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TWO-DEGREE-OF-FREEDOM COMPOUND CONTROL BASED ON RBF NEURAL NETWORK FOR AIR CONDITIONING TEMPERATURE CONTROL SYSTEM

Qixin Zhu[1,2], Ye Lu[3], Jinsong Zhou[3], Xuemei Niu[1], Ou Xie[1], Yehu Shen[1]
Fuzhou Niu[1] and Yonghong Zhu[4]

[1]School of Mechanical Engineering
[2]Jiangsu Province Key Laboratory of Intelligent Building Energy Efficiency
[3]School of Environmental Science and Engineering
Suzhou University of Science and Technology
No. 99, Xuefu Road, Huqiu District, Suzhou 215009, P. R. China
bob21cn@163.com

[4]School of Mechanical and Electronic Engineering
Jingdezhen Ceramic Institute
No. 27, Taoyang South Road, Zhushan District, Jingdezhen 333001, P. R. China

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Abstract. *Aiming at time delay problem of temperature control system in air-conditioned room, this paper proposes a new two-degree-of-freedom compound control approach based on RBF neural network. The new approach is mainly based on RBF neural network to adjust PID parameters. And the Smith predictor is used to eliminate the effect from lag term of the controlled object. Then, a feedforward controller is used to make the whole system have better tracking performance and anti-interference ability. The simulation results show that the dynamic performance of the new control system can be improved obviously by using the two-degree-of-freedom composite controller.*

Keywords: Feedforward, RBF neural network, Smith predictive compensation, Incremental PID

1. **Introduction.** Temperature control is the most intuitive factor in determining whether an air conditioning system is effective. Intelligently controlling the temperature of an air-conditioned room can effectively improve the comfort of the environment inside the room.

At present, the temperature control of air-conditioned rooms has always been a hotspot and a difficult point in researches at home and abroad [1]. The system in the air-conditioned room is a complex and variable, whose parameters such as temperature and humidity, personnel density and heat dissipation of equipment all have strong coupling, which is a kind of complex system with characteristics of nonlinear, time-varying and time-delay [2].

Traditional PID controller is characterized by simple structure and easy implementation, which is widely used in industrial control. However, the temperature change in the air-conditioned room is not only related to enclosure structure, but also has a great relationship with the illumination of the sun, the heat dissipation of the equipment and the flow of people. The temperature system in the whole room is so complicated that the traditional PID control method is difficult to achieve the control requirements with

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high-precision and high-performance [3-5], which can no longer meet people's comfort requirements for indoor environment today.

Scholars at home and abroad have proposed a variety of intelligent control methods for this problem. Kazemian [6] proposed a fuzzy adaptive PID control method, which adaptively selects the controller parameters through the selection of fuzzy rules, and obtains certain control effects. Jiang [7] proposed a control algorithm based on BP neural network combined with PID, which greatly improved the performance of the control system, but its disadvantage is that the learning rate and convergence rate of BP neural network are slow and its training time is too long. Luo and Da [8] studied the genetic algorithm of temperature control and performed Multisim simulation analysis to improve the control effect. Ji and Huang [9] used a composite control structure of a genetic algorithm and a neural network for control system of DFB laser temperature. This method combines the advantages of the two algorithms and can achieve accurate temperature control in a wide range. Zhou et al. [10] studied the temperature control of biological fermentation system, and proposed a nonlinear PID controller, and applied adaptive genetic algorithm to the parameter optimization of the controller, which achieved better control precision. For the characteristics of time-delay systems, foreign engineer Smith first proposed a control strategy with pure lag compensation, namely Smith predictive compensation control. Yuan and Zhang [11] applied the Smith compensation controller to the cascade control of the temperature of the variable air-volume air-conditioner; Chen and Zhang [12] proposed to connect two compensators in series to improve the stability of the control system. Majhi and Atherton [13] proposed fuzzy Smith predictive controllers, and related improvement strategies are investigated in [14-16]. However, these control methods are not outstanding in anti-jamming ability, which makes the control system difficult to cope with the sudden external interference, and is not helpful to the popularization and application of these control algorithms in the complex environment.

In this paper, a new compound control algorithm is proposed, which is based on Smith predictive compensation control, RBF neural network PID control and a feedforward controller. The control algorithm utilizes RBF neural network with strong nonlinear fitting ability, can map the advantages of arbitrary nonlinear relations, and its learning algorithm is simple and convergent, and it can be used to set PID control parameters online. It overcomes the shortcoming of traditional PID controller because it cannot automatically set the three parameters of PID online, which cannot meet the comfort requirements of people in different air-conditioned rooms. At the same time, the Smith predictive compensation control algorithm is adopted, and a compensation link is connected with the RBF-PID controller to compensate the effect of pure lag part in the controlled object. The Smith-RBF-PID controller with strong adaptive and adjustable parameters is constructed. The response of the controlled system is fast and stable. Finally, a feedforward compensation link is added, which makes the whole controller have strong anti-interference ability and tracking ability.

The organization of this paper is as follows. The RBF neural network and the shortcoming of traditional PID controller are presented in Section 2. The RBF-PID controller is presented in Section 3. The Smith predictive compensation approach is presented in Section 4. The feedforward controller is designed in Section 5. The simulations are presented in Section 6. Section 7 concludes the paper.

2. Traditional PID Controller and RBF Neural Network.

2.1. Traditional PID controller.

The deviation of traditional PID controller is as follows.

$$e(t) = x - y \tag{1}$$

In this equation, x is input value, y is actual output value.

The mathematical model of PID controller is as follows,

$$u(t) = K_P e(t) + K_I \int_0^t e(t)dt + K_D \frac{de(t)}{dt} \tag{2}$$

where K_P is proportion coefficient, K_I is integration coefficient, K_D is differentiation coefficient.

However, when the control object is nonlinear and random, the traditional PID control method cannot achieve the ideal control effect. The process of PID tuning parameters is actually a compromise between proportional, integral and differential control. It should be pointed out that although there are many tuning methods and empirical formulas for PID parameters, these tuning approaches not only take time, but also affect each other between the parameters, and it is often difficult to obtain the desired effect. PID control cannot solve the contradiction between stability and accuracy. In order to ensure that the PID controller has a set of satisfactory control parameters in real time, this paper chooses RBF neural network to adjust the PID parameters.

2.2. **Overview of RBF neural network.** The neural network not only has a very strong nonlinear fitting ability, but also can map any complex nonlinear relationship, and its learning rules are simple and easy to implement. In the late 1980s, J. Moody and C. Darken proposed an RBF (Radial Basis Function) neural network, whose structure is a three-layer feedforward network with a single hidden layer. Because it simulates the neural network structure of acceptable areas of local adjustment and mutual coverage in the human brain, the RBF neural network is a locally approximation network, and it can approximate any objective function with arbitrary precision.

The structure diagram of the RBF neural network is shown in Figure 1. It is a three-layer forward network. The first layer has n input nodes, the second layer has m hidden nodes, and the third layer has 1 output node. The mapping from the first input layer to the third output layer is nonlinear, but the mapping from the hidden layer to the output layer is linear, which greatly speeds up the learning and avoids local minima [17].

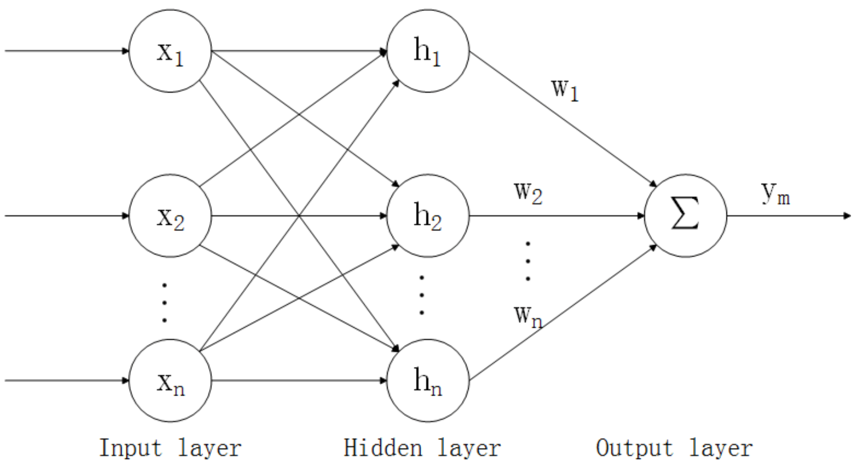

FIGURE 1. Structure diagram of RBF neural network

In Figure 1, $x_1, \ldots, x_n$ – Input of Neural Network, $h_1, \ldots, h_n$ – Output of Hidden Layer Neurons, $w_1, \ldots, w_n$ – Weights of Neural Networks, y_m – Output of Neural Network.

3. RBF-PID Controller.

In Section 2, it has been shown that when the traditional PID control faces the nonlinear object, its stability and accuracy cannot be guaranteed at the same time, while the neural network has the adaptive ability to cope with the real-time change of the control system. When BP neural network is used for function approximation, it uses negative gradient drop method to adjust the weight, which leads to slow convergence speed and easy to fall into local minimum. RBF neural network is superior to BP neural network in learning speed, approximation ability and classification ability, so RBF neural network is used to adjust PID parameters in this paper.

3.1. PID parameter setting of RBF neural network.

Combining the advantages of traditional PID and RBF neural networks, the PID control structure of RBF neural network is designed. The gradient information is obtained by online identification of RBF, and then the PID parameters of the control system are adaptively adjusted by the gradient information, so that the system is adaptive.

Definition control deviation is

$$e(k) = r(k) - y(k) \tag{3}$$

In this equation, $r(k)$ is input, $y(k)$ is output and $e(k)$ is control deviation.

The PID control structure of the RBF neural network is shown in Figure 2.

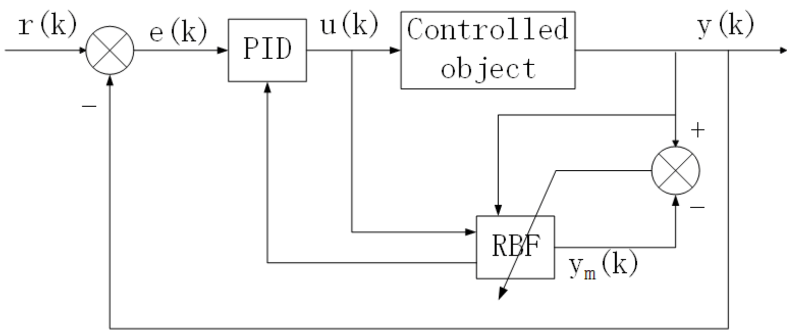

FIGURE 2. PID control structure diagram of RBF neural network

Discretization Equation (1) is:

$$\begin{cases} u(k) = u(k-1) + \Delta u(k) \\ \Delta u(k) = K_P[e(k) - e(k-1)] + K_I e(k) + K_D[e(k) - 2e(k-1) + e(k-2)] \end{cases} \tag{4}$$

That is the control algorithm of the incremental PID controller, wherein the three inputs are:

$$\begin{cases} x_{e1} = e(k) - e(k-1) \\ x_{e2} = e(k) \\ x_{e3} = e(k) - 2e(k-1) + e(k-2) \end{cases} \tag{5}$$

The output of control algorithm is:

$$u(k) = u(k-1) + K_P x_{e1} + K_I x_{e2} + K_D x_{e3} \tag{6}$$

Introduce input deviation square function as a performance indicator:

$$E = \frac{1}{2}\left[r(k) - y(k)\right]^2 = \frac{1}{2} e(k)^2 \tag{7}$$

In the equation, K_P, K_I, K_D adopt gradient descent method to adjust:

$$\begin{cases} K_P(k) = K_P(k-1) + \Delta K_P \\ K_I(k) = K_I(k-1) + \Delta K_I \\ K_D(k) = K_D(k-1) + \Delta K_D \end{cases} \tag{8}$$

$$\begin{cases} \Delta K_P = -\eta_P \frac{\partial E}{\partial K_P} = -\eta_P \frac{\partial E \partial y \partial u}{\partial y \partial u \partial K_P} = \eta_P e(k) \frac{\partial y}{\partial u} x_{e1} \\ \Delta K_I = -\eta_I \frac{\partial E}{\partial K_I} = -\eta_I \frac{\partial E \partial y \partial u}{\partial y \partial u \partial K_I} = \eta_I e(k) \frac{\partial y}{\partial u} x_{e2} \\ \Delta K_D = -\eta_D \frac{\partial E}{\partial K_D} = -\eta_D \frac{\partial E \partial y \partial u}{\partial y \partial u \partial K_D} = \eta_D e(k) \frac{\partial y}{\partial u} x_{e3} \end{cases} \tag{9}$$

In the equation, η_P, η_I, η_D are learning rate, $\frac{\partial y}{\partial u}$ is Jacobian information of the accused object, which can be obtained by neural network identification.

3.2. **RBF network identification.** In the RBF network structure, $X = [x_1, x_2, \ldots, x_n]^T$ is neural network input. Assuming that the radial basis vector of the RBF network is $H = [h_1, h_2, \ldots, h_j, \ldots, h_m]^T$, where h_j is the Gaussian function:

$$h_j = \exp\left[-\frac{\|X - C_j\|^2}{2b_j^2}\right], \quad j = 1, 2, \ldots, m \tag{10}$$

where $\|\cdot\|$ represents Euclidean distance, C_j represents the center vector of the j node in the hidden layer of network, b_j represents the base width parameter of the node and is a number more than 0. $C_j = [c_{j1}, c_{j2}, \ldots, c_{ji}, \ldots, c_{jm}]^T$, $j = 1, 2, \ldots, n$, $B = [b_1, b_2, \ldots, b_m]^T$. The weight vector of the network is the identification network output of $W = [w_1, w_2, \ldots, w_j, \ldots, w_m]^T$:

$$y_m(k) = w_1 h_1 + w_2 h_2 + \cdots + w_m h_m \tag{11}$$

The performance indicator function of the recognizer is:

$$J = \frac{1}{2}\left[y(k) - y_m(k)\right] \tag{12}$$

According to the gradient descent method, the iterative algorithm for output weight, node center and node base width parameters is as follows:

$$w_j(k) = w_j(k-1) + \eta(y(k) - y_m(k))h_j + \alpha(w_j(k-1) - w_j(k-2)) \tag{13}$$

$$\Delta b_j = (y(k) - y_m(k)) w_j h_j \frac{\|X - C_j\|^2}{b_j^3} \tag{14}$$

$$b_j(k) = b_j(k-1) + \eta \Delta b_j + \alpha(b_j(k-1) - b_j(k-2)) \tag{15}$$

$$\Delta c_{ji} = (y(k) - y_m(k)) w_j \frac{x_j - c_{ji}}{b_j^2} \tag{16}$$

$$c_{ji}(k) = c_{ji}(k-1) + \eta \Delta c_{ji} + \alpha(c_{ji}(k-1) - c_{ji}(k-2)) \tag{17}$$

In the equation, η is learning rate, α is momentum factor [18].

Using the RBF network to identify the output to approximate the system output, the object Jacobian information is

$$\frac{\partial y}{\partial u} \approx \frac{\partial y_m(k)}{\partial u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_j - x_1}{b_j^2} \tag{18}$$

in which, we can pick $x_1 = u(k)$.

4. **Smith Predictive Compensation Control.** In order to solve the problem of pure lag in the control system, O. J. Smith proposed a scheme of predictive compensation control in 1957. For the lag term contained in the closed-loop characteristic equation of pure lag system, based on the PID feedback control, a predictive compensation link [19] is added, so that the closed-loop characteristic equation does not contain pure lag term, thus improving the control quality [20].

A block diagram of an indoor temperature control system with pure lag is shown in Figure 3. $G_1(s)$ is a transfer function for the temperature controller, $G_2(s)e^{-\tau s}$ is transfer function of the controlled object, where $G_2(s)$ is the transfer function that does not contain a pure lag part, the transfer function of the pure lag part is $e^{-\tau s}$.

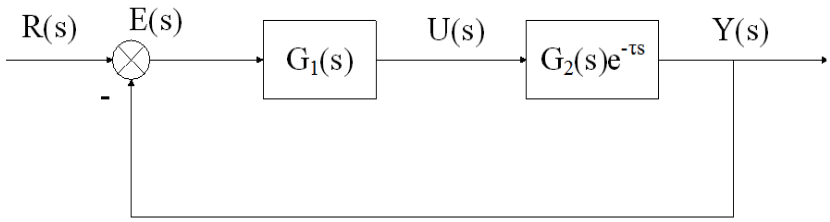

FIGURE 3. Diagram of the control system with pure lag

The closed-loop transfer function of the temperature control system is:

$$\Phi(s) = \frac{Y(s)}{R(s)} = \frac{G_1(s)G_2(s)e^{-\tau s}}{1 + G_1(s)G_2(s)e^{-\tau s}} \tag{19}$$

Characteristic equation is:

$$1 + G_1(s)G_2(s)e^{-\tau s} = 0 \tag{20}$$

It can be seen from Equation (20) that the characteristic equation contains $e^{-\tau s}$, that is, a pure lag link, which reduces the stability of the system. If the signal of N point in Figure 4 can be measured, the signal of N point is fed back to the controller, and the pure lag link can be transferred outside the control loop.

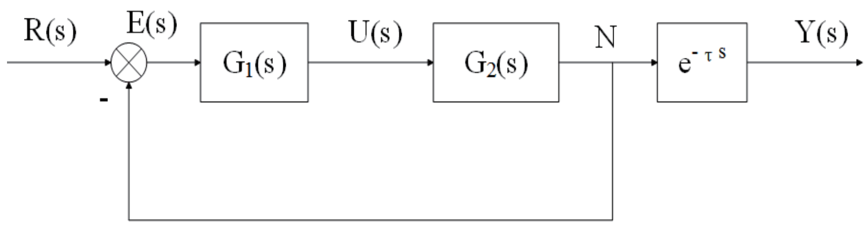

FIGURE 4. Block diagram of the ideal control system

The closed-loop transfer function of the ideal control system is:

$$\Phi(s) = \frac{Y(s)}{R(s)} = \frac{G_1(s)G_2(s)e^{-\tau s}}{1 + G_1(s)G_2(s)} \tag{21}$$

Characteristic equation is:

$$1 + G_1(s)G_2(s) = 0 \tag{22}$$

Since the output signal of $G_1(s)$ is used as the feedback signal, the signal is advanced τ correspondingly. It can be seen from Equation (22) that the pure lag term is not included, so that the control quality is greatly improved. However, in the practical application of air-conditioned room temperature control, the system is a large lag system, which will be disturbed at point N, so it cannot be used in actual engineering.

In the actual project, the Smith predictor compensator $G_0(s)$ is often introduced, and it is connected in parallel to the PID controller, we can set $G_0(s) = G_m(s)(1 - e^{-\tau_m s})$, where $G_m(s)$ is the transfer function of the predictive model of the controlled object, and τ_m is the estimated lag time, as shown in Figure 5.

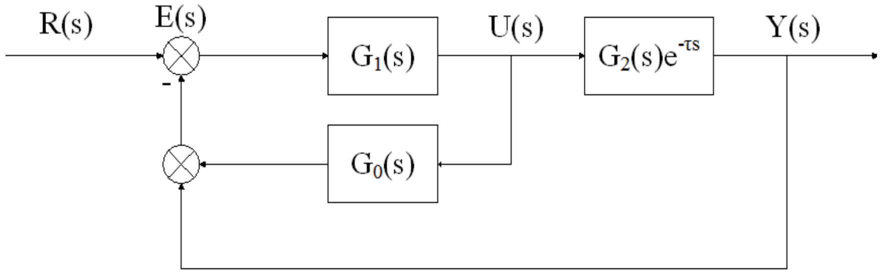

FIGURE 5. Block diagram of Smith predictive compensation control system

The closed-loop transfer function of the system with Smith predictive compensation control is:

$$\begin{aligned}\Phi(s) &= \frac{Y(s)}{R(s)} = \frac{G_1(s)G_2(s)e^{-\tau s}}{1+G_1(s)G_0(s)+G_1(s)G_2(s)e^{-\tau s}} \\ &= \frac{G_1(s)G_2(s)e^{-\tau s}}{1+G_1(s)G_m(s)+G_1(s)[G_2(s)e^{-\tau s}-G_m(s)e^{-\tau_m s}]}\end{aligned} \tag{23}$$

If the model is accurate, you can make $G_2(s) = G_0(s)$, $\tau = \tau_m$, and then,

$$\Phi(s) = \frac{Y(s)}{R(s)} = \frac{G_1(s)G_2(s)e^{-\tau s}}{1+G_1(s)G_2(s)} \tag{24}$$

As can be seen from Equation (24), consistent with the results obtained by the ideal control shown in Figure 4, their characteristic equations is $1+G_1(s)G_2(s) = 0$. After Smith predictive compensation, the pure lag link has been shifted out of the closed-loop control loop, and the characteristic equation has no pure lag term, which improves the control performance of the air-conditioned room temperature control system. However, from Equation (23), Smith predictive compensation depends on the precise controlled object model. If it cannot meet that $G_2(s) = G_0(s)$, $\tau = \tau_m$, it will cause system turbulence. To overcome this shortcoming, this paper combines Smith predictive compensation with the RBF neural network described above.

5. **Feedforward Controller Design.** In this paper, the research object of the control system is the temperature control system in the air conditioning room. Through testing and repeated experiments, the mathematical model of the controlled object is established as follows,

$$G_2(s) = \frac{K}{1+Ts} \tag{25}$$

where K is amplification factor, T is time constant.

The structure diagram of two-degree-of-freedom composite control is shown in Figure 6. $G_c(s)$ is a feedforward controller transfer function, and then the closed-loop transfer function of the system is:

$$\Phi(s) = \frac{Y(s)}{R(s)} = \frac{[G_c(s)+G_1(s)]G_2(s)e^{-\tau s}}{1+G_1(s)G_0(s)+G_c(s)G_0(s)+G_1(s)G_2(s)e^{-\tau s}+G_c(s)G_2(s)e^{-\tau s}} \tag{26}$$

The error transfer function is:

$$E(s) = R(s) - Y(s) = \frac{1+G_1(s)G_0(s)+G_c(s)G_0(s)}{1+[G_1(s)+G_c(s)][G_0(s)+G_2(s)e^{-\tau s}]}R(s) \tag{27}$$

According to the principle of invariance, when $1+G_1(s)G_0(s)+G_c(s)G_0(s) = 0$, the error of the system is zero.

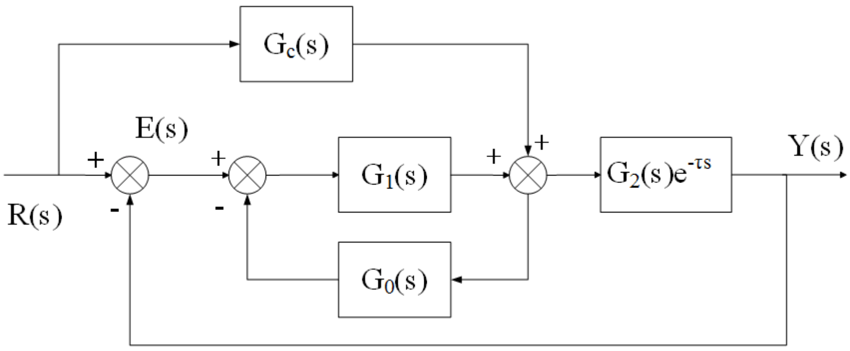

FIGURE 6. Block diagram of compound control system

Because $G_1(s)$ is a PID controller transfer function, then

$$G_1(s) = K_P\left(1 + \frac{1}{T_I s} + T_D s\right) = K_P + \frac{K_I}{s} + K_D s \tag{28}$$

According to Equations (24), (25), (28) and invariance principle, the feedforward controller is designed.

$$G_c(s) = -\left(G_1(s) + \frac{1}{G_0(s)}\right) = -\left(K_P + \frac{K_I}{s} + K_D s + \frac{1 + Ts}{K(1 - e^{-\tau s})}\right) \tag{29}$$

6. **The Simulations.** The design of composite controller based on RBF neural network is completed through the design of the above links. The structure diagram is shown in Figure 7. The principle is to use RBF neural network to control the mathematical model with low precision, and to adjust the three control parameters of PID by online learning – K_P, K_I, K_D. The time-varying and nonlinear problems of the control system are solved. At the same time, the pure delay problem in the control system is solved by combining with the Smith predictor. Finally, the anti-interference ability and tracking ability of the system can be improved by feedforward control, and the performance of the control system can be greatly improved.

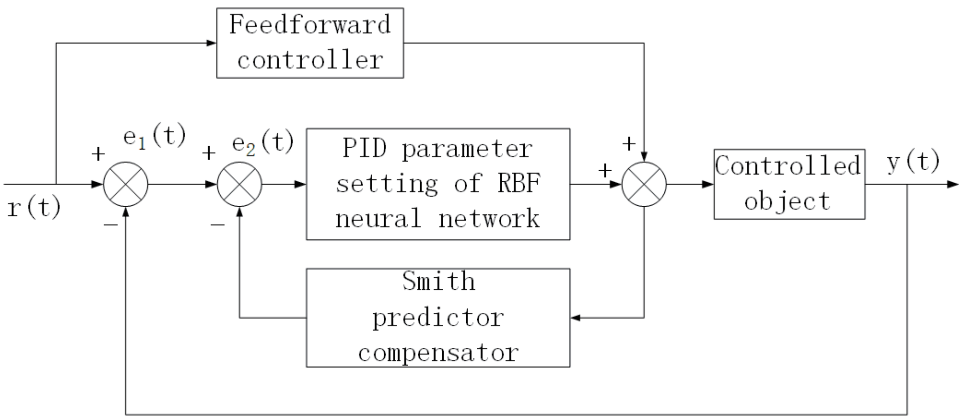

FIGURE 7. Two-degree-of-freedom composite control structure diagram

The input signal of simulation system is step response, sampling time is $t = 10$ s, time constant is $T = 144$, delay time is $\tau = 30$, gain coefficient is $K = 0.92$, and the controlled object is expressed as:

$$G_2(s)e^{-\tau s} = \frac{0.92}{144s + 1}e^{-30s} \tag{30}$$

Table 1. ZN equation is calculated based on parameter setting of the single-capacitance time-delay model PID controller.

Controller parameter / Controller type	K_P	T_I	T_D
P	$\frac{T}{K\tau}$		
PI	$\frac{0.9T}{K\tau}$	3.3τ	
PID	$\frac{1.2T}{K\tau}$	2τ	0.5τ

Based on ZN formula setting for the single-capacitance time-delay model as shown in Table 1, the traditional PID control parameters are be got. According to Equation (30) and Table 1, $K_P = 6.26$, $T_I = 60$, $T_D = 15$ can be available.

The initial value of the PID parameters in RBF-PID control are set to $K_P = 3.5$, $K_I = 0.003$, $K_D = 5$. The input of the RBF neural network is $x = [u(k), y(k), y(k-1)]$, the output is y_m, and the initial value of the output weight vector is 10, the initial value of center vector of the node is set to 45, and the parameters are selected: network learning rate is $\eta = 0.05$, proportion learning rate is $\eta_p = 0.3$, integration learning rate is $\eta_i = 0.001$, differentiation learning rate is $\eta_d = 0.1$, and momentum factor is $\alpha = 0.05$. The algorithm steps are as follows.

1) Select network structure 3-6-1 to initialize each parameter.
2) Sampling to get $r(k)$, $y(k)$, and calculating to get $e(k)$.
3) Calculate the output of the RBF recognizer, modify data center of the hidden layer, the normalization constant, the output weighting coefficient and calculate the Jacobian value according to the performance index function of the recognizer.
4) According to the deviation and Jacobian value, adjust the proportion, integration, and differentiation coefficients of the PID controller, calculate $u(k)$ and update the output of the controlled object.
5) Return to step 2) to execute loop until the sampling time is over.

In RBF-Smith-PID control, the initial value of PID parameters can be set as $K_P = 5.5$, $K_I = 0.01$, $K_D = 2$, and the other learning rate parameters can be consistent with those in RBF-PID control.

The parameters of K_P, K_I, K_D in the feedforward controller are tuned by the RBF neural network. For the controller, the initial value of the PID parameter are set as $K_P = 18$, $K_I = 0.11$, $K_D = 6.5$, and the learning rate parameter is invariant.

The four control systems are simulated by Matlab [21-23], and the simulation results of the control system are shown in Figure 8.

From Figure 8, it can be seen that the traditional PID control system has large overshoot and slow response time, the tracking performance of the closed loop system is obviously improved by adding RBF neural network, but it is still not ideal. Combined with Smith predictor, the overshoot of the system has been reduced and the response time has been decreased. Through compound control, the overshoot of the system is almost zero, and the adjustment time is much better than the other three controllers. Compared with the traditional PID control, the system performance has been greatly improved.

In order to verify the anti-jamming ability of the control system, a random disturbance with a limited value of 50% relative to the input signal is added. The results shown in Figure 9 and Figure 10 are obtained by simulation.

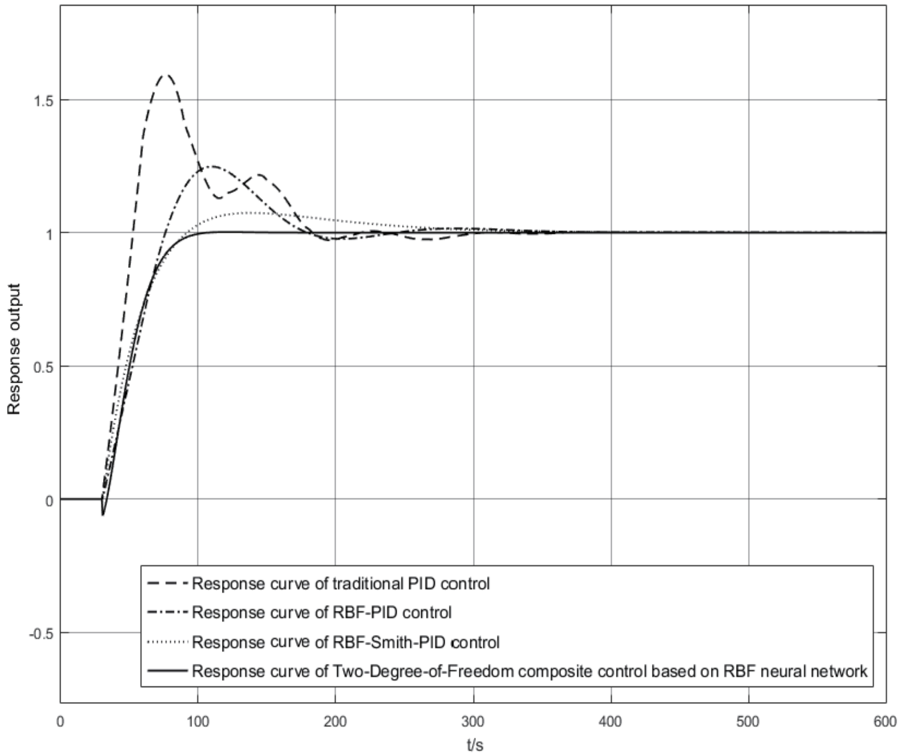

Figure 8. Response curve of various controllers

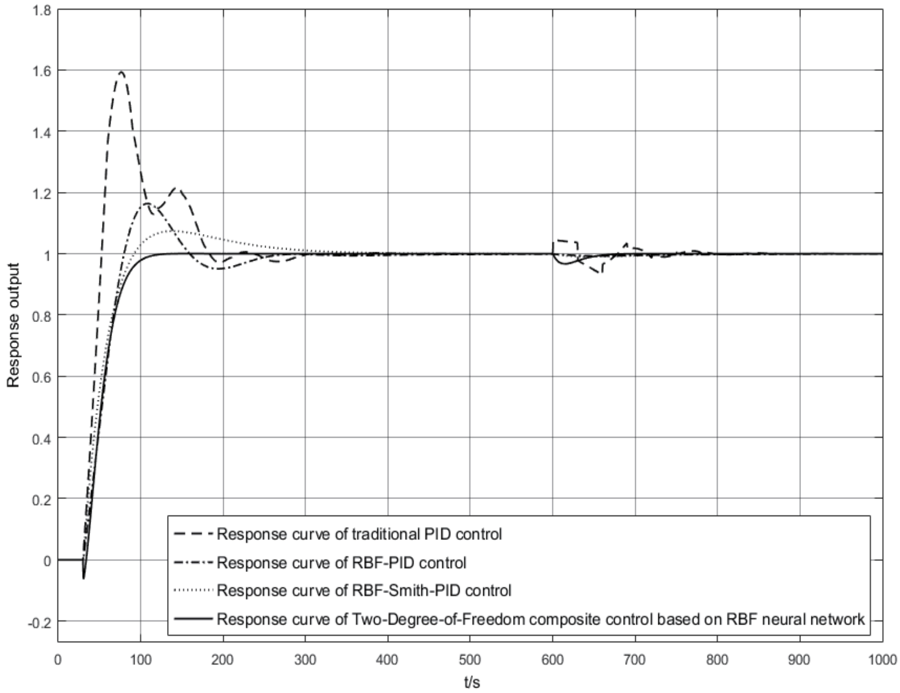

Figure 9. Response curve of control system after adding disturbance

It can be seen from Figure 10 that although the curve of compound control has a transient mutation after the interference signal is added, it can stabilize quickly, while the other control systems are far slower than the composite control system.

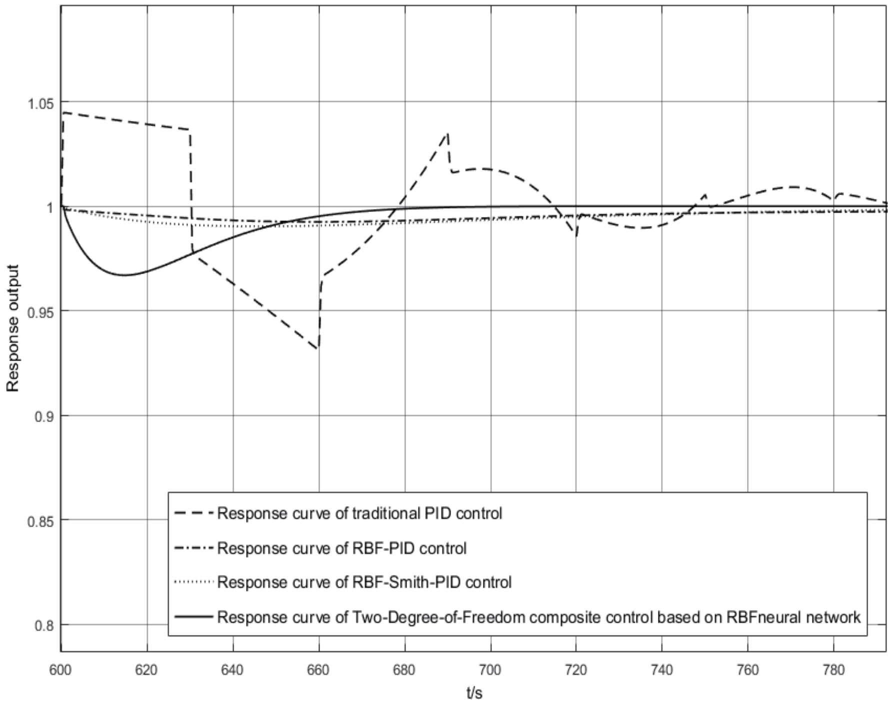

FIGURE 10. Partial enlarged drawing

7. **Conclusion.** In this paper, a two-degree-of-freedom compound control for temperature in air-conditioned room based on RBF neural network is proposed. The controller combines the advantages of RBF neural network, Smith predictive compensation control and feedforward compensation control. Compared with the traditional PID controller, the two-degree-of-freedom composite controller based on RBF neural network has the characteristics of fast response speed, small overshoot, short adjustment time and good dynamic performance. It is a successful attempt for the control of large time-delay and multi-disturbance systems. However, this method requires high accuracy of the model of the control object. The predicting control of temperature in air-conditioned room will be investigated in the future.

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