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Short Term Load Forecasting of Power System

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Abstract. In this paper, short-term load forecasting of power system considering meteorological factors is studied. The power system load is divided into three parts: basic component, weather sensitive component and random component. Then the correction strategy of similar days is introduced and the meteorological factors is considered to improve the original BP model. And the similar days are determined according to the periodic characteristic of the load value and the grey relational analysis. Finally, by comparing the predicted data with the actual data, it is proved that the prediction model agrees with the actual situation and has higher prediction accuracy.

1. Introduction

Power system load forecasting is a mathematical method. It can deal with the past load systematically with taking some important conditions into account and predict the load at a particular time in the future at a certain accuracy [1]. Short term load forecasting is the basis of power system operation and analysis and has important significance for unit commitment, economic dispatch, security check and so on. Improving the accuracy of load forecasting is an important means to ensure the scientific decision of power system optimization. In modern power system, there are many kinds of electric appliances that form power load. The proportion of load of air conditioning and other equipment affected by meteorological conditions continued to increase. The impact of meteorological factors on the power system load is more prominent. Considering meteorological factors is one of the main means to further improve the accuracy of load forecasting.

The original BP neural network did not take the meteorological factors into account. If the meteorological factors are considered, the temperature, the relative humidity, the precipitation and so on will affect the prediction results of the neural network. So, the load is divided into basic, weather sensitive and random components. New BP neural network which is more mature is used to analyze the influence of meteorological factors on weather sensitive components. Using the grey relational analysis method to choose the appropriate similar day, which is used to improve and modifie the relevant meteorological sensitive component of the BP neural network model. Thus, the whole forecasting model is improved under the consideration of meteorological factors.

2. Assumptions

1. Meteorological factors only consider temperature, relative humidity and precipitation;
2. This paper doesn’t consider the increase and reduction of power system load under extreme conditions;
3. This paper doesn’t consider the cumulative effects of previous meteorological factors on the day's load;
4. This paper doesn’t consider the impact of holidays, such as Spring Festival on the load.

3. Symbol Specification

Table 1. Symbol and its meaning

symbol	meaning
$L_{weather}$	weather sensitive load
T_h, T_a	maximum temperature and average temperature of forecast daily
H	relative humidity after correction
$k_{1\sim5}$	related undetermined parameters
T_0, T_i	daily characteristic vector of meteorological factors
$t_{1\sim m}$	meteorological factors
$\xi_i(k)$	grey relational coefficient
$\Delta_i(k)$	absolute value of the difference between meteorological factors
ρ	weight coefficient
r_i	weather similarity factor
L'_{weather}	historical meteorological load
L_{w}	the average of predicted daily load
L'_{w}	the average of similar temperature daily load

4. Establishment of BP neural network model

4.1 Model Preparation

(1) Classification of loads

Base load component: It reflects a general trend of load over a long period of time and has stability, periodicity and seasonality. From a numerical point of view, the basic load component accounts for a larger proportion.

Weather sensitive load component: It reflects the influence of meteorological factors on the load change, which a load component is fluctuating with the fluctuation of weather.

(2) The concept of similar days

The basic principle of the similar days is to analyze all kinds of meteorological factors that affect the daily load of electricity first and form a dimensionless daily feature vectors. Then selecting the appropriate evaluation method for similar days to compare the similarity degree of different daily feature vectors and determine the history of similar days. The load to be predicted is determined by weighted average of the load data for historical similar days.

Considering the meteorological factors, if the temperature of the two dates is similar, their load curve shows similar change characteristics. So it can be used to correct the load curve of the forecast day [2].

4.2 Selection of similar days

The search method for similar days uses meteorological similarity factors for comprehensive evaluation. The meteorological similarity factors were determined by 5 indexes: maximum temperature, minimum temperature, average temperature, rainfall and relative humidityand. They are used as the daily feature vector. Then, the grey relational analysis method is used to calculate the meteorological similarity factors between the forecast day and the historical day [3].

As the power load is generally positively correlated with temperature and negatively correlated with humidity, a multivariate nonlinear regression model between the weather sensitive load and the real-time temperature and humidity can be established [4].

$$L_{weather} = k_1 T_h^2 + k_2 T_h + k_3 T_a^2 + k_4 T_a + k_5 H + C \tag{1}$$

Establish daily characteristic vector for forecast day and historical day of meteorological factors

$$T_0 = [t_0(1), t_0(2), \cdots, t_0(m)] \quad (2)$$

$$T_i = [t_i(1), t_i(2), \cdots, t_i(m)] \quad (3)$$

By grey relational analysis, the grey relational coefficient between the i historical days and the current forecast days is obtained

$$\xi_i(k) = \frac{\min_i \min_k \Delta_i(k) + \rho \max_i \max_k \Delta_i(k)}{\Delta_i(k) + \rho \max_i \max_k \Delta_i(k)} \quad (4)$$

The absolute value of difference between the k meteorological factors of the forecast day and the historical day is

$$\Delta_i(k) = |t_0(k) - t_i(k)| \quad (5)$$

Then, the meteorological similarity factors between the forecast day and the historical day can be determined:

$$r_i = \frac{1}{m} \sum_{k=1}^{m} \xi_i(k) \quad (6)$$

The meteorological similarity factor changes from 0 to 1. And the greater the value is, the higher the grey relational degree between the two days is, the higher the similarity is.

After the meteorological similarity factors are calculated, the similar days can be selected. The weather load is modified according to the similar temperature day:

$$\Delta L_{weather} = \frac{L_w}{L'_w} L'_{weather} - L_{weather} \quad (7)$$

5. Example calculation

According to the power load data of an area from January 1, 2012 to January 10, 2015 (one per 15min daily sampling points, 96 points, dimension MW) and the data of meteorological factors (daily maximum temperature, daily minimum temperature, daily average temperature, relative humidity and rainfall) from January 1, 2012 to January 17, 2015.

Similar days corresponding to seven days to be predicted are obtained in this area

Table 2. Similar day selection

Day to be predicted	20150111	20150112	20150113	20150114	20150115	20150116	20150117
Similar days	20150109	20150109	20150108	20150108	20150107	20150107	20150110

The prediction power load results in the area in January 11, 2015 to 17 is

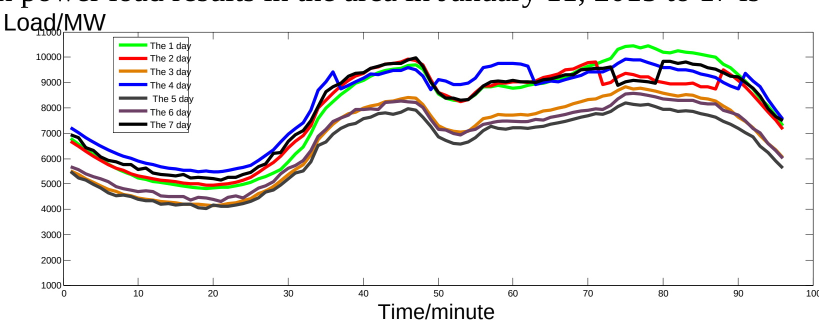

Fig. 1 Seven day load forecast curve

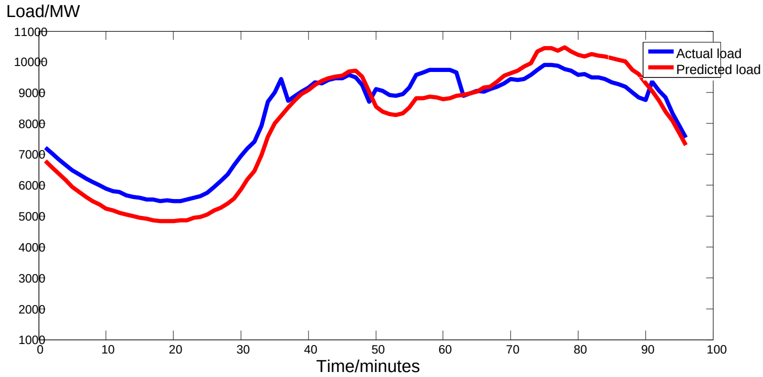

Fig. 2 Comparison of predicted and actual values

The prediction results are in line with the daily periodicity and cycle periodicity of the load and have higher accuracy

6. Conclusion

By introducing the concept of similar days to study the impact of meteorological factors on short-term power load forecasting and Fix the previous BP neural network model. We get the area after the modified average absolute percent error was 2.2088% and the old one is 2.6025%. It can be seen that the absolute percentage error of new prediction model was less than old one. So it can be deduced that the new model is better than the old one. It is also shown that the accuracy of the load forecasting is improved after considering the meteorological factors.

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