In-Service Power Transformer Life Time Prospects: Review and Prospects

Edwell. T. Mharakurwa
Department of Electrical & Electronic Engineering, Dedan Kimathi University of Technology (DeKUT), Private Bag 10 143, Nyeri, Kenya
Correspondence should be addressed to Edwell. T. Mharakurwa; edwell.tafara@dkut.ac.ke
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Power transformers are essential assets in power system networks that must be meticulously monitored throughout their operational life cycle. Given that a substantial percentage of in-service power transformers around the world have reached the end of their projected technical lifespan, utilities are adopting various transformer condition-based maintenance strategies to minimize potentially devastating equipment failure. Thus, further usage of aging fleet of power system assets can be improved by gaining a better understanding of life threatening factors. In-service power transformers and their auxiliary components are susceptible to a variety of operational risks, which can compromise their performance and efficiency, thus resulting in devastating failures, financial losses, and power outages. Hence, it is necessary to investigate transformer life time issues so as to fully grasp the operational and performance status in order to reduce failures and operating costs. This paper presents a unified framework of attributes pertaining to life time issues for transformer operation evaluation together with a summary of recent findings in order to explore the current status and progress of this rapidly progressing field. The failure statistics analysis is presented first, followed by an examination of the transformer’s insulation degradation and aging mechanism. Furthermore, emphasis was on detailing the commonly adopted models and strategies in transformer condition evaluation, fault diagnostics, and remnant life estimation. Despite significant advancements in ascertaining transformer health diagnosis and prognosis technologies, including test accuracy, quick, precise fault localization, and fault type classification, there are still several shortcomings that require additional research, and thus future research perspectives are also discussed.

1. Introduction

Technology advancement has paved the way for new innovations and creativity in the provision of continuous and sustainable power through implementation of power systems grids, whose features in form of greater capacity, high to ultra-voltage, smart, minimal power losses, reliable monitoring and communication capabilities, etc. have cemented greater reliability to the end user [1–4]. Power utilities are facing substantial pressure to minimize operating costs and enhance power system asset availability and thereby mandated to continuously deliver quality power and services to the consumers. One way power utilities can reduce operational costs is to extend the lifespan of aged in-service grid equipment especially power transformers. However, the increasing demand of electrical power particularly in industrious developing countries has led to critical loading of power transformers. Subsequently, the possibility of equipment failure rises as they are subjected to operate in more strenuous conditions.

An in-service transformer typically ages over time as it is subjected to various dynamic loads and environmental factors, and as a result, it loses its ability to withstand extraneous operational stresses and system abnormalities [5–9]. Among other ancillary equipment, power transformers’ core, bushings, tap changers, and windings apparently have longer life as their aging is extremely slow. Therefore, the performance and life issues of an oil-imregnated power transformer depend on the status of paper insulation system that has a limited life cycle [5–11]. In
addition, paper is the most critical element of the transformer insulation system since its dielectric and mechanical properties cannot be recovered once compromised [11]. The inevitable irreversible chemical degradation of paper can be further escalated in the presence of accelerating agents such as excessive temperatures, moisture, and oxygen (that influence the rate of reaction), which are detrimental in life expectancy of the transformer [12–15]. Generally, transformers are designed to be online in the grid for more than 40 years [6]. With a good fleet of transformers around the globe already exceeding their design life, there is need to monitor operational stresses to determine when circumstances are such that an unexpected failure can occur. If an emerging fault of a transformer is discovered before it leads to a total failure, the asset can be maintained in accordance with the asset management strategies.

The approximate stress levels of the transformer insulation can be determined by a variety of tests. Researchers divided transformer stresses sources into two categories: faults and aging [8, 9, 12]. They further articulated that if electrical and thermal insulation withstanding thresholds are exceeded, fault stresses occur which are noticeable through partial discharge, arcing, and localized overheating. Currently, in many utility organizations, transformer incipient faults are routinely diagnosed by dissolved gas analysis (DGA) approaches [5–10, 16–22]. On the other hand, insulation degradation leads to aging stresses that also reduce transformer lifespan. Aging can be accelerated than normal under the influence of numerous weakening agents. This degradation is evidenced through oxidative, hydrolytic, and pyrolytic byproducts of oil-paper insulation system. These stresses are assessed by measuring insulation variables such as moisture content, interfacial tension, dielectric strength, acidity, furanics, degree of polymerization (DP), dielectric dissipation factor (DDF), aldehydes, alcohols, and ketones [12, 16–22].

Researchers have confirmed that the transformer insulation system is the crucial source to distinguish emerging faults and degradation trending, and it mostly mirrors the health status of the transformer. Electrical and thermal stresses can lead to transformer incipient faults whereby oil and paper decomposition occurs evolving some principal gases that decrease the heat dissipation ability and the dielectric strength of the insulation oil [6]. Several diagnostic techniques have been established for transformer state valuation as highlighted in Figure 1. Nevertheless, the analysis of measurement results attained from these technical assessments is ordinarily centered on the pragmatic models, which are sometimes erroneous and incomplete, particularly when the transformer is subjected to strenuous operation setups. Hence, accurate and explicit interpretation of the measurement data attained by these approaches is still a challenging task in valuation of transformers state.

Among the existing methodologies for detecting the incipient faults, transformer oil dissolved gas analysis (DGA) is a widely used and accepted method. The applications of soft computing techniques in the clarification of DGA results are mainly to overcome the shortcomings that arise from the use of conventional DGA techniques that include failure to ascertain fault classification in case of multiple fault conditions. Many AI techniques have been used for transformer condition assessment and fault diagnostics. These include but not limited to artificial neural network, fuzzy logic and expert systems, neural-fuzzy, genetic algorithms, Bayesian network, self-organizing map, and discrete wavelet network [23, 24]. Due to the increased need for reliable power supply, reducing maintenance budgets, and stringent minimum downtime, accurate transformer stress evaluation models are required. These models must incorporate as much data regarding the condition and remaining useful life of the transformer as practically possible.

The need for innovative ideas of the remaining lifespan of the transformer is increasing because this knowledge can avert expensive and unpredicted outages of power transformers, which are sometimes disastrous. Satisfactory new procedures, technologies, systems, and test equipment which consists of smart sensors, actuators, signal condition and processing system, and diagnosis and prognosis system were established for asset (power transformer) useful life expectancy estimation.

This paper presents the essential theories and critical assessment of the recent progress made in literature in formulation and development of practically accepted power transformer related models. It presents the main arguments by different experts in the subject of conventional and intelligent systems on how its merits can be harnessed in diagnosis of transformer incipient faults, transformer insulation aging and degradation mechanism, condition assessment strategies, and transformer remnant life estimation. Additionally, the deficiencies existing in the reviewed studies are discussed and finally prospects for improvement in developing transformer life prospect models are proposed.

2. Transformer Failure Statistics and Analysis

Grid connected power transformers are frequently subjected to strenuous electrical, chemical, and mechanical abnormalities, and sometimes operating weather conditions are harsh. Furthermore, as operating time progresses, the dielectric strength and mechanical strength of transformer insulation materials reduce, potentially increasing the likelihood of failure and decreasing residual life [25]. As per the statistics of the 1983 CIGRE on grid connected transformer failure records with an operational lifetime of at most two decades, the sequence of transformer failure and origin is mostly on components, as depicted in Figure 2 [26].

As illustrated in Figure 3, power transformers are complex equipment that includes integration of circuits, insulation, and mechanical mechanisms [27]. These mechanisms are susceptible to diverse interior and exterior stresses and other influencing factors. The multi-field unified operating environment, such as the electromagnetic fields and temperature profile, has an effect on the inner insulation condition. Water content, impurities, defects, winding thermal transients, and other attributes will all have an impact on the interior insulation and safe operation of transformers. Concurrently, external factors (e. g., extreme
lightning strikes [28], noxious gases, current, and load implications created by power grid operation) could result in significant uncertainties in the secure and continuous operation of transformers. In Figure 2, data for the most common causes of transformer faults are also highlighted [29]. Because transformers have complex architectures and many components, the relationship between failure causes and components is not always plainly evident, and certain faults have inductivity and compliance characteristics. That is, one fault could be triggered by another, and the other faults may be induced by it [27].

Occasionally, a number of different failures occur simultaneously. For instance, when a power system short circuit develops, more than one problem occurs at the same time, for example, winding deformation, arcing, solder joint fracture, insulation damage, etc. occur at the same time. The primary cause of transformer problems is that the transformer’s internal insulation has gradually deteriorated, resulting in transformer outages. Overloading a transformer causes solid insulation materials to deteriorate, releasing huge volumes of gases, which has an impact on the transformer’s mechanical, electrical, and insulation qualities. Figure 4 exemplifies the development mechanism of a transformer’s internal faults as suggested in [27]. In addition, there are complicated electrical and informational interactions between transformers and other power
equipment. Thus, it is critical to correctly estimate the operational condition and detect probable faults using contemporary electrical science, data science, and scientific methodologies, all of which are key points in this paper.

3. Transformer Insulation Degradation and Aging Mechanism

Transformer condition determination and aging process is usually difficult to ascertain as it is a function of time and it involves many variables acting at the same time in an intricate manner. Insulation degradation is a multi-faceted and irremediable phenomenon that signifies a substantial part in the life expectancy of a transformer. In the transformers, paper (cellulose) is the most precarious component of the insulation system because once compromised, its dielectric and mechanical properties are not recoverable [11]. The reliable lifespan of solid insulation is centered on the cellulose degradation rate that is characterized by an irreversible chemical breakdown process of macromolecular chains. Estimation of the degree of aging and degradation can be done by measuring the average number of glucose rings that compose the cellulosic chain, i.e., the degree of polymerization (DP) [30]. Over time, as the transformer is in operation, the cellulosic chain bonding strength weakens by exposure to moisture, oxygen, acidic environment, and heat, and the mechanical tensile strength of paper is lowered leading to transformer failure [11, 30, 31].

Aging processes result not only in changes in mechanical properties but also in dielectric properties. The IEC 60450
standard procedure is typically used to determine the degree of polymerization. In a new transformer, a practical value for DP falls within the range of 1000–1200 and decreases with time in service of the transformer. Researchers in [32–35] considered that the transformer’s end of life usually coincides with DP values of the paper of less than 200, and its tensile strength is approximately less than 40% of its initial value. However, Duval et al. [31] observed that careful consideration of network conditions and minimizing mechanical risks can enable transformers with a paper DP of 200 to continue in service for several more years, perhaps until the DP falls as low as 100, without significantly increasing the risk of failure.

Chemical breakdown of solid insulation can be accredited to three different processes, namely, oxidation, hydrolysis, and pyrolysis. However, paper decomposition due to the pyrolysis reaction requires much higher temperatures than those to which the paper is subjected during normal power transformer operation [36]. Thus, the deterioration of paper in transformer insulation systems under normal transformer operating temperatures of up to 120°C is normally attributed to oxidation and hydrolysis reactions. Moreover, the oxidation reaction is significantly prominent because its activation energy value (85 kJ/mole) is lower than the activation energy (120 kJ/mole) of hydrolysis [11, 33, 36]. Under the collective action of oxygen, moisture, and temperature, many reaction byproducts manifest which are good indicators of the degradation condition of paper insulation. The most significant ones are furan composites, carbon oxides, H₂O, H₂, CH₄, and carboxylic acids (with low molecular weight) [4, 8, 30–32, 36, 37]. Furans have been used as transformer insulation health assessment indicator because of their significant correlation with DP of insulation system. The correlation between DP and furan (2-FAL) concentration and their significance in the interpretation of paper insulation aging criticality are addressed in [13, 35].

Transformer operation reliability and aging highly depend on the dryness of the insulation system. Increase in moisture level acts as an additive to the degradation process of insulation system as it lowers paper tensile strength and oil dielectric integrity, activates inter-winding partial discharges, and may even promote internal transformer flashovers [38]. Therefore, measures should be put into consideration on ways to limit moisture existence within the transformer. Moisture content can exist in a transformer through atmospheric water ingress due to leaks, paper or pressboard degradation, and inadequate drying out of cellulose insulation throughout manufacturing process [11].

It is further voiced in [11] that the cellulose aging rate is approximately proportional to the amount of moisture in it. The moisture level of at most 4% is not desirable as it leads to imminent paper failure [11]. The water in oil and its movement from solid to oil are highly temperature dependent. Thus, due to temperature non-uniformity in transformer, materials exposed to extreme temperatures will normally experience accelerated thermal aging of cellulose which weakens its mechanical properties. In addition, sludge, acidic environment, and metal particles affect the degradation process. Faults incurred in the transformer such as short circuits and high voltage transients have significant contribution in insulation deterioration. Winding vibrations can lead to inter-strand insulation breakdown in transformer resulting in insulation overheating [11, 13, 33].

In a nutshell, the aging and degradation of transformer oil-paper insulation which affects its life expectancy depend on transformer design and operational stresses imposed on the transformer (thermal, electrical, chemical, and mechanical stresses) under the influence of accelerating agents (moisture, oxygen and heat) and its accorded maintenance strategies.

4. Transformer Condition: Diagnostic Strategies

Most transformers degrade in a changing, dynamic, and quasi-process that starts with an early deficiency, incipient fault, or deterioration and progresses to failure due to the prolonged synergy of “electric-magnetism-force-heat” stresses and external factors. To counteract these undesirable states, it is critical to evaluate transformer performance based on condition monitoring outcomes [39]. Due to the intrinsic complexity of transformers’ structures, different datasets, multiple agents, and condition indicators should be adopted to enable transformer valuation from various angles.

Apart from routine checkups, condition-based maintenance (CBM) has been the norm for many power utility companies in evaluating the health condition of power transformers. The emerging faults can affect the credibility of the transformer operation significantly if not detected and addressed early. This section discusses various condition monitoring techniques used in diagnosis of power transformers. Figure 5 shows some of the typical conventional transformer condition valuation techniques that are discussed separately in the following sections.

4.1. Dissolved Gas Analysis (DGA) Technique. Even under normal operating conditions, a long in-service transformer generates gases. However, over time, it is repetitively subjected to dynamic operation strain and sometimes severe environmental stresses, resulting in a high rate of gas evolution in the transformer insulation system. Nonetheless, in the presence of an anomaly, the concentration of these gases rises. Thereby, internal faults are typically revealed by the decomposition of oil-paper, which produces seven primary key gases. Carbon monoxide (CO) and carbon dioxide (CO₂) reveal paper degradation related faults; ethylene (C₂H₄) and ethane (C₂H₆) are significant in indicating increase of oil temperature; partial discharge being low level energy yields hydrogen (H₂) and methane (CH₄); arcing can be recognized by noting the progression of acetylene (C₂H₂) and hydrogen (H₂) [17–20, 40].

Since it is a non-intrusive test and online analysis is possible, DGA has been acknowledged as a powerful tool available to diagnose potential transformer incipient faults. Nevertheless, there is no universally accepted standard method of fault diagnostics; though conventional techniques
such as IEEEstd C57.104 2008 Key gas, Rogers’ gas ratio method, IEC 60599 gas ratios, and Duval triangle and pentagon methods are mostly adopted as guides to fault identification [17, 19, 41–43].

4.1.1. **Key Gas Method.** Key gas method primarily relies on the magnitude of individually measured six dissolved gases which are, H\(_2\), CH\(_4\), C\(_2\)H\(_6\), C\(_2\)H\(_2\), and CO. During fault event, different principle gases are evolved depending on the type of the incipient fault the transformer experiences. By calculating the relative percentage concentration of each gas, the four types of early-stage fault conditions involving thermal stress on insulation system, partial discharge, and arcing can be differentiated [17]. Since the interpretation pattern of key gas method is founded upon practical experience of different experts, it has not been extensively acceptable as an accurate method of determining transformer incipient faults [17, 44]. However, this method is very easy to implement. Surveys based on IEC database showed that approximately 42% of DGA dataset of the physically assessed faulty transformers can be correctly determined by the key gas method [17, 45]. Since there are no definite boundaries for the key gas method, this may compromise the accuracy in fault interpretation.

4.1.2. **Doernenburg Ratio Method.** The Doernenburg ratio method is centered upon the formulation of four different gas ratios (C\(_2\)H\(_2\)/C\(_2\)H\(_6\), C\(_2\)H\(_6\)/C\(_2\)H\(_2\), C\(_2\)H\(_2\)/CH\(_4\), and CH\(_4\)/H\(_2\)) amid five gas magnitudes to identify the incipient faults of transformers [41, 46]. As detailed in [41], the fault categories are established using the predetermined ranges of these four ratios. Accordingly, the Doernenburg ratio approach can only be used if the concentration of at least one principle gas exceeds twice the threshold concentrations.

4.1.3. **Rogers Ratio Method.** The Rogers ratio method embraces analogous interpretation of the aforesaid Doernenburg ratio method. However, unlike the Doernenburg ratio approach which necessitates the minimal concentrations of the dissolved gases, this scheme can be used even when the magnitudes are within threshold values [41]. Based on the interpretation of four gas ratios, i.e., C\(_2\)H\(_2\)/C\(_2\)H\(_6\), CH\(_4\)/H\(_2\), C\(_2\)H\(_2\)/C\(_2\)H\(_6\), and C\(_2\)H\(_6\)/CH\(_4\), approximately twelve incipient faults can be defined by this method [47]. Nevertheless, latter research disclosed the ratio of C\(_2\)H\(_2\)/CH\(_4\) as insignificant in fault determination [46] and thus it was dismissed in the revised IEEE Standard C57.104-199. Accordingly, only six faults including normal health condition can be detected by this technique [41]. Rogers ratio interpretation had some inconsistencies comparable to the key gas approach, and an overall diagnostic accuracy of 58.9% was recorded in [48].

4.1.4. **IEC Ratio Method.** Analogous to the Rogers ratio method, the IEC ratio also uses the same three gases’ ratios. However, there are differences between these three ratios’ ranges and the related fault kinds. IEC codes and their validity are outlined in [49]. Additionally, in the IEC ratio method, a new C\(_2\)H\(_2\)/H\(_2\) ratio was presented to categorize faults associated with abnormalities in on-load tap changer (OLTC) [50]. Noted in [51], some improvements were made in IEC ratio whereby graphical representations of ratio ranges were used to identify faults. This can improve on accuracy in fault diagnosis and identification when the equivalent gas proportions are out of the stated ranges.

4.1.5. **Duval Triangle Method.** The Duval triangle method was established by incorporating the IEC ratio and IEC TC10 databases [49]. This method employs the different portion of three dissolved gases plotted along three sides of a graphically represented triangle in form of \(\%C_2H_2 = \frac{a}{(a + m + y)}\), \(\%C_2H_4 = \frac{m}{(a + m + y)}\), and \(\%C_2H_6 = \frac{y}{(a + m + y)}\).
\[ CH_4 = y/(a + m + y) \], where \( a \), \( m \), and \( y \) represent the magnitude of \( C_2H_2 \), \( C_2H_4 \), and \( CH_4 \) gases, respectively [52]. Figure 6 demonstrates a Duval triangle fault interpretation method. The fault lies where the percentages of the employed gases intersect. Seven sectors are allotted in a triangle as portrayed in Figure 6 to differentiate faults.

In [48–53], it is reported that Duval triangle outclasses other ratio centered techniques and it is capable of providing consistent diagnoses. However, the Duval triangle method can only be applied when faults do manifest in a transformer since the fault-free segment does not exist in the triangle. This triangle method also led to the genesis of alternative Duval triangles to distinguish faults related to on-load tap changers and non-mineral oil filled equipment. In type I Duval triangle method, \( CH_4 \), \( C_2H_6 \), and \( CH_4 \) gases are employed, whilst in type II Duval triangle method, \( C_2H_4 \), \( CH_4 \), and \( C_2H_6 \) dissolved gases were implemented [19]. However, these two triangles are relevant only when PD, T1, or T2 faults have been detected by the original Duval triangle method [49].

Power utilities still need to further investigate other important issues in order to perform an accurate diagnosis on power transformers, even if the DGA approach has been acceptably utilized to identify impending faults and evaluate the health state of power transformers. Different DGA interpretation methodologies indicate that not all combinations of gas proportions from measurements may be classified into a particular fault category. Erratic diagnostic outcome may result due to use of different interpretation methods. Another drawback of traditional methods of DGA data interpretation is inability to appropriately interpret DGA result collected from a single transformer with multiple faults. Furthermore, existing DGA interpretation methods make use of statistical analysis on historical DGA data and skill of power utility skilled personnel [19]. It can be concluded that conventional DGA schemes have not yet fully explored the relationship between the quantified gas evolved and the different fault types in power transformers. Thus, there is a need for some intelligent soft computing interpretation techniques to establish the correlation between evolved gases and transformers’ insulation conditions [23, 24]. Additionally, sole application of the DGA approach cannot quantify the severity of detected fault within a transformer.

4.2. Thermal Analysis Approach. The deterioration of transformer’s insulation is associated to the thermal strain, which is mainly determined by the loading and variations in environmental conditions. Most faults cause change in the thermal performance of the transformer. Thus, inclusive thermal models of transformer and correct quantification of hot spot temperatures are also considered as some of the necessities for transformer condition assessment. Different studies have highlighted models and techniques to predict the hot spot temperatures of a transformer. As technology improves, many techniques are being suggested by different researchers based on different notions and these are not limited to IEEE [54], IEC [55], convectional thermal-electric based models [56–61], moisture-dependent and multi-parameter-based thermal models [62, 63], and artificial intelligent-based models [64, 65]. Although the best method of hot spot detection is through optical fiber sensor [66] installed within the lining of transformer winding, this method tends to be capital intensive and also impracticable to undertake without disruption of power delivery of already-in-service transformers.

Godina et al. [67] proved that some of assumptions made in thermal modeling through IEC and IEEE models, including those of the top oil temperature having an instant response to changes in ambient temperature and temperature of oil in the cooling duct being homogeneous to the top oil temperature, may not give a good judgment for estimating the correct hot spot temperature. These assumptions may not stand if the transformer is under varying temperatures and load transients including fluctuating environmental conditions. In addition, the thermal resistance of a transformer in most models was considered constant for every loading condition and temperature. To provide a precise estimation of hot spot temperature of transformer windings, multi-parameter-dependent thermal models cascaded with soft computing techniques need to be investigated.

4.3. Partial Discharge Analysis Approach. Partial discharge (PD) manifests when the electric field strength surpasses the dielectric breakdown strength in a confined area, in which electrical discharges partially link the insulation between the windings [68]. The dielectric properties of the insulation may be compromised if exposed to continual partial discharge activity and this could lead to failure if the situation remains uncontrolled over long time. Therefore, it is of paramount importance to develop PD diagnostic or prognosis measures based on the electromagnetic phenomena of in-service transformers. The typically accepted methodologies for PD diagnosis are based on the emanated signals by PD through electrical or acoustic signature detection. In [69], a conventional pulse-current method is reported as a technique to assess PD signals. Studies showed that this technique has exceptional sensitivity and is easy to compute the change. Nevertheless, the current sensed by pulse-current technique is not the definite PD, which may result in misleading interpretation of the evidence of PD in the transformer.

A capacitive enhanced factor method has been developed to address the shortfalls of the pulse-current method. It is observed that with this enhanced capacitive technique, error ratio of PD location is minimized to around 4.6% through utilization of data obtained from the current pulse signal of the transformer windings [70]. However, owing to the environment in which the power transformer is subjected to, such as extreme levels of electromagnetic noise induced by numerous instabilities, the PD measurement setups habitually have noticeable limitations of differentiating the electrical noise and PD. This paved the genesis of ultra-high-frequency (UHF) sensors in detecting the electromagnetic waves created by PD at the frequency
approaching 3 GHz [71]. Other techniques reported in literature for PD detection and measurement include use of piezoelectric sensors (online detection of PD), acoustic sensors, and optical fiber sensors. Additionally, existence of PD faulting process can be noted through manifestation of $\text{H}_2$ and $\text{CH}_4$ gases in transformer oil that can be interpreted using the dissolved gas analysis (DGA) method. The strength of acoustic sensors is their ability to withstand electromagnetic interference and they are also easy to install. However, they are less sensitive equated to electrical signal approaches with the dynamic mechanism inside the transformer.

To improve the prevalence of acoustic sensors for signal detection, fiber optic acoustic sensors that can be installed inside transformers have been constructed. Although application of fiber optic acoustic sensors is expensive, they have vast merits inclusive of being immune to electromagnetic disturbance and interferences, being reliably stable under harsh environmental conditions, and being corrosion resistant [72]. Table 1 depicts a summary of some of charge detection approaches for PD valuation [72]. In [73], it is reported that a transient earth voltage (TEV) sensor-based method can be utilized in the localization assessment of PD source in oil-immersed power transformer. Since most of the insulation problems originate from PD activity, PA analysis is widely used to assess the transformer insulation condition. However, on-site PD measurement is often compromised by strong coupled electromagnetic interference, which raises the difficulties of obtaining PD signals minus noise. The gating sensing and the directional sensing methods have been commonly used as denoising techniques [74]. Additionally, the application of the wavelet transform for PD denoising was accomplished in [75, 76].

**4.4. Vibration Analysis Approach.** Transformer vibrations comprise of core vibrations, winding vibrations, and on-load tap changer vibrations [77, 78]. The produced vibrations spread through the transformer oil until they extend to the transformer tank walls, where they can be detected via vibration sensors. Through the use of comparison in terms of vibration signatures (signals) of the transformer tank produced, the health condition of the core can be noted [77]. Vibration analysis is a much vibrant method for evaluating the health status of on-load tap changers [77–79].

**4.5. Frequency Response Analysis.** Once a power transformer is exposed to the extremes through fault currents, the windings are exposed to strenuous mechanical stresses which may result in winding movement and deformations [80, 81]. Winding deformation usually leads to changes of the internal electromagnetic behavior which can be distinguished through the frequency response analysis (FRA) technique [80]. Comparison of healthy winding fingerprints with those of the damaged winding determines the extent of winding damage. Deviations in fingerprints can be used to approximate the severity of winding damage and its locality [81]. Although FRA helps in assessing the integrity of transformer winding, its measurement can only be done when the transformer is out of service, unlike the other routinely done assessments that can be performed when the transformer is in service.

**4.6. Developments in Condition Monitoring and Assessment.** Multiple parameters can be tracked simultaneously thanks to advancements in sensor technology and communication technologies [5]. There are new commercially available online condition monitoring and condition assessment techniques [74]. Additionally, the application of the wavelet transform for PD denoising was accomplished in [75, 76].

![Figure 6: Typical Duval triangle [19].](image-url)
systems that keep track of multiple transformer parameters. These innovative devices allow for the online monitoring of numerous parameters, including but not limited to HST, dissolved gases, partial discharge, water content in insulation, oil temperature, and others. In these modern condition monitoring systems, parameter measurements are made using high-tech sensors. Utilizing a data collecting subsystem, all measured data are then gathered and evaluated, followed by an operator-provided interpretation. For data processing and interpretation, intelligent systems like multi-agent systems have recently been deployed. With these modern condition monitoring technologies, any transformer-related issue can be quickly and accurately diagnosed and interpreted.

### 5. Artificial Intelligence in Transformer Condition Assessment

To overcome the drawbacks of the conventional transformer condition and fault diagnostic interpretation schemes, various soft computational techniques including fuzzy logic and expert systems, artificial neural networks (ANNs), and decision-making and hybrid algorithms have been widely explored and have to some acceptable extent achieved success in transformer state diagnosis based on oil test characteristics. However, these techniques still have some shortfalls in their developments as outlined in the following sections. The summarized merits and demerits of the commonly adopted artificial intelligence transformer diagnosis techniques are pointed out in Table 2.

#### 5.1. Fuzzy Logic and Expert System

The fuzzy logic methodologies mimic the experience attained by skilled personnel in diagnosis into inference decision rules and membership functions. This can allow transformer insulation system diagnosis to be achieved by mapping the transformer oil features to a set of linguistic rules. Application of fuzzy logic inferences to power transformer state diagnosis has been reported by many researchers not limited to. A fuzzy logic system for diagnosing transformer insulation was developed in [84], where the fuzzy set concept was implemented to overcome the uncertainties in conventional key gas analysis and gas ratio boundaries. In [85], the researchers presented a basis for steering transformer diagnostics by using fuzzy information theory. Thus, a combination of fuzzy relations and decision tree was established to perform diagnosis of transformer incipient faults. Su et al. [86] proposed a fuzzy logic system that can distinguish multiple faults occurring concurrently in a transformer insulation system.

Arshad and Islam [87] presented a novel fuzzy-based model for transformer asset management. They extended on enhancing the decision making in power transformer diagnostics by incorporating fuzzy logic. In the proposed framework, based on diagnostics and data interpretation techniques with the inclusion of criticalities in a power transformer, a fuzzy logic rule-based power transformer management and decision-making model was established. Duraisamy et al. [88] used different membership functions to design a fuzzy logic system, which was then cascaded with backpropagation neural network for diagnosing transformer faults.

The application of the rule-based expert system to transformer diagnosis has seen researchers integrate it with fuzzy logic to address uncertainties in the diagnosing processes. An expert system and a type 2 fuzzy logic system were combined by Flores et al. [89] in order to evaluate the transformer insulation using the properties of the oil. The results of this hybrid system were satisfactory in determining whether paper insulation deterioration was involved in any insulation faults. Abu-Siada et al. [90] merged multiple DGA interpretation schemes into a sole expert model to address the human expert’s deficiencies. It was noted that such method enhances the diagnosis performance that could lead to standardizing DGA interpretation approaches. Ghoneim [20] developed an intelligent prediction model for transformer fault classification and severity quantification based on DGA unified with thermodynamics theory. The author further integrated the developed fuzzy logic system with an autonomous condition assessment system in order to detect the transformer state online. In [91], a model based on fuzzy-DGA and energy of fault formation was utilized in determining the type of fault and its severity in a power transformer. This approach managed to show some satisfactory results; however, there are still challenges in this technique since the chemistry behind the hydrocarbon breakdown of the mineral oil involved was not comprehensively analyzed and

### Table 2: Comparison of charge detection techniques of PD [72].

| Detection techniques | Detection attribute | Sensitivity | Analysis type | Anti-interference | Comprehensive diagnosis ability |
|----------------------|---------------------|-------------|---------------|-------------------|-------------------------------|
| HFC                  | Current             | 0.2–1 pC    | Quantitative  | Poor              | Discharge type judgment according to phase position |
| UHF                  | Electromagnetic wave | ≥10 pC (outdoor) <5 pC (indoor) | Qualitative | Good              | Discharge existing |
| Ultrasonic method    | Ultrasonic          | >50 pC      | Qualitative   | Good              | Discharge existing |
| Flash spotting       | Optical signal      | <1 pC       | Qualitative   | Ok                | Discharge existing |
| DGA                  | Gas in oil          | ≥4 μV·mL/mg | Qualitative/quantitative | Ok | Discharge existing/discharge style |

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| Ultrasonic method  | Ultrasonic  | >50 pC        | Qualitative       | Good                          | Discharge existing |
| Flash spotting     | Optical signal | <1 pC       | Qualitative       | Ok                           | Discharge existing |
| DGA                | Gas in oil  | ≥4 μV·mL/mg   | Qualitative/quantitative | Ok | Discharge existing/discharge style |
also the rate of change of gas was not included which may lead to inaccuracy in fault diagnosis and severity determination.

Though the fuzzy and expert systems have found an edge in applications in transformer insulation diagnosis, they still have some limitations as noted in Table 2. Additionally, most of the developed fuzzy systems are focusing on incipient fault detection with little emphasis on the fault severity issues. Therefore, there is a need to address this key factor of fault severity so as to enhance in asset management of power utilities.

### 5.2. Artificial Neural Network (ANN).

Artificial neural networks have been applied in transformer insulation diagnosis using either DGA or oil quality properties. A significant benefit of ANN-based fault diagnostics is that it can learn directly from the training samples and update its knowledge when necessary. Zhang et al. [92] suggested a two-stage ANN to diagnose transformer insulation condition using DGA data. In this work, tenfold cross-validation was used in determining the ideal number of neurons in the hidden layer of ANN. Vanegas et al. [93] developed a two-input system using the ANN framework for fault determination. The authors proved that the suggested network through associated input features of the five gases might achieve better classification accuracy compared to the ICE gas ratio.

Guardado et al. [94] compared ANNs’ effectiveness for transformer insulation diagnosis where training process was achieved using different conventional interpretation schemes. It was observed that a network consisting of three layers with hidden layer composed of few neurons could be appropriate for transformer insulation incipient fault detection and is capable of attaining accuracy of at least 87%.

Transformer fault diagnosis was also achieved in [95] where a novel probabilistic neural network (PNN) was established to improve the adaptation capability and fast-

### Table 2: Commonly used intelligent diagnosis methods [6].

| Technique     | Method introduction and merits                                                                 | Method limitation                                                                 |
|---------------|-------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| Fuzzy logic   | (i) Utilizes the fuzzy set methods to enable fuzzy comprehensive judgment                      | (i) Several human factors involved                                               |
|               | (ii) Inference based on linguist language                                                        | (ii) Replication of inference is difficult                                       |
|               | (iii) Easy to understand the formulated rules                                                    | (iii) Cannot learn if new knowledge is provided                                  |
|               | (iv) Suitable for qualitative analysis for complex and large system; closer to people's thinking | (iv) Difficult to analyze the fault trend; diagnosis                            |
|               | expression                                                                                       | accuracy depends heavily on parameter selection                                  |
| ANN           | (i) ANN is characterized by robust data processing and learning ability, which is generally used | (i) It requires a fairly large size of dataset for training and testing          |
|               | in classification and forecasting problems                                                       | the networks to guarantee the reliability                                        |
|               | (ii) Simulates the human brain thinking function including parallel distributed processing      | (ii) Depending on data samples, easy to fall into local optimum                  |
|               | ability, associative memory, self-organization and self-learning ability, and non-linear        |                                                                                 |
|               | mapping characteristics                                                                          |                                                                                 |
| Support vector | (i) SVM is a broadly used binary classification scheme, which can use the kernel technique to    | (i) It may lead to overlapping or indivisible classification for multiple        |
| machine       | address non-linear classification                                                                | classification problems                                                           |
|               | (ii) Centered on structural risk minimization principle to train the network, together with the  | (ii) Classification performance depends largely on the choice of its model       |
|               | unknown distribution of random invisible data fault probability of the classifier               | parameters                                                                       |
| Rough set     | (i) Simplifies the acquisition of information and knowledge at maximum                           | (iii) Can only use limited specific instances of fault diagnosis                 |
| theory        | (ii) A better means of describing or solve the fuzzy state of fault diagnosis of complicated     | (iv) Hard to fix network weights; long training time and analyzing stability     |
|               | systems                                                                                          | of large network is not straightforward                                           |
| Bayesian       | (i) Visual presentation. Inferring using conditional probability.                                  | (v) Sometimes it is hard to ensure the algorithm convergence                     |
| network       |                                                                                                  |                                                                                 |
track the retraining process when the neural network is presented with new data. Also, a fuzzy learning vector quantization (FLVQ) network to assess power transformer condition was suggested in [96]. The extension theory-based clustering algorithm that does not involve tuning of any specific artificial parameters was also adopted for identifying transformer incipient faults as outlined in [97]. In this scheme, no learning takes place. To relay the data visualization capability in neural networks, the self-organizing map (SOM)-based network was adopted in [98]. The SOM has the ability to enhance the visualization on the evolution of an incipient fault by plotting the DGA pattern using the past datasets. Comparable to SOM, a set of auto-associative neural networks were employed to provide visualization and clustering in transformer insulation diagnosis [99]. Furthermore, some scholars embraced Bayesian network for transformer fault diagnosis using DGA datasets [100]. A unified self-adaptive-training-based radial basis function (RBF) based on fuzzy C-means (FCM) clustering and quantum-inspired particle swarm optimization (QPSO) for transformer diagnosis was developed in [127]. Lately, the wavelet has also been merged in ANNs for examining DGA data as articulated in [128, 129]. Though ANN have been extensively used in transformer insulation diagnosis by utilization of DGA and oil features, ANN schemes still suffer some congenital drawbacks. For instance, it requires a fairly large size of dataset for training and testing the networks. Also, depending on data samples, ANN can easily fall into local optimum.

5.3. Decision-Making Algorithms. Decision-making algorithms have also been incorporated in transformer diagnostic techniques. Tang et al. [101] implemented evidence reasoning algorithm to address deficiencies brought by uncertainties in transformer condition inspection. Basing maintenance necessities, the algorithm managed to provide overall evaluation and ranked the transformer condition. In [102], a fuzzy set theory-based algorithm aggregated with evidential reasoning was established and the diagnosis outcome for fault classification was accomplished in a probabilistic notation. A multi-level and multi-aspect expert system based on information fusion strategy was developed in [103]. In [9], fuzzy logic and evidential reasoning methodologies were applied in transformer insulation stress assessment. Both approaches were effective and systematic ways of assessing transformer fault level. Yang et al. [96] presented an intelligent decision support system based on fuzzy learning vector quantization (LVQ) networks to improve the assessment capability of power transformers. Significant classification accuracy was realized and training effort needed in this approach was reduced. However, the limitation of this scheme is that it utilized the sets of codes defined by specified gas proportions in fault assessment. The ultimate transformer health state valuation is significantly influenced by the data sources and personnel knowledge of uncertainty. Aizpurua et al. [104] incorporated various sources of expert knowledge to deduce confidence intervals for transformer health condition decision making under uncertainty. Noting that transformer winding hotspot temperature (HST) was projected using indirect measurements, Aizpurua et al. [104] presented a Bayesian inference framework for quantifying the uncertainty-informed residual transformer life. An analysis to establish the effects of temperature and load measurement errors on residual transformer life prediction was presented in [106]. The uncertainty envelope was used by Dey et al. [107] to minimize noise in dielectric response measurements for transformer condition monitoring. Ma et al. [108] used DGA and depolarization current to illustrate the hitches in achieving diagnosis conclusions when measurement uncertainty exists, and a SVM algorithm was developed to address the uncertainties. Other researchers primarily focused on uncertainty-based techniques, such as Dempster–Shafer evidence theory [109], Bayesian network [110], matter element theory [111], rough set [112], and evidential reasoning [101, 113, 114], which can complement crucial status parameters and infer an intelligent decision for transformer condition assessment.

5.4. Hybrid Algorithms. Hybrid algorithms have also been applied in transformer insulation diagnosis where they address the limitation of individual algorithms. In [115], the authors applied a multi-layer SVM classifier and confirmed its applicability in power transformer fault analysis. In [116], the SVM algorithm was merged with genetic algorithm to provide the estimation of gas quantity in transformer oil. Also, research has proved that particle swarm optimization (PSO) can also be integrated with SVM, where PSO explores the optimal parameters for SVM [117, 118]. Moreover, the authors in [119] explored the application of artificial immune network classification algorithm (AINC) in transformer diagnosis.

Xu et al. [120] suggested a consultative mechanism to merge fuzzy logic and ANN, whilst a cascaded expert system and ANN were also developed in [121]. In these hybrid procedures, IEEE/IEC interpretation techniques including the experts’ proficiencies were used to formulate the knowledge base. Several hybrid schemes presented in different manuscripts include incorporation of conventional DGA interpretation inferences with ANNs and fuzzy logic [122], neural-fuzzy approach [123], decision making based on amalgam of fuzzy approach, and evidential reasoning methodology [114]. By incorporating ANN into fuzzy logic inference system for self-learning and auto-tuning of fuzzy rules, the model diagnosis capabilities were enhanced by enabling constant updating and upgrading of the system by learning from new transformer fault data. Furthermore, the Dempster–Shafer evidential theory was merged with backpropagation neural network (BP-NN) and fuzzy logic in [124]. In [125], neuro-fuzzy scheme and PNN were integrated. Additionally, a novel DGA method for power transformer incipient fault diagnosis based on combined adaptive neuro-fuzzy inference system (ANFIS) and Dempster–Shafer theory (DST) was presented in [21]. Majority of the developed hybrid algorithms make use of the combined effect of the learning ability of ANNs, the knowledge formation of expert system, and the uncertainty representation of fuzzy logic.
The authors in [126] developed a framework that can be adopted in developing algorithms that can be applied in evaluating the condition of an oil filled power system equipment on the basis of the degree of healthiness (DOH) and degree of faultiness (DOF). The procedure flowchart is depicted in Figure 7.

6. Intelligent Algorithms vs. Traditional Approaches in Transformer Condition Assessment

Transformer condition assessment and diagnosis are mainly centered on the data collected from the in-service transformer. Therefore, the methodologies utilized in gathering, transmitting, processing, and interpreting the data have a high influence in ascertaining the condition of the transformer. It has been noted in literature that the emergence of online monitoring tools, cyber-physical systems, and the Internet of Things has contributed to the rise of big data in the form of the collected transformer data. The investigation of the health and functioning state of power transformers cannot be completed using conventional data processing and analysis methods due to the involvement of big data. The conventional approaches rely on IEC and IEEE standards, which divide the status rank into “normal,” “caution,” “abnormal,” and “severe” categories. Additionally, the outcomes of the transformer condition evaluation are typically presented as a condition score or health ranking [40, 130, 131].

Although conventional techniques are generally easy, straightforward, and extensively employed, there are three issues with existing standards, namely,

(i) Applying the coordinated mathematical model's parameters, weightings, and baselines to a variety of transformers for various types, areas, and manufacturers is challenging.

(ii) Uncertain effects of various data sources, degradation mechanisms, and other factors are not taken into account.

(iii) With regard to the operational condition of transformers, current methods are unable to thoroughly examine and make the most of vast volumes of state data.

In comparison to the conventional condition valuation techniques based on codes and data acquisition, the evolution of intelligent systems has the following main qualities: i) rapid extraction of important state parameters; ii) comprehensively exploiting the universality and uniqueness of the transformer to achieve distinguishable evaluation of the transformer status; iii) thoroughly utilizing a data-driven evaluation process, which not only successfully minimizes the intervention of human factors but also improves the rationality of the evaluation results.

7. Overview of Transformer Remnant Life Estimation Approaches

Transformers have a limited lifespan and become more prone to failure as they get older. They also take longer to repair. Despite the fact that maintenance activities can lengthen the lifespan of power system equipment, they may prove to be costly for equipment and assets that are getting close to their end of life. Numerous papers investigating the relationship between some condition monitoring parameters such as furan, dissolved gases, water content, and temperature with the transformer remaining life through mathematical-based approaches can be found in the literature [132–134]. However, due to the involvedness in developing a mathematical model for non-linear problems, these models are limited to few parameters, thus leaving some accelerating aging factors which may lead to incorrect estimation for the transformer remnant life [61]. Figure 8 shows the basic framework of residual life estimation model development for oil-immersed power transformer.

The correlation between furan concentration in oil and degree of polymerization (DP) of paper insulation which mirrors the remaining life of transformer insulation is presented in [134]. Pandey et al. [35] suggested an ANFIS-based approach to estimate remnant life of power transformer by predicting furan content. However, the challenge of utilizing furan content alone to map the remnant life is that if the oil is reconditioned or filtered, the furan representation of the new oil might not reflect the true degradation of cellulose paper. In [135], a method which involves generation of data using Monte Carlo techniques thereby leading to the development of an empirical regression model to estimate the elapsed life and also the remaining life of power transformer is presented. Siada et al. [136] introduced a technique based on Ultraviolet-to-Visible (UV-Vis) to measure the concentration of furan content in insulation oil. They further developed a novel fuzzy logic model to estimate the transformer expected remnant life using UV-Vis oil spectral response. Also, in [137], a fuzzy logic-based UV-Vis spectroscopy technique to measure interfacial tension of transformer oil was proposed.

Transformer remnant life and asset decision fuzzy logic model is highlighted in [12, 87]. Although the developed model in [87] has covered a variety of condition monitoring parameters, the model could not be implemented online as several input parameters are only measured offline. The model in [12] was based on parameters that can potentially be measured online or on-site which facilitates a better and timely maintenance action based on the model output. A comprehensive multi-attribute residual life estimation model based on fuzzy logic was developed in [10, 13]. However, some factors such as failure history, maintenance data, and loading regimes have been ignored when determining the remaining life of a power transformer. As a result, the fundamental factors used in life estimation were
taken on an individual basis, which could potentially jeopardize the outcome because the parameters are closely interrelated. A weighting factor approach cascaded with a fuzzy inference system to determine the residual life of a power transformer was discussed in [14]. Rather than individual attributes, the model makes use of the grouping factor of technical life threatening agencies. The model was developed using a multi-criteria analysis, with the remnant life obtained by the collective effect of distinct suboutcomes using fuzzification of all the active grouping attributes. The results obtained portray the adequacy of the model; however, statistical data on transformer failure were not included in the model.

A statistical analysis approach for transformers’ failure-rate population was used in [138, 139] to estimate the transformer remaining life based on analytical model. However, due to varying, environmental conditions and maintenance procedure, the accuracy of the developed estimation analytic model is lowered. In [140], a hybrid method based on theory of belief and neuro-fuzzy systems was presented for evaluating the remaining useful life of power system equipment. The authors based their approach on a classification of prediction strategy (CPS), and thereby consist of two phases: the prediction step using an evolving neurofuzzy system (eXTS) for online multistep ahead prediction of observations. The predicted observations are then classified into functioning modes using an evidential Markovian classifier and Dempster-Shafer theory. In order to make more precise decisions about operation and maintenance that can enhance the practicality of life estimation models, future research should concentrate on merging different datasets and expert knowledge, investigating the complex interactions between health indices, and thoroughly examining the condition state of transformers.

8. Summary and Prospects

The power transformer residual life estimation facilitates in ascertaining proper asset management decision making. However, the main challenge within many power utility organizations is the ability to predict when faults will happen in power transformers, thus affecting their asset...
management capabilities in whether to continue using the asset or retiring it. When certain diagnostic properties deteriorate to the point that further use is deemed undesirable, a power transformer has reached the end of its technical life. Accordingly, frequent assessment of the asset diagnostics improves better estimation of transformer residual life. With the adoption of condition-based monitoring techniques, transformer maintenance can be done when the need arises. From the review presented in this paper, it can be perceived that there has been significant research into modern techniques in transformer condition and fault diagnostic strategies. Much focus has been on the analysis of soft computing adequacy on DGA, hot spot temperature, and furanic estimations in assessing transformer health status, thereby forming basis for remaining life estimation models for power transformers. However, not much emphasis has been made in remnant life estimation models based on the results of maintenance schedules done on the transformers. Thus, the relationship between life expectancy of a transformer and the outcome of faults or failure has not been fully exhausted, and thus extensive research still needs to be done.

Transformer assessment can offer strong technical and financial support as well as decision-making approaches for transformer condition-based maintenance and asset management. This article presented a unified framework of attributes that forms the basis of transformer remnant life estimation from failure statistics and analysis, condition evaluation, data gathering, data processing, and different inferences, to deal with different patterns of transformer insulation degradation and failures. When it comes to data acquisition, the information needed to determine the operating condition of transformers is gathered from various subsystems using various condition monitoring techniques, such as inspections, vibration analysis, PD analysis, FRA, and infrared thermography. A thorough overview of the aspects of AI in condition evaluation methods is offered by reviewing the prior studies with a view to data analysis and decision making for transformer condition assessment, including benefits and drawbacks. Furthermore, the overview of models suggested for power transformer remnant life estimation was presented. When compared to conventional evaluation and remnant life estimation techniques, the development of intelligent algorithms can swiftly extract

![Figure 8: Block for remnant life and management decision model.](image-url)
crucial condition and thereby perform data-driven transformer valuation.

The evaluation of transformer state is a crucial tool for the secure and dependable transfer of electrical energy, which demands regular attention. In light of the growing study interests in transformer condition evaluation to enhance longevity of in-service transformer, the following trends and propensities mainly improvement on data quality for transformer remnant life estimation are proposed to be further explored.

8.1. Data Quality Improvement. Power transformer data, such as online monitoring, operating conditions, DGA, oil characteristic tests, fault problems, maintenance records, and so on, are currently being gathered by research organizations, power utilities, and manufacturers. Contrarily, the transformer state data, which are kept in various forms in dispersed, different subsystems, are characterized by heterogeneity, uneven quality, and asynchrony. The accuracy of assessing the status of transformers is subpar due to measurement errors, duplicate data, and missing data. Transformer state diagnosis and prediction analysis outcomes will differ from the actual outcomes if the data quality is poor. Additionally, utilities do not have a common framework that they have adopted for defining the process of training, cross-validation, testing, and valuation of data processing algorithms. The quality of transformer data must therefore be greatly improved.

8.2. Enhancing Data Mining Techniques. Usually, transformer datasets are characterized by non-uniformity, and thus some data quality manipulating techniques can be employed in future research studies to handle issues with missing data that can compromise reliability of the developed algorithms. Thus, much emphasis must be put in data collection, condition, and processing techniques. Accordingly, researchers should harness the innovative technologies, such as Internet of Things (IOT), cloud computing, big data, and other information and communication strategies for power transformer valuation to map the residual life. Further, expert knowledge can be enhanced by harnessing the capabilities of machine learning algorithms in intelligently analyzing the data, discovering potential problems, and excavating hidden laws. Huge volumes of multi-variate data must be collected, sent, accessed, and quickly analyzed in real time in order to maintain the power transformer’s dependable operation. As a result, the domains of massive data gathering and access, online analytical mining, and visualization can all greatly benefit from the usage of big data technologies. Vast amounts of condition, diagnostic, and maintenance data will be reliably saved and quickly accessed through the development of a “cloud computing framework” centered on the transformer condition and its accessories, considerably increasing the accuracy of transformer valuation.

8.3. Integration of Multiple Schemes and External Factors. Improvement on remnant life determination can also be realized by integrating multiple methods amalgamating external factors. Power transformers and other electrical equipment could be severely harmed by externally imposing, demanding environmental variables. These extraneous factors can lead to strenuous loading and harmonics of the power grids also posing various problems to the transformer. Additionally, extreme environmental factors can pose false data injection attacks and other transformer-substation communication network attacks that endanger the safety and dependability of power substations. Models for transformer diagnostic, prognosis, and assessments are still far from “compatibility.” Since each strategy has its own unique advantages, it is challenging to generalize them. Therefore, it is critically important to integrate various ways for assessing the status of transformers so as to complement one another and achieve the mutual coordination of various models. However, much care and proactiveness need to be initiated when adopting hybrid models on limited training sets as this may accelerate the risk of overfitting on training data, which may compromise the outcome of the models.

8.4. Embracing Modern Manufacturing Technology. Chemical detection and offline power testing at low voltage remain the two most common techniques for determining the condition of transformers especially in developing countries. The fault locations in transformers cannot, however, be disclosed by either of them. Improvements should be made to sensors’ sensitivity and anti-interference capabilities for PD detection. The test that holds the most promise for the future is a collection of tools or systems that can foresee and identify transformer failures. These tools or systems may be used to forecast forced outages and take prompt corrective action. The development of power systems and power equipment could be aided by new smart sensors. Reliable and affordable distributed intelligent sensor networks will be widely used in smart grids as Internet of Things and mobile Internet technologies progress. In addition, many high-precision smart sensors have been developed and put to use, including gas sensor arrays [141], photoacoustic spectroscopy [142], gas chromatography techniques [143, 144], and so on, and have been explored, factory-made, and applied, exhibiting a more inclusive data basis for big data analysis. The innovative smart transformer is another trend [145] that can be adopted. This will enable equipment with self-diagnosis capabilities, though its implementation might be capital intensive. Smart transformers have more electronic components than conventional transformers, intelligent sensors and actuators, a good communication interface, operating information management, condition diagnosis and evaluation, operation data monitoring, and fault alarm functionality that will enable easy asset management schemes for asset managers. It is essential to continue exploring smart transformers that can withstand the widespread adoption of intermittent new energy sources (DG) and applications [146].

Data Availability
No data were used to support this study.
Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this article.

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References

[1] H. Farhangi, “The path of the smart grid,” IEEE Power and Energy Magazine, vol. 8, no. 1, pp. 18–28, 2010.
[2] P. McDaniel and S. Mclaughlin, “Security and privacy challenges in the smart grid,” IEEE Security and Privacy Magazine, vol. 7, no. 3, pp. 75–77, 2009.
[3] M. Amin and P. F. Schewe, “Preventing blackouts: building a smarter power grid,” Scientific American, vol. 296, no. 5, pp. 60–67, 2007.
[4] D. C. Huang, Y. B. Shu, J. J. Ruan, and Y. Hu, “Ultra high voltage transmission in China: developments, current status and future prospects,” Proceedings of the IEEE, vol. 97, no. 3, pp. 555–583, March 2009.
[5] A. E. Abu-Elanien and M. A. Salama, “Asset management techniques for transformers,” Electric Power Systems Research, vol. 80, no. 4, pp. 456–464, 2010.
[6] W. H. Tang and Q. H. Wu, Condition Monitoring and Assessment of Power Transformers Using Computational Intelligence, Springer-Verlag Limited, London, UK, 2011.
[7] G. K. Irungu, A. O. Akumu, J. Munda, and B. Lubisi, “Application of key fault gases and oil testing for evaluation of transformer condition and its maintenance requirement,” in Proceedings of the 23rd South African Universities Power Engineering Conference, pp. 502–507, Southern Africa, January 2015.
[8] M. Arshad, S. M. Islam, and A. Khaliq, “Fuzzy logic approach in power transformers management and decision making,” IEEE Transactions on Dielectrics and Electrical Insulation, vol. 21, no. 5, pp. 2343–2354, 2014.
[9] G. K. Irungu, A. O. Akumu, and J. L. Munda, “Application of fuzzy logic and evidential reasoning methodologies in transformer insulation stress assessment,” IEEE Transactions on Dielectrics and Electrical Insulation, vol. 23, no. 3, pp. 1444–1452, 2016.
[10] E. T. Mharakurwa, G. N. Nyakoe, and A. O. Akumu, “Transformer remnant life estimation and asset management model based on insulation stress assessment,” in Proceedings of the IEEE 2019 Electrical Insulation Conference (EIC), Calgary, Alberta, Canada, June 2019.
[11] M. Arshad and S. M. Islam, “Significance of cellulose power transformer condition assessment,” IEEE Transactions on Dielectrics and Electrical Insulation, vol. 18, no. 5, pp. 1591–1598, 2011.
[12] N. A. Bakar and A. Siada, “Fuzzy logic approach for transformer remnant life prediction and asset management decision,” IEEE Transactions on Dielectrics and Electrical Insulation, vol. 23, no. 5, pp. 3199–3208, 2016.
[13] S. Forouhari and A. Siada, “Application of adaptive neuro fuzzy inference system to support power transformer life estimation and asset management decision,” IEEE Transactions on Dielectrics and Electrical Insulation, vol. 25, no. 3, pp. 845–852, June 2018.
[14] E. T. Mharakurwa and S. A. Juma, “A weighting factor-fuzzy logic-based transformer residual life estimation model,” in Proceedings of the 2021 IEEE PES/IAS Power Africa Conference, Nairobi, Kenya, August 2021.
[15] E. T. Mharakurwa, G. N. Nyakoe, and A. O. Akumu, “Transformer insulation degree of polymerization estimation through adaptive neuro fuzzy inference system Approach,” in Proceedings of the IEEE 2019 Electrical Insulation Conference (EIC), Calgary, Alberta, Canada, June 2019.
[16] R. A. Prasojo, K. Divyacitta, S. Suwarno, and H. Gumilang, “Transformer paper expected life estimation using ANFIS based on oil characteristics and dissolved gases (case study: Indonesian transformers),” Energies, vol. 10, no. 8, p. 1135, 2017.
[17] M. Duval, “A review of faults detectable by gas-in-oil analysis in transformers,” IEEE Electrical Insulation Magazine, vol. 18, no. 3, pp. 8–17, 2002.
[18] I. B. M. Taha, S. S. M. Ghoneim, and H. G. Zaini, “A fuzzy diagnostic system for incipient transformer faults based on DGA of the insulating transformer oils,” International Review of Economics Education, vol. 11, no. 3, pp. 305–313, 2016.
[19] N. Bakar, A. Siada, and S. Islam, “A review of dissolved gas analysis measurement and interpretation techniques,” IEEE Electrical Insulation Magazine, vol. 30, no. 3, pp. 39–49, 2014.
[20] S. S. M. Ghoneim, “Intelligent prediction of transformer faults and severities based on dissolved gas analysis integrated with thermodynamics theory,” IET Science, Measurement & Technology, vol. 12, no. 3, pp. 388–394, 2018.
[21] T. Kari, W. Gao, D. Zhao et al., “An integrated method of ANFIS and Dempster Shafer theory for fault diagnosis of power transformer,” IEEE Transactions on Dielectrics and Electrical Insulation, vol. 25, no. 1, pp. 360–371, 2018.
[22] O. E Gouda, S. M Saleh, and S. H. Elhoshy, “Power transformer incipient faults diagnosis based on dissolved gas analysis,” Indonesian Journal of Electrical Engineering and Computer Science, vol. 1, no. 1, pp. 10–16, 2016.
[23] H. C. Sun, Y. C. Huang, and C. M. Huang, “Fault diagnosis of power transformers using computational intelligence: a review,” Energy Procedia, vol. 14, pp. 1226–1231, 2012.
[24] N. K. Sharma, P. K. Tiwari, and Y. R. Sood, “Review of artificial intelligence techniques application to dissolved gas analysis on power transformer,” International Journal of Computer and Electrical Engineering, vol. 4, no. 3, pp. 577–582, 2011.
[25] L. Su, H. Huang, L. Qin, and W. Zhao, “Transformer vibration detection based on YOLOv4 and optical flow in background of high proportion of renewable energy access,” Frontiers in Energy Research, vol. 10, Article ID 764903, 2022.
[26] A. Bossi, J. E. Dind, and J. M. Frisson, “An international survey on failures in large power transformers,” Cigré Electra, vol. 88, pp. 21–48, 1983.
[27] J. Wang, X. Zhang, F. Zhang, J. Wan, L. Kou, and W. Ke, “Review on evolution of intelligent algorithms for transformer condition assessment,” Frontiers in Energy Research, vol. 10, Article ID 904109, pp. 1–15, 2022.
[28] K. Chen, J. Wang, C. Xie, and L. Yu, “A probabilistic model of lightning trip-out rate calculation for overhead contact lines,” in Proceedings of the 2021 IEEE 2nd China International Youth Conference on Electrical Engineering (CIYCEE), pp. 1–6, IEEE, Chengdu, China, December 2021.
[29] X. Zhang and E. Gockenbach, “Asset-management of transformers based on condition monitoring and standard diagnosis [feature article] diagnosis,” IEEE Electrical Insulation Magazine, vol. 24, no. 4, pp. 26–40, 2008.

[30] A. Teymouri and B. Vahidi, “CO2/CO concentration ratio: a complementary method for determining the degree of polymerization of power transformer paper insulation,” IEEE Electrical Insulation Magazine, vol. 33, no. 1, pp. 24–30, 2017.

[31] M. Duval, A. D. Pfab, I. A. Hoehlein, and M. Grisaru, “Significance and detection of very low degree of polymerization of paper in transformers,” IEEE Electrical Insulation Magazine, vol. 33, no. 1, pp. 31–38, 2017.

[32] M. Duval, “Transformers with low degree of polymerization of paper in transformers,” Transform Magazine, vol. 1, no. 3, pp. 26–31, 2014.

[33] B. Gorgan, P. V. Notingher, J. M. Wetzer et al., “Calculation of the remaining lifetime of power transformers paper insulation,” in Proceedings of the IEEE, International Conference on Optimization of Electrical and Electronic Equipment, pp. 293–300, Brasov, Romania, May 2012.

[34] A. Siada, S. P. Lai, and S. M. Islam, “A novel fuzzy-logic approach for furan estimation in transformer oil,” IEEE Transactions on Power Delivery, vol. 27, no. 2, pp. 469–474, 2012.

[35] P. K. Pandey, Z. Husain, and R. K. Jarial, “ANFIS based approach to estimate remnant life of power transformer by predicting furan contents,” International Journal of Electrical and Computer Engineering, vol. 4, no. 4, pp. 463–470, 2014.

[36] P. V. Notingher, L. V. Badicu, L. M. Dumitran, R. Setnescu, and T. Setnescu, “Transformer board lifetime estimation using activation energy,” in Proceedings of the IEEE 2011–XV International Symposium on Electromagnetic Fields in Mechatronics, Electrical and Electronic Engineering, Funchal, Portugal, 2011.

[37] A. Schaut, S. Autru, and S. Eeckhoudt, “Applicability of methanol as new marker for paper degradation in power transformers,” IEEE Transactions on Dielectrics and Electrical Insulation, vol. 18, no. 2, pp. 533–540, 2011.

[38] N. Ledekakis, D. Martin, W. Guo, J. Wijaya, and M. Lee, “A field study of two online dry-out methods for power transformers,” IEEE Electrical Insulation Magazine, vol. 28, no. 3, pp. 32–39, 2012.

[39] J. L. Velasquez-Contreras, M. A. S. Bobi, and S. A. Galceran, “General asset management model in the context of an electric utility: application to power transformers,” Electric Power Systems Research, vol. 81, no. 11, pp. 2015–2037, 2011.

[40] E. T. Mharakurwa and R. Goboza, “Multi-parameter-based fuzzy logic health index assessment for oil-immersed power transformers,” Advances in Fuzzy Systems, vol. 2019, Article ID 2647157, pp.1–12, 2019.

[41] “IEEE guide for the interpretation of gases generated in oil-immersed transformers,” IEEE Std C57.104-2008 (Revision of IEEE Std C57.104-1991), 2009.

[42] M. Duval and L. Lamarre, “The Duval pentagon - a new complimentary tool for the interpretation of dissolved gas analysis in transformers,” IEEE Electrical Insulation Magazine, vol. 30, no. 6, pp. 9–12, 2014.

[43] M. Duval, “Use of pentagons and triangles for the interpretation of DGA in electrical equipment,” in Proceedings of the TechCon North America Conference, Albuquerque, NM, USA, February 2016.

[44] S. A. Ward, “Evaluating transformer condition using DGA oil analysis,” in Proceedings of the 2003 Annual Report Conference on Electrical Insulation and Dielectric Phenomena, pp. 463–468, Albuquerque, NM, USA, October 2003.

[45] S. Corporation, Serveron White Paper: DGA Diagnostic Methods, S Corporation, Longmont, CO, USA, 2007.

[46] R. R. Rogers, “IEEE and IEC codes to interpret incipient faults in transformers, using gas in oil analysis,” IEEE Transactions on Electrical Insulation, vol. 13, no. 5, pp. 349–354, 1978.

[47] “IEEE guide for the detection and determination of generated gases in oil-immersed transformers and their relation to the serviceability of the equipment,” ANSI/IEEE Std C57.104, 1978.

[48] A. Abu-Siada and S. Islam, “A new approach to identify power transformer criticality and asset management decision based on dissolved gas-in-oil analysis,” IEEE Transactions on Dielectrics and Electrical Insulation, vol. 19, no. 3, pp. 1007–1012, 2012.

[49] M. Duval, “The Duval triangle for load tap changers, non-mineral oils and low temperature faults in transformers,” IEEE Electrical Insulation Magazine, vol. 24, no. 6, pp. 22–29, 2008.

[50] M. Duval and A. D. Pfab, “Interpretation of gas-in-oil analysis using new IEC publication 60599 and IEC TC 10 databases,” IEEE Electrical Insulation Magazine, vol. 17, no. 2, pp. 31–41, 2001.

[51] H. C. Sun, Y. C. Huang, and C. M. Huang, “A review of dissolved gas analysis in power transformers,” Energy Procedia, vol. 14, no. 1, pp. 1220–1225, 2012.

[52] T. K. Saha, “Review of modern diagnostic techniques for assessing insulation condition in aged transformers,” IEEE Transactions on Dielectrics and Electrical Insulation, vol. 10, no. 5, pp. 903–917, 2003.

[53] V. Miranda and A. Castro, “Improving the IEC table for transformer failure diagnosis with knowledge extraction from neural networks,” IEEE Transactions on Power Delivery, vol. 20, no. 4, pp. 2509–2516, 2005.

[54] “IEEE guide for loading mineral-oil-immersed transformers and step-voltage regulators,” IEEE Std C57.91-2011 (Revision of IEEE Std C57.91-1995), 2012.

[55] IEC, IEC 60076-2, power transformers-temperature rise, international electro-technical commission (IEC) std, IEC, Switzerland, 1993.

[56] G. Swift, T. Molinski, and W. Lohn, “A fundamental approach to transformer thermal modeling-Part I: theory and equivalent circuit,” IEEE Transactions on Power Delivery, vol. 16, no. 2, pp. 171–175, 2001.

[57] G. Swift, T. Molinski, R. Bray, and R. Menzies, “A fundamental approach to transformer thermal modeling-Part II: field verification,” IEEE Transactions on Power Delivery, vol. 16, no. 2, pp. 176–180, 2001.

[58] D. Susa, M. Lehtonen, and H. Nordman, “Dynamic thermal modelling of power transformers,” IEEE Transactions on Power Delivery, vol. 20, no. 1, pp. 197–204, 2005.

[59] M. Djamali and S. Tenbohlen, “A dynamic top oil temperature model for power transformers with consideration of the tap changer position,” in Proceedings of the 19th International Symposium on High Voltage Engineering (ISH), Pilsen, Czech Republic, January 2015.

[60] S. Tenbohlen and M. Djamali, “A dynamic top-oil temperature model for online assessment of overload capability of power transformers,” in Proceedings of the CIGRE SC A2 COLLOQUIUM 2015 Challenges of the future for transformers & other substation equipment, Shanghai, China, September 2015.

[61] D. Martin, Y. Cui, C. Ekanayake, H. Ma, and T. Saha, “An updated model to determine the life remaining of...
transformer insulation,” *IEEE Transactions on Power Delivery*, vol. 30, no. 1, pp. 395–402, 2015.

[62] Y. Cui, H. Ma, T. Saha, C. Ekanayake, and D. Martin, “Moisture dependent thermal modelling of power transformer,” *IEEE Transactions on Power Delivery*, vol. 31, no. 5, pp. 2140–2150, 2016.

[63] E. T. Mharakurwa, G. N. Nyakoe, and A. O. Akumu, “Power transformer hot spot temperatures estimation based on multi-attributes,” *International Journal of Applied Engineering Research*, vol. 7, pp. 1584–1592, 2019.

[64] S. Chakravorti, D. Dey, and B. Chatterjee, *Recent Trends in the Condition Monitoring of Transformers, Theory, Implementation and Analysis; Power Systems*, Springer-Verlag, Berlin, Germany, 2013.

[65] Y. Cui, H. Ma, and T. Saha, “Transformer hot spot temperature prediction using a hybrid algorithm of support vector regression and information granulation,” in *Proceedings of the IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, pp. 1–5, Australia, November 2015.

[66] A. Y. Arabul, F. K. Arabul, and I. Senol, “Experimental thermal investigation of an ONAN distribution transformer by fiber optic sensors,” *Electric Power Systems Research*, vol. 155, pp. 320–330, 2018.

[67] R. Godina, E. Rodrigues, J. Matias, and J. Catalao, “Effect of loads and other key factors on oil-transformer ageing: sustainability benefits and challenges,” *Energies*, vol. 8, no. 10, pp. 12147–12186, 2015.

[68] S. M. Strachan, S. M. D. Judd, and J. R. McDonald, “Incremental knowledge-based partial discharge diagnosis in oil-filled power transformers,” in *Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems*, pp. 6–12, Arlington, VA, USA, November 2005.

[69] S. Tenbohlen, S. Coenen, M. Djamali, A. Muller, M. Samimi, and M. Siegel, “Diagnostic measurements for power transformers,” *Energies*, vol. 9, no. 5, pp. 347–372, 2016.

[70] A. Akbari, P. Werle, H. Borsi, and E. Gockenbach, “Transfer function-based partial discharge localization in power transformers: a feasibility study,” *IEEE Electrical Insulation Magazine*, vol. 18, no. 5, pp. 22–32, 2002.

[71] I. Fofana and Y. Hadjadji, “Electrical-based diagnostic techniques for assessing insulation condition in aged transformers,” *Energies*, vol. 9, no. 9, pp. 679–705, 2016.

[72] S. Li and J. Li, “Condition monitoring and diagnosis of power equipment: review and prospective,” *High Voltage*, vol. 2, no. 2, pp. 82–91, 2017.

[73] I. M. K. Akihiko and M. Hikita, “Partial Discharge Detection and Induced Surface Current Analysis Using Transient Earth Voltage Method for High Voltage Equipment,” in *Proceedings of the 2016 International Conference on Condition Monitoring and Diagnosis (CMD)*, pp. 455–459, Xi’an, China, September 2016.

[74] J. S. Foo and P. S. Ghosh, “Artificial neural network modeling of partial discharge parameters for transformer oil diagnosis,” in *Proceedings of the Annual Report Conference on Electrical Insulation and Dielectric Phenomena*, pp. 470–473, Cancun, Mexico, October 2002.

[75] H. Zhang, T. R. Blackburn, B. T. Phung, and M. S. Naderi, “A novel wavelet de-noising method for on-site PD measurements on HV cables,” in *Proceedings of the International Symposium on Electrical Insulating Materials, (ISEIM 2005)*, vol. 3, no. 3, pp. 845–848, Kitakyushu, June 2005.

[76] H. Mingyou, H. Xie, T. B. Tiong, and X. Wu, “Study on a spatially selective noise filtration technique for suppressing noises in partial discharge on-line monitoring,” in *Proceedings of the 6th International Conference on Properties and Applications of Dielectric Materials*, vol. 2, pp. 689–692, Xi’an, China, June 2000.

[77] J. Shengchang, S. Ping, L. Yanning, X. Dake, and C. Junling, “The vibration measuring system for monitoring core and winding condition of power transformer,” in *Proceedings of the 2001 International Symposium on Electrical Insulating Materials, (ISEIM)*, pp. 849–852, Himeji, Japan, November 2001.

[78] P. Kang and D. Birtwhistle, “Condition assessment of power transformer onload tap-changers using wavelet analysis,” *IEEE Transactions on Power Delivery*, vol. 16, no. 3, pp. 394–400, 2001.

[79] P. Kang and D. Birtwhistle, “Condition assessment of power transformer on-load tap-changers using wavelet analysis and self-organizing map: field evaluation,” *IEEE Power Engineering Review*, vol. 22, no. 8, p. 69, 2002.

[80] P. M. Nirgude, B. Gunasekaran, C. Channakshева, A. D. Rajkumar, and B. P. Singh, “Frequency response analysis approach for condition monitoring of transformer,” in *Proceedings of the Annual Report Conference on Electrical Insulation and Dielectric Phenomena, CEIDP ’04*, pp. 186–189, Boulder, CO, USA, October 2004.

[81] Z. Wang, J. Li, and D. M. Sofian, “Interpretation of transformer FRA responses Part I: influence of winding structure,” *IEEE Transactions on Power Delivery*, vol. 24, no. 2, pp. 703–710, 2009.

[82] A. Manickam, S. Kamalasadan, D. Edwards, S. Simmons, and S. Simmons, “A novel self-evolving intelligent multiagent framework for power system control and protection,” *IEEE Systems Journal*, vol. 8, no. 4, pp. 1086–1095, 2014.

[83] S. D. J. McArthur, E. M. Davidson, V. M. Catterson et al., “Multi-agent systems for power engineering applications—Part I: concepts, approaches, and technical challenges,” *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1743–1752, 2007.

[84] S. M. Islam, T. Wu, and G. Ledwich, “Novel fuzzy logic approach to transformer fault diagnosis,” *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 7, no. 2, pp. 177–186, 2000.

[85] K. Tomsovíc, M. Tapper, and T. Ingvarsson, “A fuzzy information approach to integrating different transformer diagnostic methods,” *IEEE Transactions on Power Delivery*, vol. 8, no. 3, pp. 1638–1646, 1993.

[86] C. M. Q. Su, L. L. Lai, and P. Austin, “Fuzzy dissolved gas analysis method for the diagnosis of multiple incipient faults in a transformer,” *IEEE Transactions on Power Systems*, vol. 15, no. 2, pp. 593–598, 2000.

[87] M. Arshad and S. M. Islam, “A novel fuzzy logic technique for power transformer asset management,” in *Proceedings of the IEEE Industry Applications Conference Forty-First IAS Annual Meeting*, pp. 276–286, Tampa, FL, USA, October 2006.

[88] V. Duraisamy, N. Devarajan, D. Somasundareswari, A. A. M. Vasanth, and S. N. Sivanandam, “Neuro-fuzzy model for fault diagnosis in power transformer FRA responses Part I: influence of winding structure,” in *IEEE Transactions on Power Delivery*, vol. 24, no. 2, pp. 692–699, 2009.

[89] A. M. Corvo, “Expert system for the assessment of power transformers,” in *Proceedings of the IEEE Industry Applications Conference Forty-FirstIAS Annual Meeting*, pp. 276–286, Tampa, FL, USA, October 2006.
A. Abu-Siada, S. Hmood, and S. Islam, “A new fuzzy logic approach for consistent interpretation of dissolved gas-in-oil analysis,” *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 20, no. 6, pp. 2343–2349, 2013.

E. T. Mharakurwa, G. N. Nyakoe, and A. O. Akum, “Power transformer fault severity estimation based on dissolved gas analysis and energy of fault formation technique,” *Journal of Electrical and Computer Engineering (JECE)*, vol. 2019, Article ID 9674054, pp. 1–10, 2019.

Y. Zhang, X. Ding, Y. Liu, and P. J. Griffin, “An artificial neural network approach to transformer fault diagnosis,” *IEEE Transactions on Power Delivery*, vol. 11, no. 4, pp. 1836–1841, 1996.

O. Vanegas, Y. Mizuno, K. Naito, and T. Kaniya, “Diagnosis of oil-insulated power apparatus by using neural network simulation,” *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 4, no. 3, pp. 290–299, 1997.

J. L. Guardado, J. L. Naredo, P. Moreno, and C. R. Fuerte, “A comparative study of neural network efficiency in power transformers diagnosis using dissolved gas analysis,” *IEEE Transactions on Power Delivery*, vol. 16, no. 4, pp. 643–647, 2001.

W. M. Lin, C. H. Lin, and M. X. Tasy, “Transformer-fault diagnosis by integrating field data and standard codes with training enhanceable adaptive probabilistic networks,” *IEEE Proceedings - Generation, Transmission and Distribution*, vol. 152, no. 3, pp. 335–341, 2005.

C. L. H. Yang, J. Chou, and H. C. Jeng, “Fuzzy learning vector quantization networks for power transformer condition assessment,” *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 8, no. 1, pp. 143–149, 2001.

H. Wang, “A novel extension method for transformer fault diagnosis,” *IEEE Transactions on Power Delivery*, vol. 18, no. 1, pp. 164–169, 2003.

K. F. Thang, R. K. Aggarwal, A. J. McGrail, and D. G. Esp, “Analysis of power transformer dissolved gas data using the self-organizing map,” *IEEE Transactions on Power Delivery*, vol. 18, no. 4, pp. 1241–1248, 2003.

V. Miranda, A. R. G. Castro, and S. Lima, “Diagnosing faults in power transformers with auto-associative neural networks and mean shift,” *IEEE Transactions on Power Delivery*, vol. 27, no. 3, pp. 1350–1357, 2012.

A. j. Q. Carita, L. C. Leite, A. P. P. Medeiros, R. Barros, and L. Sauer, “Bayesian networks applied to failure diagnosis in power transformer,” *IEEE Latin America Transactions*, vol. 11, no. 4, pp. 1075–1082, 2013.

W. H. Tang, K. Spurgeon, Q. H. Wu, and Z. J. Richardson, “An evidential reasoning approach to transformer condition assessments,” *IEEE Transactions on Power Delivery*, vol. 19, no. 4, pp. 1696–1703, 2004.

K. Spurgeon, W. H. Tang, Z. Richardson, Q. Wu, and G. Moss, “Dissolved gas analysis using evidential reasoning,” *IEE Proceedings - Science, Measurement and Technology*, vol. 152, no. 3, pp. 110–117, 2005.

X. L. Wang, Q. M. Li, C. R. Li, R. Yang, and Q. Su, “Reliability assessment of the fault diagnosis methodologies for transformers and a new diagnostic scheme based on fault information integration,” *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 20, no. 6, pp. 2292–2298, 2013.

J. I. Aizpurua, B. G. Stewart, S. D. J. McArthur, B. Lambert, J. G. Cross, and V. M. Catterson, “Improved power transformer condition monitoring under uncertainty through soft computing and probabilistic health index,” *Applied Soft Computing*, vol. 85, Article ID 105530, 2019.

J. I. Aizpurua, V. M. Catterson, B. G. Stewart, S. D. J. McArthur, B. Lambert, and J. G. Cross, “Uncertainty-aware fusion of probabilistic classifiers for improved transformer diagnostics,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 1, pp. 621–633, 2021.

J. I. Aizpurua, S. D. J. McArthur, B. G. Stewart, B. Lambert, J. G. Cross, and V. M. Catterson, “Adaptive power transformer lifetime predictions through machine learning and uncertainty modeling in nuclear power plants,” *IEEE Transactions on Industrial Electronics*, vol. 66, no. 6, pp. 4726–4737, 2019.

D. Dey, B. Chatterjee, S. Chakravorti, and S. Munshi, “Importance of denoising in dielectric response measurements of transformer insulation: an uncertainty analysis based approach,” *Measurement*, vol. 43, no. 1, pp. 54–66, 2010.

H. Ma, T. K. Saha, S. Member, and C. E. Member, “Predictive learning and information fusion for condition assessment of power transformer,” in *Proceedings of the 2011 IEEE Power and Energy Society General Meeting*, pp. 1–8, Detroit, MI, USA, July 2011.

A. Akbari, A. Setayeshmehr, H. Borsi, E. Gockenbach, and I. Fofana, “Intelligent agent-based system using dissolved gas analysis to detect incipient faults in power transformers,” *IEEE Electrical Insulation Magazine*, vol. 26, no. 6, pp. 27–40, 2010.

S. Li, H. Ma, T. Saha, and G. Wu, “Bayesian information fusion for probabilistic health index of power transformer,” *IET Generation, Transmission & Distribution*, vol. 12, no. 2, pp. 279–287, 2018.

Y. Liang, K. J. Li, L. Niu et al., “An integrated three-level transformer condition assessment model based on optimal weights and uncertainty theory,” in *Proceedings of the 2013 IEEE Industry Applications Society Annual Meeting*, pp. 1–7, Lake Buena Vista, FL, October 2013.

D. Chen and Y. Yang, “Attribute reduction for heterogeneous data based on the combination of classical and fuzzy rough set models,” *IEEE Transactions on Fuzzy Systems*, vol. 22, no. 5, pp. 1325–1334, 2014.

R. Liao, Y. Zhang, L. Yang, H. Zheng, and X. She, “A cloud and evidential reasoning integrated model for insulation condition assessment of high voltage transformers,” *International Transactions on Electrical Energy Systems*, vol. 24, no. 7, pp. 913–926, 2014.

R. Liao, H. Zheng, S. Grzybowski, L. Yang, Y. Zhang, and Y. Liao, “An integrated decision-making model for condition assessment of power transformers using fuzzy approach and evidential reasoning,” *IEEE Transactions on Power Delivery*, vol. 26, no. 2, pp. 1111–1118, 2011.

G. Lv, H. Cheng, H. Zhai, and L. Dong, “Fault diagnosis of power transformer based on multi-layer SVM classifier,” *Electric Power Systems Research*, vol. 75, no. 1, pp. 9–15, 2005.

S. W. Fei and Y. Sun, “Forecasting dissolved gases content in power transformer oil based on support vector machine with genetic algorithm,” *Electric Power Systems Research*, vol. 78, no. 3, pp. 507–514, 2008.

R. Liao, H. Zheng, S. Grzybowski, L. Yang, C. Tang, and Y. Zhang, “Fuzzy information granulated particle swarm optimisation-support vector machine regression for the trend forecasting of dissolved gases in oil-filled transformers,” *IET Electric Power Applications*, vol. 5, no. 2, pp. 230–237, 2011.

T. F. Lee, M. Y. Cho, and F. M. Fang, “Features selection of SVM and ANN using particle swarm optimization for power transformer’s incipient fault symptom diagnosis,” *Journal of Electrical and Computer Engineering*, vol. 2019, Article ID 9674054, pp. 1–10, 2019.
20 Journal of Electrical and Computer Engineering

[119] X. Hao and S. C. xin, “Artificial immune network classification algorithm for fault diagnosis of power transformer,” *IEEE Transactions on Power Delivery*, vol. 22, no. 2, pp. 930–935, 2007.

[120] W. Xu, Z. Zhou, H. Chen, and D. Wang, “Fault diagnosis of power transformers: application of fuzzy set theory, expert systems and artificial neural networks,” *IEE Proceedings - Science, Measurement and Technology*, vol. 144, no. 1, pp. 39–44, 1997.

[121] Z. Wang, Y. Liu, and P. Griffin, “A combined ANN and expert system tool for transformer fault diagnosis,” *IEEE Transactions on Power Delivery*, vol. 13, no. 4, pp. 1224–1229, 1998.

[122] D. Morais and J. Rolim, “A hybrid tool for detection of incipient faults in transformers based on the dissolved gas analysis of insulating oil,” *IEEE Transactions on Power Delivery*, vol. 21, no. 2, pp. 673–680, 2006.

[123] R. Naresh, V. Sharma, and M. Vashisth, “An integrated neural fuzzy approach for fault diagnosis of transformers,” *IEEE Transactions on Power Delivery*, vol. 23, no. 4, pp. 2017–2024, 2008.

[124] D. Bhalla, R. K. Bansal, and H. O. Gupta, “Integrating AI based DGA fault diagnosis using Dempster-Shafer theory,” *International Journal of Electrical Power & Energy Systems*, vol. 48, no. 4, pp. 31–38, 2013.

[125] H. Malik, A. K. Yadav, S. Mishra, and T. Mehto, “Application of Neuro-Fuzzy scheme to investigate the winding insulation paper deterioration in oil-immersed power transformer,” *International Journal of Electrical Power & Energy Systems*, vol. 53, no. 1, pp. 256–271, 2013.

[126] G. K. Irungu and A. O. Akumu, “Application of dissolved gas analysis in assessing degree of healthiness or faultiness with fault identification in oil-immersed equipment,” *Energies*, vol. 13, no. 18, p. 4770, 2020.

[127] K. Meng, Z. Y. Dong, D. H. Wang, and K. P. Wong, “A self-adaptive RBF neural network classifier for transformer fault analysis,” *IEEE Transactions on Power Systems*, vol. 25, no. 3, pp. 1350–1360, 2010.

[128] Y. C. Huang and C. M. Huang, “Evolving wavelet networks for power transformer condition monitoring,” *IEEE Transactions on Power Delivery*, vol. 17, no. 2, pp. 412–416, 2002.

[129] Y. C. Huang, “A new data mining approach to dissolved gas analysis of oil insulated power apparatus,” *IEEE Transactions on Power Delivery*, vol. 18, no. 4, pp. 1257–1261, 2003.

[130] A. Naderian, S. Cress, R. Piercy, F. Wang, and J. Service, “An approach to determine the health index of power transformers,” in *Proceedings of the Conf Rec 2008 IEEE Int Symposium in Electrical Insulation (IEEE)*, pp. 192–196, Canada, June 2008.

[131] J. Jahromi, R. Piercy, S. Cress, J. Service, and W. Fan, “An approach to power transformer asset management using health index,” *IEEE Electrical Insulation Magazine*, vol. 25, no. 2, pp. 20–34, 2009.

[132] R. J. H. A. M. Emsley, X. Xiao, and M. Ali, “Degradation of Cellulosic insulation in power transformers, Part 2: formation of furan products in insulating oil,” *IEEE Proceedings - Science, Measurement and Technology*, vol. 147, pp. 110–114, 2000.

[133] L. E. Lundgaard, W. Hansen, D. Linhjell, and T. Painter, “Aging of oil-impregnated paper in power transformers,” *IEEE Transactions on Power Delivery*, vol. 19, no. 1, pp. 230–239, 2004.

[134] L. Cheim, D. Platts, T. Prevost, and S. Xu, “Furan analysis for liquid power transformers,” *IEEE Electrical Insulation Magazine*, vol. 28, no. 2, pp. 8–21, 2012.

[135] D. Pandurangaih, C. Reddy, T. P. Govindan, M. Mandlik, and T. S. Ramu, “Estimation of remaining life of power transformers,” in *Proceedings of the Conference Record of the 2008 IEEE International Symposium on Electrical Insulation*, pp. 243–246, Vancouver, Canada, June 2008.

[136] A. Abu-Siada, S. P. Lai, and S. Islam, “Remnant life estimation of power transformer using oil UV-Vis spectral response,” in *Proceedings of the IEEE/PES Power Systems Conference and Exposition*, pp. 1–5, Seattle, WA, USA, April 2009.

[137] N. A. Baka, A. Siada, S. Islam, and M. F. E. Naggar, “A new technique to measure interfacial tension of transformer oil using UV-Vis spectroscopy,” *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 22, no. 2, pp. 1275–1282, 2015.

[138] L. Chmura, P. H. F. Morshuis, J. J. Smit, and A. Janssen, “Life-data analysis for condition assessment of high-voltage assets,” *IEEE Electrical Insulation Magazine*, vol. 31, no. 5, pp. 33–43, 2015.

[139] R. A. Jongen, P. F. Morshuis, E. Gulsik, J. Smit, J. Maksymiuk, and A. J. Janssen, “Application of statistical methods for making maintenance decisions within power utilities,” *IEEE Electrical Insulation Magazine*, vol. 22, no. 6, pp. 24–35, 2006.

[140] E. Ramasso and R. Gouriveau, “Remaining useful life estimation by classification of predictions based on a neuro-fuzzy system and theory of belief functions,” *IEEE Transactions on Reliability*, vol. 63, no. 2, pp. 555–566, 2014.

[141] B. Jang, M. H. Kim, J. Baek, W. Kim, and W. Lee, “Highly sensitive hydrogen sensors: Pd-coated Si nanowire arrays for detection of dissolved hydrogen in oil,” *Sensors and Actuators B: Chemical*, vol. 273, pp. 809–814, 2018.

[142] Z. Mao and J. Wen, “Detection of dissolved gas in oil-insulated electrical apparatus by photoacoustic spectroscopy,” *IEEE Electrical Insulation Magazine*, vol. 31, no. 4, pp. 7–14, 2015.

[143] J. Fan, C. Fu, H. Yin, Y. Wang, and Q. Jiang, “Power transformer condition assessment based on online monitor with SOFC chromatographic detector,” *International Journal of Electrical Power & Energy Systems*, vol. 118, Article ID 105805, 2020.

[144] J. Fan, F. Wang, Q. Sun, F. Bin, H. Ye, and Y. Liu, “An online monitoring system for oil immersed power transformer based on SnO2 GC detector with a new quantification approach,” *IEEE Sensors Journal*, vol. 17, no. 20, pp. 6662–6671, 2017.

[145] H. Ma, T. K. Saha, C. Ekanayake, and D. Martin, “Smart transformer for smart grid – intelligent framework and techniques for power transformer asset management,” *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 1026–1034, 2015.

[146] C. Hunziker, J. Lehmann, T. Keller, T. Heim, and N. Schulz, “Sustainability assessment of novel transformer technologies in distribution grid applications,” *Sustainable Energy, Grids and Networks*, vol. 21, Article ID 100314, 2020.