Fuzzy Control Method Based on Dynamic Self-optimization

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Abstract. The most commonly used in industrial control is the digital PID control method. For most control objects, the use of digital PID control can achieve satisfactory control results. But in the ball mill controller, the PID control will produce time lag effect, resulting in decision-making mistakes. This paper designs a fuzzy control method based on dynamic self-optimization, which can use the sensitive output of the controlled process as the input of the fuzzy controller in the fuzzy control loop, and the output of the fuzzy controller is the adjustment value of the controlled system. Input. Another input of the fuzzy controller is the set value input. The simulation results show the effectiveness of this method.

Keywords: Dynamic self-optimization · PID · Fuzzy control

1 Introduction

The fuzzy controller of the ball mill is a controller with a single input-single output structure. The input is the vibration signal on the rear shaft of the ball mill detected by the vibration transmitter, and the output control value is converted into a 0–10 mA direct current after D/A conversion to act on the vibrating coal feeder. The commonly used PID method has poor control performance and poor effect[1–3]. The dynamic self-optimization proposed in this paper can start self-optimization after the system enters the steady state (entering the 5% error band), increase the given R, and wait for the system to approach again after the steady state, check the value of the vibration signal change and repeat the above steps. After several adjustments, the system can run stably near the maximum output point, ensuring that the ball mill always runs near the maximum output point, which really has the effect of energy saving[4, 5].

2 Control Strategy

For objects with pure hysteresis characteristics, there are Smith predictive control algorithm and Darling algorithm to choose from. But Smith predictive control needs to know the mathematical model of the controlled object to construct the compensation function.

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If the mathematical model of the controlled object is not accurately identified, it will have a great impact on the control effect.

The basic block diagram of Smith predictive control algorithm can be shown in Fig. 1. In the figure, it is the transfer function of the controller, the transfer function of the controlled object, the Smith compensation function, and

$$G_L(s) = G_0(s) \cdot \left(1 - e^{-\tau s}\right) \tag{1}$$

If the transfer function of the controlled object is known, the compensation function can be constructed according to the above formula. The transfer function is the simulation result obtained by applying the Smith predictive control shown in Fig. 1 to the object shown in formula (1).

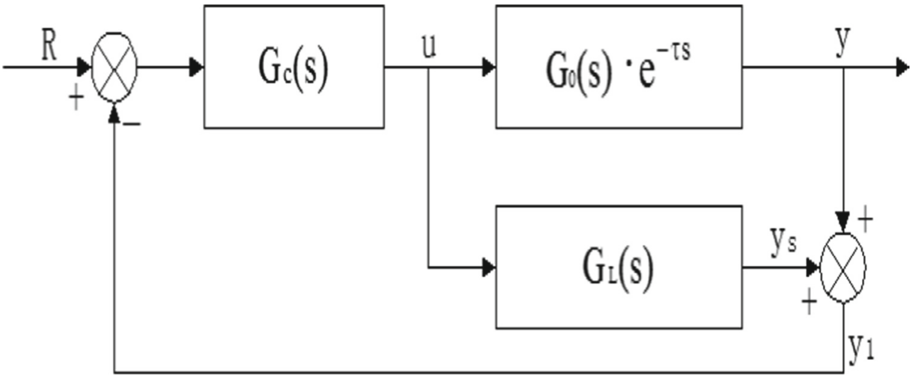

Fig. 1. Smith predictive control block diagram

3 Self-optimization-Fuzzy Cntroller

As the number of inputs of the fuzzy controller increases, the control rules that need to be established will increase exponentially. For example, for a two-dimensional fuzzy controller, assuming that each input variable takes 7 linguistic values, there are only 7 × 7 = 49 control rules, but for a three-dimensional fuzzy controller, the control rules will reach 7 × 7 × 7 = 353. For complex systems, the establishment of control laws (knowledge accumulation) is very difficult. The exponential growth of the control law greatly increases the workload of controller design [6, 7].

$$\mu_{ZR}(x) = \begin{cases} 0 & -80 \le x < -10 \\ \frac{x+10}{10} & -10 \le x < 0 \\ \frac{10-x}{10} & 0 \le x < 10 \\ 0 & 10 \le x < 80 \end{cases} \tag{2}$$

Fuzzy language value is actually a fuzzy subset, which is finally described by a membership function defined in a certain universe. Therefore, it is necessary to determine the scope and membership function of the universe of discourse. According to the graph of each membership function, its mathematical expression can be written. For example, for the deviation, the membership function of the fuzzy subset ZR is[8–10]:

$$\mu_{NB}(x) = \begin{cases} 1.0 & -100 \le x < -75 \\ -\frac{x+50}{25} & -75 \le x < -50 \\ 0.0 & -50 \le x < 100 \end{cases} \tag{3}$$

The continuous realization of fuzzy control means that the input of the controller does not need to be discrete first, but is directly sent to the fuzzy controller realized by the software, and the fuzzy theory is carried out according to the fuzzy theory, fuzzy inference and defuzzification, and the control is calculated online by the program The system has high precision and versatility, as shown in Fig. 2. To illustrate the implementation steps of fuzzy inference in continuous implementation, take two control rules in the fuzzy controller of a ball mill as an example:

if e = PS and e = ZR then u = NS

or if e = PM and e = PS then u = NM

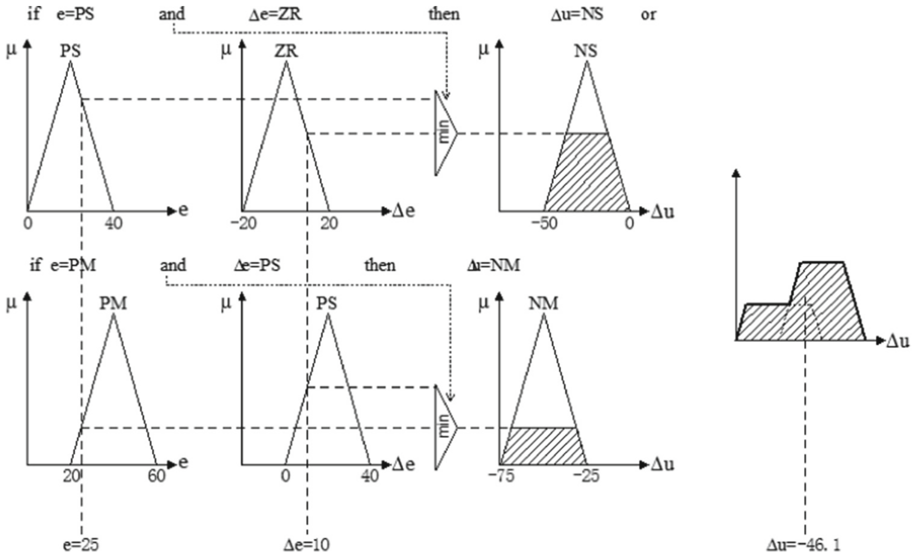

Fig. 2. Continuous realization of fuzzy controller

Finding the best working point of the ball mill depends on the in-depth analysis of the working characteristics of the ball mill. The vibration signal decreases as the amount of coal in the ball mill increases. For convenience, the vibration signal is simply processed in the vibration transmitter, that is, the actual measured vibration signal value is subtracted from a fixed value, so that the decreasing vibration characteristic curve becomes an increasing curve. At this time, A large vibration signal indicates a large amount of coal stored in the ball mill.

4 Simulation Analysis

The ball mill self-optimizing-fuzzy controller designed in this paper has been installed and debugged on site, and has been put into actual production and operation in the power plant. In the measurement of the amount of coal in the ball mill, a large amount of data was measured in the power plant, and it was found that when the acceleration sensor was installed on the front shaft of the ball mill, there were many spikes in the signal from the transmitter. A typical curve is shown in Fig. 3. The abscissa in the figure is the running time, and the ordinate is the output m_A value of the vibration transmitter. It can be seen from Fig. 3 that before t1 and after t4, the output value of the transmitter is relatively small, indicating that the amount of coal stored in the ball mill is small; during this period of time between t2 and t3, the transmitter The output value of the device is relatively large, indicating that the amount of coal stored in the ball mill during this period is relatively large.

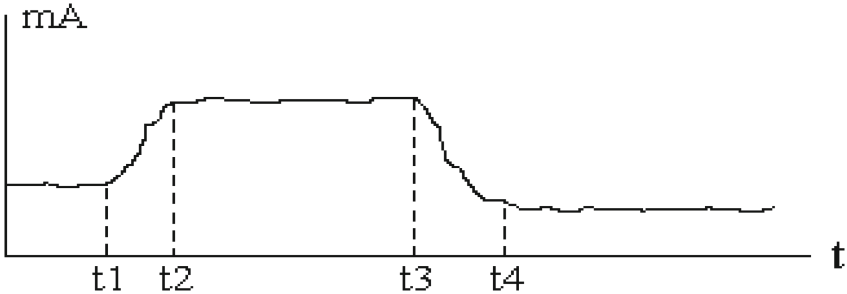

Fig. 3. The output waveform of the vibration transmitter when the acceleration sensor is installed on the front axle

The result has an impact. However, the ball mill in Yan'an Power Plant is relatively small, so this interference signal is clearly reflected in the measurement results. If the acceleration sensor is moved to the rear axle of the ball mill, this phenomenon can be avoided. The measured curve is shown in Fig. 4.

Fig. 4. The output waveform of the vibration transmitter when the acceleration sensor is installed on the rear axle

5 Conclusion

The intelligent optimization and energy-saving controller of the ball mill finally adopts self-optimization-fuzzy control. Because its energy-saving effect takes a long period of operation to be reflected, it is not appropriate to directly analyze the operating curve, and it is better to use statistical data to illustrate the problem. Through practical tests, the controller has obvious energy-saving effects and can produce good economic benefits.

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