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Three-Dimensional Maturity Model of Regional Power Users Against the Background of the Ubiquitous Power Internet of Things

LILI WANG[1], LINJUAN ZHANG[1], CHANGQING XU[1], HONGBO WU[2], YIMING LI[2], AND HAONAN SUN[3]

[1]State Grid Henan Economic Research Institute, Zhengzhou 450052, China
[2]State Grid Henan Electric Power Company, Zhengzhou 450052, China
[3]School of Electrical Engineering, State Key Laboratory for Alternate Electrical Power System With Renewable Energy Sources, North China Electric Power University, Beijing 102206, China

Corresponding author: Haonan Sun (haonan_1994@foxmail.com)

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ABSTRACT As the Ubiquitous Power Internet of Things (UPIoT) is being developed, the data volume collected by various terminals such as smart electricity meters is increasing daily. The efficient extraction of information from massive data and the provision of value-added services to users, power grids, and market entities are crucial aspects and research directions. A data analysis and application framework for smart meter data based on cloud-fog computing and data contextualization is established, and a data contextualization model based on three-dimensional (3d) maturity analysis of industrial power users is proposed to evaluate the power consumption characteristics of users from the three aspects of the load level, power consumption behavior, and interaction. The results of a case study show that this model allows power grid operators to understand quickly and intuitively the load behavior pattern and power demand of industrial power users, thereby enabling an efficient and accurate assessment of the power supply and an ability to provide value-added services.

INDEX TERMS Ubiquitous power Internet of things, cloud and fog computing, data contextualization, 3d maturity analysis.

I. INTRODUCTION

Due to the continuous increase in the world's energy consumption, energy-related and environmental problems are intensifying, and the development of a clean, low-carbon, safe, efficient, open, and shared energy system is urgently required. The integration of the energy revolution and the digital revolution represented by "new energy + Internet" will play an important role [1].

In China, the State Grid Corporation actively adapts to market changes, implements new development concepts, and creatively has proposed the strategic goal of developing a world-class energy Internet enterprise referred to as the "three types and two networks" in the presentation in 2019. "Three types and two networks" refers to developing the Ubiquitous Power Internet of Things (UPIoT) on the basis of strong and smart grid and establishing a modern enterprise consisting of a hub, platform, and sharing method. The objective of this project is to enhance the vitality of the power grid industry and related enterprises by sharing and co-development, improve efficiency, reduce costs, and promote the leapfrog development of the digital economy in smart power systems and the energy field [2].

The UPIoT connects people and devices that are related to the power grid, unblocks the resource side, production side, and consumption side, and is guided by user needs and business pain points. The development of the UPIoT significantly promotes the efficiency of power and energy

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services, improves the user experience, promotes the consumption of new energy, and cultivates emerging businesses [3]. At present, the development of the UPIoT is in the initial stage and research has been conducted only on the concept, framework, and other macro levels. In the literature [4]–[7], the UPIoT has been investigated from various aspects, including an overview of the IoT, the characteristics, key technologies, and typical application scenarios, as well as analyses and prospects of its development. References [8], [9] discussed the deep integration of 5G communication technology and the UPIoT and analyzed different application scenarios and energy management mechanism of 5G communications in the UPIoT. In [10], the development concept, implementation characteristics, and structure of the IoT are explained. In [11], three different development schemes of the IoT were proposed based on the operating characteristics of three kinds of power equipment, including transmission, transformation, and distribution equipment. In [12]–[15], the operating mechanism and key technologies of virtual power plants and integrated energy systems under the UPIoT were discussed. A data processing framework for the UPIoT based on edge computing was established and a new perceptive adaptive data processing method was proposed to address the problem of the large data volume in the UPIoT [16], [17].

The reviewed literature only focused on broad-scale studies, the potential framework, and key technologies in various fields of the UPIoT; however, there are no specific methods or models to integrate the massive amount of shared data generated by the UPIoT so that value-added service can be provided to users, power grids, and other entities. Therefore, in this study, A specific data processing method is proposed based on the characteristics of the data in the UPIoT. The contributions of this paper can be summarized as follows:

1) A data analysis and application framework for smart meter data based on cloud-fog computing and data contextualization is established, which significantly reduces the workload of the main platform while improving the system's operational efficiency.

2) The maturity evaluation system of industrial power users is established to evaluate the power consumption characteristics of users from the three aspects of the load level, power consumption behavior, and interaction.

3) The maturity evaluation model based on G1 method modified by entropy value and weighted TOPSIS method is proposed to evaluate the maturity of regional power users.

II. DATA ANALYSIS AND APPLICATION FRAMEWORK FOR REGIONAL SMART METER DATA IN THE CONTEXT OF THE UPIOT

A. DATA CHARACTERISTICS IN THE UPIOT

The UPIoT is the second network of the "three types and two networks". Through the use of modern information technology and advanced communication technology such as big data, cloud computing, the IoT, mobile internet, smart city, and blockchain, the interconnection of everything and the human-computer interaction is achieved in all aspects of the power system. Taking the power grid as the hub; UPIoT generates shared data, creates opportunities for the development of the industry and new market participants, and provides valuable services. It is worth noting that data are the core of the UPIoT. The characteristics of data collection, storage, analysis, and application in the UPIoT are shown in Fig. 1.

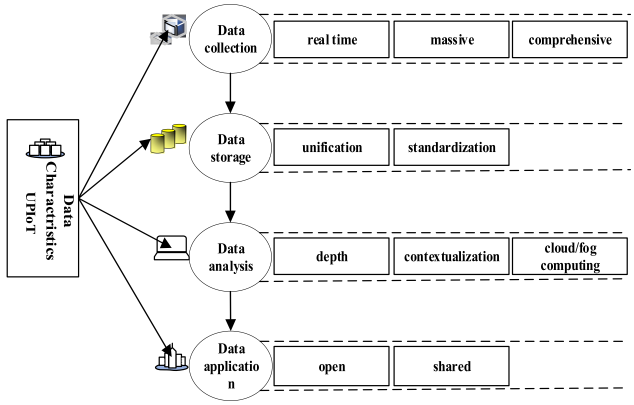

FIGURE 1. Data characteristics in the UPIoT.

1) Data collection: real-time, massive, and comprehensive

The UPIoT uses multi-parameter, high-precision sensor integration technology and terminals with intelligent technology to collect static and dynamic data from the power system; the operation status of each link of the power system is determined to achieve real-time and comprehensive perception of the power grid and customer status. At present, the daily data volume obtained from various IoT terminals such as smart meters is more than 60 TB, and the data volume is increasing continuously.

2) Data storage: unification, standardization

The UPIoT is based on a unified model of perceptual data, the unification of data storage, and standards for calling and the service interface. Additional concepts associated with the UPIoT are building a data ceter, breaking professional barriers, opening up data islands, and supporting various types of intelligent IoT terminals in a plug and play manner. The objective is the use of all types of collected data anytime, anywhere.

3) Data analysis: depth, contextualization, cloud/fog computing

The UPIoT incorporates data mining, machine learning, and other technologies to mine the underlying value hidden in the massive amount of data; edge computing technology is used to create an open platform at the edge nodes to conduct data analysis and data contextualization. Following analysis, the information is uploaded to the cloud, and additional data analysis is performed using cloud-fog computing to improve operational efficiency and significantly reduce the workload of the main station platform.

4) Data application: open, shared

By using a unified data center and data model, the UPIoT creates data sharing services, develops big data applications such as customer personas, develops digital products, provides analysis services, and promotes data operation; this approach is based on a user-centered service concept, and extends the traditional power supply services by creating a digital economy.

B. DATA ANALYSIS AND APPLICATION FRAMEWORK OF SMART METER TERMINAL

An industrial park has a large amount of information on power consumption data that has been collected by the user's smart meter terminals; this information is often scattered in different locations. In the UPIoT, it is difficult to upload the scattered data to the cloud and process the information due to the large data volume and service demand, and large computing capacity is required for the cloud application.

In this study, a data analysis application framework for smart meter data based on cloud-fog computing and data contextualization is developed; the proposed framework significantly reduces the workload of the main platform while improving the system's operational efficiency, as shown in Fig. 2.

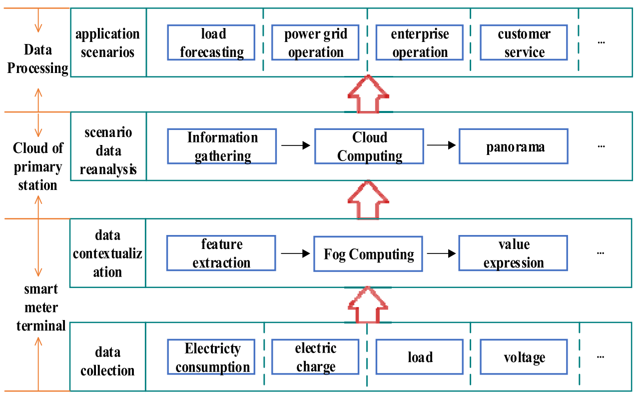

FIGURE 2. Data analysis and application framework for smart meter data.

1) SMART METER DATA CONTEXTUALIZATION BASED ON FOG COMPUTING

The real-time and historical information collected by the smart meters of industrial power users, including power, voltage, and current are filtered and processed in the smart meter terminal. According to different data application scenarios such as load forecasting, customer classification, and precision marketing, the terminal data are processed in different contexts. For example, the characteristics of different dimensions of electricity consumption data are extracted, and different "labels" are created for the data to achieve contextualization of smart meter data based on fog computing calculation on the data source side at the edge of the master station.

2) REANALYSIS OF SITUATIONAL INFORMATION BASED ON CLOUD COMPUTING

After processing in the smart meter terminal, the relevant information is uploaded to the main station cloud. The information is mined and analyzed using cloud computing and the data characteristics of different terminals are integrated. Subsequently, different data value services can be performed using different data application scenarios; for example, power users can be classified according to different power consumption characteristics so that different power supply services are provided to different types of users.

3) TWO-WAY FEEDBACK OF DATA APPLICATION SCENARIOS

The application scenarios determine the direction of the contextualization of the edge data. In turn, the cloud-fog data analysis method guides the efficient development of application scenarios.

III. THREE-DIMENSIONAL MATURITY MODEL FOR EVALUATING INDUSTRIAL POWER USERS BASED ON BIG DATA ANALYSIS OF SMART METERS

A contextualized model for electricity data is proposed in this study and integrated with the proposed data analysis and application framework for smart meter data in the UPIoT. In the 3d model, the power user's maturity is evaluated in the smart meter terminal; the massive amount of data on electricity consumption is condensed into a maturity index and uploaded to the regional grid operator for analysis and application.

A. MATURITY OF INDUSTRIAL POWER USER

Maturity refers to the relative value of the current state of the research object and its perfect state. There are two main connotations: one is to determine the relative perfect state of the research object based on the current cognition; the other is to determine the current state of the subject and ascertain the difference between that state and the perfect state. Since the American scholar Watts Humphrey proposed the capability maturity model (CMM), the concept of maturity has been widely applied in project management [18], hospital information systems [19], industrial manufacturing [20], and information technology [21]. To date, the concept of maturity has not been used in the evaluation of load behavior patterns and power demand.

In general, the maturity of the research object is measured in one or more dimensions, and the result is expressed in percentages, decimals, or levels. The assessment of the dimension of measuring the maturity of regional power users and the development of a comprehensive and objective evaluation index system are key to analyzing the maturity of the power usage characteristics of regional power users.

From the perspective of power grid operators, users with higher maturity, i.e., regional power users with nearly perfect power load characteristics, exhibit the following three characteristics:

(1) Load level: Stable and saturated power load, relatively stable annual electricity consumption, and low growth rate of power consumption.

(2) Power consumption behavior: Fixed power consumption mode, predictable power usage behavior, little abnormal

power usage behavior, low load fluctuations, and small peak-to-valley differences.

(3) Interaction: Strong interaction with grid operators, flexible production scheduling, and greater potential for demand-side response.

Therefore, we analyze the power consumption characteristics of industrial power users from three aspects: the load level, power consumption behavior, and interaction. We establish a 3d maturity evaluation model of industrial power users, thus providing power grid operators with a new method to utilize the distributed power consumption data of regional edge nodes.

B. THE THREE-DIMENSIONAL MATURITY EVALUATION SYSTEM OF INDUSTRIAL POWER USERS

1) MATURITY EVALUATION INDEX OF THE LOAD LEVEL

In general, the power load of enterprise users usually exhibits an S-shaped growth trend that increases initially and then stabilizes. Therefore, the prediction of the load at the saturation stage is the key to measuring the maturity of the user load.

To make full use of the information in each load forecasting model, we combine a logistic curve model and the grey Verhulst model based on the equal weight recursion theory to predict the annual electricity consumption of regional power users and the saturation scale of the annual maximum load. The logistic curve model is shown in equation (1).

$$y = \frac{k}{1 + ae^{-bk}} \tag{1}$$

where y is the annual electricity consumption or the annual maximum load of regional power users, k represents the saturation value of the user's annual electricity consumption or the annual maximum load. From a mathematical point of view, k represents the limit value of variable y, and the parameters a and b determine the growth rate of the user's load at different development stages.

The grey Verhulst model is defined in equation (2).

$$\begin{cases} x^{(0)}(k) + az^{(1)}(k) = b(z^{(1)}(k))^2 \\ x^{(1)}(k) = \dfrac{ax^{(0)}(1)}{bx^{(0)}(1) + (a - bx^{(0)}(1))e^{a(k-1)}} \\ x^{(0)}(k+1) = x^{(1)}(k+1) - x^{(1)}(k) \end{cases} \tag{2}$$

where $x^{(0)}$ is the historical annual electricity consumption or the maximum load data sequence, $x^{(1)}$ is the first-order accumulation sequence of $x^{(0)}$, $z^{(1)}$ is the sequence immediately adjacent to the mean value of $x^{(1)}$, a is the development coefficient, and b is the grey action quantity.

Based on the equal weight recursion theory [22], we combine the prediction results of the logistic curve model and the grey Verhulst model to obtain the saturation scale of the maximum load (EL max) and the user's annual electricity consumption (EC max). Subsequently, the saturation of the user's current annual electricity consumption (A1) and the maximum load (A2) are calculated using equation (3).

$$\begin{cases} \text{A1} = \dfrac{EC(t)}{EC\max} \\ \text{A2} = \dfrac{EL(t)}{EL\max} \end{cases} \tag{3}$$

where $EC(t)$, $EL(t)$represent the user's current annual electricity consumption and the maximum annual load scale, respectively.

In addition, the annual growth rate of electricity consumption (A3) and the growth rate of the annual maximum load (A4) are used to describe the change in the load of the industrial power user; these parameters are also used as the evaluation indices of the maturity of the load level of the industrial power user.

2) MATURITY EVALUATION INDEX OF THE POWER CONSUMPTION BEHAVIOR

The maturity of the user's power consumption behavior depends on the amount of abnormal power usage and the degree of load fluctuation in a year. Therefore, we use the abnormal power usage of users and the degree of load fluctuation as the maturity evaluation indices of the electricity consumption behavior of the users.

We extract the following characteristics of the user's daily electricity consumption from the annual electricity data: the average load, load rate, and peak-valley difference. The local outlier factor (LOF) of each characteristic is determined; B1 indicates the number that the LOF is greater than 2 and B2 indicates the largest value of the LOF; this is used as the index of the abnormal power consumption behavior.

The LOF of the object p is defined in equation (4) [23].

$$\begin{cases} LOF_{MinPts}(p) = \dfrac{\sum\limits_{o \in N_{MinPts}(p)} \dfrac{lrd_{MinPts}(o)}{lrd_{MinPts}(p)}}{\left|N_{MinPts(p)}\right|} \\ lrd_{MinPts}(p) = 1/[\dfrac{\sum\limits_{o \in N_{MinPts}(p)} r\_d_{Minpts}(p,o)}{|N_{MinPts}(p)|}] \end{cases} \tag{4}$$

where $LOF_{MinPts}(p)$ and $lrd_{MinPts}(p)$ are the LOF and local reachable density of the object respectively; $N_{MinPts}(p)$ is the MinPts distance neighborhood of the object p; $r\_d_{MinPts}(p, o)$ is the reachable distance of object p from object o.

In addition, the following four indicators are used to represent the annual load fluctuation degree of the users: the annual maximum peak-valley difference (B3), the annual average peak-valley difference (B4), the quarterly imbalance coefficient (B5), and the standard deviation of the monthly average load (B6). B5 is the radio of the average of the monthly maximum load and the annual maximum load. B6 is the standard deviation of the users' average monthly load for 12 months of the year.

3) MATURITY EVALUATION INDEX OF THE INTERACTION

Users can change their power consumption behavior according to the load requirements of the system or their needs to

TABLE 1. The maturity evaluation system for industrail power users.

Goal	Dimension	Index	Properties	Index source
Determine the maturity of the regional power users	Load level A	A1: annual electricity saturation	Positive	Historical annual electricity consumption data and annual maximum load data
		A2: annual maximum load saturation	Positive	
		A3: annual growth rate of electricity consumption	Negative	
		A4: growth rate of maximum annual load	Negative	
	Power consumption behavior B	B1: abnormal amount of electricity consumption	Negative	Current 8760 h electricity load data
		B2: maximum outlier factor	Negative	
		B3: annual maximum peak-valley difference	Negative	
		B4: annual average peak-valley difference	Negative	
		B5: quarterly imbalance coefficient	Negative	
		B6: standard deviation of monthly mean load	Negative	
	Interaction C	C1: demand response potential	Positive	
		C2: demand response potential	Positive	

prevent usage during peak grid loads and participate in ''two-way interaction'' in the form of demand response. Therefore, we use the demand response potential of users as the maturity evaluation index for the interaction.

The adaptive k-means algorithm [24] is used to extract the daily typical power consumption behavior of the users, and the demand response is quantitatively evaluated by determining the minimum power consumption and the reduction rate of the demand response; these two indexes (C1 and C2) reflect the maturity of the user's interaction.

The minimum power consumption of the user refers to the load mode with the minimum total load among all typical daily load modes of the user, as follows:

$$P_{\min}(t) = C_g(t), \quad if \sum_t C_g(t) = \min \sum_t C_k(t) \tag{5}$$

where $P_{\min}(t)$ is the user's minimum power consumption; $C_k(t)$ is the k-th load mode of the user.

The user's demand response potential is calculated as follows:

$$C1 = \sum_{k=1}^{m} (\sum_t (C_k(t) - P_{\min}(t))) \cdot N_k \tag{6}$$

where N_k is the total number of similar days with the k-th load mode.

In addition, the user's demand response potential can also be determined according to the load reduction rate of the user's demand response [25], as follows:

$$C2 = \lambda \cdot \sum_{k=1}^{m} \frac{N_k}{N_{sum}} \cdot (l_{t_1}^k + l_{t_2}^k + \ldots + l_{t_z}^k)/Z \tag{7}$$

where λ is the average load reduction rate of users for the demand response, i.e., the ratio of the average load reduction amount and the maximum load when the demand response is implemented, N_{sum} and N_k respectively represent the total number of daily load curves of the users and the total number of daily load curves in the k-th load mode; $l_{t_1}, l_{t_2}, \ldots, l_{tZ}$ are the Z peak load periods in the region.

The maturity evaluation system of industrial power users is shown in Table 1.

C. MATURITY EVALUATION MODEL OF INDUSTRIAL POWER USERS

1) INDEX WEIGHTING BASED ON G1 METHOD MODIFIED BY ENTROPY VALUE

The G1 method modified by the entropy value is an improved index weighting method based on an analytic hierarchy process, which combines subjective and objective factors. This method determines the degree of importance of several indices by using the entropy value of the indices as a weight.

First, we normalize the indices. Suppose y_{ij} is the observed value of the j-th index of user i. $y_j^{\max}$ is the largest observed value of the j-th index, and $y_j^{\min}$ is the smallest observed value of the j-th index. Let x_{ij} be the normalized value of y_{ij}.

If y_{ij} is a positive index, then:

$$x_{ij} = \frac{y_{ij} - y_j^{\min}}{y_j^{\max} - y_j^{\min}} \tag{8}$$

If y_{ij} is a negative index, then:

$$x_{ij} = \frac{y_j^{\max} - y_{ij}}{y_j^{\max} - y_j^{\min}} \tag{9}$$

Subsequently, the entropy value and the weight of the indices are calculated. Suppose that e_j is the entropy value of the j-th index, then:

$$\begin{cases} e_j = -\dfrac{1}{\ln(m)} \sum\limits_{i=1}^{m} (f_{ij} \ln f_{ij}) \\ f_{ij} = \dfrac{x_{ij}}{\sum\limits_{i=1}^{m} x_{ij}} \end{cases} \tag{10}$$

The ratio of the importance degree r_j of the neighboring (j-1)-th and j-th index is defined as follows:

$$r_j = \begin{cases} e_{j-1}/e_j, e_{j-1} \geq e_j \\ 1, e_{j-1} < e_j \end{cases} \tag{11}$$

Assuming that the index sequence number of a dimension in the evaluation index system is j_0 to j_1, then the weight w_{j_1} of the j_1-th index in this dimension is:

$$w_{j_1} = (1 + \sum_{s=j_0+1}^{j_1} \prod_{j=s}^{j_1} r_j)^{-1} \tag{12}$$

When $s = j_1 - 1, j_1 - 2, \ldots, j_0$, the weight w_s of the s-th index is:

$$w_s = r_{s+1} w_{s+1} \tag{13}$$

2) MATURITY EVALUATION MODEL BASED ON WEIGHTED TOPSIS METHOD

TOPSIS is a method that ranks the evaluation objects according to the proximity between the evaluation objects and the ideal solution; the method is used to evaluate the relative merits of the objects. The procedure for evaluating the maturity of regional power users using the weighted TOPSIS method is as follows:

According to the original normalized value x_{ij} and the weight w_j of each index, the weighted normalized matrix Z is created, where:

$$z_{ij} = w_j x_{ij} \tag{14}$$

Subsequently, the positive and negative ideal solutions of the dimensions are determined.

$$A^+ = (z_1^+, z_2^+, \ldots, z_n^+); \quad A^- = (z_1^-, z_2^-, \ldots, z_n^-) \tag{15}$$

where z_j^+ and z_j^- are the optimal value and the worst value of the j-th index, respectively.

The maturity $m_{i,l}$ of the user i dimension l is calculated as follows:

$$m_{i,l} = \frac{\sqrt{\sum_j \left(z_{ij} - z_j^{-2}\right)^2}}{\sqrt{\sum_j \left(z_{ij} - z_j^-\right)^2} + \sqrt{\sum_j \left(z_j^+ - z_{ij}\right)^2}} \tag{16}$$

The closer the value is to 1, the higher the maturity of each dimension is, and the closer the value is to 0, the lower the maturity of each dimension is.

IV. CASE STUDY

We use an industrial park in China as a case study to determine the power consumption behavior and the electricity demand of six typical industrial users. We use the large data volume acquired from the smart meters to conduct the maturity assessment from three aspects: the load level, the power consumption behavior, and the interaction. The dataset consisted of smart meter data (8760 hours) in 2018 for 6 users and the annual power consumption and maximum load consumption of the users in the past 10 years.

A. MATURITY OF THE LOAD LEVEL

The saturated load is predicted using the four indices A1∼A4, which indicates the maturity of the load level. The results of user 1 and user 6 are shown in Fig. 3, and the maturity assessment indices of the load level of the users are shown in Table 2.

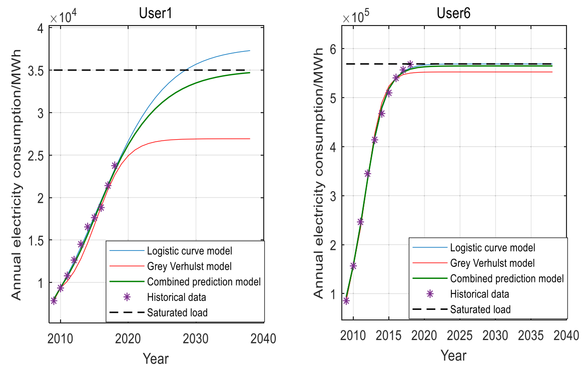

FIGURE 3. Saturated load prediction results.

The results indicate significant differences in the load level of user 1 and user 6. The load of user 1 exhibits rapid growth; the growth rate of the annual electricity consumption is 10%. The electricity consumption of user 1 in 2018 is 23,748.26 MWh, and it is expected to saturate at around 2040 with a saturated load or 35,000 MWh and saturation of 67.9%. In contrast, the load level of user 6 is already saturated in 2018, and the annual electricity consumption remains almost unchanged with a growth rate of less than 1% and saturation of 98.8%.

B. MATURITY OF THE ELECTRICITY CONSUMPTION BEHAVIOR

The electricity consumption behavior of the users is extracted using adaptive k-means clustering. In which the number of patterns varies with the error tolerance of the clustering algorithm, as shown in Fig. 4. The daily electricity consumption of user 1 for a threshold of 200 of the adaptive k-means is shown in Fig. 5.

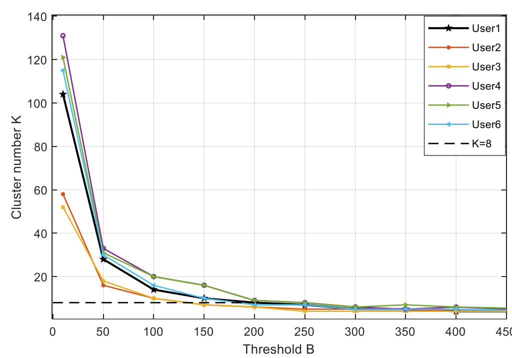

FIGURE 4. Relationship between the number of clusters and the threshold.

Fig. 4 shows that the larger the error tolerance, the lower the number of clusters is. For example, for user 1, the number

TABLE 2. Results of the maturity evaluation of the industrial power users.

USER	Dimension	Load level A				Maturity A	Power consumption behavior B						Maturity B	Interaction C		Maturity C
	Index	A1	A2	A3	A4		B1	B2	B3	B4	B5	B6		C1	C2	
	Weight	0.26	0.26	0.25	0.23		0.18	0.18	0.18	0.18	0.14	0.14		0.5	0.5	
User1		0.68	0.59	0.14	0.22	**0.32**	1.00	3.05	2.55	1.22	0.87	0.11	**0.81**	0.39	0.12	**0.04**
User2		0.42	0.48	0.25	0.34	**0.56**	2.00	2.53	5.30	2.10	0.93	0.30	**0.72**	2.69	0.47	**0.19**
User3		0.65	0.60	0.16	0.29	**0.52**	4.00	2.24	3.49	2.07	0.87	0.44	**0.73**	1.65	0.30	**0.12**
User4		0.90	0.88	0.05	0.08	**0.73**	8.00	3.17	1.01	0.28	0.68	0.05	**0.83**	0.07	0.03	**0**
User5		0.92	0.85	0.03	0.13	**0.90**	5.00	2.61	0.66	0.29	0.89	0.06	**0.77**	0.27	0.04	**0.01**
User6		0.98	0.95	0.01	0.04	**0.93**	10.00	6.55	27.04	12.90	0.89	1.58	**0.02**	16.16	2.15	**1**

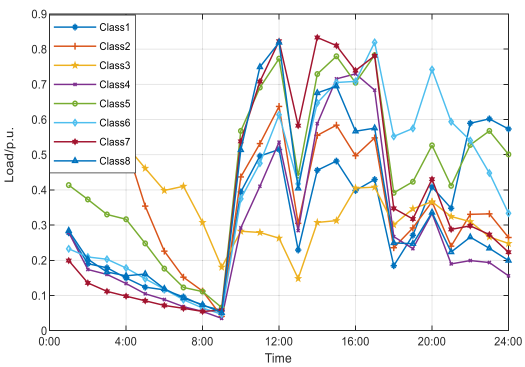

FIGURE 5. Daily electricity consumption behavior of user 1.

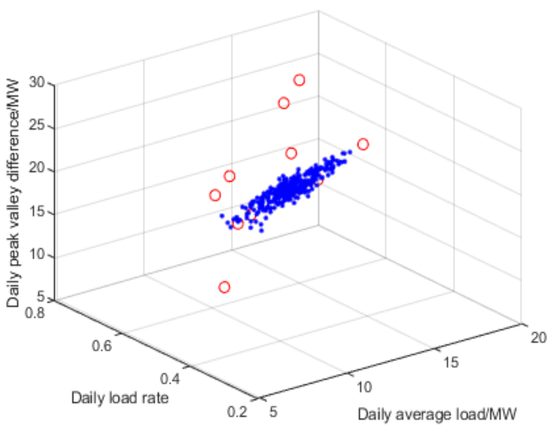

FIGURE 6. Abnormal behavior of electricity consumption of user 6.

of clusters is 8 when the error tolerance is 200. For the calculation of the maturity indices, the error tolerance of the adaptive k-means clustering algorithm is set to 200.

We use the 24-hour load data of the users and extract the three daily indices (average load, load rate, peak-valley difference) to evaluate the daily electricity consumption. The abnormal behavior of electricity consumption is calculated using the LOF. Fig. 6 shows the daily electricity consumption of user 6, where the red circles indicate the abnormal behavior (i.e., an LOF > 2).

As is shown in Fig. 6 and Table 2, the number of days of abnormal behavior is 10 for user 6, and the maximum LOF is greater than 6.5. The four indices (annual maximum peak-valley difference, annual average peak-valley difference, quarterly imbalance coefficient, and standard deviation of the monthly average load) indicate that the load fluctuations are largest for user 6, suggesting that user 6 exhibits greater anomalous behavior and greater load uncertainties. Therefore, the maturity of electricity consumption is lowest for user 6.

C. MATURITY OF THE DEMAND RESPONSE CAPABILITY

The frequency distribution of the peak load occurs is shown in Fig. 7; in the one-year 8760-h load data of the park, the maximum load was exceeded 70% of the time (for 1372 h), which represents an average of 3.76 h per day.

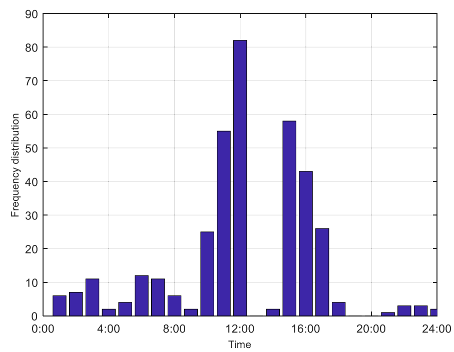

FIGURE 7. Frequency distribution of peak load time.

As shown in Fig. 7, four periods (10:00∼11:00, 11:00∼12:00, 14:00∼15:00, and 15:00∼16:00) are the peak-load periods; the demand response capability of each user is evaluated by determining the rate reduction of the demand response load and the minimum load. The result is shown in Table 2.

The demand response capability is largest for user 6; the indices of the demand response capability are larger than 2 MW, which indicates good interaction with the power grid. In contrast, the indices of the demand response capabilities for user 4 and user 5 are only 1% of the indices of user 6, indicating less interaction.

The three maturity indices of regional electricity consumption based on the weighted TOPSIS method are shown in Fig. 8.

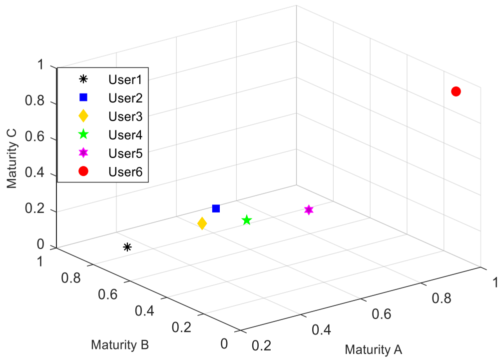

FIGURE 8. **Results of the three maturity indices of the regional power users.**

From the load level dimension, the maturity of User 1 is relatively low, then the maturity of User 3, User 2, User 4 and User 5 increases, and User 6 has the maximum maturity index in load level which is close to saturation. Users 1 to 5 have less abnormal behavior of electricity consumption, smaller load fluctuations, and higher maturity than User 6. User 6 exhibits much greater interaction than the other 5 users.

V. CONCLUSION

Smart meter data has the characteristics of large data volume and wide spatial dispersion. In consideration of the development of the UPIoT, these types of data require large computing resources. A data analysis and application framework for smart meter data based on cloud and fog computing and data contextualization were developed, and a data contextualization model describing three dimensions of maturity of power users was established. The power consumption characteristics of users were investigated from the three aspects of the load level, power consumption behavior, and interaction. In this manner, the smart meter data were condensed into maturity indices and uploaded to the cloud, which greatly reduced the computational complexity.

This study is a static evaluation of the maturity of electricity consumption characteristics of industrial power users; the data will be dynamically updated and evaluated in the future. In addition, the proposed data analysis framework and methods will be applied to a integrated energy system to analyze the energy consumption characteristics of users.

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LILI WANG received the B.S. and Ph.D. degrees from Zhengzhou University, in 2006 and 2012, respectively.

He is currently a Senior Engineer with the State Grid Henan Economic Research Institute. His research interests include smart grid, the energy Internet, and data mining.

LINJUAN ZHANG received the M.S. degree in electric circuit and system and the Ph.D. degree in communication and information system from Beijing Jiaotong University, in 2009 and 2014, respectively.

She is currently a Senior Engineer with the State Grid Henan Economic Research Institute. Her research interests include vehicular networks, the energy Internet, and data mining.

CHANGQING XU received the B.S. degree from North China Electric Power University, in 1996.

He is currently a Senior Engineer with the State Grid Henan Economic Research Institute. His research interests include smart grid, the energy Internet, and data mining.

HONGBO WU received the B.S. degree in electrical engineering and automation from Zhengzhou University, in 2004.

His research interests include smart grid, the energy Internet, and data mining.

YIMING LI received the M.S. degree in electrical engineering from North China Electric Power University, in 2011.

His research interests include smart grid, the energy Internet, and data mining.

HAONAN SUN was born in Liaoning, China, in 1994. He received the B.S. degree in electrical engineering and automation from Northeast Electric Power University, in 2016, and the M.S. degree in electrical engineering from North China Electric Power University, Beijing, China, in 2019, where he is currently pursuing the Ph.D. degree in electrical engineering.

His research interests include data mining in electric power systems, integrated energy management, and optimal operation of integrated energy systems.