Application of feedforward predictive control in DC furnace coordination system

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Abstract. In order to solve the control difficulties such as large dynamic delay, serious coupling between machine and furnace and strong nonlinearity, the feedforward and feedback predictive control is proposed to control the coordinated system on the basis of multi-model predictive control, and the static feedforward part designs the feed line feedforward of coal quantity against coal quality disturbance on the basis of the accurate balance of energy. Thus, the reference total fuel quantity under the target load instruction is determined, and the dynamic part fully considers the dynamic compensation of the unit energy storage, gives a certain overshoot fuel quantity to the boiler regulation, speeds up its response, and ensures the rapidity of the unit. The real-time simulation results of virtual DPU (Distributed Processing Unit) show that the designed feedforward-feedback predictive control can quickly respond to load change, improve the resistance to fuel disturbance, reduce the fluctuation of main steam pressure, and better ensure the safe, economic and stable operation of the coordination system.

1. Introduction

With the improvement of unit parameters and the complexity of ultra-supercritical units, it is increasingly difficult for traditional control methods to ensure that their coordinated control system achieves a good control effect, and the adjustment of its parameters becomes more difficult. However, with the application of more and more advanced optimization control strategies in the unit coordinated control system, these problems are better solved, such as neural network control, predictive control, multi-group intelligent control algorithms, and robust control [1-13]. Among them, Zhang studied the restricted multiple-input multiple-output predictive control algorithm [1]. This algorithm uses matrix operations to fundamentally overcome the decoupling defects of traditional control structures. It can be used without decoupling and without feedforward. To solve the problem of strong coupling and large delay of the MIMO system, the responsiveness of the algorithm still needs to be improved. Yu used the artificial fish school algorithm to optimize the initial weight of the PID neural network, and substituted the optimized initial weight into the PID neural network controller [2]. Simulation showed that the PID neural network control based on the artificial fish school algorithm optimized for the coordinated control of the unit has good network convergence speed and strong robustness, but the neural network training algorithm is expensive and difficult to run in real time online. Ma established a neural network prediction model of unit load and main steam pressure considering the unit heat recovery cycle characteristics. Based on this, the condensate water throttling technology and model
predictive optimization control strategy were organically combined to propose an advanced The coordinated system intelligently optimizes the control scheme, but the condensate water throttling will have a greater impact on the water level of the deaerator, and there are certain safety risks in the actual implementation process [3]. Hu designed the optimal control law of multiplicative predictive function with disturbance signal, and applied the predictive function control system and optimized control method to the main steam pressure and superheated steam temperature control circuit of ultra-supercritical unit, which effectively solved Coupling issues of the system [4]. Cai reduced the order of the controlled object model with the idea of Pade approximation, and reduced the complexity of the system without changing the original dynamic characteristics of the controlled object. Variable generalized predictive controller, simulation results show that the effect is better than the traditional PID control algorithm [5]. Ma designed a linear auto-disturbance disturbance coordination controller based on the "furnace-follower coordination mode" for a 1000MW ultra-supercritical unit, and carried out detailed variable load disturbance simulation experiments with the full-range simulation system of the unit fully validate the performance of the algorithm [6]. Ke designed a coordinated control strategy of segmented PID and variable load feedforward controller based on optimized variable load and slip pressure rate. The coordinated control system can better meet the grid AGC assessment requirements while ensuring the stability of the unit [7]. Huang designed a linear ADRC controller through feedforward decoupling to achieve optimal control of the coordination system [8]. Based on T-S model, the transfer function model of a coordinated control system of a unit is fuzzy controlled. Then, based on the inversion of the model, the control strategy with the fuzzy model as the internal model is given. The simulation results show that the scheme has a certain effect. However, the internal model control requires high precision of the model, so the robustness of the control is poor [9]. Wang performed online identification of predictive control models with delay based on a rolling window online identification algorithm, which improved the accuracy of the prediction model [11]. Zhang used neural networks to decouple the coordinated control system, and simulations showed that it has strong adaptability and control accuracy [12]. Zhu optimize the basic fuzzy control, and solved the large delay and large inertia problems on the boiler side by enhancing the flexible analogue ability of the algorithm [13].

In this paper, it is based on the nonlinear model of coordinated control system [14], through multi-model switching strategy and giving full play to the robustness and decoupling performance of predictive control, feedforward-feedback predictive control is designed by adding feedforward control, which further accelerates the responsiveness of the system and optimizes the control effect. Finally, the real-time simulation is carried out on virtual DPU. The effectiveness of the control method is verified, which lays a foundation for the application of the controller in the actual field.

2. Model of coordination system
The model is based on the mass balance, energy balance and momentum balance of DC furnace unit, combined with system identification, a simplified model which can be used in the research and design of control system is established by composite modeling method. The model consists of three links: boiler heating, cooling water and steam turbine. Finally, the following nonlinear equations of state differential equations are obtained by simplification:
\[
\begin{align*}
    x_1 &= \frac{e^{\frac{\tau}{\tau_1}}}{C_2 \tau} + u_1 \\
    x_2 &= \frac{k_1}{C_1} x_1 + f[x_2 - g(x_2)] \frac{h[x_2 - g(x_2)]}{c_l} \left( \frac{b - b_i}{C_1} + \frac{h_{fu} - d_i}{C_2} \right) \\
    x_3 &= \frac{k_2}{C_2} x_2 + f[x_3 - g(x_3)] \frac{h[x_3 - g(x_3)]}{c_l} \left( \frac{b - b_i}{C_1} + \frac{h_{fu} - d_i}{C_2} \right) \\
    y_1 &= x_1 - g(x_1) \\
    y_2 &= x_2 - g(x_2) \\
    y_3 &= \frac{k_3}{C_3} y_1 + g[x_2 - g(x_2)] - h_{fu}
\end{align*}
\]

where: \( x_1 \) is the amount of pulverized coal into the furnace (kg/s), \( x_2 \) is the intermediate point pressure (MPa), \( x_3 \) is the intermediate point enthalpy (kJ/kg); \( u_1 \) is the coal feed instruction (kg/s) \( u_2 \) is the feed water flow rate (kg/s), \( u_3 \) is the opening degree of the steam turbine valve; \( y_1 \) is the main steam pressure (MPa), and \( y_2 \) is the unit power (MW). \( k_0, k_1, k_2, l \) are the static parameters of the model, which can be obtained from the steady-state data of the unit. \( c, c_0, c_1, c_2, d_1, d_2 \) are the dynamic parameters of the model, which can be identified based on the data with severe fluctuations of the unit. \( f(\cdot), h(\cdot), g(\cdot) \) are unknown functions. \( h_{fu} \) is the enthalpy of the feedwater. When the load fluctuates, its change is small, so it is regarded as a constant.

Taking the characteristics of a 1000MW ultra-supercritical DC furnace between 50% load and 100% load as the modeling object, the static and dynamic parameters in formula (1) are identified by using the closed-loop operation history data of the unit. The value is shown as table 1:

| Parameters | Value |
|------------|-------|
| \( k_0 \)  | 19212 |
| \( k_1 \)  | 74554 \((x_1-x_3)^{1.3}\) |
| \( k_2 \)  | 0.00055 |
| \( l \)    | 1.33  |
| \( c_0 \)  | 180   |
| \( c_1 \)  | 1060000 |
| \( h_{fu} \)| 1205  |

Table 1. The value of model Parameters.

3. Feedback-forward-feedback predictive control

3.1. Multi-model predictive control of coordination system

The coordination system is a strong nonlinear system, and the structural parameters of the model vary greatly under different working conditions. In order to improve the control accuracy under multiple working conditions, a coordinated multi-model predictive control scheme is designed on the basis of the above models. The concrete steps are as follows: firstly, the working area of the whole controlled object is divided into n stable working points, and the nonlinear model is linearized by small deviation linearization at each working point, and a more accurate local linearization model is obtained.

Then the predictive controller based on the equation of state is designed according to each linear model. Finally, the "distance" between the actual working point and the controller design working point is calculated in real time, and the calculated results are sorted and weighted. As shown in figure 1, the control input of the controlled object is calculated according to the following formula:
\[ u = \frac{d_{\text{index}+1}}{d_{\text{index}} + d_{\text{index}+1}} u_{\text{index}} + \frac{d_{\text{index}}}{d_{\text{index}} + d_{\text{index}+1}} u_{\text{index}+1} \]  

(2)

where: \(d\) and \(d\) are the nearest and second "distance" between the actual working point and the design working point of each controller, respectively, and \(u\) and \(u\) are the outputs of the corresponding controller.

For the coordinated control system, the "distance" formula is shown in formula (3):

\[ d_i = \sqrt{\left|y_1^{sp} - y_1^i\right| + \left|y_2^{sp} - y_2^i\right| + \left|y_3^{sp} - y_3^i\right|} \quad i = 1, 2, \cdots n \]  

(3)

where: \(y_1^{sp}, y_2^{sp}\) and \(y_3^{sp}\) are the set values of main steam pressure, intermediate point enthalpy, and unit power at the actual operating point; \(y_1^i, y_2^i\) and \(y_3^i\) are respectively the main steam pressure, intermediate point enthalpy, and unit power corresponding to the controller design operating point \(i\).

### 3.2. Design of predictive controller based on state space

Consider the following multiple input and multiple output systems

\[ x(k+1) = Ax(k) + Bu(k) \]

\[ y(k) = Cx(k) \]  

(4)

The constraints are as follows:

\[ u_{\text{min}} \leq u(k) \leq u_{\text{max}} \]

\[ \Delta u_{\text{min}} \leq \Delta u(k) \leq \Delta u_{\text{max}} \]  

(5)

where: \(x \in \mathbb{R}^n, y \in \mathbb{R}^m, u \in \mathbb{R}^n, A \in \mathbb{R}^{nxn}, B \in \mathbb{R}^{nxn}, C \in \mathbb{R}^{mxn}\)

The extended state space forms are as follows:

\[
\begin{bmatrix}
\Delta x(k+1) \\
y(k+1)
\end{bmatrix} =
\begin{bmatrix}
A & 0 \\
CA & I
\end{bmatrix}
\begin{bmatrix}
\Delta x(k) \\
y(k)
\end{bmatrix} +
\begin{bmatrix}
B \\
CB
\end{bmatrix}
\Delta u(k)
\]  

(6)

Abbreviated as:

\[
X'(k+1) = A'X'(k) + B'\Delta u(k)
\]

\[
y(k) = C'X'(k)
\]  

(8)

Further:

\[ \hat{y} = Q_1X'(k) + Q_2\Delta \dot{u}(k) \]  

(9)

where:
In the formula, $P$ is the predictive time domain and $M$ is the control time domain. Considering Quadratic objective function:

$$ V(k) = \|\hat{y}(k) - r(k)\|_Q^2 + \|\Delta u(k)\|_R^2 $$

(11)

Substituting (9) into the above formula gives:

$$ V(k) = \left[ Q_{i}X^{'}(k) - r(k) \right]^{T} Q \left[ Q_{i}X^{'}(k) - r(k) \right] - 2 \left[ Q_{i}X^{'}(k) - r(k) \right] Q Q_{o} \Delta u(k) + \Delta u(k)^{T} \left( R + Q_{o}^{T} Q Q_{o} \right) \Delta u(k) $$

(12)

where: $Q$ is the error weighting matrix and $R$ is the control weighting matrix.

Order $x = \Delta u(k)$, $H = 2 \left( R + Q_{o}^{T} Q Q_{o} \right)$, $c^{T} = 2 \left[ Q_{i}X^{'}(k) - r(k) \right] Q Q_{o}$, Then the upper equation can be transformed into a standard quadratic programming form:

$$ \min f(x) = \frac{1}{2} x^{T} H x + c^{T} x $$

s.t. $Bx \leq d$

(13)

where:

$$ B = \begin{bmatrix} I^{\text{max}}_{\text{min}} & 0 & 0 \ I^{\text{max}}_{\text{min}} & 0 & 0 \ 0 & I^{\text{max}}_{\text{min}} & 0 \ 0 & -I^{\text{max}}_{\text{min}} & 0 \end{bmatrix}, d = \begin{bmatrix} -u(k-1) + u_{\text{max}} \ u(k-1) - u_{\text{min}} \ u_{\text{max}} \ u_{\text{min}} \end{bmatrix} $$

(14)

where $m$ is the dimension that controls the input $u$.

3.3. Predictive control of feedforward-feedback structure

Feedforward compensation is to act directly on the system with the unknown disturbance which can be predicted in advance (for the coordinated control system, the measured disturbance is mainly fuel disturbance), and the system error caused by feedback correction can go through many links before it can act on the object, so feedforward compensation can effectively reduce the delay of the system, and in solving the feedforward compensation problem, the key is on the basis of the original predictive model. The causal information of predictable uncontrollable input that affects the output of the system is included. Therefore, when forming the whole prediction model, on the one hand, the object output pair $\{a_i\}$ of controllable input $u$ should be obtained. On the other hand, it is also necessary to obtain the response sequence $\{b_i\}$ of the output amount to the uncontrollable input amount $v$ with a known law. At each sampling time of the control system, the change in the output value of the object is ultimately caused by the control amount $u$ and the uncontrollable input amount $v$, that is, the total prediction model becomes the following form:

$$ \tilde{y}_{pm}(k) = \tilde{y}_{pu}(k) + A \Delta u_{pu}(k) + B \Delta v_{pu}(k) $$

(15)
where: \( \tilde{y}_{pM} \) is the predicted output value under the action of \( M \) (control time domain) step control quantity, \( y_{p0} \) is the predicted initial value, that is, the current time value.

\[
B = \begin{bmatrix}
  b_1 & \cdots & 0 \\
  \vdots & \ddots & \vdots \\
  b_p & \cdots & b_1
\end{bmatrix}, \Delta v_p = \begin{bmatrix}
  \Delta v(k) \\
  \vdots \\
  \Delta v(k+P-1)
\end{bmatrix}
\]  

(16)

Here \( \Delta v(k) = v(k) - v(k-1) \) is the increment of uncontrollable input \( v \). The output prediction value after one step can be expressed in the form of vector as follows:

\[
\tilde{y}_{p1}(k) = y_{p0}(k) + a\Delta u_M(k) + b\Delta v_p(k)
\]  

(17)

where \( b=(b_1, \ldots, b_N)^T \), \( y_{p1} \) is the prediction output under the action of one-step control quantity.

Without considering the constraints, the optimal control vector can be obtained:

\[
\Delta u_M(k) = \left( A^TQA + R \right)^{-1} A^TQ \left( w_p(k) - y_{p0}(k) - B\Delta v_p(k) \right)
\]  

(18)

The real-time control increments are:

\[
\Delta u(k) = c^T \left( A^TQA + R \right)^{-1} A^TQ \left( w_p(k) - y_{p0}(k) - B\Delta v_p(k) \right)
\]  

(19)

where \( M \) dimension row vector \( c^T=[1 \ 0 \ \ldots \ 0] \) represents the operation to take the first line in a subsequent matrix.

The block diagram of the predictive control algorithm with feedforward compensation is shown in figure 2.

![Figure 2. Block diagram of feedforward-feedback prediction control.](image)

4. Virtual DPU real-time simulation

By developing the corresponding predictive control module in the virtual DPU of Guodian, the stability, rapidity, robustness of the predictive controller and the effectiveness and superiority of the feedforward-feedback predictive control are verified one by one after the configuration is carried out with or without feedforward, fuel quantity disturbance and large-scale variable working condition simulation experiments of the unit, and the stability, rapidity, robustness of the predictive controller and the effectiveness and superiority of the feedforward-feedback predictive control are verified one by one. Each control parameter of predictive control is shown in table 2.

In the table 2, \( P \), \( M \), \( Q \) and \( R \) represent predictive time domain, control time domain, output error weight matrix and control error weight matrix respectively, while \( q_1, q_2, q_3, r_1, r_2 \) and \( r_3 \) are the error weight coefficients corresponding to each output and control quantity, respectively. The matrices \( Q \) and \( R \) are diagonal matrices composed of these coefficients.

From the physical meaning, it can be known that \( M \leq P \), the larger \( P \), the better the system stability, but the dynamic response process becomes slower, and the larger \( M \), the greater the control flexibility, but the stability and robustness of the system become worse; and \( Q \) and \( R \) is the result of multiplying each control quantity and controlled quantity by their weights (the original weighting coefficients are
all 1), so that the initial impact of each coefficient on each variable is consistent, and subsequent debugging is easy to configure.

**Table 2. Multivariable predictive controller parameters.**

| P  | M | Q | R  | q1 | q2       | q3       | r1 | r2 | r3 |
|----|---|---|----|----|---------|---------|----|----|----|
| 10 | 6 | 1 | 0.12 | 0.056537 | 0.001903 | 0.0009952 | 0.4 | 1  | 1  |

4.1. With or without feedforward simulation experiment

With and without feedforward experiments, the load setpoint was reduced from 1004.8MW to 904.8MW, the load drop rate was 30MW / min, and the pressure changed along the slip pressure curve shown in formula (15). Shown in figure 3. And the detailed control effect comparison results are shown in table 3 and table 4.

![Unit response curve of with and without feedforward predictive control.](image)

**Table 3. Comparison of single item performance of No feedforward and feedforward control.**

| Regulating performance | Maximum dynamic deviation | Overshoot |
|------------------------|---------------------------|-----------|
|                         | Ne(MW) |Pt(MPa) |Hm(kJ/kg) | Ne  |Pt  |Ub |
| Without feedforward    | 22.387 |0.529   |1.562     | 10.312% |8.721% |41.021% |
| With feedforward       | 13.586 |0.380   |2.484     | 0.244% |0.890% |18.736% |
**Table 4.** Comparison of comprehensive performance of No feedforward and feedforward control.

| Regulating performance | $Ne$ | $Pt$ | $Hm$ | $K1$ | $K2$ | $K3$ | $Kp$ |
|------------------------|------|------|------|------|------|------|------|
| Without feedforward    | 4349.571 | 108.435 | 318.848 | 1.384 | 1.360 | 0.933 | 1.756 |
| With feedforward       | 2536.725 | 88.757  | 318.163 | 1.495 | 1.051 | 1.558 | 2.448 |

In the table above, $Ne$, $Hm$, and $Pt$ represent the unit power, intermediate point enthalpy, and main steam pressure, respectively; $Ub$, ITAE, and $Kp$ represent fuel quantity command, controlled quantity time and absolute value error integral, and AGC assessment based on two rules. The index adjusts the performance. Each data is the average value of two variable loads. From the data in the table, it can be seen that the coordinated control system has added the intelligent feedforward link on the basis of multivariable predictive control. Significant improvement, the dynamic deviation of unit power and main steam pressure has been reduced by 39% and 28%, respectively, and the overshoot of the fuel amount has also been greatly reduced; the three controlled ITAE indicators have significantly reduced unit power and main steam pressure. The middle enthalpy value is basically unchanged, and the unit's regulating performance $Kp$ is also optimized as a whole; this shows that the addition of the intelligent feedforward link has a significant effect on the control system.

4.2. *Fuel quantity disturbance experiment*

In order to test the robust performance and anti-disturbance performance of the multivariable predictive controller, the verification was performed by adding a random disturbance with a plus or minus 1% on the basis of the fuel output of the multivariable controller. A real-time simulation test was performed under the feed-forward situation, and the simulation results are shown in figure 4.

It can be seen from figure 4 that after the disturbance of the fuel amount is added, the dynamic response of the controlled unit’s power, enthalpy at the intermediate point, and the main steam pressure is still good, and the set value can be tracked well. In steady state, there is a small fluctuation near the set value, and in the absence of feedforward, the maximum fluctuations of unit power, midpoint enthalpy, and main steam pressure are 3.5MW, 0.1Mpa, and 1.1KJ / Kg, respectively. After adding feedforward, the maximum fluctuations are 1.2MW, 0.06Mpa, and 0.6KJ / Kg respectively. It can be seen that although there are small fluctuations in the controlled quantity, they are all within the controllable and acceptable range (1%). At the same time, the anti disturbance ability of the coordinated control system is further enhanced by adding the intelligent feedforward link.
4.3. Large-scale variable working condition experiment

In order to further verify the effectiveness of the algorithm, a comparison is made with the fuzzy gain scheduling (FGS) coordinated control system scheme based on Evolutionary Algorithm in reference Yan [15]. The simulation of the two schemes is aimed at the same DC furnace nonlinear model and under the same working condition, and the simulation effect is shown in figure 5 and figure 6. And the control results of the two algorithms are shown in table 5 and table 6.
Figure 5. Unit response curves of Feedforward predictive control for large-scale variable-load.

Figure 6. Unit response curves of Fuzzy gain scheduling large-scale variable load.
Table 5. Comparison of single effects between feedforward-feedback predictive control and fuzzy gain scheduling control.

| Regulating performance | Maximum dynamic deviation | Overshoot |
|------------------------|----------------------------|-----------|
|                        | Ne(MW) | Pt(MPa) | Hm(kJ/kg) | Ne | Pt | Ub |
| SMPC                   | 14.346 | 0.537   | 2.785     | 0.271% | 0.934% | 19.414% |
| FGS                    | 34.627 | 0.411   | 24.738    | 10.257% | 1.461% | 34.544% |

Table 6. Comparison of comprehensive effects between feedforward-feedback predictive control and fuzzy gain scheduling control.

| Regulating performance | ITAE | AGC assessment |
|------------------------|------|----------------|
|                        | Ne   | Pt            | Hm           | K1   | K2     | K3   | Kp  |
| SMPC                   | 2465.854 | 176.482 | 336.323 | 1.488 | 1.049 | 1.567 | 2.446 |
| FGS                    | 6328.735 | 121.674 | 1523.197 | 1.356 | 1.021 | 0.972 | 1.346 |

The meaning of each variable in the table is the same as that in table 3 and table 4, and each data is the average value of eight times of variable load. It can be seen from the data in the table that under the condition that the simulation time of each stage is the same, both the fuzzy gain scheduling algorithm and the multivariable predictive control algorithm have achieved good control effect, but compared with that, the overall effect of feedforward feedback multivariable predictive control is better, except for the main steam pressure which he maximum dynamic deviation of force under fuzzy gain scheduling is 0.12mpa less than that under predictive control, and the effect of predictive control in other aspects is better, especially the overshoot of control quantity and controlled quantity and the response time of unit, which further shows that the feedforward feedback predictive control algorithm is effective.

5. Conclusion

In view of the nonlinear and strong coupling characteristics of the coordinated control system of the once through boiler unit, a multivariable feedforward feedback predictive control scheme is designed by combining the traditional feedforward control and decoupling control concepts. The principle and feasibility of the feedforward link are analyzed. The real-time simulation results show that the designed control scheme accelerates the system response, improves the anti disturbance ability and output stability. The stability and robustness of the coordinated control system ensure the safe and stable economic operation.

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