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A Comprehensive Review of Transformer Fault Detection Using Machine Learning and Diagnostic Techniques

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ABSTRACT:

Fault detection and diagnosis (FDD) in power transformers plays a critical role in ensuring the reliability and safety of modern power systems. Recent developments in this field emphasize the integration of advanced monitoring technologies and sophisticated data analysis techniques. By adopting effective FDD approaches, power utilities can avoid expensive repairs, reduce system downtime, and boost overall system dependability. This study presents a comprehensive review of transformer FDD, with a particular focus on the use of machine learning and hybrid methodologies. A structured and systematic approach was employed to collect, screen, and evaluate relevant literature from the Scopus database. Tools such as VOSviewer and Bibliometrix were used to analyze and visualize the results. The findings reveal significant advancements in transformer fault detection, transitioning from conventional methods like Dissolved Gas Analysis (DGA) to modern machine learning techniques, including Random Forest and Convolutional Neural Networks (CNN). Moreover, hybrid models that integrate machine learning with optimization algorithms have enhanced detection accuracy. Innovations like optical sensors have enabled real-time fault monitoring capabilities. Despite these advancements, challenges such as data limitations and model complexity persist. This review contributes by examining the application of machine learning in transformer fault detection, highlighting hybrid techniques that blend traditional diagnostics like DGA with modern computational models. It also identifies emerging research trends, recurring themes, and existing gaps, providing valuable insights and recommendations for future research aimed at improving diagnostic accuracy and real-time monitoring systems.

Keywords: Transformer Fault Detection, Machine Learning, Hybrid Diagnostic Methods

Introduction

Machine learning (ML) is an increasingly prominent branch of computer science that empowers computers to learn and enhance their performance automatically through experience, without the need for explicit programming instructions [1], [2]. Positioned at the crossroads of computer science, statistics, and artificial intelligence, ML finds applications across diverse sectors such as healthcare, manufacturing, and finance [3].

ML algorithms are typically divided into four categories: **supervised**, **unsupervised**, **semi-supervised**, and **reinforcement learning** [4]. These algorithms are designed to detect patterns, classify data, and make predictions using both historical and real-time data [5]. Many of these techniques are inspired by biological processes, notably **artificial neural networks**, which are modeled after the functioning of the human brain's neurons [6].

The rapid advancement of machine learning has been fueled by breakthroughs in algorithm design, the growing availability of data, and enhanced computational capabilities [3]. Its strength lies in managing complex tasks that are difficult to address through traditional programming, leading to its adoption in areas such as **email filtering**, **computer vision**, and **cybersecurity** [7].

In the field of **power systems**, ML has garnered substantial interest due to its capacity to tackle nonlinear problems and process large datasets effectively [8], [9]. It has been successfully applied to tasks like **load forecasting**, **power quality assessment**, **system resilience analysis**, and the **integration of renewable energy sources** [10], [11]. Compared to conventional analytical methods, ML techniques offer significant advantages, especially in managing the complexities introduced by renewable energy and power electronic devices [12].

Machine Learning Algorithms

Machine learning algorithms have shown significant effectiveness in various power system applications such as **customer clustering**, **electricity price forecasting**, **predicting system dynamics**, and **optimal load flow** [9]. Their integration in power systems enhances observability, boosts operational efficiency, and supports data-driven decision-making processes [13], [14]. However, experts advocate for a hybrid approach—**combining data-driven models with traditional physics-based (model-driven) methods**—to achieve optimal performance in power system analysis [15].

In this context, **power transformers** emerge as critical and high-cost components in electrical networks, essential for enabling voltage transitions in both transmission and distribution systems [16], [17]. Their reliability is paramount, as failures may result in service interruptions, costly repairs, and potential environmental hazards [18]. Therefore, **condition monitoring** and **diagnostic techniques** are vital to avoid unexpected breakdowns, extend operational life, and improve maintenance planning [19].

A wide range of sensors and techniques—including electrical, mechanical, optical, chemical, and acoustic methods—are employed to monitor transformer parameters [20]. Among these, **Dissolved Gas Analysis (DGA)** stands out as a commonly used diagnostic method for detecting early-stage faults in oil-immersed transformers [21], [22]. Although traditional DGA approaches have limitations, **artificial intelligence (AI)** and **machine learning** techniques have significantly improved diagnostic accuracy [23].Recent developments have explored **fuzzy logic**, **neural networks**, and **meta-heuristic algorithms** to enhance DGA interpretations [24], [3]. Furthermore, **IoT** and **cloud computing** technologies have enabled real-time transformer condition monitoring [25]. Effective diagnostics help evaluate transformer health and guide optimal maintenance strategies [26], [27].

Case studies have shown that DGA, especially when used alongside other diagnostic tools, effectively identifies transformer faults [28]. It remains a vital technique by analyzing gases dissolved in transformer oil [29]. Several DGA interpretation methods—such as **Total Dissolved Combustible Gas (TDCG)**, **Roger's Ratio**, **Duval Triangle**, and **key gas analysis**—are used to predict the type and severity of faults [30], [31].To overcome the limitations of traditional DGA, researchers have introduced **hybrid techniques**, such as combining **fuzzy logic with evidential reasoning** and implementing **machine learning algorithms like Support Vector Machines (SVM)** [32]. For example, one comparative study found the **three-ratio method** to be 90% accurate, while another hybrid model achieved 97.42% accuracy in identifying fault types and 90.59% in determining fault severity [19], [33]. DGA has also been widely used in **hydropower plants** to evaluate transformer oil quality and correlate findings with operating conditions [34].

Multiple advanced approaches have been proposed, including **hybrid models** that integrate traditional diagnostics with machine learning [35], [36]. Comparisons between standard ML algorithms and **automated machine learning (AutoML)** approaches reveal that robust AutoML systems handle imbalanced datasets effectively [37]. Many ML algorithms demonstrate high accuracy in predicting transformer health parameters [38], and optimized neural networks have further improved performance [39].

Additionally, hybrid models such as **extended Kalman filters combined with SVM** and **ensemble techniques** like **bagged tree classifiers** paired with conventional preprocessing steps have shown promising outcomes [40], [41]. Various comparative studies on machine learning classifiers aim to identify the most effective algorithms for transformer fault diagnosis [42]. Despite notable progress, a significant research gap remains. Most existing studies focus on individual methods, and a comprehensive review consolidating recent developments is lacking. A **systematic evaluation of the latest techniques** for transformer fault detection and diagnosis could provide deeper insights into current capabilities and future improvement areas.

Transformer fault categorization

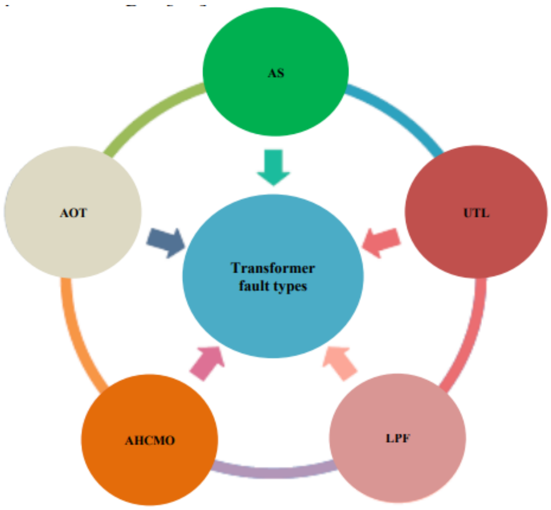
Transformer faults can generally be divided into **internal** and **external** categories, with **internal faults** being significantly more critical due to their potential to result in severe damage, extended outages, and costly repairs [43]. Internal faults typically arise within the windings or insulation system of the transformer and may include **turn-to-ground**, **turn-to-turn**, **phase-to-phase**, or **inter-turn insulation failures**. Among these, turn-to-ground and turn-to-turn faults are particularly dangerous because they can escalate quickly into complete transformer failure if not detected and mitigated promptly. Advanced modeling techniques, such as **Finite Element Analysis (FEA)** and **Discrete Wavelet Transforms (DWT)**, have been employed to simulate and analyze the behavior of these faults under different operating conditions [44], [45]. These methods help in understanding the fault initiation mechanisms, transient behaviors, and electrical signatures associated with various internal fault scenarios.

One of the critical aspects of transformer protection is the **accurate calculation of fault current**. Fault current values must be precisely estimated, not only based on the transformer's own impedance characteristics but also considering the interaction with the surrounding power system, such as upstream and downstream network elements, protection settings, and load conditions [46]. Accurate fault current computation ensures that **protective relays and circuit breakers** operate correctly and promptly during fault events, thereby minimizing damage and system disruption.

To enhance transformer reliability and prevent catastrophic failures, **regular diagnostic testing**, **predictive maintenance**, and **continuous condition monitoring** are essential practices. These methods help in identifying **incipient faults**—those that are in their early stages and not yet causing observable performance degradation—before they develop into serious issues [47], [18]. Technologies such as **Dissolved Gas Analysis (DGA)**, **partial discharge measurement**, **thermal imaging**, and **vibration analysis** are frequently used for this purpose. In recent years, the integration of **smart sensors**, **Internet of Things (IoT)** devices, and **real-time monitoring platforms** has further improved the early detection capabilities for internal transformer faults, enabling data-driven decisions and condition-based maintenance strategies.

Overall, the classification, modeling, and early detection of internal faults are fundamental to transformer health assessment. Advancements in fault simulation techniques and the growing role of data analytics and intelligent systems are contributing significantly to the development of robust protection schemes and improved operational resilience in power transformers.

Figure 1 Transformer fault categorization



Transformer faults can be broadly categorized into several types, each associated with specific symptoms and underlying causes. Common fault categories include **Abnormal Sound (AS)**, which may indicate internal arcing or mechanical displacement; **Abnormal Oil Temperature (AOT)**, which often results from insulation degradation or overloading; **Abnormal Height and Colour of Mineral Oil (AHCMO)**, suggesting potential contamination, oxidation, or oil leakage; Unbalanced Three-Phase Load (UTL), which can lead to uneven thermal stresses; and Lead Part Faults (LPF), typically caused by mechanical loosening or aging of connection leads [74]. In addition to these faults, abnormal conditions such as excessive oil temperature or oil quality deterioration are also frequently observed and can significantly impact transformer performance and lifespan [75].

To identify and diagnose these faults, a range of diagnostic methods is employed. Among them, Dissolved Gas Analysis (DGA) is widely used for detecting incipient faults in oil-immersed transformers, as it identifies gases generated by thermal and electrical stresses inside the transformer [76]. Specialized DGA techniques have been developed for different transformer components, including on-load tap changers (OLTCs), and are also applicable to transformers using non-mineral insulating oils, such as ester-based or synthetic fluids.

Both online and offline monitoring systems play a critical role in early fault detection, allowing maintenance teams to address issues before they escalate into severe failures. Online monitoring enables continuous real-time surveillance of critical parameters, while offline diagnostic testing is used during scheduled maintenance for in-depth analysis [77].**Regular electrical diagnostic testing**, such as insulation resistance testing, polarization index measurement, and tan delta testing, is crucial for maintaining transformer health and extending operational life [78].Recent advancements in transformer diagnostics include the adoption of **gas-to-liquid (GTL) oils**, which have demonstrated superior resistance to thermal aging and improved performance under fault conditions when compared to conventional mineral oils [79]. These alternative insulating fluids offer better stability, longer service life, and lower environmental impact.

Moreover, **artificial intelligence (AI)** and **machine learning techniques** are increasingly being integrated into transformer diagnostics. These intelligent systems can analyze large volumes of monitoring data to detect patterns, classify fault types, and provide predictive maintenance recommendations with high accuracy [75]. The ongoing research in this area aims to enhance diagnostic precision, reduce false alarms, and optimize maintenance strategies, thereby ensuring improved reliability and efficiency in power transformer operations.

Conclusion

This review paper has provided a comprehensive analysis of fault detection and diagnosis (FDD) in power transformers, emphasizing their critical role in ensuring the reliability and safety of electrical power systems. Traditional techniques like Dissolved Gas Analysis (DGA) remain widely used, but recent advancements in artificial intelligence and machine learning have significantly improved diagnostic accuracy and real-time fault detection. Various algorithms, including Random Forest, Support Vector Machines, Convolutional Neural Networks, and hybrid models, have demonstrated effectiveness in identifying fault types and severities. Moreover, the integration of modern monitoring systems, use of advanced sensor technologies, and adoption of alternative insulating materials such as gas-to-liquid (GTL) oils have further enhanced transformer diagnostics. While challenges such as data limitations and model complexity persist, ongoing research and the combination of conventional and intelligent methods show strong potential for improving transformer health monitoring and maintenance strategies.

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