Study on Productive Process Model Basic Oxygen Furnace Steelmaking Based on RBF Neural Network

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Abstract

The endpoint temperature and carbon content of basic oxygen furnace (BOF) are the control of the BOF steelmaking process. There exists a complex relationship among them and each control variable. While the multiple linear model is limited to predict the endpoint temperature and carbon content through each control variable, and the online continue measurement can't be made. So the predictive model of some control variables of the BOF steelmaking based on RBF neural network was put forward, and the study of verifying model was made by comparing the predictive value with the practical data of 89 converters in a factory. It turned out that the method has high accurate prediction, and it can be used in the process of prediction in steel enterprises.

Keywords: *RBF neural network, the multiple linear model, Natural language*

1. Introduction

The old problem of converter steelmaking are operating according to the production process of relevant control variables (oxygen or oxygen blowing time, the quality of the coolant and additive, etc.) to predict the endpoint temperature and endpoint carbon content. Such as Yongfu Wang Xiaoping Li [1] and others using the hybrid model dynamic process was studied for the end point, Tianyou Chai [2] by using the improved RBF neural network to forecast the finish, the same, and Youliang Yang Zhao Xu [3] and others RBF neural network is used to research of end phosphorus content in forecast.

But in the actual operation process, the qualified endpoint temperature and carbon content of molten steel are the ultimate goal of the operation (value), in order to achieve the desired goal, we need to determine the sublance after the relevant control variables of the optimal value in the process of steelmaking, therefore we propose a RBF neural network model is established to solve the end goals determine, some relevant control variables unknown production process operation problem, made out to the end of the molten steel temperature and carbon content with their minimum deviation between the set point.

2. Modeling

2.1The multiple linear regression model

The BOF steelmaking is a very complicated process, so in order to meet the requirements of qualified molten steel, the endpoint temperature and carbon content(following we use ET and ECC to instead) of BOF must be precise control. By establishing multiple linear regression model to determine the relationship among the ET and

ECC and each control variable which including the quality of molten iron and scrap steel , steel temperature at the time of the sublance, ECC at the time of the sublance, oxygen blowing, the coolant and the quality of the additives etc.

2.2.Data processing

Our model was based on the practical data of 89 converters in a factory.

In the process of BOF, there may exists several orders of magnitude in the quality of inputting material, because the amount of molten iron and oxygen blowing amount value is compared commonly big, while the amount of coolant is small. So in order to overcome this shortcoming, we should deal with the original data by standard. The following is the standardized formula:

$$x_i^{'}(k) = \frac{x_i(k) - x_j}{\sigma_i} \quad (1)$$

$$x_i = \frac{1}{p}\sum_{i=1}^{p} x_i(k) \quad ;$$

$$\sigma_i = \sqrt{\sum_{k=1}^{p}(x_i(k) - x_j)^2}$$

$$(i = 1, 2, \cdots 11, k = 1, 2, \cdots p)$$

i is corresponding to the input variables,, k is corresponding to the sample.

Due to the steel in the process of converting, some abnormal data might be occurred, because of spillage or furnace of improper operation, and these part of data are free outside the main body of data, they also do not agree with the existence of other data, which will affect the establishment of the multiple regression model, so we have to modify or remove data.

First of all, using the hierarchical clustering method[4] to find out the abnormal data and remove them according to the similarity. Then using Chauvenet criterion[5] dose the same as the hierarchical clustering method, at last there remain 78 converters steel data. On the basis of these data, linear regression model is established.

2.3Solution of the multiple linear regression model

In this model, we use and to represent the ET and ECC , and these two variables have the same impact factors which including the quality of molten iron , the quality of scrap steel , oxygen blowing , lime stone , grey , Magnesium the ball , Dolomite .However, the eighth variable steel temperature at the time of the sublance have a relationship with ET , and ECC at the time of the sublancehave a relationship with ECC .

The multiple linear regression model of ET and ECC can be represented by the following formula:

$$Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_8 X_8 \quad (2)$$

$$Y_c = \beta_0^{'} + \beta_1^{'} X_1 + \beta_2^{'} X_2 + \ldots + \beta_8^{'} X_8^{'} \quad (3)$$

According to the processed data, we can get the regression model by using MATLAB software programming:

$$Y_t = -0.1275 - 0.1819 X_1 - 0.0725 X_2 + 0.7555 X_3 - 0.0243 X_4 - 0.3558 X_5 - 0.1625 X_6 - 0.5049 X_7 + 1.7916 X_8 \quad (4)$$

$$Y_c = -0.1287 + 0.4202 X_1 + 0.413 X_2 - 0.3205 X_3 + 0.3631 X_4 - 0.1075 X_5 + 0.0970 X_6 - 0.1045 X_7 + 2.1567 X_8 \quad (5)$$

2.4 Error analysis

We do error analysis in the regression equation of ET. By using MATLAB software programming can get available basic index error and residual analysis diagram.

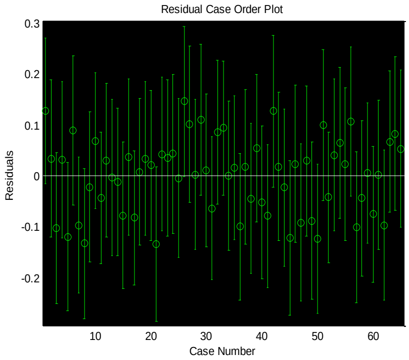

Fig.1 Multiple linear residual analysis

From the program we can know the correlation index =0.8840, F=53.3291, the significance level p=0<0.05, so the regression equation of the molten steel ET was established.

Similarly, we get some related parameters of steel ECC of the regression equation, the correlation index =0.7406, F=12.2560, the significance level p=0<0.05, it was established, too.

3 .RBF neural network

RBF neural network is a forward network of three layers, including the input layer, hidden layer and output layer. Set the number of input nodes is n, the hidden nodes are m, and the output nodes are l.

Setting the input of RBF neural network is , the output of the network:

$$y = w_0 + \sum_{j=1}^{m} w_j \phi(|X - c_j|) \qquad (6)$$

Mathematically speaking, $w_0 \in R$ is offset item, $w_j \in R(j=1,2,\cdots,m)$ are weights from the hidden layers to the output layers; are radial basis function; $|X - c_j|$ are the European norm; $c_j \in R^n$ are the center of the network.

The radial basis function, $\phi(|X - c_j|)$ has many forms, generally including the thin plate spline function, Gaussian function, Multiple quadratic function and so on. This article chooses the following Gaussian function:

$$\phi(v) = \exp(-v^2 / \beta^2) \qquad (7)$$

Mathematically speaking, β is a real constant to decide the shape of Gaussian function.

3.1 Productive Process Model of BOF Steelmaking

We establish a neural network with some known relevant variables and the end target value in productive process as shown in figure 2. We take the initial quality of molten iron 0.7406, scrap steel quality 0.4621, steel temperature at the time of the sublance 0.5208, ECC at the time of the sublance 0.2221, ET and ECC of molten steel are 0.6224 and 0.2521 with production experience as the basis.

Substantially， the terminal optimal control model is Multi-objective optimization problem which is based on prediction model, for the amount of input variables including liquid iron and various accessories, and the output variables including the ET and ECC.

In our subject, optimization goal is to achieve the minimum distance from the predict carbon temperature value and the setting temperature value. In order to simplify the problem, we use the weighted operation to link two objectives into one goal. Shown by the following formula:

$$f(C,T) = \omega_c |C - C_0| + \omega_t |T - T_0| \qquad (8)$$

$f(C,T)$ is optimization function, the minimum is the optimal value of the multi-objective optimization. C and T respectively stand for ECC and temperature which are calculated by prediction model, C_0 and T_0 respectively stand for preset ECC and temperature, ω_c and ω_t is equal to 1, then stand for weights.

This paper references to the graduate dissertation of Bingyao Cai [7], The converter steel-making endpoint carbon temperature prediction and control key technology research,

values for 0.4, ω_t values for 0.6.

$$Min \quad f(C,T) = 0.4|C - C_0| + 0.6|T - T_0| \qquad (9)$$

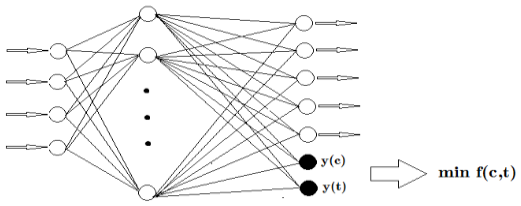

Fig. 2 Neural network of Operation Process

3.2 Model application

We take the actual data as the network training data from 78 furnaces in 1.2, $f(C,T)$ is the evaluation standard in network test. $f(C,T) \to 0$ stands for the greatest degree to close to the molten steel of ET and ECC under required values.

We use the MATLAB to solve this problem. Learning speed plays an important role in RBF neural network, we need to add the number of training because learning speed is too slow to study; on the other hand, learning speed is too fast, it is easy to cause the network learning convergence, then affect the training accuracy. After training the model again and again, we get the best effect when vector is 0.01, number of training for 3000 times, the training accuracy of 0.01. The results are shown in table 1.

Table 1 The analysis table of neural network optimal results

Oxygen absorption	*Limestone*	*Grey*	*Magnesium the ball*	*Dolomite*	*Final temperature*	*Final carbon content*	*Error*
0.3037	0.9988	0.9848	0.8105	0	0.8363	0.5195	0.4813
0.5104	0.0074	0	1	1	0.6733	0.1620	0.0992
0.4414	0	1	0	0	0.7057	0.7189	0.5501
0.5584	0.2635	0.9975	1	0	0.5385	0	0.3360
0	0	0	1	0	0.4162	0.1184	0.3399
0	0	0.9793	0	0	0	0	0.8745
0.7487	0	0	1	0	0.8851	0.3100	0.3206
0	0	0	0	0	0.4867	0.8691	0.7527
0	0	0	0	0.2637	0.3514	0.7940	0.4023
0.2802	0.8107	0	0.9996	0	0.8900	0.3797	0.3952

By the table above, when control the oxygen intake 0.5104, limestone 0.0074, grey 0, magnesium the ball 1, Dolomite 0.6733, $f(C,T)$ =0.0992 is the best answer. Because of the deviation which is between the network and the actual value, there is a certain deviation between carbon temperature value and target value, but the deviation is in the allowed range. We take the results into the linear equation (4), (5), shown in the following table:

Table 2 The comparison of RBF neural network model and multiple linear regression

Variable	*Target value*	*RBF neural network method*		*Multiple linear regression method*	
		Predictive value	*Relative error*	*Predictive value*	*Relative error*
ECC	0.2521	0.1620	0.1448	0.5122	0.4179
ET	0.6224	0.6733	0.0818	0.3554	0.4290

By the table above, RBF neural network model has higher accuracy and practicability and is better than multiple linear regression model. So we can use the RBF neural network to solve the converter steelmaking related control variable inputs in the production process.

4. Conclusion

Each control variable and the molten steel in the course of converter steel-making endpoint carbon content and molten steel temperature there exists a complex relationship. We set up multiple linear programming model, although could indicate the relationship between the various data, but there are still insufficient.

The model of converter steelmaking based on RBF neural network has high precision. It Can be applied to target steel carbon content and oxygen content and relevant control variables unknown or known only know that some of the control variable values this kind of problem, so as to improve the work efficiency of converter steelmaking.

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