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Research Article

Thermal Power Industry NO_X Emissions Forecast Based on Improved Tandem Gray BP Neural Network

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Abstract: In this study, we build a new thermal power sector NOx emissions prediction model of tandem gray BP neural network. Firstly we use 1994-2010 years NOx emissions data to establish three gray prediction models: GM (1,1), WPGM (1,1) and pGM (1,1); Secondly, by comparison, we select the best prediction model pGM (1,1) and at the same time take NOx emissions factors as the BP neural network input, 1994-2010 year of NOx emissions data for training and testing. Lastly we proceed to predict thermal power industry NOx emissions in China in 2013 and 2020. Prediction result is: mean relative error of the improved tandem gray BP neural network prediction results is 1.92%, which is lower 0.158% than pGM (1,1) model and 0.28% than BP neural network model respectively.

Keywords: BP neural network, grey forecast, NOx emissions forecast, tandem gray BP neural network

INTRODUCTION

70% nitrogen oxides (NOx) discharged into the atmosphere come from the direct combustion of coal, thermal power based on coal consumption has the biggest proportion of electricity production in China, Therefore, grasping the thermal power industry NOx emissions status is the premise and basis of controlling NOx pollution (Gao *et al.*, 2004). Because of NOx emissions restrictions by technical conditions and basic conditions, NOx emissions data statistics is quite difficult, so accurate prediction of NOx emissions of the thermal power industry is particularly important.

Relevant Chinese NOx emissions prediction research is also less. Liu (2007) had come up with several NOx emissions estimation methods in the study “Thermal Power Industry nitrogen oxides emissions estimates in China”, such as emission factor method, the numerical simulation method and statistical methods and so on. However, the error of these estimates is larger, the prediction accuracy is lower; Wang *et al.* (2010) put forward the exponential model of the NOx emissions and the gray prediction model of NOx emissions after deep study of a high-temperature of hypoxia flame image. NO_X emissions belong to the gray system of typical small sample size, poor information (Dang *et al.*, 2009), so it is more appropriate to use the method of gray to predict emissions, however, due to the dynamic nature of the flame itself and environmental factors, they will bring some influence to the results of the prediction model.

In view of advantages and limitations of the above study, this study proposes a tandem gray BP neural network model to predict NOx emissions. First of all, substitute the original data of 1994-2010 NOx emissions into the three gray prediction model GM (1,1), WPGM (1,1) and pGM (1,1), then compare the prediction accuracy of the three models and last select the predictive results of the most accurate gray model and the main factors of impacting NOx emissions as the input of BP neural network. This method combines the strengths and weaknesses of the gray theory and artificial neural network algorithm, the results show that the relative error of predicted results of the improved tandem gray BP neural network model is smaller than the actual results, which has a good feasibility on application of NOx emissions prediction.

THE GRAY BP NEURAL NETWORK MODEL

Gray thoery prediction model: The basic idea of the gray system theory is to take the system of small sample size, poor information and the uncertainty based on partial information known and some of the information unknown as the research object, extract valuable information mainly through the generation and development of the part known information, make sure the correct description and effective monitoring to the system running behavior and the evolution (Xiao *et al.*, 2005). In this study we select three gray forecasting model GM (1,1), WPGM (1,1) and pGM (1,1) to predict the thermal power industry NOX emissions.

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GM(1, 1) model: Assume that time series have n observations, $x^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\cdots x^{(0)}(n)\}$, generate new series by accumulating, $x^{(1)}=\{x^{(1)}(1),x^{(1)}(2),\cdots x^{(1)}(n)\}$ then the corresponding differential equations of GM (1,1) model is: $\frac{dx^{(1)}}{dt}+ax^{(1)}=\mu$, in which a called the developing gray number, u known as endogenous control gray number.

Set $\hat{a}$ as a be estimated parameters vector, $\hat{a}=(\frac{a}{\mu})$, which can be solved by the least squares method, the solution is:, in which:

$$B=\begin{pmatrix} -\frac{1}{2}[x^{(1)}(1)+x^{(1)}(2)] & 1 \\ -\frac{1}{2}[x^{(1)}(2)+x^{(1)}(3)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}[x^{(1)}(n-1)+x^{(1)}(n)] & 1 \end{pmatrix} Y_n=\begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix} \tag{1}$$

Solve the differential equations, then we can obtain Discrete-time response function of gray prediction:

$$\hat{x}^{(1)}(k+1)=[x^{(0)}(1)-\frac{\hat{\mu}}{\hat{a}}]e^{-\hat{a}k}+\frac{\hat{\mu}}{\hat{a}}$$
$$k=0,1,2,\cdots n \tag{2}$$

Is the accumulating prediction value, restore the predictive value, we can see the gray prediction model:

$$\hat{x}^{(0)}(1)=x^{(0)}(1) \tag{3}$$

$$\hat{x}^{(0)}(k)=\hat{x}^{(1)}(k)-\hat{x}^{(1)}(k-1)=(1-e^{\hat{a}})[x^{(0)}(1)-\frac{\hat{u}}{\hat{a}}]e^{-\hat{a}(k-1)} \tag{4}$$

WPGM (1,1)model: If the original data is an index sequence, that is:

$$x^{(0)}=Ae^{a(k-1)} \quad \text{k=1,2}\cdots N \tag{5}$$

Its one time accumulated generating sequence:

$$x^{(1)}=A(1-e^{a(k-1)})/(1-e^{a}) \quad \text{k=1,2}\cdots N \tag{6}$$

Using the GM (1,1) to build a model, we obtain:

$$x^{(0)}(\text{k})+\text{a}z^{(1)}(\text{k})=\text{u} \tag{7}$$

$$B=\begin{bmatrix} -\frac{1}{2}A\frac{2-e^{a}-e^{2a}}{1-e^{a}} & 1 \\ \vdots & \\ -\frac{1}{2}A\frac{2-e^{ka}-e^{(k+1)a}}{1-e^{a}} & 1 \\ \vdots & \\ -\frac{1}{2}A\frac{2-e^{(N-1)a}-e^{Na}}{1-e^{a}} & 1 \end{bmatrix} \tag{8}$$

$$Y_n=[\text{A}e^{a},\text{A}e^{2a},\cdots,\text{A}e^{(N-1)a}]^T \tag{9}$$

After derivation available:

$$(\hat{a},\hat{u})=(B^TB)^{-1}B^TY_n=[\frac{2(1-e^{a})}{1+e^{a}},\frac{2A}{1+e^{a}}]^T \tag{10}$$

The ultimate simulation result is:

$$\hat{x}^{(0)}(1)=\text{A} \tag{11}$$

$$\hat{x}^{(0)}(\text{k})=\frac{Ae^{a}(1-e^{a})}{1-e^{a}}e^{-\hat{a}(\text{k}-1)} \tag{12}$$

By (12), we can get:

$$a=\ln\frac{2-\hat{a}}{2+\hat{a}},\ A=\frac{2\hat{u}}{2+\hat{a}} \tag{13}$$

Use the GM (1,1) model parameters $\hat{a}$, $\hat{u}$ to express the parameters of the original data sequence. Assume the established model on index sequence is:

$$\hat{x}^{(0)}(\text{k})=\hat{\text{A}}e^{\hat{a}(\text{k}-1)};\ k=1,2,3\cdots N \tag{14}$$

If, then $\hat{a}'=a$, At this point (14) is the no deviation model of (5).

pGM (1,1) model: Set the original data sequence is, $x^{(0)}=\{x^{(0)}_{(1)},x^{(0)}_{(2)},\cdots x^{(0)}_{(n)}\}$. Its one time accumulated generating sequence, $x^{(1)}=\{x^{(1)}_{(1)},x^{(1)}_{(2)},\cdots x^{(1)}_{(n)}\}$ the sequence's albino equation of pGM (1,1) model is:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=u \tag{15}$$

In which the albino value of gray parameters. $\beta=[\text{a, u}]^T$ Determine the optimal weights and generate background value sequence:

$$z'=\{-z'(2),z'(3),\cdots,z'(n)\} \tag{16}$$

In which: $z'(t+1)=px(t+1)+(1-p)x(t)$

Using the least squares method to calculate β, then:

$$\beta=[\text{a,u}]^T=(A^TA)^{-1}A^TB \tag{17}$$

In which:

$$A=\begin{bmatrix} -z^{'}(2) & -z^{'}(3) & \cdots & -z^{'}(n) \\ 1 & 1 & \cdots & 1 \end{bmatrix}^T$$

$$B = \left(x^{(0)}_{(2)},\ x^{(0)}_{(3)} \cdots ,\ x^{(0)}_{(n)} \right)^T$$

Substitute the obtained gray parameters into (15) and then find the solution of differential equations:

$$\hat{x}^{(1)}_{(t+1)} = (x^{(0)}_{(1)} + u/a)e^{-at} + u/a \tag{18}$$

If $\hat{x}^{(1)}_{(t+1)}$ is the model calculated value, tired less generate it, you can get the analog value of the model, $\hat{x}^{(0)}_{(t+1)}$ that is:

$$\left.\begin{aligned} &\hat{x}^{(0)}_{(1)} = \hat{x}^{(1)}_{(0)} \\ &\hat{x}^{(0)}_{(t+1)} = (1-e^{a})(y^{(0)}_{(1)} - u/a)e^{-at} = \hat{x}^{(1)}_{(t+1)} - \hat{x}^{(1)}_{(t)} \end{aligned}\right\} \tag{19}$$

(18) and (19) is a specific formula for calculating pGM (1,1) model.

BP neural network prediction model: BP network has a three-tier structure, namely the input layer, the hidden layer and the output layer, which are fully connected. Set the input layer is i, the hidden layer is h and the output layer is j, the number of nodes of three layers respectively are ni, nh, nj, the threshold value of the hidden layer nodes and output layer nodes respectively are θh and θj, the wiring weight between the input layer nodes and the hidden layer node is, the wiring weight of hidden layer nodes and output layer nodes is, each node input is x.

- Normalize the input and output samples
- The initialization. Assume the input and output samples after normalized are:

$$\{x_{k,i}, d_{k,j} \mid k=1,2,\cdots nk; i=1,2,\cdots ni; j=1,2,\cdots nj\}$$

- nk = The sample capacity, each connection weights $\{w_{ih}\}\{w_{hj}\}$ and threshold $\{\theta h\}\{\theta j\}$ = Taken to a random value in the interval (-0.1, 0.1)
- Set $k=1$, provide the input and output samples to the network
- Calculate the input and output of each node of the hidden layer $(h=1,2,\cdots nh)$

$$x_h = \sum_{i=1}^{ni} w_{ih} * x_{ki} + \theta_h ; y_h = 1/(1+e^{-x_h}) \tag{20}$$

- Calculate the input and output of each node of the output layer $(j=1,2,\cdots nj)$

$$x_j = \sum_{h=1}^{nh} w_{hj} * y_h + \theta_j ; y_j = 1/(1+e^{-x_j}) \tag{21}$$

The calculation of the change rate of the total input changes the output layer node receives a single sample error.

$$\frac{\partial E_k}{\partial x_j} = y_j(1-y_j)(y_j - d_{k,j}) \quad (j=1,2,\cdots nj) \tag{22}$$

The calculation of the change rate of the total input changes the Hidden layer node receives a single sample error.

$$\frac{\partial E_k}{\partial x_h} = y_h(1-y_h)\sum_{j=1}^{nj}\left(\frac{\partial E_k}{\partial x_j} * w_{hj}\right) \quad (h=1,2,\cdots nh) \tag{23}$$

The correction of the connection weights and thresholds.

$$w^{t+1}_{hj} = w^{t}_{hj} - \eta \frac{\partial E_k}{\partial x_j} y_j + a(w^{t}_{hj} - w^{t-1}_{hj}) \tag{24}$$

$$\theta^{t+1}_{j} = \theta^{t}_{j} - \eta \frac{\partial E_k}{\partial x_j} + a(\theta^{t}_{j} - \theta^{t-1}_{j}) \tag{25}$$

$$w^{t+1}_{ih} = w^{t}_{ih} - \eta \frac{\partial E_k}{\partial x_h} x_{k,i} + a(w^{t}_{ih} - w^{t-1}_{ih}) \tag{26}$$

$$\theta^{t+1}_{h} = \theta^{t}_{h} - \eta \frac{\partial E_k}{\partial x_h} + a(\theta^{t}_{h} - \theta^{t-1}_{h}) \tag{27}$$

In which correction number is, Learning rate, momentum factor, algorithm converges is slowly while is smaller, algorithm converges is faster while is larger, but it is instable, may shock and the function of is opposite.

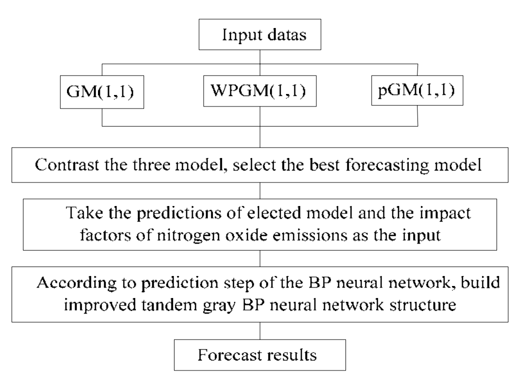

Fig. 1: Overall framework of NO_X emissions prediction model

Table 1: The original sample data

Years	NOx emissions/ (10,000 tons)	The coal consumption/ (10,000 tons)	The installed capacity/ (10,000 kwh)	Power generation/ (100 million kwh)	GDP/ (100 million yuan)
1994	298.6	40053.1	14874	7470	48197.9
1995	327.1	44440.2	16294	8074	60793.7
1996	359.3	48808.6	17886	8781	71176.6
1997	350.3	48979	19241	9252	78973
1998	360.5	49489.3	20988	9441.0	84402.3
1999	430.0	51163.5	22343	10205.4	89677.1
2000	469.0	55811.2	23754	11141.9	99214.6
2001	497.5	57687.9	25314	11767.5	109655.2
2002	536.8	65600.0	26555	13273.8	120332.7
2003	597.3	77976.5	28977	15803.6	135822.8
2004	629.1	91961.6	32500	17955.9	159878.3
2005	687.4	103263.5	38354	20473.4	183084.8
2006	759.2	118763.9	48405	23696.0	211923.8
2007	811.0	130548.8	55442	27229.3	249530.6
2008	810.3	135351.7	60132	27820.2	300670.0
2009	829.4	142100.1	65108	30116.9	340506.9
2010	954.1	150122.4	70967.21	42278	401202.0

Thermal power NOx emissions data from 1994 to 2002 come from fahua Zhu's paper in 2004 (Zhu *et al*., 2004); NOx emissions data from 2003 to 2010 is from the statistics of the State Environmental Protection Department (Ministry of Environmental Protection of the People's Republic of China, 2010); Coal consumption, electricity generation, and GDP data are from the website of the National Bureau of Statistics of the People's Republic of China (National Bureau of Statistics, 2008); The installed capacity data come from the power industry statistics of the China Electricity Council (China Electric Power Yearbook Editorial Board, 2009).

Table 2: Forecast results of three gray models

Years	Actual value	Predictive value of GM	Predictive value of WPGM	Predictive value of PGM
1994	298.6	298.6	298.6	298.6
1995	327.1	347.2167	345.0777	341.6887
1996	359.3	381.8281	379.7293	374.8936
1997	350.3	372.7893	369.3196	364.277
1998	360.5	383.0313	380.519	378.2366
1999	430.0	456.1999	453.4354	447.2
2000	469.0	498.07	494.9607	486.787
2001	497.5	529.825	524.5235	519.3525
2002	536.8	568.504	567.0226	561.4832
2003	597.3	636.119	631.4648	624.1541
2004	629.1	666.873	663.2907	653.0111
2005	687.4	728.622	726.132	713.548
2006	759.2	807.076	801.1777	791.084
2007	810.3	860.509	859.7068	842.706
2008	811.0	862.93	858.1682	844.22
2009	829.4	882.6475	877.1734	862.3272
2010	954.1	1014.399	1007.339	992.3594

Set, $k = k+1$ provide ($x_{k,i}$, $d_{k,j}$) to the network, then go to step 4), until all the samples are completely trained.

Repeate steps 3) to 9), until the network global error function.

$$E = \sum_{k=1}^{nk} E_k = \sum_{k=1}^{nk} \sum_{j=1}^{nj} \left| y_j - d_{k,j} \right|^2 \tag{28}$$

Learning frequency is bigger than the pre-set value or less than a smaller value of the pre-set.

Improved tandem gray BP neural network model: Tandem gray BP neural network is to take the results of gray prediction model as input of neural network, utilizing the non-linear fitting ability to obtain the final predicted value. But this approach ignores the impact of the other main factors to results prediction, based on which, we put forward a Improved tandem gray BP neural network model to predict thermal power NOX emissions In this study, that is: select a best forecast model among GM (1,1), WPGM (1,1) and pGM (1,1), at the same time take the main factors of effecting nitrogen oxide emissions as the input of the neural network to achieve the best fit. As shown in Fig. 1:

NOX EMISSIONS PROJECTIONS OF THERMAL POWER BASED ON SERIES GRAY BP NEURAL NETWORK MODEL

The selection of the basic data: Neural network and gray neural network model need some data including NOX emissions data, the coal consumption, installed capacity, power generation as well as GDP. The raw data of the study sample is selected from annual NOx emissions of the thermal power industry from 1994 to 2010 (Ministry of Environmental Protection of the People's Republic of China, 2010; Zhu *et al*., 2004), the coal consumption (National Bureau of Statistics, 2008), the installed capacity (China Electric Power Yearbook Editorial Board, 2009), power generation, the GDP (National Bureau of Statistics, 2008), the specific data is shown in Table 1.

The gray model selection of NOX emissions: According to the original sample data in Table 1, we establish gray prediction model GM (1,1), WPGM (1,1), pGM (1,1), program Three models using MATLAB language and forecast NOX emissions from

Table 3: Analog performance of the three models

Model	GM (1,1)	WPGM (1,1)	PGM(1,1)
Average relative Error %	6.2457	5.6115	4.1793

Table 4: Accuracy class reference table

Accuracy class	level 1	level 2	level 3	level 4
Relative error (%)	1	5	10	20

Table 5: NOx emissions predictive results with artificial neural network model from 2006 to 2010

Years	Predictivevalue	Actualvalue	Relative error (%)
2006	790.3	759.2	0.041
2007	841.1	810.3	0.038
2008	849.1	811	0.047
2009	865.9	829.4	0.044
2010	992.0	954.1	0.0397
Average relative error			0.04194

Table 6: NOx emission projections with the improved series gray BP neural network

Years	Predictivevalue	Actual value	Relative error (%)
2006	772.3	759.2	0.0172
2007	822.8	810.3	0.0154
2008	824.2	811	0.0163
2009	841.9	829.4	0.0151
2010	968. 7	954.1	0.0153

1994 to 2010, the predicted results are shown in Table 2.

Relative error is used as an explanation for the accuracy of the prediction model:

$$\Delta h = \frac{|\varepsilon(h)|}{x(h)} \quad \varepsilon(h) = x(h) - \hat{x}(h) \tag{29}$$

In the formula, $x(h)$ means the actual value, $\hat{x}(h)$ means the predictive value.

According to the formula (29), calculating the relative error after simulating China's thermal power NOX emissions from 1994 to 2010 using forecasting model GM (1,1), WPGM (1,1), pGM (1,1), which is shown in Table 3.

As is shown in Table 3, the analog performance of pGM (1,1) is higher than GM (1,1) and WPGM (1,1).

According to Table 4, the relative error for GM (1,1), WPGM (1,1) and pGM (1,1) belong to level 2, the simulation accuracy is acceptable.

In summary, pGM (1,1) is compared to GM (1,1) and WPGM (1,1) whose predictive effect is better, so pGM (1,1)is put into the combined model.

The accuracy validation of nox emissions projections model based on improved series gray bp neural network: NOx emissions factor is the input of NOx emissions projections network, in theory, the number of impact factors is the number of input layer neurons, Coal consumption, electricity generation, installed capacity and GDP are selected as the input, therefore, input nodes of NOx emissions artificial neural network model are four. Based on trial and error method, a hidden layer has 13 neurons according to empirical formula of node algorithm, the network training adopts the Levenberg- Marquardt algorithm.

After training the data from 1994 to 2005 using above neural network model, predicted results of NOx emissions are shown in Table 5 from 2006 to 2010.

According to above analysis, pGM (1,1) is compared to GM (1,1) and WPGM (1,1) whose predictive effect is better, pGM (1,1) model prediction results is taken as the input of improved series gray neural network model. Combined with the above trained neural network structure, we can see the structure of the improved series gray neural network model: The input layer 5 neurons: pGM (1,1) model prediction results, coal consumption, power generation, installed capacity and GDP, Output layer has one neuron, hidden layer has 13 neurons, network training

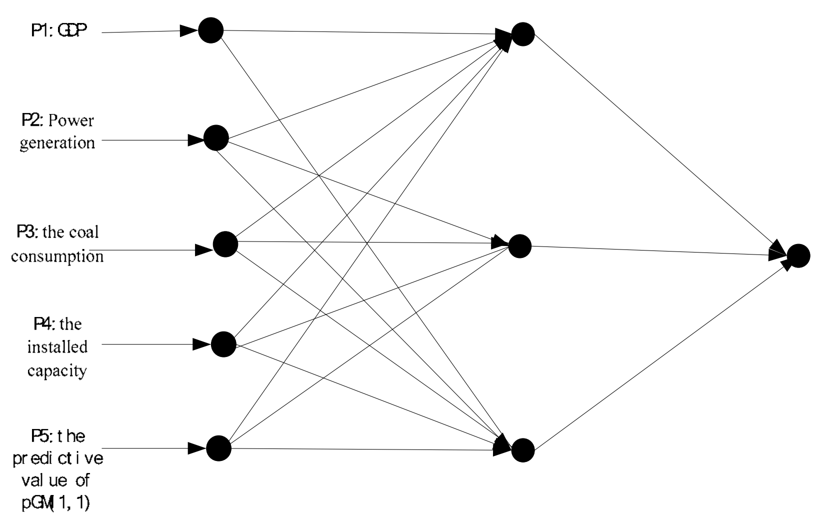

Fig. 2: Network diagram

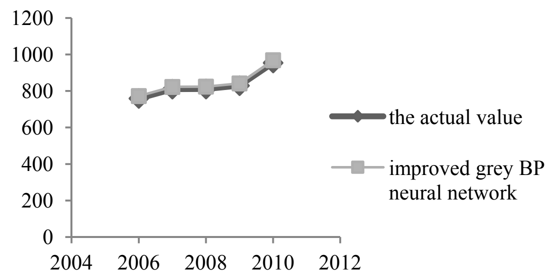

Fig. 3: Accuracy validation: the comparison between NOx emissions predicted value and the actual value with improved series gray BP neural network

Table 7: The determination of input vector in 2012 and 2020

Years	GDP	Coal consumption	Installed capacity	Power generation
2012	509527.2	181935.6	94217	32164.5
2020	821469.4	284636.2	131525	41132.5

adopt the Levenberg-Marquardt algorithm, the network structure is shown in Fig. 2.

Forecasting NOx emissions from 2006 to 2010 adopts the improved series gray neural network, prediction results are shown in Table 6 and in Fig. 3.

Mean relative error of this prediction results is 1.586%, which is smaller for 4.179% than pGM1,1model and for 2.608% than neural network model. Therefore improved series gray neural network can be used to predict NOx emissions of the thermal power industry in China from 2013 to 2020.

NOX emissions forecast of China's thermal power industry: We can find GDP, coal consumption, installed capacity, power generation data from 2009 to 2011 from China Statistical Yearbook, China Electric Power Yearbook and other relevant information. As is known from the content, prediction effect of pGM (1, 1) is best, so through the pGM (1, 1) model, forecast the data of all the factors in 2012 and 2020 on the basis of historical data. Specific results are shown in Table 7:

Use 1998-2008 NOX emission data modeling pGM (1,1), forecast NOX emissions for 2012 and 2020,the results respectively are 879.3621 ten thousand tons and 982.1435 ten thousand tons.

Input vector in 2012 and 2020 of improved tandem gray BP neural network model respectively are:

$$\{509527.2,181935.6,94217,32164.5,879.3621\}$$

and

$$\{821469.4,284636.2,131525,41132.5,982.1435\}$$

Transporting two sets of vectors to the improved tandem gray BP neural network, we can obtain NOX emissions of the thermal power industry in China in 2012 and 2020: 894.3113 ten thousand tons and 1000.804 ten thousand tons.

CONCLUSION

The study sets up a newly improved series gray neural network model for NOx emissions projections of the thermal power, with the problems that there are not enough long-term forecasting data for NOx emissions, we established three gray prediction models which include pGM(1,1), GM(1,1), WPGM(1,1) using time series of NOx emissions from 1994 to 2010. Combining the advantages and disadvantages of gray theory and neural network algorithm, a new model that the best accuracy PGM (1,1) model, GDP, coal consumption, installed capacity as well as power generations are all taken as the input of neural network is constructed. Then the new model is put to test the NOx emissions from 2006 to 2010, the average relative error of the predicted results is 1.586% which is smaller than pGM (1,1) model for 4.179% and is also smaller than neural network model for 2.608%. Finally, we make a forecasting for NOx emissions of the china thermal power in 2013 and in 2020. Therefore, the newly improved series gray neural network model has a higher prediction accuracy that can be regarded as an effective way for thermal power NOX emissions projections.

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