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A Review of Methods for Diagnosing Incipient Faults in Power Transformers using Dissolved Gas Analysis

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Abstract: Power transformers play an important role in ensuring efficient and reliable transmission and distribution of electrical power. Their failure can lead to significant disruptions in power supply and safety concerns. Transformer incipient faults may occur due to various reasons, including electrical, mechanical or environmental factors. They develop slowly and can lead to serious damage if not diagnosed and corrected in time. In this review, various techniques for diagnosing this category of faults are highlighted before focusing on Dissolved Gas Analysis (DGA). Discussion on DGA centres on the traditional methods for fault diagnosis as well as various stand-alone and hybrid artificial intelligence techniques developed to improve the fault diagnostic ability of the traditional methods.

Keywords: Dissolved Gas Analysis, Power Transformer, Incipient Faults, Gas ratio methods, Artificial Intelligence methods

I. Introduction

Power transformers are crucial components of the electric power grid that are responsible for the efficient and reliable transmission and distribution of electrical power. They are used to step-up or step-down the voltage of electricity, depending on the requirements of the system. This is necessary because different parts of the grid operate at different voltage levels, and the voltage needs to be stepped up or down as required to ensure efficient and reliable operation. By stepping up the voltage of electricity before transmission, power transformers reduce the amount of energy lost due to resistance in the transmission lines, thereby improving energy efficiency in the grid.

Power transformers are often connected to standby generators or battery systems that can supply power to critical loads in the event of a power failure. With increasing prevalence of wind and solar energy sources in the grid, power transformers are needed to integrate renewable sources into the system. They are used to step-up the voltage of electricity generated by these sources to match the voltage levels of the grid, and to regulate the flow of power through the system.

Power transformers are central to effective and reliable power system operation and their failure can lead to significant disruptions and safety concerns. Transformer failure may be described as the loss of its ability to operate in normal condition and this can occur due to various reasons, including electrical, mechanical, or environmental factors. Some of the common causes of transformer failure include overloading, short circuits, insulation failure and overvoltage. Mechanical faults can occur when the cooling mechanism such as fans fail to operate properly. Exposure of transformers to

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extreme environmental factors such as temperature, moisture and chemicals can also cause corrosion, rusting, and other forms of damage.

Transformer internal faults can be classified into short circuit faults and incipient faults. Internal short circuit faults are sudden faults which occur when turns of transformer windings get in contact with one another or in contact with earth, and so, they require fast action by protective devices to disconnect the transformer from the electric system. Incipient faults, on the other hand, develop slowly and can lead to serious damage if not diagnosed and corrected in time [1]. They often involve a gradual deterioration of winding or core insulation, overheating, overloading or oil contamination, and their presence cannot be detected by using fuses or relays. Timely detection and correction of these faults in a transformer is important to prevent more serious damage and to ensure safe and efficient operation of the power system.

In this study, a review of different techniques for transformer incipient fault diagnosis is carried out, with emphasis on Dissolved Gas Analysis (DGA) technique, followed by a discussion of various traditional and artificial intelligence methods used for DGA interpretation and fault diagnosis.

II. Techniques for Incipient Fault Diagnosis

There are various techniques for diagnosing incipient faults in power transformers. These include infrared thermography, frequency response analysis, insulation resistance testing, partial discharge analysis, power factor testing and dissolved gas analysis.

A. Infrared Thermography

This technique which uses Infrared thermography (IRT) imaging measures the temperature distribution across the transformer surface to identify any areas of overheating or insulation breakdown [2]. This method is based on the fact that most components in a system experience a temperature rise when not functioning properly. IRT is a technique that is not invasive and that requires no contact to transform heat energy into a visible thermal image. This method is often used in conjunction with artificial intelligence techniques to detect the occurence and type of incipient faults [3].

B. Frequency Response Analysis

Frequency Response Analysis (FRA) as a diagnostic approach involves the application of an AC voltage signal to the transformer and measuring the resulting current at different frequencies. The frequency response of the transformer is then analyzed to detect any deviations from the expected response, which can indicate the presence of incipient faults [4]. The FRA test can detect various faults such as winding deformation, core faults, and changes in the transformer's magnetic properties [5].

C. Insulation Resistance Testing

Insulation resistance testing is a commonly used diagnostic method for detecting transformer incipient faults related to insulation degradation. This test involves measuring the resistance of the insulation material between two conductors, such as transformer windings, with a megohmmeter, also known as an insulation resistance tester. During the test, a high-voltage direct current source is applied across the insulation material, and the resulting current flow is measured. The measured current flow is then used to calculate the insulation resistance [6,7]. A decrease in insulation resistance over time may indicate insulation degradation, which can be caused by environmental factors such as moisture, heat, or chemical contamination. Degraded insulation can result in a decrease in the transformer's dielectric strength and an increased risk of short circuits or ground faults.

D. Partial Discharge Analysis

This test which measures electrical discharges within the transformer insulation is used to identify areas of insulation breakdown or degradation [8]. Partial discharge analysis typically involves the use of sensors or probes that are placed on the transformer's insulation surface to detect electrical discharges. The electrical signals are then recorded and analyzed to determine the location and severity of the partial discharges. Various techniques for carrying out partial discharge tests exist for online and offline transformers and these include electrical, electromagnetic, optical, gas presence and acoustic emission methods [9].

E. Power Factor Testing

This test measures the power factor of the transformer to identify any changes in the dielectric properties of the insulation material [10]. A decrease in power factor can indicate a potential insulation breakdown or degradation.

F. Dissolved Gas Analysis

Dissolved Gas Analysis (DGA) works by identifying and analyzing the gases dissolved in transformer oil [11]. Transformers operate at high temperatures, and the insulating oil is exposed to high electric and magnetic fields, leading to the production of gases. When incipient faults occur, they cause additional gas production, which alters the gas levels and ratios present in the transformer oil.

III. DGA Methods

DGA is a major approach capable of diagnosing incipient faults in transformers. It involves taking a sample of the transformer oil and performing an analysis on gases dissolved in it. The sample is usually taken during routine maintenance or when there is suspicion of a fault in the transformer. Gases could be generated as a result of arcing, corona discharge, low energy sparks, and overheating. The types and concentration of gases produced is then used as a basis for identifying the fault type [12-16].

Some of the methods used to analyse the composition of dissolved gases in transformer oil include spectroscopic methods like gas chromatography, Fourier Transform infra-red spectroscopy (FTIR), photoacoustic spectroscopy (PAS) and ultraviolet-visible spectroscopy (UV-Vis) [17-18]. Compact and portable chemical sensors that can detect and quantify the presence of specific gases in the insulating oil can also be used but generally have sensitivity and selectivity issues [19].

The interpretation of DGA results is a function of the type and concentration of gases, the ratios of different gases present in the insulating oil, trend analysis in DGA results collected over time as well as the history of the equipment being analyzed, such as its age, maintenance history, and operating conditions. Various approaches have been put forward for interpretation of the results of DGA tests. These methods can be divided into both traditional and artificial intelligence methods and are discussed in the following sections.

A. Traditional Methods

In this section, various traditional methods for DGA interpretation are discussed.

i. *Expert analysis*

Interpreting DGA results often requires expertise and experience to accurately diagnose faults or abnormalities. An expert analyst can take into account the equipment history and operating conditions, as well as other diagnostic information, to provide a comprehensive interpretation of the results. The quality of diagnosis produced by this method however depends, to a large extent, on the quality of the human knowledge base available. Expert analysis by different personnel may therefore not necesarily lead to the same diagnosis for the same oil sample [20, 21].

ii. *Key gas method*

In this method, the concentration of specific gases found to be dissolved in insulation oil is measured [22, 23]. The presence of nitrogen and oxygen indicates non-fault condition but the presence of hydrocarbons like Methane (CH_4), Acetylene (C_2H_2), Ethylene (C_2H_4), Ethane (C_2H_6), and Hydrogen (H_2) as well as Carbon oxides (CO, CO_2) signal the presence of incipient faults. The key gas method involves identifying the gases that are present in the highest concentrations in the DGA sample and using those gases to determine the abnormality present in the equipment [14].

Elevated levels of hydrogen gas can indicate the presence of corona and partial discharge, elevated levels of methane and ethane gas can indicate low temperature overheating, elevated levels of ethylene gas can indicate thermal faults, such as overheating or hot spots in the equipment while elevated levels of acetylene gas can indicate severe thermal faults, such as arcing or combustion in the equipment. Elevated levels of carbon oxides can indicate a fault a degradation of cellulose insulation [14, 24].

For accurate diagnosis using the key gas method, adequate expert experience is required since the method does not specify the relationship between the actual fault present and the dissolved gas types in numerical terms [12].

iii. *Dornenburg ratio method*

The Dornenburg ratio method [25] identifies possible problems developing in a transformer using gas ratios obtained from its oil sample. These ratios are used in classifying faults as thermal, corona discharge or arcing. The gas ratios used in the interpretation of the method include methane/hydrogen, acetylene/methane, ethylene/ethane and acetylene/ethylene. Further details on concentration limits that the various gases present must satisfy for the method to come up with a valid diagnosis can be found in [22]. However, the method is susceptible to numerous "no interpretation" cases in its output as a result of mismatch between actual ratio ranges calculated and the expected ratios specified as the basis of diagnosis in the method [14].

iv. *Rogers ratio method*

Just like the Dornenburg ratio technique, this method uses ratios of key gases to identify fault types. It is however capable of identifying more fault types than the Dornenburg ratio method [14]. The gas ratios used are methane/hydrogen, ethane/methane, ethylene/ethane and acetylene/ethylene [26]. Depending on the value range for each of these four ratios, a specific fault diagnosis is made. Different faults identifiable include normal deterioration or ageing, partial discharge, varying degrees of overheating, circulating currents in winding, core and tank, flashover, arcing, partial discharge with tracking, continuous sparking etc. However, in some cases, the ratio values obtained from calculation do not agree with the codes specified in this method for diagnosis of various faults.

Later studies have indicated that the ethane/methane ratio does not have close relationship with the faults [14, 26] and as such, is excluded from the modified Rogers ratio method [27].

v. IEC ratio method

In the IEC ratio method [28], the C2H6/CH4 ratio is excluded just like in the modified Rogers Ratio method. In specifying codes for diagnosing a fault, the ranges assigned for the other three gas ratios are different from that used in the Rogers ratio method. Fault types identifiable using the IEC method include ageing, low energy density partial discharge, high energy density partial discharge, discharge of low energy (continuous sparking), discharge of high energy (arcing), and thermal faults of varying severity.

vi. Duval triangle method

This is a graphical DGA analysis technique used to detect fault in a power transformer [29-31]. It uses only the concentration values of methane, acetylene and ethylene plotted on all the three sides of a triangle. This triangle contains seven fault zones and can be used to identify faults like partial discharge, discharge of low/high energy, thermal faults at various temperatures, and electrical arcing. However, this method may lead to wrong diagnosis if fault data point lies at the intersection of fault zones. Also, no region of the triangle maps to normal ageing condition in a transformer [32, 33].

Two additional Duval triangle variants–called Duval Triangle 4 (based on hydrogen, methane, and ethane), Duval Triangle 5 (based on methane, ethane, and ethylene) have been developed to take into account the effect of hydrogen and lower molecular weight hydrocarbon gases which the original Duval triangle method failed to consider [34].

vii. Improved traditional methods

Different authors have tried to refine these traditional methods to improve their capability and accuracy. In [26], the overall accuracy of the IEC and Rogers ratio methods was improved by using diagnostic results from laboratory tests to refine the codes for IEC and Rogers methods. This was then used in building a fault diagnosis system. Also, an improvement to the Duval triangle method called the Duval pentagon method was presented in [35, 36], while a heptagon graph was presented in [37] to enhance the diagnostic accuracy. In [38], a three ratio technique (TRT) in which three diagnostic ratios formed from combinations of dissolved gas concentrations was presented. An extended method which combines the Duval's triangle and IEC ratio methods was presented in [32] to take care of difficulties that the Duval triangle method experiences with fault points located at the intersection of fault zones. These improved methods may however be plagued by generalization difficulties since many of them are based on isolated case studies [39].

B. Artificial Intelligence Methods

The interpretation of most traditional methods depends on the level of experience of the analyst, and the results may sometimes be unreliable [39]. In order to further enhance diagnostic accuracy, different artificial intelligence (AI) techniques have been developed to improve the accuracy of the conventional and graphical methods. This is achieved by reducing cases of failed diagnosis due to inconclusive codes in the case of ratio methods and challenges with diagnosis when the fault lies at the intersection of fault boundaries in the case of Duval triangle methods.

AI methods include artificial neural networks, fuzzy logic and support vector machine. In addition, various evolutionary and swarm optimization techniques, such as particle swarm optimization (PSO), genetic algorithm (GA), bat algorithm etc. have been used to yield improved performance.

i. Artificial neural networks

ANN-based incipient fault diagnosis models are trained using gas concentration/ratio data obtained from power transformers under varying conditions of operation. During training, the main parameters of the network model are progressively adjusted until a mapping is established between the information on the dissolved gas ratios and the actual fault present [40].

In [41, 42], an ANN trained using the Levenberg-Marquardt algorithm was developed to classify seven transformer incipient fault types. Three combustible gas ratios were calculated and the IEC ratio method was deployed in interpreting the fault present. The Levenberg-Marquardt algorithm was selected because of its fast training time. In [43], a multi-layer ANN trained using the "trainlm" training algorithm in MATLAB was utilized in transformer fault prediction. Fault interpretation was based on both the key gas and Duval triangle methods. Different linear activation functions were used in the neural network architecture.

A comparative study of neural networks using different traditional approaches as the diagnostic criteria was presented in [44] while [45] integrated the results of different neural network models for DGA in a smart fault diagnostic system to improve overall fault condition monitoring. In [46], probabilistic neural network models were developed for dissolved gas analysis based on IEC ratios while [13] presented a deep learning convolutional neural network model based on the various gas ratio methods and their hybrids.

ii. Support vector machine

Support Vector Machine (SVM) is employed in power transformer DGA fault diagnosis because it generalizes excellently to new knowledge requires minimal control parameters for its operation and works well with nonlinear problems [47]. In [48], SVM was used to predict transformer faults while the k-Nearest Neighbour method was used to supply missing values in the DGA dataset. In [49], SVM was used alongside kNN with Duval triangle as the diagnostic criteria. A multilayer SVM classifier was developed for transformer fault identification in [50].

It has been reported however that SVMs fail to perform well when the dataset is complex and of high dimension [46].

iii. Fuzzy logic

Using fuzzy logic (FL) techniques in transformer fault diagnosis [51] involves the use of a fuzzy inference system (FIS) which includes a fuzzifier, a fuzzy inference engine and a defuzzifier. Fuzzification is the process of converting exact inputs into fuzzy values using membership functions. Membership functions represent the degree of membership of an input value in a fuzzy set. Fuzzification is necessary because real-world inputs are often vague, imprecise, or uncertain. By using fuzzy values, the system can reason about the inputs in a more flexible and robust manner. The fuzzy inference engine operates on the fuzzy inputs by means of the fuzzy rules to determine the extent of membership of the output in the associated fuzzy set. Defuzzification converts the fuzzy output into a crisp exact value by taking into account the degree of membership of the output in the corresponding fuzzy set.

In [51], a FL diagnostic system for the IEC ratio was presented, a fuzzy logic system based on both IEC and Rogers ratio methods was presented in [52] while in [53], the method presented is based on a combination of three traditional methods. Although the fuzzy logic technique has the advantages of convenience and intuition, when faced with large data sets, their classification ability declines sharply [46].

iv. Hybrid methods

In [46], the probabilistic neural network model was hybridized with different algorithms such as modified moth flame optimization algorithm, particle swarm optimization algorithm, bat algorithm and genetic algorithm. The optimization algorithms were used to obtain optimal smoothing factor of the PNN to get improved performance. In [54, 55], genetic algorithm was used to select appropriate parameters for the support vector machine algorithm. A hybrid of SVM with the modified PSO algorithm with time varying acceleration coefficient was presented in [56] for improved fault diagnosis while in [57], an improved krill herd (IKH) algorithm was used to select optimal SVM parameters. In the presence of measurement uncertainties, [58] hybridized the fuzzy logic technique with the Hybrid Grey Wolf Optimizer algorithm to reduce the effect of uncertainties on the diagnostic ability of the fuzzy logic method. In [59], fuzzy C-means and quantum-inspired particle swarm optimization algorithms were used in selecting the configuration of a radial basis function neural network developed for automatic incipient fault diagnosis.

IV. Conclusion

In dissolved gas analysis, the goal is to correctly identify which incipient fault generated the detected gases in the transformer oil. In this study, different traditional and artificial intelligence methods used in fault diagnosis using DGA were discussed. Improvements on the traditional methods as well as hybrids of AI methods with various optimization techniques were also highlighted. A summary of the advantages and disadvantages of the different methods is provided in Table 1. This study will assist in selection of appropriate transformer fault diagnosis techniques by various practitioners.

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Table 1: Advantages and Disadvantages of Various Methods Discussed

Methods discussed	Advantages	Disadvantages
Expert analysis	An expert analyst can take into account the equipment history, operating conditions, etc to arrive at comprehensive diagnosis	Expert analysis by different personnel may not necesarily lead to the same diagnosis for the same oil sample
Key Gas method	Simple to use	Human expert knowledge required for interpretation
Ratio methods (Rogers Ratio, Dornenburg Ratio, IEC Ratio)	Methods are simple and quantitative; their applicability is independent of transformer oil volume.	Only applicable when the gas levels in the oil samples are not too low; results in many inconclusive or wrong fault identifications; human expert knowledge required for interpretation
Duval triangle method	Simple to apply; always identifies a fault, with good accuracy; allows for fault evolution with respect to time to be followed visually.	The use of information on three gases may not be sufficient to fully characterize transformer condition; only applicable when the gas levels in oil samples are not too low; care should be exercised in using the method since it will identify a fault even if none is present; difficulty classifying faults at the boundary of fault zones; non-detection of concurrent (multiple) faults; human expert knowledge required for correct fault diagnosis.
Improved traditional methods (using new gas ratios, pentagon, heptagon etc)	Improved diagnostic accuracy; low complexity involved in the improved techniques	May suffer from generalization problem since many of them are produced using isolated case studies.
Stand-alone AI methods (ANN,FL, SVM)	Improved diagnosis over traditional methods- inconclusive fault diagnosis in the traditional ratio methods is well taken of; ANNs and SVMs have excellent generalization capability; FL is simple to use and intuitive; SVMs have minimal control parameters for its operation; methods have less dependence on human expert to arrive at a diagnosis.	Membership functions in fuzzy logic have to be selected appropriately; parameters of ANN or SVM have to be tuned to achieve good results; performance depends on the quality and mix of the training data; FL and SVMs fail to perform well when the dataset is complex and of high dimension.
Hybrid AI methods	Improved diagnosis; optimization techniques are used to select appropriate network architecture for ANN, SVM, FL; less dependence on human expert.	More complex to implement; performance depends on the quality and mix of the training data.

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