

The Short-term Load Forecasting Based on Wavelet Transform

Huang Yuqing, Wu Bowei, Zhao Dongchu, Chen Shengbo, Fang Yidong

Electrical Engineering and Technology, College of Engineering and Technology, Zhuhai Branch of Beijing Normal University, Xiangzhou District, Zhuhai

ABSTRACT

This paper presents an improved technique in load forecasting based on discrete wavelet transform (DWT). The DWT splits up load time series into low and high frequency components which improve forecast each components by adopting the appropriate parameters forecasted components are summed up to produce a final forecasted load in the end. In experiment, all data from a certain area in Qinghai province is used to verify the load forecasting in one year, the performance of algorithm is compared with that of real load. The experimental results show that the deviation between forecasted value and true value is limited in 2% excluding the interference of environment and temperature. The proposed algorithm can improve the calculation accuracy.

Keywords: Wavelet Transform; Power System; Short-term Load Forecasting

INTRODUCTION

Power load forecasting is the basis of power system for its varieties of operation and control work. For a long time, scholars at home and abroad have been doing a lot of research on both theory and method of load forecasting. These methods including Time Series Method, wavelet transform, combination forecasting method, etc have been widespread so far.

Power system load sequence has its volatility and a special periodic. Generally speaking, the obvious manifestation of load change periodically with the days and weeks. But this kind of periodicity also has a considerable complexity, which is often nested in a large cycle of a small cycle. From the perspective of frequency domain, this phenomenon means that the energy of power load series is relatively concentrated in some frequency bands. At the same time, the entire load sequence can be seen as the superposition of multiple frequency components with different frequency components, which have similar frequency characteristics and consistent variation rules. We can isolate these sequences and analyze each component individually in the frequency domain, then model as well as forecast based on the characteristics, which can't be completed by the traditional method of time-frequency.

Wavelet transform is a method of time domain and frequency domain analysis in both tend to have good localization property. According to the frequency of the signal, adjusting the density of sampling automatically, which can be focused to signal any details. In particular, discrete wavelet transform is very effective in dealing with unstable discrete signals. It can decompose load signal interlaced by different frequency into corresponding frequency bands independently so that the periodic variation of the load sequence can be more clearly represented. Wavelet transform has been applied in many fields of power system at present. In this paper, the idea of wavelet transform is used to realize the forecast of power load sequence, and establish the forecast load model. Finally, the complete load forecast results can be obtained through sequence recombination.

SHORT-TERM LOAD FORECASTING

2.1 Division of Power Load

At first, It can be divided into long term power load, medium term power load and short term power load concentration type. Short-term power load refers to the load in one day to one week, medium-term power load covers the total load in the next few weeks to several

months, and long-term power load covers the power load in the next year.

Secondly, taking the difference of power consumption departments as the standard to divide the power load, the power load can be divided into several common types, such as commercial load, agricultural load, industrial load and civil load. Among the industrial power load, the heavy industry power load occupies the bigger proportion. Commercial load refers to the power load consumed by air conditioners, machines and lighting equipment in various enterprises, which presents obvious seasonal variation characteristics. Holidays and festivals become the main factors affecting commercial power load. Agricultural load refers to the electrical energy consumed by agricultural planting and production, which has a strong correlation with weather and precipitation. Civil power load refers to the electrical energy consumed by rural and urban residents for household appliances and heating in their daily life.

Third, the characteristics of the power load as a basis for the division, the power load can be divided into the highest load, the lowest load, peak load, trough load concentration type.

Fourthly, the power load can be divided into several common forms, such as communication electricity, station name electricity, electric heating electricity and power electricity, etc.

2.2 Load Forecasting

Only uncertain events and random events require people to adopt appropriate forecasting technology to infer the trend of load development and possible situation. Load forecasting is based on historical data of power load and its influencing factors, establish relevant models according to the actual situation, scientific prediction of electric load in the future. Load forecasting have the following obvious perspectives:

(1) Conditionity:

All kinds of load forecasting are made under certain conditions. For the conditions, they can be divided into two kinds: necessary conditions and hypothetical conditions.

(2) Timeliness:

All kinds of load forecasting have a certain time range. Because load forecasting belongs to the category of scientific forecasting, it is necessary to

have a more precise concept of quantity and to specify the time of forecasting.

(3) Multi-plan:

Because of the inaccuracy and conditionity of forecasting, load forecasting schemes under different conditions can sometimes be obtained if the load is forecasted under various possible development conditions. Load forecasting is an activity that predicts or judges the future development trend and state of electric power load according to the law of development and change of electric power load. Therefore, the basic principle of load forecasting must be summarized scientifically to guide the work of load forecasting.

(4) Principle of knowability:

That is to say, the law of development of the predicted object, its future development trend and situation can be recognized by people, and the objective world can be recognized. People can not only know its past and present, but also speculate its future by summarizing its past and present. This is the basic principle of forecasting activities.

(5) Principle of possibility:

Because the development and change of things are carried out under the combined action of internal and external factors, the changes of internal factors and external forces will make things develop and change in a variety of possibilities. Therefore, the prediction of a specific index is often based on the multiple possibilities of its development and change.

(6) Principle of continuity:

Also known as the principle of inertia, it means that the development of the predicted object is a continuous process, and its future development is the continuation of this process. It emphasizes that the predictors are always from the past to the present and then from the present to the future. There is also inertia in the development and change of power system. For example, some load indicators will be maintained and continued with the original trend and characteristics. Therefore, if we understand the past and present of things and grasp their laws, we can use the continuity principle to predict the future development.

(7) Principle of similarity:

Although the development of various things in the objective world is different, there are similarities between the development of things. People can use this similarity principle to predict. In most cases, as a forecasting object, its current development process and development situation may be similar to that of other things in the past stage. People can predict the future development process and situation of the forecasted object according to the known development process and situation of the latter thing, which is the similarity principle.

(8) Principle of Feedback:

Feedback is to return the output to the input and then adjust the output. In fact, the feedback principle of prediction is to adjust the feedback in order to continuously improve the accuracy of prediction. In the practice of forecasting activities, it is found that when there is a gap between the forecasting results and the actual values obtained through a period of practice, the gap can be used to adjust the long-term forecasting values in order to improve the accuracy of forecasting.

(9) Systematic principle:

The forecasting object is a complete system, which has its own internal system, and its external system is formed by its connection with external things. These systems are integrated into a complete overall system, which should be considered in forecasting. That is, the future development of the forecasting object is the dynamic development of the whole system, and the dynamic development of the whole system is related to the interaction and interaction between its various components and influencing factors. Systematic principle also emphasizes that the system as a whole is the best. Only when the system as a whole is the best prediction, can high-quality prediction be achieved and the best prediction scheme be provided for decision makers.

2.3 Influencing Factors of Power Load Forecasting

Meteorological conditions are one of the main factors affecting the accuracy of power load forecasting. Climatic conditions mainly include temperature and humidity. With the popularity of household appliances, the civil power

load has become a relatively high type of overall power load. The temperature variation has a direct effect on the total power load. For example, in winter, when the temperature is lower, and in summer, when the temperature is higher, residents need to start air conditioning for heating and cooling, resulting in an increase in the total power load; But in the spring and autumn the temperature suitable season will not appear the phenomenon which the electricity use load increases suddenly.

What's more, The total amount of civil load and commercial load will show a sharp rise and drop trend in the statutory holidays; The industrial load will be significantly reduced. Investigate its reason, during the holiday, factories and enterprises are mostly on holiday, and residents in order to celebrate the festival, often choose to go out to eat and play, resulting in the increase of commercial load. Compared with weekdays, the total civil load on Saturday and Sunday also increased significantly.

And emergencies will also lead to an increase in the total electricity load to a certain extent. Due to planned maintenance, limited power supply and unexpected accidents, it will form interference to daily power supply. For example, the sudden failure of the transmission line will lead to the abnormal decline of electricity load, which also has a serious impact on the accuracy of electricity load prediction in the future.

WAVELET TRANSFORM

Before the advent of wavelet analysis, Fourier transform was the most widely used and most effective analysis method in the field of signal processing. Fourier transform is a tool to transform each other from time domain to frequency domain. Physically speaking, the essence of Fourier transform is to decompose this waveform into the superposition and sum of sine waves of different frequencies. It is the important physical significance of Fourier transform that determines its unique position in signal analysis and signal processing. Fourier transform is used in both directions have infinite sinusoidal wave as the orthogonal basis functions, the periodic function into Fourier series, the generative Fourier integral, aperiodic function by using Fourier transform spectrum analysis function, reflects the time of the signal spectrum characteristics, reveals the characteristics of stationary signal well.

As a kind of global change, Fourier transform has many certain limitations, such as not having the capability of local analysis and not being able to analyze non-stationary signals

Wavelet transform is a new transform analysis method, which inherits and develops the idea of localization of STFT, and overcomes the disadvantages of window size not changing with frequency, and can provide a “time-frequency” window changing with frequency. It is an ideal tool for signal time-frequency analysis and processing. Its main characteristic is through the transform can fully highlight some aspects of the problem characteristics, can in time (space) frequency localization analysis, through the telescopic translation operations (functions) of signal gradually multi-scale refinement, ultimately achieve high frequency time segment, the low frequency in the frequency segment, can automatically adapt to the requirement of time-frequency signal analysis, which focuses on the arbitrary signal details, solved the difficult problem of Fourier transform, become the Fourier transformation since the breakthrough on the scientific method.

Suppose $f(t)$ and $\varphi(t)$ are the square integrable function. And the function $\varphi(\omega)$, $\varphi(\omega)$ which arrcords with the FFT transformation of function $\varphi(t)$ satisfies following condition:

$$\int_{\mathbb{R}} \frac{|\varphi(\omega)|^2}{\omega} d\omega < \infty$$

Then it can set up the formula:

$$W_{f(a,b)} = \frac{1}{a} \int_{\mathbb{R}} f(t) \cdot \bar{\varphi}\left(\frac{t-b}{a}\right) dt.$$

It called $\varphi(t)$ as a wavelet function, $W_{f(a,b)}$ as the continuous wavelet transform of function $f(t)$, where a is a scale factor, b is a translation factor. So this becomes a continuous wavelet transform. The inverse transformation equation of that is:

$$f(t) = \frac{1}{C_\varphi} \iint_{\mathbb{R}^2} W_{f(a,b)} \varphi_{a,b}(t) \frac{da}{a^2} db$$

where, C_φ satisfies the following formula:

$$\iint_{\mathbb{R}^2} W_{f(a,b)} \overline{W_{f(a,b)}} \frac{da}{a^2} db = C_\varphi(f, h)$$

Where b represents the displacement in time and a represents the time length. $W_{f(a,b)}$ refers to the wavelet function components of the original signal $f(t)$ at time b contains the length of a . It represents the degree of correlation between signal and wavelet function. When scale factors and translation parameters are discrete by

binary, which means, . Its binary orthogonal wavelet is:

$$\varphi_{m,n}(t) = 2^{-\frac{m}{2}} \varphi(2^{-m} \cdot (t - n))$$

When scale a is large, the time domain part of the time-frequency window is wide, so the analysis frequency is low, which is suitable for general observation. On the contrary, when scale is small, the time domain part of the window is narrow and the analysis frequency is high, which is suitable for detailed observation. Using the performance of wavelet, different information of adjacent frequency bands can be extracted.

Because the information in each frequency band is orthogonal to each other and there is no redundant information, it avoids the difficulty of analysis caused by the correlation between the wavelet transform results. Therefore, it is possible to achieve a wide range of band-pass component processing, so as to easily reveal the regularity of the load sequence and obtain a more accurate load prediction mode

3.1 Discrete Spectrum of Load Change

Discrete spectrum is only an approximation in engineering. Considering that the input signal is of high frequency band limitation, the following assumptions can be made according to engineering requirements:

(1) The input signal consists of steady linear, fundamental wave and finite harmonic components.

$$L(t) = A_0 + B_0 t + \sum_{i=1}^n A_i \sin(\omega_i t + \phi_i)$$

(2) The input signal consists of steady linear, fundamental wave and integer harmonic components.

The above analysis shows that choosing the appropriate input signal analysis model according to the specific load characteristics and index requirements is the first step in designing load forecasting. Therefore, the sequence processing of the original load data has always been an important basis for load forecasting. Before forecasting, power load is decomposed into trend term, periodic variable term and stochastic model by some mathematical means. Then, according to the characteristics of various variables, appropriate forecasting models are selected to extrapolate time series, and their extrapolation results are superimposed to obtain the forecasting results.

3.2 Frequency Domain Characteristics of Load Change

Power load characteristics can also be decomposed and

analyzed by time-frequency diagnostic tools to obtain the prediction results. According to the actual situation of sample data, short-term load forecasting will involve a wider frequency band, so different band-pass filters can be selected. At the same time, the harmonic components are used in load forecasting, so not only the amplitude-frequency characteristics of the filter are required, but also the phase-frequency characteristics of the filter must be considered, because the relative phase changes of different load components will have a great impact on the forecasting results. For the second case of continuous spectrum, if the linear component can be extracted and analyzed, the model can be chosen as the form of discrete spectrum. There will be some shortcomings in the usual mathematical methods. Wavelet analysis is undoubtedly the best choice for this application.

On the other hand, in load forecasting calculation, when the time series changes, especially when sudden changes occur, the prediction results of commonly used algorithms are not ideal, and they can not keep up with the actual data for a long time, reflecting slowly. Wavelet analysis has good localization properties in both time and frequency domains. Moreover, due to the gradual fine step size of high-frequency components in time domain and the coarse analysis of low-frequency components, it can show a certain adaptive ability for such data.

3.3 Load Component Decomposition Based on Discrete Wavelet

The application of wavelet analysis in power system is increasing gradually, but its application in load forecasting is relatively less. The continuous wavelet transform of signal $x(t)$ is defined as

$$WTx(a, t) = \frac{1}{a} \int x(\tau) \varphi\left(\frac{t-\tau}{a}\right) d\tau$$

a is the scale factor. φ is Wavelet Requires Admissibility Conditions.

$$\int_0^{\infty} \frac{|\varphi(w)|^2}{w} dw = \int_{-\infty}^0 \frac{|\varphi(w)|^2}{w} dw = C_{\varphi} < +\infty$$

At this time, the original signal can be recovered by the wavelet transform of the signal, and the recovery formula is as follows:

$$f(x) = \frac{1}{C_{\psi}} \int_0^{\infty} \int_{-\infty}^{\infty} WTx(a, t) \overline{\varphi}_a(\tau - t) \frac{dad\tau}{a}$$

In formula $\overline{\varphi}_a$ is complex conjugate. The family of functions $\psi(t)$ in time-frequency space generated by integer scaling and translation of wavelet function

constitutes discrete wavelet. Let $f(t) \in L^2(\mathbb{R})$ be the signal to be decomposed, $\varphi_{n,0} = \{\psi(t-n)\}_{n \in \mathbb{Z}}$ and $\psi_{n,0} = \{\psi(t-n)\}_{n \in \mathbb{Z}}$ be the standard orthogonal bases of V_0 and W_0 , respectively, and then expand according to the wavelet series.

$$f(t) \approx f_N(t) = f_J + \sum_{j=J}^{N-1} W_j$$

$$f_J \in V_J \subset V_N, w_j, 0 \leq J \leq N-1$$

Compared with $f(N)$, f_J contains frequency components below scale J , but does not contain frequency components between scale J and N , which is an ideal environment for low-pass filtering. Similarly, w_j is a frequency component of $f(t)$ that contains only scale J . Because the wavelet components at different scales are orthogonal, this provides a good tool for band-pass filtering.

Therefore, different information of adjacent frequency bands can be extracted by using the frequency division performance of wavelet. Because the information in each frequency band is orthogonal to each other and there is no redundant information, the difficulty of analysis caused by the correlation between the results of wavelet transform is avoided, so the wider band-pass component processing can be realized. For High Pass, Low Pass, notch and other situations, only a slight adjustment can be made. In this way, the spectrum of the linear component and the high frequency random component in the load information will show distinct separation characteristics after the wavelet transform. Because B-spline function has better smoothness and approximation, the derivative wavelet of B-spline smoothing function is applied. The results show that it is appropriate to decompose the load signal with the cubic central B-spline function as the wavelet function and the quadratic spline function as the scale function (the corresponding wavelet coefficients are referred to in reference).

MODEL OF LOAD FORECASTING

At present, according to the forecasting scheme and forecasting process, the model samples in the technical field usually select the historical coincidence forecasting model samples, and forecast the daily coincidence of the model. For short-term electrical load, this model can combine historical data information to form a relatively accurate prediction scheme. In the model, the selection

of sample content mainly comes from historical load data and similar daily load data samples. Among them, the historical load data samples of similar days Precision Specificity, so the information of historical data samples is selected to have the ability of searching and screening, so as to ensure that the historical load data generated by similar days can fully represent the power load state of a certain kind of power activities. The universality of the state is studied by the model, and finally the prediction conclusion of the model is obtained.

In the past theoretical research, researchers proposed to use artificial neural network to retrieve and analyze historical data samples, so as to obtain a similar day selection scheme. The application layer of artificial neural network can train a large number of historical data samples, so as to obtain the law of power load in historical data. However, the application of artificial neural network in sample monitoring and training can not reflect the addition of new samples. Therefore, in the analysis of electrical load forecasting, it is difficult to analyze the changes of active new loads and load conditions of power system caused by climate and environmental factors. In order to remedy this shortcoming, the author chooses a mapping algorithm with application advantages and experience when choosing the sample analysis scheme. The mapping algorithm can select the sample data through the mapping algorithm. The mapping algorithm can complete the comparison between different days, thus forming the result of feature analysis. The analysis results can be used for database statistics by mapping logic, which is helpful to the construction of the selected intelligent model of wavelet decomposition.

The establishment of the model is divided into five stages. First, preprocess the original data. Second, using wavelet transform on load sequence to get each branch sequence. Next, make use of the formed sequence, utilizing them as the input sample and training samples, which become the basis for the analysis of the forecast model. Then, forecast multi-domain wavelet sequences.

Finally, generate the final forecast results of load series through the superposition of each sequence's result. Figure 1 shows the establishment of the prediction model.

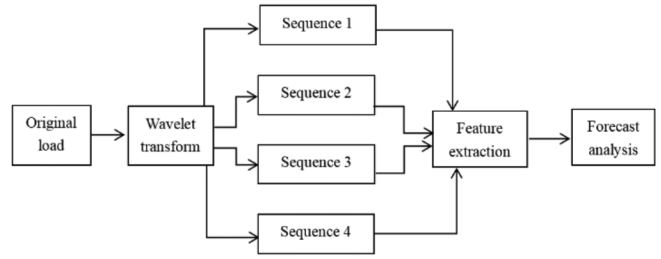


Fig. 1. The short-term load forecasting model

The load sequence is represented by $x\{n\}$, N represents how many days of load data. (There is the relation: $1 < n < N$). The mean value E and variance V of load in the N day were calculated by the following formula

$$E = \frac{1}{N} \sum_{k=2}^n x(k).$$

$$V = \sigma^2 = \frac{1}{N} \sum_{k=2}^n [x(k) - E]^2.$$

In order to accurate representation of the load changes, Let's define a load deviation rate:

$$\rho = \frac{|x(n) - E|}{\sigma}.$$

When $\rho \geq 1.1$, the load is considered to be in an abnormal position; otherwise, it's considered to be at a normal point.

4.1 Selection of Wavelet Function

Due to the multiple periodicity of power load sequences, it is required that the wavelet function used to analyze the sequences must have good tight support, which means that it does well in showing the time-domain characteristics of the signal. Only in finite time, the value of wavelet function is not zero. In addition, it is required to have good regularity, which is used to describe the smoothness of the function. The higher the regularity is, the better the smoothness of the function is.

The regularity of wavelet affects the stability of wavelet coefficient reconstruction. The favourable regularity of wavelet can realize smooth reconstruction of signal. In this experiment, Daubechies wavelet with time-frequency tight support and high regularity was selected to decompose the previous power load

sequence. So daubechies4 was used as the mother-wavelet to decompose the sequences in wavelet analysis. By using the wavelet analysis, the result of load forecasting is obtained by the superposition of each coefficient sequence after reconstruction. If the decomposition level is too low, it is not easy to extract the localization characteristics in the load sequence; if the decomposition level is too high, it is easy to lead to the accumulation error. Therefore, the decomposition scale of wavelet must be determined reasonably.

4.2 The Example Analysis

For the short-term load forecasting of power system, the predictors that affect the load forecasting form the input parameters of the training samples. According to previous research conclusions [6-7], meteorological data that have great influence on power load include maximum temperature, minimum temperature, average temperature, humidity, rainfall, wind speed, etc. Table 1 shows the selected sample inputs.

Table: 1 . The input parameter of series of forecasting value

Sequence	Samples	Forecasting value	
D1	D1(-1)	-D1(-7), D(1)(-1) -1 - D1(-7) -1L(-1), T(0)	D1(0)
D2	D2(-1)	-D2(-7), D(2)(-1) -1 - D2(-7) -1L(-1), T(0)	D2(0)
D3	D3(-1)	-D3(-7), D(3)(-1) -1 - D3(-7) -1L(-1), T(0)	D3(0)
D4	D4(-1)	-D4(-7), D(4)(-1) -1 - D4(-7) -1L(-1), T(0)	D4(0)
D5	D5(-1)	-D5(-7), D(5)(-1) -1 - D5(-7) -1L(-1), T(0)	D5(0)
A3	A3(-1)	-D3(-7), A(3)(-1) -1 - A3(-7) -1L(-1), T(0)	A3(1)

L(),T() is on behalf of the load and to predict the actual average temperature. A3,D3,D2,D1 are the load sequence after discrete wavelet transform. The marks (0),(-N),(-N)-1 respectively represent the forecasting time, the same time of the N day and the last time of the predicted point in the N day. In this paper, the data is in an area of Qinghai Province. It include load data and temperature data throughout the day from January 1, 2005 to December 31, 2005. Table 2 shows the actual historical load in 2005.

curve according to the daubechies4 wavelet changes in table 2, which can be seen that the low frequency part of the signal is similar to the original signal by using the quadratic decomposition transformation.

Tab. 2 The related informational historic power load in 2005

Month	Daily maximum load	Daily minimum load	Daily mean
1	283.56	717.41	440.45
2	136.25	822.44	369.21
3	205.44	718.97	442.87
4	278.62	583.07	442.43
5	262.28	659.70	441.08
6	281.24	616.19	457.25
7	203.6	637.26	464.58
8	303.98	632.55	451.63
9	262.56	629.86	456.21
10	243.81	605.79	452.21
11	302.99	627.45	468.23
12	354.23	625.33	487.22

Based on the above data, according to wavelet transform the historical data of power load is decomposed into low-frequency part (similar part) and high-frequency part (detailed part). After wavelet transformation, the low-frequency part has certain y, which is similar to the actual load curve in trend. The high frequency part changes violently and its fluctuation range is small. Figure 2 is the quadratic decomposition

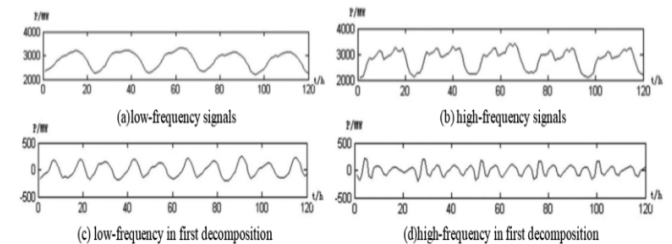


Fig. 2. The curve of wavelet decomposition

Also, forecasting results data is shown in table 3 and figure 3. (the solid line represents the actual operating value while the dotted line represents the forecasting value.) Excluding the influence of temperature, environment and other factors, the transformation trend of the two is basically consistent.

Tab. 3 The comparison result real value and forecasting value

Time domain	Actual value	Forecasting value	Error rate
T00: 00	1 091.95	1 096.53	0.42
T00: 3	1 074.7	1 088.34	1.27
T01: 00	1 058.73	1 066.88	0.77
T01: 30	1 011.99	1 008.95	-0.30
T02: 00	1 030.19	1 035.5	0.52
T02: 30	1 011.86	1 017.62	0.57
T03: 00	978.79	966.84	-1.22
T03: 30	987.92	998.68	1.

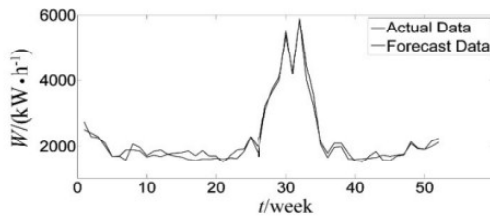


Fig. 3 The comparison result between load forecasting value and real value in 1. 11. 2005.

CONCLUSION

This paper proposes a short-term load forecasting based on wavelet transform. wavelet transform to extract the power load time series of fine ingredients, stronger regularity in the sequence of bifurcation. Besides, forecasting the analysis with the actual data, the results show that under the premise that remove the influence of external factors, forecast results are basically consistent with the actual load results. From the results of example analysis, we can draw the following conclusions:

- (1) Wavelet analysis can find out the the characteristics of the power load variation well.
- (2) The signal after wavelet decomposition and reconstruction can describe the influence of various random disturbance factors on load changes in detail.
- (3) Different load sequences are processed with different forecast models, which can effectively improve the forecast accuracy and overcome the shortcomings of a single forecast method.
- (4) Wavelet analysis combined prediction method is simple in principle. Its prediction model is easy to establish and implement, which can effectively improve the accuracy of prediction. What's more, it can provide strong support for short-term load forecasting.

In conclusion, based on the wavelet decomposition method, the short-term power load is predicted with high accuracy. It is helpful to form a reference basis for the scientific dispatch of power departments, so as to provide continuous electric energy for the public, improve the continuity and security of power supply, and meet the needs of the public.

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