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Delay Separated Neural Network Inverse Control in Main-Steam Temperature System

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Abstract

In order to improve the control effect of the main steam temperature with large time delay, this paper proposed a delay separated neural network inverse (DSNNI) control scheme. We got the delay time and the positive model without delay by using adaptive linear element and BP network. Then we made the neural network inverse model of the positive model without delay. An appropriate reference model was selected to make the inverse model's output smoothing. It is an open-loop control system when the model is cascaded into original system. It will avoid the instability caused by the closed-loop control systems. Off-line identification and on-line identification are combined to get the inverse model in order to reduce the steady-state error and make the system have fine adaptive capacity. Detail simulation tests are carried out on the given 300MW power unit. Tests show that the neural network inverse control with delay time separation can get rapid and smooth output for the main steam temperature system. It is able to overcome the adverse effects caused by the time delay and the parameters changes. Compared with the cascade PID controller, it has faster response, better robustness and anti-interference performance.

Keywords: *main steam temperature system, large time delay, neural network, inverse dynamics, adaptive linear element*

1. Introduction

The main steam temperature of a coal-fired power generating unit is one of the key parameters required to be controlled strictly to ensure boiler's safety and economy [1].

However, due to the long pipes of the superheater resulting the thermal inertia and lag larger, the conventional feedback control is difficult to achieve good effect. Some new control strategies, such as predictive control, fuzzy PID control, genetic algorithm and IMC-NN(Internal Model Control-Neural Network)control have been applied to the main steam temperature system with the development of intelligent control technology [2-6]. But most research is based on feedback control and its control effect is not good for the large delay system, such as the main steam system. So we introduce the concept of inverse dynamics of the thermal system in this paper. The basic idea of inverse control is to drive the plant with a signal from a controller whose transfer function is the inverse of the plant itself [7]. It's an open loop control system when the inverse model is cascaded into the original system [8]. Feedback is used only for the adjustment of the controller parameters. The design principle of this control method is simple.

Delay separated neural network inverse (DSNNI) control is proposed to solve the delay's effect on the main steam temperature system. In this paper, section 2 presents the neural network inverse modeling process and the method of delay time identification. Then a control strategy of delay separated neural network inverse control was proposed at the end of section 2. In section 3, we carried out detail simulation tests on a given 300MW power unit to verify the validity of the control system proposed in this paper. Section 4 gives a conclusion to the whole paper that the DSNNI control system has faster response better robustness and anti-interference performance**.**

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2. Neural Network Identification of Inverse Dynamics Process

2.1. Neural Network Inverse Modeling

Inverse system is a system that implements a mapping relationship of a system from the output to the input. That is, if the desired output $y_d(t)$ is the input of inverse model, then the output of inverse model is the amount of control $u(t)$ which drives the plant gets the desired output $y_d(t)$. The diagram is shown in Figure 1 [9].

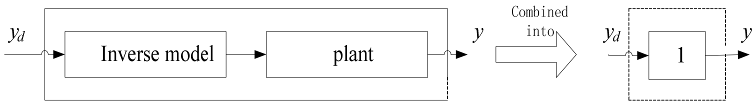


Figure 1. Inverse System and Its Compound System

Inverse system can be divided into the right inverse system and the left inverse system. The left inverse system can be called functional observability. The system will get two different outputs if the inputs are different at the same initial state. The system's input can be restored through the left inverse system; the right inverse system can be called functional reproducibility or functional control-ability. In the broad sense, it refers to the tracking capability of the system to a given reference signal. For any desired output for the given system, the inverse model's output is the control amount $u(t)$ which will make the original system to track the desired output. Therefore we need to build the right inverse model and the specific modeling method is shown in Figure 2.

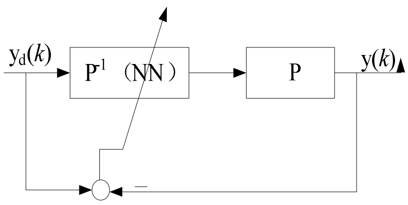


Figure 2. Right Inverse Systems Modeling Structure

2.2. Delay Time Parameter Identification

It is impossible to get the complete inverse model for the large time delay system. This is because system's output is zero in delay time, and the inverse model's output should be tend to infinite to offset the delay portion at the same time. There is no so much energy in the inverse model. So we exclude the delay part and get the inverse model for the portion without delay of the system. This means we need to know the delay parameter exactly.

Adaptive linear element (Adaline) is proposed by Dr.Widrow from Stanford University in 1961. It is a continuous-time linear network as Figure 3. $Z(nT)$ Is the input vector, $W(nT)$ is the weight vector. The network's output is:

$$\hat{y}(nT) = W^{\mathrm{T}}(nT)Z(nT) \tag{1}$$

The weights training use least mean square learning algorithm (LMS) [10]. The objective function is J, whose form is:

$$J = E[y(nT) - \hat{y}(nT)]^2 \tag{2}$$

The delay time is estimated using the error function minimization- $F(i)$. We suppose the trained weights are ω_i, $i = (1, 2, ..., p)$ and combine ω_i with the error function.

$$F(i) = \left| W^* - w_i \right| \tag{3}$$

W^* Is the sum of weights coefficients. When $F(i)$ is minimum, we get the delay time estimated value $\hat{d}$,

$$\hat{d} = d_{\min} + i \tag{4}$$

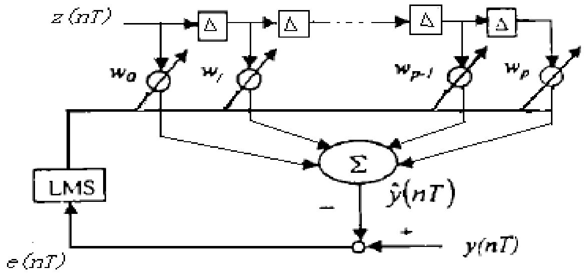


Figure 3. Adaline Structural Model

The method to separate the delay time from positive model is shown in Figure 4.

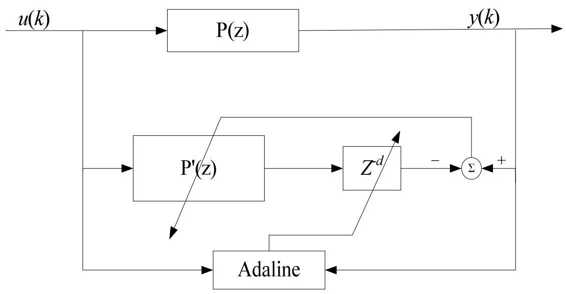


Figure 4. Delay Separated Neural Network Modeling Diagram

Using parallel network structure to identify the positive model and delay time can avoid the shortage of using a single network to identify. The two types of networks use different algorithms to train respectively. The positive model without delay is identified by BP neural network. And before that we should know the delay time exactly. The plant's output is $y_d(k)$ and the network's output is $y(k)$. $\hat{d}$ Is the estimated value of delay time identified by Adaline. The error function is:

$$e = y_d(k) - y(k - \hat{d})$$

$$E = \frac{1}{2} e^2 \tag{5}$$

We use BP algorithm with momentum to train the network.

$$\omega(l+1) = \omega(l) + \eta[(1-\alpha)D(l) + \alpha D(l-1)] \tag{6}$$

2.3. Delay Separated Neural Network Inverse Control System

Figure 5. shows the whole control system's structure. We got the delay time and $P^{'}(z)$— the model without delay by using adaptive linear element and BP network, and then we made the neural network inverse model of $P^{'}(z)$. It can avoid the limit caused by delay for inverse modeling. Considered the stability and robustness of the whole inverse control system, we add a reference model to make a model-reference inverse. The whole control system accuracy depends on the accuracy of the model identification. In order to minimize the system's static error, we combine off-line identification and on-line identification to get the final inverse model.

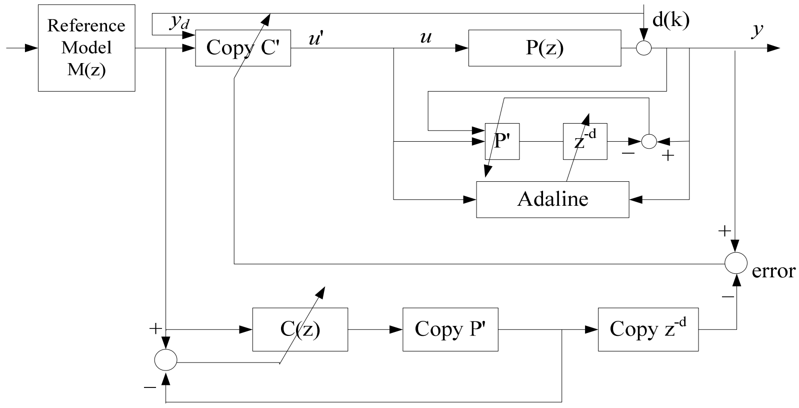


Figure 5. Delay Separated Neural Network Inverse Control System

3. Control Simulation Tests

In order to verify the quality and robustness of the control system, we take a 300MW boiler unit as the plant. Two cases are included in this simulation tests: original cascaded PID control and the delay separated neural network inverse control. The system can be described as:

Inert zone: $W_{01}(s) = \dfrac{8}{1+89s} e^{-53s}$

Leading area: $W_{02}(s) = \dfrac{1.25}{1+33s} e^{-6s}$

In inert zone, τ =53s, T=89s, τ /T$\approx$0.6>0.5. It is a typical large time delay system. For the cascaded PID control, we use PI controller for the main circuit and P controller for auxiliary circuit. PID parameters are obtained by decay curve method.

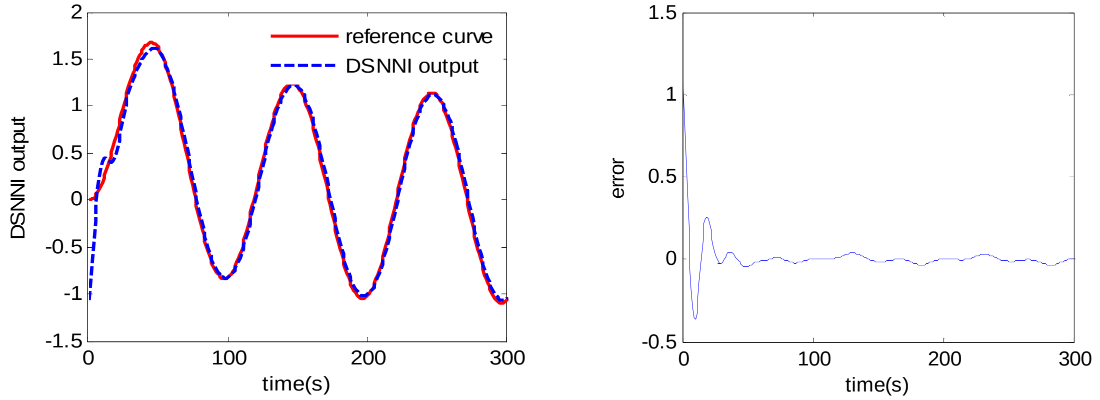
Auxiliary controller: δ_2 =2.5;

Main controller: $\delta_1 = 3.92, T_i = 98s$

While for DSNNI control system, we use the main steam temperature as control amount instead of desuperheater outlet temperature, so we need no inert zone. We use off-line identification to get a convergent controller which will meet the control requirements in some degree. But error still exists and the whole system cannot adapt to the interference and time-varying. Therefore, we add on-line identification to improve the adaptive capacity of the controller. The identification of controller is identification of the inverse model. We use a three layer BP network whose input layer, hidden layer and output layer's nodes is 7, 10, 1, respectively. We adopt output values of the reference model in the previous moments and the disturbance as the network's input to ensure the dynamic characteristic and the anti-interference ability. The input vector of the network which will be trained is:

$$\hat{y}(k) = NN[y_m(k-1), y_m(k-2), y_m(k-3), y_m(k-4), y_m(k-5), y_m(k-6), d(k)]$$

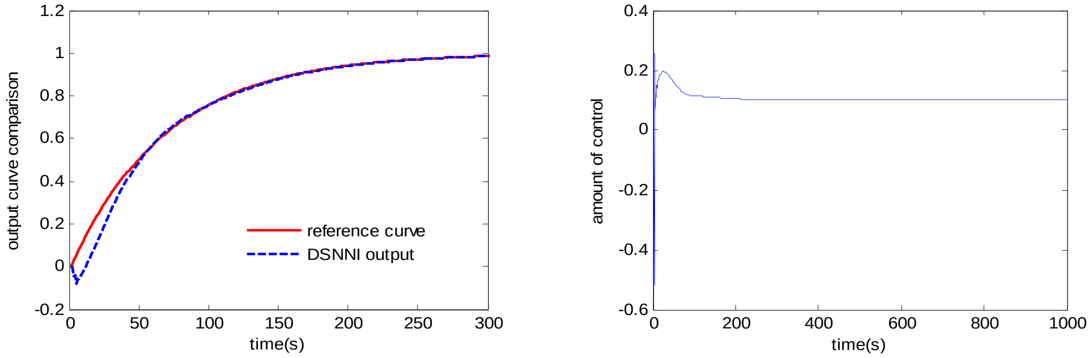
Using a sine wave as the excitation signal, after training, the comparison of the inverse system's output and the reference curve and the training error are shown in Figure 6.



(a) Training signals contrast curve (b) Error curve

Figure 6. Neural Network Inverse System Training Curve

The output of the system will appear shock in short time and then follow the reference curve stability. A step signal is given to the system, the comparison of the inverse system's output and the reference curve and the amount of control are shown in Figure 7.



(a) Follow curve (b) Amount of control

Figure 7. DNSSI Output

We make a unit step perturbation experiment for these two control system and the comparison of the two systems is shown in Figure 8. From the diagram we can see the cascaded PID control system exist overshoot and shock seriously. While DSNNI control system's response is faster and more stable. It has good dynamic characteristics.

The main steam system is a time-varying system at the same time and the changes often appears in inert zone. So we changed the T in inert zone from 89s to 200s, the outputs of the two control system is shown in Figure 9.

When T changed greatly, the adjustment time of cascaded PID control becomes longer. While DSNNI control still shows good dynamic characteristics, and the adjustment time is much shorter than cascaded PID control's.

In order to verify the anti-interference ability of the system, we added a perturbation $d(k)$=0.1 at 800s. Though DSNNI's disturbance is a little larger than PID control's, the time it eliminate the disturbance is much shorter than PID control's. Therefore, DSNNI has a good anti-interference ability. Figure 10 shows the step response with disturbance of these two control case.

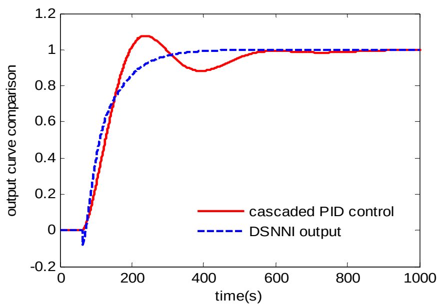


Figure 8. Control System Step Response Curve Comparison

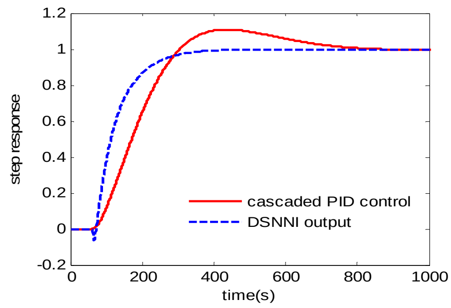


Figure 9. Curve Comparison After Constant Time Changes

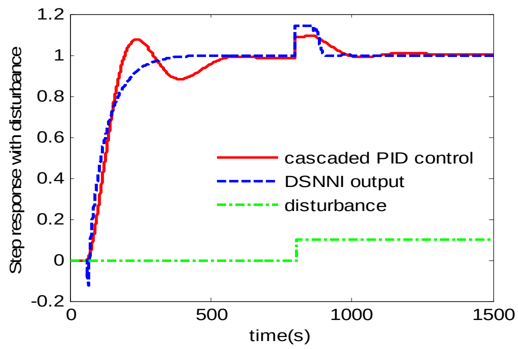


Figure 10. Step Response with Disturbance

4. Conclusion

A delay separated neural network inverse (DSNNI) control system was proposed for the main steam system in this paper. It avoids the limit caused by delay for inverse modeling. Adaline and BP neural network are used here to get the delay time and the inverse model. It is an open-loop control system when putting the trained inverse model in front of the plant which will avoid the instability caused by the closed-loop control systems. The whole system's output can track the predetermined trajectory accurately. When applying this system to the main steam temperature system, it shows good dynamic characteristics. The response is faster and stable. It is able to overcome the external perturbation quickly. When the object's parameter changed, the whole system can get stable output without large overshoot and shock. So DSNNI control system proposed in this paper is significantly improved compared with the case of original cascade PID control. Though this control scheme shows better performance than the cascade PID control, some curve shocks appeared when tracking the given output curve inevitably. So, we will try to find out a feasible method to reduce or eliminate the tracking shocks in future.

References

[1] Liangyu Ma, Zhenxing Shi, Kwang Y Lee. Superheater steam temperature control based on the expanded-structure neural network inverse models. *ISECS International Colloquium on Computing, Communication, Control, and Management*. Yangzhou. 2010; 131-134.

[2] Lichuan Yuan, Yanjun Ding, Donghai Li. Field Application of multiple model predictive control for superheat temperature in boilers. *J Tsinghua Univ (Sci&Tech)*. 2010; 50(8): 1258-1262.

[3] Wang Ting, Feng Xiaolu, Chen Jiangtao, Zhang Rong, et al. Multivariable predictive control of the main steam temperature in power plant. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013; 11(4): 2008-2012.
[4] Haibo Luo. Design and simulation on PID controller. *Computer Simulation*. 2012; 345-348.
[5] Shihe Chen, Xin Li, Chunlei Cui, Yanjun Fang. Research on improved GA boiler of the main steam temperature controller parameters optimization. *Automation & Instrumentation*. 2012; (7): 6-10.
[6] Xie Peizhang, Zhou Xingpeng. Sanitizer dosing decoupling control based on IMC-NN inverse system. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013;11 (9): 5048-5054.
[7] Shou Ding, Qinghui Wu. Research on rubustenss of BP neural network based inverse model for induction motor drives. *International Conference on Electronics and Optoelectronics (ICEOE 2011)*. Dalian. 2011; 127-131.
[8] Ping Wang, Baohua Chen, Wenchao Xing, Hui Ding. The direct inverse-model control based on neural networks for inverts. *2010 International Conferece on Measuring Technology and Mechatronics Automation*. Changsha. 2010; 855-858.
[9] Widrow B. Adaptive inverse control. *US*: *IEEE Press Series on Power Engineering*. 2007.
[10] Luo Peng, Li Shiping, Zhou Yun. Research on periodic error separate based on adaptive linear element. *Foreign Electronic Measurement Technology*. 2011; 30(6): 127-131.