

A combined gray neural network model of seasonal heating load forecast

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Abstract: Seasonal heating load time sequence has the double trends of increasing and fluctuating, so it's difficult to select a model to forecast it. In this paper, a combined model of gray model and artificial neural network model was presented to forecast seasonal heating load. A concrete model was established and was verified through actual examples.

Keywords: heating load; gray model; artificial neural network model

1. Introduction

To improve the efficiency of natural energy, central heating-supply has been adopted in quite a lot of cities in our country. There is a severe problem, however, that is the inconsistency between the supply and demand of heating. To solve the problem is to predict the heating load as in engineering. At present, though there are lots of methods available to predict it, the majority has some limitation for their restricted adaptive occasions. It cannot achieve satisfactory result with just one simple prediction method. Then, people begin to combine these methods that make the best of the inner information to acquire a comparative higher-precision result.

2. The feature of seasonal heating load

Heating load is inconstant itself. The amount of heating will be greatly affected by the development rate of economic and the economical situation. In addition, whether it's a warm winter and a sunny day or not will fluctuate the usage of the amount of heating.

Seasonal heating load has the distinct feature of fluctuation with season alternation, that is more heating used in winter and spring and less in summer and autumn. In a long run, it also has the feature of the similar fluctuation tendency. In CHINA, seasonal heating load has trend to increase with time going on for the persisting higher economic development. The increasing is inconstant and fluctuated as that of the economic increasing rate of China. So, seasonal heating load has the complicated two trend-combined increasing and undulation.

Therefore, we try to use a compounding prediction model combining gray system method with artificial

neural network (ANN) method considering the specialty of seasonal heating load. The Gray Method has the better capability of imitating exponential increasing relation that is fit to model the increasing trend of the seasonal time sequence. While Artificial Neural Network model can be used to imitate the fluctuation trend of seasonal heating load for its powerful ability of simulating complicated non-linear function.

3. The gray artificial neural network combined model

First build up the two models of each single method, and then combine them into the gray artificial neural network combined model.

3.1 Gray system model

To build up GM (1,1) model is to have an accumulating addition to the original data to find some relations between these data. Then, we can predict it with the imitating curve made by the differential equation model.

One original data time sequence is

$$X^{(0)} = (X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n))$$

Making 1-AGO:

$$X(1) = \text{AGO}, X^{(1)} = (X^{(1)}(1), X^{(1)}(2), \dots, X^{(1)}(n))$$

where

$$X^{(1)}(k) = \sum_{i=1}^k X^{(0)}(i) \quad k=1,2,n \quad (1)$$

To build up the differential equation in transparent form based on the relation between the new data sequence.

$$\frac{dX(1)}{dt} + aX(1) = u(1) \quad (2)$$

where a, u are the parameters and written as

$$A = [a, u]^T,$$

and A was given by the less square equation.

$$A = (B^T B)^{-1} B^T Y_N \quad (3)$$

where

$$B = \begin{bmatrix} -X(2) & 1 \\ -X(3) & 1 \\ \vdots & \vdots \\ -X(n) & 1 \end{bmatrix} \quad Y_N = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ \vdots \\ X^{(0)}(n) \end{bmatrix}$$

From the answer of the above differential function, the GM(1,1) prediction model is

$$\hat{X}^{(1)}(k+1) = (X^{(0)}(1) - \frac{u}{a})e^{-ak} + \frac{u}{a} \quad (k=0,1,2,\dots,n) \quad (4)$$

Then $X^{(1)}(k=0,1,2,\dots,(n-1), n)$ can be calculated with the above formula, so the prediction can be acquired by making a diverse 1-AGO with $\hat{X}^{(1)}(k)$

$$\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1) \quad (k=1,2,\dots,n) \quad (5)$$

For the above prediction results, the back check remnant is used to check the precision. Here the remnant formula is

$$e(k) = X^{(0)}(k) - \hat{X}^{(0)}(k) \quad (k=1,2,\dots,(n-1),n) \quad (6)$$

The features of GM(1,1) model are

1) Comparative less information is needed and the model can be established with only four data or more.

2) No need for having the pre-attribute characteristic of the original data and to the disordered or arbitrary slippery disperse original data sequence, a regular sequence can be got in limited times of creation.

3) Higher model precision and holding the characteristic of the original system so that it can preferably reflect the practice status of the system.

3.2 BP artificial neural network model

As a nonlinear dynamics system, it is capable of making a massive parallel process, storing information distributive, and has a better self-adaptability and self-organizing as well as strong learning, imagination, wrong tolerance and anti-jamming ability. Presently there are scores of different kinds of ANN models, in which some typical ones are BP network, Hopfield network and CPN network etc. BP network, an error back-propagation ANN put up by Mr. Rumelhart and Mr. McClelland, was adopted in this paper.

BP network is a multi-layer Artificial Neural Network and it is made up of several layers nerve cell, which can be divided as input layer, hidden layers and output layer with different functions. The input information will be sent to the output layer through

middle layers, and the difference is fed back through the supervised network and the network's weights are adjusted, accordingly. The training cycle of a supervised network is therefore an iterative process of minimizing the error. The state of every layer nerve cell will affect the state of the next ones and every nerve cell corresponds to one operation function and one connection weight. The elementary processing units of the network related nonlinearly that the threshold of the input cells is zero and $f(x)=0$, while the operation functions of middle layers and the output layer are all the linear function—the sigmoid function type.

The function is:

$$F(X) = 1/(1+e^{-X}) \quad (7)$$

Assuming that there are L couples of learning samples (X_k, O_k) ($k=1,2,\dots,L$), here X_k is the input unit, O_k is the output, and Y_k is the real output of X_k . Then the mean square error between Y_k and the desired O_k is:

$$E_K = \frac{1}{2} \sum_P (Y_{K,P} - O_{K,P})^2 \quad (8)$$

where: m is the number of output cell; Y_{kn} is the real output of the K sample to its n feature; O_{kn} is the desired output of the K sample to its n feature.

The total error of the samples is:

$$E = \sum_{k=1}^L E_K \quad (9)$$

The minimizing error E can be got through alternating the connection weights with grads method. The modification of a learning sample to W_{ij} is

$$\Delta W_{ij}(k) = -\eta (\delta E_k / \delta W_{ij}) \quad (10)$$

where η is the learning rate and is within 0 and 1.

The modification of all learning samples to connection weights W_{ij} is:

$$\Delta W_{ij} = \sum_{K=1}^L \Delta W_{ij}(k) \quad (11)$$

To enhance the stability of the learning course, we usually revise W_{ij} by the following formula.

$$\Delta W_{ij}(t) = \sum_{K=1}^L \Delta W_{ij}(k) + \beta (W_{ij}(t) - W_{ij}(t-1)) \quad (12)$$

where β is a constant, and $w_{ij}(t)$ is the connection

weights of the t -th cycle training and learning; $w_{ij}(t-1)$ is the connection weights of the $t-1$ time cycle training and learning.

3.3 The modeling of the gray artificial neural network combined model.

Assuming that f_1 is the prediction value from the Gray method, f_2 is the prediction value from the BP ANN method and f_3 is the prediction value from the optimal compounding method and the respective prediction errors are e_1 , e_2 and e_c . w_1 and w_2 are the corresponding connection weights, and $w_1 + w_2 = 1$. Then we can get

$$f_c = w_1 f_1 + w_2 f_2 \quad (13)$$

Their errors and square errors respectively are

$$e_c = w_1 e_1 + w_2 e_2 \quad (14)$$

$$X(e_c) = w_1^2 X(e_1) + w_2^2 X(e_2) + 2 w_1 w_2 \text{cov}(e_1, e_2) \quad (15)$$

Then we can get the minimal w_1 to $X(e_c)$:

$$w_1 = \frac{X(e_2) - \text{cov}(e_1, e_2)}{X(e_1) + X(e_2) - 2\text{cov}(e_1, e_2)} \quad (16)$$

And $w_2 = 1 - w_1$, apparently we can make $\text{COV}(e_1, e_2) = 0$, written as $X(e_1) = \delta_{11}$, $X(e_2) = \delta_{22}$. Then the connection weights of the optimal compounding prediction are

$$w_1 = \frac{\delta_{22}}{\delta_{11} + \delta_{22}} \quad (17)$$

$$w_2 = \frac{\delta_{11}}{\delta_{11} + \delta_{22}} \quad (18)$$

It can be proved that this optimal compounding method is superior to each simple method and we can get the optimal compounding model finally from the above process.

4. A forecast of the seasonal heating load

We have analyzed to the heating load in one area based mainly on the data provided by the local thermoelectricity work. The data are the heating loads of every season from 1992 to 1996. The heating load of every season in 1996 was predicted with the GM(1,1) model, the ANN model and the GANN model made by this paper. The results are shown in Table 1.

Table1 The prediction of the heating load of each season in 1996

Model	Spring		Summer		Autumn		Winter		Total error /%
	Load /(10^6 t)	Relative error /%	Load /(10^6 t)	Relative error /%	Load /(10^6 t)	Relative error /%	Load /(10^6 t)	Relative error /%	
Real value	29.50		17.75		23.04		35.97		
GM	28.61	3.08	16.73	5.76	22.76	1.22	36.28	-0.87	10.93
ANN	30.19	-2.23	17.20	3.09	23.40	-1.43	35.35	1.71	8.56
GANN	29.50	0.01	17.00	4.24	22.97	0.31	35.72	0.60	5.16

From the table: We can draw the conclusion that the prediction precision of the heating load has been greatly improved with the optimal combined forecasting method than that with each of the two simple methods. It has combined the strongpoint of the two simple methods. Therefore, it's an effective forecasting method of the seasonal heating load.

5. Conclusions

The combined gray neural network model of seasonal heating load forecast in this paper showed one feature of the combined prediction method that it was able to make the best use of the strongpoint of all its component methods. It has not only exerted the less information needed of the gray method and the strong adaptability of ANN method, but also considered the

time sequence's trend of increasing and the similar fluctuating in the same season. Therefore, it can imitate the complicated non-linear increasing trend and non-linear fluctuating trend and make further improvement than the classical simple factor considering methods. It provides a new and effective method of the seasonal heating load forecast.

References

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