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


**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.

**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>
<thead>
<tr>
<th>Dependent variable</th>
<th>Symbols</th>
<th>Variable</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>LF refining slag addition</td>
<td>X1</td>
<td>Refining time</td>
<td>0,468</td>
</tr>
<tr>
<td></td>
<td>X2</td>
<td>alloy addition</td>
<td>0,337</td>
</tr>
<tr>
<td></td>
<td>X3</td>
<td>heating power</td>
<td>-0,296</td>
</tr>
<tr>
<td></td>
<td>X4</td>
<td>ladle pouring times</td>
<td>0,047</td>
</tr>
<tr>
<td></td>
<td>X5</td>
<td>argon blowing in</td>
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<tr>
<td></td>
<td>X6</td>
<td>steel grade</td>
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<tr>
<td></td>
<td>X7</td>
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<tr>
<td></td>
<td>X8</td>
<td>initial temperature</td>
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<tr>
<td></td>
<td>X9</td>
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<td>0,271</td>
</tr>
<tr>
<td></td>
<td>X10</td>
<td>impurity content</td>
<td>-0,075</td>
</tr>
</tbody>
</table>


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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).

\[
x_i^* = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}, \quad i = 1, 2, 3, \ldots
\]

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:

\[
A = 2a \text{levy}(\lambda) - ae
\]

\[
D = \| E \cdot X'(t) - X(t) \|
\]

\[
D_1 = \| X'(t) - X(t) \|
\]

\[
D_2 = \| E \text{rand} - X(t) \|
\]

**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.

\[
f(x) = \frac{1}{2} (f_1(x) + f_2(x)) = \frac{1}{2} K(x', A') (\omega_1 + \omega_2) + \frac{1}{2} (b_1 + b_2)
\]

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

\[
\max(\frac{1}{2} a^T G (G')^T G' a + f^T G (G')^T G' a - f^T a)
\]

\[
\max(\frac{1}{2} y^T G (G')^T G' \gamma - h^T G (G')^T G' \gamma + h^T \gamma)
\]

where: \(G = [K(A, A'); e]\); \(f = Y - e \varepsilon_1\); \(h = Y + e \varepsilon_1\).

Using the obtained optimal solution, \(\omega_1\) and \(\beta\) can be obtained as Eq(10) and (11), which can be substituted into Eq(7) to obtain the objective regression function as:

\[
\begin{align*}
[\omega_1, b_1] & = (H^T H + \gamma I)^{-1} H^T (f - \omega) \\
[\omega_2, b_2] & = (H^T H + \gamma I)^{-1} H^T (h + \beta)
\end{align*}
\]

Where: \(\gamma\) - a normal number; \(L\) - 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 parame-
ters, 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.

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.

**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.

**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).

REFERENCES


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