Intelligent Power Equipment for Autonomous Situational Awareness and Active Operation and Maintenance

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Abstract—**The rapid development of the power system requires high reliability and real-time situational awareness of power equipment. The current agent-based condition-monitoring perception mode is not suitable for widely distributed power equipment due to the potential of single-point failure and high communication and data costs. Therefore, the technical development path of the power equipment perception mode is analyzed based on the development trend of the future power system. The concept of intelligent power equipment (IPE) is introduced, which combines online sensing, data mining, remote communication, and primary and secondary fusion technologies to develop an intelligent object that can realize autonomous situational awareness. IPE can actively interact with the control center and operation and maintenance (O&M) personnel according to its situation. This gives the power company an efficient and comprehensive perception of the equipment. Then, based on the actual situation of the power grid and emerging technology research directions, the challenges faced by each key technology supporting IPE and the corresponding technology enhancement solutions are presented. In addition, the O&M method applicable to IPE is discussed, which achieves proactive maintenance and prognosis management through autonomous equipment perception. Finally, the feasibility and effectiveness of IPE are verified by the performance of current IPE applications in an actual power grid.**

Index Terms—**Intelligent power equipment, perception mode, data mining, primary and secondary fusion, situational awareness.**

I. Introduction

POWER system operators are now promoting the development of intelligent, decentralized, and self-healing technologies, including the deep integration of the industrial Internet of Things (IOT) with the power system [1], [2]. The above development trends of the power grid require high reliability of power equipment. Moreover, the implementation of the future power market and demand response concept also requires the deep involvement of power equipment. Power equipment is the infrastructure of the power grid, whose condition directly affects the operation safety and intelligent development of the power grid. Therefore, improving the perception ability of power equipment can provide an important support for realizing grid intelligence [3]. There are several stages in the development of the power equipment perception mode. In the early stages of the power system, measures were taken only when power equipment had an accident [4]. This after-the-fact maintenance is very costly for power equipment, which is a backward state that is seriously incompatible with the long-term benefits of power companies [5].

Subsequently, the periodic maintenance is used for power equipment. This mode enhances the ability to perceive the condition of power equipment. To date, this mode is still used by many power companies. However, the disadvantages of periodic maintenance are also prominent. First, it requires manual operation, testing, and recording, which lead to a large workload. Second, there are overhauls due to periodic dismantling, which add risks to the operation [6].

The agent-based perception mode is introduced for power equipment with the improvement of computer technologies [7]. Sensors monitor the condition of power equipment, and communication devices transmit the data to the remote backend server [8], [9]. The backend server performs fault diagnosis and health assessment. The advantage of this mode is that the condition of equipment can be accurately perceived in real time. However, the power equipment is widely distributed, numerous, and diverse. This mode requires remote communication and unified background computing resources to be configured for all equipment, and there are no intermediate caches and computing units in the entire system.

The number and types of power equipment are surging currently. Taking transformers as an example, the global transformer market size was expected to have a large increase compared with 2017 [10]. The power grid has increased the demand for deep involvement in the operation of power equipment, which needs precise perception of the equipment condition. This huge volume creates a great challenge for the power equipment perception mode.

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1) For the periodic maintenance mode, the future volume of ponderous equipment will create great pressure on the operation and maintenance (O&M) personnel. The economic cost for expanding human resources is more than that power companies can afford.

2) For the agent-based power perception mode, introducing such a large volume of power equipment can bring a significant security risk of single-point fault [11]. The widely distributed power equipment requires specially laid communication lines, which directly leads to a significant increase in communication costs [12]. Due to the economic and reliability limitations, the agent-based perception mode is not suitable for large-scale power distribution equipment. Neither of these modes can support the volume of power equipment in the future grid. Therefore, the power equipment perception mode requires a paradigm shift.

To this end, [13] proposes a fast anomaly detection method for the condition data of power transmission and transformation equipment based on big data analysis. Reference [14] proposes a big data model based on high-dimensional random matrix theory to achieve key performance evaluation and abnormal condition detection of the power equipment. Reference [15] develops a condition-monitoring strategy based on the IoT for the primary and secondary power equipment. Reference [16] proposes a real-time monitoring and maintenance method combining IoT and machine learning for gas-insulated switchgear. However, the above studies are all improvements based on the agent-based perception mode, which has not yet been improved as a paradigm.

To get rid of the agent-based power perception mode, the future development trend of power equipment is analyzed. Then, the concept of intelligent power equipment (IPE) is proposed and its meaning and technical content are clarified. IPE is a new power equipment management mode, which is a paradigm shift.

This paper is organized as follows. Section II analyzes the development of the power equipment perception mode. In Section III, we describe the concept of IPE includung its conceptual meaning, intelligent functions, and situational awareness system. The key technologies required for IPE and their solutions are proposed in Section IV. In Section V, we discuss the IPE O&M system. In Section VI, we introduce the field application of this concept in an actual power grid. A review of related work concludes this paper in Section VII.

II. Development of Power Equipment Perception Mode

The limiting factor in the development of the current power equipment sensing model is that it lacks intelligence. As a result, it cannot provide reference information for the O&M system in real time, and it cannot interact intelligently with other power equipment. The popularity of the IoT provides a new solution to the improvement of power equipment perception mode [17]. In this regard, the Energy Internet concept is proposed to lead the direction of grid construction [18]. This concept maps the actual grid architecture combined with advanced technologies such as sensing, artificial intelligence, and modern communication to a virtual network to build a safer, more efficient, and more interconnected power system [19]. Based on this concept, the development trend of power equipment perception mode can be summarized as autonomous computing, self-perception, and information interconnection.

Autonomous computing meets its high requirements for real-time services, intelligent perception, and security and privacy by configuring computing power for the equipment itself [20]. Autonomous computing can make full use of communication and computing resources to significantly reduce the data processing delay [21]. The risk of a single-point fault is avoided, which is in line with the concept of Energy Internet [22]. The market for this computing approach is vast, with the economy for grid-edge computing and distributed intelligence expected to reach $6.5 billion by 2027 [23].

Self-perception refers to the introduction of online monitoring technology and intelligent algorithms based on edge computing for power equipment to autonomously collect real-time information of itself and locally detect, analyze, and evaluate its condition [24]. The power equipment performs timely fault identification and alerts for its abnormalities, by enabling dynamic threshold setting, local fault diagnosis, equipment degradation modeling, and evaluation of health index (HI). It can also perform protective actions in extreme cases.

Information interconnection is based on IoT technology to manage power equipment [25] and the information interconnection between the equipment and the control center is realized. Based on the IoT system, forming an event-driven power equipment perception mode can achieve the real-time perception of its condition changes [26]. Its analysis results are directly shared with the O&M system, making the power equipment itself an independent object that can intelligently interact with other power equipment.

In summary, the power equipment perception mode in the future needs to configure autonomous computing capabilities for power equipment to realize its autonomous situational awareness. The information interconnection function is used to achieve comprehensive perception and real-time interaction of equipment information to meet the construction requirements of the Energy Internet. Based on the analysis of the future development trend, we propose the concept of IPE.

III. Concept of IPE

IPE mainly includes two parts of technical content, namely autonomous situational awareness and active O&M. Autonomous situational awareness refers to IPE using embedded sensors and artificial intelligence (AI) modules to achieve its sensing, status analysis, and health management. Active O&M refers to IPE actively interacting with the O&M system as an independent agent based on realizing autonomous situational awareness. The above two parts of technical content require IPE to have autonomous computing and information interconnection capabilities. Thus, it establishes information interoperability and early warning linkage with the logical environment of the power grid, peripheral equipment, and O&M platforms. Compared with ordinary power equipment, IPE can become an intelligent object for autonomous situational awareness in power system operation. In addition, IPE adopts primary and secondary fusion technology in hardware development, so that it also remains physically independent.

Figure 1 shows the functional flow and related support algorithm for IPE to achieve autonomous situational awareness. The AI module first pre-processes the real-time data collected from the self-sensing system of the equipment and sets dynamic thresholds based on the monitoring data. Then, anomaly detection, fault diagnosis, and fault prediction are performed. Meanwhile, the data are mined and the health degree is assessed in real time based on the degradation model. The equipment autonomously sends alarm information to the control center and associated O&M personnel based on the analysis results. It receives condition data sent by surrounding IPE and recognizes information based on its decision mechanism. It also receives and executes remote control policies and protects itself in case of crisis.

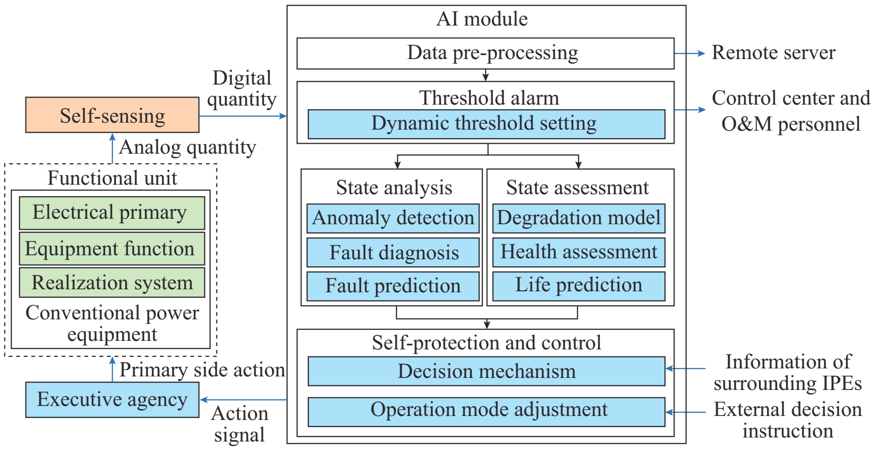

Fig. 1. Functional flow and related support algorithm for IPE to achieve autonomous situational awareness.

In the overall management, the backend server is only responsible for sending the updated parameters of the algorithm to the equipment. It reduces the amount of communication data, communication costs, and reliance on highly reliable communication while reducing the pressure on backend computing. Autonomous computing improves the timeliness of the information and avoids data congestion. IPE provides a paradigm shift for power equipment perception modes to meet the need for an efficient and comprehensive perception of power equipment in the future power grid.

To make this idea a reality, the key technologies for IPE will need to be developed and implemented with the following characteristics.

1) Self-sensing: sensors must be compact, sensitive, and cost-effective to ensure that they can be used in IPE for large-scale engineering applications.

2) Data pre-processing: the algorithm must have the ability to process multi-source heterogeneous data, including structured and unstructured data. The full exploitation of the IPE panoramic monitoring data by the algorithm realized at a later stage.

3) State analysis: the fault diagnosis and fault prediction must use lightweight algorithms and consider the correlation between multi-dimensional quantities to ensure the analysis accuracy of IPE condition.

4) State assessment: the degradation model of IPE with varying performance must be both accurate and generalizable. The health assessment system must achieve equipment health ratings while obtaining time-continuous equipment reliability.

5) Self-protection and control: self-protection and control of IPE can cause a change in the logical structure of the grid. Therefore, it must be confirmed that no chain of faults in the grid will be triggered when the IPE protects itself.

6) Remote communication: a communication method with high-security flexibility and outstanding economy must be selected to meet the communication needs of the widely distributed IPE to the remote servers and O&M personnel.

IV. Key Technologies of IPE

The implementation of IPE requires the support of several key technologies. This section examines the challenges faced by each key technology in the implementation of IPE and the corresponding improvement schemes.

A. Self-sensing

Self-sensing is the data basis for IPE to realize its autonomous situational awareness. Table I shows the types of characteristic quantities, including the operation data and condition-monitoring data of IPEs.

TABLE I
Types of Characteristic Quantities

Category	Quantity	Problem representation
Electricity	Voltage U_k Current I_k	Working condition of equipment k
	Partial discharge u_k	Minor internal defect of equipment k
Machinery	Vibration signal V_{Ik}	Physical or electrical fault of equipment k
Environment	Temperature T_{Ek}	Internal short circuit of equipment k
	Humidity H_{Uk}	Environmental humidity condition of equipment k
	Gas $G_{k,m}$	Fault of equipment k characterized by gas m
	Infrared image P_k	Localized overheating of equipment k

In order to make IPE remain independent, the condition-monitoring sensors need to be embedded in the IPE body. It faces many challenges.

1) Hardware performance: the condition-monitoring data change frequently and unstably, e.g., partial discharge (PD) and vibration data, etc. This requires the signal sampling system to have a high data acquisition rate and data volume. Various performance requirements are imposed on the hardware system, such as sampling frequency, communication bandwidth, and energy consumption.

2) Economy: the cost of IPE data collection system needs to be low enough to facilitate large-scale promotion of IPE. On the one hand, the price of an analog-to-digital converter (ADC) increases exponentially as the sampling frequency increases. On the other hand, the data communication and storage costs are also the factors that cannot be ignored.

An effective measure to address these challenges of IPE sensing units is to develop auxiliary software algorithms. Among them, the compressed sensing (CS) can reconstruct the original signal from low-rank data [27]. Therefore, we use CS theory to solve the conflict between the cost and performance. This technique can losslessly acquire one-dimensional signals such as PD and vibration with low sampling frequency. CS can also manage high-dimensional signals such as infrared images.

The measurement matrix is used to realize the mixing of time-domain information. Subsequently, the measurement vector $\boldsymbol{y}$ is obtained by sampling with a low-frequency ADC. The sampling model can be developed as:

$$\boldsymbol{y}=\boldsymbol{\Phi x}=\boldsymbol{\Phi \Psi s}=\boldsymbol{W s} \tag{1}$$

where $\boldsymbol{\Phi} \in \mathbb{R}^{m \times n}$ is the measurement matrix, m is the number of measurement channels, and n is the original signal length; $\boldsymbol{\Psi} \in \mathbb{R}^{n \times l}$ is the signal sparse basis, and l represents the sparse basis dimension; $\boldsymbol{s} \in \mathbb{R}^{n \times 1}$ is the corresponding sparse coefficient; $\boldsymbol{y} \in \mathbb{R}^{m \times 1}$ is the m-dimensional measurement vector; $\boldsymbol{x}$ is the original signal; and $\boldsymbol{W}$ is the CS operator.

$\boldsymbol{\Phi}$ needs to be set in advance. $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ need to have low relevance, so that the original information can be preserved to the greatest extent. Meanwhile, $m \ll n$ can achieve compressed collection and transmission of data.

Since the dimension of $\boldsymbol{y}$ is much smaller than that of $\boldsymbol{x}$, it is necessary to use the sparsity of $\boldsymbol{x}$ in $\boldsymbol{\Psi}$ to solve (1). As $\boldsymbol{s}$ only contains a few non-zero elements, the reconstruction algorithm can get $\boldsymbol{s}$ from $\boldsymbol{y}$, and then perform a sparse inverse transformation to obtain $\hat{\boldsymbol{x}}$. The solution model can be described as:

$$\begin{cases} \hat{\boldsymbol{s}}=\arg\min \|\boldsymbol{s}\|_0 \\ \text{s.t. } \boldsymbol{y}=\boldsymbol{W s} \end{cases} \tag{2}$$

Due to the sparsity of $\boldsymbol{x}$ and the low relevance between $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$, the l_0-norm algorithm can be used to reconstruct the original signal $\hat{\boldsymbol{x}}$ from $\boldsymbol{y}$.

We have achieved the sub-Nyquist data output rate of the PD signal, which mainly includes three technical methods. A joint sparse dictionary learning method based on multi-dimensional parameters of PD signals, a three-valued observation matrix design method based on incoherent continuation, and a sparse decomposition method of PD signals based on dual residual ratio thresholds are proposed [28], [29].

B. Multi-dimensional Soft-sensor

IPE for autonomous situational awareness requires data pre-processing to obtain panoramic monitoring data. The challenges faced by IPE data pre-processing are as follows.

1) Heterogeneous data processing: IPE data sources include structured data such as electrical quantities and mechanical characteristics and unstructured data such as infrared images and recorded text. Normalizing the heterogeneous data and forming a unified data model are difficult problems to be solved by pre-processing.

2) Error data detection: to prevent false or missing data from monitoring resulting from sensing, communication, and other reasons, it is necessary to detect error data. The equipment monitoring data exhibit the 4V characteristics, i.e., volume, variety, value, velocity, of big data and vary in magnitude and dimension. The quick detection of such a large amount of data is a problem that must be solved by pre-processing.

We built a multi-dimensional soft-sensor model in the AI module to perform data pre-processing and integration. As a data middleware, a multi-dimensional soft-sensor can provide data sources for self-perception, and output real-time cross-sectional information of equipment condition. This model is developed as:

$$\begin{cases} \boldsymbol{X}'_{\text{Str}}=\boldsymbol{X}_{\text{Str}} F_{\text{Str}} \\ \boldsymbol{X}'_{\text{Uns}}=\boldsymbol{X}_{\text{Uns}} F_{\text{Uns}} \end{cases} \tag{3}$$

where $\boldsymbol{X}$ and $\boldsymbol{X}'$ are the pre-processed monitoring data and original data, respectively; F is the processing function; and the subscripts Str and Uns denote the structured and unstructured data, respectively.

Normalization can be performed directly on the structured data. For the unstructured data, an ontology dictionary can be constructed based on a hidden Markov model, and the k-nearest neighbor algorithm is used to classify the data. The corresponding vector space model is then used to vectorize the data.

For the error data detection, we conduct multi-dimensional data comparisons to make the algorithm both accurate and fast. The monitoring data $x_{i,t}$ are compared with 2-dimensional data both horizontally and vertically to detect error data. The error data detection model is expressed as:

$$\left|x_{i,t}-x_{ref}\right|>3\sqrt{\frac{\sum_{i=1}^{M+1}(x_{i,t}-\bar{x}_i)^2}{M+1}} \;\&\; \left|x_{i,t}-\bar{x}_j\right|>3\sqrt{\frac{\sum_{j=1}^{N-1}(x_{j,t}-x_{j+1,t})^2}{N}} \tag{4}$$

where x_{ref} is the median of x_i sequence; and $\bar{x}_i$ is the average of N correlation covariates $x_{j,t}$ $(j \neq i)$ of $x_{i,t}$ at time t. That is, the data credibility is judged from the M data in the neighborhood of $x_{i,t}$ at time t and the changes of the other N correlation covariates $x_{j,t}$ $(j \neq i)$ at time t.

$x_{i,t}$ satisfying (4) is error. That is, there are abrupt changes in the time series and no corresponding changes in other relevant quantities. It requires data rejection or correction, and troubleshooting of the corresponding sensing unit.

If a sensor has long-term data anomalies due to the factors such as energy, the data will be defaulted. We use the tensor decomposition method for data filling [30]. First, the characteristics of the missing data are analyzed and a standardized missing tensor of the feature quantity is constructed. Then, the multi-dimensional intrinsic correlation of historical data characteristics and other feature quantities is considered. The low-rank property of the completion tensor is used to establish a model, and the alternating direction multiplier method is used to iteratively solve it.

C. State Analysis

State refers to the operating characteristics of power equipment, i.e., equipment fault or abnormality, health degree as characterized by data performance, and change trends. State analysis means that IPE analyzes its operating characteristics in real time based on access to monitoring data by AI modules, including anomaly detection, fault prediction, and fault diagnosis.

The framework of the state analysis is illustrated in Fig. 2. IPE first determines whether there is any abnormality. If yes, the fault diagnosis algorithm is directly called to determine the faulty component and fault type, and perceive the information about its fault behavior. Otherwise, the fault prediction algorithm is called to determine whether there is an early fault in itself.

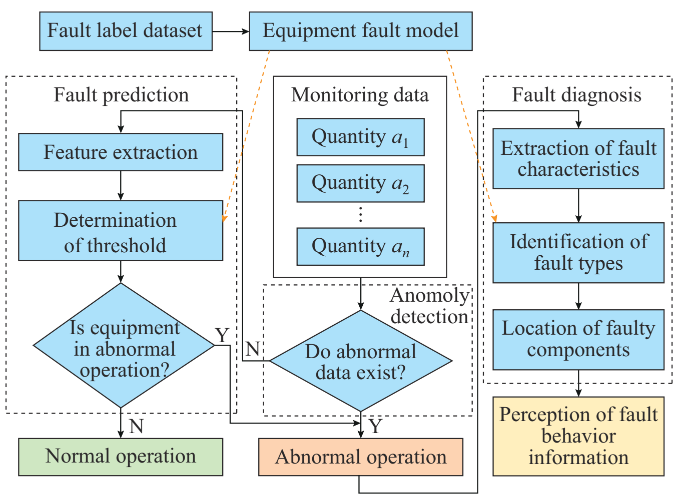

Fig. 2. Framework of state analysis.

1) Anormaly Detection

Anormaly detection is applied to sudden functional faults. That is, characteristic quantities suddenly exceed the threshold range and there is no abnormal trend in the previous period. The mathematical model is expressed as:

$$\exists\, a_{it} \in A \cap a_{it} \notin [L_{i,\min}, L_{i,\max}] \tag{5}$$

where A is the monitoring data; a_{it} is the value of quantity i at time t; and $L_{i,\min}$ and $L_{i,\max}$ are the thresholds.

This part focuses on setting threshold for each quantity. The IPE needs to set dynamic thresholds based on its monitoring data to achieve both accuracy and robustness.

For this, we embed the trend evolution algorithm with the adaptive thresholding function in the AI module of the IPE, where the threshold for the quantity i is expressed as:

$$L_i = f(a_i, \eta_i, N_i, p_i) \tag{6}$$

where a_i, η_i, N_i, and p_i are the monitoring data, data standard deviation, noise, and trend evolution of the quantity i, respectively.

When a threshold is exceeded, the IPE calls the fault diagnosis algorithm, which sends alarm information to the control center and the associated O&M personnel.

2) Fault Prediction

When each quantity is within the normal threshold range, the fault prediction should be used to determine whether there is a trend of data dispersion, i.e.,

$$\exists\, a_{it} \in A: \begin{cases} a_{it} \in [L_{i,\min}, L_{i,\max}] \\ p_{i,\Delta t} = a_{it} + a_i' \Delta t \\ p_{i,\Delta t} \notin [L_{i,\min}, L_{i,\max}] \end{cases} \quad \forall\, t \in [1, T] \tag{7}$$

where T is the length of the detection time interval; a_i' is the change rate; and $p_{i,\Delta t}$ is the predicted value.

The equipment fault prediction is divided into 2 methods: physical model based and data-driven methods [31]. Physical model based methods have strong interpretability and high accuracy. However, it is difficult to model complex systems [32]. The data-driven methods can automatically learn patterns and regularities in data to handle complex systems and nonlinear relationships [33]. Therefore, the challenge of implementing fault prediction algorithm in IPE is the prevention of misjudgment caused by uniform changes in multi-dimensional data.

The real-time cross-sectional information of IPE contains multi-dimensional quantities. The change of correlations among the quantities can better indicate the real operating condition of the equipment. Therefore, we make full use of high-order moment correlations among the quantities to design the fault prediction algorithm for the IPE.

First, the network is trained with the labeled dataset to learn the dynamic features of the equipment under each operating condition and extract the correlation relationships between the quantities. The stable correlations among the data are broken under the abnormal condition, and the abnormal dataset $\boldsymbol{E}$ deviates from $\boldsymbol{e}$ reconstructed using the normal denoising auto-encoder network.

Define the reconstruction error R_e as an evaluation index for the detection of abnormal equipment:

$$R_e = \| \boldsymbol{E} - \boldsymbol{e} \|^2 \tag{8}$$

The threshold J_{UL} is adaptively set based on the confidence interval of the parameter to monitor the trend of $\boldsymbol{R}_e$ as an alarm condition of equipment anomaly. Equipment anomalies will be reflected in the residual trends of the relevant variables. The use of changes in parameter residuals can enable a preliminary analysis of anomalies, and then isolate the relevant variables, analyze the cause of the anomaly, and proactively report the information. The residual $\boldsymbol{\zeta}_i$ of quantity i is related to its reconstructed value $\boldsymbol{e}$ and the actual value $\boldsymbol{a}_i$:

$$\boldsymbol{\zeta}_i = \boldsymbol{e} - \boldsymbol{a}_i \tag{9}$$

We have conducted research on this issue and the related characteristics of IPE. We have conducted in-depth research in this technical path and designed a fault diagnosis algorithm based on a deep autoencoding (DAE) network and XGBoost [34]. Based on the above-mentioned DAE, a multiclass early fault prediction model is established in combination with the XGBoost fault identification algorithm.

3) Fault Diagnosis

The role of fault diagnosis is to determine the fault location and type, and provide reference information for O&M personnel. The key part is given by the extraction and classification of fault features in monitoring data. The current fault diagnosis mainly has 2 kinds of algorithms: signal decomposition and deep learning.

In signal decomposition, the feature vector $\boldsymbol{V}_f$ is extracted and clustered to discern its fault type. This algorithm is simple, but it is not suitable to handle high-dimensional mixed data.

The deep learning algorithm of the convolutional neural network (CNN) has a powerful feature extraction capability, which is suitable for fault diagnosis based on complex data [35]. The feature extraction and classification model of CNN are:

$$\boldsymbol{g}_s=\sum_o\sum_p\sum_q \boldsymbol{A}(o,p,q)\boldsymbol{w}_s(o,p,q)+\boldsymbol{b}_s \tag{10}$$

$$f(\theta^{(s)}o)=\mathrm{P}(p=s|o;\theta)=\frac{\exp(\theta^{(s)}o)}{\sum\limits_{s=1}^{K}\exp(\theta^{(s)}o)} \tag{11}$$

where $\boldsymbol{g}_s$ is the feature map learned by the s^{th} convolutional kernel; $\boldsymbol{w}_s(\cdot)$ is the weight of each feature data; $\boldsymbol{b}_s$ is the bias term; $f(\cdot)$ is the output of CNN; $P(\cdot)$ is the probability of selecting the s^{th} convolution kernel after determining the input data and model parameters; o, p, and q are the input data dimensions; K is the number of convolutional kernels in the network; and $\theta^{(s)}(1\le s\le K)$ denotes the model parameters.

However, the deep learning algorithms have problems of poor generalization and long calculation cycles, which cannot meet the real-time requirements of IPE.

We propose a power equipment fault identification algorithm based on multi-deep neural networks [36]. This algorithm contains two parts. The first part builds multiple deep neural network (DNN) recognizers based on Spark, and introduces Dropout to enhance network generalization capabilities. Then, multiple DNN recognition tasks are assigned to each slave node in the Spark cluster to improve computing efficiency. The second part is the fusion of recognition results and the decision-making algorithm. The Reduce module of the Spark framework is used to aggregate the recognition results of each recognizer. Finally, a lightweight fault diagnosis algorithm with high accuracy is obtained to meet the computing power limitation.

D. State Assessment

State assessment enables IPE to perform deep data mining on its condition information. Thus, it can evaluate the health degree in real time. It supports control center queries and own information upload.

1) Degradation Model

Equipment degradation refers to the existence of failure behavior over time [37]. Simple degradation models have low accuracy, whereas complex models exhibit poor generalization [38]. The challenge of degradation modeling for IPE is to make the model both accurate and generalizable.

Given that degradation is initially stochastic, IPE first builds a degradation model based on a stochastic process. The data collection process considers the extreme behavior possibility and real average degradation behavior information. Subsequently, the degradation model of IPE is established based on the monitoring data. The nonlinear function of the degradation condition at time t $D_{\mathrm{e}}(t)$ is solved based on time variables and random variables, which is expressed as:

$$\mathrm{d}D_{\mathrm{e}}(t)=\gamma(D_{\mathrm{e}}(t),t)+\sigma(D_{\mathrm{e}}(t),t)\mathrm{d}B(t) \tag{12}$$

where $B(t)$ is the random factor; and $\gamma(\cdot)$ and $\sigma(\cdot)$ are the drift and diffusion coefficients, respectively. Decomposing the stochastic differential equation according to (11), we can obtain:

$$\begin{cases}\mathrm{d}D_{\mathrm{e}}(t)=\tau(t)\mathrm{d}t+\sigma\mathrm{d}B(t)\\ \tau(t)=h(t,B(t))\end{cases} \tag{13}$$

where $\tau(t)$ is the standard Brownian motion concerning t; and $h(\cdot)$ is the Brownian motion function. The probability of the transition of $D_{\mathrm{e}}(t)$ to $D_{\mathrm{e}}(t)=x$ at $D_{\mathrm{e}}(t_0)=y$ is counted by (13), and the degradation condition is derived as:

$$v(x,t|y,t_0)=\frac{1}{\sqrt{4\pi\sigma(t-t_0)}}\exp\left(-\frac{\left(x-\int_{t_0}^{t}\tau(u)\mathrm{d}u-y\right)^2}{4\sigma^2(t-t_0)}\right) \tag{14}$$

The initial values of the model parameters are estimated based on the expectation maximization (EM) algorithm. However, different IPEs have different degradation paths due to different operating environments and workloads.

To this end, a real-time degradation model of power equipment based on an improved Wiener stochastic process relying on a strong tracking filter (STF) is proposed [39]. First, a deterioration model based on the Wiener stochastic process needs to be established. As the monitoring data increase, the STF algorithm is used to update the model parameters to conform to its degradation path. Thus, the degradation model meets the dual requirements of accuracy and generalization.

2) Health Assessment

The equipment health assessment refers to using condition monitoring data to determine the current health condition of the equipment. The current method is to manually assign weights without considering the degradation distribution of the equipment [40]. Therefore, the challenges for IPE health assessment are as follows. Local health assessment needs to be combined with the specific degradation conditions of the equipment [41]. The assessment process also needs to be autonomous.

Thus, we propose a health assessment method for IPE. We integrate discrete and continuous model assessment methods in establishing the IPE health assessment system. Weights are determined autonomously based on contingency theory to enhance sensitivity to data changes. The reliability combined with the real-time degradation condition of the equipment is obtained based on the continuous model. A discrete model for health assessment is established, as shown in Fig. 3.

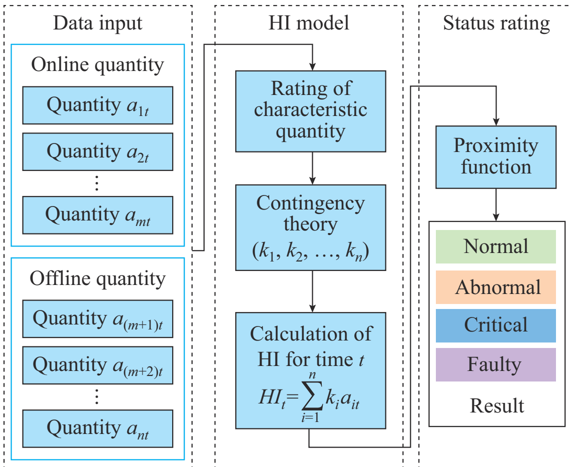

Fig. 3. Discrete model for health assessment.

The equipment quantities are first graded. The weight vector $\boldsymbol{W}$ of each quantity is determined according to the contingency theory, as shown in (15). Subsequently, the HI model is established based on the data distribution distance. Finally, based on the object topological model, the equipment condition is rated using the closeness function.

$$\boldsymbol{W}=[d(\boldsymbol{a}_1) \quad d(\boldsymbol{a}_2) \quad \ldots \quad d(\boldsymbol{a}_n)]^{\mathrm{T}} \tag{15}$$

where $d(\boldsymbol{a}_i)$ is the weight of the data vector $\boldsymbol{a}_i$.

After obtaining the health rating, a continuous model for health assessment is also studied to incorporate the real-time degradation condition of the equipment, modeled as follows.

Suppose $z(t)$ denotes the maintenance index of the equipment at time t, and $z(0)=0$. And the variables $(z(t_1)-z(0))$, $(z(t_2)-z(t_1))$, …, $(z(t_n)-z(t_{n-1}))$ are independent of each other. The distribution of the random increment $m(t_n)-m(t_{n-1})$ is denoted by F_R. Subsequently, a continuous model of reliability L_e as a function of $\boldsymbol{A}$, F_R, and t is developed as:

$$L_e=q(\boldsymbol{A},F_R,t) \tag{16}$$

where $q(\cdot)$ is the reliability function. The Weibull proportional failure model is introduced to establish the function $q(\cdot)$, which can consider both $\boldsymbol{A}$ and t and is expressed as:

$$L_e(t)=k_0 \cdot \exp\left(\sum_{i=1}^{n}\delta_i C_{oi}(t)\right) \tag{17}$$

where k_0 is the initial risk function that follows the Weibull distribution. The algorithm uses the product of the covariate of $\boldsymbol{A}$ $C_{oi}(t)$ and its parameter δ_i to represent the relationship between $\boldsymbol{A}$ and $L_e(t)$.

IPE can integrate HI and $L_e(t)$ to characterize its health degree and the ability to maintain health using our method. Meanwhile, IPE supports independent reporting of health information and real-time queries from the control center.

E. Communication Method and Transmission Protocol

In IPE, there is an electric connection between the AI module and sensors. The communication method becomes very important when IPE sends information to remote servers and O&M personnel. Table II compares the characteristics of communication methods.

TABLE II
COMPARISON OF COMMUNICATION METHODS

Method	Economy	Security	Reliability	Anti-interference	Anti-eavesdropping
Wireless	M	M	G	M	L
Optical fiber	P	G	M	G	E
Carrier	G	P	P	P	G

Note: E means excellent, G means good, M means medium, and P means poor.

The communication method of the IPE must satisfy the following characteristics.

1) Economy: the communication cost is one of the limiting factors for IPE rollout. Therefore, the cost should be controlled to meet the engineering application requirements of IPE.

2) Security: the power system has the highest requirement for stability [42]. Information theft and tampering in remote communication can cause instability in the grid operation.

3) Flexibility: IPE, as an independent body, needs to realize the self-organizing characteristics in its communication method.

Therefore, it is necessary to combine local conditions when configuring communication methods for IPE. For switchgear stations or substations with centralized equipment and fiber-optic access, IPE in the station can access fiber optics for high communication security. Carrier communication can be used for IPE that is close to the backend, but the encoding and decoding need to use special keys to prevent information theft.

For the rest of the scattered IPE, it is not economical to build communication lines. The virtual private network can be established based on a cellular network to achieve secure wireless remote communication. When establishing VPN lines, a key management system should be established to ensure key security. Meanwhile, the identity authentication encryption algorithm is introduced in the network to identify the device ID and realize two-way authentication of the device and network. Cellular wireless networking enables the automatic access and exit of authorized devices by establishing wireless channels at the network layer. The resulting scalability of the network is outstanding.

In addition, the communication protocols are selected to interconnect equipment with different communication message formats. The commonly-used protocols include TCP/IP, NetBEUI, and IPX/SPX. Among them, the connection-oriented TCP/IP protocol is implemented with high reliability and profitability, which is suitable for IPE.

F. Self-protection and Execution of Control Commands

Based on the hardware principle of primary and secondary convergences, IPE protects itself and can autonomously execute external decision commands. The self-protection of IPE is achieved by breaking itself actively before it is damaged by an accident.

Owing to the limitation of edge-side computing capability, IPE cannot consider the global operation conditions of the power grid. The technical difficulty of self-protection lies in how to avoid chain faults caused by the self-protection of a single IPE.

To this end, IPE prevents chain faults by interfacing with the coordination system of the control center. IPE presets the alarm time delay before self-protection, sends the corresponding priority alarm message to the control center according to its importance, and sends a breaking warning to its neighboring IPEs. The neighboring IPEs need to be manually set according to the topological relationship of the power grid and equipment functions at the beginning of IPE operation. The control center adopts the appropriate coordination scheme. External decision commands refer to the instructions sent by the control center for switching or changing the operation mode, and the IPE executes the above decisions independently.

V. IPE O&M System

Given that IPE has the ability of autonomous situational awareness, the active maintenance based on process supervision can meet the O&M requirements of IPE. It transforms the maintenance from fault repair to equipment prognosis management.

Active maintenance requires interfacing the computerized maintenance management system (CMMS) processes of work order management, planning and scheduling, and maintenance metrics with an expert system based on web services. Experts operate remotely or develop maintenance strategies online based on the relationship of each piece of equipment. A schematic diagram of the IPE O&M system is shown in Fig. 4, where D_k is the key pre-processed data of IPE; A_r is the analysis result processed by the backend server; S_a is the alarm signal; O_c is the control command; and I_c is the command and feedback message.

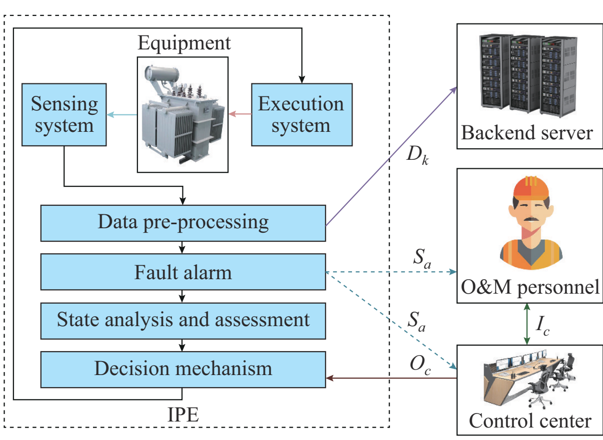

Fig. 4. Schematic diagram of IPE O&M system.

In this O&M system, IPE obtains the equipment conditions in real time based on local data flow, and the internal algorithms improve the accuracy and robustness by synchronizing their information. There is a two-way connection between the control center and O&M personnel for assigning work orders and feedback. The control center can also send control commands to the equipment. The backend server can call the pre-processed data for a model update when the channel is free to make full use of its abundant computing resources.

VI. Field Applications

We move out of the laboratory and deployed IPE in a real grid. A regional distribution system owned by the State Grid Corporation of China is selected for a pilot application to verify the effectiveness of IPE. The pilot region is located in a remote area with a harsh operating environment for power equipment.

The ideal IPE is to configure software and hardware during the manufacturing process. IPE can be directly connected to the network. However, it is unrealistic to replace the current power equipment operating in the grid at a large scale. The current application method is to utilize the physical assets of existing power equipment and upgrade them into IPEs by adding non-intrusive sensors, AI modules with corresponding algorithms, intelligent terminals, and communication capabilities, without affecting the security of the equipment. It can interact with other IPEs, control centers, and O&M personnel, as shown in Supplementary Material A Fig. S1.

In addition to the development of IPE-related technical content, we have developed a supporting mobile terminal application for O&M personnel, as shown in Supplementary Material A Fig. S2. We have also developed a real-time monitoring and display interface based on the Web, as shown in Supplementary Material A Fig. S3, for the control center. The complete IPE object and O&M prototype are established.

During the operation, the IPE triggers an abnormal PD alarm, as shown in Fig. 5(a). This helps the control center and O&M personnel complete preventive maintenance and release alarms after troubleshooting. In case of local overheating of the transformer, the abnormality is recognized in time, as shown in Fig. 5(b). State analysis locates the faulty component and determines that the fault is a local defect. It substantially reduces the work pressure of O&M personnel and avoids downtime faults. The field application of IPE has been well received by O&M personnel and control centers.

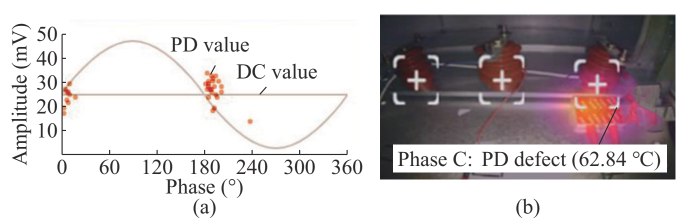

Fig. 5. IPE PD monitoring case. (a) Ultrasonic PD mapping of switchgear. (b) Abnormal temperature of transformer components.

The above results demonstrate that IPE actively participates in O&M management as an intelligent object. While significantly improving the reliability of the power grid, it makes the power equipment become an intelligent object that can perceive itself and interact with the O&M system.

VII. Conclusion

In this paper, the concept of IPE and its intelligent functions are systematically described. Through the configuration of embedded sensors and AI modules to make power equipment with autonomous thinking, it can carry out its real-time detection and alarm, state analysis, and state assessment. IPE becomes an intelligent object that can realize autonomous situational awareness. In the O&M system, IPE serves as an independent intelligent entity that can analyze its condition in real time, enabling the power company to have an efficient and comprehensive awareness of equipment. Then, the corresponding technology enhancement solutions are given for the challenges faced by each key technology applied in IPE. This lays the theoretical foundation for IPE and shows that IPE can be applied in engineering at a large scale. The process of interaction between IPE and other entities or platforms in the O&M system is illustrated based on its perception mode. IPE meets the needs of managing the proliferation and variety of equipment in the complex power grid and is in line with the development trend of the Energy Internet.

We are now in close contact with equipment manufacturers to develop an IPE-independent object. We aim to achieve a paradigm shift in the perception mode of equipment in the future power grid.

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