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Prediction Model of Smelting Endpoint of Fuming Furnace Based on Grey Neural Network

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Abstract

Since grey theory and neural network could improve prediction precision, the technology of combination prediction was proposed in this study. Then the algorithm was simulated by Matlab using practical data of a fuming furnace. The results reveal that the smelting endpoint of fuming furnace could be accurately predicted with this model by referring to small sample and information. It shows that the GNN algorithm not only has strong global search capability, but also is easy to implement. A Smelting Endpoint of Fuming forecasting empirical example has shown that compared with back-propagation artificial neural networks and single gray theory algorithm, GNN algorithm can achieve higher prediction accuracy, better computational speed, and which is more suitable for Prediction of Smelting Endpoint of Fuming forecasting. Therefore, GNN model is effective with the advantages of high precision, fewer samples required and simple calculation.

Keywords: *smelting endpoint, gray neural network, prediction, sintering process, gray model*

1.Introduction

Fuming furnace consisted of two layers which were cooled by cold water to keep the safety of furnace shell. Tertiary air orifice was used to observe the flame in the furnace-furnace temperature and smelting status could be determined based on brightness and color of the flame. Volatile dusts of the fuming furnace was gradually cooled by climbing flue, furnace gas cooler and array cooler in the climbing. Finally, they were recovered by bag dust collector.

Fuming furnace sintering point is difficult to be controlled using conventional methods. In recent years, most studies focus on using BP neural network model to describe the entire sintering process and predict these parameters. BP neural network has high prediction accuracy and some defects. For example, there is no deterministic rule for the selection of BP neural network hidden layer; the network easily falls into local minimum, with relatively poor system generalization ability. These defects greatly limit its application in real-time prediction. The initial weights and network structure of BP neural network are randomly given values, so the number and weight of every train are slightly different. That is, network optimization is not unique, and there will be a local minimum value; besides, the initial weight of train has blindness and slow convergence. Combining gray theory and BP neural network, this work presented a gray neural network algorithm, a new algorithm based on gray model and neural network model. This new information processing and prediction methods take advantage of the randomness of gray model weakening data, regularity of accumulating data and highly nonlinear of neural network. It has been widely used in the power, transport, social, agricultural and other fields [1, 2]. However, it still remains a blank in Metallurgical industry. This work utilized gray neural network to predict the smelting endpoint of sintering, achieving good results.

2. Grey Neural Network Model

2.1. Modeling of Grey GM (1,1) Model

Grey theory is a method of studying small sample, poor information and the problem of uncertainty. Its objects of study refer to small samples with some known information and unknown information, poor information and uncertainty. Through data mining of known information, valuable information can be extracted to achieve the correct description of system behavior [6], effective monitoring of evolution law and system location prediction. Compared

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with traditional prediction methods, statistical prediction methods have many advantages: e.g., it is not necessary to determine.

Whether predictive variables are normally distributed; rather than large sample statistics, it specializes in small sample or poor information uncertainty; the prediction model will not change with the change of input variables. Through gray sequence generation, gray system theory believes that in spite of the complex objective representation and data, the system still has the whole function and inevitably some inherent laws. The key is to choose a proper way to dig and use it. All gray sequence can be generated by weakening randomness with the regularity. Unified differential equations model has high prediction accuracy. GM (1,1) modeling is basically the cumulative generation of original data, so that the generated sequence has a certain regularity. Then the fitting curve can be obtained through the differential equation modeling, thus predicting the unknown part of the system [3, 4].

In GM model, once accumulation is conducted on the raw data to generate 1-AGO. The accumulated data will have certain regularity after data mining. The original data $X^{(0)}$ is not obviously regular, with swinging development trend. After accumulation generation, raw data will contain more obvious regularity.

Assuming time sequence $x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \ldots\ldots, x^{(0)}(n)\right)$ as a first-order accumulative generated 1-AGO, a new data sequence $x^{(1)}$ can be obtained through once accumulation of $x^{(0)}$:

$$x^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \ldots\ldots, x^{(1)}(n)\right), \quad where \;\; x^{(1)}(\kappa) = \sum_{i=0}^{k}\left(x^{(0)}(k)\right) \tag{1}$$

After constructing a first-order linear differential equation, the whitening differential equations can be obtained:

$$\frac{d\,x^{(1)}}{dt} + a\,x^{(1)} = u \tag{2}$$

The column of least square estimation parameter can solve a and u:

$$\alpha = \begin{bmatrix} a \\ u \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y_N, \tag{3}$$

Where $B = \begin{bmatrix} -0.5\left(x^{(1)}(2) + x^{(1)}(1)\right) & 1 \\ -0.5\left(x^{(1)}(3) + x^{(1)}(2)\right) & 1 \\ \vdots & \vdots \\ -0.5\left(x^{(1)}(n) + x^{(1)}(n-1)\right) & 1 \end{bmatrix}$, and $Y_N = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}$.

Time response function sequence expression of GM (1,1) model will be obtained, namely the gray prediction model of $x^{(1)}$.

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{u}{a}\right)e^{-ak} + \frac{u}{a} \tag{4}$$

Where a is the development factor; b the amount of gray effect.

Grey prediction model of $x^{(0)}$ is:

$$\hat{x}^{(0)}(k+1) = \left(1 - e^{a}\right)\left(x^{(0)}(1) - \frac{u}{a}\right)e^{-ak}, (k = 1,2,\cdots,) \tag{5}$$

2.2. Establishment of Grey Neural Network Model

Set original data $x^{(0)}$ as $x(t)$, the once-cumulative data is obtained as $y(t)$; prediction result $\hat{x}^{(0)}(k+1)$ as $z(t)$. Then the differential equation expression of gray neural network of a parameter is:

$$\frac{dy_1}{dt} + ay_1 = b_1 y_2 + b_2 y_3 + \cdots + b_{n-1} y_n$$

Where $y_1, y_2, \cdots, y_n$ are system input vectors; y_1 is the system output variable; the others are coefficients of differential equation.

Then the time response formula is:

$$d = \frac{b_1}{a} y_2(t) + \frac{b_2}{a} y_3(t) + \cdots + \frac{y_{n-1}(t)}{a} y_n(t)$$

Through complex transformation and mapping, an extended BP neural network will become a gray neural network with n input parameters and one output parameter. Grey neural network consists of four layers-LA, LB, LC and LD, thus determining the connection weight and error.

$$z(t) = (y_1(0) - \frac{y_1}{a} - \frac{b_2}{a} y_3(t) - \ldots \frac{y_{n-1}(t)}{a} y_n(t)) e^{-at}$$
$$+ \frac{b_1}{a} y_2(t) + \frac{b_2}{a} y_3(t) + \ldots + \frac{y_{n-1}(t)}{a} y_n(t)$$
$$z(t) = ((y_1(0) - d) - y_1(0) \times \frac{1}{1+e^{-at}} + 2d \times \frac{1}{1+e^{-at}}) \times (1+e^{-at}) \quad (6)$$

2.3. Artificial Neural Network (ANN)

In recent years, much research has been conducted on the application of artificial intelligence techniques to forecasting problems. However, the model that has received extensive attention is undoubtedly the ANN, cited as among the most powerful computational tools ever developed.

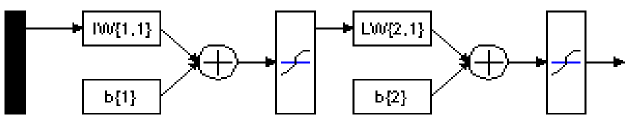

Figure 1. Architecture of two layers BP neural network used in the study

BP neural network is a multi-layer architectur. For the two layers BP network used in this study (Figure 1), the transfer function of neuron in hidden layer is the sigmoid function and the transfer function of neuron in output layer is a linear function.

$$u_j = \frac{1}{1+\exp^{(-B_x)}} \quad (7)$$

Levenberg-Marquardt rule was used to train the two-layer BP network. It was developed and trained to fit functions and make extrapolation. Two learning procedures are included in BP network training [4]. The first one is the positive propagation process in which input signal is transferred layer by layer and practical outputs of every neurons are computed; the second procedure is the back-propagation in which the errors between practical and expected outputs are progressively computed layer by layer, and weights are adjusted according to the errors [5].

2.4. Gray Neural Network Combination Model

Grey neural network model is the integration of two algorithms-gray model and neural network, so it has the advantages of both. Modeling approach of gray neural network is: Firstly, after establishing a GM (1,1) model of variables, the predicted value of raw sequence data can be obtained. There is a certain deviation between the predicted value and the original data, wherein the original sequences also have certain relationship. We may not be able to figure out this relationship. These association and deviation are considered in the neural network model: predictive value of GM (1,1) is regarded as the input sample; the actual value as the output samples of neural networks. Certain network structure is adopted to train the network, thereby obtaining the right values and threshold values of corresponding nodes. The predictive values of GM (1,1) model on the next one moment or several moments are regarded as the input of neural network, and the corresponding output is the final predictive value of the next moment [7].

Grey neural network primarily consists of input layer, hidden layer and output layer, with some deviation and at least one S-type hidden layer and linear output layer. The network has the characteristic of approximating any rational function, simulating the relationship between the sequence data by training the neural network [8].

It is supposed that there are m samples of interrelated data columns, and each column contains n data. Grey neural network prediction model is established as follows:

1) The m raw data sequence was used to establish corresponding GM (1,1) model;

2) The m models were used to predict the second to n-th data of each column, obtaining m data sequences P with the length of n-1;

3) P values of data sequence were regarded as the input vector of neural networks; T as the output vector of neural network; the network structure, initial weights and thresholds are set;

4) The prediction accuracy of neural network was also set to train the BP network. After the training was qualified, we could obtain a series of weights and thresholds corresponding to each node;

5) GM (1,1) model established in the first step was used to predict the value of future time. These predicted values were regarded as input of network for simulation, thus obtaining the corresponding output, the results of gray neural network predictive model;

3. Simulation Results and Analysis

3.1. Input and Output Layer Design

The first fuming furnace of a lead-zinc smelter plant has two fuming furnaces, with a monitoring system developed by the Citect. The judgment variables of smelting sintering endpoint include cold input (usually two warehouses or a warehouse half), smelting time after feeding, coal converter frequency (coal frequency) and three outlet temperature. Furthermore, since the flame image in three outlets has obvious features at various stages. A high-definition digital video camera was installed at the site, so images of three outlets can be captured and analyzed at all stages of the smelting process. These provided convenience for multi-sensor data fusion. Firstly, this work conducted fusion simulation on four variables-coal input, smelting time, coal frequency and outlet temperature, which can be directly obtained from the monitoring system. Then the image feature of three outlets was also obvious, so brightness of the image was added on the basis of four variables. Finally, fusion simulation was conducted on these five variables. The tool of simulation was MATLAB6.5 [5].

Result of above fusion simulation on four variables showed that the judgment of fuming furnace smelting endpoint became more effective. But the image feature of three outlets also had great impact on smelting endpoint, so this work adopted the brightness of image as another variable. The fusion simulation was conducted on these five variables [7].

This work established GM (1,1) prediction model on input variables related to fuming furnace smelting endpoints, obtaining several predictive value as the input of BP neural network. Using a hidden layer, the transfer function is (0, 1) S-type function $f(x)=\frac{1}{1+e^{-x}}$; the output is the time from fuming furnace smelting endpoint. Gray neural network is utilized to predict fuming furnace smelting endpoint, which is one of the most important performance indicators in sintering production. In the entire sintering production process, variables related to the end of the sintering smelting influence should be carefully selected, so we can determine the input variables of gray neural network. 60 data sets of input variables are stored in the excel database and embedded in Matlab6.5. In Matlab6.5, the import wizard can easily call out the data in the excel database: simply typing the database name in the window can call out the right database.

3.2. Training Sample Normalization and Network Set Up

1) Training data is the actual production record of a lead-zinc plant from March 1 to March 31 in 2012. According to the requirements, stable 60 sets of data were selected, with better control effect [10].

2) To facilitate network learning and speed up convergence speed, normalization process was conducted on the actual sample data, dividing the actual physical variables as values in [-1,1].

3) Gray neural network predicting process was written using Matlab programming language, with the prediction accuracy of 0.01. This accuracy fully met the production of sintering. The maximum number of training was 10,000 times, and learning rate = 0.7. Three-layer BP neural network adopted one single hidden layer, so the transfer function of hidden layer and output layer were logarithmic Sigmoid transfer function and positive linear transfer function; number of neurons in the hidden layer was 50; the number of neurons in the output layer 1; the training and adaptive adjustment function was elasticity back-propagation algorithm. The hidden layer and output layer transfer function, as well as the number of hidden layer neurons, was determined through a number of repeated training comparisons, based on the rule of faster training and better predicted output. So the architecture of fuming furnace smelting end neural network was 5 × 50 × 1.

Mathematical expression of MSE mean square error function is:

$$\text{MSE}=\frac{1}{N}\sum_{i=1}^{N}(e_i)^2=\frac{1}{N}\sum_{i=1}^{N}(t_i-a_i)^2$$

MSE deviation in training process curve is shown in Figure 2; the actual value T and predicted values of the contrast curve are shown in Figure 3. The horizontal axis represents smelting time (minutes); the ordinate the output of fusion system-the time from smelting end (minutes). In addition, fuming furnace state data of ten times smelting process are collected from the scene as the test sample, thus obtaining predictive output through simulation. Contrast curve of predicted output and actual output of two furnaces is shown in Figure 3 and 4, where horizontal axis represents smelting time; the ordinate the time from the smelting end.

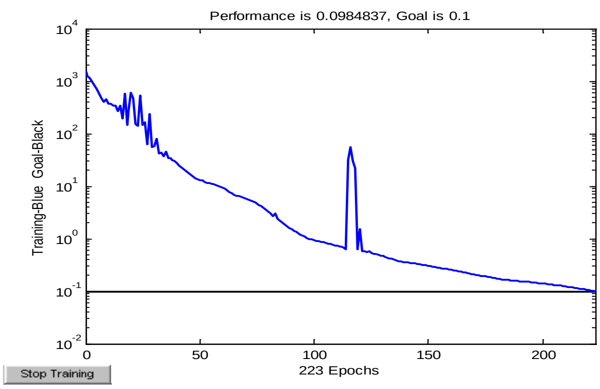

Figure 2. MSE changes graph

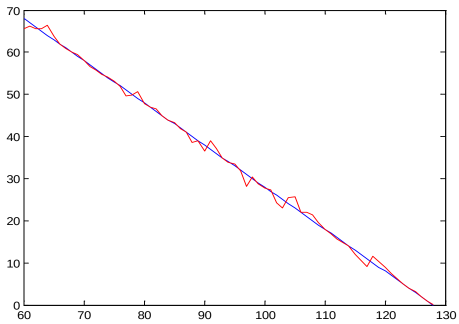

Figure 3. Actual output and predicted output curve

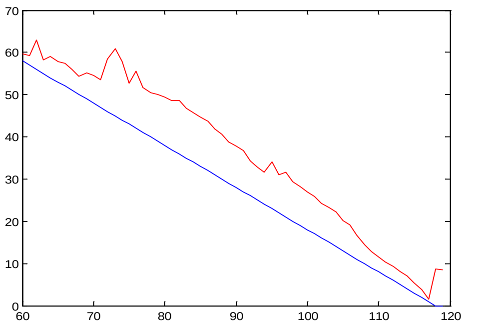

Figure 4. Target vector and simulation output curve

3.3. Prediction with Gray System Model and Combined Neural Network Model

Let λ_1 be gray prediction value, λ_2 be the prediction value by BP neural network, while λ_c be prediction value by optimal combined model. The prediction errors are η_1, η_2 and η_c respectively. The corresponding weighted coefficients are ω_1, ω_2 and ω_c, and $\omega_1 + \omega_2 = 1$.

$$\eta_c = \varpi_1 \eta_1 + \varpi_2 \eta_2 \tag{12}$$

$$\begin{aligned} Var(\eta_c) &= Var(\omega_1\eta_1 + \omega_2\eta_2) = \omega_1^2 Var(\eta_1) + \omega_2^2 Var(\eta_2) \\ &+ 2\omega_1\omega_2 Cov(\eta_1, \eta_2) \\ &= \omega_1^2 Var(\eta_1) + 2(1-\omega_1)^2 Var(\eta_2) + 2\omega_1(1-\omega_1) Cov(\eta_1, \eta_2) \end{aligned} \tag{13}$$

As to ω_1, in order to determine the functional minimum value, let:

$\dfrac{\partial Var(\eta_c)}{\partial \omega_1} = 0$ *and, because* $Cov(\eta_1, \eta_2) = 0$

Let $Var(\eta_1) = \gamma_{11}, Var(\eta_2) = \gamma_{12}$

Then the weighted coefficients of combined prediction are:

$$\omega_1 = \frac{\gamma_{12}}{\gamma_{11} + \gamma_{12}}, \omega_1 = \frac{\gamma_{11}}{\gamma_{11} + \gamma_{12}} \tag{14}$$

In Figure 2, when the gray neural network is trained to 300 steps, the system output mean square error will reach 0.01%, then the train stops. In Figure 3, after the neural network training was complete, the predictive value of training samples could well fit actual project value. In Figure 4, the deviation between prediction curve and the actual curve was small, with two alternative smelting furnace status data as the test sample. Their basic trends were the same: the actual output curve was relatively straight, while predicted output curve was slightly bent. Deviation of the predicted output and actual output was about 10 minutes, namely the fusion system has been able to more accurately determine smelting endpoint. Therefore, the prediction algorithm has high efficiency and prediction accuracy.In Figure 4, the horizontal axis was the smelting time, and ordinate the time from the end of the smelting. Compared to previous simulation results, the simulation results were improved with the added brightness of the image. However, the improvement was not clear, so further studies were needed. Besides, other features affecting the judgment of smelting endpoint should be introduced.

4. Conclusion

In order to get a better solution of application, combining predicting model of gray GM (1,1) and BP neural network was applied in fuming furnace smelting endpoint, with high precision. It can further adjust the production process time as a quantitative basis to improve the refining cycle, product quality and yield, thus laying a solid foundation for further energy-saving and green steel. Grey neural network, a new information processing and prediction mode, takes full advantage of the randomness of the gray model weakening data, showing the high regularity of accumulating data and neural network non-prediction method. This new, practical and high-accuracy prediction algorithm should be promoted and further studied, gradually applied in the metallurgical industry. The whole industry will benefit more from this high technology.

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