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Variable weight combined forecast of China's energy demand based on grey model and BP neural network

Jianguo Zhou and Yilai Peng

North China Electric Power University, School of Economics and Management, Baoding Hebei, China

ABSTRACT

In the energy demand forecast, since national energy demand contains complex elements, it is virtually impossible to make an accurate forecast of energy demand with one single forecasting model. The combined forecasting model applied in this paper is constructed through comparing the predictive effects brought about by grey GM (1,1) model, regression-type BP neural network (BPNN), triple exponential smoothing (TES) and linear regression model (LRM) on China's energy demand. Variable Weighted Combined Forecasting method is used to raise forecast accuracy. China's energy demand forecast is practiced based on synchronous GDP, fixed assets investment, power generation capacity and population size. The calculation results show that GM(1,1) model and regression-type BP neural network forecast method's forecast accuracy is higher than others, and that the forecast model combined by these two forecast method's forecast data are more accurate and robust.

Key words: energy demand; BP neural network; grey forecast; Combined Forecasting method

INTRODUCTION

Since China's reforming and opening up, the rapid development of the Chinese economy lead to the increasing demand for energy. Energy plays a very important role in China's economic development. Therefore, in order to guarantee the healthy development of the China's economy, forecasting China's energy demand accurately is necessary. In recent years, many scholars have proposed a number of energy forecasting methods. Lu Qi and others proposed combined forecasting method using gray model, neural network model and multiple regression model [1]. Li Jinkai establish a long-term co-integration formulation and generalized differential equation regression models between energy consumption and the national economy, the method can predict China's future energy demand [2]. Wang Jue proposed wavelet neural network China's energy demand forecasting model based on scenario analysis [3]. But all kinds of methods have their drawbacks. Energy demand time-series data forecasting method fails to take into account factors affecting energy demand, so its prediction accuracy needs to be improved. Regression analysis method is not practical because the future influencing factor data is not available, furthermore artificial growth rate of the energy demand influencing factors is not scientific.

In this paper, considering the complexity of the issue of China's energy demand forecasts, we respectively use gray model, BP neural network for regression, cubic exponential smoothing and linear regression of the four forecasting methods to forecast China's energy demand then select two more accurate methods, the gray model and regression-based BP neural network model to forecasts. from 2004 to 2011 China's energy demand by using China's 2004~2011 energy consumption and GDP, investment in fixed assets, electricity generation population data over the same period. Variable weight combined forecast is used in forecasting process.

1 Theory overview of gray model and BP neural network variable weight combined forecasting

1.1 Grey theory

Chinese scholar Professor Deng Julong first proposed the theory of gray theory after years of theoretical study and practical analysis [4]. He believes that, under certain conditions, some of the known information that exist in the gray system should be fully utilized, and we should allow the uncertain information exists in the system. On this basis, we can analyze the grey systems by making full use of the known information. Grey prediction is a prediction method for systems containing uncertainties. Deng Julong gets an approximate exponential growth curve by accumulating and generating the historical data. The exponential growth is in line with the form of Differential Equations[5]. After the above process of the raw data, by establishing appropriate equations, the future development trend of things can be predicted.

1.2 BP neural network
BP (Back Propagation) neural network model, proposed by a team of scientists led by Rumelhart and McCelland, is a multilayer feedforward networks trained by error back propagation algorithm [6]. BP neural network can learn and store large amounts of input - output mapping relationship, without manually entering this mapping of mathematical equations. Its learning rule is using the steepest descent method: constantly adjust the weights and thresholds of the network, and then minimize the quadratic sum of the network error, finally achieving prediction function.

1.3 Variable weight combined forecasting
There are two concepts of combined forecast. One is focusing on the results of forecast methods, and then selecting an appropriate weight to weighted average the forecast result. The other is comparing several forecasting methods to select the minimum error model as the optimal model forecasts. In this paper, the first method is applied.

In the combined forecast, the weight is the key to determine the accuracy of combined forecast. According to whether the weight is determined, combined forecast can be divided into fixed and variable weight combined forecast. Fixed weight is a fixed constant, while variable weight will change as a function of time. Fixed weight combined forecast is so simple that cannot absorb the advantages of various forecasting methods. Only using "adaptive" real-time algorithm to give different weights at different times is more appropriate. "Adaptive" real-time algorithm enables the combined forecasting model to learn the advantages of various types of forecast models to improve forecast accuracy[7].

2 Variable weighted combined forecast model of China's energy demand based on grey model and BP neural network
2.1 Establishment of GM(1,1) model
The first step, accumulated generation: Set up a time series of observations $X^{(0)}=\{x^{(0)}(1),\ x^{(0)}(2),\ldots,\ x^{(0)}(n)\}$, then generate a new sequence which is $X^{(1)}=\{x^{(1)}(1),\ x^{(1)}(2),\ldots,\ x^{(1)}(n)\}$ by accumulation.

The second step, the determination of the data matrix:

$$\mathbf{B}=\begin{pmatrix} -\frac{1}{2}(x^{(1)}(1)+x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2)+x^{(1)}(3)) & 1 \\ \cdots\cdots & \\ -\frac{1}{2}(x^{(1)}(n-1)+x^{(1)}(n)) & 1 \end{pmatrix}$$

$$\mathrm{Y_N}=[x^{(0)}(2),\ x^{(0)}(3),\cdots,\ x^{(0)}(n)]^T$$

Then use matrix B and Y_N, estimate parameter $\hat{\mathbf{a}}=(B^{\mathbf{T}}B)^{-1}B^{\mathbf{T}}Y_{\mathrm{N}}$ by least square method.

The third step, the establishment of forecast model, by soluting the first order linear differential equations:

$$\frac{dX^{(1)}}{dt}+aX^{(1)}=\mu \qquad \text{Formula (1)}$$

Solving differential equations, we can get forecast model.
$\hat{X}^{(1)}(k+1)=[X^{(0)}(1)-\mu/a]e^{-ak}+\mu/a$, k=0, 1, 2,…, n

2.2 Establishment of BP neural network model

The first step, determination of the network structure: BP artificial neural network algorithm is one of the most classical learning algorithms whose main structure is composed of three parts: an input layer, one or more hidden layers, and an output layer [8]. Each layer consists of a number of internal neurons (or nodes), while the output value in each layer is determined by the input value, the effect function and the threshold value function (weight value). Each layer has different functions: the input layer to outside information; output layer to identify the information from input layer; intermediate hidden layers to represent or store information. For BP neural network, there is a very important theorem that any closed interval in a continuous function can be used, but BP network hidden layer approximation. Therefore a BP neural network which contains an input layer, a hidden layer and an output layer is established. China's GDP, fixed asset investment, power generation, the population is the input of the BP neural network, and the energy demand over the same period is its output. So the input layer comprises four nodes, while the output layer comprises a node. According to the formula:

$$n_1 = \sqrt{n+m} + a \qquad \text{Formula(2)}$$

In Formula(2) n1 is the optimum number of hidden units, m is the number of input neurons, n is the number of output neurons, a is a constant between 1 and 10. Set a = 2, then the optimum number of hidden units is 4.

The second step, the network initialization: Assign each connection weights a random number interval (-1, 1). Set the error function e and the maximum learning number M, and then randomly select samples input and the corresponding expected output.

$$d_o(k) = \left(d_1(k), d_2(k), \cdots, d_q(k)\right)$$

$$x(k) = \left(x_1(k), x_2(k), \cdots, x_n(k)\right)$$

The third step, the calculation of the input and the output of each neuron: Use the network expected output and actual output to calculate the partial derivative of the error function of each neuron in the output layer. The partial derivative can be defined as $\delta_o(k)a$.

The fourth step: use the connection weights of hidden output layer to the output layer and the output of the output layer and the hidden layer to calculate partial derivative of the error function of each hidden layer neuron which can be defined as $\delta_h(k)$.

The fifth step: calculate the global error E to judge whether the error of network can meet the requirements. When the error reaches a preset accuracy or learning times exceed the set maximum number of times, end the algorithm. Otherwise, select the next learning samples and the corresponding expected output, and return to the third step, begin next round of learning.

2.3Variable weight combined forecast

2.3.1 Combined forecast

Assume forecast model number is 'n' and forecast time point is N, then set y(t) as the actual value of the period t (t=1,2,…,N) , $\hat{y}_i(t)$ as the forecast value of the i-th model in period t, variable weight $\omega_i(t)$ as weight of the i-th forecast model in period t. All the values should satisfy the equation

$$\sum_{i=1}^{n} \omega_i(t) = 1$$

Then the variable weight combination forecast value can be expressed as

$$\hat{y}(t) = \sum_{i=1}^{n} \omega_i(t)\hat{y}_i(t) \qquad \text{Formula (2)}$$

2.3.2 Determination of weight

First, the forecast error should be expressed as

$$e_{it} = \hat{y}_i(t) - y_i(t) \qquad \text{Formula (3)}$$

Variable weight $\omega_i(t)$ can be expressed by e_{it}. To improve the prediction accuracy, the weights should be inversely proportional to the square of the error, which can be expressed as:

$$\omega_i(t) = \frac{1/e_{it}^2}{\sum_{i=1}^{n}(1/e_{it}^2)} \qquad \text{Formula (4)}$$

3 Variable weight combination forecast of China's energy consumption

3.1.1 the Basic data of China's energy consumption forecast

China's energy consumption and the corresponding period of GDP, investment in fixed assets, power generation, and population data from 2004 to 2011 is shown in Table 1.

Table 1 Original Sample Data

year	Energy consumption/ 10^4 tons of standard coal	GDP/ 10^8 ￥	investment in fixed assets/10^8 ￥	power generation /10^8 kW·h	Population/10^4
2004	213456	159878	70477	21972	129988
2005	235997	184937	88774	24941	130756
2006	258676	216314	109998	28588	131448
2007	280508	265810	137324	32712	132129
2008	291448	314045	172828	34541	132802
2009	306647	340903	224599	37033	133450
2010	324939	401513	251684	41937	134091
2011	348002	472882	311485	47217	134735

Note: Data in Table 1 is from China's National Bureau of Statistics

3.1.2 GM(1,1) Forecast of China's energy demand

According to the data in Table 1, China's energy demand is forecasted by using GM (1,1) model. Forecast result is shown in Table 2:

Table 2 GM (1,1) forecast result

year	2004	2005	2006	2007	2008	2009	2010	2011
GM (1,1) forecast result	228008	242165	257201	273170	290130	308144	327276	347595

By using posterior-variance-test model, we can analyze the forecast result. The posterior-variance-test ratio C==0.018<0.35, and the error frequency P=0.98>0.95. According to the two indicators C and P, the accuracy level of the forecast model can be integrated assessment as "good".

3.1.3 BP network forecast of China's Energy demand

Use Matlab2011b software, to write prediction code. The input of the network p is China's GDP, investment in fixed assets, power generation, and population data from 2004 to 2011, and the output t is he corresponding period of China's energy demand. The key program code is:

```
net= newff (minmax(p),[4,4,1], {'purelin','purelin', 'purelin'}, 'trainlm')
```

Minmax () function means the normalization of input data. [4,4,1] means nodes of the input layer, hidden layer and output. {'purelin', 'purelin', 'purelin'} means the transfer function of the input layer, hidden layer and output layer. 'Trainlm' is the training function. The forecast result is shown in Table 3:

Table 3: BP network forecast result

year	2004	2005	2006	2007	2008	2009	2010	2011
BP network forecast result	212265	233742	259458	281110	280469	302562	326142	354242

3.1.4 China's energy demand combined forecast

Table 4 shows the confrontation of the four forecast model's result of GM(1,1), BP neural network(BPNN), linear regression mode(LRM), and triple exponential smoothing (TES).

Table 4 Comparison of Energy Demand individual Forecast Model

Year	Energy Consumption	Energy Demand Forecast Data				The absolute value of the forecast Result's relative error			
		GM	BPNN	LRM	TES	GM	BPNN	LRM	TES
2004	213456	228008	212265	227487	213456	6.82%	0.56%	6.57%	-
2005	235997	242165	233742	237717	223599	2.61%	0.96%	0.73%	5.25%
2006	258676	257201	259458	250526	240905	0.57%	0.30%	3.15%	6.87%
2007	280508	273170	281110	270732	262692	2.62%	0.21%	3.49%	6.35%
2008	291448	290130	280469	290424	282465	0.45%	3.77%	0.35%	3.08%
2009	306647	308144	302562	301388	302449	0.49%	1.33%	1.72%	1.37%
2010	324939	327276	326142	326132	323729	0.72%	0.37%	0.37%	0.37%
2011	348002	347595	354242	355267	347836	0.12%	1.79%	2.09%	0.05%

Table 4 shows that the prediction accuracy of gray GM (1,1) model and BP neural network model is significantly higher than the linear regression model and triple exponential smoothing model.

Therefore, in this paper, GM (1, 1) model and BP neural network model are chosen to build an energy combined forecast model. According to Formula (4), the weight of the combined forecast is shown in Table 5.

Table 5 combined forecast weight

Year	2004	2005	2006	2007	2008	2009	2010	2011
GM(1,1)	0.0067	0.1179	0.2194	0.0067	0.9858	0.8816	0.2095	0.9958
BPNN	0.9933	0.8821	0.7806	0.9933	0.0142	0.1184	0.7905	0.0042

According the weight above, China's energy demand from 2004 to 2011 is forecasted based on a variable weight combination forecast model (CF), and the forecast result of GM (1,1) model and BP neural network model. The variable weight combination forecast result is shown in Table 6.

Table 6 China's energy demand variable forecast result

Year	combination forecast result	The absolute value of the forecast Result's relative error		
		GM	BPNN	CF
2004	212369.7529	6.82%	0.56%	0.51%
2005	234735.0886	2.61%	0.96%	0.53%
2006	258962.7952	0.57%	0.30%	0.11%
2007	281056.9183	2.62%	0.21%	0.20%
2008	289992.7497	0.45%	3.77%	0.50%
2009	307483.1189	0.49%	1.33%	0.27%
2010	326379.5435	0.72%	0.37%	0.44%
2011	347623.158	0.12%	1.79%	0.11%

CONCLUSION

①China's energy demand is influenced by many factors, linear regression model cannot include all factors, which leads to its poor forecast accuracy. Besides, China's energy demand would fluctuate when some factor changes like economic fluctuation, so triple exponential smoothing model only able to represent the development trend of the future, and its forecast accuracy is not able to meet the actual needs.

② GM(1,1) model and BP neural network model have higher forecast accuracy than linear regression model and triple exponential smoothing model. The forecast of variable weight combined forecast based on these two forecast models can be controlled below 0.55%. Variable weight combined forecast built in this paper is reliable and Practical.

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