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A New Control Strategy for Greenhouse Environment Control System Based on Inverse Model

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ABSTRACT

The greenhouse environment control system is a type of non-linear system since the temperature and humidity of the system are highly coupled. Besides, the time lag of the temperature and humidity control process is large, so it's quite difficult to linearize and decouple the temperature and humidity of the system. To cope with this issue, this paper proposed a novel control strategy for greenhouse environment control system based on Back Propagation Neural Network (BPNN) and inverse model, the proposed method can perform inverse identification on the temperature and humidity control system to attain higher accuracy. Then, the inverse model and the original system were connected in series to form a pseudo linear system to realize the decoupled control of temperature and humidity. After that, aiming at the impact of some non-linear factors on the greenhouse environment system, this paper adopted the adaptive fuzzy Proportion Integration Differentiation (PID) controller to enhance the adaptability of the system, thereby reducing control error and the interference caused by non-linear factors of the temperature and humidity control system. At last, the experimental results showed that, the temperature error of the system could be controlled within 1.2℃ and the error of relative humidity was less than 2.5%. The proposed method can improve the control effect of the greenhouse environment to a certain extent, and it provides a novel approach of greenhouse control.

1. INTRODUCTION

Greenhouses are now have been widely used in agriculture as basic facilities. Compared with common lands for growing field crops, the greenhouse production process is not vulnerable to external interference, and can satisfy the requirements of crops in different life cycles for the environment [1]. Common greenhouses are film greenhouses or glass greenhouses equipped with heating and humidifying devices to create an environment suitable for crop growth. Among the various influencing factors of greenhouse environment, temperature and humidity are the most important factors for the yield and quality of crops. Generally, greenhouses are in a closed state, the temperature and humidity are coupled, if they are not adjusted in time, then it's easy to form a high temperature and high humidity environment, which can affect the growth of the crops [2]. Therefore, improving the multi-variable decoupling performance of the temperature and humidity control system of the greenhouse and reducing the impact of the nonlinearity of the system are important works for increasing crop yield and improving crop quality.

The research on greenhouse environment control system started in the 1970s, relevant studies can be divided into three main aspects: conventional PID control, modern control theory, and intelligent control, however, few of them have concerned about the decoupled control. Simply adopting the fuzzy PID control method to control the complex greenhouse environment can only achieve unsatisfactory effect. In view of the decoupling of temperature and humidity and the nonlinearity problems of greenhouse environment [3], this paper proposed to introduce the inverse model into the field of greenhouse environment control, perform inverse identification on the original system through neural network, build a pseudo linear composite system with the controlled object, and adopt the fuzzy PID control strategy to realize the control of temperature and humidity in the system. This method doesn't rely on the mathematical model of the original system, for systems like greenhouses that are non-linear, highly coupled, and have multiple variables, it can well improve the control accuracy and robustness of the system and reduce the effect of nonlinearity. The method provides a new research idea for the temperature and humidity control of greenhouse environment.

2. PRINCIPLE OF THE INVERSE MODEL OF GREENHOUSE ENVIRONMENT AND THE CONTROL SCHEME

2.1 Decoupling principle of the inverse model

Definition of the inverse system: in a greenhouse temperature and humidity control system, assuming: $u(t) = [u_1, u_2, \cdots, u_p]^T$ and $y(t) = [y_1, y_2, \cdots, y_p]^T$, wherein $p = 2$ represents the two-dimensional inputs of fan rotate speed and heating device current; $q = 2$ represents the two-dimensional actual outputs of temperature and humidity, then the input-output relationship can be described by the state equation shown in Formula 1 below:

$$\begin{cases} \dot{x} = f(s,u) \\ y = h(s,u), s(t_0) = s_0 \end{cases} \tag{1}$$

Assuming: θ represents the operator for describing the mapping relationship from inputs to the outputs, there is $y(\cdot) = \theta(x_0, u(\cdot))$, which can be written in a simpler form $y = \theta u$; assuming $u_d = \bar{\theta} y_d$ represents the mapping relationship of system *Π*, wherein $y_d(t) = [y_{d1}, y_{d2}, \dots, y_{dq}]^T$, $u_d(t) = [u_{d1}, u_{d2}, \dots, u_{dq}]^T$, and $y_d(t)$ represents any given differentiable function vector in a certain domain and it satisfies the initial conditions at t_0, if operator $\bar{\theta}$ meets Formula 2:

$$\theta \bar{\theta} y_d = \theta u_d = y_d \tag{2}$$

Then, it's called that system *Π* is the unit inverse system of system *Σ*, correspondingly, system *Σ* is called the original system [4].

Assuming: $u_d = \bar{\theta} \varphi$ represents the mapping relationship of system Π_α, wherein input $\varphi(t) = [\varphi_1, \varphi_2, \dots, \varphi_q]^T$, output $u_d(t) = [u_{d1}, u_{d2}, \dots, u_{dq}]^T$, φ is any given continuous function vector in a certain domain, and it satisfies the initial conditions at t_0. When it takes $\varphi(t) = y_d^{(\alpha)}(t)$, and $\alpha(t) = [\alpha_1, \alpha_2, \dots, \alpha_q]^T$, that is, φ_i is the α_i-order derivative of y_d, if operator $\bar{\theta}_\alpha$ meets Formula 3:

$$\theta \bar{\theta}_\alpha \varphi = \theta \bar{\theta}_\alpha \left(y_d^{(\alpha)} \right) = \theta u_d = y_d \tag{3}$$

Then, it's called that system Π_α is the *α*-th order integral inverse system of the original system *Σ*, in simpler words, it's called the *α*-order inverse system [5].

If an original system *Σ* has a unit inverse system or a *α*-order inverse system as shown in Figure 1(a) and 1(b), then it's called that system *Σ* is a reversible system.

According to the definition of the *α*-order inverse system the composite system denoted as $\theta \bar{\theta}_\alpha$ is equivalent to the linear transfer function in the form integrators, as shown in Figure 2, the controlled system had achieved decoupling and linearization, and there is $y^{(\alpha)} = \varphi$, then the input-output relationship of the composite system can be theoretically expressed as a linear integral decoupling transfer function, as shown in Formula 4:

$$\begin{aligned} G(s) = diag\left(G_1(s), G_2(s), \dots, G_q(s)\right) \\ = diag(s^{-\alpha_1}, s^{-\alpha_2}, \dots, s^{-\alpha_q}) \end{aligned} \tag{4}$$

The α-order inverse system Π_α was put in series before the original system *Σ*, together they formed a composite system $\theta \bar{\theta}_\alpha$ with a transfer relationship similar to the linear relationship, and this system can be called a α-order pseudo linear composite system, referred to as a pseudo linear system for short. Figure 2 shows the principle of the linearization of the α-order inverse system with multiple inputs and outputs. By constructing the inverse model of the system and combining it with the original system into a pseudo linear system, linearization and decoupling of the nonlinear system can be realized. Therefore, adopting the linear system control method could meet the requirements and reduce the complexity of system control [6, 7].

2.2 Composition of the fuzzy control system

Controller of the greenhouse temperature and humidity control system adopted the fuzzy PID control strategy, and its structure is shown in Figure 3. The application of fuzzy control does not rely on the mathematical model of the controlled object, and fuzzy reasoning is carried out according to the knowledge of fuzzy rules to obtain the appropriate controlled quantity and to reach the online-tuned PID parameters, it has the merits of real-time, good robustness, and high control accuracy. After the identified inverse system was combined with the original system, the fuzzy PID was directly applied to the pseudo linear composite system, which could effectively reduce the impact of nonlinearity on the system [8].

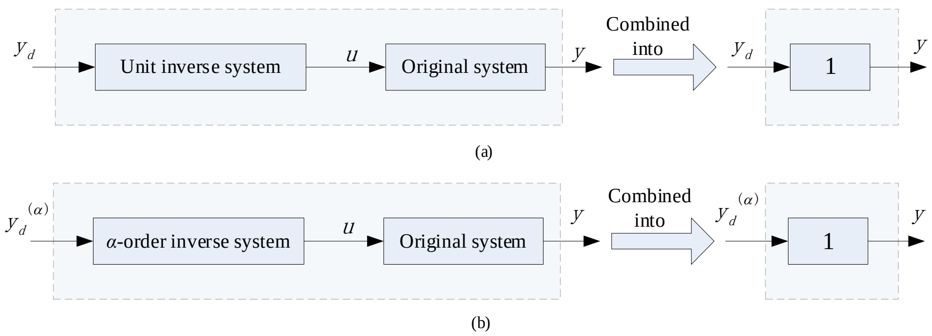


Figure 1. Unit inverse system, α-order inverse system, and composite system

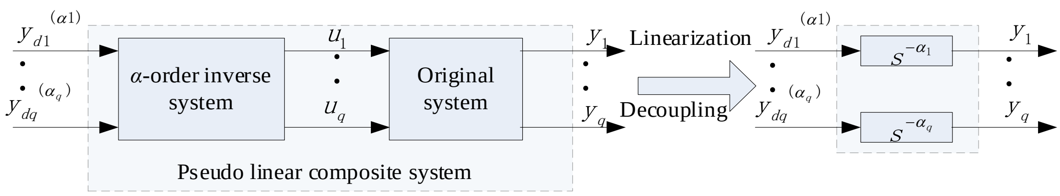


Figure 2. Linearization of the *α*-order inverse system of MIMO

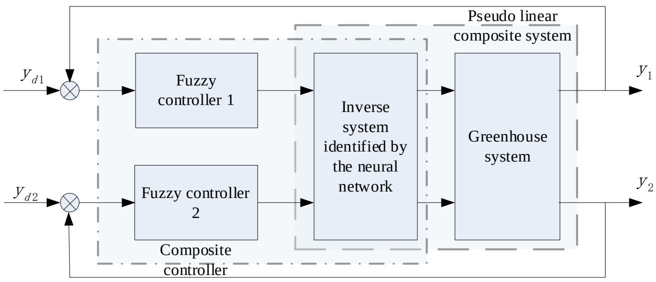


Figure 3. Structure of the control system

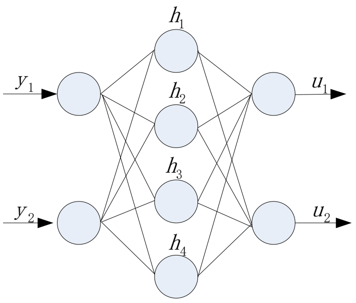


Figure 4. Inverse system BPNN structure

3. INVERSE MODEL IDENTIFICATION OF NEURAL NETWORK

According to the multi-variable environmental factors in the greenhouse, researchers have proposed a few research methods such as the diagonal matrix method, feedforward compensation decoupling method, and fuzzy decoupling method [9], and these methods all require that the mathematical model of the controlled system is accurate and the specific internal parameters are known. The identification of the neural network can approximate the complex static nonlinear mapping with any accuracy, and adapt to the system through learning, therefore, using neural networks to identify nonlinear systems has been widely used in the field of nonlinear control and achieved good effect.

Neural network has the merit of fast learning, it can perform dynamic learning on the greenhouse environment control system within a certain time period under the condition that the process parameters are relatively stable, thereby identifying the inverse model of the original system. The neural network was designed from several aspects including the determined number of network layers, the number of hidden layer neurons, the number of input and output points, the activation function, the initial values, and the learning rate, etc. [10].

3.1 Determination of the number of neural network layers

Before using BPNN to identify the inverse model of the original system, it's necessary to determine the number of neural network layers, and select the three-layer structure of the neural network that contains the input layer, hidden layer, and output layer. According to the analysis of the temperature and humidity control principle of the greenhouse environment, the system inputs were the controlled quantity of the heating device and the controlled quantity of the dehumidifier fan of the greenhouse, which were respectively represented by u_1 and u_2. The system inputs were the temperature and humidity of the greenhouse, which were respectively represented by y_1 and y_2. In order to realize the inverse identification of the original system, the outputs of the original system were taken as the inputs of the inverse model, and the inputs of the original system were taken as the outputs of the inverse model. Since the numbers of input and output layer nodes are determined by the number of controlled quantities, therefore, according to the requirements of the controlled quantities of the system, it's determined that the number of input layer nodes in the BPNN was N=2, the number of hidden layer nodes was M=4, and the number of output layer nodes was L=2.

Structure of the BPNN used for inverse model identification is given in Figure 4. In the figure, y_1 is the temperature, y_2 is the humidity, h_1, h_2, h_3, h_4 are hidden layer nodes, u_1 is the working current of the heating device, u_2 is the rotate speed of the dehumidifier fan. The entire network realizes the inverse identification of the original system via the 2-dimensional output layer consisted of fan rotate speed and electric wire current, the single hidden layer consisted of four neurons, and the 2-dimensional input layer consisted of temperature and humidity.

3.2 Data preprocessing and operator selection

The opening degree of the heating device is the ratio of the current opening degree to the maximum opening degree. Since the relative humidity of air is a decimal number between (0,1), in order to minimize the damage to the measured data caused by normalization, the relative humidity of air was represented by the decimal number and didn't participate in normalization, and the rest values were all normalized by Formula 5:

$$y_i = \frac{x - 0.95x_{min}}{1.05x_{imax} - 0.95x_{imin}} \tag{5}$$

In Formula 5, y_i is the normalized value, its variation range is [0,1]; x_i is the measured value, x_{min} is the minimum value among the measured values, x_{imax} is the maximum value among the measured values.

Since the environment in the greenhouse is quite complicated and the various factors of the greenhouse have mutual influence on each other, which can affect the convergence speed of the BPNN to a certain extent and result in the problem of local results, making the inverse model unable to achieve the global optimal effect or meet the accuracy requirement, therefore, in order to solve the slow convergence speed and improve the accuracy of the model, the momentum method had been introduced. The momentum method adopts the changing learning rate and the changing momentum [11, 12], wherein the changing learning rate means that the learning rate δ keeps changing constantly, in the early stage of the neural network training, δ takes a larger value, so as to attain a faster learning speed. During the neural network training process, when the model established by the neural network is closer to the required network, δ could take a smaller value, so as to accelerate the convergence of the neural network. Formula 6 gives the introduced momentum term:

$$\omega_i(k+1) = \omega_i(k) + \delta[(1-\alpha)D(k) + \alpha D(k-1)] \tag{6}$$

In Formula 6, δ is the learning rate, $\delta > 0$; α is the momentum factor, and it satisfies $0 \le \alpha \le 1$; $D(k)$ is a single weight value;

$D(k) = \frac{-\alpha E}{\partial \omega(k)}$ is the negative gradient at time moment k; $\omega_i(k)$ represents the weight coefficient between the input layer and the hidden layer at time moment T; $\omega_i(k+1)$ represents the weight coefficient between the input layer and the hidden layer at time moment $(k+1)T$.

4. FUZZY PID CONTROL

4.1 Principle of fuzzy controller

The temperature and humidity controller in the greenhouse determines the changes of temperature and humidity in the greenhouse environment, and it plays an important role in stabilizing the changes of temperature and humidity in the greenhouse. During the temperature and humidity control process of the system, the temperature and humidity will change with the changes of the overall environment. Since internal factors will cause some deviations to the performance of the electric wire and the rotate speed curve of the fan, and this will bring certain interference to the control accuracy of the entire system, the conventional PID controller can hardly meet the requirements of the complex greenhouse environment [13].

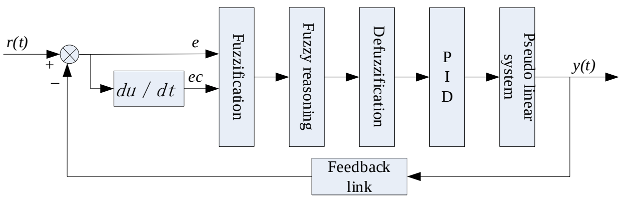


Figure 5. Structure of fuzzy PID controller

Fuzzy PID controller has the characteristics of being able to control nonlinear systems, it contains a few aspects including fuzzification, fuzzy reasoning, and defuzzification. Because it does not require accurate mathematical models to control, it is more suitable for nonlinear and time-varying control systems [14]. As shown in Figure 5, by taking deviation *e* and deviation change rate *ec* as inputs and using the fuzzy change parameters to adjust the PID parameters, the different requirements of *e* and *ec* for PID controller parameters could be satisfied.

4.2 Design of fuzzy controller

4.2.1 Fuzzification

During the temperature and humidity control process of the system, due to the limitation of the measurement range of thermocouple and humidity detection device, the measured value of the temperature and humidity won't be any value. In view of such limitation, the fuzzification of the temperature and humidity inputs of the fuzzy controller, namely the mapping relationships of the detected values of temperature and humidity to their respective domain, was calculated according to the method shown in Formula 7:

$$E = L \times \frac{e - (e_L - e_H)/2}{(e_L - e_H)/2} \tag{7}$$

In Formula 7: L represents the value range of the domain; e_L and e_H represent the detected minimum value and maximum value of temperature and humidity; E represents the fuzzification result of temperature and humidity.

4.2.2 Fuzzy rule reasoning

The fuzzy controller of the system adopts a double-input single-output structure to adjust the controlled quantity. Taking temperature control as an example, the two inputs of the controller are respectively the deviation e_f and deviation change rate ec_f between the real-time collected temperature and the set temperature of the greenhouse, and the output is the amount of current adjustment. The deviation $e_1$between the actual temperature and the set temperature was divided into 7 levels: {PB positive bigger, PM positive moderate, PS positive smaller, ZO moderate, NS negative smaller, NM negative moderate, NB negative bigger}, its domain E_1 is [-7,7]. The deviation change rate ec_1 between the actual temperature and the set temperature was divided into 7 levels: {PB, PM, PS, ZO, NS, NM, NB}, and its domain ec_1 is [-6, 6]. The amount of current adjustment of the electric wire u_1 was also divided into 7 levels: {PB fast speed temperature drop, PM medium speed temperature drop, PS slight temperature drop, ZO holding, NS slight temperature rise, NM medium speed temperature rise, NB fast speed temperature rise}, and its domain u_1 is: [-7, 7]. The fuzzy control of the humidity was carried out in the same way, and the membership function is an important factor to determine the control effect of the fuzzy controller. In order to better suppress the impact of the changes of environmental parameters on the greenhouse environment, this paper took the triangle function as the membership function of the input and output of the temperature fuzzy controller [15], as shown in Formula 8.

$$F = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & b \le x \le c \\ 0 & x \ge c \end{cases} \tag{8}$$

In Formula 8, F is the value of membership degree; x is the value of the domain of the fuzzy controller; a, b, c are the parameters of the triangle membership function. Then, according to the reasoning and defuzzification methods mentioned above, the fuzzy control rules were attained, as shown in Table 1. All rules in the table were attained based on the logic results of the experiments [16].

Table 1. Fuzzy control rules

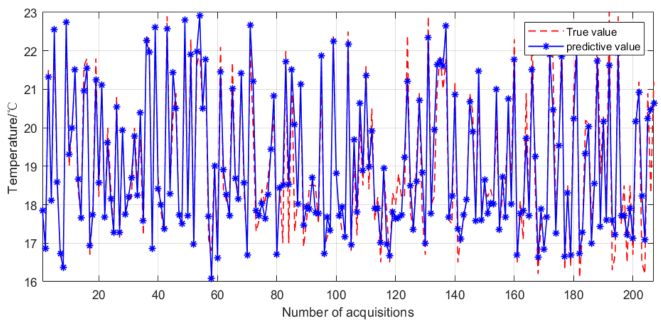
U		E						
		NB	**NM**	**NS**	**ZO**	**PS**	**PM**	**PB**
	NB	PB	PB	PM	PM	PS	ZO	ZO
	NM	PB	PB	PM	PS	PS	ZO	NS
	NS	PM	PM	PM	ZO	ZO	ZO	NM
EC	ZO	PM	PM	PS	ZO	NS	NS	NM
	PS	PS	PS	ZO	NS	NS	NM	NM
	PM	PS	PS	ZO	ZO	NM	NM	NB
	PB	ZO	NS	NS	NM	NM	NB	NB

4.2.3 Defuzzification

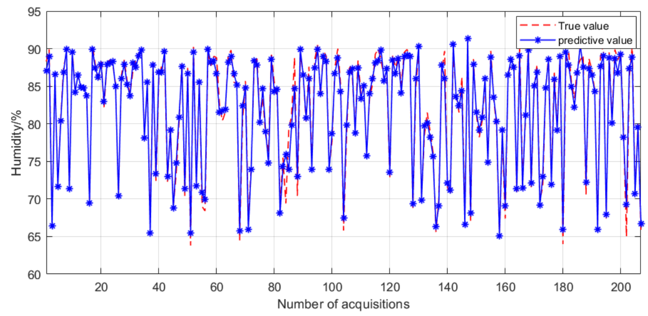
Fuzzy reasoning and defuzzification were performed, and the fuzzy control query table was calculated. During the fuzzy control process, the calculation of the control variables must be obtained through fuzzy reasoning according to the fuzzy rules. In this paper, the Mamdani reasoning method based on weighted average was adopted [17, 18].

5. SIMULATION ANALYSIS

5.1 Inverse system identification



(a) Temperature prediction simulation curve



(b) Humidity prediction simulation curve

Figure 6. Fitting results of temperature and humidity

BPNN was adopted to perform inverse identification on the original temperature and humidity control system. The identification sample is a greenhouse located in the Daqing City (46.35°N, 125°E). In order to reduce the interference of other factors on the greenhouse system, the sunshade curtains in the greenhouse were kept closed, and the wet curtains were in a closed state as well. 1000 groups of measured data of temperature, humidity, electric wire current, and fan rotate speed generated during the normal operation of the greenhouse were collected, among which 200 groups of data were taken as the experimental samples to perform simulation tests. The fitting curves of temperature and humidity corresponding to the inverse system identified by the neural network are shown in Figure 6.

According to Figure 6, for non-linear systems with large time-delay such as the greenhouse, BPNN can effectively identify them with a small amount of data samples and attain high-accuracy inverse system models, in this paper, the fitting errors of temperature and humidity were 3.7% and 6.7% respectively, which had basically met the requirements for system identification.

5.2 System performance test

By combining the inverse model of the system with the fuzzy PID controller, a composite controller was built and used to adjust the original system. Experiment was conducted to compare with that of controlling the original using the fuzzy controller alone, and the simulation results are shown in Figure 7 and Figure 8. According to the results, by introducing the identified inverse model before the original system, a pseudo linear composite system was built, which had effectively reduced the coupling between temperature and humidity, in the meantime, both the electric heating wire and the dehumidifier fan can directly act on the controlled object, speeding up the system response time. By introducing fuzzy PID, it can be clearly seen from the simulation results that the control accuracy of temperature and humidity in the greenhouse had been improved significantly and the steady-state error had been reduced further.

In Figure 7 and Figure 8, Curve 1 is the fuzzy PID control curve of the original system, Curve 2 is the curve of the composite control system constituted by the fuzzy PID and the inverse system. In the simulation process, the initial temperature was set to 0℃, the expected temperature was 25 ℃; the initial humidity was set to 90%, and the expected humidity was 70%. The data of Simulink simulation showed that, the fuzzy PID controller of temperature reached the stable state at around 1700s with an overshoot of 11%, the composite temperature controller reached the stable state at around 800s with an overshoot of 1.2%; the fuzzy PID controller of humidity reached the stable state at around 2000s with an overshoot of 12%, and the composite humidity controller reached the stable state at around 800s with an overshoot of 2.5%. Through the above test verification, after the original system was decoupled and linearized by the inverse model, the temperature error can be kept less than 1.2℃, and the relative humidity error was only 2.5%, which means that the high accuracy of the system had been ensured, the system control error had been reduced, and the composite system achieved a better effect in terms of control stability and response than only applying fuzzy PID to system control.

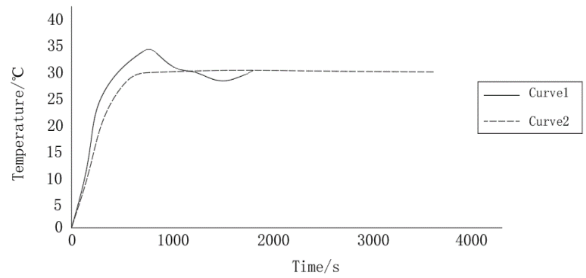


Figure 7. Comparative experiment curve of temperature control

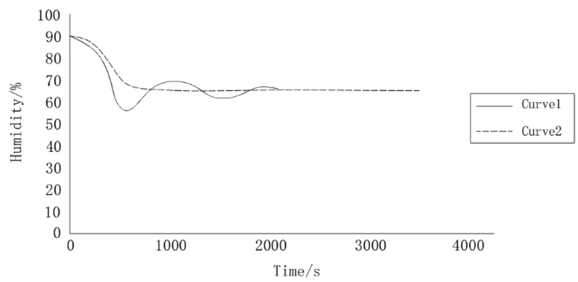


Figure 8. Comparative experiment curve of humidity control

6. CONCLUSION

Aiming at the problems of nonlinearity, time delay and high coupling in conventional greenhouse environment control systems, this paper proposed to use BPNN to perform inverse identification on the original system and build the pseudo linear composite system, in this way, the linearization and decoupling of the system had been realized. The simulation results have verified that: (1) The inverse model identified by BPNN for multi-input/output systems exhibited a high accuracy, and the fitting errors of temperature and humidity of the system had been controlled at 3.7% and 6.7%, which had met the accuracy requirements of system identification; (2) By combining fuzzy PID with inverse system to build composite controller, the control accuracy of temperature and humidity of the system had been improved, the errors of temperature and humidity in the system had been reduced, the response time and stability of the system had been obviously improved, and the impact of multi-variable coupling and nonlinearity in the greenhouse environment control system had been solved.

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