Application of BP Dual Network Model Considering Internal and External Factors in Short-Term Load Forecasting

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Abstract. In the reform of electricity sales, the accuracy of short-term load forecasting is very important for power grid operation scheduling, user demand response and pricing mechanism. Based on the theory of internal and external factors, the paper accurately extracted temperature, humidity, entropy of peak load and load volatility as the main influencing factors. Based on the artificial intelligence learning method, it introduced experts' experience to build a dual neural network short-term load prediction model, simulated load characteristics from multiple angles, and accurately predicted the trend. The simulation results show that the improved short-term load prediction model is more suitable to deal with dynamic problems due to its fast convergence speed and high prediction accuracy.

1. Introduction
Short-term load forecasting [1] is an important basis for power system operation and dispatch, which directly affects the safe and stable operation of the distribution network. In recent years, my country's time-sharing electricity price policy has been continuously promoted, the electricity sales market has been continuously liberalized, and the market-oriented electricity reform mechanism has been continuously improved. This allows power companies and third-party electricity sales companies to strive for timely and accurate grasp of short-term load change trends and to achieve accurate delivery of customer energy services. From sales, services and other aspects of business to obtain greater benefits for electricity sales enterprises. At the same time, in the face of national energy reform, the restructuring of an integrated energy system with price as a constraint is more suitable for future energy development. In summary, new energy trends and changes in energy policies have put forward higher requirements for short-term load forecasting and refined building and user forecasting. Correspondingly, how to solve the problems of large sample data, diverse influencing factors, and model input redundancy has become the focus of scholars.

In distribution network load forecasting, commonly used methods include time series method, regression analysis method, supervised learning, unsupervised learning and deep learning methods. Refs. [2-3] summarizes the power load forecasting methods. It is summarized as regression analysis method and gray forecasting method. It is suitable for medium- and long-term load forecasting with few data samples and simple data relationships; intelligent algorithms such as neural networks and support vector machines are suitable. For short-term real-time load forecasting with a large number of data samples and high forecasting accuracy. In Refs. [4-6], LSTM and SVR methods are used to construct load forecasting model of distribution network before hours. The prediction accuracy LSTM is better than the SVR prediction method, but the influence of meteorological factors is only taken into account for the model input items, and no in-depth analysis is made, which cannot fully explain the
load curve characteristic information. Ref. [7] also considers the external meteorological influence factors, but it does not excavate its internal influence factors from the load itself, and the internal factors are the fundamental factors that cause changes in things. In-depth analysis of the internal and external factors affecting short-term load, and accurate input of model inputs can further optimize the model and improve forecast accuracy.

Therefore, in the paper, through the analysis of the main influencing factors of short-term load forecasting of the distribution network, two internal characteristic indicators reflecting the load characteristics, such as peak load entropy and load volatility, are added. Considering the expert experience at the same time, a prediction model of BP dual neural network considering expert revision is proposed. By establishing a double network structure, the limitation of a single model is broken, and a multiple combined prediction model is established to predict the short-term load of the distribution network. It is verified by examples that the prediction model enhances the network diversity and effectively improves the network generalization ability, which provides an effective basis for the establishment of smart grid dispatching and distribution network sales mechanisms, and further expands the economic benefits of grid operations.

2. Analysis of Internal and External Factors

Internal and external factors refer to the method used by psychologists to infer causality, seeking behavioral dynamic factors from behavioral results. The external cause is the inducing condition of motivation, and the internal cause is the existence basis of motivation. In order to analyze the characteristics of distribution network load characteristics from all angles and accurately select the input of the prediction model, the paper first analyzes the internal and external factors affecting the short-term load of the distribution network based on this theory.

In order to prove the feasibility of the forecasting model in the paper, the actual load data and influencing factor data of a city in Zhejiang from 2016 to 2018 were selected. Through curve decomposition and characteristic analysis, a high-precision distribution network short-term load forecasting model was gradually constructed.

(1) Externally influenced meteorological indicators

It can be seen from a large amount of Ref. [8] that economic, meteorological, energy and other indicators have different degrees of influence on the power load of the distribution network. The main influencing factors of annual scale load data are macro indicators such as economy and trade; monthly scale load data more reflect the seasonality and trend of load. Generally, the sensitivity of temperature and humidity in winter and summer is relatively high, and the impact is the largest; The finer the time scale, the greater the influence of meteorological factors. The monthly load sensitivity of the same factor is 80 to 400 times higher than the annual load. In particular, as the global climate keeps warming, the high temperature in summer continues to increase, and the maximum load in summer also breaks through the maximum year after year. Therefore, this article will select daily load and temperature data from 2016 to 2018 to conduct an in-depth analysis of the impact of continuous high temperature weather on the load.

As shown in figure 1, the maximum temperature of the city in 2016-2018 is 40.4℃, and the maximum peak load is 7421.5MW. According to the load curve, a multi-step linear regression model [9] is used in the paper, and the temperature of n days of continuous backtracking corresponds to n predictors, and the peak load value of that day is the only regression variable y. Take \( n = 3, 4, 5, 6, 7 \) different values as 5 kinds of test cases, determine the corresponding regression P value to choose.

After calculation, the regression models obtained under the five scenarios have the same conclusion: the temperature of the previous day and yesterday has a greater weight on the peak load of the day, and the degree is significant. That is, the temperature for 3 consecutive days is most closely related to the peak load of the day.

The regression model constructed is:

\[
D_i = 316.9T_i + 158.46T_{i-1} + 2073.49 \quad \text{(MW)}
\]
The calculation from the above formula shows that the city has the greatest impact on the peak load and the most sensitive change when the temperature in 3 weathers continues above 32°C, and it will reach the peak value throughout the year.

In summary, the paper will use temperature and humidity as input for the short-term load forecasting model, and explain the uncertainty of short-term load through external factors.

(2) Intrinsic influence load characteristic index

The load characteristic index is an important refinement index that effectively describes the load characteristics of regions and users through change rates, curves, etc. Traditional user load characteristic analysis is mostly qualitative analysis, which is mainly limited by incomplete collection methods, incomplete information management, and difficulty in obtaining historical data. With the development of various information technologies such as perception, Internet of Things, cloud computing, and 5G, the frequency of grid data collection increases, and the analysis and mining of massive data provide the necessary conditions for quantitative analysis of load characteristics and trend simulation.

Therefore, the paper proposes two peak load entropy value and load fluctuation rate to describe the peak characteristics and load stability indicators, as short-term load forecasting model input, through the inherent characteristics to explain the uncertainty of short-term load.

Peak load entropy value: In information theory, entropy is usually used to characterize the uncertainty of information and is called information entropy. The peak load entropy is a measure of the uncertainty of peak load and is used to describe the change of peak load.

$$ S_n = - \sum_{i=1}^{k} p_i \log p_i \quad i = 1, 2, \ldots, k $$

In the formula, the logarithm generally takes 2 as the base, which is the probability of more than 90% of the peak load in a certain period, and k is the value of multiple periods. In general, the systematic law is orderly, the lower the information entropy, and vice versa.

Load fluctuation rate: The degree of load dispersion per unit of average load is the ratio of the average load to the standard deviation of the load within a certain period of time. What is shown is the relative situation of load fluctuation or dispersion degree. The smaller the load fluctuation rate, the better the power supply.

3. BP Dual Network Prediction Model

With the continuous accumulation of massive grid load data and related factor data, in many studies in the industry, the single trend extrapolation model is no longer used, and most factors such as meteorology, energy, and economy are considered. Intelligent learning models such as artificial neural
networks are constructed. Through long-term data accumulation and iteration, the model continuously corrects errors through model self-learning to simulate historical trends to the greatest extent. However, these analyze historical curve characteristics from the perspective of objective data. In the actual operation of the distribution network, it is also affected by multiple factors such as systems, humans, and policies. Because of the minute impact, it is difficult to accurately analyze the degree of influence of these factors on the model. Therefore, it is necessary to introduce expert intervention to further modify the predicted value, construct a dual network structure from the subjective and objective perspectives, and better simulate the historical trend of the load. Therefore, the paper proposes a BP dual network prediction model considering expert correction.

3.1. BP Neural Network Prediction Method
Considering the short-term load forecasting model revised by experts based on the BP neural network, the first layer network first predicts the maximum output power.

BP (Back Propagation) neural network [10] was first proposed by the Rumelhart and McClelland team in 1986 and is a network intelligence algorithm. With the ability to learn and store complex mapping relationships, it is a multi-layer feedforward neural network trained according to the error back propagation algorithm. Because of its easy operation and wide application, it is widely used in various fields of society such as power, medical treatment, and finance. BP neural network has the ability to arbitrarily complex pattern classification and excellent multi-dimensional function mapping ability. Through the calculation of output accuracy, the weights and thresholds of the network are continuously adjusted by means of back propagation, and the feedback and adjustment are continuously performed. The square error is the smallest.

The commonly used BP neural network model is a model that includes an input layer, a hidden layer, and an output layer. According to the characteristics of the input data, each layer is equipped with a different number of neurons. According to the short-term load output characteristics of the distribution network and the analysis results of the influencing factors in the previous chapter, the paper finally determines that the model input layer is the four main factors that affect the load of the distribution network, namely temperature, humidity, peak load entropy, and load fluctuation rate. The output layer is the maximum output power. The structure of BP neural network is shown in figure 2.

![Figure 2. Topology diagram of BP neural network structure.](image)

According to the above structure, for the output layer

\[ o_k = f(n_{et_k}), \ k=1,2,...n \]  

\[ net_k = \sum_{j=0}^{m} w_{jk} y_j, \ k=1,2,...n \]  

For hidden layers

\[ y_j = f(n_{et_j}), \ j=1,2,...m \]  

\[ net_j = \sum_{i=0}^{n} v_{ji} x_i, \ j=1,2,...m \]
In general, the unipolar Sigmoid function, bipolar Sigmoid function or hyperbolic tangent function are usually used as the transfer function of the output layer and the hidden layer. The paper considers the characteristics of power load data, conducts comparative training on different functions, and determines that the transfer function from the input layer to the hidden layer of the short-term load forecasting model of the distribution network is a unipolar Sigmoid function based on the principle of fast convergence speed and small root mean square error. The transfer function from the hidden layer to the output layer is a linear function.

Define the error function as follows:

\[ E = \frac{1}{2} \sum_{k=1}^{l} (d_k - o_k)^2 \]  

(7)

Expand the error to the hidden layer until the input layer, the calculation function is as follows:

\[ E = \frac{1}{2} \sum_{k=1}^{l} [d_k - f(\sum_{j=0}^{m} w_{jk}f(\text{net}_k))]^2 = \frac{1}{2} \sum_{k=1}^{l} [d_k - f(\sum_{j=0}^{m} w_{jk}f(\sum_{i=0}^{n} v_{ji} x_i))]^2 \]  

(8)

During network training, it is necessary to continuously feedback and adjust the weights until the error accuracy meets the set requirements. Therefore, in the paper, the minimum root mean square error is used as the weight adjustment principle, and the fast gradient descent method is used to make the weight adjustment amount proportional to the negative gradient of the error during network training, so as to speed up the network convergence speed:

\[ \Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}}, \quad j=1,2,...m, \quad k=1,2,...n \]  

(9)

\[ \Delta v_{ji} = -\eta \frac{\partial E}{\partial v_{ji}}, \quad i=1,2,...n, \quad j=1,2,...m \]  

(10)

The gradient descent is represented by a minus sign, and the learning speed is represented by \( \eta \in (0,1) \).

\[ \delta_k^\infty = -\frac{\partial E}{\partial \text{net}_k} \]  

(11)

\[ \delta_j^\infty = -\frac{\partial E}{\partial \text{net}_j} \]  

(12)

After adjusting the weights, adjust the error formula as follows:

\[
\begin{align*}
\Delta w_{jk} &= \eta \delta_k^\infty y_j = \eta (d_k - o_k) o_k (1 - o_k) y_j \\
\Delta v_{ji} &= \eta \delta_j^\infty x_i = \eta (\sum_{k=1}^{n} \delta_k^\infty w_{jk}) y_j (1 - y_j) x_i
\end{align*}
\]  

(13)

And

\[ \delta_k^\infty = (d_k - o_k) o_k (1 - o_k) \]  

(14)

\[ \delta_j^\infty = (\sum_{k=1}^{l} \delta_k^\infty w_{jk}) y_j (1 - y_j) \]  

(15)

3.2. BP Double Network Prediction Model Considering Expert Revision

Electricity load is closely related to our daily production and life, but its output prediction is often uncertain. Mainly due to many influencing factors, although the multi-input multi-output neural network model is considered, the single prediction model still has defects such as slow network...
training speed, unsound feature information of objects, and poor robustness, which is difficult to meet real-time online learning and prediction accuracy Requirements. Therefore, in order to consider the comprehensiveness of the analysis of things, the paper proposes a dual neural network prediction model that considers expert revisions to predict the short-term load of the distribution network. Through the combination of subjective and objective prediction methods, it enriches the characteristics of things and accurately captures the characteristics of changes in things. To improve prediction accuracy. The BP dual network prediction model modified by experts is shown in figure 3.

**Figure 3.** The BP dual network prediction model modified by experts is considered.

First, the first neural network uses external weather information and internal load characteristic information as inputs to predict the maximum output power of the distribution network load. Second, organize experts to give correction opinions on the load forecast results, and establish an expert correction database with the correction differences. Third, the maximum output power prediction results and expert correction library data are used as the input of the second neural network to predict the short-term load of the distribution network. This method not only considers the influence of internal meteorological factors and external load characteristics on the short-term load of the distribution network, but also uses the expert experience correction value as the subjective influencing factor input, and uses the second neural network to predict the short-term load of the distribution network. Compared with the past, a single mathematical method is used to make predictions. Considering the BP double network prediction model modified by experts, the input terminal starts with internal and external factors to accurately grasp the characteristics of things without increasing input redundancy. At the same time, due to the addition of expert experience error value as a correction term, more subjective features are enriched, and objective theoretical methods are combined with expert subjective opinions. The combination of subjective and objective methods can make the prediction model reveal the characteristics of things from all angles, the prediction result is closer to the actual value, improve the accuracy of load prediction, and provide a reliable basis for power grid dispatching and electricity bidding.

4. Example Simulation and Analysis
In the paper, the actual load data of a city in Zhejiang Province in 2018 is selected as the sample data, and the sample is standardized and interpolated considering the data consistency and validity. Finally, 200 sets of data were used to build prediction samples, of which 1-180 groups were used as model training samples, and 181-200 groups were used as test samples. Through continuous training and learning, a short-term load forecast model for a distribution network in Zhejiang was selected, and June 2019 was selected. Actual load data predicts the 24-hour load on a given day. The sample data is shown in table 1 below.

In the construction of short-term load forecasting model, the main parameters were compared and calculated. Finally, the parameters of the first-level maximum output power neural network prediction model are: the number of hidden layer nodes is 10, the number of iterations is 7000, and the learning
The classic prediction model is used as a comparison, and the maximum absolute error of each model’s prediction result is as follows in table 2.

| Prediction model               | Sequentially | BP neural network | Dual neural network model |
|--------------------------------|--------------|------------------|--------------------------|
| Maximum absolute error (%)     | 8.7%         | 5.2%             | 3.79%                    |

It can be drawn from table 2 that the maximum absolute errors predicted by the three models are 8.7%, 5.2%, and 3.79% in turn. It shows that in the short-term load forecasting of a distribution network in Zhejiang, the BP neural network prediction model is superior to the time series model, the dual neural network prediction model is superior to the single BP neural network prediction model, and Figure 4 shows the prediction curve of the dual neural network prediction model. It can better reflect the trend characteristics of actual power, and the prediction error is minimum.

5. Conclusion
The paper analyzes the main influencing factors of short-term load forecasting of the distribution network. Based on the internal and external factors theory, it accurately extracts temperature, humidity, peak load entropy value, load fluctuation rate from the model input, expands the sample
characteristics, and comprehensively reflects the load development trend. At the same time, the subjective correction value of experts is considered, and a BP double neural network prediction model considering expert correction is proposed. The model comprehensively considers the subjective and objective multiple influences, introduces subjective experience of experts, continuously forms deep learning interaction with objective data, continuously corrects model errors in the form of subjective and objective superposition, and improves prediction accuracy. It has been verified by examples that the BP dual neural network prediction model proposed by this paper considering expert correction is superior to the traditional prediction model and the single intelligent prediction model. It does not increase the complexity of the model, and can effectively accelerate the network convergence and reduce the prediction error. The model has been gradually promoted and applied in Jiangsu and Zhejiang areas, with feasibility and effectiveness. It provides auxiliary decision support for intelligent dispatch of power grids, precise planning of power grids, and the formulation of rules for placing electricity bids.

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