An Improved Method of Power System Short Term Load Forecasting Based on Neural Network

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Abstract

Load forecasting is an important content of planning and operating power system. It is the prerequisite to ensure the reliable power supply and economic operation. In this paper, an improved method of short-term load forecasting for load data of two different regions is proposed. Firstly, we analyze the relationship between weather factors and load, and then the greatest impact on load of weather factors are selected. The Elman neural network is used to predict unknown one-week load data taking into account without whether factors situation and whether factors situation. In the predicting situation of considering whether factors, the multi-weather factors are integrated with the temperature and humidity index , which are used as the neural network input training samples. The prediction result is good.

Keywords: Load forecasting , Elman neural network, Temperature and humidity index

1. Introduction

Short-term load forecasting is an important part of load forecasting, which is of great significance for economic dispatch, electrical market transactions and so on.

In the load forecast theory and methods field, academia and industry have done a lot of research and have made fruitful progress. In recent years, experts and scholars have proposed a variety of methods. These methods include: single consumption method, elasticity coefficient method, partitioned load density method[1], time series method[2], trend extrapolation method[3], regression analysis method[4] and gray model method[5], artificial neural network method[6,7], expert system method[8], wavelet analysis[9], genetic algorithm[10] and support vector machine[11] and so on

Short-term load forecasting is becoming more and more important. In recent years, the maximum load of power supply increased year by year, which constitute the peak load of electricity. The load is very sensitive to meteorological changes, and the impact of meteorological factors is growing[12]. Although many models have taken into account the effect of weather on power load, most of these models only consider temperature as a single meteorological factor[13,14,15]. However, relative humidity, air pressure, wind speed, radiation and other meteorological factors will have a great impact on power load.

Most of the neural network for short-term power load forecasting requires a large number of data samples, and only forecast the power load of one day, and there is little work to predict the unknown one-week load[16,17,18]. In this paper, an improved short-term load forecasting algorithm based on Elman neural network is proposed, which can predict unknown power load data with a small amount of known load data, and achieves good results by combining the characteristics of temperature and humidity meteorological factors.

2. Short Term Load Forecasting

The feedback neural network is suitable for power system load forecasting because of input delay. According to the historical data of load, the input and output nodes of feedback neural network are selected to reflect the inherent law of power system load operation, so as to forecast the load of future time. Therefore, the primary problem of the artificial neural network for power system load forecasting is to determine the neural network input and output nodes, so that it can reflect the power load operation law.

2.1 Data sample preprocessing

2.1.1. *Processing of abnormal data*

The power load has a clear weekly change characteristics, working days Monday to Friday high, weekends low. This is due to weekend industrial electricity load reduction reasons. In addition, some holidays load, such as International Labor Day, National Day, the New Year, the Spring Festival, compared with usual day is significantly lower, which is due to the holiday industry caused by a substantial reduction in electricity. Therefore, the weekday and holiday electricity load is removed from the data sample, and only the electricity load of the working day is chosen as the historical data to improve the accuracy of the prediction result.

2.1.2. *Data sample normalization*

If the neural network directly use the original data as input, it will make the neuron training saturation. Therefore, before the network training, the data must be normalized to the same number level, so that the neural network can be converged. Finally, we can get the real load through the anti-normalization process[19].

Commonly the normalization means [0,1] is used, the formula is as follows:

Normalization：

$$y_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Anti-normalization：

$$x_i = (x_{max} - x_{min})y_i + x_{min}$$
(2)

2.2 The framework of the neural network

This paper aims to predict the two regions total of 7 unknown days load data from January 11, 2015 to January 17, 2015, based on the historical load data. We select the load data from December 25, 2014 to January 2015 10 , a load data of 17 days to be as a training sample, excluding large fluctuations changes in relatively data: the region 1 December 28, December 31, January 1 data and the region 2 December 30, December 31 Day, January 1 data. After removing the abnormal data, a total of 8 days of data from December 25, 2014 to January 4, 2015 were selected as the training samples of the network. The load is used as the input vector every 3 days and the load on the 4th day as the target vector. Thus, five sets of training samples can be obtained. A total of six days of data ,January 5, 2015 to January 10, 2015 can be as a network of test samples to verify the network reasonably predict the day's load data or not. As the daily load data are 96 points, three days of load data is as a set of input, the day's load data is as the output, so the input variable is 288 variables, the output variable is 96 variables.

The number of hidden layers is two layers, the number of the first layer nodes is 11, the number of the second layer nodes is 5, the practice effect is better.
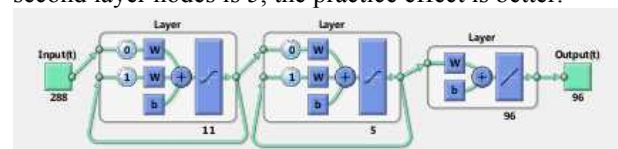

Fig. 1. The framework of the neural network for short term load forecasting

3. Short Term Load Forecasting Based on Weather Factors

The relationship between temperature, humidity and rainfall is analyzed[19]. The influence of humidity factor

on the load is more significant. Based on the above, the short-term load model based on Elman neural network is established in this section considering the effect of meteorological factors on load forecasting.

3.1 Comprehensive meteorological factors

It has been pointed out that the change of the electric load is affected by various meteorological factors, and the meteorological factors also have some coupling effect. Therefore, it can not be evaluated on the basis of single temperature or other meteorological factors. It is an important content of short-term load forecasting how to use all meteorological factors reasonably and effectively to reduce the input judgment amount and improve the prediction precision. Fig.2. shows the influence of various meteorological factors on the power load.
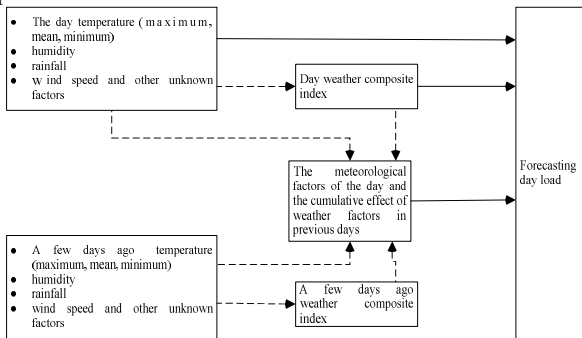

Fig. 2. The influence of various meteorological factors on the power load daily prediction

In practice, although the rainfall has a certain impact on the load forecast. However, since the rainfall mainly concentrates at a certain time of the day, the study of rainfall should be carried out for the time period during when rainfall occurs, and should not be added to each point throughout the day in a general manner. In this way, a comprehensive temperature and humidity index (Temperature and Humidity Index) is derived[19], which is derived from the effective temperature formula established by the well-known Russian scholar, and can be well described the effect of temperature and humidity on the power load. The formula is as follows.

$$THI = T_H - (0.55 - 0.55H_L) * (T_H - 58) \quad (3)$$

where, T_H is Fahrenheit, it is necessary to convert the given temperature data firstly.

Considering the correlation of meteorological factors and short-term load forecasting model based on historical load data, In this paper, the neural network input is mainly selected temperature and humidity meteorological factors, and then on the basis of the previous model this paper build a meteorological factors in the load forecasting model.

3.2 The load prediction algorithm flowchart

In this paper, the temperature and humidity index is added to each input sample of the Elman neural network (the temperature and humidity index has been normalized). Firstly, the neural network model is trained with the known date load data and the temperature humidity index. Then, when the load data of January 11, 2015 is forecasted, the actual temperature humidity index THI (1) replaces the neural network prediction THI (1), which is added to the training and iteration of the neural network. The actual temperature humidity index THI (2) of January 12 is instead of the neural network predictive THI (2) to train and iterate the neural network. Until the data of January 17 is predicted. The flow chart of the whole algorithm is shown in Fig.3.
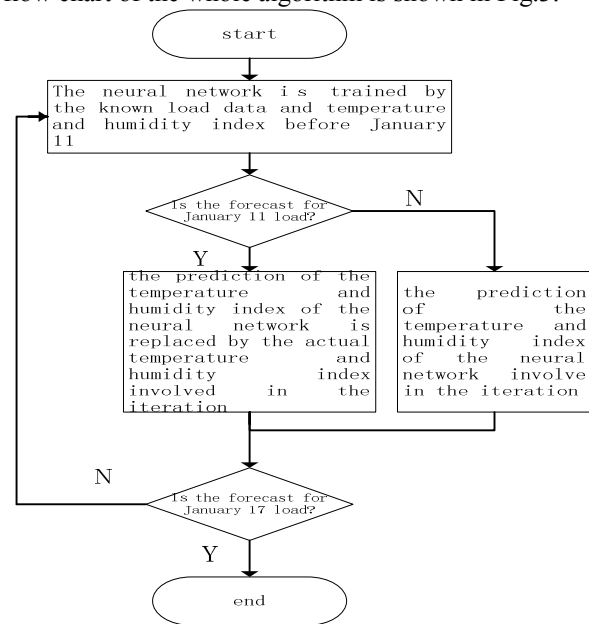

Fig. 3. Flow chart of load forecasting algorithm with meteorological factors

3.3 Experiment results

In order to test the accuracy of the forecasting model, the paper first calculates the power load of the area 2 from January 5, 2015 to January 10, 2015 (576 points) ,by taking account of the meteorological factors. The predicted results are shown in Fig. 4, and the resulting prediction errors are shown in Fig. 5.
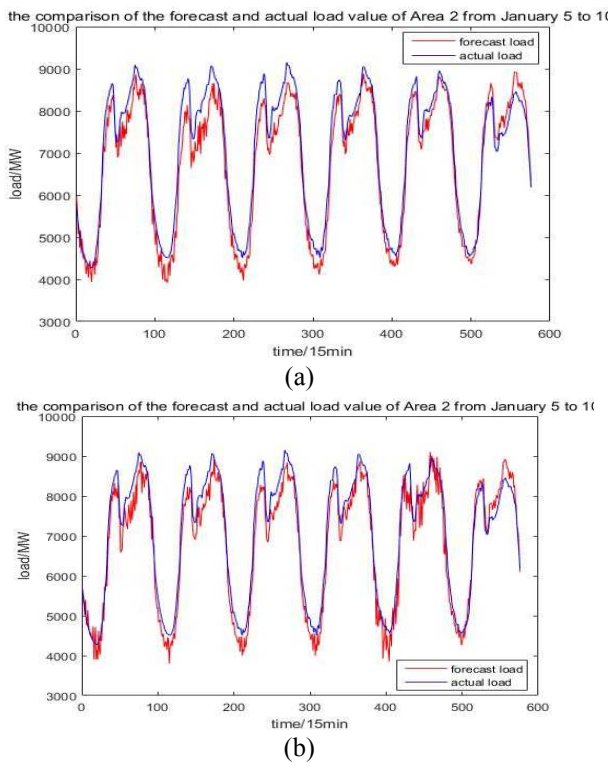

(a)

(b)

Fig.4. The forecasting result of area 2 load from from January 5, 2015 to January 10, 2015 (a) the prediction result without consideration the Meteorological Factors (b) the prediction result with consideration the Meteorological Factors
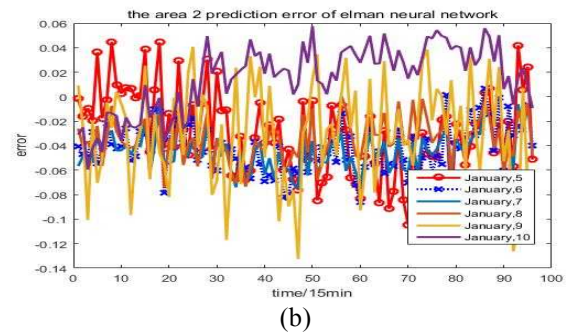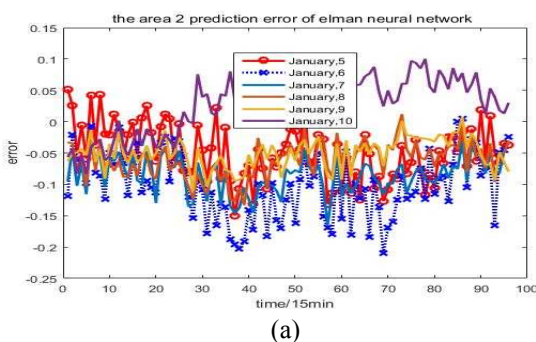

(a)

(b)

Fig.5. The prediction error of area 2 load from January 5,2015 to January 10,2015 (a)the prediction without consideration the Meteorological Factors (b) the prediction error with consideration the Meteorological Factors

In Figure 4, the difference between the predicted results in the two cases is not obvious, but it is clear from Fig. 5 that the error of the prediction result of the region 1 is greatly reduced by meteorological factors, and controlled to half of the error without considering meteorological factors, the precision of the prediction is greatly improved. In order to show the superiority of the forecasting with the meteorological factors, the power load from January 11 to 17, 2015 (672 points) is forecasted without meteorological factors. The predicted results for region 2 are shown in Fig.6.
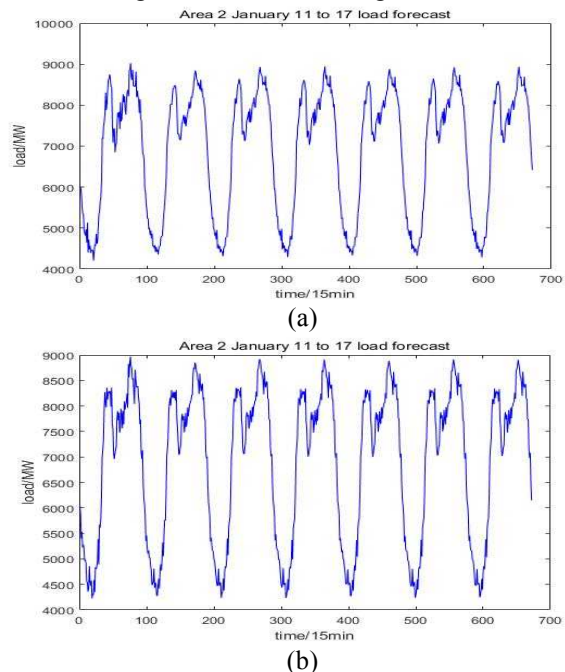

(a)

(b)

Fig.6. The forecasting result of area 2 load from January 11, 2015 to January 17, 2015 a)the prediction result without consideration the Meteorological Factors (b) the prediction result with consideration the Meteorological Factors

Based on the comparison of forecasting error and meteorological factors between meteorological factors and meteorological factors in the above two regions, it is clear that the prediction accuracy has been significantly improved with the meteorological factors. In this way, the result, which prediction model based on the Elman neural network and meteorological factors is used to forecast the load of the two regions in the period from January 1 to 17, 2015, is valuable.

4. Conclusion

In this paper, we have proposed an improved power system short term load forecasting method. We analyze the factors affect the power load and use the temperature and humidity index to be as an input sample of Elman neural network. To validate the method effectively, we use the neural network to predict two different area load data .We only use a few history load data to predict an unknown week load. The prediction result is reasonable and prediction error is small. Our method will help the manager to analyze and plan weekly load data.

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