Multi Model Robust PID Control of Main Steam Temperature based on Gap Metric

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Abstract. In order to adapt to the current construction of smart power plants, thermal power plants put forward higher requirements for the main steam temperature control. The traditional cascade PID control scheme is difficult to achieve satisfactory control quality. In this paper, several models of the main steam temperature plant are classified according to the gap metric, and then the corresponding robust PID controller is designed for different models. The simulation results show that the multi model robust PID control based on gap metric can effectively solve the large delay and nonlinearity of the main steam temperature plant, and the control performance is better than the cascade PID control, which is worth popularizing in engineering application.

1. Introduction

Smart power plants[1][2][3][4] are the future trend. The purpose of building smart power plant is to establish modern energy power system, so as to realize the safe, efficient, green and low-carbon power generation. The characteristics of smart power plant are that the production process can be optimized independently, its own behavior can be collected, analyzed, judged and planned, and its equipment and parameters can be intelligently and dynamically optimized online. Intelligent power generation is to realize the intelligent monitoring, operation and management of the whole process of power generation. It is the foundation of smart power plants, and it is also necessary to realize smart energy in the future. The digitalization, automation, informatization and standardization of power generation process are the foundation of intelligent power generation, and also the key to build smart power plant. Therefore, with the goal of digitalization, automation, informatization and standardization, optimizing and designing the control strategy of complex thermal process is the basis of realizing intelligent power generation, and it is also the hot spot of scholars' research[3][4].

The thermal process of thermal power plant is very complex. Main steam temperature is an important parameter of boiler. The steam temperature of boiler in thermal power plant directly affects the thermal efficiency of the whole plant and the safe operation of equipment, such as superheater pipe, steam turbine, etc. There are many interference factors and large amount of disturbance that cause the change of main steam temperature. For example, the lag of steam temperature plant is very large, the spray desuperheater valve has certain nonlinearity and time-varying, and the thermal power unit has deep peak regulation. Therefore, how to control the main steam temperature quickly and accurately is an important research task of boiler combustion control system[5][6][7].
In order to build smart power plants, thermal power plants have higher and higher requirements for thermal process control. The main steam temperature plant has obvious nonlinear and dead-time characteristics, so it is difficult for traditional cascade PID to achieve satisfactory control quality[5][6], so scholars have carried out extensive research. For example, active disturbance rejection technology[5], robust control[6], dynamic matrix control[7], predictive control[8][9], fuzzy theory[10][11], neural network[12], intelligent algorithm[13], adaptive control[14] and other advanced theories[15][16] are used to control the main steam temperature. However, these methods are not only very complex in structure but also difficult in calculation, so it is difficult to configure and realize in DCS. So, a multi model robust PID control of main steam temperature based on gap metric is proposed in this paper. First, several models of the main steam temperature plant are classified according to the gap metric, and then the corresponding robust PID controller is designed for different models. The simulation results show that the proposed method in this paper has the advantages of simple structure, easy setting, and its control performance is better than the cascade PID control, which is worth popularizing in engineering application.

2. Dynamic Characteristics of Main Steam Temperature System

The main steam temperature plant has obvious nonlinear and dead-time characteristics. The transfer functions of the main steam temperature plant at five typical working points are shown in Table 1[9]. At present, cascade PID control is still the main method to control the main steam temperature in thermal power plants. The cascade PID control system is shown in Fig. 1. \( G_1(s) \) is the transfer functions of leading section of the superheater. And \( G_2(s) \) is the transfer functions of inertial section of the superheater. Usually in Fig. 1, the inner loop controller \( C_1(s) \) adopts the proportional (P) regulation while the outer loop controller \( C_2(s) \) uses proportional integral (PI) regulation. The generalized controlled plant within the dotted box in Fig. 1 is \( G_{pd}(s) \). It can be fitted to first-order-plus-dead-time model (FOPDT) shown in equation (3) by least squares or other methods.

\[
\begin{align*}
G_1(s) & = K_{c1} \\
G_2(s) & = K_{c2} + \frac{K_i}{T_s s} \\
G_{pd}(s) & = G_p(s)e^{-\tau s} = \frac{K}{T_s s + 1} e^{-\tau s}
\end{align*}
\]
Tab. 1 Dynamic characteristic of Main Steam Temperature

| Load (%) | $G_1(s)$ | $G_2(s)$ | $G_{pd}(s)$ |
|----------|---------|---------|------------|
| 30%      | $\frac{8.07}{(24s+1)^2}$ | $\frac{1.48}{(46.6s+1)^2}$ | $\frac{1.48}{108.5s+1}$ $e^{-65s}$ |
| 44%      | $\frac{6.62}{(21s+1)^2}$ | $\frac{1.66}{(39.5s+1)^2}$ | $\frac{1.66}{93.02s+1}$ $e^{-79s}$ |
| 62%      | $\frac{4.35}{(19s+1)^2}$ | $\frac{1.83}{(28.2s+1)^2}$ | $\frac{1.83}{55s+1}$ $e^{-65s}$ |
| 88%      | $\frac{2.01}{(16s+1)^2}$ | $\frac{2.09}{(22.3s+1)^2}$ | $\frac{2.09}{48.9s+1}$ $e^{-44s}$ |
| 100%     | $\frac{1.58}{(14s+1)^2}$ | $\frac{2.45}{(15.8s+1)^2}$ | $\frac{2.45}{30.5s+1}$ $e^{-35.8s}$ |

3. Gap metric

The concept of gap metric[17][18] is an extension of the traditional infinite norm metric method. It can be used to evaluate the similarity of two plants dynamic characteristics. Both stable and unstable plants can be analyzed by gap metric. The gap metric is between 0 and 1, that is $\delta \in [0,1]$. If the gap metric is smaller, then the dynamic characteristics of the two plants are more similar. If the gap metric is greater, then the dynamic characteristics of the two plants are more different. If $\delta = 0$, then the two plants are exactly the same. If the gap metric between the two plants is relatively small, then there is at least one feedback controller to make the two plants stable at the same time.

M, N are two linear subspaces in Banach space $Z$. If $(M, N)$ is a transfer function matrix, its normalized right coprime decomposition can be obtained.

It is $P = NM^{-1}$, in which

$$M^{-1}M + N^{-1}N = I, \quad M^{-1}(s) = M^T(-s)$$  \hfill (4)

If $P_1, P_2$ are two linear systems, their right coprime decompositions are

$P_1 = N_1M_1^{-1}, \quad P_2 = N_2M_2^{-1}$, so

$$\delta(P_1) = \begin{bmatrix} M_1 \\ N_1 \end{bmatrix} H_1, \quad \delta(P_2) = \begin{bmatrix} M_1 \\ N_1 \end{bmatrix} H_2$$  \hfill (5)

The gap metric of two linear systems $P_1$ and $P_2$ is:

$$\delta(P_1, P_2) := \|\Pi \delta(P_1) - \Pi \delta(P_2)\|$$  \hfill (6)

In which $\Pi$ is orthogonal projection.

$$\delta(P_1, P_2) = \max (\bar{\delta}(P_1, P_2), \bar{\delta}(P_2, P_1))$$  \hfill (7)

Formula (7) is one-way distance, in which

$$\bar{\delta}(P_1, P_2) := \| (I - \Pi_{F}) \Pi_{H} \|$$  \hfill (8)

It can be calculated by formula (9):
\[ \delta(P_1, P_2) = \sup_{x \in P_1, y \in P_2} \text{dist}(x, K_2), \]

in which

\[ \text{dist}(x, K_2) = \inf_{y \in K_2} \|x - y\|_2 \]

\[ \tilde{\delta}(P_1, P_2) = \inf_{Q \in H_\infty} \|M_1 - N_1\|_{\infty} \|M_2 - N_2\|_{\infty} \]

If \( \delta(P_1, P_2) < 1 \), then

\[ \delta(P_1, P_2) = \tilde{\delta}(P_1, P_1) - \tilde{\delta}(P_2, P_1) \]

If \( P \) is nominal linear system, \( K_\gamma \) is a stabilization controller of \( P \), then the robust stability target of the system is \( b_{\rho k} \) and the optimal robust stability target is \( b_{opt} \).

\[ b_{\rho k} = \| I \left[ K_\gamma \right] (I + PK_\gamma)^{-1} [I \ P] \|^{-1}_\infty \]

\[ b_{opt} = \| I \left[ K_\gamma \right] (I + PK_\gamma)^{-1} [I \ P] \|^{-1}_\infty \]

If the nominal feedback system \((P, K_\gamma)\) is stable and \( \Sigma = \{ P_\alpha : \delta(P, P_\alpha) < \gamma \} \), so \( \forall P_\alpha \in \Sigma \), then the feedback system \((P_\alpha, K_\gamma)\) is stable when and only when \( \gamma \leq b_{\rho k} \). \( b_{\rho k} \) is the robust stability target of the system. \( \Sigma \) is a set of uncertain model \( P_\alpha \) satisfying the gap metric target of the system.

Therefore, the gap metric can be applied to the design of nonlinear control system. In general, through the system identification, nonlinear plants can get many different linear models at different equilibrium working points. Based on the gap metric of each linear model, the nominal model \( P \) can be selected reasonably and its controller \( K_\gamma \) can be designed. Thus, the feedback system \((P, K_\gamma)\) is obtained which makes the nonlinear system globally stable. That is to say, reasonable design of controller \( K_\gamma \) makes the linear models stable at several other equilibrium points[11][12].

4. Design of robust PID controller
Robust control[19] is a design method for uncertainties of systems. The influence of uncertainties on control systems can be minimized through robust controllers, which can enhance the disturbances rejection performance of the system. It is a common method at present to design robust controller based on mixed sensitivity function. The design steps of robust PID controller are as follows.

(1) The PID controller is shown in Form (15).

\[ C(s) = k_c + \frac{k_i}{s} + \frac{k_d}{T_d s + 1} \]

(15)

\( k_c, k_i, k_d \) are respectively proportional gain, integral gain and differential gain of the controller. \( T_d \) is differential time.

(2) The robust controller design based on mixed sensitivity can be described by formula (16).
\[ \min_{k,s} \left| \frac{W_1 S(s)}{W_2 T(s)} \right| \leq 1 \]  

(16)

\( S(s) \) is sensitivity function. \( T(s) = 1 - S(s) \) 
is complementary sensitivity function. \( W_1, W_2 \) is weighting function.

(3) Computation of weighting function:
If the control plant has dead-time, the weighting function can be chosen as the lead block, as shown in equation (17).

\[ W_i(s) = \frac{k_i (m_i s + 1)}{n_i s + 1}, \quad m_i > n_i, \quad i = 1, 2 \]  

(17)

If there is no dead-time in the control plant, the weighting function can be selected as a constant, that is, \( W_i(s) = m_i \).

(4) The desired transfer function of the closed-loop system is \( H(s) \), which can be derived from the desired dynamic characteristics. Let \( T(s) = H(s) \). After determining the optimization indexes of step response (such as attenuation rate \( \phi(x) \), dynamic overshoot \( M_p \) and rise time \( T_{up} \) based on \( H(s) \), the design of robust PID controller is transformed into the optimization problem of parameters \( m_i, k_c, k_i, k_d, T_d \).

Because the disturbance variables have more influence on SCR denitration system (in section 1.2), the disturbance rejection performance of denitration control system is more important than the task of set-value tracking. Therefore, in addition to the robustness of the system, the integrated time absolute error criterion (ITAE) can also be selected as the disturbance rejection performance index of the system. ITAE can characterize the comprehensive performance of the system in time domain.

The integrated time absolute error criterion (ITAE) is shown in formula (18).

\[ \min_{\chi} J = \int_{0}^{\infty} |e(t)| dt \]  

(18)

\( e(t) \) is the error between the output of the closed-loop system and the setting point.

5. Multi model robust PID control system

5.1. Model classification
The gap metric between some models in Tab. 1 can be calculated:

\[ \delta[G_{100}(s), G_{68}(s)] = 0.1621, \]
\[ \delta[G_{68}(s), G_{62}(s)] = 0.3156, \quad \delta[G_{62}(s), G_{44}(s)] = 0.2687, \quad \delta[G_{44}(s), G_{30}(s)] = 0.1787 \]
\[ \delta[G_{100}(s), G_{62}(s)] = 0.3421, \quad \delta[G_{62}(s), G_{30}(s)] = 0.2988, \quad \delta[G_{68}(s), G_{44}(s)] = 0.3312 \]

According to the gap metric between the models, the models are divided into different zones. Generally, when the gap metric between two plants is more than 0.3, it is difficult to use one controller to make both plants stable. Therefore, different robust PID controllers are designed for different model sets. According to the change of unit load, the controller parameters are changed adaptively to achieve the purpose of switching controller.

According to the gap between models, many models can be roughly divided into two intervals. They are \( (0,62\%), (62\%, 100\%) \). In two intervals, the robust PID controller is designed according to the low frequency plant with the minimum time constant to complete the control of other load point models.
5.2. Control system

The multi model robust PID control scheme of main steam temperature based on gap metric is shown in Figure 2.

6. Simulation analysis

Taking 62% and 100% load models as nominal plants, robust PID controllers $C_1$ and $C_2$ are designed. The controller parameters are shown in Tab 2. The controller $C_1$ is used to control 37%, 44% and 62% load models, and the simulation results are shown in Figure 3. With the controller $C_2$, the simulation results of 88% and 100% load models are shown in Figure 4.

| $C_1$ | $k_c$ | $k_i$ | $k_d$ |
|-------|-------|-------|-------|
| $C_2$ | 0.192 | 0.00508 | 0 |

In order to further verify the effectiveness and robustness of this method, two new models can be used to test its control performance. The two new models can be obtained by linear interpolation with equal gap metric, between 88% load and 62% load, and between 62% load and 44% load. The calculation formulas of model parameters are as follows:

$$K_i = K_{	ext{max}} + (i-1) \frac{K_{\text{max}} - K_{\text{min}}}{m-1}, (i = 1, 2, \cdots, m)$$
\[ \tau_i = \tau_{\min} + (i-1) \frac{\tau_{\max} - \tau_{\min}}{m-1}, (i = 1, 2, \cdots, m) \] \hspace{1cm} (20)

In Formula (19) and (20), \( K_{\min} = 1.48 \), \( K_{\max} = 2.45 \), \( \tau_{\min} = -85 \), \( \tau_{\max} = -35.8 \).

The time constant \( T_i \) is obtained under the following objective function.

\[ \delta[G_1(s), G_2(s)] = \lambda, \quad \lambda = 0.17 \] \hspace{1cm} (21)

The two models are \( G_1(s) \) and \( G_2(s) \). They are between 62% and 88% loads and between 44% and 62% loads, respectively.

\[ G_1(s) = \frac{2D}{5.2s+1} e^{0.2s} \] \hspace{1cm} (22)

\[ G_2(s) = \frac{18}{77s+1} e^{0.8s} \] \hspace{1cm} (23)

The robust PID controller \( C_1 \) and \( C_2 \) are used to control the two models respectively, and the control performance is compared with that of the cascade PID. The results are shown in Figure 5. It can be seen that the multi model robust control scheme still has better set point tracking ability and robustness, and its control performance is better than the cascade PID.

**Fig. 5** Comparison results with cascade PID

### 7. Conclusion

(1) The gap metric can measure the dynamic characteristics between two plants. According to the gap metric, multiple models can be classified, and then corresponding controllers can be designed for a class of models.

(2) The multi model robust PID control based on gap metric can effectively suppress the dead-time and nonlinearity of main steam temperature plant, and its control performance is better than that of cascade PID.

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