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# Maximum Power Demand Prediction Using Fbprophet With Adaptive Kalman Filtering

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**ABSTRACT** It is very difficult to predict the Maximum Power Demand (MPD) of customers in high performance because of various factors. In this paper, the problem of MPD prediction is studied by using fused machine learning algorithms. Firstly, an improved grey relation analysis method is adopted to analyze relevant influencing factors. Secondly, a modified prediction algorithm based on an adaptive cubature Kalman filter combined with Fbprophet is proposed according to the characteristics of customers' MPD. Finally, the proposed algorithm of this paper is applied to predict MPD and cost is evaluated. Experiment results show that the improved MPD prediction algorithm can comprehensively consider the relevant factors, and has good performance in time series prediction.

**INDEX TERMS** Kalman filter, Fbprophet, grey relation analysis, maximum power demand.

## I. INTRODUCTION

Since the beginning of the 21st century, applications of modern control theory have entered a prosperous period. Emerging intelligent technologies will certainly push the energy management of enterprises to a higher level. The existing MPD forecasting methods mainly include classical and artificial-intelligence-based methods [1], [2]. For large industrial users whose transformer capacity is equal or greater than 315kVA, the basic electric charge is determined by the capacity of transformer and the MPD. The transformer capacity is fixed, while the MPD is unknown, which needs to be predicted based on historical information [3]. Monthly MPD refers to the average power consumed during a certain period (15 minutes in China currently) of one month, and a maximum indication value is retained as the MPD in this settlement period [4]. Affected by the economic environment, the current load rate of enterprises is generally low. Due to restrictions of various conditions, it is difficult for electricity enterprises to apply to power supply enterprises for volume reduction or change of the charging method. In many high energy-consuming enterprises in China, energy management is still in the stage of manual statistics. Therefore, it is very necessary to design an accurate and intelligent MPD forecasting system that benefits the interests of power grid enterprises and customers [5].

Large industrial consumers take electrical energy mainly for industrial production. Their electrical characteristics and prediction process of MPD will be affected by many factors, such as weather conditions, temperature, wind rating, power policy, production planning, etc. [6]. The influence of various factors should be considered comprehensively to improve prediction accuracy. The basic electricity price adjustment policy, released in June 2016 by the National Development and Reform Commission of China, carries on a quarterly adjustment instead of the original annual-change of basic electricity price model and changes the basic power cost charging period from a half year to one month. Power consumers can select a charge mode according to their developments rationally [7], [8]. An insight study of power policy impact on load characteristics can help to apply MPD prediction models to practice more appropriately. It is necessary to collect and analyze such policy information in advance. Meteorological factors are mainly composed of temperature,

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weather conditions, and wind grades. In summers, the power load of cooling equipment increases, and in winters, the load of heating equipment increases. Wind and temperature have similar impacts on MPD. The difficulty for such influencing factors lies in the collection and quantification of meteorological information. Since interruption maintenance, emergencies, and industrial product order numbers will have great impacts on a load of power enterprises, it is particularly important to collect relevant information. Due to the above factors, it is difficult and challenging to predict the MPD of power enterprises accurately.

MPD prediction methods mainly consist of the grayscale prediction method, neural network method and time series method. Among them, the grayscale prediction method is suitable for considering a variety of uncertain factors and analyzing the correlation between system factors [9], [10]. In [11], [12], the Elman and Feed Forward Neural Network (FFNN) were used respectively to predict the MPD to realize energy saving. However, as a result of using an artificial neural network to do a prediction, it has the disadvantage of non-interpretability. In parameter setting procedure, how to ensure convergence and uniformity of operation rate should also be considered [13]. In [6], [14], the short-term electricity demand of a family was modeled with background information, and a good effect was achieved. However, loads of households and electricity enterprises are quite different, an appropriate prediction model should be selected according to application situations. The time series analysis method of lifting wavelet was used for prediction in [15]. The time series method requires high-accuracy historical data, and prediction accuracy will reduce when to step length becomes bigger. With the rapid development of the social economy, the changes in production structure and production model make various factors affect MPD. Fbprophet [16], an open-source algorithm of Facebook developed in 2017, is a universal time series model. A time-series prediction problem has been transferred into a curve fitting process. Fbprophet has a good effect in modeling data with piecewise trend and multi-cycle characteristics; it is suitable for forecasting the MPD of power enterprises and has good potential for further improvement.

The model of Fbprophet includes items of trend $g(t)$, cycle $s(t)$, holidays $h(t)$, and error $e_t$. In correlational research [17], [18], the ARIMA model is suitable for short-term forecasting and there is still room for improvement in long-term forecasting. Fbprophet could not identify the distance point well [17]. Besides, this study only improved the algorithm structure and did not consider the influence of relevant factors on the prediction results. In this work, the Adaptive Cubature Kalman Filtering (ACKF) algorithm with forgetting factor was adopted to improve Fbprophet, to assist it to fit the trend and seasonal structure accurately in the process of long-term prediction. The influence of historical data on filtering results had been reduced, and it improved the ability to deal with nonlinear problems. Besides, Grey Relation Analysis (GRA) was adopted to consider the influence of relevant meteorological factors on the prediction of MPD comprehensively, as well as production plan factors, which made the prediction algorithm have better prediction performance.

This paper focuses on the core problems, including load characteristics, selection of main influencing factors and construction of high-precision forecasting model, of MPD forecasting for large industrial users. According to the theory of previous research [6], [9]–[15], the selected influence factors are electricity policy, meteorological conditions, and production scheduling. The proposed solution includes the following steps: firstly, collect and analyze relevant policy information, and determine a prediction model according to the load characteristics; secondly, because Fbprophet algorithm has a good effect in modeling data with characteristics of segmented trend and multi-cycle, it is suitable for predict the MPD of power enterprises; thirdly, the influencing factors are analyzed from multiple perspectives. In this work, the entropy method is used to improve the GRA, which carries on a thorough analysis of meteorological factors to get a weighted correlation of electric power load characteristic value. Then, Fbprophet based prediction algorithm is used to establish an MPD model for power users. Since MPD is predicted monthly, steps are usually about 30 days and longer steps are not conducive to the performance of the time series prediction. To improve the prediction effect, ACKF with a forgetting factor is introduced based on influence factor analysis, to assist Fbprophet in reducing the influence of remote historical data on the filtering results. The improved MPD prediction method based on the combination of Fbprophet and ACKF is proposed. Finally, according to the electricity price policy and the predicted value of MPD, the electricity cost is evaluated.

According to the MDP characteristics of industrial consumers, this paper took four large industrial power users to carry out MPD prediction research. The remaining parts of this paper are organized as follows: in Section II, the basic principle of MPD forecasting and the research motivation of this work are described. In Section III, the production plan, the relevant weather factors by Scrapy framework [19], and the improved GRA adopted to analyze these factors are presented. In Section IV, the prediction model is established with Fbprophet and optimized by an improved ACKF to further increase the accuracy of the prediction model. Then, based on the MPD forecast of large industrial consumers, their electricity consumption is evaluated. In Section V, Users' electricity bills were assessed. In Section VI, simulation experiments are carried out by using Python and MATLAB to simulate the selected large industrial consumers. Simulation results show that the proposed method can analyze the influencing factors and predict the MPD of power consumers correctly. The MPD forecasting system is composed of three parts: influence factor analysis, MPD prediction, and cost evaluation. The system of this work can quantitatively analyze the influencing factors and use an intelligent algorithm to predict the MPD accurately.

## II. PROBLEM DESCRIPTION

### A. PROBLEM ANALYSIS

From the perspective of power system operation planning, the MPD shows a trend of gradually rising in a certain period. However, from the perspective of actual operation, the characteristics of the power load show strong random fluctuations due to the influence of various emergencies and influencing factors. To realize high efficiency and accurate prediction of the power system, it need not only to research the development laws of power load characteristics sufficiently but also to consider the external influence factors comprehensively. The basic steps of the MPD prediction method [3] are shown in FIGURE 1.

1) Collect users' historical demand data.
2) Preprocess the collected historical demand data.
3) Determine characteristics and factors that affect the MPD of research objects.
4) Based on the considerations of relevant influencing factors, a prediction method is selected and established.
5) According to the prediction model above-mentioned, a suitable algorithm is adopted to predict the MPD of consumers.

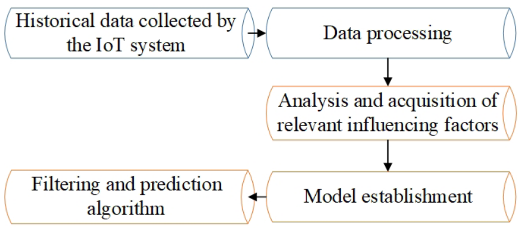


**FIGURE 1. Block diagram of the traditional MPD prediction.**

### B. RESEARCH MOTIVATION

The load prediction method of industrial enterprise consumers based on machine learning is mainly divided into five modules and its basic framework is shown in FIGURE 2. The innovation parts of this paper are as follows:

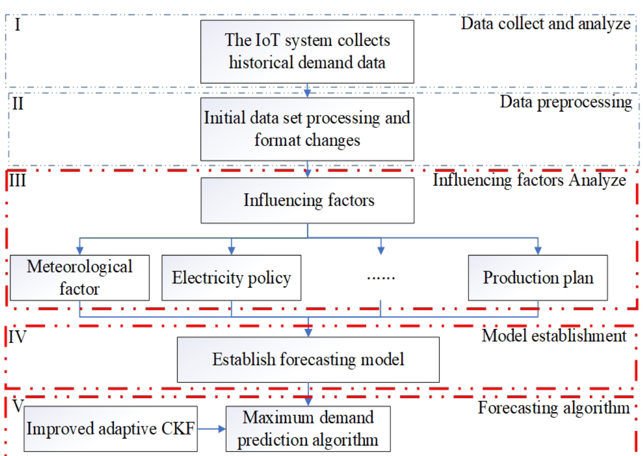


**FIGURE 2. General flow diagram of MPD forecasting method.**

1) Collect users' historical demand data by the Internet of Thing (IoT) systems. The main task of the MPD forecast is to predict the MPD for large industrial consumers and to help them choose a more appropriate metering solution.
2) Preprocess the collected historical demand data. Since the data sets are daily demand data, they need to be converted to daily MPD data.
3) Determine characteristics and factors that affect the MPD by improved GRA. Electricity consumption habits of industrial consumers should be investigated.
4) Based on the considerations of relevant influencing factors, the Fbprophet forecasting method is selected in this work, and the model of prediction is established.
5) According to the prediction model determined in the previous step and improved adaptively CKF algorithm is adopted to modify the Fbprophet and predict the MPD.

From the above analysis, it can be seen that the traditional MPD forecasting methods are difficult to consider various influencing factors comprehensively, and accuracy will drop when the prediction steps are too long. The MPD forecasting methods based on data-driven can hardly guarantee good prediction performance when they are used to fit nonlinear models. This paper is based on previous work [6], [9]–[16] and takes the influence factors analysis into account. Acquire meteorological data, such as temperature, weather conditions, and wind scales from the website of "http://www.tianqihoubao.com/". Besides, information about the consumer's production plan is collected, and an analysis method based on improved GRA [20] is adopted to analyze the relevant factors influencing the MPD. Aiming at the shortcoming that the existing GRA method does not fully consider the different importance degree of each factor [21], an entropy-based method is adopted to calculate the reference weight after the dimensionless method, and the influence degree of each historical influence factor is considered. Fbprophet can get trend decomposition conveniently, and based on the Back-end probabilistic programming language Stan, which can give full play to superiority of Bayesian algorithm [16]. One of the purposes of this study is to obtain monthly MPD values from the collected daily MPD data sets. If the original data is directly used as training samples, the predicted values will be smaller than the expected ones. Because of the above defects, and improved ACKF algorithm is considered in this work to improve the trend term of the Fbprophet nonlinear model and the fitting accuracy of the trend term function.

In traditional filtering algorithms, because statistical characteristics of noise are unknown, the standard CKF algorithm may lead to a large estimation error [22]. Therefore, ACKF based on noise statistical characteristics was proposed [22]–[26]. In [23], the CKF with forgetting factor was adopted to adjust the weight coefficients of old and new data by limiting the length of filter. [24], [26] extracted samples from the noise prior distribution to approximate the object's relative pose as well as the noise statistics. The process noise covariance Q and observed noise covariance R were adjusted; the traditional CKF and the square root cubature Kalman (SCKF) were improved respectively. In [22], [25], the adaptive Sage-Husa algorithm was adopted to increase the filtering accuracy caused by unknown statistical characteristics of noise and to improve the anti-noise interference performance. The adaptive method can reduce the noise estimation error, but can not give full play to the filtering performance. In this study, an adaptive approach is designed with consideration of a forgetting factor, the noise in the adjustment process, and the observed noise covariance Q and R; this method can not only adjust the weights of the old and new data in the filter but also reduce the noise estimation error; accordingly, the filtering accuracy could be improved to the greatest extent. At the same time, the Kalman filter has strong real-time performance, which can improve the fitting ability of the prediction model and improve its performance when it is used to predict the MPD of large industrial users. In this paper, with the improved ACKF fusion method, the Fbprophet prediction algorithm is improved to achieve monthly MPD high-precision prediction of large industrial users.

## III. ANALYZING MPD INFLUENCE FACTORS OF LARGE INDUSTRIAL CONSUMERS

### A. RELATED INFLUENCING FACTORS OF MPD

Power demand characteristics generally show a trend of gradual rise within a certain period; but in actual operation, power demand includes strong random fluctuations due to the influence of various emergencies and influencing factors [27], [28]. To achieve efficient and accurate prediction of MPD, it is necessary to fully study development laws of power load characteristics and to comprehensively consider external influencing factors. Meanwhile, the characteristics of influencing factors and their internal relationship with power demand characteristics both need to be analyzed deeply. To carry out this work better, firstly, the relevant factors that affect MPD are analyzed; the specific impact of each factor on the MPD and their relationships are explained in this section. Then an improved GRA method is proposed to analyze the problem.

(1) Power policy factors: power policy has a significant impact on the reliability of MPD prediction in terms of price setting, demand-side management technology innovation, and smart grid construction. The electricity price stipulated by electric power policy not only directly affects the time and quantity of electricity consumption of users but also affects the economic benefits of the power supply department. Therefore, a reasonable price structure plays an important role in the effective distribution and utilization of electric resources.

(2) Meteorological factors: meteorological factors cover many contents, such as maximum and minimum temperatures, weather conditions, wind scale, etc. Among them, temperatures have great impacts on electricity demand. For example, during the high-temperature period in summers, the electrical load of cooling equipment will increase, and during the cold period in winters, the electrical load of air conditioning and other heating equipment will increase. The quality of weather conditions will also affect the electrical load. For example, the indoor lighting load will increase on cloudy days, and the temperature may rise when light is strong on sunny days. Wind speed has a certain relationship with air temperature; for example, in stuffy summers, increasing wind speed will reduce air temperature. The change of MPD depends on a comprehensive function of meteorological factors. A deep analysis of meteorological factors is conducive to the determination of the relationship between meteorological factors and the power load characteristics. Since the data provided by IoT systems only include the daily MPD data from July 2017 to September 2019, this work gets meteorological data of the region in Linhai city from July 2017 to September 2019, including weather conditions, maximum temperature, minimum temperature, and maximum wind scale. Weather conditions include fourteen categories; to convert them into data, the above fourteen weather conditions are fuzzified and assigned values were set at 0.07 intervals, in which the minimum value of Sunny/Sunny = 0.07 and the maximum value of Light rain/Sleet = 0.98, which as shown in TABLE 1.

**TABLE 1.** The average value of grey correlation degree.

| | | | |
|---|---|---|---|
| Sunny/Sunny | 0.07 | Cloudy/Light rain | 0.56 |
| Sunny/Cloudy | 0.14 | Overcast/Light rain | 0.63 |
| Sunny/Overcast | 0.21 | Overcast/Moderate rain | 0.70 |
| Fine/Light rain | 0.28 | Light rain/Light rain | 0.77 |
| Cloudy/Cloudy | 0.35 | Moderate/Light rain | 0.84 |
| Overcast/Cloudy | 0.42 | Overcast/Sleet | 0.91 |
| Overcast/Overcast | 0.49 | Light rain/Sleet | 0.98 |

(3) Production plan factors: a production schedule includes the product, stratum, status, order numbers, product numbers, names and specifications, quantity, and material. Big prediction error could be caused when the production scheduling plan and power failure are not considered. For industrial production consumers, the product order numbers could affect their MPD because an increasing order number will cause a short-term increase in the power demand. This work also collects order quantity information. Order information for March are shown in TABLE 2 without presenting product names and specifications. In TABLE 2, the plug-in line is a pipeline equipment used in various production lines widely; the assembly line is a production line that completes the corresponding assembly work in each assembly station according to certain requirements; the Surface Mounted Technology (SMT) is the most popular technology and process in electronic assembly industries, and the numbers on the left of SMT indicate the production line number. All the above factors will interfere with the MPD and affect the prediction performance.

**TABLE 2. Module production schedule.**

| Product 1 | Mon | Tues | Wed | Thur | Fri | Sat | Sun |
|---|---|---|---|---|---|---|---|
| 1. Plug-in line | 450 | 100 | | | | | |
| 1. Assembly line | 330 | | 230 | 330 | 70 | | |
| **Product 2** | **Mon** | **Tues** | **Wed** | **Thur** | **Fri** | **Sat** | **Sun** |
| 1. SMT | 500 | | 200 | 500 | 300 | | |
| 2. SMT | 1500 | | | | | | |
| 1. Plug-in line | | | 450 | 550 | 450 | 450 | |
| 2. Plug-in line | 350 | 450 | | 3000 | | | |
| 2. Assembly line | 150 | | 200 | 360 | 260 | 160 | |
| 3. Assembly line | | 800 | 400 | | 400 | 800 | |

### B. INFLUENCE FACTOR ANALYSIS METHOD

GRA belongs to the applied category of the gray system. Compared with the commonly used correlation analysis methods, GRA has the advantage of less requirement on the regularity and quantity of sample sets, and it has better extensive adaptability. By judging the degree of closeness between each influencing factor and power load characteristics according to the size of the grey correlation degree, main influencing factors could be determined, and the reduction of forecasting efficiency due to too many considerations of the secondary influencing factors could be avoided. The closer the value of the correlation degree is getting to 1, the more sensitive the index is to the evaluation objects; in contrast, the closer the value of correlation degree is getting to 0, the less sensitive the influence is. The basic framework of GRA in this work is shown in FIGURE 3. The overall analysis steps are as follows:

*Step1:* Select data from the original data sets to form an analysis index system x.

*Step2:* Conduct dimensionless processing to calculate the initial data sequence. To eliminate interferences and errors caused by different units of the original data, the original sequence is processed dimensionless according to equation (1) and (2). To avoid the existence of extreme values, a new processing method is adopted in this paper. Among the sequence, the maximum demand data is processed logarithmically to calculate the sequence $x'_{i,j}$ as follows:

$$x'_{i,j} = lg\left(x_{i,j}\right) \tag{1}$$

where $x'_{i,j}\,(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$ is the *ith* initial value data of the *jth* index.

Due to the difference with the processed maximum demand data, different normalization formulas are adopted for the relevant meteorological influencing factors as follows:

$$x'_{i,j} = \frac{x_{i,j} - x_{jmin}}{x_{jmax} - x_{jmin}}, \quad i = 2, \ldots, n;\ j = 1, 2, \ldots, m \tag{2}$$

where, $x_{i,j}$ is the original parameter; $x_{jmin}$ and $x_{jmax}$ are minimum and maximum values of $x_{1j}, x_{2j}, \ldots, x_{nj}$ respectively; $x'_{i,j}$ is the normalized meteorological parameter data.

*Step3:* Calculate difference sequence $\Delta$, maximum difference $max_\Delta$, and minimum difference $min_\Delta$.

*Step4:* Calculate the correlation degree coefficients $\xi$.

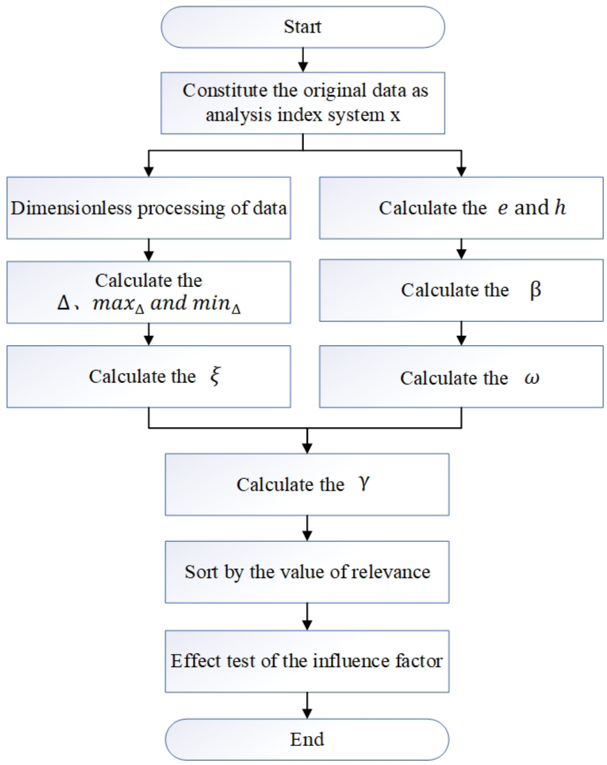


**FIGURE 3. Flow chart of grey relational degree analysis.**

*Stpe5:* Calculate weight coefficient $\omega$ according to the entropy $e$.

*Stpe6:* Calculate relational degree $\gamma$ according to the $\xi$, $\omega$.

*Step7:* Sort the data according to the size of the correlation degree.

*Step8:* Evaluate the influence factor analysis effect.

GRA is adopted to calculate the relational degree. Using averaging relational degree coefficient to avoid loose placing information and to facilitate global analysis. To make the analysis results more consistent with actual situations, the data closer to the current event should be assigned bigger weights, and the data farther away should be assigned smaller weights; in this way, the analysis result can cover information of the latest data. As long as the correlation coefficients for all the points algebra and $\sum_{i=1}^{n} \xi_{i,j}$ remain the same, then no matter how to change the volatility factor $\xi_{i,j}$, it can't change its correlation, this is unreasonable. If we do not consider the fluctuation, it is likely to lead to wrong conclusions [21]. Therefore, based on the new processing method, this paper adopts entropy weight and GRA to analyze the influencing factors.

## IV. IMPROVED MPD PREDICTION ALGORITHM BASED ON FBPROPHET AND A KALMAN FILTER

### A. FBPROPHET SYSTEM DESCRIPTION

Fbprophet is an open-source time-series prediction framework of Facebook. For the above trend-term nonlinear-saturated-growth model, a Kalman filter is used to eliminate random disturbance error of the trend term. In Fbprophet, the prediction model consists of superpositions $y(t) = g(t) + s(t) + h(t) + \epsilon_t$, where $g(t)$ is a trend function used to fit non-periodic changes in time series, such as piecewise linear growth or logical growth, and to model non-periodic changes in time series; $s(t)$ is a periodic term, reflecting the periodic change (e.g., the seasonality of each year); $h(t)$ is a holiday term, reflecting the influence of irregular holiday effects that may occur in one or more days. $\epsilon_t$ is an error, reflecting abnormal changes in the model and assumed to be a normal distribution. The most important item is the trend term g(t), and when the trend model is nonlinear-saturated-growth, its basic form is as follows [16]:

$$g(t) = \frac{C}{1 + exp(-(k + \boldsymbol{a(t)}^T \delta)(t - (m + \boldsymbol{a(t)}^T \gamma))} \tag{3}$$

where $C$ is the expected capacity of the system at any time; $k$ is the growth rate; $m$ is the compensation parameter. Since the growth rate $k$ and the offset parameter $m$ are not constants, a variable quantity $\boldsymbol{a(t)}$ needs to be included to accommodate the historical data. Suppose at $s_j, j = 1, 2, \ldots, S$, there are S variables. An adjustment vector is $\delta \in R^S$, where $\delta_j$ is the change rate $s_j$. At any time the rate of $t$ is the basic rate of k with all the adjustments before the point of $k + \sum_{j:t>s_j} \delta_j$, the definition of $\boldsymbol{a(t)} \in \{0, 1\}^S$ is as follows [16]:

$$\boldsymbol{a_j(t)} = \begin{cases} 1, & if\ t \geqslant s_j \\ 0, & otherwise \end{cases} \tag{4}$$

The rate at time $t$ is $k + a(t)^T \delta$. When adjusting the rate k, the offset parameter m must also be adjusted to connect the endpoints of the segment. The adjustment at variable j is calculated as following [16]:

$$\gamma_j = \left( s_j - m - \sum_{l<j} \gamma_l \right) \left( 1 - \frac{k + \sum_{l<j} \delta_l}{k + \sum_{l \leqslant j} \delta_l} \right) \tag{5}$$

### B. DESCRIPTION OF FBPROPHET SYSTEM IMPROVED BY KALMAN FILTER

Consider the following nonlinear system [29]:

$$\begin{cases} X_k(t) = f\left[X_k(t-1)\right] + \boldsymbol{W_k(t-1)} \\ Z_k(t) = h\left[X_k(t)\right] + \boldsymbol{V_k(t)} \end{cases} \tag{6}$$

where $X_k$ is the state vector of the system; $Z_k$ is the measured value. Assuming that the process noise $\boldsymbol{W_{k-1}}$ and the measurement noise $\boldsymbol{V_k}$ are independent of each other, and they are gaussian white noises with a mean of zero and covariance of $Q_{k-1}$ and $R_k$. $f(\cdot)$ and $h(\cdot)$ are the state equation and measurement fuction of the system. Since the trend term does not change much in a very short time, it fluctuates within a small range in this short period. According to this idea, the equation of state can be described as [29]:

$$X_k(t) = X_k(t-1) + \boldsymbol{W_k(t-1)} \tag{7}$$

where state $X_k(t) \in R_n$ is the n-dimensional state sequence of the system, and $\boldsymbol{W_k(t-1)}$ is the process noise, its expectation and variance are unknown and need to be estimated [29] with the following equation:

$$\begin{cases} E\left[\boldsymbol{W_k(t)}\right] = q_k(t) \\ cov\left[\boldsymbol{W_k(t)}, \boldsymbol{W_k^T(t\ \mathcal{C}\ t_0)}\right] = Q_k(t) \end{cases} \tag{8}$$

The observation equation can be described as [29]:

$$Z_k(t) = \frac{C}{1+exp[-(k + \boldsymbol{a(t)}^T \delta)(X_k(t) - (m + \boldsymbol{a(t)}^T \gamma))]} \tag{9}$$

where $Z_k(t) \in R_m$ is the system m-dimensional observation sequence; and $\boldsymbol{V_k(t)}$ is the observation noise with its expectation and variance unknown [29]:

$$\begin{cases} E\left[\boldsymbol{V_k(t)}\right] = r_k(t) \\ cov\left[\boldsymbol{V_k(t)}, \boldsymbol{V_k^T(t\ \mathcal{C}\ t_0)}\right] = R_k(t) \end{cases} \tag{10}$$

### C. ADAPTIVE CUBATURE KALMAN FILTERING BASED ON MULTI-MODEL FUSION

In [23], the adaptive method with a forgetting factor was adopted to improve the filtering algorithm. The forgetting factor can limit the length of the filter and made the weights of the old data in the filter smaller and the weights of the new data bigger. The calculation reference for the forgetting factor is [23]:

$$M_k = \boldsymbol{H_k F_k} \hat{P}_k \boldsymbol{F_k^T H_k^T} \tag{11}$$

$$N_k = (\boldsymbol{z_k} - \boldsymbol{\hat{z}_k})(z_k - \boldsymbol{\hat{z}_k})^{\boldsymbol{T}} - \boldsymbol{H}_k Q_{k-1} \boldsymbol{H_k^T} - R_k \tag{12}$$

$$\lambda = max\left\{1, trace(N_k)/trace(M_k)\right\} \tag{13}$$

where $\lambda \geqslant 1$ is the forgetting factor. The prediction expression of variance considering forgetting factors is as follows [23]:

$$\bar{P}_k^* = \lambda \times \left( \sum_{j=1}^{m} \varpi_j \boldsymbol{X_{j,k} X_{j,k}^T} - \boldsymbol{\bar{x}_k \bar{x}_k^T} \right) + Q_{k-1} \tag{14}$$

When the process noise covariance matrix $Q_{k-1}$ is inaccurate, the covariance can be predicted by adding a forgetting factor, which limits the memory length of the filter, increases the proportion of the current measurement in the estimation, and improves the filtering accuracy. The adaptive method in [24] adopted the multi-model method, adjusted the filter parameters through sampling noise and initial state covariance prior, and carried out a posterior approximation to the system [24] as follows:

$$\Sigma_k = \frac{1}{N_s} \sum_{i=1}^{N_s} \left( \boldsymbol{y_k} - H_k \boldsymbol{\hat{x}_k^i} \right) \left( \boldsymbol{y_k} - H_k \boldsymbol{\hat{x}_k^i} \right)^{\boldsymbol{T}} \tag{15}$$

$$\Omega_k = \frac{1}{N_s} \sum_{i=1}^{N_s} \left( \boldsymbol{\hat{x}_k^i} - \boldsymbol{\hat{x}}_k \right) \left( \boldsymbol{\hat{x}_k^i} - \boldsymbol{\hat{x}}_k \right)^{\boldsymbol{T}} \tag{16}$$

$$\hat{R}_k = \frac{1}{k} \left( (k-1)\, \boldsymbol{\hat{R}}_{k-1} + \Sigma_k - \boldsymbol{H_k} P_k \boldsymbol{H_k^T} \right) \tag{17}$$

$$\hat{Q}_k = \frac{1}{k} \left( (k-1)\, \boldsymbol{\hat{Q}}_{k-1} + \Omega_k + P_k - \boldsymbol{F_k} P_{k-1} \boldsymbol{F_k^T} \right) \tag{18}$$

However, in some practical cases, a single adaptive method, such as the one taking into account the forgetting factor, the sampling noise, or the initial state covariance prior, can not have a good estimation performance when estimating the process noise and measuring the noise variance. To solve this problem, this study combines the above two adaptive methods and introduces the variance prediction results of the forgetting factor to update measurement noise and to observe noise covariance. The recursive estimation is as follows:

$$\hat{R}_k^* = \frac{1}{k}\left((k-1)\hat{R}_{k-1} + \Sigma_k - \boldsymbol{H_k}\bar{P}_k^*\boldsymbol{H_k^T}\right) \tag{19}$$

$$\hat{Q}_k^* = \frac{1}{k}\left((k-1)\hat{Q}_{k-1} + \Omega_k + \bar{P}_k^* - \boldsymbol{F_k}P_{k-1}\boldsymbol{F_k^T}\right) \tag{20}$$

where, the form in [30] is the observation matrix:

$$\boldsymbol{H_k} = \left(\boldsymbol{P_{k|k-1}^{-1}P_{xz}}\right)^{\boldsymbol{T}} \tag{21}$$

state-transition matrix:

$$\boldsymbol{F_k} = T_k S_{k-1}^{-1} \tag{22}$$

where, $T_k = chol(P_{k|k-1})$ and $S_{k-1} = chol(P_{k-1|k-1})$.

### D. ACKF WITH A FORGETTING FACTOR TO IMPROVE FBPROPHET WORKING FLOW

After the introduction of ACKF, the prediction steps of the combined method including the improved ACKF and Fbprophet are given in this section. The specific steps are as follows:

*Step1:* Initialize parameters $\hat{x}_0$ and error covariance $P_0$.

*Step2:* Update time item:

(1) Calculate cubature points $X_{j,k-1|k-1}$ and propagation cubature points with the nonlinear equation of state $X_{j,k|k-1}^*$.

(2) Calculate forecast state $\bar{x}_{j,k|k-1}$ and covariance of the $\bar{P}_{k|k-1}$.

*Step3:* Replace cubature points $X_{j,k|k-1}$, calculate measured equation propagation value of the cubature points $Z_{j,k|k-1}$, and estimate the predicted measurements $\hat{z}_{k|k-1}$.

*Step4:* With the above fusion adaptive method, the estimation measurement noise covariance $\hat{R}_k^*$ and process noise $\hat{Q}_k^*$ are obtained. The calculation process is shown in equation (19) and (20).

*Step5:* Judge whether to iterate. According to the fitness function ratio, the deviation degree between the sampling point and the real estimation of the target are determined to adaptively judge whether to carry out iteration and re-use. The specific steps are as follows:

(1) Define fitness functions. The fitness function $f_1$ of the predicted value and actual observed value, the fitness function $f_2$ of the cubature points transfer value and actual observed value, and the fitness function $\rho$ are calculated.

(2) If $\rho < 1$, the sampling point effectively approximates the real estimate, and no iteration is performed.

*Step6:* Update measurements. Calculate the variance of new interest $P_{zz}$, covariance $P_{xz}$, gain $K_k$, and the status updates of the system $\hat{x}_k$ to update the covariance $P_k$. If $\rho \geqslant 1$, the sampling point deviates greatly from the real estimate, and an iteration needs to be carried out. Return to Step 1 to reinitialize. Note the iteration number as $N$, then the state estimation and error covariance estimation at moment $k$ are as follow:

$$\hat{x}_k = \hat{x}_k^N \tag{23}$$

$$P_k = P_k^N \tag{24}$$

Use the state estimation obtained by the above improved ACKF method as the trend term in Fbprophet:

$$y_t = \hat{x}_k + s(t) + h(t) + \epsilon_t \tag{25}$$

The superposition of the terms in $y_t$ is used to predict the MPD of the research object. The algorithm flow chart is shown in FIGURE 4.

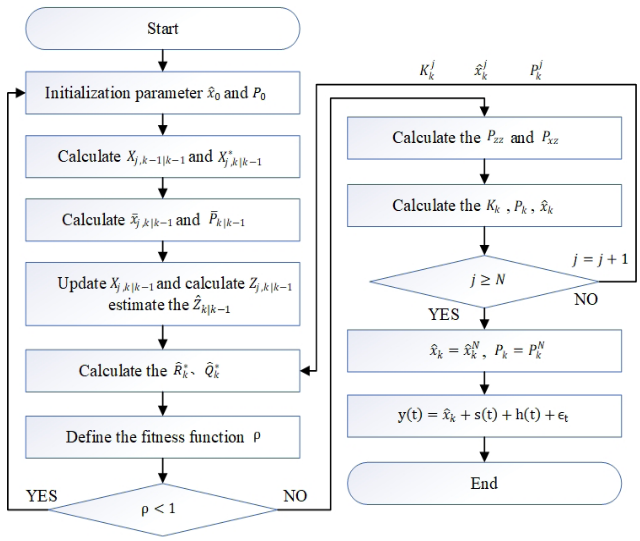


**FIGURE 4.** **The algorithm flow chart of improved ACKF to modify Fbprophet.**

## V. ELECTRICITY COST ASSESSMENT FOR LARGE INDUSTRIAL CONSUMERS

At present, the conventional power load in China is seriously homogenized and lacks personalized marketing services, which makes it difficult to provide differentiated services for users. There are two main standards for large industrial users: MPD-based charge and transformer-capacity-based charge. Suppose a user's transformer capacity is $S(kVA)$ and the monthly MPD is $P_{real}(kW)$; the unit price by volume in the region is $C_{kVA}(yuan/kVA)$; the total price is $V_S(yuan)$; the unit price according to the MPD is $C_{kW}(yuan/kW)$; and the total price is $V_P$ [31].

$$V_S = C_{kVA} \times S \tag{26}$$

$$V_P = C_{kW} \times P_{real} \tag{27}$$

If the MPD is used to charge with consideration of saving basic charge of electricity $V_P \leqslant V_S$ and $P_{real} \leqslant S \times C_{kVA}/C_{kW}$, MPD billing can save basic electricity bills. $C_{kVA}/C_{kW}$ is the capacity and demand ratio, normally is set to 2/3. In this paper, the transformer rated capacity data of the four power customers are also provided by the IoT system, which are 800kVA, 250kVA, 1250kVA, and 400kVA respectively.

Some users of the above four do not fully understand the difference between the two pricing methods, especially the MPD-based billing often involves a variety of variable factors. The provisions of MPD charging is relatively complex, the pricing of the dimension of ease and risk analysis, choose according to the capacity of billing. With the increasingly mature construction of smart grids, it is becoming a trend for power grid enterprises to optimize the structure of the basic electricity charges and to reduce the cost burden of the electricity charges. This section mainly discusses the MPD as a billing standard.

### A. MPD-BASED CHARGING METHOD

According to the "maximum demand" of MPD, the recorded values represent the maximum load in 3 quarters of an hour within a month, which is the charging value of the user's monthly MPD. The MPD shall be based on the following provisions:

(1) If a user applies for MPD and gets approval from the power enterprise, the user should be charged for the parts exceeding the basic fee.

(2) If any high-voltage motor does not need a special transformer, it should be included in the capacity of the high-voltage motor when calculating the MPD.

(3) If the MPD applied by the user is less than 40% of the total capacity of the high-voltage motor and transformer, the MPD should be calculated as 40% of the total capacity.

(4) For customers with multiple incoming lines, the maximum capacity of each incoming line should be calculated separately; and in principle, power supply lines should not be duplicated as backups.

Electricity customers can choose a pricing model according to their product supply and load properties, such as the change of the season in electrical characteristics. Assuming that a user chooses to calculate and charge the basic electricity according to the MPD, to reduce the charge, the MPD must be actively reduced. In this case, the management demand of the electrical power department could be achieved to form a win-win situation between the electricity customer and the power grid enterprise.

### B. DETERMINE THEORETICAL MPD

Assuming that the MPD value is $P_C$; if the customers choose to charge electricity according to the MPD, they shall sign a contract with the power grid enterprise and charge basic electricity according to the MPD. The maximum contract demand and customized changing-cycle are changed monthly; a user can submit an application to the power grid enterprise within 5 working days for an approved maximum contract demand of the change sheet cycle. When the actual MPD of power users exceeds 105% of the specified value in the contract, the basic electricity charge of the part exceeding 105% shall be doubled; otherwise, it shall be charged according to the value specified in the contract. If the MPD applied by the user is less than 40% of the total capacity of the high-voltage motor and transformer, the MPD shall be contracted with a total capacity of 40%. The relationship between $V_p$ and $P_C$ is as follows:

(1) When $P_{real} \leqslant P_C < S * 40\%$, $V_P = C_{kW} * P_C$.

(2) When $S * 40\% \leqslant P_{real} \leqslant P_C$, $V_P = C_{kW} * P_C$.

(3) When $P_C < P_{real} \leqslant P_C * 1.05$, $V_P = C_{kW} * P_{real}$.

(4) When $P_{real} > P_C * 1.05$, $V_P = C_{kW} * P_C * 1.05 + C_{kW} * (P_{real} - P_C * 1.05) * 2$.

With the MPD-based method, the lowest value of basic electricity charge can be calculated with the above relationship (1); with the relationship (2), the electricity fee is calculated when the value determined in the contract is relatively large. The above two calculations of basic electricity charges show that the agreed MPD is too large, and there is room to predict cost savings through the MPD. With the relationship (3), the MPD is calculated within the range of +5% determined by the contract, which is the most economical value. While meeting the production requirements of the electric power enterprise, it minimizes the electricity bill. If the MPD is exactly 5% larger than the contract-determined value, it is the most ideal state. The relationship (4) indicates the agreed MPD is too small, it will fail to meet the production demand of users, and can hardly play an economic role.

## VI. SIMULATION EXPERIMENT

### A. GREY RELATIONAL DEGREE SIMULATION

In this paper, four power consumers in Zhejiang province Linhai city are taken as research objects, and meteorological factors of Linhai city are analyzed. The daily MPD, weather conditions, maximum wind scale, maximum temperature and minimum temperature of user A were normalized. Acquire date of the meteorological factors in Linhai city through the website of "http://www.tianqihoubao.com". Firstly, define the data structures we need to grab, which including the city name, data, weather, wind power, maximum temperature, and minimum temperature. Secondly, modify the downloader middleware to access user-agent and IP address randomly. Thirdly, modify the pipeline file, process the returned item from the Spyder file. Finally, Spyder files are written to parse data, and store data as mongo. The grey relational degree values of the above four terms are shown in FIGURE 5, and the average values of simulation results are shown in TABLE 3.

**TABLE 3. The average value of grey correlation degree.**

| | |
|---|---|
| weather conditions | 0.820 |
| maximum temperature | 0.810 |
| minimum temperature | 0.808 |
| maximum wind scale | 0.796 |

It can be concluded from the above TABLE 3, that the correlation degree between the daily MPD values and the factors affecting weather conditions is the highest, and followed by the daily maximum and minimum temperature, the minimum

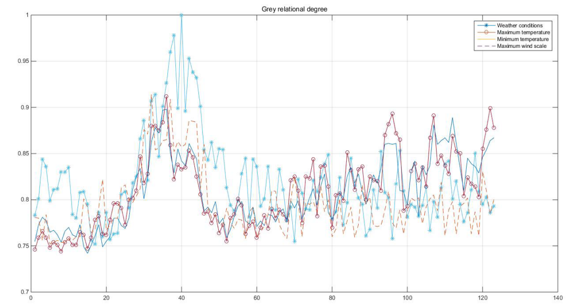


**FIGURE 5. Simulation diagram of GRA relevant factors for the research object.**

correlation degree between the maximum wind force level. The X label represents the date corresponding to each influencing factor, and the Y label represents the grey relational value calculated.

### B. MPD PREDICTION SIMULATION EXPERIMENT

The data sets of four research objects are from the IoT system of Hangzhou Zhongheng Power Cloud Technology Company, Ltd. User A is a furniture manufacturing industry power consumer, User B is a handicraft manufacturing industry power consumer, User C is a chemical industry power consumer, and user D is a handicraft manufacturing industry power consumer. All these four users are in Linhai city. The predicted results are shown in FIGURE 6 - FIGURE 9. As shown in the figures, the black lines present the monthly MPD actual data. Data sets derived from the IoT system are daily electricity demand data. Since the purpose of this work is to obtain the monthly MPD values, if the exported data sets are used as training sample directly, they will lead to the predicted result is smaller than the actual value. Therefore, this paper takes the monthly MPD values instead of daily demand as training samples. The black lines in the figures are horizontal line segments, the blue lines are fitting curve obtained from the training data and the light blue areas present confidence interval. The black horizontal lines are the training sample data sets, and the demand values corresponding to the last date in the figures are predicted values of MPD after the one-month interval.

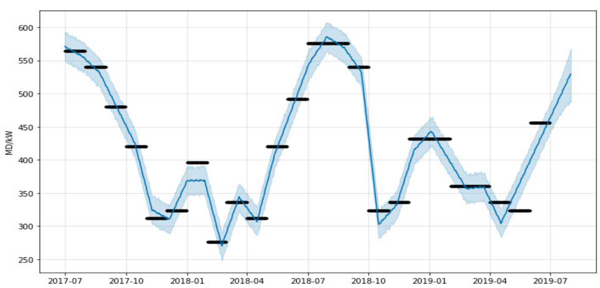


**FIGURE 6. MPD forecasting of User A by the improved ACKF-Fbprophet algorithm.**

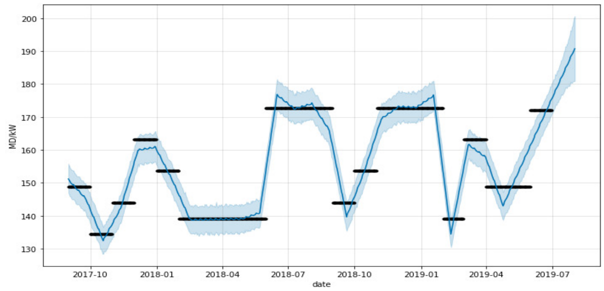


**FIGURE 7. MPD forecasting of User B by the improved ACKF-Fbprophet algorithm.**

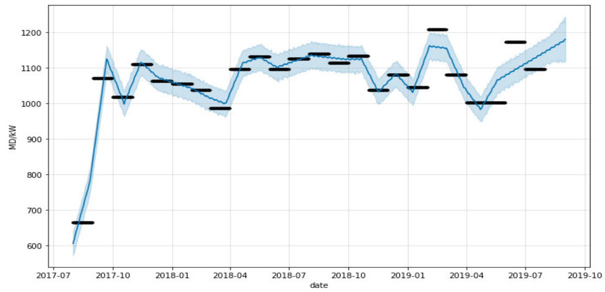


**FIGURE 8. MPD forecasting of User C by the improved ACKF-Fbprophet algorithm.**

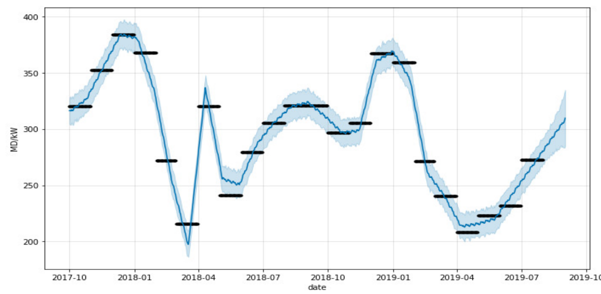


**FIGURE 9. MPD forecasting of User D by the improved ACKF-Fbprophet algorithm.**

The evaluation metric Relative Error (RE) is used to evaluate prediction performance in this paper. $E_{RE}$ is defined by

$$E_{RE} = \frac{\left|y_i - y_i'\right|}{y_i} \times 100\% \tag{28}$$

where $y_i$ is the actual value and $y_i'$ is the predicted value [17].

### C. EXAMPLE 1

Through the above clustering analysis method, the MPD data of User A in FIGURE 6 shows that there is a lower peak in January and higher peaks in July and August. It can be speculated that the increase of the MPD is mainly caused by the cooling in summer and heating in winter. The top peak of MPD is in July and August, and it has continuous decline until January. Around January and February, there is a lower peak, which is much less than the top peak. Because of User A belongs to the furniture manufacturing industry, its MPD data curve has obvious periodicity. It can be concluded

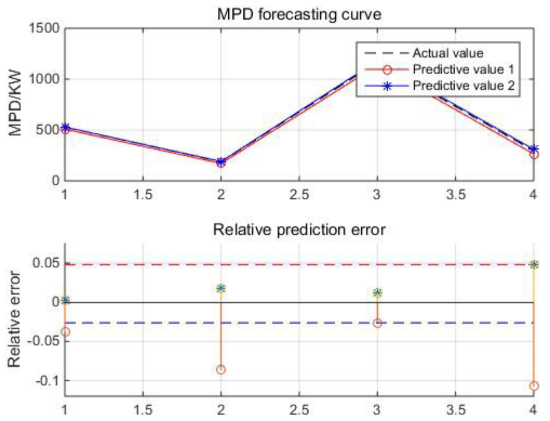


**FIGURE 10.** MPD forecasting value and errors of four power consumers by the improved algorithm. The $E_{RE}$ of predicted values are 0.26, 1.78, 1.26, and 4.82 percent respectively.

from the analysis that the maximum demand characteristic of this consumer is closely related to seasonal factors. The forecasting result of User A predicted by ACKF-Fbprophet is 529.4, and the $E_{RE}$ is 0.26%.

### D. EXAMPLE 2

The User B in FIGURE 7 can't show significant annual periodicity, but there are still many peaks. The peaks of User B are mainly focused on July to August and December to January. There is a lower peak in January 2018. From June to August 2018, and from November 2018 to January 2019, there are two peaks of MPD for User B. There is a marked increment in July 2019. It is similar to that of User A about the increase of the MPD is mainly caused by the cooling in summer and heating in winter. The forecasting result of User B predicted by ACKF-Fbprophet is 190.8, and the $E_{RE}$ is 1.78%.

### E. EXAMPLE 3

Since the MPD of the chemical enterprises is characterized by a single production pattern, the curve of User C almost only has one type and keeps at a high level, and it is shown in FIGURE 8. Except for something unusual around August 2017, compared to the overall curve only has a smaller fluctuation. It can be concluded that the MPD of User C has little relation with meteorological factors and close relation with the production plan, and the overall MPD value is significantly higher than that of the other three users. The forecasting result of User C predicted by ACKF-Fbprophet is 1180.4, and the $E_{RE}$ is 1.26%.

### F. EXAMPLE 4

User D is handicraft manufacturing industry power consumers just like User B, and it is similar to that of User B about characteristics of MPD, but the peaks are higher in winter and lower in summer. In FIGURE 9, there is a higher peak in January 2018. From July to October 2018, and from December 2018 to January 2019, there are two peaks of MPD for User D. The only exception is a short-term spike in April 2018. The forecasting result of User D predicted by ACKF-Fbprophet is 309.6, and the $E_{RE}$ is 4.82%.

**TABLE 4.** Comparison of prediction results and relative errors.

| Error comparison | User A | User B | User C | User D |
|---|---|---|---|---|
| Actual value | 528 | 187.4 | 1165.7 | 295.3 |
| Fbprophet result | 508 | 171.2 | 1135.2 | 263.8 |
| **ACKF-Fbprophet result** | **529.4** | **190.8** | **1180.4** | **309.6** |
| $E_{RE}$ of Fbprophet | -3.79% | -8.66% | -2.62% | -10.6% |
| **$E_{RE}$ of ACKF-Fbprophet** | **0.26%** | **1.78%** | **1.26%** | **4.82%** |

The prediction results and errors of the simulation experiment with the adaptive Kalman based Fbprophet are shown in FIGURE 10. The predicted values $E_{RE}$ are 0.26, 1.78, 1.26, and 4.82 percent respectively. The comparison of predicted values and errors between the prediction results of the original Fbprophet algorithm and the improved ACKF-Fbprophet algorithm is shown in TABLE 4. The prediction effect of the improved algorithm on the four research objects is better than that of the original algorithm, and the predicted value is higher than the actual maximum demand, which is very important for the maximum demand prediction.

## VII. CONCLUSION

In this work, an intelligent MPD forecasting algorithm for industrial power users have been proposed, which has the following three main characteristics. Firstly, a variety of related influencing factors are considered comprehensively, including meteorological factors, production schedules, etc, which can have a great influence on the MPD of consumers. Secondly, aiming at the imprecision of model parameters, in this work, the forgetting factor adaptive method is combined with the parameter adaptive estimation and adjustment method. Thirdly, the cost of MPD is evaluated based on the above MPD forecast results. Although the MPD prediction method proposed in this paper has improved the prediction accuracy on some occasions, on some specific occasions, there are still spaces for improvement. It is likely necessary to combine neural networks with machine learning to analyze the characteristics of the data sets for further improvement.

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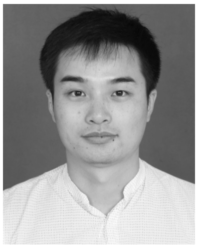

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