Research on Intelligent Manufacturing Problem in Process Industry

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Abstract. In this paper, the practical problems of blast furnace iron making are considered, taking into account the influence of sulfur content [S], coal injection volume PML, blast volume FL and molten iron silicon content [Si], and extracting parameters according to data and data analysis. Because the parameters of this problem are more parameters and the nonlinear relationship is stronger, the control of parameters in the BP neural network model has become the focus of this paper. This paper finds that the BP neural network prediction model has a relatively high success rate for both numerical and furnace temperature rise and fall directions, and has wide applicability. At the same time, in the context of intelligent manufacturing in the process industry, the blast furnace iron making process can be greatly optimized, which is reflected in the reduction of raw material usage, production increase, and emission reduction.

1. Introduction

"Made in China 2025" is a national strategy for upgrading China's manufacturing industry, and its key areas include process industries for new energy and new materials manufacturing. Especially in the context of intelligent manufacturing in the process industry, blast furnace iron making technology has developed rapidly. The iron making process is a complex production process with discrete addition, continuous smelting, and discrete output. The mechanism of the iron making process includes both a chemical reaction process constrained by heat balance/material balance and a physical motion process mixed by three-phase fluid dynamics. In order to simplify the problem, this paper only provides a database composed of hot metal silicon content [Si], sulfur content [S], coal injection amount PML and air volume FL as the basis of data mining.

2. Prediction model of silicon content in molten iron

2.1. *Principle of BP neural network model*

The BP neural network is a collection of individual parallel processing elements, and we are inspired by the biological nervous system. In nature, the network function is mainly determined by the ganglion. We can train the BP neural network to perform specific functions by changing the weight of the connection point. The general BP neural network is adjustable, or trainable, so that a particular input can get the desired output. As shown below. Here, the network adjusts based on the comparison of the output and the target until the network output matches the target. This model is a three-layer BP network model, which consists of three parts: input layer, hidden layer and output layer. The schematic diagram is as follows:

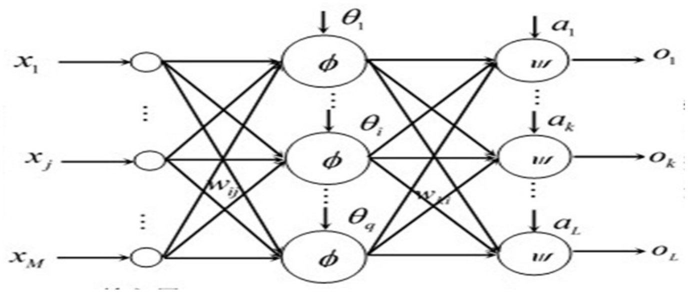

Figure 1. Schematic diagram of BP neural network

2.2. Data pre-processing

The value of the Sigmoid function is between (0, 1), so the input and output values of the model should be between (0, 1). On the other hand, considering the inconsistency of various data dimensions, the absolute difference is large and must be normalized. Processing, this model uses the following treatment:

$$x = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Where is the normalized data sample, $x \in [0,1]$ X is For raw data; $X_{\min}$, $X_{\max}$ are the maximum and minimum values in the original number.

2.3. BP neural network hierarchy determination

Determination of the input layer: The input layer of the BP neural network acts as a buffer memory. According to the analysis in the model preparation, three nodes of the input layer, that is, the sulfur content [S], the coal injection amount PML, and the air volume FL can be obtained.

Determination of the hidden layer: The hidden layer of the network is a layer. The number of neurons in the hidden layer expresses the degree of nonlinearity between the input and output of the network, and has an important influence on the training speed and forecasting ability of the BP neural network model. There is no uniform method for selecting the number of implicit neurons. It can only rely on the empirical formula: $n = \sqrt{N+M} + m$, which takes an integer between 1 and 8, and the number of nodes in the model is 10.

Determination of the output layer: The number of neurons in the output layer depends on the output variable of the BP neural network model. The output variable of this model is the silicon content of molten iron, so there is only one neuron in the output layer.

2.4. Test of BP neural network model

The Matlab program of BP neural network was written by the above principle to further fit. In the case of basic balance of blast furnace condition, the first 700 sets of data were used for learning training, and the last 150 sets of data were used to predict the silicon content of molten iron [Si], and the remaining 150 The group data is used to test the prediction value success rate, and the Levenberg-Marquardt optimization method is used to train the training error curve.

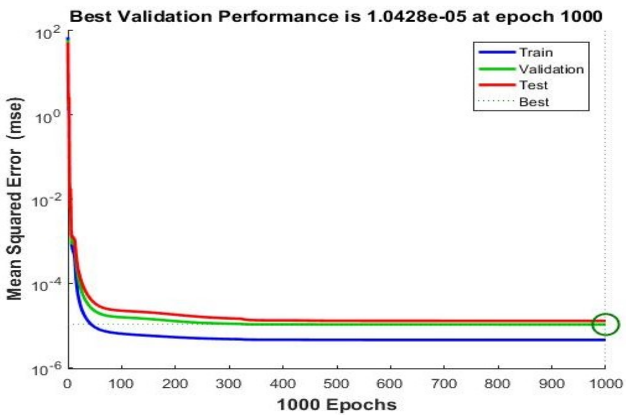

Figure 2. Training error curve

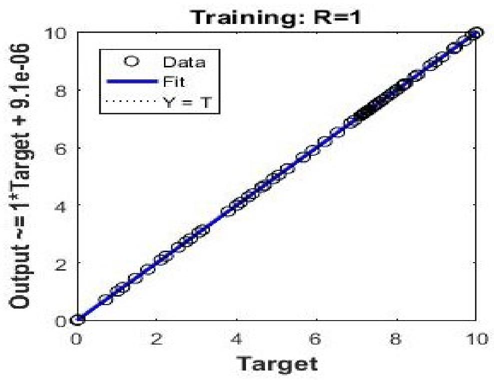

Figure 3. Training error pattern

It can be seen from the figure that only 50 trainings is needed to achieve the training purpose, and at the same time. The training pattern under the Levenberg-Marquardt optimization method can be obtained.

2.5. Final establishments of time series-BP neural network combined prediction model

First, the time series ARIMA model has the following structure:

$$\begin{cases} \phi(B)\Delta^d x_t = \Theta(B)\varepsilon_t \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\varepsilon{}^2, E(\varepsilon_t\varepsilon_s) = 0, s \neq t \end{cases}$$
$$E(\varepsilon_t\varepsilon_s) = 0, \forall \text{s<t}$$

x_t represents time series data, x_t is related with x_{t-i} (i=1, 2, ……,p); ε_t represents residual terms, ***B*** represents delay operator, *q* represents moving average order, *d* represents difference order, Δ represents difference operator, $\Delta^d = (1-B)^d$

$\phi(B)$ represents autoregressive coefficient polynomial, $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p$

$\Theta(B)$ represents moving average coefficient polynomial $\Theta(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_q B^q$

ε_t is a white noise sequence independent of x_{t-i} and ε_{t-j}, and the model is ARIMA (P, d, q), which is the summation autoregressive moving average model. The model combines the ARMA (p, q) model with the difference operation organically. High-precision short-term prediction function, and do not have strong structural structure, only need to find the law from the data itself, and can better fit the data.

After reviewing the data, it is known that the general form of the combined prediction model is the weighted average of each individual prediction model, so the focus of the combined prediction model is the determination of the weighting coefficient. If the weighting coefficients of each individual prediction model isproperly assigned, the prediction accuracy of the entire combined prediction model will be correspondingly improved. However, when using the combined prediction model, how to determine the weighting coefficient of the single prediction model becomes a big problem.

Fortunately, many scholars have proposed their own methods for determining the weight. Commonly used methods are arithmetic average method, optimal weight method, and variance reciprocal method. Among them, the inverse of variance method was proposed by Bates and Granger. The basic principle is: first calculate the sum of squared errors of each single prediction model, and then assign the weights of each single prediction model by the principle of the smallest square of the total error. The method provides a unique insight for the academic community to study the combined prediction model. Its calculation formula is as follows:

$$W_{\mathrm{j}} = e_j^{-1} / \sum_{j-1}^{m} e_j^{-1}$$

Thus, the prediction result obtained by the combined prediction model can be expressed as:

$$X = \sum_{j-1}^{m} w_j \hat{x}_j$$

2.6. Numerical prediction success rates

The Matlab program of the neural network is programmed by the above principle to further fit. After the blast furnace condition is basically balanced, the next 100 sets of data are taken. Six sets of abnormal data are removed by statistical methods, and the first 66 sets of data are used for training, and then docked. 14 sets of data are predicted, and the last 14 data are used as learning samples. The Levenberg-Marquardt optimization method are used for training. The test set data areused to test the trained network, and then the data is predicted. The comparison between the predicted result and the actual value is shown. As follows:

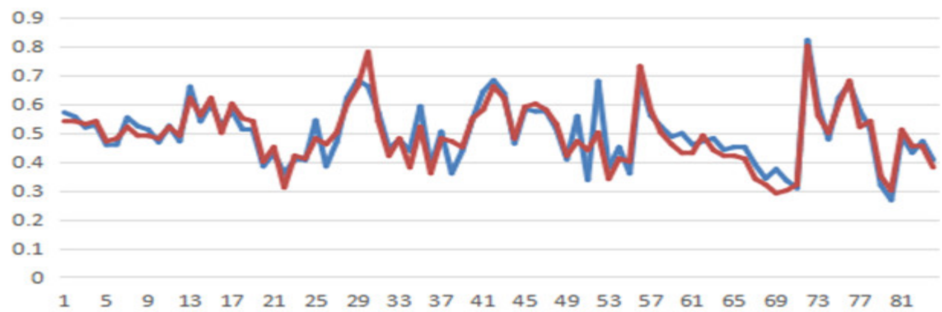

Figure 4. Numerical prediction curve

According to the formula, the numerical prediction success rate is 93.61%.

2.7. Solving the prediction success rate of furnace temperature rise and fall direction

According to the time series-BP neural network combined prediction model established by Problem 1, the mass fraction of silicon can reflect the blast furnace temperature well according to the meaning of the problem, which can represent the blast furnace temperature. By using the Matlab toolbox, the first 100 sets of data are taken. The first 70 sets of data are used for training, and then the next 15 sets of data are predicted. Last 15 data are used as learning samples, and the time series optimized neural network model is used for training. The test set data are used to test the trained network, and then the data are predicted. The comparison between the predicted result and the actual value is as follows:

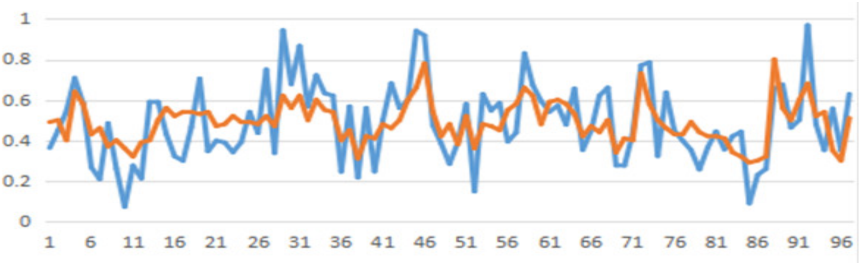

Figure 5. Furnace temperature rise and fall prediction curve

According to the formula, the numerical prediction success rate is 82.37%.

3. Conclusion and suggestion

3.1. Use coke as the main fuel
Coke is necessary for blast furnace iron making. Coke is not only the main source of blast furnace reductant and heat, but also the backbone of the column in the furnace. A large amount of metallurgical coke is an indispensable fuel for modern blast furnace iron making.

1 coking coal resources are getting less and less. The supply of coking coal is even more tense and difficult than in countries with coking coal resources like ours. In particular, the price of coke has doubled, resulting in a significant increase in the cost of pig iron. This has become a bottleneck for the development of steel companies far from coking coal. Since resources are non-renewable, in the long run, this situation cannot be reversed. At the same time, you should leave more for future generations and you should not use them.

2 In order to ensure the source of blast furnace iron making coke, it must also be equipped with the corresponding construction coke oven production facilities. Not only is its investment cost quite expensive, but the process of producing coke in modern coke ovens still causes great pollution to human ecology and environment, and it is difficult to fundamentally overcome it. Therefore, in developed countries, it is already banned from new construction and strict control of production. The large amount of coke used in China and the large-scale construction of coke ovens to produce coke has caused pollution to the environment, and it has reached a level that cannot be condoned.

3.2. Smelting in a certain size of massive iron ore
The blast furnace adopts shaft furnace blasting technology, and the blocky coke and lump ore constitute a permeable column, and the gas flow generated by the tuyere combustion and the reverse convection movement of the charge are used for efficient heat exchange, rapid temperature rise and accelerated chemical reaction. For this reason, the charge must not only be in the form of a block, but also have a uniform particle size composition in order to have good gas permeability to maintain continuous and smooth production.

As the scale of the steel industry grows larger and larger, the demand for iron ore is increasing, but the output of high-grade iron-rich ore is becoming less and less. The current and future mass production in the world is fine ore and selected fine concentrates. Therefore, in order to adapt to the charge for the blast furnace, these fine ore and concentrate must be agglomerated, that is, the production of sintered ore and pellets. It is also necessary to build large-scale factories, and the investment in these facilities is quite high. With the improvement of the level of equipment for modern production and the realization of concentrates, the total investment in raw material fields and processing facilities and sintering (or pellet) plants, coking plants and blast furnace iron making systems before iron making is enormous. In this way, the starting point for the benefit of new steel enterprises is getting higher and higher. Experts estimate that the starting point of the benefit should be more than 3 million yuan / t.

4. References

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