C.Y.SHI, B.S. WANG, S.Y. GUO, X.X. YIN, Y.K. WANG, L. ZHANG, R. CHEN, Z. C. MA
ISSN 0543-5846
METABK 62(3-4) 359-362 (2023)
UDC – UDK 669.15:669.182-66.061:66.15.7:705 / 165.13=111

PREDICTION OF ALLOY ADDITION IN LADLE FURNACE(LF) BASED ON LWOA-SCN

Received – Primljeno: 2023-01-06
Accepted – Prihvaćeno: 2023-03-30
Original Scientific Paper – Izvorni znanstveni rad

The amount of alloy added during the LF refining process affects the hit rate of steel composition control. Therefore, improving the accuracy of the alloy addition amount can help improve efficiency and reduce production costs. To address the existing problem of inaccurate alloy addition in the refining process, the group established an alloy addition prediction model based on an improved whale swarm optimization algorithm and stochastic configuration network (LWOA-SCN) with the historical smelting data of a steel mill. The model can effectively improve the prediction accuracy and convergence speed of the model. The research results show that the model is more advantageous in improving the hit rate of alloy addition, which provides theoretical guidance for practical production.

Keywords: steel, LF refining, alloy addition, stochastic configuration network, improved whale swarm algorithm

INTRODUCTION

The refining of molten steel outside the furnace is an important process for large iron and steel enterprises to produce high-quality steel at home and abroad. One of the main tasks is to fine-tune the composition of molten steel. The accuracy of alloy addition directly affects the performance of finished steel. The influencing factors of LF refining liquid steel are complex, and each factor has a non-linear correlation, so it is difficult to establish a mechanism model. Therefore, the alloy addition amount of LF generally adopts artificial intelligence method. As the level of refining progresses, the choice of the production process and raw materials changes, which makes the traditional prediction model inappropriate for industrial production. Therefore, it is necessary to study the LF refining process and control the amount of alloy addition in-depth, considering the actual production process [1,2].

At present, China mainly uses the traditional BP neural network model to calculate the ingredients in alloy addition, but the traditional neural network has the problem of local minima, which leads to the model parameters are not unique and making the modeling more difficult. To solve the above problem, the group adopts the hybrid algorithm of LWOA-SCN. This model can solve the internal complex system modeling and establish the alloy addition setting model by correlation analysis between historical production data. [3,4] Firstly, based on the experimental data of the LF refining process in a steel plant, the random parameters are assigned by inequality constraints and the range of random parameters is selected adaptively [5,6]. then, the target parameters are adjusted by the feedback values of the forecast model. finally, the setting of alloy addition is realized. The study shows that the proposed model meets the requirements of the actual production line for detection accuracy and provides a new research method for the alloy addition amount of LF refining.

INDUSTRIAL TRIALS

The 500-furnace LF refining furnace in the refining plant of a steel mill is used as the object of study and the corresponding variables are used as inputs. Firstly, the corresponding argon blowing, and slagging schemes are formulated according to the molten steel information. After the ladle has been fed, the ladle is transported to the heating station, where argon is strongly stirred to break the slag crust and even out the temperature, and a heating strategy is developed based on the measured temperature. The alloy is added to the melt bath and the strong stirring of argon is initiated to promote the mixing of the steel components and to enhance the desul-

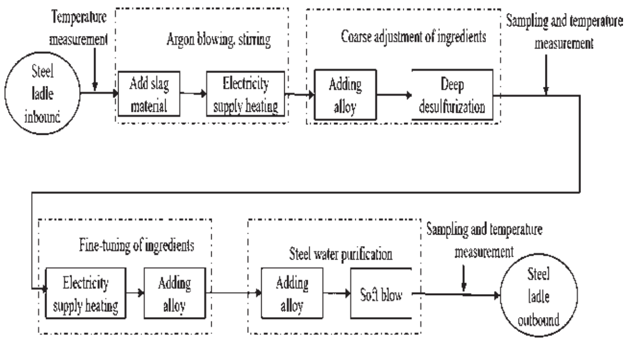

Figure 1 LF refining process flow chart

C.Y. Shi, B.S. Wang, S.Y. Guo, X.X. Yin, Y.K. Wang, L. Zhang, R. Chen, Z.C. Ma: School of Global 100-100, Liaoning Institute of Science and Technology, Benxi, China.
Corresponding author: C.Y. Shi. E-mail:scy9090@126.com.

phurization reaction. A second sample is then taken for temperature measurement. When feedback is received from the sample analysis, the composition is fine-tuned by adding the appropriate amount of alloying material and starting strong stirring with argon to speed up the homogeneous mixing of the components. After finishing the fine adjustment of the steel, the ladle is transported to the lifting station and then softly blown with argon to remove inclusions from the steel and purify the steel before the ladle leaves the station. The LF refining process is shown in Figure 1.

ESTABLISHMENT OF LWOA-SCN MODEL

Sample data processing

The data collected in this paper are the raw production data of a steel mill. Since there are too many kinds of factors affecting alloy addition and there is no definite basis for concluding the magnitude of the effect of these factors on the purity of the steel. Therefore, SPSS was used for correlation analysis to measure the correlation degree between each variable and alloy addition, and several factors with small correlation coefficients were eliminated to finally obtain five factors, namely, outgoing temperature, refining time, arrival temperature, molten steel tonnage and slag addition, as inputs to the model. The correlations of the influencing factors are shown in Table 1.

Table 1 **Data correlation analysis**

Dependent variable	Variable	Correlation coefficient
Alloy addition	Station temperature	0,412
	Refining time	0,231
	The amount of slag added	0,653
	Out-station Temperature	0,531
	Tonnage of molten steel	0,113

Improved whale optimization algorithm

The whale swarm optimization algorithm is fast, simple to adjust parameters, and has some ability to jump out of local optimum. However, due to the limitation of the coefficient vector B, the algorithm has a certain risk of falling into local optimum. To solve the above defects of WOA algorithm, this paper proposes an improved whale swarm optimization algorithm based on the improved type. The improvement is carried out by using Lévy flight, and the improved algorithm has a faster convergence speed, a higher convergence accuracy and a stronger ability to jump out of the local optimum. The whale swarm algorithm is modeled mathematically as follows:

$$X(t+1) = X^*(t) - BD_1 \tag{1}$$

where: t- the current number of iterations; B and M- coefficient vectors.

$$B = 2aLevy(\lambda) - a \tag{2}$$

The improved whale swarm optimization algorithm is used, and the optimal solution of SCN is finally obtained by repeated iterations. The whale swarm optimization strategy is shown in Equation (3).

$$X(t+1) = \begin{cases} \begin{cases} X^*(t) - lH, ifa < 1 \\ X_{rand}(t) - lH, ifa \geq 1 \end{cases}, if \ n < 0.5 \\ X^*(t) + \tau_p e^{\varepsilon \cdot m} \cdot \cos\cos(2\pi m), if \ n \geq 0.5 \end{cases} \tag{3}$$

where: $X^*(t)$ - The position vector of the current optimal solution; $X(t)$ - Current humpback whale position vector; $X_{rand}(t)$ - Stochastic position vector of a whale population; τ_p - Distance between whales and their prey.

SCN algorithm

In contrast to traditional machine learning models, the SCN hidden layer structure can be generated adaptively based on the training effect by gradually adding new hidden nodes with random parameters until the training accuracy of the network satisfies the termination condition.

The output of the neural network with single-layer forward propagation for L-1 nodes is as follows:

$$f_{L-1}(x) = \sum_{l=1}^{L-1} \beta_l g \sigma_l \left(w_l^T x + b_l\right) \tag{4}$$

where: $\beta_l = \left[\beta_{l,1}, \beta_{l,2}, \cdots \beta_{l,m}\right]$ - Output weights; $w_l = [-v, v]^{m\times d}$ - The weights of the lth hidden neuron; $b_l = [-v, v]^{m\times d}$ - Bias of the lth hidden neuron; $e_{L-1} = \left[e_{L-1,1}, \cdots e_{L-1,m}\right]$ - Residuals of L-1 hidden layer nodes.

If the specified error tolerance is not reached, the model will generate new hidden layer nodes under the constraints and satisfy the trend of decreasing deviation as the number of nodes increases, finally achieving.

$$\lim_{L-\infty} \| f - f_L \| = 0 \tag{5}$$

$$f_L = \sum_{l=1}^{L} \beta_L \sigma_L \tag{6}$$

To avoid the overfitting phenomenon of SCN, the L2 parametric penalty term is introduced in the objective function of the model; meanwhile, the empirical risk and structural risk are minimized to improve the generalization performance of the network.

$$\left[\beta_l^*, \beta_2^*, \beta_3^*, \cdots \beta_L^*\right] = \arg\min_\beta \left\| f - \sum_{l=1}^{L} \beta_l \sigma_l \right\| + C\|\beta\| \tag{7}$$

The output weights according to the least squares method are defined as:

$$\beta^* = \left(GG^T + \lambda I\right)^{-1} GT \tag{8}$$

$$G = \sigma\left(w^T x + b\right) \tag{9}$$

The LWOA algorithm is used to perform a parameter search for the penalty term coefficient C of the SCN, and the flow chart of the LWOA optimized SCN is shown in Figure 2. Firstly, the actual production data is used for extraction and normalization; then the regression model is trained and tested by combining the optimal solution; finally, the training results adjust the mod-

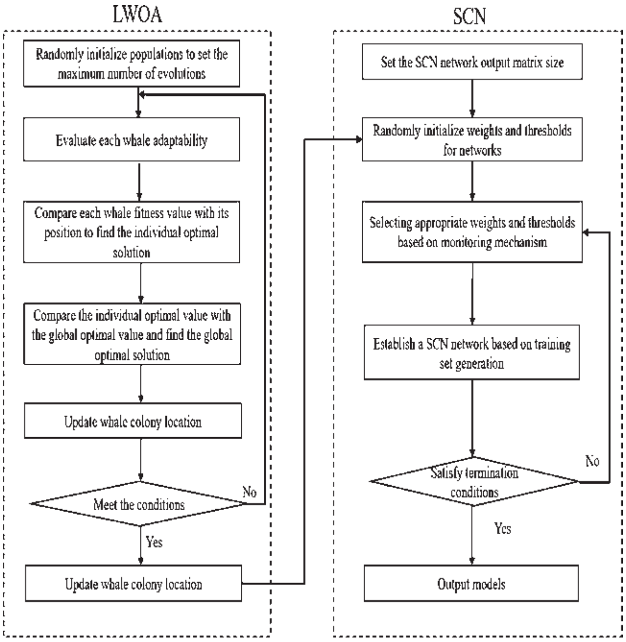

Figure 2 LWOA optimized SCN flow chart

el parameters and finally, the prediction model of alloy addition is obtained.

Through the above steps, the final forecast effect of the alloy addition prediction model of the LWOA-SCN algorithm is compared with the actual data, as shown in Figure 3.

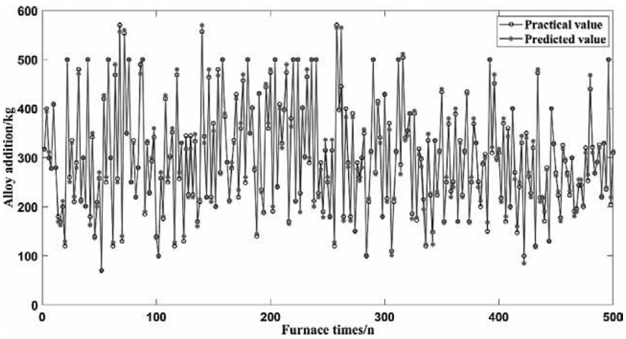

Figure 3 Predicted effect of LWOA-SCN alloy addition

MODEL COMPARISON AND ANALYSIS OF RESULTS

The hybrid model based on LWOA-SCN converges faster, has higher prediction accuracy, can better utilize the field refinement data for adaptive purposes, and improves the effectiveness of the model. To examine the prediction effectiveness of the LWOA-SCN algorithm relative to the traditional algorithm, four algorithms (BP, RBF, TSVR, and LWOA-SCN) are used for model comparison. In this paper, SSR/SST values and SSE/SST values are used to judge the model fitting effect; MAE, RMSE, and prediction accuracy of the model are used to evaluate the model; HR (hit rate) is used to examine the degree of model attainment. The relevant parameters of SCN in the experiment are set: the maximum number of nodes in the implicit layer is 250 and the learning rate is 1. The population size in the LWOA algorithm is 30 and the maximum number of iterations is 500. The predicted values of the four algorithms are compared with the actual production data and the results are shown in Figure 4.

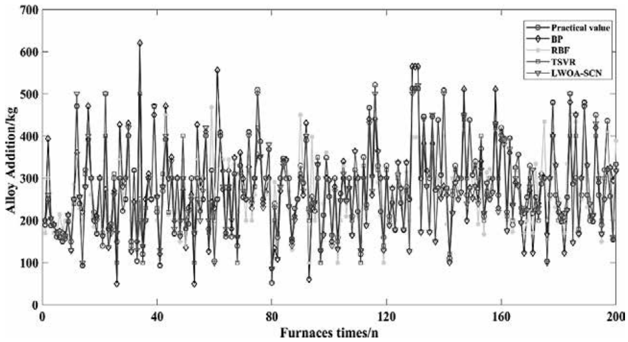

Figure 4 Comparison results of alloy addition model

From Figure 4, it can be seen that the deviations of the four models relative to the actual production data are small to large in order: LWOA-SCN, TSVR, RBF, and BP. combined with the evaluation indexes of the four models in Table 2, it can be seen that among the alloy addition prediction models, the RMSE and MAE of the LWOA-SCN model are smaller than the other three algorithms, and the SSR/SST is closer to 1, and the predicted values and The oscillation degree of the true value is closer; the SSE/SST value is the lowest, and the model gets the best fit.

Table 2 **Comparison of the regression effects of the four models**

Indicators	BP	RBF	TSVR	LWOA-SCN
RMSE	9,642	8,348	6,874	3,467
MAE	9,098	8,648	5,642	4,984
SSE/SST	0,213	0,201	0,106	0,054
SSR/SST	0,787	0,799	0,894	0,946

Table 3 **Alloy addition hit ratio**

Furnace times	Various model			
	BP	RBF	TSVR	LWOA-SCN
200	66 %	74 %	85 %	92 %

To examine the degree of compliance of the model, the HR (hit rate) performance index was used for the analysis, and the alloy addition hit rates are shown in Table 3.

In summary, the analysis shows that the prediction model of LWOA-SCN has the best prediction performance evaluation index and the highest hit rate by comparing the RMSE, MAE, SSE/SST values, SSR/SST values, and hit rate, which indicates that the prediction accuracy of LWOA-SCN algorithm is better than other algorithms. Thus, it shows that the LWOA-SCN prediction model has better prediction performance and can be applied to guide practical production.

APPLICATION AND VALIDATION

To verify the practical application of the established LWOA-SCN alloy addition prediction model, the mod-

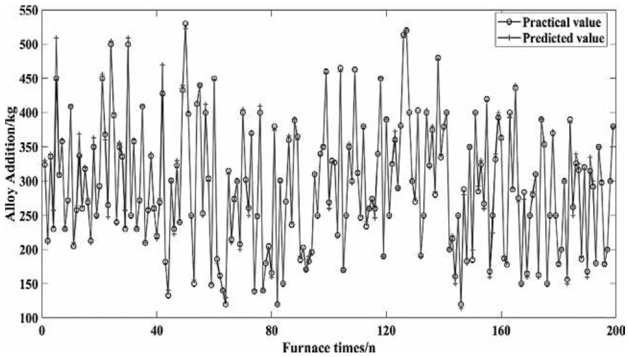

Figure 5 Comparison of predicted and true values of alloy addition model in practical application

el was applied to a steel mill 200-furnace LF furnace refining line for testing. According to the final hit rate, the alloy addition hit rate is 92 %. From Figure 5, the predicted and actual values of alloy addition are close to each other, and the prediction accuracy level of the model established in this paper has reached the requirement of guiding production practice and can make an effective prediction for smelting production.

CONCLUSION

A prediction model based on LWOA-SCN is established for the LF refining process, and the test shows that the model can accurately forecast the alloy addition, which makes up for the defects of slow convergence speed and low convergence accuracy of traditional modeling. Through the application test to the field, it was learned that within the error tolerance: the alloy addition hit rate was: 92 %, which achieved good results for the model field use. The model is compared and validated, and the results show that the LWOA-SCN model follows the best effect and has the highest prediction accuracy, providing a new idea and method for the optimization of the refining process affecting the alloy addition.

ACKNOWLEDGMENTS

This research was supported by the natural science fund program projects of the Department of Science & Technology of Liaoning Province in 2022(2022-BS-297), the basic scientific research fund projects of the Educational Department of Liaoning Province in 2021 (LJKZ1071), and the industrial research and industrialization (key R&D project) (2020JH2/10100019).

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