Temperature Control Strategy of the Heating Furnace Used in Adsorption Desulfurization Device

Haozhi Liu [a], Haiyun Chen, Daokai Yang

School of Mechatronic Engineering, Southwest Petroleum University, Chengdu 610500, China

[a]276071264@qq.com

Abstract

Analyzed the cascade PID control scheme used to control the temperature of the adsorption desulfurization device (S Zorb) heating furnace and its big lag features, this paper propose a predictive control model that combine cascade PID and RBF neural network predictive model to control the temperature of the S Zorb heating furnace. This paper takes RBF neural network as predictive model to control the outlet temperature of the heating furnace, neural network predictive value as the feedback signal of the main loop of the cascade system and uses off-line learning to build the neural network predictive model ,on-line update to modify the parameters of the RBF neural network timely. The simulation results showed that the scheme could effectively control some dynamic performance, temperature overshoot, adjustment time and steady error, and control effects were better than those in cascade PID control scheme. The cascade-RBF neural network system has better control character and stronger robustness to overcome the disturbance and model mismatch on S zorb heating furnace.

Keywords

S Zorb heating furnace; Cascade - RBF; Predictive control; The temperature control.

1. Introduction

With the development of automobile industry, the increase of the consumption of fossil energy, the environment problem becomes more and more serious. Production of clean gasoline with low sulfur becomes the focus of the work of petrochemical enterprises. This paper takes the S zorb device used in SINOPEC to product the low sulfur gasoline as the research object. S zorb was developed primarily for adsorption desulfurization technology of FCC gasoline fraction by ConocoPhillips. This technology has advantages of higher desulfurization rate, lower octane number loss and lower operation cost. The heating furnace used in S zorb is used to heat hydrogen-gasoline mixture and circulatory hydrogen, and its outlet temperature fluctuation will determine the reactor’s desulfurization quality and octane number loss which are important technical indicators. So, the research on furnace temperature control strategy used in S zorb device has important significance and necessity.

At present time, the strategy of temperature control of the furnace mostly adopt scheme of controlling the outlet temperature of the furnace. Also, S zorb adopt the pressure-temperature cascade control scheme to control the temperature of the furnace, take outlet temperature control as the main loop of the scheme, take the pressure of fuel gas control as the secondary loop. Even though the cascade control strategy has preferable control performance to suppress disturbance in secondary loop, improves the dynamic performance of the controlled system and frequency of the system, but can’t overcome its big lag. So the temperature control has large constant time and big lag.

This paper propose a predictive control model that combined cascade PID and RBF neural network predictive model to control the temperature of the S-Zorb heating furnace, took RBF neural network as predictive model to control the outlet temperature of the heating furnace and neural network predictive value as the feedback signal of the main loop of the cascade system. Finally, a comparison between cascade PID and cascade-RBF neural network system with simulation results is simulated by MATLAB.

2. The research on temperature control used in S zorb furnace based on cascade – RBF neural network predictive control Section Headings

2.1 Introduction of the S zorb heating furnace control

S zorb heating furnace is convection-radiation vertical cylindrical type heater shown in fig.1. firstly, material pump send Hydrogen-gasoline mixture to heat transfer Hydrogen-gasoline mixture is conveyed from heat exchanger to convection chamber after preheated by heat exchanger, then been sent to bottle of the furnace after heated by radiant coil, finally the mixture was sent to reactor for adsorption desulfurization reaction. The temperature of material has been heated completely is important parameter of S zorb technology and must be control precisely to ensure reaction effectively in reactor. So, S zorb device choose outlet temperature of Hydrogen-gasoline mixture as main control parameter.

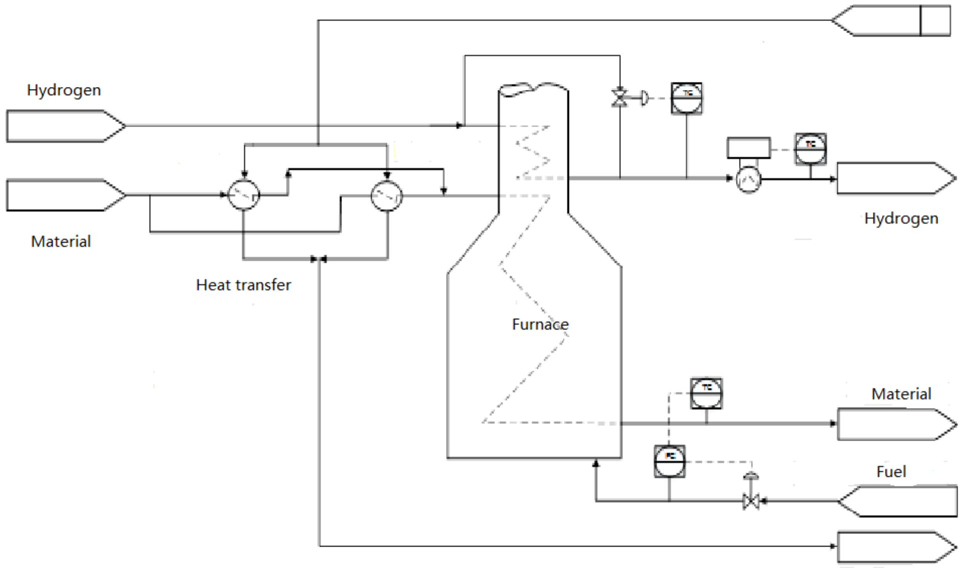

Fig.1 S-Zorb heating furnace temperature control scheme

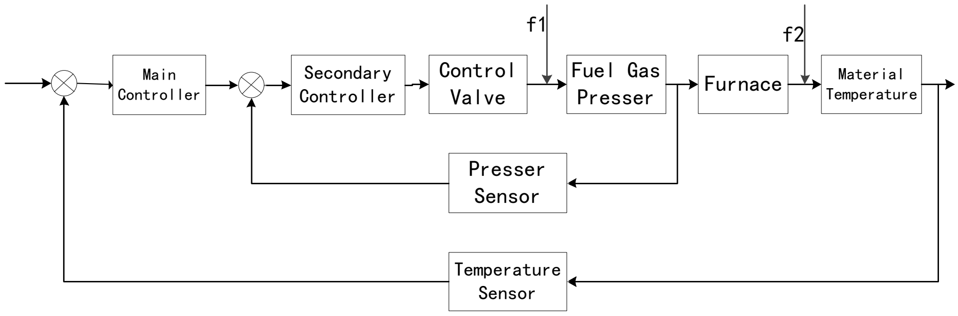

Fig.2 Outlet temperature of the material - the fuel gas pressure cascade control block diagram

As shown in Fig.2, the control scheme of S zorb heating furnace adopts outlet temperature of material - the fuel gas pressure cascade control strategy at present time. The scheme takes temperature of hydrogen-gasoline mixture as main control parameter, the pressure of fuel as senior loop control parameter, PID as controller. Interference f_1 produced by fuel gas pipe depressurization when lock hopper convey catalyst, Interference f_2 produced by initial temperature of the hydrogen-gasoline mixture, both of them will be eliminated by controllers of main loop and senior loop. The pressure of fuel is measured by intelligent pressure sensors; temperature of mixture is measured by k thermal couples. The scheme has large constant time and big lag feature.

2.2 Recursive predictive control model based on neural network

It's difficult to obtain the accurate model on outlet temperature control of S zorb heating furnace. This paper proposes to use neural network to build predictive model and take neural network advantage of strong approximation ability of nonlinear function. Neural network can adapt to nonlinear and time-varying characteristics of heating furnace, avoid influence of model mismatch on control performance. As shown in Fig.3, this paper build the predictive model by taking use of neural network, takes neural network predictive value as the feedback signal of the main loop of the cascade system. Fig.3 is recursive predictive control model based on neural network. where $R(k)$ represents the set point of system, $Y(k)$ is output of system, $U(k)$ is regulating variable, $\hat{y}(k)$ is predictive value of k step.

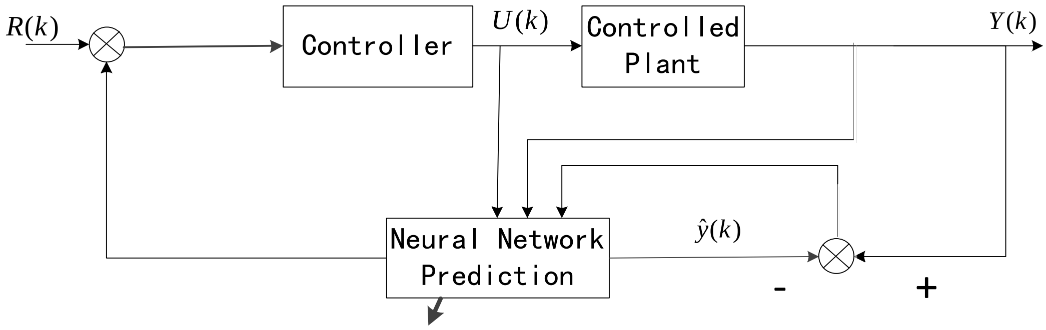

Fig.3 Neural network predictive control model

The SISO nonlinear system could be present by following discrete model. $y(k)$ and $u(k)$ represent respectively output and input value of system.

$$y(k) = f\left[y(k-1),\ldots,y(k-n),u(k-d-1),\ldots u(k-d-m)\right] \quad (1)$$

Predictive model based on neural network could be present as following, f_{NN} is neural network function.

$$\hat{y}(k) = f_{NN}\left[y(k-1),\ldots,y(k-n),u(k-d-1),\ldots u(k-d-m)\right] \quad (2)$$

Predictive value of the $k+d$ step are

$$\hat{y}(k+b) = f_{NN}\left[y(k+b-1),\ldots,y(k+b-n),u(k+b-d-1),\ldots u(k+b-d-m)\right] \quad (3)$$

Using the predictive value to replace input value could obtain following equation .

$$\hat{y}(k+b) = f_{NN}\left[\hat{y}(k+b-1),\ldots,\hat{y}(k+b-n),u(k+b-d-1),\ldots u(k+b-d-m)\right] \quad (4)$$

It is concluded that recursive predictive control model based on neural network can get any step output of system just giving the model of system. Due to the recursive way need previous forecasts as input, the final predictive value will accumulate error with increasing steps when any predictive value is not accurate. Therefore, in order to meet the requirements of controlling system real-time, it is necessary to use on-line update to modify the parameters of the neural network every step.

2.3 Cascade - RBF neural network predictive control scheme

Radial Basis Function (RBF) neural network is a three-layer network put forward by Meoody, its input layer node number is equal to the number of independent variables in the research problem, its hidden layer take radial basis function as transfer function, its output layer is a linear adder. So the output of the network is a weighted linear addition of hidden layer outputs, the network weight can be obtained by way of solving linear equations. Compared with BP neural network, Radial Basis Function (RBF) neural network has stronger capability of nonlinear approximation with high reconstructing accuracy and faster training rate.

Cascade - RBF neural network predictive control scheme is improved from cascade PID control scheme of S zorb heating furnace. Compared with the former, Cascade - RBF neural network predictive control scheme introduce RBF neural network predictive controller to the former and take the predictive value as feedback parameters. Fig.4 is control block diagram. In Fig.4, the scheme takes increment PID control arithmetic as controller; $e(k)$ is the error between setting value $y_r(k)$ and predictive value $y_p(k+b)$; f_1 , $f_2(k)$ are interference added to senior loop and main loop respectively; $r(k)$ is the error between predictive value and measured value.

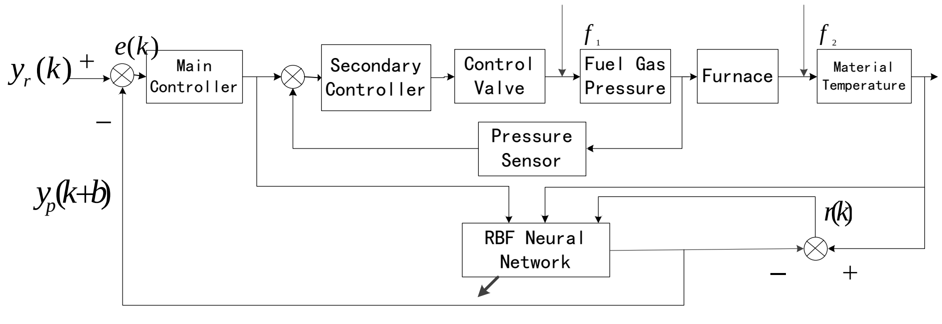

Fig.4 Cascade - RBF neural network predictive control scheme

2.3.1 The establishment of off-line model

The establishment of RBF neural network off-line model is mostly obtaining parameters of RBF neural network. The RBF network configuration is formulated as a minimization problem with respect to the number of hidden layer nodes, the center locations and the connection weights. the relationship between input and output could be present by follows.

$$y(x) = \sum_{i}^{m} w_i G(\|X - c_i\|, \delta_i) \tag{5}$$

The basis functions use Gaussian function: $\alpha_i = \exp(\frac{-\|X - c_i\|^2}{2\delta_i^2})$. Where c_i is center position of basis function, δ_i is width value of basic function. Obtaining the center locations of hidden layer usually take use of clustering method, such as k-means clustering algorithm. The width value of basic function can be obtained by follow equation:

$$\delta_i = \frac{d}{\sqrt{2K}} \tag{6}$$

Where d is the maximum distance between cluster centers, K is the number of clustering center. The complex-valued weights between hidden and output layer are updated by solving linear system based on finding the complex-valued weights between input and hidden layer

$$W = G^+ y \tag{7}$$

Where W is weight, G^+ is pseudo inverse of the matrix G .

Matrix G is determined by corresponding output of hidden layers

$$\begin{cases} G = \{g_{ij}\} \\ g_{ij} = \exp(\frac{-\|x_j - c_i\|^2}{2\delta_i^2}) \end{cases} \tag{8}$$

The establishment of RBF neural offline prediction model is completed.

2.3.2 The on-line adjustment of RBF neural network predictive model

Due to the error would be accumulated with dynamic characteristics change, off–line RBF neural network can’t meet the needs of the real-time prediction. In older to make neural network prediction model can real-time follow the change of the system, it is necessary to build on-line update scheme to adjust the parameters of function and the connection weights, to ensure the error between actual value and prediction trends to reduce. The goal of neural network adjustment on-line is making the predictive error as small as possible. The object function is following

$$J = \frac{1}{2}[y(k+1) - y_p(k+1)]^2 \tag{9}$$

Due to unable to get output of next step $y(k+1)$, it is reasonable to consider that the change range of actual system output is similar to its prediction, and obtain the following formula

$$y(k+1) \approx y(k) + y_p(k+1) - y_p(k) \tag{10}$$

The objective function can be simplified as :

$$J(t) = \frac{1}{2}[y(k) - y_p(k)]^2 \tag{11}$$

The updating of hidden layer nodes, the center locations, the connection weights could be obtained by gradient descent algorithm.

$$\begin{cases} c_i(k+1) = c_i(k) - \alpha \dfrac{\partial J}{\partial c_i} \\ \sigma_i(k+1) = \sigma_i(k) - \beta \dfrac{\partial J}{\partial \sigma_i} \\ \omega_i(k+1) = \omega_i(k) - \gamma \dfrac{\partial J}{\partial \omega_i} \end{cases} \tag{12}$$

Where parameters α is learning rate of RBF center, β is learning rate of width, γ is learning rate of weight.

When output of neural network is $x(k)$,the predictive error is $\mathrm{r}(k)$

$$\mathrm{r}(k) = y(k) - \sum_{i=1}^{m} w_i(k) \exp\left(\frac{-\|x(k) - c_i(k)\|^2}{2\delta(k)_i^2}\right) \tag{13}$$

The objective function of the neural network on-line correction could be adjusted as

$$J = \frac{1}{2}\left[y(k) - \sum_{i=1}^{m} w_i(k) \exp\left(\frac{-\|x(k) - c_i(k)\|^2}{2\delta(k)_i^2}\right) \right]^2 \tag{14}$$

To update the formula (12) (13) (14), the function center, width, weight could be adjusted as formula (15)

$$\begin{cases} c_i(k+1) = c_i(k) - \alpha r(k) \sum\limits_{i=1}^{m} w_i(k) \exp\left(\dfrac{-\|x(k) - c_i(k)\|^2}{2\delta(k)_i^2}\right)\left(\dfrac{x(k) - c_i(k)}{\delta(k)_i^2}\right) \\ \sigma_i(k+1) = \sigma_i(k) - \beta r(k) \sum\limits_{i=1}^{m} w_i(k) \exp\left(\dfrac{-\|x(k) - c_i(k)\|^2}{2\delta(k)_i^2}\right)\left(\dfrac{\|x(k) - c_i(k)\|^2}{\delta(k)_i^3}\right) \\ \omega_i(k+1) = \omega_i(k) - \gamma r(k) \exp\left(\dfrac{-\|x(k) - c_i(k)\|^2}{2\delta(k)_i^2}\right) \end{cases} \tag{15}$$

Updating hidden layer nodes, the center locations and the connection weights step by step, the neural network could follow the system dynamically.

3. Simulation analysis

The cascade-RBF neural network can be simulated by MATLAB. Control model can be described as a first-order process with time delay. The main loop is $G_T(s) = \frac{1}{100s+1} e^{-180s}$,the minor loop is $G_P(s) = \frac{0.5}{3s+1} e^{-s}$,parameters setting: node point number of input layer is 8, 2 of them are output data of system ,6of them are input data of system.; the number of implication layer is 10; the number of output layer is 1; predictive step is 10; learning rate is 0.001; sampling period is 10S; PID Parameters turned in Table1, K_p is proportionality coefficient, K_i integral coefficient, K_d is differential coefficient

Table 1. PID Parameters

Parameters	K_p	K_i	K_d
Major Loop	0.4	0.0035	1
Minor Loop	3	1	0

When the model is matched, unit step response curve of cascade PID system and cascade PID-RBF neural network system were shown in Fig.5. as shown in Fig.5 and Table 2, compared with cascade PID system, the rise time, setting time, overshoot and steady state error of cascade-RBF neural system are better than the former. 20% and 10% step disturbance were added respectively to main loop and minor loop at the time of T=4000S and T=3000S .learning from Fig.5, step disturbance almost have no effect on minor loop and setting time of cascade-RBF system is shorter than its cascade system when main loop was effected by step disturbance.

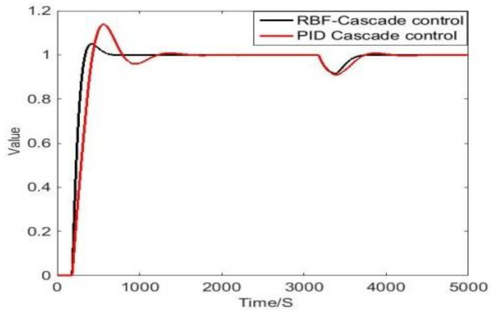

Fig.5 Simulation of the matched model

Table 2. The cascade control and cascade - RBF control performance of the matched model

Control Scheme	Rise Time(s)	Setting Time(s)	Overshoot(%)	Steady State Error
Cascade	201	1330	16.2	0
Cascade -RBF	110	540	5	0

When the model of controlled plan has changed because of environmental change or the establishment of the forecast control model is not accurate, the ratio coefficient, the time constant and lag time of system all will be changed. At that moment, the dynamic performances of systems were shown in Fig.6, Fig.7 and Fig.8.

Fig.6 is cascade and cascade - RBF response curve of the ratio coefficient mismatch, the transfer function of controlled object in main loop is : $G_T(s)=\frac{1.2}{100s+1}e^{-180s}$; Fig.7 is cascade and cascade - RBF response curve of the time constant mismatch, the transfer function of controlled object in main loop is : $G_T(s)=\frac{1}{120s+1}e^{-180s}$; Fig.8 is cascade PID and cascade - RBF response curve of the lag time mismatch, the transfer function of controlled object in main loop is : $G_T(s)=\frac{1}{100s+1}e^{-190s}$.

Learning from these figures of model mismatch, the overshoot of cascade-RBF neural network was less than cascade PID system, the rise time and setting time of cascade-RBF neural network were much better than cascade PID system.

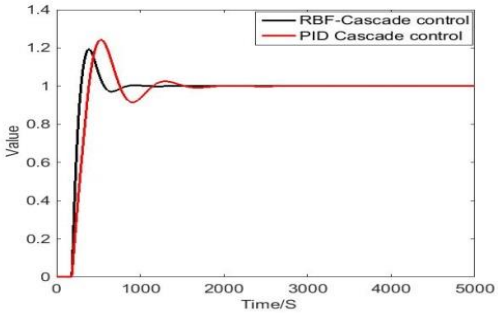

Fig.6 Cascade and cascade - RBF response curve of the ratio coefficient mismatch

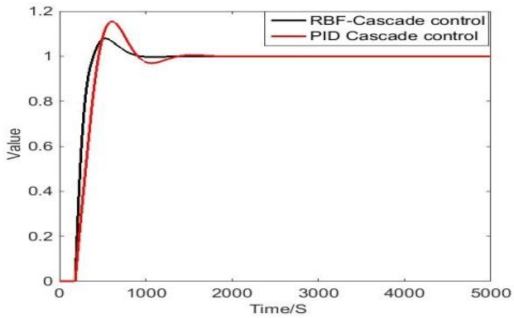

Fig.7 Cascade and cascade - RBF response curve of the time constant mismatch

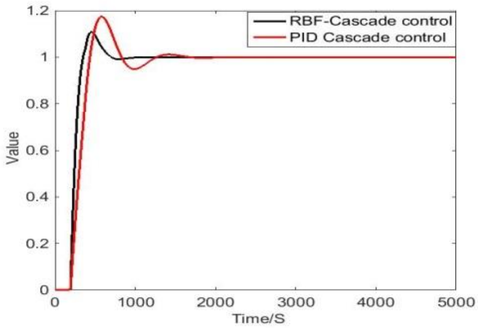

Fig.8 Cascade PID and cascade - RBF response curve of the lag time mismatch

4. Conclusion

1. The predictive control scheme that combined RBF neural network and cascade PID could solve the big lag of temperature control on S zorb heating furnace, could control overshoot, the rise time and setting time effectively. Its performance of control is much better than conventional cascade PID control system.

2. Compared with cascade PID system, the cascade-RBF neural network system has better control character and stronger robustness to overcome the disturbance and model mismatch on S zorb heating furnace.

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