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Distribution Line Load Predicting and Heavy Overload Warning Model Based on Prophet Method

Longjin Lv [1,*], Lihua Luo [2] and Yueping Yang [3]

[1] School of Finance and Information, Ningbo University of Finance and Economics, Ningbo 315000, China
[2] State Grid Zhejiang Cixi Power Supply Co., Ltd., Ningbo 315100, China
[3] State Grid Zhejiang Electric Power Co., Ltd., Ningbo Power Supply Company, Ningbo 315000, China
* Correspondence: lvlongjin@nbufe.edu.cn

Abstract: The load prediction of distribution network lines and the accurate prediction of impending overload lines can provide an important reference for the formulation of the power supply plan of distribution networks. This paper designs a line load predicting and heavy overload early warning model based on the Prophet method, where the time series decomposition and machine learning technologies are used. Firstly, we used the 5-day moving average to automatically fill the missing values in the data and automatically detect and correct the abnormal values in the data. Then, we decomposed the prediction model into the trend component, periodic component, and data mutation component by fully considering the periodicity, seasonality, holidays, and other factors of power data, which effectively improves the prediction accuracy and gives early warning of potential heavy overload risk. Finally, we tested the model according to the processing speed, root-mean-squared error (RMSE), recognition accuracy, and overload warning hit rate. The results showed that the model obtained in this paper has high accuracy and practicability.

Keywords: distribution line; load predicting; heavy overload warning; Prophet method

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1. Introduction

With the continuous development of urban construction, the urban electricity load is increasing day by day, and the requirements for the reliability of power supply are becoming higher and higher. Some important loads will cause significant economic losses even if the power is interrupted for a short time, which puts forward higher requirements for the stability of the urban distribution network [1]. At present, the distribution network station area is the last-level power supply unit for low-voltage users, so the operation status of the power supply equipment in the station area directly affects the power supply quality of the area. However, the heavy overload operation of equipment is one of the main reasons for power outages, and heavy overload is usually accompanied by other problems such as three-phase unbalance, voltage offset, etc., which seriously affect the safe and reliable power consumption of users. Therefore, the monitoring, early warning, and governance of heavy overload in the station area has become the most important content of the operation and maintenance of the distribution network [2].

At present, the conventional method for the management of the overload situation of the distribution transformer is real-time monitoring or post-processing. This processing method is passive and requires much monitoring time cost and maintenance labor cost [3]. In addition to fully considering the performance and status of equipment and lines, distribution network operation is also affected by various complex factors such as the external climate, environment, and users, which shows that it has obvious big data characteristics. Using big data technology to mine valuable information from power data and establish an accurate load forecasting model can provide a theoretical basis for the safety monitoring, preventive control, and emergency treatment of the power supply department.

Based on the concept of electric power big data, the internal data of the power grid and the external environmental data are combined to carry out research on the mining and prediction of the influencing factors of the power distribution transformer overload, which can avoid the loss of the power grid and users caused by the passive maintenance of the power grid equipment and improve the governance efficiency and effect of the heavy overload equipment.

A load monitoring system is usually carried out for large-scale distribution lines, and there is no unified load monitoring system for distribution networks, especially for distribution lines in cities. However, the capacity of urban distribution lines is relatively small, so it is more likely to be overloaded, resulting in accidents such as power outages, line losses, and component burnout [4]. Therefore, monitoring of the operation status of urban distribution lines should be strengthened. In addition, the load prediction and heavy overload warning of distribution network equipment are mainly based on manual methods through expert experience, which leads to the shortcomings of the low accuracy and real-time performance of forecasting and early warning [5]. The grid load forecasting and early warning system is of great significance to the daily operation and maintenance of the power grid. There are many linear regression methods based on time series. The authors used improved robust estimation and fuzzy linear regression models to reduce prediction errors and increase robustness [6]; the authors first performed cluster analysis on the data and then made a prediction model for each category, which effectively improved the prediction accuracy [7,8]; this represents short-term load forecasting, which predicts load for the next few hours to few weeks, midterm load forecasting, which usually covers a week to a year, and long-term load forecasting, which predicts load for more than a year [9]. The widely used ARIMA model and other technologies were organically combined to improve the prediction accuracy [10–13]. Currently, machine learning and deep learning methods are also used for load prediction, such as XGBoost [14,15], LSTM [16–18], neural networks [19–21], and the Bayesian model [22]. In addition, there are some new methods derived from the combination of the above methods. For example, in the literature [23,24], the particle swarm optimization algorithm was used to select better parameters for the LSTM network to improve the accuracy. The authors combined CNN and LSTM to construct a load forecasting model. First, CNN was used to process multi-dimensional data to extract effective features, and then, the LSTM network was used for time series prediction [25,26]. In [27], an effective methodology using the LSTM network was developed for precise forecasting that was capable of handling more complex time series load data with long-term dependencies. In general, the processing speed of the linear regression method is relatively fast, which can meet the real-time requirements of this early warning model. However, the linear regression method cannot capture the nonlinear laws in essence, so it has higher requirements on the quality of the dataset. Deep learning methods can usually learn nonlinear features in the data better, so they are more suitable for general data, but such methods often require a long time to train the model, so they cannot run new data in real-time to update the parameters of the model. Machine learning algorithms usually need to perform feature analysis on multi-dimensional data, so they do not conform to the characteristics of power load data [28].

Aiming at the above problems in reality, this paper designs a model based on the Prophet model, which can assist the staff to monitor the operation status of the distribution network in real-time, predict the future status of the distribution line, and give early warning of heavy overload. This paper mainly solves the following problems: (1) automatically filling in missing values and detecting and correcting outliers in the data; (2) fully considering the periodicity, seasonality, and holidays and other characteristics of power data, the predicted value is automatically decomposed into the trend components, periodic components, and data mutation components, which effectively improves the accuracy of model prediction; (3) early warning of potential heavy overload risks leaves enough time for staff to prepare.

2. Load Predicting Model

2.1. Prophet Algorithm

The Prophet algorithm is a time series prediction algorithm proposed by Facebook in 2017. It can capture the data change rules of different time dimensions according to the length of historical data and has the advantage of a fast fitting speed and a good effect. By improving the conventional time series decomposition method, the Prophet algorithm decomposes the time series to be predicted into four parts, as shown in the following formula:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t, \tag{1}$$

where $g(t)$ is the trend term representing the trend of the time series on the non-period; $s(t)$ is the period term (also called the seasonal term) representing the periodic pattern, whose unit depends on the length of the input data and can be in weeks, months, or years; $h(t)$ is the holiday term representing the effect of holidays; ε_t is the error term representing the abnormal fluctuations outside the model.

There are two optional functions for the trend term in the Prophet algorithm, and the algorithm will automatically choose one of them based on the data: one is the logistic function, and the other is the piecewise linear function. In this paper, the piecewise linear function was chosen to fit the trend term, as shown in the following formula:

$$g(t) = (k + a(t)\delta) \cdot t + (m + a(t)^T\gamma), \tag{2}$$

where δ is the change in the growth rate, which obeys the Laplace distribution $Laplace(0, \tau)$. k denotes the growth rate. In a real time series, the trend of the curve will definitely not remain the same all the time. At some specific time or in some potential period, the curve will change. The corresponding points when the growth rate k changes are called change points, denoted by $C = (c_1, c_2, ..., c_s)$, where s denotes the number of change points and c_j denotes the time of the change point. In the Prophet model, the position of the change point needs to be set, and the trend of each segment will also change according to the change point. m denotes the offset parameter. $a(t)$ is a time series generated by a binary function, which is equal to 1 when the current time point is exactly the position of the change point, otherwise equal to 0. $\gamma = (\gamma_1, \gamma_2, ..., \gamma_s)^T$, where $\gamma_j = -c_j\delta_j$.

The periodic term $s(t)$ is represented by a Fourier series, and its calculation formula is as follows:

$$s(t) = \sum_{n=1}^{N} (a_n \cos(\frac{2\pi nt}{P}) + b_n \sin(\frac{2\pi nt}{P})). \tag{3}$$

Here, P is the period of the time series, which is usually on a yearly cycle. N represents the number of such cycles to be used in the model; a larger value of N can fit a more complex seasonal function. According to historical experience, for the yearly time series, $P = 365.25$ and $N = 10$. Let $X(t) = [\cos(\frac{2\pi(1)t}{365.25}), ..., \sin(\frac{2\pi(10)t}{365.25})]$. For the weekly time series, $P = 7$ and $N = 3$, then $X(t) = [\cos(\frac{2\pi(1)t}{7}), ..., \sin(\frac{2\pi(3)t}{7})]$. Here, we used the parameter vector to represent the coefficients of the above formula $\beta = (a_1, b_1, ..., a_N, b_N)^T$, then the seasonal term of the time series can be expressed as $s(t) = X(t)\beta$, where $\beta \sim Normal(0, \sigma^2)$, and the default value of the standard deviation σ is 10, which can also be preset. The larger the value of the standard deviation, the greater the impact of seasons on the data distribution is, and vice versa.

In the real environment, holidays or some major events will have a significant impact on the distribution network load. The Prophet algorithm regards different holidays as independent models and sets different front and rear window values for different holidays, which shows that the holiday will affect the time series before and after a period of time. For the i-th holiday, D_i denotes the period before and after the holiday. K_i represents the

influence value of the i-th holiday. Assuming there are L holidays, then the holiday effect model is

$$h(t) = Z(t)K = \sum_{i=1}^{L} k_i 1_{\{t \in D_i\}}, \quad (4)$$

Here, $K \sim N(0, \nu^2)$, and the default value of the standard deviation ν is 10, which can also be preset. The larger the value of the standard deviation, the greater the impact of holidays on the data distribution is, and vice versa.

The Prophet model has been used to predict the satellite clock bias to improve the accuracy of precision point positioning [29]. The authors propose a hybrid method using Prophet and Long Short-Term Memory (LSTM) models to overcome the above limitations in an effort to predict accurate load. The Prophet model utilizes linear, as well as nonlinear data to predict the original load data, but still, some of the residuals are left, which are regarded as nonlinear data [30].

2.2. Modeling Process

Before training the model, it is necessary to prepare the required data. In addition to the already stored historical data of the distribution network load, it is also necessary to be able to collect the latest data in real-time to update the model, so as to ensure that the model can adapt to the new laws, which are constantly evolving. In this paper, we used the line electric current value to indicate the line load, since the line electric current is the original data collected by the distribution automation system. In some articles, the authors use power to express the line load, which is obtained by multiplying the line electric current by the voltage level of the line. For a line whose voltage level remains constant, we have 10 kv, 35 kv, and 110 kv, etc. Here, we studied the line voltage level of 10 kv. The data were derived from the transformer current variation of a distribution line within a region for one year from 2020 to 2021. The data were collected at a frequency of 5 min with time points and corresponding electric current values, as shown in Figure 1. y represents the line electric current value, whose unit is amperes (A). It can be seen from the figure that the average daily load peak value in February is far less than that in July, which indicates that seasons have a significant impact on the line load.

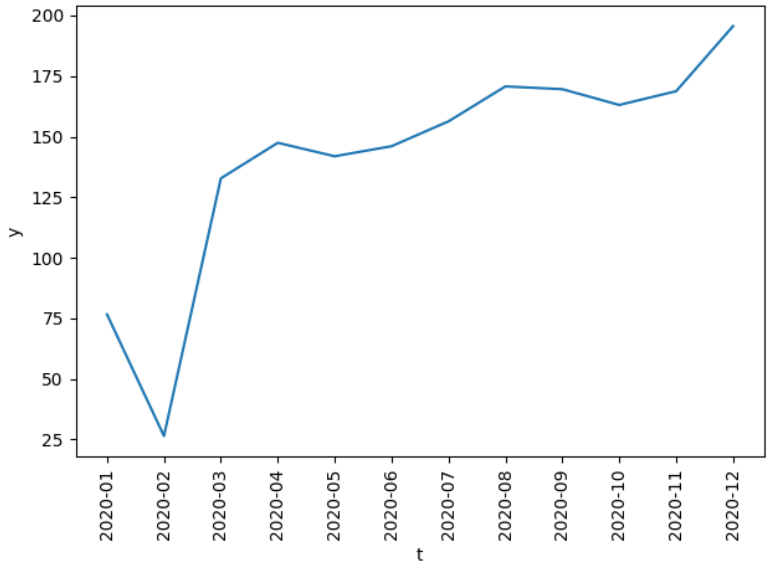


Figure 1. Load curve of distribution lines in 2020.

It can be seen from Figure 2 that the peak load of the line in the week before New Year's Eve generally shows a gradual downward trend. The peak load from the first day to the fifth day is obviously smaller than the peak load before the Spring Festival, and the

load gradually recovers to the level before the Spring Festival from the sixth day. It can be seen that the load affected by the Spring Festival has a low power load from the first day to the fifth day.

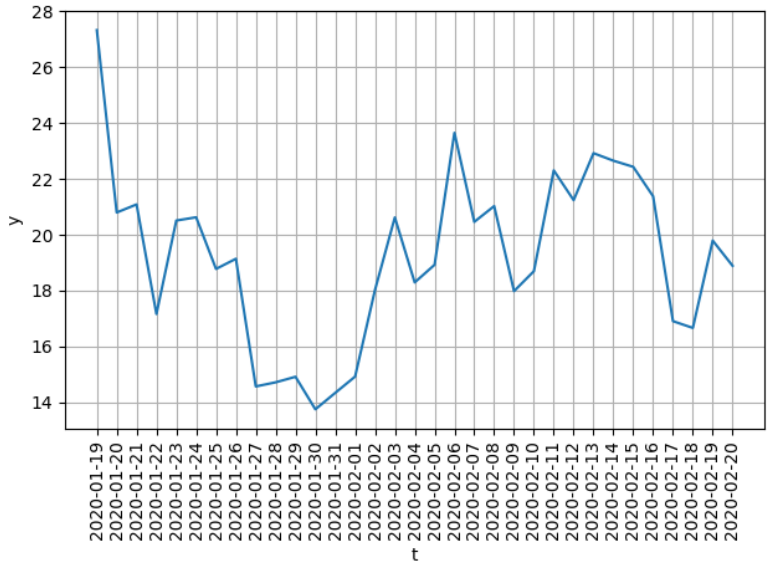


Figure 2. Line load curve before and after the Spring Festival in 2020.

To sum up, the line load of distribution network is affected by holidays and seasons and has a specific change trend. Prophet is very suitable for line load forecasting.

Due to the presence of invalid/null values and outliers, the data need to be preprocessed before they can be used to train the model. For invalid/missing values in the data, we filled them with the average of the five preceding valid values $[x_{t-1}, x_{t-2}, ..., x_{t-5}]$. For the outliers, we first calculated the mean μ and standard deviation σ of the previous day's load. If x_t is not in the interval $[\mu - 2\sigma, \mu + 2\sigma]$, then it is determined to be an outlier. The values greater than the upper bound are replaced by the upper bound, and the values less than the lower bound are replaced by the lower bound. Then, we also need to normalize the data by using the following form:

$$\bar{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}. \tag{5}$$

After the data have been prepared, some parameters in the Prophet algorithm need to be tuned. The parameters that have a greater impact on the model training results are the number of change points, the smoothness of seasonal items and trend items, and the correct early warning rate, used as an indicator, manually dividing the training/test set to ensure the continuity of the time series, and finally, using the grid search method to optimize the parameters to obtain the optimal parameter configuration. The parameters that have a greater impact on the model training results in the Prophet algorithm need to be tuned, including the number of change points and the smoothness of seasonal items and trend items. In this paper, the selection of change points was based on the first 80 percent of the historical data of the time series, and then, the 25 change points were found by the method of equal division. We chose $\tau = 0.05$. According to the empirical value, the line load trend has the characteristics of a period of years, so we chose $P = 365.25$ and $N = 10$. By applying the grid search method, we obtained the optimized parameters $K = 2.42$, $m = 0.89$, $\sigma = 15.2$, and $\nu = 7.4$, which shows that seasonality has a greater impact on the load than holidays.

In Figure 3, we show the fitting effect of the model on the past data and the prediction of the future week, where the x-axis is the time axis and the y-axis is the electric current

value (A). The dark blue curve in the figure is the model prediction value yhat; the light blue part is composed of the upper and lower bounds of the prediction value; the black points are the real data. It can be found that the model can accurately fit the overall change trend of the current loadand make predictions.

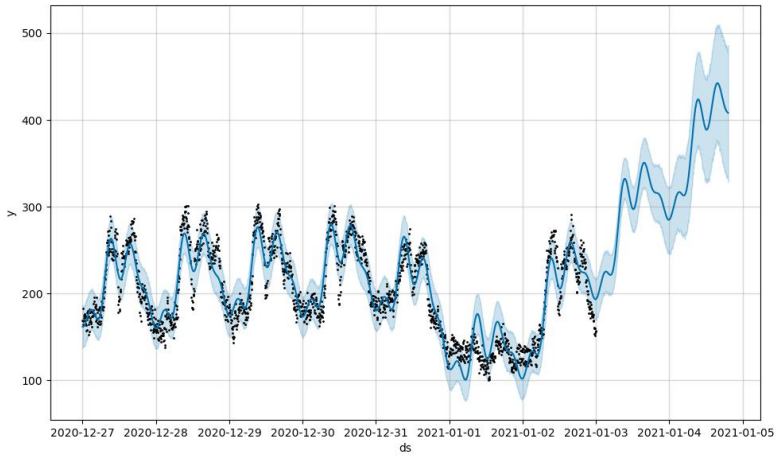


Figure 3. Model fitting and prediction results.

The load change trend under different cycles is shown in Figure 4. We can find that the load of the line reaches the highest in August and September, and the load is light in February; in terms of the weeks, the load pressure of this line on Tuesday, Wednesday, and Thursday is greater than that on other days; in terms of days, the period from 8:00 a.m. to 4:00 p.m. is the period with high load pressure on the line. These periodic trends conform to the characteristics of the line. The model can fit the load data and capture the laws in the data. In order to prove the effectiveness of the model, we calculated the root-mean-squared error and R squared. The calculation formulas are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} = 0.1166, \tag{6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} = 99.43\%. \tag{7}$$

where y_i, $\bar{y}_i$, and $\hat{y}_i$ represent the real value, the average value, and the predicted value of the model of the load at a certain time in the sequence, respectively. Theseindicators once again show that the prediction error of the model is small and the fitting degree is high. We also tested the running speed of the model and compared the test results with the ARIMA model, which is widely used. The comparison results are shown in Table 1.

Table 1. Comparison between the Prophet model and the ARIMA model.

Model	Running Time	RMSE	R Square
Prophet	2.4218	0.1166	99.43%
ARIMA	2.7187	0.1972	99.02%

It can be seen from Table 1 that the running time, RMSE, and R^2 of the Prophet model are significantly improved compared with the ARIMA model. This is due to the fact that distribution line loads are naturally cyclical and very unstable. This can be affected by a variety of external impact factors and, thus, involves a high level of uncertainty, such as sudden rises at holiday time points, while the ARIMA model requires that the time series

data be stationary or stable after differencing, which in essence can only capture linear relationships, not nonlinear ones.

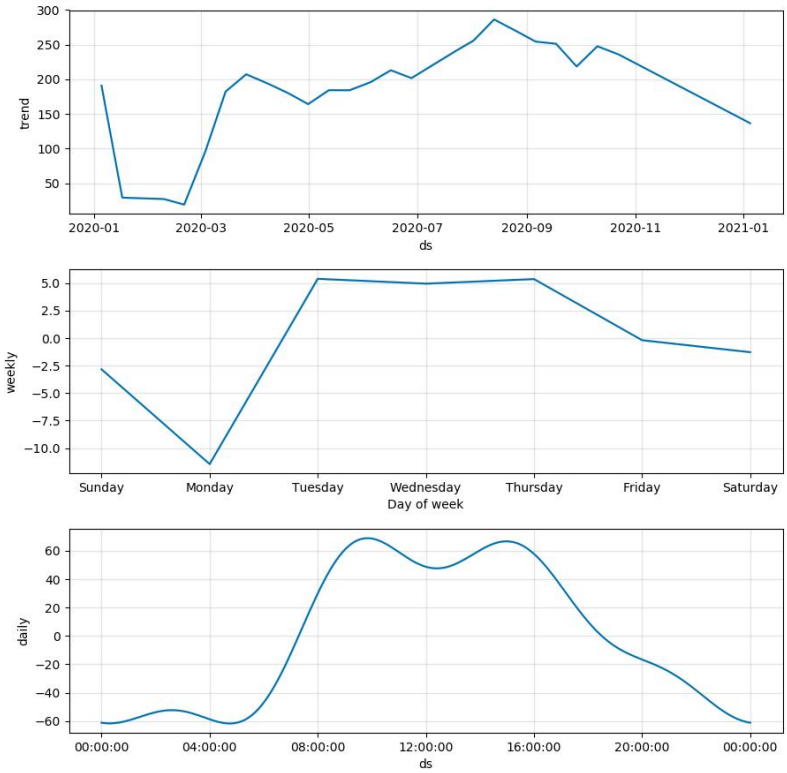


Figure 4. Trend of various components of the model.

3. Heavy Overload Identification

We applied the prediction model to line overload warning. In this paper, 80% of the maximum carrying current of the line is defined as the warning threshold. For example, if a line can carry a maximum of 400A of current, the warning needs to be issued when it is predicted that the line current will reach 320. We denote the total number of samples as N_{all}, the number of samples exceeding the warning threshold in the actual data as N_{fact}, the number of samples exceeding the threshold in the prediction as N_{pre}, the number of correct warnings (the threshold was actually exceeded, and the system issued a warning) as T_p, the number of incorrect warnings (the system issued a warning, but the threshold was not actually exceeded) as T_f, and the number of missed warnings (the threshold was actually exceeded, but the system did not issue a warning) as T_{miss}. Therefore we can obtain the model recognition accuracy, defined by $P_{all} = \frac{N_{all}-T_f-T_{miss}}{N_{all}}$. The load correct hit rate of the model is $P_p = \frac{T_p}{N_{fact}}$, which has special significance for the power system. The loss caused by the failure to anticipate the heavy overload phenomenon in advance is far greater than identifying a normal event as an overload event, which is just one more manual on-site inspection to confirm the work, while the former may lead to power outages in the whole grid area. The higher the load hit rate, the more effective the model is. With the above definition, we applied the Prophet load prediction model for early warning identification of heavy line overloads. After the statistical analysis, we obtained the results shown in Table 2.

Table 2. Pre-warning result.

Classification	System Warning	No System Warning	Total
Overload	29,867	606	30,473
Normal	23,508	50,851	74,359
Total	53,375	51,457	104,832

In this test, the actual total number of overloads occurring was $N_{fact} = 30,473$. The number of times the model triggered a warning for overload was $N_{pre} = 53,375$. The number of correct warnings was $T_p = 29,867$. The number of error warnings was $T_f = 23,508$. The number of missed warnings was $T_{miss} = 66$. Substituting the values into the evaluation index, the model recognition accuracy and load correct hit rate can be calculated as follows, respectively.

$$P_{all} = \frac{29,867 + 50,851}{104,832} = 77.00\% \tag{8}$$

and

$$P_p = \frac{29,867}{30,473} * 100\% = 98.01\%. \tag{9}$$

It can be seen that, although the overall accuracy of our model was only 77%, the correct hit rate for heavy overload events was 98%, which shows that the model can greatly reduce the scope of inspection and improve the efficiency of the work.

4. Conclusions

In this paper, we studied and designed a distribution network load prediction and heavy overload warning model, which was implemented based on the open-source Prophet algorithm. It can monitor and predict line loads and provide early warning of heavy overload phenomena in real-time, as well as capture the risk of the heavy overload of distribution network components such as distribution lines in a timely and accurate manner. The performance of the proposed model was validated by forecasting real-time electrical load data. The test results corroborated that the proposed Prophet model has a lower running time (2.4218) and RMSE (0.1166) and a higher R^2 (99.43%) in comparison to the ARIMA model. Based on the proposed load forecasting model, we developed the heavy overload warning model with a high correct hit rate (98.01%). The application of the proposed models can greatly improve the efficiency of line operation and maintenance.

Load prediction and heavy overload warning are an integral part of equipment condition detection, which is an important part of the lean management of distribution networks. The multimodal load prediction and heavy overload warning methods can be studied in the future, and the accuracy of prediction and warning can be further improved by analyzing multi-dimensional power equipment condition information through big data and artificial intelligence technology.

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