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Study on Medium and Long Term Power Load Forecasting Based on Combination Forecasting Model

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Load forecasting is an important work in the electric power department, and the medium and long term load forecasting is mainly aimed at the electric power generation planning and development planning. Accurate forecasting is the basis of rational planning, and the planning will greatly affect the investment. Therefore, it has a great significance to improve the accuracy of load forecasting. Accuracy of the medium and long term load forecasting is affected by various stochastic factors, such as economy, policy, and climate. So, the accurate forecast is a very complex work. In order to improve the accuracy of load forecasting, this paper introduces a combined forecasting model, which can obtain more accurate results by combining the advantages of each model. In this paper, we use the gray prediction model, neural network prediction model, and regression analysis model for the whole society annual electricity consumption in long-term load combination forecast. The method of this paper can make full use of the advantages of the grey prediction which requires less data, simple operation, and easy to test. It can make full use of the advantages of the neural network method which has the function of self adaptation, and has a strong ability of learning and mapping. It can also make full use of the advantages of the regression analysis method that does not need to take into account the distribution of the data and the trend of change. Finally, we conduct an example verification. We choose the proposed method, the traditional GM (1,1) model, regression analysis prediction model and BP neural network prediction model for comparison. The results show that the proposed method is feasible and effective.

1. Introduction

Load forecasting is an important work in the electric power department, and the medium and long term load forecasting is mainly aimed at the electric power generation planning and development planning. Accurate forecasting is the basis of rational planning, and planning will greatly affect the investment. Accuracy of the medium and long term load forecasting is affected by various stochastic factors, such as economy, policy, and climate. So, the accurate forecast is a very complex work. The commonly used forecasting methods include artificial intelligence prediction method, regression analysis method and gray prediction method. Next, we will introduce the research status of these three methods in power load forecasting.

Artificial neural network method. Artificial neural network has adaptive function for a large number of data with non structural and non-accurate rules, and it has strong learning and mapping ability, which can be easily fitted to any complex nonlinear relation, so it is suitable for power load forecasting. Therefore, it has been widely used in power load forecasting in recent years. However, the learning process of neural networks is usually slow, and the adaptability to unexpected events is poor. The commonly used method is the feed forward network method (Miao and Xing, 2000; Zheng et al., 2002; Jiang and Lu, 2001) and radial basis function method (Zhang et al., 2001; Zhao and Zhang, 2003).

Grey forecasting method. The grey system theory, which is widely used in network, uses all random variation as the grey quantity which is changed in a certain range. The commonly used accumulated generation method is to collate the raw data into a regular data columns. After that, the differential equation of the grey model is used to forecast the power load. After verifying the accuracy and reliability of the model, the model can be applied to predict the future load (Zhang et al., 2001; Xing et al., 2005; Bao et al., 2004). In addition, this method is suitable for short, medium and long period of load forecasting.

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Regression analysis method, the change of long-term load in power system is restricted by many factors, which is difficult to describe qualitatively. In view of the complexity and uncertainty of load influencing factors, the multiple linear regression analysis is applied to the medium and long term load forecasting. In the regression analysis, the random variable is the independent variable, and the non random variable is the dependent variable. Of course, we can also define the dependent variable is the power system load, the independent variable is the various factors that affect the power system load, such as economy, population, climate and so on. In the end, the relationship between the independent variables and dependent variables is studied by the given data, so as to form the regression equation(Wang, 2009; Hu, et al., 2008).

2. Combination forecasting model with the square sum of minimum prediction errors

Suppose there are m kinds of unbiased single prediction methods to predict a certain index sequence $\{x_t, t=1,2,\cdots,N\}$ of the same object. Then, we use x_{it}, $i=1,2,\cdots,m$, $t=1,2,\cdots,n$ as the predictive value of the i th single prediction method on the t time, use $e_{it}=x_t-x_{it}$ as the prediction error of the i th single prediction method on t time, and set $l_1,l_2,\cdots,l_m$ as the weighted coefficient of m single prediction methods. In order to keep the unbiasedness of combination forecasting, the weighted coefficient should be satisfied as:

$$\sum_{i=1}^{m} l_i = 1 \text{ , } l_i \geq 0 \text{ , } i=1,2,\cdots,m \tag{1}$$

Let $\hat{x}_t = l_1x_{1t}+l_2x_{2t}+\cdots l_mx_{mt}$ be the combination forecast value of $\hat{x}_t$, and let e_t be the prediction error on the t time. Then, we have:

$$e_t = x_t - \hat{x}_t = \sum_{i=1}^{m} l_i e_{it} \tag{2}$$

We use Q_1 to represent the sum of squared error of the combination forecast, and we have:

$$Q_1 = \sum_{t=1}^{n} e_t^2 = \sum_{t=1}^{n}\sum_{i=1}^{m}\sum_{j=1}^{m} l_i e_{it} l_j e_{jt} \tag{3}$$

Therefore, the combination forecasting model which uses the square sum of prediction error as the criterion is the following optimization problem.

$$\begin{cases} \min Q_1 = \sum_{t=1}^{n}\sum_{i=1}^{m}\sum_{j=1}^{m} l_i e_{it} l_j e_{jt} \\ \qquad\quad \sum_{i=1}^{m} l_i = 1 \end{cases} \tag{4}$$

Let $L=(l_1,l_2,\cdots,l_m)$, $R=(1,1,\cdots,1)$, $e_i=(e_{i1},e_{i2},\cdots,e_{iN})$, then L represents the column vector of the weighted coefficient of the combination forecast, R indicates that all the elements of column vector are 1, and e_i represents the column vector of prediction error of the i th single prediction method.

$$E_{ij} = e_i^T e_j = \sum_{i=1}^{N} e_{it} e_{jt} \text{ , } i,j=1,2,\cdots,m \text{ , } E=(E_{ij})_{m*n} \tag{5}$$

For the combined forecasting model, the weighted coefficient of combination forecasting is given by the follow formula:

$$L = \frac{E^{-1}R}{R^T E^{-1} R} \tag{6}$$

$$Q_1 = \frac{1}{R^T E^{-1} R} \tag{7}$$

3. Combination forecasting model

In this paper, three different prediction models are used to build a long-term combined forecasting model of power load. Next, we introduce the basic concepts and the calculation methods of the neural network prediction model, the grey forecasting model and the regression analysis prediction model.

3.1 BPNN model

Next, we will introduce the basic knowledge of BPNN model. BPNN (Back Propagation neural network) is a Multilayer Feed-forward Neural Networks based on the error back propagation algorithm. The input layer is provided with *M* input signals, wherein any input signal is expressed by *m*. The hidden layer has *I* neurons, wherein any neuron is represented by *i*, and the output layer has *p* neurons, wherein any neuron is represented by *p*. The weight of the input layer and the hidden layer is expressed by w_{mi}, and the weight of the hidden layer and the output layer is expressed by w_{ip}. The input of the neuron is expressed by *u*, and the output of the excitation is expressed by *v*. Then, we use $X=[X_1,X_2,\cdots,X_k,\cdots,X_N]$ as the training sample set that corresponding to any training sample $X_k=[x_{k1},x_{k2},\cdots,x_{kM}]^T$, $k\in(1,2,\cdots,M)$. The input training sample of neural network is X_k. Through the forward propagation, we can get:

$$u_i^I=\sum_{m=1}^{M}w_{mi}x_{km}\ ,\ v_i^I=f(u_i^I)=f(\sum_{m=1}^{M}w_{mi}x_{km})\ ,(i=1,2,\cdots,I) \tag{8}$$

$$u_p^P=\sum_{i=1}^{I}w_{ip}v_i^I\ ,\ v_p^P=\varphi(u_p^P)=\varphi(\sum_{i=1}^{I}w_{ip}v_i^I)\ ,(p=1,2,\cdots,P) \tag{9}$$

$$y_{kp}=v_p^P \tag{10}$$

The error signal of the p th neuron in the output layer is:

$$e_{kp}(n)=d_{kp}(n)-y_{kp}(n) \tag{11}$$

The error energy of the neuron is defined as $\frac{1}{2}e_{kp}^2(n)$, and the total error energy of all the neurons in the output layer is $E(n)=\frac{1}{2}\sum_{p=1}^{P}e_{kp}^2$.

Through the output of the network, the learning error can be calculated, and the forward propagation is finished. In the back propagation process, the error signal is transmitted from back to front, and the connection weights are modified by each layer.

3.2 Grey model

The grey prediction model uses accumulated generating operator to generate the accumulated generating sequence of the target state, which is used to reduce the randomness of the state. Then, the parameters of the grey differential equation are estimated by using the accumulated value, and the future accumulated value is predicted by the grey differential equation. In the end, the predictive value of the target state is obtained by using the inverse accumulation generating operator. GM (1,1) is the most commonly used grey forecasting model, its modeling and forecasting process can be described as:

(1) the length of the grey prediction sequence is m, and the target history sequence is:

$$X^{(0)}=(\hat{x}_{k-m},\hat{x}_{k-m+1},\cdots,\hat{x}_{k-1}) \tag{12}$$

(2) the accumulated generating sequence is:

$$X^{(1)}=(\hat{x}_{k-m}^{(1)},\hat{x}_{k-m+1}^{(1)},\cdots,\hat{x}_{k-1}^{(1)}) \tag{13}$$

Where, $\hat{x}_{k-n}^{(1)}=\sum_{i=m}^{n}\hat{x}_{k-i}$, $n=1,2,\cdots,m$.

(3) the mean generating sequence is:

$$Z^{(1)}=(\hat{z}_{k-m+1}^{(1)},\hat{z}_{k-m+2}^{(1)},\cdots,\hat{z}_{k-1}^{(1)}) \tag{14}$$

Where, $\hat{z}_{k-n}^{(1)} = \frac{\hat{x}_{k-n}^{(1)} + \hat{x}_{k-n-1}^{(1)}}{2}$, $n = 1, 2, \cdots, m-1$.

(4) according to the minimum variance criterion, the GM (1,1) grey differential equation is:

$$X^{(0)} + aZ^{(1)} = b \tag{15}$$

Where, a and b are the parameters of the grey differential equation.

$$[a,b]^T = (B^T B)^{-1} B^T Y \tag{16}$$

$$Y = [\hat{x}_{k-m+1}^{(1)}, \hat{x}_{k-m+2}^{(1)}, \cdots, \hat{x}_{k-1}^{(1)}] \tag{17}$$

$$B = \begin{bmatrix} -z_{k-m+1}^{(1)} & 1 \\ -z_{k-m+2}^{(1)} & 1 \\ \vdots & \vdots \\ -z_{k-1}^{(1)} & 1 \end{bmatrix} \tag{18}$$

(5) put the a and b into the follow formula, then we can predict the state on the k time:

$$\hat{g}_k = [\hat{x}_{k-m} - \frac{b}{a}] e^{-ak} (1 - e^a) \tag{19}$$

3.3 Regression analysis model

The univariate regression prediction method is based on the correlation between the independent variables x and the dependent variable y , so as to establish the linear regression equation of x and y .

(1) The prediction model of univariate regression analysis.

$$Y_i = a + bx_i \tag{20}$$

Where, x_i represents the value of the independent variable at i time, Y_i represents the value of the dependent variable at i time. The x and y represent the parameters of a linear regression equation, which can be calculated by the following formula:

$$\begin{cases} a = \dfrac{\sum_{i=1}^{n} Y_i}{n} - b\dfrac{\sum_{i=1}^{n} x_i}{n} \\ b = \dfrac{n\sum_{i=1}^{n} x_i Y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} Y_i}{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \end{cases} \tag{21}$$

(2) Using the sample data (x_i, y_i) , $i = 1, 2, \cdots, n$ to establish the model.

$$y = a + bx + \varepsilon \text{ , } \varepsilon \sim N(0, \sigma^2) \tag{22}$$

(3) The parameters of $\hat{a}$ and $\hat{b}$ are estimated, and the linear regression equation $\hat{y} = \hat{a} + \hat{b}x$ is obtained.

(4) Hypothesis testing of the model to determine its use value.

(5) Calculate the predicted value.

4. Simulation experiment and result analysis

From Figure 1 shows that the power industry has maintained a rapid and healthy development, the total electricity consumption in the society is in a rapid growth phase. However, the total electricity consumption has slowed the growth twice times during this period. The first time is in 1997 and 1998, the reason is mainly that the Southeast Asian financial crisis has had a impact on the domestic economy, which makes the whole society electricity consumption growth slowed. The second time is in 2007 and 2008,due to the emergence of a global financial crisis, electricity production and consumption has been greatly affected. If the above factors are ignored, and the direct use a single model for modeling, it is not consistent with the reality, and the accuracy of the model is not reliable.

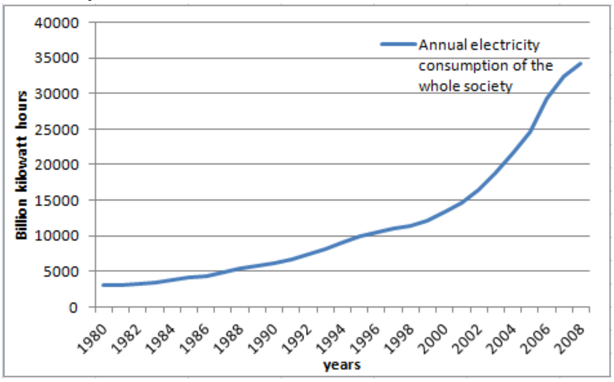

Figure 1: Annual electricity consumption of the whole society

Next, the data of 1980~2008 is used as modeling data, three methods are used to fit the historical data, and the fitting results are shown in Table 1.

Table 1: The fitting results of Annual electricity consumption of the whole society

Years	Annual electricity consumption (100 million kilowatt hours)	BPNN model	GM model	Regression analysis model
1980	3006.3	3090.339	3169.122	3173.154
1981	3095.7	3138.801	3238.675	3329.072
1982	3280.1	3285.276	3316.109	3336.051
1983	3518.7	3601.456	3698.205	3793.21
1984	3777.6	3790.609	3860.442	3867.818
1985	4117.6	4192.01	4248.273	4326.397
1986	4429.04	4432.138	4482.403	4524.606
1987	4902.69	4926.553	4977.349	4982.938
1988	5358.65	5380.727	5388.888	5448.535
1989	5761.98	5844.521	5911.357	5977.235
1990	6125.96	6219.479	6219.961	6269.884
1991	6696.79	6724.243	6793.891	6860.738
1992	7455.39	7474.573	7562.45	7574.135
1993	8201.08	8298.236	8359.507	8365.843
1994	9046.49	9127.851	9134.284	9219.725
1995	9886.36	9908.031	9952.677	9959.821
1996	10570.29	10620.77	10677.54	10743.05
1997	11039.11	11109.93	11156.24	11197.45
1998	11347.3	11428.13	11520.02	11575.2
1999	12092.28	12162.25	12165.64	12172.26
2000	13466.22	13487.77	13513.63	13559.73
2001	14682.51	14742.91	14756.14	14809.92
2002	16386.28	16418.63	16449.6	16457.61
2003	18891.21	18988.31	19028.35	19103.18
2004	21761.3	21821.61	21849.94	21882.41
2005	24688.54	24769.4	24850.72	24936.16
2006	29368	29388.86	29399.29	29425.08
2007	32458	32477.22	32486.53	32543.92
2008	34268	34355.91	34417.14	34516.42

Finally, we use the above three methods to synthesize the combination forecasting method. Then, we use it and the other 3 models to predict the whole society electricity consumption between 2009 to 2012. Next, we compare it with the actual value to obtain the table of prediction error comparison.
Choose the following two kinds of error indicators to evaluate the effectiveness of the method in this paper:

(1) Mean absolute percentage error

$$MSPE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}[(x_t - \hat{x}_t)/x_t]^2} \quad (23)$$

(2) Mean Square Percent Error

$$MSPE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}[(x_t - \hat{x}_t)/x_t]^2} \quad (24)$$

Where, x_t is the actual value at t time, $\hat{x}_t$ is the predicted value of some kind of prediction method at t time. According to the above 2 indexes, the prediction error of each prediction method is showed on Table 2, and the numerical value is expressed as a percentage.

Table 2. Comparison of prediction results

Evaluation index of prediction effect	MAPE	MSPE
Combination forecasting method	2.46	1.37
GM model	6.88	5.11
Regression analysis model	10.22	6.93
BPNN model	8.23	5.01

5. Conclusion

In order to improve the accuracy of load forecasting, this paper introduces a combined forecasting model, which can obtain more accurate results by combining the advantages of each model. In this paper, we use the gray prediction model, neural network prediction model, and regression analysis model for the whole society annual electricity consumption in long-term load combination forecast. Finally, we conduct an example verification. The results show that the proposed method is feasible and effective..

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