A Method of Neural Network Internal Model Control in Unstable Time-lag Process

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Abstract

The phenomenon of unstable time-lag process is usually familiar in the process industry, but it is hard to be controlled by the conventional method. In this paper a control method called double-loop feedback is put forward, first internal feedback stabilization is adopted, then neural network is used to form the internal model control system, finally it solves the problem of bias and instability between the model and the real process. Through the simulation, it is seen that the method has short adjusting time and high control accuracy, which shows the validity and superiority of neural network internal model control.
Keywords: *Unstable time-lag process; Internal feedback; RBF; Neural network; Internal model control; Double-loop control.*

1. Introduction

Superheated stem temperature of power plant has the highest temperature in steam-water channel of boiler, and the temperature of superheater is close to the limiting temperature of metal materials. If the temperature of superheated steam is too high, strength of the metal materials and service life of steam pipeline will decrease, also excessive thermal expansion in steam turbine will be caused, as a result metal of the high-pressure part will be damaged, but if the temperature of it is too low, the thermal efficiency of the equipments will be reduced, and when the steam temperature changes greatly, fatigue in piping material and related components will be caused, in consequence the steam turbine rotor and differential expansion will change, when serious, turbine vibration will occur, which is dangerous to production safety. The over-heat steam temperature system has some features, such as large delay, large inertia, integration, time-varying and so on, and the control quality directly affect safety and economy of the electric power production [1].

Time-lag process has the traits of great inertia, nonlinearity and uncertainty of model structure, for stable time-lag process, Smith predictor control system is utilized [2]. But when the controlled plant is unstable time-lag process, such as some chemical process, the conventional method can not reach satisfying control effect. According to this problem, large of research work has been done [3], [4], [5], [6], [7].

Phenomenon and things with uncertainty are generally existing in the nature and society. But how to express and deal with the uncertainty is a hot-spot and key point in the research on nature science, which is also a blockage at the same time. In all kinds of uncertainty, fuzziness and randomness are most important, which are paid more attention to.

Neural network has strong ability of nonlinear mapping, which can be used to approach the nonlinear model. In this paper, according to the unstable time-lag process, first internal feedback [8] is adopted to stabilize the generalized controlled plant, then neural network is used to form the internal model control system, which solves the problem of bias between the model and the real process, as well as the problem that robustness and stability of closed-loop system are hard to be determined.

2. Internal feedback stabilization of unstable time-lag process

2.1 Unstable time-lag process

Superheated steam temperature system is a multiple input and single output object. There are several influence factors for temperature changes, such as steam flow rate, the heat of flue gas, water flow rate.

When the boiler load is disturbed, change of the steam flow will make the steam flow velocity change almost at the same time along different points of the entire superheater pipeline, thus if the convective heat transfer coefficient of the superheater changes, the steam temperature of each points of the superheater changes almost the same time.

Therefore the steam temperature responses fast, which has properties of time-delay, inertial and integration. Suppose both τ and T are small.

the dynamic characteristics of steam flow which is influenced by the change of steam flow is showed as equation (1).

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

As the integration process in equation (1) is difficult to control, some self-turning method [9], [10], [11], [12], [13] of integration process has large overshoot and long adjusting time. Because there are structural defects in the integration process, it is difficult to be controlled by traditional PID controller [8].

2.2 Control structure of internal feedback

According to unstable time-lag process, the double feedback circuit is put forward by Sung and Lee[8], for this algorithm, first a control structure of internal feedback is introduced, shown as fig.1.

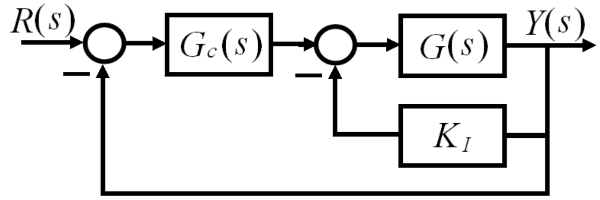

Fig. 1. The diagram for unstable time-lag process

The proportional controller K_I in the internal feedback circuit can change the unstable process into generalized stable processes, and the external feedback circuit can be designed by the expectation performance index.

By adding the proportional controller K_I in the internal feedback circuit, the close-loop transfer function is shown as equation (2).

$$\begin{aligned} G_p(s) &= \frac{G(s)}{1+K_I G(s)} \\ &= \frac{Ke^{-\tau s}}{Ts-1+KK_I e^{-\tau s}} \end{aligned} \tag{2}$$

Use Taylor series to expanse, it can obtain:

$$e^{-\tau s} \cong 1-\tau s+0.5\tau^2 s^2 \tag{3}$$

Combine equation (3) with $e^{-\tau s}$ in the denominator of (2), the model of second order delay is shown as equation (4).

$$G_p(s) \cong \frac{Ke^{-\tau s}}{0.5KK_I\tau^2 s^2+(T-KK_I\tau)s+KK_I-1} \tag{4}$$

According to louts criterion, to achieve stability of the system, the following equation should be meet.

$$\frac{1}{K} < K_I < \frac{T}{K\tau} \tag{5}$$

The gain of proportion controller which can greatly suppress disturbance is brought forward by Sung and Lee.

$$K_I = \frac{1}{K}\sqrt{\frac{T}{\tau}} \qquad (6)$$

3 Method of neural network internal model control

3.1 Internal model control

Equation (2) is the mathematical model of the first-order unstable process after stabilization, and the second-order Taylor approximation is shown as equation (7).

$$G_p(s) \cong \frac{K(1-\tau s+0.5\tau^2 s^2)}{0.5KK_I\tau^2 s^2+(T-KK_I\tau)s+KK_I-1} \qquad (7)$$

The general structural diagram of internal model control system [14], [15] is shown as Fig.2, in which $G_c(s)$ is the internal model controller, $G_p(s)$ is the controlled plant after internal feedback stabilization, and $\hat{G}_p(s)$ is the internal model.

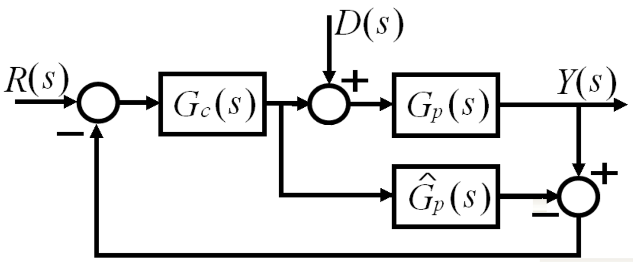

Fig. 2. Sstructure of internal model control

The closed-loop response of the system shown in figure 2 is:

$$Y(s) = \frac{G_c(s)G_p(s)}{1+G_c(s)[G_p(s)-\hat{G}_p(s)]}R(s) + \frac{1-G_c(s)\hat{G}_p(s)}{1+G_c(s)[G_p(s)-\hat{G}_p(s)]}D(s) \qquad (8)$$

If there is no bias in the model, that is $G_p(s)=\hat{G}_p(s)$, then equation (8) can be simplified as:

$$Y(s) = G_c(s)G_p(s)R(s) + [1-G_c(s)\hat{G}_p(s)]D(s) \qquad (9)$$

Overcoming the disturbance is a main task in the industrial process control, if the change of balance point is totally removed, the following equation has to be meet:

$$G_c(s) = \frac{1}{\hat{G}_p(s)} \qquad (10)$$

3.2 Method of neural network internal model control

The structure of internal model control based on neural network is shown as Fig.3, separately two RBF is used to replace $G_c(s)$ and in Fig.2.

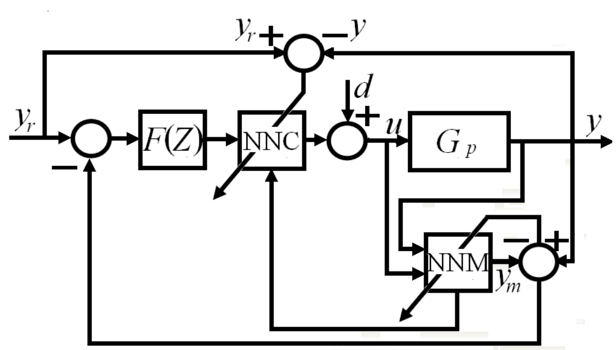

Fig. 3. Structure of neural network internal model control

NNM is the state estimator of RBF, which is parallel set according to the real system.

NNC is an inverse system model of RBF, neural network can correct the weighting coefficient according to the inputs and outputs, and finally control system the parameters.

The return signal is obtained from the difference of output between system and model, and is handled by NNC.

F(z) a linear filter, which is used to satisfy necessary robustness.

3.3 Design of the neural network internal model (NNM)

Generally, NNM is expressed by the following discrete-time nonlinear system:

$$y_m(k) = f[y(k-1),\ldots,y(k-n), u(k-1),\ldots,u(k-m)] + d(k) \tag{11}$$

The internal model is formed by RBF, and input layer is described as:

$$x_i(k) = \begin{cases} y(k-i), & 1 \le i \le n \\ u(k+n-i), & n+1 \le i \le n+m \end{cases} \tag{12}$$

The hidden layer is:

$$s_j(k) = \exp\left[\frac{\|x(k)-c_j(k)\|}{\sigma_j^2(k)}\right] \tag{13}$$

The output layer is:

$$y_m(k) = \sum_{j=1}^{a} s_j(k-1)v_j(k-1) \tag{14}$$

The performance index function is:

$$J = \frac{1}{2}\left[y(k)-y_m(k)\right]^2 \tag{15}$$

3.4 Design of neural network internal model controller (NNC)

The internal model controller is an inversion of the object model, and the inverse dynamic model is:

$$u(k) = f^{-1}\left[y_r(k+1),\ldots,y_r(k-n+1), u(k-1),\ldots,u(k-m+1), e_m(k)\right] \tag{16}$$

The nonlinear function of equation (16) is obtained by RBF, and the input layer is described as:

$$x_i(k) = \begin{cases} y(k-i), & 1 \le i \le n \\ u(k+n-i), & n+1 \le i \le n+m \\ e_m(k) & \end{cases} \tag{17}$$

The hidden layer is:

$$h_j(k) = \exp\left[-\frac{\|x(k)-a_j(k)\|}{\varphi_j^2(k)}\right] \tag{18}$$

The output layer is:

$$u(k) = \sum_{j=1}^{b} h_j(k-1)v_j(k-1) \tag{19}$$

The performance index function is:

$$J_r = \frac{1}{2}\left[y_r(k+1)-y(k+1)\right]^2 \tag{20}$$

The output equation of close-loop system is determined by (21).

$$y(k) = \frac{u(k)G_p\left[y_r(k)-d(k)\right]}{1+u(k)\left[G_p-y_m\right]} + d(k) \tag{21}$$

In the above equation G_p is the controlled plant.

The error equation of close-loop system output is:

$$E(k) = \frac{u(k)y_m-1}{1+u(k)\left[G_p-y_m\right]}\left[y_r(k)-d(k)\right] \tag{22}$$

Seen from equation (22) it can be known that NNM can totally describe the dynamic response, and NNC can totally describe the inverse dynamic response, at this time the error between step input and disturbance is $E(\infty)$=0, and the system can realize unbiased tracking to the input signal.

3.5 Procedure of RBF neural network internal model control algorithm

The concrete steps of algorithm are shown as follows:

Step1: Set k=1, select value domain and initialize the network function;

Step2: Calculate $u(k)$ by NNC;

Step3: According to equations (12)-(14), use $y_r(k)$, $y(k)$ to calculate $y_m(k)$;

Step4: Train forward model NNM by RBF neural network;

Step5: Train inverse model NNC by RBF neural network;

Step6: Set k= k+1, and return to Step2.

4 Simulation

The method of neural network internal model control is applied in unstable time-lag process.

The change of steam flow makes a fast reaction of the steam temperature, generally the gain is K=1~3, delay is τ=10~20s, and time constant is T=30~60s, in this paper, it is deemed that K=2, τ=10s and T=40s.

As a result the dynamic characteristics of steam flow is shown as equation (23).

$$G(s)=\frac{2}{40s-1}e^{-10s} \tag{23}$$

After adding the proportional controller K_I into the internal feedback circuit, according to the gain of K_I , the generalized stable processes can be obtained, shown as equation (24).

$$G_0(s)\cong\frac{e^{-10s}}{50s^2+10s+1} \tag{24}$$

The unit step response is shown as Fig.4, and it can be seen that the control method put forward in this paper has great control performance.

The unit ramp response is shown as Fig.5, and it can be seen that the control method put forward in this paper has great control performance.

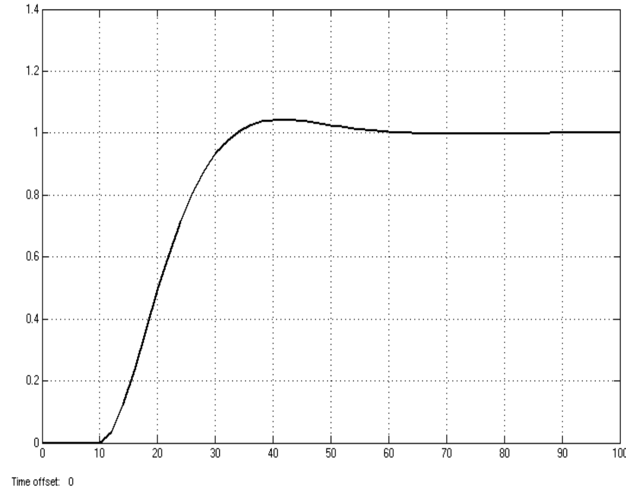

Fig. 4. Unit step response of neural network internal model control

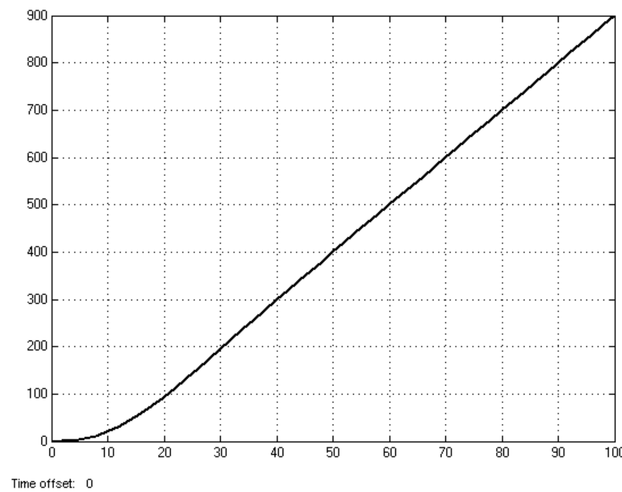

Fig. 5. Unit ramp response of neural network internal model control

5 Conclusion

The neural network has great learning function. In this paper, according to the problem that unstable time-lag process can not be well controlled by conventional method, a new algorithm is put forward, first internal feedback stabilization is adopted, then neural network is used to form the internal model control system, which solves the bias and instability between the model and real process. Through simulation of the first-order time-lag process, method of neural network internal model control has got satisfying results, which shows the validity and superiority of the method.

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