SUPERHEATED STEAM TEMPERATURE SYSTEM OF THERMAL POWER CONTROL ENGINEERING BASED ON NEURAL NETWORK LOCAL MULTI-MODEL PREDICTION

by

Jinsong ZHAN[a], Jing DU[b], Shaofeng DONG[a*], and Wei HU[a]

[a] Xidian University, Xi'an, China
[b] Shijia Zhuang Division of PLA Infantry Academy, Shijiazhuang, China

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The superheated steam temperature object of thermal power plant has the characteristics of time lag, inertia and time-varying parameters. The control quality of the conventional proportional integral derivate controller with fixed parameters will decrease after the object characteristics change. The generalized predictive control strategy of superheated steam temperature based on neural network local multi-model switching can achieve the goal of designing sub-controllers for fixed models under several typical operating conditions. When the system operating conditions change, the effective switching strategy is timely and accurate. Switch to the most suitable controller. The paper proposes a new smooth switching method, which can effectively suppress the large disturbance phenomenon of the object when switching. The simulation results verify the effectiveness of the control strategy.

Key words: *multi-model, neural network, generalized predictive control, smooth switching*

Introduction

The boiler superheated steam temperature object has the outstanding characteristics of large time delay, large inertia and time-varying parameters with changing working conditions. The traditional proportional integral derivate (PID) cascade controller based on specific operating point tuning will significantly reduce the control quality when the object time lag and object characteristics change. The predictive control developed in the 1970's has good control performance for systems with considerable time delays and large inertia. Some scholars have applied dynamic matrix control (DMC) and conventional PID controller to form a cascade control strategy, which has received good results in the application of superheated steam temperature control.

Since the parameters of the predictive controller are still selected based on a fixed model under a certain working condition, when the object characteristics change too much, the predictive control performance will also decrease significantly [1]. The multi-model method is an effective way to solve this problem. The paper proposes a multi-model DMC method. The algorithm obtains its local third-order sub-model set under typical working conditions. Based on the sub-models, the sub-controllers are designed, respectively, and the sub-controllers are weighted to obtain a suitable control increment. This paper takes advantage of the robustness of

* Corresponding author, e-mail: shaofengdong66371@163.com

the generalized predictive control (GPC) algorithm and the low degree of model dependence, and proposes a GPC strategy for superheated steam temperature based on neural network local multi-model switching, and gives a new switching method, To solve the problem of superheated steam temperature control under variable working conditions. The simulation study of the supercritical 600 MW once-through boiler superheated steam temperature object in the thesis confirmed the effectiveness of the method.

Generalized predictive control basic algorithm

Use CARIMA model to describe objects subject to random interference:

$$A(q^1)y(t) = B(q^1)u(t-1) + \frac{C(q^1)\xi(t)}{\Delta} \tag{1}$$

where $\{y(t), u(t-1)\}$ is the output and input sequence of the system, respectively, $\{\xi(t)\}$ – the zero-mean white noise sequence, q^1 – the backshift operator, $A(q^1)$, $B(q^1)$, and $C(q^1)$, – the polynomials about $C(q^1)$, and $\Delta - 1 - q^1$. Define the objective function:

$$\min J(t) = E\left\{\sum_{j=N_2}^{N_2}\left[y(t+j) - \omega(t+j)\right]^2 + \sum_{j=1}^{N_u}\lambda\left[\Delta u(t+j-1)\right]^2\right\} \tag{2}$$

where E is the mathematical expectation, ω – the expected value of the object output, N_1, N_2 are the initial and final values of the optimized time domain, respectively, N_u – the control time domain, and λ – the control weighting coefficient. Introducing the Diophantine equation and minimizing the objective function, the optimal control value of GPC can be obtained:

$$\Delta u(t) = [1, 0, L, 0]_{1\times N_u}\left(G^T G + \lambda\right)I^{-1}G^T\left(\vec{\omega} - \vec{f}\right) \tag{3}$$

where $\vec{\omega}$ is the softening set value sequence, and

$$\vec{\omega} = \left[\omega(t+1), \omega(t+2), L, \omega(t+N)\right]T; \vec{f} = H\Delta u(t-1) + Fy(t); G, H, F$$

is the polynomial about q^{-1}.

Generalized predictive control of superheated steam temperature based on neural network local multi-model switching

The GPC system structure of superheated steam temperature based on neural network local multi-model switching is shown in fig. 1. The basic structure is cascade control. The main loop adopts GPC and the secondary loop adopts proportional controller. When the system working condition changes greatly, based on the secondary performance index, switch to the corresponding controller. Different from the commonly used neural network local multi-model switching structure, the switch in fig. 1 is located before the N controllers are switched. At each sampling moment, the first judge and select the controller that best matches the object at the current moment. Then start the controller to adjust the system deviation. In this way, at each moment, only one controller in the sub-controller set is operating. Compared with the system where the controller first calculates and then switches, it dramatically reduces the amount of online calculation and speeds up the response time [2]. Each generalized predictive sub-controller in this control system adopts an incremental algorithm, and the system control quantity at the current time is the sum of the system control quantity at the previous time and the incremental output of the sub-controller at the current time.

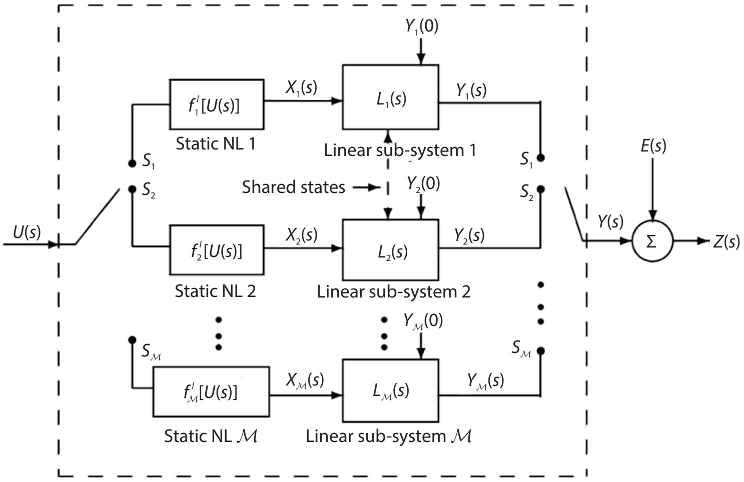

Figure 1. Multi-model GPC cascade switching control system

Selection of sub-models

For the thermal power plant superheated steam temperature system, the model parameters are closely related to the change of unit load. Literature analyzed the mechanism of the high temperature superheater of a 600 MW supercritical once-through boiler, and gave the transfer function model of the superheated steam temperature to the water spray disturbance under four typical working conditions, as shown in tab. 1. This article uses these four fixed models as the control system sub-models.

Table 1. The dynamic characteristics of the disturbance of the superheated steam temperature on the injection volume

Load	Leading area [°C/(kg/s)]	Inert zone
37%	$5.072(1 + 28s)^2$	$1.048/(1 + 56.6s)^8$
D = 179.2 kg/s, p = 10.14 MPa		
50%	$-3.067/(1 + 25s)^2$	$1.119/(1 + 42.1s)^7$
D = 242.2 kg/s, p =13.70 MPa		
75%	$-1.657/(1 + 20s)^2$	$1.202(1 + 27.1s)^7$
D = 347.9 kg/s, p =19.10 MPa		
1	$-0.815/(1 + 18s)^2$	$1.276/(1 + 18.4s)^6$
D = 527.8 kg/s, p = 25.40 MPa		

Predictive controller design and parameter tuning under typical working conditions

The leading area object and the proportional controller constitute the secondary loop system, and the secondary loop controller parameters are adjusted according to the follow-up system. In the main loop GPC, there are four parameters that need to be adjusted: the maximum prediction time domain, N_2, the control time domain, N_u, the control increment weighting coefficient, λ, and the softening coefficient, α. To simplify the calculation, take the minimum prediction time domain N_u = 1.

When the maximum prediction time domain N_2 is smaller, the speed is good, but the stability and robustness are poor. In practical applications, N_2 is generally used to cover the main dynamic response of the controlled object. Control time domain N_u affects system tracking performance, increasing N_u can improve control sensitivity, but system stability and robustness will decrease. The control increment weighting coefficient, λ, is used to limit the drastic change of the control increment. In the local multi-model switching strategy of the neural network in this paper, the control increment can be reduced by increasing λ, thereby reducing the control increment caused by the controller switching process. Subject disturbance [3]. It is proved that under the conditions given by N_1, the softening coefficient, α, is sufficiently close to 1 to ensure the stability of the closed-loop system. Many research and simulation experiments show that N_2 and λ are the two most important parameters that affect the performance of GPC, and they affect each other. The increase of these two parameters will slow down the reaction speed of the system and *vice versa*.

Handover strategy

An important part of neural network local multi-model switching control is the switching strategy of the controller. When the system changes from one working condition another, it is necessary to design a set of switching strategies to enable it to quickly switch to the sub-controller that best matches the current object, and avoid system vibrations, divergence*, etc.*, to achieve no disturbance switch. This article will adopt the following switching strategy:

– Select the secondary performance index reflecting the error of the actual object and the sub-model as the switching index. We set it at the k^{th} moment, $e_i(k) = y(k) - y_k(k)$ the actual output and the i^{th} model output error, and the switching index:

$$J_i(k) = ae_1^2(k) + \beta^{k-1} e_1^2(k-j), \ i = 1, 2, ..., N \tag{4}$$

where α is the error weight at the current moment, β – the error weight at the past moment, and the values of α and β determine the relative importance of the error at the present moment and the past moment, ρ – the memory effect of the performance index, L – the past moment taken length of the error, N – the number of sub-models, J_i – the degree of matching between the sub-models and the controlled object. The smaller the J_i, the smaller the model mismatch [4]. At time k, judge and select the sub-controller corresponding to the sub-model that minimizes the performance index J_i as the current controller.

– Select incremental GPC algorithm to achieve switching smoothness. In the neural network local multi-model switching cascade control system of this article, when the object changes from i working condition j working condition, the controller should make corresponding adjustments according to the judgment of the switching performance index, and switch from the i controller to j control device. When switching, since each sub-GPC controller in this system adopts an incremental algorithm, the system control quantity at the previous time (*i.e.*, the output value of the i controller) is used as the initial value of the j controller, and the current time j controller. The output value is the sum of the system control quantity $u(k-1)$ at the previous time and the controller calculation quantity $u(t)$ at the current time, namely $u(k) = u(k-1) + \Delta u_j(k)$.

  In this way, because the system control quantity at each moment is accumulated on the basis of the previous moment, the change range is relatively small. The output value of the object is related to the current and previous control variables, so when the change of the control variable is small, the output change of the object is relatively smooth. When describing the structure of the control system, I pointed out that this control system adopts the operating mechanism of the controller firstly judges and then calculates, and its purpose is to realize the aforementioned switching algorithm. Compared with the operating mechanism of the controller first calculating and then judging, the variation of the control amount can be effectively suppressed, and at the same time, it can avoid the occurrence of large oscillations and even divergence of the system after the wrong switch to a wrong sub-controller.

– Further improve smoothness. In a type of superheated steam temperature system characterized by a multi-capacity inertial transfer function model, since the control goal is to maintain a constant superheated steam temperature, it is easy to obtain the steady-state output value of the sub-controller offline from each sub-model [5]. When the system is relatively stable under variable conditions, a first-order inertia link module can be added between the two controllers. By adjusting the inertia time constant, the control variable can be terminated by the previous sub-controller relatively quickly within the allowable range of speed. The value changes to the steady-state value of the next sub-controller. After reaching the stability, the system completely switches to the next sub-controller operating state. In this way, human intervention on the control of the system makes the change of the control smoother, so that the output disturbance of the object is suppressed.

In the aforementioned smooth switching process, the system essentially has no actual controller to participate in the control, but an ideal controller with a preset trajectory to output the control quantity. Although this process can be relatively short by adjusting the inertial time constant, in practical applications, the switching process may be unstable due to the influence of external noise interference [6]. Therefore, if the output deviation exceeds the limit due to external interference during the switching process, the system should immediately switch to the actual controller operating state, and the actual controller will eliminate the transient deviation and overcome the interference.

Simulation research

Variable condition simulation test

First, check the control performance of the conventional PID controller with fixed parameters when the system operating conditions change in a large range and the object characteristics change. Suppose that the superheated steam temperature system initially performs a set value step disturbance at 75% load. After the steam temperature stabilizes, the load drops to 37% at a rate of 3% per minute at 3000 seconds, and the PID controller parameters are constant at 37%. The setting value under load. The object output and load change curve are shown in fig. 2. When the load drops from 75% to 37%, if the PID controller tuned at 75% load is still used, the system will diverge uncontrollable.

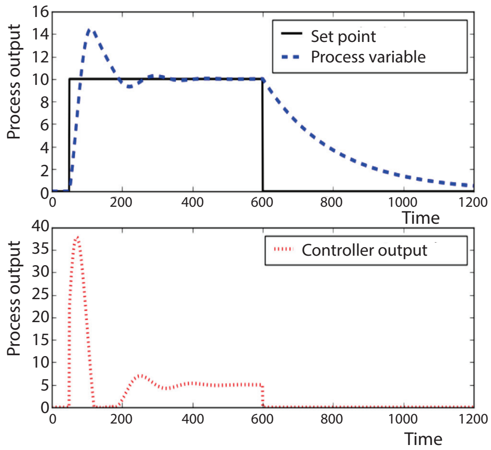

Figure 2. Variable condition control effect diagram of fixed parameter PID cascade system

In response to this situation, a multi-model strategy is implemented for PID controllers with fixed parameters. Under a particular performance index (φ = 0.75, the same for the primary and auxiliary circuits), the cascade PID controller parameters under the two load models of 37% and 75% are set. When the load changes, we use the aforementioned switching

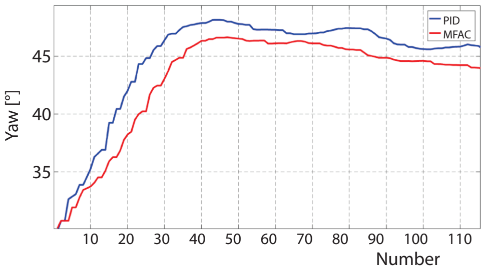

Figure 3. Neural network local multi-model switching PID cascade system variable condition control effect diagram; *MFAC-model-free adaptive control*

performance indicators to judge the current state of the system, and then switch to the controller that best matches the current object [7]. Under the same simulation conditions, the output curve of the object during the period of 2500-7000 seconds before and after the switch was intercepted and compared with the control effect of the PID cascade system with fixed parameters, as shown in fig. 3. It can be seen from the figure that after an oscillating process, the PID cascade control system with multi-model strategy can still maintain the object output at a given value, and the system is controllable.

Control strategy comparison simulation test

It can be seen from the variable-condition simulation test that the conventional PID cascade control system adopts the multi-model strategy, and the control performance is significantly improved when the system operating conditions change in a wide range. But when the controller is switched, the object will shake to a certain extent [8]. For this reason, this paper proposes a GPC strategy for superheated steam temperature based on neural network local multi-model switching to solve the switching jitter problem. Under specific performance indicators, set the GPC controller parameters at 37% and 75% loads. Set the superheated steam temperature system to initially do a set value step disturbance at 75% load. After the steam temperature stabilizes, the load is at 3000 seconds. Reduce to 37% at a rate of 3% per minute. The output curve of the object in the time period of 2500~7000 seconds before and after the switch is intercepted, as shown in fig. 4.

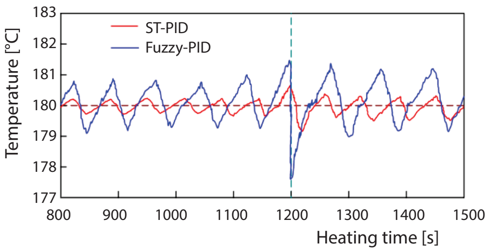

Figure 4. Comparison of switching effects between multi-model GPC and multi-model PID

At the same time, if the intermediate load object model of the switching process is added to the neural network local multi-model switching PID control system, and the corresponding controller is designed, the output jitter caused by the mismatch between the controller and the object is also reduced. A practical and effective method to solve handover jitter [9]. This paper also simulates this method. That is, according to the actual production data, the object model of superheated steam temperature at 50% load is established, and the cascade PID controller parameters under the 50% load model are set. During the load change from 75-37%, the controller first switches from 75% load controller to 50% load controller, and then to 37% load controller. The output curve of the object during the period of 2500-7000 seconds before and after the switch is intercepted, as shown in fig. 5.

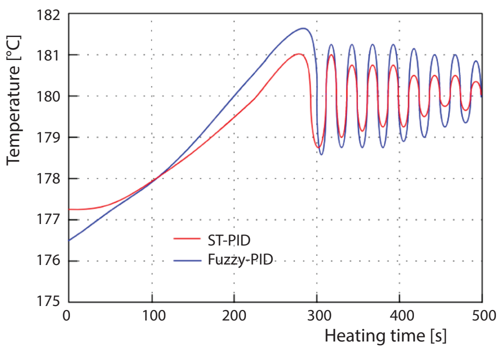

Figure 5. Multi-PID controller switching effect comparison chart

From the simulation results, the two methods to improve the handover jitter have achieved certain results. We use the GPC as the main controller of the cascade steam temperature control system. Due to the predictive characteristics of the control algorithm, it can quickly respond to changes in the object, and the transition time is significantly less than the PID control system. After adding a sub-controller that matches the 50% load of the intermediate process, the dynamic deviation of the multi-model PID control system during the switching process is significantly reduced. From this we can infer that the greater the number of sub-models and sub-controllers, the smaller the oscillation of the switching process, but the complexity and calculation of the control system will also increase [10]. In practical applications, the optimal method can be selected to improve the switching jitter according to the limitation of the switching time and switching amplitude in the production process.

Smooth handover simulation test

In order to verify the effectiveness of the improved smooth switching method on jitter suppression, we choose the multi-model GPC system with shorter switching time in the 4.2 experiment for simulation, and the simulation conditions remain unchanged. Assuming that the noise is zero during the load change, the output curve of the object during the 2500-5000 seconds period before and after the switch is intercepted, as shown in fig. 6.

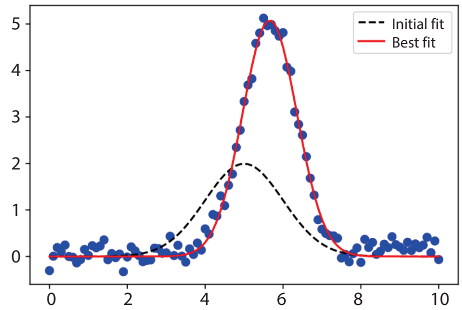

Figure 6. Smooth switching object and controller output effect diagram

It can be seen from fig. 6 that during the switching process, the output of the main controller of the multi-model cascade system changes from the control value of the 75% load sub-controller to the steady-state value of the 37% load sub-controller according to the inertia link curve. Compared with the direct switching of the controller, the control quantity of the system does not oscillate, and the disturbance of the target output is greatly reduced. Therefore, in the absence of noise, this paper proposes an improved multi-model GPC switching control strategy to control the superheated steam temperature system, which cannot only reduce the switching time, but also effectively suppress the switching disturbance.

Conclusion

The simulation research results of the thesis on a 600 MW supercritical once-through boiler high temperature superheater object show that the cascade steam temperature control system using neural network local multi-model switching control strategy can achieve good control performance under large-scale changes in working conditions; increase the system the number of sub-models and sub-controllers can reduce the shock of the switching process. The multi-model GPC smooth switching strategy proposed in this paper has achieved satisfactory results in reducing switching time and restraining switching oscillations.

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References

[1] Chen, J., Zhong, P. A., A Multi-Time-Scale Power Prediction Model of Hydro Power Station Considering Multiple Uncertainties, *The Science of the Total Environment*, *677* (2019), 8, pp. 612-625
[2] Dong, Z., *et al*., Automatic Generation Control for the Flexible Operation of Multimodular High Temperature Gas-Cooled Reactor Plants, *Renewable and Sustainable Energy Reviews*, *108* (2019), 7, pp. 11-31
[3] Wu, S., Study and Evaluation of Clustering Algorithm for Solubility and Thermodynamic Data of Glycerol Derivatives, *Thermal Science*, *23* (2019), 5, pp. 2867-2875
[4] Chang, H., *et al*., Technical Performance Analysis of a Micro-Combined Cooling, Heating and Power System Based on Solar Energy and High Temperature PEMFC, *International Journal of Hydrogen Energy, 44* (2019), 38, pp. 21080-21089
[5] Kanalik, M., *et al*., Temperature Calculation of Overhead Power Line Conductors Based on Cigre Technical Brochure 601 in Slovakia, *Electrical Engineering*, *101* (2019), 3, pp. 921-933
[6] Oyvang, T., *et al*., Online Model-Based Thermal Prediction for Flexible Control of an Air-Cooled Hydro-Generator, *IEEE Transactions on Industrial Electronics*, *66* (2019), 8, pp. 6311-6320
[7] Wu, L. J., *et al*., On-Load Field Prediction of Surface-Mounted PM Machines Considering Non-Linearity Based on Hybrid Field Model, *IEEE Transactions on Magnetics*, *55* (2019), 3, pp. 1-11
[8] He, Y., *et al*., A New Model of Acid Fracturing Based on Boundary Element Method Coupled with Multi-Field Multi-Phase Process, Engineering Analysis with Boundary Elements, *115* (2020), 6, pp. 96-107
[9] Wu, S., Construction of Visual 3-D Fabric Reinforced Composite Thermal Perfomance Prediction System, *Thermal Science*, *23* (2019), 5, pp. 2857-2865
[10] Huang, S. S., *et al*., Observer-Based Capacitor Sensorless Control Applied to a Single-Phase Inverter System with Seamless Transfer, *IEEE Transactions on Power Electronics*, *34* (2019), 3, pp. 2819-2828

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