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THE FORCAST OF SLAG ADDITION DURING THE LADLE FURNACE (LF) REFINING PROCESS BASED ON LWOA-TSVR

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LF refining slag addition is an important factor affecting the end steel composition of the refining process. In order to better control the end steel composition and improve the production efficiency, this paper uses an improved whale optimization algorithm to optimize twin support vector machines to establish a LF refining slag addition prediction model. The LWOA-TSVR model is trained and tested by historical data, and the model has a strong generalization capability and high accuracy. Applying the model to the industrial production process, it was verified that the model has high prediction accuracy and can provide guidance for the actual refining production process of LF refining slag addition, which is important for the control of the end steel composition.

Keywords: LF, refining, slag addition, prediction model, validation

INTRODUCTION

LF refining slag is the oxidation of iron, silicon, manganese, phosphorus, sulfur and other elements in the steelmaking process and the chemical reaction of the components in the solvent [1]. Refining slag has proven to be of great value. The use of refining slag can better perform the tasks of desulfurization, deoxidation, de-gassing and de-entrainment of the refining process [2]. However, the refining slag contains lime, which will inevitably bring water into the steel and lead to an increase in hydrogen content in the steel, which will seriously affect the quality of steel [3]. If the requirements of desulfurization of steel and stopping the increase of hydrogen content in steel are met at the same time, the actual amount of addition needs to be further studied to obtain the most suitable amount of refining slag addition. However, for the LF refining slag addition, the existing prediction models are not comprehensive, such as BP neural network in the process of finding the optimal weights, it is easy to fall into the local minimum [4], which will lead to the accuracy of the model is difficult to guarantee, and the error with the actual production is large, while the study of other factors on the accuracy of steel production has been difficult to make a breakthrough. In order to solve the above problems, this paper uses the LWOA-TSVR hybrid intelligent algorithm to establish a prediction model for the LF refining slag addition in the LF refining process. Taking advantage of the modeling efficiency and high accuracy of twin support vector machines in prediction, the model parameters are optimally searched by an improved whale optimization algorithm to improve the accuracy of the prediction model. Industrial experiments are used to obtain actual production data in the trial, and the computational effectiveness of the model is tested by the test set of the model.

Finally, the tested model is applied to industrial production to realize real-time online prediction, so as to judge the practical application effect of LWOA-TSVR.

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DATA PROCESSING

Correlation analysis

Due to the large variety of parameters affecting the amount of refining slag addition at each stage of the LF refining process and the fact that there is no definite basis for concluding the magnitude of the influence of

Table 1 **Data correlation analysis**

Dependent variable	Symbols	Variable	Correlation coefficient
LF refining slag addition	X_1	Refining time	0,468
	X_2	alloy addition	0,337
	X_3	heating power	-0,296
	X_4	ladle pouring times	0,047
	X_5	argon blowing in	0,627
	X_6	steel grade	-0,103
	X_7	slag layer thickness	0,738
	X_8	initial temperature	-0,258
	X_9	ladle state	0,271
	X_{10}	impurity content	-0,075

these factors on the refining results. Therefore, SPSS was used for correlation analysis to obtain correlation coefficients between the LF refining slag addition and its influencing factors as shown in Table 1, to measure the relationship between the respective variables and the dependent variable, to eliminate the influencing factors with small correlation coefficients, and to filter out the input variables with high correlation with the LF refining slag addition to the degree of correlation as shown in Figure 1.

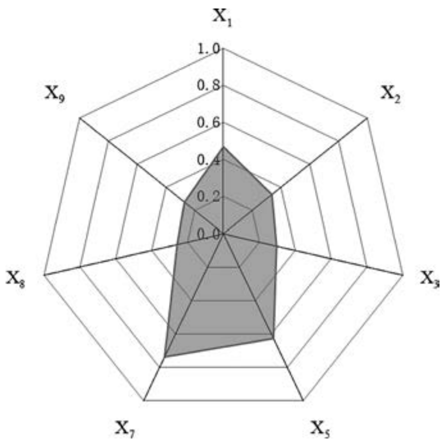

Figure 1 Correlation degree of influencing factors

DATA NORMALIZATION

In order to eliminate the model prediction error caused by the gap between different orders of magnitude of data, the input and output quantities of the model need to be normalized, and the input and output data are mapped to the [-1,1] interval data normalization using Eq(1).

$$x_i' = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)},\ i = 1,2,3,\ldots \tag{1}$$

where: $\min(x_i)$ - Minimum value of original data of model; $\max(x_i)$ - Maximum value of original data of model; x_i - Original data of the model.

THE ESTABLISHMENT OF THE MODEL

LWOA algorithm

The overdependence of the LWOA on randomness limits the search speed of the algorithm, so the Levy flight is introduced to do random perturbation on the optimal individuals and the following mathematical model is established:

$$A = 2alevy(\lambda) - ae \tag{2}$$

$$D = \left| E \cdot X^*(t) - X(t) \right| \tag{3}$$

$$D_1 = \left| X^*(t) - X(t) \right| \tag{4}$$

$$D_2 = \left| EX_{rand} - X(t) \right| \tag{5}$$

$$X(t+1) = \begin{cases} \begin{cases} X^*(t) - DA,\ if\ a < 1 \\ X_{rand}(t) - D_2 A,\ if\ a \geq 1 \end{cases} & p < 0.5 \\ X^*(t) + D_1 e^{\varepsilon \cdot n} \cdot \cos(2\pi n), & p \geq 0.5 \end{cases} \tag{6}$$

where: $X^*(t)$ - Optimal individual generated by previous t iterations; X(t) - Position vector of current humpback whale; ε-A constant used to describe the shape of a spiral motion; n-Random vector in [-1,1] interval; p-Random number between (0,1).

During the iterations, the two methods of choosing to surround the prey or the vapor bubble net to drive the prey have equal probability. If p > 0,5, the whale updates the next position by the prey-driving method through the bubble net, and if p < 0,5, the next position is determined by the encircling prey. If a>1, global random search is used to update the position, and if a<1, the current optimal solution is used to surround the prey to update the position of the search agent. Finally, by iterating repeatedly until the optimal solution is found.

TSVR algorithm

TSVR is used to obtain the objective function by solving two quadratic programming problems to obtain two regression functions. The training samples are mapped to a high-dimensional space, and the objective function is obtained by linear regression through the high-dimensional space.

$$f(x) = \frac{1}{2}(f_1(x) + f_2(x)) = \frac{1}{2}K(x^T, A^T)(\omega_1 + \omega_2)^T + \\ + \frac{1}{2}(b_1 + b_2) \tag{7}$$

The dual problem of the objective function is Eq(8) and (9):

$$\max(\frac{1}{2}a^T G(G^T G)^{-1} G^T a + fG(G^T G)^{-1} G^T a - f^T a) \tag{8}$$

$$\max(-\frac{1}{2}y^T G(G^T G)^{-1} G^T \gamma - h^T G(G^T G)^{-1} G^T \gamma + h^T \gamma) \tag{9}$$

where: $G = \left[K(A, A^T); e \right]$; $f = Y - e\varepsilon_1$; $h = Y + e\varepsilon_2$.

Using the obtained optimal solution, ω and β can be obtained as Eq(10) and (11), which can be substituted into Eq(7) to obtain the objective regression function as:

$$\left[\omega_1, b_1 \right]^T = (H^T H + \gamma I)^{-1} H^T (f - \alpha)\ldots \tag{10}$$

$$\left[\omega_2, b_2 \right]^T = (H^T H + \gamma I)^{-1} H^T (h + \beta)\ldots \tag{11}$$

Where: γ - a normal number; I - A matrix of units of the appropriate dimensions.

PREDICTION MODEL

The flow chart of TSVR algorithm using LWOA optimization is shown in Figure 2. Firstly, the industrial production data are normalized; then the LWOA is used to optimize the optimization process of TSVR parameters, select the corresponding kernel function, initialize the size of the whale, evaluate the fitness of each whale, compare the fitness value of each whale, determine the optimal whale position, compare the individual optimal value with the global optimal solution, find the global optimal solution, and update the current position of the whale by Levy flight, and finally If it is judged to be at the global optimum at this time, the whale position is updated, and the data is fed into the TSVR algorithm, and the model is trained and tested by combining the optimal solution and the kernel function; finally, the LF refining slag addition prediction model is established.

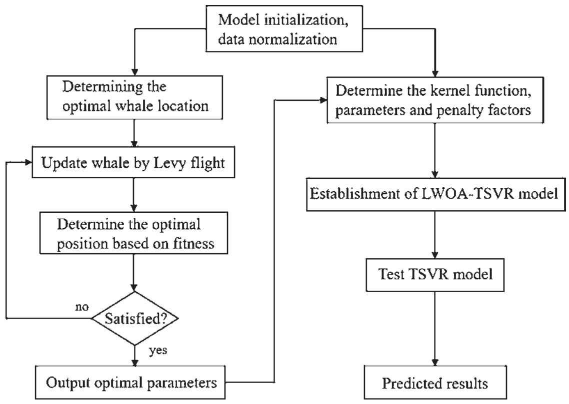

Figure 2 Flow chart of LWOA-TSVR

To validate the prediction accuracy of the model, a hybrid prediction model of LWOA-TSVR is developed by analyzing the refining slag addition in the context of LF refining production in a steel mill. In this paper, 2,000 sets of data collected on site are used for prediction, of which 1,500 sets are used for training set to train the model and the remaining 500 sets are used as test set to test the prediction accuracy of the model. The results of comparing the model prediction values with the actual production data are shown in Figure 3, and the relative model errors are shown in Figure 4.

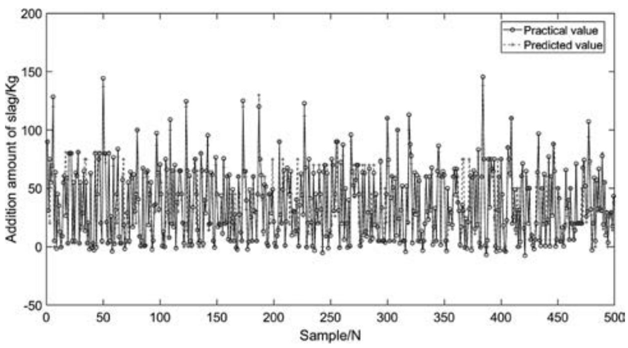

Figure 3 Comparison between predicted value and actual value of LWOA-TSVR

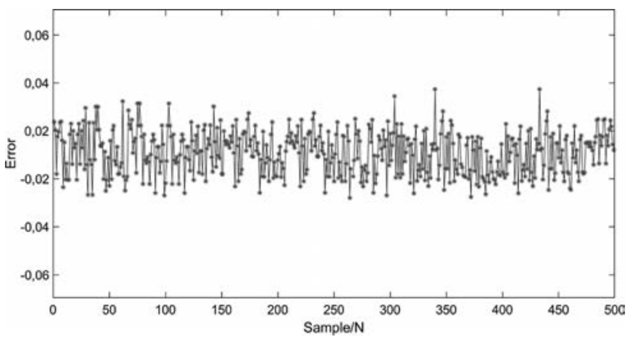

Figure 4 Relative error of LWOA-TSVR model

From Figure 3, it can be seen that the predicted and actual values of the model follow each other well and have a good fit. As can be seen from Figure 4, the model distribution has the most samples in the ±0,02 error range, thus verifying that the model has high prediction accuracy and low error, and fully meets the site process requirements of a steel mill.

APPLICATION AND VALIDATION

The model was applied to a steel mill LF refining process for industrial trial, and the results of 500 online tests are shown in Figure 5. The model had a hit rate of 94,6/% within ±1,5 /kg error and 97,2/% within ±3,0/kg error. The model has fast convergence and can accurately predict the LF refining slag addition. This shows that the LWOA-TSVR refining slag addition prediction model meets the actual production raw material requirements and can effectively predict the smelting production.

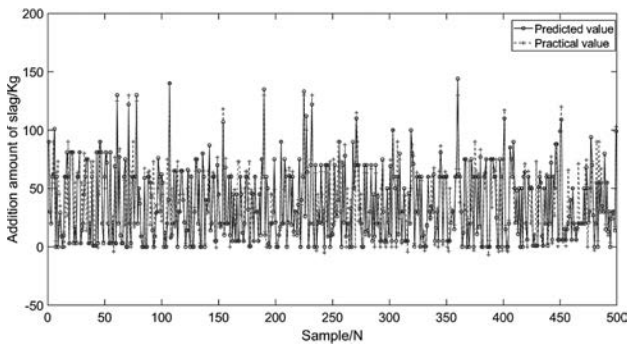

Figure 5 Comparison between actual value and predicted value

CONCLUSION

The LWOA-TSVR refining slag addition prediction model is applied to the industrial production process, and the results show that the hit rate of LF refining slag addition is 94,6 % within ±1,5 kg error and 97,2 % within ±3,0 kg error. The model achieves the accurate prediction of LF refining slag addition and provides a theoretical basis for the optimization of LF refining slag addition in steel mills.

Data analysis using SPSS, the results show that the main factors affecting the LF refining slag addition are: refining time, alloy addition, heating power, argon blowing in, slag layer thickness, initial temperature, and ladle state.

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Note: The responsible for English is LI Jun Yuan, Liaoning Institute of Science and Technology, Benxi, China.