CCET JOURNAL OF SCIENCE AND ENGINEERING EDUCATION

ISSN(Print) :2582-0680 ; ISSN(Online) :2455-5061 *Vol. – 6, Page-46-54, Year-2022*

A REVIEW ON DGA BASED CONDITION MONITORING OF POWER TRANSFORMER

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Abstract

Power transformer is one of the most influential and exorbitant equipment in the power plant. It is a connecting link between generation and distribution systems. If the Power transformer is under good health condition, then only the reliability of transmission and distribution system reaches a satisfying level. Dissolved Gas Analysis (DGA) is the most widely used methodology for condition monitoring of power transformers. It currently permits simple online monitoring in the working transformer. The study presents a review of the major DGA fault detection techniques, advance methodology, measure range, reliability and accuracy. The review shows the advantages and disadvantages of conventional and new incipient fault detection techniques and aims to select the most appropriate DGA diagnostic method in specific fault cases.

Index Terms: *Power plant, Power transformer, Dissolved gas analysis*

1. 1. INTRODUCTION

Power transformer is pivotal in-stream equipment in the overall power system and suffers countless internal and external stresses throughout its lifespan [1-6]. Therefore, it must be monitored and inspected throughout the operation. The transformer has electrical windings, which embrace paper insulation soaked in oil insulation, both are important sources to evaluate incipient faults and thus reflect the health of the transformer. Transformer oil performs many functions: provides insulation, helps extinguish arcs and provides cooling [1]. Oil and paper insulation mainly decompose during electrical and thermal stresses. Consequently, the dielectric strength and heat dissipation capacity of oil and paper decreases, and some gases are released [2-3]. From the amount and composition of gases, it is evaluated whether there is an internal irregularity or not and how critical it is.

- Paper decomposition: Carbon monoxide (CO) and Carbon dioxide (CO_2).
- Oil decomposition: Hydrogen (H_2), Ethylene (C2H4), Ethane (C2H6), Methane (CH4), and Acetylene (C2H2).

Under the normal operating condition of the transformer, it releases gases (mostly hydrocarbons) mentioned above. When a faulty condition occurs the concentration level of these gases increases and indicates a different type of electrical and thermal faults in equipment. According to IEC60599 and IEEE C57.104 standards electrical and thermal faults can be classified into six types, examples are shown in Table I [4,5 ,41].

Table-1: Fault Classification [4, 5, 41]

Symbol	Fault	Examples
PD	EF- Corona partial discharge	Formation of X-wax in insulating paper, discharges of the cold plasma type in voids and gas bubbles.
D1	EF- Low energy discharge	PD of the sparking type, carbonized puncher in insulating paper, formation of carbon particles in oil.
D2	EF- High energy discharge	Metal fusion, tripping of the equipment, gas alarms, resulting in extensive damage to paper and oil.
T1	TF - t<300ºC	Paper turning carbonized and brownish
T2	TF - 300ºC<t<700ºC	Carbonization of paper, formation of carbon particles in oil.
T3	TF- t>700ºC	Metal coloration (800ºC), metal fusion(>1000ºC)

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When a fault is identified, it is necessary to keep a record of the trend of “rate of increase of gas concentration”. If it is more than 10% per month from its normal concentration, then it is clear that the fault is still active [6].

2. DISSOLVED GAS ANALYSIS (DGA)

DGA of the oil-immerged electrical equipment is the best way to investigate its overall health condition [10-19]. It provides important parameters for measuring the transformer health conditions, these parameters allow simple online monitoring of an energized transformer [7]. The review analyses various DGA diagnostic methods in detail. However, there are many other traditional methods, like IEC Gas ratio method [1], IEEE key gas method [4,42], Rogers ratio method [6,8], Dornenburg ratio method [6,9], CIGRE ratio method [10] and Duval triangle method [41,42]. To limit the drawbacks of the conventional methods new models are proposed for DGA interpretation, based on Evidential reasoning [39], Fuzzy logic [19,20,23,24], Adaptive Neuro-fuzzy inference system [29], and Gene expression programming [36]. Besides these, another new advance method is developed called Hidden Markov model [44,48].
Various conventional incipient fault detection DGA techniques are presented in [6,11,42]. Different methods give distinct results for the specific sample, the situation dependent diagnostic system established different DGA classical ratio methods- IEC gas ratio method, Rogers ratio method, CO2/CO method, Dornenburg ratio method, and CIGRE ratio method [6,24].

The proposed method is designed by consolidating all the existing conventional DGA ratio methods into a single apt template software model, presented in Fig.7 [6]. The entire hierarchy of the proposed method can be explained by the below flowchart (Fig.1)

Samples of pre-estimated faults from different research papers [12-14] are taken and tested on above DGA ratio methods. After invigilating the results from Table X [6], it is clear that Rogers method is the most accurate method of all. Though this method is better than Dorrnenburg ratio method, still chances of misinterpretation are there because of the inconsistency of some ratio value with the predefined diagnostic codes of numerous faults [11].

Table-2: Classical Ratio Methods Fault Type

Methods	F1 Thermal fault (TF) (Cellulose)	F2 Thermal fault (TF) (oil)	F3 Electrical fault (EF) (Corona)	F4 Electrical fault (EF) (Arcing)
IEC	-TF <150ºC -TF 150-300ºC	- TF 300-700ºC - TF >700	D1	- D2
Rogers	- TF <150ºC - TF 150-300ºC	- TF 300-700ºC - TF >700	D1	- D2
CO_2/CO	- TF <150ºC - TF 150-300ºC	- TF 300-700ºC - TF >700	-	-
Dorenenburg	- Thermal decomposition	- Thermal decomposition	D1	- D2
CIGRE	- TF	- Overheating of cellulose	- PD	- Electrical discharge
Principle gas	CO	C_2H_4	H_2	C_2H_2

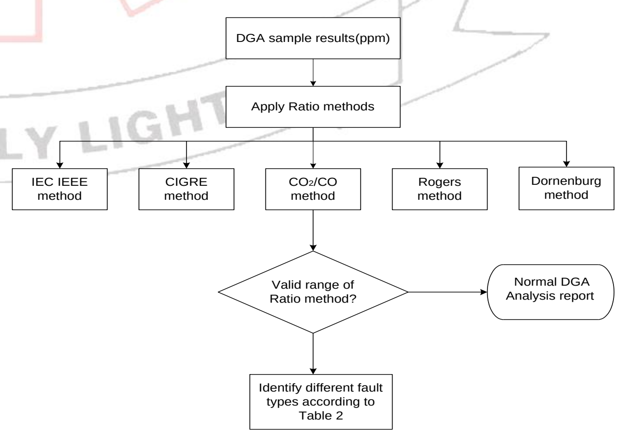

Fig. 1. Flowchart of the proposed method

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This model can be considered as a generic model to estimate incipient faults introduced by stress, but for some samples, it fails to differentiate between the overheating in cellulose and oil. If in the proposed method, data falls within the range, the accuracy rate will be high, but if it falls out of the estimated range, no computation can be done, making it difficult to conduct DGA [15-17].

All the traditional DGA incipient methods give crisp results. After comparing crisp and fuzzy logic [19], it becomes evident that fuzzy logic can detect the faults with a specific 0 reliability. Fuzzy logic is one of the most simple and high accuracy DGA diagnostic techniques [14,19,20,23,24]. The fuzzy logic technique provides a much better and accurate way to evaluate the transformers for their degradation. Fuzzy logic gives an estimated but feasible way or remaining life assessment.

Fuzzy logic technique based on the IEC gas ratio is working as a fault diagnostic method in DGA; it gives an intermediate value between 0 and 1. The Fuzzy logic operations can be understood in the following three steps [20]:

- Fuzzification: fuzzy inputs are obtained after fuzzified real values.
- Fuzzy processing: fuzzy inputs are processed as per the set of rules and generate fuzzy outputs.
- Defuzzification: generating a crisp real value from fuzzy outputs.

In the proposed Fuzzy model, Demi-Cauchy membership functions are used to determine the criticalities of transformers [21-22]. The membership degree is given as:

$$Fz[x \in A] = \mu A(x) : \Re \rightarrow [0,1] \qquad (1)$$

In this fuzzy operations based on AND = min is used, because of the simultaneous appearance of inputs from different models and are reliant on each other. In Fuzzy Rules, using the "IF-THEN" type a set of knowledge-based semantic rules is developed. After inspecting numerous transformers in their best to worst working conditions these rules are developed. The defuzzification process is done by evaluating the weighted average of the fuzzy region using the Centroid method [23]. This model gives us a simplified and appropriate way to make the working and performance of diagnostic systems under many online/offline operating conditions. Further, this model is a cost-effective method for asset performance analysis by reducing expensive risks and providing appropriate information about the retirement time of a transformer [23].

In most of the conventional methods of DGA outcomes fall outside the preferred codes of the leading techniques and thus different conclusions are formed for the same sample of oil [15,16,24]. To avoid these confusions fuzzy logic is used to lessen the dependency on manpower and to support in calibrating DGA methods. The new technique talks about the amalgamation of all prevailed DGA interpretation techniques into a single proficient model [24]. The fuzzy logic models are evolved for different conventional DGA techniques. The input elements are the 7 key gases (ppm) and the output is split up in 5 units of triangular membership function constituting fault state [25-27]. The graphical user interface tool given in MATLAB is used to develop fuzzy model, in which each input is fuzzified into a different set of membership functions. For the defuzzification of the fuzzy model, the Centre-of-gravity phenomenon is used [28]. The consistency and accuracy of these models are analysed, and the results show that the DGA interpretation is not a perfect science. To get over these drawbacks a fuzzy logic model is proposed which is built on the integration of traditional methods (Key gas method, Ratio methods, and Duval triangle method). Based on the accuracy level of each method the overall decision (E) is calculated by the below formula:

$$E = \frac{\sum_{i=1}^{5} l_i E_i}{\sum_{i=1}^{5} l_i} \qquad (2)$$

Where E_i is the decision of individual method measured by its accuracy level l_i. The step-by-step procedure is shown in Fig.2. To prove the validity of the model, collected DGA data and known fault samples from issued experimental papers are tested on the proposed model. The results show that the model is best suited for electrical faults, but it flunks in few samples to disintegrate thermal fault including ignition of oil or cellulose and in these cases an engineering verdict is necessary.

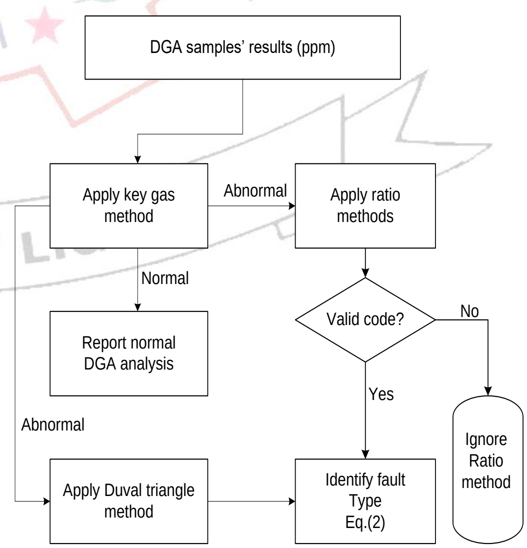

Fig. 2. Flowchart of the model

CCET JOURNAL OF SCIENCE AND ENGINEERING EDUCATION
ISSN(Print) :2582-0680; ISSN(Online) :2455-5061 Vol. – 6, Page-46-54, Year-2022

An Adaptive Neuro-fuzzy Inference System (ANFIS) is proposed for investigating the various thermal and electrical faults occurring in the oil-immersed transformer [29]. ANFIS is accomplished in agreement with IEC-60599 DGA interpretation standards. ANFIS is an integration of two famous models: Fuzzy Inference System (FIS) [30-31] and Artificial Neural Network (ANN) [32-33]. ANFIS's network is considered an adaptive FIS with the ability to understand fuzzy rules. The 5-layer architecture of ANFIS [34-35] is shown below Fig.3:

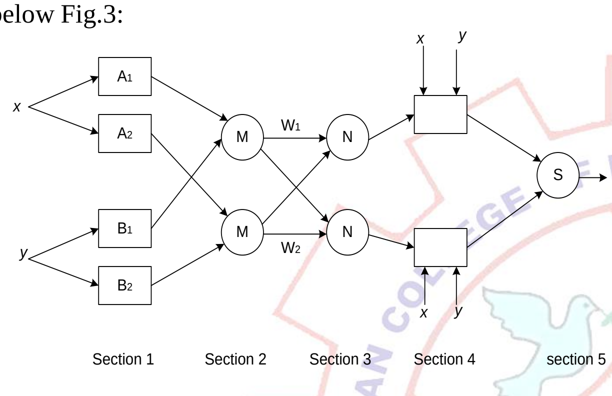

Fig.3. ANFIS model architecture

The "x" and "y" are the two-inputs, and "f" represents an output system in which the square represents an adaptive node and circle represents a fixed node. Section 1 (input node) contains premises parameter. Section 2 (Rule node) uses AND/OR operator to determine the minimum value of two inputs and it is termed as firing strength. Section 3 (Average nodes), each node is fixed node represented by "N" and calculates normalized weight called standardized firing strength. Section 4 (consequence nodes), this section is a linear function of input signals. Section 5 (Output node), has a single fixed node represented by "S" and sum all incoming signals.

Proposed ANFIS classified into two stages: training stage and testing stage. In both the stages the input data should be different to clear overlapping issues during the fault estimation processes.

Training stage: The input datasets are in the form of gas ratios $\left(\frac{CH_4}{H_2}, \frac{C_2H_4}{C_2H_6}, and \frac{C_2H_2}{C_2H_4}\right)$ and outputs contain various faults listed by IEC-60599. Tagaki-Sugeno FIS is applied and an "IF-THEN" rule is used for estimation purposes. ANFIS structure acquires after this stage for DGA is shown in Fig. 3 [29].

Testing stage: This stage is necessary because, if the training data is insufficient or noisy for specific fault type then after each iteration error may shoot up at the output side.

After these two stages, the system has been carried out for fault diagnosis. From various utility dataset of faulty samples is collected and represented in Table 2 [29]. A collation of fault identification by the developed method, conventional IEC-60599, and actual inspection is shown in Table 3 [29]. It is evident by the comparison that the method can identify faults even when the dissolved gases are very close to their threshold value which is not possible in other conventional methods. One disadvantage of the Neuro-fuzzy approach is that it is a bit complex as it has 5 neurons in the input section and 41 neurons in the second section [18].

Gene expression programming (GEP) [36], is a novel method that is used to standardized DGA techniques, it determines the critical grading of electrical equipment based on DGA outcomes and consequently proposes the needed maintenance action. In the proposed GEP one prototype software model is made which integrates different DGA interpretation techniques. The basic idea of the preferred approach is shown by below flowchart (Fig.4) which uses the results of DGA.

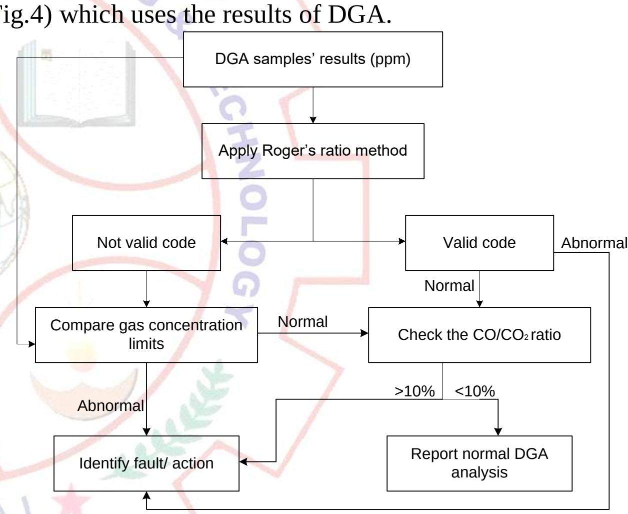

Fig.4. Flowchart of the proposed GEP model

GEP is close to the genetic algorithm (GA) and genetic programming (GP) model as it uses a population of individuals, shortlist is based on their fitness and using few genetic operators initiates genetic variation [37-38]. In this way, GEP amalgamates the benefit of both GP and GA while compensates for their shortcomings. Roulette-wheel sampling is used to select individuals based on their fitness and the best one is preferred. To accomplish the above flow chart, the DGA results of 250 oil samples are given as input variables at the learning stage of GEP, while the 88 oil samples are stored to support the proposed model for the testing stage [36]. At last, the results from all the samples are categorized in four health conditions, based on which the fault is diagnosed, and the asset management decision is taken for the transformer. Further by the help of graph corresponding absolute and target error for each oil sample is determined. GEP technique introduces a mathematical relationship between the target and dependent variables which is very helpful for the field engineers [36-37].

The health condition of a transformer is evaluated using three major methods DGA, testing of transformer oil, and evidential reasoning [39]. The oil testing parameters and dissolved gases initially normalized and then using membership function transformed into fuzzy variables. Under an evidential reasoning shell, fuzzy variables are converted into a multi-attributed decision-making problem. To support the methodology two case studies are assessed by real field data. In this research, the method shows a different manner of utilizing long term plant health indicator (LTPHI) and routine DGA data. In LTPHI there are 2 branches, one is oil and another one is paper. Oil test is divided into 3 categorize and the paper test has two input indices. In DGA the thermal and electrical fault of oil and paper is detected by seven input indices.

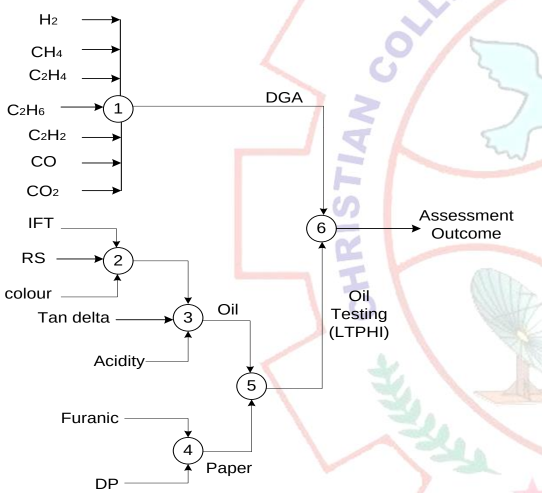

Fig.5. Tree model: Transformer condition assessment

The outcome from the tree model gives assessing grade "A", A = {critical, poor, average, good, excellent}, which is used for maintenance planning by the engineer.

The field data has dissimilar magnitude and dimension, so they are normalized to make dimensionless quantities. Now by using trapezoidal membership function, these normalized values are converted into fuzzy variables.For evidential reasoning, Dempster-Shafer theory (DS theory) is used. For this frame of discernment is defined as Ω and basic hypothesis defined as A_n, where $A_n \subset \Omega$. The overall hypothesis set is given as:

$$A_n = \{A_1, A_2, A_3, A_4, A_5\} \tag{3}$$

In DS theory the different evidence sources, DGA and LTPHI are aggregated by combination rule and designated as f_1 (DGA) and f_2 (LTPHI). The combination rule for $f_1 \oplus f_2$ is given as:

$$m(\Psi) = \sum_{f_1 \cap f_2 = \psi} \frac{m_1(f_1) m_2(f_2)}{1-k} \tag{4}$$

$$K = \sum_{f_1 \cap f_2 = \phi} m_1(f_1) m_2(f_2) \tag{5}$$

Where, k is the degree of conflict [40]. For validation purposes, the data of two distinguish transformers from power generating stations are taken, and by the help of (2) and DGA gas weight, the fuzzy BBAs assisting DGA at each node (1-5) are determined. The assessing grade of the transformer at each node is analysed. At node 6, LTPHI and DGA are given equal weight 0.5 and introduce a belief coefficient β=0.95 to measure the final BBAs. Consequently, the gross health condition assessment of the transformer is measured at node 6 and accordingly the maintenance work is carried out.

One of the biggest drawbacks of the gas ratio method (Dornenburg, IEC, Rogers) is that some of the outcomes of DGA analysis fall out of the ratio code and diagnosis remains unresolved. Duval triangle is the best method in such cases as it is a closed system [36,41].

Duval triangle was developed in 1974, it includes three hydrocarbons (Methane, Ethylene, and Acetylene) [40-41]. The Duval triangle method is shown in Fig.6. The 6 zones are shown in Fig.7, which indicates transformer fault as mentioned in Table 1. There is one more intermediate zone DT which shows the mixture of electrical and thermal faults:

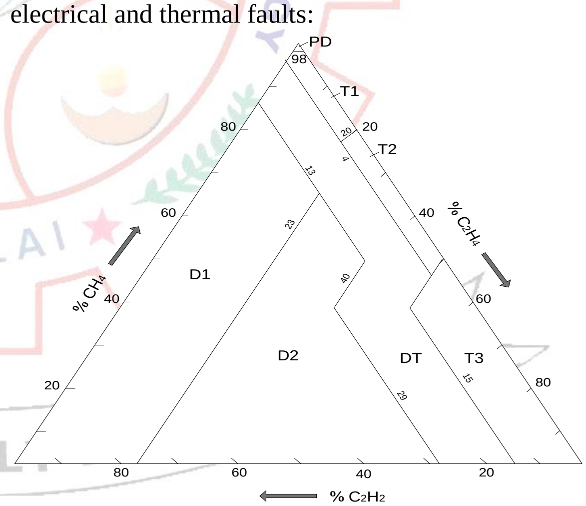

Fig.6. Duval triangle model

Based on the Duval triangle, some advance methods have been developed for detection and monitoring faults in electrical equipment [42-43].

Dual of Duval triangle [42], like in Duval triangle the three main hydrocarbon gases Methane, Ethylene, and Acetylene are involved. The gases are firstly normalized such that their combined concentration lies in the range of 0 to 1. For fault identification, these three gases are converted into empirically obtain mathematical equations which are best suitable for fuzzy trapezoidal membership

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functions. The fuzzy trapezoidal membership functions for different gases in all five faults are represented in mathematical expressions. These equations form the basic belief assignments (BBAs), the BBAs are then normalized and fall under the range of 0 to 1. The three normalized BBAs obtained from the gases are regarded as 3 distinct origins of evidence indicating a fault type and are represented as μ1(M)(CH4), μ2(M)(C2H2), and μ3(M)(C2H4). Each one furnishes a BBA to a subset of Y, which is $m_1(l_1)$, $m_2(l_2)$, and $m_3(l_3)$. With the help of Dempster-Shaffer amalgamation rule evidence combination for $l_1 \oplus l_2 \oplus l_3$ is evaluated.

$$m(\Psi) = \sum_{l_1 \cap l_2 \cap l_3 = \psi} \frac{m_1(l_1)m_2(l_2)m_3(l_3)}{1-k} \tag{6}$$

$$K = \sum_{l_1 \cap l_2 \cap l_3 = \phi} m_1(f_1)m_2(f_2)m_3(f_3) \tag{7}$$

The advantage of this method over the conventional Duval triangle is that the same or different kind of tow or more faults overlapping each other can be anticipated at the same interval. However, unlike the Duval triangle, the anticipation of fault evolution is not possible in this method [42].

Two more new methods named Hidden Markov model [44,48] and advanced software provided with a DGA analyzer are developed [49]. They are different from conventional methods and have an advanced algorithm.

A model based on the Hidden Markov model combined with the Gaussian mixture model is developed for prognostic health management of oil-immersed power transformers by subdividing their in-service working stages into three parts i.e. healthy state, sub-healthy state and fault state [44-45] as shown in Fig.7.A transition from healthy to faulty state is reflected by the sub-healthy state and then a specific library containing numerous healthy and faulty cases to achieve the state characteristics is established. Using the Gaussian mixture model, the overall data is crumbled into a summative form of many Gaussian probability density functions which can be used to appraise the concentration distribution of dissolved gasses and each one of them act like a characteristic of the group [46-47].

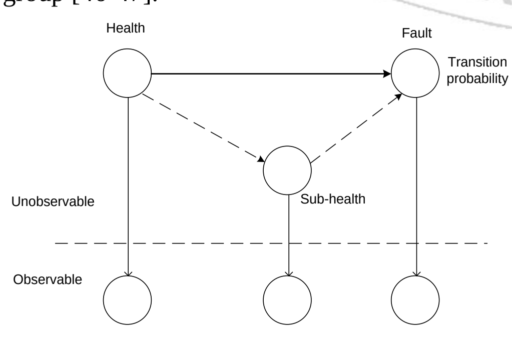

Fig.7. Health index versus dissolved gases in transformer oil

This Gaussian probability density function is obtained from Bayesian theorem and can be calculated by the following formula:

$$p(x) = \frac{1}{2\pi^{\frac{n}{2}} \left|\Sigma\right|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)}$$

(8)

Where μ is a d dimensional vector denoting the mean of the distribution and $\sum$ is the n×n covariance matrix. On performing assembled analysis on the library case data, health evaluation of the status of transformers is evaluated and then it is observed that lower the concentration of gases better is the health of the transformers and vice versa. Then to check the accuracy of the developed GMM model cross-validation is done. This GMM model gives static characteristics of transformers while the gas concentration keeps on varying in power transformers so to convert the static characteristics to dynamic ones and to develop a better time-based model HMM model is selected. Instead of the dependence of different states on each other, linking to states through probability distribution is the basic principle of HMM. HMM is derived from the Markov chain and has two parts [44,48]:

- Visible part specifications that are observable like dissolved gasses concentration in transformer oil.
- Hidden part – states which are not directly visible like the three states of power transformers; healthy, sub-healthy, and faulty states.

Baum-Welch algorithm is used to resolve the first state and state transition probabilities in HMM. In HMM the aim is to evaluate the time for transforming from healthy to faulty state for which proper attention on the sub-healthy state must be given as shorter the time poorer the health of the transformer, and repair and maintenance is required. For making HMM more efficient, iterative approach based on the Viterbi algorithm is used, thus avoiding duplicated calculations [44,48]. HMM is a feasible method for short-term fault prediction in power transformers and hence increasing their life span.

The last method is based on advanced software provided with a DGA analyzer [49]. First of all, the concentration percentage of dissolved gases concerning the sum of 5 main gases (Hydrogen (H_2), Acetylene (C_2H_2), Methane (CH_4), Ethylene (C_2H_4), and Ethane (C_2H_6)) and some gas ratios are measured. According to these measurements, fault type is decided (PD, D1, D2, T1, T2, and T3) then the dissolved gas data is collected and Total Combustion Gases (TCG) is calculated (TCG is the sum of all five

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gases concentration). After this Gas Concentration Percentage (GCP) is calculated by the given formula:

$$GCP = \left(\frac{H_2}{TCG} \frac{CH_4}{TCG} \frac{C_2H_6}{TCG} \frac{C_2H_4}{TCG} \frac{C_2H_2}{TCG} \right)^T \times 100\% \qquad (10)$$

Based on these GCP values different fault type is determined by the help of the proposed integration technique. Here an accuracy flag is introduced, when interface occurs between different types of the fault then the accuracy flag is “0.5”, it is “1” if the diagnose is equal to actual fault otherwise it is “0” [49]. Now the result obtained from the new approach is compared with different traditional methods. After comparison, a visible reduction of accuracy can be seen, and this is due to the interference area of different faults.

The overlap is illustrated by the help of the probability distribution function which is established on mean and standard deviation [49-50]. To overcome this drawback now a modified version of the new DGA interpretation technique is introduced considering new some gas ratio (Table III) and these gas ratios are based on the empirical study.

A remarkable hike in the accuracy level is acquired as compared to traditional DGA diagnostic methods Table 10 [49].

Table-3: New Gas Ratios

P1	C_2H_2/H_2
P2	C_2H_2/CH_4
P3	C_2H_2/C_2H_6
P4	C_2H_4/H_2
P5	C_2H_4/CH_4
P6	$(C_2H_4/H_2) + (C_2H_4/CH_4)$
P7	C_2H_4/C_2H_6

3. CONCLUSION

Power transformers have a wide range of industrial and commercial applications, due to their high efficiency and reliability. However, thermal, mechanical, and electrical defects may occur due to the long-term continuous operation. The insulating oil is likely to be decomposed to several hydrocarbon gases stressed by abnormal conditions. DGA in oil becomes a widespread practice for identifying the incipient fault diagnosis in oil-filled power transformer. DGA aims to support dynamic early prediction and warning model for incipient faults in liquid and solid insulation.

A review of conditioning monitoring of the transformer by DGA is performed in this study. Several DGA diagnostic methods: traditional as well as advance logic methods are presented. The set of fault detection and fault diagnosis methods are defined in the study, with their detailed methodology. DGA methods have differences in accuracy, repeatability and measurement range. The selection of the method depends on the number of gases required for fault recognition.

In this review paper comparison between distinct DGA methods is done, which clearly shows the superiority of methods from one another. The paper aims to help the selection of DGA interpretation techniques for specific electrical equipment depending on its abnormal or faulty conditions.

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