Research on Single User Ultra Short-Term Load in Power Supply Thermal Diagram Prediction Algorithm through Markov Process

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Abstract. Different from the load prediction of lines above 10kV, the super-short-term load curve of single user tends to show high uncertainty. This paper first analyzes the source of this kind of uncertainty, and shows that this kind of uncertainty is unavoidable. To solve this problem, this paper no longer takes the load curve as the prediction target, but puts forward the idea of using thermal diagram to represent the load prediction results. Then, this paper combines the thermal diagram with the basic principle of Markov process, and designs a single-user super-short-term load prediction algorithm. The algorithm consists of initialization, updating and generation of prediction results. Finally, the experimental results of user data in Gusu District of Suzhou show that the algorithm described in this paper has high accuracy and practical value.

Keywords: Markov process, Load forecasting, Super short term, Heatmap.

1. Introduction

Ultra-short-term load forecasting refers to load forecasting several hours later than the current period. In recent years, the emerging demand response and multi-energy control technology have put forward new requirements for ultra-short-term load forecasting [1]. One is that the computation time is short. The second is a higher degree of system refinement. This requires the system not only to forecast the regional load, but also to forecast the single user quickly [2].

The research on super-short-term load forecasting methods mainly includes load model construction, artificial intelligence technology, wavelet analysis and vector machine.

The load model mainly USES the time series analysis method, establishes the correlation model, then combines other technology, carries on the load forecast. Literature USES ARIMA to stabilize the load data, then classicizes the data according to temperature, and USES neural network to calculate the sensitive factors of meteorological changes, and finally obtains the predicted load [3]. Literature obtained the predicted load for individual industrial users by means of series summation. In reference, under the framework of chaos theory, the correlation dimension was calculated to obtain the optimal embedding dimension, and Lyapunov index was used to calculate and predict the load [4].

There are many achievements in artificial intelligence, most of which are based on neural network or fuzzy clustering [5]. Literature introduced DBN layer by layer unsupervised learning and proposed a short-term load prediction algorithm based on deep belief network. This algorithm combines training speed and precision and is suitable for load solving under complex factors. Literature obtained relevant
parameters of k-mean clustering algorithm based on two-year data in an area of Ireland in an experimental manner.

In terms of wavelet analysis, literature combines fuzzy clustering with functional wavelet core non-parametric regression, USES historical days for weighting calculation, and USES N-WE algorithm to obtain the prediction algorithm. Literature USES wavelet decomposition method to decompose load data into high and low frequency components. Then gray clustering and neural network are combined to realize the load prediction. Literature proposed a probabilistic prediction algorithm. The generalized limit learning machine (GELM) is used to train the wavelet neural network (IWNN), and the load prediction is realized. The confidence interval is adopted in this paper to represent the predicted load in a regional way, which inspires the research in this paper.

In terms of vector machine, literature combines the smoothness of prediction with the error loss function to form the objective function of the problem. LIBSVM algorithm is adopted to realize load prediction. Literature applied support vector regression machine (SVRM) to day-ahead prediction.

These algorithms play a unique role in different scene requirements. However, there is a lack of a single user-oriented ultra-short-term prediction method and prediction algorithm. On the other hand, the rapid development of intelligent technology makes it possible for refined integrated energy management and demand response. Comprehensive energy management and control is based on the ultra-short-term prediction of a single user. The lack of this algorithm has increasingly become a bottleneck restricting the development of comprehensive energy management and demand response.

This paper first analyzes the difficulties of single user super short-term prediction and proposes a new prediction representation method. Then, based on Markov process, a single user super-short-term load forecasting algorithm is proposed. Finally, the effectiveness of the algorithm is proved by practical application.

2. Accuracy analysis of predictions
The traditional load forecasting method is usually to predict a specific curve. In this way, the accuracy of the prediction curve is really a comparison of the prediction curve and the actual curve.

A common accuracy calculation method is the standard developed by the National Power Dispatching Communication Center. The calculation formula is as follows:

\[
E_i = \frac{|L_{ei} - L_{gi}|}{L_{ri}} \times 100\%
\]

\[
A = 1 - \sqrt{\frac{1}{n} \sum_{i=1}^{n} E_i^2} \times 100\%
\]

3. A representation of a single user forecast
At some point, the prediction of a user's load, there is often a large deviation. This bias can be described in terms of probability. For example, at 12 o'clock at noon, the probability of a user's load being 15~20W is 20%, the probability of 20~50W is 5%, the probability of 50~60W is 35%, and the probability of 60~70W is 40%. This probabilistic approach gives a better representation of the future loads than the traditional form of the curve.

This is very close to the probability density. However, the data in the actual calculation is discrete, and the probability density of the load data is difficult to be described by functions, so the load value can only be divided into several intervals, and the probability that the load value falls in a certain interval is used to represent the forecast result of the load. And the way to represent the probability of each interval is the thermal diagram.
4. Application of Markov process in load forecasting
The historical load of forecast day is an important basis for ultra-short-term forecast. Through the historical load curve of the day, the user's load change trend can be judged. The type of equipment used by the user can even be determined by non-invasive measurement of load. However, the integration of these data often requires a lot of calculations. But the super - short - term forecast has higher requirement on time. From the proposal of the forecast demand to the completion of the forecast, it is generally completed within a few seconds. A lot of calculations will slow down the predicted speed of the system.

Based on this forgetting characteristic of load, markov process can be considered to deal with the ultra-short-term prediction of load. That is, before the prediction date, the data is preprocessed to generate the transfer matrix. When the prediction occurs, the predicted load is obtained according to the Markov process and the pre-generated transfer matrix.

5. Load forecasting algorithm
5.1. Initialization of predictive data
In the first run of this algorithm, it is necessary to comprehensively calculate the data, obtain the initial transition relationship between each state, and form the transition matrix. Specific steps are as follows:
(1) Obtain the historical load data of all predicted users;
(2) Traversed historical data to obtain the maximum daily load;
Among all the highest loads, the position of the previous TD ratio (rounded up upward) is taken as the threshold. Td is specified by the forecaster.

For example, a five-day maximum load for a user is 23kW, 25kW, 29kW, 31kW, 36kW, and TD is specified as 31%. Then

$$\left\lfloor 5 \times 31\% \right\rfloor = \left\lfloor 1.55 \right\rfloor = 2$$

(2)

Here, \( \left\lfloor \cdot \right\rfloor \) means to round up. The number 2 is 31kW, so the threshold is 31kW.

(4) \(|M|\) is the Number of load value intervals specified by users. Intervals below the threshold are all divided into \(|M| - 1\).

(5) To traverse all historical data for the second time and count the number of jumps between all states.

(6) Update all data. Calculate the jump probability between each state. The calculation formula is as follows:

$$P_{t,m_{\text{start}},m_{\text{end}}} = \frac{\sum N_{t,m_{\text{start}},m_{\text{end}}}}{\sum_{m_{\text{end}} \in M} N_{t,m_{\text{start}},m_{\text{end}}}}$$

(3)

In the above formula, \(N_{t,m_{\text{start}},m_{\text{end}}}\) refers to the historical jump times when the load value of a user is assumed to belong to the interval \(m_{\text{start}}\) at the measured time point \(t\), and at the next measured time point \(t+1\), the load value jumps to the interval \(m_{\text{end}}\). \(P_{t,m_{\text{start}},m_{\text{end}}}\) is the probability of jumping between the corresponding states.

$$\sum_{m_{\text{end}} \in M} P_{t,m_{\text{start}},m_{\text{end}}} = 1$$

(4)

(7) For some states that have never appeared in the historical data, the jump probability starting from this state is assigned. The calculation formula is as follows:

$$P_{t,m_{\text{start}},m_{\text{end}}} = \begin{cases} 1, & \text{if } m_{\text{start}} = m_{\text{end}} \\ 0, & \text{if } m_{\text{start}} \neq m_{\text{end}} \end{cases}$$

(5)

At this point, the transfer matrix is obtained and the initialization of prediction data is completed.

5.2. Incremental updates to forecast data

According to the calculation of Formula (3) and (5), the state transition probability can be obtained. At time point \(T\), these transition probabilities can be composed of order transition matrix \(M_t\) as follows:
\[
M_t = \begin{pmatrix}
P_{t, a_1, a_1} & P_{t, a_1, a_2} & \cdots & P_{t, a_1, a_j} \\
P_{t, a_2, a_1} & P_{t, a_2, a_2} & \cdots & P_{t, a_2, a_j} \\
\vdots & \vdots & \ddots & \vdots \\
P_{t, a_j, a_1} & P_{t, a_j, a_2} & \cdots & P_{t, a_j, a_j}
\end{pmatrix}
\] (6)

In the data of the new day, at the time point \( t \), the load value is in the interval \( m_p \); At the time point \( t+1 \), the load is in the interval \( m_q \). Set the total sample number as \( N_{\text{sample}} \), and the jump probability is updated according to the following formula:

\[
P_{t, m_p, m_q} = \frac{N_{\text{sample}} - 1}{N_{\text{sample}}} P_{t, m_p, m_q}^\prime \quad \text{if} \quad q' \neq q
\]

\[
P_{t, m_p, m_q} = \frac{1}{N_{\text{sample}}} P_{t, m_p, m_q}^\prime \quad \text{if} \quad q' = q
\] (7)

\( P_{t, m_p, m_q}^\prime \) is the probability before update, \( P_{t, m_p, m_q} \) is the probability after update. \( q' \) iterate through all load ranges. \( \frac{N_{\text{sample}} - 1}{N_{\text{sample}}} \) Equivalent to the aging coefficient of the algorithm.

6. Experimental verification

In this paper, load data of 20 power users in Hailing District, Taizhou city in the last 3 years were randomly selected. Among them, the load data of the first two years are initialized with the algorithm in Section 4.1 to generate the transfer matrix. In the data of the last year, a number of time points were randomly selected and the instantaneous value of user load was used for the prediction calculation in Section 4.3. The predicted probability load is compared with the actual load to verify the prediction algorithm.

![Figure 3. The prediction results.](image-url)
7. Conclusion
This paper demonstrates the source of this instability and proves that this instability is inevitable. In the face of such instability, this paper, instead of predicting a curve like the traditional forecasting method, predicts the probability of occurrence of each load value. The probability is presented intuitively in the form of thermal diagram. Finally, according to the basic principle of Markov process, a super-short-term prediction algorithm based on thermal chart is designed. Experiments in Gusu District of Suzhou show that the algorithm described in this paper is effective.

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