Transformer Fault Diagnosis Techniques: A Review

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Abstract - The efficient transmission and distribution of electricity, as well as the overall operation of the power system, are dependent on the transformer. The study lays out the history of transformer failure detection methods and gives an overview of them. A large number of academics have sought to improve upon these time-honoured techniques by using smart technologies like support vector machines, neural networks, and machine learning. A new approach and technology for the safe and dependable operation and routine maintenance of power systems are provided by combining transformer fault prediction with a machine learning algorithm. This helps maintenance personnel of power systems to accurately predict the running state of power equipment.

Indexed Terms- Transformer Fault Diagnosis, Machine Learning, Support Vector Machine.

I. INTRODUCTION

The operation of contemporary power systems is predicated on the safe, high-quality, and cost-effective delivery of electric energy. The transformer, being an essential piece of machinery for both the electrical grid and the national grid, comes in a variety of forms, may be used in different ways, and is widely used. In order to distribute electric energy and accomplish voltage changes, it is essential to have this equipment in the power system. The power system transformer has a greater failure probability than other power equipment due to the lengthy periods of operation under load. Meanwhile, cross-regional networking and dispatching are becoming increasingly common as a result of China's present power grid system's upgrade. A local chain reaction in a specific electrical grid can easily arise if the transformer problem is not identified and fixed in a timely manner. Because of this, power grid personnel must perform transformer fault detection and diagnostics everyday to aid in the repair process prior to transformer problems [1].

Prevention of safety accidents and improvements in the power market have been greatly aided by early defect diagnostic methods for transformers, such as dissolved gas analysis (DGA), vibration analysis, impulsive voltage waveform testing, and preventative electrical tests [2]; Lu et al. [3]. Unfortunately, the diagnostic accuracy is sometimes compromised by the limits of these conventional methods in terms of the amount and precision of diagnostic features under certain situations. This means they can't keep up with the ever-changing needs for power transformer diagnostics.

Intelligent transformer diagnostics has been the subject of much study in an effort to circumvent these shortcomings of conventional diagnostic procedures [4,5]. Algorithms powered by AI are very good at learning and processing large datasets. By analysing large amounts of transformer failure data, these algorithms can make accurate predictions and analyses, solving problems with traditional diagnostic approaches including missing data and a lack of clarity in the link between characteristics and defects. Particularly useful in transformer diagnostics, the result is a considerable improvement in the precision of detection and diagnosis. Fault detection in transformers has made use of a number of methods, such as neural networks [6], support vector machines [7], machine learning [8], and others. Using these smart algorithms in conjunction with more conventional approaches is still not without its difficulties, though, because of the intricacy of transformer internal systems and external surroundings [9]. Consequently, scientists have optimised algorithms and improved feature extraction techniques to reduce measurement noise and make intelligent diagnostic methods more flexible for different types of transformers [10], which has contributed to the rapid advancement of these technologies. However, with the development of AI technology, the idea of integrating several diagnostic procedures has surfaced.

Intelligent diagnosis technology, according to Taneja's [11] DGA evaluation, should include a thorough diagnosis including several characteristic criteria rather than being limited to a single approach. In his study on the transformer insulation system's health index, Badawi [12] found that a comprehensive analysis of several characteristics (e.g., DGA, winding resistance, acidity, moisture content of the insulation oil, etc.) yielded significantly more accurate results than a single DGA verification. A more precise estimate of the health index was achieved by combining data from many sources using a transformer detecting system. Thus, intelligent transformer failure detection is moving in the direction of multi-source information integration, making use of the data gathering, analysis, and processing capabilities of such technology. An improved level of protection for the transformer may be achieved with the use of diagnostic technology that integrates data from several sources, which allows for the efficient and precise identification of various fault types [13]. This highlights the need of continuing to study and develop technologies for diagnosing transformer faults, which will help improve the power system's stability and dependability.

II. TRANSFORMER FAULT DIAGNOSIS

Interturn problems in the windings, dampness, overheating, winding open, grounding, mechanical failure, and other failures are common in power transformers; Connectors that are loose, short circuits, damp, lead breaks, and other issues on the terminal row; Cracks, wetness, low oil level, flange grounding, and other defects in the aged casing; Core lamination short circuits, loose components, and faulty insulation are all examples of core insulation issues. Various problems might arise with the tap switch, including mechanical failure, overheating, lead failure, electrical failure, physical damage, and more. [1]. The foundation of diagnosis is fault detection in transformers, which encompasses both classic off-line detection and new on-line monitoring methods. One of the most frequent ways to avoid power transformer failure is using an off-line detection system, which is also the most visible one in the field. In comparison to more traditional detection methods, online monitoring allows for real-time attention to the transformer's fault state, allowing for early diagnosis and treatment. [1].

In order to keep tabs on monitoring data and the health state of transformers, fault detection is crucial [14,15]. The insulating material decompresses during transformer operation to release gases due to environmental influences; the particular gas content increases after transformer failure. Gases such as CH_4, C_2H_2, C_2H_4, C_2H_6, CO, CO_2, H_2, etc. are members of the characteristic gas class [16]. The amount of gas decomposed by insulating materials is negligible under typical operating conditions. However, when the power transformer is not functioning properly in the power system, the accelerated decomposition and ageing of the oil and solid insulating materials causes an increase in the current and temperature within the transformer, which in turn causes a change in the content of dissolved gas in the oil [17]. The operational status of a transformer may be effectively assessed by tracking and analysing the concentration of dissolved gas in the transformer oil [18]. The Chinese power system's transformer fault analysis has made extensive use of dissolved gas analysis in oil (DGA), the principal method of transformer fault detection [19].

The conventional approach to transformer failure diagnostics involves summarising data from ongoing experimental research and then analysing dissolved gas. Methods for identifying typical gases and ratios are the mainstays of traditional transformer failure diagnostics. An old-fashioned technique for diagnosing transformer faults, the characteristic gas identification method relies on the type of gas that is dissolved in the fluid. The basic idea behind this approach is that different types of transformer faults have different degrees of influence on the insulating material's main dissolved gas composition and secondary gas composition in the transformer oil. By studying the transformer fault, one can determine the difference in the dissolved gas composition [18].

An old-fashioned way for diagnosing transformer faults using the ratio approach is to look at the oil's gas proportions. Instead of utilising the coding that corresponds to the dissolved gas ratio interval, the uncoded ratio approach directly utilises a specific ratio range that corresponds to a certain sort of transformer malfunction. The ratio method's failure to account for the relatively modest likelihood throughout statistical analysis of a large number of transformer breakdowns makes it an inaccurate tool for analysing these problems [18]. That being said, there have been some successes with the aforementioned conventional approaches to transformer problem diagnostics. Most of them, nevertheless, use hard-coded weights and thresholds that don't reflect the interplay between performance, defect features, and objective laws very well. More and more machine learning algorithms are being used for transformer failure diagnostics as a result of the fast advancement of science and technology. Consequently, it is crucial to employ smart algorithms in conjunction with conventional techniques of transformer diagnosis in order to achieve rapid and precise intelligent diagnosis and to anticipate potential future transformer defects using the adaptable DGA approach. A few examples are ANNs [20], SVMs [21], Bayesian networks [22], and random forests [23] among others. An enhanced Grasshopper optimisation algorithm-based transformer defect diagnostic model was suggested by Li et al. [24].Support Vector Machine with Optimisation (SVM). To fine-tune SVM's kernel function parameters and penalty coefficient, we turned to the improved Grasshopper Optimisation Algorithm (IGOA). The usefulness and superiority of IGOA-SVM in recognising transformer failure states were validated by comparing it with PSO-SVM and GOA-SVM. The model was developed in the SVM optimised by the oil-based IGOA algorithm and is based on Dissolved Gas Analysis (DGA). In order to increase the estimation accuracy by over 0.1 using a sequential Kalman filter, DemirciMerve et al. [25] integrated gas data categorised by a machine learning technique with a sensor fusion approach. In order to construct a model for transformer problem diagnostics, Hu [26] et al. employed the slime mould algorithm (SMA) to determine the characteristic wavelength of the oil fluorescence spectra of transformers. They utilised SMA to screen the characteristic wavelength of transformer oil LIF spectra and utilised it for fault detection of transformers after demonstrating its benefit in screening fluorescence spectra of transformer oil. The cloud computing approach was used by Liu Rongsheng et al. [27] to compare chromatographic data with electrical test data of transformers, combining the benefits of neural networks and evidence theory. We provide a cloud-based evidence theory and multi-neural network–based comprehensive fault diagnostic approach for transformers.

Looking at the broken transformer is a good way to gauge how well it detects faults. Through the comparison of various types of data, the findings demonstrate that the suggested technique may enhance the diagnostic reliability and accuracy in comparison to the conventional single data alignment. One of the most fundamental pieces of nuclear power system equipment is the transformer, which must be more secure, of higher quality, and more cost-effective for the current power system to function. Unfortunately, the present power grid system upgrade in China cannot be met by the outdated, unreliable, and impractical methods of fault detection and diagnostics used in transformers. To ensure that power grid personnel can fix transformers before a fault happens—a crucial guiding importance for the power system—daily fault detection and diagnostics is a vital component of the power grid. That is why there has to be more study and development into using machine learning techniques to diagnose transformer faults [1].

III. TRANSFORMER FAULT TYPES

Knowing the many types of transformer problems and what causes them is essential for accurate diagnosis. Power transformer capacity is always rising to satisfy market demands as the power industry develops. Establishing a proper maintenance plan is vital to maintain ongoing functioning. While investigating what goes wrong, Kumar et al. [28] divided transformer failure mechanisms into three categories: electrical, mechanical, and thermal. External, ground, interphase short-circuit, and interturn faults are some subcategories of these problems [29]. Winding distortion, ageing insulating oil, overheating, system overload, design flaws, and other issues are common causes of these failures (Figure 1). One way to better understand the goals and methods of transformer fault diagnostics is to categorise transformer failures and examine their causes.

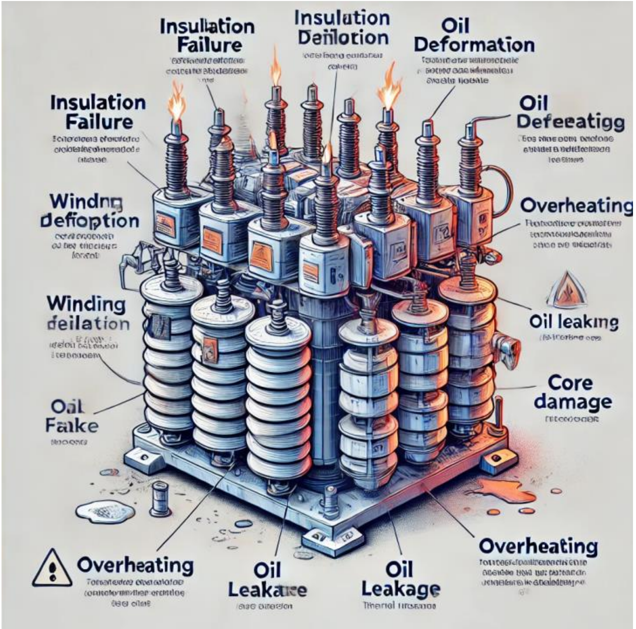

Figure 1: Transformer Faults

External Faults

When we talk about transformers having external faults, we usually mean problems with the power grid or the connecting line. Issues like these can develop when the external power transformer, transmission lines, or other components linked to it malfunction. Other examples of external problems are power system overloads and overvoltages induced by lightning strikes [30]. As an example, the transformer can be damaged by the overvoltage that occurs when the power system switches. Power system safeguards, including overcurrent protection and instantaneous overcurrent protection, are in place to prevent faults from happening before they do [31]. Frequency analysis and preventative electrical tests are tools used in the problem diagnostic toolbox for keeping tabs on transformer voltage, current, and frequency. This makes it easier to identify and anticipate problems, which in turn allows maintenance staff to attend to them when they arise.

Ground Faults:

Insulation ageing, insulation material deterioration, equipment humidity, external damage, operational mistakes, and low voltage or high voltage windings of a transformer are all potential sources of grounding issues. Both the associated electrical system and the device itself are vulnerable to grounding issues. To improve the safety and dependability of transformers, researchers frequently use Restricted Earth Fault (REF) relays in addition to conventional differential relays [32]. When they happen, ground faults can cause problems including localised discharge and overheating because grounding sites might vary. Techniques including electrical analysis, infrared imaging, and dissolved gas analysis (DGA) allow for the quick identification of these defects.

- Short Circuit Faults:

Power outages and unstable voltage are only two of the major problems that might result from a phase-to-phase short-circuit in a transformer. Thus, finding and fixing such errors as soon as they happen is of the utmost importance. The insulating system of the transformer ageing, excessive current, and mechanical deformation are the main reasons for these defects [33]. Techniques including dissolved gas analysis (DGA), vibration analysis, and sweep frequency analysis may effectively diagnose insulation breakdown and mechanical deformation in transformers. Preventing significant safety events and economic losses can be achieved by quick detection prior to phase-to-phase short-circuit problems.

- Turn-Turn Faults

The iron core and winding play crucial roles in the power transformer, which is a critical component of the power system. Most transformer problems may be attributed to core and winding turn-to-turn failures. Regarding instances where transformers stopped working. Many reasons, including mechanical vibration, high voltage stress, high current stress (particularly during external short circuits), thermal overload, contamination, and repetitive overloading, can cause inter-turn insulation to age and eventually fail. In order to find faults, diagnostic methods such as polarisation current analysis, frequency response analysis, and vibration analysis are needed. Mechanical deformation and insulation failure are two major problems that these approaches may detect in transformers. Because it does not involve physical touch, infrared imaging has great promise for detecting overheating.

CONCLUSION

In order to keep the power grid running smoothly, transformer problem diagnostics is vital, as transformers are an integral part of power systems. Techniques for diagnosing transformer faults are thoroughly covered in this work. It begins by outlining the several kinds of transformer problems and what could trigger them. From both electrical and nonelectrical detection vantage points, it then examines the historical development of conventional methods for defect identification. Problems with improving detection accuracy, complicated fault analysis, and more complicated fault characteristics make it clear that conventional diagnostic approaches have their limitations. As a result, an increasing number of academics are integrating classical methodologies with AI technology such as neural networks and machine learning. These smart algorithms tackle problems with conventional fault detection, such as poor correlation between fault characteristics and features, imprecise fault descriptions, and challenging feature analysis, by analysing data and classifying features. This helps the transformer business grow and greatly improves the accuracy of problem diagnostics.

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