Forecasting Method of Monthly Clearing Price Under the Background of Continuous Adjustment of Power Market Supply and Demand

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Abstract. The monthly clearing price forecasting method is commonly used. The model input is used to construct a monthly electricity clearing price data set. The collected electricity monthly clearing price time series characteristics are too single, resulting in a large average absolute percentage error of the monthly clearing price forecast. For this reason Propose a method for forecasting monthly clearing prices in the context of the continuous adjustment of supply and demand in the electricity market. To study the impact of the continuous adjustment of power market supply and demand on the monthly clearing price, design the electricity monthly clearing price forecasting process, and use the normalization method to preprocess the data; extract time information and load information to construct a training sample set for the monthly clearing price of electricity; The non-linear mapping relationship between electricity price and various influencing factors, using BP neural network, establishes a monthly electricity clearing price prediction model, and predicts the monthly electricity clearing price. The experimental results show that the average absolute percentage error of the research method predicting the monthly electricity clearing price is smaller than the two commonly used methods, and it has better prediction accuracy of the monthly electricity clearing price.

Keywords: Electricity market · Market supply and demand · Adjustment of supply and demand · Monthly clearing · Price forecast

1 Introduction

The traditional system of the power industry is a vertical monopoly integrating generation, transmission, distribution, and supply. This system played an indispensable role in the initial stage of power development. It not only improved the efficiency of regional grid planning, but also benefited the internal power system. Coordination and cooperation. With the rapid development of the socialist economy, various problems in

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this system have become increasingly prominent, such as the slow development of power companies, bloated personnel and organizations, high electricity prices, and poor services provided [1]. However, with the further deepening of the restructuring and deregulation of the power industry worldwide, the reform of the power market has become an inevitable trend in the development of the power industry. Establishing a reasonable electricity price mechanism is the core issue of the electricity market reform. From a long-term perspective, a transparent electricity price mechanism is more conducive to attracting power investment, thereby ensuring the stable and sustainable development of the power industry.

My country's power industry strongly supports socialist economic construction. However, the monopoly of power generation, transmission, and distribution has increasingly restricted the development of my country's power industry, and conflicts with the construction of the socialist market economic system have become increasingly prominent, resulting in unfair social distribution problems. Increasingly prominent [2]. On the other hand, theoretically speaking, electric energy is a commodity, which has value and use value in itself, and this commodity should enter the market competition. The monopolistic operation under the planned economy is the direct cause of the non-separation of government and enterprise. Too much government intervention makes power companies have no independent market players and their development has no vitality. Based on this, my country has clearly put forward the policy of "separating power plants and grids, and bidding for the Internet", which intends to introduce competitive factors into the power industry, enhance the market competitiveness of power companies, and establish a standardized and orderly power market. As an independent economic entity in the market environment, power generation companies no longer arrange power generation based on planned electricity in the traditional way, but participate in market competition to fight for power generation indicators and draw on-grid electricity prices based on market conditions. Accurate electricity price forecasting can provide reliable reference information for the strategic quotation of power generation companies to maximize revenue; similarly, electric energy users also need accurate electricity price information to guide the signing of long-term bilateral contracts and make the best purchase strategy.

Therefore, the more accurate the short-term electricity price forecast is provided, the more reliable information market participants can obtain in the transaction, which provides a favorable reference for them to formulate the optimal quotation strategy, and thus obtains greater benefits. However, the reform of my country's electricity market is still in its infancy. The market structure and trading rules are still changing. The market system is not perfect. Electricity prices tend to fluctuate and jump. It is very difficult to accurately predict short-term electricity prices [3]. Therefore, short-term electricity price forecasting has become one of the urgent problems to be solved in the electricity market.

In the electricity market environment, electricity price is a core indicator to evaluate the efficiency of market competition, reflecting the operation status of the electricity market. As an important part of the electricity market bidding system, short-term electricity price forecasting in the electricity market can provide effective information for all participants in the electricity market, which is of great significance for maximizing corporate profits.

At present, short-term electricity price forecasting methods mainly include time series forecasting, artificial neural network method, wavelet theory, gray model method, combined model method and other methods [4]. Reference [5] tries to apply it to the electricity market for the first time, and takes into account different power price influence factors, and the accuracy of short-term electricity price forecasts is gradually improved. Reference [6] first uses the fuzzy C-means clustering method to classify market information, and then uses neural networks to make predictions for each category, and the prediction error is low.

In order to solve the shortcomings of traditional methods, this paper designs a new monthly clearing price forecasting method under the background of constant adjustment of supply and demand in the electricity market. In this method, the monthly settlement price prediction process is designed according to the influence of constant adjustment of supply and demand on the monthly settlement price. Then the normalized method is used to preprocess the data and extract the time information and load information, so as to construct the training sample set of monthly settlement electricity price. On this basis, using the nonlinear mapping relationship between the price of electricity and the influencing factors, the BP neural network is used to establish the monthly clear price prediction model.

2 Forecasting Method of Monthly Clearing Price Under the Background of Continuous Adjustment of Power Market Supply and Demand

2.1 Study the Impact of the Continuous Adjustment of Supply and Demand in the Electricity Market on the Monthly Clearing Price

In the context of the continuous adjustment of supply and demand in the electricity market, the Liku model and the bilateral transaction model are currently the two relatively mature electricity market transaction models [7]. Electricity prices are also affected by factors such as social development, government activities and policies, environmental protection, power technology, and supply and demand.

Market factors. It mainly includes the entire historical load of the power market, the load rate of the system, overcapacity or/shortage, the historical reserve of energy, hydroelectric power generation, power generation capacity, power system constraints, nuclear power generation and thermal power, etc. For example, when the system load increases, the electricity price will increase accordingly.

Non-strategic uncertainties include weather, temperature, crude oil prices, natural gas prices, fuel prices, energy reserves, load forecasts, and dew point temperature. For example, electricity needs depend on the environment, especially the daily temperature, and changes in weather affect the load and price. In addition, if there is not enough energy reserves, consumers will face a lack of energy, which will cause a balance between supply and demand and cause price changes.

Random uncertainties mainly include production outages, line emergency, line blockage, etc. For example, some power plants are far away from consumers, and transmission requires corresponding network facilities. There will be some physical factors that hinder the energy trading of market participants.

The behavior index mainly refers to the historical electricity price, elastic load, bidding strategy, and electricity price shock index.

Time effects include settlement period, day, month, season, holiday, summer index and winter index. For example, due to weather in summer and winter, load demand will increase, and electricity price fluctuations will increase accordingly. Electricity prices will also increase during a certain peak period of the working day, and electricity prices will also fall when electricity consumption is less at midnight. Therefore, compared with general commodities, the setting of electricity prices is more complicated.

At present, the domestic and foreign electricity price pricing system is mainly divided into three categories: non-market pricing, market pricing (competitive pricing), and contract pricing (agreement pricing). However, in the context of the continuous adjustment of supply and demand in the electricity market, competition is usually introduced in the on-grid electricity price, and electricity prices are set through the market; the government regulates transmission and distribution prices and sets prices independently; the government regulates the sale of electricity prices based on market leadership. In different markets, due to different operating models and different bidding mechanisms, different types of price bidding have appeared.

For the first mock exam, there is a system marginal price bidding and bidding system bidding. Under the bilateral transaction, there are market clearing price and high-low matching transaction price. When a power company purchases electricity from a power producer through bidding as a monopoly, it then sells electricity to consumers through bidding or direct pricing as a monopoly. This price is called systematic marginal price bidding; The price based payment bidding is the actual price settlement method adopted by the power trading center, according to the market demand to the power suppliers' respective quotation; High matching transaction price is similar to the transaction mechanism of stock price, that is, the transaction is matched in the power trading center according to the principle of high and low matching of purchase price and selling price.

Based on the above analysis, there are five main factors that cause price fluctuations:

1. Electricity demand, an important factor of the spot price is the total demand of the system.
2. It is the weather conditions, the power demand depends on the environmental conditions, especially the daily temperature. Weather fluctuations will affect demand, so spot prices will also be affected.
3. Fuel price. Fuel cost is one of the main parts of power generation cost, and its changes have a significant impact on the spot price of electricity.
4. Available transmission capacity. Electricity is generally provided by generators far away from consumers. It is sent to consumers through the transmission network facility. If there are some physical constraints in the transmission network, it will become an obstacle for market participants to buy or sell energy. This will affect the changes in spot prices.

5. Energy reserve. Adequate energy reserve is an important factor to ensure the spot price of electricity. If there is a sudden increase in power demand, and if there is enough power reserve capacity to use, then the service to consumers will be guaranteed. But if there are not enough available reserves, consumers will face a lack of energy, which will increase the balance of power spot prices between supply and demand.

2.2 Price Prediction Process and Data Preprocessing

Forecast Form

Based on the research results in the previous section that the monthly clearing price is affected by the continuous adjustment of power market supply and demand, the formal calculation process of the designed monthly clearing price forecast is as follows:

If given a set $(y_1, y_2, \cdots, y_t)$ and x_{t+1}, estimate Y_{t+1}, the goal is to minimize $E(Y_{t+1}, y_{t+1})$. Among them, $(y_1, y_2, \cdots, y_t)$ is the observed value of the target variable y at time t, and $t = 1, 2, \cdots$; x_{t+1} is the observed value of the input vector x at time $t+1$, the input vector may include some observed values of the target vector y; Y_{t+1} is the predicted value at time $t+1$, y_{t+1} is the actual value of $t+1$ at time; E is the error function, used to measure how close the predicted value is to the actual value. The task of prediction is to estimate the relationship between the estimated input vector and the predicted value:

$$Y = f(x, a) \tag{1}$$

In the formula (1), Y represents the prediction model; a represents the parameters of the model [8].

According to the above-mentioned monthly clearing price forecast form, the monthly clearing price is predicted. There will be a certain gap between the predicted value of the monthly clearing price and the true value, that is, an error. Therefore, it is necessary to evaluate the forecast value to reduce the forecast error of the monthly clearing price.

In error evaluation, the larger the error, the smaller the accuracy of the prediction; on the contrary, the smaller the error, the higher the accuracy of the prediction.

Generally, there are two reasons for errors. One is sample error, which is mainly caused by sample inaccuracy; the second type of error is called model error, and different prediction models produce different results. The error is also different. At present, in the field of monthly clearing price forecasting, in order to evaluate the efficiency of the monthly clearing price forecasting model, error criteria such as absolute error M, mean square error S, average absolute percentage error P, root mean square error R are often used as judgments Index, its calculation formula is as follows:

$$
\begin{aligned}
M &= \frac{1}{n}\sum_{i=1}^{n} |Y_i(t) - y_i(t)| \\
P &= \frac{1}{n}\sum_{i=1}^{n} \left| \frac{Y_i(t) - y_i(t)}{Y_i(t)} \right| \\
R &= \sqrt{\frac{1}{n}\sum_{i=1}^{n} (Y_i(t) - y_i(t))_i^2} \\
S &= \frac{1}{n}\sum_{i=1}^{n} (Y_i(t) - y_i(t))_i^2
\end{aligned}
\tag{2}
$$

In the formula (2), n represents the predicted number of points; Y_i represents the true value; y_i represents the predicted value. In the monthly clearing price data, a large number of peak monthly clearing prices and abnormal monthly clearing prices directly affect the distribution of monthly clearing prices. Sometimes the value of the monthly clearing price may be close to zero, which will make the average absolute percentage error very small. Especially when the monthly clearing price has a negative value, if the positive and negative values are offset, the error metric will be small, and the result of this judgment is not very reasonable. Therefore, it is not appropriate to use the traditional definition of the average absolute percentage error to analyze the prediction results. For this reason, the weighted average absolute error D and Theil index U are used to evaluate the performance of the prediction method. The calculation formula is as follows:

$$
\begin{aligned}
D &= \frac{1}{n}\sum_{i=1}^{n} \frac{|Y_i - y_i|}{Y} \\
0 < U &= \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} (Y_i(t) - y_i(t))^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} Y_i(t)^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i(t)^2}} < 1
\end{aligned}
\tag{3}
$$

Based on the above content, the designed monthly clearing price forecast form and the evaluation method of forecast error, the designed monthly clearing price forecast steps are as follows:

1. Select input data. Usually comes from historical electricity price data in a certain market.
2. Data preprocessing. In order to obtain accurate predictions, data needs to be preprocessed, such as data cleaning, missing value supplementation, outlier removal, data feature extraction, and so on.
3. Choose the right model. After a simple statistical analysis of the input data, such as mean and volatility, a suitable prediction model is selected based on some implicit information. The important factors for choosing a suitable model also include the scope of the prediction and the accuracy of the prediction.

4. Optimize the parameters of the model and check the predictive efficiency of the model.
5. Model evaluation. Some error criteria are used to evaluate the degree of fit between the predicted value of the model and the true value, and to measure the prediction accuracy of the model.
6. Successfully apply the model to the actual electricity price forecast.

Preprocessing of Electricity Monthly Clearing Price Data

Changes in electricity prices are affected by various factors, so the time series of electricity prices are almost always non-stationary and non-linear. If some data preprocessing techniques are used before prediction to reduce some data fluctuations, and then a prediction model is constructed on the processed data, the final prediction accuracy is often higher than that of direct prediction. At present, the data preprocessing technology used in the field of electricity price forecasting mainly includes normalization technology.

1. Data normalization. This technology is a data processing method that is often used at present. If the magnitude of the data in each dimension differs greatly, it will lead to a large prediction error. Therefore, data normalization can eliminate the difference between input data and output data. At the same time, in order to speed up the training speed of the neural network, data normalization is also adopted. At present, there are mainly two commonly used data normalization methods. The first is the maximum minimum method. The specific form is as follows:

$$x_t = \frac{x_t - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

In the formula (4), x_k is the original data sequence; $x_{\max}$ is the maximum value in the data sequence; $x_{\min}$ is the minimum value in the data sequence [9].

Based on the price prediction process and data preprocessing technology designed this time, in the context of the continuous adjustment of supply and demand in the electricity market, the BP neural network is used to predict the monthly clearing price of electricity.

2.3 Constructing a Training Sample Set of Electricity Monthly Clearing Prices

Time Information Extraction

The monthly electricity clearance data has significant periodicity, but this periodicity contains very important information. For this reason, the time characteristics of the monthly electricity clearance data are extracted according to Table 1.

Table 1. Time characteristics of monthly electricity clearance data

Serial number	Feature name	Description
1	Day of the week	Day of the week
2	Day of the year	The day of the year
3	Day of the month	The day of the month
4	Week of the year	Week of the year
5	Hour of the day	Which hour of the day
6	Month of the year	Which months of the year

Electricity prices are obviously cyclical, and this cyclicality is determined by a number of aspects. For example, the price of electricity on day d and hour τ is definitely the same as the price of electricity on day $d - 1$ and hour τ. There is a certain periodicity, etc., so based on the above questions, six time features related to electricity price forecasts are extracted.

Load Information Extraction

Regional load and overall load are two very important features provided by the data set. Because the price of electricity fluctuates, the electric load plays a very important role in it, because if the electric load is very high, in order to reduce The pressure of equipment, the market will increase the price of electricity, which will cause some price-sensitive users to reduce the generation of unnecessary electricity, thereby reducing the overall electricity consumption, and this feature is lagging, that is, at time τ It is found that after the power load increases, the power price will be increased at time $\tau + 1$ to reduce the power consumption, and there is a great correlation between the power price and the load information, and the impact of the load characteristics on the power price is fully considered, so the following table is extracted. Table 2 shows the electrical load characteristics.

Table 2. Electrical load characteristics

Serial number	Feature name	Description
1	t value from $N \times 24$ h earlier	N $\times$ the overall load value 24 h ago
2	z value from $N \times 24$ h earlier	N $\times$ the overall load value 24 h ago
3	t value from N h earlier	Overall load value N hours ago
4	z value from N h earlier	Area load value N hours ago
5	Difference between total load and zonal load	Difference between regional load and overall load
6	Difference between zonal load and $N \times 24$ h earlier zonal load	The difference between the area load and the area load N $\times$ 24 h ago
7	Difference between total load and $N \times 24$ h earlier total load	The difference between the overall load and the overall load N $\times$ 24 h ago

As shown in Table 1, where N is the dimension of the corresponding feature. Take N × the overall load 24 h ago as an example. If N is 1, the feature is a one-dimensional and only contains the overall load 24 h ago. If N is 3, the feature includes three dimensions, namely, the overall load at 24 h, 48 h, and 72 h ago.

2.4 Establish a Model for Forecasting Electricity Monthly Clearing Prices

Since the electricity price model of the power system reflects the non-linear mapping relationship between the electricity price and various influencing factors, the BP neural network is a multilayer non-linear mapping network that uses the minimum mean square error learning method to minimize its evaluation function., Complete the mapping of input signal to output mode [10]. It can realize complex and highly non-linear mapping for complex type pattern recognition. To this end, the BP neural network is used to predict the monthly clearing price of electricity under the background of the continuous adjustment of supply and demand in the electricity market.

BP neural network is a three-layer network structure, which is composed of input layer, hidden layer and output layer. Each layer may contain a different number of neurons. At different layers, each neuron has a nonlinear transfer function. The basic structure of BP neural network is shown in Fig. 1.

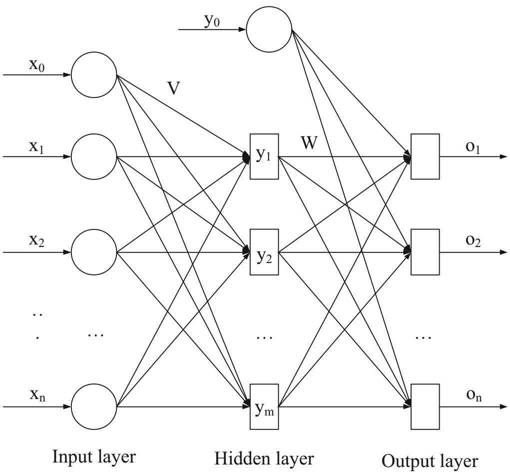


Fig. 1. Basic prediction structure of BP neural network

Figure 1, the input vector of BP neural network is $X = (x_1, x_2, \cdots, x_i, \cdots x_n)^T$, $x_0 = -1$ is set for the hidden layer neuron reference threshold; the implicit output vector is $Y = \left(y_1, y_2, \cdots, y_j, \cdots y_m\right)^T$, $y_0 = -1$ is the output layer neuron reference threshold and Set; the output vector of the output layer is $O = (o_1, o_2, \cdots, o_k, \cdots o_l)^T$; the expected output vector is $C = (c_1, c_2, \cdots, c_k, \cdots c_l)^T$. The weight matrix between the input layer and the hidden layer is represented by V: $V = \left(V_1, V_2, \cdots, V_j, \cdots V_m\right)^T$, where the column vector V_j is the weight vector corresponding to the j neuron in the hidden layer; the weight matrix between the hidden layer and the output layer is represented by W: $W = (W_1, W_2, \cdots, W_k, \cdots W_l)^T$, The column vector W_k is the weight vector corresponding to the k neuron in the hidden layer.

Based on the basic prediction structure of the BP neural network selected in this experiment, the unipolar Sigmoid function is selected as the transfer function $f(x)$ of the prediction model:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

The basic prediction structure of the BP neural network selected this time, the input layer calculation formula is:

$$\begin{aligned} o_k &= f(net_k) \quad k = 1, 2, \cdots l \\ net_k &= \sum_{j=0}^{m} w_{jk} y_j \quad k = 1, 2, \cdots l \end{aligned} \tag{6}$$

In the formula (6), *net* represents the number of input networks in the BP neural network.

The calculation formula for the output layer is:

$$\begin{aligned} y_i &= f\left(net_j\right) \quad j = 1, 2, \cdots m \\ net_j &= \sum_{i=0}^{n} v_{ij} x_i \quad j = 1, 2, \cdots m \end{aligned} \tag{7}$$

In addition to the above calculation process of the input layer and output layer, it is also necessary to determine the learning algorithm of the network. In this study, considering the training error existing in the prediction process, two processes of forward propagation and reverse broadcasting of errors are adopted. As the learning algorithm of this study, the specific process is as follows: when forward propagation, the input samples are transferred from the input layer The input is processed by various layers and then passed to the output layer. If the actual output of the output layer does not match the expected output, then it goes to the error back propagation stage. Error backpropagation is to pass the output error back to the input layer layer by layer through the hidden layer in some form, and apportion the error to all the units of each layer, so as to obtain the error signal of each layer unit, and this error signal is used as a correction for each unit The basis of the weight [11]. The weight adjustment process of each layer of this signal forward propagation and error backward propagation is carried out in a round-robin fashion. The process of constant weight adjustment is the learning and training process of the network. This process continues until the network output error is reduced to an acceptable level, or until the preset number of learning times. Then the network error definition and weight adjustment process are as follows:

When the network output is not equal to the expected output, there is an output error e:

$$e = \frac{1}{2}(c - o)^2 = \frac{1}{2}\sum_{k=1}^{l}(c_k - o_k)^2 \tag{8}$$

Expanding the output error shown in formula (1) to the hidden layer and the input layer, there are:

$$e = \frac{1}{2}\sum_{k=1}^{l}[c_k - f(net_k)]^2 = \frac{1}{2}\sum_{k=1}^{l}\left[c_k - f\left(\sum_{j=0}^{m} w_{jk}y_j\right)\right]^2 \tag{9}$$

It can be seen from formula (9) that the network error is a function of the weights w_{jk} and v_{ij} of each layer, so adjusting the weights can change the error e. Obviously, the principle of adjusting the weight is to continuously reduce the error, so the adjustment of the weight should be proportional to the gradient of the error, that is:

$$\begin{aligned} \Delta w_{jk} &= -\eta \frac{\partial e}{\partial w_{jk}} \quad j = 1, 2, \cdots m;\ k = 1, 2, \cdots l \\ \Delta v_{ij} &= -\eta \frac{\partial e}{\partial v_{ij}} \quad j = 1, 2, \cdots m;\ k = 1, 2, \cdots l \end{aligned} \tag{10}$$

In the formula (10), the negative sign represents the gradient descent, and the constant $\eta \in (0, 1)$ represents the proportional coefficient, which reflects the efficiency of learning in training [12]. Under the effect of this learning algorithm, the flow characteristics of the predicted model signal constructed this time are shown in Fig. 2.

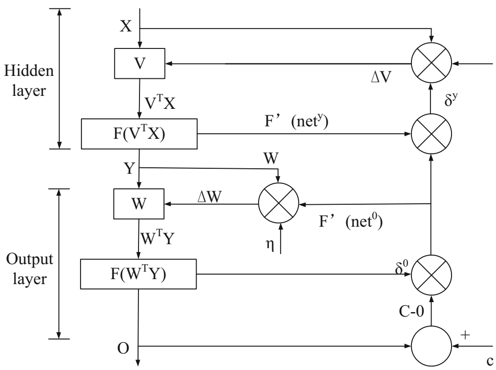


Fig. 2. The flow of predictive model signals

It can be seen from Fig. 2 that the forward process: After the input signal X enters from the input layer, the output signal Y of the layer is obtained through the internal weight vector V_j of each node of the hidden layer; the signal is input forward to the output layer, and the weight of each node is Vector W_k, get the output O of this layer. The reverse process is: the expected output c in the output layer is compared with the actual output O to obtain the error signal δ^0, from which the adjustment of the weight of the output layer can be calculated; the error signal δ^0 is transmitted back to the hidden layer through the vector of each node of the hidden layer each node obtains the error signal δ^y of the hidden layer, from which the adjustment amount of the weight of the hidden layer can be calculated [13].

In summary, the monthly electricity clearing price forecast model established this time, the process of predicting the monthly electricity clearing price is as follows:

1. Initialization: Assign random numbers to the weight matrix W and V, set the sample mode counter p and the training times counter q to 1, the error e to 0, the learning rate η to a decimal in the interval (0,1), The accuracy $e_{\min}$ achieved after training is set to a positive decimal.
2. Input the training samples and calculate the output of each layer: use the current samples X^p and c^p to assign values to the vector arrays X and c, and calculate the components of Y and O.
3. Calculate the output error of the network: suppose there are P pairs of training samples, the network has different errors $e^P = \sqrt{\sum_{k=1}^{l} \left(c_k^p - o_k^p\right)^2}$ for different samples, and the root mean square error $e_R = \sqrt{\frac{1}{P}\sum_{p=1}^{P} \left(e^P\right)^2}$ is used as the total error of the network.
4. Calculate the error signal of each layer: calculate δ_k^0 and δ_j^k.
5. Adjust the weights of each layer: Calculate the components of W and V.
6. Check whether one round of training is completed for all samples: if $e_R < e_{\min}$, the training is over, otherwise $e = 0$ and p are set to 1, and return to step 2.
7. After training, take the quantity to be demanded as input, and the output obtained is the quantity to be demanded.

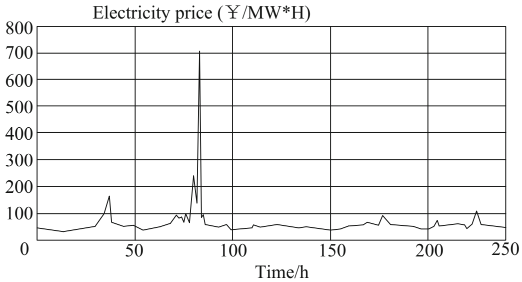
3 Experiment and Analysis

Two sets of commonly used forecasting methods are selected, and the monthly clearing prices of power plants in a certain area are selected as the data set of this experiment by means of comparative experiments, and the three sets of forecasting methods are compared to predict the average absolute percentage error of the monthly clearing prices.

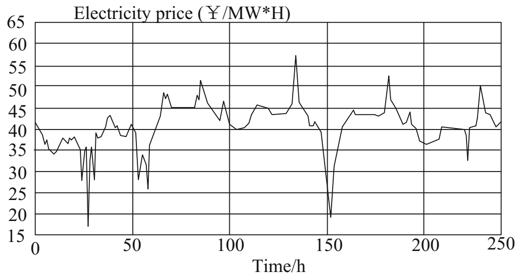
3.1 Experiment Preparation

In this experiment, the monthly clearing price of power plants in a certain region is selected. According to the climate of the region, the most typical month is selected from the four seasons of summer, autumn, spring and winter as the three sets of prediction data, as shown in Fig. 3. As shown, and use one week's historical data to predict the electricity price on the last day of the week.

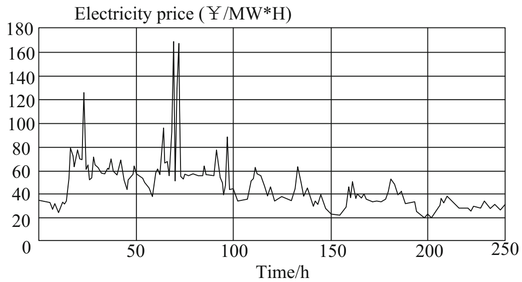
It can be seen from Fig. 3 that the characteristics of electricity price fluctuations in these four months are different. The price curve is constantly changing at different



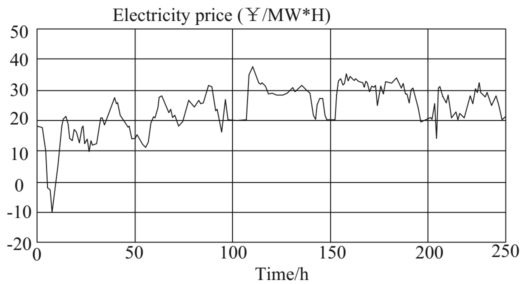
(a)Electricity price graph for one week in January



(b)Electricity price graph for one week in April



(c)Electricity price graph for one week in July



(d)Electricity price graph for one week in October

Fig. 3. Monthly clearing price of power plants in a certain area

times of the day. It can be seen that the electricity prices in this area fluctuate a lot in January and July and there are extremely high electricity prices.

Based on the monthly clearing price of the power plant shown in Fig. 3, three sets of forecasting methods are used to predict the monthly clearing price of electricity at different times in the above four months. The prediction results are as follows.

3.2 Experimental Result

The First Set of Experimental Results

Based on the experimental data selected in this experiment, three sets of forecasting methods are used to predict the monthly electricity price of the area in the first 10 days of January according to the monthly electricity price of the first 10 days of January as shown in Fig. 3 (a). The electricity price is cleared, and the average absolute percentage error in the formula (2) is used to calculate the relative error between the forecast results of the three sets of forecasting methods and the actual results of the monthly electricity clearing price in the region. The calculation results are shown in Table 3.

Table 3. Forecast results of the monthly clearing price of electricity in January (%)

Time/day	Method		
	Research method	Common method 1	Common method 2
1	0.01	2.23	0.84
2	0.05	4.35	0.30
3	0.07	4.90	0.87
4	0.09	2.34	0.71
5	0.06	2.27	0.49
6	0.03	2.25	0.49
7	0.02	2.66	0.91
8	0.04	2.59	0.55
9	0.03	2.49	0.59
10	0.02	2.44	0.27

As can be seen from Table 3, based on the monthly settlement electricity price in Fig. 3 (a) in early January, the method in this paper predicted the monthly settlement electricity price and the actual monthly settlement electricity price in late January in this region. The average absolute percentage error of the proposed method is less than 0.1%, which is obviously superior to the two traditional methods. This result shows that the method presented in this paper has a good prediction accuracy for monthly settlement electricity price.

The Second Set of Experimental Results

Using three sets of forecasting methods, according to the monthly clearing price of electricity in the first 10 days of April shown in Fig. 3 (b), predicting the monthly clearing price of electricity for the 10 days after April in the area, and adopting formula (2) the average absolute percentage error, calculate the relative error between the prediction results of the three sets of forecasting methods and the actual results of the monthly clearing price of electricity in the region. The calculation results are shown in Table 4.

Table 4. Forecast results of monthly electricity clearing price in April (%)

Time/day	Method		
	Research method	Common method 1	Common method 2
1	4.31	8.88	9.15
2	4.43	8.15	9.35
3	4.54	8.10	9.13
4	4.69	8.59	9.27
5	4.75	8.64	9.91
6	4.72	8.52	9.22
7	4.05	8.59	9.84
8	4.67	8.55	9.73
9	4.51	8.61	9.69
10	4.48	8.60	9.76

It can be seen from Table 3 that the research method is based on the monthly clearing price of electricity in the first 10 days of April as shown in Fig. 3 (b), and predicting the monthly clearing price of electricity for the 10 days after April in this area, and the actual monthly clearing price. The average absolute percentage error of the cleared electricity price is less than 5%, which is significantly better than the two commonly used methods, and has better prediction accuracy of the monthly cleared electricity price.

The Third Set of Experimental Results

Using three sets of forecasting methods, according to the monthly clearing price of electricity in the first 10 days of July shown in Fig. 3 (c), predicting the monthly clearing price of electricity for the 10 days after July in the area, and adopting formula (2) The average absolute percentage error P in, calculate the relative error between the prediction results of the three sets of forecasting methods and the actual results of the monthly clearing price of electricity in the area. The calculation results are shown in Table 5.

Table 5. Forecast results of electricity monthly clearing price in July (%)

Time/day	Method		
	Research method	Common method 1	Common method 2
1	1.49	4.98	6.98
2	1.45	4.94	6.94
3	2.81	6.30	8.30
4	2.35	5.84	7.84
5	2.72	6.21	8.21
6	2.59	6.08	8.08
7	2.79	6.28	8.28
8	2.03	5.52	7.52
9	1.55	5.04	7.04
10	1.37	4.86	6.86

It can be seen from Table 3 that the research method is based on the monthly clearing price of electricity in the first 10 days of July as shown in Fig. 3 (c), and predicting the monthly clearing price of electricity for the 10 days after July in this area, and the actual monthly clearing price. The average absolute percentage error of the cleared electricity price is less than 3%, which is significantly better than the two commonly used methods, and has better prediction accuracy of the monthly cleared electricity price.

The Fourth Set of Experimental Results

Using three sets of forecasting methods, according to the monthly clearing price of electricity in the first 10 days of October shown in Fig. 3 (d), predicting the monthly clearing price of electricity for the 10 days after October in the area, and adopting formula (2) The average absolute percentage error in, calculate the relative error between the forecast results of the three sets of forecasting methods and the actual results of the monthly clearing price of electricity in the region. The calculation results are shown in Table 6.

Table 6. October electricity monthly clearing price forecast results (%)

Time/day	Method		
	Research method	Common method 1	Common method 2
1	0.68	3.67	6.49
2	0.81	3.80	6.62
3	0.87	3.86	6.68
4	0.73	3.72	6.54
5	0.61	3.60	6.42
6	0.53	3.52	6.34
7	0.62	3.61	6.43
8	0.65	3.64	6.46
9	0.54	3.53	6.35
10	0.66	3.65	6.47

It can be seen from Table 3 that the research method is based on the monthly clearing price of electricity in the first 10 days of October as shown in Fig. 3 (d), and predicting the monthly clearing price of electricity for the next 10 days of October in this area, and the actual monthly clearing price. The average absolute percentage error of the clearing electricity price is less than 1%, which is significantly better than the two commonly used methods, and has better prediction accuracy of the monthly clearing electricity price.

4 Conclusion

This study fully analyzes the impact of the constant adjustment of supply and demand on the electricity price in the electricity market, and uses the time information and load information to construct the training sample of monthly settlement electricity price, thus combining with the BP neural network to complete the prediction of the monthly clearing price. The prediction accuracy of this method is high, and the average absolute percentage error of the prediction results is obviously less than that of the traditional method, which proves that it is suitable for popularization and application.

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