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INTELLIGENT PREDICTION OF CAPACITY MARGIN IN DIFFERENT TIME PERIODS BASED ON WAVELET ANALYSIS ALGORITHM

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Abstract. In order to understand the intelligent prediction of capacity margin in different time periods, the author proposes a research on intelligent prediction of capacity margin in different time periods based on wavelet analysis. The author first uses wavelet decomposition and neural networks as tools to predict electricity prices in different time periods. The changes in the electricity price sequence during different time periods are relatively single, which is conducive to the learning and training of neural networks, thereby improving prediction accuracy. Secondly, compare the predicted results of time slot capacity margin based on wavelet analysis technology with the actual values. Finally, the experimental results indicate that the average relative percentage error of short-term electricity price prediction can reach 11.40%. The intelligent Jun page measurement method for capacity margin based on wavelet analysis proposed by the author can effectively improve the prediction accuracy of power grid capacity margin, and has strong practicality and effectiveness.

Key words: Wavelet analysis, Time division, Power

1. Introduction. The intelligent prediction of time slot capacity margin based on wavelet analysis is a method that utilizes wavelet transform to analyze and predict the capacity margin of power systems. The prediction method decomposes the time series into multiple sub series, and then carries out wavelet analysis on Subsequence with different frequencies to obtain corresponding wavelet coefficients, thus realizing the prediction of capacity margin. The advantage of this method is that it can identify periodic changes at different scales, has good adaptability to the processing of nonlinear time series, has high prediction accuracy, and has certain reference value for effective management and scheduling of capacity margin in power systems. The price of electricity is the most significant factor in the electricity market that has a direct impact on both the supply and demand of electricity. It is also an essential component of the electricity market. How to accurately predict electricity prices has become an important part of electricity market reform as the market for electricity has grown. Different prediction methods can be used for different electricity markets, such as in demand side management, where electricity prices can be divided into time period electricity prices and real-time electricity prices; Under the Market clearing mechanism, the real-time price can be divided into time of use price and daily price. Due to the numerous and complex factors that affect changes in electricity prices, establishing accurate, reliable, and efficient prediction models is the key to improving the accuracy of short-term electricity price prediction. The combination of wavelet analysis and neural network is used to forecast short-term electricity price, and wavelet analysis is used to decompose and reconstruct the time series to construct a neural network forecasting model with nonlinear mapping ability, thus improving the accuracy of short-term electricity price forecasting. Short term electricity price prediction is an important link in the electricity market. It is a prediction of future short-term electricity prices, and its results can guide the operation of the electricity market. There are many factors that affect electricity prices, mainly including supply and demand relationships, seasonal factors, unit combinations, load characteristics, weather changes, etc. Due to the influence of various factors on electricity prices, there is a close relationship between price and time. Short term electricity price forecasting generally adopts linear models, which describe various price relationships in the electricity market by establishing a series of mathematical models. When predicting short-term electricity prices, it is first necessary

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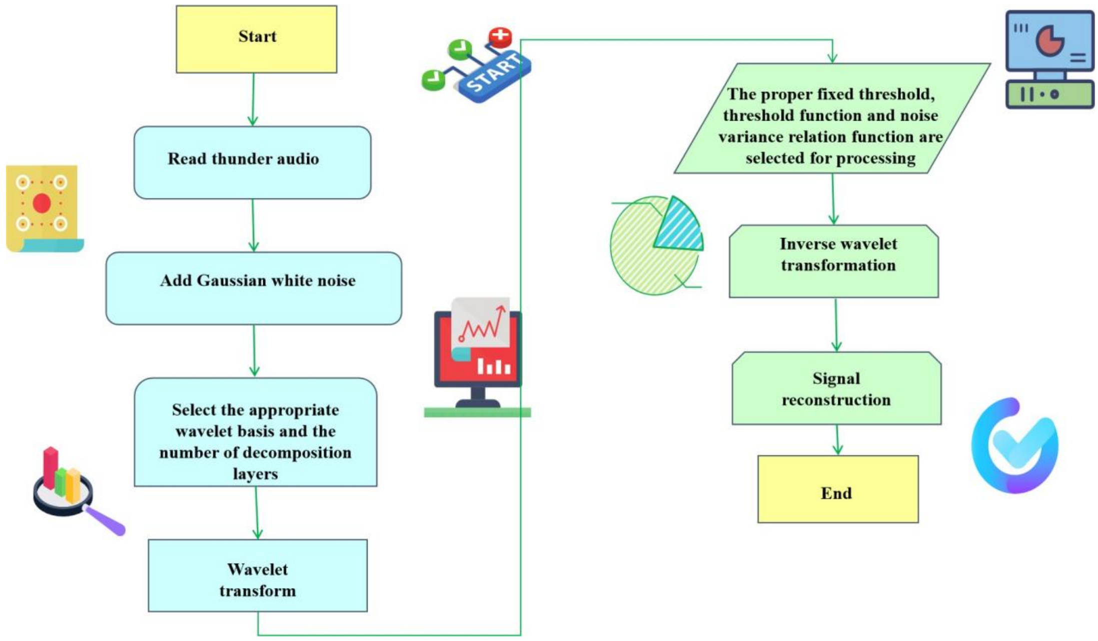

Fig. 1.1: Intelligent prediction of time slot capacity margin using wavelet analysis

to quantify and classify the factors that affect electricity price changes, and then select a suitable model for prediction based on the degree of impact of each factor on electricity price changes [1,2]. It should be noted that this method is only a prediction method for the capacity margin of the power system, and the prediction results are not absolutely accurate and are influenced by various factors, such as climate and load characteristics. Therefore, in practical applications, it is necessary to combine other methods for comprehensive evaluation and decision-making (as shown in Figure 1.1).

2. Literature Review. Wavelet analysis is an effective tool for analyzing and processing signals. It mainly decomposes and reconstructs signals to achieve nonlinear transformation and reveal the relationships between various components in the signal. The core of wavelet transform is to represent signals through the continuous and discontinuous boundaries of the scale function and time function of wavelet functions, while wavelet functions can be single scale or multi-scale wavelets. Therefore, wavelet analysis mainly studies the time series analysis between signals and noise. For a non-stationary time series, the continuous wavelet transform is a process of Discretization of the time series in the time domain. After discretization, a series of wavelet basis functions are obtained, and each wavelet basis function has a small-scale coefficient corresponding to that wavelet basis. For continuous wavelet transform, since the signal has the same frequency component at each scale, each frequency component in the signal can be represented as a weighted sum of a series of wavelet coefficients. In this way, by reconstructing the wavelet coefficients at any scale, a reconstructed sequence containing all the information of the original signal can be obtained. That is, the original time series is decomposed into multiple Subsequence at different scales through wavelet transform, and then the wavelet coefficients with different information content at different scales are obtained through reconstruction, so as to achieve multi-resolution analysis of the original time series. The original time series can be obtained by reconstructing the Subsequence obtained from each level of decomposition.

Wavelet transform is a transformation that analyzes signals in the frequency domain. It is a multi-scale analysis method aimed at identifying various frequency components in the signal, ranging from high to low frequencies. Wavelet transform has good time-frequency localization characteristics, multi resolution analysis, and tight support properties, and the singularity performance of the signal is well detected. It has a wide range of applications, including signal denoising, singularity detection, denoising, reconstruction, and data compression. Wavelet transform is an adaptive signal processing method that can improve the resolution of signals. Wavelet transform has been widely applied in the field of signal processing.

Nieves Gonzalez, A. et al. believe that fault current and voltage signals are the main factors affecting the safe and stable operation of the power system. Therefore, analyzing fault current and voltage signals can predict the safe and stable state of the power system [3]. Mohammadi, E. et al. believe that in order to ensure the safe and stable operation of the power system, it is necessary to predict accidents in advance. In actual production, it is necessary to predict the load changes of the power system and take corresponding measures before faults occur to prevent accidents [4].

The selection of parameters such as wavelet basis function, wavelet decomposition layers, threshold, and optimal scale for fault current and voltage signals. Faults in the power system can happen at any time, and accidents are also unpredictable. Accidents must be anticipated in advance in order to guarantee the power system's safe and stable operation. In actual production, it is necessary to anticipate power system load changes and take the necessary precautions before faults occur to prevent accidents. There are many methods for predicting power grid load, such as neural network prediction, fuzzy mathematics, and so on. Neural network has good nonlinear mapping ability, and can accurately reflect the nonlinear relationship between the variables in the system. However, the computational speed of neural networks is slow and cannot meet the real-time requirements of power system operation. The fuzzy mathematics method combines fuzzy mathematics with neural networks to study problems, compensating for the slow computational speed of neural networks. However, in practical applications, fuzzy mathematical methods cannot fully reflect the relationship between variables caused by changes in the operating state of the power system. Wavelet analysis has good time-frequency localization characteristics and good adaptive ability, and Time–frequency analysis of signals has good results. The author uses wavelet analysis technology to predict the capacity margin of the power system, which has good application value [5,6].

3. Research methods.

3.1. Intelligent Prediction of Time Period Capacity Electricity Price Based on Wavelet Analysis. According to the economists' study of the electricity market, there are marginal costs and marginal benefits in the electricity market. Marginal cost refers to the cost needed to produce and provide the same product or service; Marginal revenue refers to the revenue that exceeds Marginal cost when producing the same product or providing the same service under certain production technology and conditions. The main determinants of electricity price are production cost and Marginal revenue [7]. Electricity prices are influenced by many factors, such as: Load rate; Load distribution; User nature; Seasonal changes; Type of user load curve; Seasonal changes; Other factors such as taxes and fuel prices will have an impact on electricity prices.

Load rate. Refers to the ratio of electricity consumption to electricity consumption during a certain period of time, expressed as a percentage. During a certain period of time, the higher the load rate, the more electricity is consumed. The load rate can be calculated using the following equation 3.1:

$$p = q/(1+i)p = q/(1+i)p = q/(1+i) \tag{3.1}$$

where p is the load rate of the period; q is the electricity consumption during this period; i is the population during this period.

Load distribution. Refers to the changes in load within a certain area at the same time. For example, in the electricity market, the larger the electricity consumption in a certain area, the higher its proportion and the higher the electricity price [8,9], as shown in equation 3.2:

$$M_{APE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_i - \hat{P}_i|}{\overline{P}} \tag{3.2}$$

Here, P_i represents the actual electricity price and represents the predicted electricity price, Is the average actual electricity price, where N represents the number of time periods.

User nature. Different users have varying degrees of impact on electricity and electricity prices, such as residential and agricultural users.

Seasonal variation. Refers to the variation of electricity consumption and electricity consumption during a certain period of time with the seasons. For example, electricity consumption is higher in winter than in summer; Summer consumes more electricity than winter, etc.

3.2. Wavelet Analysis and Neural Networks. Wavelet analysis is a useful tool for signal analysis that is utilized extensively in numerous fields like image analysis and signal processing. The market's supply-demand relationship determines electricity prices, but at the same time, there are various complex factors that affect electricity prices, such as unpredictable factors such as power generation games and equipment failures, which endow electricity prices with more high-frequency and detailed components, resulting in electricity prices deviating from normal values and concealing the true changing rules of electricity prices, which is not conducive to accurate prediction of electricity prices [10]. The author uses wavelet decomposition technology to extract the approximate components of the electricity price sequence, thereby eliminating the high-frequency components in the electricity price sequence, and trains the neural network using the approximate components as the historical electricity price of the neural network.

A type of feedforward network known as a radial basis function (RBF) neural network is based on function approximation theory. This kind of network's learning is like looking for the best training data surface in multiple bit space. Each hidden layer neuron transfer function of the Radial basis function neural network constitutes a basis function of the fitting surface. It is a local approximation network, that is, for each local area of the input space, only a few neurons determine the output of the network. A global approximation network is the most frequently utilized BP network. Although radial basis function networks are typically larger in scale than BP networks, they are capable of better function approximation and faster learning. The radial basis function network's structure is comparable to that of the generalized regression network (GRNN). A regularized radial basis function network is the special linear layer that serves as its output layer. The generalized regression network can accurately approximate a smoothing function when there are sufficient hidden neurons. The number of input sample vectors and the number of neurons in the hidden layer and output layer of GRNN are the same. The GRNN network is very big when there are a lot of input samples. Time phased electricity price prediction is used by the author. If historical data from the previous 28 days are used as training samples, there are only 28 sample vectors per time period—that is, there are 28 neurons in a GRNN—and the network can calculate very quickly. As a result, the author relies on the GRNN neural network to forecast electricity prices over a variety of time frames [11,12].

The electricity price prediction process is shown in Figure 3.1, where each input of the neural network is obtained from historical data and trained. The predicted prices for each time period are obtained through this process, which can form a full day predicted electricity price for the predicted day.

4. Experimental analysis. Assuming that the data on electricity load and quantity in a certain region comes from the National Bureau of Statistics. The historical data of electricity load and quantity in the region is decomposed and reconstructed using wavelet transform to obtain data for each frequency band, and grouped according to different time periods. The wavelet decomposition results of electricity load and electric satellite data for each time period are shown in Figure 4.1 and Figure 4.2. Through analysis, it can be seen that the electricity price time series is a non-stationary time series, and its maximum trend of change is to change with time. There are significant differences in electricity prices between different time periods, and the differences in electricity prices between two or more adjacent time periods are also significant. The electricity price time series mainly includes two parts of data: load and electricity quantity. Use the wavelet decomposed data of each frequency band as input signals, train and predict them using a BP neural network, and then train and predict the data of each frequency band that has not undergone wavelet decomposition. Input the trained network into the original data, and get the prediction results of each frequency band as shown in Table 4.1 [13,14].

From Table 4.1, it can be seen that the electricity consumption during periods 1, 2, 4, 6, 7, and 8 is relatively high. The electricity price for the fourth quarter of 2012 in the electricity market was predicted using a phased method. If the market is cleared once an hour, there will be 24 clearing prices per day, and each hour's electricity price will form its own electricity price sequence. For example, the 1 o'clock electricity price on each day will form a 1 o'clock electricity price sequence. After predicting the electricity prices for 24 periods, a full day forecast electricity price can be formed. Based on the segmented electricity price sequence, the predicted electricity price error using GRNN is 11.40%, while the predicted error based on the sequential electricity price

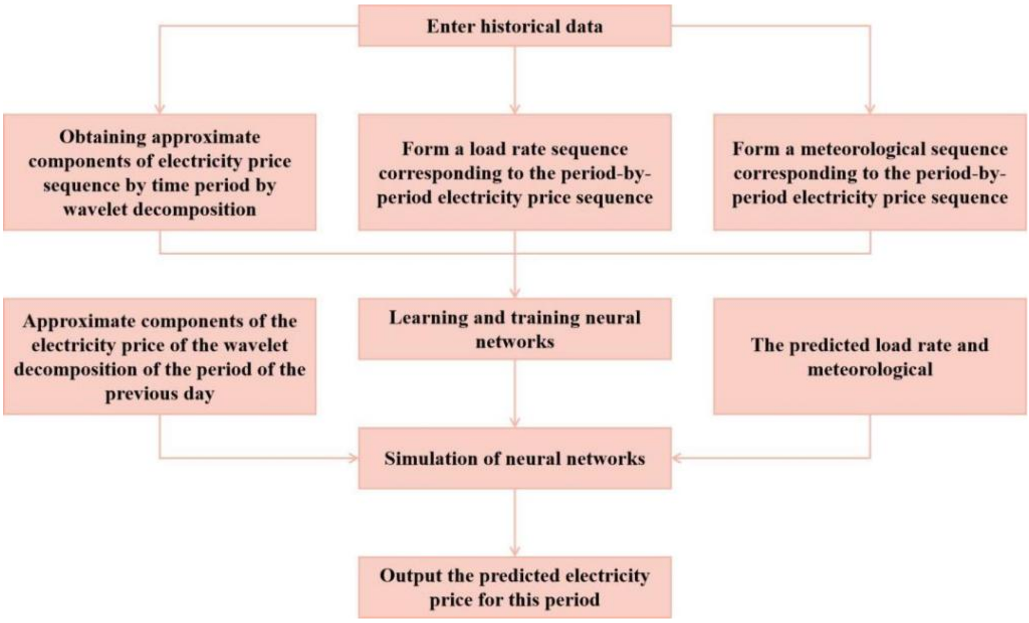

Fig. 3.1: Prediction Process of Timeslot Electricity Prices

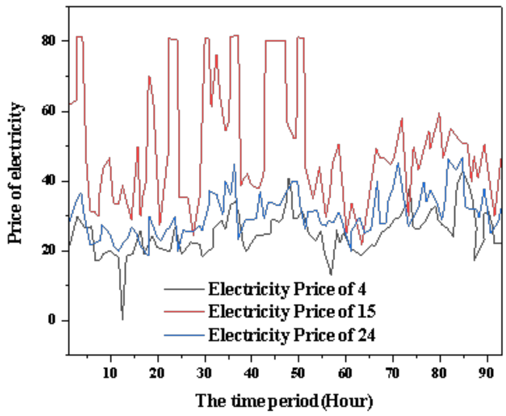

Fig. 4.1: Four point electricity price in the third quarter of the electricity market

sequence is 15.08. The prediction accuracy based on the segmented electricity price method is higher, indicating that the segmented electricity price prediction is more conducive to neural networks capturing the changes in electricity prices. The prediction errors for each time period are shown in Table 4.1. The percentage difference of Mean absolute error in each period is large. High errors mainly occur during the periods from 1:00 to 8:00, when the relative load is low and the electricity price is also low. However, the changes in electricity prices during these periods are not smooth, with more zero and negative electricity prices, which seriously affects the accuracy of electricity price prediction [15,16].

The accuracy of electricity price predictions is affected in different ways by the various input factors. In the segmented electricity price sequence, Table 4.2 depicts the effect of various input quantities and neural networks

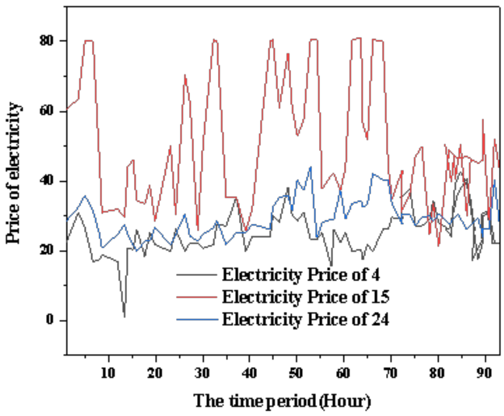

Fig. 4.2: Electricity Price of 15 in the Third Quarter of the Electricity Market

Table 4.1: Prediction Error of Each Time Period

Period of time	MAPE
1	13.485
2	14.596
3	13.245
4	14.236
5	11.362
6	15.362
7	13.256
8	15.236
9	11.352
10	11.236

Table 4.2: Impact of different input quantities and prediction methods on accuracy under segmented electricity price sequences

	Electricity price and load rate	Electricity price, load rate, and temperature
RBF	11..34	17.25
GRNN	11.36	11.40

on prediction accuracy. The prediction accuracy of the RBF network decreases when temperature factors are taken into consideration, whereas the prediction accuracy of the GRNN network slightly increases. Because the correlation coefficient between temperature factors and electricity prices is so low, it can be assumed that temperature factors have been incorporated into the load and no longer considered separately when predicting electricity prices. Compared with RBF network, GRNN network has smaller prediction error and is more suitable for electricity price prediction [17,18].

4.1. Short term electricity price prediction using BP neural network. BP neural network is a typical feedforward network, which is composed of one or more network nodes with nonlinear characteristics. There is a nonlinear mapping relationship between its input nodes and output nodes, and it can approach any complex nonlinear relationship through learning samples. Therefore, the BP neural network can be used for short-term electricity price prediction. Due to the existence of many complex influencing factors in the time series of electricity prices, using them as input signals can effectively reduce the uncertainty in the modeling process. Wavelet analysis decomposed the frequency bands of the electricity price time series and obtained good prediction results. However, the frequency band obtained after wavelet decomposition only contains less information. If you want to obtain more predictive information, you need to reconstruct the frequency band. However, there are very complex nonlinear relationships between different frequency bands, so there is a serious nonlinear relationship between the reconstructed frequency bands, and there is great uncertainty in the reconstructed data of each frequency band. These will have a significant impact on the prediction results of the BP neural network. In order to solve these problems, we use the Chaos theory to analyze the chaotic characteristics of each frequency band after reconstruction. The analysis results indicate that each frequency band has strong chaotic characteristics, which can effectively reduce the uncertainty between the reconstructed frequency bands and make the prediction results more accurate [19,20].

5. Conclusion. With the deepening of research on power system capacity margin prediction methods, in order to achieve intelligence in power system capacity margin prediction, the author proposes a time-phased capacity margin intelligent prediction method based on wavelet analysis and applies it to practical systems, effectively improving the prediction accuracy of power system capacity margin. Finally, the following conclusions are drawn: 1. Using wavelet analysis technology to decompose the operation mode of the power grid can accurately reflect the impact of changes in the operation mode on the safe and stable operation of the power grid; 2. The use of wavelet analysis technology can reduce the peak load while ensuring the safe and stable operation of the power grid, thereby improving the utilization rate of the load at various time periods; 3. Determine a time slot capacity margin prediction model based on the load growth situation of each time slot. According to this model, it is possible to predict the peak point and decrease point of load; When predicting the capacity margin in different time periods based on wavelet analysis technology, a prediction model for the capacity margin in different time periods is determined based on the load growth situation.

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