Power Transformer Fault Diagnosis using DGA and Group Decision Making with Intuitionistic Fuzzy Preference Relations

C. H. R. Martins, M. A. Araujo Araujo and R. A. Flauzino {IEEE member}
Department of Electrical and Computer Engineering
University of Sao Paulo (USP)
Sao Carlos, Brazil
cesar.martins@outlook.com, marcel.araujo@usp.br, raflauzino@sc.usp.br

***Abstract*—Because of the importance of power transformers to the electrical system, operating from transmission lines to distribution, understand their condition is critical. Analysis of dissolved gases in the insulating oil of transformers is an efficient and reliable way to perform a diagnosis. However, in some situation each method of dissolved gases interpretation can indicate one different type of fault. Thus, this paper present a multi-criteria decision making method that aggregates the information of four traditional methods, and indicates the condition of transformer. The results were promising, in way that was possible to obtain a consistent response through three different interpretations.**

***Keywords*—dissolved gas analysis, fault diagnosis, group decision making, intuitionistic fuzzy preference relation, power transformer.**

I. Introduction

One of the most important aspects of a smart grid is how the transmission and distribution assets are managed and maintained to ensure a high degree of reliability, allowing the optimization of operation and maintenance activities. To ensure this a set of strategies are employed in modern grid operation, such as the coordinated asset management, equipment condition monitoring, condition based inspection and maintenance, dynamic adjustment of operating limits and equipment rating based on their condition. That way is possible to enhance system capacity and improve system reliability. However, reliable delivery of electric power, in greater part, depends on the reliable operation of power transformers in the system. What ensure transformers reliability in service is a well-written test plan, consisting in a selection of appropriate tests and the specification of correct test levels [1] [2].

Being one of the most expensive and important elements, a power transformer is a highly essential element, whose failures and damage may cause the outage of a power system. Diagnostic is extremely important factor in determination of transformer technical condition, because incipient faults may decrease the electrical and mechanical integrity of the insulation system. Thus, if a fault is detected before it leads to a catastrophic failure, predictive maintenance can be deployed to minimize the risk of failure and further prevent loss of service. That way, techniques for early detection of the faults would be very valuable to avoid outages [2] [3].

During incipient faults occurs the breakdown of electrical insulating materials and related components inside the transformer liberates gases within the unit. Thus, to find out the incipient faults, dissolved gas analysis (DGA) is a prevailing method, in industrial practice, with periodically samples which test the insulation oil of transformers to obtain the composition of the gases dissolved in the oil due to the breakdown of the insulating materials inside. The DGA methods then analyze and interpret the attributes acquired: ratios of specific dissolved gas concentrations, their generation rates and total combustible gases are used to conclude the fault situations. Diverse diagnostic criteria were developed for identification of the possible fault types, e.g., the conventional IEC ratios method, Rogers ratios method, Doernenburg ratios methods, Duval triangle and others [3] [4].

However, each methods have its own accuracy in predicting each fault type and an overall consistency in the diagnose. In that way, is possible to obtain one fault identification for each method, using the same dissolved gas sample. Thus, this paper aims to present a multi-criteria decision-making model that considers the interpretation of four DGA methods to provide fault identification. To achieve this goal, were used the Muhamad study [4] to provide the preference parameter between two types of faults, predicting success of each fault type, and the weight of each method in the final decision, method consistency in fault identification.

II. DGA Methods

Transformer oil is prone to undergo irreversible changes in it chemical and dielectric properties due to aging. Factors, such as temperature, oxygen, humidity, copper, electrical field and electrical discharges may accelerate the aging process. Partial discharge, overheating and arcing, from less to high energy dissipation, are the three major causes of fault related gases. Along with a fault, there are increased oil temperatures and generation of certain oxidation products such as acids and soluble gases. These gases, hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), together with carbon monoxide (CO) and carbon dioxide (CO_2) are

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considered as fault indicators and can be generated in certain patterns and amounts depending on the characteristics of the fault [5].

Various interpretative techniques have been reported in the literature to predict development of faults, such as IEC 60599 Standard's ratio codes [6], IEEE Standard's [7], Roger's and Dornenburg's ratio codes, the Key gas method and graphical techniques such as Duval Triangle method [8]. All these methods have been based on years of experience in fault diagnosis using DGA. None of them are based on mathematical formulation and interpretations are heuristic in nature and vary from utility to utility [5]. Nevertheless, if these interpretation schemes are not applied cautiously, they may incorrectly identify faults because they only indicate possible faults. In some cases, DGA interpretation schemes may differ in terms of identified faults, which is clearly unacceptable for a reliable fault diagnosis system [9].

A. Key Gas Method

Decomposition of gases in oil and paper insulation of transformers caused by faults depends on temperature of faults. Various faults produce certain gases and the percent of some gases have been found to indicate fault types, such as overheated oil and cellulose, corona in oil and arching in oil [5].

B. Gas Ratio Methods

The advantage of using ratio methods is that, they overcome the issue of volume of oil in transformer by looking into the ratio of gas pairs rather than absolute values. Roger, Dornenburg and IEC ratios are all used by the utilities. Diagnosis of faults is accomplished via a simple coding scheme based on ranges of ratios (CH_4/H_2; C_2H_6/CH_4; C_2H_2/C_2H_4; C_2H_4/C_2H_6). Typically, three or four ratios are sufficient to diagnose several incipient fault conditions and a normal condition. But, the drawback of these ratio methods is that it fails to cover all ranges of data and quite often ratios fall outside the scope of the tables [10] [5].

C. Duval Triangle Method

The Duval triangle method uses values of only three gases CH_4, C_2H_4 and C_2H_2 and their location in a triangular map. To plot the triangle, gases are transformed into triangular coordinates. The detectable fault types are partial discharges, high and low energy arcing (electrical faults) and various ranges of thermal faults. Although this method is easily performed, careless implementation can obtain false diagnoses since no region of the triangle is designated as an example of normal aging [9].

D. Comparative Study of DGA Methods

According to the work of Muhamad [4], those methods using specific codes in their interpretation are more accurate if they make a prediction. However, whenever the data does not match with available codes, these methods are not able to give their prediction. Resulting in their lower level of consistency in predicting the fault and less accurate based on total case prediction. In contrast, those methods that use direct value of fault gases in their interpretation give higher consistency and same values of accuracies as they attempt to provide predictions for all cases. The results are summarized in I [4]. It can be seen that the Duval triangle method is the most consistent method followed by the Key Gas, IEC ratio, Roger ratio and lastly the Doernenburg method.

The intuitionistic preference relations used in this work will be determined by this comparative study.

TABLE I. ANALYSIS FOR EACH TYPE OF FAULTS [4].

Method	Fault Type	Successful Prediction	Consistency
Roger	Thermal, T <300 ^{o}C	50%	45%
	Thermal, T >300 ^{o}C	39%	
	Arcing	55%	
	Partial discharge	57%	
	Normal	23%	
IEC	Thermal, T <300 ^{o}C	50%	60%
	Thermal, T >300 ^{o}C	79%	
	Arcing	82%	
	Partial discharge	64%	
	Normal	23%	
Doernenburg	Thermal, T <300 ^{o}C	20%	40%
	Thermal, T >300 ^{o}C	45%	
	Arcing	36%	
	Partial discharge	43%	
	Normal	54%	
Duval	Thermal, T <300 ^{o}C	100%	88%
	Thermal, T >300 ^{o}C	91%	
	Arcing	100%	
	Partial discharge	50%	
	Normal	100%	

III. GROUP DECISION MAKING WITH INTUITIONISTIC FUZZY PREFERENCE RELATIONS

Atanassov [11] introduced the concept of intuitionistic fuzzy set, which emerges from the simultaneous consideration of the degrees of membership and non-membership with a degree of hesitancy. An intuitionistic preference relation is a powerful means to express decision makers' information of intuitionistic preference over criteria in the process of multi-criteria decision making. This concept has been studied and applied in a variety of areas [12].

Priority weight generation from the preference relations is the main issue of group decision making concept. Preference relation present a common format which provides the opportunity to explain decision maker's preference information in decision making problems by pairwise comparisons. However, in the process of decision making it is very difficult for a decision maker to construct a consistent preference relation. Since an inconsistent preference relation may lead to wrong conclusions, priority weight generation methods should take into consideration the consistency of preference relations. Most of the priority weight generation methods in the fuzzy set theory paper in the literature are based on fuzzy interval preference relations. To solve that, was proposed a number of linear programming models for deriving the priority weights from various fuzzy interval preference relations considering additive and multiplicative consistency [13].

A. Definition

The notion of intuitionistic fuzzy sets is introduced as [11]:

$$A = \{\langle x_i, \mu_A(x_i), v_A(x_i)\rangle | x_i \in X\} \tag{1}$$

which is characterized by a membership function $\mu_A : X \to [0,1]$ and a non-membership function $v_A : X \to [0,1]$ with the condition:

$$0 \leq \mu_A(x_i) + v_A(x_i) \leq 1, \quad \forall x_i \in X. \tag{2}$$

The value, $\pi_A(x_i) = 1 - \mu(x_i) - v_A(x_i)$ is called the indeterminacy degree or hesitation degree of x_i to $A, 0 \leq \pi_A(x_i) \leq 1$. Especially, if $\pi_A(x_i) = 1 - \mu_A(x_i) - v_A(x_i) = 0, \forall x_i \in X$ then, the intuitionistic fuzzy set A is reduced to a common fuzzy set [13].

An intuizionisti fuzzy preference relation B on X is defined as a matrix $B = (b_{ij})_{n\times n} \subset X \times X$ where $b_{ij}\left((x_i x_j), \mu(x_i x_j), v(x_i x_j)\right)$ for all $i, j = 1, 2, \ldots, n$. Let $b_{ij} = (\mu_{ij}, v_{ij}$ is an intuitionistic fuzzy value, composed by the certainty degree μ_{ij} to which x_i is preferred to x_j and the certainty degree v_{ij} to which x_i is non-preferred to x_j. The hesitation degree to which x_i is preferred to x_j is defined by (3).

$$\pi_{ij} = 1 - \mu_{ij} - v_{ij}. \tag{3}$$

In the real life decision making problems, a decision is usually made by a group of experts, $E_k (k = 1, 2, \ldots, m)$ with different weights $\lambda_k = (\lambda_1, \lambda_2, \ldots, \lambda_m)^T$ in the decision process. In such cases, the individual preference relations of the experts are aggregated to derive a collective preference relation $\overline{B} = (\overline{b_{ij}})_{n\times n}$ [13].

An intuitionistic fuzzy preference relation $B = (b_{ij})_{n\times n}$ is an additive consistent preference relation, if there is a vector $w = (w_1, w_2, \ldots, w_n)^T$ such that Eq. (4) holds.

$$\begin{gathered}\mu_{ij} \leq 0.5\,(w_i - w_j + 1) \leq 1 - v_{ij} \quad i = 1, 2, \ldots, n-1; \\ j = i+1, \ldots, n; w_i \geq 0; i = 1, 2, \ldots, n; \sum_{i=1}^{n} w_i = 1.\end{gathered} \tag{4}$$

Since the preferences of decision makers are very subjective and depend on personal psychological aspectts, this equation does not always hold. In this situation, $B = (b_{ij})_{n\times n}$ will not be an additive consistent intuitionistic fuzzy preference relation, then we relax Eq. (4) by introducing the non-negative deviation variables d_{ij}^- and d_{ij}^+, $i = 1, 2, \ldots, n-1; j = i+1, \ldots, n$ [13]:

$$\begin{gathered}\mu_{ij} - d_{ij}^- \leq 0.5\,(w_i - w_j + 1) \leq 1 - v_{ij} + d_{ij}^+ \\ \text{for all } i = 1, 2, \ldots, n-1; \quad j = i+1, \ldots, n; \\ w_i \geq 0, \quad i = 1, 2, \ldots, n, \quad \sum_{i=1}^{n} w_i = 1.\end{gathered} \tag{5}$$

As the deviation variables d_{ij}^- and d_{ij}^+ becomes smaller, B becomes closer to an additive consistent intuitionistic fuzzy preference relation. As a result, in order to find the smallest deviation variables and determine the priority vector was developed the following linear optimization model [13] [12]:

$$\begin{aligned} & \delta = \min \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \left(d_{ij}^- + d_{ij}^+\right) \\ s.t. \quad & 0.5\,(w_i - w_j + 1) + d_{ij}^- \geq \mu_{ij} \\ & 0.5\,(w_i - w_j + 1) - d_{ij}^+ \leq 1 - v_{ij} \\ & w_i \geq 0, i = 1, 2, \ldots, n, \sum_{i=1}^{n} w_i = 1, d_{ij}^-, d_{ij}^+ \geq 0 \\ & i = 1, 2, \ldots, n-1, \quad j = i+1, \ldots, n.\end{aligned} \tag{6}$$

IV. Proposed Method for Fault Diagnosis

In the presence of multiple DGA interpretations for one sample of dissolved gases, the proposed method apply a multi-criteria decision model to evaluate all diagnosis and determine the possible fault of transformer. The diagnosis obtained from the tradicional DGA interpretation methods, normalized as shown in Table II, will be used to identify the fault type. The characteristics of consistency and prediction rate of each method will be used in the decision making process.

TABLE II. Fault type codes.

Fault Type Code	Fault Type
F1	Thermal fault at low temperature
F2	Overheating and sparking
F3	Arcing
F4	Partial discharge and corona
F5	Normal or inconclusive

The flowchart in Fig. 1 represent the steps performed by this method to realize a diagnosis. Three stages can be defined during the method application, the classification, the aggregation and the selection. The process of identify the faults through traditional methods are performed in the classification, if more than one type of fault is obtained then method define four matrices of intuitionistic fuzzy preference relations for the identified faults, one matrix for each method (expert). In aggregation, the individual preference relation of the experts are aggregated into a collective preference relation. Then, the priority weight vector is determined applying the linear model (6). The final phase, selection, is responsible by rank the priority weight vector and identify the possible fault type. These phases can be divided in five steps:

Step #1: Transformer fault diagnosis through traditional DGA methods (Roger, IEC and Doernburg ratios and Duval triangle).

Step #2: Determination, for the faults identified, the experts intuitionistic fuzzy preference relations, in the form of: $B_k = \left(b_{ij}^{(k)}\right)_{n\times n}$; where, $b_{ij}^{(k)}$ is the pairwise comparison of two faults, being $\mu_{ij}^{(k)}$ and $v_{ij}^{(k)}$ defined by the prediction ratio of the method for each fault, these values are given in Table II.

Step #3: Performs the aggregation of experts individual preference relations. The experts weights, λ_k, was defined with the consistency values of each method, according Table I.

Step #4: Applies the linear model (6) to determine priority weight vector.

Step #5: Rank the priority weight vector and classify the possible fault type.

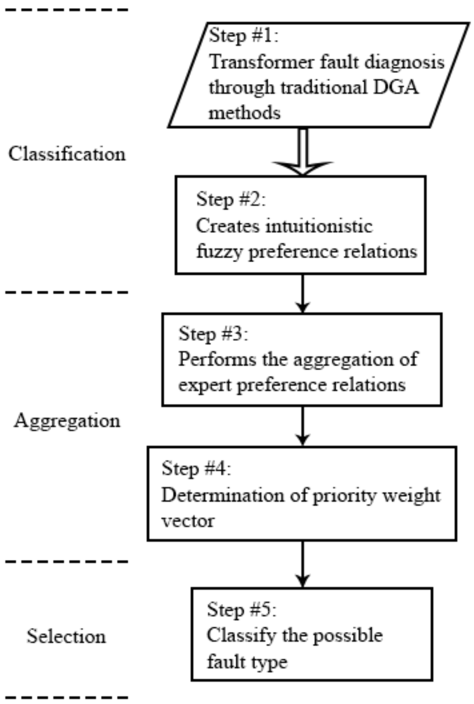

Fig. 1. Proposed method flowchart.

A. Illustrative Example

A transformer 132 kV/11 kV, 20 MVA, foreign case one presented by Lin [14], will be used to illustrate the proposed method. Using the acoustic location technique, a discharge source was located inside the 11 kV internal Voltage Transformer (VT) fuse, that fault was confirmed by the maintenance. The relation of dissolved gases in ppm are as follows — H_2: 160, CH_4: 10, C_2H_2: 1, C_2H_4: 1, C_2H_6: 3, CO: 705, and CO_2: 2000 with a total combustible gases of 880.

With the traditional DGA methods was obtained three different fault classification: two F2 (Duval), one F3 (IEC), and one F5(Roger, Doernburg). Thus, is necessary to make a decision about the possible fault type. To aim that objetive, is constructed the following experts intuitionistic fuzzy preference relations:

$$B_1 = \begin{bmatrix} (0.50, 0.50) & (0.39, 0.55) & (0.39, 0.23) \\ (0.55, 0.39) & (0.50, 0.50) & (0.55, 0.23) \\ (0.23, 0.39) & (0.23, 0.55) & (0.50, 0.50) \end{bmatrix}$$

$$B_2 = \begin{bmatrix} (0.50, 0.50) & (0.79, 0.82) & (0.79, 0.23) \\ (0.82, 0.79) & (0.50, 0.50) & (0.82, 0.23) \\ (0.23, 0.79) & (0.23, 0.82) & (0.50, 0.50) \end{bmatrix}$$

$$B_3 = \begin{bmatrix} (0.50, 0.50) & (0.45, 0.36) & (0.45, 0.54) \\ (0.36, 0.45) & (0.50, 0.50) & (0.36, 0.54) \\ (0.54, 0.45) & (0.54, 0.36) & (0.50, 0.50) \end{bmatrix}$$

$$B_4 = \begin{bmatrix} (0.50, 0.50) & (0.91, 1.00) & (0.91, 1.00) \\ (1.00, 0.91) & (0.50, 0.50) & (1.00, 1.00) \\ (1.00, 0.91) & (1.00, 1.00) & (0.50, 0.50) \end{bmatrix}$$

Then, all experts intuitionistic fuzzy preference relations are aggregate, through a weight $\lambda = (0.45, 0.60, 0.40, 0.88)^T$:

$$\overline{B} = \begin{bmatrix} (0.50, 0.50) & (0.70, 0.76) & (0.69, 0.57) \\ (0.76, 0.70) & (0.50, 0.50) & (0.76, 0.57) \\ (0.57, 0.70) & (0.57, 0.76) & (0.50, 0.50) \end{bmatrix}$$

Solving the model (6), the optimal priority vector $w = (0.00, 0.35, 0.39, 0.00, 0.26)^T$ is obtained. When ranked, this vector indicates the possible fault type is F3, a high energy fault. This diagnosis is consistent with the problem found during the transformer maintenance.

B. Results

Each method was tested against all the 166 cases in the IEC TC 10 databases [15]. The percentages of successful prediction and consistency were calculated, and the results are summarized in Table III.

Can be observed that the Duval triangle method is the most consistency method followed by the proposed method. The proposed method shows good performance for fault diagnosis, having a high successful prediction ratio for most of the fault types and presented a consistent diagnosis. Beside that, only 19 of all cases in the database has the same diagnosis from all tradicional methods. However, can be seen a decrease in prediction ratio of normal condition and fault type F4. Because the proposed method make a decision through the diagnostics of traditional methods, this decrease means a greater number of miss identification for these cases. A possibility to improve the accuracy of this method is via the use of a learning system. Thus, we can construct better intuitionistic fuzzy preference relations, minimizing the effect of wrong diagnosis.

TABLE III. RESULT ANALYSIS FOR EACH TYPE OF FAULT.

Method	Fault Code	Correct Predictions	Successful Prediction	Consistency
Roger	F1	4	25%	51%
	F2	11	61%	
	F3	40	83%	
	F4	1	3%	
	F5	40	82%	
IEC	F1	0	0%	41%
	F2	14	78%	
	F3	0	0%	
	F4	25	71%	
	F5	27	55%	
Doernenburg	F1	0	0%	53%
	F2	16	89%	
	F3	41	85%	
	F4	4	11%	
	F5	39	80%	
Duval	F1	7	44%	66%
	F2	16	89%	
	F3	47	98%	
	F4	30	86%	
	F5	6	12%	
Proposed Method	F1	7	44%	60%
	F2	16	89%	
	F3	47	98%	
	F4	19	54%	
	F5	7	14%	

V. CONCLUSION

In the situation of multiples interpretations about the power transformer condition, the proposed method demonstrate to be a good tool, to aggregate all information and provided one diagnostic. The general consistency of this method was of 60% and prediction rate stayed above 40% for all conditions, excluding normal condition. However, is needed some improvements in the method to minimize the wrong diagnostics. Thus for future works, will be investigated the possibility of use a learning algorithm to define intuitionistic fuzzy preference relations.

REFERENCES

[1] B. Shahbazi and M. Vadiati, "Transformer condition monitoring system for smart grid," *The 2nd International Conference on Control, Instrumentation and Automation*, pp. 32–37, 2011.

[2] G. Gavrilovs, "Technical condition asset management of power transformers," *2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies*, pp. 1–5, 2011.

[3] S. Souahlia, K. Bacha, and A. Chaari, "MLP neural network-based decision for power transformers fault diagnosis using an improved combination of Rogers and Doernenburg ratios DGA," *International Journal of Electrical Power and Energy Systems*, vol. 43, no. 1, pp. 1346–1353, 2012.

[4] N. a. Muhamad, B. T. Phung, T. R. Blackburn, and K. X. Lai, "Comparative study and analysis of DGA methods for transformer mineral oil," *2007 IEEE Lausanne POWERTECH, Proceedings*, pp. 45–50, 2007.

[5] B. Németh, S. Laboncz, and I. Kiss, "Condition Monitoring of Power Transformers using DGA and Fuzzy Logic," *Ratio*, no. June, pp. 373–376, 2009.

[6] International Electrotechnical Commission, "IEC 60599 - Mineral oil-impregnated electrical equipment in service - Guide to the interpretation of dissolved and free gases analysis," Tech. Rep., 2007.

[7] "IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers - Redline," *IEEE Std C57.104-2008 (Revision of IEEE Std C57.104-1991) - Redline*, pp. 1–45, 2009.

[8] M. Duval, "Dissolved Gas Analysis:It Can Save Your Transformer," *IEEE Electrical Insulation Magazine*, vol. 5, no. 6, pp. 22–27, 1989.

[9] H.-C. Sun, Y.-C. Huang, and C.-M. Huang, "A Review of Dissolved Gas Analysis in Power Transformers," in *Energy Procedia*, vol. 14, no. 2011, 2012, pp. 1220–1225.

[10] D. Sarma and G. Kalyani, "Ann approach for condition monitoring of power transformers using DGA," *2004 IEEE Region 10 Conference TENCON 2004.*, vol. C, pp. 444–447, 2004.

[11] K. Atanassov, "Intuitionistic Fuzzy Sets," *Fuzzy Sets and Systems*, vol. 20, pp. 87–96, 1986.

[12] Z. Xu, "A method for estimating criteria weights from intuitionistic preference relations," *Advances in Soft Computing*, vol. 40, pp. 503–512, 2007.

[13] H. Behret, "Group decision making with intuitionistic fuzzy preference relations," *Knowledge-Based Systems*, vol. 70, no. 8, pp. 33–43, Nov. 2014.

[14] C. H. Lin, C. H. Wu, and P. Z. Huang, "Grey clustering analysis for incipient fault diagnosis in oil-immersed transformers," *Expert Systems with Applications*, vol. 36, no. 2 PART 1, pp. 1371–1379, 2009.

[15] M. Duval and A. DePablo, "Interpretation of gas-in-oil analysis using new IEC publication 60599 and IEC TC 10 databases," *IEEE Electrical Insulation Magazine*, vol. 17, no. 2, pp. 31–41, 2001.