Hourly gas load forecasting based on an improved wavelet neural network

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Abstract

Hourly load forecasting of city gas plays an important guidance role in planning and arranging work of peak shaving for gas enterprises. However, hourly gas load presents strong randomness and volatility, which brings difficulties in the accuracy of hourly gas load forecasting. Therefore, this paper puts forward a wavelet neural network forecasting model based on wavelet theory and the neural network forecasting model after analyzing hourly gas load data of recent three years in the H city of Sichuan Province in China. Parameters of the wavelet neural network are optimized by the gradient algorithm. Meanwhile, BP neural network forecasting model is set up to make comparison with wavelet neural network. Results show that the wavelet neural network can forecast hourly gas load more accurately in the 24 hours in a day, which is of great significance in guiding the direct actual production for gas enterprises.

Keywords

hourly gas load, forecasting, wavelet neural network, improved gradient descent method

1. Introduction

With the expanding of city natural gas pipeline network in recent years, hourly gas load forecasting is important to guarantee the consuming amount of gas, network planning and optimization scheduling. Accurate hourly gas load forecasting is the key to carrying out gas peak shaving and production plans for gas enterprises. However, hourly gas load shows strong randomness and volatility due to being affected by the temperature, holidays and other weather factors as well as national policies and performance, which brings load forecasting great difficulties.

Currently, the methods of hourly gas load forecasting mainly are divided into two major categories, including traditional forecasting methods and intelligent forecasting methods at home and abroad [1]. The traditional forecasting methods establish the nonlinear mapping between the input and output vectors by use of knowledge of statistics and regression to realize forecasting, such as time series forecasting, gray forecasting model [2]. The intelligent forecasting methods mainly adopts influence factors and history gas load of hourly load to build l forecasting model, such as neural network and support vector machine forecasting model [3-4]. Compared with the traditional forecasting methods simply using statistical knowledge, intelligent forecasting methods consider the influence of many factors and model on the basis of the internal mechanism of load data changes, so they have higher forecasting precision and stronger robustness [5].

As a widely used intelligent forecasting model, neural network establishes the highly complicated nonlinear dynamic system consisting of many neurons based on the theory of biological simulation. Having a strong adaptability and self-study ability, it can well approximate gas hourly load curve. However, neural network forecasting models face some hard problems. For instance, back propagation (BP) neural network is difficult to avoid local minimum value because of using the gradient descent method and its modeling mechanism is difficult to reflect the variety regulation of daily load [6]. However, the momentum term is able to improve its learning efficiency, which is used in this paper. Besides, due to good local features of time-frequency and multi-scale resolution, the wavelet transform is a good way to reflect the variety regulation of hourly gas load [7-9]. Therefore, many researches try to combine wavelet analysis and neural network to build a wavelet neural network forecasting model with more degree of freedom and more strong function approximation ability [10-12].

Based on the theory of wavelet and neural network knowledge, this study establishes an improved wavelet neural network model for hourly gas load forecasting by use of the wavelet function as the activation function in the hidden layer. The model is verified by the forecasting effect of the actual example.

2. Modeling of the improved Wavelet Neural Network

Wavelet transform is able to effectively extract specific and local information and ultimately achieve time breakdown in high frequency as well as frequency segments in low-frequency through time and frequency domain transform, including scaling function, panning and signal multi-scale analysis. By wavelet analysis of hourly load curve of volatility, mutant attributes can be good recognition, to build more accurate forecasting models. The wavelet neural network is a kind of network that regards the wavelet function as hidden layer's transfer function of relay nodes in the neural network based on the neural network topology. The topology structure of wavelet neural network is shown in Figure 1.

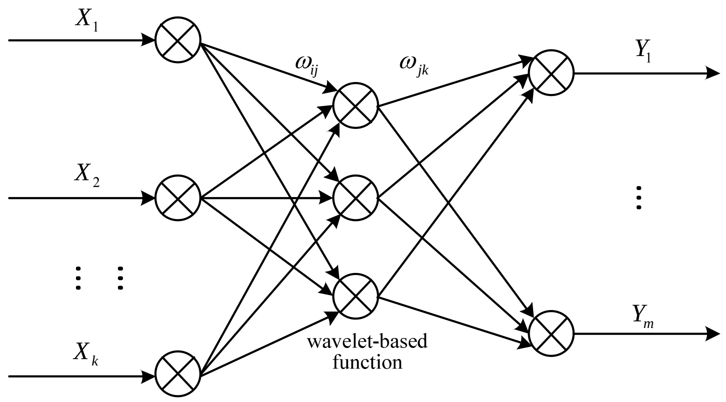

Fig. 1 Topology structure of wavelet neural network

In Figure 1, $\{X_1, X_2, \ldots, X_k\}$ is the input vector; $\{Y_1, Y_2, \ldots, Y_m\}$ is the output vector; ω_{ij} and ω_{jk} are the weights of wavelet neural network. Assume that the input signal sequence is $x_i (i = 1, 2, \ldots, k)$, the output formula of hidden layer is

$$h(j) = h_j\left(\frac{\sum_{i=1}^{k} \omega_{ij} x_i - b_j}{a_j}\right), j = 1, 2, \ldots, l \tag{1}$$

Where $h(j)$ is the output of node j in the hidden layer, ω_{ij} is the weight between input layer and hidden layer, b_j is the shifter factor of wavelet neural network, a_j is the stretch factor of wavelet neural network, h_j is the wavelet basis function. The function expression of the output layer is

$$y(k) = \sum_{j=1}^{l} \omega_{jk} h(j), k = 1, 2, \ldots, m \tag{2}$$

Where ω_{jk} is the weight between hidden layer and output layer, $h(j)$ is the output of node j in hidden layer, l is the number of hidden layer nodes, m is the number of output layer nodes.

2.1 The Training Algorithm of Wavelet Neural Network

The training algorithm and steps of the wavelet neural network are listed as follows.

(a) Randomly initialize stretch factor a_k , translation factor b_k , the network connection weights ω_{ij} , ω_{jk} , and set the learning rate η ;

(b) Sample selection and classification. Filter the collected data and divide them into training sample and testing sample, where the training samples is used to network training and the test sample is used to test the network accuracy;

(c) Forecasting output. Input the training sample to network, calculate the forecasting output, the expected output and network output error e ;

(d) Weight and parameter correction. Correct network weights and parameters of the wavelet basis function based on error e , and make network forecasting approximate the expected;

(e) Determine e whether meets the requirement or not, if it meets the requirement, the process will end. Otherwise, return to step (c).

2.2 Weight Optimization based on the Gradient Algorithm with Momentum Term

To improve the adaptability and precision of forecasting model, it is necessary to optimize related parameters (such as weights and parameters) of the wavelet neural network. Here, gradient algorithm is a common optimization method. However, calculation speed of traditional gradient algorithm is slow and it is easy to obtain a local minimum. Therefore, momentum term v is added to the formula to improve the learning efficiency, which ensures the forecasting output of network approximately satisfy the actual output. The process of parameter optimization is as follows.

(1) Calculate network forecasting error

$$e=\sum_{k=1}^{m} y_p(k)-y(k) \tag{3}$$

Where $y_p(k)$ is the desired output, $y(k)$ is the forecasting output.

(2) Correct network weights and related parameters of the wavelet function according to the forecasting error.

$$\begin{aligned}\omega_{n,k}(i+1)&=\omega_{n,k}(i)+\nabla\omega_{n,k}(i+1)+v*(\omega_k(i)-\omega_k(i-1))\\ a_k(i+1)&=a_k(i)+\nabla a_k(i+1)+v*(a_k(i)-a_k(i-1))\\ b_k(i+1)&=b_k(i)+\nabla b_k(i+1)+v*(b_k(i)-b_k(i-1))\end{aligned} \tag{4}$$

Where, $\nabla\omega_{n,k}^{i+1}$, ∇a_k^{i+1} , ∇b_k^{i+1} are calcuated by network forecasting error.

$$\begin{aligned}\nabla\omega_{n,k}(i+1)&=-\eta\frac{\partial e}{\partial\omega_{n,k}(i)}\\ \nabla a_k(i+1)&=-\eta\frac{\partial e}{\partial a_k(i)}\\ \nabla b_k(i+1)&=-\eta\frac{\partial e}{\partial b_k(i)}\end{aligned} \tag{5}$$

Where η is the learning rate.

3. Hourly Gas Load Forecasting Based on Improved Wavelet Neural Network

3.1 Analysis and Preprocessing of Hourly Gas Load Samples

Take hourly gas load data of a half month in November, 2014 as an example in H city of Sichuan Province in China. The curve of hourly gas load is shown in Figure 2-a and the curve of hourly load data in one day in Figure 2-b.

Figure 2-a and Figure2-b show that hourly gas load data have strong volatility and randomness as well as obvious cyclicity and similarity. Hourly gas load curve has three peaks and troughs in one day, which also reflects people's living habits and work habits of the city predominated by civil and

commercial users. Among them, volatility in the period from 6 a.m. to the noon is most obvious and difference between peak and valley the largest.

However, as hourly gas load is affected by weather mutations, holidays, stopping of gas supply and other factors, hourly urban gas load tends to existing deviation from the normal value range, which is called the abnormal data point. In view of the abnormal data having a negative effect on the training and stability of the neural network stability, the sample data need to be filtered before training sample data of a neural network, to eliminate abnormal data points. Here, the Markov square distance selection rule for data selection is adopted to identify the abnormal points, which is as follows.

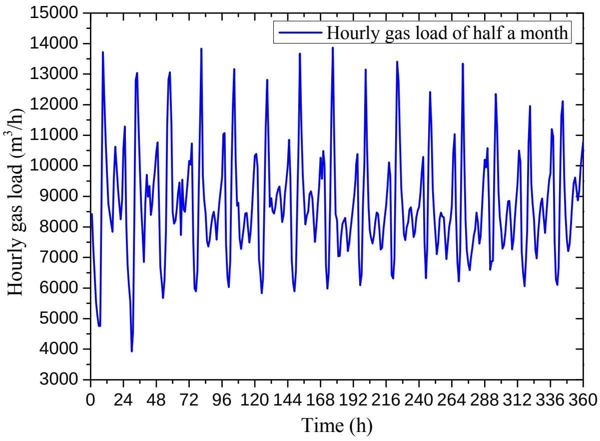

Fig. 2-a Hourly gas load in half a month

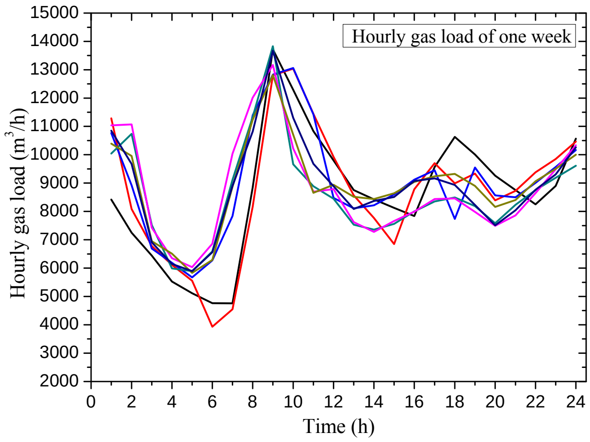

Fig. 2-b Hourly gas load variation in a day

For a sequence $x(1), x(2), \cdots, x(n)$, $x(i)=[x_{i1}, x_{i2}, \cdots, x_{ip}]'$ are n pieces of records from $N_p(\bar{X},\Sigma)$; $\bar{x}_k$ is the average of $x_k=[x_{1k}, x_{2k}, \cdots, x_{nk}]'$ and $\bar{X}=[\bar{x}_1, \bar{x}_2, \cdots, \bar{x}_p]'$. Then the markov square distance is as follows.

$$D_i^2=(x_{i1}-\bar{x}_1, \cdots, x_{ip}-\bar{x}_p)\Sigma^{-1}(x_{i1}-\bar{x}_1, \cdots, x_{ip}-\bar{x}_p)' \tag{6}$$

Where, N_p obeys normal distribution of p dimension, Σ can be estimated by the sample covariance matrix.it is demonstrated that the critical value could be looked up through χ^2 distribution if D_i^2 approximately obeys the χ_p^2 distribution when n is bigger. And the ith data is judged as an abnormal point if $D_i^2 \geq D_b$.

3.2 Modeling and Error Analysis

The wavelet neural network includes a input layer, a hidden layer and a output layer. The input data of the input layer are hourly gas load of n days before the day to be forecasted. The wavelet function of the hidden layer usually adopts the Morlet wavelet. The flow chart of modeling wavelet neural network is shown in Figure 3.

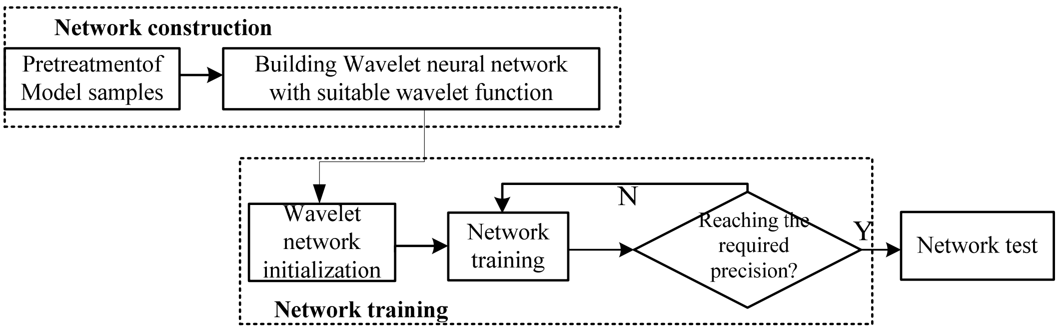

Fig.3 Flow chart of modeling wavelet neural network

To evaluate the forecasting effect, the absolute percentage error APE and the average absolute percentage error MAPE are adopted to measure the forecasting error.

$$APE = \frac{|Y_f - Y_p|}{Y_p} \times 100\% \qquad (7)$$
$$MAPE = \frac{1}{N} \times \sum_{N} APE \times 100\%$$

Where, Y_f and Y_p are the forecasted hourly gas load and actual hourly gas load,respectively.

3.3 Case Study

Hourly gas load from November 2012 to November 2014 in city H of Sichuan Province in China are taken for an example. The training samples are the data from November 2012 to October 2014 and the test samples from November 1 2014 to November 8 2014. Data of November 8 2014 are the test target.

As hourly gas load of the city is related with few hours before it and gas load data show week periodicity, hourly load data of 7 days before the day to be forecasted are set as training samples. Firstly, gas load data of each hour of 7 days are recorded and 162 points remain after filtering the recorded 168 data points. BP neural network and wavelet neural network are respectively established by with the input of total 140 load data points of 7 days. Finally, hourly gas load forecasting of the 8th day could be realized through neural networks which finish training after repeatedly training 500 times. The above neural network program are realized by using MATLAB programming language.

In this case, the structure wavelet neural network is 7-8-1, namely the input layer sets 7 nodes representing hourly gas load time hour of the 7 days before the day to be forecasted, hidden layer 8 nodes and the output layer one node representing the gas consumption forecasting values of the network. In the network weights and parameters of wavelet functions are obtained randomly during initialization.

After training and testing, wavelet neural network and BP neural network forecast hourly gas load, respectively. Forecasting error accuracy comparison results of actual hourly load and forecast hourly load diagram are shown in Figure 4-a. In order to compare the forecasting precision of the above two forecasting models more clearly, the APE of them is calculated as shown in Figure 4-b. Table 1 shows the concrete errors of the two models.

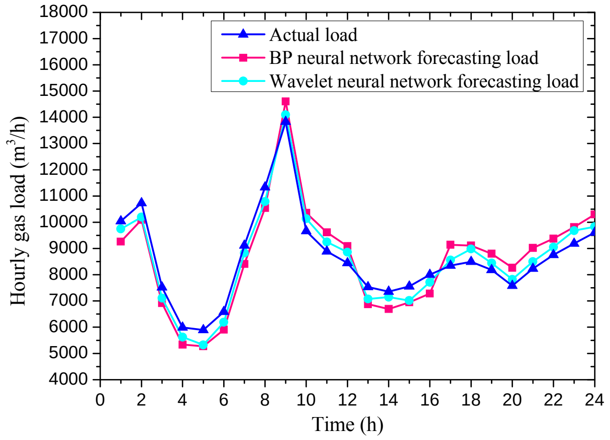

Fig.4-a real load and forecasting load comparison

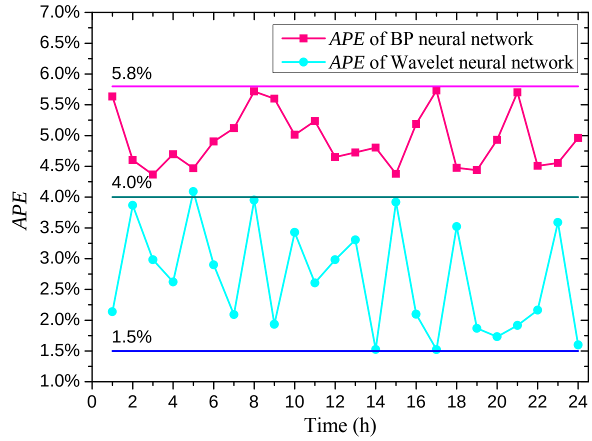

Fig.4-b APE comparison

Table 1 Forecasting error statistics of the two neural networks

error	wavelet neural network	BP neural network
Maximum of APE (%)	4.09	5.73
1.5%≤APE≤4.0%	23 points	0 point
4.0%≤APE≤5.8%	0 point	24 points
MAPE (%)	2.68	4.93

Figure 4-a shows that the forecasting values of wavelet neural network is closer to the relative observed values than those of BP neural network, lower than the maximum forecasting error that is set. Figure 4-b and Table 1 show that the absolute errors of all the points of wavelet neural network forecasting model is between 1.5% and 4% while that of BP neural network forecasting model is between 4.0% and 5.8%.

4. Conclusion

(1) This paper has built an improved wavelet neural network forecasting model. Experiment results illustrate that this model is capable of gas load forecasting and more precise than traditional BP neural network. Forecasting values of the network are close to actual values of hourly gas load, proving that the wavelet neural network is a good method of gas load forecasting for its better reflecting the law of gas load.

(2)Due to limited space, only the wavelet neural network and BP neural network forecasting model are compared. Readers can compare wavelet neural network, RBFNN, HEBBNN, TDNN to get more valuable results. Besides, the parameter optimization methods of wavelet neural networks include genetic algorithm, particle swarm and other evolutionary algorithms. Optimization of the wavelet function still needs further research.

(3) Different gas companies have different number and ratio of gas users as well as gas price. And some qualitative influencing factors of hourly gas load are not easy to get. Therefore, data collection work should be attached more importance.

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