A Comparison of Top-down Load Forecasting and Bottom-up Load Forecasting in Distribution Network

Zeyu Mu, Hayinaer · Tueraili and Bin Song*
School of Electrical Engineering and Automation, Wuhan University, Wuhan, China

*592276269@qq.com

Abstract. In this paper, the electricity load of a certain region is taken as the research object. Firstly, the back propagation neural network (BP) model is used to predict the macro load of the region from top to bottom. Then, on the premise of comprehensive consideration of the region's meteorological, economic, large user registration and other causes, the power grid of the region is divided. On this basis the differential integration moving average autoregressive (ARIMA) model is used to carry out the bottom-up micro load forecasting: First, the load forecasting of each cell is carried out, and then the prediction results are summarized in proportion to obtain the overall prediction results of the region. Through the comparative analysis of the two load forecasting results, it is found that although the two forecasting errors are fewer than 9%, the bottom-up load forecasting method which combines grid partition and fine classification has a prediction error of fewer than 5%. The results show that the bottom-up load forecasting method is better.

1. Introduction
Load forecasting is the premise and foundation of distribution network planning. It is mainly from the perspective of future power demand, comprehensively considering various factors such as policy, society, economy and meteorology, and using reliable methods and models to explore the variation law of historical load data, so as to make scientific prediction of future load [1-3]. At present, with China’s economy from high-speed development stage to high-quality development, accuracy requirements of load forecasting are also increasing, but the traditional load forecasting methods cannot meet the needs of social development. In the traditional top-down distribution network load forecasting, there are the following problems which have severe impact on the scientific and efficient management of the power grid [4-7].

- The distribution of substations is unreasonable.
- Electric power distribution reliability is not high.
- Make cross power supply within the distribution network.

In recent years, bottom-up distribution network grid planning has been widely used. The basic idea is to divide the complex distribution network in the planning area into multiple power supply areas and analyze the current situation. Then, combined with the overall urban planning and regulatory detailed planning, plots with different development depths and land use types are divided into multiple power supply networks. Finally, the typical load forecasting model is applied to load forecasting in each power grid [8].
In this paper, a bottom-up load forecasting method based on grid is proposed, and several factors are considered in the forecasting process. On the one hand, on the basis of the combination of urban planning and land use nature, the power supply units in a region are divided, so that the forecasting can take into account the different situations of different units [9-10]. On the other hand, consider the weather, economy, large users and many other factors affecting the load forecasting results to further improve the accuracy of load forecasting [11].

In summary, this paper takes a certain region as the research object. On the one hand, BP neural network model is used for top-down load forecasting. On the other hand, ARIMA model is used for bottom-up load forecasting based on grid with several factors. By comparing the forecasting results of the two models, it is found that the bottom-up load forecasting results are more accurate and this method is better. The research results can provide guidance for the expansion and planning of regional distribution networks, which have certain practical significance.

2. Two Load Forecasting Models

2.1. Construction of top-down load forecasting model
Top-down load forecasting is a load forecasting method based on the historical load data of the terminal and the measured data to predict the overall future load characteristics. In this paper, the top-down load forecasting of a region as a whole is only conducted from a macro perspective.

This paper uses BP neural network model to build a top-down load forecasting model. BP neural network, full name is back propagation multilayer feed-forward neural network. Artificial neural network is a network system formed by a large number of simple processing units. BP neural network is a supervised learning algorithm. No matter what initial weights and thresholds are given to the network, it can conduct network learning on the basis of comparing samples, and then use the error between the actual output and the expected output after learning to repeatedly adjust the weights, gradually reduce the error, and ultimately achieve the specified accuracy. Its characteristic is that each node of input layer and hidden layer, hidden layer and output layer is interactive. At the same time, BP neural network has the characteristics of parallel processing, adaptive, self-organizing, associative memory, high fault-tolerant rate and forced into arbitrary nonlinear, especially suitable for dealing with nonlinear complex open system dynamics problems [12-13].

Suppose the connection weight between the input layer and the hidden layer is \( w_{ij} \), the connection weight between the hidden layer and the output layer is \( w_{jk} \), the input threshold is \( a \), and the output threshold is \( b \).

Calculate of each hidden layer value based on Formula (1).

\[
H_j = f \left( \sum_{i=1}^{n} w_{ij} X_i - a_i \right) \tag{1}
\]

Where, \( H_j \) is the value of the hidden layer in the j layer of the neural network; \( f \) is the activation function Sigmoid of hidden layer in neural network, \( X_i \) is the i\(^{th}\) input node variable in the hidden layer of neural network.

The actual output value of the node can be calculated by Formula (2).

\[
O_k = \sum_{j=1}^{i} H_j w_{jk} - b_k \tag{2}
\]

\( O_k \) is the actual output value for each learning.

The excitation function is the Sigmoid function, as shown in Formula (3).

\[
f(x) = \left(1 + e^{-x}\right)^{-1} \tag{3}
\]
2.2. Construction of bottom-up load forecasting model
The bottom-up load forecasting steps are as follows: Firstly, the power supply area is divided into several independent power supply units, and then the load forecasting is carried out from the power supply units in the power supply area. Finally, the whole is composed of layers. The bottom-up load forecasting carried out in this paper is gridded load forecasting based on multi-factor consideration. This paper uses ARIMA model to build a bottom-up load forecasting model. ARIMA model, fully known as differential integrated moving average autoregressive model, also known as integrated moving average autoregressive model, is one of the time series prediction analysis methods. Through the d-order difference of non-stationary sequences, the sequence is stabilized [13-14]. The form of the model is shown in Formula (4).

\[
(1 - L)^d y_t = \frac{\left(1 + \sum_{j=1}^{q} b_j L^j \right) \epsilon_t}{1 - \sum_{i=1}^{p} a_i L^i}
\]  

Where, \( L \) is the lag order, \( a_i \) is the corresponding p-order autoregressive coefficient, \( b_j \) is the corresponding q-order moving average coefficient, \( d \) is the difference order, \( \epsilon_t \) is the random error term.

2.3. Multi-factor grid load forecasting
In this paper, several factors that have a greater impact on the load forecasting of a certain region are mainly considered, including weather, economy, and large user registration. The meteorological factors mainly include the monthly average high temperature, monthly average low temperature and monthly average precipitation in a certain area. When establishing the ARIMA model, they are introduced as parameters. Economic factors mainly include the level of economic development, per capita GDP and industrial structure.

Gridding of distribution network means that in a specific planning area, the distribution network is divided into multiple power supply areas, and then it is divided into several independent power supply networks, and further subdivided into smaller power supply units [15]. Finally, a three-layer structure of ‘power supply area—power supply grid—power supply unit’ is formed. According to “DL/T 5729-2016 Distribution Network Planning and Design Technical Guidelines(China Standard)”, the regional division of power supply network is mainly determined by the administrative level and future load development. Based on the Guidelines, this paper divides the power supply units on the basis of comprehensive consideration of the economic factors of each unit and the situation of large user registration [16-18].

3. Comparative Analysis of Application Practice in Some Area
The sources of historical data from 2017 to 2018 used in the two models are shown in Table 1.
Table 1. Statistical table of historical data of each month of a certain region in 2017-2018

|       | Load(kW) | AHT(℃) | ALT(℃) | MP(mm) | Load(kW) | AHT(℃) | ALT(℃) | MP(mm) |
|-------|----------|--------|--------|--------|----------|--------|--------|--------|
| Jan.  | 19607000 | 11     | 3      | 139.5  | 18966000 | 7      | 0      | 238.7  |
| Feb.  | 16589800 | 13     | 3      | 134.4  | 13663800 | 11     | 2      | 148.4  |
| Mar.  | 14272545 | 15     | 7      | 381.3  | 11677200 | 18     | 8      | 303.8  |
| Apr.  | 13664981 | 23     | 13     | 276.0  | 10957200 | 24     | 14     | 312.0  |
| May   | 16381223 | 28     | 18     | 461.9  | 12606000 | 27     | 19     | 511.5  |
| June  | 18387429 | 27     | 20     | 873.0  | 14245800 | 30     | 22     | 267.0  |
| July  | 27864800 | 34     | 26     | 613.8  | 19934400 | 34     | 25     | 406.1  |
| Aug.  | 24250800 | 32     | 24     | 937.7  | 19543200 | 33     | 24     | 427.8  |
| Sept. | 15751200 | 27     | 21     | 222.0  | 14718600 | 29     | 20     | 303.0  |
| Oct.  | 13893400 | 19     | 12     | 93.0   | 10656600 | 23     | 12     | 96.1   |
| Nov.  | 14824800 | 17     | 8      | 84.0   | 15242400 | 17     | 8      | 219.0  |
| Dec.  | 21209600 | 12     | 1      | 40.3   | 23225900 | 8      | 3      | 210.8  |

Note: AHT is Monthly average high temperature; ALT is Monthly average low temperature; MP is Monthly precipitation.

3.1. Practical analysis of top-down load forecasting

In this paper, the electricity consumption data of a regional distribution network from January 2017 to December 2018 are used as the basic samples. Through the collection, analysis and selection of data, the BP neural network model is selected to calculate the predetermined input and output data, so that the network has the ability of self-learning. The training is completed according to the set parameters, and then the corresponding load forecasting data for the whole year of 2019 are obtained. Finally, the results are compared with the actual values. Results are shown in Figure 1.

The continuous adjustment of prediction methods and model parameters will eventually maintain the error in a reasonable range. Through the analysis of simulation results, it can be concluded that the method of applying BP neural network to regional medium-term power load forecasting in the form of
monthly total power consumption has good accuracy [19]. The overall relative error is controlled within 9%.

3.2. Practical analysis of bottom-up load forecasting

According to the above power supply unit principle, a region is divided into six power supply units. The division results are shown in Figure 2.

Unit 1, unit 2, unit 4, unit 5, unit 6 are mainly residential land and commercial land, and unit 3 is mainly residential land and industrial land.

The region is powered by a 220kV substation and two 110kV substations, of which there are 5 main transformers, and a transformer capacity is 443 MVA. The number of the total interval of 10kV is 45, and the remaining 10kV interval is 2. Of the two 110kV substations, one of which is a single main transformer substation can not meet the N-1 calibration.

![Grid division results of power supply in a certain region](image)

**Figure 2.** Grid division results of power supply in a certain region

Based on the historical data from January 2017 to December 2018, the electricity load of each unit for the whole year of 2019 is predicted by considering the weather, economy and large user registration. Then the total load of a certain area can be obtained by summing the load prediction results of the six units. The predicted value is compared with the actual value, and the relative error rate between the predicted value and the actual value is calculated to detect the reliability of the model. Results are shown in Figure 3.
According to the above data analysis, it can be clearly found that the R-square value of each unit model is 0.880, and the overall relative error is controlled within 5%. It indicates that the fitting curve of each unit has high fitting with the observation curve, which proves the credibility of the model.

### 3.3. Verification of prediction results of two models

The top-down prediction results are compared with the bottom-up prediction results, and the relative errors are calculated. The results are shown in Table 2.

**Table 2. Summary of the prediction results of the two models**

| Time  | Actual load(kW) | Top-down prediction results(kW) | Bottom-up prediction results(kW) | Top-down relative error(%) | Bottom-up relative error(%) |
|-------|-----------------|---------------------------------|----------------------------------|---------------------------|-----------------------------|
| 2019.1 | 19676449        | 20471423                        | 19979173.62                      | 4.04                      | 1.54                        |
| 2019.2 | 14874952        | 15625280                        | 15297534.72                      | 5.04                      | 2.84                        |
| 2019.3 | 13021747        | 11884157                        | 12895251.26                      | 8.74                      | 0.97                        |
| 2019.4 | 12915741        | 13774580                        | 12884738.53                      | 6.65                      | 0.24                        |
| 2019.5 | 13357286        | 14555286                        | 13030947.80                      | 8.97                      | 2.44                        |
| 2019.6 | 15012649        | 15838855                        | 14819313.25                      | 5.50                      | 1.29                        |
| 2019.7 | 18542752        | 19838855                        | 18346064.83                      | 6.99                      | 1.06                        |
| 2019.8 | 20753285        | 21773070                        | 20633319.07                      | 4.91                      | 0.58                        |
| 2019.9 | 15694279        | 16786927                        | 15337155.11                      | 6.96                      | 2.28                        |
| 2019.10| 12993654        | 12842093                        | 12900819.71                      | 1.17                      | 0.71                        |
| 2019.11| 13784732        | 14040164                        | 13981185.43                      | 1.85                      | 1.43                        |
| 2019.12| 19353865        | 20914426                        | 19468872.27                      | 8.06                      | 0.59                        |
It can be seen from Table 2 that the relative error of the top-down prediction model is within 9\%, while the bottom-up prediction model is smaller and basically stable within 5\%. It shows that the bottom-up model has better accuracy and accuracy in load forecasting. It can be found that under the premise of grid division of a certain region, through the consideration of a series of factors such as temperature, precipitation and economy, the prediction results are more reliable by using the bottom-up model.

4. Conclusion
In order to compare the accuracy of the top-down and bottom-up load forecasting models, this paper takes the electricity load of a certain region from January 2015 to August 2020 as the research object. On the one hand, the BP neural network model is used top-down load forecasting. On the other hand, based on the ARIMA model, the refined and grid-based bottom-up load forecasting is carried out under the premise of considering the factors that have great influence on the load forecasting, such as meteorological factors, economic factors and large user registration.

The results show that the results of the bottom-up load forecasting based on grid with several factors are more accurate. It provides a scientific guidance method for distribution network planning and lays a foundation for solving the common problems in the past power grid.

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