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Research Article

Research on Indoor Environment Art Design Model Using Genetic Algorithm

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The requirements of human beings for the comfort of the built environment are gradually improving with the development of the economy and the progress of science. In the rapid development of smart home environment, the simple temperature control as the goal of the air conditioning system control cannot meet people's needs, to thermal comfort as the control goal of air conditioning control strategy can not only meet people's requirements for environmental indicators such as temperature and humidity, but also achieve the purpose of energy saving. In the smart home environment, in order to meet the user's requirements for the thermal comfort of the indoor environment, the indoor equipment is accurately controlled, and the thermal comfort index of the indoor environment is predicted and analyzed. In order to improve the data quality, the K-means clustering algorithm is first used to process the experimental data; secondly, in order to get rid of the negative impact of the randomness of the initial threshold and weight on the prediction accuracy of the model, which leads to the prediction result falling into a local minimization, it is proposed to use the genetic algorithm to prioritize the initial threshold and weight of the model and then establish a prediction model based on the BP neural network to predict the thermal comfort of the indoor environment, and the existing experimental data prove that the prediction effect is good. The research results show that the system can automatically change the control strategy and adjust the operating state of the controlled equipment according to the current thermal environment, so that the indoor thermal environment of the smart home is kept in the best state of comfort, stability, and balance.

1. Introduction

Most of a person's life is spent in an indoor environment, which has an important impact on people's physical health. In the process of indoor environment design, it is necessary to consider environmental factors and optimize them. At the same time, with the improvement of living standards, people's requirements for indoor environment continue to increase and also promote the research of indoor environment design methods [1]. The air conditioning system can be reversed according to the comfort value to obtain the best indoor environment. Many scholars have proposed methods combined with intelligent algorithms for comfort value prediction. They propose a comfort prediction model based on the BP (Error Backpropagation, BP) neural network, but this method tends to fall into extremely small values and is more dependent on the initial weights and thresholds of the BP neural network. Literature Prediction is performed by support vector machine (SVM); although this method improves the phenomenon of overfitting, the prediction result is more errors [2].

Interior design consists of three main elements: design variables, design goals, and design methods [3]. Design variables are design parameters that can affect the indoor environment, such as air conditioning supply parameters, building structure, etc. [4]. The design goal was to be able to evaluate parameters of the indoor environment, such as relative humidity, thermal comfort, air quality, etc. [5]. In the indoor environment design process, the design goals and design variables are determined according to the needs of the user or the experience of the designer [6]. The design method is the core content of the interior environment design, which can be divided into two categories according to the design direction: forward design and reverse design [7]. Forward design is based on the order of cause and effect; that is, according to the design variable value to determine the corresponding design target value, through continuous attempts or the use of the designer's own experience, the design variable value is corrected, and gradually make the design target value reach the design requirements, and then complete the design process of the indoor environment [8]. However, due to the complexity of indoor environmental design problems and the nonlinearity of design parameters, it is often difficult to obtain the desired results in the forward design process [9]. Conversely, reverse design is based on the order of the causes, the corresponding design variable values are determined according to the design target values, and there is a clear directionality in the design process, and the designer does not need to have extensive experience. Therefore, the reverse design method is more applicable in the design of indoor environments [10].

Worldwide, research on the problem of reverse design of indoor environments is still in its infancy, and there is currently no recognized best reverse design method [11]. Existing reverse design methods often have defects such as large amount of calculation, difficult calculation, and poor design accuracy [12]. Therefore, it is necessary to study the reverse design method of the indoor environment. The research results are of great significance for improving the safety of the indoor environment and guiding the optimal design of the indoor environment [13].

There is a big difference between traditional design styles and modern design styles. Traditional design styles pay more attention to the artistry of space, while modern design styles tend to pay more attention to the practicality of space [14]. Modern design style is loved by the public and is widely used in interior space design. Designers should fully understand people's needs for the living environment and ensure that the designed indoor space can provide convenience for people's lives and meet people's needs. At the same time, it is necessary to combine people's needs with modern design styles to achieve high-quality design of the indoor environment [15]. For example, in the process of interior design, designers generally fully understand the customer's life hobbies and then buy the corresponding style of furniture according to the customer's relevant hobbies. At the same time, in the interior design process, the designer will communicate with the customer in real time, understand the customer's ideas on the interior design, and try to achieve the final effect of customer satisfaction in the indoor environment. At the same time, in modern design, the designer will also consider the customer's economic situation, according to the customer's economic conditions reasonable planning design costs, to ensure that the interior design can meet the needs of customers within the expected cost [16].

2. State of the Art

With the advancement of building technology and the use of emerging building materials, today's residential and commercial buildings have a high degree of air tightness and good thermal insulation, which reduces the energy consumption that meets the comfort temperature requirements to a certain extent, but it may also cause indoor water vapor to accumulate high humidity or even condensation, or indoor air is too dry. Researchers at home and abroad have proposed many mathematical models to predict indoor environmental humidity, such as the well mixed zonal simulation model [13]. The distribution of physical quantities such as temperature and humidity in the actual indoor environment is nonuniform, and many times it is necessary to consider the different needs of different locations. Therefore, it is necessary to apply a quick and effective method to analyze the wet source conditions required to achieve the ideal indoor humidity distribution, that is, the idea of antidesign.

The reverse design problem is one of the mathematical physical inverse problems; often unsure problems, characterized by the existence, uniqueness, and stability of the solution, cannot be guaranteed [17]. In the mid-1960s, scientists began to pay extensive attention to and in-depth research on the counterproblem, and the regularization method proposed by Tikhonov, an academician of the USSR Academy of Sciences, was one of the earliest methods used to solve the antiproblem. The basic idea is to use some additional information of the specific problem to constrain the solution of the inverse problem and to obtain a stable method that can approximate the real solution of the original inverse problem by introducing a calm function. On the basis of Tikhonov regularization, people have also developed iterative regularization, horizontal set regularization, full variational regularization, and other methods to solve inverse problems, mainly used in geophysics, atmospheric sciences, life sciences, and other fields. However, due to the limitations of experimental conditions, experimental costs, and problem complexity, the research and application of reverse design methods in the field of indoor environment started late [18].

In recent years, numerical simulation technology has been rapidly developed, and its application in indoor environments has become increasingly mature, and the research objects include aspects from airflow distribution to thermal comfort and air quality [19]. These achievements have promoted the research of reverse design methods for indoor environments, and numerical simulation technology has gradually become an important part of reverse design methods. In terms of indoor environment simulation, cfD (computational fluid dynamics) model is the most widely used computing model; its calculation accuracy is high and can be better combined with other models and has been widely used to study indoor air quality, human thermal comfort, building energy consumption, and other different indoor environmental problems. Li et al. used Airpak software based on CFD models to study indoor air quality, analyzed the velocity field, temperature field, and air age distribution in the building room, and evaluated the adjustment effect of the air conditioning system based on the calculation results. Ramponi and Blocken used cfD models to study air convection in the room and used experimental data to verify the calculation results obtained under the conditions of different model calculation parameters and then analyzed the influence of parameters such as the number of meshes, turbulence model, and inlet turbulence kinetic energy on the accuracy of CFD calculation results.

Habchi et al. used CFD technology to study a new air supply mode, that is, seat air supply, and the calculation results showed that this air supply method can ensure that the human surrounding environment meets the requirements of thermal comfort and air quality, and the energy consumption required is reduced compared with the traditional air supply method, 30% [20]. Liu et al. used cfD models to calculate the air environment in the first-class cabin of the McDonnell Douglas 82-passenger aircraft, obtained information such as speed field, temperature field, humidity field, etc., and analyzed the heat loss and thermal comfort of passenger surfaces. The results showed that 74.1% of the heat loss was caused by convective heat transfer, and the variation range of PMV (Predicted Mean Vote) on the human surface was −2 to −0.5, and the variation range of PPD (Predicted Percentage Dissatisfied) was 30% to 60%, which belonged to the cold environment. Liu et al., Zhai et al., and Zhang et al. used different turbulence models to calculate the indoor air flow, and after considering the calculation accuracy and calculation cost, it was found that the turbulence model was more suitable for the study of indoor environment. Since the application of numerical simulation technology in indoor environment has been widely recognized, the reverse design method developed on the basis of numerical simulation has gradually been applied to the indoor environment.

The reverse design of the indoor environment based on numerical simulation technology includes three components: design variables, design goals, and design methods. The main role of the numerical simulation method is to determine the correspondence between design variables and design goals. Using this correspondence, the reverse design method can find the corresponding design variable values according to the given design target values and complete the reverse design process. Therefore, this reverse design process can be reduced to a parameter recognition problem. The methods to solve such problems can be roughly divided into analytical methods, probability methods, direct methods, and optimization methods. The analytical method is highly accurate and fast, but the formula derivation process is complex and is only suitable for solving simple problems. The generalization method generally requires a lot of calculations to produce a probability density distribution curve. Direct methods often involve modifying the control equations of the model, have limited adaptability, and affect the accuracy of calculation results. Compared with the previous methods, the optimization method has the strongest applicability and the widest range of use. Optimization methods can be divided into gradient-based optimization methods and non-gradient-based optimization methods. Gradient-based optimization algorithm: In the calculation process, it is necessary to calculate the gradient of the change of the design target to the design variable and use the gradient descent method to gradually optimize the design target. However, due to the strong nonlinear relationship between the design goal and the design variable in the indoor environment, it is generally difficult to obtain this gradient value. Therefore, most of the research uses non-gradient-based optimization algorithms to solve the problem of reverse design of indoor environments. Genetic algorithm is the most widely used nongradient optimization algorithm; compared with other optimization algorithms, it is easier for genetic algorithms to explore the entire design space and find the global optimal solution. When reverse design is done using genetic algorithms, the design target can be represented in a nonequation form, thus largely avoiding the problem of no solution. Genetic algorithms can obtain multiple solutions at the same time, which in turn solves the multisolution problem that can occur in reverse design problems. During the design process, the genetic algorithm uses forward calculations to obtain the value of the new individual objective function, so the solution process is stable.

This paper proposes an indoor environment art design model based on genetic algorithm, and its main process framework is shown in Figure 1. The artificial neural network and fuzzy control technology are introduced into the reverse design, the artificial neural network is used to predict the target value of the new individual, the fuzzy control and neural network are used to obtain the calculation probability of the individual, and the fuzzy control and genetic algorithm are combined to obtain the evolution interval of the individual. It reduces the amount of computation for reverse design.

3. Methodology

3.1. Reverse Design Theory and Methods. The inverse problem treatment method can be divided into forward solution method and reverse solution method. Among them, forward methods include traditional trial-and-error methods and optimization methods, specifically adjoint methods of gradient classes and genetic algorithms of nongradient classes (genetic algorithm, GA). The forward method does not solve the inverse control equations but looks for the best design variables by constructing different objective functions, so its solution is present and relatively stable.

With reverse design, that is, according to the given design target value, determine the corresponding design variable value. Reverse design contains three main components of design variables, design goals, and design methods, and the key to achieving reverse design is (1) establishing a mapping relationship between design goals and design variables; (2) determining an appropriate reverse design method. If there is a reversible one-to-one mapping relationship between the design target and the design variable, the reverse design problem is appropriate, and the corresponding design variable value can be directly determined according to the given design target value, which can be called direct reverse design. If there is no reversible one-to-one mapping relationship between the design goal and the design variables, a specific reverse design method needs to be used to solve the problems of the existence, uniqueness, and stability of the solution, which can be called indirect reverse design.

In reverse design of indoor environments, there is a complex nonlinear mapping relationship between the design goals and design variables, so the indirect reverse design method is used. The reverse design method used in this study

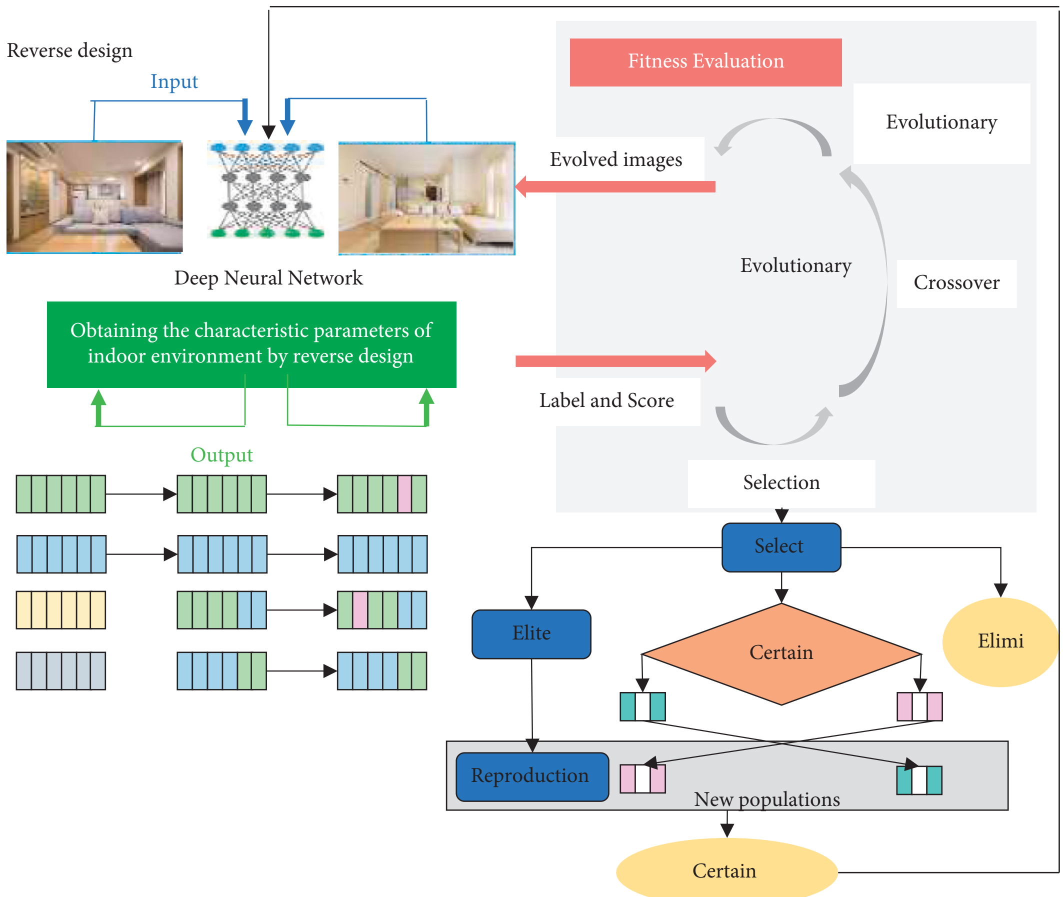

Figure 1: Overall algorithm flow framework.

uses genetic algorithms as the basis for solving methods. With reverse design using genetic algorithms, the design goal can be a restrictive condition rather than a deterministic condition, expressed in the form of an inequality, and largely avoids the situation of no solution. Genetic algorithms can obtain multiple solutions to the reverse design problem at the same time, solving the uniqueness problem of understanding. At the same time, the genetic algorithm uses the forward computing model (CFD) to obtain the mapping relationship between the design target and the design variable, and the solution process is stable. Therefore, when using genetic algorithms for reverse design, the problem of unsuitability of reverse design is solved.

On the basis of genetic algorithm, the reverse design method in this study further couples artificial neural networks and fuzzy control methods to improve the efficiency of reverse design. In the reverse design process, the optimization function of the genetic algorithm is used to search for individuals who meet the design requirements, and CFD is used to calculate the design target value of new individuals. However, due to the complexity of indoor environment models, the calculation time of CFD models is longer, and the use of genetic algorithms to search for more new individuals will produce more new individuals, which in turn will produce many CFD calculation processes, resulting in a large amount of reverse design calculation. In this study, the mapping relationship between design variables and design targets is established by using the prediction function of artificial neural network, and the prediction value of neural network is used instead of part of the CFD calculation result, thereby reducing the number of CFD calculations and reducing the amount of computation required for reverse design. At the same time, fuzzy control technology is used to control some parameters of the reverse design method, thereby improving the efficiency of reverse design. The reverse design approach for indoor environments used in this study is shown in Figure 2.

3.2. Theories Related to Genetic Algorithms. Genetic algorithm (GA) was founded in 1975 by Holland of Michigan University in the United States; the professor first proposed in his monograph “Applicability of Natural and Artificial Systems”. Genetic algorithm, also known as evolutionary algorithm, is a heuristic search algorithm inspired by Darwin’s theory of evolution and drawn on the process of biological evolution. Drawing on the theory of biological evolution, genetic algorithms simulate the problems to be solved into a biological evolutionary process, generate the next generation of solutions through replication, crossover, mutation, and other operations, and gradually eliminate the solutions with low adaptability function values and increase

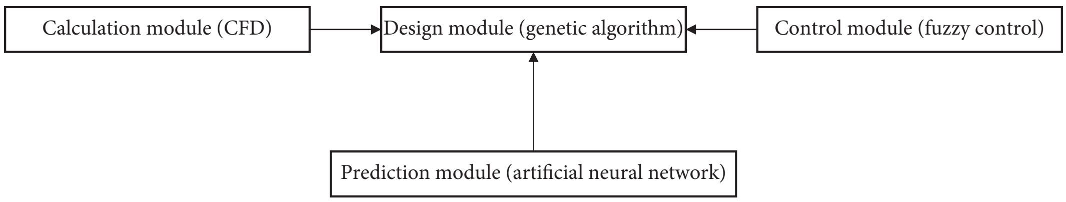

Figure 2: Schematic diagram of the reverse design method of indoor environment.

the solutions with high adaptability function values. In this way, after evolving N generations, it is very likely that individuals with high fitness function values will evolve.

(1) Genetic algorithms are the encoding of the parameters of the problem, that is, the "chromosomes," rather than the operation of the parameters themselves. In the process of evolution, it is only necessary to use specific information about the problem when evaluating individual fitness values, while other parts do not need to understand the information of the problem itself, which makes the genetic algorithm not limited by functional constraints (such as continuous or differentiable), simple design, and wide adaptability.

(2) The search process of the genetic algorithm starts from the set of solutions to the problem, rather than from a single solution, with the implicit parallel search feature. The search can be focused on the high-performance parts, which can improve the search efficiency and reduce the possibility of falling into the local minimax, and it is easy to obtain the global optimal solution.

(3) The genetic algorithm is a directional heuristic search completed under the guidance of probability in the entire search process of the problem solution space, which is different from the exhaustive or completely random search, so it has high efficiency. In the initial stage, isoprobabilistic initialization ensures that the search points cover the entire solution space uniformly; then, under the guidance of the probability selection of the fitness value, and the probabilities of crossover and variation, the search gradually concentrates on the region with high fitness value until it converges to the region with the highest fitness value.

3.3. Genetic Algorithms Are Coupled with Neural Networks. Neural networks are used to deal with nonlinear relationships, the relationship between input and output can be determined (there is a nonlinear relationship), you can use the self-learning of neural networks (you need to train the dataset with explicit inputs and outputs), after training the weights are determined, and you can test the new input. Genetic algorithms are used to solve the most valuable problems, biological evolution, and survival of the fittest. There are no limitations to being more flexible, and the only difficulty is the choice of code chromosomes and evaluation functions.

When the genetic algorithm is coupled with the neural network for reverse design, the main process can be divided into two parts: (1) the neural network training process and (2) the genetic algorithm design process. In the process of neural network training, a series of design variables are generated by using a specific sampling method, and the combination of these variables is calculated using CFD to obtain the corresponding design target values, which together constitute the training sample of the neural network. The neural network is trained using training samples, and the input of the neural network is the design variable value and the output is the design target value. In the process of genetic algorithm design, the adaptability of the new individual is calculated using a trained neural network, and the calculation time of the neural network is much lower than that of CFD calculation, so the amount of computation can be greatly reduced. The reverse design process is shown in Figure 3. Using this method, the Blay model and the 2D cockpit model are inverted. The predictive power of neural networks and the effect of reverse design methods were studied.

3.4. Design of GA-CNN Algorithm. In the CNN network structure, there are many parameters and structures that can be discussed. In the algorithmic exploration of GA-CNN, each layer of network structure is treated as a chromosome. The system architecture of the GA-CNN algorithm is shown in Figure 4; its overall process is shown in Algorithm 1.

3.5. Analysis Methods for the Interaction Effects of Genotype and Environment

3.5.1. Analysis Method. Fisher et al. first used analysis of variance (ANOVA) for the comparative experiment of Margaret cultivars, which decomposed the total yield variation into three sources: genotype main effect, environmental main effect, and genotype and environmental interaction effect. Analysis of variance estimates the variance components of all parties, and the variance component method is important in multienvironment experiments, so ANOVA is widely used to analyze multienvironment test data.

Suppose there are I varieties and J environments in the regional test, and the number of tests under the combination of each variety environment is R, $R > 1$, and the ith y_{ij} genotype is in J. The average yield of R replicates in the environment; the two-way classification model with interaction effect is

$$y_{ij} = \mu + g_i + e_j + (ge)_{ij} + \varepsilon_{ij}, \tag{1}$$

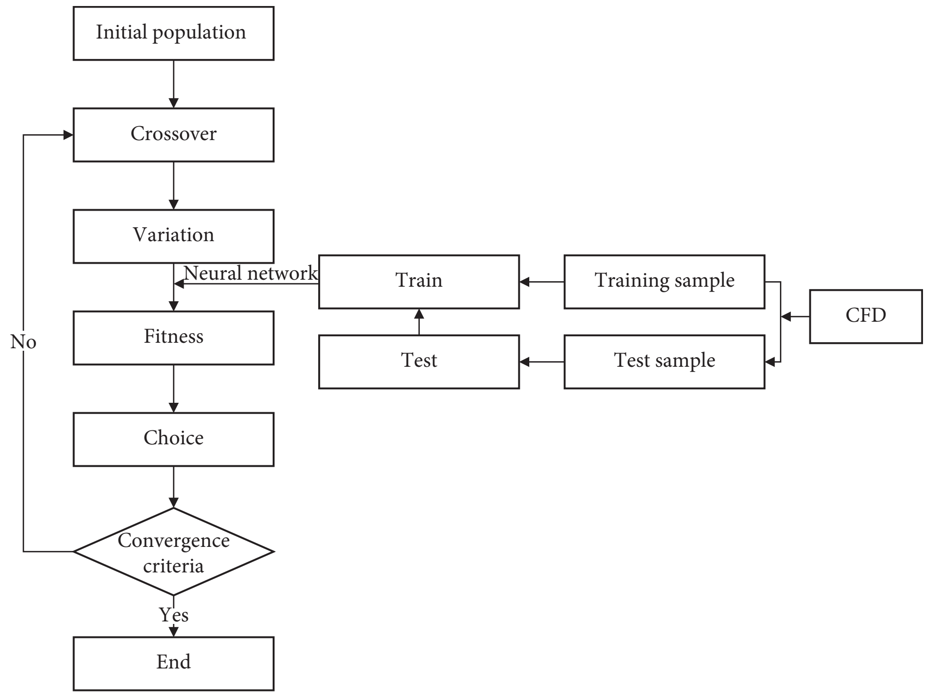

Figure 3: Flowchart of a reverse design method combining genetic algorithms with neural networks.

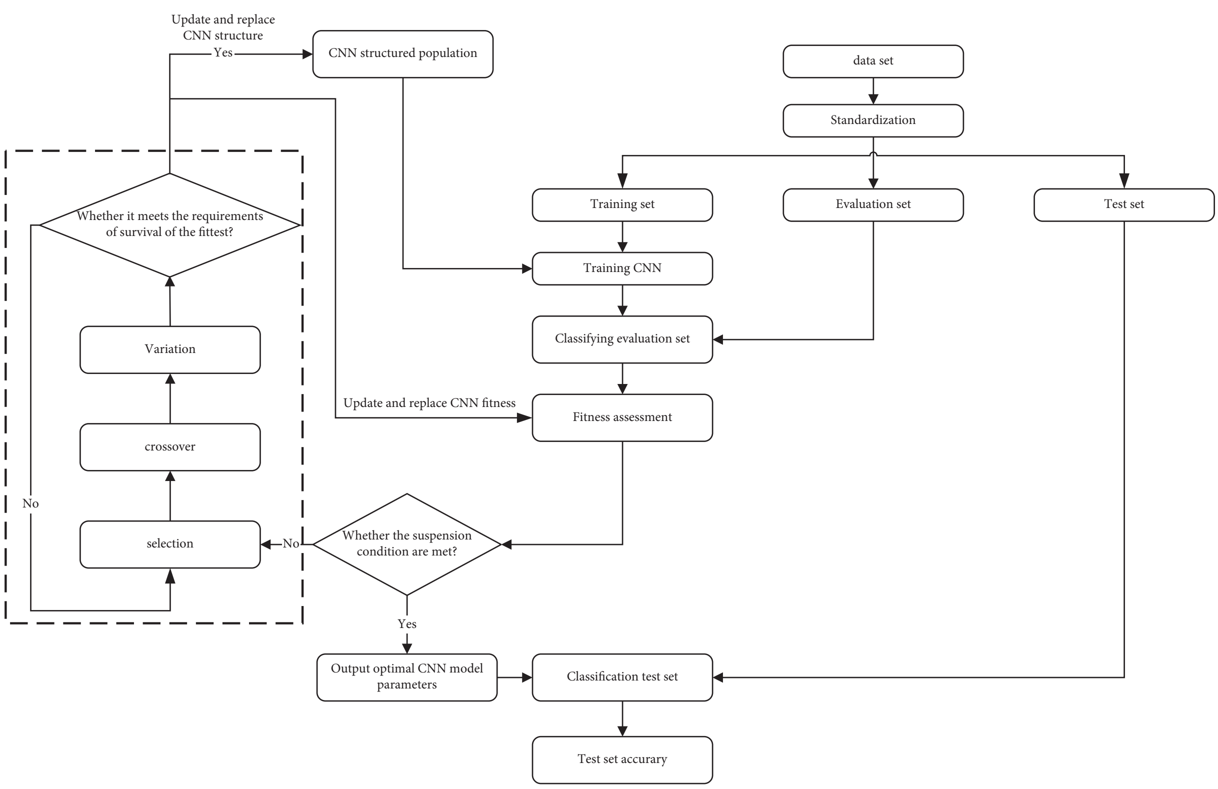

Figure 4: System architecture of GA-CNN algorithm.

where it is the total mean, the main effect of the μg_i ith genotype, the main effect of the jth e_j environment, the interaction effect of the ith $(ge)_{ij}$ genotype and the jth environment, and the corresponding random error and assumed to follow a normal distribution $\varepsilon_{ij} y_{ij}$.

3.5.2. Linear Regression Analysis Methods. Regression analysis attempts to obtain more information from the interaction effects of genotypes and the environment. Since 1938, when Yetes et al. analyzed GE interactions by regression methods, linear regression methods have been

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Step 1 The data is processed in a standardized manner and divided into training sets, evaluation sets and test sets
Step 2 Initialize the population of the CNN framework structure, preset the maximum number of iterations G, and the current population algebra $g = 1$;
Step 3 Learn to train each frame structure in the CNN population;
Step 4 Evaluate the trained CNN model with the evaluation set to obtain the corresponding adaptability of the CNN framework structure population
Step 5 Use the roulette method to generate mating targets;
Step 6 Crossover the mating target and perform training to assess fitness;
Step 7 Use the variation operation to mutate the crossover results and perform training to assess fitness;
Step 8 Determine whether the newly generated results are better than the mating target, update the CNN structure population, and update the corresponding adaptability
Step 9 If $g < G$ and the convergence condition is not met, $g = g + 1$, go to step 5, otherwise go to step 10;
Step 10 Output the elite individual model as the final classification model.
END

ALGORITHM 1: GA-CNN algorithm

continuously developed, and Bingmin et al. have discussed in detail various linear regression models. Yunli only introduces the commonly used joint regression model, also known as the F–W model. It further breaks down the interaction terms in ANOVA into linear regression of genotypes to environmental effects, i.e.,

$$y_{ij} = \mu + g_i + e_j + (ge)_{ij} + \varepsilon_{ij}. \tag{2}$$

Substitute it into formula (1) available,

$$y_{ij} = \mu + g_i + e_j + \alpha_i e_j + \delta_{ij} + \varepsilon_{ij}, \tag{3}$$

where a_i is the regression coefficient for the ith genotype.

3.5.3. AMMI Model. The AMMI model organically combines analysis of variance and principal component analysis to further decompose the GE interaction effects in ANOVA into genotype components and environmental components, which can be used for special adaptation analysis, cluster analysis, and other studies.

The AMMI model is

$$y_{ijr} = \mu + g_i + e_j + \sum\nolimits_{k=1}^{t} \lambda_k \alpha_{ik} \delta_{jk} + \delta_{ij} + \varepsilon_{ijr}. \tag{4}$$

The AMMI model is widely used in multienvironment experiments by performing principal component analysis or singular value decomposition of GE interaction effects in ANOVA analysis and then visually demonstrating the patterns of GE interaction through double-scale plots. However, this model only analyzes GE interaction, and it is difficult for W to make a comprehensive evaluation of the genotype of the variety from the perspective of breeding, nor is it suitable for the evaluation of the rationality and ideality of the variety ecological zone division, W, and the test site based on variety selection.

3.5.4. BP Neural Network: Output Algorithm. The output algorithm of each layer of neurons is

$$\delta(x) = \frac{1}{1 + e^{-\partial x}} \, (\partial > 0), \tag{5}$$

$$\delta(x) = \sum_{I=1}^{N} w_{ij} t_j, \tag{6}$$

where ω_{ij} is the node weight from the input layer (or hidden layer) to the hidden layer (or output layer); n is the number of node input values, in this case from the input layer to the hidden layer $n = 10$. Weight correction ω_{ij}: The theoretical initial value can be a random number on [−1, 1], but if the weight does not meet the requirements, it must be corrected. From the output layer to the middle layer, the calculation formula is

$$w_{ij}(t + 1) = w_{ij}(t) + \eta \delta_i M_i + \alpha \left[w_{ij}(t) - w_{ij}(t - 1) \right]. \tag{7}$$

In the formula: $\omega_{ij}(t)$ is the connection weight from neuron j to the previous layer (input layer or hidden layer) at time t; η is the actual output of neuron j at time t; α is the step size adjustment factor; take (0, 1); for the smoothing factor, take (0,1); δ_i is the error weight adjustment factor.

For the output layer node, $\delta_i = x_j (1 - x_j)(t_j - x_j)$ is the output target value; for the hidden layer node, $\sum_K \delta_k w_{kj}$ is the actual output value of the hidden layer node j.

Error analysis: select the network relative error function

$$E_k = \frac{M_{k0} - M_k}{M_{k0}}, \tag{8}$$

where E_k is the network relative error function; M_{k0} is the actual value; M_k is the predicted network output value. Usually, if the error E_k is not greater than the allowable value of the network error, it can be considered that there is no error in the calculation of the model. For the final output value x of the network, the inverse normalization transformation is performed using the following formula:

$$x = x \left(x\min_{\max} + x_{\min} \right), \tag{9}$$

where $x_{\min}, x_{\max}$ are the maximum and minimum values of the calculated output data, respectively; x is the calculated output value. Calculate the actual output value of the neural network layer by layer.

$$\begin{aligned} Y_j &= f\left[\sum_{i=1}^{n} w_{ij}x_i - \theta_j\right], \\ Z_k &= f\left[\sum_{i=1}^{n} w_{ij}x_i - \theta_k\right]. \end{aligned} \tag{10}$$

Starting from the output layer, the weights are adjusted in reverse, and the formula consensus is as follows:

$$\begin{aligned} W_{jk+1} &= W_{jk} + \eta\delta_k V_j, \\ W_{ij+1} &= W_{ij} + \eta\delta_j V_i, \end{aligned} \tag{11}$$

where

$$\begin{aligned} \delta_k &= (Z_k - Z_K)Z_k(1 - Z_k), \\ \delta_j &= y_j(1 - y_j)\sum_{k=0}^{L-1}\delta_k W_{jk}. \end{aligned} \tag{12}$$

Calculate the total error E; if $E \le \varepsilon$, then the learning stops; otherwise recalculate. In the actual design of the network, if the step size is small, the learning speed will be slow, and if the step size η is too large, the network will oscillate. To solve this problem, a momentum α $(0 < \alpha < 1)$ can be added, namely,

$$\begin{aligned} w_{ij+1} &= w_{jk} + \eta\delta_k y_j + \alpha\Delta W_{jk}, \\ w_{ij+1} &= w_{ij} + \eta\delta_j y_i + \alpha\Delta W_{ij}. \end{aligned} \tag{13}$$

This is an iterative process, the dynamic parameter is selected as 0.001, and each value is adjusted once in each round, and so on, until the dynamic parameter is less than the set target. Such a good network training succeeded. Select appropriate network parameters and carry out a sufficient number of iterations and the final results of the network training, and the error between the simulation results and the actual results will fall within the allowable range.

4. Result Analysis and Discussion

4.1. Blay Model Neural Network Training Results. Before training the neural network, the input and output data are first normalized. The input data is normalized to equation (5). The range of variation of the output data is unknown and can be normalized using the maximum and minimum values in the current sample. When normalizing the output data, make the following corrections to the normalization formula:

$$x(\text{net}) = 0.2 + 0.6\frac{x_i - x(\min)}{x(\max) - x(\min)}. \tag{14}$$

After normalization and postprocessing, the input data in the training samples ranges from 0 to 1, and the output data changes from 0.2 to 0.8, providing a certain margin for predicting that the output data exceeds the range of the training samples.

The neural network uses a three-layer network structure with 2 input layer elements, 8 hidden layer elements, and 2 output layer elements. The conversion function uses the logsig function, whose output values range from 0 to 1. Neural networks are trained using Bayesian regularization training methods at a training rate of 0.1, and the convergence condition of the training process is that the mean variance (MSE) is less than 0.001 or the number of iterations exceeds 5000. The mean variance is calculated as follows:

$$\text{MSE} = \sum_{i=1}^{n}\frac{(T_i - Y_i)^2}{n}. \tag{15}$$

The time required for network training using different training samples is shown in Table 1. The results show that the neural network training process is completed quickly, the training time at different sample sizes is less than 10 s, and the calculation time of a single CFD is about 300 s, so the neural network training time is much lower than the calculation time of CFD. When analyzing the computational amount of reverse design, the training time of the neural network can be ignored and only the number of cases calculated by CFD can be counted.

To compare the results of different training sample sizes, the trained neural network is tested using the same 30 test samples. During the test, the design variable values of these 30 test samples are used as input, the neural network is used to predict the design target values of these 30 samples, the prediction value of the neural network is obtained, and then the prediction accuracy of the neural network is evaluated by using the average relative error, and the calculation formula of the average relative error is as follows:

$$\text{Mean relative error} = \frac{1}{m}\sum_{i=1}^{m}\frac{\left|F_{\text{CFD}}^{i} - F_{\text{ANN}}^{i}\right|}{F_{\text{CFD}}^{i}} \times 100\%. \tag{16}$$

The results of the neural network obtained by different training sample sizes are shown in Table 2. The neural network predicts both speed and temperature accurately, with an average relative error of less than 1% and a temperature of less than 4%. The prediction accuracy of the speed is better than the prediction accuracy of the temperature, because the velocity value at the monitoring point is mainly affected by the inlet velocity and is less affected by the inlet temperature, while the temperature value is greatly affected by the inlet temperature and velocity, resulting in a more complex mapping relationship. As the training sample size increases, the average relative error shows a downward trend, indicating that increasing the training sample size can improve the prediction accuracy of the neural network.

The Blay model is reversely designed using the combination of genetic algorithm and neural network. The calculation parameters of the genetic algorithm are consistent with the previous ones. A genetic algorithm is used to search for a solution that meets the design requirements, a neural network is used to predict the design target value of the Blay model,

Table 1: Blay model neural network training time.

Training sample size	40	60	80	100
Training time (s)	5	6	7	9

and the reverse design results with different training sample sizes are compared. The parameters are shown in Table 2.

The change curve of the objective function with the genetic algebra is shown in Figure 5. The results show that, at the beginning of the calculation, the objective function curve decreases rapidly, but when the genetic algebra reaches a certain value, the objective function value remains basically unchanged. When the training sample size is 40, 60, and 100, the minimum objective function value begins to remain unchanged after the genetic algorithm is calculated for 50 generations as seen in Table 3. When the training sample size is 80, the minimum objective function value remains unchanged after the 20th generation, so there is no obvious correlation between the convergence speed of the objective function and the training sample size. When the genetic algorithm is calculated to 100 generations, the objective function value in each design process does not reach 0, indicating that each design process has not converged.

The results in Table 4 show that although the predicted value of velocity and temperature at the monitoring point is not much different from the real value (0.1325 m/s, 17.67°C), FBlay cannot be equal to 0 due to a small prediction error. When the training samples increase from 60 to 80, the FBlay predicted by the neural network increases instead, indicating that increasing the number of training samples may lead to a decrease in the prediction accuracy of the neural network for specific individuals.

4.2. BP Neural Network Prediction Model Optimized by Genetic Algorithm. Aiming at the initial weights and thresholds in the training process of BP neural networks, which are generated by random numbers, which have an impact on the network structure of the training, the genetic optimization algorithm is used to optimize the initial weights and thresholds of the BP neural network, so as to obtain a relatively stable GA-BP neural network model. In order to solve the problem caused by the abovementioned defects of the BP neural network itself, this paper considers that the genetic algorithm directly uses the fitness function as the search information; the search process is not constrained by the continuity of the function, has a good global search ability, and can overcome the problem that the BP neural network is easy to fall into the local minimum and find it quickly and accurately. The optimal value of the BP neural network is optimized first by using the genetic algorithm to improve the accuracy of the prediction model in order to achieve an accurate grasp of the thermal comfort level of the indoor thermal environment, and the optimization process is shown in Figure 6.

The initial thresholds and weights of the optimized object, the BP neural network, are used as the initial population and optimized using MATLAB's own GA toolbox. The parameter settings of the genetic algorithm optimization model are shown in Table 5.

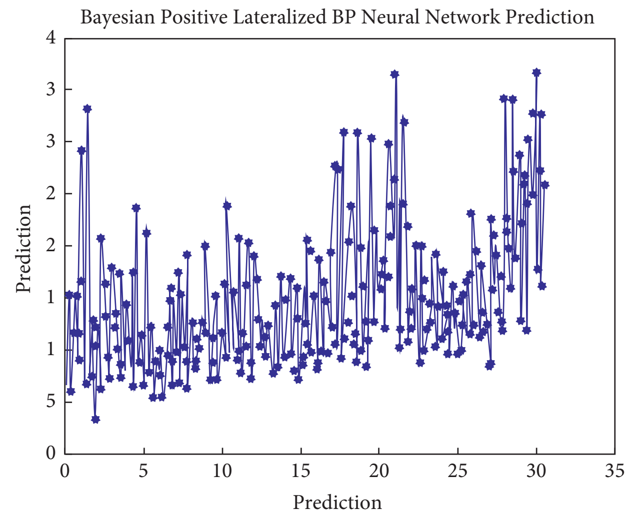

Figure 5: The curve of objective function changing with genetic algebra.

Table 2: Test results of neural networks.

Training sample size	40	60	80	100
Velocity average relative error (%)	0.97	0.46	0.28	0.11
Temperature average relative error (%)	3.80	2.10	1.78	1.51

Table 3: Reverse design results under different training sample sizes.

Sample size	40	60	80	100
Inlet velocity (m/s)	0.57	0.57	0.57	0.57
Inlet temperature (°C)	17.7	15.4	15.4	15.1
Objective function value	0.0047	0.0098	0.0028	0.0035

After the genetic algorithm optimizes the initial threshold and weight, the error between the prediction result and the expected output of the model is reduced, and the curve fit is better, which proves the necessity and practicality of optimization with actual data. The prediction effect of A and B sets was studied, and the comprehensive regression parameter $R \approx 0.999\ 8$ of the three sets of data of training, verification, and sample was closer to the ideal value 1, and the optimal value and target value of the training curve were found, so the overall performance of the model was good. The results before and after the network algorithm improvement are listed and are shown in Table 6 and Figures 7 and 8.

It can be seen from the results that the absolute error of the prediction of the optimized neural network using genetic algorithm is between (−0.09, 0.27), and the average accuracy is 98.16%. Compared to predictive models using a single BP neural network, the prediction accuracy is improved by 21.9%, sacrificing runtime within the acceptable range. In summary, the use of genetic algorithms to optimize neural networks can make prediction accuracy higher and better results, thus proving the necessity of optimization.

Table 4: The prediction results of the neural network for the target solution.

Sample size	40	60	80	100
Predict velocity (m/s)	0.1327	0.1331	0.1321	0.1321
Predict temperature (°C)	17.49	17.51	17.49	17.61
F	0.0103	0.0101	0.0106	0.0045

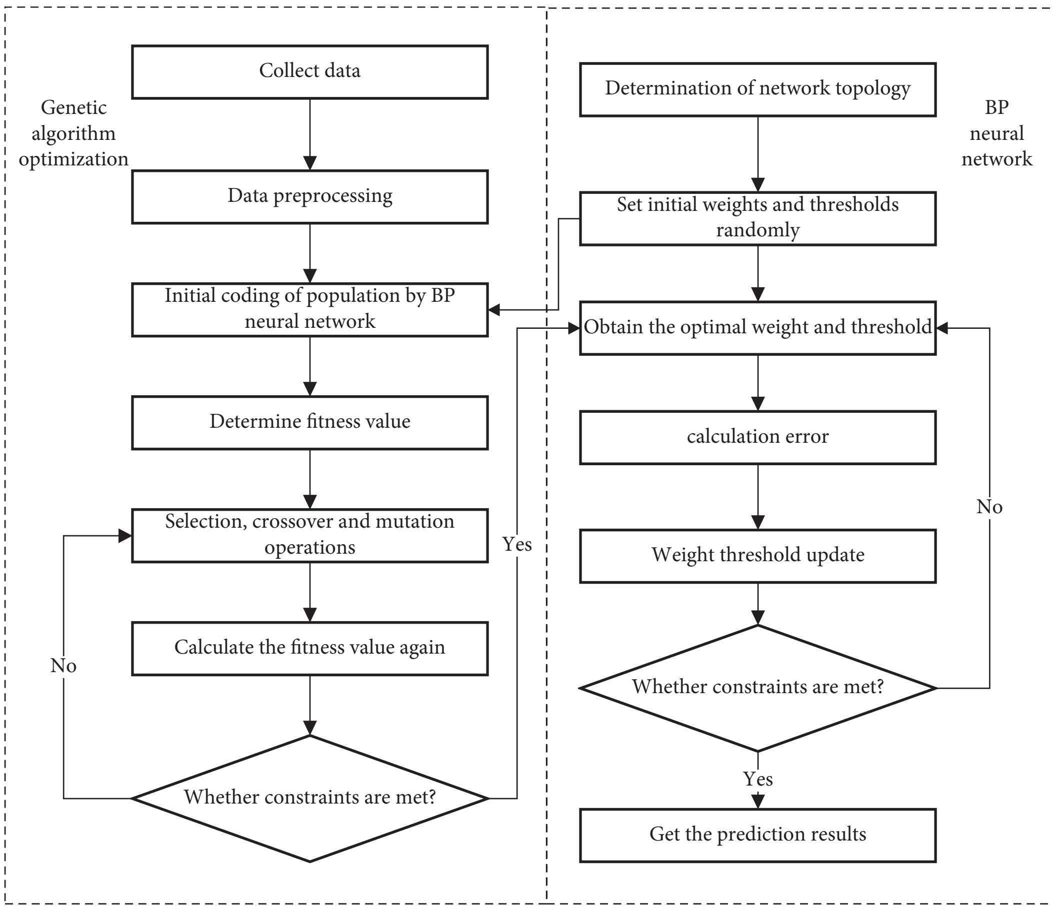

Figure 6: Schematic diagram of the genetic algorithm optimizing the BP neural network process.

Table 5: Genetic algorithm improvements BP neural network model parameter table.

	Parameter category	Parameter value preset
1	Individual length of genetic	Lenchrom = 5
2	Genetic evolution times and population size of genetic algorithm cross rate	Maxgen = 100
3	Population size	Sizepop = 20
4	Cross rate	Pcross = 0.4
5	Variation rate	Pmutation = 0.2
6	The maximum number of iterations of neural network	Net.trainParam.epochs = 100
7	The training and learning rate of neural network	Net.trainParam.lr = 0.1
8	The allowable error range of neural network	Net.trainParam. Goal = 0.0004

5. Conclusion

Indoor colors are divided into three categories: First, large area colors: this color is generally used as a background color; second, under the background color of a large area, the main tone of the furniture becomes the main tone of the indoor living space; third, the key color that is not large in size but can play a finishing role. In the process of carrying out indoor color design work, designers must first consider the layout of the main color, key color, and background color. And in the process of actual design, it is often necessary to use a variety of colors. Designers can apply multiple types of colors to interior decoration design solutions and ensure the unity of the overall color style.

In today's indoor environment art design process, it is necessary to scientifically transform the architectural

Table 6: Comparison table of performance before and after algorithm improvements.

	Genetic algorithm optimization neural network algorithm	BP neural network algorithm		Genetic algorithm optimization neural network algorithm	
		Test group A	Test group B	Test group A	Test group B
1	Running time	5 s		9 s	
2	Prediction error range	(−0.47, 1.90)	(−0.44, 1.95)	(−0.09, 0.19)	(−0.06, 0.27)
3	Prediction accuracy	77.36%	76.15%	98.15%	98.17%
4	Total accuracy	76.775%		78.16%	

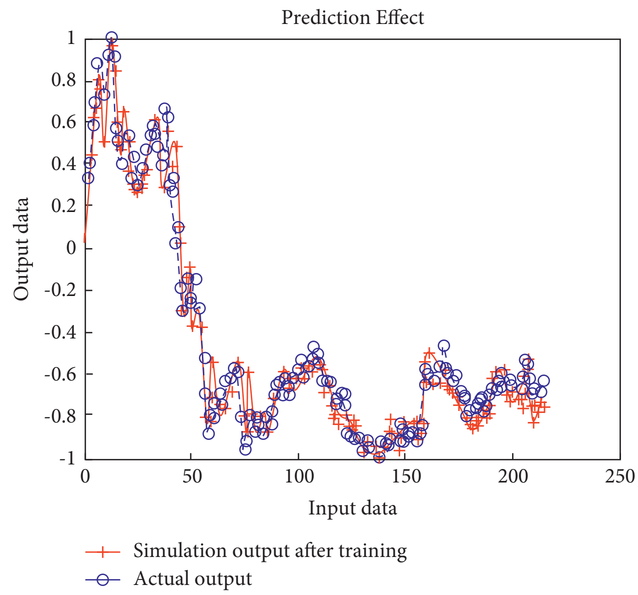

Figure 7: The training curve of BP neural network optimized by genetic algorithm.

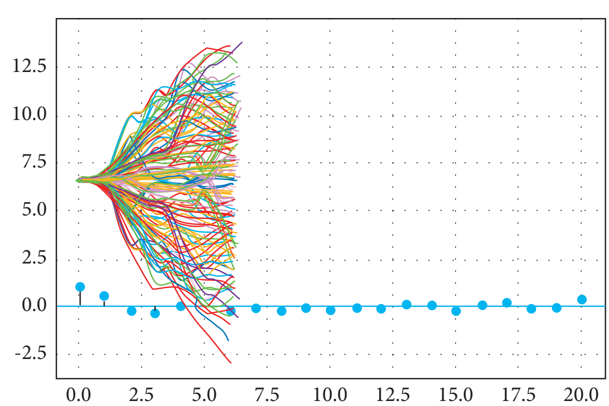

Figure 8: Schematic diagram of improved training, validation, and test sample data regression.

space, so that the city where people live is closer to nature in the true sense and better shows the natural beauty. Judging from the current situation, our people have a fairly strong yearning and desire for the natural world. Based on this, in the process of carrying out indoor environment design work, designers should effectively integrate elements that are closely related to nature, and through this method, the organic combination of tradition and modernity can be realized. In the process of carrying out this work, it is also necessary to reflect the characteristics of art and better reflect the beauty of nature. Contemporary people's requirements for indoor space are not purely functional but more need to obtain a sense of beauty from indoor space and enjoy life more. Therefore, only by combining practicality and artistry, fully embodying the natural beauty of indoor space, and showing the unity and overall beauty of the occupants, can we better meet people's needs.

Throughout the text, this paper completes a series of comprehensive research on the prediction, control, and simulation of the indoor thermal environment in the smart home environment. Experimental results show that the joint control strategy has a certain degree of advancedness and contributes certain value to the research of indoor thermal environment control system in the future. Using the prediction results of this paper as the control parameters of the smart home control system, a linkage control strategy is formulated for air conditioning, ventilation, and other equipment, and the state of the controlled equipment can be automatically adjusted according to the needs of comfort, thereby maximizing the adaptability of the system to the environment.

In the process of carrying out interior design work, it is necessary for designers to appropriately introduce modern advanced science and technology and skills and, through various methods, organically combine indoor color, light, sound, and shape, so that indoor design fully reflects the modern characteristics, so as to show the functionality and artistry of the indoor environment. At the same time, when designers implement indoor environment art design, it is necessary to organically combine technology and emotion, display the technical and artistic nature of interior design, and let people feel humane in the indoor environment. In addition, designers also need to pay attention to the personalization of indoor environmental art design.

In the process of project construction, improving the level of indoor environmental art design has gradually become the focus, and under the influence of the current environmental protection ideas, the design concept has also changed. Therefore, in the process of art design of the actual indoor environment, it is necessary to update the design concept, find out the design concept that is inconsistent with the development of the times, and improve it, innovate in combination with the development of urbanization, and apply the concepts of ecology, harmony, people-oriented, and diversification. This can greatly improve the level of indoor environmental art design and better meet people's needs. From the original practical performance research, to the current emphasis on the artistic components and humanistic connotations in design, China's indoor environment art design is constantly developing and progressing.

Data Availability

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

Conflicts of Interest

The author declares that there are no conflicts of interest.

Acknowledgments

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