Whale Optimization End-point Control Model for 260 tons BOF Steelmaking

Miao WANG,1) Chuang GAO,2) Xingang AI,1) Baopeng ZHA3) and Shengli LI1)*

1) School of Materials and Metallurgy, University of Science and Technology Liaoning, Anshan, 114051 P. R. China.
2) School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, 114051 Liaoning, P. R. China.
3) Angang Group Automation Co., Ltd, Anshan, 114000 P. R. China.

(Received on November 9, 2021; accepted on April 21, 2022)

The end-point control technology of basic oxygen furnace (BOF) steelmaking is a very important production process in the later stage of smelting, and it has become a research hotspot in the smelting industry. In this paper, the carbon content and temperature prediction models were established based on a twin support vector regression (TSVR). In order to ensure the stability of the model, the input variables of the model were determined by using grey relational analysis (GRA) and partial correlation analysis (PCA). The results of the prediction models demonstrate that the hit rate of carbon content error bound within 0.005 wt% is 90%, and the hit rate of temperature error bound within 10°C is 94%, respectively. Moreover, a double hit rate reached 84%. By comparing with the back propagation (BP) neural network model, the hit rates of the proposed prediction model are higher than those of the BP model. Based on prediction models, a whale optimization control model was established for the calculations of auxiliary materials and oxygen blowing volume. The simulation results illustrate that the proposed control model has the mean absolute error of 9.3114 tons for scrap weight, mean absolute error of 2.5791 tons for lime weight, 0.7919 tons for dolomite weight and 537.8215 Nm³ for oxygen blowing volume, which are better than the other two control models in the aspects of the calculation accuracy.

KEY WORDS: end-point control model; twin support vector regression; grey relational analysis; partial correlation analysis; whale optimization algorithm; basic oxygen furnace.

1. Introduction

Basic oxygen furnace (BOF) steelmaking depends on the additions of raw materials such as molten iron, scrap steel and so on. The BOF steelmaking process contains very complex multi-element and multi-phase high-temperature reactions. In this process, the fluctuation of the end-point carbon content and end-point temperature will have a greater influence on the parameter adjustment of the subsequent process and the performance of the final product.1) The end-point control technology of BOF is divided into manual experience control, static control and dynamic control. Static control can avoid the inconsistency of manual experience control. Based on static control, dynamic control acquires molten pool information by sublance detection and furnace gas analysis. The accuracy of static control has a direct influence on the hit rate of dynamic control. Therefore, static control is still a reliable method for improving the management level and production technology of steelmaking. In recent years, the prediction and control model of the BOF end-point have been greatly developed. Han et al.2) proposed a two-part dynamic model in 2011. Firstly, a calculation model is established based on an adaptive network fuzzy inference system. Then, the robust correlation vector is used to build a prediction model. This novel dynamic model can provide a reference for the actual production of steel plants. In 2013, the relationship between variables in the desulfurization process was analyzed, and a prediction model was established by using a combination of multiple regression analysis and multi-level recursion.3) In 2014, a case analysis was carried out to establish an optical regression model to predict the end-point of BOF steelmaking by Han et al.4) Recently, a multi-channel diffusion graph convolutional network model was designed.5) To avoid the occurrence of extreme learning machine (ELM) overfitting, it is proposed to use the membrane algorithm to adjust the parameters of the ELM model, and the proposed model is used to predict the end-point parameters of molten steel.6) The original data is inputted to a stacked autoencoder, and the intelligent optimization algorithm based on improved
differential evolution is used to optimize the hyper parameters of the model and more accurate predictions were achieved.\textsuperscript{7} With the accelerated development of artificial intelligence methods, many scholars establish BOF steelmaking models based on neural networks algorithm.\textsuperscript{8–12}

As a kind of intelligence algorithm, support vector machine (SVM)\textsuperscript{13} is highly regarded for its strong learning ability and efficient classification performance. This method also performs well in the application of BOF steelmaking.\textsuperscript{14–16} After that, in order to further improve the classification ability, twin support vector machines (TSVM) were proposed by Jayadeva et al.\textsuperscript{17} Compared with the traditional SVM, it has the advantages of fast training speed and strong classification ability,\textsuperscript{18} which has widely used in classification applications. Peng\textsuperscript{19} proposed the twin support vector regression (TSVR) based on the TSVM in 2010, which classifies two non-parallel hyper planes and constructs a pair of insensitive upper and lower bound functions. It makes the amount of calculation in the solution of each bound function decreases. Besides fast calculation, this method has good generalization. Compared with neural networks, TSVR has a fast convergence speed and is not easy to fall into the local minimization problem, and is gradually applied to the establishment of industrial prediction models.\textsuperscript{20} Swarm intelligence method is a kind of algorithm inspired by the social behavior of natural organisms. The most representative ones are ant colony optimization algorithm,\textsuperscript{21} firefly algorithm\textsuperscript{22} and fruit fly optimization algorithm,\textsuperscript{23} etc. Compared with these algorithms, whale optimization algorithm (WOA)\textsuperscript{24} has the advantages of simple principle, few parameters and strong optimization ability, and has received extensive attention.

In this paper, a static control model is proposed. Firstly, a prediction model of end-point carbon and temperature was established using the TSVR algorithm. The input variables of the model are determined by the combination of grey relational analysis (GRA) and partial correlation analysis (PCA), which can reduce the complexity of the model. Then, based on the difference between the output value of the prediction model and the actual value as the target problem, the whale optimization algorithm is used to optimize the target problem. Finally, the proposed control model is used to calculate the scrap weight, lime weight, dolomite weight and oxygen blowing volume. The calculated results can provide a reference for technicians and improve the smelting efficiency of steel plants.

### 2. Description of 260 tons BOF Steelmaking

The 260 tons BOF located in a steel plant, P. R. China, takes scrap steel, hot metal and alloys as the main steelmaking raw materials to produce steels containing carbon and alloys. When the molten iron is delivered to the converter, it needs desulfurization treatment. After pouring scrap steel, molten iron, and auxiliary materials (such as lime, dolomite, etc.) into the converter, the blowing oxygen was oxidized with silicon, carbon, manganese, phosphorus and some iron. At the end of oxygen blowing, the carbon content and temperature of molten steel in the furnace meet the tapping requirements. At this time, pour the molten steel into the ladle and add deoxidizer to achieve qualified molten steels. Molten steel can be used to cast ingots or other steel castings. The essence of BOF steelmaking is the physical heat released by the chemical reaction between the raw material components, which melts the main raw materials of iron and iron compounds, so the smelting cycle is short and the smelting process cannot be sampled. In addition, due to the actual production model of the steel plant, the steel grades produced in the same batch will be different. Therefore, the modeling of 260 tons BOF is a challenging task.

The system control diagram of 260 tons BOF steelmaking is illustrated in Fig. 1. According to the raw material ratio requirements, pour scrap steel and hot metal, etc. into the converter in turn, and suitable additions of auxiliary materials are calculated by the relative control model in the industrial computer, the computer gives the blanking instruction, then they are added into the furnace according to the guided calculation results. The following step is to insert the oxygen spray gun into the furnace from the converter top and blow high-purity oxygen into the furnace, so that it will directly oxidize hot metal to remove impurities with the high-temperature. The industrial computer is used to calculate the oxygen for supplemental blowing, and send the oxygen blowing instruction to the PLC system. Finally, the PLC system controls the oxygen lance to add oxygen. Precise control of the oxygen lance and accurate addition of auxiliary materials are particularly important for the BOF steelmaking to improve production efficiency and save costs. Therefore, a static control model is proposed in this paper. The proposed model can calculate the lime weight, other auxiliary materials and oxygen blowing volume needed in the blowing stage. After computer modeling, the oxygen lance is controlled by a PLC system. The system block diagram of the control model is shown in Fig. 2. The control model consists of carbon content and temperature prediction model, an optimization model and a parameter adjustment unit $Q$. Firstly, on the basis of the TSVR algorithm to establish the carbon/temperature prediction model, the model consists of a carbon content prediction model and temperature prediction model. The inputs of these two prediction models are molten steel information ($x_{1–7}$ shown in Table 1), scrap steel addition ($x_8$), lime addition ($x_9$), dolomite addition ($x_{10}$) and total oxygen blowing volume ($x_{11}$), and the output is the end-point carbon content ($C_t$) and temperature ($T_t$).

In the adjustment unit $Q$, the model parameters are adjusted according to the principle of minimum error between the predicted value ($C_t$ or $T_t$) of carbon content or temperature and the actual value ($C_t$ or $T_t$); the model parameters are selected based on a certain number of histori-

![Fig. 1. Control system diagram of 260 tons BOF steelmaking.](image-url)
3. Establishment of Mathematical Model

At present, BOF steelmaking has become the most important steelmaking method in the world. The key to applying this method for steelmaking is to control the carbon content (denoted as C) and temperature (denoted as T) of the final molten steel to ensure product quality. BOF steelmaking is a very complicated high-temperature physicochemical reaction process. During the smelting process, the C and T in the hot metal cannot be detected all the time, which makes it difficult to build a mathematical model. Therefore, some intelligent methods can be used to establish the BOF model. In this paper, the end-point prediction model with TSVR is established by collecting real samples. The prediction model is composed of two independent models, namely the end-point carbon content prediction model (CM) and the end-point temperature prediction model (TM). The input of both models is the initial condition of the molten iron, and the output is the end-point carbon content and the end-point temperature, respectively. Based on the prediction model, a static end-point control model can be established. The input variables of the control model are the initial conditions of the molten iron and the required end-point carbon content and end-point temperature, and the output is the scrap weight, lime weight, dolomite weight and oxygen blowing volume. The proposed control model is established by the following sections.

3.1. Establishment of End-point Prediction Model for BOF Steelmaking

3.1.1. Sample Preprocessing

In the actual application of the BOF smelting process, considering the different orders of magnitude of data characteristics, there are great differences between values. In the training process, the model takes a long time to find or cannot find the optimal solution of the model, so that the algorithm is forced to shift to the larger value sample, resulting in the weakening of the influence of small values on the model, and the ideal prediction results cannot be obtained. To solve this problem, it is necessary to normalize the BOF samples before training the model. Suppose there are n sets of BOF datasets with m feature variables. Define the BOF datasets as \( \mathbf{C} = [\mathbf{x}_1, \mathbf{y}_1]^T \), where \( \mathbf{X} = [\mathbf{x}_1, \cdots, \mathbf{x}_n]^T \in \mathbb{R}^{m \times n} \) is the input samples matrix, \( \mathbf{x}_i = [x_{i1}, \cdots, x_{im}]^T \in \mathbb{R}^m \), \( i = 1, \cdots, n \) represents one set sample with m input variables, and \( \mathbf{Y} = [y_1, \cdots, y_n]^T \in \mathbb{R}^n \) is the output samples vector (end-point carbon content or temperature). In this paper, the linear transformation method is adopted to transform the data to the [-1,1] interval, and the following transformation formula is adopted:

\[
\mathbf{x}_i = 2\left(\mathbf{x}_i - \mathbf{x}_{\text{min}}\right) / \left(\mathbf{x}_{\text{max}} - \mathbf{x}_{\text{min}}\right) - 1 \quad \cdots \cdots \cdots \quad (1)
\]

where \( \mathbf{x}_i \) is the i-th input variable in BOF datasets, \( \mathbf{x}_{\text{max}} \) and \( \mathbf{x}_{\text{min}} \) represents the maximum and minimum vectors of the i-th input variable, ./ represents the division of the corresponding position elements of the vectors, and \( \mathbf{x}_i \) is the normalized vector of the i-th input variable, respectively. According to the rules of (1), the normalized results are that output samples are \( \mathbf{Y} = [y_1, \cdots, y_n]^T \), input samples matrix is \( \mathbf{X} = [x_{11}, \cdots, x_{1m}]^T \in \mathbb{R}^{m \times n} \), and the BOF datasets are \( \mathbf{C} = [x_{i1}, y_i]^T \), respectively.

3.1.2. Grey Relational Analysis

The GRA method is to analyze the historical samples...
of the factors and use the gray correlation degree to examine the size, strength and order relationship among the factors. Based on the normalized dataset C, the evaluation problem is constructed, the comparison sequence is defined as X, and the reference sequence is Y.

Due to the different physical meanings of each factor in the BOF samples, the dimensions of the data are not necessarily the same, which is inconvenient for comparison. Therefore, the data needs to be dimensionless. Generally, there are the averaging method, initial value method and interval method. In this paper, the initial value method is selected as follows:

\[
\hat{x}_j' = \frac{x_{ij}}{x_{jj}}, i = 1, \cdots, n, j = 1, \cdots, m
\]

\[
y_j' = \frac{y_j}{y_i}, j = 1, \cdots, n
\]

The matrix dimensionless data S is obtained:

\[
S = \begin{bmatrix}
y_1 & x_{11} & \cdots & x_{1m} \\
y_2 & x_{21} & \cdots & x_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
y_n & x_{n1} & \cdots & x_{nm}
\end{bmatrix}_{n \times (m+1)}
\]

After dimensionless processing, the absolute difference between the comparison sequence and the reference sequence is obtained, namely \(|y_i' - x_j'|\) is the absolute value between elements.

The gray correlation coefficient between each comparison sequence and the corresponding element of the reference sequence can be obtained, that is, the gray correlation coefficient between \(x_j\) and \(y_i\):

\[
\theta_{ij} = \min_{j=1}^{m} \min_{i=1}^{n} |y_i' - x_j'| + \rho \max_{j=1}^{m} \max_{i=1}^{n} |y_i' - x_j'| \cdot |y_i' - x_j'| \cdot |y_i' - x_j'|
\]

where, \(\min_{j=1}^{m} \min_{i=1}^{n} |y_i' - x_j'|\) and \(\max_{j=1}^{m} \max_{i=1}^{n} |y_i' - x_j'|\) are the minimum and maximum values in the difference sequence, and \(\rho \in (0, 1)\) is an adjustable parameter. In this article, let \(\rho = 0.5\). Then, calculate the average value of the gray correlation coefficient of each feature to form the gray correlation degree, which is denoted as:

\[
\gamma_0(j) = \frac{1}{n} \sum_{i=1}^{n} \theta_{ij}, j = 1, \cdots, m
\]

The larger the gray correlation coefficient \(\gamma_0(j)\) has the greater influence between the corresponding two variables. The gray correlation coefficients \(\gamma_0(j)\) are arranged from largest to smallest, and \(l (l \leq m)\) the number of features that have a greater impact on the output variable can be selected, and the selected variables are served as the corresponding input variable for the BOF prediction model.

3.1.3. Partial Correlation Analysis

PCA is adopted to control the linear influence of other variables, and analyze the correlation between two variables. The partial correlation coefficient calculation formula can be derived from the simple correlation coefficients between all variables. Pearson correlation coefficient is used in this paper.\(^{26}\) When the number of control variables is 0, that is, without considering the influence of other variables, the Pearson correlation coefficient between the input variables \(x_k\) and \(x_l\) in X is:

\[
f_{kl} = \frac{\sum_{j=1}^{n} (x_{kj} - \bar{x}_k)(x_{lj} - \bar{x}_l)}{\sqrt{\sum_{j=1}^{n} (x_{kj} - \bar{x}_k)^2 \sum_{j=1}^{n} (x_{lj} - \bar{x}_l)^2}}
\]

where \(\bar{x}_k = \frac{1}{n} \sum_{i=1}^{n} x_{ik}\) and \(\bar{x}_l = \frac{1}{n} \sum_{i=1}^{n} x_{il}\).

When \(g\) variables are controlled, the \(g\)-order partial correlation coefficients of any two variables \(x_k\) and \(x_l\) is:

\[
f_{kl, l_k(2: g) = j} = \frac{\sum_{i=1}^{n} (x_{kj} - \bar{x}_k)(x_{lj} - \bar{x}_l)}{\sqrt{\sum_{i=1}^{n} (x_{kj} - \bar{x}_k)^2 \sum_{i=1}^{n} (x_{lj} - \bar{x}_l)^2}}
\]

where, each \(r\) on the right side of (7) represents the \(g\)-order partial correlation coefficient that controls different variables. The partial correlation coefficient can reflect the strength of the net correlation between two variables, and the absolute value is large, indicating that the degree of linear correlation between the two factors is higher, and its absolute value is smaller, indicating that the degree of linear correlation between the two factors is lower, the partial correlation coefficient is positive or negative, and the sign reflects the correlation relationship. For direction, the positive sign reflects the positive correlation, and the negative sign reflects the negative correlation. Finally, according to the size of the partial correlation coefficient, \(d (d \leq l)\) input variables are determined.

3.1.4. Twin Support Vector Regression

The traditional support vector regression (SVR) algorithm solves a quadratic programming problem (QPP) and finds a linear regression function. The TSVR algorithm\(^{19}\) finds the \(\varepsilon\)-insensitive up-bound and down-bound functions for the final regression function. The essential difference is that TSVR solves two small QPP problems, while traditional SVR solves one big QPP problem. TSVR is more efficient than traditional SVR in learning. Let matrix A = \([x_1, \cdots, x_d]^{T} \in R^{m \times d}\) be the normalized input training samples, the vector Y (see 3.1.2) be the output training samples. The vector \(\varepsilon = [1, \cdots, 1]^{T}\) is a unit vector of suitable dimensions. Define \(K(\cdot, \cdot)\) as a nonlinear kernel function, let \(K(A, A')\) be a kernel matrix with order \(n\), where the \((i, j)\)-th element \((i, j = 1, 2, \cdots, n)\) is defined as \(K(A, A')_{ij} = K(x_i, x_j)\).

The BOF steelmaking can be taken as a multi-input single-output non-linear system. It is necessary to introduce a kernel function, a radial basis function (RBF) is chosen in this article, that is \(K(x, x) = \exp(-\|x_{i} - x_{j}\|^{2}/2\sigma^{2})\).

where \(\sigma > 0\) is the width of the kernel function, and \(\|\|\) represents the Euclidean norm, i.e., \(L_{2}\)-norm. Let \(\hat{K}(A, A') = (K(x, x_1), K(x, x_2), \cdots, K(x, x_n))\) be a row vector in \(R^{n}\). The samples are mapped to high-dimensional space, and then linear regression is carried out through high-dimensional feature space to obtain the regression function \(g(x) = \mathbf{w}^{T} \hat{K}(A, x) + b\).
K(x^T, A^T)\omega_1 + b_1 and \( g_2(x) = K(x^T, A^T)\omega_2 + b_2 \), where \( \omega_1, \omega_2 \in \mathbb{R}^n \) are the normal vectors and \( b_1, b_2 \in \mathbb{R} \) are the bias values.

The regression functions \( g_1(x) \) and \( g_2(x) \) can be obtained by solving the following original problem:

\[
\min \frac{1}{2} \left( \mathbf{Y} - \mathbf{e} \mathbf{e}^T - \left( K\left( A, A^T \right) \omega_1 + h_1 \right) \right)^T \\
\left( \mathbf{Y} - \mathbf{e} \mathbf{e}^T - \left( K\left( A, A^T \right) \omega_1 + h_1 \right) \right) + C_1 \mathbf{e}^T \mathbf{e} \quad \text{s.t.} \quad \mathbf{Y} - \left( K\left( A, A^T \right) \omega_1 + h_1 \right) \geq \mathbf{e} \mathbf{e}^T - \xi, \xi \geq 0 
\]

\[
\min \frac{1}{2} \left( \mathbf{Y} + \mathbf{e} \mathbf{e}^T - \left( K\left( A, A^T \right) \omega_2 + h_2 \right) \right)^T \\
\left( \mathbf{Y} + \mathbf{e} \mathbf{e}^T - \left( K\left( A, A^T \right) \omega_2 + h_2 \right) \right) + C_2 \mathbf{e}^T \eta \quad \text{s.t.} \quad \left( K\left( A, A^T \right) \omega_2 + h_2 \right) - \mathbf{Y} \geq \mathbf{e} \mathbf{e}^T - \eta, \eta \geq 0 
\]

where \( C_1, C_2 > 0, \epsilon_1, \epsilon_2 \geq 0 \) are adjustment parameters, and \( \xi, \eta \) are slack vectors.

By introducing Lagrange multipliers \( \alpha \) and \( \beta \) vectors combined with Karush-Kuhn-Tucker conditions, the dual problem of the final regression function can be obtained as follows:

\[
\max -\frac{1}{2} \mathbf{e}^T \mathbf{H}^{-1} \mathbf{H}^T \mathbf{H}^{-1} \mathbf{H}^T \alpha + \mathbf{f}^T \mathbf{H} \left( \mathbf{H}^T \mathbf{H} \right)^{-1} \mathbf{H}^T \alpha - \mathbf{f}^T \alpha \\
\text{s.t.:} 0 \mathbf{e} \leq \alpha \leq C_1 \mathbf{e} 
\]

\[
\max -\frac{1}{2} \beta^T \mathbf{H} \left( \mathbf{H}^T \mathbf{H} \right)^{-1} \mathbf{H}^T \beta - \mathbf{h}^T \mathbf{H} \left( \mathbf{H}^T \mathbf{H} \right)^{-1} \mathbf{H}^T \beta - \mathbf{h}^T \beta \\
\text{s.t.:} 0 \mathbf{e} \leq \beta \leq C_2 \mathbf{e} 
\]

where, \( \mathbf{H} = [K(A, A^T) \mathbf{e}] + \mathbf{f} = \mathbf{Y} - \mathbf{e} \mathbf{e}^T, \mathbf{h} = \mathbf{Y} + \mathbf{e} \mathbf{e}^T \).

Considering that \( \mathbf{H}^T \mathbf{H} \) is always positive semidefinite, it may not be well-conditioned in some cases. Therefore, the regularization term \( \mu \mathbf{I} \) is introduced here, where \( \mu \) is a small positive number, such as \( \mu = 1e^{-7} \), and \( \mathbf{I} \) is an identity matrix. Based on the optimal solutions of (10) and (11), we can get the weight vector and offset as \( [\alpha, \beta] = (\mathbf{H}^T \mathbf{H})^{-1} \mathbf{H}^T (\mathbf{f} - \alpha), [\omega_1, \omega_2] = \mathbf{K} \mathbf{H}^{-1} \mathbf{H} \mathbf{h} + \beta \). It is worth noting that for the ill-conditions, we use \( [\alpha, \beta] = (\mathbf{H}^T + \mathbf{e} \mathbf{e}^T)^{-1} \mathbf{H}^T (\mathbf{f} - \alpha) \).

Finally, substitute the weight vector and bias value into the regression functions \( g_1(x) \) and \( g_2(x) \). Then, the final regression function of the BOF steelmaking end-point prediction model can be obtained by \( f_C(x) = \frac{1}{2} \left( g_1(x) + g_2(x) \right) \), where \( C_y = f_C(x) \) and \( T_y = f_T(x) \).

### 3.1.5. Input Variable Selection of Prediction Model and Modeling Steps

The excessive number of input parameters and the correlation between the input parameters in the training process of the model will affect the stability of the prediction model. The model will oscillate and it is not easy to stabilize. Through simulation experiments, the input parameters of the model are made appropriately, and when there is no correlation between the input variables or the correlation is small, the prediction effect of the model can be better.

There are 13 factors \( (m) \) in this paper, including 11 factors in Table 1 and the other two factors (furnace age and smelting time). According to (4) and (5), the GRA method is carried out to analyze the correlation between 13 factors and the end-point carbon content or end-point temperature, because the gray correlation coefficient of the other two factors is not ideal (less than 0.6). Therefore, Table 2 only shows the better results of 11 factors \( (l) \). The calculation results show that although the values are different, the gray correlation coefficient \( C_r \) and \( T_r \) are in the range of \((0.90,1)\), and there is no prominent extreme value, it is indicating that all factors have an impact on the output value. Finally, according to (7), for each influencing variable, the principle of PCA is used to obtain the partial correlation coefficient between the independent variables. The partial correlation coefficient between two variables can reflect the degree of influence between them to a certain extent. The results of partial correlation analysis are shown in Table 3. The partial correlation coefficients of most variables are less than 0.3, which can indicate that they are independent. Although there are individual variables partial correlation coefficients greater than 0.3, all are less than 0.5, which can indicate that there is a weak correlation between them. It should be noted that the partial correlation coefficient of \( x_2 \) (mold iron weight) and \( x_8 \) (scrap weight) is \( |r_{28}| = 0.687 \), it means that they are related. They should not be used as input together. In actual production, they are added into the molten pool as the main raw materials, and the amount of addition will affect whether the subsequent molten steel needs to be processed. Based on the combination of the mechanism analysis of the BOF and the actual production experience, the reason why molten iron and scrap are related may be due to the proportion of raw materials. Therefore, 11 variables \( (d) \) are finally selected as the input variables of the model.

Using the input variables of the model and combining the principles of TSVR, the model building process can go through the following steps:

1. Step 1: According to (1), normalize the training samples from their original range to \([-1,1]\).

2. Step 2: Initialize or update the \( C_1, C_2, \epsilon_1, \epsilon_2, \sigma \) parameters.

3. Step 3: Solve the dual problem of (10) and (11), and obtain the vectors \( [\alpha_1, \beta_1]^T \) and \( [\alpha_2, \beta_2]^T \).

4. Step 4: Substitute the result \( f_C(x) \) to obtain the BOF prediction model.

### Table 2. Grey correlation coefficients.

<table>
<thead>
<tr>
<th>( \Omega )</th>
<th>( x_1 )</th>
<th>( x_2 )</th>
<th>( x_3 )</th>
<th>( x_4 )</th>
<th>( x_5 )</th>
<th>( x_6 )</th>
<th>( x_7 )</th>
<th>( x_8 )</th>
<th>( x_9 )</th>
<th>( x_{10} )</th>
<th>( x_{11} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C )</td>
<td>0.9802</td>
<td>0.9744</td>
<td>0.9800</td>
<td>0.9632</td>
<td>0.9725</td>
<td>0.9773</td>
<td>0.9211</td>
<td>0.9698</td>
<td>0.9661</td>
<td>0.9681</td>
<td>0.9777</td>
</tr>
<tr>
<td>( T )</td>
<td>0.9978</td>
<td>0.9933</td>
<td>0.9973</td>
<td>0.9563</td>
<td>0.9851</td>
<td>0.9917</td>
<td>0.9260</td>
<td>0.9580</td>
<td>0.9798</td>
<td>0.9831</td>
<td>0.9968</td>
</tr>
</tbody>
</table>
Step 5: When the criteria of the model are satisfied, then CM or TM is established. If not, repeat Steps 2 to 4.

3.2. Establishment of End-point Control Model for BOF Steelmaking

Based on the prediction models, a whale optimization control model is proposed to calculate the output value by finding the minimum relative error. WOA is an algorithm originally proposed by Mirjalili.\(^{29}\) It is a new heuristic algorithm that mimics the hunting behavior of humpback whales. It utilizes search agents to determine the global optimum for optimization problems. The search process starts with creating a set of random solutions for a given problem. It improves this set until the satisfaction of an end criterion. (12) is the optimization principle followed by whale optimization.

\[
X(t+1) = \begin{cases} 
X'(t) - \lambda \cdot E, & \text{if } a < 1, \\
X_{\text{rand}} - \lambda \cdot E, & \text{if } a \geq 1, \\
X'(t) + \lambda \cdot \epsilon \cdot \cos(2\pi k), & \text{if } z \geq 0.5
\end{cases} \quad \text{(12)}
\]

where, \(t\) represents the current number of iterations, \(z\) is a random number in \([0,1]\), \(X(t)\) represents the best whale position so far, and \(X_{\text{rand}}\) is a randomly selected whale position vector. \(\lambda = |F \cdot X'(t) - X(t)|\) is the distance between the whale and its prey, \(\nu\) is a constant used to define the shape of the spiral, \(k\) is a random number in \([-1,1]\), and \(\cdot\) represents an element-by-element multiplication.

The modeling method of the whale optimization control model is as follows:

Step 1: Establish the objective function of the following calculation variables:

\[
\min g_{\sigma}(u) \\
\text{s.t.: } -\epsilon \leq u \leq \epsilon
\]

where, \(g_{\sigma}(u) = (f_{CT}(u) - D_{CT})^2\) is a fitness function; \(u = [x_1, \ldots, x_{11}] \in R^{11}\) is the input vector, where the \(x_8 - x_{11}\) are optimized variables, and other 7 variables are shown in Table 1; \(f_{CT}(u)\) is the predicted value of the carbon temperature of the TSVR prediction model, and \(D_{CT}\) is the target value of the end-point carbon content or temperature.

Step 2: Set the number of whales \(J\) and the maximum number of iterations \(N_{\text{max}}\); normalize each variable, map it to the interval \([-1,1]\), according to the number of groups \(J\) generates an equal amount of initial random solutions.

Step 3: Combine each group of initial solution variables with the initial furnace information to obtain \(u\), and substitute them into the TSVR prediction model to obtain the predicted value \(f_{CT}(u)\) of carbon content and temperature.

Step 4: According to the fitness function \(g_{\sigma}(u)\) in (13), calculate the fitness of each set of solutions, and save the current optimal vector \(u^*\) with the smallest fitness.

Step 5: Using the whale swarm optimization strategy of (12), if the current iteration number is less than \(N_{\text{max}}\), update \(a\), \(r_1\), \(r_2\), \(E\), \(F\), \(\lambda\), determine the solution required for the next iteration, check whether there is a solution beyond the search space, and if the answer is yes, then map it to the feasible region, and repeat Step 4 and Step 5; otherwise, return to the optimal solution, complete the whale optimization process, and obtain the optimal material additions and oxygen volume vector \(B = \text{invnorm}(u^*)\), where \text{invnorm} means denormalization processing.

4. Experimental Simulation

4.1. Verification of Prediction Models

In this section, according to section 3.1.1, the verification of the prediction model is carried out with 1 100 samples of 260 tons BOF low carbon steel. 1 000 samples are used to train the prediction model, and 100 samples are used to verify the model. By tuning the model parameters in unit \(Q\), the optimal parameters are obtained for \(CM : C_1 = 0.1, C_2 = 0.1, \epsilon_1 = 0.1, \epsilon_2 = 0.1, \sigma = 1.28\) and for \(TM : C_1 = 0.1, C_2 = 0.1, \epsilon_1 = 0.1, \epsilon_2 = 0.1, \sigma = 0.73\). Then the end-point prediction model of BOF steelmaking is established. The quality of the BOF end-point prediction model needs to be verified through criteria. The criteria are chosen as \(\text{RMSE}, \text{MAE}, \text{SSE}/\text{SST}, \text{SSR}/\text{SST}, \text{HR}, \) and \(\text{DHR},^{29}\) which represent the root mean square error, the mean absolute error, the degree of model fit, the degree of fluctuation of the
model output, hit rate and double hit rate, respectively. In this paper, all algorithms are carried out on a PC with Intel Core i5-1135G7 2.42 GHz and 8 GB RAM.

To verify the validity of the prediction model, the proposed model is compared with the BP model. In the comparison, the BP model uses a three-layer network structure for network training, namely the input layer, the hidden layer and the output layer, respectively. The number of input neurons is 11 (input variables), the number of output layer neurons is 2 (end-point carbon content and temperature), and the number of hidden layer neurons is 12. The maximum training times are 1000, the learning rate is 0.01, the minimum training error is set to 0.0001, and the sigmoid function is taken as the activation function. 100 groups of samples are used for training, and 100 samples are adopted for the validation. Then, the comparison results of the TSVR prediction model and BP prediction model are listed in Table 4. From the results, for the prediction of the end-point carbon content, the RMSE and MAE of the TSVR model are 0.0031 and 0.0026, respectively, which is lower than the set error tolerance of 0.005%, and the two indicators are less than the BP model. The SSE/SST of the TSVR model is the smallest among the two models, it shows that the fitting degree of the TSVR model is better than the BP model. The SSR/SST of the TSVR model is 0.9051, which is closer to 1 than the BP model. It illustrates that the matching degree between the predicted value fluctuation and the actual value fluctuation of the TSVR model is higher. For the prediction of the end-point temperature, the RMSE and MAE results of the TSVR model are smaller than the BP model, which are 5.5162 and 4.4930, respectively, which meet the set error tolerance of 10°C. Comparing the SSE/SST and SSR/SST of the TSVR model with the BP model, a conclusion similar to the carbon content is obtained. Therefore, the prediction effect of the TSVR model is better than that of the BP model.

The prediction performances of the TSVR model and BP model are shown in Fig. 3. It shows that the carbon content is within the error range of 0.005 wt%, the TSVR model and BP model have 90 and 89 heats within this range, respectively. The TSVR model has 94 heats and the BP model has 89 heats within the error bound of 10°C in temperature. Overall, the TSVR model performs better than the BP model. The prediction errors of the TSVR model and BP model are shown in Fig. 4. It shows that 90 errors of the TSVR CM fall within the error range of 0.005 wt%, which means the single hit rate is 90%, while the BP model has a single hit rate of 89%. The errors of the TSVR TM fall within the error range of 10°C with a single hit rate of 94%. The BP model has 89 errors that fall within the same error range with a single hit rate of 89%. Therefore, the single hit rate of the TSVR model is better than the BP model. After calculation, the TSVR model achieves a double hit rate of 84% for the prediction error bound with 0.005 wt% in carbon content and 10°C in temperature. If the carbon temperature accuracy is properly adjusted, the double hit rate of the model can reach to 93% when the prediction error is bound with 0.006 wt% in carbon content and 11°C in temperature, which meets the requirements of actual production. To sum up, it can be concluded that for the actual production samples, the TSVR prediction model can better fit the nonlinear prediction problems in complex situations and exert its ability to reflect the dynamic characteristics of the system. The defect of poor error stability of the single BP neural network model is reduced. The obtained predicted value is consistent with the expected value, and can meet the requirements of establishing a control model.

### 4.2. Verification of the Control Model

Through the above analysis, the feasibility of using the TSVR algorithm to establish a prediction model is verified. After that, the scrap weight, lime weight, dolomite weight and oxygen blowing volume can be optimized by the proposed control model. The quality of the control model needs to be verified through the following criteria: RMSE, MAE and SD, where SD represents the standard deviation, the smaller value of the SD means a less deviate value from the average. To verify the effect of the proposed control model, 100 sets of 260 tons BOF are selected for verification, the results are compared with the incremental control model and static control model.

The special search mechanism of WOA makes the output value of the model unstable. Therefore, the output of the model is averaged as shown in Fig. 5. Figure 5 shows that the mean absolute error fluctuation of the model output value tends to be stable. The basic principle of the whale optimization algorithm is to set the whale to capture the prey. When the number of whales increases, the best location to catch prey can be found and the simulation time for 10 sets and 10 times average values increases. Considering the time problem, only four consecutive heats are simulated in a single heat this time. The simulation results are shown in Table 5. Compared with the other set numbers of whales (1, 20, 50), when the number of whales is set to 100, the smaller mean absolute errors of scrap weight, lime weight, dolomite weight and oxygen blowing volume are obtained. It illustrates that the optimization results of the proposed control model become accurate with more whales are set. Although the number of whales is 100, the accuracy of the model is relatively high. However, the running time of the model increases. Therefore, this paper selects the number of whales as 1. In addition, from the convergence results

**Table 4.** Comparison between TSVR model and BP model.

<table>
<thead>
<tr>
<th>Model</th>
<th>Criteria</th>
<th>TSVR</th>
<th>BP</th>
</tr>
</thead>
<tbody>
<tr>
<td>CM (±0.005 wt%)</td>
<td>RMSE, wt%</td>
<td>0.0031</td>
<td>0.0036</td>
</tr>
<tr>
<td></td>
<td>MAE, wt%</td>
<td>0.0026</td>
<td>0.0028</td>
</tr>
<tr>
<td></td>
<td>SSE/SST</td>
<td>0.5835</td>
<td>0.7820</td>
</tr>
<tr>
<td></td>
<td>SSR/SST</td>
<td>0.9051</td>
<td>0.6659</td>
</tr>
<tr>
<td></td>
<td>HR, %</td>
<td>90</td>
<td>89</td>
</tr>
<tr>
<td>TM (±10°C)</td>
<td>RMSE, °C</td>
<td>5.5162</td>
<td>6.5421</td>
</tr>
<tr>
<td></td>
<td>MAE, °C</td>
<td>4.4930</td>
<td>5.3659</td>
</tr>
<tr>
<td></td>
<td>SSE/SST</td>
<td>0.5428</td>
<td>0.7635</td>
</tr>
<tr>
<td></td>
<td>SSR/SST</td>
<td>0.8570</td>
<td>0.8044</td>
</tr>
<tr>
<td></td>
<td>HR, %</td>
<td>94</td>
<td>89</td>
</tr>
<tr>
<td></td>
<td>DHR, %</td>
<td>84</td>
<td>79</td>
</tr>
<tr>
<td></td>
<td>93% DHR (±0.006 wt%) &amp;&amp; (±11°C)</td>
<td>(±0.008 wt%) &amp;&amp; (±13°C)</td>
<td></td>
</tr>
</tbody>
</table>
of WOA in [29], it can be seen that when the number of iterations reaches to 300, the convergence rate of WOA tends to be stable. Therefore, 350 is randomly chosen as the maximum number of iterations for the model. The spiral shape parameter is not sensitive to the model, so \( v \) is set to 1.

The incremental control model is implemented by setting the search step size according to the interval of the target to be searched and then searching within this interval. Assume that the search interval of the scrap weight, lime weight, dolomite weight and oxygen blowing volume is \([M, N]\), the step length is \( q \), and the relative additions are optimized within this interval. The search interval of the incremental control model variables depends on the actual historical production experience of the plant, hence choosing the scrap weight search interval as \([4,70]\), the lime weight search interval as \([0.5,16]\), the dolomite weight search interval as \([1,7]\), and the oxygen blowing volume search interval as \([11 \,000,17 \,000]\). The following search step sizes are selected for modeling: 16 tons for scrap weight, 1 ton for lime weight, 1 ton for dolomite weight and 1,000 Nm\(^3\) for oxygen blowing volume.

According to the existing static control model, the scrap weight, lime weight, dolomite weight and oxygen blowing volume were calculated using direct prediction. In the comparison, the static control model is realized based on the TSVR algorithm, which consists of four independent models, namely scrap steel control model (SM), lime control model (LM), dolomite control model (DM) and oxygen blowing control model (OM). The input variables of the control model are chosen by the rules in [20], and the output interval as \([0.5,16]\), the dolomite weight search interval as \([1,7]\), and the oxygen blowing volume search interval as \([11 \,000,17 \,000]\). The following search step sizes are selected for modeling: 16 tons for scrap weight, 1 ton for lime weight, 1 ton for dolomite weight and 1,000 Nm\(^3\) for oxygen blowing volume.

According to the existing static control model, the scrap weight, lime weight, dolomite weight and oxygen blowing volume were calculated using direct prediction. In the comparison, the static control model is realized based on the TSVR algorithm, which consists of four independent models, namely scrap steel control model (SM), lime control model (LM), dolomite control model (DM) and oxygen blowing control model (OM). The input variables of the control model are chosen by the rules in [20], and the output

![Fig. 3. Performance of end-point carbon content and temperature prediction models.](image1)

![Fig. 4. Distribution of prediction errors of end-point carbon content and temperature prediction models.](image2)

![Fig. 5. 10 times average errors for 10 sets of the optimized additions.](image3)
variables are scrap weight, lime weight, dolomite weight and blowing oxygen volume, respectively. For the static control model, the model parameters of $SM$ are $C_1=1$, $C_2=1$, $\varepsilon_1=1$, $\varepsilon_2=1$, $\sigma=0.4$, and the model parameters of $LM$, $DM$ and $OM$ are $C_1=1$, $C_2=1$, $\varepsilon_1=1$, $\varepsilon_2=1$, $\sigma=0.2$.

To illustrate the performance of the proposed control model, the model comparisons are carried out from the following two aspects:

1. Calculation accuracy. From the comparison results shown in Table 6, the proposed model and static control model run faster per heat than that of the incremental model. The scrap weight error ($RMSE$ or $MAE$) of the static model is at least 2 tons lower than those of the other two models, respectively.

2. Model ranking. First, the calculation results of each model on each data set need to be obtained, and then rank them from small to large according to the calculation results on each sample set, and assign the rank values of 1, 2 and 3. The results are shown in Table 7, where the average rank value is obtained by averaging the rank values of each column. The average ranking of scrap weight in the proposed model is 2, and the average ranking of lime weight, dolomite weight, and blowing oxygen volume are all 1. In terms of accuracy and ranking, the proposed model is better than the other two models in calculating lime weight, dolomite weight, and oxygen blowing volume. Therefore, the proposed model performance is optimal.

Further, if the number of whales in this experiment is increased, the mean absolute errors of the control model for calculating scrap weight, lime weight, dolomite weight

### Table 5. Performance of different whale number of the proposed control model.

<table>
<thead>
<tr>
<th>Heat serial number</th>
<th>Number of whales</th>
<th>Criteria</th>
<th>Scrap weight, tons</th>
<th>Lime weight, tons</th>
<th>Dolomite weight, tons</th>
<th>Oxygen blowing volume, Nm$^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>MAE</td>
<td>9.1743</td>
<td>1.2850</td>
<td>0.8878</td>
<td>431.423</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td></td>
<td>8.5693</td>
<td>1.0157</td>
<td>0.8073</td>
<td>365.293</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td></td>
<td>6.9735</td>
<td>0.9495</td>
<td>0.6615</td>
<td>333.6907</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td></td>
<td>6.0162</td>
<td>0.9062</td>
<td>0.4644</td>
<td>271.1769</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>MAE</td>
<td>6.273</td>
<td>1.3182</td>
<td>0.7512</td>
<td>474.1088</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td></td>
<td>5.9799</td>
<td>1.1755</td>
<td>0.7158</td>
<td>382.3305</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td></td>
<td>4.8498</td>
<td>1.1621</td>
<td>0.5879</td>
<td>342.4564</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td></td>
<td>4.7871</td>
<td>1.0487</td>
<td>0.5042</td>
<td>338.6034</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>MAE</td>
<td>6.377</td>
<td>1.3031</td>
<td>0.8208</td>
<td>449.2109</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td></td>
<td>5.5449</td>
<td>0.9668</td>
<td>0.8866</td>
<td>442.2555</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td></td>
<td>4.7214</td>
<td>0.6991</td>
<td>0.8343</td>
<td>362.1775</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td></td>
<td>3.5499</td>
<td>0.4614</td>
<td>0.7939</td>
<td>310.4828</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>MAE</td>
<td>8.4131</td>
<td>1.36</td>
<td>0.7692</td>
<td>437.2128</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td></td>
<td>7.845</td>
<td>0.9768</td>
<td>0.742</td>
<td>423.5394</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td></td>
<td>7.4892</td>
<td>0.9345</td>
<td>0.5941</td>
<td>354.7961</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td></td>
<td>6.3841</td>
<td>0.8396</td>
<td>0.3687</td>
<td>308.9255</td>
</tr>
</tbody>
</table>

### Table 6. Comparison between three control models.

<table>
<thead>
<tr>
<th>Control Model</th>
<th>Calculation Variables</th>
<th>RMSE</th>
<th>MAE</th>
<th>SD</th>
<th>Run time, s/heat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Model</td>
<td>Scrap weight, tons</td>
<td>11.7196</td>
<td>9.3114</td>
<td>4.7448</td>
<td>0.4830</td>
</tr>
<tr>
<td></td>
<td>Lime weight, tons</td>
<td>3.0401</td>
<td>2.5791</td>
<td>1.1039</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dolomite weight, tons</td>
<td>1.0048</td>
<td>0.7919</td>
<td>0.5904</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Oxygen blowing volume, Nm$^3$</td>
<td>653.9993</td>
<td>537.8215</td>
<td>387.6443</td>
<td></td>
</tr>
<tr>
<td>Incremental Model</td>
<td>Scrap weight, tons</td>
<td>21.4563</td>
<td>17.5244</td>
<td>20.7801</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lime weight, tons</td>
<td>5.2364</td>
<td>4.3882</td>
<td>4.2580</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dolomite weight, tons</td>
<td>2.2029</td>
<td>1.6918</td>
<td>1.8665</td>
<td>20.4160</td>
</tr>
<tr>
<td></td>
<td>Oxygen blowing volume, Nm$^3$</td>
<td>1763.9311</td>
<td>1459.8300</td>
<td>1524.8448</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lime weight, tons</td>
<td>3.6209</td>
<td>2.7230</td>
<td>2.9172</td>
<td>0.0797</td>
</tr>
<tr>
<td></td>
<td>Dolomite weight, tons</td>
<td>1.1241</td>
<td>0.8538</td>
<td>0.9514</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Oxygen blowing volume, Nm$^3$</td>
<td>722.5982</td>
<td>591.1539</td>
<td>562.6289</td>
<td></td>
</tr>
</tbody>
</table>
and oxygen blowing volume may be better than the results of this experiment.

5. Conclusion

The results of the established whale optimization control model are summarized as follows:

(1) The input variables are determined by GRA and PCA to improve the accuracy of the algorithm. The simulation results show that the hit rate of CM error within 0.005 wt% is 90%, and the hit rate of TM error bound within 10°C is 94%, respectively. Moreover, a double hit rate reached 84%. Compared with the BP model, the proposed model is better.

(2) The input variables of the control model consist of the initial conditions of molten iron and the output of the prediction models. The result shows that the weights mean absolute error of scrap calculated by the whale optimization control model is 9.3114 tons, the weight mean absolute error of lime is 2.5791 tons, the weight mean absolute error of dolomite is 0.7919 tons, and the volume mean absolute error of oxygen blowing is 537.8215 Nm³.

(3) Compared with the incremental control model and static control model, the scrap weight error (RMSE or MAE) of the static model is at least 2 tons lower than those of the other two models. The lime weight error (RMSE or MAE), dolomite weight error (RMSE or MAE) and oxygen blowing volume error (RMSE or MAE) of the proposed model are at least 0.2 tons, 0.06 tons and 50 Nm³ lower than the other two models, respectively, which is suitable to provide a reference for the production of steel plants.

Based on the proposed static model, a dynamic control model is established. The model can use feedback information in the furnace to correct the blowing error, can significantly improve the accuracy and hit rate of the end-point control, and solve the end-point control problem.

Table 7. The rank of the calculated variables of the three control models.

<table>
<thead>
<tr>
<th>Calculation Variables</th>
<th>Criteria</th>
<th>Proposed Model</th>
<th>Incremental Model</th>
<th>Model of Ref. [20]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scrap weight</td>
<td>RMSE</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>MAE</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Average rank</td>
<td>2</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Lime weight</td>
<td>RMSE</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>MAE</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Average rank</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Dolomite weight</td>
<td>RMSE</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>MAE</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Average rank</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Oxygen blowing volume</td>
<td>MAE</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Average rank</td>
<td>1</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

Conflict of Interest

The authors declare that they have no conflict of interest.

Acknowledgments

This work is supported by the PhD Start-up Fund of Liaoning Province, China. Grant (No. 2021-BS-244), the Liaoning Province Education Department of China (No. 2020LZD05), the National Natural Science Foundation of China (51774179 and 51974155), and Liaoning Province Science and Technology Major Special Project (2020H1L1/10100001).

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