A Short-term forecasting model of load demand in summer of Chongqing based on BP neural network

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Abstract. Based on the historical load data collected in July and August 2020 in Chongqing, and in view of the characteristics of the regional load in summer Chongqing, a new short-term load forecasting method was put forward in this paper, which is based on BP neural network and takes into account social activities and meteorological factors. The simulation results show that the proposed short-term load forecasting method can accurately realize the daily maximum load forecasting, it provides a theoretical reference for load forecasting and power resource optimization of smart grid in the future.

1. Introduction
As an important energy source in national economy, electric power plays an important role in supporting and guaranteeing the development of social economy and the improvement of people's living standard. Because electricity is easy to control, large-scale production and long-distance transmission, etc., the development and application of electric power has become a measure of a country and regional level of social modernization, as well as the level of material civilization and spiritual civilization of one of the important signs. In accordance with the relevant requirements of the state power reform, the overall objectives of the power system reform are: to break monopoly, introduce competition, improve efficiency, reduce costs, improve the power pricing mechanism, optimize the allocation of resources, promote power development, and promote national interconnection, to establish a power market system under the supervision of the government, which is characterized by separation of government from enterprise, fair competition, opening and orderly, and healthy development[1].

With the deepening of power market reform and the rapid development of power industry in China, the development of power market has become the focus of attention [2]. At the same time, the unbalanced development of regional power supply and demand has existed in China for a long time. In the past, China's regional power demand has been in a shortage stage. In recent years, with the development of the electric power industry, the output of electric power is increasing year by year, gradually meeting the demand of electric power. But some areas in the face of excess power, while other areas have electricity shortage. With the increasing dependence of modern social life on power supply, the economic will loss caused by power-off. The development of power industry should be maintained reasonable speed in harmony with the national economy, especially, the development law of regional power demand growth is an issue we should actively explore.
The research on the relationship between electric power demand and various economic and social factors is of great significance to the rational distribution of electric power, and to the timely and accurate prediction of the future electric power demand [3]. Under the new economic situation, new changes have taken place in the economic environment in various regions, and the factors affecting the growth of electricity demand have become more complex and changeable. Therefore, the electricity demand forecasting must keep up with the situation, strengthen the investigation and analysis of the regional power market, study the law of regional power demand development in depth, improve the accuracy of forecasting, and put forward the corresponding countermeasures for power development, make the electric power industry serve the development of national economy better.

2. Influencing Factors of Electric Power demand in Chongqing

Electricity demand depends mainly on two factors, electricity price and GDP. However, with the gradual deepening of the reform of the market economy system, Chongqing's economy has made considerable progress, the industrial structure has been greatly adjusted, the people's living standards have also been significantly improved, and the energy consumption structure has also been significantly improved, all this has had an impact on power demand in Chongqing. At the same time, the gradual opening of the electricity market and the gradual implementation of the reform measures of the electricity price system also have an impact on its electricity market. Therefore, based on the current situation of Chongqing region and the theoretical and empirical research of integrated power demand forecasting model, the following factors are considered as the main factors affecting the power demand of Chongqing.

2.1. Regional gross domestic product
Regional Gross Domestic Product (GDP) is the most important determinant of electricity consumption. Economic Growth and its impact on living standards are the main drivers of growth in electricity consumption. The empirical study shows that there is a significant and stable positive correlation between GDP and electricity consumption. But in short-term load forecasting, the effect of GDP can be ignored.

2.2. Electricity price
The electricity prices are set administratively based on supply costs in China, which include all fuel, operating and maintenance costs, as well as construction costs to be recovered and reasonable profits. As many authorities at all levels of government and many stakeholders involved in the approval of the electricity price process. Electricity pricing in China is therefore a complex and sensitive issue. In spite of this, the electricity price still becomes an important variable in the electricity demand function because of its influence on the electricity demand. However, the daily electricity price is mainly affected by the purchase of electricity and hydropower, and has no effect on the market demand in Chongqing.

2.3. Industrial structure
Different stages of economic development have different industrial structure and consumption structure. The secondary sector of the economy has been a major source of electricity consumption, accounting for more than 70 percent of total annual electricity consumption. With the adjustment of industrial structure, the proportion of industrial electricity consumption in the total electricity consumption has decreased. In the short-term load forecasting, the industrial structure is basically unchanged.

2.4. Climate
Natural factors such as climate and temperature have more and more influence on the maximum load of power grid. The main manifestation is that the climate temperature has a great influence on the electric load of the primary industry, the tertiary sector of the economy and the residents, while the
electric load and the electric load of the secondary sector of the economy are relatively stable. The influence of air temperature on tertiary sector of the economy and residential electricity consumption is mainly reflected in the sensitive load of air conditioning, especially on the load characteristics

3. Short-term load forecasting model

The BP network is also called error back propagation neural network. It adopts error back propagation learning algorithm (BP algorithm), and its structure model is shown in Fig.1. The BP network consists of three neuron layers, the first layer is input layer, the second layer is middle layer, also known as hidden layer, and the last layer is output layer. A neural network system can have many hidden layers according to the needs [4].

![Fig.1 The structure of BP network](image)

The neurons in each layer form a full interconnection connection, and there is no connection between the neurons in the same layer. In addition to the output layer, the output of each node is the weighted sum of the output values of all nodes in the previous layer. The BP network has the characteristics of realizing highly complex nonlinear mapping through its own learning [5].

Learning algorithm is the key problem to design BP network. The traditional BP learning algorithm is a supervised learning algorithm. Its learning process includes forward calculation of input information and error propagation. It uses gradient search technology to reduce the error between the actual output value and the expected output value by calculating the derivative of error when each weight changes, adjusting the connection weight and neuron threshold between neurons, so that the error gradually reaches the maximum small or expected.[6]

Analyzing the historical data of Chongqing power market from July to August in 2020, it is found that the daily relative humidity, the highest temperature and the condition of holidays have a great influence on the daily load demand, so these three variables are selected as input variables, the output variable is the daily maximum load demand.

When the input variable of the neural network is determined, it needs to be normalized, which is reduced to the interval [0, 1]. The normalized data are easier to train and learn for neural networks. Because the size of the original data amplitude is not the same, and sometimes quite different. If it is put into use directly, the fluctuation of the measured value will monopolize the learning process of the neural network, which cannot reflect the change of the small measured value. The normalization process is carried out as follows.

$$X_n = \frac{x_0 - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$

(1)

Based on the historical data, the range of each input parameter is shown in Table 1. It is clear that relative humidity and holiday conditions do not require normalization.
Table 1. The range of input parameters

| Input parameter            | Range          |
|----------------------------|----------------|
| Relative humidity          | [0,1]          |
| the highest temperature    | [26.4,40.1]    |
| The holiday conditions     | [0,1]          |

The transfer function of hidden layer neurons is hyperbolic tangent type transfer function, the expression is

\[ f(x) = \tanh(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \]  

(2)

The transfer function of the output neuron is s type, and its expression is

\[ f(x) = \frac{1}{1 + e^{-x}} \]  

(3)

So as to ensure output range is between [0,1], both to meet the nonlinear and membership function range requirements. In the training process, Levenberg-Marquardt Algorithm is used, the target error is 0.0001, and the network is trained with 50 groups of historical data.

The determination of the number of hidden layer neurons is another key problem in the design of BP neural network. If there are too few networks, they cannot converge to the target error, even if they can converge to the target error, they cannot extract the exact characteristic information of the samples. If the number of hidden layer units is too many, the network structure will be too complex, which will lead to too long network training time and real-time applications in engineering. Too many hidden layer elements and too fine feature space partition make the decision surface of the network only contain training samples, which leads to the problem that the generalization ability of the network is unknown.

There are many ways to determine the number of hidden layer nodes, usually by formula (4) to determine the initial, and then based on the actual training results.

\[ n_h = \sqrt{n_i + n_o + \alpha} \]  

(4)

\( n_i \) is the number of input layer neurons, \( n_o \) is the number of output layer neurons, \( n_h \) is the number of hidden layer neurons, the integer between 1 and 10 can be taken. The effect of hidden layer neurons on the training error is shown in Fig. 2. There are too few hidden layer neurons for the network to converge to the target error, and too many hidden layer neurons for the long training time. So 10 hidden layer neurons were selected.

![Graph showing performance](image-url)
50 sets of data from July to August in 2020 were selected as training samples, and the remaining 10 sets of data were used as test samples. The actual load demand is compared with the results predicted by the neural network as shown in Table 2. As can be seen from Table 2, the average error of load forecasting is less than 2%, which meets the national standard of load forecasting accuracy (less than 5%) [5] and meets the needs of practical application. Of course, it is necessary to accumulate a large number of field data and adjust the model repeatedly.

| No. | RH | Temperature/degree | holiday conditions | Actual demand/10^7W | Calculated value/10^7W | Relative error |
|-----|----|-------------------|-------------------|----------------------|------------------------|----------------|
| 1   | 52%| 38.8              | 0                 | 2061                 | 2028                   | -1.6%          |
| 2   | 54%| 38                | 0                 | 2041                 | 2017                   | -1.1%          |
| 3   | 50%| 38.9              | 1                 | 2057                 | 2094                   | 1.7%           |
| 4   | 44%| 38                | 1                 | 1987                 | 2007                   | 1%             |
| 5   | 48%| 38.3              | 0                 | 1925                 | 1948                   | 1.2%           |
| 6   | 49%| 39.6              | 0                 | 1938                 | 1914                   | -1.2%          |
| 7   | 47%| 40.1              | 0                 | 2038                 | 2074                   | 1.8%           |
| 8   | 53%| 36.4              | 0                 | 2129                 | 2097                   | -1.5%          |
| 9   | 64%| 32.7              | 0                 | 1705                 | 1683                   | -1.3%          |
| 10  | 72%| 27.5              | 1                 | 1411                 | 1440                   | 1.4%           |

4. Conclusion
Based on the historical data of Chongqing Electric Power Company, three parameters were selected as input variables, which are daily relative humidity, daily maximum temperature and holiday conditions, a short-term forecasting model of daily maximum load demand based on BP neural network is established, and the forecasting results are verified, the BP neural network model realizes the
nonlinear mapping between daily maximum load demand and relative humidity, maximum temperature and holiday conditions, the model can accurately reflect the laws between the maximum daily load demand in summer and the relative humidity, the maximum temperature and holiday conditions, the results have certain reference value for establishing optimal scheduling based on load demand in engineering. In the spot trading of electricity market, the accuracy of short-term load forecasting is one of the key factors, the model in this paper can provide a reference for the on-site transaction in the coming power market.

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