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Grey Neural Network Model and its Application in Coal Demand Prediction

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Abstract: Grey Neural Network is an innovative intelligent computing approach combing grey system model and neural net-work, which makes full use of the similarities and complementarities between grey system model and neural network to settle the disadvantage of applying grey model and Neural Network separately. Therefore, the Grey Neural Network model can be applied practically in a wide range. Coal is basic energy in China and it supports the rapid development of the national economy. Therefore the forecast of coal demand is particularly important for the rational use of coal resources and the sound development of China economy. In recent years, there are some limitations of the demand for coal forecast. The three layers grey neural network model is established based on Matlab technology and to be simulated in this study. After actual data testing, the coal demand is forecasted with the methods.

Key words: Grey system, neural network, grey neural network model, coal demand, forecasting

INTRODUCTION

Coal is major energy in China. It has an important strategic position in the national economic development. Coal industry is an important basic industry of the national economy and it supports Chinese industrialization industry. China is a developing country and the demand of coal is large in economic development over a long time. The new structure of the coal market with suitable mode and coal logistics system is gradually taking shape (Cui *et al*., 2010). With the rapid development of the coal industry, how to accelerate the development of coal bulk flow of coal and build a new pillar industry of China's coal industry is the inevitable choice that we seize opportunities and meet challenges (Deng, 2001).

With the further development of oil and natural gas resources and the growing shortage of clean coal technology, the importance and status of coal will gradually increase. Coal plays an important role both in energy production and consumption of China. The total coal production of China in 2001 accounted for the proportion of total energy production was 73% and was up to 76.5% in 2010. The total coal consumption was 68.3% attributable to energy consumption in 2001 and was remained around 70% in 2010. It indicates that coal plays an important role to China's economic development (Hsieh *et al*., 2011).

The basic characteristic of energy in China is coal-rich, oil-poor and less-gas. It determine that coal plays an important role in energy consumption. The structure with coal as the main energy will last a long time. In a fairly long period it will not change (Abidin *et al*., 2001).

Due to the dominant position of coal in the energy, coal demand forecasts can provide the fundamental basis for China to develop long-term energy strategy for the sustainable development of China's coal energy (Hao and Wang, 2000).

Coal demand is not only affected by its own historical data, but also affected by many other factors. How to use existing data reasonably and effectively making a more favorable forecast for coal demand is an important task of the current time. We have to choose appropriate specific data on the actual situation and determine the appropriate forecasting model. If the selection is not appropriate, it will result in large forecast errors. It is necessary to amend or change the model and therefore combination forecasting method can be used if necessary (Wang *et al*., 2011).

In summary, there is no prediction method which can be applied to any situation. We should select appropriate forecasting model to specific conditions, according to the available information at different times and in different regions. Overall, because of the complexity and nonlinear characteristics of the coal requirements of the system, a model is not a good base in forecasting (Julio-Miranda *et al*., 2012). It is necessary to preclude the use of combination forecasting method. In this study grey system and artificial neural network prediction are combined to forecast coal demand. Grey neural network forecasting can be an effective utilization of information provided by each individual model to improve prediction accuracy (Liu and Lin, 2011).

GREY NEURAL NETWORK FORECASTING MODEL

Grey prediction model: GM (1,1) model is the most widely used grey prediction model currently. It is a variable number of columns on the prediction of a first-order differential equations, which is based on the original random time series, after the new time series formed by the time accumulation rule presented solutions available to first-order linear differential equation approach. After the theory proved by the solution first order linear differential equations approximation of the original time series revealed an exponential variation. Therefore, the grey model GM (1,1) at the time when the original sequence with index variation, predicted to be very successful.

Let the variables:

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots x^{(0)}(n)\} \tag{1}$$

are original data sequence. And the variables:

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots x^{(1)}(n)\} \tag{2}$$

are accumulated generating sequence. Where:

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, \cdots n \tag{3}$$

The following differential equation is called the whitenization equation of the GM (1,1) model:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{4}$$

The solution of above differential equation is as follow:

$$x^{(1)}(t) = (x^{(0)}(1) - \frac{b}{a})e^{-a(t-1)} + \frac{b}{a} \tag{5}$$

If $\hat{a} = (a, b)^T$ is the parameter column and:

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{6}$$

We have $\hat{a} = (B^T B)^{-1} B^T Y$:

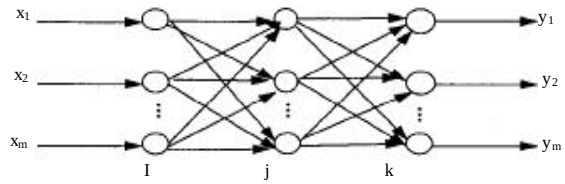

Fig. 1: BP neural network model

$$\begin{aligned} \hat{x}^{(0)}(k+1) &= \alpha^{(1)}\hat{x}^{(1)}(k+1) \\ &= \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \\ &= (1 - e^{a})(x^{(0)}(1) - \frac{b}{a})e^{-ak} \\ k &= 1, 2, \cdots, n \end{aligned} \tag{7}$$

Neural network model: Demand for coal is determined by a number of factors. The traditional forecasting methods often consider a very small part of them. As a nonlinear adaptive system the neural network has the advantage learning by extracting information from the internal characteristics. It can be adapted factors intricate interactions exists between the coal and suited to solve the coal market demand forecast. Currently the most widely used artificial neural network is a feedforward back-propagation network (Back-Propagation-Network). It referred to as the BP neural network. Theory has been proved that the BP neural network, as long as a sufficient number of hidden layer nodes, it has the ability to simulate arbitrarily complex nonlinear mappings. This study also uses three BP Neural network, the network structure is shown in Fig. 1.

The number of neurons in the input layer is i and the input vector is $X = (x_1, x_2, \cdots x_n)^T$, $x_0 = -1$ is threshold for the hidden layer neurons. The number of hidden layer is j and the output vector of hidden layer is $O = (o_1, o_2, \cdots o_l)^T$, $o_0 = -1$ is threshold for the output layer neurons. The number of neurons in the output layer is k and the output vector is $Y = (y_1, y_2, \cdots y_m)^T$. The mathematical expectation of output vector is $D = (d_1, d_2, \cdots d_m)^T$. w_{ji} is the weights between the input layer to the hidden layer. Excitation function is Sigmoid logarithmic type function as follow:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{8}$$

$$f'(x) = f(x)(1 - f(x)) \tag{9}$$

The j-th hidden layer neuron input and output functions are as follow:

$$u_j = \sum_{i=0}^{n} w_{ji} x_i \tag{10}$$

$$o_j = \varphi(u_j) \tag{11}$$

The k-th output layer neuron input and output are as follow:

$$u_k = \sum_{j=0}^{1} w_{kj} o_j \tag{12}$$

$$y_k = \varphi(u_k) \tag{13}$$

When the network output and the desired output are not equal.The output error exists. The output layer error is E:

$$\begin{aligned} E &= \frac{1}{2}\sum_{k=1}^{m}(d_k - y_k)^2 = \frac{1}{2}\sum_{k=1}^{m}(d_k - \varphi(u_k))^2 \\ &= \frac{1}{2}\sum_{k=1}^{m}\left(d_k - \varphi\left(\sum_{j=0}^{1} w_{kj} o_j\right)\right)^2 \\ &= \frac{1}{2}\sum_{k=1}^{m}\left(d_k - \varphi\sum_{j=0}^{1} w_{kj}\varphi(u_j)\right)^2 \\ &= \frac{1}{2}\sum_{k=1}^{m}\left(d_k - \varphi\sum_{j=0}^{1} w_{kj}\varphi\left(\sum_{i=0}^{n} w_{ji} x_i\right)\right)^2 \end{aligned} \tag{14}$$

The change items of hidden layer to the output layer weights is as follow:

$$\begin{aligned} \Delta w_{kj} &= -\eta\frac{\partial E}{\partial w_{kj}} = \eta\left(-\frac{\partial E}{\partial y_k}\right)\frac{\partial y_k}{\partial u_k}\frac{\partial u_k}{\partial w_{kj}} \\ &= \eta(d_k - y_k) y_k' o_j \\ &= \eta(d_k - y_k) y_k (1 - y_k) o_j \end{aligned} \tag{15}$$

The change items of input layer to the hidden layer weights is as follow:

$$\begin{aligned} \Delta w_{ji} &= -\eta\frac{\partial E}{\partial w_{kji}} = -\eta\frac{\partial E}{\partial o_j}\frac{\partial o_j}{\partial u_j}\frac{\partial u_j}{\partial w_{ji}} \\ &= -\eta\frac{\partial E}{\partial o_j} o_i (1 - o_i) \end{aligned} \tag{16}$$

Then we have:

$$\begin{aligned} \frac{\partial E}{\partial o_j} &= \sum_{k=1}^{m}(d_k - y_k)\frac{(d_k - y_k)}{\partial o_j} \\ &= \sum_{k=1}^{m}(d_k - y_k)\frac{(d_k - y_k)}{\partial u_k} \\ &= \sum_{k=1}^{m}(d_k - y_k)\left[-y_k(1 - y_k)\right] w_{kj} \end{aligned} \tag{17}$$

Where:

$$\begin{aligned} &\Delta w_{ji} \\ &= \eta\sum_{k=1}^{m}(d_k - y_k) y_k (1 - y_k) w_{kj} o_j (1 - o_j) x_j \\ &= \eta\delta_j^0 x_j \end{aligned} \tag{18}$$

Grey neural network model: The combination of coal demand forecasting methods are mainly parallel type and tandem type. Shunt is a weighted linear combination model. The weighting factor is determined by the validity of the prediction results and then a weighted combination of the weighted average value are as the actual prediction. Some proposed a linear regression model, the combination of BP neural network forecasting model and gray model , which is to give these three models corresponding weights , combined with predictions of these three models come more reasonable predictions ; preclude the use of a neural network model to predict the value of the gray model, ARMA model (series model) and sectoral analysis model four models were weighted combination treatment model; literature proposed based on maximum likelihood Bayesian model averaging combination forecasting model then and compare with the Bayesian model averaging combination forecasting model based on the marginal likelihood, the results show the effect of the former is predicted to be superior to the latter. Nonlinear fitting model is the ability to use a tandem combination of multiple gray neural network model to predict the result of the combination, enter the artificial neural network model to predict the results of multiple gray prediction model, the heavy weights of the gray model using artificial neural networks obtained.

The grey system and neural network integration, construction gray neural network model that can complement each other, learn from each other: the gray prediction model, a small amount of computation required in case of a small sample can achieve high accuracy; built using BP neural network high precision mold and error control, the integration of the two together, you can play the advantages of both.

Most of the above composition model is a single model simple linear weighted sum, there will be two models are completely fused together, so this study presents an improved coal demand forecast gray neural network model (Fig. 2), enter the neural network to take the main factors predicted demand for coal and gray model, improved combined forecasting model has played a role in nonlinear prediction error correction and the influence of factors gray neural network model weights training process for coal demand to achieve the predicted value the best fit of the actual value.

Table 1: Grey forecasting model error

Date	Actual data	Forecastin data	Relative error (%)
2000	124537.4	124537.4	0.00
2001	126312.3	143702.4	-13.85
2002	136605.5	157599.6	-15.87
2003	169525.2	172580.3	-2.13
2004	193596.5	158996.2	2.08
2005	231851.3	201456.2	10.33
2006	239652.8	227859.5	4.68
2007	258641.5	250041.2	3.32
2008	281096.3	274222.6	2.44
2009	295822.6	300742.9	-1.66
2010	311512.6	329827.9	-5.85

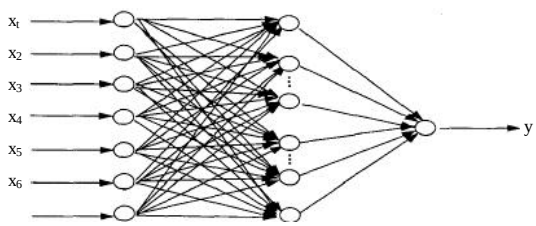

Fig. 2: Improved grey neural network combined model

In the improved gray prediction model, the input vector is not just a simple vector factors, but increased the gray model to predict the results in this study, there are seven inputs, the former six input factors of coal demand, namely industrial coal consumption, GDP, urban population, per capita consumption levels, total energy consumption, coal production; section 7 input gray model to predict coal consumption results. Part of the network parameters of the hidden layer solution to insinuate gray differential equations; rest of the parameters used to study the role of the main factors affecting the nonlinear energy demand for energy demand. In predicting the future when coal demand is not simply to calculate the input data of each factor with the growth rate of each of the factors, but with the gray model to predict the future impact of input factors, to further strengthen the prediction accuracy.

CASE STUDY

Forecasting by grey system model: This study selects 2000-2010 of 11 years of data with grey forecasting models to predict future demand for coal consumption in six years.Using MATLAB programming language for grey forecasting model, we derived class ratio in the range of (0.8072,0.9867). Judging by the earlier stage than theory, we can use grey prediction model. The result calculated GM(1,1) model is as follow.

$$a = -0.0983, b = 12564.386 \tag{20}$$

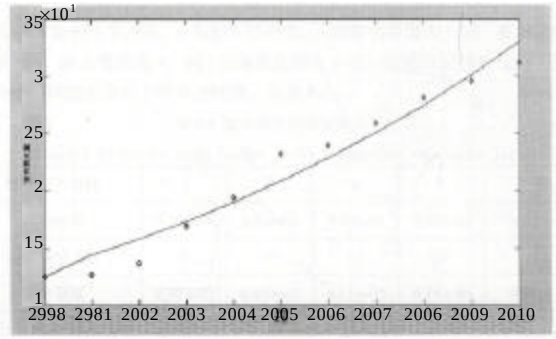

Fig. 3: Grey forecasting model fitting results

The forecasting equation is as follow:

$$\hat{x}_1(k+1) = 1486215.38e^{0.0983k} - 1361590.16 \tag{21}$$

Grey prediction model data comparison with the actual data shown in Table 1.

Average relative error is $\bar{\varepsilon}$:

$$\bar{\varepsilon} = 6.55\% \tag{22}$$

Accuracy of the model is p:

$$p = (1-\bar{\varepsilon})\times 100\% = 93.47\% > 90\% \tag{23}$$

$$S_1^2 = \frac{1}{n}\sum_{k=1}^{n}\left(X^0(k)-\bar{X}\right)^2 = 4341517878 \tag{24}$$

$$S_2^2 = \frac{1}{n}\sum_{k=1}^{n}\left(Z(k)-\bar{Z}\right)^2 = 318012635 \tag{25}$$

$$C = \frac{S_1^2}{S_2^2} = 0.073 < 0.35 \tag{26}$$

Residual test shows the prediction accuracy is two level, but closer to 1 level. The prediction accuracy is good. The model can be used for coal consumption forecast. Prediction data and the actual data Fitting result of the comparison is shown in Fig. 3 (curve predicted value).

Basic grey model predictions about the actual values fluctuate within a certain range. The fluctuation in some years shows that the predicted values are closer to the actual values. The error is small. But in other years the fluctuation is large. The predicted stability is not high.

Table 2: BP neural network forecasting errors

Date	Actual data	Forecasting data	Relative error (%)
2008	281095.3	275645.6	1.63
2009	295866.3	295520.6	0.11
2010	311521.5	319248.7	-2.48

Table 3: BP neural network forecasting errors

Date	Actual data	Forecasting data	Relative error (%)
2008	281095.3	276945.4	1.48
2009	295866.3	289753.1	2.50
2010	311521.5	310717.5	0.26

Forecasting by BP neural network model: We choose BP neural network to forecast in this section. The input section points are six. They are the amount of industrial coal the total energy consumption urban population? gross domestic production?per capita consumption level?coal production. We choose the coal consumption as an output node. We select the 1995-2007 data as training samples, 2008-2010 data as the test samples.

Set the maximum number of training is epoch steps. It is 5000 steps. The expected error goal is 0.0001. The learning rate is generally selected between 0.01 and 0.1. Hidden layer function is S-tangent function tansig. The training function is traincgf functions. We use MATLAB 7.8.0 to program. The training part of the program code is as follow:

```
net=newff(minmax(P),[6,11,1 ],{'tansig'tansig','logsig'},'traincgf');
net.trainParam.show=50;
net.trainParam.epochs=5000;
net.trainParam.lr=0.01 ;
net.trainparam.goal=0.0001 ;
net=train(net,P,T);
save 7 net;
```

We can get the result of training curve in Fig. 4. As can be seen from Fig. 3, the training error reaches 9.64e-05 after step 55. We verify that coal consumption in 2008-2010.

```
p_test=[0.7729 0.7617 0.6952 0.7849 0.7299 0.7239;
0.8355 0.8245 0.7583 0.8380 0.8086 0.7927;
0.9000 0.9000 0.9000 0.9000 0.9000 0.9000]';
T_test=[0.7699 0.8329 0.9000];
y=sim(net,p_test)
```

We get the predicted results y = [0. 7503 0.8315 0.9331]. Anti-normalization, get the 2008-2010 forecast coal consumption volume and compare actual consumption, as shown in Table 2.

From Table 2 the mean relative error can be calculated by the BP neural network. The mean relative error is 1.41%. The error is small and the prediction accuracy is relatively high.

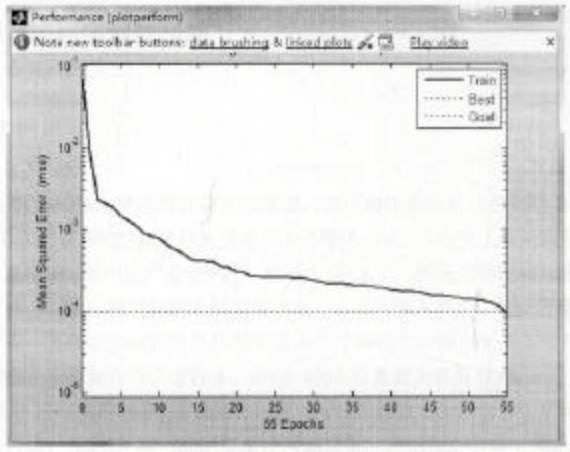

Fig. 4: BP neural network training curl

Forecasting by grey neural network model: According to the steps to determine the neural network model, we determine the structure of grey neural network model network. The network uses 3-layer BP neural network. We set seven input nodes in the input layer. They are industrial coal volume, the total energy consumption, gross domestic product, urban population, per capita consumption level, coal production and gray model predicted coal consumption. We choose coal consumption as the output node. Through selection we choose seven neurons nodes in the hidden layer and one neurons node in the output layer. The sample data in 1995-2007 are selected as training data and the data in 2008-2010 are selected as test samples. Calculated by MATLAB programming, the output is [0.7521 0.8069 0.8966]. After anti-normalization, the final forecast results obtained in 2008-2010 and the predicted value and the actual value of the resulting coal demand In contrast, as shown in Table 3.

From Table 5-5 we can see that grey neural network predictive value are basically similar to the actual value. The relative error is small, the prediction accuracy is higher than BP neural network accuracy and more suitable for coal demand forecast.

CONCLUSION

When we select predictive factors, the factor of price is rounded because the price is rigid demand. When prices of coal or other energy rise, the impact on coal demand is not great. Because demands for coal and coal production are closely related and the amount of coal and industrial coal consumption is an important part of the

amount, so in this study we select six factors including coal and industrial coal production capacity to predict coal consumption.

In this study, the traditional grey neural network model is improved. Conventional coal grey neural network forecasting model are a simple linear weighted sum of basically grey model and neural network model. This study established grey neural network prediction model by fusion the grey model and neural network model together.

Comparison of three model predictions, the forecast result of combined model is better than a single prediction model. Then using grey neural network combination model forecast for coal consumption, according to the prediction result of coal consumption.

Scientific prediction the demand of coal logistics, can effectively avoid blind investment to coal logistics infrastructure, so that the coal logistics supply and demand to match each other. According to the forecast results, put forward the policy recommendations about development of coal logistics, in order to achieve the sustainable development of coal energy.

This study established the coal demand forecasting index system. Then, make use of grey prediction model, BP neural network model and grey neural network model to forecast coal demand.

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