Bus load forecasting method considering user interaction response in electricity market environment

Qiuna Cai 1, Sijie Liu, Qiaoyu Zhang, Yun Yang and Binjie Yan

Electric Power Dispatching Control Center of Guangdong Power Grid Co., Ltd.,
Guangzhou, Guangdong 510600, China.

1 Email: 32016521@qq.com

Abstract. To improve the accuracy of bus load forecasting under the environment of electricity market, a bus load forecasting framework considering user interaction response is proposed. Since bus load components are complex and the response of each load to real-time electricity price is different, the identification and proportion calculation model of bus load components is firstly established. Secondly, the interactive response models of each load to real-time electricity price are established from the perspective of overall price elasticity and time-price difference elasticity. Thirdly, four different forecasting strategies are proposed with considering of electricity price elasticity, and the sequence of interaction analysis and load forecasting. Finally, a case study is carried out to verify the effectiveness of the proposed forecasting framework using the actual bus load data of a certain area in Guangdong Province.

1. Introduction

Accurate short-term bus load forecasting is the basis of power grid security check and fine management of dispatching [1,2]. Along with the deepening of electric power reform, the enthusiasm and interactive ability of market participants are greatly stimulated, and demand-side response will significantly change the temporal and spatial characteristics of bus loads [3]. Therefore, it is of great theoretical significance and practical value to research bus load forecasting technology considering demand-side response in electricity market environment.

At present, bus load forecasting methods are mainly divided into the methods based on the system load distribution [4] and the bus load variation law [5]. The former forecasting method firstly predicts the system load, and then distributes it to the corresponding bus according to a certain proportion. This method can realize the fast forecasting of bus load, but this method has been phased out due to its low accuracy. However, there is still a lack of mature solutions and theoretical guidance for the incomplete bus load information and the inconspicuous change trend when the bus load is forecasted by the latter method. Many researchers focus on exploring new forecasting methods or improving existing methods to improve the forecasting accuracy and efficiency. In [6], the day-ahead and real-time bus load forecasting models were proposed based on the artificial neural network (ANN), and the clustering analysis technique is used to improve the forecasting accuracy. Reference [7] proposed a two stage identification and recovery method to improve bus load forecasting accuracy. Reference [8] presented an aggregate forecasting model, which can be used to group buses according to the bus loads of similar days. This method has been applied to the northeastern Brazilian power grid, and the forecasting accuracy has been improved by 2%. Many scholars have studied the impact of demand response on power system load [9-12], reference [9] deeply discussed the challenges associated with...
load forecasting and demand response; reference [10] proposed a load forecasting approach with considering of active demand based on gray-box model, in which the seasonal component of load was extracted using a preprocessing method; reference [11] proposed a short-term load forecasting model based on radial basis function neural network (RBF-NN), which incorporated the comprehensive factors that affecting demand response; in [12], the demand response was introduced into the short-term load forecasting model of active distribution network (AND), and better forecasting results were obtained. However, little attention has been paid on bus load forecasting model considering user response.

This paper is not confined to the exploration of new forecasting methods, or the accuracy improvement of existing algorithms, but aims to innovate the forecasting strategies and put forward a "disassembly" forecasting framework for future bus load forecasting in Guangdong Province under the background of electricity market. Therefore, a new bus load forecasting framework with considering of user interaction response is proposed, including bus load components identification and proportional calculation module, interactive response quantitative analysis of various loads to real-time electricity price module, and bus load forecasting strategies considering price elasticity module. Each module is independent and closed, and only a fixed information flow is used as the data interface between each module, so the prediction process can be "modularized". In addition, because of the encapsulation between modules, each module can adopt different methods to solve the model. The algorithms used by each module are also independent of each other as long as the interface data are consistent, so as to achieve the "independence" of the prediction model. Meanwhile, the following model modification does not need to modify the entire module, and only the algorithm characteristics of a single module is needed to improve to achieve the disassembly of the prediction module, as shown in Figure 1. This forecasting framework has been applied to the case study of a region in Guangdong Province, through which some meaningful conclusions have been drawn.

![Figure 1. The proposed forecasting framework.](image-url)

2. Methodology

2.1. Bus load components identification and proportion calculation

Bus load components are usually complex, including industrial load, commercial load, residential load and other load. For industrial users, electricity consumption is an important part of enterprise cost.
Large-scale industry consumes a lot of electricity, so the adjustment of electricity price level will have a great impact on the cost of industrial users. Enterprises can adjust the production process to avoid peak power consumption to achieve the reduction of electricity expenditure. For commercial users, whose electricity consumption periods are relatively fixed, usually concentrating after 8 a.m. till evening, and the total commercial load is also relatively fixed, so the sensitivity of commercial users to price adjustment is small. For residential users, whose electricity consumption is relatively small, and this kind of electricity consumption mode is mainly affected by daily life habits, it is difficult to change or adjust. Therefore, when electricity price fluctuates, the change of residents' living load is not big, and the capacity of load transfer is also small. It can be seen that the residents are less sensitive to the change of electricity price. To sum up, industrial users are most sensitive to changes in electricity prices. Each load has different response characteristics to the change of electricity price, which is helpful to identify the corresponding load type. Therefore, the process of bus load components identification and proportion calculation should firstly be done when lunching effective interactive analysis.

The indices used in this paper are declared as follows, the subscript $i$ represents bus load category ($i = 0$ means the total bus load); the subscript $j$ is the number of days; the subscript $t$ represents time period, if $\Delta t = 60 / 30 / 15 / 5 \text{min}$, then the number of daily load points are $T = 24 / 48 / 96 / 288$. $P_i(t)$ is the actual load value of load category $i$ in time period $t$; $P_i'(t)$ is the standardized value of load category $i$ in time period $t$; $P_i'' = \max_{1 \leq t \leq T} |P_i(t)|$ is the base value of load category $i$ in time period $t$; $\alpha_i$ is the proportion of load category $i$ to bus load, and $i = 1, 2, \cdots, m$.

1) Proportion calculation

$$P_i(t) = P_i'' \cdot P_i'(t)$$

$$\alpha_i = \frac{\sum_{t=1}^{T} P_i(t)}{\sum_{t=1}^{T} P_0(t)} = \frac{\sum_{t=1}^{T} P_i'(t)}{\sum_{t=1}^{T} P_0(t)}$$

It can be seen from formula (2) that the proportion of load category $i$ to bus load can be calculated if only $P_i'(t)$ and $P_i''$ are known.

2) Typical load unitary curve generation

Multiple proportions smoothing method is a common short-term load forecasting method. This method divides the forecasting process into two parts: standard unitary curve forecasting and base value forecasting, and the process of standard unitary curve forecasting is adopted to generate typical load unitary curve here.

In this paper, peak load is selected as the base value $P_j''$, and then the corresponding standard value

$$\hat{P}_j(t) = [\hat{P}_j(1), \hat{P}_j(2), \cdots, \hat{P}_j(T)]$$

$\in$ can be calculated through formula (3).

$$\hat{P}_j(t) = P_j(t) / P_j'' (t = 1, 2, \cdots, T)$$

Through point by point smoothing results of curves of the relevant load sets, the typical unitary curve for load category $i$ can be obtained.

$$P_i'(t) = \beta \hat{P}_i'(t) + \beta(1 - \beta) \hat{P}_i'(t) + \beta(1 - \beta)^3 \hat{P}_i'(t) + \cdots + \beta(1 - \beta)^{n-1} \hat{P}_n'(t)$$

$$P_i'(t) = [P_i'(1), P_i'(2), \cdots, P_i'(T)]$$

Where, $\beta \in (0, 1)$ is the smoothing coefficient.
3) Load base value calculation

With the base values as independent variables, a function can be constructed using the error between predicted value and actual value of bus load, and the problem of finding the base value can be transformed into the problem of finding the minimum value of formula (6), where $\hat{P}_0(t)$ is the actual value of bus load at time period $t$.

$$f(P^B_1, P^B_2, \ldots, P^B_n) = \sum_{i=1}^{T} (\hat{P}_0(t) - \sum_{i=1}^{n} P_i(t))^2 = \sum_{i=1}^{T} (\hat{P}_0(t) - \sum_{i=1}^{n} P^B_i \cdot P_i(t))^2$$  \hspace{1cm} (6)

This function can be solved by stationary point condition, as shown in formula (7).

$$\frac{\partial f}{\partial P^B_k} = 0 (1 \leq k \leq n)$$  \hspace{1cm} (7)

Combining formula (6) and (7), formula (8) is obtained.

$$\sum_{i=1}^{n} \left( \sum_{i=1}^{T} P^B_i \cdot P_i(t) \right) = \sum_{i=1}^{T} \sum_{i=1}^{n} P_0(t) \cdot P_i(t)$$  \hspace{1cm} (8)

$$\begin{bmatrix}
\sum_{i=1}^{T} P^B_1 \cdot P_1(t) \\
\sum_{i=1}^{T} P^B_2 \cdot P_2(t) \\
\vdots \\
\sum_{i=1}^{T} P^B_n \cdot P_n(t)
\end{bmatrix} = \begin{bmatrix}
\sum_{i=1}^{T} \hat{P}_0(t) \cdot P_1(t) \\
\sum_{i=1}^{T} \hat{P}_0(t) \cdot P_2(t) \\
\vdots \\
\sum_{i=1}^{T} \hat{P}_0(t) \cdot P_n(t)
\end{bmatrix}$$  \hspace{1cm} (9)

By solving the matrix formula (9), the corresponding load base value can be obtained, and then the proportion of various loads to the bus load can be calculated with formula (2).

2.2. Interactive response of different loads to real-time electricity price

The incentive of real-time electricity price to users include two stages: day-ahead market and real-time market. The former makes full-dimension electricity utilization arrangement based on the real-time electricity price forecast value of the next day, and the latter makes dynamic correction based on the real-time electricity price and electricity consumption information obtained on the current day. This paper focuses on analyzing the response characteristics of day-ahead market load to real-time electricity price.

1) Overall electricity price elasticity model

Overall price elasticity $\varepsilon_{d}$ is defined as the amount of user load transferred on the basis of the average price of each time period.

$$\varepsilon_d = \frac{\Delta d_{all}}{\Delta p_{all}} / \frac{d_{all}^0}{p_{all}^0}$$  \hspace{1cm} (10)

Where, $d_{all}^0$ is user daily baseline load, that is $d_{all}^0 = \sum_{i=1}^{T} d_i^0$; $\Delta d_{all}$ is the variation amount of total load; $\Delta p_{all}$ is the variation amount of synthetic electricity price.

Synthetic electricity price $p_{all}$ is defined as weighted average of electricity price in each time period, and $\Delta p_{all}$ is the variation amount of synthetic electricity price.

$$p_{all}^{0.1} = \frac{\sum_{i=1}^{T} d_i^0 \cdot p_i^{0.1}}{\sum_{i=1}^{T} d_i^0}$$  \hspace{1cm} (11)
In this model, if the Synthetic electricity price of the target day is higher than that of the base day, the load of the target day will decrease, so the overall price elasticity is negative. The load variation amount can be obtained by formula (12):

\[ d^i_j = \frac{\varepsilon d \Delta P_{all}}{P^0_{all}} \cdot d^0_j \]  

(12)

2) Time-electricity price difference elasticity model

This model is directly oriented to different time periods, and mainly focus on load transfer capability to price differences in each time period. Time-electricity price difference elasticity is defined as follows:

\[ e_{d,k\rightarrow j} = \frac{\Delta d_{k\rightarrow j}}{\Delta \eta_{k\rightarrow j}} (\eta_{k\rightarrow j} \geq 0) \]  

(13)

Where, \( \Delta d_{k\rightarrow j} \) represents the amount of electricity transferred from time period \( k \) to \( j \); \( \eta_{k\rightarrow j} \) represents electricity price difference between time period \( k \) and \( j \); \( \Delta \eta_{k\rightarrow j} = \eta_{k\rightarrow j}^i - \eta_{k\rightarrow j}^0 \) represents variation amount of electricity price difference between time period \( k \) and \( j \).

The transfer factor \( \alpha_{i\rightarrow m} \) is defined as formula (14), and load variation amount of target day in time period \( i \) can be calculated through formula (15). Considering the limitations of load cost and capacity, it is impossible to transfer all the variation amount of time period \( i \) to time period \( m \). Thus, the corresponding electricity amount transferred to time period \( m \) can be obtained through formula (16), where, \( \delta \) is load transfer coefficient.

\[ \alpha_{i\rightarrow m} = \begin{cases} \frac{\varepsilon d_{i\rightarrow m}^i d^0}{\eta_{i\rightarrow m}^i} & (\eta_{i\rightarrow m}^i \geq 0) \\ -\alpha_{i\rightarrow m} & (\eta_{i\rightarrow m}^i < 0) \end{cases} \]  

(14)

\[ \Delta d_{i\rightarrow m} = \sum_{m=1}^{T} \alpha_{i\rightarrow m} \Delta \eta_{i\rightarrow m} \]  

(15)

\[ \Delta d_{trans} = \delta \sum_{i=1}^{T} \alpha_{i\rightarrow m} \Delta \eta_{i\rightarrow m} \]  

(16)

Considering the joint response of two price elasticities, the load of target day can be obtained as follows:

\[ d^i_j = \{d^0_j - \sum_{m=1}^{T} \alpha_{i\rightarrow m} \Delta \eta_{i\rightarrow m}\} \times (1 + \frac{\varepsilon d \Delta P_{all}}{P^0_{all}}) \]  

(17)

In conclusion, the load amount after interaction is mainly determined by the price difference between target day and reference day, as well as two electricity price elasticity coefficients.

2.3. Bus load forecasting strategy considering electricity price interaction

2.3.1. Analysis of bus load overall price elasticity

Similar to industrial, commercial and residential loads, overall electricity price elasticity \( \varepsilon \) and time-electricity price difference elasticity \( \varepsilon_{r,k\rightarrow j} \) can also be defined when analyzing the overall price of bus load, and then the interactive response of bus load to real-time electricity price can be further analyzed.

\[ \varepsilon_{r} = \sum_{i=1}^{T} \varepsilon_{i} \alpha_{i} \]  

(18)
2.3.2. Analysis of bus load forecasting strategies. This section focuses on the bus load forecasting strategies. In order to study bus load forecasting under interactive characteristics, the following two aspects are considered in this paper:

1) The sequence of bus load forecasting and load interaction response analysis;
2) The interactive response analysis of bus load is based on overall electricity price elasticity or classified electricity price elasticity.

Thus, four different forecasting strategies are proposed as follows:

A. The interactive response analysis based on bus overall electricity price elasticity is firstly carried out, and then the bus load is forecasted.
B. The interactive response analysis based on bus classified electricity price elasticity is firstly carried out, and then the bus load is forecasted.
C. The bus load forecasting is firstly carried out, and then the interactive response analysis based on bus overall electricity price elasticity is carried out.
D. The bus load forecasting is firstly carried out, and then the interactive response analysis based on bus classified electricity price elasticity is carried out.

3. Results and discussions
The proposed bus load forecasting framework has been successfully applied to the case study of a region in Guangdong Province, China. All those data used in this paper are acquired from the region’s actual value. This section presents results analysis of proportion calculation and different forecasting strategies, and these results have been compared from horizontal and vertical perspectives. It is expected that these results will have far-reaching influences on future bus load forecasting in Guangdong Province.

3.1. Results analysis of proportion calculation
Table 1 displays the load proportion calculation results and corresponding comparisons with actual proportion. It can be seen from this table that all kinds of errors obtained by this classification method meet the classification requirements and are within an acceptable range. Thus, these results can be used for further research.

| Load | Commercial load | Industrial load |
|------|-----------------|-----------------|
|      | Actual proportion | Calculated proportion | Relative error | Actual proportion | Calculated proportion | Relative error |
| Target day | 21.3868% | 23.9268% | 11.8764% | 61.6799% | 59.2188% | 3.9901% |
| Load | Residential load | Other load |
|      | Actual proportion | Calculated proportion | Relative error | Actual proportion | Calculated proportion | Relative error |
| Target day | 12.0975% | 10.7988% | 10.7353% | 4.8358% | 6.0486% | 25.0796% |

3.2. Results analysis of forecasting strategies
(1) Results analysis of horizontal comparison
Horizontal comparison aims to make comparisons between strategy A and B, C and D. In other words, the interactive response analysis based on bus overall electricity price elasticity or classified electricity price elasticity is firstly carried out, and then the bus load is forecasted (A and B); the bus load forecasting is firstly carried out, and then the interactive response analysis based on bus overall electricity price elasticity or classified electricity price elasticity is carried out (C and D). The final
forecasting results for strategy A and B, C and D are shown in Figure 2 and 3 respectively. It can be seen from Figure 2 and 3 that for the same real-time price incentive, the interaction ability based on the bus overall electricity price elasticity is higher than that based on bus classified electricity price elasticity, which is reflected in the relatively large load reduction during the high price period and the relatively large load increase during the low price period.

(2) Results analysis of vertical comparison

Vertical comparison aims to make comparisons between strategy A and C, B and D. In other words, the sequence of interactive response analysis based on bus overall electricity price elasticity or bus load forecasting is considered (A and C); the sequence of interactive response analysis based on bus classified electricity price elasticity or bus load forecasting is considered (B and D). The final forecasting results for strategy A and C, B and D are shown in Figure 4 and 5 respectively. It can be seen from Figure 4 that when interactive response is based on bus overall electricity price elasticity, the sequence of interactive response and forecasting has little effect on the final bus load forecasting results. However, it is not the same when interactive response is based on bus classified electricity price elasticity, the sequence of interactive response and forecasting has some effect on the final bus load forecasting results. It can be seen from Figure 5 that the interactive response ability of strategy B is worse than strategy B.

**Figure 2.** Forecasting results comparison of strategy A and B.

**Figure 3.** Forecasting results comparison of strategy C and D.

**Figure 4.** Forecasting results comparison of strategy A and C.

**Figure 5.** Forecasting results comparison of strategy B and D.
4. Conclusions
An attempt has been made to establish a bus load forecasting framework considering interaction response in electricity market environment, and this forecasting framework has been successfully applied to the case study of a region in Guangdong Province. The proposed bus load components identification and proportion calculation model can achieve relatively higher accuracy's proportion calculation. The proposed prediction strategies are effective and can achieve high accuracy’s bus load forecasting. Besides, the electricity price elasticity category as well as the sequence of interactive response and forecasting have certain effect on the final bus load forecasting results under the background of electricity market.

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References
[1] Panapakidis I P 2016 Expert Systems with Applications 54(C) 105-120
[2] Wang P, Wang C S, Hu Y K, Varga L, Wang W 2018 Energies 11(6) 1498
[3] Garulli A, Paoletti S, Vicino A 2015 IEEE Transactions on Control Systems Technology 23(3) 1087-1097
[4] Wu Y, Han J J, Yang X W 2015 Guangxi Electric Power 38(6) 1-4
[5] Zhao R, Kang C Q, Liu M, Cheng H Y, Huang W Y, Chen Z, Wang Q 2009 Electric Power 42(6) 32-36
[6] Panapakidis I P 2016 International Journal of Electrical Power & Energy Systems 80 171-178
[7] Chen X Y, Kang C Q, Tong X, Xia Q, Yang J F 2014 IEEE Transactions on Power Systems 29(4) 1634-1641
[8] Salgado RM, Ballini R, Ohishi T 2009 IEEE Bucharest PowerTech 4(3) 1-8
[9] Luh PB, Michel LD, Friendland P, Guan C, Wang Y 2010 IEEE Power & Energy Society General Meeting 1-3
[10] Garulli A, Paoletti S, Vicino A 2015 IEEE Transactions on Control Systems Technology 23(3) 1087-1097
[11] Zhang Z S, Yu D L 2018 Proceedings of the CSEE 38(6)
[12] Su X J, Liu X J, Yan X X, Wang M Q, Han X N 2018 Automation of Electric Power Systems 42(10)