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Study on Temperature Control in Plant Factory Based on Neural Network PID Controller

Shigang Cui [1, 2], Jianhua Qin [1, 2 +], and Kun Liu [1, 2]

[1] Tianjin University of Technology and Education, Tianjin, 300222, China
[2] Tianjin Key Laboratory of Information Sensing & Intelligent Control, China

Abstract. In view of the characteristics of temperature in Plant Factory, such as nonlinearity, large delay, large delay, large inertia and so on, when the traditional strategy of PID control is used to control temperature, the effect of control is not ideal. Therefore, the paper combines the intelligent algorithm of Back Propagation (BP) neural network with the theory of traditional PID control, proposing the PID controller based on BP neural network self-tuning, and giving the corresponding algorithm and MATLAB simulation. Compared with the traditional PID control, the simulation results show that the BP neural network PID controller designed in this paper has better stability and robustness to control the temperature, and the quality of control has obvious advantages.

Keywords: Plant Factory, temperature, BP neural network PID, MATLAB simulation

1. Introduction

In recent years, with the continuous improvement of living standards, people's demand for green pollution-free vegetables and the gap between China's cultivated agriculture have become increasingly prominent [1-2]. Especially in some parts of northwest China, due to geographical location, seasonal and climatic factors, people's daily consumption of vegetables is not only expensive, and not fresh, which is unhealthy for human. The development of agriculture in China is faced with the enormous challenge of using limited farming land to meet people's demand for green food [3]. The Plant Factory is an important product of modern science and technology innovation and is an important part of modern agriculture. By providing the suitable environment for the growth and development of the plant and carrying out automatic control, the plant has realized the multiple objectives of high yield, high quality, ecology and safety.

Temperature is a key environmental factor in growth cycle of the plant. It has a comprehensive effect on plant growth, which not only affects the process of plant photosynthesis, respiration and transpiration, but also affects the process of plant organic matter synthesis and transportation. At present, most of people use traditional PID to regulate the temperature, and the method is simple and convenient. However, the temperature is a complex object of multivariable coupling. When temperature is controlled by the traditional PID control strategy, the optimal parameters, such as K_p, K_I and K_D, are difficult to set, and the control quality and stability are difficult to guarantee. Therefore, in this paper, the BP neural network and PID are combined to obtain the PID controller based on BP neural network, which can make the system run better.

2. The Overall Design of BP Neural Network PID Controller

2.1. The Structure of BP Neural Network PID

When the traditional PID control strategy is used to regulate the temperature in Plant Factory, the parameters can not be adjusted in real time, resulting in large delay and large hysteresis in the control process,

+ Corresponding author. Tel.: 15122360134.
E-mail address: 2451321946@qq.com.

which affects the stability and robustness of the system. The BP neural network has a complex nonlinear mapping ability and strong learning ability, through the real-time adjustment of the weight coefficient, achieving the fastest speed to approach the set value. Its principle block diagram is shown in figure 1.

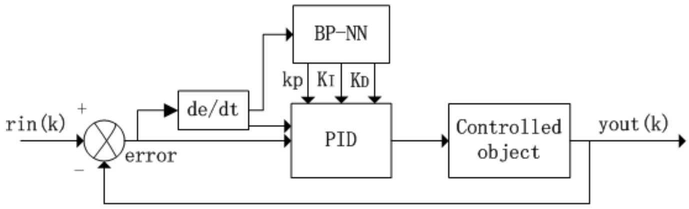

Fig. 1: BP neural network PID controller structure diagram.

In this paper, author uses the simplest 3 layer BP neural network and the structure selects the 4-5-3-typed model, as shown in figure 2. In the input layer, r is expected value, y is actual output value, e is error, and l is unit of measurement. In the output layer, K_P, K_I and K_D are three parameters of PID control. The w_{ji} and w_{il} are the weight coefficient of hidden layer and output layer, respectively.

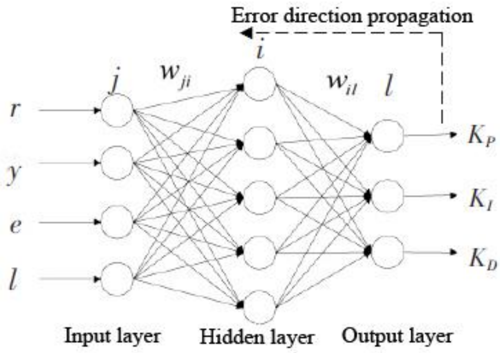

Fig. 2: Layer 3 BP neural network structure.

2.2. Forward Algorithm of Working Signal

The input of the neural network in the input layer:

$$O_j^{(1)} = x(j) \qquad j = 1,2,3,4 \tag{1}$$

The input and output of the neural network in the hidden layer:

$$\begin{aligned} net_i^{(2)}(k) &= \sum_{j=1}^{4} w_{ji}^{(2)} O_j^{(1)}(k) \qquad i = 1,2,3,4 \\ O_i^{(2)}(k) &= f[net_i^{(2)}(k)] \end{aligned} \tag{2}$$

where $f(x)$ is $\frac{e^x - e^{-x}}{e^x + e^{-x}}$.

The input and output of the neural network in the output layer:

$$\begin{aligned} net_l^{(3)}(k) &= \sum_{i=1}^{5} w_{il}^{(3)} O_i^{(2)}(k) \\ O_l^{(3)}(k) &= g[net_l^{3}(k)] \\ O_1^{(3)}(k) &= K_P \qquad l = 1,2,3 \\ O_2^{(3)}(k) &= K_I \\ O_3^{(3)}(k) &= K_D \end{aligned} \tag{3}$$

where $g(x)$ is $\frac{e^x}{e^x + e^{-x}}$.

2.3. Inverse Algorithm of Error Signal

In the training of the weights of the BP neural network, the weight of the connection between the layer and the interlayer is improved from the output layer in the direction of reducing the error. As the number of learning times increases, the deviation becomes smaller and smaller. Performance index function:

$$E(k)=\frac{1}{2}[rin(k)-yout(k)]^2 \tag{4}$$

Using the steepest descent method to adjust the weight of each layer, the change of the weight coefficient of the output layer is:

$$\Delta W_{il}^{(3)}(k)=-\eta\frac{\partial E(k)}{\partial W_{il}^{(3)}}+\alpha\Delta W_{il}^{(3)}(k-1) \tag{5}$$

where k is learning times and α is momentum factor.

According to the differential chain rules:

$$\frac{\partial E(K)}{\partial W_{il}^{(3)}}=\frac{\partial E(K)}{\partial y(k)}\cdot\frac{\partial y(k)}{\partial\Delta u(k)}\cdot\frac{\partial\Delta u(k)}{\partial O_i^{(3)}(k)}\cdot\frac{\partial O_i^{(3)}(k)}{\partial net_l^{(3)}(k)}\cdot\frac{\partial net_l^{(3)}(k)}{\partial W_{il}^{(3)}(k)}$$

$$\frac{\partial net_l^{(3)}(k)}{\partial W_{il}^{3}(k)}=O_i^{(2)}(k) \tag{6}$$

Based on the above formula, the learning algorithm of BP neural network output layer weights is:

$$\begin{aligned}&\Delta W_{il}^{(3)}(k)=\alpha\Delta W_{il}^{(3)}(k-1)+\eta\delta_l^{(3)}O_i^{(2)}(k)\\&\delta_l^{(3)}=error(k)\operatorname{sgn}\left(\frac{\partial y(k)}{\partial\Delta u(k)}\right)\frac{\partial\Delta u(k)}{\partial O_l^{(3)}(k)}g'(net_l^{(3)}(k))\end{aligned} \tag{7}$$

where $g'(x)$ is $g(x)[1-g(x)]$.

Similarly, BP neural network hidden layer weights learning algorithm:

$$\begin{aligned}&\Delta W_{ji}^{(2)}(k)=\alpha\Delta W_{ji}^{(2)}(k-1)+\eta\delta_i^{(2)}O_j^{(1)}(k)\\&\delta_i^{(2)}=f'[net_i^{(2)}(k)]\sum_{l=1}^{3}\delta_l^{(3)}W_{il}^{(3)}\end{aligned} \tag{8}$$

where $f'(x)$ is $\frac{1}{2}[1-f^2(x)]$.

3. Simulation and Analysis

In order to compare the control effect of traditional PID controller and BP neural network based PID controller on temperature. In this paper, author uses BP neural network PID controller and conventional PID controller to simulate the temperature of the Plant Factory. The transfer function of the controlled temperature control process is

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

In the formula: K represents a static gain, T represents the time constant, τ represents pure lag. Taking K =1, τ =3, T =6, using Z transform:

$$\frac{\partial\Delta u(k)}{\partial O_1^{(3)}}=error(k)-error(k-1)$$

$$\frac{\partial\Delta u(k)}{\partial O_2^{(3)}}=error(k)$$

$$\frac{\partial\Delta u(k)}{\partial O_3^{(3)}}=error(k)-2error(k-1)+error(k-2)$$

After discretization, the discrete object after Z transform is:

$$y(k)=-den(2)y(k-1)+num(2)u(k-4)$$

Conventional PID controller parameters: K_p =1, K_I =0.2, K_D =0.02. In the BP neural network PID controller, the structure of BP neural network is the 4-5-3-typed model, and learning efficiency (η) is 0.1, and inertial coefficient (α) is 0.01. The initial values of the weights are taken as random numbers on interval [-0.5,0.5].The temperature simulation curves of traditional PID controller and BP neural network PID controller are shown in figure 3. It can be seen from figure 3 that BP neural network PID controller has small overshoot, and the transition process is more stable. Therefore, the control quality of BP neural network PID controller is better than the conventional PID control, and the comparison of the performance index of the whole transition process is shown in table 1.

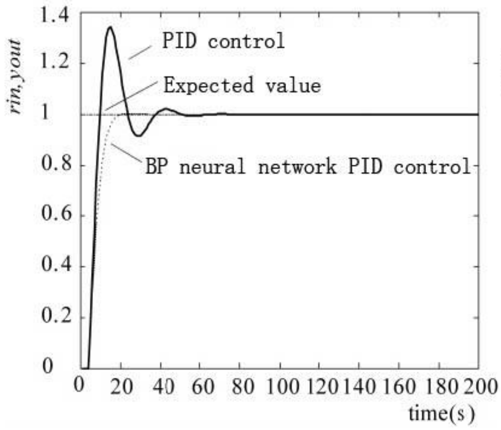

Fig. 3: Simulation curve graph.

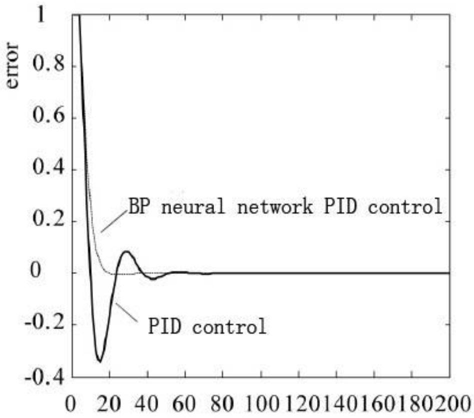

Fig. 4: Error curve graph.

Table 1: Comparison of Performance Index of Transient Process

Control method	Delay time	Transition time	Overshoot
PID control	10s	60s	22%
BP neural network PID control	10s	20s	0

The error curves of the conventional PID control and BP neural network PID control are shown in figure 4. It can be seen from the comparison chart that the error curve of BP neural network PID control is more stable.

Through the self-learning of neural network and the weighted coefficient adjustment, the curves of the corresponding output parameters are shown in figure 5. In the 100th sampling time, the controller is added to the interference of the amplitude of 0.2. In this case, the simulation results are shown in figure 6. It can be seen from the figure that BP neural network PID controller has some advantages, such as short adjustment time, fast recovery, good stability and good anti-interference ability.

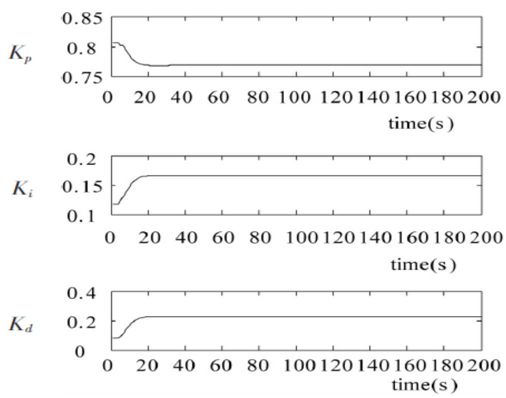

Fig. 5: BP neural network PID controller parameter variation curve.

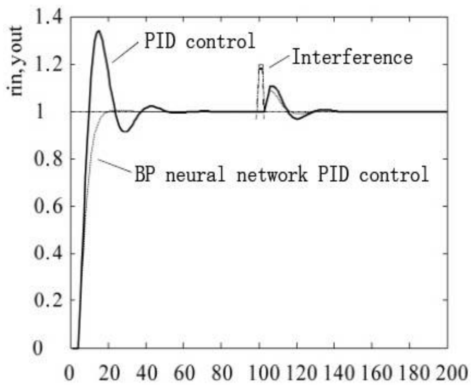

Fig. 6: Under the disturbance of the amplitude of 0.2.

4. Conclusions

The temperature in Plant Factory is a controlled object with large delay, large inertia, and nonlinear, and it is difficult to guarantee the quality of control by applying the traditional PID control system [4-5]. The paper combines the classical incremental PID controller with BP neural network intelligent algorithm, using complex nonlinear mapping ability and strong learning ability of BP neural network, and BP neural network PID controller is designed based on self-tuning PID controller, giving the algorithm of control. In order to verify the effect of the BP neural network PID controller, the temperature in Plant Factory is taken as the research object, and the dynamic model of temperature is established and simulated by MATLAB. The simulation results show that, compared with the traditional PID control, the transition time of BP neural network PID controller is short and less overshoot. All in all, the BP neural network PID controller has better accuracy and robustness and can achieve the ideal effect.

5. Acknowledgement

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