

AUTOMATIC CONTROL SYSTEM OF BOILER THERMAL ENERGY IN THERMAL POWER PLANT BASED ON ARTIFICIAL INTELLIGENCE TECHNOLOGY

by

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Thermal processes tend to have large inertia and hysteresis, non-linearity, and slow time-varying. Therefore, the fixed-parameter proportional integral derivative conventional regulation system cannot meet the higher and higher control requirements in production. Based on this research background, the paper proposes an automatic control method for thermal boiler steam based on artificial intelligence technology. Through the real-time monitoring of the boiler, the state monitoring method is used to estimate the influence factors of the boiler, and the estimated error output is artificially supplemented to realize the accurate control of the boiler. After being put on the market, it is found that the control method proposed in the article can overcome the randomness and inertia of the temperature and accurately realize the temperature control of the boiler. Moreover, compared with the traditional proportional integral derivative control, this method is more effective.

Key words: automatic control, circulating fluidized bed boiler, thermal energy, artificial intelligence technology, thermal power plant

Introduction

Circulating fluidized bed boiler (CFBB) has the advantages of high combustion efficiency, less pollution, and wide adaptability and has been widely studied and applied at home and abroad. At present, domestic CFBB still has many urgent problems in automated control technology. The CFBB central steam temperature has non-linearity characteristics, large inertia, time-varying parameters, and large hysteresis, making it difficult for conventional cascade proportional integral derivative (PID) control schemes to achieve ideal control effects. When the load conditions change significantly, the characteristics of the CFBB main steam temperature object vary greatly. The conventional control scheme cannot quickly adapt to the drastic changes in the dynamic characteristics of the controlled object, and it is difficult to realize the full control of the CFBB main steam temperature. Because of this, the author is based on active disturbance rejection control (ADRC). The basic idea is to propose a CFBB main steam temperature auto disturbance rejection control scheme.

The ADRC was first proposed by Han [1], a researcher at the Institute of Systems Science of the Chinese Academy of Sciences in the late 1980's. Its most prominent feature is that all the uncertain effects on the controlled object are attributed to *unknown disturbances*. The extended state observer (ESO) uses the input and output data of the object to estimate and compensate for the *unknown disturbance*, to realize the control of the uncertain object [1].

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The CFBB main steam temperature transition process arrangement

In practical applications, we usually use tracking differentiators based on optimal control theory. However, for high-order objects such as CFBB main steam temperature, it is very difficult if we apply optimal control theory to design a tracking differentiator. This limits the application of ADRC in high-level system control. Therefore, we use a high-order inertia link as shown in eq. (3) as a flexible link to design the transition process of the main steam temperature object. Therefore, referring to selecting of the expected dynamic equation in the non-linear inverse control system, we use a high order inertia link as shown in eq. (3) as the flexible link to arrange the transition process of the main steam temperature object:

$$M(s) = \frac{V(s)}{K(s)} = \frac{\omega^2}{s^2 + 2\xi\omega s + \omega^2} \left[\frac{T\omega(n-2)}{s + T\omega(n-2)} \right]^2 \tag{3}$$

where $M(s)$ is the transfer function of the flexible link, T – the dynamic characteristic parameter, $V(s)$, $R(s)$ – the Laplace transform of the output $v(t)$ of the flexible link and the given input $r(t)$, respectively, n – the order of the controlled object, ξ – the damping ratio, and ω – the angular frequency.

The time domain expression of this flexible link:

$$v^{(n)} + k_1 v^{(n-1)} + k_2 v^{(n-2)} + \dots + k_{n-1} v^{(1)} + k_n v = kr(t) \tag{4}$$

Them among:

$$\begin{aligned} k_1 &= C_{n-2}^1 [T\omega(n-2)] + 2C_{n-2}^0 \xi\omega \\ k_i &= C_{n-2}^i [T\omega(n-2)]^i + 2C_{n-2}^{i-1} \xi\omega [T\omega(n-2)]^{i-1} + C_{n-2}^{i-1} \omega^2 [T\omega(n-2)]^{i-2}, \quad i = 2, 3, \dots, n-2 \\ k_{n-1} &= 2C_{n-2}^{n-2} \xi\omega [T\omega(n-2)]^{n-2} + C_{n-2}^{n-3} \omega^2 [T\omega(n-2)]^{n-3} \\ k_n &= k = \omega^2 [T\omega(n-2)]^{n-2} \end{aligned} \tag{5}$$

Therefore, the output of the transition process of the flexible link arrangement and the output of each order derivative are:

$$\begin{aligned} \dot{v}_1 &= v_2 \\ \dot{v}_2 &= v_3 \\ &\vdots \\ v(n) &= kr(t) - k_1 v^{(n-1)} - k_2 v^{(n-2)} - \dots - k_{n-1} v^{(1)} - k_n v \end{aligned} \tag{6}$$

In this way, on the premise of meeting actual engineering needs, the transition process arrangement is conveniently solved. From eq. (3), the main parameters that affect the output of flexible link M are T , ξ , and ω . Parameter T affects the speed of the transition process, ξ affects the shape of the step response transition curve, and ω directly determines the speed of the step response process, thereby determining the tracking performance and softening effect of M . According to the dynamic characteristics of the CFBB main steam temperature object and the control target requirements, we take M the order of is the order of the transfer function of the inertia zone of the main steam temperature object, that is, $n = 5$, and the other parameters are $T = 9$, $\xi = 0.9$, $\omega = 0.01$, so that the transition of M arrangement can be obtained the process is shown in fig. 2.

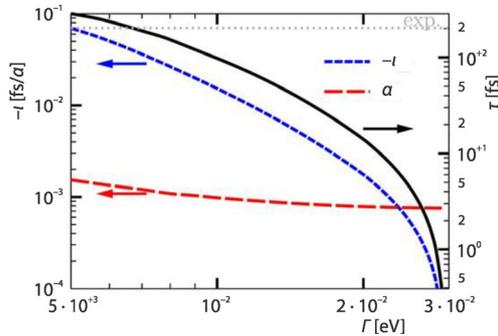


Figure 2. The transition process of high order inertial link arrangement

known, $u(t)$ – the leading steam temperature object, b – the coefficient of the input variable, and $x, \dots, x^{(n-1)}$ – the state variable of the main steam temperature object:

$$x_1 = x, \quad x_2 = x', \dots, x_n = x^{(n-1)} \quad (8)$$

The state space equation of the main steam temperature object:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= x_3 \\ &\vdots \\ \dot{x}_n &= f(x_1, \dots, x_n, t) + \omega(t) + bu(t) \end{aligned} \quad (9)$$

This can build a state observer:

$$\begin{aligned} \dot{z}_1 &= z_2 - l_1 g(z_1 - x) \\ \dot{z}_2 &= z_3 - l_2 g(z_1 - x) \\ &\vdots \\ \dot{z}_n &= z_{n+1} - l_n g(z_1 - x) + bu(t) \\ z_{n+1} &= -l_{n+1} g(z_1 - x) \end{aligned} \quad (10)$$

where l_n is the coefficient in the non-linear ESO and $g(\bullet)$ – the non-linear function. The paper uses $a(t)$ to represent the unmodeled dynamic characteristics and unknown disturbances of the main steam temperature object:

$$a(t) = f(x_1, \dots, x_n, t) + \omega(t) \quad (11)$$

According to the state observer theory, as long as the appropriate non-linear function $g(z)$ is selected, the state variables of the state observer can track the corresponding state variables of the system and the external disturbance $a(t)$. Using non-linear ESO to analyze the unmodeled dynamic characteristics and $a(t)$. After estimation, it can be compensated during the control process, thereby improving the regulation quality and robustness of the control system [5]. To facilitate the tuning of the coefficient l_1, l_2, \dots, l_{n+1} in the non-linear ESO, we take:

$$l_i = \frac{m_i}{g'(z)} \quad (12)$$

The CFBB main steam temperature object ESO design

Assuming that the CFBB main steam temperature object adopts a non-linear differential equation, it can be expressed:

$$\dot{x}^{(n)} = f[x, \dots, x^{(n-1)}, t] + \omega(t) + bu(t) \quad (7)$$

where $f[x, \dots, x^{(n-1)}, t]$ is a non-linear time-varying function composed of the state variables of the main steam temperature object of CFBB, its exact model is unknown, $\omega(t)$ – the external disturbance of the main steam temperature object, and its dynamic characteristics are unknown,

$u(t)$ – the leading steam temperature object, b – the coefficient of the input variable, and $x, \dots, x^{(n-1)}$ – the state variable of the main steam temperature object:

Convert eq. (10) into:

$$\begin{aligned}
 \dot{z}_1 &= z_2 - \frac{m_1}{g'(z_1-x)} g(z_1-x) \\
 \dot{z}_2 &= z_3 - \frac{m_2}{g'(z_1-x)} g(z_1-x) \\
 &\vdots \\
 \dot{z}_n &= \dot{z}_{n+1} - \frac{m_n}{g'(z_1-x)} g(z_1-x) + bu(t) \\
 \dot{z}_{n+1} &= -\frac{mn+1}{g'(z_1-x)} g(z_1-x)
 \end{aligned} \tag{13}$$

The coefficient m_1, m_2, \dots, m_{n+1} can form a matrix \mathbf{A} :

$$\mathbf{A} = \begin{bmatrix} -m_1 & 1 & 0 & \dots & 0 \\ -m_2 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -m_n & 0 & 0 & \dots & 1 \\ -m_{n+1} & 0 & 0 & \dots & 0 \end{bmatrix} \tag{14}$$

Assuming that the expected pole of the state observer shown in eq. (13) is p_1, p_2, \dots, p_{n+1} , the parameter $m, m_1, m_2, \dots, m_{n+1}$ should satisfy:

$$|sI - \mathbf{A}| = \prod_{i=1}^{n+1} (s - p_i) \tag{15}$$

Therefore, as long as the expected poles of the state observer are specified, we expand the left and right sides of eq. (15) into polynomials of s , respectively, and then make the coefficients of the corresponding terms equal. The value of the coefficient m_1, m_2, \dots, m_{n+1} can be determined to realize the non-linear expansion state observer [6]. Aiming at the main steam temperature object of CFBB, the paper uses 6-order ESO to estimate the five states x_1-x_5 and the unknown dynamic characteristics and external disturbance, (t) , of the object. Suppose the expected pole of ESO is 6. Heavy pole -5 , the tuning parameters can be obtained: $m_1 = 30, m_2 = 375, m_3 = 2500, m_4 = 9375, m_5 = 18750$, and $m_6 = 15625$. To test the performance of the non-linear ESO for the main steam temperature object at 100% load. We can get six states z_1-z_6 of the non-linear ESO, five states x_1-x_5 of the object, and unknown dynamic characteristics and external disturbance $a(t)$, as shown in fig. 3. So visible, ESO can achieve good observation and tracking of the state of the CFBB main steam temperature object and the unknown dynamic characteristics and external disturbances.

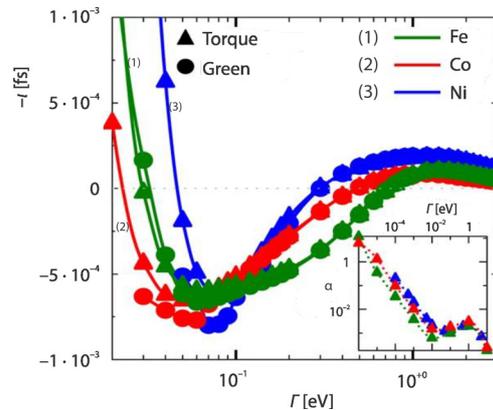


Figure 3. The state curve of ESO to CFBB main steam temperature object

The CFBB primary steam temperature status error feedback control

We adopt the compensation law for the CFBB main steam temperature object described by non-linear differential eq. (7):

$$u = u_0 - \frac{z_{n+1}}{b} \quad (16)$$

where u_0 is the output of the non-linear state error feedback controller. Since ESO has estimated the uncertain object and unknown external disturbance $a(t)$ as z_{n+1} , we can transform the eq. (9) into:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= x_3 \\ &\vdots \\ \dot{x}_n &= xu_0 \end{aligned} \quad (17)$$

The output:

$$y = x_1 \quad (18)$$

Therefore, we can use the state error feedback method to design the controller, and the non-linear state error feedback control law obtained:

$$u_0 = \sum_{i=1}^n q_i h(v_i - z_i) \quad (19)$$

where $v - z_i$ is the transition process of the softening link arrangement and the difference between its derivatives and the object state variables observed by ESO, $h(x)$ – the non-linear function, and q_i – the corresponding coefficient [7]. By appropriately selecting the value of q_i , you can make the controller have good dynamic performance and robustness.

Simulation experiment and analysis

To test the performance of the ADRC system in tracking the main steam temperature command signal, the paper added a unit step signal to the main steam temperature command signal input terminal to investigate the rapidity, accuracy and robustness of the system in tracking the given value [8].

Simulation under 100% load condition

To fully use of the advantages of cascade control, the CFBB central steam temperature regulation system still adopts a cascade structure. Since the main regulator adopts an active disturbance rejection controller, there is currently no effective method for determining the parameter setting of the state error feedback controller [9]. Therefore, combined with the simulation experiment, the paper gives the coefficients of the non-linear state error feedback controller: $q_1 = 450$, $q_2 = 27000$, $q_3 = 1.65 \times 10^6$, $q_4 = 2.35 \times 10^7$, $q_5 = 2.35 \times 10^8$. The secondary regulator P adopts a pure proportional regulator, and the proportional coefficient is $kp_2 = 8$. For comparison, the traditional proportional-integral derivative-proportional (PID-P) cascade control simulation experiment is performed on the CFBB central steam temperature control system at the same time. The parameter is the recommended value. The proportional coefficient of the auxiliary regulator, P , is $kp_2 = 8$. The PID parameter value of the principal regulator is $kp_1 = 3.4$, $ki_1 = 0.084$, and $kd_1 = 227$.

The simulation results are shown in fig. 4. It can be seen that the traditional PID-P control has significant overshoot and large oscillation. The ADRC-P control scheme proposed in this article can achieve fast and accurate tracking when the primary steam temperature command signal changes stepwise. With a slight overshoot, the control quality is good.

Simulation under other load conditions

To test the adaptability of the ADRC to the dynamic characteristics of the controlled object, the parameters of the ADRC controller and the PID controller are kept unchanged. Thus, the ADRC-P control scheme and the PID-P control scheme are 60% and 110%. A unit step experiment of a given value is carried out under load conditions, and the results are shown in fig. 5 and 6. Comparing figs. 4-6 shows that when the dynamic characteristics of the object change significantly. The ADRC-P control scheme can use non-linear expansion observer to estimate the change of the object characteristics and compensate, so the control quality is almost not attenuated. In contrast the control quality of the conventional PID-P control scheme deteriorates sharply, and it is difficult to meet the control requirements [10].

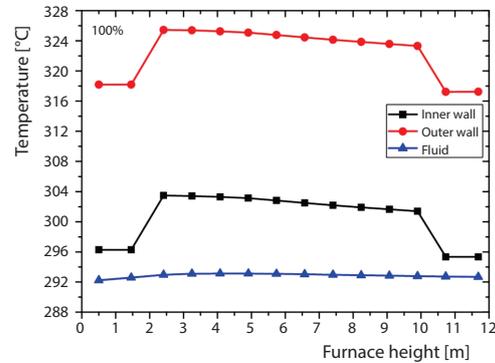


Figure 4. The simulation curve of main stream temperature at 100% load

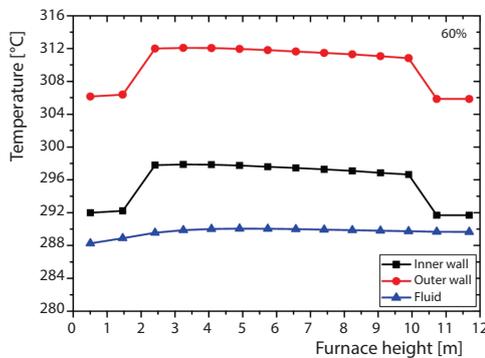


Figure 5. Simulation curve of main stream temperature at 60% load

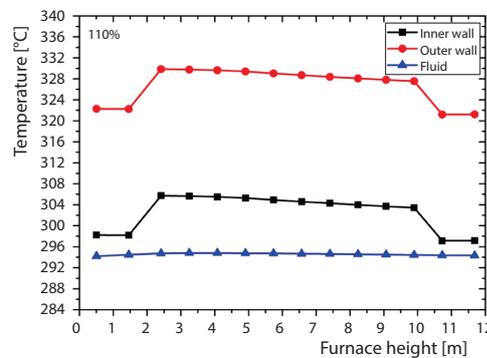


Figure 6. Simulation curve of main stream temperature at 110% load

Conclusion

Based on the basic idea of ADRC, the paper proposes a CFBB main steam temperature ADRC control scheme. This control scheme does not need to know the precise model of the CFBB main steam temperature object, and realizes the unknown, uncertain and external control of the controlled object by designing an expanded state observer. Disturbance estimation. Through the high order inertia link to arrange the transition process, we use non-linear state error feedback technology to achieve precise control of the main steam temperature object. The simulation results show that the CFBB central steam temperature ADRC control scheme proposed in the paper can be used in the controlled object. When the dynamic characteristics change significantly, it can achieve good tracking of the given value, the control quality is excel-

lent, and it has strong robustness. The proposed ADRC algorithm only uses the nominal model information of the object, and does not require an accurate model of the controlled object. Engineering application value provide a solution for non-linear object control with time-varying dynamic characteristics, unknown external disturbances, and difficult to accurately model.

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