Hierarchical Evaluation of Distribution Network Access Capacity Taking Into Various Prosumer Group Load Forecasts

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ABSTRACT Now the measurement means of access capacity at all levels of distribution network are insufficient and it is difficult to calculate effectively based on limited data. This paper proposes a hierarchical evaluation method of access capacity of distribution network with multiple prosumer group load forecasting. Firstly, a load dynamic prediction model is constructed. According to the typical load model of historical data mining, a unit prediction model of typical users is established by using the conjugate gradient RBF neural network learning algorithm. Then, according to the charge-discharge dynamic model of the energy storage power station and the load dynamic prediction results, an assessment model of access capacity at the 10kV side was constructed. By analyzing the known load type, load type ratio and transformer capacity on the low-voltage side, the conversion coefficient of 10kV side load to 0.4kV side transformer capacity is obtained by weighting different types of loads proportionally. Then, access distribution capacity of different prosumer group can be obtained based on conversion coefficient. It can ensure the effective measurement of access capacity at all levels of distribution network under the premise of meeting N-1 safety criteria. Finally, an example is given to demonstrate the effectiveness of the proposed method.

INDEX TERMS User accessible capacity (UAC), energy storage power station (ESS), load forecasting, RBF neural network, conversion coefficient.

I. INTRODUCTION

With the development of the national economy and the adjustment of industrial structure, the electricity consumption is also increasing year by year. The distribution network often needs to connect new loads to meet the demand of users [1]. However, when the new load is connected, the current user load in the distribution network will also increase year by year with the development of economic industry or the improvement of living standard. It has gradually become an important factor in the maximum power supply capacity assessment of distribution network. At the same time, in the face of seasonal load peaks in the electricity network, compared with the newly built substation, power supply enterprises often choose to connect energy storage power stations to expand capacity economically. With the addition of diversified power sources to the distribution network, it becomes more difficult to evaluate the accessible capacity of the distribution network.

At present, many scholars have done a lot of research on load forecasting and ESS. Literature [2] proposes a trackless kalman filtering algorithm for load prediction. In this method, the traditional load is used for modeling, and the Kankel matrix method based on impulse response sequence is used to identify the order of the model. The results show that the prediction accuracy of this method is high, but the prediction accuracy at peak and valley is poor. Literature [3]–[5] proposed various improved algorithms based on RBF neural network, improved the neural network by optimizing the connection of weights and thresholds between the hidden layer and the output layer of the neural network, and proved these equations through experiments. Compared with the traditional RBF neural network, the method has higher accuracy, but it also has the problem of poor convergence speed and local convergence. In terms of energy storage power station,
the scholars research mainly focused on the use of energy storage power to tame volatility load carried on the thorough research, useful [6]–[8] dynamic programming method of solving the volatility of load optimization problem. Compared with artificial intelligence algorithm, this method is simple and clear considering the factors such as the remaining power or the state of charge of the energy storage power station. In terms of power supply capacity, the influence of network topology on power supply capacity is considered in literature [9], and the network maximum power flow method is established. Literature [10] studies the calculation method of real-time power supply capacity.

The main contributions of this paper can be summarized as follows:

1) In this paper, the RBF neural network learning algorithm with conjugate gradient is adopted to build the load dynamic prediction model. On this basis, the unit prediction model of typical users is developed.

2) According to the charge-discharge dynamic model of ESS combined with the dynamic load prediction results, an assessment model of 10kV accessible capacity (TAC) was generated.

3) Analyze the known load classification data and transformer capacity of 0.4kV side, calculate the conversion coefficient from the load size of 10 kV side to the transformer capacity of 0.4kV side, and obtain the access transformer capacity of each feeder user side based on the conversion coefficient.

II. MULTIPLE PROSUMER LOAD DYNAMIC PREDICTION MODELS BASED ON RBF NEURAL NETWORK ALGORITHM

A. ANALYSIS OF USER LOAD CHARACTERISTICS

Because all kinds of loads have different changing rules, this paper divides the urban electric load into the following four types according to the difference of its typical daily load curve: industrial load, commercial load, residential load, and other load. Large differences between different types of load form, such as: commercial load influenced by people’s consumption and living habit. Figure 1 shows the unit load curve of several typical users. Bimodal peak occurs at noon and night, and the load trough occurs around 4:00 a.m., while the living load of residents starts to rise significantly around 17:00 on weekdays due to the impact of people’s commuting, and reaches the peak load around 20:00 [11]–[15].

The demand base of the power load on the user side is small, and some slight changes will cause obvious fluctuations in the load curve. For the most of users in the power grid, there are obvious periodicity in these changes based on the reasons that people have similar production and life rules, including:

1) The overall variation law is roughly the same between different days. The peak time of the daily load peak is basically fixed, and the time of the trough of the daily load is also basically the same.

2) The load curve of the same week, such as Monday, is generally similar, while the load value of each Sunday is also similar.

3) There are similarities between working days and daily rest days.

4) Major holiday loads are similar.

The load curves at different time scales of the power load of users can show the overall peak and valley state of the load [16], [17]. Take the residential load as an example, as shown in Fig. 1, the daily load curve of a typical user in a week, and the trend of the weekday curve from Monday to Friday is relatively close. There is a big difference on Saturday and Sunday due to the different hours of work and rest.

B. LOAD FORECASTING METHOD BASED ON RBF NEURAL NETWORK ALGORITHM

The user types were divided according to section A. Then, the neural network learning algorithm based on conjugate gradient was given. RBFNN was trained to build the unit sub-prediction model corresponding to each typical load pattern grouping.

The current RBF learning algorithms usually adopt gradient method to train and learn parameters. The basic idea of the current RBF network is to use RBF as the "basis" of the hidden unit to form the hidden layer space, so that the input vector can be directly mapped to the hidden space without weight connection. The learning algorithm usually
uses the gradient method to train and learn the parameters. However, the gradient method has the defects of slow learning speed and low accuracy, whereas the conjugate direction method has the characteristics of secondary termination, small memory requirement, simple calculation and easy realization [18]–[21]. Therefore, this paper presents an improved RBF neural network learning algorithm based on conjugate gradient. The specific steps are as follows.

1) INITIALIZE NEURAL NETWORK PARAMETERS
   a. Set the number of neurons in the hidden layer and output layer \( p \) and \( q \).
   b. Initial assignment of network parameters using random numbers.
   c. Determine the iteration termination precision or the maximum number of iterations \( N \).
   d. Standardize the raw data. In this paper, the maximum value of the original load data is normalized, and the maximum value of the user load curve \( p_{\text{max}}^0 \) is selected as the standardization factor, then \( A_{nt} = \frac{p(t)}{p_{\text{max}}^0} \) is the normalized load of user \( n \) at the time \( t \). The value, \( A_{nt} \in [0, 1] \) is called the unit load value.

2) EVALUATE THE ERROR INDEX
   a. Calculate the output of neurons in the output layer
   \[
   y_k = \sum_{i=1}^{p} w_{ki}z_i \quad k = 1, 2, \ldots, q, \ i = 1, 2, \ldots, p \tag{1}
   \]
   where, \( z_i \) is the output of the hidden layer; \( w_{ki} \) belongs to the weight of the hidden layer \( i \) of output neuron \( K \); \( y_k \) is the output of the output layer neuron.
   b. Evaluate accuracy of errors
   \[
   EA = \sqrt{\frac{1}{qN} \sum_{n=1}^{N} \sum_{k=1}^{q} (r_{nk} - y_{nk})^2} \tag{2}
   \]
   where, \( EA \) is the accuracy of the evaluation; \( r_{nk} \) is the output value of historical data; \( y_{nk} \) is the neuron output when iterating for \( n \) times.

3) JUDGE WHETHER THE ACCURACY REQUIREMENTS ARE MET
   If \( EA \leq \epsilon \), The training is over; Otherwise, go to step 4).

4) ADJUST THE WEIGHT, CENTER AND WIDTH PARAMETERS
   \[
   \omega_{kj}(t) = \omega_{kj}(t-1) + \eta g_{w_{kj}(t)}(t-1) \alpha [\omega_{kj}(t-1) - \omega_{kj}(t-2)] \tag{3}
   \]
   \[
   c_{kj}(t) = c_{kj}(t-1) + \eta g_{w_{kj}(t)}(t-1) \alpha [c_{kj}(t-1) - c_{kj}(t-2)] \tag{4}
   \]
   \[
   d_{kj}(t) = d_{kj}(t-1) + \eta g_{w_{kj}(t)}(t-1) \alpha [d_{kj}(t-1) - d_{kj}(t-2)] \tag{5}
   \]
   where, \( \omega_{kj} \), \( c_{kj} \) and \( d_{kj} \) respectively represent the weight value, center value and width value from node \( j \) of the current layer to node \( k \) of the next layer; \( g_{w_{kj}}, c_{kj}, \) and \( d_{kj} \) respectively represent the decreasing search direction of weight, center, and width.

5) IF \( n \geq N \), THE TRAINING IS OVER; OTHERWISE, \( n = n + 1 \), RETURN STEP 2)

III. CALCULATE THE ACCESSIBLE CAPACITY OF THE 10kV SIDE OF ESS ACCESS

A. ESS DYNAMIC CHARGE-DISCHARGE MODEL

Equation (6) below describes the dynamic change process of state of charge (SOC) of ESS in a time interval.

\[
E_{e,soc}(t + \Delta t) = E_{e,soc}(t) + \eta \int_t^{t+\Delta t} p(t)dt / S_{WM,h} \tag{6}
\]

\[
S_e(t) = \eta \int_t^{t+\Delta t} p(t)dt / S_{WM,h} \tag{7}
\]

\( E_{e,soc}(t) \) is the SOC of ESS \( e \) at time \( t \); \( \eta \) is the coefficient, taking into account the temperature correction, charge/discharge efficiency and battery life; \( S_{WM,h} \) is the capacity of the battery; \( p(t) \) is the charge-discharge power of ESS \( e \) at time \( t \); \( S_e(t) \) represents the power change of ESS over time interval \( \Delta t \).

At the same time, the battery power at each moment should be limited to the upper and lower limits of the battery capacity, as shown in (8) below; Similarly, the charge and discharge capacity should also be limited within a certain operating range, as shown in (9).

\[
E_{e,soc}^{\text{low}} \leq E_{e,soc}(t) \leq E_{e,soc}^{\text{high}} \tag{8}
\]

\[
0 \leq p(t) \leq P_e^{\text{high}} u_{e,c} \quad \forall e \in \Omega^i
\]

\[
0 \leq p(t) \leq P_e^{\text{high}} (1 - u_{e,c}) \quad \forall e \in \Omega^i \tag{9}
\]
$E_{\text{low soc}}$ and $E_{\text{high soc}}$ represent capacity security margin. $P_{\text{high e-c}}$ and $P_{\text{high e-dc}}$ are the maximum power value of the amount of charge and discharge of ESS $e$. For avoid simultaneous charging and discharging of the energy storage power station, $u_{\text{e-c}}$ is defined as a binary indicator, and $i$ represents the charging state.

When constructing the BESS charging and discharging dynamic model, it is necessary to ensure that the remaining capacity of the BESS after the end of one day of charging and discharging operation can still meet the normal working requirements of the next day (the BESS failure, maintenance, etc., are not considered here), so add the charge and discharge capacity Constraints: The charge and discharge power are equal throughout the day.

$$\sum_{t=1}^{24} P_{\text{e-c},t} = \sum_{t=1}^{24} P_{\text{e-dc},t}$$

where, $P_{\text{e-c},t}$, $P_{\text{e-dc},t}$ are the charge and discharge power of the energy storage system $e$ during $t$ period.

**B. CALCULATION MODEL OF 10kV SIDE TAC**

The objective function of the model is as follows:

$$P_{T_i}(t) = \sum_{m \in \Omega_i} R_{\text{fm}}(t)$$

$P_{T_i}(t)$ represents the TAC of the main change $i$ at time $t$.

Equation (12) considers the growth of different types of loads in the planning years $c$. Secondly, in order to show that the load after the failure of N-1 of the main transformer is completed by the feeders that are connected with each other between the main transformer, (13) is shown in column.

$$L_{\text{r-mn}}(t) = S_{\text{n}}(t) \cdot (1 + \delta_u)c$$

$$T_{\text{r-ij}}(t) = \sum_{m \in T_i, n \in T_j} L_{\text{r-mn}}(t)$$

$L_{\text{r-mn}}(t)$ represents the load transferred to feeder $m$ when feeder $n$ fails at time $t$; $S_{\text{n}}(t)$ represents the actual load value of feeder $n$ at time $t$; $\delta_u$ represents the annual load growth rate of load type $u$; $T_{\text{r-ij}}(t)$ represents the load transferred to the main variant $i$ when the main variant $j$ fails.

Equation (14) describes the N-1 constraint of the feeder, and (15) describes the N-1 constraint of the main variant, both of which indicate that the TAC value of the feeder $m$ (main variant $i$) should be greater than the transferred load value and not exceed its rated TAC.

$$R_{\text{fm}}^i - S^i_{\text{m}}(1 + \delta_u)c - \sum_{e \in \Omega_m} S^i_{e} \geq R_{\text{fm}}^i - \sum_{e \in \Omega} S^i_{e} \geq L_{\text{r-mn}}^i \quad \forall m, n$$

$$R_{\text{i}}^i - \sum_{m \in \Omega_i} S^i_{\text{m}}(1 + \delta_u)c - \sum_{e \in \Omega_i} S^i_{e} \geq P_{\text{T_i}}^i \geq T_{\text{r-ij}}^i \quad \forall i, j$$

where, $R_{\text{fm}}^i$ is the rated capacity of feeder $m$; Rated capacity of $R_{\text{i}}^i$ principal variable $i$; $S_{\text{m}}$ is the current actual load of feeder $m$ at time $t$; $m \in \Omega_i$ said feeder $m$ out independent variable $i$ corresponding bus; $e \in \Omega_i$ said $e$ is for main transformer $i$ corresponds to the ESS on the bus.

It should be pointed out that, when a single radiation line exists in a certain main transformer, the capacity of the main transformer and its co-station main transformer is equivalent to subtracting the load on the single radiation line, that is, the original main transformer capacity can be amended as:

$$R_{\text{i}}^{(1)} = R_{\text{i}}^{(0)} - S_{\text{fm}}$$

where, $R(0) i$ is the main variable rated capacity; Load of single radiation feeder on $S_{\text{fm}}$ main variable $i$; $R(1) i$ is the modified main variable capacity.

So far, the TAC model can transform the model into a linear programming model by introducing main variable contact matrix and feeder contact matrix. It can be solved by some commercial solvers efficiently and the global optimality is guaranteed.

**IV. EVALUATION MODEL OF 0.4kV SIDE USER ACCESSIBLE CAPACITY BASED ON CONVERSION COEFFICIENT**

Acquiring the total load curve is the key to calculating $\lambda$. Total load curve method for load weighted superposition method and FCM clustering algorithm [22]–[25] These two algorithms are mainly used for the implementation of demand side management and the calculation of load forecasting, the process of calculation, need a lot of raw data. Because this paper calculation TAC and user accessible capacity are more focused on the calculation of a time section, so the above two calculation methods of load curve are not very suitable for computing access user capacity in this paper.

In order to obtain a simple and practical method for calculating the capacity of access users without extracting a large amount of raw data, which can be calculated at any time section, a new practical method for calculating the conversion coefficient $\lambda$ is proposed in this paper. The calculation for the conversion coefficient $\lambda$ is based on load type, load type ratio, and the total capacity of the distribution transformer on the feeder. The classification can be roughly divided according to the type of government land. The proportion of each load type can be obtained according to the proportion of the total load on different types of government land. The total capacity of distribution transformer can be calculated according to the number and capacity of distribution transformer on the known line, that is, total capacity $= \text{number of units} \times \text{capacity}$.

For a route, for example, if the civil load, commercial load, industrial load and mixed load on the section on a certain time are $L_1$ MVA, $L_2$ MVA, $L_3$ MVA and $L_4$ MVA respectively, the total capacity of distribution transformer is $S_1$ MVA, $S_2$ MVA, $S_3$ MVA and $S_4$ MVA respectively, the conversion coefficient of access users of different load classes on the line can be calculated according to (19)–(22) respectively.

$$\eta_{\text{civil}} = L_1 / S_1, \quad \eta_{\text{com}} = L_2 / S_2, \quad \eta_{\text{ind}} = L_3 / S_3, \quad \eta_{\text{mix}} = L_4 / S_4 \quad (17)$$

$$L_{\text{sum}} = L_1 + L_2 + L_3 + L_4 \quad (18)$$

In equation (18), $L_1 / S_1$ represents the ratio of civil load to the total capacity of civil distribution transformers;
\( \eta_{\text{civil}} \) represents the load factor of civil distribution transformers; \( L_{\text{sum}} \) in equation (19) represents the sum of various types of electrical loads.

\[
\lambda_{\text{civil}} = (\eta_{\text{civil}} \times \frac{L_1}{L_{\text{sum}}} + \eta_{\text{com}} \times \frac{L_2}{L_{\text{sum}}} + \eta_{\text{ind}} \times \frac{L_3}{L_{\text{sum}}} + \eta_{\text{mix}} \times \frac{L_4}{L_{\text{sum}}}) \times \frac{3L_1}{L_{\text{sum}}} \cdot \beta
\]

where: \( \eta_{\text{civil}} \) means the conversion coefficient of civil load, \( \eta_{\text{com}} \times \frac{L_1}{L_{\text{sum}}} + \ldots + \eta_{\text{mix}} \times \frac{L_4}{L_{\text{sum}}} \) denotes the conversion coefficient obtained by weighting civil load, commercial load and industrial load according to different load proportions; \( \frac{M_{\text{mix}}}{L_{\text{sum}}} \) distribution transformer parameters representing the total line load accessible size converted to civil load, and \( \frac{L_1}{L_{\text{sum}}} \) similar in meaning; \( \beta \) represents the best load rate for the distribution based on experience.

Similarly, the conversion factor for commercial and industrial loads is calculated as follows:

\[
\lambda_{\text{com}} = \frac{3L_2 \beta}{(L_{\text{sum}})^2} \times \left( \frac{L_1}{S_1} + \frac{L_2}{S_2} + \frac{L_3}{S_3} + \frac{L_4}{S_4} \right)
\]

\[
\lambda_{\text{ind}} = \frac{3L_3 \beta}{(L_{\text{sum}})^2} \times \left( \frac{L_1}{S_1} + \frac{L_2}{S_2} + \frac{L_3}{S_3} + \frac{L_4}{S_4} \right)
\]

\[
\lambda_{\text{mix}} = \frac{3L_4 \beta}{(L_{\text{sum}})^2} \times \left( \frac{L_1}{S_1} + \frac{L_2}{S_2} + \frac{L_3}{S_3} + \frac{L_4}{S_4} \right)
\]

The calculation method of accessible capacity of each feeder or feeder segment at 10kV and the calculation equation of access user conversion coefficient \( \lambda \) are given above. For the next level of power grid, the distribution transformer capacity, namely user accessible capacity (UAC), can be calculated according to the following equation.

\[
\text{UAC} = \frac{R_{\text{lin}}}{\lambda}
\]

In the equation, the access user conversion coefficient \( \lambda \) is related to the total load curve on each feeder segment, the different type of load ratio, and the total capacity of the feeders.

V. CASE ANALYSIS

A. EXAMPLE ANALYSIS OF LOAD DYNAMIC PREDICTION MODEL

Combined with the distribution network data of a practical example, the dynamic load forecasting model was used to calculate the annual dynamic change trend of industrial load, commercial load, residential load, and mixed load.

1) DATA PREPROCESSING

The distribution network group load data were selected and the data were collected every day from June 1 to August 31 (a total of 460 days) for 5 consecutive summers. First, distinguish between working days and non-working days and standardize the above data. Then, according to the simple classification of load data based on center of mass similarity.

Four typical load patterns are obtained, and several abnormal load data are eliminated.

2) EXPERIMENTAL PARAMETER SETTING

The remaining load data were randomly divided into 10 parts that were roughly uniform, among which 9 parts were training data and 1 part was test data. By using the training algorithm based on conjugate gradient, the RBF neural network is trained to build the forecasting sub-model corresponding to various typical load modes. The maximum number of network learning is set to 60,000, and the expected error limit is 0.1.

3) ANALYSIS OF EXPERIMENTAL RESULTS

To evaluate the accuracy of the intuitive analysis algorithm, a histogram of relative error distribution is made as shown in Fig. 4 below.

As for the prediction error results in the figure below, the error changes little and the distribution is uniform, so this method can effectively smooth the error fluctuation. Given that the annual load growth rate at different times of the day is basically the same for the same load type, the predicted average value is taken as the final annual load growth rate, and the results are shown in Table 1 below:

| TABLE 1. Annual load growth rate \( m \) value. |
|---|---|---|---|---|
| Load type | Industrial load | Commercial load | Appliance load | Mixed load |
| \( m \% \) | 3.34 | 4.72 | 5.16 | 4.87 |

B. EXAMPLE ANALYSIS OF ACCESS USER EVALUATION

1) INTRODUCTION TO CALCULATION EXAMPLES

The distribution network diagram of the calculation example is shown in Fig. 5.

In Fig. 5, there are a total of 2 substations, 4 main transformers, 20 feeders coming out, and 22 feeders or feeder segment loads, respectively expressed as F1~F22. Three energy storage power stations are advance access, and the specific parameter information is shown in Table 2 below. It should be point out that load refers to the concentrated load on the feeder or feeder section, while the actual feeder or feeder section has many switch stations as load nodes. At the same time, energy storage power stations are also installed on these
2) TAC ANALYSIS OF 10kV DISTRIBUTION NETWORK SIDE
In order to compare the influence of load growth and ESS charging-discharge effect on 10kV distribution network TAC, the ESS installation position was fixed at three positions of feeder 2, feeder 7 and feeder 22. TAC of this example distribution network was calculated by using the above 10kV side accessible capacity calculation model in three different schemes. The specific schemes are shown in Table. 3 below.

| Case       | Consider ESS | Consider load growth | load growth+ESS |
|------------|--------------|----------------------|-----------------|
| Case1      |              |                      |                 |
| Case2      |              |                      |                 |
| Case3      |              |                      |                 |

TAC0 represents the calculated open capacity of 10kV distribution network side without considering both load growth and energy storage. The comparison and calculation results with the above three schemes are shown in Fig. 7(a) and (b) below. The local TAC at 18:00 in a day is taken. The result of case1 is denoted as TAC1. The result of case2 is TAC2; The result of case3 is denoted as TAC3, as shown in Table. 4.

![Schematic diagram of an example distribution network.](image1)

![Locally enlarged wiring diagram.](image2)

![Comparison of scheme results.](image3)

![Comparison of TAC compared under different scenarios at 18:00.](image4)

It can be seen from the Fig. 6(a) that the ESS is generally in charging state from 22:00 to 7:00 in a day, so the TAC during this period is smaller than the distribution network without the ESS. However, TAC values in the peak hours at noon and at night when both ESS were in discharge state were larger than those in the distribution network without ESS. In the rest period, each ESS carries out different charging and discharging behaviors according to different consumption habits of different users on its feeder. Local results can be found from Table. 4, case2 considering the fixed number of year for five years in the planning of load growth, the TAC value of distribution network as the growth of the load will be significantly reduced, and improve the effect of TAC case3 energy storage effect, this is because the plan in 5 years, with cumulative ESS cycle count, the capacity of the battery and charging and discharging efficiency all have different degrees of attenuation.

C. ANALYSIS OF CALCULATION RESULTS OF UAC AT 0.4kV SIDE
The data shown in Table. 5 below are TAC of each feeder or feeder segment at the peak load time of the whole network, taking into load growth and ESS.
TABLE 5. Each feeder or feeder segment TAC3.

| Feeder number | TAC3 (MVA) | Feeder number | TAC3 (MVA) |
|---------------|------------|---------------|------------|
| F1            | 1.53       | F12           | 1.09       |
| F2            | 1.46       | F13           | 0.89       |
| F3            | 1.12       | F14           | 0.73       |
| F4            | 1.08       | F15           | 0.97       |
| F5            | 0.87       | F16           | 1.11       |
| F6            | 0.3        | F17           | 0.87       |
| F7            | 2.14       | F18           | 1.11       |
| F8            | 1.11       | F19           | 1.08       |
| F9            | 1.11       | F20           | 1.08       |
| F10           | 1.21       | F21           | 1.21       |
| F11           | 1.21       | F22           | 1.23       |

According to Table 5, its accessible capacity is 24.51MVA. After obtaining the Fig. 5 grid in PMS2.0 data, the load can be divided into industrial load, civil load, commercial load, and mixed load. The load sizes are 20.79 MVA, 15.78 MVA, 10.78 MVA and 11.12 MVA. Total load size is 57.91 MVA, four types of access with variable load capacity respectively 30 MVA, 25 MVA, 20 MVA, 20 MVA. According to type (20)∼(23), load conversion coefficient is:

TABLE 6. Conversion coefficient results.

| λ   | Industrial | Commercial | appliance | Mixed |
|-----|------------|------------|-----------|-------|
| 0.644 | 0.49       | 0.34       | 0.35      |

Fig. 5 is an example of UAC of access user capacity of civil load, commercial load, industrial load on distribution network diagram feeders, as shown in Table. 7 below.

TABLE 7. Each feeder or feeder segment UAC.

| Feeder number | UAC (MVA) | Feeder number | UAC (MVA) |
|---------------|-----------|---------------|-----------|
| F1            | 4.50      | F12           | 1.69      |
| F2            | 2.27      | F13           | 1.38      |
| F3            | 3.29      | F14           | 1.13      |
| F4            | 2.20      | F15           | 1.51      |
| F5            | 1.78      | F16           | 3.17      |
| F6            | 0.88      | F17           | 1.35      |
| F7            | 4.37      | F18           | 1.72      |
| F8            | 3.26      | F19           | 3.09      |
| F9            | 3.26      | F20           | 3.09      |
| F10           | 3.56      | F21           | 2.47      |
| F11           | 1.88      | F22           | 3.51      |

VI. SUMMARIZES

This paper studies the problem of power load forecasting and the theoretical calculation of the accessible capacity of 0.4kV feeder in distribution network and solves the problem of long-term dependence on empirical estimation and lack of theoretical basis. The main contributions of this paper are as follows:

1) The neural training algorithm based on conjugate gradient was built, and the unit prediction model of typical users was built according to the typical load model of historical data mining and taking into account various prosumer groups, which effectively improved the convergence speed and prediction accuracy of network learning.

2) Considering the load growth and ESS charging and discharging effect, a layered accessible capacity calculation model of distribution network is proposed, which can obtain the accessible distribution transformer capacity of feeder under the premise of considering N-1 security constraints.

3) The conversion coefficient is determined by load type, load type ratio and the total capacity of distribution transformer on the feeder. For the specific evaluation of prosumer group load, the capacity evaluation model for low-voltage side users is proposed in coordination with the capacity planning of medium-voltage feeders.

The method in this paper is based on the theory of available power supply capacity and combined with conjugate gradient neural training algorithm to scientifically predict the load growth in the planning year. Considering the combined effect of load growth and ESS charge and discharge, the capacity of feeder access users can be determined scientifically, which can maximize the power supply capacity of distribution network and improve the utilization rate of assets.

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