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Data-Driven Abnormity Assessment for Low-Voltage Power Consumption and Supplies Based on CRITIC and Improved Radar Chart Algorithms

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ABSTRACT With the wide deployment of advancing metering infrastructure (AMI) in power distribution systems, the quantity of power consumers' electricity data is increasing rapidly and the data also become more and more accurate. To make full use of these power consumers' AMI data, a data-driven abnormity assessment algorithm for low-voltage power consumers is proposed based on the CRITIC (CRiteria Importance Though Intercrieria Correlation) method and the improved radar chart method. First, the indexes that characterize the consumer's abnormal features of power consumption and supplies are extracted from the original AMI data. Then, the abnormity assessment algorithm is used to determine power consumers' abnormal features of power consumption and supplies by using the extracted indexes, in which the weights of indexes are determined by the CRITIC method and the assessment value of abnormal features is determined by the improved radar chart method. Next, the abnormity assessment algorithm is used again to assess power consumers' power consumption and supplies abnormities. Finally, the effectiveness of proposed algorithm is demonstrated in case studies by employing AMI data collected from power utilities in Zhejiang Province, China, and the results show that the algorithm can be used in actual applications.

INDEX TERMS Power consumption and supplies data, abnormity assessment, abnormal feature of power consumption and supplies, CRITIC method, improved radar chart method.

I. INTRODUCTION

With the rapid development of economy, the highest electricity load in Zhejiang Province has set a new record, and various of highly risk power consumption and supplies abnormities of power consumers have also existed extensively. In the past few years, smart grid technologies are widely used in power systems around the world [1]–[4] and the number of advanced metering infrastructure (AMI) [5], such as high-frequency overhead and underground current, voltage sensors, and smart meters connected to power systems, has increased significantly in the meanwhile. Some related researches have been done in the hardware design of the AMI, such as openZmeter (oZm) [6], [7], Open Power Quality (OPQ) [8], [9] and some other high-precision sensors, to achieve data collection capability with larger range, higher accuracy and faster speed. oZm is an advanced low-cost and open-source hardware device for high-precision energy and power quality measurement in low-voltage power systems [6], [7]. OPQ is another advanced AMI that can realize end-to-end capture, analysis,

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and visualizations of distributed real-time power quality (PQ) data [8], [9]. In the meanwhile, the widespread installation of smart meters makes the collection of large amounts of fine-grained data on power supplies more and more easily [10]. Relying on smart grid technologies and multitudinous AMI, the power consumption and supplies data of power consumers can be accessed more easily. At present, the data scale of power consumer side in the smart grid has increased from GB to TB and even PB level [11]. Due to the complex characteristics of power systems, electric power data are with features of large scale, fast transmission speed and multiple types, which are consistent with the concept of big data [12]. Big data technology is widely used to extract the required information from intricate power consumer's data [13], [14]. Based on these electricity data, in order to prevent the occurrence of power accidents and ensure the safety of power consumers' power consumption and supplies, a data-driven abnormity assessment algorithm is proposed to identify these potential power consumption and supplies abnormities in time.

With the increase of power consumers and the diversification of electricity consumption forms, there are more and more types of power abnormities. In power utilities, the amount of data of power abnormities generated are quite large. For example, there are about 55,000 abnormal electricity records for power consumers from January to October, 2018 for power utilities in Zhejiang Province, China. However, the accuracy of abnormity assessment is still low, and the screening requires a lot of manpower and material resources. Some power abnormities cannot be detected and dealt with in time, which cause massive economic losses to power utilities and threaten the secure operation of power systems. Therefore, it is great significant to perform power consumers' abnormity assessment to prevent power accidents and reduce security vulnerabilities effectively by analyzing the power consumers' data of smart meter from AMI.

There is few research work on the abnormity assessment of power consumption and supplies for low-voltage consumers in power distribution systems, so it is necessary to propose an algorithm to deal with this problem appropriately. Some related research work is done and the decision-making methods for the abnormity assessment are proposed in [15], [16]. The multiple-criteria decision-making methods, which considers the decision maker's subject desires, are used in [15] for assessing the risk of thousands of underground vaults. In [16], several indexes for node importance evaluation are extracted, and a multi-index node importance evaluation method based on CRITIC is proposed. Besides, the Monte Carlo simulation is used to assess the risk [17]–[19] in some research work. In [17], the Monte Carlo simulation is used to select system state in transmission systems and distribution systems, and a hierarchical risk assessment method for transmission systems is put forward based on the system state. In [18], Monte Carlo simulation techniques are used to assess the risks of the reinvested projects under consideration, and the research work shows the significant impact of risk strategies on the selection of reinvestment projects. In [19], the sequential Monte Carlo method enhanced by the temporal wind storm sampling strategy accurately assesses the impact of all types of storms, effectively revealing the impact of storms on the distribution system. Besides, risk assessment theory for state assessment is discussed in [20], [21]. For example, a risk assessment model is established by taking full account of wind uncertainties and line flow fluctuations, thus, the risk values of individual lines and the entire system can be obtained for helping perform necessary actions to reduce the risks [20]. In [21], the risk assessment method of time correlation between random variables input in distribution systems is considered, and the accuracy of risk assessment results is improved. Also, a new data-driven method has been used for abnormity assessment of power equipment in [22], and the transformer overloading risk was assessed by the data-driven method that combines a transformer temperature rise and insulation life loss simulation model with clustering analysis technique.

At present, most of research studies on abnormity assessment of distribution systems mainly focuses on the abnormities of the whole distribution systems. There are few studies on the abnormity assessment for low-voltage power consumers of distribution systems. Given this background, this paper aims to propose an effective data-driven algorithm to assess the abnormities of electricity consuming of low-voltage power consumers in distribution systems based on the AMI data collected from the Electricity Information Acquisition System (EIAS). The main contributions of the proposed algorithm are as follows:

i) The abnormity assessment algorithm of low-voltage power consumers is presented considering statistical indexes and electrical indexes, which makes the features of abnormity assessment more comprehensive.
ii) In the abnormity assessment of low-voltage power consumers, the CRITIC method is adopted to determine the weights of the abnormal features, so the weights can be more objective compared with the traditional expert system.
iii) The improved radar chart method is adopted in the abnormity assessment, so the assessment result of power consumers can be more intuitive. Besides, considering weights and values of the features, the improved radar chart method in this paper can be more comprehensive compared with traditional radar chart method which only displays the values of the features.

II. ABNORMAL FEATURES EXTRACTING FOR POWER CONSUMERS

Since smart meters are installed in power distribution systems more and more widely, massive power consumption and supplies data including kinds of intricate and heterogeneous information can be collected. However, due to the limited ability of data collection and storage in power distribution systems, strategies for big data application have not been

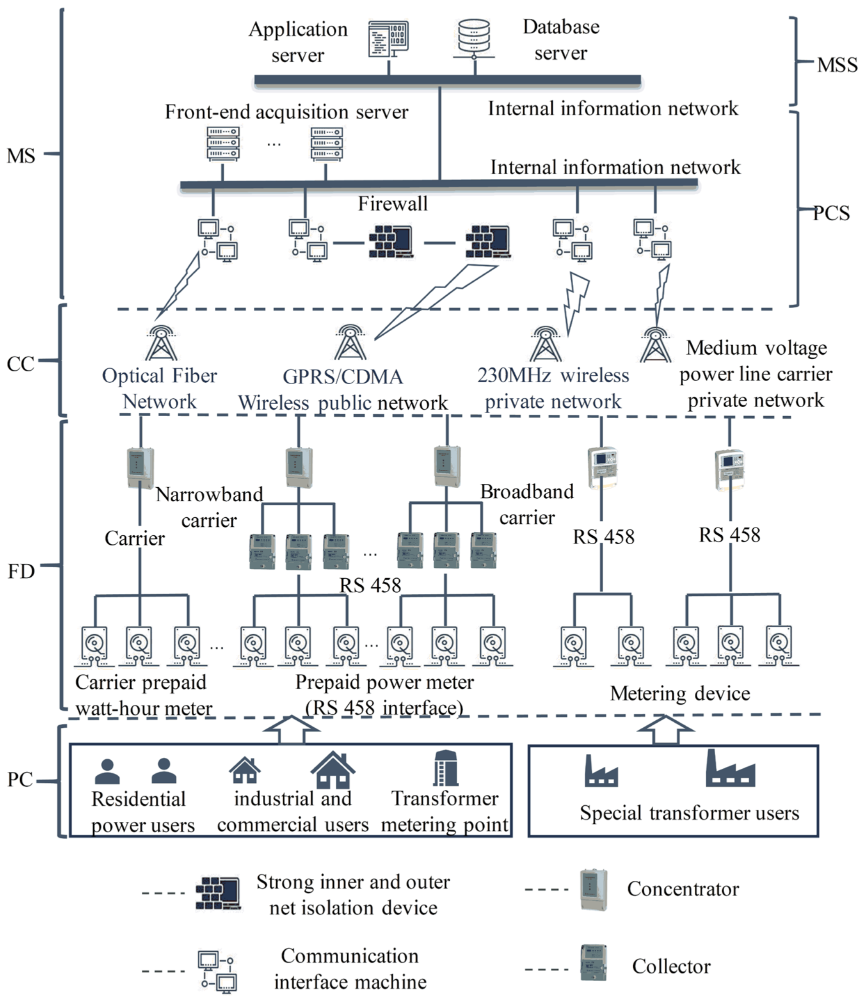

FIGURE 1. The physical structure of the electricity information acquisition system (EIAS).

studied widely. In order to improve the utilization rate of big data in power systems, power utilities have established the EIAS. The EIAS can collect various power supplies data of power consumers through AMI. The physical structure of the EIAS is shown in Figure 1, and this system constituted by four parts: main station (MS), communication channel (CC), field device (FD) and power consumers (PC). The physical structure of MS network is mainly composed of marketing system servers (MSS, including database servers, disk arrays, application servers), pre-collection servers (PCS, including pre-servers, workstations, GPS clocks, firewall devices) and related network devices. The CC refers to the remote communication channel between the MS and the FD, mainly including Fiber Channel, GPRS/CMDA wireless public network channel, 230MHz wireless power dedicated channel, etc. The FD refers to the terminal and metering equipment installed in the field, which mainly includes the special transformer terminal, the multi-function electric energy meter, concentrators, collectors and electric energy meters, etc. Based on data collection capability of the EIAS, an effective data-driven algorithm is proposed to analyze and assess the power consumption and supplies abnormities of power consumers in this paper. With the aid of the data collection function of EIAS platform, an abnormity assessment of power consumption and supplies module for low-voltage power consumers can be deployed in the application severs of MSS.

With the wide deployment of AMI in distribution system, various data of power consumers such as the voltage, current active power, line loss rate can be collected by the EIAS. The power consumer data analyzed in this paper collecting from AMI are as follows: the active power $\prod^{\mathrm{P}}$, the line loss rate $\prod^{\mathrm{LL}}$, the voltage of phase $p(p \in \{\mathrm{A}, \mathrm{B}, \mathrm{C}\})$ of three-phase power consumers $\prod^{\mathrm{V}_{\mathrm{user}}^{p}}$, the voltage of single-phase power consumers $\prod^{\mathrm{V}_{\mathrm{user}}}$, the voltage of courts $\prod^{\mathrm{V}_{\mathrm{TG}}}$, the neutral line voltage of courts $\prod^{\mathrm{V}_{\mathrm{TG}}^{\mathrm{NL}}}$, the current of phase p of three phase consumers $\prod^{\mathrm{I}_{\mathrm{user}}^{p}}$, the neutral line and live line current of single-phase consumers $\prod^{\mathrm{I}_{\mathrm{NL}}}$ and $\prod^{\mathrm{I}_{\mathrm{FL}}}$, the equivalent line impedance $\prod^{\mathrm{R}_{\mathrm{LI}}}$ and the neutral line voltage of there-phase consumers $\prod^{\mathrm{V}_{\mathrm{user}}^{\mathrm{NL}}}$.

The time interval of data acquisition of electricity data collected by AMI can be 15min, 30min, or 1hour. Using the data collecting by the AMI, some indexes that reflect the power consumption and supplies abnormities of power consumers can be extracted. For the extracted indexes, they can be divided into two categories, i.e., statistical indexes and electrical indexes. The statistical indexes are utilized for the statistics of power consumers' electricity data, including occurrence frequency of over-limit, over-limit time and amplitude of various electrical parameters. The electrical indexes are commonly used in power systems, which are related to the operating states of electrical equipment, such as load rate, neutral line voltage, and line impedance.

A. STATISTICAL INDEXES OF ABNORMITY ASSESSMENT FOR POWER CONSUMERS

1) OCCURRENCE FREQUENCY OF OVER-LIMIT

The occurrence frequency of over-limit of the AMI data $\prod^{\psi}$ can be reflected by the occurrence frequency of over-limit index I_{ol}^{ψ}. ψ refers to different kinds of AMI data of power consumers, such as voltage, line loss rate and active power. The higher the occurrence frequency of over-limit of the AMI data is, the more dangerous the power consumers' power supplies abnormities will be. The occurrence frequency of over-limit index I_{of}^{ψ} can be defined as

$$I_{\text{of}}^{\psi}(i) = \frac{1}{n_d T_d} \sum_{d=T_{\text{start}}^{\psi}}^{T_{\text{end}}^{\psi}} \sum_{t=1}^{n_d} \varepsilon_{d,t}^{\psi}(i),\ \psi \in \{\text{P, LL, V}_{\text{user}}, \text{V}_{\text{user}}^{p}, \text{V}_{\text{TG}}\} \tag{1}$$

$$\varepsilon_{d,t}^{\psi}(i) = \begin{cases} 1, & \prod_{d,t}^{\psi}(i) \geq \prod_{\text{up}}^{\psi}(i) \text{ or } \prod_{d,t}^{\psi}(i) \leq \prod_{\text{down}}^{\psi}(i) \\ 0, & \prod_{\text{up}}^{\psi}(i) < \prod_{d,t}^{\psi}(i) < \prod_{\text{down}}^{\psi}(i) \end{cases} \tag{2}$$

$$\begin{cases} \prod_{\text{up}}^{\psi}(i) = (1+\beta^{\psi}) \prod_{N}^{\psi}(i) \\ \prod_{\text{down}}^{\psi}(i) = (1-\beta^{\psi}) \prod_{N}^{\psi}(i) \end{cases} \tag{3}$$

where n_d is the sampling frequency of AMI, and T_d is the sampling period length; $\varepsilon_{d,t}^{\psi}(i)$ is a 0-1 variable. If $\varepsilon_{d,t}^{\psi}(i)$ equals to 0, it means that the AMI data $\prod_{d,t}^{\psi}$ of power consumer i is not over-limit in time t of day d. If $\varepsilon_{d,t}^{\psi}(i)$ equals to 1, the AMI data $\prod_{d,t}^{\psi}$ of power consumer i is over-limit in time t of day d; $\prod_{\text{up}}^{\psi}$ and $\prod_{\text{down}}^{\psi}$ represent the upper and lower limits of the AMI data $\prod_{d,t}^{\psi}$ respectively; T_{start}^{ψ} and T_{end}^{ψ} represent the start and the end monitoring times of the AMI data $\prod_{d,t}^{\psi}$, respectively; $\prod_{N}^{\psi}$ is the rated value of the AMI data $\prod_{d,t}^{\psi}$; β^{ψ} is the over-limit threshold of the AMI data $\prod_{d,t}^{\psi}$. The specific values of over-limit thresholds of voltage, line loss rate and active power are respectively set as 10%, 20% and 30% on the basis of consulting power system operators and maintenance personnel of power utilities in China. It means that the values of voltage, line loss rate and active power should not exceed the standard value for 10%, 20% and 30% respectively.

2) AMI DATA OF POWER CONSUMERS ON A YEAR-ON-YEAR BASIS

Some kinds of AMI data of power consumers on a year-on-year basis can reflect abnormal features of power consumers to some extent. Generally speaking, the larger the quantity of the AMI data on a year-on-year basis of power consumers is, the more serious the secure hazards of the power consumers will be. The AMI data of power consumers on a year-on-year basis I_{equ}^{ψ} can be defined as

$$I_{\text{equ}}^{\psi}(i) = \frac{1}{n_d T_{\text{equ}}} \sum_{d=T_0-T_{\text{equ}}}^{T_0-T_{\text{equ}}+T_d} \sum_{t=1}^{n_d} \prod_{d,t}^{\psi}(i),\quad \psi \in \{\text{P, I}_{\text{NL}}, \text{R}_{\text{LI}}, \text{V}_{\text{user}}^{\text{NL}}\} \tag{4}$$

where T_{equ} is the time internal of the AMI data of power consumers on a year-on-year basis; T_0 is the start time of abnormity assessment of power consumption and supplies for power consumers.

3) RING RATIO OF POWER CONSUMPTION AND SUPPLIES DATA

A lot of historical information can be reflected by the ring ratio data of power consumers. From power consumers' ring ratio data, the information such as electricity consumption, voltage and current of the power consumers in the previous month can be found. Like AMI data of power consumers on a year-on-year basis, the larger the power consumption and supplies ring ratio data of power consumers are, the more serious the secure hazards of power consumers will be. The ring ratio data of power consumers I_{cir}^{ψ} can be defined as

$$I_{\text{cir}}^{\psi}(i) = \frac{1}{n_d T_{\text{cir}}} \sum_{d=T_0-T_{\text{cir}}}^{T_0} \sum_{t=1}^{n_d} \prod_{d,t}^{\psi}(i),\quad \psi \in \{\text{P, I}_{\text{NL}}, \text{R}_{\text{LI}}, \text{V}_{\text{user}}^{\text{NL}}\} \tag{5}$$

where T_{cir} is the time internal of the AMI data of power consumers on ring ratio.

4) VARIATION COEFFICIENT

Variation coefficient is a commonly used statistical index in statistics [23], and it is mainly used to compare the dispersion of degree of different AMI data. Generally speaking, the power consumers with large variation coefficient of AMI data usually relate to abnormities compared with those with small variation coefficient. The variation coefficient I_{div}^{ψ} can be defined as

$$I_{\text{div}}^{\psi}(i) = \sum_{d=T_{\text{start}}^{\psi}}^{T_{\text{end}}^{\psi}} \frac{(\prod_{d}^{\psi}(i) - \overline{\prod^{\psi}}(i))^2}{\overline{\prod^{\psi}}(i)},\quad \psi \in \{\text{P, I}_{\text{NL}}, \text{V}_{\text{user}}, \text{V}_{\text{user}}^{p}, \text{R}_{\text{LI}}, \text{V}_{\text{user}}^{\text{NL}}\} \tag{6}$$

$$\prod_{d}^{\psi}(i) = \sum_{t=1}^{n_d} \prod_{d,t}^{\psi}(i) \tag{7}$$

$$\overline{\prod^{\psi}}(i) = \frac{1}{n_d(T_{\text{end}}^{\psi} - T_{\text{start}}^{\psi})} \sum_{d=T_{\text{start}}^{\psi}}^{T_{\text{end}}^{\psi}} \sum_{t=1}^{n_d} \prod_{d,t}^{\psi}(i) \tag{8}$$

where $\prod_d^{\psi}$ is the total value of the AMI data $\prod_{d,t}^{\psi}$ of day d; $\overline{\prod^{\psi}}$ is the mean value of $\prod_{d,t}^{\psi}$ in the sampling period.

5) AMPLITUDE OF POWER CONSUMER POWER CONSUMPTION AND SUPPLIES DATA

The maximum value of AMI data $\prod_{d,t}^{\psi}$ of power consumers such as voltage and current, usually reflects the power consumers' overload state. The index amplitude $I_{\max}^{\psi}$ can be defined as

$$I_{\max}^{\psi}(i) = \max(\prod_{d,t}^{\psi} / \prod_{N}^{\psi}),\ \psi \in \{\mathrm{V_{user}},\ \mathrm{V_{user}^{\mathit{p}}}, \mathrm{V_{TG}}\},$$
$$\forall d \in [T_{\text{start}}^{\psi}, T_{\text{end}}^{\psi}],\ t \in [1, n_d] \tag{9}$$

B. ELECTRICAL INDEXES OF ABNORMITY ASSESSMENT FOR POWER CONSUMERS

1) NEUTRAL LINE VOLTAGE

For normal-operating three-phase power consumers, the voltage of the neutral line is low and often close to zero [24]. If the neutral line voltage of a three-phase power consumer fluctuates greatly and is high, it can be deducted that there may exist some abnormities for the power consumer. The neutral line voltage index I_{nlv}^{ψ} can be defined as

$$I_{\text{nlv}}^{\psi}(i) = \frac{1}{n_d T_d} \sum_{d=T_0}^{T_0+T_d} \sum_{t=1}^{n_d} \prod_{d,t}^{\psi}(i), \quad \psi \in \{\mathrm{V_{user}^{NL}},\ \mathrm{V_{TG}^{NL}}\} \tag{10}$$

2) LOAD RATE OF POWER CONSUMERS

Power consumers' load rate refers to the ratio of actual load of power consumers to its capacity [25]. The over-limit of power consumers' load rate often leads to the occurrence of power accidents. The power consumer load rate I_{LR} can be represented as

$$I_{\text{LR}}(i) = \frac{1}{n_d T_d} \sum_{d=T_0}^{T_0+T_d} (\sum_{t=1}^{n_d} \prod_{d,t}^{\mathrm{P}}(i) / \prod_{N}^{\mathrm{P}}(i)) \tag{11}$$

where $\prod_N^{\mathrm{P}}(i)$ is the rated capacity of power consumer i.

3) DIFFERENCE BETWEEN LIVE LINE AND NEUTRAL LINE CURRENT

For single-phase power consumers, the difference between the neutral line and the live line current should be small under normal circumstances. When the current difference between the neutral line and the live line is large, there always exists some abnormities for the power consumer. The difference of live line and neutral line current I_{diff} can be defined as

$$I_{\text{diff}}(i) = \frac{1}{n_d T_d} \sum_{d=T_0}^{T_0+T_d} \sum_{t=1}^{n_d} \frac{(\prod_{d,t}^{\mathrm{I_{FL}}}(i) - \prod_{d,t}^{\mathrm{I_{NL}}}(i))}{\prod_{d,t}^{\mathrm{I_{NL}}}(i)} \tag{12}$$

4) EQUIVALENT LINE IMPEDANCE

The equivalent line impedance reflects aging degree of the power supply line to power consumers. The larger the impedance is, the more serious the power consumers' aging is and the more dangerous the abnormity is [26]. The equivalent line impedance index is compared among power consumer groups to rank the degree of abnormity on equivalent line impedance of power consumers in the proposed algorithm. These power consumers with larger equivalent line impedance are considered more likely to have abnormities compared with the others. The equivalent line impedance index I_{LI} can be represented as

$$I_{\text{LI}}(i) = \frac{1}{n_d T_d} \sum_{d=T_0}^{T_0+T_d} \sum_{t=1}^{n_d} \prod_{d,t}^{\mathrm{R_{LI}}}(i) \tag{13}$$

$$\prod_{d,t}^{\mathrm{R_{LI}}}(i) = \left| \frac{\prod_{d,t+1}^{\psi}(i) - \prod_{d,t}^{\psi}(i)}{\prod_{d,t+1}^{\phi}(i) - \prod_{d,t}^{\phi}(i)} \right|,$$
$$(\psi, \phi) \in \{(\mathrm{V_{user}^{\mathit{p}}},\ \mathrm{I_{user}^{\mathit{p}}}), (\mathrm{V_{user}},\ \mathrm{I_{FL}})\} \tag{14}$$

5) DEGREE OF THREE-PHASE UNBALANCE

Three-phase unbalance refers to the inconsistent of three-phase current (or voltage) amplitude in the power system, and the amplitude difference exceeds the specified range [27]. If the degree of three-phase unbalance of power consumer is excessively high, the power loss of the power supply line will increase and the secure power consumption and supplies of power consumers will be affected. The degree of three-phase unbalance I_{unb} can be represented as

$$I_{\text{unb}}(i) = \frac{1}{n_d T_d} \sum_{d=T_0}^{T_0+T_d} \sum_{t=1}^{n_d} \rho_{d,t}^{\text{unb}}(i) \tag{15}$$

$$\rho_{d,t}^{\text{unb}}(i) = \frac{\max\limits_{p\in P}(\prod_{d,t}^{\mathrm{V_{user}^{\mathit{p}}}}(i)) - \min\limits_{p\in P}(\prod_{d,t}^{\mathrm{V_{user}^{\mathit{p}}}}(i))}{\sum\limits_{p\in P} \prod_{d,t}^{\mathrm{V_{user}^{\mathit{p}}}}(i)},$$
$$P \in \{\mathrm{A, B, C}\} \tag{16}$$

where $\rho_{d,t}^{\text{unb}}(i)$ is the degree of three-phase unbalance of power consumer i in time t of day d.

These are five statistical indexes and five electrical indexes that reflect the abnormity assessment of power consumption and supplies for power consumers. For statistical indexes, the power consumption and supplies abnormities of power consumers are analyzed from the perspective of data statistics. As for electrical indexes, the conditions of power consumers are analyzed from the perspective of electrical information. The larger these indexes are, the more severe the abnormities of power consumption and supplies of power consumers will be.

III. ABNORMITY ASSESSMENT BASE ON CRITIC METHOD AND IMPROVED RADAR CHART METHOD

For power consumption and supplies abnormity assessment algorithm of power consumers, the first is to form the feature vectors and decision matrices. After the extraction of statistical indexes and electrical indexes, feature vectors and decision matrices are determined. To construct a power consumption and supplies abnormity assessment algorithm for power consumers, the power consumer's feature vector I_F^τ and decision matrix M_F^τ can be respectively represented as

$$I_F^\tau(i) = [I_1^{\tau,f}, I_2^{\tau,f}, \cdots, I_m^{\tau,f}] \tag{17}$$

$$M_F^\tau = \begin{bmatrix} I_F^\tau(1) \\ I_F^\tau(2) \\ \vdots \\ I_F^\tau(n) \end{bmatrix} = \begin{bmatrix} I_1^{\tau,f}(1) & I_2^{\tau,f}(1) & \cdots & I_m^{\tau,f}(1) \\ I_1^{\tau,f}(2) & I_2^{\tau,f}(2) & \cdots & I_m^{\tau,f}(2) \\ \vdots & \vdots & \ddots & \vdots \\ I_1^{\tau,f}(n) & I_2^{\tau,f}(n) & \cdots & I_m^{\tau,f}(n) \end{bmatrix} \tag{18}$$

where $I_k^{\tau,f}(i)(1 \le k \le m, 1 \le i \le n)$ is the value of the kth index of feature F; n is the number of power consumers; m is the index number of the features; τ represents different kind of type of power consumers. $\tau = \mathrm{s}$ represent the consumer i is singe-phase consumer, and $\tau = \mathrm{t}$ represent the consumer i is three-phase consumer.

For three-phase power consumers and single-phase power consumers, the feature vectors and decision matrices formed are different because there exists difference between their indexes. For example, neutral line voltage can only be extracted in three-phase power consumers while the difference of live line and neutral line current can only be extracted from single-phase power consumers, since there are not neutral line voltage and neutral line current for singe-phase power consumers and three-phase power consumers respectively. Therefore, the power consumers need to be divided into single-phase power consumers and three-phase power consumers for analytics, respectively.

1) For single-phase power consumers, four types of feature vector including overload feature, overvoltage feature, neutral line current feature and equivalent line impedance feature are determined according to the extracted indexes. These feature vectors are composed of indexes belonging to their feature categories:

Overload feature:

$$I_{\mathrm{ol}}^{\mathrm{s}}(i) = [I_{\mathrm{LR}}(i), I_{\mathrm{of}}^{\mathrm{LL}}(i), I_{\mathrm{of}}^{\mathrm{P}}(i), I_{\mathrm{equ}}^{\mathrm{P}}(i), I_{\mathrm{cir}}^{\mathrm{P}}(i), I_{\mathrm{div}}^{\mathrm{P}}(i)] \tag{19}$$

Overvoltage feature:

$$I_{\mathrm{ov}}^{\mathrm{s}}(i) = [I_{\mathrm{of}}^{V_{\mathrm{user}}}(i), I_{\mathrm{of}}^{V_{\mathrm{TG}}}(i), I_{\mathrm{max}}^{V_{\mathrm{user}}}(i), I_{\mathrm{max}}^{V_{\mathrm{TG}}}(i), I_{\mathrm{equ}}^{V_{\mathrm{user}}}(i)] \tag{20}$$

Neutral line current feature:

$$I_{\mathrm{nc}}^{\mathrm{s}}(i) = [I_{\mathrm{diff}}(i), I_{\mathrm{equ}}^{I_{\mathrm{NL}}}(i), I_{\mathrm{cir}}^{I_{\mathrm{NL}}}(i), I_{\mathrm{div}}^{I_{\mathrm{NL}}}(i)] \tag{21}$$

Equivalent line impedance feature:

$$I_{\mathrm{li}}^{\mathrm{s}}(i) = [I_{\mathrm{LI}}(i), I_{\mathrm{equ}}^{R_{\mathrm{LI}}}(i), I_{\mathrm{cir}}^{R_{\mathrm{LI}}}(i), I_{\mathrm{div}}^{R_{\mathrm{LI}}}(i)] \tag{22}$$

Also, the decision matrix M_F^{s} of the single-phase power consumers can be formed as

$$M_F^{\mathrm{s}} = \begin{bmatrix} I_F^{\mathrm{s}}(1) \\ I_F^{\mathrm{s}}(2) \\ \vdots \\ I_F^{\mathrm{s}}(n) \end{bmatrix}_{n\times m} = \begin{bmatrix} I_1^{s,f}(1) & I_2^{s,f}(1) & \cdots & I_m^{s,f}(1) \\ I_1^{s,f}(2) & I_2^{s,f}(2) & \cdots & I_m^{s,f}(2) \\ \vdots & \vdots & \ddots & \vdots \\ I_1^{s,f}(n) & I_2^{s,f}(n) & \cdots & I_m^{s,f}(n) \end{bmatrix},$$

$$F \in \{\mathrm{ol}, \mathrm{ov}, \mathrm{nc}, \mathrm{li}\} \tag{23}$$

2) For three-phase power consumers, four types of abnormal feature vector including overload, overvoltage, neutral line voltage and equivalent line impedance are determined according to the extracted indexes. These feature vectors are composed of indexes belonging to their feature categories:

Overload feature:

$$I_{\mathrm{ol}}^{\mathrm{t}}(i) = [I_{\mathrm{LR}}(i), I_{\mathrm{of}}^{\mathrm{LL}}(i), I_{\mathrm{of}}^{\mathrm{P}}(i), I_{\mathrm{equ}}^{\mathrm{P}}(i), I_{\mathrm{cir}}^{\mathrm{P}}(i), I_{\mathrm{div}}^{\mathrm{P}}(i)] \tag{24}$$

Overvoltage feature:

$$I_{\mathrm{ov}}^{\mathrm{t}}(i) = [I_{\mathrm{of}}^{V_{\mathrm{user}}^p}(i), I_{\mathrm{of}}^{V_{\mathrm{TG}}}(i), I_{\mathrm{max}}^{V_{\mathrm{user}}^p}(i), I_{\mathrm{max}}^{V_{\mathrm{TG}}}(i), I_{\mathrm{equ}}^{V_{\mathrm{user}}^p}(i)] \tag{25}$$

Neutral line voltage feature:

$$I_{\mathrm{nv}}^{\mathrm{t}}(i) = [I_{\mathrm{unb}}(i), I_{\mathrm{nlv}}^{V_{\mathrm{user}}^{\mathrm{NL}}}(i), I_{\mathrm{equ}}^{V_{\mathrm{user}}^{\mathrm{NL}}}(i), I_{\mathrm{cir}}^{V_{\mathrm{user}}^{\mathrm{NL}}}(i), I_{\mathrm{div}}^{V_{\mathrm{user}}^{\mathrm{NL}}}(i)] \tag{26}$$

Equivalent line impedance feature:

$$I_{\mathrm{li}}^{\mathrm{t}}(i) = [I_{\mathrm{LI}}(i), I_{\mathrm{equ}}^{R_{\mathrm{LI}}}(i), I_{\mathrm{cir}}^{R_{\mathrm{LI}}}(i), I_{\mathrm{div}}^{R_{\mathrm{LI}}}(i)] \tag{27}$$

Besides, the decision matrix M_F^{t} of the three-phase power consumers can be formed as

$$M_F^{\mathrm{t}} = \begin{bmatrix} I_F^{\mathrm{t}}(1) \\ I_F^{\mathrm{t}}(2) \\ \vdots \\ I_F^{\mathrm{t}}(n) \end{bmatrix}_{n\times m} = \begin{bmatrix} I_1^{\mathrm{t},f}(1) & I_2^{\mathrm{t},f}(1) & \cdots & I_m^{\mathrm{t},f}(1) \\ I_1^{\mathrm{t},f}(2) & I_2^{\mathrm{t},f}(2) & \cdots & I_m^{\mathrm{t},f}(2) \\ \vdots & \vdots & \ddots & \vdots \\ I_1^{\mathrm{t},f}(n) & I_2^{\mathrm{t},f}(n) & \cdots & I_m^{\mathrm{t},f}(n) \end{bmatrix},$$

$$F \in \{\mathrm{ol}, \mathrm{ov}, \mathrm{nv}, \mathrm{li}\} \tag{28}$$

After the formation of decision matrixes M_F^τ, CRITIC method can be used to determine the weights of each index [28]. Compared with other subjective weighting methods such as Delphi method, CRITIC method takes a pure data-driven approach, and the weight setting is more objective. Compared with other objective weighting methods such as entropy weight method (EWM), CRITIC method considers the conflict and difference of indexes, and the weight settings are more comprehensive. The Gini coefficient [29]–[31] of the indexes can be defined as

$$G_j = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n}\left|I_j^{\tau,f}(i) - I_j^{\tau,f}(k)\right|}{2\sum_{i=1}^{n}\sum_{k=1}^{n} I_j^{\tau,f}(k)} = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n}\left|I_j^{\tau,f}(i) - I_j^{\tau,f}(k)\right|}{2n\sum_{k=1}^{n} I_j^{\tau,f}(k)},$$

$$j \in \{1, 2, \ldots, m\}, \quad \tau \in \{\mathrm{s}, \mathrm{t}\} \tag{29}$$

where G_j is the Gini coefficient of the variable j, and the value range of the G_j is [0, 1]; $I_j^{\tau,f}(i)$ is the variable j's value for consumer i.

Then Kendall coefficient is adopted in CRITIC method to reflect the correlation between indexes. For two columns of index $I_j^{\tau,f}(i) = (I_j^{\tau,f}(1), I_j^{\tau,f}(2), \ldots, I_j^{\tau,f}(n))^{\mathrm{T}}$ and $I_k^f(i) = (I_k^{\tau,f}(1), I_k^{\tau,f}(2), \ldots, I_k^{\tau,f}(n))^{\mathrm{T}}$, the value of power consumer i of the index j and k are $I_j^{\tau,f}(i)$ and $I_k^{\tau,f}(i)(1 \le i \le n)$, respectively. Let $I_{jR}^{\tau,f}$ and $I_{kR}^{\tau,f}(i)$ denote the rank of $I_j^{\tau,f}(i)$ and $I_k^{\tau,f}(i)$ in $I_j^{\tau,f}$ and $I_k^{\tau,f}(i)$, respectively, so the corresponding sorting result of $I_{jR}^{\tau,f}(i)$ and $I_{kR}^{\tau,f}(i)$ can be collocated to form a set $I_{\rm R}$ of variable pairs $(I_j^{\tau,f}, I_{kR}^{\tau,f})$ of power consumer i. Hence, the Kendall coefficient of the electricity abnormal features i and j can be defined as

$$\upsilon_{jk} = \frac{N_{cc} - N_{dc}}{\sqrt{(C - \sum_{i=1}^{n} \frac{N_i^{Tj}(N_i^{Tj}-1)}{2})(C - \sum_{i=1}^{n} \frac{N_i^{Tk}(N_i^{Tk}-1)}{2})}} \tag{30}$$

where C is a constant, and the value of C is $n(n-1)/2$; N_{cc} and N_{dc} respectively represent the number of the variable pairs whose two values are equal and unequal in variable pairs set $I_{\rm R}$; N_i^{Tj} and N_i^{Tk} respectively represent the number of variables with the same value in $I_j^{\tau,f}$ and $I_k^{\tau,f}$. Therefore, the overall Kendall coefficient between the electricity abnormal feature j and other features can be represented as

$$\upsilon_j = \sum_{k=1}^{m} \upsilon_{jk}/m \tag{31}$$

If the Kendall coefficient of the feature j is 1, it represents that the feature has consistent rank correlation; If the Kendall coefficient of the feature is 0, it represents that the feature is relatively independent.

It can be seen that the Gini coefficient and Kendall coefficient can be used to measure the contrast intensity of assessment indexes and the conflict between assessment indexes. Hence, they can be used to determine the objective weight of each feature. Therefore, the objective weight of the feature j can be represented as

$$\omega_j = G_j(1-\upsilon_j)/\sum_{k=1}^{m}[G_k(1-\upsilon_j)] \tag{32}$$

After the weights of all the electricity abnormal features are determined, the comprehensive assessment method, i.e., improved radar chart method, is used to assess the overall abnormal degree of power consumption and supplies of low-voltage power consumers. Compared with other types of decision-making methods, the improved radar chart method is more intuitive, and the power consumption and supplies condition of various indexes of different power consumers can be seen through the radar chart. Compared with the traditional radar chart method which weakens the influence of the index weight is difficult to clearly determine the weight of each index in comprehensive assessment, the improved radar chart method in this paper uses the weights of the indexes as the central angles [32]. Therefore, it can reflect more information, including not only the value of the indexes but also the weights of the indexes. Besides, the size of area of the radar chart can also reflect the comprehensive abnormal degree for power consumption and supplies [33]. In summary, the improved radar chart method presented in this paper is effective and suitable for decision making.

An illustration of improved radar chart method is given in Fig. 2. The comprehensive assessment results are given by obtaining the characteristic parameters of consumer radar charts, which can vividly reflect the independent weights of each assessment index and the interaction between the electricity abnormal features. The steps of the data-driven abnormity assessment of power consumers are as follows.

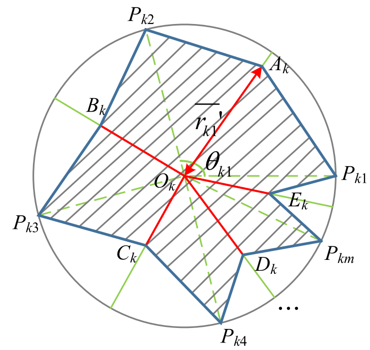

FIGURE 2. Radar chart for the comprehensive assessment with multiple indexes.

i) Determine the weights of abnormal features of power consumers as $\omega' = (\omega_1, \omega_2, \ldots, \omega_m)$, and plot central angle $\theta' = 2\pi\omega' = (\theta_1, \theta_2, \ldots, \theta_m)$ after the ranking.
ii) Make radius $O_kP_{k1}, O_kP_{k2}, \ldots, O_kP_{km}$ intersect the circle at point $P_{k1}, P_{k2}, \ldots, P_{km}$, and $\angle P_{ki}O_kP_{k(i+1)}$ equals to θ_i $(i = 1, 2 \ldots, m)$; Then, draw angular bisectors of each sector in turn.
iii) Mark the corresponding points $Q_1, Q_2, \ldots, Q_m$ on the angular bisector line according to the feature value $R_k = (I_1^f(k), I_2^f(k), \ldots, I_m^f(k))$ of consumer k.
iv) Sequentially connect $P_{k1}, Q_{k1}, P_{k2}, Q_{k2}, \ldots, Q_{km}, P_{k1}$.

The larger the total area $S(i)$ of the closed polygon is, the more severe the power supplies abnormities of the power consumer will be. The comprehensive assessment result of power consumer i can be represented as

$$S(i) = \sum_{j=1}^{m} I_j^f(i)\sin(2\pi\frac{\omega_j}{2}) \tag{33}$$

Figure 3 is the flow chart of abnormity assessment of power consumption and supplies for power consumers.

The main step for assessing the power consumers abnormity can be described as:

i) Form the decision matrix $M_{\rm F}$;
ii) Determine the weight of each index for each feature F by using the CRITIC method. $f_{\rm CR}(\cdot)$ is adopted to represent the CRITIC method. W_F can be represented as

$$W_F^\tau = f_{\rm CR}(M_F^\tau) = [\omega_{F1}^\tau, \omega_{F2}^\tau, \ldots, \omega_{Fm}^\tau] \tag{34}$$

iii) Obtain the value $S_F(i)$ of each feature F for each power consumer i by using the improved radar chart method. $f_{\rm RD}(\cdot,\cdot)$ is used to represent the improved radar chart method. S_F can be represented as

$$S_F^\tau = f_{\rm RD}(M_F^\tau, W_F^\tau) = [S_F^\tau(1), S_F^\tau(2), \ldots, S_F^\tau(n)]^{\rm T} \tag{35}$$

iv) Form the decision matrix $M^{\rm s} = [S_{\rm ol}, S_{\rm ov}, S_{\rm nc}, S_{\rm li}]$ and $M^{\rm t} = [S_{\rm ol}, S_{\rm ov}, S_{\rm nv}, S_{\rm li}]$ for single-phase power

TABLE 1. The results of the single-phase consumers.

Consumer ID	S_{ov} (p.u.)	S_{ol} (p.u.)	S_{nc} (p.u.)	S_{li} (p.u.)	S (p.u.)
****058239	76.336	100.000	100.000	5.423	100.000
****058375	88.775	89.457	65.141	4.702	88.710
****058401	74.815	83.652	76.524	8.307	85.794
…	…	…	…	…	…
****058232	25.004	49.833	10.895	5.579	27.635
****058240	23.295	51.976	11.692	4.158	27.395
****000493	19.519	54.725	0.032	7.142	27.256
****058361	0.000	12.377	0.000	10.863	23.928

consumers and three-phase power consumers by using the power consumers feature value, respectively.

v) Determine the weight of each feature W^τ by using the CRITIC method. W_A can be represented as

$$W^\tau = f_{CR}(M^\tau) = [\omega_1^\tau, \omega_2^\tau, \omega_3^\tau, \omega_4^\tau] \tag{36}$$

vi) Determine the final assessment result S^τ for single-phase power consumers and three-phase power consumers by using the improved radar chart method combined with the decision matrix S_A. S_A can be represented as

$$S^\tau = f_{RD}(M^\tau, W^\tau) = [S^\tau(1), S^\tau(2), \ldots, S^\tau(n)]^T \tag{37}$$

IV. CASE STUDIES

In this section, electricity data of 83 power consumers in Zhejiang province of China are employed to demonstrate the proposed method. Among these consumers, there are 52 singe-phase consumers and 31 three-phase consumers. For different type of consumers, different electricity abnormal features are extracted. Then, CRITIC method is used to determine the weights of the abnormal features and the improved radar chart method is used to assess the total electricity condition of the consumers. The analysis results of two different types of consumers are shown in Cases 1 and 2.

A. CASE 1: ABNORMITY ASSESSMENT OF POWER CONSUMPTION AND SUPPLIES FOR SINGLE-PHASE POWER CONSUMERS

For single-phase power consumers, abnormal feature on overvoltage S_{ov}, abnormal feature on overload S_{ol}, abnormal feature on neutral line current S_{nc} and abnormal feature on equivalent line impedance S_{li} are extracted. The weights of these abnormal features are 0.276, 0.260, 0.250 and 0.214 respectively. It is clear that the weights of all features are relatively average. Therefore, these four features have rather similar effects on abnormity assessment for single-phase power consumers.

The overall assessment of the single-phase consumer's power consumption and supplies abnormal features is carried out by using the improved radar chart method. The results are shown in Table 1. Figure 4 shows the radar chart of first-ranked single-phase power consumer ****058239. It can be seen from the radar chart that consumer ****058239 has rather severe power consumption and supplies abnormities, especially for S_{nc}, S_{ov} and S_{ol}..

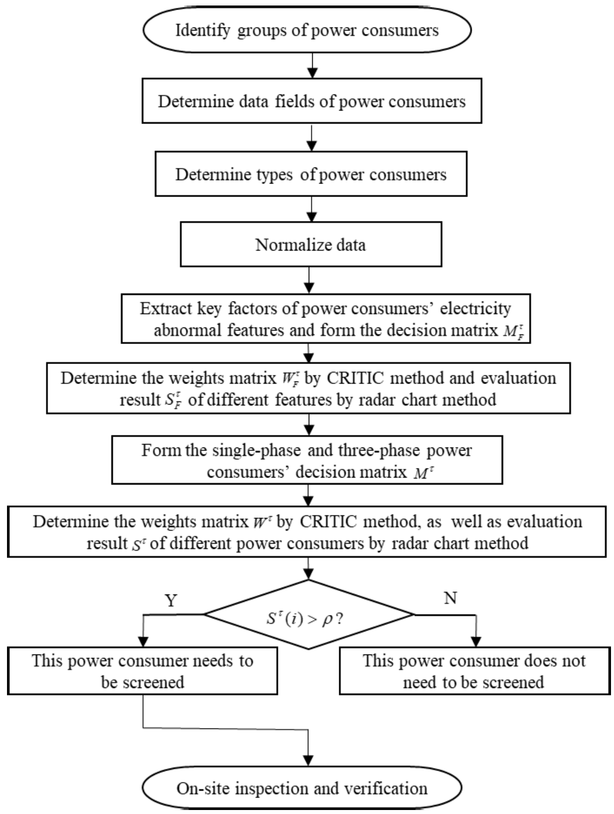

FIGURE 3. The flow chart of abnormity assessment of power consumption and supplies for power consumers.

The accuracy of these abnormal features is analyzed from Figs. 5-7 and as follows.

a) Abnormal feature on overvoltage S_{ov}: The load data of consumer ****058239 in Case 1 are analyzed, and the corresponding result is shown in Fig. 5. The consumer's active power exceeds the consumer's operating capacity constraint frequently. From the consumer's active power curve, there may be an overload abnormity for the consumer ****058239.

b) Abnormal feature on overload S_{ol}: The voltage data of consumer ****058239 in Case 1 are analyzed, and the result

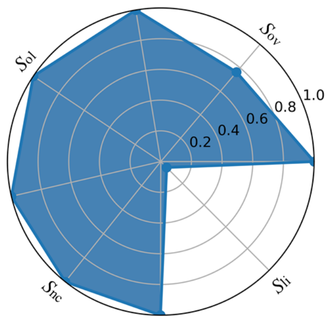

FIGURE 4. The radar chart of single-phase consumer ****058239 with the most severe power consumption and supplies abnormities.

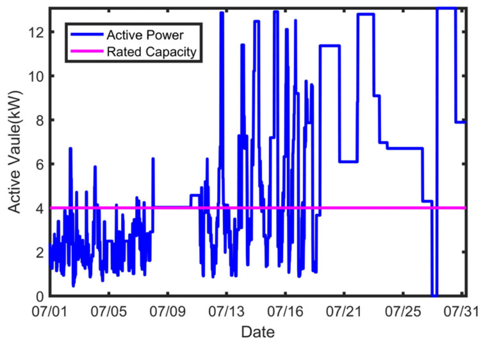

FIGURE 5. Active power and operating capacity curve of single-phase consumer ****058239 with the most severe power consumption and supplies abnormities.

is shown in Fig. 6. The consumer's live line voltage often exceeds the consumer's standard voltage constraints. From the consumer's voltage curve, there may be an overvoltage abnormity for consumer ****058239.

c) Abnormal feature on neutral line current S_{nc}: The live line current and neutral line current data of consumer ****058239 in Case 1 are analyzed, and the result is shown in Fig. 7. The consumer's live current and neutral current vary greatly. From the consumer's current curve, there may be neutral line current abnormity for consumer ****058239.

B. CASE 2: ABNORMITY ASSESSMENT OF POWER CONSUMPTION AND SUPPLIES FOR THREE-PHASE POWER CONSUMERS

For three-phase power consumers, abnormal feature on overvoltage S_{ov}, abnormal feature on overload S_{ol}, abnormal feature on neutral line voltage S_{nv} as well as abnormal feature on equivalent line impedance S_{li} are extracted. The weights of these abnormal features are 0.369, 0.223, 0.200 and 0.208 respectively. It can be seen from the weights that the degree of abnormal feature on overvoltage for three-phase consumers is rather higher compared with other three features. The probabilities of occurrence of the other three types of abnormities are similar.

The overall assessment of the three-phase consumer's power consumption and supplies abnormities is carried out by using the improved radar chart method. The results are shown in Table 2. Figure 8 shows the radar chart of the first-ranked

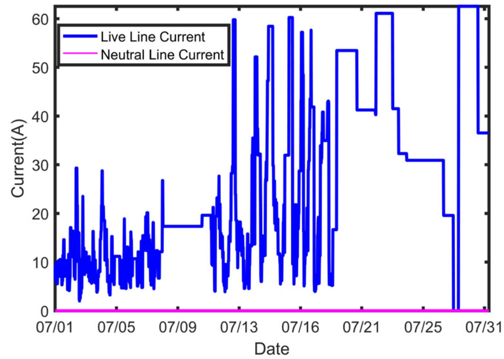

FIGURE 6. Live and neutral current curves of single-phase consumer ****058239 with the most severe power consumption and supplies abnormities.

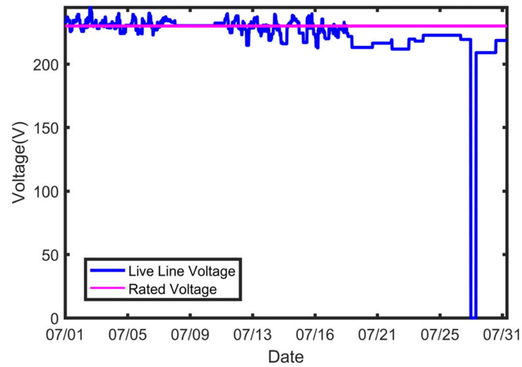

FIGURE 7. Voltage curve of single-phase consumer ****058239 with the most severe power consumption and supplies abnormities.

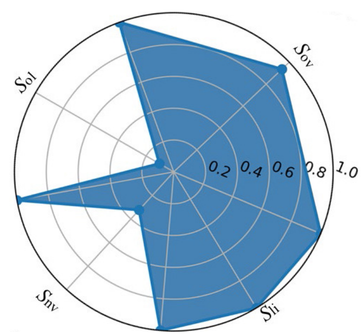

FIGURE 8. The radar chart of three-phase consumer ****039078 with the most severe power consumption and supplies abnormities.

three-phase consumers ****039078. It can be seen from the radar chart that there is high probability of some abnormities, especially for S_{ov} and S_{li}. But, there is little probability of some other abnormities (S_{ol} and S_{nv}).

It can be concluded from Figs. 9-10 that there may be overvoltage and equivalent line impedance abnormities for the consumer ****039078. The voltage data of the three-phase consumer in Case 2 is analyzed, and the result is shown in Fig. 9. The consumer's voltage of phases A, B and C exceeds the consumer's standard voltage constraints frequently. From the consumer's voltage curve, there may be an overvoltage abnormity for the consumer ****039078. In Fig. 10, the neutral line voltage curve of the power consumer shows that the consumer's neutral line voltage is high

TABLE 2. The results of the three-phase consumers.

Consumer ID	S_{ov}(p.u.)	S_{ol}(p.u.)	S_{nv}(p.u.)	S_{li}(p.u.)	S(p.u.)
****039078	93.613	10.356	32.292	100.000	100.000
****039505	81.540	77.524	48.939	17.021	95.006
****072552	24.323	54.740	73.304	98.396	91.489
****058235	71.838	59.969	40.092	17.241	75.019
…	…	…	…	…	…
****120308	9.937	38.327	47.819	45.730	36.377
****027475	2.326	59.438	67.728	7.397	33.427
****120304	3.379	30.984	46.621	7.397	9.699
****072536	15.027	30.834	24.765	7.397	7.556

TABLE 3. The screening results of the three-phase consumers.

Consumer ID	Overvoltage abnormity		Overload abnormity		Neutral line voltage abnormity		Line impedance abnormity		Correctness of algorithm
	Algorithm result	Screening result	Algorithm result	Screenin g result	Algorithm result	Screening result	Algorithm result	Screening result	
3620039078	√	unconfirmed	-	-	-	-	√	√	√
3615039505	-	-	√	√	√	√	-	-	√
3620072552	-	-	-	-	√	unconfirmed	√	√	√

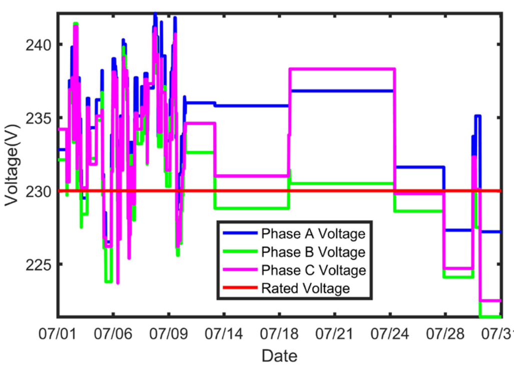

FIGURE 9. Voltage curve of three-phase consumer ****039078 with the most severe power consumption and supplies abnormities.

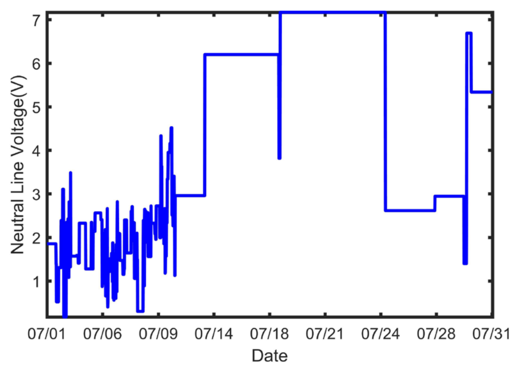

FIGURE 10. Neutral line voltage of three-phase consumer ****039078 with the most severe power consumption and supplies abnormities.

and variational. A high degree of three-phase unbalance often leads to a large loss of the power supply line, which will speed up the aging of the user line to some extent. Hence, there are equivalent line impedance abnormity for the consumer ****039078.

V. DISSCUSSION

The validity of the algorithm is proved through the screening of power consumers of Zhejiang Province in China. Table 3 shows the results of the screening. According to the result of screening, power consumption and supplies abnormities are found in almost all the consumers with high rank. According to the experience of screening results, there is a great probability of power consumption and supplies abnormities for the Top 10% consumers in the abnormity assessment algorithm and these consumers need to be examined on-site. Besides, there is little possibility of power consumption and supplies abnormity for the rest consumers. The number of consumers to be examined can be selected according to the ability of screening.

The precision ratio and recall ratio of proposed method in this paper and traditional expert system are compared. The main steps of the traditional expert system are as follows:

i) Judgement of abnormal feature on overload
Calculate the ratio of absolute active power $\prod_{d,t}^{\mathrm{P}}(i)$ to operating capacity $\prod_{N}^{\mathrm{P}}(i)$. If $\prod_{d,t}^{\mathrm{P}}(i)/\prod_{N}^{\mathrm{P}}(i)$ exceeds the overload threshold β^{P} for 20% time period in the total sampling period, the power consumer i is considered to have the abnormity on overload. In the power supply company of Zhejiang province, China, β^{P} always equals to 110%.

TABLE 4. The number of abnormal power consumers determined by two different algorithms.

Abnormal Type	The Expert System	Algorithm in This Paper
Overload abnormity	2	5
Overvoltage abnormity	3	5
Neutral Line Current abnormity	2	5
Neutral Line Voltage abnormity	0	5

ii) Judgement of abnormal feature on neutral line voltage
Compare the neutral line voltage $\prod_{d,t}^{\mathrm{V}_{\mathrm{user}}^{\mathrm{NL}}}(i)$ of power consumer i with neutral line voltage threshold β^{NLV}. If $\prod_{d,t}^{\mathrm{V}_{\mathrm{user}}^{\mathrm{NL}}}(i) > \beta^{\mathrm{NLV}}$, the power consumer i is considered to have abnormity on neutral line voltage. In the power supply company of Zhejiang province, China, β^{NLV} always equals to 40V.

iii) Judgement of abnormal feature on neutral line current
Determine the absolute difference between the value of live line current $\prod_{d,t}^{\mathrm{I}_{\mathrm{FL}}}(i)$ and neutral line current $\prod_{d,t}^{\mathrm{I}_{\mathrm{NL}}}(i)$ of power consumer i. If $\left|\prod_{d,t}^{\mathrm{I}_{\mathrm{FL}}}(i) - \prod_{d,t}^{\mathrm{I}_{\mathrm{NL}}}(i)\right| > \beta^{\mathrm{NLC}}$, the power consumer i is considered to have the abnormity of neutral line current. In the power supply company of Zhejiang province, China, β^{NLC} always equals to 20A.

iv) Judgement of abnormal feature on overvoltage
Collect the voltage $\prod_{d,t}^{\mathrm{V}_{\mathrm{user}}}(i)$ of power consumer i. If $\prod_{d,t}^{\mathrm{V}_{\mathrm{user}}}(i)$ exceeds the voltage thresholds $\beta^{\mathrm{V}_{\mathrm{user}}}$ for 3 consecutive time intervals, the power consumer i is considered to have abnormity on overvoltage. In the power supply company of Zhejiang province, China, $\beta^{\mathrm{V}_{\mathrm{user}}}$ always equals to 240V.

v) Judgement of abnormal feature on line impedance
The cross-sectional area $\prod_{d,t}^{\mathrm{CSA}}(i)$ of power supply line of power consumer i is used to determine whether the power consumer i has abnormity on line impedance. If $\prod_{d,t}^{\mathrm{CSA}}(i) < \beta^{\mathrm{CSA}}$, the power consumer i is considered to have abnormity on line impedance. β^{CSA} is the threshold of the cross-sectional area of power supply line. In the power supply company of Zhejiang province, China, β^{CSA} always equals to 6mm^2.

A. DISCUSSION ABOUT THE PRECISION RATIO OF ABNORMITY ASSESSMENT OF POWER CONSUMPTION AND SUPPLIES

According to the experience of the screening, consumers with higher ranks in the assessment show more severe power consumption and supplies abnormities in the investigation. The comprehensive identification precision ratio of abnormity assessment of power consumption and supplies for power consumers can reach 100% for the top 10% consumers. Through screening, the precision ratio of abnormity assessment of power consumption and supplies for power consumers determined by both the algorithm in this paper and the expert system can reach 100%.

B. DISCUSSION ABOUT THE RECALL RATIO OF ABNORMITY ASSESSMENT OF POWER CONSUMPTION AND SUPPLIES

Compared with the traditional expert system, the recall ratio of the data-driven abnormity assessment algorithm based on CRITIC and improved radar chart methods in this paper is higher. The algorithm in this paper can detect more potential abnormal consumers. The comparisons between the two algorithms are shown in Table 4. It can be seen from Table 4 that the number of abnormal power consumers determined by expert system is less than the number of power consumers determined by the proposed algorithm. Besides, through the validation of screening result on the spot, the abnormal consumers determined by the algorithm in this paper do really have some abnormities. Hence, in the case of 100% precision ratio for both algorithms, the recall ratio of abnormity assessment algorithm in this paper is higher.

There are two reasons why the traditional expert system cannot identify some abnormal power consumers:

i) For the traditional expert system, the indexes of abnormity assessment extracted from power consumers just consider the real-time electricity consumption data of power consumers. For the proposed method in the paper, not only the real-time electricity consumption data but also the historical electricity consumption data are taken into account, like the occurrence frequency of over-limit, ring ratio of power supplies data and so on. Thus, the proposed method in the paper can be more comprehensive compared with the traditional expert system.

ii) For the traditional expert system, the abnormities of power consumers are determined totally based on the thresholds set by the expert experience. In the other words, the traditional expert system is a very subjective algorithm. For the proposed algorithm in the paper, the CRITIC method and improved radar chart method are used to determine the weights and assessment results of power consumers. Both the CRITIC method and the improved radar chart method are data-driven methods. Thus, the proposed method in the paper is more objective compared with the traditional expert system.

Compared with the traditional expert system, the abnormity assessment algorithm proposed in the paper is more comprehensive and objective. So, the recall ratio of abnormity assessment of power supplies can be higher.

VI. CONCLUSION

In this paper, an abnormity assessment algorithm of power consumption and supplies for power consumers based on CRITIC method and improved radar chart method is proposed to achieve accurate assessment of power consumption and supplies abnormities of power consumers. Through the analysis of part of power consumers in Zhejiang Province, the accuracy of the results obtained by proposed algorithm is demonstrated. Compared with the traditional expert system, the algorithm proposed in this paper can detect more abnormal power consumers. Besides, the consumer's electrical condition and overall power condition can be displayed more intuitively by employing the improved radar chart method. With the application of proposed algorithm, abnormal power consumer groups can be determined, the early warning of electric power accidents can be realized, the occurrence of electric power accidents can be reduced, and economic and social benefits can be enhanced.

REFERENCES

[1] S. Uludag, K.-S. Lui, W. Ren, and K. Nahrstedt, "Secure and scalable data collection with time minimization in the smart grid," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 43–54, Jan. 2016.

[2] X. He, Q. Ai, R. C. Qiu, W. Huang, L. Piao, and H. Liu, "A big data architecture design for smart grids based on random matrix theory," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 674–686, Mar. 2017.

[3] H. Chen, X. Wang, Z. Li, W. Chen, and Y. Cai, "Distributed sensing and cooperative estimation/detection of ubiquitous power Internet of Things," *Protection Control Mod. Power Syst.*, vol. 4, no. 4, pp. 151–158, Dec. 2019.

[4] E. Spano, L. Niccolini, S. D. Pascoli, and G. Iannaccone, "Last-meter smart grid embedded in an Internet-of-Things platform," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 468–476, Jan. 2015.

[5] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—The new and improved power grid: A survey," *IEEE Commun. Surv. Tutr.*, vol. 14, no. 4, pp. 944–980, 4th Quart., 2012.

[6] E. Viciana, A. Alcayde, F. Montoya, R. Baños, F. Arrabal-Campos, A. Zapata-Sierra, and F. Manzano-Agugliaro, "OpenZmeter: An efficient low-cost energy smart meter and power quality analyzer," *Sustainability*, vol. 10, no. 11, p. 4038, Nov. 2018.

[7] E. Viciana, A. Alcayde, F. Montoya, R. Baños, F. Arrabal-Campos, and F. Manzano-Agugliaro, "An open hardware design for Internet of Things power quality and energy saving solutions," *Sensors*, vol. 19, no. 3, p. 627, Feb. 2019.

[8] A. Christe, S. Negrashov, and P. Johnson, "Open power quality: An open source framework for power quality collection, analysis, visualization, and privacy," in *Proc. IEEE Power Energy Soc. Innov. Smart Grid Technol. Conf. (ISGT)*, Sep. 2016, pp. 1–5.

[9] A. J. Christe, S. I. Negrashov, P. M. Johnson, D. Nakahodo, D. Badke, and D. Aghalarpour, "OPQ Version 2: An architecture for distributed, real-time, high performance power data acquisition, analysis, and visualization," in *Proc. IEEE 7th Annu. Int. Conf. CYBER Technol. Autom., Control, Intell. Syst. (CYBER)*, Jul. 2017, pp. 1415–1419.

[10] Y. Wang, Q. Chen, T. Hong, and C. Kang, "Review of smart meter data analytics: Applications, methodologies, and challenges," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3125–3148, May 2019.

[11] E. Birney, "Lessons for big-data projects," *Nature*, vol. 489, no. 7414, pp. 49–51, Sep. 2012.

[12] K. Shim, "MapReduce algorithms for big data analysis," *Proc. VLDB Endowment*, vol. 5, no. 12, pp. 2016–2017, Aug. 2012.

[13] A. Yassine, A. A. Nazari Shirehjini, and S. Shirmohammadi, "Smart meters big data: Game theoretic model for fair data sharing in deregulated smart grids," *IEEE Access*, vol. 3, pp. 2743–2754, 2015.

[14] Y. Huang and X. Zhou, "Knowledge model for electric power big data based on ontology and semantic web," *CSEE Power Energy Syst.*, vol. 1, no. 1, pp. 19–27, Mar. 2015.

[15] T. V. Garcez and A. T. De Almeida, "Multidimensional risk assessment of manhole events as a decision tool for ranking the vaults of an underground electricity distribution system," *IEEE Trans. Power Del.*, vol. 29, no. 2, pp. 624–632, Apr. 2014.

[16] Z. Lin, F. Wen, H. Wang, G. Lin, T. Mo, and X. Ye, "CRITIC-based node importance evaluation in skeleton-network reconfiguration of power grids," *IEEE Trans. Circuits Syst. II, Exp. Briefs*, vol. 65, no. 2, pp. 206–210, Feb. 2018.

[17] H. Jia, W. Qi, Z. Liu, B. Wang, Y. Zeng, and T. Xu, "Hierarchical risk assessment of transmission system considering the influence of active distribution network," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 1084–1093, Mar. 2015.

[18] K. Alvehag and L. Söder, "Risk-based method for distribution system reliability investment decisions under performance-based regulation," *IET Gener. Transm. Distrib.*, vol. 5, no. 10, p. 1062, 2011.

[19] G. Li, P. Zhang, P. B. Luh, W. Li, Z. Bie, C. Serna, and Z. Zhao, "Risk analysis for distribution systems in the Northeast U.S. under wind storms," *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 889–898, Mar. 2014.

[20] X. Li, X. Zhang, L. Wu, P. Lu, and S. Zhang, "Transmission line overload risk assessment for power systems with wind and load-power generation correlation," *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1233–1242, May 2015.

[21] T. Xiao, W. Pei, H. Ye, G. Niu, H. Xiao, and Z. Qi, "Operation risk assessment of distribution network considering time dependence correlation coefficient," *J. Eng.*, vol. 2017, no. 13, pp. 2489–2495, Jan. 2017.

[22] M. Dong, A. B. Nassif, and B. Li, "A data-driven residential transformer overloading risk assessment method," *IEEE Trans. Power Del.*, vol. 34, no. 1, pp. 387–396, Feb. 2019.

[23] Y. H. Zhao, R. F. Xing, and S. R. Zhang, "A sampling distribution with coefficient of variation," *Basic Sci. J. Textile Univ.*, vol. 23, no. 3, pp. 328–330, Sep. 2010.

[24] M. Cash, T. Habetler, and G. Kliman, "Insulation failure prediction in AC machines using line-neutral voltages," *IEEE Trans. Ind. Appl.*, vol. 34, no. 6, pp. 1234–1239, Nov. 1998.

[25] H. Turker, S. Bacha, D. Chatroux, and A. Hably, "Low-voltage transformer loss-of-life assessments for a high penetration of plug-in hybrid electric vehicles (PHEVs)," *IEEE Trans. Power Del.*, vol. 27, no. 3, pp. 1323–1331, Jul. 2012.

[26] H. Wang, C. Jiang, B. Wu, and X. Zou, "Online monitoring method for low-voltage user distribution lines," *Electr. Eng.*, vol. 2018, no. 23, pp. 23–26, Jul. 2018.

[27] Y.-J. Kim, "Development and analysis of a sensitivity matrix of a three-phase voltage unbalance factor," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 3192–3195, May 2018.

[28] D. Diakoulaki, G. Mavrotas, and L. Papayannakis, "Determining objective weights in multiple criteria problems: The critic method," *Comput. Oper. Res.*, vol. 22, no. 7, pp. 763–770, Aug. 1995.

[29] T. Tanikawa, H. Ohba, K. Ogasawara, Y. Okuda, and Y. Ando, "Geographical distribution of radiotherapy resources in Japan: Investigating the inequitable distribution of human resources by using the Gini coefficient," *J. Radiat. Res.*, vol. 53, no. 3, pp. 489–491, May 2012.

[30] F. Wenli, H. Ping, and L. Zhigang, "Multi-attribute node importance evaluation method based on Gini-coefficient in complex power grids," *IET Gener., Transmiss. Distrib.*, vol. 10, no. 9, pp. 2027–2034, Jun. 2016.

[31] R. Ma, W. Xu, S. Liu, Y. Zhang, and J. Xiong, "Asymptotic mean and variance of Gini correlation under contaminated Gaussian model," *IEEE Access*, vol. 4, pp. 8095–8104, 2016.

[32] W. Peng, Y. Li, Y. Fang, Y. Wu, and Q. Li, "Radar chart for estimation performance evaluation," *IEEE Access*, vol. 7, pp. 113880–113888, 2019.

[33] Y. L. Wang and Y. J. Li, "Comprehensive evaluation of power transmission and transformation project based on improved radar chart," *Adv. Mater. Res.*, vols. 354–355, pp. 1068–1072, Oct. 2011.

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