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Research Article

A Multiobjective Optimization Algorithm for Building Interior Design and Spatial Structure Optimization

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Based on the global big data environment, people have more and more requirements for the interior design and spatial structure of buildings, and the traditional design has been unable to meet people's needs, and the importance of artificial intelligence decision-making is reasonably reflected in the process of building interior design and space structure optimization. There are a variety of algorithms for artificial intelligence decision-making, artificial neural networks, and correlation coefficient analysis methods, and expandable interior design mining methods are currently being continuously improved and evolved, and these algorithms are used to analyze each case and then screen and finally obtain the optimal results, and the proposed multiobjective optimization and constraint optimization make the research work provide a new strategy for the design development of the data age. In the case of the Library of Extremely Cold Lands, the solution set quality of the nonadaptive solution is verified, the convergence, uniformity, and extensiveness are optimized, and then the experimental process is analyzed, and finally the multiobjective conclusion that building interior design and spatial structure still needs to be further optimized for artificial intelligence decision-making is obtained.

1. Introduction

In the globalized international environment, artificial intelligence will have an immeasurable impact on human life in the future, and it will play a crucial role in the design of designers in design decision-making. The essence of artificial intelligence is a tool, and, in the process of design innovation, it should play its four major dimensions of responsibility of anticipation, reflection, negotiation, and response. Design has an important driving force for social innovation, and responsible artificial intelligence should be linked to design decision innovation to bring better development to social innovation [1]. Every designer has a preference; according to the preferences of each designer to improve the efficiency of design decisions, ResNet artificial intelligence is proposed, and decision accuracy can be effectively improved. Decision-making problems and pattern recognition problems are transformed into each other, effectively avoiding the adverse effects of designers' decision-making preferences [2]. The computational model consists of two aspects, visual distance and viewing angle, which are used to analyze and evaluate the spatial quality of the building, and then these methods are used to evaluate the combination to obtain the spatial quality of each subdivision of the enclosed space [3].

The problem of housing based on artificial intelligence should be investigated and solved from three aspects: its concept, method, and realization technology. Artificial intelligence can achieve more optimized design decisions for housing from many aspects to optimize its spatial structure with multiple objectives [4]. The computational nature of architectural design consists of design thinking and process characteristics, and the important points in computability are mainly information, mapping, and decision-making [5]. Users generate and maintain spatial objects in computer-aided design models that contain geometry for such bounded regions that can be used to calculate area and volume equivalents associated with that region. The area and volume calculated according to the geometry of the space object may comply with the established criteria for calculating the total area, net area, and useable area of the building or other structures. This is through the use of big data and artificial intelligence to design the interior of a building [6].

Not only is the interior design of a building related to the interior designer, but also the architect of its building has a say in it. Interior designers pay attention to many aspects including color, lighting, and decoration which will have a certain impact on people; a good interior design will have a pleasant mood for people, as well as physical comfort of the work. The architect's supervision of the designer is also crucial. The addition of artificial intelligence will make design decisions more accurate, and artificial intelligence decisions are very popular in interior design and space structure [7]. Using the ACT-R cognitive architecture and reconstructing it into Python ACT-R is conducive to the exploration of possible models and architectures based on the core ACT-R theory. Eventually, it will allow us to investigate the possibility of using basic ACT-R components in a new way [8].

In today's international environmental protection environment, the new concept of green innovation is proposed for interior design and space structure, which is to reduce building consumption and greenhouse gas emissions, and artificial intelligence decision-making can put forward constructive suggestions for indoor building design and add appropriate green innovation concepts to establish an environmentally friendly indoor environment [9]. In tropical areas, due to its extreme summer weather conditions, ventilation of buildings, and shading and heat dissipation, multiobjective optimization problems are proposed, capturing the needs of regional households and conflicting goals that need to be optimized, and a lexicographic method is adopted. To visualize pareto curves, a two-objective analysis based on the ε constraint method is used. The proposed model provides guidance to designers through AI decision-making, resulting in optimized designs and layouts to ensure the sustainability of the buildings they design [10].

We study networks that connect geospatial midpoints, such as transportation networks and the Internet. We found that there are strong features in these terrain and usage pattern networks that make the shape of the network very different from each other as well as nongeographic networks. We explain these differences in terms of the costs and benefits of transportation and communications and give a simple model based on Monte Carlo optimization that reproduces the qualitative characteristics of the network under study well [11]. Recent architectural theories can be combined with charts; charts are the embodiment of previous experience and needs, as well as an integration of data; the embodiment of big data through charts can make artificial intelligence decisions to use for building interior design and space structure for strict multiobjective structural optimization. Charts are becoming more and more common in everyday life, and the use of charts is becoming more and more important in today's era of big data artificial intelligence [12]. The problem to be solved is as follows: provide a modular and modular building structure that can be adapted to a wide range of applications and arbitrarily molded. The solution is a combination of basic units and assembling multiple modular units in 3D to construct the building structure. The surface of the module unit is covered with surface decorative panels, and at least one surface of the module unit is shielded, living space, and so forth; non-transparent metal or wood panels, translucent glass structures, openable windows, or door structures form a frame section at the end of the module unit, and each functional panel can be attached to a variety of applications [13].

Architectural space is an important element of social phenomena that reflect social, economic, and cultural change. This study is to provide research materials for theoretical data on regenerative methods. The main method of this research is to analyze reports and papers of regenerative companies and institutions, and the study also analyzes objective cases from four perspectives [14]. First, from an aesthetic point of view, the combination of historical space and new space is manifested as an interdependent relationship and an interdependent structure. Second, from an economic point of view, changes in spatial programmes have led to the regeneration of regions. Third, from a functional point of view, accessibility improvement is reflected through the characteristics of community formation and space openness, and, from a psychological point of view, image construction based on community formation and architectural symbolic design achieves regional regeneration. This study analyzes through various case studies characteristics of regenerative strategy design and through these studies aims to use artificial intelligence decision-making to contribute to the establishment of appropriate regeneration directions to maintain the characteristics of historic buildings [15].

2. Research Methods Related to Artificial Intelligence Decision-Making

In view of the current building interior design and spatial structure multiobjective optimization, a variety of advanced technologies of artificial intelligence are introduced, building interior design and spatial structure optimization decision support system modeling research, a combination model is established, the existing methods are improved, and new algorithms are proposed. Apply artificial intelligence technology, overcome practical problems one by one, use classical statistical forecast and advanced machine learning methods, and verify model; use data interpolation method to solve outlier problems in data; apply correlation coefficient analysis method for statistical evaluation and forecast related factor screening; apply signal decomposition algorithm and group intelligence algorithm to improve model prediction accuracy.

2.1. Statistical Forecasting

2.1.1. Autoregressive Moving Average Model. The autoregressive model is a statistical method for processing time series. In the natural regression model, there are inevitable errors, and the accumulation of these errors is the meaning of the moving average model, reducing the random volatility of the prediction. It has a better estimation and resolution capability than the two basic models, with the following formula:

$$\mathrm{X}t = \varphi_0 + \sum_{i=1}^{p} \varphi_i \mathrm{X}_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \quad (1)$$

where Xt is the value of the variable X at moment t; $\varphi 0$ is a constant term; p and q are the order; φi is the autoregressive coefficient; θi is the moving average coefficient; εt is the error.

2.1.2. Differential Integration of the Autoregressive Moving Average Model. Differential integration of the mobile autoregressive average model, which transforms the non-stationary time series into the stationary time series processing through the differential operation, is an extension of the autoregressive mobile average model. The formula is as follows:

$$\left(1 - \sum_{i=1}^{p} \varphi i L^i\right)(1-L)^d \mathrm{X}_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right)\varepsilon_t, \quad (2)$$

where L is the lagging operator and d is the order of difference.

2.2. Artificial Neural Networks. Artificial neural network is the simulation of the brain neural network from the perspective of information processing. Just like the human brain, the connection of neurons forms a model in which neurons are nodes. This model is an operational model whose output varies from the structure and parameters of the network, which can be explained in nature or requires expression logic.

2.2.1. BP Neural Networks. Back-propagation Neural Network (BPNN) is a multilayer feedforward neural network [16]. In addition to the input and output layers, there is also a hidden layer. The data pass through the hidden layer from the input layer. If the expected output is not achieved, the data will flow back and iterate to make it close to the expected output.

2.2.2. Radial Basis Function Network. Radial basis function (RBF) is a function of the nonnegative, nonlinear local response to the central point. RBF network structure is not as simple as it looks, but it has a strong ability and learning speed and is nonlinearly projective, which is widely used in research fields such as timing analysis. The structure and calculation formula are as follows:

$$y_i = \sum_{i=1}^{h} w_{ij} \exp\left(-\frac{1}{2\sigma^2}\|x - ci\|^2\right), \quad j = 1, 2, \ldots, n. \quad (3)$$

where y_i is the output; w_{ij} is the connection weight of the implicit layer and the output layer; σ is the variance of the basis function; $x = (x_1, x_2, \ldots, x_m)^T$ is the input sample; ci is the center of the hidden layer node; m, h, and n are the numbers of nodes in the input layer, the implicit layer, and the output layer, respectively.

2.2.3. Generalized Regression Neural Networks. General regression neural networks (GRNNs) are improvements on RBF networks that combine radial basis neurons and linear neurons [17]. Dealing with nonlinear problems is better than RBF and is widely used in signal processing, control decision system design, and other fields. The structure and calculation formula of GRNN are as follows:

$$\begin{aligned}
pi &= \exp\left[-\frac{(x - x_1)^T (x - x_i)}{2\sigma^2}\right], \quad i = 1, 2, \ldots, n, \\
S_D &= \sum_{i=1}^{n} p_i, \\
S_{Nj} &= \sum_{i=1}^{n} y_{ij} p_i, \quad j = 1, 2, \ldots, k \\
y_j &= \frac{S_{Nj}}{S_D}, \quad j = 1, 2, \ldots, k,
\end{aligned} \quad (4)$$

where p_i is the mode layer output; S_D, S_{Nj} are the two types of output of the summation layer, namely, arithmetic summation and weighted sum of all mode layer outputs; $y_{ij}$is the i-th element of the output sample j; y_j is the first element of output j.

2.2.4. Deep Belief Network. Deep Belief Network (DBN) is the generative model of deep learning. RBM consists of visible layer (input data) and hidden layer (feature detection), where nodes are connected and nodes within layers are not connected. The energy function of the RBM is shown in equation (8) and is jointly distributed according to the energy function when determined (equation (9)). Therefore, the principle of DBN is to complete the initialization of BPNN parameters through the training of RBM and to overcome the insufficient local optima and training time caused by random initialization.

$$\begin{aligned}
\varepsilon(v, h \mid \theta) &= -\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij} h_i v_j - \sum_{j=1}^{m} a_i v_j - \sum_{i=1}^{n} b_i h_i, \\
p(v, h \mid \theta) &= \frac{1}{Z(\theta)} e^{-\varepsilon(v,h \mid \theta)} = \frac{1}{Z(\theta)} \exp(-\varepsilon(v, h \mid \theta)),
\end{aligned} \quad (5)$$

where v_j is the input of the j visible node; h_i is the output of the i hidden node; w_{ij} is the weight of both; $a_j$andb_i are deviations of $v_j$andh_i; $\theta = \{w_{ij}, a_j, b_i\}$ is a parameter.

2.2.5. Elman Neural Network. The Elman neural network is a classical recurrent neural network. Elman neural network not only has hidden layers but also adds time-lapse operators through feedback connection; historical data can be recorded to make it better in real time and have better stability, and later RNN also used this structure [18]. Nowadays, recurrent neural networks have been successful in many fields with the following formula:

$$\begin{aligned} h(t) &= f(Ux(t) + Wh(t-1) + a), \\ o(t) &= g(h(t)) = g(Vh(t) + b), \end{aligned} \tag{6}$$

where $x(t)$, $h(t)$, and $o(t)$ are input vectors, implied vectors, and output vectors, respectively; f And j are the implicit layer (commonly used Tansig function) and the output layer (commonly used Purelin function) of the activation function.

2.3. Correlation Coefficient Analysis Method. Correlation coefficient is a statistical indicator of the degree of correlation between variables. Its value is located in [−1, 1]. Positive/negative sign indicates positive/negative correlation between variables, and the correlation degree is usually judged according to the range of values (Table 1). The correlation coefficient has different forms according to the study variables. The three common correlation coefficients are as follows.

2.3.1. Pearson's Correlation Coefficient. Pearson's correlation coefficient was used to quantitatively analyze the linear relationships between the two variables. The calculation formula is as follows:

$$r = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n} (y_i - \overline{y})^2}}. \tag{7}$$

In the above formula, x_i and y_i are the i correlation variables for the pair of samples; $\overline{x}$ and $\overline{y}$ are the x, y average of the sums.

2.3.2. Spearman's Rank Correlation Coefficient. Spearman rank correlation coefficient uses the rank of variables instead of the statistical value and calculates the correlation of two columns of graded and ordered variables, which can be considered as a special form of Pearson's correlation coefficient. Features: as a nonparametric statistic, there is no requirement for data distribution; the correlation coefficient is wider but lower than that of Pearson, and the statistical efficiency is higher; it is not sensitive to extreme values. The calculation formula is as follows:

$$r_s = \frac{\sum_{i=1}^{n} (a_i - \overline{a})(b_i - \overline{b})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n} (b_i - \overline{b})}} = 1 - \frac{6\sum_{i=1}^{n} d_i^{\,2}}{n(n^2-1)}. \tag{8}$$

In the above formula, a_i and b_i are the i level of the sample to the relevant variable; $\overline{a}$ and $\overline{b}$ are the a, b average of the sums; $d_i = a_i - b_i$ is the difference in rank.

Table 1: Ranges and meanings of correlation coefficients.

The absolute value of the correlation coefficient	Degree of relevance
0–0.2	Extremely weak correlation
0.2–0.4	Weak correlation
0.4–0.6	Medium and somewhat relevant
0.6–0.8	Strong correlation
0.8–1	Extremely relevant

2.3.3. Kendall Rank Correlation Coefficient. Kendall rank correlation coefficient is used to reflect the correlation of categorical variables. Features: nonparametric test requires data distribution and Spearman rank correlation coefficient; applicable to ordinal category variables; insensitive to extreme values. The calculation formula is as follows:

$$\tau = \frac{n_c - n_d}{(n(n-1)/2)}. \tag{9}$$

In the above formula, (x_i, y_i): (x_j, y_j) for two sample $x_i < y_i$ pairs and $x_j < y_j$, if and $x_i > y_i$, $x_j > y_j$ or, is a homogeneous pair, otherwise it is an out-of-order pair; n_c is a logarithm of the same order; n_d is an anorder logarithm; n is the total logarithm.

3. Extensible Interior Design Excavation Methods

3.1. Elaboration of Extendable Interior Design Issues. Interior design creation is a systematic and complex process, which covers design philosophy, environmental science, and other disciplines. Interior design follows the objective development law of things, and we can find excellent design [19] under the background of big data. Interior design needs a long time of systematic professional training to create and should be combined with the designer's own ideas to design excellent design works. Of course, excellent designers should also consider the needs of customers and the limitations of objective and practical conditions and will pay their own efforts for the design work, for example, Figures 1 and 2.

The interior design study is based on extended data mining techniques. For example, in Figure 3, the process of design creation is based on a large amount of high-quality design data, based on machine learning, as well as intelligent generation of design strategies for computer-aided design methods. It is driven by two-way data and requirements. In the case of data mining design rules, it is found that the artificial intelligence of interior design will inevitably encounter many problems, quality problems innovation problems, and even the design data into knowledge has become contradictory [20].

Like artificial intelligence learning, using the expanding thinking to face the design works, a reasonable creation and design is carried out. With learning and creation methods like artificial intelligence, we should rationally use human's unique subjective initiative to make dynamic transformation or design and creation.

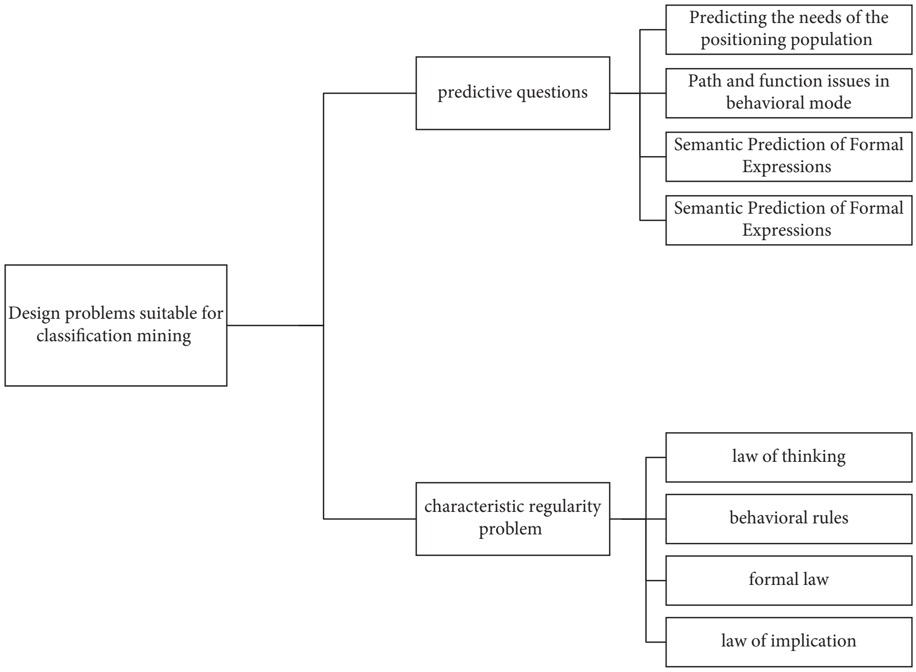

Figure 1: Types of design problems suitable for categorical mining.

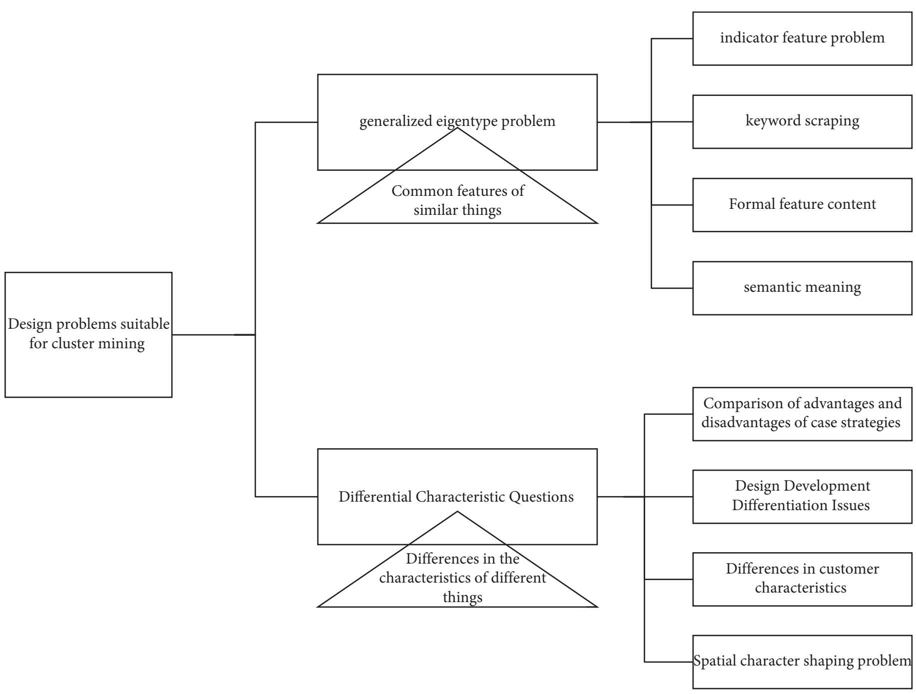

Figure 2: Types of design problems suitable for cluster mining.

However, whether out of the learning of artificial intelligence big data or the learning of human subjective initiative and accumulated experience, the design analysis and discovering its rules are one of the necessary conditions to realize the computer intelligence creation (Figure 4). However, it is worth noting that not all information are valid through data mining.

3.2. Analysis of Extensibility Interior Design Algorithms. If all the content to be expressed in the design is set to the domain U of discourse and any design content in the room $u \in U$, $y \in k(u)$ indicates the degree to which the design of the place meets the actual requirements, that is, the (T) correlation function of the place, then the expandable set of the domain of discussion U is expressed as

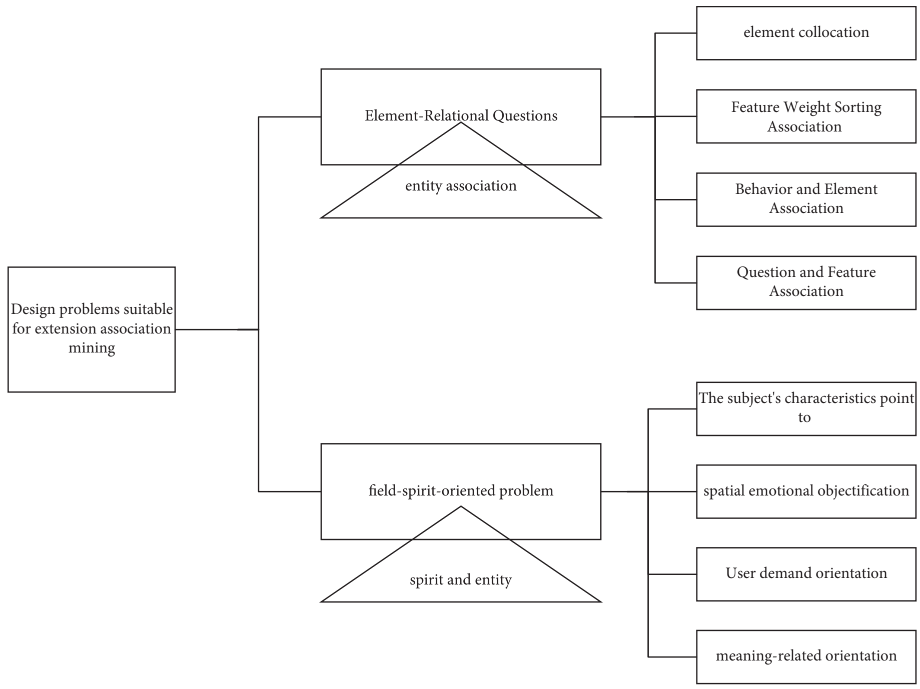

FIGURE 3: Problem types suitable for extendable association mining.

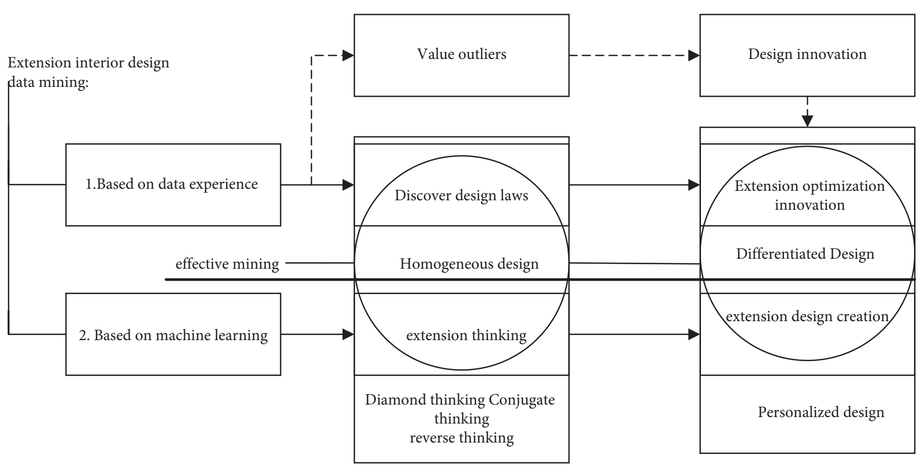

FIGURE 4: Scalable data mining intelligent authoring diagram.

$$E(T)=\{(u,y,y')\,|\,u\in T_U U, y=k(u)\in R, y'=T_k k(T_u u)\in R\}. \tag{10}$$

Where $y' = T_k k(T_u u)$is the extension function of $E(T)$; $T_U, T_k,$ and T_u are, respectively, the extension transformations of the universe U, the association criterion k and the content element u. $T_U T = (T_U, T_k, T_u)$ is the design change plan implemented, and R is the interior design domain.

At this point, the content that coincides with the design goals and design conditions is the positive field E, expressed as $E_+ = \{(u, y)\,|\,u \in U, y = k(u) > 0\}$, that is, the part of the design that is far away from the column, and the column has no obvious oppressive effect on it.

The content that contradicts the design goals and design conditions is the negative field of E, expressed as $E_- = \{(u, y)\,|\,u \in U, y = k(u) < 0\}$; that is, the part that is close to the column and is clearly affected by the compression of the column form is not in line with the design requirements.

The part that basically meets the design requirements and does not meet the use requirements is the zero boundary, which is expressed as $E_0 = \{(u, y)\,|\,u \in U, y = k(u) = 0\}$; that is, the distance from the column is moderate, and the viewing angle makes the line of sight of the column have little impact, which can be used as a zero boundary.

Establish an information metaset of information elements composed of multiple features $S = \{I\}$ and having a $V(C_{oi})x_i$ positive range, as well as the positive domain that meets the requirements of functional space classification X_{oi}, $X_{oi} \subset V(C_{oi})$, and establish a

$k_i(x_i)$, $i = 1, 2, \ldots, m$, evaluation vector for the correlation function I to remember:

$$k(C_0(I)) = (k_1(C_{01}(I)), k_2((C_{02}(I)), \ldots, k_m(C_{0m}(I))) = (k_1(x_1), k_2(x_2), \ldots, k_m(x_m)). \tag{11}$$

At this time, it is possible to establish an expandable set of information elements S on multiple evaluation features:

$$E(I)(T) = \{(I, Y, Y') \mid I \in T_S S, Y = K(I) \in R, Y' = T_K K(T_1 I) \in R\}. \tag{12}$$

4. Optimization Issues

4.1. Multiobjective Optimization. Multiobjective optimization problems convert problem maximization to minimization, also known as multicriterion decision-making problems and multivector optimization problems [21], with the following formula:

$$\begin{aligned} &\min \vec{y} = \vec{f}(\vec{x}) = (f_1(\vec{x}), f_2(\vec{x}), \ldots, f_m(\vec{x})), \\ &\text{s.t.}: \begin{array}{ll} g(\vec{x}) \leq 0, & i = 1, 2, \ldots, q, \\ h(\vec{x}) = 0, & j = 1, 2, \ldots, p. \end{array} \end{aligned} \tag{13}$$

In the above formula, for $\vec{x} = (x_1, x_2, \ldots, x_n) \in X \subset \mathfrak{R}^n$, X is a decision space with n dimensions, and $\vec{x} = (x_1, x_2, \ldots, x_n)$ is a decision vector. For $\vec{y} = (y_1, y_2, \ldots, y_m) \in Y \subset \mathfrak{R}^m$, Y is the with dimension m, $\vec{y} = \vec{f}(\vec{x}) = (y_1, y_2, \ldots, y_n)$ is the target vector. $\vec{y}$ is a mapping from X to Y. X is an n-dimensional cuboid in the decision space, and $x_k' \leq x_k \leq x_k''$, x_k' andx_k'' are the upper and lower bounds of the k-th dimension, respectively, $k = 1, 2, \ldots, n$.

$g(\vec{x}) \leq 0 \, (i = 1, \ldots, q)$ is an inequality constraint, the number of which is q; $h(\vec{x}) = 0 \, (j = 1, 2, \ldots, p)$ is an equation constraint whose number is p.

When $q = 0$ and $p = 0$, there is no constraint condition limit, which is an unconstrained optimization problem. In other cases, they are all constrained optimization problems. In the single-goal optimization problem, the solution is measured by the comparison of target values, and the multitarget optimization problem has multiple conflicting goals, and the solution cannot be determined by the comparison of a certain target value. In the optimization process, in order to achieve multiple goals as best as possible, it is finally necessary to obtain an optimal solution set that balances each goal.

Under the Pareto system, the advantages and disadvantages of the solution in a multiobjective optimization problem are determined by the following definition.

Define 1. Q is the feasible region, if and only if

$$\Omega = \left\{\vec{x} \in X \mid g_i(\vec{x}) \leq 0, i = 1, \ldots, q; h_j(\vec{x}) = 0, j = 1, \ldots, p\right\}. \tag{14}$$

In a decision space, the complement of a feasible field is an unworkable field. The solution in the feasible field is called the feasible solution. Other solutions after the feasible solution are excluded, which is not feasible. If the inequality constraint $g_i(\vec{x}) \leq 0 \, (i = 1, \ldots, q)$ is met, it is said to be $g_i(\vec{x})\vec{x}$ active everywhere. All equation constraints are active for any point in the $h_j(\vec{x}) = 0 \, (j = 1, \ldots, p)$ feasible field Ω.

Definition 1. Pareto Dominate. $\vec{x}_u (\vec{x}_u \in X)$ and $\vec{x}_v (\vec{x}_v \in X)$ are decision vectors, $\vec{x}_u$ is dominated by Pareto $\vec{x}_v$, denoted as $\vec{x}_u \prec \vec{x}_v$, taking minimization as an example, if and only if

$$\begin{aligned} &\{\forall a \in \{1, \ldots, m\}, f_a(\vec{x}_u) \leq f_a(\vec{x}_v)\} \\ &\wedge \{\exists b \in \{1, \ldots, m\}, f_b(\vec{x}_u) < f_b(\vec{x}_v)\}. \end{aligned} \tag{15}$$

At this point, pareto is inferior to meta. If elements and elements do not form a Pareto dominance relation, then $\vec{x}_u$ and $\vec{x}_v$ are said to be noninferior.

Define 2. Pareto Optimality. If and only if no $\vec{x}_v \in X$ exists, this makes $\vec{x}_v \prec \vec{x}_u$, $\vec{x}_u \in X$ called pareto optimal solution.

Define 3. Pareto Optimal Set. For a given multiobjective optimization problem, the optimal solution is defined as the following problem.

For $\vec{f}(\vec{x})$ problems, pareto optimal solution set ρ^* is defined as

$$\rho^* = \{\vec{x}_u \in X \mid -\exists \vec{x}_v \in X, \vec{x}_v \prec \vec{x}_u\}, \tag{16}$$

where ρ^* is a set of all optimal solutions and the individuals in this optimal solution set are called noninferior individuals.

Define 4. Pareto Front.. If ρ^* pareto is the optimal solution set, the pareto frontier ρf^* is defined as

$$\rho f^* = \left\{\vec{f}(\vec{x}_u) \mid \vec{x}_u \in \rho^*\right\}. \tag{17}$$

It is worth noting that ρf^* located in the target space is a ρ^* collection of corresponding target vectors.

4.2. Constraint Optimization Problems. Constrained optimization problems, divided into constrained single-target and constrained multitarget problems, are optimized according to the number of targets. In the general case of minimization, the constrained one-objective optimization problem is described as follows:

$$\begin{aligned} &\min \vec{f}(\vec{x}) \\ &\text{s.t.}: \begin{array}{l} g(\vec{x}) \leq 0, i = 1, 2, \ldots, q, \\ h(\vec{x}) = 0, i = q + 1, \ldots, m, \end{array} \end{aligned} \tag{18}$$

where $\vec{x} = (x_1, x_2, \ldots, x_n) \in X \subset \mathfrak{R}^n$; that is, in the n-dimensional decision space, $\vec{x} = (x_1, x_2, ..., x_n)$ is the decision vector and $\vec{f}(\vec{x})$ is the objective function. $g(\vec{x}) \leq 0 \, (i = 1, 2, \ldots, q)$ is an inequality constraint function, the number is q one; $h(\overrightarrow{x}) = 0\,(i = q+1, \ldots, m)$ is an equality constraint function, the number is $m - q$ one.

Ω is the feasible region, the decision vector $\overrightarrow{x} \in \Omega \subseteq X$, X is an n-dimensional cuboid in $\mathfrak{R}^n$, $x_k' \le x_k \le x_k''$, x_k', and x_k'' are the upper and lower bounds of the k-th dimension, respectively, and k, $k = 1, \ldots, n$. In a decision space, a solution that can satisfy a constraint at the same time m is called a feasible solution, and the feasible field is a space composed of all feasible solutions.

In constraint optimization, equation constraints are often converted to inequality constraints. The degree of constraint violation of individual x on the ith constraint in the population is expressed as

$$G_i(x)\begin{cases}\max\{g_i(x), 0\}, & 1 \le i \le q,\\ \max\{|h_i(x)| - \delta, 0\}, & q+1 \le i \le m.\end{cases} \tag{19}$$

The constraints are m in total. When an equation constraint is converted to an inequality constraint, the tolerance parameter of the equation constraint δ is generally 0.001 or 0.0001. Therefore, the x degree of total constraint violation of the individual is expressed as

$$v(x) = \sum_{j=1}^{m} G_i(x). \tag{20}$$

5. Example Analysis

In the process of experimental design, through artificial intelligence decision for interior design and spatial structure multiobjective optimization of cold library design proposal, through different performance problems and artificial intelligence algorithm for the library construction scheme optimization, and multiobjective optimization analysis, the optimal construction scheme is extracted, in order to achieve the reasonable construction design and spatial structure multitarget optimization design. In addition, it is hoped that this experiment can see whether the multiobjective [22] characteristic of building interior design and spatial structure can be optimized based on artificial intelligence decisions.

5.1. Project Overview. The project is located in the new campus of a university in Harbin, covering an area of about 399,996 square meters. The total construction area of the project is 299,800 square meters, with a green rate of 40% and a floor area ratio of 75%. The shape of the project land is irregular and rectangular, with about 113.8 meters north, 89.8 meters south, 74.8 meters east, 44.8 meters west, and a total area of about 8,000 square meters. It is estimated that the library construction area is about 12,000 square meters, and the construction height of the project is not more than 25 meters. The library needs reading room, storage room, reference, and other functional areas, and the design should guarantee the flexibility of the spatial structure and user experience.

Therefore, designers should conduct multiobjective optimization analysis of various performance and space of the project through artificial intelligence decisions. The data used in this example is shown in Tables 2–4.

5.2. Comprehensive Verification of the Solution Set Quality of Nondominant Solutions. The closer the performance target DA, UDI, and EUI values are to the origin, the concave the overall distribution of marker points in the solution set space to the origin and the better the performance of the optimization target.

5.2.1. Optimize the Convergence Properties. Optimization convergence is to ensure the accuracy of multiobjective optimization and provide reference for the design scheme. The marker point generations in the figure show a concave surface distribution representing convergence, as shown in Figure 5.

Finally, the determination of the convergence can be based on the performance target. Figures 6–8 are the convergence charts of the performance target after iterative calculation, in which the maximum value, minimum value, and average value of each generation of each performance target are the trend charts with the number of iterations. It can be seen that the performance target value tends to be stable after 9 generations, indicating that the optimization process tends to converge. Figures 6–8 show the convergence maps of full natural lighting percentage DA, DI of effective natural light intensity UDI, and energy utilization intensity EUI, respectively. It can be seen from the average of the three plots that the optimization rate tends to a stable state, and there is no significant change in the later optimization process. Therefore, based on the iterative calculation of the maximum, minimum, and average values and the change analysis of the optimization rate, it can be shown that the optimization process shows convergence and does not fall into the local optimal solution.

5.2.2. Optimize the Uniformity. In spacing metric (SM), the main evaluation is to evaluate the distribution of the solution set in space by calculating the distance standard deviation of the last two individuals. This method can relatively objectively reflect the uniformity of the solution set in the target space, and the formula is as follows:

$$\begin{aligned}\Delta' &= \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(\overline{d} - d_i\right)^2},\\ d_i &= \min_j\left(\left|z_1 - z_1'\right| + \left|z_2 - z_2'\right|\right),\\ &(i, j = 1, 2, \ldots, N),\ z = \left(z_1, z_2, \ldots, z_j\right),\end{aligned} \tag{21}$$

where N is the population size, J is the target dimension, and $\overline{d} - d_i$ is the distance of the average to each target.

Figure 9 shows the distribution trend of the spatial evaluation index SM under iterative calculation. As the number of iterations increases, after 9 iterations, the value distribution of SM tends to be stable at about 0.55, indicating

Table 2: Design constants for building exterior morphology and window morphology determined by design practice.

Design constants	Constant name		Study's selection of values	Unit
External morphological yield	Building length		75.6	m
	Building width		42	m
	Column spacing		8.4	m
	The number of space direction spans		9	Straddle
	Depth direction span		5	Straddle
	Number of layers		6	Layer
	Floor height		4.2	m
Window morphological parameters	Through-wall ratio	Eastbound	0.39	Dimensionless
		Westbound	0.29	Dimensionless
		Southbound	0.39	Dimensionless
		Northbound	0.29	Dimensionless
	Window height	South and east	3	m
		North and west	2.4	m

Table 3: Spatial morphological optimization parameters determined by design practice.

Parameter	Parameter name		The range of values	Step	Unit
Central position parameter	Open space orientation	Cut positions 1–3	−4	1	—
		Cut spans 1–3	0–4	1	Straddle
	Depth direction	Cut positions 1–7	0–1	1	—
		Cut spans 1–7	0–2	1	Straddle
		Cut position	0–6	1	—
Edge position parameter	Southbound	Cut the number of spans	0–3	1	Straddle
	Northbound	Cut the number of spans	0–3	1	Straddle
	Eastbound	Cut position	0–2	1	—
	Westbound	Cut the number of spans	0–3	1	Straddle
		Cut the number of spans	0–3	1	Straddle

Table 4: Algorithm parameter settings.

Elite retention	Probability of variation	Rate of variation	The rate of crossover	Population size
0.500	0.100	0.500	0.800	150

that the nondominated solution set gradually tends to be centralized from discrete, and the distance between two individuals in the nondominated solution set gradually decreases. Therefore, it can effectively explain that the uniformity of the solution set of multiobjective optimization in design practice is better.

5.2.3. Wideness of Optimization. As shown in Figures 10–12, all other solutions are distributed on the Pareto front, except for the relationship distribution of DA and EUI. The two endpoints of DA were 54.48% and 94.49%, while the two extreme values of UDI were 16.24% and 78.21%, and the energy utilization intensity (EUI) values were 118.68 and 172.95 kW.h.

Figure 10 shows the distribution diagram of all-natural lighting percentage DA and UDI in 2D space. The two extreme points are (92.78, 16.24) and (54.48, 77.38), respectively. Figure 11 shows the distribution diagram of DA and energy utilization intensity (EUI) in 2D space. The two extreme points are (60.68, 172.95) and (92.46, 123.60), respectively. Figures 12 and 13 show the distribution diagrams of the solution sets of UDI and EUI in 2D space. The two extreme points are (16.24, 127.03) and (75.21, 172.95), respectively. Except for the distribution of the relationships between DA and EUI, all other solutions are distributed on the Pareto front.

5.3. Experimental Analysis Process

5.3.1. Range Distribution Breadth Validation for Performance Targets. The value range distribution of performance objectives is related to the size of the range of solution set space explored by multiobjective optimization. In the design project, the selected optimization goal is all-natural lighting percentage (DA), effective natural lighting (UDI), and energy utilization intensity (EUI). This section analyzes the minimum and maximum values achieved by these three performance objectives and determines the value range distribution of the performance targets by the difference between the optimal and worst values. When the span is large, the proof is better to explore the solution space. Similarly, when the span is small, the proof is not good to explore the solution space.

5.3.2. Trade-Off Verification of Performance Objectives. For natural lighting percentage (DA) and effective natural lighting (UDI), with increasing DA, the UDI value is decreased. The percentage DA of all-natural lighting was positively correlated with energy utilization intensity (EUI), and the UDI decreased with DA value, EUI is inversely related to the UDI energy target, and EUI value gradually increased with

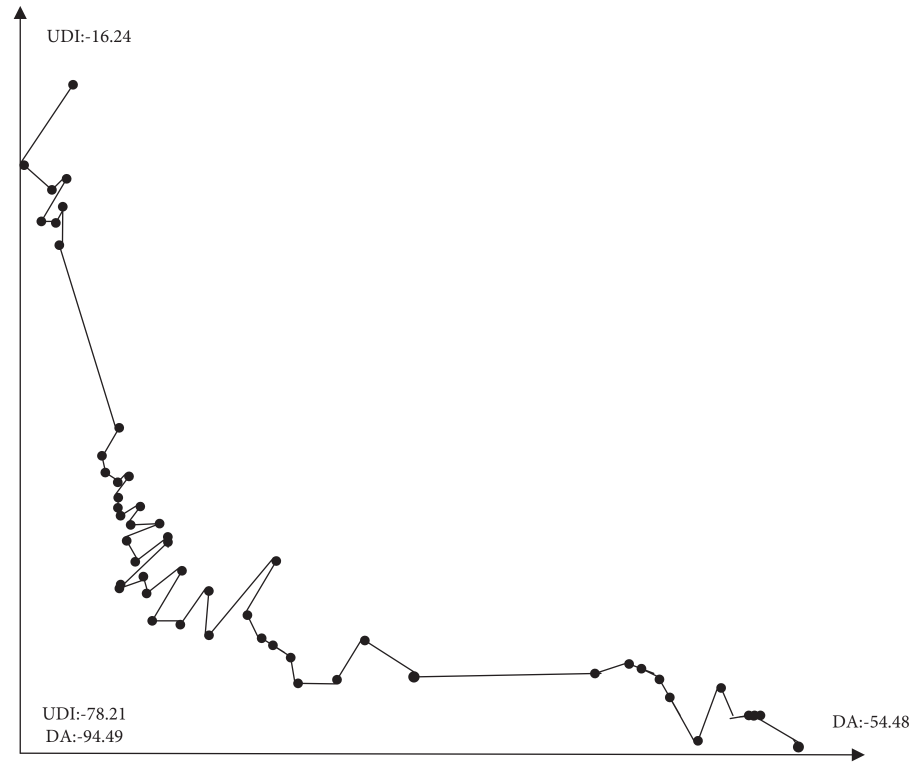

Figure 5: Distribution map of the Pareto frontier.

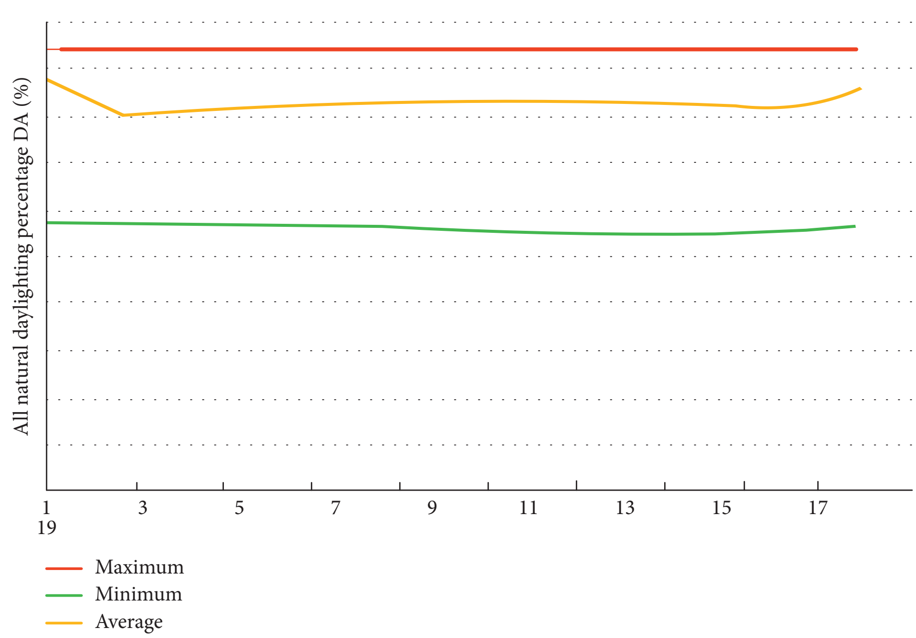

Figure 6: Percentage DA convergence plot of all-natural lighting.

UDI. Therefore, in the process of optimizing the design, each performance requirement, and not only one of its performances, must be taken into account. Firstly, the natural lighting environment of the library should provide a good lighting demand; secondly, consider the energy consumption in the library, and reasonably optimize it to reduce the energy consumption [23].

5.3.3. Optimization and Improvement Effect Verification of Performance Objectives. The improvement of building physical environment performance in the process of design project is the goal of multiobjective optimization design. DA, UDI, and EUI carry out objective optimization design at the same time in the experiment. Table 5 is designed for the practice of multiobjective optimization design of library

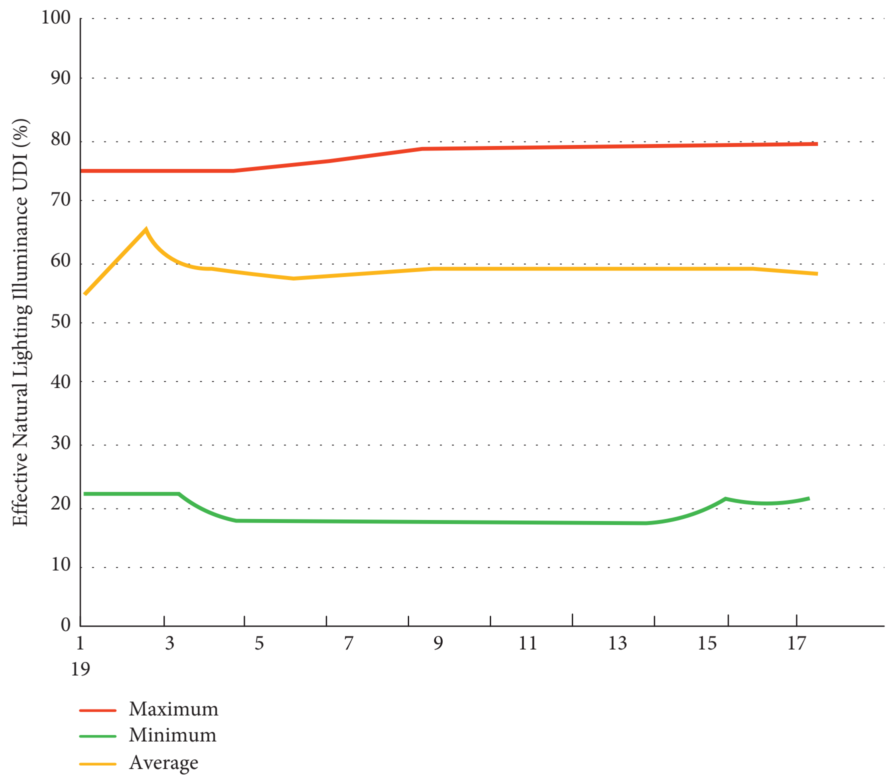

Figure 7: Effective natural illumination UDI convergence plot.

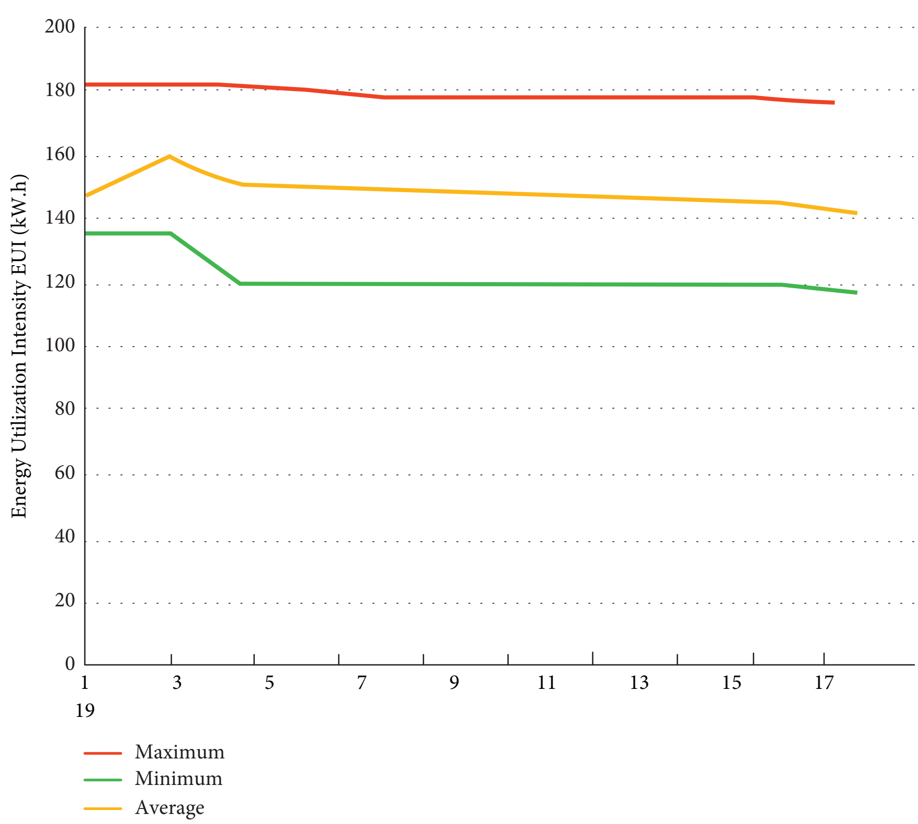

Figure 8: Energy use intensity EI convergence plot.

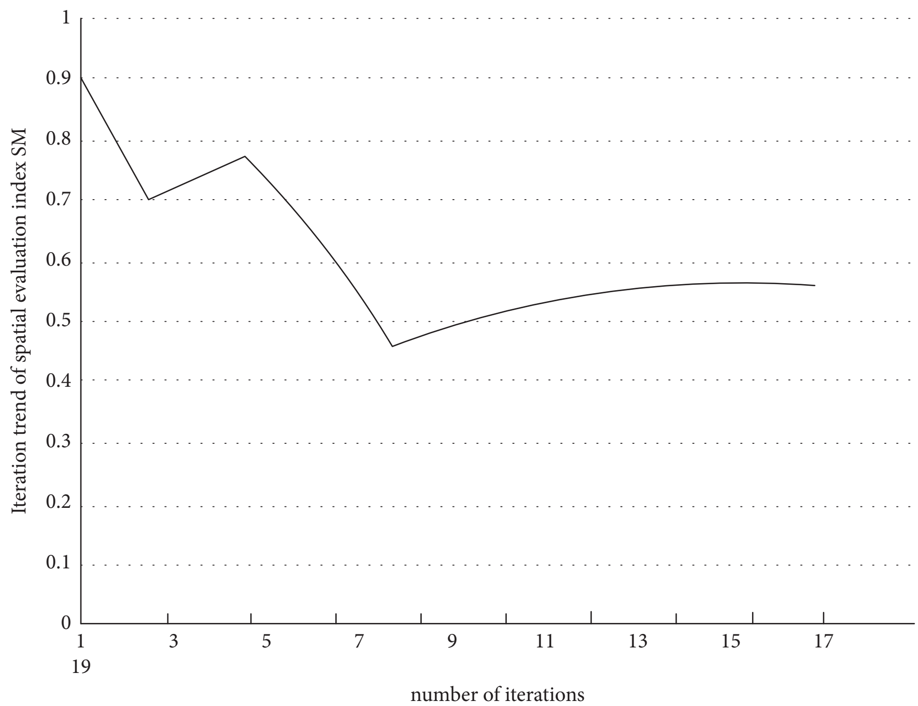

Figure 9: Spatial evaluation index SM iteration trend chart.

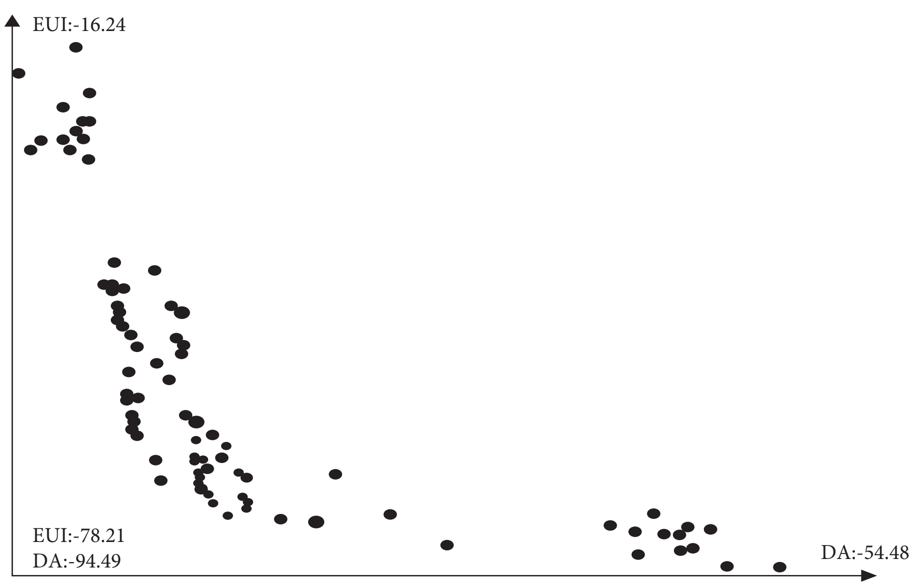

Figure 10: Two-dimensional spatial solution distribution plot of DA and UDI.

building space form. Because there are many nondominated solutions, the designer should analyze them and select the optimal solution.

Although the changes in the spatial form of the building lead to an increase in internal energy consumption, the amplitude is very small, which is worth sacrificing relative to the improvement in natural lighting. Therefore, in general, the changes in the richness of architectural space forms not only bring about complex spatial and visual experience but also improve the natural lighting level, with a slight increase in energy consumption [25].

5.4. Comprehensive Verification Results Analysis of Performance Objectives. The first few sections analyze the design and construction of the library, including the value domain

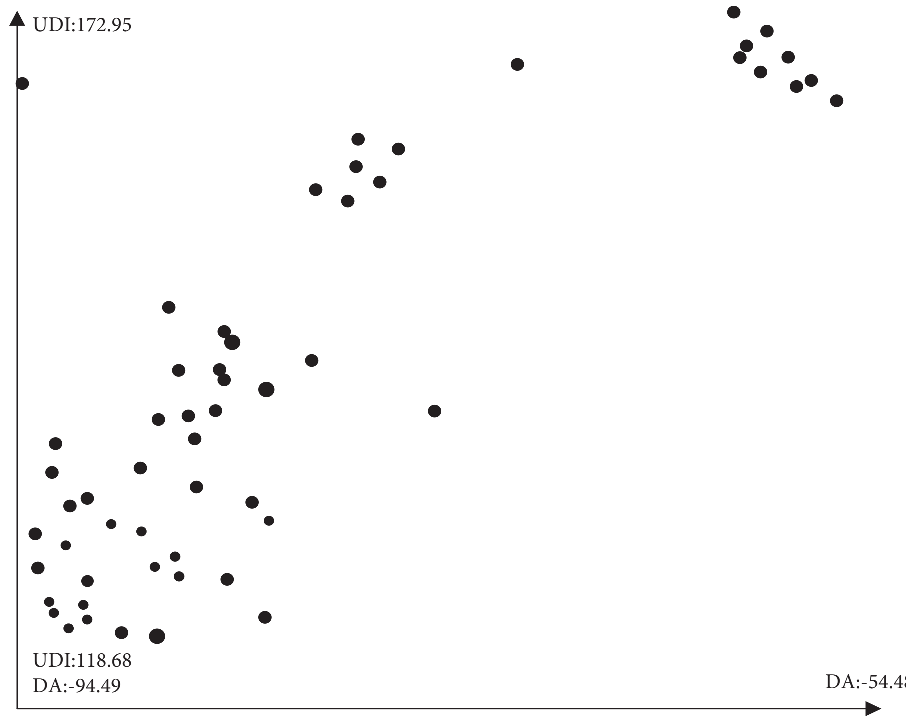

Figure 11: DA and UI 2D spatial solution set distribution plot.

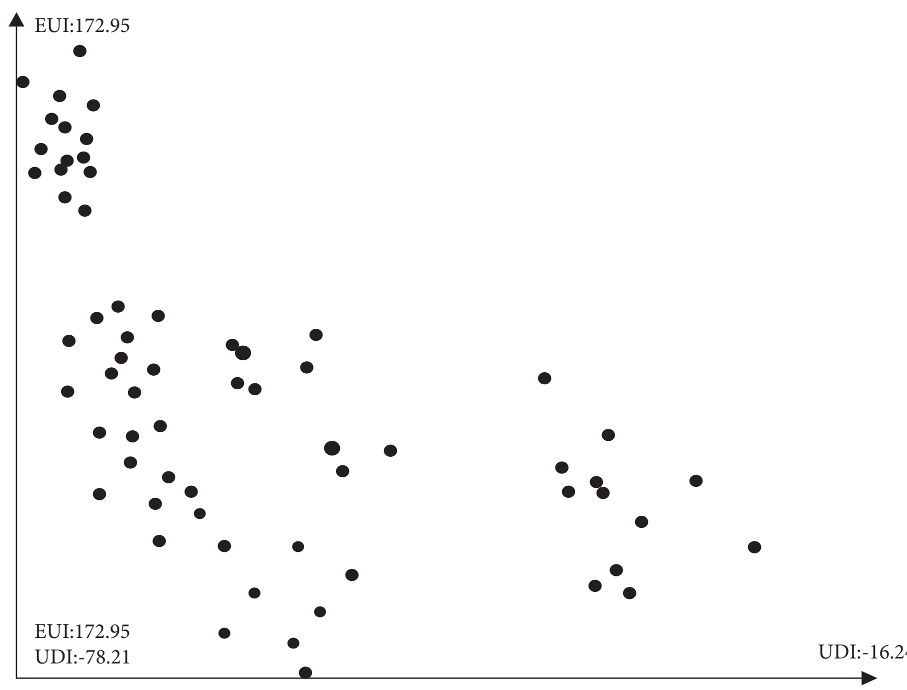

Figure 12: EUI and UDI two-dimensional spatial solution set distribution plot.

distribution breadth and the interrelationship balance, and the comprehensive discussion provides reasonable suggestions for the selection of the final design scheme of the library.

(1) In the verification of value domain distribution breadth, DA, UDI, and EUI have a relatively large value domain distribution breadth and multitarget optimization of many performance targets.

Figure 13: Iterative trend chart of the widely distributed indicator values.

Table 5: Multiobjective optimization design practice of library spatial morphology is better than the performance target value and optimization rate of nondominated solution.

Numbering	Performance target value			Performance optimization rate		
Performance targets	DA%	UDI%	UEI (kW.h)	OF	UDI	EUI
Refer to the scenario	41.24	55.13	135.1	—	—	—
1	88.64	62.22	145.94	114.50%	12.86%	8.02%
2	88.06	62.2	142.85	113.53%	12.82%	5.74%
3	80.87	64.93	132.59	96.10%	17.78%	−1.86%

Therefore, in the library construction and design, the impact of the spatial form change on the lighting performance in the multiobjective optimization cannot be underestimated.

(2) In the process of library interior design, it is necessary to fully consider the evaluation index of each performance target and to carry out the multiobjective optimization design of multiple performance objectives. Since the natural lighting problem is fully considered, it must also be weighed on the energy consumption problem. Combine natural lighting with energy consumption problems. We should also do our best to save energy.

(3) The design effect is improved and verified, and the performance goal is weighed and selected.

To sum up, multiobjective optimization method can effectively improve the shading on the library building space structure, bring colorful indoor space experience, provide good natural lighting environment, and effectively reduce indoor energy consumption level to a certain extent, for multitarget optimization method application in library design provides scientific support. Finally, the selection of optimization results should take into account the multiperformance requirements of the library building space to maximize the energy expenditure and provide the optimal natural lighting level for the library indoor space.

5.5. Experimental Summary. In this chapter, we optimize the interior design of the cold library, fully consider many aspects of performance problems, such as lighting and functional areas to develop the design optimization scheme, optimize the design performance and objectives of the library, analyze the library lighting and other performances based on DIVA for Grasshopper and Ladybug & Honeybee, and conduct the multiobjective optimization design practice through the Octopus platform. This chapter makes full use of artificial intelligence algorithms for library design. Multiobjective optimization design is used for interior design and space structure. For the schemes with various performances, the verification analysis is adopted and the optimal scheme is selected. It can not only improve the natural lighting of the library but also save energy.

6. Conclusion

In view of the current problems in building interior design and multiobjective optimization evaluation model of spatial structure, the artificial intelligence related technologies and methods are preliminarily studied, but they still need to be further explored. The application of artificial intelligence technology, especially deep learning, has just started in the field of air pollution research and faces many uncertainties and challenges, but it has broad application prospects.

(1) Aiming at the forefront of artificial intelligence development and constantly introducing the latest machine learning technology methods, the interior design of the building is the focus of research, the characteristics of different artificial intelligence algorithms are compared and analyzed through simulation experiments, and the model prediction ability is improved step by step.

(2) In the face of the doubts about the nature of the "black-box model" of artificial intelligence in the traditional natural science field, to study the interpretability of deep learning, based on domain knowledge, interpretable models are built to promote the development of interdisciplinary research on architectural design and artificial intelligence.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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