ISSN 1392-1207. MECHANIKA. Vol. 30, No. 4, 2024: 365–370

Water-Coal Ratio Control Strategy of Ultra Supercritical Unit Based on Neural Network Inverse Model

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https://doi.org/10.5755/j02.mech.35874

1. Introduction

The increasing demand for energy requires the power system to balance power supply and demand, meanwhile maintaining high energy conversion efficiency. At present, vast majority of countries around the world are vigorously promoting environmental protection and economy of generating process. While, coal-based energy structure determines that thermal power generation is the main mode of electrical power production in China. And in the future for a long time, this situation that Chinese electric power industry will give priority to coal-fired thermal power unit will not change. Power plant as a large energy consumption, therefore, should not only ensure the efficiency of power plant production, but also save energy and reduce environmental pollution. It is necessary to strengthen the work of energy saving and emission reduction to effectively improve the thermal efficiency of boilers, and increasing the capacity of a single unit to develop clean coal power generation technology is an effective means. Ultra-supercritical units with high cycle thermal efficiency and low pollutant emission have gradually become the mainstream of coal-fired power plants. The current level of boiler units has reached the supercritical ultra-supercritical level, however, with the increase of the capacity scale of a single unit, which has now reached the 1000 MW level, the unit system and boiler structure become increasingly complex and large. In the process of power plant production and operation, the flexibility of thermal power plants is primarily constrained to safety issues, and the stability of key parameters should be maintained, so it is necessary to achieve effective and stable control of the water-to-coal ratio during the operation of the unit [1].

The water-coal ratio control output indicates the deviation degree of the ratio of feed water and fuel during unit operation, regulating the water-coal ratio is one of the major difficulties in power plant control and is the key to regulating once-through boilers, the control level of water-coal ratio is the restriction factor to improve the control level of the whole unit, for which it is important to choose the appropriate control strategy for the production of the power plant. Ultra-supercritical once-through boiler is a complex system with strong coupling and nonlinear multi-parameters. It is the guarantee of safe, economical and stable operation for the boiler to measure its water-coal ratio quickly and accurately. In Ref. [2], a new control method of burning water ratio is proposed in which both fuel quantity and feed water flow are involved in intermediate point temperature correction, so that the total control gain and system stability of the entire fuel-water ratio regulation system remain unchanged. The decoupling circuit from the feed side correction amount to the fuel side is further added to the control logic, which can eliminate the disturbance of the unit load and vapor pressure caused by the feed water flow adjustment of the fuel flux ratio. Ref. [3] proposed a coordinated decoupling control strategy for adjusting the amount of coal feed and water flow at the same time, and the generalized prediction controller is used in the feedback loop to improve the control performance of the separator temperature. Ref. [4] proposed an improved water-fuel ratio (WFR) control strategy based on heat storage differences and tested it on an established coal-fired power plant model. The results show that the cumulative deviation between the load rate command and the real-time load rate during the load cycling process is significantly reduced after the introduction of the proposed WFR control strategy. Ref. [5] developed a detailed dynamics model of a supercritical coal-fired boiler in Dymola and established the necessary control model. A first-order inertia compensation element was developed prior to the water flow rate command, which effectively improved the water-fuel ratio control performance. However, as the rate of load change increases, the deviation of the transient process of thermodynamic parameters increases, and the time required for stabilization is prolonged.

Since then, many domestic and foreign experts have conducted a lot of research on the water-coal ratio control problem, however, due to the different response speed of supercritical unit output to coal feed volume and feed water flow instructions, it is difficult for the existing control scheme to quickly stabilize the unit output. Currently commonly used control methods include fuzzy control [6,7], inverse control [8], neural network control [9], fuzzy neural network [10]and so on. Among them, the neural network has excellent learning and approximation ability for nonlinear functions and strong self-adaptive ability. The method of inverse control is based on the controlled object to build an inverse model to compensate for the controlled object, making the object become a system with linear relationship. The physical concept of the method is clear and easy to be understood. Therefore, the inverse model control method of neural network can combine the common advantages of the two control methods, the expression ability of neural networks is used to approximate unknown distributions and solve inverse problems related to stochastic models [11]. Ref. [12] provides an inverse model-based Iterative Learning Control (ILC) nonlinear system for unknown Multiple-Input Multiple-Output (MIMO) using Neural Networks (NNs), where a novel gradient adaptive law is used to update the NN weights of the hidden and output layers to achieve faster convergence. Widaryanto et al. applied the inverse model control of the nonlinear process of artificial neural networks to the inverse object modeling of the rudder model ship, and the model performance was satisfactory [13]. Ishitsuka et al. used neural network terminology for inverse modeling of natural state geothermal systems and showed that the method outperforms conventional neural networks in terms of prediction accuracy, with a significant reduction in the predicted temperature error in the undeveloped region [14]. The control system using Elman recurrent neural network as a direct inverse control scheme for attitude and height control of quadcopter UAV is proposed, and experiments prove that it has reasonable errors [15]. M. A. Perez-Villalpando used an inverse optimal controller to track the water level of hydropower stations, combined with a recurrent neural network based on feature engineering techniques to help the system predict and manage external disturbances, and the combined control scheme exhibits good performance in the presence of parameter changes and external disturbances [16]. In addition to wind power, hydropower, ships, and drones, researchers have also used NNI models to solve control problems in supercritical units. Ma, Liangyu established a dynamic fuzzy neural network (DFNN) inverse model of supercritical unit load and main steam pressure, then conducted simulation experiments on 600-MW supercritical units. Compared with the original PID control, the DFNN reverse control method greatly improves the speed of load regulation and the stability of steam pressure [17]. Prof. LeeK.Y firstly used the inverse control method of neural network in supercritical unit superheat steam temperature control and developed a coordinated control optimization system with intelligent nature [18]. In order to achieve the control of water-coal ratio effectively during the coal-fired power generation process, this paper presents a neural network inverse system scheme for the control of the water-coal ratio of ultra-supercritical units.

2. The model for the water-coal ratio system of an ultra-supercritical unit

The subject of this paper can be viewed as a three-input, three-output multi-variable regulation object, where the inputs are water feed W, coal feed B, desuperheating water flow W_j, and the outputs are mid-point temperature T_m (micro-superheated steam temperature at the separation), main steam pressure P_T, and superheated steam temperature T. Since the effect of desuperheating water flow W_j on main steam pressure and mid-point temperature T_m is negligible, in order to make the discussion easier, we simplified the problem to a two-input, two-output system model [19], as shown in Fig. 1.

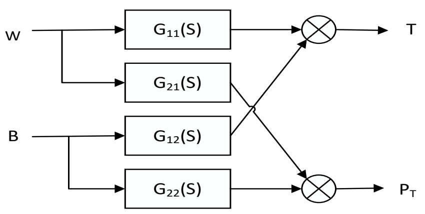


Fig. 1 Block diagram of the water and coal feed system

According to the data given in the [20] for the field operation of the power plant, the MATLAB identification toolbox was used for the identification of the system, and the transfer function of the mathematical model of the water-coal ratio system was derived as:

$$G_{11}=\frac{0.8024s+0.001512}{s^2+2.182s+0.02241},$$
$$G_{21}=\frac{0.05007s+0.001304}{s^2+3.11s+0.3358},$$
$$G_{12}=\frac{-1.417s+0.02593}{s^2+0.9813s+0.01276},$$
$$G_{22}=\frac{0.01067s+0.005812}{s^2+0.6453s+0.06336}. \quad (1)$$

3. Neural network inverse model control methods

3.1. Inverse systems for nonlinear systems

Inverse is a concept with a broad meaning, in the field of functions it includes functions and inverse functions, in the field of matrices it includes matrices and inverse matrices. An inverse system is a system with dynamic processes and it contains two different modes of operation: a left inverse system and a right inverse system. Its structure is illustrated in Fig. 2.

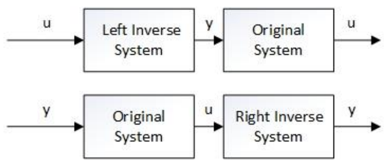


Fig. 2 Left system and right inverse system

For the inverse system is defined as follows [21]. Let the system Π_a, its input is $u=\bar{\theta}_\alpha\phi$. Here the input $\phi(t) = (\phi_1, \phi_2, \ldots, \phi_q)^T$ is the initial value that satisfies the initial value condition of the system Σ, $x(t_0) = x_0$. The output is $u(t) = (u_1, u_2, \ldots, u_p)^T$. If you take $\phi(t)=y_d^{(\alpha)}(t)$, $\alpha(t) = (\alpha_1, \alpha_2, \ldots, \alpha_q)^T$. That is, ϕ_i is defined as the derivative of the order α_i of y_{di} and the operator $\bar{\theta}_\alpha$ satisfies the following equation:

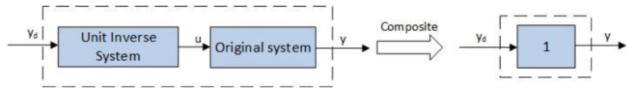
$$\theta\bar{\theta}_\alpha\phi=\theta\left[\bar{\theta}_\alpha\phi\right]=\theta\left[\bar{\theta}_\alpha\left(y_d^{(\alpha)}\right)\right]=\theta u=y_d\,. \quad (2)$$

Then the system Π_a is said to be the α order inverse system of the original system Σ. As shown in Fig. 3, the system is a unitary inverse system when $\alpha = 0$.

In general, when the α-order inverse system of a system exists, its unitary inverse system also exists. And there is interconversion between the two. Take a single-input single-output system for example, the conversion relationship between the two inverse systems is shown in Fig. 4. For the α-order inverse system, the unitary inverse system is formed by a series of α differential links in front of it (Fig.4, a); for the unitary inverse system, the unitary inverse system is formed by a series of α integral links in front of it (Fig.4, b).

3.2. Structure of the inverse neural network model

Fig. 5 shows a simple neural network inverse system containing a static neural network and a series of integrators, where the properties of the inverse system deter-



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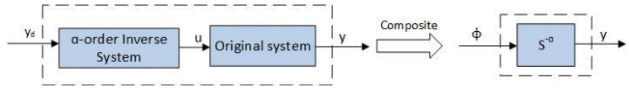
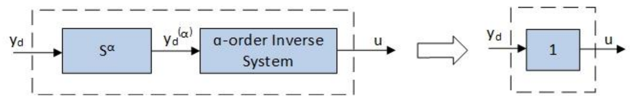


b

Fig. 3 Unit inverse system with α-order inverse system (a) and its composite system (b)



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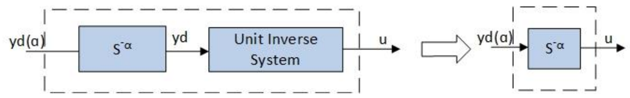


b

Fig. 4 Diagram of the transformation relationship between two inverse systems: a – the unit inverse system, b – the α-order inverse system

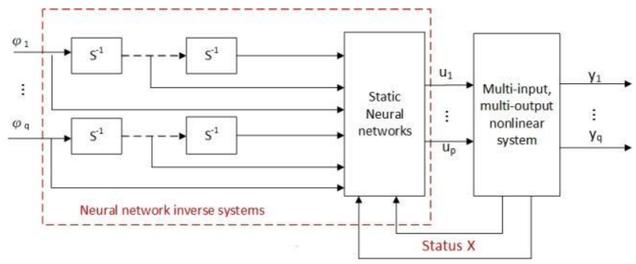


Fig. 5 Schematic diagram of the basic structure of a neural network inverse system

mine thenumber of integrators. The static neural network has only the current input signal information and no signal feedback, the structure is relatively simple, and only the static network will have an impact on the approximation of the non-linear system, with a single nature. However, in practical industrial production, the systems are mainly dynamic nonlinear systems, relatively complex, so it is necessary to add integrators before the static neural network to characterize the dynamic characteristics of the inverse system, thus forming a dynamic neural network, realizing the static and dynamic characteristics of the inverse system completely [22].

3.3. Neural network inverse system control methods

As shown in Fig. 6, for the invertible multi-input multi-output nonlinear system, its neural network inverse system consists of a static neural network and a dynamic neural network composed of several integrators, which is connected in series with the original system, then the controlled system is linearized and decoupled to form a pseudo-linear composite system. Next, an additional closed-loop controller is designed for each linear subsystem to form the neural network inverse composite controller together with the neural network inverse system, so as to obtain excellent static and dynamic characteristics and anti-interference ability [22].

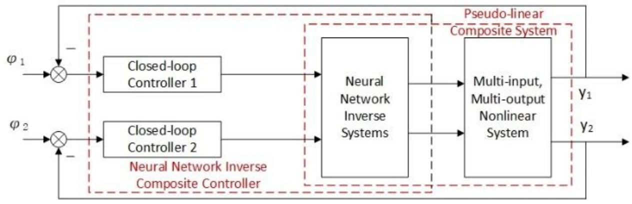
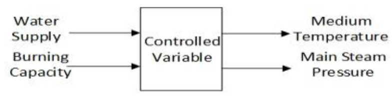


Fig. 6 Schematic diagram of a neural network inverse composite controller

Due to various factors in practice, the pseudo-linear system formed by connecting the neural network inverse system in series with the original system is not an ideal simple linear system. If the neural network inverse system is simply used as the controller to form the open-loop control, the control effect is often poor. Therefore, additional controllers should be designed to form closed-loop control for the linear subsystem after linear decoupling, and the composite controller is formed with the neural network inverse system.

4. Modelling of the inverse water-coal ratio by neural network

The control scheme in this paper requires inverse modelling of the controlled object, and according to the definition of inverse, we can design an inverse model of the positive model, as shown in Fig. 7.



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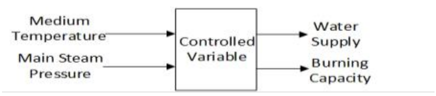

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Fig. 7 Positive and negative models: a – positive model, b – inverse model

Due to the complexity of the water-coal ratio system, the neural network toolbox was used for learning and training to build a neural network water-coal ratio non-linear inverse model. The input data of the neural network inverse model is then the output data of the study object; the output data is the input data of the study object.

For nonlinear, coupled water-coal ratio control systems, all the data is used to learn and train to build the inverse water-coal ratio system, and the algorithm can fit it better, as shown in Fig. 8.

The established neural network inverse system is connected in series with the original system, where the input is the system step signal, the results are shown in Fig. 9. It can be seen from the figure that the water-coal ratio pseudo-linear composite system has become a linear unit system, so when designing additional controllers, an integrator is added after each additional controller to form the dynamic characteristics of the system.

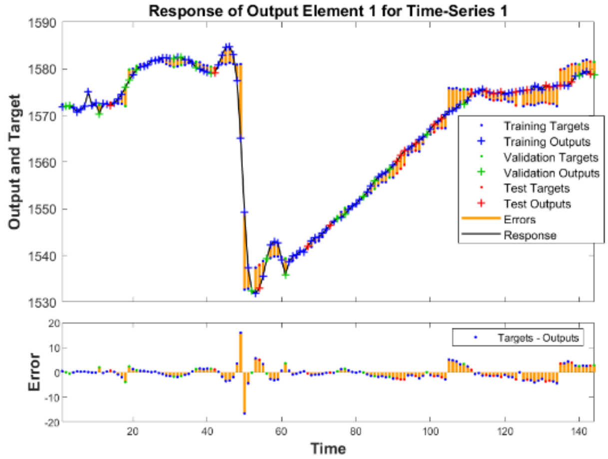
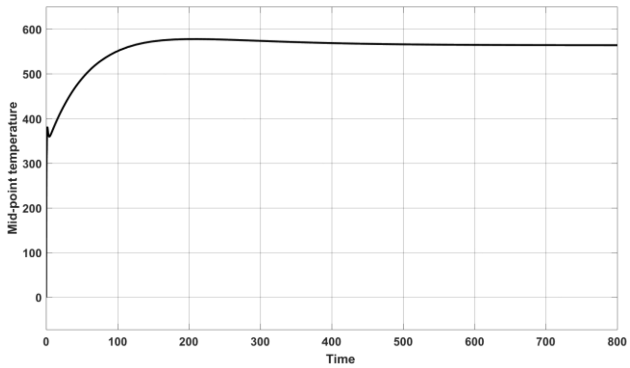


Fig. 8 BP network fitting results and errors



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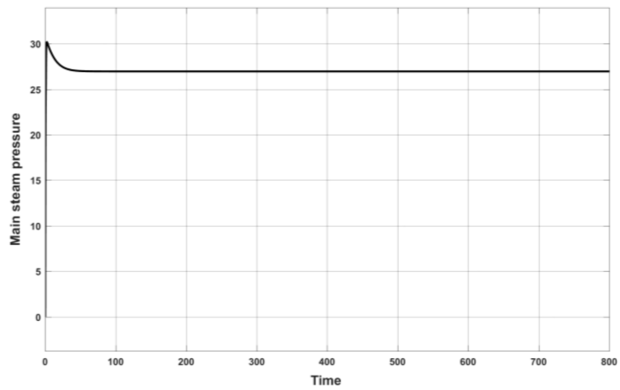

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Fig. 9 Response diagram for pseudo-linear composite system with coal to water ratio: a – mid-point temperature response curve, b – main steam pressure response curve

5. Simulation experiments

Following the control principles designed in the paper, we will simulate and design the control system for the proposed two-input, two-output boiler unit model. As shown in Fig. 10, the box in front of the controlled object is the identified neural network inverse model. Combined with the previously mentioned, the application of the inverse model can eliminate the nonlinear links of the control system, that is, the control system is approximately linearized, which greatly reduces the effect of system nonlinearity.

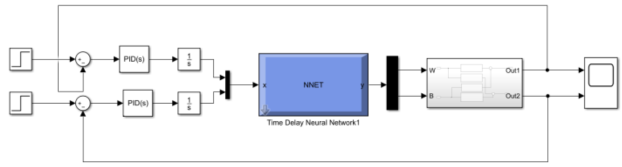
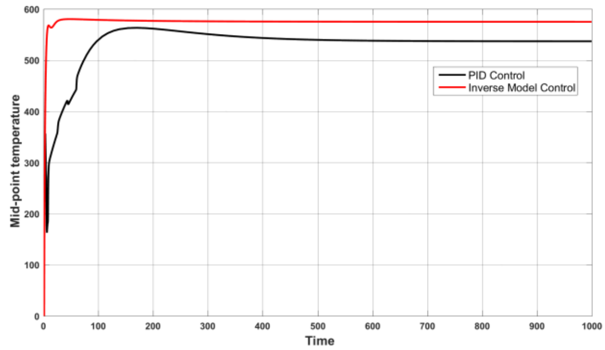


Fig. 10 Neural network inverse model control simulation



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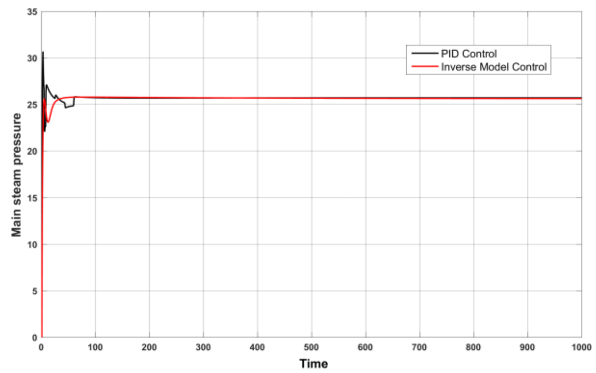

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Fig. 11 Response curves comparison of neural network inverse model control and PID control: a – mid-point temperature response curve, b – main steam pressure response curve

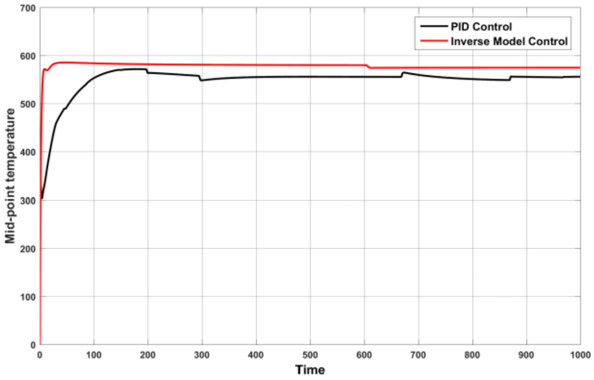
According to Fig. 11, it can be intuitively seen that the overshoot of the neural network inverse model control system is smaller and the response time to reach the steady state is shorter than that of the ordinary PID control, and in general, the control performance of the neural network inverse model control is much better than that of the ordinary PID control.

5.1. Interference resistance

A 10% step disturbance in both water and coal feed was added to the control system, where the disturbance time was 600 s, observe the response curve. As shown in Fig. 12, under the disturbance, the ordinary PID control system will oscillate. Therefore, compared with PID control, the neural network inverse model control will have better anti-interference ability.

5.2. Robustness

The robustness of the system is verified by varying the constants of the transfer function of the controlled object.



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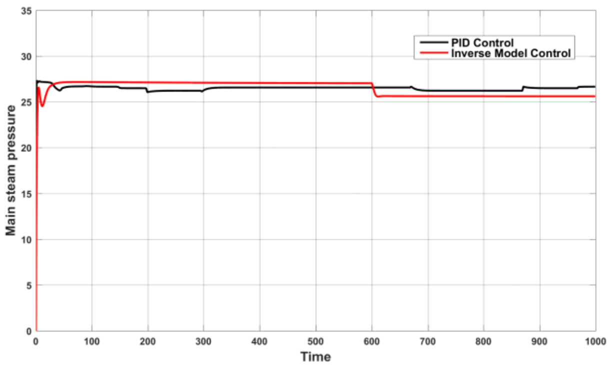

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Fig. 12 Response curves comparison of NNI model control and PID control with disturbance: a – mid-point temperature response curve, b – main steam pressure response curve

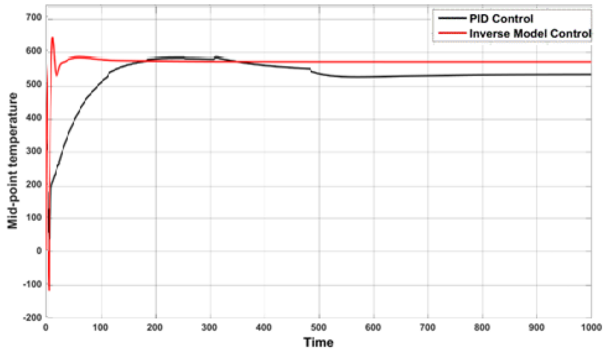
The simulation results are shown in Fig. 13. The neural network inverse model control is compared with the ordinary PID control system, and although the neural network inverse model control system has overshoot, the time to reach steady state is shorter, and the ordinary PID control system curve exists oscillation. In short, it can be intuitively seen that the neural network inverse model control system is more robust than the ordinary PID control system, and the control effect is better.

6. Conclusion

As the boiler water-coal ratio control system has many characteristics such as non-linearity coupling and so on, the paper uses the neural network toolbox for data training and learning, establishes a neural network inverse model to eliminate the nonlinearity and coupling of the system and adds a linear controller to the system to form a neural network inverse composite controller. Combined with the simulation test results, the inverse neural network model control method can achieve better control results in the control of water-coal ratio in ultra-supercritical units. Compared with the conventional PID control, it is obvious that the neural network inverse model control is more excellent in terms of anti-interference and robustness.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.



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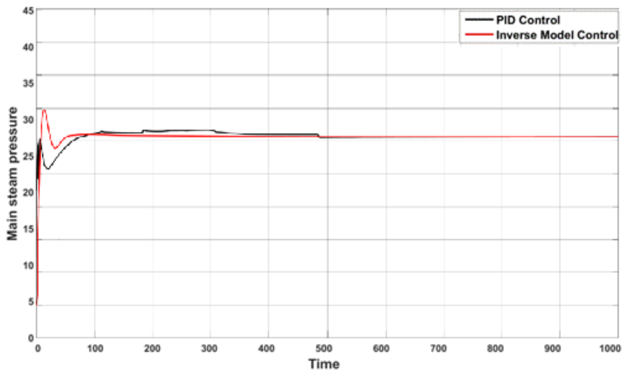

b

Fig. 13 Response curves comparison of NNI model control and PID control with varying time constants: a – mid-point temperature response curve, b – main steam pressure response curve

Conflicts of Interest

The authors declare no conflict of interest.

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WATER-COAL RATIO CONTROL STRATEGY OF ULTRA SUPERCRITICAL UNIT BASED ON NEURAL NETWORK INVERSE MODEL

S u m m a r y

Since the boiler water-coal ratio control system is a complex system with the characteristics of non-linearity and strong coupling, water-coal ratio control is one of the most difficult problems in the coal-fired power generation process control engineering, whose control strategy is of great importance. While, in order to achieve the control of water-coal ratio effectively during the coal-fired power generation process, the neural network inverse system scheme is proposed for the control of the water-coal ratio of ultra-supercritical units. Firstly, the model for the water-coal ratio system of an ultra-supercritical unit is presented in allusion to the characteristics of the water-coal ratio control system. Then the concept of the neural network based inverse system, the principle and method of the design of the neural network inverse controller are discussed. Finally, the control scheme is verified by establishing neural network inverse system on MATLAB toolbox. The experimental results show that the neural network based inverse system models has better control effect in terms of anti-interference ability, stability time than that of PID control system.

Keywords: ultra-supercritical unit, water-coal ratio control, neural network inverse model, simulation.

Received January 3, 2024
Accepted August 19, 2024