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Sulfur Dioxide Emission Combination Prediction Model of China Thermal Power Industry

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Abstract

The prediction of regional sulfur dioxide (SO_2) emission of thermal power belongs to gray system which has small amounts of samples and little information, so a appropriate forecasting method is essential. Based on thermal power industry SO_2 emission data from state department authorities, considering the main factors of China's thermal power industry SO_2 predicted emission, we established a combination prediction model connecting gray prediction model with BP neural network model to predict SO_2 emission, and we get more satisfied prediction.

Keywords: *thermal power industry; SO_2 emission; gray model; BP neural network*

1. Introduction

In China's thermal power industry, as for pollution, the percentage of sulfur dioxide **(**SO_2) emission is more than 50%, which belongs to China's heavy polluting industry. To accurately predict SO_2 emission is pretty meaningful for making SO_2 control strategies and specific control measures. In addition, it is also can control SO_2 emission effectively.

SO_2 emission is emitted into the atmosphere mixed with the flue gas, which is difficult to calculate directly. So, we commonly used estimation methods [1] to measure or predict SO_2 emission, such as material balance algorithm [2] [3], field measurement method and data-line monitoring method. In this part, apart from estimation, the mathematical method is also used to predict SO_2 emission. Sheng Zhoujun uses gray prediction method to measure Anhui SO_2 emission, Wang Yanling [4] takes Grey Markov model to forecast China's industrial SO_2 emission, Zheng Yanlin uses regression model to predict the sulfur dioxide emission of the thermal power plant in Shandong Province. After compare and analysis of many different prediction methods, it can be seen that the gray prediction method is more reasonable and scientific. However, a single prediction model has certain limitations. Therefore, on the basis of gray forecast and thermal power industry SO_2 emission data from state department authorities [5], considering the main factors of China's thermal power industry SO_2 predicted emission [6] [7], we established a combination prediction model connecting gray prediction model with BP neural network model to predict SO_2 emission.

2. SO_2 Emission Prediction Model of Regional Thermal Power Plant

The part is to establish a combination prediction model conncecting gray prediction model with BP neural network model [8].

2.1.GM (1, N) Grey Forecasting Model

Assuming the original data sequence, represents n-factor value of m states. In order to enhance the regularity and reduce the randomness of the original data sequence [9], do incremental cumulative formula:

$$X_i^{(1)}(k) = \sum_{j=1}^{k} x_i^{(0)}(j) \tag{1}$$

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Establish a first-order differential equations using GM (1, N) gray prediction model.

$$\frac{dx_1^{(1)}}{dx}+\alpha x_1^{(1)}=b_1x_2^{(1)}+b_2x_3^{(1)}+\cdots+b_{n-1}x_n^{(1)} \tag{2}$$

Call it as GM (1, N) model parameter sequence, denoted by the vector form.
Order parameter B, y ,take the following numbers:

$$B=\begin{vmatrix} -\frac{1}{2}[x_1^{(1)}(1)+x_1^{(1)}(2)] & x_2^{(1)}(2) & \cdots & x_n^{(1)}(2) \\ -\frac{1}{2}[x_1^{(1)}(2)+x_1^{(1)}(3)] & x_2^{(1)}(3) & \cdots & x_n^{(1)}(3) \\ \cdots & \cdots & \cdots & \cdots \\ -\frac{1}{2}[x_1^{(1)}(m-1)+x_1^{(1)}(m)] & x_2^{(1)}(m) & \cdots & x_n^{(1)}(m) \end{vmatrix} \quad y=\begin{vmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \cdots \\ x_1^{(0)}(m) \end{vmatrix}$$

Apply least-squares method to calculate the GM (1, N) model parameters:

$$\hat{\alpha}=(B^TB)^{-1}B^Ty \tag{3}$$

The time response function of GM (1, N) model is:

$$\hat{x}_1^{(1)}(k+1)=[x_1^{(0)}(1)-\frac{\sum_{i=2}^{n}\hat{b}_{i-1}x_i^{(1)}(k+1)}{\hat{\alpha}}]e^{-\alpha k}+\frac{\sum_{i=2}^{n}\hat{b}_{i-1}x_i^{(1)}(k+1)}{\hat{\alpha}} \tag{4}$$

By using regressive prediction formula gets:

$$\hat{x}_1^{(0)}(k+1)=\hat{x}_1^{(1)}(k+1)-\hat{x}_1^{(1)}(k),(k=0,1,2...m) \tag{5}$$

2.2. BP Neural Network Model [10]

2.2.1. The composition of the network

For neurons of BP neural network, the majority of its network input functions use S function. For each neuron, its input function is:

$$net=x_1w_1+x_2w_2+...+x_nw_n \tag{6}$$

There: W - each neuron input weight;
X - each neuron input.
Corresponding to each neuron output is:

$$o=f(net)=\frac{1}{1+e^{-net}} \tag{7}$$

2.2.2. BP neural network learning [11]

The process of BP neural network learning includes the propagation of forward and reverse. Through forward and reverse propagation, the process of network memory learning is built up. When the error output value up to a certain small degree or the required number of times is meet, then stop the training, the learning process ends.

For the network output error, this paper takes the variance to measure:

$$E_p = \frac{1}{2}\sum_{j=1}^{N}(t_{pj} - O_{pj})^2 \quad (8)$$

There: Ep -the error of p-th training sample
tpj - the expectation of j-th output neuron.
Opj - the actual value of j-th output neuron.

Back-propagation algorithm of gradient descent training algorithm in the mathematical expression of the formula is:

$$\Delta_p W_{ji} \propto -\frac{\partial E_p}{\partial w_{ji}} \quad (9)$$

When taping a sample P, the weights of interconnected neurons i and j change, then use $\Delta_p W_{ji}$ represent.

2.2.3. Feedforward calculation of BP neural network

In the period of training learning, assuming there are N training samples, which p is one of the entered samples. The input sample p is:

$$net_i^p = \sum_{j=1}^{M} w_{ij} o_i^p - \theta_i = \sum_{j=1}^{M} w_{ij} x_j^p - \theta_i \quad (10)$$

There: M - indicates the number of input:
θ_i - i threshold in the middle layer;
w_{ij} - That two adjacent weights between neurons;
o_i^p - Indicates sample output of p;
x_j^p - Indicates sample input of p .

The output function in the middle layer :

$$o_i^p = g(net_i^p) \quad (11)$$

The total input of K-th neuron's in output layer

$$net_k^p = \sum_{i=1}^{q} w_{ki} o_i^p - \theta_k \quad (12)$$

There: θ_k - the threshold of k in output layer;
w_{ki} - the connection weights between output layer k and middle layer i
q - the nodes of middle layer .

The actual input of k-th neuron in output layer can be the following formula :

$$o_k^p = g(net_k^p) \quad (13)$$

When in the process of output, if the result is inconsistent with the expected result or the actual data, then feedback the output error along the lines of its input, in addition, correct the data during the process, until you get the desired result. After completing a sample study, send another sample to study until N samples are completed.

2.2.4. Weights adjustment of BP neural network:

The weights adjustment of BP neural network consists of adjusting weights of the output layer and the middle layer weights.

Adjustment of the output layer weights are as follows:

$$\Delta w_{ki} = \eta \delta_k^p o_i^p = \eta o_k^p (t_k^p - o_k^p)(1 - o_k^p) o_i^p \tag{14}$$

There: η - learning rate

o_k^p - the output of sample p in the output contacts k

o_i^p - the output of sample p in the output contacts i

t_k^p - the desired output of sample or actual value of p

Adjustment of the middle layer weights is as follows:

$$\Delta w_{ij} = \eta \delta_i^p o_i^p = \eta o_i^p (1 - o_i^p)(\sum_{k=1}^{L} \delta_k^p w_{ki}) o_j^p \tag{15}$$

There: o_i^p - the output of sample p in i-node in the middle layer

o_j^p - the output of sample p in input node j

2.3. Combined Prediction Model of SO_2 Emission in Thermal Power Industry Based on Gray Neural Network

The two predictive models in China's thermal power industry about SO_2 emission have their own strengths, so the combination forecasting model integrates the advantages of two models, and rejects weaknesses to improve the accuracy of the forecast.

Assuming f_a , f_b and are predicted values of GM (1, N) Grey forecasting model, BP neural network model [12] and the combination model. Besides, assuming e_c is the predicted error of the optimal combination, and e_a, e_b are GM (1, N) Grey, BP neural network model prediction error. Take w_a and w_b as the proportion of GM (1, N) Grey forecasting model, BP neural network model in the combination model. Then get the following formula:

$$w_a + w_b = 1 \tag{16}$$

$$w_a f_a + w_b f_b = f_c \tag{17}$$

The relationship between prediction error, variance of Combination forecasting model and the other two models is:

$$e_c = w_a e_a + w_b e_b \tag{18}$$

$$D(e_c) = D(w_a e_a + w_b e_b) = w_a{}^2 D(e_a) + w_b{}^2 D(e_b) + 2 w_a w_b \operatorname{cov}(e_a, e_b) \tag{19}$$

Bring into the formula, and then count minimum on and then get the proportion Wa of gray model predicted value in combination forecasting model :

$$w_a = \frac{D(e_b) - \operatorname{cov}(e_a, e_b)}{D(e_a) + D(e_b) - 2\operatorname{cov}(e_a, e_b)} \tag{20}$$

Similarly, get the proportion Wb of BP neural network' predicted value in combination forecasting model:

$$w_b = \frac{D(e_a) - \text{cov}(e_a, e_b)}{D(e_a) + D(e_b) - 2\,\text{cov}(e_a, e_b)} \tag{21}$$

As the GM (1, N) Grey forecasting model and BP neural network prediction model are two independent models, therefore, according to $\text{cov}(e_a, e_b) = 0$,the weight values of the gray model and BP neural network model can be simplified to:

$$w_a = \frac{D(e_b)}{D(e_a) + D(e_b)} \tag{22}$$

$$w_b = \frac{D(e_a)}{D(e_b) + D(e_b)} \tag{23}$$

And bring w_a and w_b into $w_a f_a + w_b f_b = f_c$, get the prediction equation of the optimal combination of predictive model:

$$f_c = \frac{D(e_b)}{D(e_a) + D(e_b)} f_a + \frac{D(e_a)}{D(e_a) + D(e_b)} f_b \tag{24}$$

Based on theoretical knowledge of mathematical[13] , we get this conclusion $D(e_c)_{\min} \le D(e_a), D(e_c)_{\min} \le D(e_b)$, then it is clear that the establishment of the following formula: $D(e_c)_{\min} \le \min(D(e_a), D(e_b))$, so the prediction accuracy of optimal combination of predictive model is significantly better than the two separate prediction models.

3. Prediction of SO2 Emission in China's Thermal Power Industry

First, we take grey prediction model, BP neural network model and combination prediction model to predict SO2 emission in China's thermal power industry separately, and then according to the prediction data, we get conclusion.

3.1. Prediction of SO_2 Emission Based on Grey Prediction Model

First, set GM (1,1) Grey forecasting model of each influential factor based on the original sample data, make prediction of each factor separately, as the basis for subsequent forecast data. Then use the GM (1, N) Grey forecasting model to predict SO_2 emission in China's thermal power industry.

SO_2 emission of GM (1,1) model in thermal power industry:

$$\hat{x}_1 = (e^{0.1456} - 1)33.9e^{-0.2159k} \tag{25}$$

Coal consumption of GM (1,1) model:

$$\hat{x}_2 = (1 - e^{-1})36974.6e^{-k} \tag{26}$$

Thermal power installed capacity of GM (1,1) model:

$$\hat{x}_3 = (1 - e^{-1})24984e^{k} \tag{27}$$

Thermal power industry' generating capacity of GM (1,1) model::

$$\hat{x}_4 = (1-e^{0.32})16982.4e^{-0.54k} \tag{28}$$

Gross domestic product (GDP) of GM (1,1) model:

$$\hat{x}_5 = (1-e^{-1})3259.5e^{-0.94k} \tag{29}$$

The gray GM (1, N) model gray parameter sequence predicted about China's SO_2 emission in thermal power industry is:

$$\hat{\alpha} = (\hat{\alpha}, \hat{b}_1, \hat{b}_2, \hat{b}_3, \hat{b}_4)^T = (0.1269, 0.0148, 0.1489, -0.2701, -0.0257)^T \tag{30}$$

From the above sequence of parameters, GM (1, N) first-order differential equation model of bleaching about SO_2 emission in thermal power industry can be obtained:

$$\frac{dx_1^{(1)}}{dt} + 0.1269x_1^{(1)} = 0.0148x_2^{(1)} + 0.1489x_3^{(1)} - 0.2701x_4^{(1)} - 0.0257x_5^{(1)} \tag{31}$$

Take equation (4-6) into GM (1, N) model of first-order bleaching equation, get gray equation of time response function:

$$\hat{x}_1^{(1)}(k+1) = [x_1^{(0)}(1) - \frac{\sum_{i=2}^{5}\hat{b}_{i-1}x_i^{(1)}(k+1)}{\hat{\alpha}}]e^{-\alpha k} + \frac{\sum_{i=2}^{5}\hat{b}_{i-1}x_i^{(1)}(k+1)}{\hat{\alpha}} \tag{32}$$

The values of equation (4-8) are: $x_1^{(0)}(1)$ =838.1. Gray parameter are given by the formula (4-6).Then, through the sequence of regressive reduction (IAGO), the predictive value of SO_2 emission in thermal power industry can be obtained.

3.2. Prediction of SO_2 Emission Based On BP Neural Network Model Paper Submission

Take the four factors in the original sample data--the amount of coal-fired thermal power, thermal power installed capacity, thermal power generation industry and the amount of gross domestic product (GDP) as the input vectors of the BP neural network model, regard the SO_2 emission in thermal power industry as output vector, and use BP neural network to build relationships between them.

The specific structure of BP neural network is shown below as figure 1.

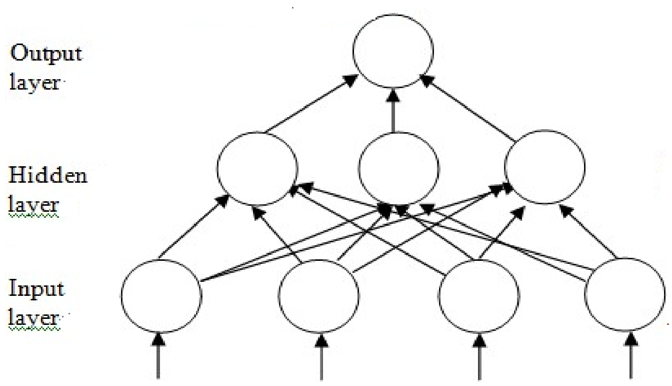

Figure 1. BP neural network structure

Apply neural netw ork toolbox of MATLAB software to calculate the data, get the forecasts of China's SO_2 emission in thermal power industry.

Predicted results based on grey prediction model and BP neural network model are listed below as Table 1.

Table 1. Forecast analysis of SO_2 emission in thermal power industry

Year	Real Value	GM（1,N）		BP neural Network model		Portfolio optimization model	
		Predictive value/(104t)	Error (%)	Predictive value/(104t)	Error (%)	Predictive value/(104t)	Error (%)
2002	857.5	850.2	0.85	873.3	-1.84	860.456	-0.35
2003	1105.3	1069.6	3.23	1125.4	-1.82	1094.375	0.99
2004	1080.0	1112.9	-3.05	1110.6	-2.83	1111.879	-2.95
2005	1277.2	1297.3	-1.57	1233.1	3.45	1268.795	0.67
2006	1320.2	1306.6	1.03	1279.4	3.09	1294.523	1.94
2007	1245.8	1198.7	3.78	1297.7	-4.17	1242.656	0.25
2008	1150.9	1129.1	1.89	1105.8	3.92	1118.755	2.79
2009	1123.6	1050.6	6.50	1083.5	3.57	1065.208	5.20
Var		8.01		10.03		4.97	

Let use Figure 2 tell the table, from this figure, we can see the trend by different wanys clearly.

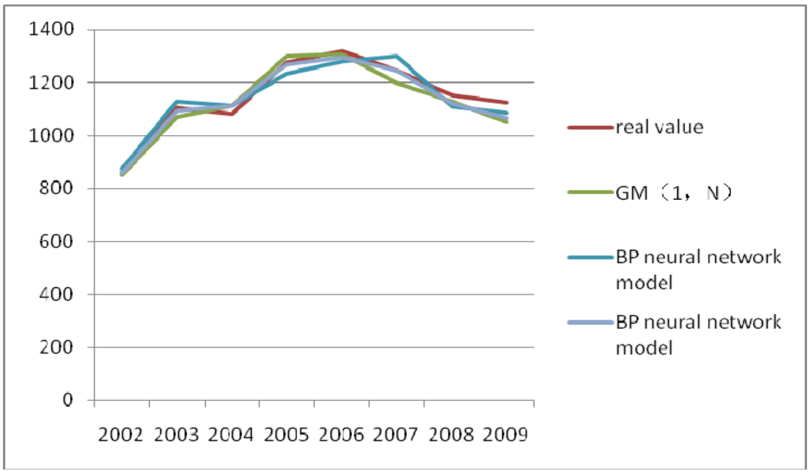

Figure 2. Forecast analysis of SO_2 emission in thermal power industry

3.3. Prediction of SO2 Emission Based On Combination of Gray Neural Network Model

According to the error between prediction values and the actual values of gray prediction model and BP neural network model , you can get the variance of the predicted values error:

$$D(e_a)=8.01, D(e_b)=10.03$$

Then we can get the proportion of gray model and BP neural network model' predicted number takes up in the combination forecasting model :

$$w_a = \frac{D(e_b)}{D(e_a)+D(e_b)} = \frac{10.03}{8.01+10.03} = 0.556$$

$$w_b = 1 - w_a = 0.444$$

Apply the predicted value' weights of the two models to predict the value of seeking the right value, the combination forecasting model predictive formula is:

$$f_c = \frac{D(e_b)}{D(e_a)+D(e_b)} f_a + \frac{D(e_a)}{D(e_a)+D(e_b)} f_b = 0.556 f_a + 0.444 f_b$$

From the above formula, take a prediction of the combination of gray neural network prediction model, the specific results in Table 1.

It shows that if prediction error is less than 3% prediction accuracy, the results is quite suitable, the average prediction error of this paper is 1.8925%, obviously, the model predictions is accurate enough.

This paper uses GM (1,1) model, based on the amount of coal, installed capacity, power output, gross domestic product data in the calendar year, predicted the basic data of SO_2 emission of China's thermal power industry in 2011 and 2020 as below:

Table 2. Basic data of thermal power' SO_2 emission

year	Coal consumption /(104t)	Capacity /(104w)	Generating Capacity /(108kw.h)	GDP /(￥108)
2011	170256.6	75962	32571.1	412364.3
2020	274969.5	1231014	40159.8	795678

Finally, use the combination of gray neural network prediction model to predict China's SO_2 emission trend in the future .Predicted results are listed below.

Table 3. Predicted SO_2 emission of combination forecasting model/(104t)

Year	GM(1,N) model	BPneural Network model	Portfolio optimization model
2010	987.2	1011.3	997.9004
2011	968.5	980.7	973.9168
2020	782.4	762.5	773.5644

3.4. Prediction of SO_2 Emission Results Analysis

In this paper, China's SO_2 emission in thermal power industry were predicted by a combination of gray neural network model, the average prediction error is only 1.8925%, indicating that the predictions are accurate. In order to show this comparation more clearly, we creat Figure3:

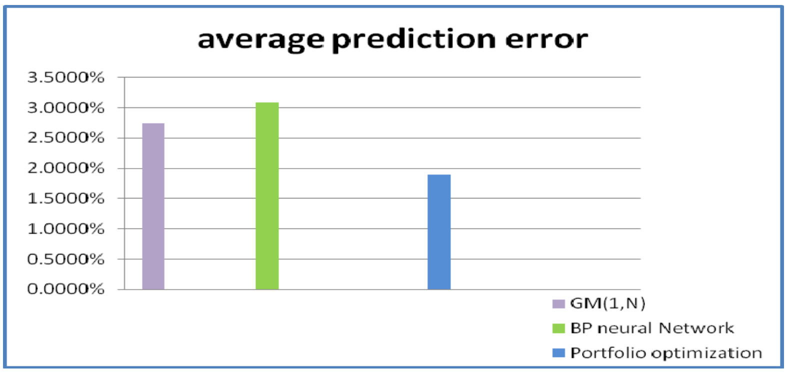

Figure 3. average prediction error

This paper makes a prediction of the thermal power industry in 2020 .The results show that in 2020, China's SO_2 emission in thermal power industry is more than 700 million metric tons, which is still at a high level, therefore, for the purpose to control SO_2 emission at a reasonable level in the thermal power industry[14], our country should continue to increase the monitoring power about SO_2 emission of thermal power plant, improve the standards of air pollutant emission of thermal power plant, accelerate the elimination of backward technology or technological transformation unit.

4. Conclusion

Based on thermal power industry SO_2 emission data from state department authorities, considering the main factors of China's thermal power industry [15] SO_2 predicted emission, we established a combination prediction model connecting gray prediction model with BP neural network model to predict SO_2 emission, and we get more satisfied prediction. In addition, through compare between predicted data and real data, the accuracy of this Portfolio optimization model is testfied.

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