.397
14	12	4	6	8	0.068	0.042	10.292	9.057
15	2	6	6	12	0.059	0.066	6.451	8.861
16	37	6	4	12	0.052	0.077	3.869	10.351
17	23	3	7	9	0.064	0.067	7.027	8.633
18	18	8	5	11	0.059	0.054	7.397	9.238
19	11	5	5	12	0.065	0.069	4.62	7.123
20	11	4	8	14	0.057	0.071	8.874	9.053
Average value	14	4.8	5.85	9.45	0.056	0.059	6.065	8.609

In Table 2, the convergence speed of SAGA algorithm is significantly better than that of GA, and its average value reaches 4.8, which indicates that it needs an average of 4.8 iterations to find the attainment result in the program to be completed, while GA needs 14 iterations. In addition, in the optimal solution size and decision space diversity, the average value of SAGA algorithm reaches 9.45 and 0.059, which is significantly higher than that of GA's 5.85 and 0.056, which indicates that the improved SAGA algorithm can effectively avoid falling into the local optimum, and its probability of finding the optimal solution in the global is increased. The SAGA algorithm can obtain the performance of the average number of design solutions up to the standard is 5.58, and in the analysis of the effectiveness of the algorithm, the average value of the SAGA algorithm is 8.609 is much larger than the GA's 0.065, which shows a better performance advantage. A comparison is to be made between the proposed optimization SAGA algorithm and the decision-making method. Two comparison scenarios are to be set for different orientations of the building. A comparison of the performance results of different algorithms in building scheme design is presented in Figure 3.

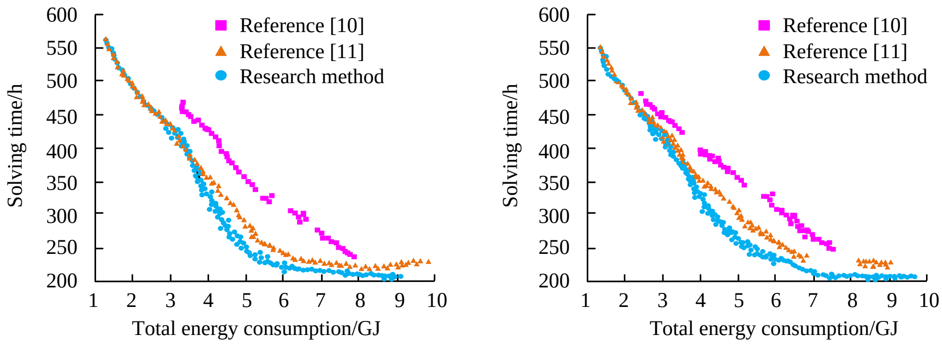


Figure 3: Pareto optimal solution results for different algorithms

The results presented in Figure 3 demonstrate that the convergence of the Pareto optimal frontier solution demonstrated by the SAGA algorithm in southbound buildings is significantly higher than that observed in reference [10]. The discrepancy between the two solutions is more pronounced when the time-energy consumption increases. Furthermore, the solution set distribution in reference [10] is more dispersed, exhibiting poor convergence. The SAGA algorithm reduces the solving time by 13.25% and 5.39% compared to references [10] and [11], respectively, while exhibiting a relatively minor increase in energy consumption. In the architectural design of the Northern Dynasties, the convergence of the SAGA algorithm is demonstrably higher than that of reference [10], and the discrepancy with reference [11] is relatively minor. This discrepancy may be attributed to the fact that reference [11] is capable of considering building parameters to a certain extent, yet its resource consumption during calculation is relatively high. In conclusion, the SAGA algorithm proposed in the study demonstrates satisfactory convergence performance. The decision diversity of the SAGA algorithm is further analyzed to obtain the variance of different decision variables, and the results are shown in Figure 4.

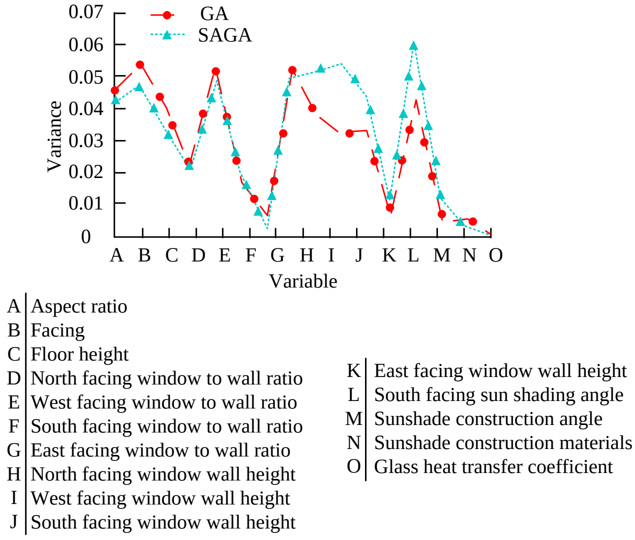
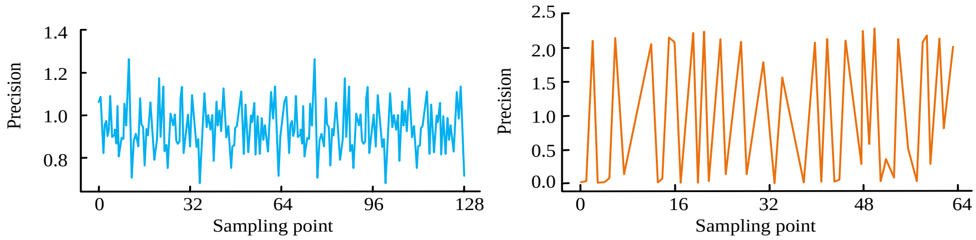


Figure 4: The variance results of two algorithms on decision variables

In Figure 4, overall, it seems that the SAGA algorithm has less variance results than the GA for the building target variables, in which the SAGA algorithm is more sensitive to the sill height, shading angle, shading member angle and material, and glass heat transfer coefficient (GHTC)) variables, and the diversity in the optimal solution is lower. Improving GA can effectively increase the sensitivity of the building variables. The study first analyzes the extraction effect on the acquired sample data and examines the variable extraction effect of the improved algorithm proposed in the study, and the results are shown in Figure 5.



(a) Before improvement (b) After improvement

Figure 5: Variable extraction effect of improved algorithm

In Figure 5, the improved algorithm shows a better sample accuracy effect, and its overall node distribution is more uniform, which can better identify the data features. The study takes the standard floor building in the cold northern region as an example, and optimizes its energy consumption and lighting with the help of Energy Plus software and Radiance software. Application results supplement: The proposed method will be used to analyze the error rate of variable data for buildings of different heights, as shown in the Figure 6.

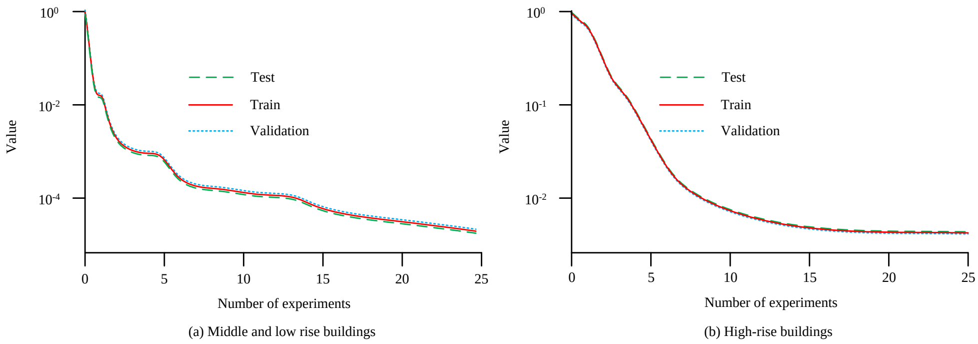


Figure 6: Error rate of variable data for buildings with different floor heights

The results presented in Figure 6 indicate that in mid- to low-rise buildings, the error rate value of the analysis of building parameter variables in the study shows a decreasing trend. Furthermore, there is a small error amplitude between the analysis and the actual effective value, with the minimum error value less than 10-4. In high-rise buildings, the algorithm proposed in the study is capable of obtaining building variable data with a minimum error value of less than 10-2. The research is based on the building model construction platform, in which the parameter programming platform is Grasshopper, with the help of Honeybee+ and other plug-ins for performance simulation and analysis, and the rest of the programming language is Python. The initial variable design of the building model is shown in Table 3.

Table 3: Variables of building models

Variable	Initial plan	First improvement	Second improvement
A	1	1	1
B	0	0	0
C	4.5	4.5	3.7
D	0.48	0.48	0.48
E	0.36	0.36	0.36
F	0.48	0.48	0.48
G	0.36	0.36	0.36
H	1	1	1
I	1	1	1
J	1	1	1
L	1	1	1
M	0	0	0
N	Aluminum alloy	Aluminum alloy	Aluminum alloy
O	2.4	1.2	2.4

On the initial building scheme, its storey height and GHTC are optimized and designed respectively. In the first improvement, the GHTC is adjusted downward from 2.4 to 1.2, and in the second improvement, the storey height is varied from 4.5 to 3.7. The results of the performance of the scheme under the improvement are obtained and shown in Figure 7.

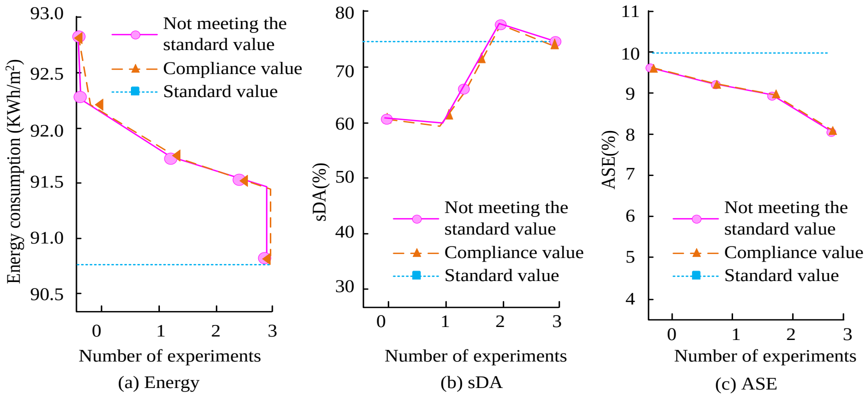


Figure 7: Performance results of the improved scheme

In Figure 7, after the improvement of the initial scheme, the energy consumption of the building is significantly reduced, and its value is reduced to reach 89.89 KWh/m2 and its performance is up to standard. Among them, the sDA indicator has a small decrease after the program modification, but it is still in the range of meeting the standard. The above results show that the modified program is effective. Subsequently, the variable impact weights of the program are analyzed and the results are shown in Table 4.

Table 4: Variable influence weights of improvement plans

Variable	Initial plan	First improvement	Second improvement
A	-0.00689	-0.002564	-0.03809
B	0.000064	0.00439	-0.031136
C	0.152747	0.157073	0.121547
D	0.050189	0.054515	0.078989
E	0.046116	0.050442	0.014916
F	0.0923524	0.0966784	0.0611524
G	0.132656	0.136982	0.101456
H	-0.000253	0.004073	-0.031453
I	-0.000286	0.00404	-0.031486
J	-0.000006	0.00432	-0.031206
L	-0.000031	0.004295	-0.031231
M	0.002013	0.006339	-0.029187
N	-0.008959	-0.004633	-0.040159
O	0.227903	0.272229	0.296703

In Table 4, the values of GHTC for the scheme design with the help of SADA algorithm have weighted values of 0.272229W/m2K and 0.296703W/m2K for the first improvement and the second improvement, respectively. The solar coefficient of the glass has a more obvious impact in the optimization of the scheme design, so the influence of this indicator should be paid attention to in the future research. The predicted results of the sDA indicator are analyzed and the results are shown in Figure 8.

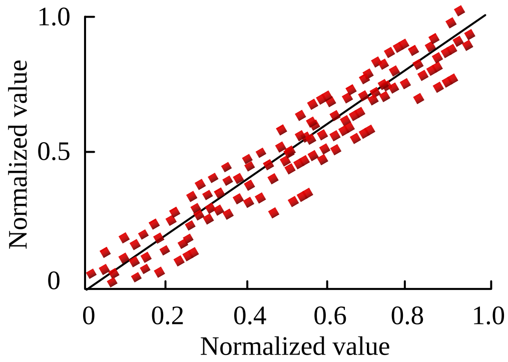


Figure 8: Fitting results

In Figure 8, the sDA indicator is analyzed in the prediction, which has a high consistency with the actual value, and its value is basically distributed on both sides of the curve. The proxy results of ASE indicators are further analyzed, and their results are shown in Table 5.

Table 5: Proxy of ASE indicators

Variable	1	2	3	4	5
R2	0.689	0.668	0.637	0.648	0.627
	0.605	0.584	0.553	0.564	0.543
RMSE	0.076	0.055	0.024	0.035	0.014
	0.81	0.789	0.758	0.769	0.748
MAE	0.059	0.038	0.007	0.018	-0.003
	0.064	0.043	0.012	0.023	0.002

In Table 5, the error results of ASE results under different number of experiments are small and the fitted values are less than 0.70 in both training and test sets, and the mean values of RMSE and MAE values reach 0.078 and 0.063 in the training set, and 0.061 and 0.067 in the test set. A total of 30 architectural professionals and engineers are also invited to modify the initial under test The design solutions are modified, and their modification criteria are based on their subjective experience in obtaining the rest of the metrics, except for the three properties mentioned in the study. The modification idea of the comparison is to modify the design variables by the system modification suggestions generated by the SADM algorithm, and the data statistics of the modifications under the two approaches are shown in Figure 9.

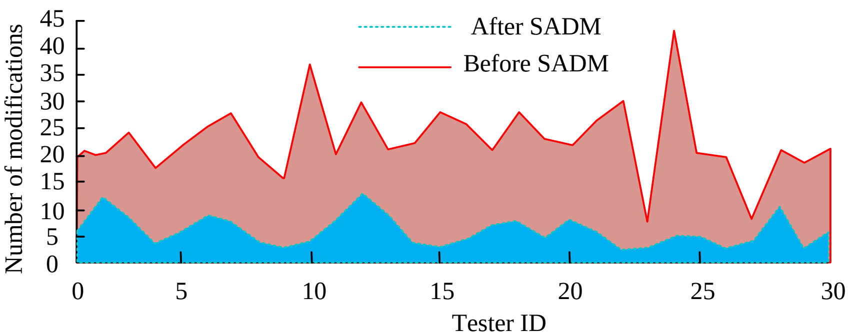


Figure 9: Number of modifications with and without the guidance of SADM method

In Figure 9, when the testers optimize the scheme without system recommendations, the number of modifications are more than 15 times, of which the maximum value is 43 times, and the average number of modifications is 22 times. While in the program recommended optimization suggestions, the tester's modification times are significantly reduced, the overall curve of the large fluctuations are significantly reduced, the number of modifications are less than 12 times, the minimum number of modifications is reached 3 times. Subsequently, the energy consumption and lighting test results of the proposed algorithm are analyzed. Three cities are selected for analysis: Beijing, Harbin, and Changchun. The results are shown in the Figure 10.

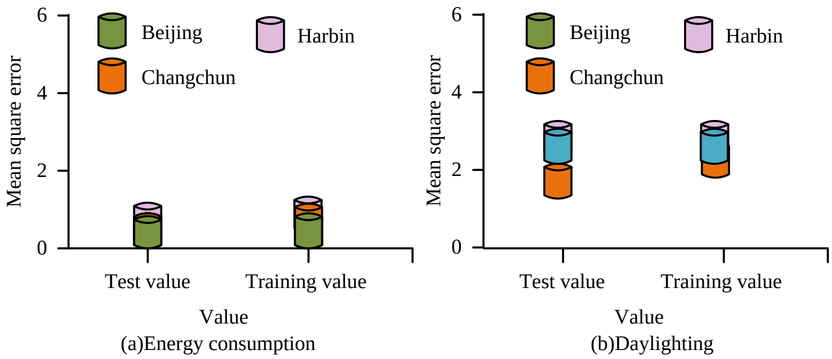


Figure 10: Test results of mean square error of SAGA algorithm in typical cold regions

Figure 10(a) depicts the mean square error of the energy consumption prediction results. It can be observed that the SAGA algorithm exhibits high accuracy in testing building energy consumption in three cities, with the error value between the test results and actual results tending to be close to 0. In the lighting results (Figure 10(b)), the SAGA algorithm also demonstrated favorable test results, with a maximum mean square error of 4 and a minimum value of 1.6. Specific analysis of the energy consumption of the building after optimization, the results are shown in Figure 11.

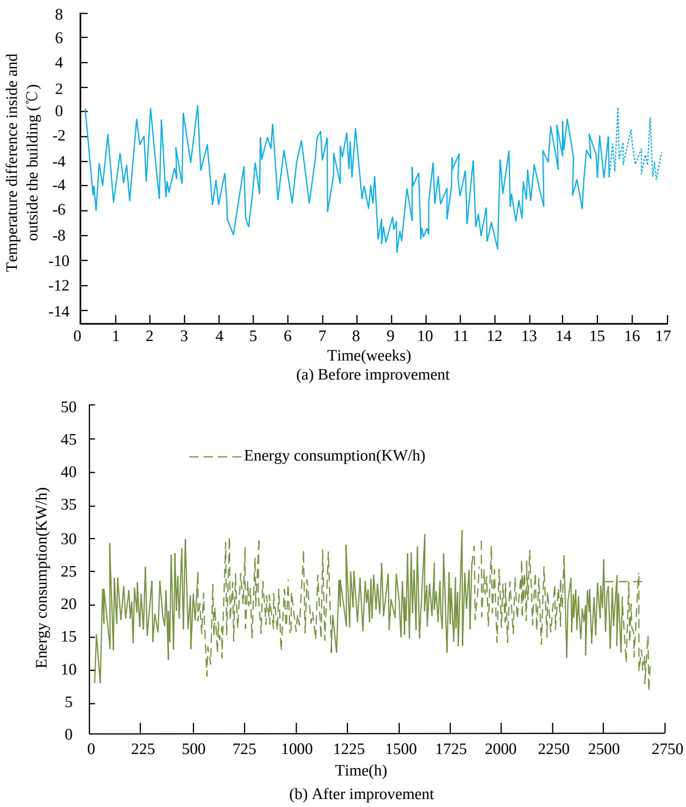


Figure 11: Water temperature change and energy consumption in hydronics

When the outdoor temperature fluctuates greatly with obvious nodal ups and downs, the temperature difference between the inside and outside of the building decreases, resulting in lower energy consumption. This also leads to a smaller overall volatility of the curve, effectively ensuring the building's low energy consumption.

5 Discussion

This research examines the optimization of SB performance design based on sensitivity multi-objective decision-making and its subsequent application analysis. The results presented in Table 2 and Fig. 3 demonstrated that the proposed SAGA algorithm exhibits superior convergence compared to traditional GA and other comparative algorithms. The SAGA algorithm required only 4.8 iterations to reach the optimal value, whereas the GA requires more than 10 iterations. The GA exhibits a tendency to converge poorly due to its proclivity to fall into local optima. In response to the limitations of the GA, scholars such as Saryazdi SME have also combined the GA with artificial neural networks to achieve construction design optimization [20]. References [10] and [11] employed multi-objective decision-making methods based on decision-maker preferences and building information model fusion for the evaluation of BP. Nevertheless, their reliance on subjective expert decision-making and high resource consumption resulted in suboptimal overall convergence of the two references. The Pareto solution set distribution in reference [10] was relatively dispersed, and the SAGA algorithm reduced the solution time compared to references [10] and [11] by 13.25% and 5.39%, respectively. In the context of data processing, the SAGA algorithm demonstrated superior accuracy in sample extraction when the variance of the building target variable was less than that of the GA. Moreover, the variable data was smaller in buildings of different heights, and the minimum error values were less than 10-4 and 10-2 in mid-to-low-rise and high-rise buildings, respectively. This outcome can be attributed to the fact that a sensitivity-based analysis of building parameters allows for a more comprehensive consideration of factors such as lighting, floor height, and building materials, which in turn ensures a high degree of consistency between test results and actual outcomes. This result was analogous to that presented in literature [13], which demonstrated the efficacy of multi-objective decision analysis on variables in improving the effectiveness of design outcomes. Following the implementation of an enhanced initial plan, the energy consumption of the building was reduced to 89.89 kWh/m2, thereby meeting the established performance standards. The predictive analysis of sDA indicators demonstrated a high degree of consistency with the actual values. The results of the building energy consumption analysis demonstrated that the optimized plan effectively ensures low energy consumption of the building. This result was consistent with the findings of previous literature. Among these, literature [21] employed the simulated annealing algorithm and sensitivity analysis to address multi-objective issues in architectural design, while literature [22] utilized an enhanced Garson algorithm and sensitivity based on parameter design to quantify building envelope structures. Both studies have demonstrated the efficacy of sensitivity analysis in the context of building parameters.

6 Conclusion

The study introduces SMDA to analyze the performance optimization of SB and examine the effectiveness of its application. The results indicated that the convergence speed of SAGA algorithm was significantly better than that of GA, and its average value reached 4.8, which indicated that it needed an average of 4.8 iterations to be completed to find the attainment result in the program. Furthermore, in terms of optimal solution size and decision space diversity, the average value of the SAGA algorithm reached 9.45 and 0.059, which is significantly higher than that of the GA, which is 5.85 and 0.056. The SAGA algorithm was more sensitive to sill height, shading angle, shading member angle, and material, as well as GHTC variables. In the case study, after the improvement of the initial scheme, the energy consumption of the building was significantly reduced, and its value reduction reached 89.89 KWh/m2. The values of the building's GHTC were weighted with values of 0.272229W/m2K and 0.296703W/m2K for the first and second improvements, respectively. The predicted results of the sDA metrics exhibited a high degree of consistency with the actual values, the fitted values of the ASE were less than 0.70 in both the training and test sets, and the mean values of the RMSE and MAE values reached 0.078 and 0.063 in the training set and 0.061 and 0.067 in the test set. The efficiency of the testers in carrying out the programmed multi-objective optimization was significantly improved with the suggested modifications of the algorithm. The proposed method of the study can effectively improve the performance of optimal building design and its performance for multi-objective optimization problems is better. Enriching the types of buildings studied and further supplementing the variable indicators are important elements for the study to focus on in the future.

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