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Review on Evolution of Intelligent Algorithms for Transformer Condition Assessment

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Transformers are playing an increasingly significant part in energy conversion, transmission, and distribution, which link various resources, including conventional, renewable, and sustainable energy, from generation to consumption. Power transformers and their components are vulnerable to various operational factors during their entire life cycle, which may lead to catastrophic failures, irreversible revenue losses, and power outages. Hence, it is crucial to investigate transformer condition assessment to grasp the operating state accurately to reduce the failures and operating costs and enhance the reliability performance. In this context, comprehensive data mining and analysis based on intelligent algorithms are of great significance for promoting the comprehensiveness, efficiency, and accuracy of condition assessment. In this article, in an attempt to provide and reveal the current status and evolution of intelligent algorithms for transformer condition assessment and provide a better understanding of research perspectives, a unified framework of intelligent algorithms for transformer condition assessment and a survey of new findings in this rapidly-advancing field are presented. First, the failure statistics analysis is outlined, and the developing mechanism of the transformer internal latent fault is investigated. Then, in combination with intelligent demands of the tasks in each stage of transformer condition assessment under big data, we analyze the data source in-depth and redefine the concept and architecture of transformer condition assessment. Furthermore, the typical methods widely used in transformer condition assessment are mainly divided into rule, information fusion, and artificial intelligence. The new findings for intelligent algorithms are also elaborated, including differentiated evaluation, uncertainty methods, and big data analysis. Finally, future research directions are discussed.

Keywords: transformer condition assessment, information fusion, artificial intelligence, big data analysis, uncertainty method, condition-based maintenance

1 INTRODUCTION

Energy, underpinning human activities, is crucial for the development of modern economies (Borunda et al., 2016; Azmi et al., 2017). The contradiction has become quite intense between traditional energy supply and the increasing demand for energy in the development of the global economy (Lu et al., 2022). To alleviate the dependence on traditional energy sources, bridge the gap between electricity supply and demand, and reduce environmental pollution, more and more renewable and sustainable energy sources are being used to generate electricity (Chen and Chang, 2015; Fu et al., 2015; Rauf et al., 2015; Rahbar et al., 2018; Fu et al., 2020). In addition, the third industrial revolution represented by new energy technology (IEEE-SA Standards Board IEEE Std C57104-2019, 2019) and energy internet technology is on the rise, and the power network has evolved from local small-scale networks to cross-regional interconnected power grids (Li et al., 2022a). Hence, it is imperative to ensure the safety, reliability, and high efficiency of power grids (Li et al., 2022b).

As smart grid technology thrives rapidly, power transformers are playing an increasingly significant role in power systems. However, transformer defects and failures may be caused by overload, overvoltage, internal insulation aging, and the natural environment, which will not only lead to huge economic losses and affect the daily lives of power consumers but also influence public safety and cause serious social losses (Malhara and Vittal, 2010; Miranda et al., 2012; Gang et al., 2014; Li et al., 2016a). Conventional periodic maintenance (e.g., preventive maintenance) has been over-estimated because the time-based strategy may fail when faults cannot be detected during the time intervals between planned maintenance periods (Trappey et al., 2015). In such cases, condition-based maintenance (CBM) is necessary, which can support proactive maintenance, alter scheduled maintenance, prolong the service life, and reduce maintenance costs, thus making maintenance work more scientific (Wang et al., 2015). CBM strategies are jointly determined by condition monitoring (Kou et al., 2022) and assessment. Therefore, in order to prevent undesirable failures and defects, it is important to keep monitoring and evaluating the operating condition of power transformers, grasp the rules of their operation state, and provide suggestions for transformer condition maintenance and asset management (Saha et al., 2015). To this end, there is an increasing need for better non-intrusive diagnostic and monitoring techniques to evaluate the overall operating condition of the transformers (Wang et al., 2002).

At present, condition assessment for power transformers mainly analyzes and judges the health condition mainly through one or a few state parameters and unified diagnostic criteria (Sheng et al., 2018; Wu et al., 2020), which fails to comprehensively take advantage of defects, maintenance history, family quality history, etc. The thresholds are determined by statistical analysis of a great deal of experimental data and subjective experience. Moreover, transformer state information is scattered in various business application systems and is characterized by a complex and diverse structure as well as uneven quality. As a result, it is difficult to obtain transformer data integration, an accurate description of the fault or defect evolution, as well as associated rules between the transformer state parameters. The accuracy, pertinence, and timeliness of the diagnosis and evaluation results may differ from the actual operation and maintenance of power transformers (Wu et al., 2021). Hence, it is significantly necessary to exploit new techniques to optimize and improve the existing research structure for transformer condition assessment and further benefit attempts for CBM and asset management.

In the last decade, various power utilities, research institutions, equipment-operating units, and manufacturers have striven to develop emerging technologies, such as big data, cloud computing, Internet of Things, mobile Internet, and artificial intelligence, which are widely applied to power grids. These new technologies can promote rule mining among transformer-operating information, environmental data, and power grid operation data. As for operation and maintenance of power transformers, advanced measurement infrastructures have been deployed in smart grids, and transformer state data has gradually emerged as large-volume, multi-type, and fast-growing, thus paving the way for the application and development of big data, artificial intelligence, and other technologies in transformer condition assessment. Hence, integrating intelligent algorithms into big data and knowledge analysis is valuable for transformation condition assessment.

Until now, several methods for transformer condition assessment have been applied to the theoretical investigation and various research (Flores et al., 2011; Liao et al., 2011; Arias Velasquez and Mejia Lara, 2018; Zhou and Hu, 2020). At the same time, several surveys on transformer condition assessment have been carried out from different perspectives (Wang et al., 2020a). A variety of condition monitoring methods and diagnostic tests were investigated in (Wang et al., 2002), (Islam et al., 2018a) and (Xie et al., 2020), including dissolved gas analysis (DGA), tap changer condition, frequency response analysis, insulation resistance measurements, partial discharge, turns ratio, oil testing, and power factor. De Faria et al. (2015) reviewed operational lifetime degradation factors and the major techniques employed for predictive maintenance based on DGA. In addition, the Doernenburg, Rogers, IEC ratio, Duval triangle, and key gas methods were introduced in detail (Faiz and Soleimani, 2017). Bakar et al. (2014) presented several methods for measuring the concentrations of dissolved gases in transformer oil and provided several interpretations of DGA. Singh and Verma (2008) presented an overview of transformer fault diagnosis (Shi et al., 2009) based on AI techniques, including fuzzy logic, neural networks, and neuro-fuzzy-based expert systems. Time-domain polarization measurements and physicochemical-based diagnostic techniques were investigated respectively in (Saha, 2003) and (Sylvestre N'cho et al., 2016) to assess the insulation condition in aged transformers. Since the health index well reflected the health and operating condition of transformers, Azmi et al. (2017) examined the previous mathematical equation/algorithm of the health index in terms of combination of scoring, scoring, and ranking method, ranking and tier method, multi-featured factor assessment model, and matrices. Wang et al. (2020b) provided a comprehensive review of the existing work for transformers from two perspectives, including fault diagnosis and operating condition prediction.

However, none of the previous work has been dedicated to a comprehensive survey of intelligent algorithms applied in transformer condition assessment, considering the intelligent demands of the tasks in each stage of condition assessment under big data. To this end, this article aims to provide a uniformed framework for transformer condition assessment, from data acquisition, data processing, and data analysis to visual application, to cope with various patterns of transformer failures and tackle the intelligent demands of big data analysis. Moreover, various data acquisition modules, data system, and the relevant data types with respect to transformer condition

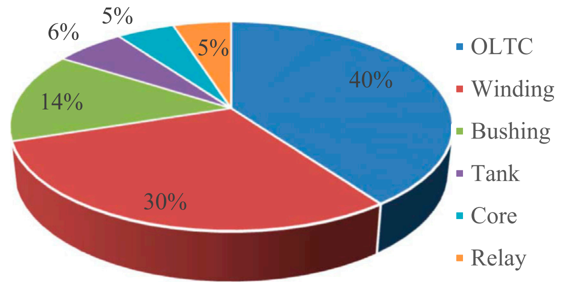

FIGURE 1 | Defective components of a transformer (OLTC: on-load tap changer).

assessment are explored in detail. Furthermore, the intelligent algorithms applied in data analysis for transformer condition assessment are exhaustively reviewed in this article. The main contributions can be summarized as follows:

- The statistical analysis of transformer failure locations and types is investigated. Moreover, the main factors related to the operational condition of a power transformer and operating mechanism in the developing process of an internal latent fault are comprehensively analyzed.
- To cope with various patterns of transformer failures and comprehensively investigate large amount of transformer stat data, a uniformed framework for transformer condition assessment, from data acquisition, data processing, and data analysis, to visual application, is proposed.
- The data acquisition and data types related to transformer state are exhaustively investigated, and the basic concept related to transformer condition assessment is discussed.
- A holistic study of traditional condition assessment methods is presented, including rule-based method, information fusion method, and artificial intelligence method.
- In addition, the state-of-the-art efforts made in three established topics about transformer condition assessment are surveyed under big data, including differentiated evaluation, uncertainty evaluation, and big data analysis.

In the following, the statistical analysis of transformer failures is presented in **Section 2**, including transformer failure locations, failure types, and operating mechanism of latent fault. **Section 3** discusses the data source, concept, and architecture of transformer condition assessment. Several traditional methods for transformer condition assessment are investigated in **Section 4**. **Section 5** explores the new findings related to transformer condition assessment. Finally, some possible further advancement is discussed.

2 TRANSFORMER FAILURE STATISTICS AND ANALYSIS

Large power transformers are generally working under high voltage, high current, suffering from wind, frost, rain, and snow, etc. frequently, and the operating environment is harsh. Moreover, as operating time increases, the dielectric strength and mechanical strength of transformer insulation materials decrease, which may increase failure probability and reduce residual life (Su et al., 2022). According to the 1983 CIGRE working group's statistics of large-scale transformer failure records with a service life of less than 20 years from 1968 to 1978, the order of transformer failure locations is generally on-load tap-changer, winding, bushing, tank, core, and relay, as shown in **Figure 1** (Bossi et al., 1983).

As shown in **Figure 2**, power transformers are extremely complex systems, involving circuits, magnetic circuits, insulation, and mechanical mechanisms (Xiao et al., 2022). They are subject to a variety of internal and external stresses (electrical, magnetic, mechanical, and thermal) and influence factors. The inner insulation condition is affected by the multi-field coupled working environment, such as electric field, magnetic field, and temperature field. The water content, impurities, defects, and other factors will also affect inner insulation and safe operation of transformers. At the same time, external factors (e.g., strong lightning strikes (Chen et al., 2021a), corrosive gases, current and load impact generated by power grid operation, monitoring information transmission safety) could cause a major uncertainty in the safe and reliable operation of transformers. The statistics of common transformer fault causes are shown in **Figure 3** (Xiang Zhang and Gockenbach, 2008).

Since transformers have complicated structures and many factors, the correlation of failure causes and components is not always obvious, and some faults have characteristics of inductivity and compliance. That is, a fault may be caused by another fault, and it may induce the other faults. Even sometimes, a variety of failures happen together; that is, faults have the characteristic of concurrency. For example, when a short circuit accident occurs in the power system, two or more faults such as deformation, solder joint breakage, or insulation damage occur simultaneously. The fundamental reason for transformer faults is that the internal insulation (including solid insulating materials and insulating oil) of the transformer has gradually decreased, which results in transformer outages. At the same time, the harmonic in the power system network could increase transformer losses and cause an abnormal rise in temperature, which will decrease efficiency, insulation aging, and the expected lifetime (Henderson and Rose, 1994; Elmoudi et al., 2005; Elmoudi et al., 2006). Transformer overload operation will lead to decomposition of solid insulation materials and a large amount of gas is generated, which affects its mechanical properties, electrical properties, and insulation properties. The development mechanism is shown in **Figure 4**. Moreover, there exist complex relationships between transformers and other power equipment in electrical and informational aspects. It is often the case that clearly good assets and clearly bad assets are given appropriate scores, but it is the journey and rete of travel between two states that is of interest. Therefore, it is vitally important to accurately judge the operating condition and detect the potential faults through modern electrical science, information science, data science, and mature system science methods, which are also the key points of this article.

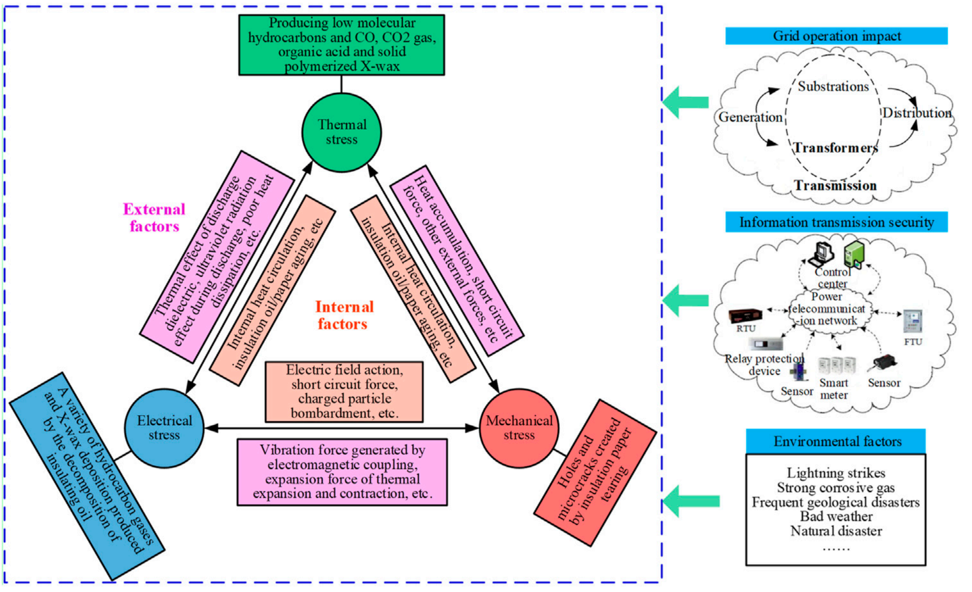

FIGURE 2 | Main factors related to transformer operation.

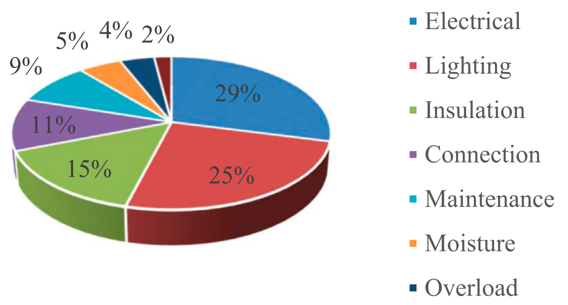

FIGURE 3 | Transformer failure causes.

3 OVERVIEW OF TRANSFORMER CONDITION ASSESSMENT

The degradation of most transformers, a changing, dynamic, and non-linear process, begins from early defect, latent fault, or deterioration to failure because of long-term bombinated stresses of "electric–magnetism–force–heat" and external environments. In an attempt to counterattack these undesirable situations, it is imperative to assess the performance of transformers according to the results of condition monitoring (Velasquez-Contreras et al., 2011). Considering that transformers have an inherent complex structure, intricate degradation mechanism, and variable operational conditions, transformer condition assessment should not only integrate state parameters and properties related to themselves and their components, but also take into account environmental information, power grid operation, and so on. Only in this way can the operational state of transformers be reflected and judged from different perspectives.

The goal of transformer condition assessment is to combine the DGA, oil quality, furan content, and oil insulation as well as inspection observations in different subsystems, analyze the correlation of these state parameters, and obtain the health and operating condition of the power transformers based on standards, algorithms, and expert knowledge (Rudin et al., 2012; Chen et al., 2016; Zhang et al., 2017). The assessment results can be used to support condition monitoring decisions, maintenance planning, and asset management.

3.1 Flowchart of Transformer Condition Assessment

The overall structure of transformer condition assessment, "data acquisition—data processing and mining—comprehensive data analysis—visual presentation of user demand," is illustrated in **Figure 5**. Transformer condition assessment requires various state parameters that can reflect the operating condition of a power transformer, such as DGA data, electrical testing data, oil testing data, historical data, family defects, load, economic dispatch, and operating environment.

As depicted in **Figure 5**, multi-modal data processing involves text mining, image recognition, and waveform analysis. After data cleaning, feature extraction, and data fusion, the assessment of the actual transformer operating condition is carried out from different perspectives, such as feature recognition, anomaly detection, fault diagnosis, and prediction (Kou et al., 2021), which can provide powerful economic and technical justifications for planned asset replacement, maintenance costs, and statistical analysis of family defects. In addition, as determined by the optimal balance among capital investment, operating maintenance, and asset maintenance cost, the maintenance strategy includes monitoring, repair, maintaining,

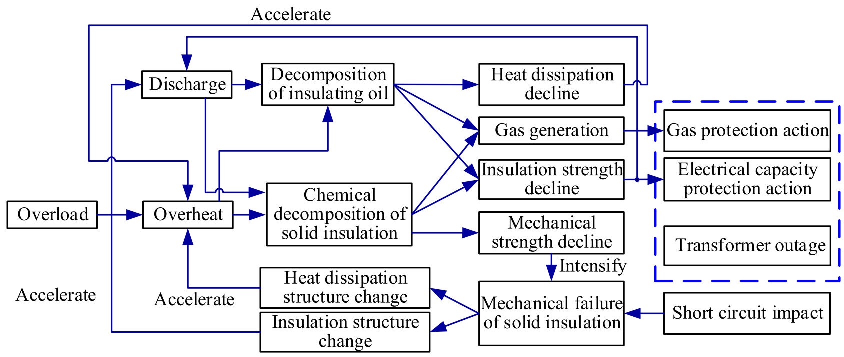

FIGURE 4 | Developing mechanism of a transformer's internal latent fault.

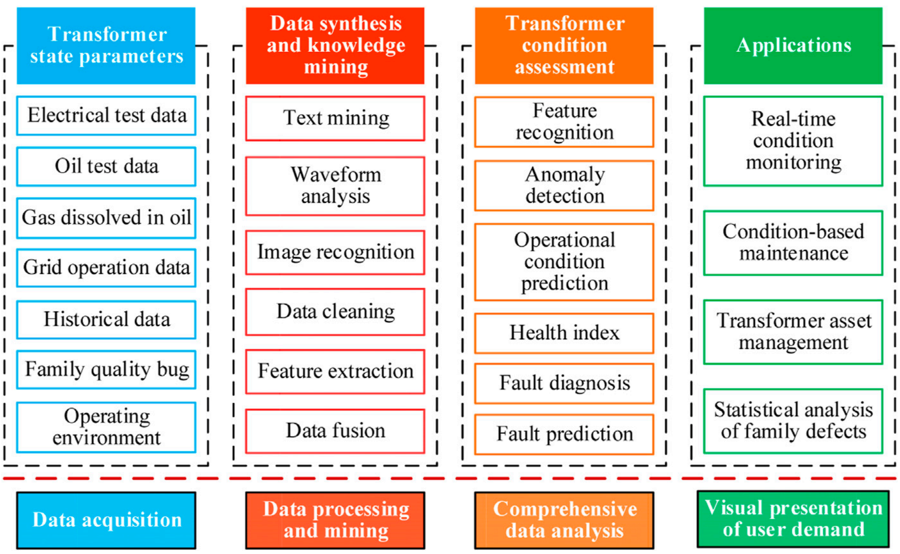

FIGURE 5 | Flowchart of transformer condition assessment.

replacing, or contingency control (Azmi et al., 2017). Thus, transformer condition assessment is expected to bridge the contradictions between the benefits of electricity power production and asset maintenance budgets.

3.2 Data Source

Data is the basis for the transformer condition assessment. The data required for the analysis of the transformer operating state (**Figure 6**) mainly comprise transformer operation attributes, inspection records, inspection, live detection, online monitoring, system operation data, fault and defect records, maintenance records, weather information, and so on. The data are scattered in each sub-business systems, including production management system (PMS), equipment condition monitoring system, geographic information system (GIS), energy management system (EMS), weather forecasting system, lightning location system, and mountain fire/ice warning system. According to different sources of transformer state data, transformer condition information can be divided into internal data (e.g., transformer operating and maintenance records, transformer online monitoring, and live detection data, etc.) and external data (e.g., power grid operation data, and environmental meteorology information, etc.).

4 TRADITIONAL METHODS FOR TRANSFORMER CONDITION ASSESSMENT

The traditional methods for transformer condition assessment represent that these methods are widely used in assessing the operating condition of power transformers. Several common transformer condition assessment methods can be classified into rule-based, information fusion-based, and artificial intelligence-based methods.

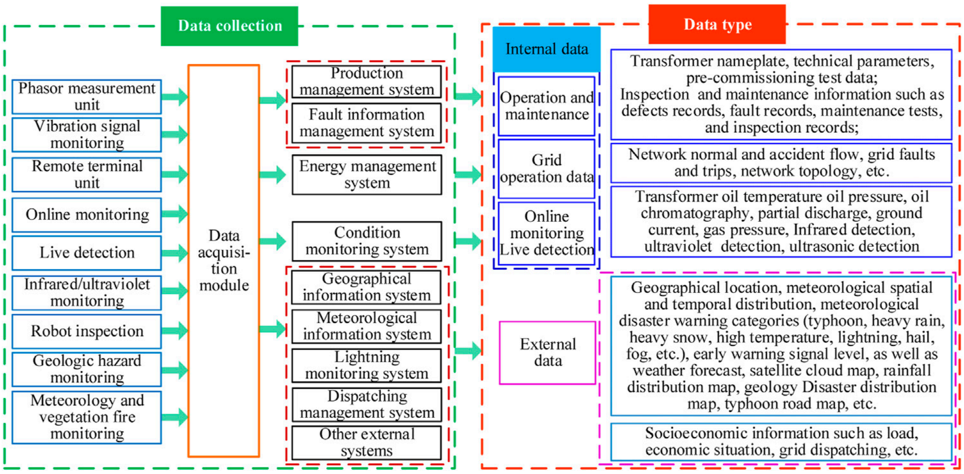

FIGURE 6 | Transformer data collection and classification.

4.1 Rule-Based Method

Doernerburg, Rogers, modified Rogers, Duval Triangle, IEC 60599, and other DGA criteria interpretations (Trappey et al., 2015) were developed to evaluate the condition of oil and paper insulation and detect faults indirectly from the gases. The IEEE (IEEE-SA Standards Board IEEE Std C57104-2019, 2019; IEEE-SA Standards Board IEEE Std C57106-2015, 2016) guides classify DGA results into three types, including "DGA Status 1" (low gas levels and no indication of gassing), "DGA Status 2" (intermediate gas levels and/or possible gassing), and "DGA Status 3" (high gas levels and/or probable active gassing). In addition, since IEEE and IEC (International Electrotechnical Commission IEC 60422-2013, 2013; International Electrotechnical Commission IEC 60567-2011, 2011) standards classify the evaluation grade into "normal," "attention," "abnormal," and "serious," the obtained results of transformer state assessment are usually presented in the form of a state grade or health index (Naderian et al., 2008; Jahromi et al., 2009). Some other state parameters, such as interfacial tension, water content, and dielectric breakdown voltage, are judged by limited values for different voltage classes.

Although rule-based condition assessment is relatively simple, easy, and widely used, there are three problems facing existing standards: 1) it is difficult to apply the unified calculation model parameters, weightings and thresholds of the standards to diversified transformers for different types, regions and manufacturers; 2) the uncertain impacts of multiple data sources, degradation mechanisms, etc. are neglected; and 3) the transformer evaluation process mainly relies on DGA data, oil test and electrical test data.

4.2 Information Fusion Method

Given that there are many state parameters related to power transformers and the information obtained from a single sensor is incomplete, it is essential to combine different information from multiple data sources to acquire an accurate description of the health and operating condition of power transformers. Moreover, multi-source information fusion can enhance the viability of transformer condition assessment and fault diagnosis (Li et al., 2009).

The existing research mainly concentrates on feature level fusion and decision level fusion. Li et al. represent different aspects of the power transformer with an index based on DGA ($HI_{C\bullet H}$), insulating paper health index (HIiso), main health index (HIm), and an index based on oil quality factor (HIoil). The weight of each index parameter was calculated through an analytic hierarchy process, and the final HI was obtained by summing the weights of the four indexes (En-Wen and Bin, 2014). Cui et al. (2016) proposed using a Bayesian Network (BN) based multisource data and information fusion method to assess the overall health condition of a transformer. Li et al. (2018) established a hierarchical Bayesian belief network to calculate a probabilistic health index and then assessed the operational state of power transformers. The method comprises four layers, which are index layer, component layer, factor layer, and data layer. Islam et al. (2018b) studied the long-term degradation of different subsystems, such as tap changer condition operations, impurity analysis, insulation condition, bushing condition, internal components, and other parameters, and then combined them into a condition-based HI score. Moreover, the maintenance history and loading information were considered. In terms of policy-making level fusion, Ma et al. (2011) adopted Bayesian fusion and Dempster–Shafer fusion to integrate the diagnosis results obtained from the conventional diagnosis algorithm, utility practices, predictive learning algorithm, and expert judgments. The detailed investigation of advantages and limitations is illustrated in **Table 1**.

To sum up, these methods only consider part of the state parameters. If there exists a big difference in different assessment layers, it is liable to lead to misleading assessment results. Meanwhile, there is little research on data-level fusion from the perspective of data science for transformer condition assessment.

TABLE 1 | Investigations of the information fusion method.

Author	Year	Method	Used state parameter	Advantage	Limitation
Li et al. (En-Wen and Bin (2014)	2014	Analytical method	Including 13 state parameters, such as CO, CO2, H2, CH4, micro-water, and acid value	Simple and convenient	Heavy workload; neglecting the differences of transformers; only considering part of state parameters
Cui et al. (2016)	2016	Bayesian network	Including 12 stat parameters, such as core earthing current, moisture, unbalanced DC resistance of winding, and partial discharge	Visual presentation Inferring using conditional probability	Only considering part of state parameters; cannot adapt to all transformers with different voltages
Li et al. (2018)	2017	Bayesian belief network	Including 14 state parameters, such as lightning capacity, overvoltage times, and short circuit capacity	Convenient; visual presentation; inferring using conditional probability	Weighting calculation is subjective and complex
Islam et al. (2018b)	2018	General regression neural network approach	A dataset of 345 power transformer including insulation condition, impurity analysis, and bushing condition	Improving the accuracy	Network structure and parameters are difficult to determine

TABLE 2 | Investigations of artificial intelligence method.

Year	Method	Method introduction and advantage	Limitation
2016	ANN (Illias et al., 2016)	ANN is characterized by strong data processing and learning ability, which is widely used in classification and prediction problems	Depending on data samples; easy to fall into local optimum
2011	Fuzzy logic (Flores et al., 2011)	Fuzzy logic method uses the fuzzy set methods to enable fuzzy comprehensive judgment	Several human factors involved
2016	SVM (Li et al., 2016b)	SVM is a widely used binary classification algorithm, which can use the kernel method to done non-linear classification	It may lead to overlapping or indivisible classification for multiple classification problems
2017	DBN (Dai et al., 2017)	DBN is a deep neural network composed of restricted Boltzmann machines, with strong feature extraction and fault tolerance	Depending on data samples

4.3 Artificial Intelligence Method

Owning to the artificial intelligence (AI) technologies with robust capacity in feature extraction and classification, several AI methods such as, artificial neural network (ANN) (Illias et al., 2016), fuzzy logic (Flores et al., 2011) support vector machine (SVM) (Li et al., 2016b), and deep belief network (DBN) (Dai et al., 2017) were introduced into transformer condition assessment and fault diagnosis. The detailed investigations of artificial intelligence methods are shown in **Table 2**. The pre-determined DGA gas content and existing DGA ratios (Roger ratios, IEC ratios, etc.) are used as input parameters of AI models (Zhang et al., 2021). Li et al. proposed classifying different fault types of power transformers by the use of a genetic algorithm (GA) and SVM (Li et al., 2016b). Dai et al. adopted the DBN to reflect the mathematical correlation between dissolved gas ratios and transformer faults (Dai et al., 2017). Flores et al. put forward the type-2 fuzzy logic system for assessing the condition of the paper-oil insulation (Flores et al., 2011).

Given that some gas ratios are not capable of transformer fault diagnosis, some researchers adopt GA (Jahromi et al., 2009; Sahri and Yusof, 2015), particle swarm optimization (PSO) (Lee et al., 2007), rough set (RS) (Zang and Yu, 2009; Zhi-bin, 2012), and principal component analysis (PCA) (Trappey et al., 2015; Kari and Gao, 2017) to select optimal DGA ratios and eliminate redundant DGA ratios that affect the correct rate of fault diagnosis, thereby enhancing the accuracy and reliability of transformer fault diagnosis results. Although these artificial intelligence methods have achieved better accuracy, they require large amounts of sample data and expert experience and a great deal of time for computation, which is not practical in the actual electrical equipment evaluation. The following are the specific drawbacks for these methods: 1) overlooking the differences of the transformer under different operating environments; 2) neglecting the uncertainty of the complex nature of the transformer, data sources, uncertain variables in the health condition assessment models; 3) facing great difficulties in heterogeneous data fusion and correlation analysis because power transformer data has typical big data characteristics.

5 EVALUATION OF INTELLIGENT ALGORITHMS FOR TRANSFORMER CONDITION ASSESSMENT

With the development of online monitoring techniques, cyber-physical systems, and the Internet of Things, the obtained transformer data also has characteristics of big data. Therefore, it is indispensable to explore new findings that can facilitate the operating condition analysis of transformers and tackle the challenges of big data analysis for transformer condition assessment. Therefore, this section summarizes the more recent literature on intelligent algorithms for transformer condition assessment.

In particular, a brief elaboration of the differences between traditional methods and the evolution of intelligent algorithms is presented. The traditional methods depend on the IEC and IEEE standards, which classify the state grade into "normal," "attention," "abnormal," and "serious." Furthermore, the obtained results of transformer condition assessment usually appear in the form of a state grade or health index (Naderian et al., 2008; Jahromi et al., 2009). Although traditional methods are relatively simple, easy, and widely used, there are three problems with existing standards, including: 1) it is difficult to apply the unified calculation model parameters, weightings, and thresholds of the standards to diversified transformers for different types, regions, and manufacturers; 2) the uncertain impacts of different data sources, degradation mechanisms, etc., are not considered; and 3) these methods cannot comprehensively explore and make the best of large amounts of state data with respect to the operating condition of transformers.

To sum up, compared with the traditional condition assessment methods based on guides, information fusion, and artificial intelligence, the evolution of intelligent algorithms has the following four characteristics:

- quickly extracting key state parameters;
- effectively mining the universality and individuality of the transformer to achieve differentiated assessment of the transformer state;
- deeply excavating the association relation and evolution rule between the transformer fault and state parameter;
- involving a data-driven evaluation process, which not only effectively avoids the interference of human factors but enhances the objectivity of the evaluation results.

5.1 Differentiated Evaluation

In general, the threshold comparison method is usually used to compare the monitored value of the state quantity with the preset threshold in condition assessment, and the operating state of the transformer is merely classified into healthy and non-healthy depending on whether the thresholds are deviated from the preset values. This method is so ambiguous that it is not conducive to maintenance decisions. In addition, the preset threshold in the above method is usually based on other countries' threshold corrections. However, transformers in different countries have great differences in voltage level, processing technology, and operating environment (Qi et al., 2020). Moreover, thresholds are divided for different types of devices, and the threshold partitioning method is rough, which leads to the evaluation results being too rough and the accuracy not being high. It is difficult to achieve a differentiated and refined evaluation of transformers of different types and regions. Therefore, this part will attempt to give an overview of existing research results with respect to differentiated evaluation.

The DGA diagnostic standard of the State Grid Corporation of China is "DL/T 722 Guide to the Analysis and Diagnosis of Gas Dissolve in Transformer Oil" (STATE GRID Corporation of China DL/T722-2014, 2014), which is established based on the recommended values in IEEE standards and IEC 60599. IEC 60599 (International Electrotechnical Commission IEC 60599-2015, 2015) collected a large amount of the global gas concentration data, which covered the different individual valves observed worldwide and surveyed by IEC and CIGRE. There were great differences between foreign transformers, such as voltage level, manufacturer, operating and loading practices, and climate. The attention values and absolute gas production rates of the volume fraction of H_2 (hydrogen), C_2H_2 (acetylene), total hydrocarbons, CO, and CO_2 were provided in the DL/T 722 Guide. However, the voltage level was merely classified into "above 330 kV" and "below 220 kV," which failed to provide warning thresholds for all dissolved gases of the power transformer under different voltages.

These issues also exist in the condition assessment of the power transformer. Therefore, several countries adopt different methods for parameter threshold determination. The United States and the United Kingdom calculate the threshold values depending on voltage level classification. Germany takes the influence of operating years and voltages into consideration. Japan presents the threshold values according to the equipment rated capacity and voltage level (DUVAL M., 2004). The statistics on fault rate and defects of transformers from three different voltage grades of 110 kV, 220 kV, and 500 kV (Zhang et al., 2015) showed that the distribution model of dissolved gas composition and gas production rate accorded with the Weibull distribution, and the attention values and alarm values of each gas were obtained by the inverse cumulative distribution function. The field experience data demonstrated that the calculated attention values and alarm values were more suitable for the actual operation and maintenance. Qi et al. (Qi et al., 2020) obtained meticulous and personalized warning results for power transformers with different properties and operating conditions by investigating the differentiated warning rules. Attentional and alarming values under different operating ages, voltage levels, and oil types were calculated and verified by the actual data. The extensive verification showed that both the gas concentration and gas increase rate conformed to the Weibull distribution with an accuracy rate of 98.21%.

In this context, it is urgent to achieve the differentiated warning values of dissolved gases and other state parameters of diversified transformers with different properties and operating environments, and classify more detailed transformer state information for elaborated and personalized condition monitoring and health condition assessment.

5.2 Uncertainty Evaluation

Power transformers are complex systems that contain many components with different state parameters related to the transformers. The relationships between state parameters and operational state are complicated and invisible. For example, the amount of any gas generated in a transformer is expected to be affected by the duration of use, loading, thermal history, the duration of any faults, the presence of one or more faults, and external factors such as voltage surges (Mirowski and LeCun, 2012). Transformer condition assessment is a process of combining multiple data sources and obtaining a specific health grade for operation and maintenance planning. There is inherent ambiguous and uncertain information in transformer condition assessment. Therefore, this part aims to provide a literature review for previous works with respect to uncertainty evaluation.

The uncertainty during transformer condition assessment is derived from four aspects: 1) the complex nature of the transformer, including its structure, degradation mechanism, and defect development law (Aizpurua et al., 2019a); 2) data sources and expert knowledge such as error-prone measurements; 3) uncertain variables in condition assessment models such as the selection and weight of health index, and the ambiguous reflection between the health grade and transformer conditions (Liao et al., 2011; Aizpurua et al., 2021); and 4) external factors such as the operating environment, the operation of power grids, and the incorporation of intermittent renewable energy and applications (e.g., photovoltaic solar power generation, electric vehicles, wind energy) (Mirowski and LeCun, 2012).

The data sources and expert knowledge of uncertainty directly influence the final transformer health state evaluation. Aizpurua et al. (2019a) combined the different sources of expert knowledge to infer the confidence intervals of transformer health condition for decision-making under uncertainty. Given that the winding hotspot temperature (HST) was inferred from indirect measurements, a Bayesian inference framework was proposed in Aizpurua et al. (2019b), quantifying the uncertainty-informed remaining useful life (RUL) and analyzing the impacts of temperature and load measurement errors on RUL prediction. Dey et al. (2010) utilized the uncertainty envelope to eliminate noise in dielectric response measurements for transformer condition monitoring. Ma et al. (2010) took DGA and depolarization current as examples to demonstrate the difficulties in obtaining diagnosis conclusions under measurement-originating uncertainty and developed a SVM algorithm to deal with any measurement-originating uncertainties.

Other research mainly concentrates on uncertainty-based methods, such as Dempster–Shafer evidence theory (Akbari et al., 2010), Bayesian network (Li et al., 2018), matter element theory (Liang et al., 2013), and rough set (Tang et al., 2004; Chen and Yang, 2014), which can effectively combine key state parameter sets and provide a soft decision for transformer condition assessment. On the other hand, some scholars adopt the fuzzy theory (Sun et al., 2016), cloud theory (Liao et al., 2014), set pair theory (Li et al., 2015; Liu et al., 2018) and other uncertain reasoning methods to deal with uncertainty conversion between qualitative concepts and quantitative representations, which avoid absolute boundaries of evaluation criteria to a certain extent.

Future research should focus on combining multiple data sources and expert knowledge, exploring the intricate relationships between health grades and indices, and comprehensively assessing the health state of transformers to obtain more accurate decision-making concerning operation and maintenance.

5.3 Big Data Analysis

Since big data has been involved in power transformer data, conventional data processing and analysis can no longer meet the analysis of the health and operating condition. As depicted in **Figure 4**, big data in transformer condition assessment is characterized by various sources (e.g., PMS, EMS, and GIS), high volume (several TBs), wide variety (e.g., DGA data, textual defect records, infrared images, videos, and partial discharge patterns), varying velocity (e.g., online monitoring, daily inspections, and quarterly/yearly maintenance), veracity (e.g., missing data, redundancies, and malicious information), and values (e.g., operational, technical, and economic) (Dijcks, 2012; Zinaman et al., 2015). In such cases, it is indispensable for power utilities to extract valuable information from large volumes and varieties of both real-time and historical data to make data-driven decisions. In particular, big data analysis contributes to better monitoring, operation, and maintenance of power transformers (Bhattarai et al., 2019).

At present, big data analysis technology has been preliminarily applied to the condition assessment of power transmission and transformation equipment, and certain research results have been obtained, mainly including abnormal state identification (Catterson et al., 2010; Liang et al., 2018; Lin et al., 2018; Zhang et al., 2018; Liu et al., 2020), association rule mining (Sheng et al., 2018), differentiated warning value calculation (Qi et al., 2020), transformer condition assessment (Yan et al., 2018), and fault diagnosis and prediction (Sheng et al., 2018; Zhou et al., 2019). Given that data loss and abnormalities result from environmental interference, internal fault, and sensors' failures (Catterson et al., 2010), Lin et al. used association rules and wavelet neural networks to identify the abnormal sensor data and the abnormal state of the transformers (Lin et al., 2018). Several anomalous state detection methods were also applied to distinguish the normal and abnormal behavior, including auxiliary feature vector and density-based spatial clustering of applications with noise (Liu et al., 2020), improved K-means clustering (Liang et al., 2018), improved Canopy model (Zhang et al., 2018). Research by (Sheng et al., 2018) utilized the probabilistic graphic model to reflect the association rules among various state parameters of the transformer. The mined association rules contributed to improve the prediction accuracy. Qi et al. (2020) used fuzzy c-means (FCM) and Euclidean distance to identify the optimal transformer properties. In these studies, they identified operation age, voltage grade, and oil type to better characterize the differences between transformers based on dissolved gas data analysis. A differentiated warning rule could be obtained by the calculation of three selected optimal classification properties through the association analysis between distribution characteristics and defect/fault rate, which effectively reduced the rate of false positives and false negatives. Zhou et al. (2019) transferred the waveform processing to the distribution characteristic analysis of partial discharge signals *via* maximum likelihood estimation, which improved the accuracy of partial discharge estimation, particularly in low signal noise ratio conditions. Dai et al. (2017) adopted multi-layer and multi-dimension mapping to extract more detailed differences between fault types based on DBN, exploring different training datasets, different characterization parameters, and sample datasets. Moreover, the effect of discharge and overheating multiple faults on the diagnosis model was studied.

6 CONCLUSION AND FUTURE TRENDS

CBM is to obtain the transformer maintenance decisions according to its conditions, and transformer condition assessment is a prerequisite and basic work for CBM in transformer asset management. In other words, transformer condition assessment can provide powerful economic and technical support and decision-making strategies for transformer CBM and asset management. Therefore, we summarized the statistical analysis for components and types of transformer failures that are prone to occur and found that on-load tap-changer, winding, bushing, tank, and core are more likely to fail, and electrical factors, lightning, and insulation are the most important causes of transformer failures. To cope with various patterns of transformer failures and comprehensively investigate large amount of transformer stat data, this article provides a uniformed framework for transformer condition assessment, from data acquisition, data processing, and data analysis, to visual application. With regard to data acquisition, the data required for transformer operating condition comes from different subsystems with different condition monitoring techniques (e.g., inspections, frequency response analysis, and infrared thermography), which can be classified into internal data (e.g., transformer operating and maintenance records, DGA, furan, and insulation resistance) and external data (e.g., load, system faults, economic factors, and power grid dispatching). Furthermore, aiming at data analysis for transformer condition assessment, a comprehensive overview of the traditional condition assessment method is presented by surveying the previous studies, including advantages and limitations. With the advancement of smart grids, data acquisition, artificial intelligence, and renewable energy technology, several state-of-the-art research studies on transformer health state evaluation have been conducted. The new findings for intelligent algorisms are comprehensively surveyed from three new perspectives, including differentiated evaluation, uncertainty evaluation, and big data analysis. Compared with traditional assessment methods, the evolution of intelligent algorisms can quickly extract key state parameters, effectively mine the universality and individuality of transformers, deeply excavate the association relations, and implement data-driven evaluation.

Transformer condition assessment is an indispensable tool for the safe and reliable transmission of electricity energy, which deserves and needs constant attention. With the development of green and clean power, there has emerged an inexorable trend that energy consumption relies more on green and clean electricity. Ultrahigh high-voltage (UHV) technology of long-distance power transmission provides an excellent chance for concentrated development of green energy. At the same time, power equipment faces new requirements. Power transformers tend to be larger and more complicated. Large-size transformers possess CPS characteristics and their components are close coupled, which pose great challenges to condition assessment and fault diagnosis (Li et al., 2016a). Owning to the increasing research interest in transformer condition assessment, the following trends and tendencies for transformer condition assessment are recommended to be further investigated.

6.1 Enhancing New Manufacturing Technology

Novel smart sensors have the potential to enhance the advancement of power systems and power equipment. With the advancement of Internet of Things and mobile Internet technologies, reliable and low-cost distributed intelligent sensor networks will be widely deployed in smart grids. Moreover, a large number of smart sensors with high precision (Chatterjee et al., 2013), such as gas sensor arrays (Uddin et al., 2016; Jang et al., 2018), infrared spectroscopy (Zhao et al., 2014), photoacoustic spectroscopy (Mao and Wen, 2015), gas chromatograph techniques (Fan et al., 2017), solid oxide fuel cell chromatographic detector (Fan et al., 2020) have been studied, manufactured and applied, providing a more comprehensive data basis for big data analysis. Another trend is the novel smart transformer (Saha et al., 2015). The development of power transformers is following the direction of large capacity, high voltage, reliability, intelligence, energy efficiency, and environmental protection. Smart transformers with self-diagnosis functions are an important issue in the current transformer industry. Compared with existing transformers, smart transformers are equipped with more electronic devices, smart sensors and actuators, a good communication interface, operating information management, condition diagnosis and evaluation, operation data monitoring, and fault alarm function. In particular, smart transformers (hybrid transformers) that can resist the large-scale penetration of intermittent new energy sources and applications (e.g., photovoltaic power generation, electric vehicles) should be further implemented and investigated (Hunziker et al., 2020).

6.2 Improving Data Quality

At present, research institutions, power utilities, and manufacturers have collected a large amount of power transformer data, including operating conditions, oil tests, live-line detection, online monitoring, maintenance records, and fault defects. However, the transformer state data is characterized by heterogeneity, uneven data quality, and asynchrony, which is stored in different formats in scattered, disparate sub-systems. Due to error-prone measurements, data duplication, and data missing, the accuracy of transformer condition assessment is poor. In the case of low data quality, the results of transformer fault diagnosis and predictive analysis will deviate from the actual results (Li et al., 2016a). Therefore, it is extremely significant to improve the quality of transformer data. In the future, data quality evaluation and data governance should be carried out further to ensure smooth research on the evaluation work from the source.

6.3 Making the Best of Unstructured Data

A large amount of unstructured data (e.g., infrared thermal images, videos, ultraviolet images, partial discharge pattern, frequency response, and waveform curves) are collected by manual inspection, online monitoring techniques and smart measurements, which can help effectively diagnose the transformer defects and failures such as oil leakage, cooling system malfunction, winding distortion or displacement, and partial discharge, and provide an important decision-making for transformer condition assessment and fault diagnosis. For instance, enormous textual documents such as trouble and defect records, operating tickets, and logs of operation and maintenance are valuable for transformer condition assessment. Therefore, it is indispensable to carry out unstructured data mining, feature extraction and structural conversion of acoustic signals, images and text related to transformer state, improve the statistical analysis and knowledge mining of transformer data, and support multi-dimensional and comprehensive evaluation of transformer operating conditions *via* text mining technology, pattern recognition technology, image processing technology, machine learning and deep learning technology. In terms of text mining, Xie et al. (2016) used hidden Markov model-based text reprocessing to extract the key information from fault and defect elimination record texts to assess the operating condition of distribution transformers and combined them with typical power-off tests and live line detecting results. To identify the causes of transformer failures, Ravi et al. (2019) studied 393 terms and 103 documents and found that "lightning," "leak," "cable," "animal," and "temperature" were the major causes. Wangfang and Liuquan (2019) utilized knowledge graph technology to construct an error recognition model of power equipment defect records.

6.4 Conducting Small Sample Data Learning

A typical characteristic of transformer state parameters is that there is massive normal operating data and small sample fault data. In essence, state data concerning the health and operating condition of power transformers have increased dramatically, and big data technology has already become a powerful data-driven tool in equipment condition assessment. It should be noted that there are still several limitations: 1) due to some factors (e.g., transformer sensor types, operation and maintenance mode, state information acquisition), state parameters of the transformer exhibit "pseudo big data" and only several types of state parameters are obtained; 2) public transformer data are not available because of national security, enterprise privacy, and trade secrets; and 3) most power transformers are under good operation and maintenance management, which makes train/test data for intelligent algorisms insufficient.

In addition, power transformer faults are small-probability events and the fault case records are not comprehensive, which leads to the lack of abnormal transformer samples. As a result, unbalanced transformer datasets cause great difficulty in the applications of machine learning and big data methods and poor results in transformer condition assessment (Cheng et al., 2019). Machine learning generally has quantitative requirements for training samples. However, transformer anomalies and fault samples are relatively small, which limits the effectiveness of machine learning. Hence, it is essential to construct a unified fault sample information management system in which fault records are collected and supplemented. On the other hand, it is critical to further study the machine learning method that can be applied to small sample datasets.

6.5 Applying Expert Knowledge to Data Mining

From the cybernetic point of view, transformers are typically complex "grey box" systems. It is necessary to focus on a scientific research paradigm that combines mechanism analysis and data-driven methods for transformer condition assessment. On the one hand, knowledge and experience related to the transformer state are accumulated in the long-term electricity production, which are valuable for actual guidance. On the other hand, machine learning technology demonstrates its great advantages in intelligently analyzing the data, discovering potential problems, and excavating hidden laws. Therefore, how to integrate the expert experience of equipment state assessment into machine learning, combine knowledge analysis with data mining, and establish a mechanized expression model of expert experience and a knowledge-driven learning model are important challenges that need to be overcome for expert knowledge sharing and inheritance (Liu et al., 2019; Kou et al., 2020). Knowledge graph technology is becoming a key enabler for large-scale processing of massive collections of semantic knowledge from structured web data, text, and images (Fensel, 2019), which has been widely applied in various modern domains (Wang et al., 2021; Wang et al., 2022). It is believed that knowledge graphs offer an effective solution that merges large-scale data processing and expert knowledge with robust semantic technologies (Galkin et al., 2017).

6.6 Analyzing Failure Mechanism

The failure mechanism refers to the correlation rules between fault features and transformer state parameters through theoretical or experimental analysis. How to combine machine learning with the existing under-fault mechanism to perceive the "correlation" of complex transformer faults and effectively extract key features of transformer operating condition are challenging issues for transformer condition assessment. Moreover, the transformers display the characteristics of CPS, with the information network and physical world being closely coupled. The power system CPS theory may be used to study the strong coupled relationships between the transformer and different states of information, which helps establish an effective and accurate mapping between the data space and the physical entity and supports operating condition assessment and CBM.

6.7 Integrating Multiple Methods

Existing condition assessment models are still far from "compatibility". Due to the fact that various methods have their own superiorities, it is difficult to generalize them. Therefore, it is urgently critical to integrate multiple methods for transformer condition assessment to complement each other and obtain the mutual coordination of different models. However, employing hybrid models on small training sets may increase the risk of overfitting the training data, thereby resulting in worse "generalization" performance on the out-of-sample test set (Mirowski and LeCun, 2012).

6.8 Incorporating External Factors

The external factors of the transformer mainly include environmental meteorology data, grid operation data, and malicious data attacks. In recent years, the worldwide harsh and extreme weather has frequently occurred, contributing to an increase in domestic and international power grid accidents. External extreme environmental factors (e.g., lightning, heavy rain, strong winds, dense fog, high temperatures, low temperatures, freezing rain) may cause catastrophic damage to t power transformers and other electrical equipment (Chen et al., 2009; Schexnayder, 2009; Chen et al., 2021b). Meanwhile, loads and harmonics of the power grids also present several challenges to the transformer, and false data injection attacks (Wang et al., 2018) and other transformer-substation communication network attacks threaten the safety and reliability of power substations and power networks (Kerr et al., 2010).

AUTHOR CONTRIBUTIONS

JIW: designed and wrote this manuscript. XZ, FZ, JUW, LK, and W-DK: investigated and revised this manuscript. All authors contributed to the writing of the manuscript and all agreed to the submitted version of the manuscript.

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