Mathematical Modeling and Optimal Control of Underground Ventilation and Air Conditioning in Station

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The underground ventilation and air-conditioning system of the station accounts for about 40% of the total energy consumption of the subway. One of the important reasons is the cooling load of the station. The related control process has typical nonlinear, time-varying, and large inertia characteristics, and the traditional PID control algorithm is difficult to achieve the ideal control effect. Therefore, it is of great significance to study the application of the intelligent algorithm in subway ventilation and air-conditioning control systems to improve the control effect. Based on the analysis of the coupling characteristics of temperature and humidity control in subway air-conditioning systems, this paper designs the feedforward decoupling link according to the identification model and analyzes the control curves with and without the decoupling link when using conventional PID control, which shows the effectiveness of the method proposed in this paper.

1. Introduction

According to statistics, in China’s energy consumption, transportation energy consumption accounts for as much as 30%. With the continuous advancement of economic development and urbanization in recent years, the transportation industry has developed rapidly, which has brought higher energy consumption. The subway system is the backbone of urban public transportation. It provides efficient and convenient services for cities, but it also brings a lot of energy consumption. For example, China’s rail transit consumed 7.23 billion kWh of electricity in 2018, accounting for 1.06% of China’s total electricity consumption. Among them, the air-conditioning system of subway stations consumes about 31% of energy consumption, second only to the train traction system. Therefore, it is of great significance to study the energy-saving optimization method of the air-conditioning system in a subway station [1].

The subway ventilation and air-conditioning control system has a wide application prospect, and the establishment of an effective system model and the effective application of intelligent algorithms for the control system is an important part of it. An air-conditioning system is a multivariable system, and there is a problem with variable coupling in multiparameter control. How to use a decoupling control strategy to eliminate the mutual influence between controlled variables and improve the control effect is seldom studied in this field at present has not been applied in ventilation and air-conditioning systems. For example, the United States and Japan have achieved good control effects in air-conditioning control and put forward many air-conditioning control methods, especially when the control level of single air conditioning is at the world leading level, such as comfort air conditioning and intelligent air conditioning. In the control technology of single air-conditioning units, intelligent control methods such as fuzzy control, neural network control, fuzzy PID control, and neural network PID control are adopted. The control accuracy and comfort are improved. The ventilation and air-conditioning system of the underground station is very different from the single air-conditioning system. The ventilation and air-conditioning
system is a multivariable system with a large time lag and large inertia, especially considering the nonlinear characteristics of the system. The conventional PID control method has poor control effect on the nonlinear system and low control accuracy. Fuzzy control has good nonlinear characteristics and is suitable for nonlinear systems, but the fuzzy control method has people's subjective consciousness, which affects the control effect, and other control methods are not ideal in ventilation and air-conditioning systems. Therefore, at present, fuzzy PID control technology is mainly used in ventilation and air-conditioning systems of underground stations at home and abroad, and DDC control technology is used in air-conditioning units. This control method can make the system achieve good control accuracy and comfort. Although this technology is relatively mature and widely used in engineering, the outstanding problem is that the controller's load capacity and adaptability to the environment are poor, which often cannot match the actual energy supply, resulting in a large amount of energy waste. With the development of science and technology, many advanced technologies are being applied to smart cities, such as blockchain technology, Internet of Things technology, machine learning technology, and big data technology [2, 3]. Machine learning technologies, including the neural network model, have been widely used in many fields, such as public transportation, taxi demand prediction [4], bicycle station planning [5], and subway passenger flow optimization [6, 7]. In the medical field, a neural network is applied to fetal ultrasonic standard plane recognition [8]. The main contribution of this study is that, in view of the lag, nonlinearity, and multivariable characteristics of ventilation and air-conditioning systems, as well as the purpose of model identification in this study is mainly used for parameter optimization and e shortcomings of traditional decoupling control and neural network control in practical applications, the RBF neural network decoupling control method is put forward, which greatly improves the ventilation and air-conditioning systems, reduces the overshoot, has strong control solving ability, improves the steady and dynamic performance, and improves the control effect of the air-conditioning system. By establishing the mathematical model of neural network, the temperature and humidity decoupling control is obtained by simulation, which makes the ventilation and air-conditioning system meet the control requirements more quickly and accurately, reflects the comfort and energy-saving characteristics of the ventilation and air-conditioning system, and provides the basis for its application in practical projects.

The underground station ventilation and air-conditioning control systems have nonlinear, large inertia, strong coupling system, etc. The variable factors in the operation of the control object itself are complex and involve variables such as temperature, humidity, and flow. In the subway ventilation and air-conditioning system, to ensure that all control parameters are in the best working condition, ensure the air-conditioning energy saving and the highest operating efficiency largely depends on the control strategy of the air-conditioning system. However, at present, most subway ventilation and air-conditioning systems adopt traditional control strategies, which are backward in control ideas and consume a lot of energy, and cannot meet the development needs of modern equipment. Moreover, the control object of VAV air conditioning is special, with large dynamic inertia and pure lag time. The traditional control method has low control efficiency and high energy consumption and cannot be adjusted timely according to the changes in the environment and system parameters, so the traditional control method is no longer competent. With the development of artificial neural network control theory, the artificial neural network is being more and more applied to practical engineering.

In this study, the ventilation and air-conditioning control system of the Jinan subway line is taken as the research object. Based on the analysis of the control system, the intelligent control algorithm based on a neural network is designed and simulated. The theoretical research of neural network decoupling control is relatively mature, but its practical application is less. The basis of neural network decoupling control in subway ventilation and air-conditioning system is as follows: (1) The ventilation and air-conditioning system is a multi-input and multi-output system, and there is coupling among temperature control, humidity control, and air quality. The key of the controller design is decoupling, reducing the unstable factors of the controlled quantity, and ensuring the stable control parameters and good control accuracy. (2) Because air-conditioning control is a nonlinear system, it is difficult to establish an accurate mathematical model. A neural network has a self-learning function, which can achieve a good control effect, control a nonlinear system, and have strong adaptability to parameter changes. Combining neural networks with decoupling control can achieve better results. (3) The operation status of fresh air units and chillers can be adjusted by the computer through frequency converters, and the fresh air feed and circulating water temperature can be controlled conveniently and intelligently.

The main structure of this study is as follows: introduce the subway ventilation and air-conditioning system, analyze the coupling relationship between variable parameters and temperature and humidity variables that affect efficiency, and provide ideas for the establishment of object model and control algorithm design. Aiming at the control process of the cooling system, which is the core of the subway ventilation and air-conditioning system, a control scheme based on the classical control method and neural network multivariable decoupling control is designed, and the identification model is obtained through historical data by the recursive least square method, which provides the basis for the design and simulation of the control algorithm. According to the control scheme, the control methods of conventional PID control and neural network multivariable decoupling control are designed, respectively, and the control effect is verified by simulation analysis with MATLAB.
2. Overview of Subway Ventilation and Air-Conditioning System

Jinan belongs to the temperate continental semihumid monsoon climate zone, and it is hot in summer. There are three operating lines of Jinan Rail Transit, which are the first phase of Jinan Rail Transit: Line 1, Line 2, and Line 3, with a total operating mileage of 84.1 kilometers and 43 stations. There are three lines under construction in Jinan Rail Transit, namely, the second phase of Jinan Rail Transit Line 3, the first phase of Line 4, and Line 6, with a total length of 96.3 kilometers. In this study, a typical station of Jinan Metro is selected as the research object.

2.1. Composition and Operation Principle of Subway Ventilation and Air Conditioning. The underground ventilation and air-conditioning system of the station consists of three parts: the air-conditioning water system (water system), the ventilation and air-conditioning system of the station equipment management room (small system), and the ventilation and air-conditioning system of the public area of the station (large system). The large system and the small system mainly adjust the temperature and humidity of public areas and equipment rooms in the station so that the ventilation in the station can achieve the best effect. The water system mainly cools the air in the station and provides a cold source for large and small systems. The chiller cools the chilled water to about 7°C and pumps it to the cooling device to provide cooling for the mixed air of fresh air and return air. Then, the cooled mixed air is sent to the public area to adjust the air temperature. Chilled water with cooling capacity is sent back to the evaporator of the cooler. At the same time, the cooling water is sent to the condenser by the cooling water pump to condense the refrigerant and then sent back to the cooling tower. In this way, the heat in the station can be successfully transferred to the outside of the station through the cooling device, cooler, and cooling tower. The system structure diagram is shown in Figure 1. The main functions of the underground station ventilation and air-conditioning systems are as follows:

1. When the subway is in normal operation, the general subway station is built underground, which is a semiclosed system, and the air circulation effect is not good, especially during the peak commuter flow. Therefore, ventilation and air-conditioning systems can provide passengers with a comfortable riding environment.

2. Bring a comfortable working environment for station staff, and ensure that all kinds of equipment and components of the subway can work under reasonable temperature and humidity conditions.

3. When a fire accident occurs in a subway station or tunnel section, the ventilation and air-conditioning system of the station can quickly exhaust smoke, providing safe conditions and sufficient time for passengers to quickly escape from the scene of the accident.

2.2. The Coupling Relationship between Temperature and Humidity. The ventilation and air-conditioning systems of the subway account for about 40% of the total energy consumption of the subway. One of the important reasons is that the cooling load of the station is designed according to the long-term maximum load and has a certain amount of wealth.

The subway air-conditioning system is different from the ground building, especially the large air-conditioning system, whose regulating object is the temperature and humidity of a large space [9]. Generally, the subway station is below the ground level, with poor air circulation and a wide range of sources of humidity. If it is not handled properly, the wall will be bedewed, the ground will be wet, or even water will be accumulated, which will be a potential safety hazard for personnel circulation, equipment operation, and subway traffic. With the improvement of people’s living standards, people have higher and higher requirements for the comfort of the air-conditioning system. Nowadays, the air-conditioning system should not only meet the temperature control but also meet the demands of passengers for humidity and air quality. When the ventilation air-conditioning system changes the air supply volume, the air-conditioning terminal device blows hot air into the subway for heat exchange, which inevitably takes away a certain humidity in the air. This causes the indoor air to dry and change the concentration of carbon dioxide, which makes it difficult to meet people’s requirements for comfort. However, in the general subway air-conditioning system, only the temperature is controlled. When the temperature meets the load demand, the humidity does not meet the requirements, and when the humidity is changed, the temperature will also be disturbed. During the humidification process, the air-volume and water-volume control technology is to control the fan frequency and the opening of the electric two-way valve simultaneously [10]. When it is determined that the load in the air-conditioned area is reduced, the temperature of the air conditioner should be reduced, and the fan frequency should be reduced at the same time. It can be seen that the VAV air-conditioning control system is actually multivariable, not just the temperature as a single input, but the temperature and humidity are the inputs of the ventilation air-conditioning control system, while the temperature and humidity are strongly coupled; that is, when one quantity changes, the other quantity will also be affected to some extent. According to the multivariable and strong coupling characteristics of subway ventilation and air-conditioning system, this study puts forward the decoupling control scheme of ventilation and air conditioning.

3. Design and Simulation of PID Control Algorithm

PID algorithm can make the controlled object achieve the ideal control effect by adjusting the parameter combination of proportional coefficient, integral time, and differential time. However, for some complex control processes with pure time delay and nonlinearity, PID is inadequate [11]. Therefore, the intelligent algorithm represented by the
neural network has been widely concerned. The research and application direction of the neural network is mainly control system optimization and process model identification. There have been many application cases in various industrial control systems. Strong nonlinear approximation ability, self-learning, and self-adaptive ability are the main advantages of neural networks in dealing with complex and uncertain problems [12]. This section verifies and analyzes the results of conventional PID control.

3.1. Classical PID Control Method. The air-conditioning temperature and humidity control is a typical dual-input dual-output multivariable control system, and the system structure diagram with feedforward decoupling link is shown in Figure 2.

As can be seen from Figure 2, SP1 is the temperature setting value, SP2 is the humidity setting value, $y_1$ and $y_2$ are the system output values, $G_{C1}(S)$ and $G_{C2}(S)$ are the temperature and humidity controllers, respectively, and $D_21$ and $D_{12}$ are the feedforward compensators. The calculation of the feedforward system is simple, and the multivariable coupling system is decoupled into two univariate systems with no influence on each other through the compensation of the feedforward link. In addition to the above structure, the classical decoupling methods include identity matrix decoupling, diagonal matrix decoupling, and feedback decoupling. In basic principle, the traditional decoupling methods are all the same; that is, the coupling effect is offset by the linear superposition principle and the compensation effect of the decoupling link. The output of the position PID controller directly corresponds to the adjustment range of the actuator. When it is realized by a computer, it needs to accumulate errors, which leads to a large amount of calculations. Moreover, it is necessary to consider integral saturation and other issues when programming. Therefore, in computer sampling control, the incremental structure of PID is often used [14].

\[
\Delta u = K_p[e(k) - e(k-1)] + K_i \int_0^t e(t) \, dt + K_D \left[e(k) - 2e(k-1) + e(k-2)\right].
\]

where $K_p$ is the proportional coefficient, $T_i$ is the integral time, and $T_d$ is the differential time constant.

The output of the position PID controller directly corresponds to the adjustment range of the actuator. When it is realized by a computer, it needs to accumulate errors, which leads to a large amount of calculations. Moreover, it is necessary to consider integral saturation and other issues when programming. Therefore, in computer sampling control, the incremental structure of PID is often used [14].

The incremental PID controller calculates the incremental value $\Delta u$ of the output control quantity in each sampling period. For the actuator with an integral function, the output can be carried out directly, and the control quantity accumulation is completed by the actuator. For the actuator without integral function, the accumulated output of the control quantity can be completed by the program.
3.2. The Optimization Mechanism of the Bat Algorithm. Bat algorithm is a kind of swarm intelligence optimization algorithm proposed by Xin-She Yang in 2010. In nature, the woven bat emits ultrasonic pulses, and the information of prey is determined by analyzing the ultrasonic waves reflected by objects. The weaving bat searches for food by randomly changing its ultrasonic frequency, speed, and position [15]. In the process of approaching the prey, the woven bat will increase the frequency of sending out ultrasonic pulses and reduce the loudness at the same time to show that the distance from the prey is getting smaller and smaller. The control structure is shown in Figure 3:

A large number of studies have shown that compared with particle swarm optimization, genetic algorithms, and other optimization algorithms, the bat algorithm has fewer iterative steps and higher optimization accuracy. Therefore, under ideal circumstances, applying the bat algorithm to offline optimization of PID can often obtain a set of better initial values of PID parameters. In this study, the bat algorithm is used to determine the initial weights of a single neuron, that is, the selection process of initial PID parameters, learning rate, magnification, and other parameters.

The ITAE function of the controlled variable is selected as the objective function: according to the object model obtained by the identification algorithm, a set of PID parameters that minimize the ITAE index are obtained through iterative algorithm optimization and then applied to PID control. The calculation process is shown in Figure 4.

Following the foraging process of bats, the frequency, speed, and location of bats are updated as follows:

\[
\begin{align*}
    f_i &= f_{\text{min}} + (f_{\text{max}} - f_{\text{min}})\beta, \\
    v_i^{t+1} &= v_i^t + (x_{\text{gbest}} - x_i^t) f, \\
    x_i^{t+1} &= x_i^t + v_i^{t+1},
\end{align*}
\]

(3)

where \( \beta \in [0,1] \) is a random number and \( f_{\text{min}} \) and \( f_{\text{max}} \) are the range of frequency \( F \). According to the specific application, it is determined that \( x_{\text{gbest}} \) is the global optimal solution at the \( t \) time. For local optimization, once the current global optimal solution is determined, each bat will make a random movement according to the following formula, thus generating a new set of solutions [17]:

\[
x_{\text{new}} = x_{\text{old}} + \varepsilon A^t,
\]

(4)

where \( \beta \in [-1, 1] \) is a random number and \( A^t \) is the average loudness of all bats at time \( t \).

3.3. Forgetting Factor Recursive Least Square Method. The purpose of model identification in this study is mainly used for parameter optimization and algorithm simulation research, so the parameter model of the object is established by the experimental method according to historical input and output data. The official authoritative data collected from Jinan Rail Group with the adopted data include about 60,000 historical data in July 2021. The platform is configured with I7 processor, GPU graphics card 3080, and memory 64 GB. Before digging deeper into the characteristics and laws of data changes, we use MATLAB to carry out data cleaning and transformation and other preprocessing steps on the collected data. Because the data of the central air-conditioning system is affected by the real-time change of the collection time, outdoor temperature, and other controllable and uncontrollable variables, there are some errors in the collected data. The inlet water temperature of the condensing device should be greater than or equal to the wet-bulb temperature, so the abnormal value less than 0 should be eliminated, and then, the original data should be linearly transformed by the lowest-maximum normalization to normalize the data.

After data preprocessing, firstly identify the expected temperature-actual temperature process model, and the premise of selecting historical data is to get the data through de-trend processing under the condition that the data quantity is fixed and stable. The parameter identification method needs to first determine or assume the structural parameters such as order and lag of the identified object or process and then further determine other parameters of the model [18]. The least square method (LS) is a classical data processing method, which has the advantages of being a simple principle, fast convergence, and easy programming, and is widely used in system identification [19]. In order to deal with different object models, it has many improved forms and methods. The core principle is to calculate the fitting error according to the fitting output and the actual
Figure 3: Structure of control system.

Figure 4: PID parameter tuning process based on bat algorithm.
value and to deduce and correct the identification parameters according to the established error criterion. The least square method and various extended methods can obtain good calculation results in the identification problems of linear, nonlinear, dynamic, and static systems, and the least square method has also become one of the basic contents of estimation theory and adaptive control theory [20]. In this study, the recursive least square method with the forgetting factor is used to identify the process model, and the obtained system model is used to simulate and optimize the designed control algorithm. According to historical data, the identification model is established by the recursive least square method, which provides the basis for algorithm design and simulation.

Generally, the least square method is used for data batch processing to calculate once, which has a large amount of calculation and takes up a lot of memory, and is not suitable for updating the real-time model of newly sampled data. Change the first least square method to the recursive form, that is, recursive least square parameter estimation method (FFRLS) [21].

Let the estimated value of time \( k \) in the least square method be

\[
\hat{\theta}(k) = (\Phi_k^T \Phi_k)^{-1} \Phi_k^T y_k. \tag{5}
\]

In this formula,

\[
\Phi_k = \begin{bmatrix} \Phi_{k-1} & \Phi_T(k) \end{bmatrix}, \quad Y_k = \begin{bmatrix} Y_{k-1} \\ y(k) \end{bmatrix},
\]

let \( P(k) = (\Phi_k^T \Phi_k)^{-1} = [P^{-1}(k-1) + \Phi(k) \Phi(k)^T]^{-1} \).

We can obtain

\[
P^{-1}(k) = P^{-1}(k-1) + \Phi(k) \Phi(k)^T. \tag{7}
\]

According to literature [22],

\[
\hat{\theta}(k-1) = (\Phi_{k-1}^T \Phi_{k-1})^{-1} \Phi_{k-1}^T Y_{k-1} = (k-1) \Phi_{k-1}^T Y_{k-1}. \tag{8}
\]

From formula (7),

\[
\Phi_{k-1}^T Y_{k-1} = P^{-1}(k-1) \hat{\theta}(k-1) = [P^{-1}(k-1) \hat{\theta}(k-1)]. \tag{9}
\]

Then, the least square estimation form of time \( k \) is

\[
\hat{\theta}(k) = P(k) \Phi_k^T y_k = \hat{\theta}(k-1) + P(k) \phi_k(y(k) - \phi^T(k) \hat{\theta}(k-1)). \tag{10}
\]

Assume that \( K(k) = P(k) \phi_k \). According to the principle of matrix inversion, we can obtain

\[
P(k) = [I - K(k) \phi^T(k)] P(k-1). \tag{11}
\]

Summarizing the above formulas, we can get the \( \theta \) estimation formula of the recursive least square method as follows:

\[
\begin{align*}
\hat{\theta}(k) &= \hat{\theta}(k-1) + K(k) \{ y(k) - \phi^T(k) \hat{\theta}(k-1) \} \\
K(k) &= \frac{P(k-1) \phi(k)}{1 + \phi^T(k) P(k-1) \phi(k)} \\
P(k) &= [I - K(k) \phi^T(k)] P(k-1)
\end{align*}
\]. \tag{12}

Aiming at the problem of parameter identification of slow time-varying systems, the recursive least square method gradually reduces \( P(k) \) and \( K(k) \) along with the iterative algorithm so that the correction ability of \( \hat{\theta}(k) \) gradually weakens. The newly acquired process data play a small role in the calculation of parameter estimation, which leads to the slow convergence rate and the inability to track the change of object parameters in real time. According to [22], the weighted parameter \( \lambda \) is added to the recursive least square method.

Usage performance indicators:

\[
J = \sum_{k=1}^{L} \lambda^{L-k} \{ y(k) - \phi^T(k) \hat{\theta} \}^2, \quad (0 < \lambda \leq 1). \tag{13}
\]

The iterative formula is

\[
\begin{align*}
\hat{\theta}(k) &= \hat{\theta}(k-1) + K(k) \{ y(k) - \phi^T(k) \hat{\theta}(k-1) \} \\
K(k) &= \frac{P(k-1) \phi(k)}{1 + \phi^T(k) P(k-1) \phi(k)} \\
P(k) &= \left[ I - K(k) \phi^T(k) \right] P(k-1)
\end{align*}
\]. \tag{14}

Generally, the value range of \( \lambda \) is [0.95, 1]. When \( \lambda = 1 \), FFRLS becomes the conventional RLS algorithm.

Compared with Figure 5, it can be seen that FFRLS can effectively and timely track the change of parameters. However, the addition of the forgetting factor makes the correction range of \( \hat{\theta} \) in newly collected process data increase in each correction period, which leads to the fluctuation of the identification curve, the fitting error, and the stability of the identification process decreasing. Therefore, while ensuring the tracking speed and stability of the identification model, the forgetting factor should be reasonably selected.

3.4 Simulation Model Acquisition. Set the process model to be identified as the standard first-order inertia time-delay link, and the model is as follows:

\[
G(s) = \frac{K}{T_1 s + 1} e^{-D_1 s}. \tag{15}
\]

The sampling time is 10 s, and when the pure delay time is an integer multiple of the sampling time, the discrete difference form after the \( Z \)-transform with zero-order holder is as follows:
Let $d = 4$, the identification shows that $a_1 = -0.9467$, $b_0 = -0.0074$, and $b_1 = 0.0045$, the fitting degree is 89.42%. When the time delay $d$ is determined, there is a small difference in the accuracy of the models fitted by equations (15) and (16). When the accuracy is guaranteed, equation (15) is used for convenience.

Identify the expected temperature-actual temperature as follows:

$$y(k) = a_1 y(k - 1) + b_0 u(k - d),$$

where $d = \text{floor}(D/T_s)$, floor means rounding down.

$G(z)$ is estimated by using the anti-interference identification algorithm of the one-dimensional search delay mentioned in [23]. For the system to be identified, according to the measured sampling data, the maximum time lag value is roughly determined by calculating the maximum cross-correlation function value between the original data arrays composed of the sampling data for many times; that is,

$$d_{\text{max}} = \arg \max_{k=N_0} \sum_{k=1}^{N} u(k - d) y(k).$$

Without prior knowledge, the minimum time-delay estimation value can be $d_{\text{min}} = 0$, that is, $d \in [d_{\text{min}}, d_{\text{max}}]$. Then, construct a one-dimensional search algorithm as follows:

$$\tilde{d}(k) = \min \{ f_i(k, \hat{d}_i(k), d_i), \forall d_i \in [d_{\text{min}}, d_{\text{max}}] \}. \quad (19)$$

Let $d = 2$, the identification shows that $a_1 = -0.9429$ and $b_0 = 0.1368$, the mean square value of estimation error is 1.0738, and the determinable coefficient $R_2 = 1 - \sum (Y_i - \bar{Y})^2 / \sum (Y_i - \bar{Y})^2 = 0.8221$. Other information in the process of parameter identification is shown in Figure 6.

Considering that the pure time lag is not an integral multiple of the sampling time, the identification object is formula (13), and the identification calculation is carried out by the least square method with $d = 4$. The parameter identification process curve and fitting error curve are shown in Figure 7.

In Figure 7, when $d = 4$, $a_1 = -0.9467$, $b_0 = -0.0074$, and $b_1 = 0.0045$, the fitting degree is 89.42%. When the time delay $d$ is determined, there is a small difference in the accuracy of the models fitted by equations (15) and (16). When the accuracy is guaranteed, equation (15) is used for convenience.

Identify the expected temperature-actual temperature as follows:

$$y(k) = 0.9769 \ast y(k - 1) + 0.1039 u(k - d),$$

$$y(k) = 0.8267 \ast y(k - 1) + 0.2858 u(k - d).$$

Using the same method, the parameters of expected temperature-actual temperature, expected humidity-actual temperature, and expected humidity-actual humidity of other channels are identified, and the discrete models are as follows:

$$G(z) = \begin{bmatrix}
G_{11} (z) & G_{12} (z) \\
G_{12} (z) & G_{22} (z)
\end{bmatrix} = \begin{bmatrix}
\frac{0.1039}{z - 0.9769} & \frac{0.1809}{z - 0.9531} \\
\frac{0.04249}{z - 0.9799} & \frac{0.3190}{z - 0.9379}
\end{bmatrix}. \quad (20)
$$

$$G(z) = \begin{bmatrix}
G_{11} (z) & G_{12} (z) \\
G_{12} (z) & G_{22} (z)
\end{bmatrix} = \begin{bmatrix}
\frac{0.2858}{z - 0.8267} & \frac{0.2102}{z - 0.8629} \\
\frac{0.5644}{z - 0.8635} & \frac{0.0532}{z - 0.8566}
\end{bmatrix}. \quad (21)
$$

The difference equation describing the coupling relationship between two inputs and two outputs is as follows:
Based on the PID tuning result of the bat algorithm, the tuning is carried out according to the bat algorithm, the iteration number is 50, the initial population number is 20, and the optimization space is $K_p \in [0.01, 5]$ and $K_i \in [0.01, 15]$. The input signal is a step signal with an amplitude of 1. In order to obtain good dynamic performance and flawless tracking of the signal, the minimum absolute error integral criterion is adopted as the objective function, and the square term of the control quantity is added to the objective function to prevent the control energy from being too large:

$$J = \int_{0}^{\infty} w_1 |e(k)| + w_2 u^2(k) + w_3 |e(k)| \, dt,$$  

(23)

where $e(k)$ is the current time error, $U(k)$ is the controller output; and $w_1$, $w_2$, and $w_3$ are weights, $w_1 = 0.999$ and $w_3 = 0.001$, when $e(k) = y(k) - r(k) < 0$, $w_3 = 10$; otherwise, $w_3 = 0$. That is to say, the overshoot is used as the penalty index for the optimization process to prevent the overshoot of the system from being too large. The number of iterations is 50, and the PID tuning results are $K_p = 0.9636$, $K_i = 0.6$, and $K_d = 0.0626$. The setting process is shown in Figure 8.

The conventional PID controller is used for control. PID1 is the temperature controller, PID2 is the humidity controller, and the feedforward decoupling link is designed according to the identified transfer function. At the beginning of simulation, the input signal is $[1, 0]$, and the test results are shown in Figures 9–11.

Change it to $[1, 1]$ in the 600th step of the simulation, and apply 0.1 step interference to $y_1$ in the 2500th step of the simulation.

It can be seen from Figures 10 and 11 that, after using the feedforward decoupling link, the step excitation and step disturbance to $y_1$ have no interference to $y_2$, and the step

$$y_1(k) = 0.9653 \ast y_1(k - 1) + 0.1021 \ast u_1(k - 4) + 0.1809 \ast u_2(k - 6)$$

$$y_2(k) = 0.9589 \ast y_2(k - 1) + 0.0425 \ast u_1(k - 5) + 0.3190 \ast u_2(k - 4)$$

$$y_1(k) = 0.8448 \ast y_1(k - 1) + 0.2858 \ast u_1(k - 4) + 0.2102 \ast u_2(k - 6)$$

$$y_2(k) = 0.8601 \ast y_2(k - 1) + 0.5644 \ast u_1(k - 5) + 0.0532 \ast u_2(k - 4).$$
excitation to $y_2$ has no interference to $y_1$, thus realizing the decoupling control effect. Using PID parameters optimized by difference algorithm to control, the control effect is better than that of manual setting, and the step curve rises faster, without overshoot, and quickly restores the set value after being disturbed. However, whether the PID parameters are optimized or the decoupling link is designed, it largely depends on the accuracy of the identification model. When there is a big error in the identification model or the parameters of the controlled object drift, the quality of the control system will be seriously reduced.

4. Design and Simulation of Neural Network Control Method

In the process of control, it is difficult for some control objects to establish mathematical models due to the complex relationship between variables, external interference, and unclear related mechanism, and the traditional decoupling method has some problems, such as insufficient accuracy in practical application. In recent years, the intelligent decoupling method has shown unique advantages in solving nonlinear systems and has become a research hotspot. It can realize online adaptive precise decoupling of complex coupled objects, mainly based on fuzzy decoupling control and neural network decoupling control [23]. Aiming at the temperature and humidity control system of ventilation and air conditioning, this study designs an adaptive PID decoupling method based on RBF neural network based on neural network theory and simulates its effect.

RBF neural network has good nonlinear mapping ability and generalization ability. Research on RBF neural network shows that RBF neural network can approach any nonlinear function with a compact set and arbitrary precision. It is a very important application field to use RBF for system identification [24]. Compared with BP neural network, RBF is a local approximation neural network, which greatly improves the convergence speed and can avoid the local minimum problem to a certain extent, and is suitable for the control requirements of online real-time identification in complex industrial control [25]. The control structure is shown in Figure 12.

4.1. Identification Principle of Radial Basis Function Neural Network. In the application of neural network to system identification, BP and RBF neural networks are two common types [26]. Compared with BP, RBF has faster convergence speed and approximation accuracy because of its simpler network structure and more effective learning algorithm. Select the “serial-parallel” identification structure,
and the established multi-input single-output RBF identification model is shown in Figure 13.

Use the input \( u(k) \) and output \( y(k) \) of the identified system’s \( n_u \) and \( n_y \)-order time-delay sampling signals as the input of the identification model. The network input layer is

\[
X(k) = [x_1(k), \ldots, x_2(k)] = [y(k-1), \ldots, y(k-n_y), u(k-1), \ldots, u(k-n_u)].
\]  

(24)
The forecast output is expressed as

\[ \ddot{y}(k) = N(X(k), w) = N[y(k - 1), \ldots, y(k - ny), u(k - 1), \ldots, u(k - nu)], \]  

(25)

The hidden layer realizes the nonlinear mapping from the input \( x \) to the hidden layer nodes. The radial basis vector \( H = [h_1, h_2, \ldots, h_n] \), and the Gaussian function is selected as the basis function:

\[ h_j(x) = \exp \left( -\frac{\|x - c_j\|^2}{2b_j^2} \right) (j = 1, 2, \ldots, n), \]  

(26)

where \( c_j \) is the node center and \( b_j \) is the base width parameter of the node, and \( b_j > 0 \).

The hidden layer output is

\[ R_j(x) = \exp \left( -\frac{\|x - c_j(k-1)\|^2}{b_j^2} \right). \]  

(27)

Output of output neuron is

\[ y_m(k) = \sum_{j=1}^{m} w_j(k-1)R_j(x(k)). \]  

(28)

Choose the quadratic error function as the performance index:

\[ E(k) = \frac{1}{2} \|y(k) - y_m(k)\|^2 = \frac{1}{2} e^2(k). \]  

(29)
Use the gradient descent method to modify network parameters.

Corrected output weight is

$$\Delta w_j = [y(k) - y_m(k)]h_j$$

$$w_j(k) = w_j(k-1) + \eta\Delta w_j + \alpha[y_j(k-1) - w_j(k-2)] + \beta[w_j(k-2) - w_j(k-3)]$$

(30)

Correction node center is

$$\Delta b_j = [y(k) - y_m(k)]w_jh_j\left\| 3 - c_j \right\|^2 b_j^3$$

$$b_j(k) = b_j(k-1) + \eta\Delta b_j + \alpha[b_j(k-1) - b_j(k-2)] + \beta[b_j(k-2) - b_j(k-3)]$$

(31)

Corrected node center width is

$$\Delta c_{ji} = [y(k) - y_m(k)]w_jh_j\left\| 3 - c_{ji} \right\|^2 b_j^2$$

$$c_{ji}(k) = c_{ji}(k-1) + \eta\Delta c_{ji} + \alpha[c_{ji}(k-1) - c_{ji}(k-2)] + \beta[c_{ji}(k-2) - c_{ji}(k-3)]$$

(32)

where $\eta$ is the learning rate and $\alpha$ and $\beta$ are inertia coefficients.

The main tasks of online design model identification using the neural network are selection and pretreatment of learning samples, determination of the structure of the identified object, selection of reasonable RBF network structure and parameters, model testing and error checking, etc. [27]. According to the control structure of the neuron controller, two RBF-NNI with the same structure are used for online identification. In order to improve the identification accuracy of RBF, the input sampling signal of the coupling control channel is added to the input of the RBF neural network, and the inputs of two RBF recognizers are

$$\begin{align*}
X_1 &= [y_1(k-1), u_1(k-4), u_2(k-6)] \\
X_2 &= [y_2(k-1), u_1(k-5), u_2(k-4)]
\end{align*}$$

(33)

4.2. Design of Radial Model Control Algorithm. In the RBF model control structure, NNC1 is responsible for the adaptive control of the temperature control channel and NNC2 is responsible for the adaptive control of the humidity control channel. Among them, the principle of the NNC controller is to use a single neuron adaptive PID structure with gain self-adjustment, and the output is as follows:

$$\Delta u(k) = K \cdot \sum_{i=1}^{3} w_i(k)x_i(k)u = u(k-1) + \Delta u.$$  (34)

In the calculation formula,

$$\begin{align*}
e(k) &= r(k) - y(k) \\
x_1(k) &= e(k) - e(k-1) \\
x_2(k) &= e(k) \\
x_3(k) &= e(k) - 2e(k-1) + e(k-2)
\end{align*}$$

(35)

adopt performance indicators:

$$J_c = \frac{1}{2} [r(k) - y(k)]^2 = \frac{1}{2} e^2(k).$$  (36)

Weight adjustment is

$$\begin{align*}
\Delta w_i(k) &= \frac{\partial J_c}{\partial w_i(k)} = \lambda [r(k) - y(k)] \frac{\partial y(k)}{\partial u(k)} x_i(k) \\
\Delta u_i(k) &= -\lambda \frac{\partial J_c}{\partial u_i(k)} = \lambda [r(k) - y(k)] \frac{\partial y(k)}{\partial u(k)} x_i(k)
\end{align*}$$

(37)

where $i = 1, 2, 3$ and $0 < \lambda < 1$. $\frac{\partial y(k)}{\partial u(k)}$ is Jacobian information of the controlled process, which is obtained according to the online identification output of RBF, that is, $\frac{\partial y(k)}{\partial u(k)} = \frac{\partial y_m(k)}{\partial u(k)}$:

$$\frac{\partial y_m(k)}{\partial u(k)} = \sum_{j=1}^{m} w_j(k-1)R_j(x(k)) c_j(n_y + 1)(k-1) - u(k)$$

(38)
Use a nonlinear transformation weighted relation to modify Ku online:

\[ K(k) = K_0(k) + \xi \frac{r(k) - y(k + d)}{r^3(k)} \]. \hspace{1cm} (39)

According to the Jacobian value identified by RBF, the controller weights are corrected to realize the internal decoupling control of the neural network.

### 4.3. Radial Basis Model Control Simulation

The weights trained by the RBF identifier are taken as initial weights, and the simulation is carried out for 5000 steps. At the beginning of the simulation, the set values are \( R_1 = 1.0 \) and \( R_2 = 0 \). Set \( R_1 = 1.0 \) and \( R_2 = 1.0 \) when the simulation reaches 600 steps. The sampling time is 10s, and the control effect is shown in Figure 14.

As shown in Figure 14, the neural network PID identified by RBF can quickly recover to a stable state after being...
disturbed by the change of the set value and has a good decoupling effect. Other information in the process of decoupling control simulation is shown in Figures 15-16.

Self-tuning PID algorithms using RBF online identification are proposed, respectively. The self-tuning PID algorithm is based on RBF model identification. The basic adaptive controller, NNC, is composed of a single neuron with self-learning and adaptive ability. At the same time, the weights and offsets are adjusted by the least mean square function (LMS) based on the predicted output error, and the dynamic RBF neural network is used to identify the control object model online, thus improving the adaptive ability of the controller.

5. Conclusions

In this study, the working mechanism of the subway ventilation and air-conditioning system is deeply understood, and a detailed algorithm design is carried out for the two control structures introduced. Through the analysis of variable parameters in the process, the internal coupling relationship in air-conditioning control is determined, and the identification model is established by the recursive least square method based on field debugging data, and on this basis, the control algorithm is designed. The conventional PID algorithm is used to simulate the control of a single closed-loop mode. The control structure is divided into two separate control loops, and the bat algorithm is used to optimize the PID parameters. According to the identification model, the feedforward decoupling link is designed, and the control curves of conventional PID control with and without a decoupling link are analyzed, and the limitations of the conventional control algorithm in air-conditioning control are also analyzed. A multivariable decoupling algorithm of self-tuning PID based on RBF online identification is proposed. The basic adaptive controller, NNC, is composed of a single neuron with self-learning and self-adaptive ability. The multivariable decoupling control of ventilation and air conditioning is completed by self-learning of the neural network, which can save energy and improve the control effect of air conditioning.

Data Availability

The data used to support the findings of this study may be released upon application to the Jicheng Electronics Co., Ltd. Jinan, China, and can be contacted at 0086-0531-88018000.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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