Ultra-short-term Load Forecasting Based on Real-Time Response of Classified Flexible Loads

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Abstract. Ultra-short-term load forecasting is an important basis for optimization and adjustment of power generation plans and dispatch plans. Based on the radial basis function neural network, the inert load is predicted, and the flexible load is predicted based on the price elasticity of electricity demand. Then, combined with the range of the flexible load, an ultra-short-term forecast interval for the total load is constructed. This paper studies the total load after considering the flexible load for demand response, and verifies the feasibility of the proposed method with an example.

1 Introduction

Load forecasting is an important link in power planning and production. It can be divided into long term, medium term, short term and super short term load forecasting according to the length of time taken for forecasting. Ultra-short-term load forecasting mainly predicts the change of load in the next hour, which is mainly used for AGC frequency modulation, security monitoring, tie line control, preventive control and emergency state handling, and the preparation of hourly trading plans in the power market.

Under the mode of comprehensive resource management on the demand side, the traditional ultra-short-term load forecasting^[1-3] has some defects, so it needs to be modified and improved. In this paper, based on the real-time response model of classified flexible load, the real-time response factors of sensitive load under integrated resource management on the demand side are taken into comprehensive consideration, and the dynamic ultra-short-term load prediction model is constructed by referring to the idea of interval prediction^[4-6].

2 Load Classification and Demand Response

Inert user load, that is, the load does not change with the demand response measures, and the power load is relatively stable. Therefore, the combined prediction based on the traditional load prediction method can meet the prediction accuracy requirements.

Flexible load refers to the load that can actively participate in the operation control of the power grid and can interact with the power grid with the characteristics of flexibility. Its denotations include adjustable load or

transferable load with elasticity of demand, electric vehicles with bidirectional regulation capacity, energy storage, distributed power supply, micro grid, etc.

Demand response refers to a variety of short-term behaviors that power users take the initiative to adjust electricity consumption modes according to price changes and incentive policies. Generally, flexible loads are regulated and scheduled through demand response projects.

3 User Load Classification Ultra-short-term Prediction Technology

Firstly, this paper differentiates inert users from flexible loads in different periods. Then, based on the flexible load model, the real-time demand forecast of the flexible load is carried out. Finally, inert user load and flexible load in each time period are superimposed to form regional ultra-short-term load prediction results.

That is: $l = l(i) + d(i)$ (1)

Where, $l(i)$ is the load of the inert user at time i , and $d(i)$ is the response load of the flexible user at time i .

3.1 Inert User Load Forecasting

There are many methods for short-term load prediction, including regression analysis, time series, artificial neural network, support vector machine, wavelet analysis and other single prediction methods. In this section, the radial basis function neural network with better performance and more mature is selected for ultra-short-term prediction.

When RBF-NN is used for short-term load prediction, it is not necessary to determine the specific functional relationship between load and external influencing

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factors such as temperature. In order to make full use of the high-dimensional nonlinear mapping capability of RBF-NN, it is necessary to reasonably determine the composition of the model input, identify the periodic law of load, and mine the model input factors that have a high correlation with the prediction results, so as to improve the prediction accuracy and robustness of the model.

(1) Model input composition:

The input quantity of neural network prediction model is shown as follows:

$$u_d^k = [h_d^k, w_d^k]^T \quad (2)$$

Where: u represents the multidimensional input of the neural network model; K represents the time series number of the load sampling point to be predicted, $k=0,1,\dots,95$; D represents the number of days where the load sampling point to be predicted is located; H represents the historical load data vector, as shown in formula (3); W represents the external influencing factors such as temperature, weather and day type (working day or rest day), as shown in equation (4).

$$h_d^k = [\text{load}_{d-3}^{k-1}, \text{load}_{d-3}^k, \text{load}_{d-3}^{k+1}, \text{load}_{d-2}^{k-1}, \text{load}_{d-2}^k, \text{load}_{d-2}^{k+1}, \text{load}_{d-1}^{k-1}, \text{load}_{d-1}^k, \text{load}_{d-1}^{k+1}] \quad (3)$$

$$w_d = [\sum_{i=d-3}^d T_{\max,i}, \sum_{i=d-3}^d T_{\text{ave},i}, \sum_{i=d-3}^d T_{\min,i}, \sum_{i=d-3}^d s_i, g_d] \quad (4)$$

In formula (3), h represents the 9-dimensional historical load data vector, and $\text{load}1$ represents the load data taking into account the demand response. In formula (4), w represents the external influencing factor vector of 17 dimensions, $T_{\max}$, T_{ave} , $T_{\min}$ and s respectively represent the maximum temperature, average temperature, minimum temperature and weather influencing factor of a day, and g represents the daily type influencing factor of the predicted day. In conclusion, u is the 26-dimensional input of the neural network prediction model.

(2) Model construction:

As shown in equation (2), components of the input quantity of the short-term load prediction model with demand response in mind include temperature, weather conditions. For different dimensions of each component, the range of values varies greatly. In order to avoid some load influencing factors being distorted or even flooded in the overall mapping effect, and at the same time to prevent the saturation of neurons in neural network training and learning process, it is necessary to conduct uniform and standardized preprocessing of various load influencing factors before model training.

Day type data: the influence factor of working day is 1, and that of rest day is 0.5.

Weather type data: the influence factors of sunny, cloudy (including cloudy), rain and snow weather were 1, 0.5 and 0, respectively.

For the temperature, since its value fluctuates within a limited range, it can be normalized just like the load. The processing method is shown in the following formula.

$$T_k' = \frac{T_k - T_{\min}}{T_{\max} - T_{\min}} \quad (5)$$

Where, k represents the serial number of each time point in a day; T_k' represents the normalized temperature value; T_k represents the value of temperature before normalization; $T_{\min}$ represents the minimum temperature value of the training sample set before normalization; $T_{\max}$ represents the maximum temperature value of the training sample set before normalization.

According to the characteristics of each neural network and the debugging of the operation process, the parameters of each neural network model are adjusted and determined.

(3) Debug the model to obtain the load prediction results of inert users in period I.

3.2 Flexible Load Forecasting

Combined with price elasticity, this paper analyzes the implementation of time-of-use electricity price and emergency demand response afterload of flexible load users in this region under the premise of maximizing user benefits, and predicts the electricity demand of flexible load users in this region.

The combined prediction model of flexible load is as follows:

$$d(i) = \left\{ d_0(i) + \sum_{j=0}^{23} E_0(i, j) \times \frac{d_0(i)}{p_0(j)} \times [p(j) - p_0(j) + A(j)] \right\} \times \left\{ 1 + \frac{E(i) \times [p(i) - p_0(i) + A(i)]}{p_0(i)} \right\} \quad (6)$$

Where:

$d_0(i)$ is the original power load;

$E_0(i, j)$ is the cross-price elasticity of the i period and the j period;

$p_0(j)$ is the original electricity price in the j period;

$p(j)$ is the time-sharing electricity price in the j period;

$A(j)$ is the emergency demand response excitation in the j period;

$E(i)$ is the electrical self-elasticity in the period i ;

$p(i)$ is the time-sharing electricity price for the period i ;

$p_0(i)$ is the original price of electricity in period i ;

$A(i)$ is the emergency demand response excitation in the i period;

Based on the parameters at different times, the power consumption of the flexible load in the region at time i can be predicted: $d(i)$.

4 The Example Analysis

4.1 Inert User Load

The historical load of inert users in a certain area is as follows:

Fig. 1. Inert User History Load Diagram.

According to the characteristics of each neural network and the debugging of the operation process, the parameters of each neural network model are adjusted and determined. RBF-NN prediction model parameter setting: The distribution density of radial basis function is 2.0 and the target error is 0.0002 and the number of added neurons between two adjacent displays is 1. The predicted results are:

Fig. 2. Ultra-short-term Load Forecasting for Inert Users.

The abscissa of the figure above is the time, with intervals of 15 minutes. Based on RBF-NN, the load curve of inert users is obtained.

4.2 Flexible User Load

Assuming that before the implementation of time-sharing electricity price and emergency demand response, the user price is 0.7 yuan/kwh; After the implementation of time-sharing electricity price and emergency demand response, according to the time-sharing electricity price scheme, users are divided into peak, flat and valley periods within 24 hours a day as follows:

- a peak time: 10:00-15:00
- b flat time: 8:00-10:00, 15:00-23:00
- c valley time: 0:00-8:00, 23:00-0:00 the next day

Accordingly, the peak-flat-valley price is 1.2 yuan/kwh for peak price, 0.8 yuan/kwh for flat price and 0.3 yuan/kwh for valley price. The incentive reward for user demand response is $A=0.2$ yuan/ kwh.

Based on foreign empirical data, it is assumed that the elastic price of user demand is as follows:

Table 1. Price elasticity of flexible user demand

	valley time	flat time	peak time
valley time	-0.1	0.01	0.012
flat time	0.01	-0.1	0.016
peak time	0.012	0.016	-0.1

Fig. 3. Flexible Load Prediction.

Extract the historical load in the corresponding period of the original flexible load in a certain region and predict it based on the historical load. The forecast result of the flexible load is as follows:

Fig. 4. Flexible Load Prediction.

4.3 Ultra-short-term Load Prediction Results

Superimposing the results of inert load and flexible load in this area can get the results of ultra-short-term load prediction.

Fig. 5. Ultra-short-term Load Prediction Results.

The figure above is enclosed by two curves, namely, the ultra-short-term load prediction results considering the response of flexible load and the ultra-short-term load prediction results excluding the response of flexible load. The interval enclosed by the maximum and minimum corresponding to the two curves is the result of ultra-short-term load prediction: ultra-short-term load interval. Considering the uncertainty of flexible load response, it is more reasonable to consider the range of load prediction results.

5 Conclusion

Based on the radial basis neural network, this paper predicts the inert load and predicts the flexible load based on the price elasticity of demand. Based on this, combined with the range of the flexible load, an overall interval for ultra-short-term load forecasting is constructed. The ultra-short-term load forecasting technology proposed in this paper takes into account the factors of flexible load demand response, and is verified by an example.

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