Fast Bus Load Forecasting for Smart Distribution System

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Abstract. Smart distribution network gathers massive load data with SCADA system. Bus load forecasting needs to increase the process speed while assuring the forecasting accuracy, to meet the real-time requirements. This paper proposed a fast bus load forecasting method for smart distribution system. This method utilizes the historical load and temperature data to establish a forecasting model, which derived the reference load data of the forecasting day. With temperature data of the forecasting day and the historical data, it is deduced the load correction of the forecasting day to realize online load forecasting, which increases the forecasting speed. By the instance analysis, the speediness and accuracy of the proposed method is verified.

Introduction

Bus load is the sum of terminal loads in a small area supplied by a main transformer in substation. Bus load forecasting is the key issue for power grid operating reliably and economically [1]. It is also very important for power grid operation scenario decision and energy market pricing [2] [3].

As some features of bus load itself, the accuracy of existing bus load forecasting methods is not high. The primary task of bus load forecasting is to improve the accuracy of the methods [4]. Secondly, it is needed to increase the calculation speed. The amount of data gathered by SCADA system is very large. The load forecasting is related to a large amount of data processing. Bus load forecasting is helpful to analyze the energy consumption of distribution system customs.

To fulfill the requirements of state estimation calculation in distribution system, a fast bus load forecasting method for distribution system is needed. Reference [5] proposes a D-S evidence theory based bus load forecasting method. Adopting D-S evidence theory to fuse the weight of multiple forecasting models, it is obtained the result of the forecasting day. Reference [6] presents a bus load forecasting method based on improved grey model and meteorological elements. This method takes into account several factors that influence bus load forecasting. Reference [7] presents a method based on the technique of pattern matching in similar days. Reference [8] presents a two-stage bad data identification method.

The above forecasting method mainly considers the accuracy of the methods. When these methods are applied to the distribution system with mass of data, it is also needed to fulfill the processing speed requirements. As there are plenty of external factors that affect distribution system bus load forecasting, considering too many factors will not only decrease the accuracy [9], but also the processing speed.

To solve this issue, this paper proposes a fast bus load forecasting method for smart distribution system. This method builds forecasting model based on the historical load and temperature data. With the correction to the forecasting load, it is achieved online forecasting. This increases the processing speed on the premise of accuracy. By the instance analysis, the speediness and accuracy of the proposed method is verified.

Historical Data Analysis

There are three parts in the bus load forecasting procedure: (1) acquisition and analysis of historical data; (2) build of load forecasting model; (3) correction of load forecasting model.

At first, it is needed to obtain the historical data. The historical data contains historical load data and historical temperature data. The historical load data should be preprocessed. Before training data sample, the load data are examined and repaired, for example, completion of the missing data, modification of the abnormal data and depressing noise process.

The analysis of the historical load data contains two parts, transverse analysis and longitudinal analysis. The transverse analysis is the analysis to load variation characteristic of adjacent two days and the relationship between temperature and load. The variation rules of adjacent two days' load curves are very similar, when the difference of temperatures is very small. The relationship of load and temperature is that the variation of the adjacent two days' loads is only affected by temperature, and there is only longitudinal variation. The longitudinal analysis studies the load variation characteristic of different time points in continuous few dozen days. The variation is very similar.

When the difference of temperatures is small, the load curve variation rules of the adjacent two days is very similar. The load of the whole day can be divided into load stable periods and load sensitive periods. Also, error analysis is needed for load sample sequence.

The rules of historical temperature data can be used to correct historical load data. The rules of historical temperature data contains two parts: the rules of daily and annual temperature variation.

The daily temperature variation is approximately expressed as:

$$\psi(t) = A\sin(\omega t + a) + b \tag{1}$$

In the type: $\omega = 0.125\pi$; $a = -1.25\pi$.

The parameters A and b is defined as:

$$A = \frac{T_{high} - T_{low}}{2} \tag{2}$$

$$b = T_{low} + A \tag{3}$$

In the type: T_{high} is the maximum temperature value of the whole day; T_{low} is the minimum temperature value.

The rule of Chinese city annual temperature variation is that the maximum temperature value appears in July, and the minimum value appears in January. The annual temperature variation characteristic curve is a parabolic shape curve.

The Load Forecasting Model

As temperature is the main factor that affects the load besides load itself, when building a load forecasting model, temperature is the only considered environment factor. The other environment factor is difficult to be obtained and quantized.

The historical load data and historical temperature data are analyzed. The rules of temperature variation and the correlation of the adjacent two days' load data variation are obtained. Then according to the historical temperature data of the day before the forecasting day, the reference load value of the forecasting day and the temperature data of each time points in the forecasting day, a daily load forecasting fitting function is built. The reference load value of the forecasting day and the fitting function are stored in the memory of computer during the load forecasting procedure. However, the reference load value of the forecasting day needs to be updated. A load correction value is deduced by the temperature data of the forecasting day and the historical temperature data. By the reference load value of the forecasting day and the load correction value, online load forecasting could be implemented to increase the speed of load forecasting.

The variation of seasons is considered as continuous variation related to climatic factor. As a result of it, a unified forecasting model is appointed to forecast the load data of any day in a year.

Assuming the load vector of the nth day is $L_n = [l_1, l_2, ..., l_m]$. Where m is the sum of time points. $\Delta L_{\mathrm{n+1}} = [\xi_1, \xi_2, ..., \xi_m]$ is the load correction by the n+1st day temperature T_{n+1}.

The load correction of n+1st day to nth day is:

$$f(T_n, T_{n+1}) = \Delta L_{n+1} = [f_1(T_n^1, T_{n+1}^1), f_2(T_n^2, T_{n+1}^2), ..., f_m(T_n^m, T_{n+1}^m)] \tag{4}$$

In the type: T_n is the temperature of nth day, and T_{n+1} is the temperature of n+1st day.

The defined forecasting function is:

$$\mathrm{Pr\,e}(T_n, T_{n+1}, L_n) = L_n + \Delta L_{n+1} = L_n + f(T_n, T_{n+1}) \tag{5}$$

The forecasting value of n+1st day is:

$$L_{n+1}^{''} = \mathrm{Pre}(T_{\mathrm{n}}, T_{\mathrm{n+1}}, L_{\mathrm{n}}) \tag{6}$$

When the historical load of the day before the forecasting day is defined as the reference value of the forecasting day, the solution of the original model turns into the correction of load by temperature. The variation of temperature is continuous in general. In a small time interval, the variation of temperature is very small. It is possible to use the difference of temperature in two days and the temperature itself, to get the load reference value of the second day by correct the load data of the first day. The relationship of temperature difference and corrected load in adjacent two days is:

$$f(T_n, T_{n+1}) = \begin{cases} a_1 x^2 + b_1 x + c_1 (T_{n+1}, T_n \ge T_{com}^{upper}) \\ a_2 x^2 + b_1 x + c_1 (T_{n+1}, T \le T_{com}^{upper}) \end{cases} \tag{7}$$

In the type: a, b and c are the binomial coefficients; x is the absolute difference of T_{n+1} and T_n; T_{com}^{upper} is the upper limit of comfortable temperature, T_{com}^{lower} is the lower limit of comfortable temperature.

The forecasting function should have the ability to realize self-correction according to newly historical data, and fully presents the variation characteristic of load data. The load value is corrected according the forecasting mean load data and the actual load mean data. The corrected load value is defined as the reference value of the n+1st day, L_n.

The temperatures of each time point are calculated by equation (1). Finally, it is obtained the fitting binomial expression $f(T_n, T_{n+1})$, according to the temperature and load data. The historical load data of the nth day is used to correct the forecasting value of the n+1st day. The correction method is shown as (8)-(10).

$$Load_{mean} = \frac{1}{m} \sum_{i=1}^{m} L_i \tag{8}$$

$$Load_{mean}^{'} = \frac{1}{m} \sum_{i=1}^{m} L_i^{'} \tag{9}$$

$$L_n = L_n + (Load_{mean} - Load_{mean}^{'}) \tag{10}$$

In the type: $Load_{mean}$ is the mean load value calculated by actual load values of m time points in the nth day; $Load_{mean}^{'}$ is the mean load value calculated by forecasting load values of m time points in the nth day.

Finally, the corrected historical load L_n is defined as the reference value of the forecasting model, and used to forecast the load of n+1st day.

Case Study with Field Data

A fast load forecasting for a power supply area of Jinan City is carried out for ten days with field data obtained by experiment. The forecasting results are shown in Table 1.

It is shown that the average value of ten days' daily mean forecasting accuracy is 0.89. The maximum forecasting accuracy in ten days is 0.93, and the minimum value is 0.79. The average value of calculation time is 0.56s. With the case study, the method is effective in improving the forecasting speed.

Table 1 Results of fast load forecasting

Days	Daily mean forecasting accuracy	Daily maximum forecasting accuracy	Daily minimum forecasting accuracy	Calculation time
1	0.91	0.92	0.81	0.3s
2	0.92	0.94	0.88	0.5s
3	0.88	0.91	0.83	0.6s
4	0.87	0.91	0.84	0.4s
5	0.90	0.92	0.82	0.3s
6	0.93	0.94	0.79	0.7s
7	0.85	0.89	0.80	0.9s
8	0.86	0.88	0.82	0.5s
9	0.88	0.90	0.83	0.8s
10	0.90	0.91	0.86	0.6s

Conclusion

Historical load data and temperature data is analyzed in this paper, and characteristics of the data are obtained. Considering the complexity of load forecasting, temperature is the only factor that is taken into account. Typical daily load curve is fitted according to historical load and temperature data. By the online update, the load forecasting model could correct the foresting results with real-time load data. Finally, the speediness and accuracy of this method is verified with a case study.

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