STATE VARIABLE-FUZZY PREDICTION CONTROL STRATEGY FOR SUPERHEATED STEAM TEMPERATURE OF THERMAL POWER UNITS

by

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With the large-scale grid connection of new energy power, the random fluctuation existing in the power system is intensified, which leads to frequent fluctuation of load instructions of thermal power units. It is of great significance to improve the variable load performance of the coal-fired units. It is more difficult to control the superheated steam temperature (SST). In order to improve the control performance of SST, a state variable fuzzy predictive control method is proposed in this paper. Firstly, Takagi-Sugeno fuzzy state observer is used to approximate the non-linear plant of the SST. At the same time, based on the state observer, a fuzzy state feedback controller is designed to improve its dynamic characteristics. Thirdly, based on the extended predictive model of the state feedback controller, a model predictive controller is designed to realize the SST tracking control. Dynamic simulation shows the effectiveness of the strategy.

Key words*: coal-fired units, SST, Takagi-Sugeno fuzzy, state observer, model predictive control*

Introduction

As of 2020, thermal power units are still the main frequency modulation power supply in China. With the large-scale renewable energy grid-connected power generation, it brings greater volatility to the power system. Such fluctuations bring great difficulties to the control of SST and affect the safe and economic operation of units [1]. The relevant study shows that the unit efficiency will increase one percent while SST increase 5 °C. The design value of SST is closed to the limited working condition of superheated steam pipelines. So the SST is difficult to maintain within a permit range when load instructions fluctuate frequently. Under such circumstances, the thermal stress fatigue of metal pipelines is accelerated, and even a series of accidents such as boiler tube explosion is caused, which seriously threaten the safe and stable operation of units [2, 3].

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The SST-controlled object is typical large inertia, large delay, and non-linear object. At present, PID cascade control is used in the site. The structure of the control method is simple, but it is difficult to achieve the ideal control effect when dealing with large changes of load and uncertain disturbances [4]. Therefore, some advanced control strategies have been proposed successively, which mainly consist of linear control methods such as fuzzy and predictive control based on the linear model [5], and neural network control and slider control based on the non-linear model [6]. Besides, to solve the problem that the control model of superheated steam system changes with the change of load, some researchers combine many advanced control methods, such as the control strategy of combining adaptive technology with multi-model control method, fuzzy neural network, compensation neural network inverse control, and other composite control methods. In addition, in view of the complex non-linear characteristics of the actual industrial control system, many applications of Takagi-Sugeno (T-S) fuzzy theory, predictive control algorithm and state observer have been involved in the SST control of thermal power units [7]. The main idea of the application of predictive control method is to reduce the complexity of calculation by directly identifying the parameters of the controller, so as to maintain the stability of the control parameters when more disturbances appear [8], As this method improves the large lag problem in industrial production fundamentally, it has been widely used in industrial production, such as the power production using advanced predictive control technology instead of the traditional PID regulation, speed up the boiler side feed water flow and fuel quantity regulation speed, reduce the fluctuation range of main steam pressure and separator temperature in the process of unit load lifting [9]. At the same time, as a typical method of modern control, researchers introduce the state observer into the main steam temperature system with large delay to replace the output feedback with state feedback, which fundamentally improves the dynamic characteristics of the system [10]. This improved idea has been applied in many power plants in China, and good results have been achieved in both main steam temperature control and reheat temperature control [11]. However, the application of T-S fuzzy theory to the prediction model and state observer method to improve the main steam control performance has not been deeply discussed.

In order to the operation characteristics of thermal power units under the new situation and combined with the characteristics of SST system, a method is proposed in this paper, which combining T-S fuzzy, state variables and predictive control based on parameter models. This control method not only improves the dynamic characteristics of system, but reduces the impact of uncertain disturbances and large load changes.

Design of state variable-fuzzy prediction controller

Considering the SST control characteristics and engineering practical value, a more mature controller design method based on a linear model is adopted in this paper. As shown in fig. 1, the control strategy mainly consists of a state feedback controller and model predictive controller. A SST system presents strong non-linearity, and the ideal effect cannot be obtained by using a single working condition model to design the controller. The method of T-S fuzzy is used to fuzzy the individual sub-state space. To approximate the global model, the load variable is chosen as a premise variable and state feedback is used in a fuzzy system. However, the state variable is hard to acquire directly in reality. Therefore, a fuzzy state observer should be introduced to realize state feedback control.

As shown in fig. 1, based on the sub-model of SST, the global model is established by using the T-S fuzzy rule. Meanwhile, to avoid the mismatch between observer and controller, the same fuzzy rules are applied to the model construction of state observer and predictive controller.

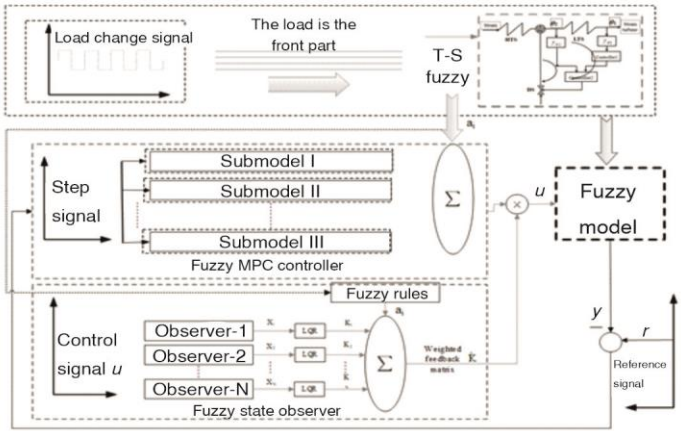

Figure 1. State variable - fuzzy prediction control schematic

The T-S fuzzy model

The T-S fuzzy is a model processing method to improve the more accurate description of non-linear system model, in which the accurate setting of fuzzy rules is an important process to realize fuzzification [12].

The i^{th} rule of fuzzy linearity is:

Rule i: If x_1 is M_1^i and x_2 is M_2^i and x_j is M_j^i then:

$$\dot{x} = A_i x + B_i u, \quad y = C_i x, \quad i = 1, 2, ..., N \tag{1}$$

where x_1 is j^{th} variable of system, M_j^i is j^{th} membership function of i^{th} rule, x – the state variable, u – the control input vector, and the number of sub-model is N.

The output of fuzzy system is:

$$\dot{\hat{x}} = \sum_{i=1}^{N} h_i A_i \hat{x} + \sum_{i=1}^{N} h_i B_i u, \quad \hat{y} = \sum_{i=1}^{N} h_i C_i \tag{2}$$

where A_i, B_i, and C_i are the state space matrix of i^{th} sub-model,

$h_i = \varepsilon_i \big/ \sum_{i=1}^{N} \varepsilon_i, \quad \varepsilon_i = \prod_{i=1}^{N} M_j^i(x_i),$

$M_j^i(x_i)$ is x_i in the membership degree of M_j^i. From the aforementioned, it can be seen that the weight coefficient of the sub-model conforms to the normalization principle. The closer coefficient of the sub-model is to 1, the close model is to the controlled object.

Fuzzy state observer

Similarly, the fuzzy model of SST system state observer can be obtained according to the T-S fuzzy principle. Its rules are:

Rule i: If x_1 is M_1^i, x_2 is M_2^i, and ... x_j is M_j^i, then:

$$\dot{\hat{x}} = A_i x + B_i u + K_{ei}\left(y - y_i\right), \quad i = 1, 2, ..., N \tag{3}$$

The state feedback of fuzzy model is $\hat{x} = \sum_{i=1}^{N} a_i x_i$ where $\hat{x}$ is global state variable, is the state feedback matrix corresponding to the i^{th} sub-model, there is:

$$\dot{\hat{x}} = \sum_{i=1}^{N} a_i \left\{ A_i \hat{x} + B_i u + K_{ei}(y - \hat{y}) \right) \tag{4}$$

If the previous equation holds, it can obtain:

$$\hat{K}_e = \sum_{i=1}^{N} a_i K_{ei} \tag{5}$$

Similarly, based on optimal feedback matrix of sub-model and observer matrix, weighting determine the global state feedback matrix:

$$\hat{K} = \sum_{i=1}^{N} a_i K_i \tag{6}$$

Fuzzy predictive controller

In this paper, based on predictive control of parameter model and compared with T-S fuzzy principle, a global model is obtained by fuzzy weighting on the base of getting the region sub-model. This model is used as the predictive model of the predictive controller [13]. As shown in the section *Fuzzy state observer*. The equation of the sub-model state is:

$$x(k+1) = A_i x(k) + B_i u(k), \quad y(k+1) = C_i x(k+1) \tag{7}$$

Control variables $u(k)$ are used for each sub-model to synchronize updates with the controlled object. With the updates of model, the operation variables $u(k)$ and the predictive output $y(k + 1)$ will be active on the next moment, while the weight coefficient to each sub-model will be updated. Its weight coefficient can be obtained by the T-S fuzzy principle, and conform with the coefficient of fuzzy modeling in section *Fuzzy state observer*. The weight model predictive output:

$$\bar{y}(k+j|k) = \sum_{i=1}^{N} h_i(k) \hat{y}_i(k+j|k), \quad i = 1, 2, ..., N \tag{8}$$

where $h_j(k)$ to predictive output of sub-model of j^{th} model is $\hat{y}_i(k+j|k)$.

The ultimate goal of rolling optimization is to obtain the optimal control rules at each moment. In this paper, based on predictive control of model, the optimization method is different from the offline global optimization of non-parameter model, but the local optimization is carried out online at all time. Although this method cannot acquire the global optimization all the time, it still compensates for the impact caused by model mismatch, uncertain disturbance, and non-linearity, to obtain the actual optimization. The key is to obtain the optimal control rule at time k. Given this, introducing the objective function:

$$J = (R - \bar{Y})^T W_y (R - \bar{Y}) + \Delta u^T W_u \Delta u \tag{9}$$

where R is the given input, Δu – the control vector increment, $\bar{Y}$ – the vector of predictive output, W_y – the correction weight of output increment, and W_u – the control increment weight.

The optimal control function of solving unconstrained problem with the aforementioned model:

$$\min J = (R - \bar{Y})^T W_y (R - \bar{Y}) + \Delta u^T W_u \Delta u \tag{10}$$

So when ordering $\partial J/\partial \Delta U = 0$, it can obtain the optimal control difference of time k:

$$\Delta U = (S_e^T S_c^T S_c S_e + W_u)^{-1} S_e^T S_c^T (R - S_x - S_c U_0) \tag{11}$$

where the expressions of S_c, S_e, and S_x and the detailed derivation of this section can be found in [14].

Then it can obtain the optimal control of time k:

$$u(k) = u(k-1) + \Delta U \tag{12}$$

State variable predictive control simulation based on T-S fuzzy model

Selection of simulation model

This paper refers to the data model of a high temperature superheater of a supercritical DC boiler at different specific working conditions, namely the four sub-model shown in tab.1. The T-S fuzzy take the load as a premise, the output as SST. The relevant state feedback data processing is similarly described in section *Fuzzy state observer*. The state observer matrix and state feedback matrix are calculated for the selected unit models at 44%, 62%, 88%, and 100% load points, respectively. The data obtained are shown in tab.2.

Here, it should be noted that the method of obtaining the state feedback variables is based on the pole placement method. Based on introducing state feedback, the closed-loop poles of the system are reassigned to the desired pole position of the stable state [15]. To consider that the response speed of the observer is faster than that of the closed-loop system, the observer pole assignment is made according to two times of the closed-loop poles, and the state feedback matrix is obtained [16, 17].

Table 1. Mathematical model of SST system for 600 MW unit

Load [%]	Dynamic characteristics	
	Advance transfer function	Lag transfer function
44	$-6.62/(21\ s + 1)^2$	$1.66/(39.5\ s + 1)^4$
62	$-4.35/(19\ s + 1)^2$	$1.83/(28.3\ s + 1)^4$
88	$-2.01/(16\ s + 1)^2$	$2.09/(22.3\ s + 1)^4$
100	$-1.58/(14\ s + 1)^2$	$2.45/(15.8\ s + 1)^4$

Table 2. Load point data computation

Load [%]	State feedback matrix, *K*	State observer matrix, *Ke*
44	[6.56 17.80 26.27 23.70 12.64 3.16]	$1.0 \cdot 10^{11}$[1.70;2.65;1.74;0.66;0.15;0.02]
62	[6.51 17.80 26.27 23.70 12.65 3.16]	$1.0 \cdot 10^{10}$[4.62;7.52;5.02;1.92;0.45;0.06]
88	[6.45 17.78 26.27 23.70 12.64 3.16]	$1.0 \cdot 10^{10}$[2.21;3.81;2.58;0.99;0.23;0.03]
100	[6.36 17.76 26.27 23.70 12.64 3.16]	$1.0 \cdot 10^{10}$[3.95;7.49;5.22;2.04;0.48;0.06]

Where the methods of obtaining the sub-model state feedback coefficient matrix and state observer gain matrix reference the [5].

To simulate and verify the state feedback methods, taking SST model at 62% load point of a 600 MW unit as an example, the state feedback matrix coefficient and state observer matrix:

$$K = [6.51\ 17.79\ 26.27\ 23.70\ 12.64\ 3.16],\ Ke = (1.0e+10)[4.62\ 7.52\ 5.02\ 1.92\ 0.45\ 0.06]^T$$

Simulation and analysis

- At 65% working condition, comparing response curve under conventional PID and new method when load is disturbing with a sawtooth wave of 1% amplitude.
- The following fig. 2 is the response curve when the load fluctuates in the small range. Due to the addition of new energy to the grid, when the proportion of such strongly random power increases, the regulatory burden of the power grid on power primary frequency will be greatly increased. This is also the most serious problem in the process of current power structure adjustment. So for realizing the simulation of the influence of such load disturbance, now aiming at fluctuation signal of specific load that is added to the process of su-

perheated steam system adjustment. The blue dashed is response curve of PID, and the red one is response curve of new control method. Through simulation, it can be found that the new control strategy has a good response to the frequent changes of load instructions.

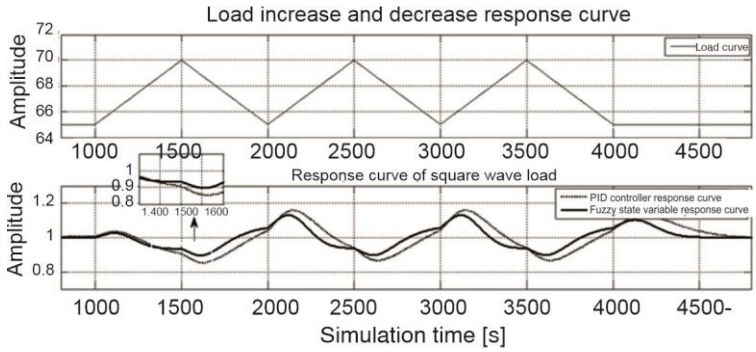

Figure 2. Sawtooth fluctuation load response curve

- On the stable state of 65% load, load increase and decrease by fluctuation of square wave with 5% amplitude, then the comparison between fuzzy state feedback model predictive controller and PID are shown in fig. 3.

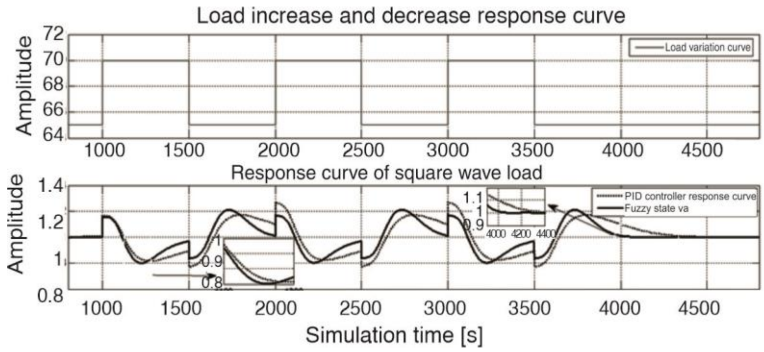

Figure 3. Fuzzy state variable predictive control square wave-

As shown in fig. 3, when square wave is fluctuating, the blue dashed is response curve of PID, the red one is response curve of new control method. The fluctuation can be caused by the unit co-ordinating, coal quality, steam pressure fluctuation and so on. Through the simulation diagram, it shows that the fuzzy state variable predictive control ability responds to the load disturbance in time to ensure the SST is relatively stable.

- When a load is changing in the big range, it is a huge influence on SST. In order to validate the new control rule characteristics, the following response curve is the SST response curve at a rate of 2% load ±20%.

As shown in the simulation curve of fig. 4, it can find that the blue dashed is the response curve of original PID control and the red one is response curve of fuzzy state variable predictive control. The SST fluctuates during the load addition and reduction process, but the new control method fluctuate in a small range, and the SST fast recovers to the set value after the load addition and reduction process, which indicates that the fuzzy state variable predictive control has good robustness in the case of rapid load addition and reduction.

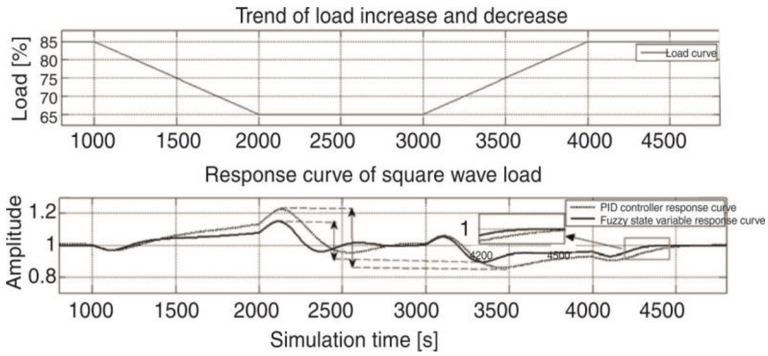

Figure 4. Fuzzy state variable predictive control response curve for large scale load addition and reduction

– Under the 65% load , the given value and load change are simultaneously varied in the form of square wave to observe the response curve of the new control strategy:

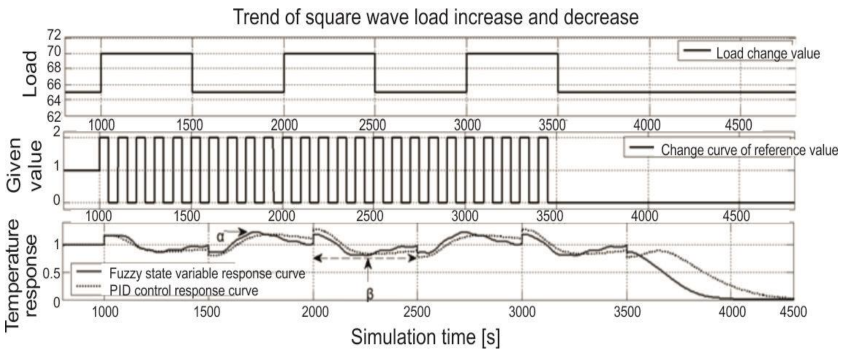

Figure 5. Response curve of input and load fluctuation at

Figure 5 shows that load square wave fluctuation. While the steam temperature reference is applied to fluctuation, and the response curve under the disturbance. The blue dashed is the response curve of PID, and the red one is the response curve of the improved control method. Through the simulation curve, it can find that, compared with traditional PID, the improved control effect of calibration is less obvious. At the specified point α, although it exceeds the conventional PID control, the difference is not huge. The overall adjustment effect in interval β is superior to the conventional PID adjustment. Compared with the whole region, the steam temperature response under the improved control method was significantly improved in most time intervals, which also reflected the value of the improved method.

Conclusions and discussion

In this paper, based on the non-linearity and hysteresis of the system, firstly the model is used to approximate the global model to improve its nonlinearity. On this basis, the paper proposes the method of fuzzy model state feedback predictive control, which is based on the predictive control-state feedback control method and combined with the T-S fuzzy model. Compared to the state feedback-predictive control of a single model, it has better robustness and adaptability when dealing with large load change. Compared with the conventional PID simulation, the feasibility of fuzzy model state feedback predictive control is verified.

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