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SELF LEARNING RESEARCH ON ROLLING FORCE MODEL OF HOT STRIP ROLLING BASED ON IMPROVED ADAPTIVE DIFFERENCE

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In order to improve the prediction accuracy of the rolling force Self-learning Model and change the phenomenon that the learning coefficient is unstable and the optimization process is not reasonable due to the experience value of the self-learning factor in the traditional self-learning, this paper proposes an improved adaptive differential evolution (IADE) algorithm based on the standard differential evolution algorithm to solve and optimize the problem quickly. The prediction accuracy of rolling force model is improved. The experimental results show that the prediction accuracy of IADE algorithm is lower than that of the traditional model, which can effectively improve the prediction accuracy.

Keywords: strip, hot-rolling, rolling force, deformation resistance, stress state

INTRODUCTION

In the process of hot continuous rolling, rolling force is a very important factor. The rolling force setting model of rolling mill is the core of process control setting model in the production process. The accuracy of prediction directly affects the accuracy of sheet shape and the quality of sheet shape.

In order to improve the prediction accuracy of rolling force model, scholars have done a lot of related research. The parameters of the rolling force model are analyzed by finite element simulation [1-4], and the structure of the model is improved and the coefficient is optimized [5-6]. In recent years, it is proposed to combine the artificial intelligence method with the theoretical model of rolling force [7-11], which has achieved certain results. Reference [12-13] optimizes the rolling force model by self-learning, so as to improve the prediction accuracy of the model, The simulation results show that the optimized self-learning algorithm can effectively improve the on-line prediction accuracy of rolling force model, which provides an important idea for improving the prediction accuracy of rolling force model.

ESTABLISHMENT OF ROLLING FORCE MODEL

Rolling force model

The Sims formula model based on the force balance theory of Orowan deformation zone generally adopts the following forms:

$$F=B\cdot L_c\cdot Q_p\cdot K_m\cdot C \tag{1}$$

In the formula, F is the rolling force / kn; B is the width of rolled piece /mm; L_C is the length of contact arc / mm; Q_p is the influence coefficient of stress state; K_m is the deformation resistance of strip steel/MPa and C are the self-learning parameters of the model.

Deformation resistance model of strip steel

Deformation resistance is the resistance of metal material to plastic deformation caused by external pressure. It is an important physical parameter in rolling force model, which directly affects the prediction accuracy of rolling force. The calculation model of deformation resistance is as follows:

$$K=\{a_{k0}+\sum\nolimits_{i=1}^{4}(a_{ki}\rho_i)\}exp[b_{k0}+b_{k1}\rho_c + b_{k2}/T_k]\varepsilon^{b_{k3}}u^{b_{k4}} \tag{2}$$

In the formula, K is the deformation resistance of strip steel; ρ_I is the chemical composition of C, Mn, Si and Cu; ρ_C is the carbon content; T_K is the thermodynamic temperature of the material; ε is the degree of material deformation during rolling; U is the deformation rate of the material; A_{KI} is the coefficient of each component, I = 0,..., 4; B_{ki} is the coefficient of each basic term, I = 0,..., 4.

The calculation formula of deformation degree is as follows:

$$\varepsilon=\log\frac{H}{h} \tag{3}$$

In the formula, h is the thickness of rolled piece, mm; H is the thickness of the rolled piece at the exit of the stand, mm.

The formula for calculating deformation rate is:

$$u=(\varepsilon\cdot v)/(R(H-h))^{1/2} \tag{4}$$

In the formula, v is the linear velocity of the roll and R is the radius after flattening.

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Influence coefficient model of stress state

The influence coefficient of stress state is closely related to the friction condition. At present, Simms rolling theory formula is widely used in hot strip rolling. The researchers simplified Q_p and regressed it.

$$Q_p = k_1 \frac{h}{h_m} + k_2 (\frac{m_u}{h_m} L_c)^{k_3} + [k_6 \frac{m_u}{h_m} L_c - k_2 (\frac{m_u}{h_m} L_c)^{k_3}][1 - \frac{k_4 h_m}{m_u^2 L_c}(k_5 - m_u)]^2 \quad (5)$$

In the formula, k_J (J = 1, 2,..., 6) is a constant; h_m is the arithmetic average thickness of the entrance and exit of the frame / *mm*; m_u is the friction coefficient.

SELF LEARNING OF ROLLING FORCE MODEL

Self learning algorithm

Due to the complexity of rolling field conditions, there are some deviations between the predicted rolling force and the actual rolling force. The self-learning correction coefficient is calculated by the following formula:

$$C_{act} = \frac{F'}{B' \cdot L_c' \cdot Q_p' \cdot K_m'} \quad (6)$$

In the formula, C_{act} is the self-learning coefficient of the model derived from the measured value; F' is the measured rolling force / *kn*; B is the measured width of rolled piece / *mm*; L_c' is the contact arc length calculated according to the measured value / *mm*; Q_p' is the stress state influence coefficient calculated according to the measured value; K_m' is the deformation resistance calculated according to the measured value / *MPa*.

In order to improve the accuracy of the self-learning parameters, the exponential smoothing method is often used for optimization. The smoothing algorithm is as follows:

$$C_{new} = (1-\alpha)C_{act} + \alpha C_{old} \ (0 \le \alpha \le 1) \quad (7)$$

In the formula, C_{new} is the self-learning parameter of the updated model, C_{act} is the self-learning parameter of the model calculated according to the measured value of the current strip; C_{old} is the self-learning parameter of the model used in the preset calculation of the current strip steel; α Is the self-learning speed factor, and the value range is [0,1].

Self learning algorithm optimization

The self-learning speed factor α reflects the utilization degree of the self-learning algorithm to the rolled strip data information. In this paper, an improved adaptive differential evolution (iade) algorithm is proposed α Optimize. The experimental results show that IADE algorithm has good convergence and stability, and obtains the coefficient which makes the prediction accuracy reach the highest value.

SELF LEARNING BASED ON IMPROVED ADAPTIVE DIFFERENTIAL ROLLING FORCE MODEL

Improved mutation strategy

Random walk model has strong development ability, the following formula is the random walk strategy based on the current optimal individual:

$$R_{wi}^G = Gaussian(y_{best}^G \cdot \tau) + (r_1 \cdot y_{best}^G - r_2 \cdot y_i^G) \quad (8)$$

In the formula, y_i^G is the ith individual in the population, y_{best}^G is the best individual in g generation population; r_1 and r_2 is a random number with uniform distribution between [0,1]; step τ Expressed as:

$$\tau = (\frac{log(G)}{G})(y_i^G - y_{best}^G) \quad (9)$$

Parameter adaptation

In the algorithm IADE the change formula of crossover rate (*CR)* is as follows:

$$CR_i(t) = CR_{min} + (CR_{max} - CR_{min}) x \frac{f_{i,t} - f_{min,t}}{f_{max,t} - f_{min,t}} \quad (10)$$

In the formula, $f_{i,t}$ is the fitness value of the ith individual in the T generation population; $f_{max,t}$ and $f_{min,t}$ is the maximum fitness value and the minimum fitness value of the individuals in the T generation were respectively.

ANALYSIS OF EXPERIMENTAL RESULTS

In order to verify the performance of IADE algorithm, the standard test function is selected for simulation experiment, and the specific details of the test function are given in reference [14].At the same time, the standard DE algorithm, SADE and MDE are selected as the comparison objects. In order to facilitate the analysis, the logarithmic coordinate system is adopted in Figure 1. The vertical axis is the logarithm of the difference between the mean value of the objective function and the theoretical optimal value of degree 30, and the horizontal axis is the number of function evaluations.

It can be seen from Figure 1 that the convergence speed of iade algorithm is faster than other algorithms in most functions. Based on the random walk strategy, this algorithm chooses whether to carry out mutation operation according to the optimization performance of individual population, so that the algorithm can quickly jump out of the local optimum and converge to the global optimum, At the same time, iade algorithm can generate the most suitable control parameters according to historical experience.

FIELD APPLICATION

In this paper, the Simulink modeling tool is used to build the simulation prediction model of rolling force, and the traditional calculated rolling force value is compared with the actual measured value. The error distribution histogram results are shown in Figure 2.

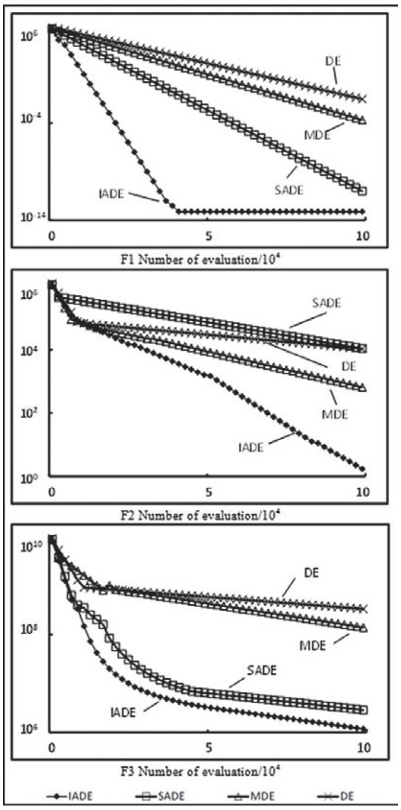

Figure 1 Convergence curve of 50 dimensional test function

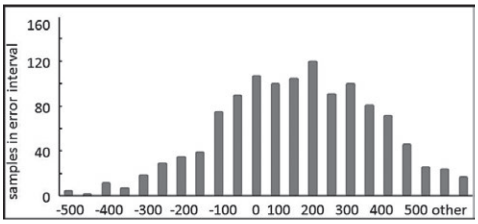

Figure 2 Histogram of rolling force error of rolling mill

The improved adaptive differential evolution (IADE) algorithm proposed in this paper is applied to the self-learning factor α The optimized rolling force data are compared with the field measured rolling force data of the first stand. The error distribution histogram of the calculated rolling force and the actual measured rolling force is shown in Figure 3.

It can be seen from Figure 3 that the rolling force error value decreases, mostly distributed in the range of [- 200,200], and is normally distributed, and the number of samples distributed in the range of [-50, 50] increases significantly.

CONCLUSION

In this paper, the self-learning of rolling force prediction model is studied, and the self-learning factor is optimized by improved adaptive differential evolution algorithm. The simulation results show that the prediction accuracy of rolling force is significantly improved after adding the optimized self-learning model, which lays a good foundation for the calculation of secondary data setting in the field production process. At the same time, it

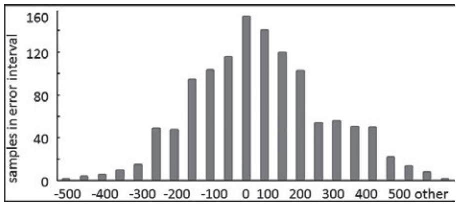

Figure 3 Error histogram after optimization of IADE algorithm

also proves that this analysis and optimization method can be popularized in other hot strip production lines.

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Note: Responsible for english language is X. L. Xi.