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Research on The Prediction and Optimization of Blast Furnace Molten Iron Temperature Based on LSTM Long and Short-Term Neural Memory Network

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Abstract: The modern steel industry pursues green, low-consumption and high-quality development, and the prediction of fuel ratio and molten iron temperature is the key. However, the traditional prediction methods are limited, and the information age requires technological updates. In this paper, OLS regression, LSTM and PSO algorithms are used to establish and optimize the blast furnace molten iron temperature prediction model. First, analyze the literature and preprocess the data. Secondly, reduce dimension processing and select key variables. Then, construct the LSTM model to predict the temperature and evaluate the effect. Next, optimize the model with PSO and evaluate again. Finally, summarize the model, the prediction accuracy is high, especially the optimized model is significantly improve the prediction performance, but still need to be combined with the actual production of real-time detection and adjustment.

Keywords: Iron and Steel industry, Green, OLS Regression Model, LSTM Long Short-term Memory Neural Network, PSO Particle Swarm Optimization Algorithm, Blast Furnace Molten Iron Temperature Prediction, Fuel Ratio.

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1 INTRODUCTION

1.1 Introduction to Blast Furnace Smelting Process

1.1.1 Overview of blast furnace smelting process

Blast furnace smelting is a metallurgical process mainly used for the production of iron, and its basic principle is to mix iron ore with coke and other reducing agents, and then carry out the reduction reaction at high temperature to reduce the iron oxide in the iron ore to metallic iron. At the same time, due to the high temperature inside the blast furnace, some other harmful substances will be removed at the same time.

The process of blast furnace ironmaking mainly has:

1. Preparation of raw materials. The raw materials for blast furnace ironmaking mainly include iron ore, coke and limestone. The main components of iron ore are usually iron oxides such as hematite and magnetite. Coke is a variant of coal, prepared by pyrolysis at high temperatures.

2. Furnace charge mixing. Limestone, iron ore and coke are mixed in a certain proportion at the top of the blast furnace and fed into the blast furnace.

3. Reduction reaction. In the blast furnace, the coke is heated to a high temperature to produce a certain amount of carbon monoxide and carbon dioxide. Carbon monoxide as a reducing agent and iron ore reduction reaction, the iron oxide will be reduced to iron.

4. Melting. The reduced iron interacts with the slag (consisting of limestone and impurities) in the lower part of the blast furnace to form liquid iron and slag.

5. Collection and discharge. The molten iron is discharged through an outlet at the bottom of the blast furnace and fed into the continuous casting machine for molding. The slag is collected and disposed of for other uses.

6. Energy recovery. Blast furnace exhaust gases can contain a large amount of heat energy, which is usually recovered through heat exchange equipment.

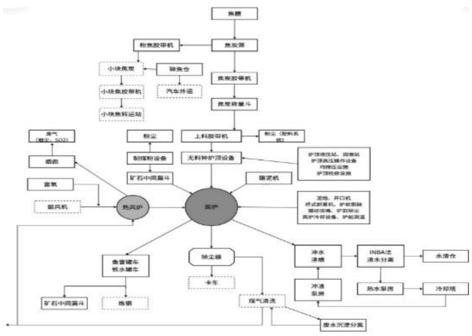

FIGURE 1. FLOW CHART OF BLAST FURNACE IRONMAKING

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1.1.2 Introduction of related key parameters

Wind volume: defined as the air circulation volume per unit time, it is mainly used to indicate the working capacity of the blower or blower equipment, and its unit is m/s.

Wind pressure: is defined as the pressure generated by the wind on the plane perpendicular to the direction of airflow. Differential pressure is the pressure difference between two points in the system, such as the pressure difference between the bottom of the well and the wellhead, and the pressure difference between the two sides of a small hole.

Pulverized Coal: are those coals whose particle size does not exceed 0.5 mm.

Fuel ratio: is the proportion of fixed carbon in the volatile fraction. It is also an important index to measure the degree of coalization, that is, the fuel ratio of coal will gradually increase with the coalization degree of coal.

Oxygen enrichment of blast furnace: it refers to the amount of oxygen added in the smelting process of blast furnace, which is one of the key factors to improve the smelting efficiency of blast furnace.

Oxygen Enrichment Rate: It refers to the percentage of increase of oxygen enrichment content in the process of blast.

Comprehensive Load: It refers to the total electric power consumed by electrical equipment used by all power users in the system.

Top temperature: is the temperature at the top of the blast furnace. This can reveal the link between carbon dioxide and oxygen, i.e. how efficiently they are used.

Top Pressure: is the gravitational pressure medium applied from the top of the bed during regeneration or flushing of a countercurrent bed to ensure that the bed is compacted and uncluttered.

Gas permeability: is the ability of the gas to permeate through polymeric materials such as films, coatings, fabrics, etc.

Furnace Belly Gas Volume Index: is the amount of gas flowing through a unit of cylinder area.

1.2 THEORETICAL FOUNDATION OF BLAST FURNACE MOLTEN IRON TEMPERATURE PREDICTION AND LITERATURE REVIEW

1.2.1 The necessity and significance of establishing blast furnace molten iron temperature prediction model

At present, the measurement of blast furnace molten iron temperature mainly adopts contact and non-contact methods. The contact method measures the temperature by placing the sensor in the same thermal equilibrium state as the object to be measured, ensuring that the sensor and the object have the same temperature. Non-contact temperature measurement, on the other hand, relies on recording the infrared energy emitted from the surface of the object to determine its surface temperature. Both techniques can simplify the process of determining the temperature of the molten iron, but the complex multi-step process of blast furnace ironmaking, coupled with the interference of external factors such as molten iron transportation and climate, can affect the accuracy of the temperature measurement. These factors make it more difficult to select appropriate physical parameters and determine initial and boundary conditions when modeling the mechanism. At the same time, the complexity of the model increases the modeling and computation time, which to some extent limits its application to measuring the temperature of molten iron in actual production.

Therefore, the use of data-driven methods to predict the molten iron temperature has become particularly critical. Data-driven models offer greater flexibility than traditional mechanistic models by employing algorithms that can be adapted or optimized to the specific problem. Such models are typically constructed using historical data to explore the intrinsic laws of the objects they describe and enable real-time model output by incorporating online data parameters. Data-driven iron temperature prediction models are able to achieve accurate prediction of iron temperatures by relying on data alone, without involving the structure, material properties or heat transfer parameters of the iron equipment.

1.2.2 Research on traditional blast furnace molten iron temperature prediction methods

Many studies have been based on data-driven prediction of molten iron temperature. Cui Guimei [5] and her team used T-S multiple regression, BP neural network, and T-S fuzzy neural network to construct a model for predicting the temperature of molten iron coming out of the blast furnace. Cui Guimei [5] used principal component analysis to reduce the dimensionality of the set of influencing factors to obtain new composite factors as input vectors and combined with support vector machine to classify them, and then used multiple linear regression equations to calculate the blast furnace molten iron temperature. The accuracy of the prediction model reached 75.79%, 80.00% and 89.47% within the temperature range of blast furnace molten iron ± 10°C, respectively. Yongming Zhao [7] used three techniques, BP neural network model, ELM (Extreme learning machine-Extreme learning machine) temperature prediction model combined with gray correlation analysis, and echo state network (ESN) to construct his model. After the study, he found that the BP neural network model has an accuracy of 88.43%, its average relative error is 0.47%, and the root mean square error between the predicted and actual values of the model output is 2.6782%. In the case of blast furnace molten iron prediction using echo state network (ESN), the hit rate reached 94.70% and the average relative error was only 0.41%, while the accuracy of blast furnace molten iron temperature prediction was 2.4575%.

Li Jing [3] suggested the use of multiple regression

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model and multiple time series model to predict the temperature of molten iron, and confirmed that the T-S fuzzy neural network model has the best prediction effect through comparative optimization. On this basis, the construction method of wavelet network model and its application prospect were further studied. Zhang Yong [4] and his team constructed a temperature prediction model using neural networks and proved through simulation experiments that compared with the traditional BP neural network model, the wavelet neural network model showed obvious advantages and stability in hit rate and prediction accuracy. Chen Yonghong et al. introduced machine learning theory in the study of blast furnace roof equipment condition assessment and developed a set of intelligent diagnostic system, which realizes the data acquisition, processing and analysis of the blast furnace production process, as well as the function of fault diagnosis and decision-making. Pan Dong [6] and his team utilized infrared vision molten iron temperature measurement technology to reveal the future development trend of blast furnace molten iron online temperature measurement technology.

In general, some experts and scholars have adopted different algorithms for the iron and steel interface of the iron and steel temperature, and established a data-driven model based on the production history data to realize the prediction function of the iron and steel temperature.

1.3 Overall model research idea

Nowadays, the iron and steel industry is the pillar industry of the national economy. Recently, in the national manufacturing upgrading and transformation of the national strategy "Made in China 2025", the iron and steel industry's energy saving, high quality, low consumption and green environmental protection put forward higher requirements. This requires more accurate prediction of molten iron temperature in blast furnace iron smelting, so as to provide better and faster reaction feedback regulation.

In this paper, the data in the appendix is used as the data set, and the prediction of molten iron temperature in blast furnace ironmaking is the main body. Firstly, the data are preprocessed. Secondly, the data are downscaled by OLS regression model, and the data with high correlation are selected as independent variables from 19 variables. Then modeling and dynamic prediction feasibility analysis are carried out through LSTM long and short-term memory neural network model. Then the model is optimized by PSO particle swarm optimization algorithm. Finally, the summary and overall evaluation are carried out.

The research idea diagram is shown below in Figure 2 Overall modeling and optimization research idea diagram of the model.

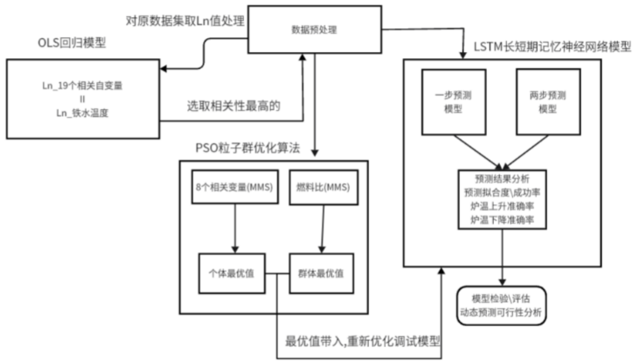

Figure 2. Overall modeling and optimization research idea diagram of the model

2 The construction and evaluation of the blast furnace molten iron temperature prediction model

2.1 Preprocessing of data

Based on the analysis of the blast furnace molten iron temperature data, it was found that some of the data in this dataset were incomplete or even erroneous. If we use these erroneous data in the modeling process, it will affect the prediction accuracy and success rate of this model. The reason for the errors may be the inevitable errors due to equipment detection, human readings, etc. when acquiring these data. Since the model's performance such as prediction accuracy and success rate fundamentally comes from these attached data sets, it is particularly important to preprocess these data before modeling. The main preprocessing includes: identification and treatment of outliers, noise reduction of data, filling of missing values and normalization.

2.1.1 Confirmation and processing of outliers

Since the blast furnace iron smelting process is a process of discrete addition, continuous smelting and discrete output, it has complexity and large volatility. In order to ensure the accuracy of the model, we need to eliminate these data. As shown in Fig. 3 with the wind volume dataset using the moving median method as an example, the moving median is taken here as a confirmation indicator to define the outliers and turn them into missing values, waiting for subsequent additions.

Moving median as an indicator for defining outliers has the unique advantages of being more robust, adapting to local variations, simple and intuitive, and capturing the dynamic characteristics of the data, which makes it more suitable for the uniquely complex and fluctuating environment in blast furnace iron smelting than the traditional method or the mean-based definition method. This is shown in Figure 4 as an

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example of using the median method for the airflow dataset. It is clear that processing at the median is far less effective than processing at the moving median.

2.1.2 Completion of missing values

For the missing values in the annexes and after the outliers are processed, certain methods or principles are used to fill in the missing values based on the trajectory and trend of the data changes. Traditional methods include the development rate projection method, smoothing method, and difference estimation method. Here the linear difference method is used to fill in the missing and processed data.

The linear difference method has high computational efficiency, wide applicability, better similarity and continuity characteristics, and can better adapt to the unique complexity and volatility of the environment in the blast furnace iron smelting. The fitting effect after processing is as follows.

As shown in Figure 3 with the airflow data set using the moving median method as an example.

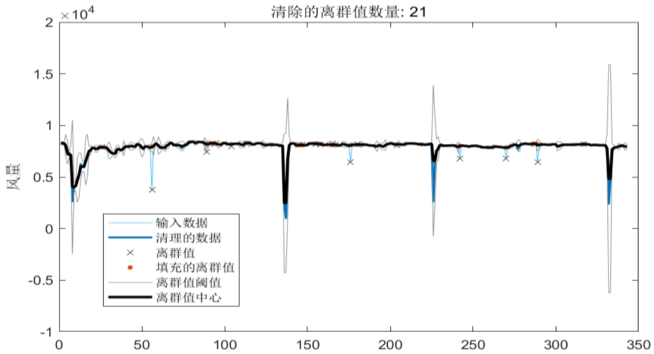

FIGURE 3. EXAMPLE OF USING THE MOVING MEDIAN METHOD WITH THE WIND VOLUME DATASET

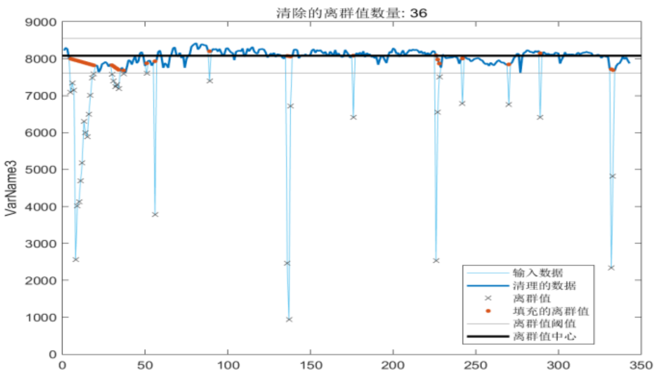

FIGURE 4 EXAMPLE OF USING THE MEDIAN METHOD WITH THE WIND VOLUME DATASET

2.1.3 Dimensionless and Normalized (MMS)

Through the analysis of the attached dataset, we found that there are significant differences in the dimension and order of magnitude between the indicators, and the direct use of these data may affect the accuracy of the indicator system. In order to ensure that the data are comparable and horizontally useful, this paper uses dimensionless and normalization to standardize the data so that the data are between [0,1]. The specific standardization method is as follows.

$$\frac{X-X_{min}}{X_{max}-X_{min}} \qquad \text{Formula (1)}$$

Note: X is the current value of the indicator, X_{max} is the maximum value of all values of the indicator, X_{min} is the minimum value of all values of the indicator

The obtained data are shown in Appendix 1: Dimensionless and Normalization of Data

2.2 OLS REGRESSION MODEL

2.2.1 Introduction to the OLS regression model

Based on the data obtained in 1.1.2, we synthesize various factors, take the Ln value for the processed data set, and construct the OLS regression model to study the relationship between 19 variable indicators, such as air volume, wind temperature, wind temperature, etc., and iron temperature, analyze the degree of correlation, and select the most correlated variable indicators to reduce the amount of indicators, which is convenient for the subsequent modeling. Taking the Ln value for the data is adopted to deal with the nonlinear relationship of the original data set, reduce the order of magnitude, stabilize the variance and distribution and highlight the reasons for the change in the proportion of the data.

2.2.2 Model construction and solution

First, we analyze the model fit to our data for R^2, even if the error is minimized.

$$L = \sum_{i=1}^{p} \epsilon_i^2 = \sum_{i=1}^{p} \left(y_j - \sum_{i=0}^{n} \beta_i X_{ij}\right)^2 \qquad \text{Formula (2)}$$

In this equation y_j is the jth sequence Ln_Ferrous Water Temperature, X_i is the indicator of the ith relevant variable of the jth sequence.

By solving the calculation of this equation, it can be obtained that the value of R^2 is 0.794, and the adjusted R^2 is 0.768, which means that the independent variable (19 Ln_related indicators) can explain the cause of the dependent variable (Ln_Iron Temperature), and the model fits well, allowing the construction of OLS regression model, and the formula of the model equation is as follows:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \epsilon \qquad \text{Formula (3)}$$

In this equation: y is the dependent variable (Ln_Iron Temperature), X_i is the independent variable 19 Ln_Related Indicators), where β_i is the number of regression coefficient variables estimated by the model, and ϵ is the model residual.

Solving the model gives the following table:

TABLE 1 RESULTS OF OLS REGRESSION ANALYSIS

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Results of OLS regression analysis

	Regression coefficients
constant	-94.904* (-2.134)
Ln_风量	0.242 (0.947)
Ln_风温	0.213 (1.365)
Ln_风压	0.442* (2.350)
Ln_压差	0.331** (3.832)
Ln_煤粉	-0.020 (-1.011)
Ln_燃料比	0.038 (0.604)
Ln_富氧量	0.007 (0.119)
Ln_富氧率	-0.007 (-0.122)
Ln_综合负荷	-0.182 (-1.800)
Ln_顶温	-0.024 (-1.127)
Ln_顶压	-0.407** (-2.790)
Ln_透气性	0.485** (3.971)
Ln_实际风速	-0.088 (-0.800)
Ln_动能	0.008 (0.132)
Ln_理燃	-0.033 (-0.690)
Ln_炉腹煤气量	18.719* (2.235)
Ln_炉腹煤气指数	-18.719* (-2.235)
Ln_净风量	-0.370** (-3.010)
Ln_湿度	-0.010** (-3.059)
样本量	323
R 2	0.794
调整 R 2	0.768
F 值	F (19,303)=6.400,p=0.000

implicit variable：Ln_铁水温度

D-W 值：1.183

* p<0.05 ** p<0.01 Inside the parentheses is the value of t

Analyze the significance of X; if it shows significance (p-

Results of OLS regression analysis
Regression coefficients

value less than 0.05 or 0.01); then it means that X has an effect relationship on Y

Other analytical directions

In particular, the regression coefficients 95% confidence intervals (95%Cl) are plotted as follows in Figure 5 Regression Coefficients 95%Cl, a graph that allows for visualization of uncertainty, comparison of different variables, assessment of stability, and validation of the model's reasonableness.

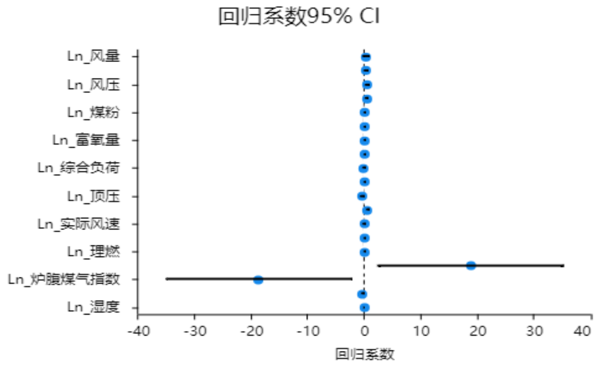

FIGURE 5 REGRESSION COEFFICIENT 95% CL

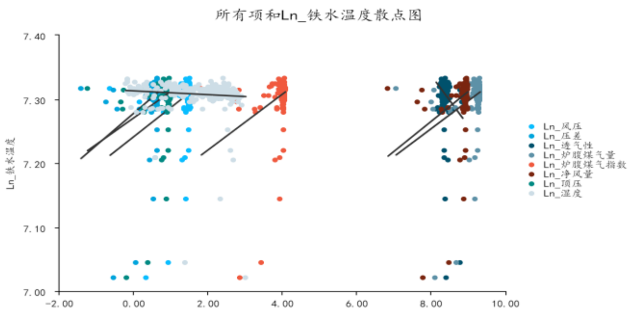

FIGURE 6 SCATTER PLOT OF ALL TERMS AND LN_FERROUS TEMPERATURE

By analyzing the above Table 1, above Fig. 5 and above Fig. 6, it can be seen that Ln_风压, Ln_压差, Ln_透气性, Ln_炉腹煤气量 will have a significant positive influence relationship on Ln_铁水温度. As well as Ln_顶压, Ln_炉腹煤气指数, Ln_净风量, Ln_湿度 will have a significant negative influence relationship on Ln_铁水温度. Therefore, we only need to use Ln_风压, Ln_压差, Ln_透气性, Ln_炉腹煤气量 Ln_顶压, Ln_炉腹煤气指数, Ln_净风量, Ln_湿度 which is the 8 variables that have significant influence with Ln_铁水温度 as the independent variables.

2.3 LSTM LONG AND SHORT-TERM MEMORY NEURAL NETWORK MODELING

2.3.1 LSTM Long Short-Term Memory Neural Network Construction Flowchart

LSTM (Long Short-Term Memory) is a special kind of recurrent neural network, which is able to learn long-term dependency, and can avoid the problems of gradient vanishing and gradient explosion that traditional RNNs have when dealing with long sequences of data.The key to the LSTM Long Short-Term Memory neural network model is that the unit possesses three gate structures inside the unit: the input gate, the output gate and the forgetting gate. forgetting gate. These gates work together to control the flow of information into and out of the cell. This structure allows the LSTM to memorize the values in any time interval and control the flow of information through the three gates, thus effectively solving the long-term dependency problem. The related specific diagram is shown in Figure 7 [11] below.

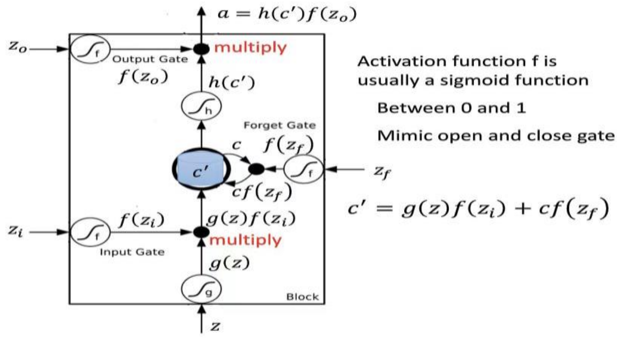

FIGURE 7 FLOWCHART OF LSTM LONG AND SHORT-TERM MEMORY NEURAL NETWORK CONSTRUCTION

The specific calculation principle is as follows [11]:

(1) Forgetting gate: used to calculate the degree of information forgotten or retained by sigmoid processing after 0 to 1 value. 1 means all retained, 0 means all forgotten. The specific formula is as follows:

$$f_t = \sigma(W_f * [h_{t-1}, X_t] + b_f) \quad \text{Formula (4)}$$

(2) Input gate: input gate is used to calculate which information is saved in the state unit, including two parts of information:

One part is: it can be taken as the current input how much information needs to be saved to the unit state.

$$i_t = \sigma(W_i * [h_{t-1}, X_t] + b_i) \quad \text{Formula (5)}$$

The other part is: it is used to add new information from the current input to the unit state.

$$\tilde{c_t} = tanh(W_c * [h_{t-1}, X_t] + b_c) \quad \text{Formula (6)}$$

These two parts generate a new memory. As a result, the cell state at the current moment consists of the product of the forgetting gate input and the state at the previous moment plus the product of the two parts of the input gate.

$$c_t = f_t * c_{t-1} + i_t * \tilde{c_t} \quad \text{Formula (7)}$$

(3) Output gate: used to calculate the extent to which information is output at the current moment.

$$o_t = \sigma\ (W_0 * [h_{t-1}, X_t] + b_0) \quad \text{Formula (8)}$$

$$h_t = o_t * tanh(c_t) \quad \text{Formula(9)}$$

2.3.2 One-Step Forecast Model Construction and Solution

One-Step Ahead Forecast (OAF) refers to using existing data to gradually add to the model and then predict the value of the next data point. By continuously predicting incrementally, the prediction results for the entire data series can be obtained. One-step forecasting is often used for short-term forecasting because it relies only on the most recent data and because the prediction error does not accumulate over time.

We divided the results after normalizing the variables screened by 1.2.1 into training, testing and validation sets, which accounted for 80%, 10% and 10% of the data in the 8*243 sets of the independent variables, respectively. The data bits are obtained by one-step prediction and finally will be fitted to Y in the original data and analyzed for root mean square error (RMSE), furnace temperature rise accuracy and furnace temperature fall accuracy for the test set. After several debugging of hyperparameters. We set the number of HiddenUnits (HiddenUnits) to be 50, meanwhile, the number of TimeSteps (TimeSteps) to be 1 and the number of Features (Features) to be 2. and start the test. The test results obtained are as follows:

The test fitting results are shown in Figure 8 below:

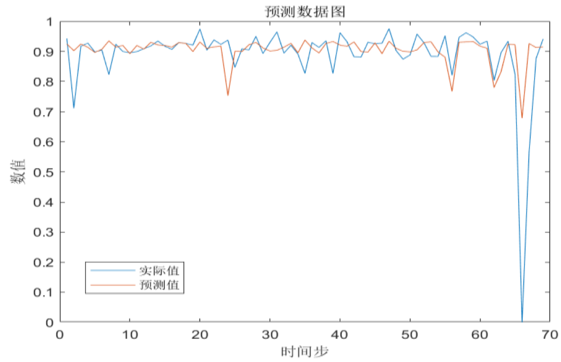

FIGURE 8 FITTING RESULTS OF ONE-STEP PREDICTION TEST

TABLE 2 PREDICTED ROOT MEAN SQUARE ERROR (RMSE), FURNACE TEMPERATURE INCREASE ACCURACY, FURNACE TEMPERATURE DECREASE ACCURACY

Root Mean Square Error (RMSE)	0.014638
Accuracy of furnace temperature increase	79.41%
Accuracy of furnace temperature decrease	82.35%

2.3.3 Two-Step Forecasting Model Construction and Solution

Two-Step Ahead Forecast refers to the use of the results of the previous step as inputs in each step of the forecast, rather than only the true values. Two-step forecasting can be used to predict "non-existent" data and can be used for long-term forecasting, but its prediction error may accumulate with

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the increase of the number of steps, leading to a decrease in the accuracy of the results. Therefore, two-step prediction is usually used for long-term prediction.

Similar to the method 1.3.2, we divide the normalized results of the variables screened in 1.2.1 into training, testing and validation sets, which account for 80%, 10% and 10% of the data in the 8*243 sets of the independent variables, respectively. The data bits are obtained by one-step prediction and finally will be fitted to Y in the original data and analyzed for root mean square error (RMSE), furnace temperature rise accuracy and furnace temperature fall accuracy for the test set. After several debugging of hyperparameters. We set the number of HiddenUnits to be 50, while the number of TimeSteps to be 9 and the number of Features to be 2. The TimeSteps on the horizontal axis are the prediction order, which can also be understood as the sequence. The value of vertical axis is K.

The formula for K is $K = \frac{Y}{Y_t}$. Formula (10)

The root mean square error (RMSE) 0 is:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Y_t - Y_i)^2}{n}} \quad \text{Formula (11)}$$

Where, is the predicted value and is the actual value. After setting up the program and starting the test. The test results obtained are as follows:

The test fitting results are shown in Figure 9 below

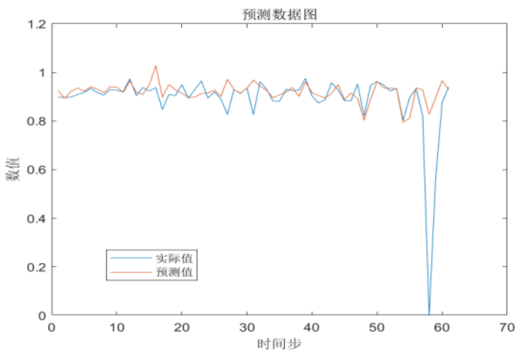

FIGURE 9. FITTING RESULTS OF THE TWO-STEP PREDICTION TEST

TABLE 3 PREDICTED ROOT MEAN SQUARE ERROR (RMSE), FURNACE TEMPERATURE INCREASE ACCURACY, FURNACE TEMPERATURE DECREASE ACCURACY

Root Mean Square Error (RMSE)	0.027964
Accuracy of furnace temperature increase	93.33%
Accuracy of furnace temperature decrease	64.52%

2.3.4 Analysis of one-step prediction and two-step prediction model test results

(1) In terms of numerical prediction success rate:

Through the comparative analysis of the two, we can know from the root mean square error (RMSE) of the prediction effect and fitting observable fitting effect in the two fitting effect are very good. In the pre-fitting effect, the one-step prediction predicts better than the two-step prediction predicts the molten iron temperature, but when the reaction continues, continuous smelting, and the temperature continues to increase, the two-step prediction fitting effect is stronger than the one-step prediction. This also fits the advantages and disadvantages in one-step prediction and two-step prediction. That is, one-step prediction is suitable for short-term prediction, and two-step prediction is suitable for long-term prediction.

(2) In the direction of furnace temperature rise and fall prediction success rate:

one-step prediction in the furnace temperature rise accuracy and furnace temperature decline accuracy prediction are more accurate, after many rounds of testing, furnace temperature rise and decline accuracy can be stabilized at about 80%, the accuracy of the two is not much difference.

two-step prediction in the furnace temperature rise accuracy and furnace temperature decline accuracy is not the same performance. In the prediction of the accuracy of the furnace temperature rise, it shows a very high accuracy. After several rounds of testing, the accuracy of furnace temperature rise can be as high as 94%. However, the accuracy of furnace temperature drop is only about 65%. This demonstrates the high fit and predictability of the two-step prediction model in the prediction of furnace temperature rise accuracy.

(3) As to why the one-step prediction and the two-step prediction perform differently in the accuracy of furnace temperature rise and furnace temperature fall, we summarize the following reasons after searching for information and discussing the model construction and results:

Since one-step prediction utilizes the previous data, i.e., the values of the eight independent variables X_i, to predict the values of the next step, i.e., the eight independent variables Y_{i+1}, while two-step prediction utilizes the values of the eight independent variables X_i to predict the values of the eight independent variables Y_{i+1} and Y_{i+2} . These two-step prediction of the value of once out of a certain range (predicted too low or predicted too high), it will be more difficult to correct the value than one-step prediction, resulting in a large error. For example, in the prediction of furnace temperature rise accuracy, if the value of Y_{i+1} and Y_{i+2} after the prediction of item X_i is too high, it will make its image deviate from the original data Y value, and when item X_{i+1} is corrected by the predicted Y_{i+2} and Y_{i+3} for the data image, it causes drastic changes at some points. At the same time, since the furnace temperature is generally on an upward trend during the smelting process, when the furnace temperature decreases at a certain point, the two-step prediction predicts that the value of the two-step prediction may cause the next prediction to continue to be on an upward trend due to the prediction results of the previous step. As

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shown in Fig. 10. But this situation is not very obvious in one-step prediction. Whether the predicted data change is up or down, the image changes more gently.

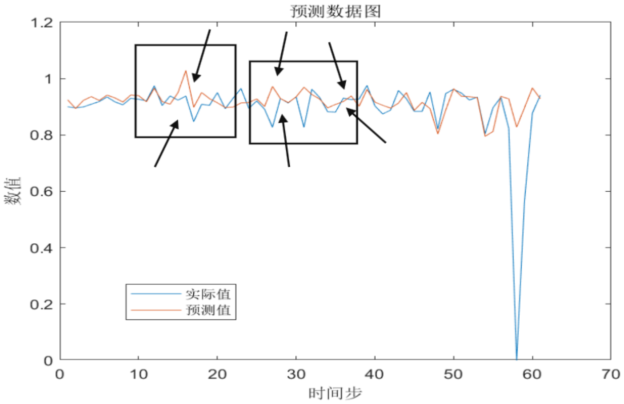

FIGURE 10. SCHEMATIC ILLUSTRATION OF SOME OF THE DIRECTIONAL PREDICTION DEVIATION POINTS IN THE TWO-STEP PREDICTION

2.3.5 Dynamic prediction feasibility analysis

According to the comprehensive analysis of the theory and model construction and results above, it is not difficult to see that when forecasting through the LSTM long- and short-term memory neural network model, it has the advantages and disadvantages of its one-step and two-step prediction models. However, in general, the model is able to deal with the time series data in blast furnace ironmaking well and has an excellent modeling fit for the nonlinear relationship, while the model prediction fit is excellent according to the analysis of the root mean square error (RMSE). Through the training of the attached data, combined with the usual smelting cycle of 6-8 hours, the model in the prediction of molten iron temperature, combined with the advantages of one-step prediction and two-step prediction, in the first 3-4 hours using a one-step prediction model, and the last 3-4 hours using a two-step prediction model is more effective. The two-step prediction model is used for the prediction of furnace temperature rise, and the one-step prediction model is used for the prediction of furnace temperature fall. The advantages of the two models complement each other, so that the dynamic prediction of blast furnace ironmaking can be better.

Considering the uncertainties in the blast furnace ironmaking process, such as raw material fluctuations, equipment failure, temperature measurement or mechanical error of the indicator equipment. Real-time detection and comparison should be carried out in conjunction with the actual production situation, so as to discover the anomalies and make feedback adjustments in time, and further optimize the model in order to improve the accuracy and stability of the model prediction. However, due to the complexity in blast furnace ironmaking, a complete and accurate dynamic prediction of its whole process is still a complicated and difficult process.

3 OPTIMIZATION MODEL OF PSO PARTICLE SWARM OPTIMIZATION ALGORITHM

3.1 OVERVIEW OF FUEL RATIO

3.1.1 Definition of fuel ratio

Fuel ratio is the ratio of fixed carbon to volatile fraction. Fuel ratio is also an indicator that characterizes the degree of coalification, i.e., the fuel ratio of coal increases as the degree of coalification of coal increases. It is also one of the key quality indicators.

3.1.2 Significance of fuel ratio

The lower the fuel ratio, the lower the production cost. Reducing the ironmaking fuel ratio is a way to improve the utilization factor of the blast furnace. It helps the iron and steel industry to save energy and reduce emissions, and realize green, low-carbon and high-quality development.

3.2 PSO PARTICLE SWARM OPTIMIZATION MODEL BASIC THEORY

3.2.1 PSO particle swarm optimization algorithm model construction diagram

Particle Swarm Optimization (PSO) is an evolutionary computing technology that originated from the study of bird flock feeding behavior. The algorithm was initially inspired by the regularity of the flocking activities of flying birds, and then a simplified model was built using group intelligence. The specific model construction flowchart 11 [12] is as follows

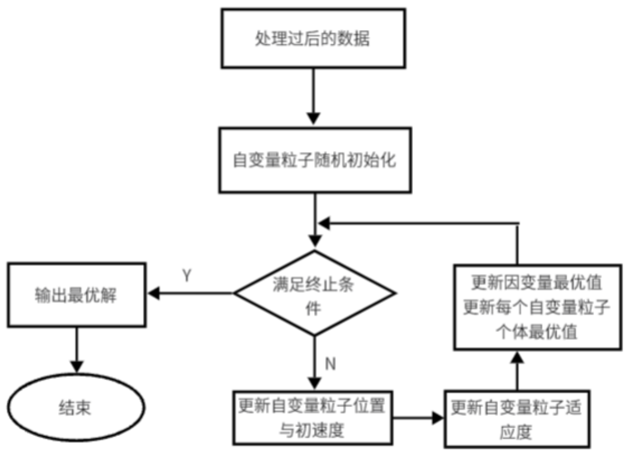

FIG. 11 PSO PARTICLE SWARM OPTIMIZATION ALGORITHM MODEL CONSTRUCTION DIAGRAM

3.2.2 Advantages of POS particle swarm optimization algorithm

Since the PSO algorithm is relatively simple to implement. It can find the optimal solution of the problem in a shorter time, and with higher accuracy and faster convergence, the optimal solution can be found faster.

3.3 Construction and Solution of PSO Particle Swarm Optimization Model

We encapsulate the one-step prediction model and the two-step prediction model as functions and name them function_m1 and function_m2 for calling. Let the inertia w be 0.5; the dimension dim be 8; the optimal value of the ith variable be set; the optimal solution be; Y_best be the comfort level corresponding to the optimal solution of fuel ratio. The principle of the formula is as follows [12].

$$v_i^k = wv_i^{k-1} + c_1(pbest_i^{k-1} - x_i^{k-1}) + \ldots + c_8(pbest_i^{k-1} - x_i^{k-1}) \quad \text{Formula (12)}$$

The hyperparameters are adjusted by running the program several times. The parameters are brought into the one-step prediction model and the two-step prediction model again to find the root mean square error (RMSE) of prediction, the accuracy of furnace temperature increase, and the accuracy of furnace temperature decrease as:

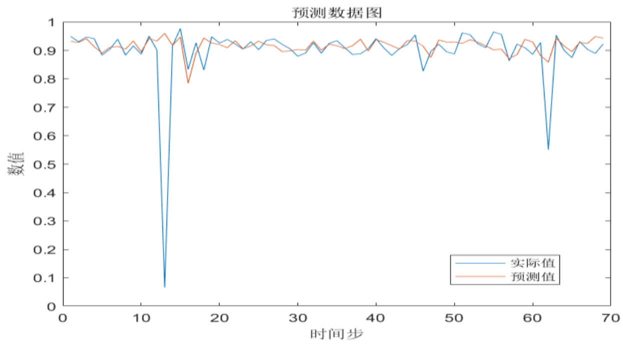

Fig. 12 One-step prediction optimization fitting effect

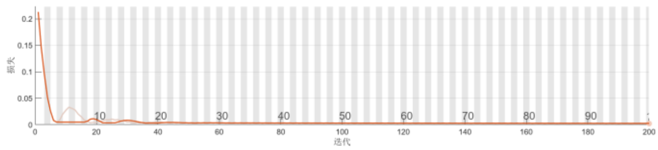

Fig. 13 One-step prediction loss value image

Table 4 Predicted Root Mean Square Error (RMSE), Furnace Temperature Increase Accuracy, Furnace Temperature Decrease Accuracy

Root Mean Square Error (RMSE)	0.013821
Accuracy of furnace temperature increase	84.38%
Accuracy of furnace temperature decrease	75.22%

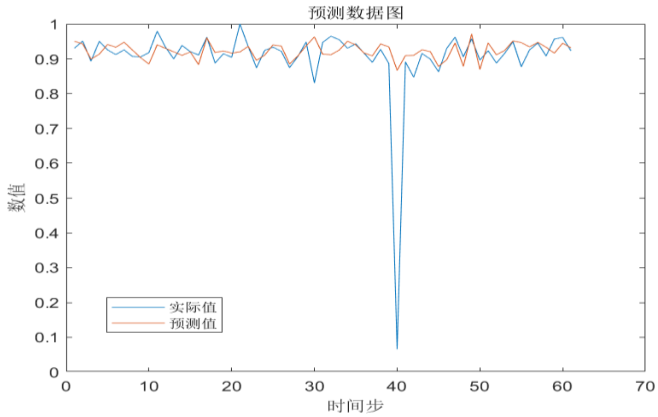

Fig. 14 Two-step prediction optimization fitting effect image

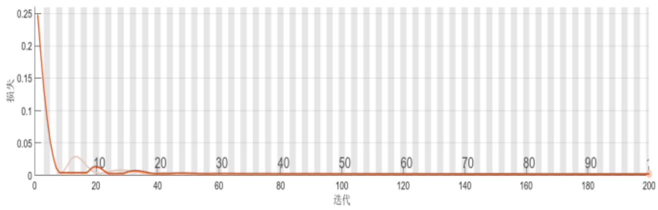

Fig. 15 Two-step prediction of loss value image

Table 5 Predicted Root Mean Square Error (RMSE), Furnace Temperature Increase Accuracy, Furnace Temperature Decrease Accuracy

Root Mean Square Error (RMSE)	0.016539
Accuracy of furnace temperature increase	90.00%
Accuracy of furnace temperature decrease	77.42%

3.4 Expected Effect of Optimization Model

According to the PSO particle swarm optimization algorithm model the results of the model after optimization show that the optimized one-step prediction model and two-step prediction model have become smaller in the root mean square error of prediction. It shows that the prediction results of the prediction model are closer to the real value, i.e., the model has higher accuracy and better performance. The accuracy of furnace temperature increase and furnace temperature decrease in general have increased compared with the pre-optimization, which indicates that the PSO particle swarm optimization algorithm has worked well for optimization. The optimized model has better performance, the model converges faster and has better generalization ability.

4 SUMMARY

In this paper, the known data and analyze it, through the data preprocessing data processing, including the identification and processing of outliers, missing values, etc., to reduce the model error so that the model is more scientific rigor. The OLS regression model was used to reduce the dimensionality of the original dataset, and the eight independent variables most relevant to the prediction of iron temperature were screened out. Then the one-step prediction model and two-step prediction model were constructed based on LSTM long and short-term memory neural network, and finally the one-step prediction model and two-step prediction model were further optimized by PSO particle swarm optimization algorithm.

After the root-mean-square error test, the model fits very well in the prediction of blast furnace molten iron temperature. Before optimization, the root mean square error (RMSE) of the one-step prediction model and two-step prediction model are 0.014638 and 0.027964, respectively, while after optimization, they are 0.013821 and 0.016539, respectively. It is obvious that the optimized model is more effective in predicting the blast furnace molten iron temperature, and the fitting effect is better. At the same time, the model has high accuracy in predicting the rise and fall of furnace temperature. Since one-step prediction and two-step prediction have their own limitations, they should be integrated to complement each other's advantages and disadvantages in the prediction of furnace temperature rise and fall. The accuracy of one-step prediction in predicting temperature drop can reach 85%, while the accuracy of two-step prediction in predicting temperature rise reaches 95%. Combined with the usual smelting cycle of 6-8 hours, the model combines the advantages of one-step prediction and two-step prediction in the prediction of molten iron temperature, using one-step prediction model to fit the prediction in the first 3-4 hours, and two-step prediction model to fit the better effect in the last 3-4 hours.

For the dynamic prediction of blast furnace molten iron temperature is feasible, but still need to be combined with the actual production situation for real-time detection and comparison, timely detection of anomalies and feedback adjustments, and do a good job of risk assessment and coping strategies, and further optimize the model, in order to improve the accuracy and stability of the model prediction.

Due to the complexity of blast furnace ironmaking, there are many influencing factors, in the subsequent optimization of the model should pay more attention to other influencing factors, such as the coal ratio, the actual wind speed, the day of the weather temperature, humidity, impurities and so on. With the existing model can not be completely accurate generalized prediction of molten iron temperature. Therefore, we need to build a comprehensive model with conventional empirical and mechanistic data-driven models to learn from each other and take the essence of each.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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