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Design of Superheated Steam Temperature Control Strategy for Heat-engine Plant

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Abstract: Superheated steam temperature is a very important monitoring and control parameter for Heat-engine plant, too high or too low temperature will affect the safe operation of the plant and its production efficiency. Superheated steam temperature control system generally contains nonlinearity and parameter instability nad it is difficult to build the precise mathematical model by the traditional control method such as PID, so a PID Superheated Steam Temperature Control System based on BP neural network (BP-NN) is designed using the characteristic of self-learning and robustness and combining with conventional PID control algorithm. According to the changes of controlled object parameter, it can automatically adjust the PID parameters using BP neural network by itself. Simulation and actual investment of the factory test show that the designed control system is feasible and the control effect is better.

Key words: Superheated steam temperature, back propagation-neural network, process control, PID controller, weighting coefficient, heat-engine plant

INTRODUCTION

The device of superheated steam temperature is made of alloy steel with the capable of withstanding high temperature for heat-engine plant boiler, when it runs well, its temperature is generally close to the maximum allowable temperature of alloy steel. If superheated steam temperature is too high, it will result in excessive thermal stress for metal material to damage equipment. If it is too low, it will reduce the thermal efficiency of the whole plant and impact the safe operation of the turbine.

Superheated steam temperature control system is a multi-link system whose control is the worst in automatic control system. It has the following problems: Its pure delay time and time constant is larger, more disturbing factors, the uncertainty object model; the middle measuring point is not easy to take. A lot of efforts have been made to develop advanced control algorithms for controlling superheated steam temperatures in power plants (Zhang *et al*., 2012). Predictive control theory has been spread in process industry; Perez *et al*. (2012) proposed superheated steam temperature system based on adaptive predictive expert control for the Scottish Power coal-fired power station. Though some linear predictive controllers have been applied by the field, however, the nonlinear predictive control law is encountering some challenges to improve its efficiency and robustness (Prakash and Srinivasan, 2009; Manenti, 2011; Akpan and Hassapis, 2011). In addition, some other adaptive control algorithms were also developed for regulating steam temperature in power plants (Huang and Yang, 2008). Wang *et al*. (2011) presented a design method of adaptive PID cascade control system for superheated steam temperature based on inverse model. Intelligent control strategies were also applied to control superheated steam temperatures. Fuzzy logic control algorithm was used to control the steam temperature in (Sanchez-Lopez *et al*., 2004; Xie *et al*., 2007). An effective neuro-fuzzy model of the de-superheating process was developed, the genetic algorithm based PI controller was proposed to regulate steam temperature of four 325 MW power plants in (Ghaffari *et al*., 2007). The credit assignment cerebellar model articulation controller neural network control was adopted in superheated steam temperature control system in (Chen *et al*., 2012).

Superheated steam temperature control system is made of temperature sensor, PLC controllers, sprinkler control valves and other components, this study realizes the online real-time tuning by BP neural network, simulates the application of the control with Matlab and analyze experimental data in the actual plant, the control error temperature is less than 3 degrees. The results of simulation and experiment show that the control gives a good control effect to the system.

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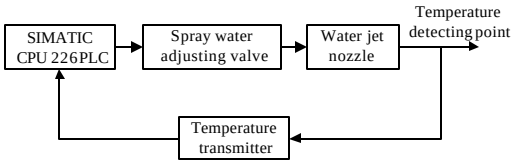

Fig. 1: Structure of superheated steam temperature control system

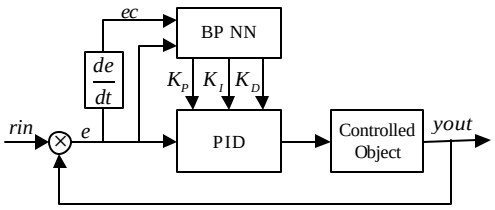

Fig. 2: PID controller structure based on BP-NN

CONTROL SYSTEM

The function of superheated steam temperature control system is that saturated steam is heated to a constant temperature required by the follow-up process using overheater, it mainly consists of SIMATIC CPU226 PLC, overheater, E+H sprinkler control valve, temperature sensor, etc. When the temperature is high, adjust the water valve opening, increase the amount of water; when the temperature is low, contrariwise. Superheated steam temperature control system is shown in Fig. 1, PLC calculates the temperature detected by temperature sensor and the set temperature value and gets the temperature deviation and the change rate, after PID operation (PID operation is completed by the program in the PLC), outputs 0-5 volts control signal as the adjustment amount into the water regulating valve to control the amount of water nad ultimately the superheated steam temperature is constant.

BP NEURAL NETWORK PID CONTROL SYSTEM DESIGN

BP neural network PID control structure: Neural network PID controller consists of the parameters controllable PID controller which has direct control for the system and BP neural network which has two inputs and three outputs, its input is the error e and the error rate ec, the output is K_p, K_I, K_D. BP neural network achieves online automatic correction for PID control parameters (K_p, K_I, K_D) (Yang and Xu, 2012).

Three control parameters (proportional, integral and derivative) of the PID controller are mutual

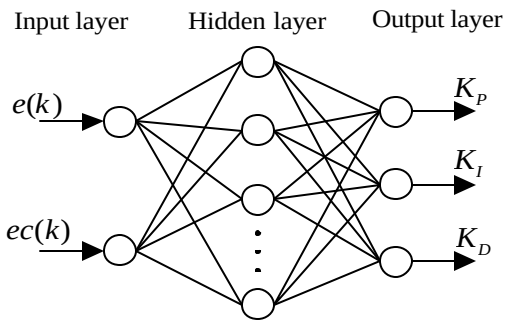

Fig. 3: Schematic of BP neural network structure

coordination and restraint, rather than a simple linear combination. For the neural network, it can be expressed as arbitrary nonlinear combination to find the best combination control parameters of PID.

PID algorithm design of BP neural network: The main idea of PID neural network algorithm is that adjust the PID controller parameters in real-time to make overheating temperature constant in accordance with the site operation of the superheated steam temperature control system; the output layer of the neural network corresponds to three adjustable parameters K_p, K_I, K_D of PID controller, through self-learning of neural network and the adjustable weighting factor, the neural network outputs best adjustable PID parameter to achieve real-time adjustment, so the superheated steam temperature is constant. BP neural network structure is shown in Fig. 3.

Classic PID control algorithm:

$$u(k) = u(k-1) + \Delta u(k) \tag{1}$$

$$\begin{aligned}\Delta u(k) &= K_P\left(e(k) - e(k-1)\right) + K_I e(k) \\ &+ K_D\left(e(k) - 2e(k-1) + e(k-2)\right)\end{aligned} \tag{2}$$

Here, e (k) is the system deviation, K_p is the proportional action coefficient, affects its response speed and accuracy; K_I is integral action coefficient, affects its steady accuracy; K_D is coefficient of the derivative action, affects the dynamic characteristics.

For convenience, $*^{(1)}$, $*^{(2)}$, $*^{(3)}$ are respectively the 1st layer (input layer), the 2nd layer (hidden layer), the 3rd layer(output layer). Let e (k) = x (1), ec (k) = x (2), the input of the network input layer:

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

The input and output of the network hidden layer:

$$net_i^{(2)}(k)=\sum_{j=1}^{2}\omega_{ij}^{(2)}O_j^{(1)}(k) \tag{4}$$

$$O_i^{(2)}(k)=g\left(net_i^{(2)}(k)\right),(i=1,2,\cdots,M) \tag{5}$$

where, $w_{ij}^{(2)}$ is the hidden layer weighting coefficients; take positive and negative symmetrical sigmoid function as the activation function of the hidden layer neurons:

$$g(x)=\tanh(x)=\frac{e^x-e^{-x}}{e^x+e^{-x}} \tag{6}$$

The input and output of the network output layer:

$$net_l^{(3)}(k)=\sum_{i=1}^{M}\omega_{li}^{(3)}O_i^{(2)}(k) \tag{7}$$

$$O_l^{(3)}(k)=\delta\left(net_l^{3}(k)\right) \tag{8}$$

where, l is 1, 2, 3, $O_1^{(3)}(k)$, $O_2^{(3)}(k)$, $O_3^{(3)}(k)$ correspond to K_p, K_I, K_D. Because K_p, K_I, K_D can not be negative, so take a non-negative Sigmoid function as the activation function of the output layer neurons:

$$\delta(x)=\frac{1+\tanh(x)}{2}=\frac{e^x}{e^x+e^{-x}} \tag{9}$$

Performance index function is:

$$E(k)=\frac{\left(yout(k)-rin(k)\right)^2}{2} \tag{10}$$

Correction coefficient for the network weights, using a gradient descent method to search the adjustment along the negative gradient direction weighting coefficients, in order to speed up the search speed to the global minimum, additional inertial term:

$$\Delta w_{li}^{(3)}(k)=-\mu\frac{\partial E(k)}{\partial w_{li}^{(3)}}+\alpha\Delta w_{li}^{(3)}(k-1) \tag{11}$$

where, μ is the learning rate, α is the inertia coefficient:

$$\frac{\partial E(k)}{\partial w_{li}^{(3)}}=\frac{\partial E(k)}{\partial y(k)}\cdot\frac{\partial y(k)}{\partial \Delta u(k)}\cdot\frac{\partial \Delta u(k)}{\partial O_l^{(3)}(k)}\cdot\frac{\partial O_l^{(3)}(k)}{\partial net_l^{(3)}(k)}\cdot\frac{\partial net_l^{(3)}(k)}{\partial w_{li}^{(3)}(k)} \tag{12}$$

Here:

$$\frac{\partial E(k)}{\partial y(k)}=e(k),\ \frac{\partial y(k)}{\partial \Delta u(k)}\approx \mathrm{sgn}\left[\frac{\partial y(k)}{\partial \Delta u(k)}\right]$$

$$\frac{\partial net_l^{(3)}(k)}{\partial w_{li}^{(3)}(k)}=O_i^{(2)}(k),\ \frac{\partial O_l^{(3)}(k)}{\partial net_l^{(3)}(k)}=\delta'\left(net_l^{(3)}(k)\right)$$

$$\frac{\partial E(k)}{\partial w_{li}^{(3)}}=e(k)\cdot \mathrm{sgn}\left[\frac{\partial(k)}{\partial \Delta u(k)}\right]\cdot\frac{\partial \Delta u(k)}{\partial O_l^{(3)}(k)}\cdot\delta'\left(net_l^{(3)}(k)\right)\cdot O_i^{(2)}(k)$$

$$\delta'(\bullet)=\delta(x)(1-\delta(x))$$

Output layer weighting factor adjustment algorithm:

$$\Delta w_{li}^{(3)}(k)=\alpha\Delta w_{li}^{(3)}(k-1)-\mu\varphi_l^{(3)}O_i^{(2)}(k) \tag{13}$$

$$\varphi_l^{(3)}=e(k)\mathrm{sgn}\left(\frac{\partial(k)}{\partial \Delta u(k)}\right)\frac{\partial \Delta u(k)}{\partial O_l^{(3)}(k)}\delta'\left(net_l^{(3)}(k)\right)O_i^{(2)}(k) \tag{14}$$

Here:

$$\frac{\partial \Delta u(k)}{\partial O_1^{(3)}(k)}=e(k)-e(k-1),\ \frac{\partial \Delta u(k)}{\partial O_2^{(3)}(k)}=e(k)$$

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

Similarly, the hidden layer weighting factor adjustment algorithm:

$$\Delta w_{ij}^{(2)}(k)=\alpha\Delta w_{ij}^{(2)}(k-1)-\mu\varphi_i^{(2)}O_j^{(1)}(k) \tag{15}$$

$$\varphi_i^{(2)}=g'\left(net_i^{(2)}(k)\right)\sum_{l=1}^{3}\varphi_l^{(3)}w_{li}^{(3)}(k) \tag{16}$$

Here:

$$(i=1,2,\cdots,M),g'(\bullet)=\frac{1-g^2(x)}{2}$$

SIMULATION ANALYSIS AND THE ACTUAL OPERATING CONDITIONS

Numerical simulation analysis: In order to validate the control system, first analyze using simulation software, take superheat control system of a factory as object model, its separate mathematical model is Eq. 17, learning rate of neural network is $\mu = 0.28$ and the inertia coefficient is $\alpha = 0.04$, take a random number in the interval [-0.5, 0.5] as the initial values of the weighting coefficients and adjustable parameters are in (0, 1). According to the set parameters and process of BP-NN control algorithm, control result of numerical simulation were carried out between the BP-NN PID and conventional PID as shown in Fig. 4 and 5, it can be drawn that the control effect of BP-NN PID was significantly better:

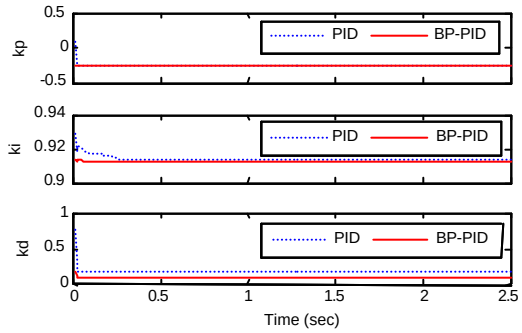

Fig. 4: PID parameters curve chart

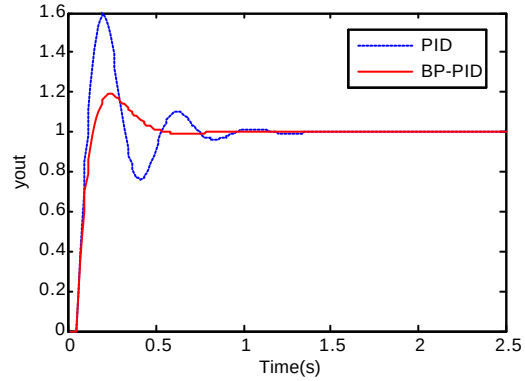

Fig. 5: Comparative control effect of BB-NN PID and classics PID

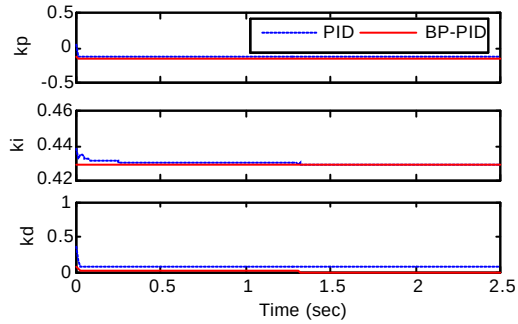

Fig. 6: PID parameters curve chart

$$S(z)=\frac{0.0026z+0.7364}{z^2-1.846z+0.8449} \quad (17)$$

Analysis of anti-jamming system: There are many factors affecting superheater outlet steam temperature, such as steam flow, combustion, boiler feedwater temperature, enthalpy of superheated steam inlet, flows through the superheater flue gas temperature, flow, flow rate and boiler heating surface slagging, fouling, scaling and so on. In order to verify the control system anti-jamming capability, join a similar pulse disturbance signal in the digital simulation process at t = 1.3S, the amplitude is 0.3.

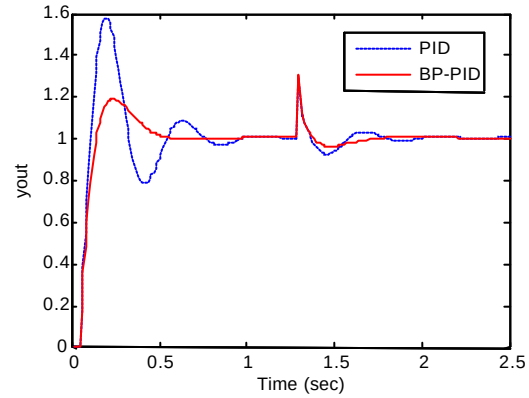

Fig. 7: Performance comparison of anti-interference

Table 1: Field temperature test data tables in the heat-engine plant

	1	2	3	4	5	6	7
T_R (□)	560	560	560	560	560	560	560
T_H (°C)	561	563	562	561	562	560	562
T_L (°C)	559	558	559	559	558	559	559

The control result with disturbance signal was carried out between the BP-NN PID and conventional PID as shown in Fig. 6 and 7.

Seen from Fig. 7 and 8, after adding disturbance, BP-NN PID controller has smaller amplitude of fluctuations in the response curve, shorter time for returning to the steady state and comparatively stable response curve than classical PID controller. In conclusion, results from the control point of view, BP-NN control algorithm has better adjustment function disturbances, so it apts. to practice application.

Actual operating results of the system: The BP-NN PID control system designed in the study has been put into trial operation in a power plant. In order to verify the control effect, the actual running has been carried out 100 times in a month, each successive observation time of 3 h, while the observation period is random. The measured superheat temperature are 3 degrees less than condition settings from the above observed data, the experimental data of 7 times extracted from the 100 experiments as shown in Table 1.

Where T_R is the set temperature, T_H and T_L are respectively the highest and lowest temperature observed for three consecutive hours, it can be seen that the temperature error control is less than 3 in Table 1, so the proposed BP-NN PID control algorithm has better control effect.

CONCLUSION

Though neural network and PID theory has been proposed by domestic and foreign scholars for many years and achieved fruitful results, the instance that it can

be effectively applied to actual engineering is still relatively small. In the study, the theory is applied to superheated steam temperature control system in a power plant, it proves feasible and has better control effect after the actual operation.

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