Research Article

Modeling and Simulation of Restorative Indoor Environment Based on Neural Network

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In the busy modern society, after experiencing fast-paced work, what people most desire is to have a relatively relaxed and comfortable indoor rest scene. At the same time, with the improvement of material living standards, people have higher and higher requirements for the office and indoor rest environment, and the indoor temperature environment is very important to create a sense of comfort. A good indoor somatosensory temperature environment can not only convey the degree of somatosensory comfort but also relax people’s bodies, in which the air conditioning control system can restore the indoor temperature environment. Based on the abovementioned problems, this paper uses the neural network modeling method, based on the indoor comfort index \(\text{SET}^*\) value and other factors that can affect the environmental temperature, aiming at the human body temperature comfort, constructs a BP neural network model with indoor environmental parameters as the input index, and uses the improved particle swarm optimization algorithm to optimize the model, so as to realize the real-time control of \(\text{SET}^*\) value, and then analyzes the relationship between indoor environmental thermal factors and \(\text{SET}^*\) value. The model is optimized through simulation experiments to improve the optimization degree of the model. The practice shows that the restorative indoor environment model based on improved BP neural network constructed in this paper can optimize the room parameters well, so as to improve indoor comfort and give people a warm accommodation environment.

1. Introduction

WTO points out that health refers to people having a relatively healthy physical and mental state, and being able to better adapt to society, rather than simply referring to physical diseases. Only when you are physically and mentally healthy can you call it health [1]. Health is not only about balancing yourself but also about balancing the relationship between yourself and your surroundings.

In the view of environmental psychology, the connection between people and the environment exists naturally. Some external environments not only provide us with daily needs but also inject new spiritual sources into us on the premise of ensuring the material basis. This is the origin of “restorative environment.” Running around the bustling city 24 hours a day, people seem to be firmly shackled. Different types of environmental pollution such as haze and noise are all around, and people are gradually far away from the simplest natural living state. In the long run, anxiety and anxiety will breed [2]. Nowadays, more and more subhealth people exist, and there are also more and more people with psychological problems [3–5]. Based on this, the vast majority of people want to be able to concentrate on their work tasks without external interference. According to the theory of self-control force model, if you want to maintain concentration in a noisy environment, you must consume self-control resources, resulting in fatigue [6]. Fortunately, this situation can compensate for self-control resources by eating, resting, and other different ways [7]. Baumeister and others made a very vivid metaphor, comparing self-control to muscles, which will be tired after use and recover to a certain extent after rest [8].

The research on the restorative environment has a relatively long history and has formed a quite deep theoretical foundation. In the 19th century, Olimsted presented the word “rehabilitation” to the world. In his view, people can
get relaxation and calm from the natural environment, and self-heating can also help urban residents release pressure. This discovery caused a shock in the field of environmental psychology. Then Kaplan and Talbot formally put forward the term “restorative environment,” believing that the restorative effect of the natural environment is quite good, which is conducive to people’s physical and mental health. With the continuous development of environmental psychology, until the middle and late last century, the research on restorative environment has achieved a great breakthrough and formed a lot of mature theories and views, such as environmental load theory, wake-up theory, and so on. Among them, Ulrich et al. have repeatedly demonstrated that people can effectively relieve pressure and burden by being close to nature and contacting nature, and this recovery effect has encountered great resistance in the urban environment [9]. Based on the abovementioned theory, the subsequent research on this theory mainly focuses on the application and practice of environmental space, considers the effect of rehabilitation through various methods such as experiments and on-site investigations, and further deepens and expands this theory by using data. Korpela et al. found that restorative experience is related to people’s preferred places. In fact, people can recover their emotions to a certain extent in familiar scenes and places [10]. et al. analyzed the environmental restoration of the monastery by means of a questionnaire and believed that the restoration function of the monastery did exist [11]. By investigating the restoration of urban parks and forests in Zurich, et al. found that sports in green spaces can relieve physical and mental stress, improve his own happiness index, and support the theory of restorative environment [12]. Gutierrez et al. deeply studied the application of restorative landscape in the campus environment, so as to reduce the load and pressure of teachers, students, and employees, which further expanded the restorative environment theory in the practice of space [13]. In addition to the abovementioned researchers and their research results, there are also a large number of research books, documents, and materials on restorative environmental theory abroad. They have made an in-depth analysis of the theory and its application effect in specific environmental sites through visits, investigations, field visits, logical derivation, and other methods, and also provided a good theoretical basis and scientific guidance for this study.

With the rapid development of science and technology, people are more inclined to spend most of their time indoors. Therefore, whether the indoor environment meets the thermal comfort of human body not only has a significant impact on people’s work efficiency but also affects people’s physical and mental health. Nowadays, almost all traditional air-conditioning control systems only use single temperature control to adjust the indoor thermal environment, not directly based on people’s thermal comfort. Such a control method is not only of general effect but also great energy consumption. Therefore, the author believes that we should first choose an appropriate evaluation index of thermal comfort, evaluate whether the human body is in the thermal comfort feeling according to this index, and control it to make it tend to the range of human comfort. Only in this way can the indoor environment truly meet the thermal comfort of the human body.

Nevertheless, there is relatively little research on the restorative theory of the indoor environment. However, people spend more than 80% of their time indoors. A good indoor environment is conducive to improving work efficiency. At present, air-conditioning systems only use temperature to measure indoor environmental comfort, ignoring other variables related to human thermal comfort [14–16]. Therefore, in many cases, it cannot meet people’s needs for thermal comfort, and it will also lead to an increase in the operating cost and energy consumption of the air conditioning system. Now we use the standard effective temperature SET* index recommended by ASHRAE standard and widely used to measure the thermal environment. SET* is directly related to people’s thermal feeling rather than the air temperature. It was proposed by Gagge and comprehensively considered the effects of temperature, humidity, average radiation temperature, wind speed, etc., under the influence of different activity levels and clothing thermal resistance. SET* can more effectively reflect the thermal comfort of the human body than simple air temperature [17–20]. The subjective evaluation criteria of heat sensation are divided into seven levels: cold, cool, slightly cool, moderate, warm, slightly warm, and hot. When the indoor environment is to be comfortable, the range of SET* index is [21, 22].

The SET* index is based on the nonlinear and time-varying characteristics of the thermal comfort index of the physiological response model. The traditional calculation method needs to calculate the influence of air temperature, humidity, wind speed, average radiation temperature, and other parameters on the temperature and humidity of human skin through repeated iterations. The calculation formula is complex and cannot be determined in real-time. Therefore, it is difficult to meet the requirements of real-time control of the air conditioning system [23–25]. Many studies assume that the sample data is taken within a certain range, but the measured sample data are more conducive to the training of SET* index model.

Therefore, in this paper, four environmental factors are obtained through actual measurement as sample data, and the particle swarm optimization algorithm is used to optimize BP neural network. The method can calculate the value of SET* in real-time, solve the complex iterative operation, and improve the convergence speed and prediction accuracy of the neural network. The corresponding neural network model is established.

2. Neural Network Model and Optimization Algorithm

2.1. BP Neural Network Model. BP (back propagation) structure is shown in Figure 1. Neurons are arranged in layers, independent within layers, and fully connected between layers. Information is transmitted and processed forward in one direction in the network, and there is no feedback loop. Where, \( x = (x_1, x_2, \ldots, x_n) \) represents an \( n \)-dimensional input sequence composed of \( n \) feature
information; $W_{ij}$ is the connection weight between the input layer and the hidden layer; $V_j$ is the connection weight between hidden layer and output layer neurons, and $\theta_j (j = 1, 2, \ldots, l)$ is the threshold of hidden layer; $y_t (t = 1, 2, \ldots, q)$ is the threshold of the output layer; $y = (y_1, y_2, \ldots, y_q)$ is the model output sequence; $\varphi(\cdot)$, $\psi(\cdot)$ represents the activation function of the network middle layer and output layer, respectively, [26–28].

2.2. BP Neural Network Learning Process. The learning process of BP neural network is as follows:

1. First, we initialize the network learning parameters of the new BP neural network model, update the weight threshold of the network, and specify the training error $E$, rated accuracy, and learning rate $\eta$, the learning rate is $[0, 1]$;
2. After modifying some basic parameters of the network, we input the training set data into the model, and then calculate the forward output of each node of the network;
3. After completing the second step, it is also necessary to calculate the deviation between the expected output and the network output;
4. After the third step, calculate the parameter correction information of each layer;
5. Repeatedly adjust the weights of each neuron node. If $E < \eta$ or the maximum number of training times is reached, the algorithm ends.

2.2.1. Signal Forward Propagation Process. The input signal $u_j$ of the $j$-th node of the hidden layer is as follows:

$$u_j = \sum_{i=1}^{n} W_{ij} x_i + \theta_j.$$  

(1)

The output signal $s_j$ of the $j$-th node after the hidden layer passes through the function $\varphi(\cdot)$ and is activated as:

$$s_j = \varphi(u_j) = \varphi\left( \sum_{i=1}^{n} W_{ij} x_i + \theta_j \right).$$  

(2)

The input signal $c_t$ of the $t$-th node of the output layer is as follows:

$$c_t = \sum_{j=1}^{l} (V_j s_j + y_t)$$

$$= \sum_{j=1}^{l} \left( V_j \varphi\left( \sum_{i=1}^{n} W_{ij} x_i + \theta_j \right) + y_t \right).$$  

(3)

After the output layer is activated by function $\psi(c_t)$, the output signal $y_t$ of the $t$-th node is as follows:

$$y_t = \psi(c_t) = \psi\left( \sum_{j=1}^{l} \left( V_j \varphi\left( \sum_{i=1}^{n} W_{ij} x_i + \theta_j \right) + y_t \right) \right).$$  

(4)

2.2.2. Signal Back Propagation Process. After the forward signal is processed by the output layer, the deviation between the network output and the actual output is calculated layer by layer, and the weight threshold of each layer of the network is inversely modified according to the gradient descent algorithm to optimize the structural parameters [29].

Suppose that the training sample contains $P$ data. For a single sample data point $p (p = 1, 2, \ldots, P)$, the error is as follows:

$$E^{(p)} = \frac{1}{2} \sum_{t=1}^{q} \left( \hat{y}_t^{(p)} - y_t^{(p)} \right)^2.$$  

(5)

The error of the whole training sample set is as follows:

$$E^{(p)} = \frac{1}{2} \sum_{p=1}^{P} \sum_{t=1}^{q} \left( \hat{y}_t^{(p)} - y_t^{(p)} \right)^2.$$  

(6)

Where $\hat{y}_t^{(p)}$ and $y_t^{(p)}$ represent the actual output and network output of the $t$-th node of the output layer when the input sample is $p$.

$$\Delta V_{jt} = -\eta \frac{\partial E}{\partial V_{jt}};$$

$$\Delta y_t = -\eta \frac{\partial E}{\partial y_t};$$

$$\Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}};$$

$$\Delta \theta_j = -\eta \frac{\partial E}{\partial \theta_j}.$$  

(7)
It can be obtained after correction as:

\[
\Delta V_{jt} = -\eta \sum_{p=1}^{P} \sum_{i=1}^{q} (\tilde{y}^{(p)}_i - y^{(p)}_i) \psi'(c_i) \\
\Delta y_{jt} = -\eta \sum_{p=1}^{P} \sum_{i=1}^{q} (\tilde{y}^{(p)}_i - y^{(p)}_i) \psi',
\]

\[
(c_i) = \eta \delta_i,
\]

\[
\Delta W_{ij} = -\eta \sum_{p=1}^{P} \sum_{i=1}^{q} V_{ji}(\tilde{y}^{(p)}_i - y^{(p)}_i) \psi'(c_i) \psi'(u_i),
\]

\[
x_i = \eta \delta_j x_i,
\]

\[
\Delta \delta_i = -\eta \sum_{p=1}^{P} \sum_{i=1}^{q} V_{ji}(\tilde{y}^{(p)}_i - y^{(p)}_i) \psi'(c_i) \psi'(u_i) = \eta \delta_j,
\]

where \( \delta_i \) and \( \delta_j \) represent the error signals of the output layer and the hidden layer, respectively.

2.3. Particle Swarm Optimization Algorithm. Particle swarm optimization (PSO) algorithm is a mobile search process in which Dr. Kennedy and Dr. Eberhart, after an in-depth analysis of the natural bird predation process, idealize the individual of the birds swarm into a particle, draw lessons from the individuality and sociality of each bird in the group behavior, and simulate and simplify it into a particle to find the individual optimal solution in the feasible solution space and the global optimal solution at the same time [30–33]. In the process of updating each position, the particle should not only refer to the historical optimal value recorded by itself but also consider the optimal value of another individual search, and adjust its search direction under the comprehensive guidance of this information to make the group approach the optimal extreme value.

The position of a single particle in PSO algorithm represents a feasible solution to the optimization problem, which is substituted into the objective function to evaluate the fitness, and the particle position is constantly updated according to the fitness comparison results to solve the problem to be optimized. PSO algorithm first randomly generates an initial population with \( m \) particles in the \( D \)-dimensional feasible solution space and is randomly equipped with a certain flight speed. For the \( i \)-th particle, its position is recorded as \( \vec{x}_i = (x_{i1}, x_{i2}, \ldots, x_{iD}) \), its flight speed is recorded as \( \vec{v}_i = (v_{i1}, v_{i2}, \ldots, v_{iD}) \), the individual historical optimal value is recorded as \( \vec{p}_i = (p_{i1}, p_{i2}, \ldots, p_{iD}) \), and the group historical optimal value is recorded as \( \vec{g} = (p_{g1}, p_{g2}, \ldots, p_{gD}) \) in the iteration process, the particle updates its speed and position through (9) and (10):

\[
v_{id}^{k+1} = \omega v_{id}^k + c_1 r_1 (p_{id}^k - x_{id}^k) + c_2 r_2 (p_{gd}^k - x_{id}^k),
\]

\[
x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1},
\]

where \( \omega \) is the inertia weight, and the range is within the range of \([0, 1]\); \( i = 1, 2, \ldots, m; d = 1, 2, \ldots, D; k \) is the current search algebra; \( c_1 \) and \( c_2 \) are learning factors, which generally take equal nonnegative values; The random numbers \( r_1 \) and \( r_2 \) are independent of each other and range between \([0, 1]\). Usually, the position and speed of particles should be prevented from crossing the boundary, which is limited to a specific space, that is, \( v_{id} \in [-v_{max}, v_{max}] \), \( x_{id} \in [-x_{max}, x_{max}] \), to avoid invalid search and speed up the optimization process.

The standard PSO algorithm flow is as follows:

1. Initialize the group size, inertia weight, learning factor, initial particle speed and position, and specify the particle speed limit \([-v_{max}, v_{max}] \) and position limit \([-x_{max}, x_{max}] \);
2. Calculate the fitness value of each particle according to the objective evaluation function of the problem to be optimized;
3. Compare the current fitness value of each particle with its own historical optimal function value. If the former evaluation value is better, the individual optimal position will be updated to the current position coordinates, otherwise, it will remain unchanged;
4. Compare the historical local optimal value of all particles with the global optimal value of the population, and use the particle position with a better fitness function value to eliminate the position of the global optimal value, otherwise, it will remain unchanged;
5. Update the velocity and position of particles according to equations (9) and (10);
6. If the maximum number of iterations has been reached or the preset fitness minimum error is met, the algorithm ends, otherwise, return to program (2) to enter the next iteration.

2.4. Restorative Environment Theory. “Restorative environment” is based on the dimension of environment setting, trying to update and restore the physical and mental resources and abilities that have been continuously consumed by human beings. It can effectively reduce people’s pressure, reduce people’s bad emotions, reduce inner fatigue, and ensure the healthy development of the body and mind. At this stage, the recovery process visible to the naked eye, such as improving the task of directional attention, actively changing emotions all depend on the behavior of individuals using resources [7]. In addition, the healing effect of the environment refers to that the environment can continuously restore and update the physical and mental resources and abilities consumed by human beings. At the same time, at the level of environmental psychology, it can scientifically evaluate the social and psychological attributes of the environment, and can also be effectively applied to physical and mental healing, landscape design, urban planning, and other aspects [9].

We can summarize the positive role of environment in promoting human beings from three aspects: comprehensively improving human long-term happiness and health; recover human mental fatigue in a short time; let human beings quickly get rid of the pain of disease and recover their
health as soon as possible. If the abovementioned requirements are met at the same time or in part, it can be called a restorative environment. The indoor ambient temperature in this study, that is, the short-term regulation of temperature, is the expected goal. The design of indoor temperature constructed by neural network modeling technology has a restorative effect and is discussed in the field of industrial design.

Since the 1980s, Kaplan and others have studied the restorative environment in depth by combining theory and empirical research, and successively put forward the theory of attention restoration and decompression. In the process of studying the restorative environment, both of them can be called two core theories. Although they have their own emphasis on evaluation criteria, concept definition, action methods, etc., from the perspective of research and development, the possibility of their final integration is greater, and the evaluation of environmental quality will become increasingly rich and systematic.

2.5. Standard Effective Temperature SET*. The SET* index comprehensively considers different activity levels and clothing thermal resistance. It is based on the human physiological response model and is obtained from the analysis of the physical process of human heat transfer, so the calculation is very complex. The SET* index is based on the two-node model theory of human body temperature regulation. That is, the model is regarded as two layers, the core layer, and the skin layer. Its model can be expressed by two heat balance equations as:

\[
(1-a)mc_p \left( \frac{dt_{cr}}{dt} \right)_{A_D} = M - W - (0.023M(44 - p_a)) + 0.0014M(34 - t_a) - (t_{cr} - t_{sk}) \times (5.28 + 1.163 \times sKBF),
\]

\[
\text{amc}_{lb} \left( \frac{dt_{cr}}{dt} \right)_{A_D} = (t_{cr} - t_{sk}) \times (5.28 + 1.163 \times sKBF)
\]

\[
- \left( f_d(h_c + h_t) \left( t_k - \frac{h_k t_k + h_{net} t_{net}}{h_c + h_t} \right) + (0.06 + 0.94w) 167 h_c (p_{sk}^* - p_a) F_{pc1} \right),
\]

where \(t_{cr}\) and \(t_{sk}\) is the temperature of the core layer and skin layer; SkBF is the peripheral blood flow rate (L/hm²); \(M\) is the metabolic rate of human body, and \(W\) is the external work of the human body; \(a\) is the proportion of human skin layer; \(m\) is the body weight (kg); \(c_{pb}\) is the specific heat capacity of the human body (kJ/kgK); \(A_D\) is the total skin surface area obtained by Dubois formula; \(t_a\) is the air temperature; \(t_{net}\) is the average radiation temperature; \(h_c\) and \(h_t\) are convective and radiant heat transfer coefficients; \(f_d\) is the area coefficient of clothing; \(F_{pc1}\) is the permeability coefficient of clothing; \(w\) is skin moisture; \(p_a\) and \(p_{sk}^*\) refers to the water pressure under the air temperature and the saturated water pressure under the skin temperature.

SET* an index that considers the comprehensive effect of air temperature, humidity, wind speed, average radiation temperature, clothing thermal resistance, and different activity levels on human thermal sensation. The calculation of SET* is complex, and it is necessary to repeatedly iterate through the computer. First, the physiological parameters of the human body must be calculated by using the two-node model, and the heat exchange equilibrium equation between humans and the environment can be obtained. If \(H_{sk}\) is the heat loss of skin, it is expressed by the following equation as:

\[
H_{sk} = h_s(t_k - SET^*) + whs \times (p_{sk} - 0.5p_{SET^*}),
\]

where \(h_s\) is the standard convective heat transfer coefficient (W/m²·C); \(h_{se}\) is the standard evaporation heat transfer coefficient (W/m²·kPa); \(p_{SET}^*\) is the saturated water pressure of water vapor in air at skin temperature (kPa); \(p_{SET}^*\) is the saturated water pressure (kPa) at SET*.

3. Algorithm Improvement and Performance Test

3.1. Improvement of Particle Swarm Optimization Algorithm. The standard particle swarm algorithm processes one set of solutions in parallel to update another set of solutions in the process of optimization. The particles move randomly in the complex field, and the balance between local search and global search is achieved through the evolution of particle cooperation and competition. Global convergence and anti-jamming capability [34, 35]. However, the local search ability of the algorithm is poor, and the optimization result is easy to fall into the local minimum value of the objective function so the algorithm converges slowly in the later stage, and a premature phenomenon occurs.

In view of the defects in the standard PSO algorithm, after further exploring the ways of bird swarm communication, Hu Wang et al. Verified that the search performance of BPSO algorithm has a low correlation with speed, and then abandoned the speed parameter in the iterative update of BPSO algorithm, and proposed an improved simplified particle swarm optimization algorithm, referred to as SPSO. SPSO only completes particle optimization through position information, effectively reducing the human interference factors added by the initialization of speed term, the accuracy and stability of the algorithm are improved. The improved particle position update formula is as:

\[
x_{id}^{k+1} = \omega x_{id}^k + c_1 r_1 (p_{id}^k - x_{id}^k) + c_2 r_2 (p_{sk}^k - x_{id}^k).
\]

3.2. Performance Test of Improved Particle Swarm Optimization Algorithm. In order to verify that PSO algorithm has better optimization and convergence ability, this paper compares PSO and SPSO through three standard test functions with different characteristics. The specific information of each test function is shown in Table 1.
The specific test contents are as follows: set the PSO and SPSO algorithm optimization test to be carried out in the same programming environment, specify that the number of particles per generation is 30, the maximum number of optimization is 200, and the two algorithms run 50 times each; inertia weight is set as: \( \omega = 0.7 \); the acceleration factor of PSO and SPSO algorithm \( c_1 = c_2 = 2.0 \); during the test, the function to be optimized is the test function; and the value of the function dimension is different, including 10 and 2. The performance of the algorithm is investigated by three indicators: the optimal value, the average value, and the success rate. The simulation results of test function optimization are shown in Table 2.

From the simulation results in Table 2, it can be seen that under the same operating environment and parameter settings, the global optimization effect of the improved SPSO algorithm is ideal, in which \( f_1, f_2 \) and \( f_3 \) can search for the theoretical optimal solution, reflecting the strong optimization ability of the algorithm for different dimensional functions, while BPSO algorithm only finds the theoretical target value in the solution process of low dimensional \( f_2 \) function, and its optimal performance is far inferior to that of SPSO algorithm. For the index of success rate, the probability of SPSO algorithm meeting the rated accuracy is 100%. Relatively speaking, the success rate of BPSO is low, even 0. Figures 2–4 shows the images of each test function. It can be seen from Figures 2–4 that the optimization paths between different test functions are different. When \( f_1 \) function is optimized, the paths are diverse, but it is not conducive to the rapid generation of optimal results. The optimization paths of \( f_2 \) and \( f_3 \) functions are basically the same, but compared with \( f_2 \) function, it can be more selective and faster in terms of optimization paths.

Figures 5–7 is the curve diagram of the optimization process of each test function algorithm. It can be seen from Figures 5–7 that the optimization process curves for different optimization functions are also different. Among them, for function 1, the overall changes tend to be consistent, but the number of iterations required is longer, and it takes more practice; for function 2, the overall performance is better, which is an ideal state; for function 3, although the number of iterations of the improved PSO model is reduced, the function is changing. The fluctuations in the process are large, which is not conducive to the optimization of the model, and the results also have large uncertainties. Therefore, by synthesizing the optimization curves of three different optimization functions, it can be found that the SPSO algorithm is obviously due to the ordinary PSO algorithm, and its outstanding performance is that the convergence speed is faster and the accuracy is higher. Especially in the process of solving complex functions, the optimization ability is more prominent.
To sum up, it can be seen from the optimization process curves of different functions that the improved particle swarm optimization algorithm (SPSO algorithm) after the improvement of the optimization algorithm in this paper is obviously due to the common PSO algorithm, which is characterized by faster convergence speed and higher accuracy, especially in the solution process of complex functions, the optimization ability is more prominent. In the actual combat process, it can also show better processing ability.

3.3. Construction of Restorative Indoor Environment Model Based on Neural Network. The standard BP neural network adopts the gradient descent method to constantly adjust the weight and threshold of the network to minimize the sum of squares of the network error. However, finding the minimum value in the error plane has its own limitations and shortcomings, mainly manifested in the fact that the learning rate is too small, resulting in too long training time, local extremum, slow convergence speed of the algorithm, poor numerical stability, etc. Therefore, this paper proposes a method to optimize the BP neural network model by using the improved particle swarm optimization algorithm, namely the SPSO BP neural network model. The flow chart of the improved neural network-based restorative indoor environment model algorithm is shown in Figure 8.

4. Simulation Experiment

4.1. Data Acquisition. After the model structure of comfort index SET* is established through the collection of experimental data, we should train according to the actual data. The experimental data were measured in a room on the second floor of the State Key Laboratory of Subtropical Building Science, South China University of technology. The room includes the measurement and sensing of four environmental factors: temperature and humidity, average radiation temperature, and wind speed, as well as comfort control equipment such as fans and air conditioners. Maintain ventilation during the experiment, other comfort control devices do not work.

A sh71 digital temperature and humidity sensor are installed in the room, it is used to measure the temperature
and humidity of the indoor environment. The average radiation temperature was measured by Agilent 34970 A data acquisition instrument. Using SDP1000/SDP2000 micro differential pressure sensor to measure indoor wind speed, install the wind speed sensor in the center of the indoor roof. Since the thermal resistance of human clothing and the metabolic rate of the human body are variables related to human body, these two variables are uncontrollable factors in comfort control, for South China, only summer comfort is considered, for South China, only summer comfort is considered, when the thermal resistance ICOL of human clothing is 0.5 and the metabolic rate $M$ is 58.2 W/m², the indoor comfort index $SET^*$ value is obtained by iterative calculation.

The experiment is carried out in the experimental room for measurement, and the experimental data collected by the sensor passes through the AD conversion module. After being converted into a digital signal, it communicates with PC through RS232, processes the received experimental data, and displays and stores it. From 1080 groups of environmental factors measured at different times collected by the sensor and $SET^*$ values obtained by iterative calculation, 880 groups of data are selected as training samples, and another 200 groups of data are selected as BP neural network model test sample data.

4.2. Model Training. Using the BP neural network model based on Improved Particle Swarm Optimization constructed above is used to train the experimental data, which is programmed with Python language of tensorflow2.0 software, and the network error target is set at $10^{-4}$. Figures 9 and 10 show the iteration and convergence curves of the standard BP algorithm and the BP neural network algorithm model based on the improved particle swarm optimization.

Based on the Figures 9 and 10, it can be found that, first of all, from the iteration times of the above two figures, the standard BP neural network model has too long training time and local extremum due to too small learning rate, slow convergence speed of the algorithm, poor numerical stability, and is difficult to converge. It does not converge until the iteration times reach 2000. It can be seen that if the standard BP neural network model is used for modeling the restorative environment, it will spend a lot of time on training time; however, compared with the standard BP neural network model, the BP neural network model optimized based on the improved particle swarm optimization algorithm not only has less iterations but also has a high learning rate. The model can converge quickly. When the iterations are about 50 times, it will converge regionally, which can save a lot of time for model training. Secondly, based on the initial value of model error, the initial value of standard BP neural network model error is much larger than the initial value of error in the training of BP neural network model optimized based on improved particle swarm optimization algorithm, and its maximum value is close to 10,
while the maximum initial value of error in the training of BP neural network model optimized based on improved particle swarm optimization algorithm is not more than $10^{-5}$; At the same time, the final error difference between the two is also large, in which the final error of the standard BP neural network model is greater than $10^{-3}$, while the final error of the BP neural network model optimized based on the improved particle swarm optimization algorithm is less than $10^{-4}$.

To sum up, it can be found that BP neural network is used to establish the prediction model of indoor environmental comfort index SET*, and the relationship between environmental factors and SET* is obtained, which overcomes the complex iterative operation of thermal environment parameters on human thermal sensation in the traditional model. In addition, the BP neural network model optimized by the improved particle swarm optimization algorithm significantly improves the convergence speed of model training. The results show that there is little error between the prediction value of the improved neural network model and the expected value of the traditional model, which ensures the effectiveness of the prediction model, so it can meet the requirements of real-time in the control process of environmental control equipment such as air conditioning system.

5. Conclusion

With the improvement of material living standards, people have higher and higher requirements for the office and indoor rest environment, and the indoor temperature environment is very important to create a sense of comfort. A good indoor somatosensory temperature environment can not only convey the degree of somatosensory comfort but also relax people’s bodies. At present, there is little research on this aspect at home and abroad, which leads to the stagnation of this theory. Therefore, in order to promote research in this field, this paper uses the neural network modeling method, based on the indoor comfort index SET* value and other factors that can affect the ambient temperature, aiming at the human body temperature comfort, adopts the improved particle swarm optimization algorithm to optimize the BP neural network method, constructs a neural network-based restorative indoor environment model, realizes the real-time control of SET* value, and then analyzes the relationship between indoor environmental thermal factors and SET* value. The model is optimized based on simulation experiments. The simulation results show that the error between the prediction value of the improved neural network model and the expected value of the traditional model is very small, which ensures the effectiveness of the prediction model. Therefore, it can meet the real-time requirements in the control process of environmental control equipment such as air conditioning systems. Relevant experiments not only verify the effectiveness of the improved algorithm in this paper but also use this algorithm model to optimize the indoor environment and ensure indoor comfort.

Data Availability

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

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References

[1] S. O. Ro, “A Study on the Physical, Mental and Social Factors Influencing the Health Status of Aged Women in Korea,” *Korean Journal of Women Health Nursing*, vol. 2, no. 1, pp. 53–67, 1996.
[2] C. Caballero-Arce, A. Insauti, and J. B. Marco, “Lighting of Space Habitats: Influence of Color Temperature on a Crew’s Physical and Mental health,” in *Proceedings of the 42nd International Conference on Environmental Systems*, p. 3615, CA, USA, July 2012.
[3] R. Slabe-Erker and S. Ličen, “Dejavniki Gibalne Aktivnosti in Z Zdravjem Povezane Kakovosti Življenja (Factors Influencing Leisure-Time Physical Activity and Health-Related Quality of life),” vol. 48, no. 2, 2014.
[4] B. Oladunni, P. A. Lyoka, and D. T. Goon, “Perceived motivational factors influencing students with disabilities towards sports participation in Amathole district, Eastern Cape Province, South Africa,” *African Journal for Physical Health Education Recreation & Dan*, vol. 21, no. 4.2, pp. 1389–1401, 2015.
[5] A. Ghahramani, “The Effect of the Relaxation Training on the General Health and Selected Physical Fitness Factors Affecting Seniors balance,” vol. 43, no. 8, pp. 608–614, 2009.
[6] R. F. Baumeister, E. Bratslavsky, M. Muraven, and D. M. Tice, “Ego depletion: is the active self a limited resource?” *Journal of Personality and Social Psychology*, vol. 74, no. 5, pp. 1252–1265, 1998.
[7] L. W. Zhang, “Control of Ego-Depletion: Research and Application in Competitive Sports,” *China Sport Science*, vol. 36, no. 5, pp. 506–515, 2013.
[8] R. F. Baumeister, K. D. Vohs, and D. M. Tice, “The strength model of self-control,” *Current Directions in Psychological Science*, vol. 16, no. 6, pp. 351–355, 2007.
[9] R. S. Ulrich, R. F. Simons, B. D. Losito, E. Fiorito, M. A. Miles, and M. Zelson, “Stress recovery during exposure to natural and urban environments,” *Journal of Environmental Psychology*, vol. 11, 1991.
[10] K. M. Korpela, T. Hartig, F. G. Kaiser, and U Fuhrer, “Restorative experience and self-regulation in favorite places,” *Environment and Behavior*, vol. 33, no. 4, pp. 572–589, 2001.
[11] P. Ouellette, R. Kaplan, and S. Kaplan, “The monastery as a restorative environment,” *Journal of Environmental Psychology*, vol. 25, no. 2, pp. 175–188, 2005.
[12] R. Hansmann, S. M. Hug, and K. Seeland, “Restoration and stress relief through physical activities in forests and parks,” *Urban Forestry and Urban Greening*, vol. 6, no. 4, pp. 213–225, 2007.
[13] J. Gutierrez, “Restorative Campus Landscapes: Fostering Education through Restoration,” Kansas State University, Manhattan, 2013.
[14] M. Daly, “Association of ambient indoor temperature with body mass index in England,” *Obesity*, vol. 22, no. 3, pp. 626–629, 2014.
[15] P. Bustelo, B. Cristina, G. Fernandez, M. Llorián, and C. Lovelle, “IoFClime: The Fuzzy Logic and the Internet of Things to Control Indoor Temperature Regarding the Outdoor Ambient conditions,” Future generations computer systems, vol. 76, pp. 275–284, 2017.

[16] S. Vellingiri, P. Dutta, S. Singh, L. M. Sathish, S. Pingle, and B. Brahmbhatt, “Combating climate change-induced heat stress: assessing cool roofs and its impact on the indoor ambient temperature of the households in the urban slums of ahmedabad,” Indian Journal of Occupational and Environmental Medicine, vol. 24, no. 1, 2020.

[17] D. G. Markov, P. S. Yordanov, I. S. Simova, M. Ivanov, N. Kehayova, and E. Georgiev, “On the Influence of Indoor Temperature on Occupant’s Performance,” in Proceedings of the International Scientific Conference, Ruse University, Bulgaria, October 2014.

[18] D. Meana-Llorián, C. González García, B. C. Pelayo G-Bustelo, J. M. Cueva Lovelle, and N García-Fernandez, “IoFClime: the fuzzy logic and the Internet of Things to control indoor temperature regarding the outdoor ambient conditions,” Future Generation Computer Systems, vol. 76, pp. 275–284, 2017.

[19] J. Gwak, M. Shino, K. Ueda, and M. Kamata, “An investigation of the effects of changes in the indoor ambient temperature on arousal level, thermal comfort, and physiological indices,” Applied Sciences, vol. 9, no. 5, p. 899, 2019.

[20] B. Mabuya and M. Scholes, “The three little houses: a comparative study of indoor and ambient temperatures in three low-cost housing types in gauteng and mpumalanga, South Africa,” International Journal of Environmental Research and Public Health, vol. 17, no. 10, p. 3524, 2020.

[21] A. Jo, H. Sang, A. Mjl et al., “Machine Learning-Based Discrimination of Indoor Pollutants Using an Oxide Gas Sensor Array: High Endurance against Ambient Humidity and Temperature,” Sensors and Actuators B, Article ID 131894, 2022.

[22] L. Ma, N. Shao, J. Zhang, and T. Zhao, “The influence of doors and windows on the indoor temperature in rural house,” Procedia Engineering, vol. 121, pp. 621–627, 2015.

[23] H. J. Kang, Y. P. Min, I. K. Lee et al., “Effects of Ambient Temperature and Dietary Glycerol Addition on Growth Performance, Blood Parameters and Immune Cell Populations of Korean Cattle steers,” Asian-Australasian Journal of Animal Sciences, vol. 30, no. 4, 2017.

[24] M. K. Sharp, “Indoor comfort achieved exclusively from ambient sources across US climates,” Journal of Solar Energy Engineering, vol. 143, no. 6, pp. 1–28, 2021.

[25] S. Yan and X. Li, “Analytical expression of indoor temperature distribution in generally ventilated room with arbitrary boundary conditions,” Energy and Buildings, vol. 208, Article ID 109640, 2020.

[26] B. Sadeghi, "A BP-neural network predictor model for plastic injection molding process," Journal of Materials Processing Technology, vol. 103, no. 3, pp. 411–416, 2000.

[27] B. Lu and Y. Wang, “Overview of Handwritten Numeral Recognition Based on BP Neural network,” in Proceedings of the 2011 International Conference on Computer Science and Network Technology, IEEE, Harbin, December 2011.

[28] M. Y. Chen and D. F. Chen, “Early cost estimation of strip-steel coiler using BP neural network Machine Learning and Cybernetics,” in Proceedings of the 2002 International Conference on, IEEE, Beijing China, November 2002.

[29] B. Zhao, C. X. Guo, B. R. Bai, and Y Cao, “An improved particle swarm optimization algorithm for unit commitment,” International Journal of Electrical Power & Energy Systems, vol. 28, no. 7, pp. 482–490, 2006.

[30] G. C. Chen and Y U. Jin-Shou, “Particle swarm optimization algorithm,” Information and Control, vol. 186, no. 3, pp. 454–458, 2005.

[31] J. Kennedy, “Particle swarm optimization,” Proc. of 1995 IEEE Int. Conf. Neural Networks, (Perth, Australia), Nov. 27, vol. 4, no. 8, pp. 1942–1948, 2011.

[32] C. J. Liao, C. T. Tseng, and P. Luarn, “A discrete version of particle swarm optimization for flowshop scheduling problems,” Computers & Operations Research, vol. 34, no. 10, pp. 3099–3111, 2007.

[33] R. C. Eberhart, “Comparing Inertia Weights and Constriction Factors in Particle Swarm optimization,” in Proceedings of the 2000 IEEE Congress on Evolutionary Computation, IEEE, La Jolla CA USA, July 2002.

[34] J. K. Zhang, S. Y. Liu, and X. Q. Zhang, “Improved Particle Swarm optimization,” Computer Engineering & Design, vol. 193, no. 1, pp. 231–239, 2007.

[35] B. Liu, L. Wang, Y. H. Jin, F. Tang, and D. X Huang, “Improved particle swarm optimization combined with chaos,” Chaos, Solitons & Fractals, vol. 25, no. 5, pp. 1261–1271, 2005.