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THE INTERNAL MODE FRACTIONAL-ORDER PID CONTROL BASED ON NEURAL NETWORK FOR THE TEMPERATURE OF AIR-CONDITIONED ROOMS

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Abstract. *Traditional proportional integral differential (PID) controller, due to the fact that its parameters cannot be self-tuning, will lead to a high overshoot and a long control time in the control process. In order to improve the temperature control effect of air-conditioned (AC) rooms, this paper presents a fractional-order internal mode controller based on neural network self-tuning to control the temperature of AC rooms. Firstly, the internal model control (IMC) principle is used to transform the traditional PID controller, and the three PID parameters are represented only by the time filter constant. Then the fractional-order PID controller is constructed by changing the integral order of integration and differentiation into fractional order. Finally, the three parameters of internal mode fractional-order controller are adjusted in real time by using neural network. Simulation results show that the proposed method is superior to other controllers in overshoot and adjustment time.*

Keywords: Internal model theory, Fractional-order control, Neural network, PID controller, Parameter self-tuning, Air-conditioned room temperature

1. **Introduction.** With the rapid development of economy, people pursue a high quality of life. AC has become an indispensable part of people's life. No matter in study or life, a proper temperature will not only make people feel comfortable, but also make people keep a clear mind and get twice the result with half the effort [1]. For the control of AC room temperature, the most commonly used is PID controller. However, as is known to all, the error between the set value and the output value of the PID controller will continuously decrease during the control process of the system. Because the PID parameters will not change according to the change of the error, this will lead to problems such as system overshooting and slow response.

On the basis of summarizing previous experience, Podlubny [2] proposed a fractional PID controller, which represented the order of integral and differential terms of traditional PID controller by fractions. Compared with the traditional PID controller, the fractional-order PID controller has a larger adjustment range and stronger robustness. Alimohammadi et al. [3] compared the fractional-order PID controller with the traditional PID controller. The former has better control effect and better anti-interference performance. Paiva et al. [4] pointed out that fractional-order PID controller is better than traditional PID controller in terms of defined limit control. Nasirpour and Balochian used particle swarm optimization to optimize the fractional-order PID controller [5].

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From the above introduction, it can be seen that the fractional-order PID controller has two more unknown parameters, which increases the complexity of the controller. Moreover, the controller has some disadvantages such as large amount of parameter setting calculation and many parameters to be solved.

The internal model control principle only uses a filter time constant to represent the three parameters of PID controller, which reduces the number of parameters and improves the performance of the controller [6-8]. The combination of internal model control and fractional-order theory will greatly reduce the parameters controlled by the system. Tavakoli and Haeri [9] applied the principle of IMC to fractional-order proportional integral (PI) controller and fractional-order PID controller. Ranganayakulu et al. [10] compared the fractional-order internal mode controller with other methods and got good results. Although the principle of IMC simplifies some of the parameters, the fractional-order PID controller is still difficult to set the parameters. There is fuzzy theory for traditional PID parameter tuning. The hybrid fuzzy PID controller has better adaptability and stability than the traditional PID controller [11-13]. However, fuzzy control requires a wealth of manual experience. Neural network has been used in many fields because of its self-learning function, associative storage function and the ability to search for optimal solutions at high speed. The neural network is applied to the parameter setting of the AC room temperature controller, and the powerful ability of the neural network is used to real-time setting of the controller parameters. Unlike fuzzy theory, which requires a lot of human experience, neural network is more convenient and efficient. Asgharnia et al. used radial basis function neural network to adjust the parameters of the controller, and the simulation result showed that it had more advantages than other methods [14]. Moghadam et al. used the neural network to set the parameters of the controller and satisfactory results were obtained [15]. Neural network is used in parameter setting, and the effect is better than that of fuzzy theory [16-18].

Based on the above inspirations, a neural network self-tuning internal model fractional-order internal model PID (NNIMCFOPID) controller is proposed in this paper to control the temperature of AC rooms. The internal mode principle is used to simplify the parameters of the controller, and the order of integration and differentiation is fractalized. Neural network is used to adjust the parameters of internal model fractional-order PID controller in real time. The simulation results show that compared with other controllers, the control system of this controller has low overshoot, short stability time and strong anti-interference ability.

The paper is organized into five sections including the introduction. Section 2 presents the mathematical model of the AC room. Section 3 presents the design of the fractional internal model PID controller and the neural network self-tuning parameters respectively. The simulation comparison and the analysis are presented in Section 4. Section 5 gives the conclusion.

2. **The Establishment of Mathematical Model of AC Rooms.** In essence, temperature control in an AC room is a hysteresis, nonlinear and time-varying complex control system. The control object can be described by a higher-order differential equation. However, as long as certain control precision can be satisfied, the control object can be approximately described by a first-order model with delay [19].

Therefore, the model of temperature control system in an AC room can be simplified as follows

$$G(s) = \frac{k}{Ts+1}e^{-\tau s} \tag{1}$$

where k is the amplification factor, T is the time constant, and τ is the delay time.

For the determination of the above three parameters, different values will be obtained due to the different process nature, envelope structure, air supply mode and ventilation frequency of the AC room [20]. Shi [21] put forward the estimation formula of these three parameters based on a large amount of data over many years.

The AC room in this paper is the office of an administrative office building in Ningbo city, whose air supply mode used diffusers. The length, width and height of the AC room are 8 m, 4 m and 3.5 m respectively, and the ventilation frequency of the room is 4.57 times/h.

Through the above room parameters and the estimation formula, the characteristic parameters of the transfer function of the AC room can be calculated, as shown in Equation (2).

$$G(s) = \frac{0.117}{19.7s + 1} e^{-1.97s} \tag{2}$$

3. Design of Neural Network Self-Tuning Internal Model Fractional-Order PID Controller.

3.1. **Design of internal model fractional-order PID controller.** In practical application, the PID controller's transfer function is shown in Equation (3):

$$G_{PID}(s) = k_p + \frac{k_i}{s} + \frac{k_d s}{k_f s + 1} \tag{3}$$

where k_p, k_i, k_d and k_f are expressed by other formulas using the principle of internal mode.

The structure diagram of the IMC system is shown in Figure 1.

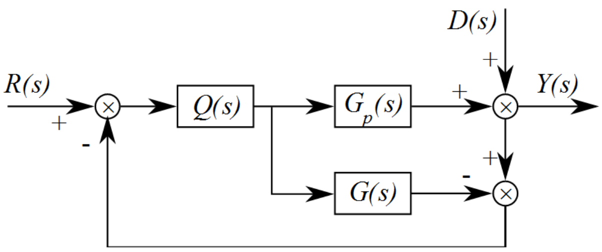

FIGURE 1. Block diagram of IMC system

In the figure, $R(s)$ is the set value, $Y(s)$ is the output, $D(s)$ is the disturbance of the system, $Q(s)$ is the internal mode controller, $G_p(s)$ is the process, and $G(s)$ is the process model.

According to the internal mode principle, $G(s)$ is decomposed, as shown in Equation (4):

$$G(s) = G_+(s)G_-(s) \tag{4}$$

where $G_+(s)$ is usually a non-minimum phase, including the time delay and the zero of the right half plane, and $G_-(s)$ is invertible.

For first-order delay process $G(s)$ as shown in Equation (1), $G_-(s)$ and $G_+(s)$ can be written as Equation (5) and Equation (6):

$$G_-(s) = \frac{k}{Ts + 1} \tag{5}$$

$$G_+(s) = e^{-\tau s} \tag{6}$$

$Q(s)$ is shown as follows

$$Q(s) = G_-^{-1}(s) f(s) \tag{7}$$

$f(s)$ is a low-pass filter, which can usually be written as Equation (8):

$$f(s) = \frac{1}{(\lambda s + 1)^r} \tag{8}$$

where the value of r depends on the order of $G_-(s)$ so that the control can be realized, and the value is 1, and λ is the filtering time constant.

The IMC structure is simplified to a classical feedback control structure, as shown in Figure 2.

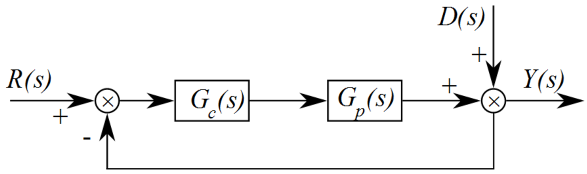

FIGURE 2. Equivalent feedback control structure

In Figure 2, $G_c(s)$ is a feedback controller.

$G_c(s)$ is shown in Equation (9):

$$G_c(s) = \frac{Q(s)}{1 - G(s)Q(s)} \tag{9}$$

Let $e^{-\tau s}$ approximate $\frac{1-0.5\tau s}{1+0.5\tau s}$ with a first order Pade series. And according to Equations (4)-(9), $G_c(s)$ can be written as follows,

$$G_c(s) = \frac{\frac{0.5\tau T}{k(\lambda+\tau)} s^2 + \frac{0.5\tau + T}{k(\lambda+\tau)} s + \frac{1}{k(\lambda+\tau)}}{\frac{0.5\tau\lambda}{\lambda+\tau} s^2 + s} \tag{10}$$

By combining Equation (3) with Equation (10), it can be obtained that

$$\begin{cases} k_p = \dfrac{T\lambda + 0.5\tau^2 + T\tau}{k(\lambda+\tau)^2} \\ k_i = \dfrac{1}{k(\lambda+\tau)} \\ k_d = \dfrac{(0.5T\tau^2 - 0.25\tau^3)\lambda + 0.5T\tau^3}{k(\lambda+\tau)^3} \\ k_f = \dfrac{0.5\tau\lambda}{\lambda+\tau} \end{cases} \tag{11}$$

Since the transfer function of AC room is known, there is only one unknown variable λ in Equation (11).

The idea of fractional order is introduced and the integral order of integral and differential of PID controller in practical application is changed into fractional order. The formula is shown in Equation (12).

$$G_{PI^aD^b}(s) = k_p + \frac{k_i}{s^a} + \frac{k_d s^b}{k_f s + 1} \tag{12}$$

The above is the design process of internal model fractional-order PID controller. From the above design, there are three unknown parameters in internal model fractional-order PID controller, which are λ, a and b.

Compared with the traditional PID controller, the internal model fractional-order PID controller has three new parameters. The λ can express the parameters of the traditional PID controller according to the mathematical model of the control object and improve the control effect. The a and b can make the design of the controller more flexible and the control performance more superior.

3.2. **Neural network self-tuning parameter.** This paper uses a three-layer forward network. The first layer is the input layer. The input parameters are the expected value $R(t)$, the actual output value $Y(t)$, and the deviation $e(t)$, where

$$e(t) = R(t) - Y(t) \tag{13}$$

The third layer is the output layer, and the output parameters are unknown parameters of internal model fractional-order PID. The second layer is the hidden layer, and the number of neurons is 7, which is obtained by multiple simulations.

The structure of the neural network is shown in Figure 3.

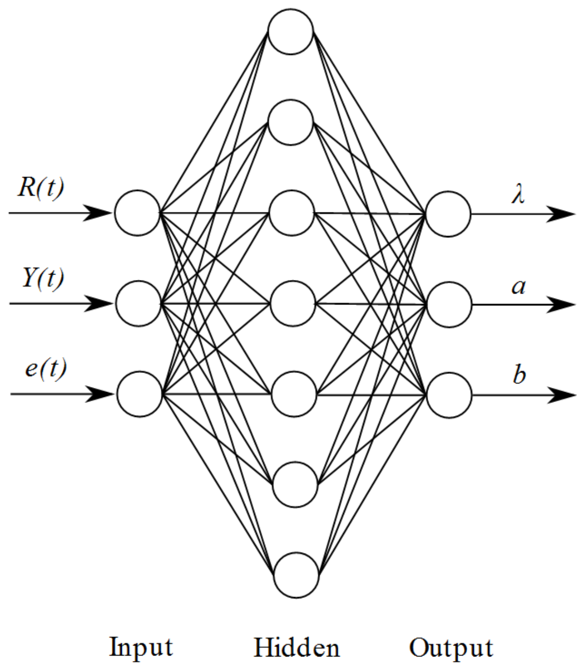

Figure 3. The structure of the neural network

First layer: Input layer

The input of this layer is represented by x_j, and the output is represented by $O_j^1(t)$. Then the output of the input layer is shown in Equation (14):

$$O_j^1(t) = x_j(t) \tag{14}$$

Second layer: Hidden layer

The number of the nodes of the hidden layer is 7. The input and output of the hidden layer are respectively

$$net_i^2(t) = \sum_{j=1}^{3} w_{ij}^2 O_j^1(t) \tag{15}$$

$$O_i^2(t) = f_2\left[net_i^2(t)\right] \tag{16}$$

$$f_2(x) = \tanh(x) = (e^x - e^{-x})/(e^x + e^{-x}) \tag{17}$$

where w_{ij}^2 is the weighted coefficient of the hidden layer, $net_i^2(t)$ is the input of the hidden layer, $O_i^2(t)$ is the output of the hidden layer, and $f_2(x)$ is the excitation function.

Third layer: Output layer

The input and output of the output layer are respectively

$$net_l^3(t) = \sum_{i=1}^{7} w_{li}^3 O_i^2(t) \tag{18}$$

$$O_l^3(t) = f_3\left[net_l^3(t)\right] \tag{19}$$

$$f_3(x) = \frac{1}{2}[1 + \tanh(x)] = e^x/(e^x + e^{-x}) \tag{20}$$

where w_{li}^3 is the weighted coefficient of the output layer, $net_l^3(t)$ is the input of the output layer, $O_l^3(t)$ is the output of the output layer, and $f_3(x)$ is the excitation function.

The output parameters of the neural network are λ, a and b. Then, $\lambda = O_1^3(t)$, $a = O_2^3(t)$, $b = O_3^3(t)$.

With its strong autonomous learning ability, the neural network can modify the weights in real time. The weights can be modified as follows.

Performance index:

$$E(t+1) = \frac{1}{2}[R(t+1) - Y(t+1)]^2 = \frac{1}{2}e(t+1)^2 \tag{21}$$

According to the gradient descent method, the weight of the output layer is modified as follows:

$$\Delta w_{li}^3(t+1) = -\eta\frac{\partial E(t+1)}{\partial w_{li}^3} + \mu\Delta w_{li}^3(t) \tag{22}$$

where η is the learning rate, μ is the coefficient of inertia, and $0 < \mu < 1$.

$$\begin{aligned}\frac{\partial E(t+1)}{\partial w_{li}^3} &= \frac{\partial E(t+1)}{\partial Y(t+1)}\frac{\partial Y(t+1)}{\partial u(t)}\frac{\partial u(t)}{\partial O_l^3(t)}\frac{\partial O_l^3(t)}{\partial net_l^3(t)}\frac{\partial net_l^3(t)}{\partial w_{li}^3} \\ &= -e(t+1)\mathrm{sgn}\left[\frac{\partial Y(t+1)}{\partial u(t)}\right]\frac{\partial u(t)}{\partial O_l^3(t)}f_3'\left[net_l^3(t)\right]O_i^2(t) \\ &= -\delta_l^3 O_i^2(t)\end{aligned} \tag{23}$$

The weight of the hidden layer is modified as follows:

$$\Delta w_{ij}^2(t+1) = -\eta\frac{\partial E(t+1)}{\partial w_{ij}^3} + \mu\Delta w_{ij}^2(t) \tag{24}$$

$$\begin{aligned}\frac{\partial E(t+1)}{\partial w_{ij}^3} &= \frac{\partial E(t+1)}{\partial Y(t+1)}\frac{\partial Y(t+1)}{\partial u(t)}\frac{\partial u(t)}{\partial O_i^2(t)}\frac{\partial O_i^2(t)}{\partial net_i^2(t)}\frac{\partial net_i^2(t)}{\partial w_{ij}^2} \\ &= \frac{\partial E(t+1)}{\partial Y(t+1)}\frac{\partial Y(t+1)}{\partial u(t)}\frac{\partial u(t)}{\partial O_l^3(t)}\frac{\partial O_l^3(t)}{\partial net_l^3(t)}\frac{\partial net_l^3(t)}{\partial O_i^2(t)}\frac{\partial O_i^2(t)}{\partial net_i^2(t)}\frac{\partial net_i^2(t)}{\partial w_{ij}^2} \\ &= -e(t+1)\mathrm{sgn}\left[\frac{\partial Y(t+1)}{\partial u(t)}\right]\frac{\partial u(t)}{\partial O_l^3(t)}f_3'\left[net_l^3(t)\right]\partial w_{li}^3 f_2'\left[net_i^2(t)\right]O_j^1(t) \\ &= -\left[\sum_{l=1}^{3}\delta_l^3\partial w_{li}^3(t)\right]f_2'\left[net_i^2(t)\right]O_j^1(t)\end{aligned} \tag{25}$$

Equations (21)-(25) are used to express the weight correction process of the neural network. In the whole control system, due to the self-tuning ability of neural network, parameters can be modified in real time, which increases the anti-interference ability of the system.

The number of the nodes of the input layer and output layer is determined by the amount of specific input and output data. The inputs of the neural network are $e(t)$, $R(t)$ and $Y(t)$, so the number of the nodes of the input layer is 3. The outputs of the neural network are λ, a and b, so the number of the nodes of the output layer is 3. The coefficient of inertia is 0.01. The number of the nodes of the hidden layer is 7. Too many nodes in the hidden layer will increase the setting time, and too few nodes will fail to achieve the desired setting effect. Through a large number of simulations, the number of the nodes of the hidden layer is finally determined to be 7.

4. **Simulation and Analysis.** In order to verify the controller proposed in this paper – **NNIMCFOPID** has better control effect, the controller is modeled and simulated. The control object is the temperature of the AC room. The transfer function of the control object is shown in Equation (2). The temperature of the room was set at 26°C. When steady state is reached, the difference between the output value of the system and the set value is ±5%. The system time step is 0.05.

In addition to the simulation of the proposed controller, the control effects of the traditional PID controller, internal model control PID (IMCPID) controller and fractional-order PID (FOPID) controller are compared. The comparison results are shown in Figure 4. In the PID controller, the values of P, I and D are changed according to different influences of P, I and D on the system performance. Through repeated adjustments, the satisfactory values can be obtained, which are 20, 1, 3. The parameter of the IMCPID is determined by the sensitivity method. See [6] for details. The sensitivity index is 1.6 in this paper. The parameter of IMCPID is 1.9 after calculation. In the FOPID controller, the values of PID also are 20, 1 and 3. The order value of FOPID was obtained through multiple simulations, which were 0.4 and 0.8 respectively.

As can be seen from Figure 4, the overshoot of the IMCPID controller is similar to that of the traditional PID controller. The FOPID controller has fewer overtones than the first two. The controller proposed in this paper has the least overshoot. The specific values of overshoot and steady-state time are shown in Figure 5.

As can be seen from Figure 5, the controller proposed in this paper has the best control effect on the system, reducing oversets and shortening steady-state time, which are

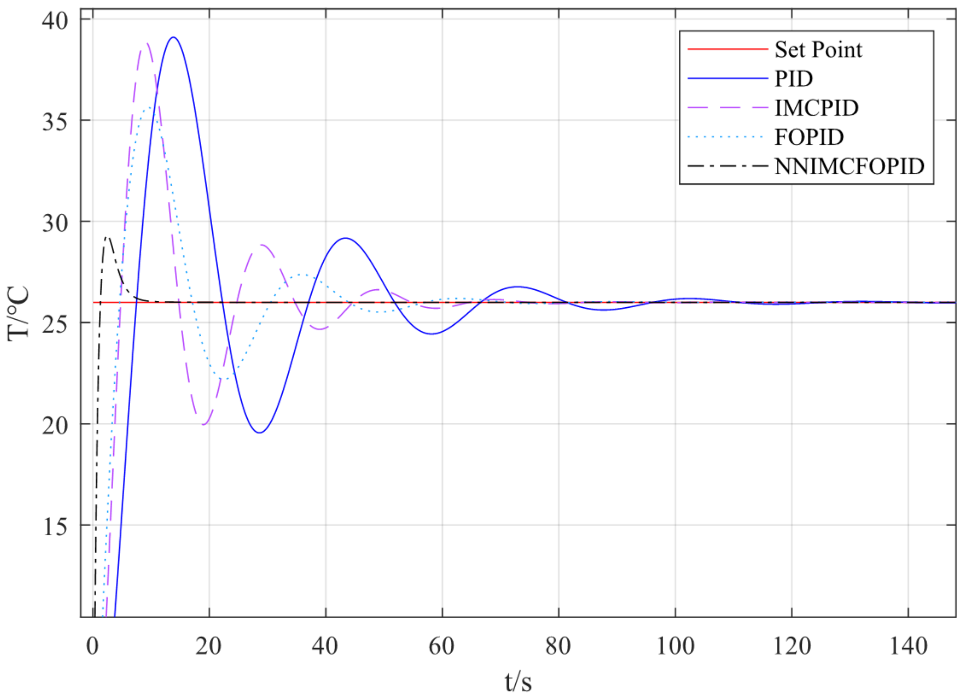

FIGURE 4. The response curve of each controller

29.3223°C and 6.1 s respectively. Among them, the traditional PID controller has the worst control effect, and both overshoot and steady-state time are larger than other controllers.

In order to verify the anti-interference performance of each controller, a disturbance is given to the system at 200 s. The curves are shown in Figure 6 and Figure 7.

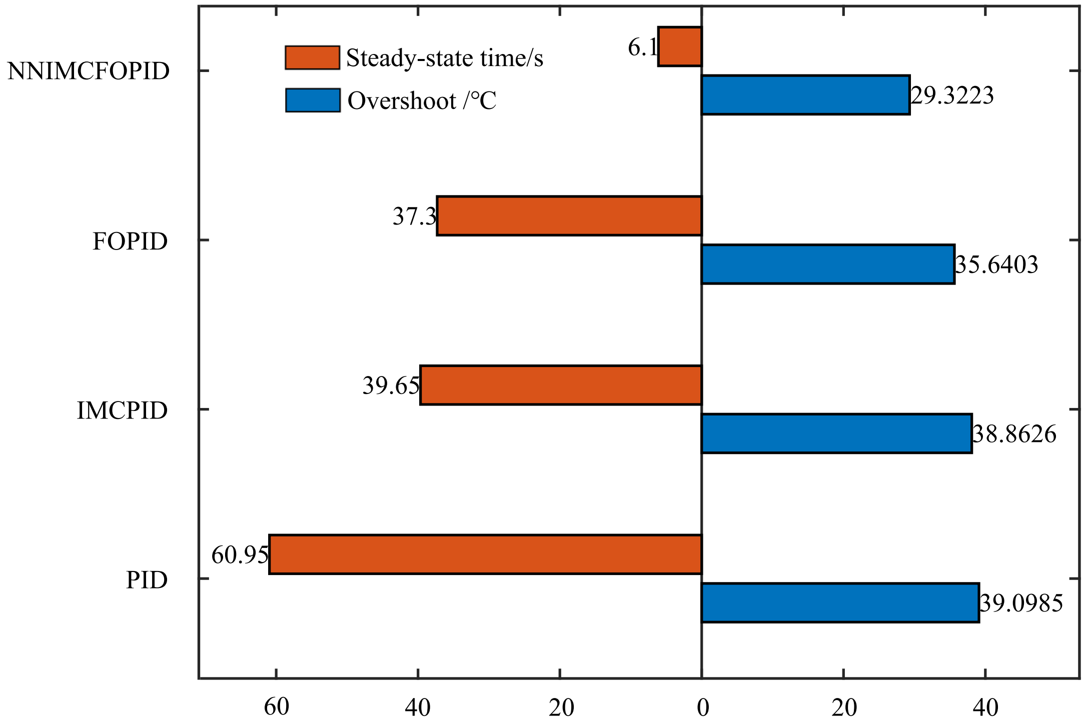

FIGURE 5. Performance indicators

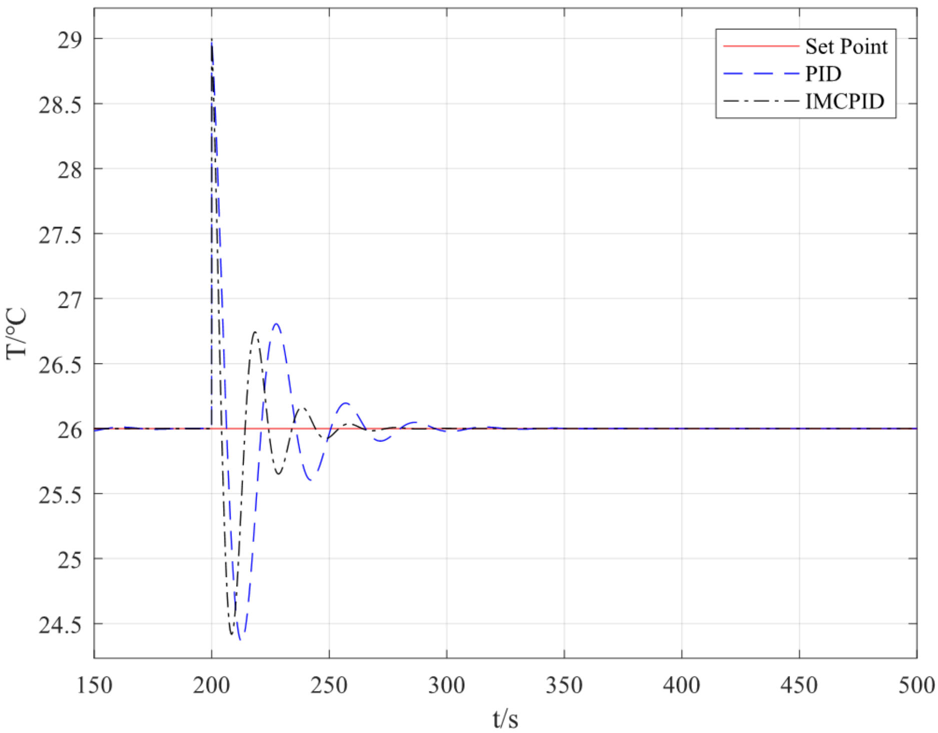

FIGURE 6. Interference curves of PID controller and IMCPID controller

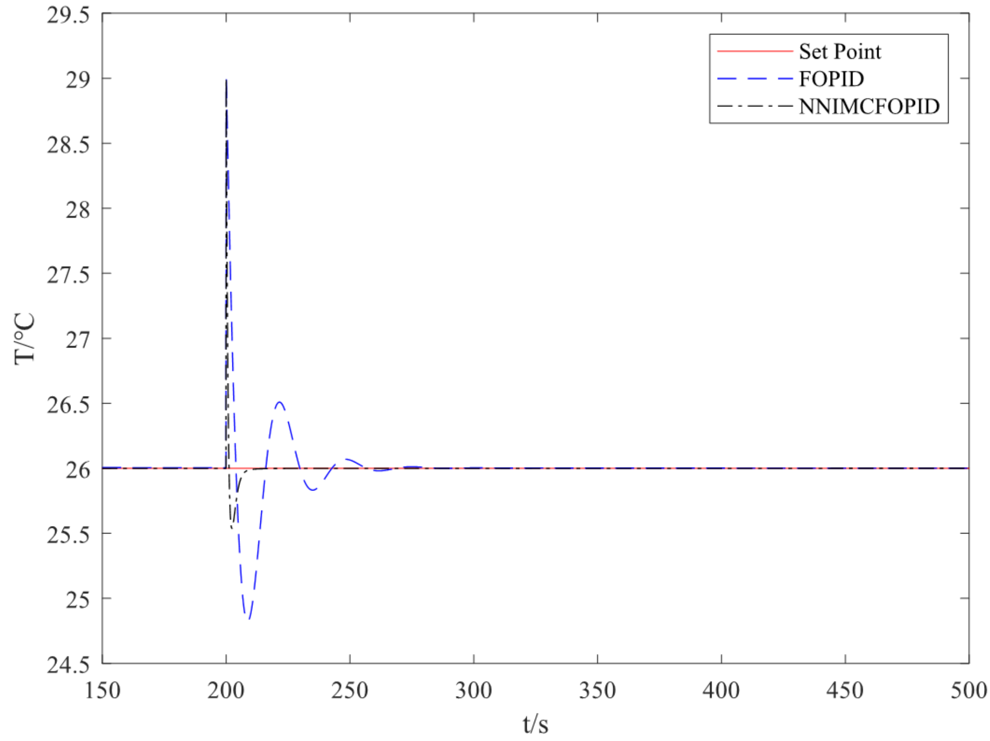

FIGURE 7. Interference curves of FOPID controller and NNIMCFOPID controller

A disturbance is added to the system at the time of 200 seconds. After 0.45 s, the controller proposed in this paper reaches a stable state with strong anti-interference capability, which is better than the other three controllers. The traditional PID controller reached the stable state after 15.8 s, with the worst effect. The IMCPID controller and FOPID controller have the anti-jamming capability in the middle, making the system reach the stable time of 10.45 s and 2 s respectively.

5. **Conclusion.** In this paper, the neural network self-tuning internal model fractional-order PID controller is proposed. The controller designed by using the principle of internal mode is directly related to the transfer function of the control object, and the unknown parameters are reduced. On the basis of integer order PID and added fractional order, the control of parameters becomes more flexible. With the powerful learning ability of neural network, the three parameters of internal model fractional-order PID controller are adjusted in real time. The traditional PID controller, internal model control PID controller and fractional-order PID controller are also compared with the controller proposed in this paper. The control effects of each controller on the system, including overshoot, steady-state time and anti-interference ability, are compared. The neural network self-tuning internal model fractional-order PID controller has the advantages of small overshoot, short stability time and strong anti-interference ability. Next are fractional-order PID controller and internal model control PID controller. The least effective controller is the traditional PID controller. The further research work is to apply the better neural network to the parameter tuning of the internal model fractional-order PID controller.

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