

Carbon Temperature Prediction Model of Small and Medium-Sized Intelligent Steelmaking Converter based on BP Neural Network

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Abstract

At present, small and medium-sized converters cannot be equipped with auxiliary gun system, resulting in low hit rate of end-point control. At the same time, they are faced with multiple pressures of "de capacity, green manufacturing and market competition". Therefore, it is necessary to build [C] & [t] prediction model based on flue gas composition to accurately predict relevant data information in the process of steelmaking system and improve the hit rate of steelmaking end-point, It is particularly important to realize intelligent steelmaking. Based on the actual situation, previous analysis experience and relevant data, this paper explores the relationship between PQ, Q, [CO], [CO₂] and [C] & [t], constructs the [C] & [t] prediction model based on flue gas composition, and gradually reduces the error according to the simulation error of the observation model, so as to improve the accuracy of the prediction model. With the help of the previous results, Build a [C] & [t] prediction model suitable for a wider range of data. The model must always have more accurate [C] & [t] prediction results in a fixed interval where the cumulative oxygen consumption ratio PQ is between 70% - 85%. To solve problem 1, SPSS is used to analyze the correlation between six types of data PQ, Q, [CO], [CO₂] and [C] & [t] in five groups of data tables, and it is concluded that PQ, Q, [CO], [CO₂] and [C] & [t] have significant correlation. Then, curve fitting is carried out for CO and CO₂ in each data table, and the regression equation is obtained: $B = -0.19225a + 23.1435$. Then, the regression analysis of CO and CO₂ with the data of [CO] and [CO₂] is carried out by MATLAB, and four groups of prediction equations are obtained. The [C] & [t] prediction model based on flue gas composition is sorted out to establish the model. For problem 2, the [C] & [t] prediction model constructed in problem 1 is applied to the sample data, and the relationships of [CO] - [C], [CO] - [t], [CO₂] - [C] and [CO₂] - [t] are established to predict the carbon content [C] and molten steel temperature [t] in molten steel respectively. The relative errors are 40.904%, 2.29%, 37.942% and 2.58% respectively. The strategies to reduce the error are as follows: (1) expand the sample size of the original data set(2) Increase the dimension of curve regression equation. In view of question 3, the data in the five tables in the annex are screened, and the data of oxygen consumption ratio PQ between 70% ~ 85% are divided into five intervals [0.70,0.73], [0.73,0.76], [0.76,0.79], [0.79,0.82) and [0.82,0.85]. A BP neural network model including four input layers, two hidden layers and two output layers is established by using MATLAB, The data of oxygen consumption ratio PQ in five groups of data tables are predicted respectively. By comparing the relative error in each interval, the interval with more accurate [C] & [t] prediction results is selected as [0.76,0.79], which is the fixed interval. The model makes full use of the data in the attached table, reasonably screens the effective data, and establishes a BP neural network with good robustness, which is suitable to be extended to metallurgy, chemical industry, transportation and other industries related to the incoming hot metal temperature of desulfurization station.

Keywords

SPSS; MATLAB; Correlation Analysis; Regression Equation; BP Neural Network.

1. Introduction

China's iron and steel industry has a long history of development. According to relevant data, there are about 500 small and medium-sized metallurgical converters with a capacity of less than 100 tons in China's iron and steel enterprises, and their capacity accounts for about 50% of the national steelmaking capacity. However, the market competition is strong, and the small and medium-sized iron and steel enterprises have many obstacles and constraints in the development process, because of their limited capacity, The secondary gun system cannot be installed, the terminal control hit rate is low, the market share is largely occupied, and the development space is insufficient. At the same time, according to the development trend of the times, "be capacity and green manufacturing" has become an important standard for the development of modern enterprises. We need to further think about how to be capacity, improve the terminal hit rate, and effectively improve the steelmaking efficiency, This problem requires the following three problems to be solved by mathematical modeling:

For question 1: Based on the data in each annex and analysis, explore the relationship between PQ, Q, [CO], [CO₂] and [C] & [t], and build the [C] & [t] prediction model based on [CO], [CO₂] in flue gas composition..

For question 2: apply the [C] & [t] prediction model in question 1 constructed based on the attached table data to the sample data of the annex, observe the error of the model prediction, analyze the relative error, and gradually reduce the error by formulating an error reduction scheme, so as to improve the adaptability and accuracy of the prediction model.

For question 3: build a [C] & [t] prediction model applicable to all annex data by relying on previous data analysis and model establishment and test. The model must always have more accurate [C] & [t] prediction results in a fixed interval where the cumulative oxygen consumption ratio PQ is between 70% - 85%, and give this fixed interval and this prediction model generally suitable for five groups of sample data.

2. Problem analysis

The According to the requirements mentioned in the title, it can be seen that there are several parameters in the process of converter steelmaking, such as oxygen consumption ratio PQ, total oxygen consumption Q, carbon monoxide content in flue gas - [CO], carbon dioxide content in flue gas - [CO₂], carbon content in molten steel [C] and molten steel temperature value [t].

Aiming at problem 1: by classifying the six parameters collected in the annex, the relationship between the six indexes in the converter steelmaking process is analyzed. SPSS software is used to analyze the correlation of six types of data in the table in the annex. Before establishing the model, the curve fitting of CO and CO₂ in each table is carried out by SPSS software to obtain the linear regression equation. Then, according to the correlation analysis results, - PQ, - Q, - [CO], - [CO₂] are selected as independent variables and [C] and [t] as dependent variables to build the relationship model of [CO] - [C], [CO] - [t], [CO₂] - [C] and [CO₂] - [t];

For problem 2: apply the models of [CO] - [C], [CO] - [t], [CO₂] - [C] and [CO₂] - [t] constructed in problem 1 to the specified sample data, analyze the relative error respectively, improve the model through the coefficient of regression equation, and formulate the error reduction strategy to optimize the error of the model.

Aiming at problem 3: screen the five data tables in the annex, retain the data with the cumulative oxygen consumption ratio PQ between 70% - 85%, evenly divide it into five intervals, establish a BP neural network including four input layers, two hidden layers and two

output layers, and use the five data tables in the annex to predict [C] and [t] respectively, The interval with accurate [C] & [t] prediction results is judged and selected through relative error analysis.

3. Model assumptions

Hypothesis 1: ignore the impact of the delay of actual response of [CO] and [CO2] index values on the acquisition and prediction of original data

Hypothesis 2: flue gas composition and flue gas flow only include - PQ, - Q, - [CO], - [CO2]

Hypothesis 3: the acquisition process is strictly vacuum and free from external factors.

4. Symbol description

Table 1. Symbol description

A	CO content in flue gas
B	CO2 content in flue gas
C	Carbon content in molten steel
T	Temperature value of molten steel
W _i	Error rate (i = 1,2,3,4,5)
h	Number of hidden layer neurons
m	Number of input layer nodes of the neural network
n	Number of nodes in the output layer of the neural network
C _y	BP neural network [C]
T _y	BP neural network [T] predicted value
S _y	The value of the standard error generated by the regression estimate
S _p	The error generated by the moving average

5. Model establishment and solution

5.1. Problem one model establishment and solution

Since there is a linear relationship between CO and CO2 contained in flue gas composition, a linear regression equation can be established for both, and flue gas composition can be transformed into a univariate, so only the univariate prediction model can be considered. The above process simplifies the complex multivariate problem to a single variable data processing problem. At this time, the MATLAB software can be used to process the original data of CO and CO2, and analyze the data of carbon content [C] and temperature value [T] in molten steel, respectively, to establish the prediction model of flue gas composition and [C]&[T].

5.1.1. Correlation analysis of data

SPSS was used to analyze the correlation between PQ, Q, [CO], [CO2] and [C]&[T] of 6 types of data in 5 groups of data tables. First analyze whether there is a correlation. The calculation formula of correlation coefficient is as follows:

$$r_{xy} = \frac{\sum xy - \frac{1}{n} \sum x \sum y}{\sqrt{\left[\sum x^2 - \frac{(\sum x)^2}{n}\right] \left[\sum y^2 - \frac{(\sum y)^2}{n}\right]}} \tag{1}$$

In order to simplify the operation, the data analysis function of "SPSS" is used, specifically: "Data" —— "analysis", —— "correlation analysis", —— "double variables" —— "ok", the "input area selected in PQ, Q," [CO], [CO2], [C], [T], click on "ok", it is concluded that 5 sets of data correlation coefficient matrix as shown in table 2. Refer to the critical value table of

correlation coefficient. When the number of samples is $n = 200$, the actual number of samples is 197, and the critical value of 99% confidence limit degree of freedom is 0.01 is 0.138. Therefore, in Table 2, the elements with correlation coefficient greater than 0.138 show significant positive correlation. Therefore, it can be concluded that PQ, Q, [CO], [CO2] and [C]&[T] have obvious correlation, which meets the conditions for regression analysis.

Table 2. Correlation test of Fj_exel_1. XLS PQ, Q, [CO], [CO2] and [C]&[T]

		PQ	Q	CO	CO2	C	T
PQ	Pearson correlation	1	1.000**	-.923**	.903**	-.997**	1.000**
	Sig. (double tail)		.000	.000	.000	.000	.000
	The case number	265	265	265	265	265	265
Q	Pearson correlation	1.000**	1	-.923**	.903**	-.997**	1.000**
	Sig. (double tail)	.000		.000	.000	.000	.000
	The case number	265	265	265	265	265	265
CO	Pearson correlation	-.923**	-.923**	1	-.972**	.900**	-.923**
	Sig. (double tail)	.000	.000		.000	.000	.000
	The case number	265	265	265	265	265	265
CO2	Pearson correlation	.903**	.903**	-.972**	1	-.893**	.903**
	Sig. (double tail)	.000	.000	.000		.000	.000
	The case number	265	265	265	265	265	265
C	Pearson correlation	-.997**	-.997**	.900**	-.893**	1	-.997**
	Sig. (double tail)	.000	.000	.000	.000		.000
	The case number	265	265	265	265	265	265
T	Pearson correlation	1.000**	1.000**	-.923**	.903**	-.997**	1
	Sig. (double tail)	.000	.000	.000	.000	.000	
	The case number	265	265	265	265	265	265

** . At level 0.01 (double tail), the correlation is significant.

Table 3. linear fitting of [CO] and [CO2] in FJ_EXel_1.xLS

Model summary and parameter estimation

Dependent variable: CO2

equation	R party	F	The model in this paper			Parameter estimation	
			Degrees of freedom 1	Degrees of freedom 2	significant	constant	b1
linear	.945	4507.371	1	263	.000	23.168	-.197

The independent variable is CO

In the establishment of the flue gas composition of [C] and [T] before forecasting model, using the SPSS software to the attachment in the form of six class data correlation analysis, through the correlation analysis shows that the fourth form of attachment data deviation is bigger problems, and to eliminate the data in table 4, thus obtained the final four images and data correlation analysis. In the process of converter steelmaking, there is a linear relationship between CO and CO2 in flue gas composition. SPSS software was used to perform curve fitting for CO and CO2 in data table 1, 2, 3 and 5 in the attachment, and the four groups of fitting equations were obtained. Then the corresponding parameters were averaged to obtain the final linear regression equation:

$$B = -0.19225A + 23.1435 \tag{2}$$

At this time, if the composition of flue gas is known, the specific fitting equation of CO and CO2 content can be used for transformation.

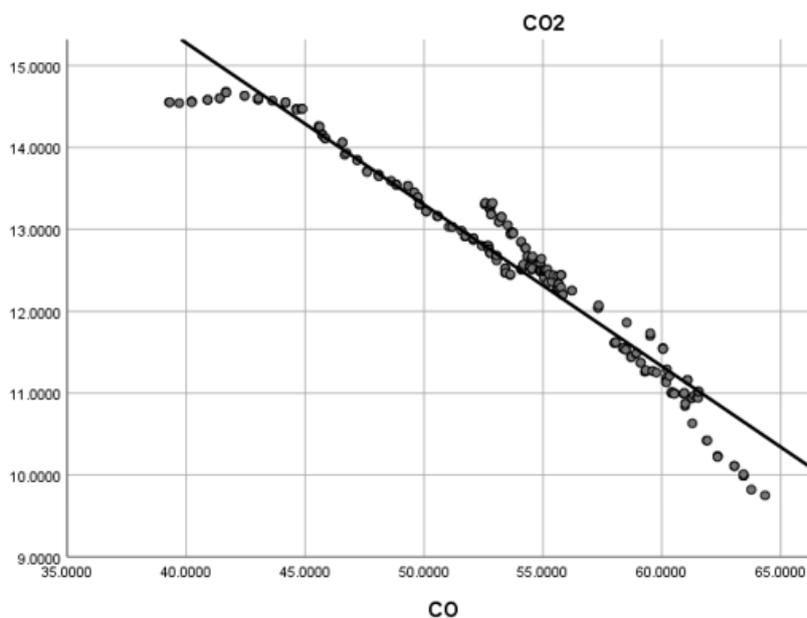


Fig. 1 Linear fitting of [CO] and [CO2] in FJ_Exel_1.xLS

5.1.2. A [C]&[T] prediction model based on flue gas composition is established

Since the linear relationship between CO and CO2 has been established in the flue gas composition, the flue gas composition can be transformed into a univariate problem, so only the univariate prediction model can be considered. The above processing simplifies complex multivariate problems to simple univariate data processing problems. At this time, THE DATA of CO and CO2 content can be processed by MATLAB software, and the data of carbon content [C] and temperature value [T] in molten steel can be used to establish the model.

(1) Composition of flue gas and carbon content in molten steel [C].

Firstly, the CO content -[CO] in flue gas was taken as the independent variable, and the carbon content [C] in molten steel was taken as the dependent variable. Each set of data was taken into MATLAB software for regression analysis and processing. After data sorting, the following mathematical model could be obtained:

$$C = -0.00060A^2 + 0.0776A - 1.3162 \tag{3}$$

Then, the CO2 content - [CO2] in flue gas was taken as the independent variable, and the carbon content [C] in molten steel was taken as the dependent variable. Each set of data was taken into MATLAB software for regression analysis and processing, and the following mathematical model could be obtained after data sorting:

$$C = 0.001B^2 + -0.1873B - 3.1146 \tag{4}$$

(2) Flue gas composition and molten steel temperature value [T]

Firstly, the CO content in flue gas -[CO] was taken as the independent variable, and the molten steel temperature value [T] as the dependent variable. The data of each group were taken into MATLAB software for regression analysis and processing. After data sorting, the following mathematical model could be obtained:

$$T = -13.3568 A^2 + 0.1144A - 1865.727 \tag{5}$$

Then, the CO2 content in flue gas -[CO2] was taken as the independent variable, and the molten steel temperature value [T] as the dependent variable. The data of each group were taken into MATLAB software for regression analysis and processing, and the following mathematical model could be obtained after data sorting:

$$T = 0.784B^2 - 0.385B + 1390.710 \tag{6}$$

5.2. Problem two: model establishment and solution

The prediction models of [C]&[T] constructed in problem 1 are respectively applied to the sample data, the errors of the models are observed, and the schemes to reduce the errors are formulated. Today in the attached five data in the table has collected data from the flue gas analysis system can sample set, a mathematical model is set up according to the problem, the attachment of the corresponding original data into the formula (3), (4), (5), (6) and the analysis of the above-mentioned data can get [C] and [T] forecasts [1-3].

Let C1 and T1 be the data predicted by the prediction model with carbon monoxide as the independent variable, and let C2 and T2 be the results predicted by the prediction model with carbon dioxide as the independent variable. The specific values are shown in Table 4 below:

Table 4. Predicted values of C1, T1, C2 and T2

C1	T1	C2	T2
1.1928	1479.9248	1.3835	1468.9928
1.1924	1479.1721	1.3717	1470.0937
1.1919	1478.7781	1.3433	1472.7994
1.1919	1478.7781	1.3433	1472.7994
1.1919	1478.7781	1.3433	1472.7994
1.1919	1478.7781	1.3399	1473.1207
1.1913	1478.3447	1.3232	1474.7366
1.1913	1478.3554	1.3232	1474.7366
1.1913	1478.3554	1.3232	1474.7366
.....
0.8683	1508.7937	0.5932	1563.4484
0.8540	1510.8033	0.5963	1562.9832
0.8540	1510.8033	0.5963	1562.9832
0.8540	1510.8033	0.5963	1562.9832
0.8346	1513.5339	0.5995	1562.5186
0.8346	1513.5339	0.5995	1562.5186
0.8346	1513.5339	0.6011	1562.2865
0.8192	1515.7240	0.6027	1562.0546
0.8071	1517.4508	0.6011	1562.2865
0.8062	1517.5818	0.6011	1562.2865
1.1928	1479.9248	1.3835	1468.9928

In the analysis of the relative error of the model, in order to reasonably reflect the error situation, the relative error analysis method is adopted. The specific calculation formula is as follows:

$$\text{The relative error } w = \frac{|\text{rowdata} - \text{forecast}|}{\text{rowdata}} \tag{7}$$

According to this formula, the relative error values corresponding to each prediction result and the original data can be obtained. By analyzing the data of each group in Table 4, the relative error rates of each group of data can be obtained. The calculated error rates of the five groups are set as W1, W2, W3, W4 and W5 respectively.

Table 5. Forecast error rate

Error rate	CO-C	CO-T	CO2-C	CO2-T
w1	0.3899	0.0298	0.3089	0.0172
w2	0.5167	0.0195	0.1120	0.0303
w3	0.4546	0.0301	0.6766	0.0283
w4	0.3825	0.0322	0.3469	0.0242
w5	0.3015	0.0351	0.4527	0.0290
Average error rate	0.40904	0.0229	0.37942	0.0258

5.3. Problem three model establishment and solution

In order to establish a prediction model under the condition that there is always a relatively accurate [C]&[T] prediction result in a fixed interval when the cumulative oxygen consumption ratio (PQ) is between 70% and 85%, and in order to meet the requirements set in the question, the data in the five tables in the attachment are firstly screened, and only the data with the oxygen consumption ratio (PQ) between 70% and 85% are retained. Using MATLAB to build contains four input layer, two hidden layer and output layer of the BP neural network model, the oxygen consumption in the five groups of data table than PQ data to estimate that between 70% ~ 85% and relative error analysis, compare the relative error of range size, select the minimum error and fixed by the corresponding interval, That is the fixed interval.

The deleted 127 groups of sample data PQ, Q, [CO], [CO₂] and [C]&[T] were divided into training sample, verification sample and test sample, accounting for 70%, 15% and 15% of the total sample number respectively.

Among them, the training sample is used to train the neural network, the verification sample is mainly used to analyze the accuracy of the neural network, and the test sample is mainly used to test the applicability of the BP neural network model. Then, the sample data PQ, Q, [CO], [CO₂] and [C]&[T] are preprocessed using the Mapminmax function [4] to normalize the sample data to [-1,1]. The normalization is carried out using Equation (1):

$$x_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (8)$$

According to the algorithm mechanism of BP neural network, the activation function from the input layer to the hidden layer is tansig (n) function, and the activation function from the hidden layer to the output layer is purelin (n) function.

In order to reduce the computing time, reduce the size of memory occupied, and accelerate the convergence rate, l-M algorithm is comprehensively considered [5]. In the simulation process, a Val fail value is set to represent the training effect of the neural network. The neural network system determines the number of times that the error signal does not decrease continuously according to the Val fail value, and then ends the training. The value is generally 20[6-11].

Through the analysis of the influence of [C]&[T], the input parameters of BP artificial neural network are determined as oxygen consumption ratio -Pq, total oxygen consumption -Q, carbon monoxide content in flue gas -[CO], carbon dioxide content in flue gas -[O], and the output parameters are carbon content in molten steel [C] and temperature value [T].

The number of nerves in the hidden layer of neural network is determined by empirical formula [12], as shown in Formula (2):

$$h = \sqrt{m + n} + \alpha \quad (9)$$

Where, h is the number of neurons in the hidden layer; M is the number of nodes in the input layer of the neural network. Since the input parameters are oxygen consumption ratio -Pq, total oxygen consumption -Q, carbon monoxide content in the flue gas -[CO], carbon dioxide content in the flue gas -[CO], and carbon dioxide content in the flue gas -[CO], m =4; N is the number of nodes in the output layer of the neural network. Since the output parameters are carbon content [C] and temperature value [T] in the molten steel, n =2. α is the adjustment constant, generally ranging from 1 to 10[13].

The model has two input layers, two hidden layers and two output layers. The forecast results are shown in Table 6:

The actual and predicted values of [C] and [T] are analyzed by line chart, as shown in Figure 2 and 3 respectively:

It can be seen from FIG. 2 and FIG. 3 that BP neural network has a good prediction effect for [C]&[T].

Table 6. Prediction value and relative error of BP neural network

[C]	Predictive value	The relative error	[T]	Predictive value	The relative error
1.1578	115.4282%	0.3032%	1433.9090	143452.4616%	0.0429%
1.1523	115.0843%	0.1231%	1434.7196	143499.5429%	0.0192%
1.1467	114.6917%	0.0225%	1435.5302	143559.7268%	0.0047%
1.1467	114.6917%	0.0225%	1435.5302	143559.7268%	0.0047%
1.1467	114.6917%	0.0225%	1435.5302	143559.7268%	0.0047%
1.1410	114.0203%	0.0676%	1436.3426	143648.8425%	0.0102%
1.1352	113.5105%	0.0115%	1437.1532	143720.7346%	0.0038%
1.1295	112.8099%	0.1202%	1437.9604	143812.5913%	0.0115%
1.1295	112.8099%	0.1202%	1437.9604	143812.5913%	0.0115%
1.1237	112.3717%	0.0056%	1438.7625	143875.0967%	0.0008%
0.5788	58.4255%	0.9480%	1509.0471	150668.9585%	0.1562%
0.5788	58.4255%	0.9480%	1509.0471	150668.9585%	0.1562%
0.5669	57.5283%	1.4799%	1510.6615	150780.9599%	0.1888%
0.5610	57.3855%	2.2948%	1511.4653	150791.8373%	0.2347%
0.5550	57.1064%	2.8929%	1512.2776	150823.8722%	0.2671%
0.5491	56.8247%	3.4852%	1513.0798	150856.6447%	0.2983%
0.5432	56.5438%	4.0869%	1513.8785	150890.0110%	0.3288%
0.5373	56.1613%	4.5275%	1514.6874	150937.6007%	0.3507%
0.5373	56.1613%	4.5275%	1514.6874	150937.6007%	0.3507%
0.5373	56.1613%	4.5275%	1514.6874	150937.6007%	0.3507%

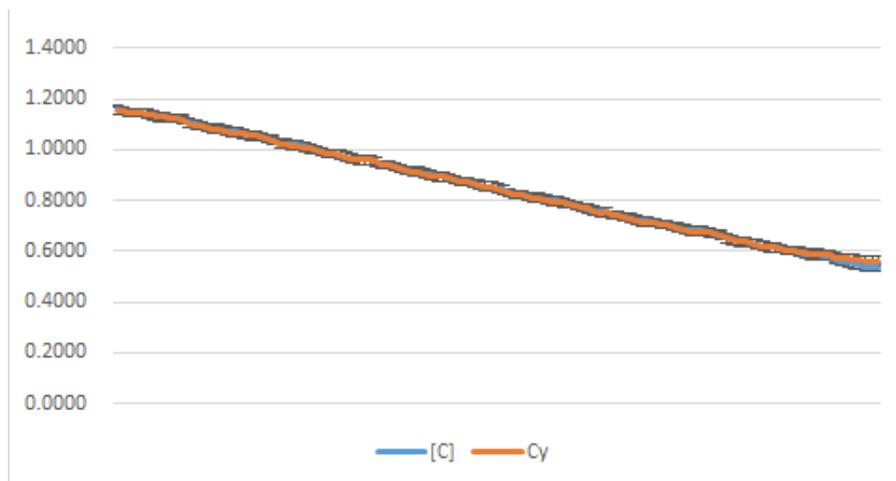


Fig. 2 [C] is a line chart of actual and predicted values

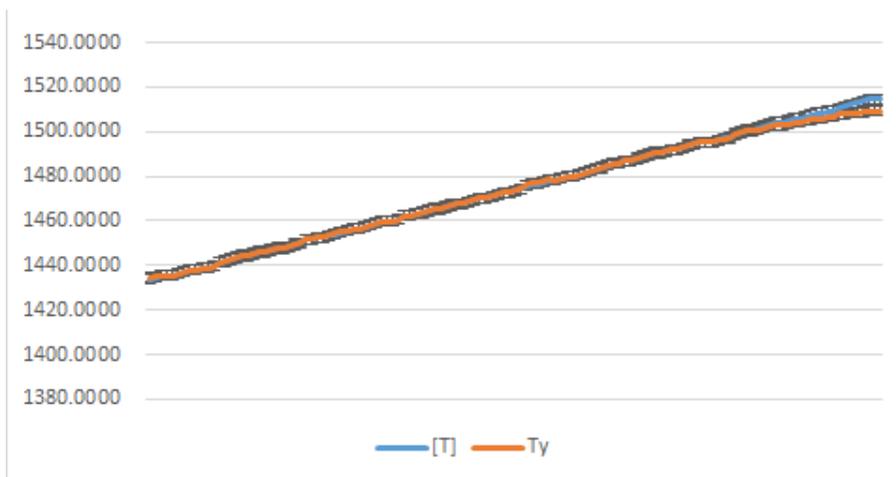


Fig. 3 [T] is a line chart of the actual value and error value

According to the partitioning rules, the 5 data tables in the attachment are evenly divided into 5 intervals. The relative errors of each interval after prediction of [C] and [T] by BP neural network are shown in Table (7-11):

Table 7. Relative errors of Fj_exel_1.xls [C] and [T] in each interval

[C]	[T]
0.1177	0.0136
0.1079	0.0118
0.0942	0.0084
0.483	0.0146
1.3245	0.1546

Table 8. Relative errors of Fj_exel_2.xls [C] and [T] in each interval

[C]	[T]
0.1141	0.0121
0.0575	0.0058
0.4737	0.0407
6.6666	0.4908
20.5507	1.2844

Table 9. Relative errors of Fj_exel_3.xls [C] and [T] in each interval

[C]	[T]
0.0821	0.0086
0.1678	0.0121
0.0725	0.0038
0.1231	0.0117
1.2839	0.1330

Table 10. Relative errors of Fj_exel_4. xLS [C] and [T] in each interval

[C]	[T]
0.0421	0.0051
0.0644	0.0071
0.0867	0.0080
0.3337	0.0290
8.9608	0.6746

Table 11. Relative errors of fj_exel_5.xls [C] and [T] in each interval

[C]	[T]
0.0663	0.0111
0.0866	0.0083
0.0907	0.0049
0.7520	0.0859
11.6964	0.8162

Next, the error analysis of this model shows that the prediction model is in a stable state, indicating that the mathematical model is of high accuracy. By comparing the relative error size and stationarity of each interval, the optimal interval can be finally obtained as [76%-79%].

6. Error analysis and model test

Problem 2: Error analysis is mainly to obtain the accuracy of regression method by comparing with the error generated by moving average. It can be seen from Table 12 that the standard error value generated by regression estimation is significantly smaller than the error value

generated by moving average, indicating that regression method is more accurate than moving average method [15].

Table 12. Standard deviation comparison between moving mean and regression method

Moving average	The regression equation	
0.3326	0.0921	0.1937
47.4092	9.6962	23.8850

Problem 3: By comparing the difference of standard deviation obtained by moving average and BP neural network, it can be seen from the table that the method of BP neural network has better fitting and prediction ability than the method of moving average.

Table 13. Standard deviation comparison between moving mean and BP neural network

	C	T
Moving average	0.1842	23.6571
BP neural network	0.18301	23.064

7. Evaluation and promotion of the model

7.1. Advantages:

- (1) Make full use of the data in the attached table, rationally screen the effective data through the analysis of the data in the chart, and improve the accuracy of model building;
- (2) BP neural network has high robustness, and can process outliers and missing values, and can process samples with large data sets;
- (3) Combined with the error analysis and correction of problem two, a more reasonable error reduction strategy is formulated.

7.2. Disadvantages:

- (1) The modeling method is relatively simple. Multiple models are not established for the same problem, and the analysis and comparison of multiple methods cannot be carried out.
- (2) The chart lacks diversity, and its contrast needs to be improved.

7.3. Improvement:

- (1) The accuracy of the model can be made more accurate by the residual test of the function.
- (2) In the process of error analysis and error reduction, the error can be reduced by the mean value of ten or more higher powers, but the amount of calculation will be greatly increased. In the process of time allowing, this can be done to further reduce the error.
- (3) the correlation analysis, regression analysis fitting function to generate a program, will greatly save time.

7.4. Promotion:

The BP neural network model used in this paper can be applied to the prediction of hot iron temperature in desulfurizing station, torpedo tank temperature drop and other related problems in metallurgical industry, and also to the prediction of chemical industry, transportation and other related industries.

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