Research on Prediction of Oxygen Consumption in Converter Steelmaking Based on IGWO-SVM Model

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Abstract: The oxygen supply for converter steelmaking is the main factor affecting the quality of molten steel. To improve the accuracy of the oxygen consumption prediction model for converter steelmaking, an improved gray wolf optimization algorithm is proposed to optimize support vector machines to establish an oxygen consumption prediction model (IGWO-SVM), effectively improving the prediction accuracy of oxygen consumption in converter steelmaking. Firstly, aiming at the problem of slow convergence of the standard gray wolf algorithm and easy to fall into local optimality, Bernoulli chaotic initialization is introduced to enhance the uniformity and ergodicity of the initial population; and an adaptive decreasing convergence factor is introduced to balance the global search of the gray wolf algorithm and local search capability, while adopting adaptive inertia weight strategy to update the population position and speed up the convergence speed. Secondly, the benchmark function is used for testing, and the results show that the improved gray wolf optimization algorithm has improved convergence speed and search accuracy. Finally, based on the measured data of a steel plant to predict the oxygen consumption of converter steelmaking, the simulation results show that the oxygen consumption prediction model of converter steelmaking based on IGWO optimized SVM has high accuracy and strong generalization ability.

1. Introduction

BOF steelmaking is a very complex multi-element multiphase high temperature physical and chemical process. Its most notable feature is that it has many influencing factors, fast reaction speed, and complex reaction. This feature determines that it is difficult to establish an accurate mathematical model for the converter steelmaking process [1]. Among them, an important process in the steelmaking process is oxygen blowing. Oxygen is injected through the top oxygen lance to reduce the carbon content in the furnace, increase the temperature of the converter bath, remove impurity elements, and obtain molten steel that meets the requirements of the steel tapping process. If the amount of oxygen blowing is not accurate, the smelting cycle will be longer, which will affect the life of the converter and reduce the production efficiency. In order to meet the increasingly fierce market competition and the needs of sustainable development, energy consumption is minimized while ensuring output and quality. Therefore, the prediction of oxygen consumption in the converter steelmaking process is of great significance.

At present, in the research of oxygen consumption prediction for converter steelmaking, literature [2] established an oxygen consumption prediction model based on BP neural network. The prediction results of this model can meet the process requirements, but the convergence speed is slow. Literature [3] improved the traditional BP algorithm, added a damping term and introduced a variable step...
method, and used the improved BP neural network to predict the oxygen consumption of converter steelmaking. This method has a fast response but low prediction accuracy. Literature [4] uses the PSO optimization algorithm to optimize the penalty coefficient of SVM and the Gaussian kernel width coefficient, and uses the optimized SVM model to predict oxygen consumption in converter steelmaking, which improves the prediction of oxygen consumption in converter steelmaking. Accuracy. However, the optimization ability and convergence speed of the PSO optimization algorithm are not good. Aiming at the above problems, this paper proposes a prediction method based on the improved gray wolf optimization algorithm to optimize SVM to complete the accurate prediction of the oxygen consumption of the converter.

2. Standard Gray Wolf Optimization Algorithm
Grey Wolf Optimization Algorithm (GWO) is a new swarm intelligence optimization algorithm based on the three links of gray wolf group hunting behavior tracking, stalking and hunting [5]. In the gray wolf group, there is a hierarchy and a division of labor system, and individual gray wolves are strictly divided into four levels: α, β, δ, and ω according to their social relationships [6]. Among them, α is the leader wolf, β is the deputy leader wolf, δ is the ordinary wolf and the bottom wolf ω. The chief wolf α is responsible for specifying the moving direction of the wolves; β wolves and δ wolves are responsible for providing reference directions for α wolves; ω wolves obey α, β, and δ wolves and provide stability for the wolves.

In GWO optimization, it is led by the leader wolf α, assisted by β and δ wolves, and other wolves complete encircling, hunting and attacking behaviors to find the global optimal solution. The mathematical model of wolves hunting prey is as follow:

\[
D = \left| C X_p(t) - X(t) \right| \tag{1}
\]

\[
X(t+1) = X_p(t) - AD \tag{2}
\]

In formulas (1) and (2): D is the distance between the gray wolf individual and the prey; t is the current iteration number; A and C are coefficient vectors; \(X_p(t)\) is the position vector of the prey in t iterations; \(X(t)\) is the position vector of the gray wolf individual in t iterations. The calculation formula of A and C is:

\[
A = 2a r_1 - a \tag{3}
\]

\[
C = 2r_2 \tag{4}
\]

Among them: \(r_1\) and \(r_2\) are random vectors in the range of [0,1], \(a\) is the convergence factor, and its value linearly decreases from 2 to 0 as the number of iterations t increases. The calculation formula of \(a\) is:

\[
a = 2\left(1 - \frac{t}{T_{\text{max}}}\right) \tag{5}
\]

In the above formula: t is the current number of iterations; \(T_{\text{max}}\) is the maximum number of iterations.

The mathematical model of wolves tracking and attacking prey is as follows:

\[
D_\alpha = \left| C X_\alpha(t) - X(t) \right|
\]

\[
D_\beta = \left| C X_\beta(t) - X(t) \right|
\]

\[
D_\delta = \left| C X_\delta(t) - X(t) \right|
\]

\[
X_1 = X_\alpha(t) - A D_\alpha
\]

\[
X_2 = X_\beta(t) - A D_\beta
\]

\[
X_3 = X_\delta(t) - A D_\delta
\]

\[
X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{8}
\]
In the above formula: $D_\alpha$, $D_\beta$, and $D_\delta$ are the distances between $\alpha$ wolves, $\beta$ wolves and $\delta$ wolves from other wolves, respectively; $A_1$, $C_1$, $A_2$, $C_2$ and $A_3$, $C_3$ are random vector; $X_\alpha(t)$, $X_\beta(t)$, $X_\delta(t)$ are the positions of $\alpha$ wolf, $\beta$ wolf and $\delta$ wolf when the number of iterations is $t$ respectively; $X(t)$ is the current wolf position; $X(t+1)$ is the current wolf update after the position.

3. Improved Gray Wolf Optimization Algorithm (IGWO)

In order to solve the problem of poor global search ability when solving the standard GWO and easy to fall into the local optimum, the random initialization, convergence factor and position update formula of the standard GWO are improved to improve the convergence speed and search characteristics of GWO.

3.1 Initialization of wolves based on Bernoulli chaotic map

The initial position of the wolf pack in GWO has a great influence on the convergence speed and solution accuracy of the algorithm, and even leads to the failure of optimization. The standard GWO uses a random initialization method to initialize the wolves. In the process of initialization, random initialization will cause the population to be unevenly distributed and poorer in diversity. In order to solve this problem, chaotic mapping is introduced. Chaotic mapping is a random state of motion obtained from a deterministic equation. It has the characteristics of randomness and ergodicity [7]. It can make the initial population individuals use the information of the solution space as much as possible. Improve global search capabilities. In this paper, the Bernoulli chaotic map is used to generate the chaotic sequence, and the wolves are initialized to the uniform distribution of the population position. The Bernoulli chaotic mapping formula is as follows:

$$
X_{n+1} = \begin{cases} 
\frac{X_n}{\varepsilon}, & X_n \in (0, 1 - \varepsilon] \\
\frac{X_n - 1 + \varepsilon}{\varepsilon}, & X_n \in (1 - \varepsilon, 1)
\end{cases}
$$

In formula (9), $X_n$ is a chaotic variable, $\varepsilon$ is an adjustment factor, $X_n \in (0, 1)$ and $\varepsilon=0.5$,$X_0 = 0.8473$. Figure 1 is a bubble chart of comparison between random initialization of 30 populations and initialization of Bernoulli chaotic map.

3.2 Convergence factor of adaptive adjustment strategy

There are two operations of global search and local search in GWO, and the convergence factor a has a balance effect on the two operations of global search and local search. From formula (5), a linearly decays from 2 to 0 with the increase of the number of iterations in the standard GWO, while the algorithm optimization process is not linear. Considering that the linear decreasing strategy of a in the
standard GWO cannot fully reflect the actual Optimize the search process. Therefore, a nonlinear polynomial adaptive adjustment strategy is proposed to better adjust the balance between the global search and local search of the GWO algorithm, so as to improve the convergence speed and stability of the algorithm. The calculation formula of the convergence factor is as follows:

\[
a(t) = a_{\text{initial}} + \gamma_1 \left( \frac{t}{T_{\text{max}}} \right)^2 + \gamma_2 \left( \frac{t}{T_{\text{max}}} \right)^3
\]

In formula (10): \( a_{\text{initial}} \) is the initial value of the convergence factor \( a \), \( a_{\text{initial}} = 2 \); \( t \) is the number of iterations; \( T_{\text{max}} \) is the maximum number of iterations; \( \gamma_1 \) and \( \gamma_2 \) are the coefficients of the convergence factor, taking \( \gamma_1 = -6 \) and \( \gamma_2 = 4 \). Therefore, the calculation formula of \( a \) is as follows:

\[
a(t) = 2 - 6 \left( \frac{t}{T_{\text{max}}} \right)^2 + 4 \left( \frac{t}{T_{\text{max}}} \right)^3
\]

(11)

The attenuation comparison of the improved convergence factor \( a \) (5) and the improved equation (11) is shown in figure 2:

Figure 2. Convergence factor before and after improvement

3.3. Position update of adaptive weights
In the GWO optimization process, according to formula (8), the standard GWO uses a weighted average strategy to assign the weights of a wolf, \( \beta \) wolf, and \( \delta \) wolf to complete the position update of the gray wolf individual. In the actual GWO optimization process, the average strategy ignores the problem that the location update should dynamically change with the gray wolf's guidance level, and the location update strategy is not perfect. Therefore, the position update formula of the adaptive dynamic weight strategy is proposed as follows:

\[
X(t+1) = \frac{2 * X_1 + X_2 + X_3}{4} + \frac{1}{2} \left( \frac{X_2 + X_3}{2} \right) + \frac{t}{T_{\text{max}}} \left[ \frac{X_1}{2} \right]
\]

(12)

4. Improved gray wolf optimization algorithm performance test
In order to verify the stability and convergence of IGWO, five international classic benchmark functions were selected for testing, and Particle Swarm Optimization (PSO), Dragonfly Algorithm (DA) [8], Ant Lion Optimizer (ALO) [9], Gray Wolf Optimization Algorithm (GWO) and the Improved Gray Wolf Optimization Algorithm (IGWO) are used for comparative testing of these 6 test functions. The six test functions are shown in Table 1. Among them, the population number \( N \) of all algorithms is
set to 30, and the total number of iterations is set to 500. The test result comparison chart is shown in figure 3.

### Table 1. Benchmark test functions

| Serial Number | Test Function |
|---------------|---------------|
| F1            | \( f(x) = \sum_{i=1}^{n} x_i^2 \) |
| F2            | \( f(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i| \) |
| F3            | \( f(x) = \sum_{i=1}^{n} \left( \sum_{j=1}^{n} x_j \right)^2 \) |
| F4            | \( f(x) = \max_{i} \{x_i, 1 \leq i \leq n\} \) |
| F5            | \( f(x) = \sum_{i=1}^{n} [x_i^2 - 10 \cos(2 \pi x_i) + 10] \) |
| F6            | \( f(x) = \frac{\pi}{n} \sin^2(\pi w) + \sum_{i=1}^{n} (w_i - 1)^2 \left[ 1 + \sin^2(\pi w_i) + 1 \right] \) |

\( w_i = 1 + \frac{x_i - 1}{4}, i = 1, 2, ..., d \)

(a) F1 benchmark function test chart

(b) F2 benchmark function test chart
Figure 3. Benchmark test function test comparison chart
In the above figure 3, the left side of the six test function test diagrams is the three-dimensional map of the parameter search space of the test function, and the right side is the convergence curve of the optimization and comparison of the five population intelligent algorithms. It can be seen that the convergence accuracy of the improved gray wolf algorithm is greatly increased, and the convergence accuracy and convergence speed are higher and faster than GWO, PSO, DA and ALO.

5. Construction of oxygen consumption prediction model for converter steelmaking

5.1. IGWO-SVM model construction

At present, the commonly used prediction models include neural networks, support vector machines, and time series models. Support vector machines (SVM), as a new technology of artificial intelligence, follow the minimization of structural risks rather than the empirical risks of neural networks. Therefore, compared with traditional neural networks, it is not only simple in structure, but also has good nonlinear processing and generalization capabilities \(^{[10-11]}\). It is suitable for solving small sample, high-dimensional, and nonlinear problems. It has been widely used in the actual application of predictive modeling process \(^{[12]}\). This paper constructs a converter steelmaking oxygen consumption prediction model based on the improved gray wolf optimization algorithm optimized support vector machine (IGWO-SVM). Use the improved gray wolf algorithm to find the two optimal values C and g as the penalty coefficient and the radius of the kernel function of the SVM model, and use the optimized SVM model to train and predict the oxygen consumption of converter steelmaking to improve the performance of the traditional SVM model. Forecast accuracy. The IGWO-SVM prediction model is shown in figure 4:

![IGWO-SVM prediction model diagram](image-url)
5.2. Case analysis of oxygen consumption prediction for converter steelmaking

5.2.1. Data preprocessing. According to actual converter steelmaking production data, Pearson correlation analysis was carried out using SPSS on the importance of factors affecting oxygen consumption. Taking oxygen consumption as a reference sequence, there are multiple influencing factors such as molten iron quality, scrap steel quality, molten iron carbon content, molten iron silicon content, molten iron manganese content, molten iron phosphorus content, target molten steel temperature, and target molten steel carbon content. In order to compare the sequences, after the normalization method is used for dimensionless processing, the correlation analysis is performed to obtain the Pearson correlation of the factors affecting oxygen consumption as shown in Table 2. According to the correlation table 2, finally select the 6 elements of molten iron quality, molten iron carbon mass fraction, molten silicon mass fraction, scrap steel quality, target molten steel carbon mass fraction and target molten steel temperature as input quantities.

Table 2. Correlation analysis of factors affecting oxygen consumption

| Variable          | The amount of molten iron | The temperature of molten iron | Carbon content | Silicon content | Manganese content | Phosphorus content |
|-------------------|---------------------------|-------------------------------|----------------|-----------------|-------------------|--------------------|
| Oxygen consumption| 0.105**                   | 0.032                         | 0.115**        | 0.109**         | 0.041             | 0.035              |
| Variable          | Sulfur content            | Scrap volume                  | Amount of lime added | Amount of iron ore added | End point carbon content | End temperature |
| Oxygen consumption| -0.028                    | 0.134**                      | 0.062 | 0.058 | -0.239**         | 0.166**           |

** The correlation is significant at the 0.01 level

5.2.2. Instance verification. The experimental data is the actual production data of converter steelmaking in a steel plant. The operating environment of the comparative simulation experiment is Intel(R) Core (TM) i5CPU, clocked at 2.40 GHz, memory 16 GB, Windows 10 operating system, and the experimental simulation software uses MATLAB R2019a. After preprocessing the converter steelmaking data, input the preprocessed data into the constructed IGWO-SVM, GWO-SVM, PSO-SVM and SVM models to predict the oxygen consumption. In order to evaluate the prediction effect of the converter steelmaking oxygen consumption prediction model, in order to ensure the fairness of the prediction results, the parameter settings of each model are kept consistent, and each prediction model is run independently for 30 times and the average value is taken. The comparison of the absolute value of the simulation error of the four oxygen consumption prediction models is shown in Figure 5. The horizontal axis is the number of sample furnaces, and the vertical axis is the absolute value of the oxygen consumption prediction error. It can be seen from the figure that the prediction effect of the IGWO-SVM model is better than others 3 models.
Figure 5. Comparison of the absolute value of the prediction errors of the four models

In order to further compare the prediction effect of each prediction model, this article uses three commonly used error indicators, namely the mean absolute error (MAE), the root mean square error (RMSE) and the mean square absolute percentage error (MAPE), using these three evaluation indicators model evaluation and analysis, the prediction results of the four models are shown in Table 3.

| Predictive Model | IGWO-SVM | GWO-SVM | PSO-SVM | SVM   |
|------------------|----------|---------|---------|-------|
| MAE              | 160.3    | 162.2   | 167.5   | 168.7 |
| RMSE             | 207.6    | 209.2   | 216.8   | 222.1 |
| MAPE (%)         | 1.92     | 1.94    | 2.01    | 2.12  |

From the comparison results in Table 3, it can be seen that compared with the GWO-SVM, PSO-SVM and SVM prediction models, the MAE, RMSE and MAPE of the IGWO-SVM model are all smaller than those of the other three models. It can be seen that the proposed improved algorithm is effective for converter steelmaking. The best results have been achieved in the oxygen consumption prediction process, and the IGWO-SVM model has higher prediction accuracy in oxygen consumption prediction.

6. Conclusion

In this paper, aiming at the slow convergence speed of the standard gray wolf algorithm, poor global search ability, and easy trapping into local extremes, chaotic sequences are generated based on the Bernoulli chaotic map, and the wolves are initialized to the uniform distribution of population positions to improve their global search ability. The improved convergence factor based on the nonlinear polynomial adaptive adjustment strategy gives it the ability to adaptively decrease, which can better adjust the balance between the global search and the local search of the GWO algorithm, and improve the convergence speed and stability of the algorithm. The adaptive dynamic inertia weight is introduced to improve the position update formula of the wolf pack, so that the algorithm is not easy to fall into the local extreme value. The improved GWO optimized SVM prediction model is applied to the prediction of oxygen consumption of converter steelmaking in iron and steel enterprises, giving full play to the optimization ability of the IGWO optimization algorithm and the unique advantages of the SVM model's generalization ability and nonlinear processing. The simulation results show that the IGWO-SVM model effectively improves the prediction accuracy of oxygen...
consumption in converter steelmaking and has certain practical significance for the prediction of oxygen consumption in converter steelmaking.

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