Adaptive PID Control of Coal Feeder Based on Single Neuron

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Abstract. The coal feeder system is a part of coal conveying system of thermal power plant, which is mainly used for supplying coal to the boiler. During the operation of the coal feeder control system, the coal feeding rate is controlled according to the set value and the feedback information from the system, which makes the amount of coal sent to the boiler match the amount of coal needed, so as to achieve ideal economic benefits. In order to control the coal feeding quantity more accurately, for the time variability, hysteretic and other features of coal feeder, the coal feeder system model is built, and a single neuron adaptive PID method is proposed innovatively. The simulation results indicate that, compared with the conventional PID control, the method presented in this paper has small steady-state error, quick dynamic response and low overshoot.

Introduction

Coal feeder is an important auxiliary equipment in coal-burning boiler heating system. In the process of system operation, the coal feeder system needs to control the coal feeding rate in time according to the comparison and analysis between the set coal amount sent to the boiler and the coal amount collected in real time to achieve accurate control of the coal amount, which can save resources, reduce energy consumption and reduce waste [1]. In order to control the coal quantity accurately, the algorithm that has stronger robustness needs to be adopted. At the present, the conventional PID algorithm is used in the coal feeder system. For the actual operation, the coal feeder control system has some features such as non-linear, time-varying uncertainty and pure hysteresis. This requires PID to have the ability of self-regulation. However, in the conventional PID algorithm, once the parameters are determined, they cannot be changed [2-3]. In neural network control, single neuron has the ability of self-learning and self-adaptation. Combined with the conventional PID, the single neuron PID can adjust its parameters online[4-6]. Experimental results show that the single neuron PID which is applied to the coal feeder system can achieve more control effect.

Establishment of Coal Feeder System Model

Control Principle of Coal Feeder System

In Fig. 1, the weighing principle of coal feeder is presented. The weighing sensor collects the belt (whose length is $l$) weight load signal in real time and feeds it back to PLC. At this time, the central processing unit of PLC processes the collected belt load signal and motor speed signal to obtain accurate real-time coal feeding rate and accumulated total coal feeding amount. After comparing the accumulated total coal feeding amount with the set total coal amount, PID calculation is carried out to adjust the driving motor’s velocity, so as to achieve accurate control of total coal amount.
The total coal feeding amount can be calculated by the following method.

Let the time taken for the coal to transport from $s_0$ to $s_1$ be $T$. The weight $q(kg/m)$ of unit length in the belt is multiplied by the speed $v(ms^{-1})$ of coal, and the total coal feeding amount $W$ can be obtained by integrating the time $t(s)$.

$$W = \int_{s_0}^{s_1} qdx.$$  \hfill (1)

Since $dx = vdt$, and the equation (1) can be converted into

$$W = \int_0^T qvdt.$$  \hfill (2)

**Transfer Function of Coal Feeder System.** The motor speed ($n$) and instantaneous coal flow ($Q$) on the electronic scale in different times are shown in Table 1.

| $t(s)$ | 100  | 600  | 1100 | 1600 | 2100 | 2600 | 3100 |
|-------|------|------|------|------|------|------|------|
| $Q(t/s)$ | 0.148 | 0.165 | 0.181 | 0.197 | 0.216 | 0.244 | 0.265 |
| $n(r/s)$ | 15 | 20 | 25 | 30 | 35 | 40 | 45 |

Curve fitting is performed on the data in Table 1, and the relationship between instantaneous coal flow $Q(t)$ and motor speed $n(t)$ in different times is obtained as shown below.

$$Q(t) = K_1n(t).$$  \hfill (3)

where $K_1 \approx 0.0039$. It can be seen from the equation (3) that the instantaneous coal flow $Q$ and motor speed $n$ can be approximately linear.

In addition, the motor speed of the coal feeder can be controlled by adjusting the frequency of the transducer, and the relationship between motor speed $n(t)$ and frequency of the transducer is shown below.

$$n(t) = K_2f(t).$$  \hfill (4)

where $K_2 = (1 - S_0)/p$; $f(t)$ is the frequency of the transducer; $p = 2$ is the number of pole pairs for the motor; $S_0 = 6\%$ is the slip of the motor.

Based on the relationship among $Q(t)$, $n(t)$ and $f(t)$, the coal feeder structure is shown in Fig. 2.
In Fig. 2, \( C(t) \) is the cumulative output value of the actual coal flow, and \( R(t) \) is given value of coal flow. Since \( Q(t) \) represents the instantaneous coal flow value, a proportional-integral link \( K_0/s \) needs to be added between \( Q(t) \) and \( C(t) \).

\[
G(s) = \frac{C(s)}{R(s)} = \frac{1}{s/K_1K_2K_0 + 1} = \frac{1}{T_0s + 1}.
\]  \hspace{1cm} (5)

where \( T_0 = \frac{1}{K_1K_2K_0} \approx 200 \).

There is a certain distance between the coal feeder and belt weigher in coal conveying system. When the motor's speed changes, the weighing sensor of the belt weigher cannot transfer the belt load signal to PLC in time. Therefore, the coal feeder control system has the time delay, and its delay time is 22s. The equation (5) with delay time is expressed as follows.

\[
G(s) = \frac{1}{T_0s + 1} e^{-\tau s}.
\]  \hspace{1cm} (6)

where \( \tau \) is 22s.

**Single Neuron Adaptive PID Algorithm**

**Classic PID Algorithm**

In the actual coal feeder control system, the coal feeding rate is usually controlled by conventional PID, which makes the amount of coal sent to the boiler match the amount of coal needed. The principle of conventional PID control algorithm is shown in Fig. 3.

![Figure 3. The principle of conventional PID control algorithm](image)

In Fig. 3, \( \text{in}(t) \) is input value, and \( \text{out}(t) \) is the output value. The system error is shown below.

\[
\text{err}(t) = \text{in}(t) - \text{out}(t).
\]  \hspace{1cm} (7)

PID control law is

\[
u(t) = k_p \text{err}(t) + k_i \int_0^t \text{err}(t) dt + k_d \frac{d\text{err}(t)}{dt}.
\]  \hspace{1cm} (8)

\( k_p, k_i, k_d \) represent proportional coefficient, integral time constant and differential time constant. For classic PID, once \( k_p, k_i, k_d \) are identified, they cannot be changed again, which lacks self-learning and adaptive ability.
Single Neuron PID Algorithm

Combining the classic PID with single neuron effectively can solve the problem of difficult parameter setting of conventional PID controller, which is called single neuron PID. It has the ability of self-learning and self-adaptation, and its control structure is shown below.

\[ u(k) = u(k-1) + K \sum_{i=1}^{3} a_i(k) x_i(k). \]  (9)

where \( a_i(k) \) is the weight coefficient corresponding to \( x_i(k) \), and \( x_i(k) \) is defined as

\[ \begin{cases} 
    x_1(k) = in(k) - out(k) \\
    x_2(k) = \Delta err(k) = err(k) - err(k-1) \\
    x_3(k) = err(k) - 2err(k-1) + err(k-2)
\end{cases} \]  (10)

In order to make the neural PID have the ability of self-adjustment, this paper adopts supervised Hebb learning rules to regulate the weighted coefficient \( a_i(k) \).

\[ a_i(k+1) = (1-c) a_i(k) + \eta v_i(k). \]  (11)

\[ v_i(k) = z(k) u(k) x_i(k). \]  (12)

where \( v_i(k) \) is the progressive signal; \( \eta \) is the learning rate (\( \eta > 0 \)); \( c \) is constant (\( 0 \leq c < 1 \)). The equation (12) is substituted into the equation (11), then

\[ \Delta a_i(k) = a_i(k+1) - a_i(k) = -c \left[ a_i(k) - \frac{\eta}{c} z(k) u(k) x_i(k) \right]. \]  (13)

It assumes that there is a function \( f_i(a_i(k), z(k), u(k), x_i(k)) \), then the partial differential for \( a_i(k) \) is calculated as

\[ \frac{\partial f_i(\cdot)}{\partial a_i(k)} = a_i(k) - \frac{\eta}{c} z(k) u(k) x_i(k). \]  (14)

We can abbreviate the equation (13) as

\[ \Delta a_i(k) = -c \frac{\partial f_i(\cdot)}{\partial a_i(k)}. \]  (15)
The whole learning algorithm is normalized to obtain

$$u(k) = u(k-1) + K \sum_{i=1}^{3} \bar{a}_i(k)x_i(k).$$  \hspace{1cm} (16)$$

$$\bar{a}_i(k) = a_i(k) / \sum_{i=1}^{3} |a_i(k)|.$$  \hspace{1cm} (17)$$

$$a_i(k+1) = a_i(k) + \eta_p z(k)u(k)x_i(k)$$

$$a_2(k+1) = a_2(k) + \eta_i z(k)u(k)x_2(k).$$  \hspace{1cm} (18)$$

$$a_3(k+1) = a_3(k) + \eta_d z(k)u(k)x_3(k).$$

Where $\eta_p$, $\eta_i$ and $\eta_d$ are the learning rates of proportionality coefficient, integration coefficient and differential coefficient, and they are used to adjust different weights. The choice of $K$ affects the stability of the system.

**Simulation Results**

The model of coal feeder control system with delay time is

$$G(s) = \frac{1}{T_0s + 1} e^{-\tau s}.$$  \hspace{1cm} (19)$$

where $T_0 \approx 200$, $\tau = 22s$.

In order to fully verify that the control performance of single neuron PID, it is compared with the conventional PID. The response curves are shown in Fig. 5, and the comparison of performance parameters is shown in Table 2.

![Figure 5. The response curves of two algorithms](image)

**Table 2. Comparison of performance parameters**

|                  | Conventional PID | Single neuron PID |
|------------------|------------------|-------------------|
| Risetime         | 9.5s             | 7s                |
| Overshoot        | 19.6%            | 2.5%              |
| Regulating time  | 44s              | 10s               |

In Fig. 5 and in Table 2, compared with the traditional PID, the overshoot of the single neuron PID is smaller, and it can reach the target value in a short time and tend to be stable. When the system
tends to be stable \( (t = 90s) \), the disturbance is applied to the coal feeder system, and the anti-interference effects of the two algorithms are shown in Fig. 6.

![Conventional PID vs Single neuron PID](image)

**Figure 6. The anti-interference effects of two algorithms**

In Fig. 6, the single-neuron PID has stronger self-learning and self-adaptive ability. After the disturbance occurs, it can stabilize to the target value at a faster speed, and its overshoot is also smaller.

**Summary**

Aiming at the problem of coal quantity control for the coal feeder, this paper proposes an algorithm of coal quantity control based on single neuron PID. Simulation results show that the coal quantity of the coal feeder can reach the target coal quantity quickly and tend to be stable without big fluctuation by using the method proposed in this paper. This method has small overshoot, strong anti-interference performance and better control effect.

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