Identification and Control of Elongation System of Skin Passing Mill Based on Intelligent Algorithm

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Abstract: In view of the nonlinear, time-varying and time-delay characteristics of elongation control system of skin pass mill, according to analysis of the mechanism model of elongation control system of skin pass mill, BP neural network was used to identify the structural parameters of the model. With reference to the regulating function of biological immune system and the function of fuzzy reasoning logic which can approach nonlinear function, a fuzzy immune PID control strategy was proposed to improve the elongation control accuracy of skin pass mill combining fuzzy control and immune feedback mechanism with traditional PID control. The simulation results show that the control strategy has the advantages of small overshoot, fast response, strong anti-interference ability and robustness, and the control effect is better than the traditional control method.

1. Introduction
In the cold rolling process, the flattening technology of continuous annealing production line is the key process to ensure the final product performance and surface quality. The most important process of skin passing mill is the elongation control of the strip, which is used to eliminate the shape defects of cold rolled strip such as wave shape and warpage, improve the quality of products and the mechanical properties of strip[1].

The elongation control system of skin passing mill is a typical double loop control system[2], in which the rolling force control system is the inner loop control system, and the elongation control system is the outer loop control system. The output of elongation regulator is used as additional set value of rolling force, and the elongation is controlled by changing the rolling force, so as to eliminate the influence of various factors on elongation control. The elongation control system has the characteristics of electro-hydraulic coupling, time-varying parameters, external interference and nonlinearity[3], so it is difficult to obtain satisfactory results by conventional control methods.

In this paper, taking the skin passing mill of 2230mm continuous annealing production line as the research object, based on the comprehensive consideration of the dynamic characteristics of each component, the mechanism model of elongation control system is established, and the BP neural network identification method is used to improve accuracy of the model setting parameters. In addition, combined with the regulation law of immune system and fuzzy inference algorithm, the fuzzy immune PID control strategy is used to control the elongation system, so as to improve the control accuracy of elongation system and the regulation ability under the condition of external interference and model.
mismatch.

2. Mechanism model of elongation control system for skin passing mill
Skin passing mill is the actuator of elongation control, which is mainly composed of hydraulic pressure subsystem and tension coordination subsystem. The hydraulic pressure subsystem of skin passing mill elongation model is mainly composed of pressure controller, servo amplifier, servo valve and oil pressure load, while the tension control subsystem is composed of automatic tension controller, current controller, rectifier circuit, front and rear tension roller group. The block diagram of elongation control system is shown in Fig. 1.

![Block diagram of elongation control system](image)

The rolling force mode of elongation control system is a rolling pressure control system based on elongation feedback. The system elongation is controlled by adjusting rolling force. The rolling force mathematical model of elongation system is shown in Fig. 2, including servo amplifier, servo valve, oil cylinder load and conversion relationship between rolling force and elongation.

![Mathematical model of rolling force for skin passing mill elongation system](image)

On the basis of not affecting the characteristics of the system, the roller system of skin passing mill is considered as a mass spring system with single degree of freedom, and the pressure sensor can be regarded as a proportional link. The transfer function model is as follows:

$$G(s) = \frac{k(k_s+1)}{s^2 + \frac{2c}{\omega_n} s + \frac{2c}{\omega_n}s + 1}$$

In the formula, $k = k_f / k_q k_n A_p / k_e$

The model is discretized, which can be described as follows:

$$G(z) = \frac{h z^{-1} + h z^{-2} + h z^{-3}}{1 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3} + a_4 z^{-4} + a_5 z^{-5} + a_6 z^{-6}}$$

In the formula, $a_i, b_i$ are the coefficients of discrete model.

3. Identification of elongation control system based on BP neural network
BP neural network is a multi-layer feedforward neural network with error correction through error reverse propagation algorithm. It is composed of input layer, intermediate layer and output layer. The connection weights of each layer can be adjusted by learning, which can realize data compression, pattern recognition, parameter identification and function Approximation and other functions. Considering the nonlinear, time-varying and time-delay characteristics of elongation control system, based on the mechanism model of skin passing mill elongation, the gain coefficient is identified by BP neural network, so as to improve the accuracy of the model. The structure of elongation identification system is shown in Fig. 3.
The set value and measured value of rolling force are collected from the actual production data. The step data of rolling force in each group of data is selected as identification data, and the data are preprocessed to obtain the stable, normal and zero mean time series.

The parameters of the discrete model are identified by neural network identification toolbox, and the fitting degree is 94.47%. The discrete identification model based on neural network is as follows:

\[ G(z) = \frac{0.0004014 z^{-1} + 0.0001098 z^{-2}}{1 - 2.916 z^{-1} + 3.315 z^{-2} - 2.114 z^{-3} + 1.441 z^{-4} - 0.9112 z^{-5} + 0.2457 z^{-6}} \]  

(3)

4. Design of Fuzzy Immune PID controller

4.1 Principle of immune algorithm

Inspired by the biological immune system, the artificial immune system realizes the functions of noise tolerance, self-learning, self-organization and memory by simulating its natural defense mechanism against external substances, which is suitable for solving practical engineering application problems with robustness, self-adaptive and dynamic requirements[7]. Due to the invasion of antigens, B cells are activated by T\(_H\) cells (helper cells) and inhibited by T\(_S\) cells (suppressor cells) on the other hand. In this way, the concentration of B cells in \(K\) times can be expressed as follows:

\[ B(k) = T_H(k) - T_S(k) = K_1 \epsilon(k) - K_2 f(\Delta B(k)) \epsilon(k) \]  

(4)

Where, \(\epsilon(k)\) is the concentration of the k-generation antigen; \(K_1\) is the promoter of T\(_H\) cells, \(K_2\) is the inhibitory factor of T\(_S\) cells; and \(\Delta B(k)\) is the concentration change of B cells. \(f(\cdot)\) is a nonlinear function, which represents the immune effect of the interaction between antibody secreted by B cells and antigen in the \((k-d)\) generation.

The relationship between B cell concentration and antigen concentration can be obtained from equation (4):

\[ B(k) = K \{1 - \eta f(\Delta B(k-d))\} \epsilon(k) \]  

(5)

Using B cell concentration \(B(k)\) as output \(U(k)\) and antigen concentration \(\epsilon(k)\) as deviation \(e(k)\), the immune controller can be obtained as follows:

\[ u(k) = K_{P1} e(k) \]  

(6)

\[ K_{P1} = K (1 - \eta f(u(k), \Delta u(k))) \]  

(7)

Where, \(k = K_1, \eta = K_2 / K_1\), denotes the proportional coefficient of the interaction between T\(_H\) and T\(_S\). \(K\) and \(\eta\) are two important parameters. The increase of \(K\) will increase the response speed, while the
increase of $\eta$ will reduce the overshoot of the system. If the two parameters are adjusted reasonably, the control system will have a faster response speed and a smaller overshoot.

4.2 Fuzzy reasoning algorithm

Using the good approximation of fuzzy controller\cite{8}, a fuzzy controller is used to realize the nonlinear function $f(\cdot)$. The output $U(k)$ and output variation $\Delta U(k)$ of the immune controller are used as the inputs of the fuzzy controller, and the nonlinear function $f(\cdot)$ is used as the output of the fuzzy controller.

Each input variable is fuzzified by two fuzzy sets, which are "positive" (P) and "negative" (N); the output variable is fuzzified by three fuzzy sets, which are "positive" (P), "zero" (Z) and "negative" (N). The above membership functions are defined in the entire $(-\infty, +\infty)$ interval.

According to the principle of "the bigger the cell receives, the smaller the inhibition ability" and "the smaller the stimulation received by the cell, the greater the inhibition ability".

(1) If $u$ is P and $\Delta u$ is P then $f(u, \Delta u)$ is N(1);
(2) If $u$ is P and $\Delta u$ is N then $f(u, \Delta u)$ is Z(1);
(3) If $u$ is N and $\Delta u$ is P then $f(u, \Delta u)$ is Z(1);
(4) If $u$ is N and $\Delta u$ is N then $f(u, \Delta u)$ is P(1).

The input and the output membership function are shown in Fig.5 and Fig.6.

![Fig.5 Membership function of $u$, $\Delta u$ of immune PID control](image1)

![Fig.6 Membership function of $f(\cdot)$ of immune PID control](image2)

In each rule, fuzzy logic of "Zadeh" are used, and the "centroid" anti-fuzzing method is used to obtain the output $f(\cdot)$ of the fuzzy controller. Then the expression of integral coefficient and differential coefficient of fuzzy control on-line adjustment is as follows:

$$K_{I1} = K_{I0} + \Delta K_I$$ (8)

$$K_{D1} = K_{D0} + \Delta K_D$$ (9)

4.3 Fuzzy Immune PID controller

Based on the conventional PID algorithm, combined with immune algorithm and fuzzy reasoning algorithm, the fuzzy immune PID controller algorithm can be obtained. The structure of Fuzzy Immune PID controller is shown in Fig.7.

![Fig.7 Fuzzy Immune PID control principle](image3)

The discrete form of conventional PID control algorithm is as follows:

$$u(k) = \left( K_p + K_i \frac{1}{z-1} + K_d \frac{z-1}{z} \right) e(k)$$ (10)

The discrete form of Fuzzy Immune PID control algorithm is as follows:

$$u(k) = \left( K_{p1} + K_{i1} \frac{1}{z-1} + K_{d1} \frac{z-1}{z} \right) e(k)$$ (11)
5. Analysis of simulation results

According to the elongation control identification system model of 2230mm continuous annealing line, three methods of conventional PID, fuzzy PID and fuzzy immune PID are used to test the system control performance under the condition of step response. While, the unit step disturbance signal is added in the 100s to test the anti-jamming performance of the system. The simulation curves are shown in Fig. 8 and Fig. 9.

![Fig.8 Comparison of elongation control system](image)

![Fig.9 Comparison of anti-interference ability](image)

The simulation results show that the conventional PID feedback control system has a large overshoot and a long transition time. The control system based on Fuzzy Immune PID not only has no overshoot, but also has fast response speed and strong anti-interference ability.

In order to further test the control performance of the control system in the case of large time delay and model parameter mismatch, a delay time with 12s is added to the original skin passing mill elongation control system, and the model parameters are changed. The simulation results are shown in Fig. 10.

![Fig.10 Robustness comparison of different control strategies](image)

The simulation results show that when the model mismatch, the control effect based on Fuzzy Immune PID is the best, and the system has better dynamic performance and strong robust performance, which verifies the feasibility and effectiveness of fuzzy immune algorithm to optimize PID parameters.

6. Conclusion

1) The elongation control system of temper mill is a typical double loop control system. Considering the dynamic characteristics of the components of the system, the mechatronics hydraulic integration mechanism model of the skin pass elongation system is established.

2) The BP neural network is used to identify the parameters of the temper elongation control system model. The output of the identification model and the actual results can be well fitted, and the identification model has high accuracy.

3) The fuzzy immune PID is used to control the skin pass elongation system, and its control characteristics are better than the traditional control strategy, and it has good anti-interference ability and robustness.

Acknowledgments

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