Condition Monitoring of Power Transformer by Dissolved Gas Analysis: A Review

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1 Introduction

A power transformer is pivotal in-stream equipment in the overall power system and suffers countless internal and external stresses throughout its lifespan [1–2]. 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 thermal and electrical stresses. Consequently, the heat dissipation capacity and dielectric strength of paper and oil decreases and some gases are released [3, 4]. From the amount and composition of gases, it is evaluated whether there is an internal irregularity or not and how critical it is.

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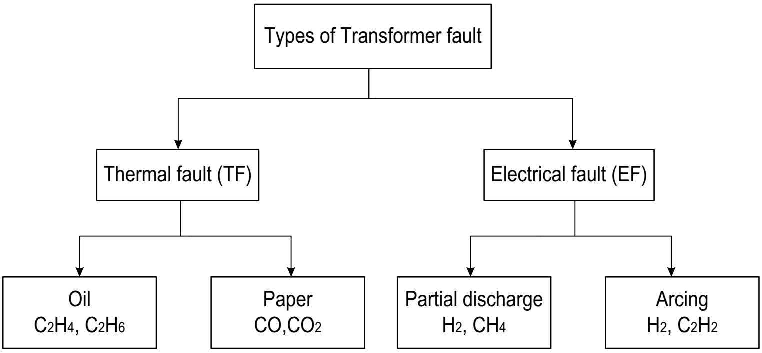

Fig. 1 Transformer fault and generated gases [5]

- Oil decomposition: Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4), and Acetylene (C_2H_2).
- Paper decomposition: Carbon monoxide (CO) and Carbon dioxide (CO_2) (Fig. 1).

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. As stated by IEC60599 and IEEE C57.104 standards electrical and thermal faults can be classified into six types, examples are shown in Table 1 [6–8].

When a fault is identified, it is necessary to keep a record of the 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 [2].

Table 1 Fault classification [6–8]

Symbol	Fault	Examples
PD	EF-corona partial discharge	X-wax formation in insulating paper, discharges of cold plasma in voids and gas bubbles
D1	EF-low energy discharge	PD of the sparking type, carbonized puncher in insulating paper, accumulation of particles of carbon in oil
D2	EF-high energy discharge	Gas alarms, tripping of the equipment, metal fusion, extensive damage to paper and oil
T1	TF- $t < 300$ °C	Paper turning carbonized and brownish
T2	TF-300 °C $< t < 700$ °C	Accumulation of particles of carbon in oil, carbonization of paper
T3	TF-$t > 700$ °C	Metal coloration (800 °C) and metal fusion(>1000 °C)

2 Dissolve Gas Analysis (DGA)

DGA of the oil-immerged electrical equipment is the best way to investigate its overall health condition [9–10]. It provides important parameters for measuring the transformer's health conditions. These parameters allow simple online monitoring of an energized transformer [11]. The review analyses various DGA diagnostic methods in detail. Under these methods, there are many traditional methods, like IEC Gas ratio method [1], IEEE key gas method [6, 12], Rogers ratio method [2, 13], Dornenburg ratio method [2, 14], CIGRE ratio method [9] and Duval triangle method [8, 12]. To limit the drawbacks of the traditional methods, new models are proposed for DGA interpretation, based on Fuzzy logic [10, 15–16], and Hidden Markov model [17, 18].

Various conventional incipient fault detection DGA techniques are presented in [2, 12, 19]. These techniques can be considered as a generic way to estimate incipient faults introduced by stresses, but for some samples, it fails to differentiate between the overheating in cellulose and oil. If 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 [20, 21].

As these conventional DGA diagnostic methods have limited accuracy and require necessary expert advice, some new software techniques are introduced such as Fuzzy logic, evidential reasoning, and HMM.

All the traditional DGA incipient methods give crisp results. After comparing crisp and fuzzy logic [10], 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 [10, 15–16]. 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 [15]:

- 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 utilized to determine the unfavourable conditions of transformers [23, 24]. The membership degree is given as:

$$\mathrm{Fz}[x \in A] = \mu_A(x) : \Re \to [0, 1] \tag{1}$$

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 evolved. 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 [22]. 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 [22].

In most of the conventional methods of DGA outcomes fall outside the preferred codes of the leading methods and thus different conclusions are formed for the same sample of oil [16, 20, 21]. 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 [16]. The fuzzy logic models are evolved for different conventional DGA techniques. The input elements are the seven main gases (ppm) and the output is split up in five units of triangular membership function constituting fault state [25–26]. The graphical user interface tool given in MATLAB is used to develop fuzzy models, in which each input is fuzzified into a different set of membership functions. For the defuzzification of the fuzzy models, the Centre-of-gravity phenomenon is used [27]. The consistency and accuracy of these models are analyzed 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 (Ratio methods, Key gas method, and Duval triangle method). Based on the accuracy level of each method the gross decision (E) is measured by the below formula:

$$E = \frac{\sum_{i=1}^{5} Li Ei}{\sum_{i=1}^{5} Li} \tag{2}$$

where Ei is the decision of individual method measured by its accuracy level Li. The step-by-step procedure is presented 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.

One of the biggest drawbacks of the gas ratio method (Dornenburg, IEC, Rogers) is that some of the outcomes of DGA analysis fall out off the ratio code and diagnosis remains unresolved. Duval triangle is the best method in such cases as it is a closed system [5, 8].

Duval triangle was developed in 1974, it includes three hydrocarbons (Methane, Ethylene, and Acetylene) [8]. The Duval triangle method is shown in Fig. 3. The 6 zones are shown in Fig. 3, 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.

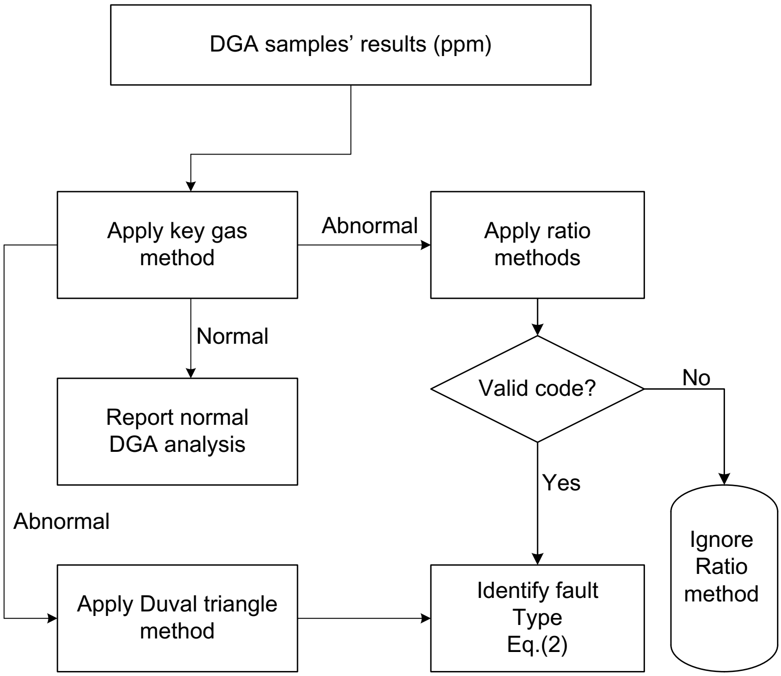

Fig. 2 Flowchart of the model [16]

Based on the Duval triangle, some advance methods have been developed for detection and monitoring faults in electrical equipment [12, 28].

Dual of Duval triangle [12], 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 identificaion, these three gases are converted into empirically obtain mathematical equations which are best suitable for fuzzy trapezoidal membership 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 $\mu_{1(M)}(CH_4)$, $\mu_{2(M)}(C_2H_2)$, and $\mu_{3(M)}(C_2H_4)$. Each one furnishes a BBA to a subset of Υ, 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.

$$m(\Psi) = \sum_{l_1 \cap l_2 \cap l_3 - \Psi} \frac{m_1(l_1)m_2(l_2)m_3(l_3)}{1 - k} \quad (3)$$

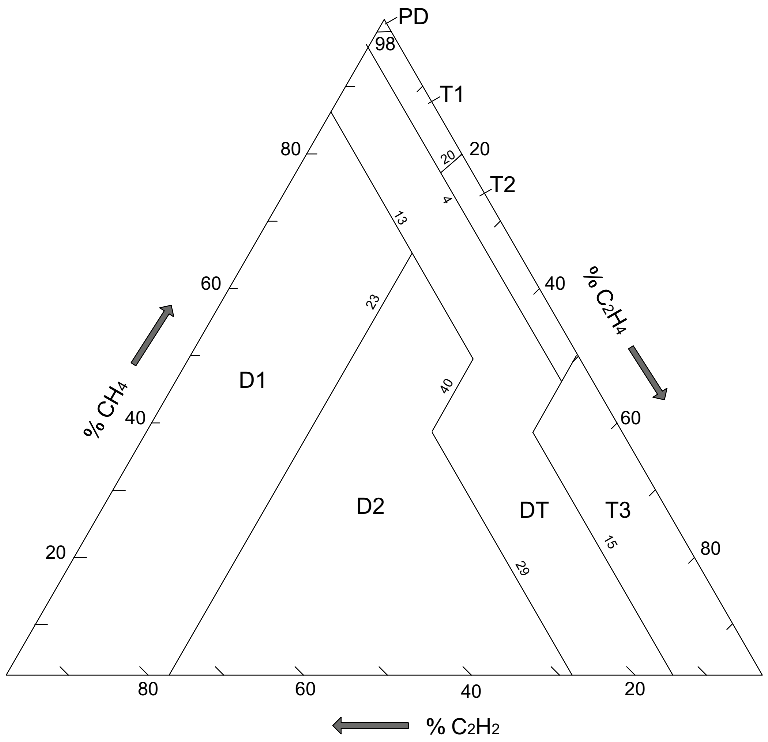

Fig. 3 Duval triangle model [12]

$$k = \sum_{l_1 \cap l_2 \cap l_3 - \Phi} m_1(l_1) m_2(l_2) m_3(l_3) \tag{4}$$

After evidence combination, the fault allied to the greater value of BBA indicates a specific fault occurring in the equipment. 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 [12].

Two more new methods named Hidden Markov model (HMM) [17, 18] and advanced software provided with a DGA analyzer are developed [29]. They are different from conventional methods and have an advanced algorithm.

A model based on the HMM combined with the Gaussian mixture model (GMM) 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 [17, 30] as shown in Fig. 4 below:

A transition from healthy to faulty state is reflected by the sub-healthy state and then a data set containing numerous faulty and healthy cases to achieve the health-state characteristics is established. Using the GMM, the gross data is crumbled into

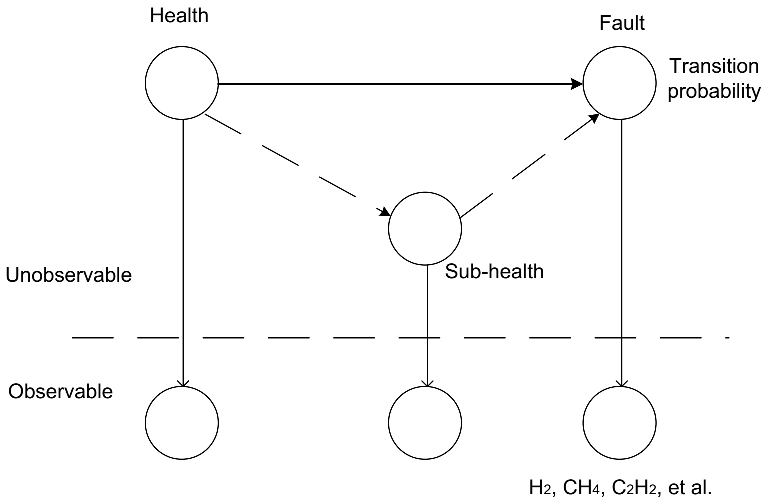

Fig. 4 Dissolved gases in transformer oil versus health index [17]

a summative form of many Gaussian probability density functions which is used to appraise the concentration distribution of gasses dissolved in oil and each one of them act like a characteristic of the group [31, 32]. This Gaussian probability density function is obtained from Bayesian theorem and is calculated by the formula:

$$P(x) = \frac{e^{-0.5(x-\mu)\sum(x-\mu)}}{2\pi^{n/2}\left|\sum\right|^{1/2}} \tag{5}$$

where $\sum$ is the $n \times n$ covariance matrix and μ is a d dimensional vector denoting the mean of the distribution. On performing assembled analysis on the library data set, 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. Markov chain is the main key of HMM and has two parts [17, 18]:

- Visible part—specifications that are observable like dissolved gasses' concentration in oil-immerged transformer.
- Hidden part—invisible states like the three states of power transformers; healthy, sub-healthy and faulty states.

Baum-Welch algorithm is used to resolve the state transition probabilities in HMM and the first state. 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 [17, 18]. 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 [29]. First of all the concentration percentage of dissolved gases concerning the sum of 5 gases (H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2) and some gas ratios are measured. According to these measurements, fault type is decided, then the dissolved gas data is collected and Total Combustion Gases (TCG) is calculated (TCG is the sum of all five gases concentration). After this Gas Concentration Percentage (GCP) is calculated by the given formula:

$$\mathrm{GCP} = \left(\frac{\mathrm{H_2}}{\mathrm{TCG}} \frac{\mathrm{CH_4}}{\mathrm{TCG}} \frac{\mathrm{C_2H_6}}{\mathrm{TCG}} \frac{\mathrm{C_2H_4}}{\mathrm{TCG}} \frac{\mathrm{C_2H_2}}{\mathrm{TCG}} \right)^T \times 100\% \tag{6}$$

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" [29]. 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 [29, 33]. To overcome this drawback now a modified edition of the new DGA interpretation method is introduced considering some new gas ratios (Table 2) and these gas ratios hinges on the empirical study.

A remarkable hike in the accuracy level is acquired as compared to traditional DGA diagnostic methods Table 10 [29].

Table 2 New gas ratio [29]

p_1	C_2H_2/H_2
p_2	C_2H_2/CH_4
p_3	C_2H_2/C_2H_6
p_4	C_2H_4/H_2
p_5	C_2H_4/CH_4
p_6	$(C_2H_4/H_2) + (C_2H_4/CH_4)$
p_7	C_2H_4/C_2H_6

3 Conclusion

A review of condition monitoring of the transformer by DGA is performed in this study. It aims to support dynamic early prediction and warning model for incipient faults in liquid and solid insulation. Several DGA diagnostic methods: traditional as well as advanced 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 dissimilarity in accuracy, reliability, measurement range and repeatability.

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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