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ORIGINAL ARTICLE

Principal Components Analysis and Adaptive Decision System Based on Fuzzy Logic for Power Transformer

Ricardo M. Arias Velásquez · Jennifer V. Mejia Lara

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Abstract Power transformers are the most critical part of power electrical system, distribution and transmission grid. The oil and the insulation system (paper properties) degradation have many chemicals inside them, they are the result of an initial problem that can be predicted. The research has established the intelligent diagnosis system based on principal component analysis (PCA) and adaptive decision system based on fuzzy logic permits to realize a dissolved gas analysis (DGA) to predict incipient fault diagnosis by different methods, to obtain deterioration rates and health index, besides it allows to analyze the degree of polymerization (DP) for the remaining life of the equipment. The classification accuracy of the proposed method with PCA and fuzzy logic intelligent system is 97.2% for normal equipment and 98.13% for failure events. The proposed method is quite interesting for the readers and the concern researchers in the area of fuzzy mathematics and power transformers.

Keywords Principal component · Fuzzy logic · Gas analysis · Power transformers · Remaining life

Ricardo M. Arias Velásquez (✉)
PhD. Engineering Program, Pontificia Universidad Católica del Perú (PUCP), Universitaria Avenue 1801. San Miguel, Lima. Perú
email: rarias@rep.com.pe
email: ricardoariasvelasquez@hotmail.com
Jennifer V. Mejia Lara
PhD. Engineering Program, Pontificia Universidad Católica del Perú (PUCP), Universitaria Avenue 1801. San Miguel, Lima. Perú

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1. Introduction

Today, become us the era of high speed machining, maintenance plans and condition monitoring techniques are samples of the general activities that can be applied to any equipment, however this methods and particular condition, for power transformers are different from those applied to other substation equipment. A lot of power transformers are working close to 40 years, and the adverse effect of aging equipment is the impact of the global unavailability of electricity service. The Fuzzy integral equations (FIE) and Fuzzy Differential equations have been rapidly growing in recent years and the application of numerical method to nonlinear fuzzy method permits to use this techniques to obtain a complex model [1]. However, aging equipment remains a great challenge for the electrical industry, especially in energy cluster, the need to increase the competitiveness of the countries' economies and the emergence of new competitors in the business. Actually, it has an important development, many researchers are writing about Fuzzy parameters on the modeling of cables, insulations properties, the authors have obtained a flexible tool, and it establishes a model of the properties with good approach in experimental values with this methodology [2]. The assessment procedures are similar the medical diagnosis method, which is a decision problem of several variables. Where information from various sources needs to be combined, seamlessly weighted and correlated in order to arrive at a single conclusion, with a method hybrid multi-attribute [3] permit to solve this analysis, to obtain an intelligent diagnosis on power transformers [4]. In this paper, an intelligent diagnosis system based on principle component analysis (PCA) and adaptive fuzzy logic program is used to analysis the gas and insulation, using the chemical component of oil and paper degradation. In here, the component of Michel Duval methodology and the document CIGRE TB-296 Recent Developments in DGA Interpretation [5], monitoring this components: carbon monoxide (CO), carbon dioxide (CO2), ethylene (C2H4), ethane (C2H6), hydrogen (H2), methane (CH4), acetylene (C2H2), nitrogen (N2), oxygen (O2) and Furan, are extracted by calculating nine gases and this interactions with this dimensions [6]. It can be reduced to 3 components using PCA, to correct diagnosis performance, the correct diagnosis performance of PCA and fuzzy logic program is calculated in 107 equipment. Being the linchpin power transformers for the links between electrical transmission grids, it is important to establish the effect of maintenance and correlate durability and support different types of stress lifetime. When older equipment was renewed in the past, the main reason for change was the growth of the load, originated overcoming their operational limits, rather than to reach the end of the lifetime of the equipment thus were removed from service before reaching their technical life. But now the condition has change, by now there are a lot of old power transformers working.

The main aim of this study is assisting to the special assessment team about diagnosis of power transformer oil and paper (Kraft) condition and remaining life. The equipment specialist can be compared the diagnosis performances of PCA – fuzzy logic program method and existing diagnosis method: Laborelec method, Dornembu IEC 60599, Duvai method, ABNT IEC 599/78, CIGRE CS15. Principal component analysis (PCA), adaptive fuzzy logic program is reviewed in Chapter 3.

2. Intelligent Diagnosis

2.1 Pattern Recognition

The pattern recognition algorithm has three phases. These phases are feature extraction and classification and determinate. A smaller number of meaningful features that best represents the given pattern without redundancy are determined in the feature extraction stage. The classification is carried out, i.e., a specific pattern is assigned to a specific class according to the characteristic features selected for it in the classification phase. Finally, the last pattern considers to determinate the health index and degradation rate with remaining life of the equipment.

2.2 Fuzzy Logic

The fuzzy set theory was introduced by Lofti A. Zadeh 1965 [7], as a mechanism for representing the vagueness and imprecision of the concepts used in natural language. Expressions like: That man is tall, it is a warm day or I'll do it later are common in our language. However, it is not easy to define what we mean by: tall, warm or later. We will hardly agree to specify at what height can be considered, taller than, for a person, or at what temperature it is said that warm weather, or how long it means waiting for do it late. However, paradoxically, humans do not encounter difficulties in reasoning with these inaccurate concepts. In the analysis of condition these vague concepts equipment type is also presented. Our reasoning is based on information, it must consider the linguistic form as a variable, whose values can be expressed in terms of natural language. Fuzzy sets were defined as an extension of the classic sets that allows modeling the imprecision of the concepts that manages specialist inductive equipment, the fundamental change proposed by Zadeh [7] is to introduce a membership degree (compliance), it is expressing the conformity of an element to a set as a real number in the interval [0, 1]. A degree of conformity 0 indicates that an item does not belong to a particular set, while a degree of conformity 1 indicates that the item belongs entirely to the set. An intermediate value indicates partial ownership of an item to set.

2.3 Fuzzy Set Representation

Assume an universe of items $\{x_1, x_2, x_3, \cdots\}$ and a fuzzy set A mapped onto it. Let $\mu(x_i)$ be the membership function that maps the element x_1 onto X to the degree in the range 0 to 1. The fuzzy set A then can be written:

$$A = \sum_{i=1}^{n} \mu_A(x_i)/x_i. \tag{1}$$

and if $x_i = x$ is a continuous function then:

$$A = \int \frac{\mu_A(x_i)}{x_i} \tag{2}$$

In the classical set theory, the intersection of two sets contains those elements that are common to both. However, in fuzzy set theory an element may be partially in both sets. This is the intersection of two fuzzy sets A and B on X is given by the logical and operations as:

$$\mu_{A\wedge B}(X) = min\{\mu_A(x), \mu_B(x)\}\forall x \in X, \tag{3}$$

$$\mu_{A\wedge B}(X) = \mu_A(x) \wedge \mu_B(x) = \mu_A(x) \cap \mu_B(x). \tag{4}$$

On the other hand, the union of two fuzzy sets comprises of those elements that belong to one or both sets. Thus union of set A and B is given by its logical or as below:

$$\mu_{A\vee B}(X) = max\{\mu_A(x), \mu_B(x)\}\forall x \in X, \tag{5}$$

$$\mu_{A\vee B}(X) = \mu_A(x) \vee \mu_B(x) = \mu_A(x) \cup \mu_B(x). \tag{6}$$

In a fuzzy set A, its complements are given by:

$$\mu_A(x) = 1 - \mu_A(x). \tag{7}$$

2.4 Membership Functions

In building fuzzy systems, membership functions are used to translate verbal judgments or linguistics into numeric expressions. A number of membership functions has been development, but the most popular ones are the trapezoidal, triangular and semi – Cauchy function.

For this research the ascending semi – Cauchy membership function $\mu_f(x)$ is:

$$\mu_{f(x)} = \begin{cases} 1, & x \geq A, \\ 1 + \left(\frac{A-x}{a}\right)^{-1}, & Otherwise, \end{cases} \tag{8}$$

The descending semi – Cauchy membership function is given by $\mu_{f(x)}$ is:

$$\mu_{f(x)} = \begin{cases} 1, & x \leq A, \\ 1 + \left(\frac{A-x}{a}\right)^{-1}, & Otherwise, \end{cases} \tag{9}$$

2.5 Principal Analysis and Fuzzy Inference System

Principal Component Analysis (PCA) is a technique that reduces the dimensions of a dataset with a large number of correlated variables. While keeping the original data variation, PCA transforms the original correlated variables into a new set of uncorrelated variables known as principal components (PCs). Generally, n number of original variables will result in n number of PCs. Dimension reduction could be achieved when the first k number of the PCs are selected for representing the original data (where $k \leq n$).

Equation 10 shows Y as the PC dataset with the same m entries corresponding to k PCs after linearly combining x with A. Essentially, a contains the individual weightages for linearly combining the n original variables into the first PC, second column for the second PC up until k_{th} column for the k_{th} PC.

$$x'_{j.raw} = \frac{1}{m}\sum_{i=1}^{n} x_{y,raw}, \tag{10}$$

$$\sigma_{y,raw} = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m} x_{y,raw} - x'_{j,raw}}, \tag{11}$$

$$X = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \dots & \dots & \dots \\ x_{m1} & \dots & x_{mn} \end{bmatrix}. \tag{12}$$

$$Y = XA, \tag{13}$$

$$\begin{bmatrix} y_{11} & \dots & y_{1n} \\ \dots & \dots & \dots \\ y_{m1} & \dots & y_{mn} \end{bmatrix} = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \dots & \dots & \dots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mn} \end{bmatrix}. \tag{14}$$

The key is to evaluate A which is done by eigenvector decomposition or singular value decomposition (SVD). SVD which is used in this work is known as a more general solution method as it can be applied to not just squared matrix.

A Fuzzy Inference System – FIS is a computational tool based on the concepts of the theory of fuzzy sets and fuzzy reasoning [8]. Generally, it provides a non-linear mapping of some input variables in some output variables. The main advantage of incorporating fuzzy reasoning is that the inference rules can be defined in a precise and consistent manner from knowledge and experience of the staff specialist, while uncertainty originating from the input information is considered by defining one or more fuzzy sets for each input. The basic structure of a SID consists of three conceptual components: a set of inference rules called rule base, a dictionary that defines the fuzzy sets used to model the propositions in the background and the findings of the rules, and a mechanism for reasoning that performs the procedure inference from rules and entry information given to derive an output. To explain: How does it develops a SID based on the Mamdani's model? It's going to present a process development condition analysis equipment, for example it is necessary to determine the dielectric oil condition of a transformer from the test results of oil dielectric strength in $[kV]$ and the power factor in $[\%]$ at 25 degrees. An example is the following diagnostic rules:

- Rule 1: If the dielectric strength is good and the power factor is good, then the dielectric oil condition is good.
- Rule 2: If the dielectric strength is good and the power factor is bad, then the dielectric oil condition is Regular.
- Rule 3: If the power factor is not adequate, then the dielectric oil condition is Bad.

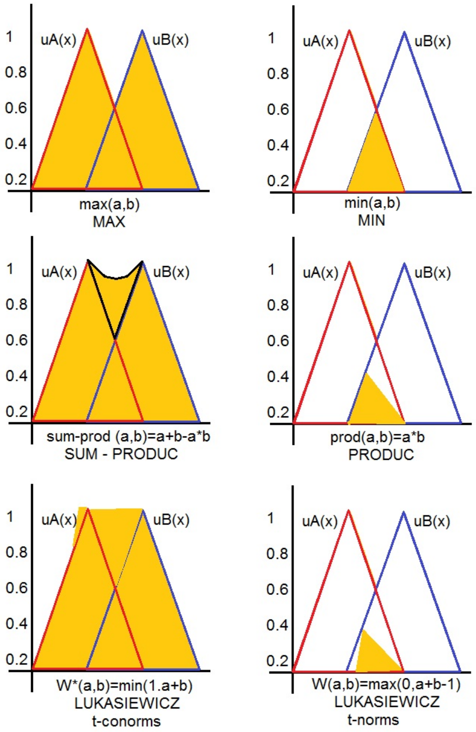

Fig. 1: Example of diagnostic rules, fuzzy norm

At the Fig.1, the functions work with the conditions as T - Conorm (T - Conorm) and triangular norm (T – Norm) the last one was development by Schweizar and Sklar at the reference [9], [13], it is introducing by operation between [0, 1], it is commutative, associative without decreasing in the two variables, one of them has one (1) as neutral and zero (0) as absorbent; they are defined as functions of membership to calculate the degree of membership from 0 to 1, for each linguistic variables (Good, Regular, Bad). For Fig.1, the ramp function increasing is for a dielectric strength type (If it is higher than other one, it would be better value) and decreasing ramp type for the power factor (the higher value is worse than other). Once defined the elements of our FIS, we will develop the Mamdani model in the following steps:

Antecedent assessment for each rule: With a given value (numerical values) we obtain different membership values for each respective language to its variable and this is called diffuser (fuzzy) of the input. If the antecedent of the rule has more than one term, then a fuzzy operator (T-norm or T-conorm) applies obtaining a single membership value to which the formula is applied as we showed at equation (15), to obtain this value for the centroid method.

$$y_{out} = \frac{\sum_{i=1}^{x} y_i \cdot \mu(y_i)}{\sum_{i=1}^{x} \mu(y_i)}. \tag{15}$$

In this research, we can obtain the same result using the method for ranking of Trapezoidal intuitionistic fuzzy numbers (TrIFNs) proposed by Satyajit Das and Debashree Gua (2016) [10] or we can use the centroid method.

The functional operation of a transformer should be determined by the ability to maintain the following key capabilities:

- Electromagnetic capability.
- Capacity circuit driving the load current.
- Ability to withstand voltage stress.
- Ability to withstand mechanical stresses.

Also for the evaluation of the paper, as the cause of deterioration of the three types are known degradation:

- Thermal degradation or pyrolysis. Pyrolysis is a thermochemical decomposition of organic material at elevated temperatures in the absence of oxygen (or any halogen). It involves the simultaneous change of chemical composition and physical phase, and is irreversible. The word is coined from the Greek-derived elements pyro“fire” and lysis “separating”

- Degradation by hydrolysis. Usually means the cleavage of chemical bonds by the addition of water. When a carbohydrate is broken into its component sugar molecules by hydrolysis, this is termed saccharification. Generally, hydrolysis or saccharification is a step in the degradation of a substance or in the language of chemistry “The reaction of cation and anion or both with water molecule due to which pH is altered, cleavage of H-O bond in hydrolysis takes place.”

In the Fig.2, the building blocks based on fuzzy logic for our application, a diffuser block (Fuzzy) system in which each input variable is assigned a degree of membership in each of the diffuser sets indicated that it has been considered. The inputs to this block are specific values of the input variables and outputs are degrees of membership in the fuzzy sets considered in the aggregation process; as the next step the process considers the inference mechanism called involvement, in Fig. 3, in which the inference mechanisms represent rules defined in the system, the inputs and outputs are fuzzy blocks. Finally, unfuzzy is created from the fuzzy set obtained in the inference mechanism and using mathematical methods a specific value of the output variable is obtained, for example an outcome. To detect the fault using the diagnostic method DGA (Dissolved Gas Analysis), indicated at the reference [11], [13]. In the Table 1, a successful Failure mode and effects analysis (FMEA) activity helps identify potential failure modes based on experience with similar products and processes or based on common physics of failure logic. It is widely used in development and manufacturing industries in various phases of the product life cycle. Effects analysis refers to studying the consequences of those failures on different system levels. Functional analyses are needed as an input to determine correct failure modes, at all system levels, both for functional FMEA or Piece-Part (hardware) FMEA. An FMEA is used to structure Mitigation for Risk reduction based on either failure (mode) effect severity reduction or based on lowering the probability of failure or both. The FMEA is in principle a full inductive (forward logic) analysis, however the failure probability can only be estimated or reduced by understanding the failure mechanism.

Table 1 : Failure modes analyzed

Capacity	Failure modes
Mechanical	Failure axial deformation windings
	Failure radial windings
	Failure mechanical paper capacity loss
Dielectric	Failure insulating oil degradation
	Failure insulating oil pollution
	OLTC failure , insulating oil pollution
	Moisture oil pollution failure
	Paper moisture contamination failure
	Dielectric insulation windings and bushings failure
Thermal	Thermal paper failure
	Cooling system fails
Electromagnetic	Partial discharges failure
	Electric arc failure

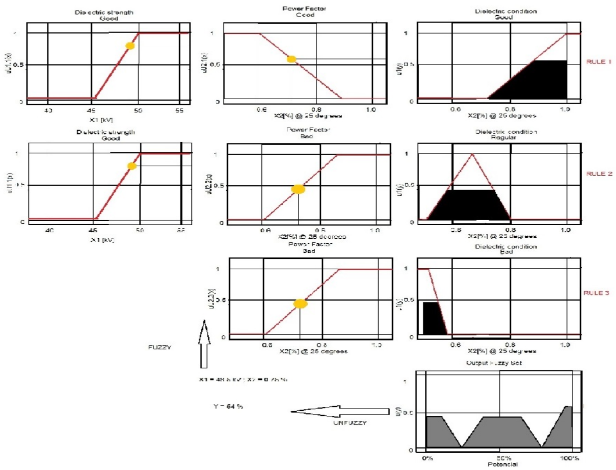

Fig. 2: Fuzzy inference system (FIS) using diagnosis rules

Table 2 : Variables, test and relation with failure modes.

Failure mode	Test	Variables
Thermal paper failure	DGA	CO, CO_2
Thermal oil failure	DGA	C_2H_4, C_2H_6
Cooling system fails	Monitoring	Oil temperature, chargeability level
Partial discharges failure	DGA	H_2, CH_4
Electric arc failure	DGA	C_2H_2, H_2
Failure axial deformation windings Failure radial windings	SFRA and impedance	Correlation index (band kHz)
Failure mechanical paper capacity loss	Physical and chemical	2FAL, furans, CO, CO_2
Failure insulating oil degradation	Physical and chemical	Interfacial, Neutralization Number
Failure insulating oil pollution	Physical and chemical	dielectric strength power factor oil particle content
OLTC failure, insulating oil pollution	Physical and chemical	Dielectric, moisture content, content particles
Moisture oil pollution failure	Physical and chemical	Moisture content, relative saturation, temperatures
Paper moisture contamination failure	Power factor, Physical and chemical	Moisture Content, Relative saturation, temperature, humidity
Dielectric insulation windings and bushings failure	Power factor, dielectric monitoring	Power factor, capacitance

On the other hand, it considers all fuzzy diagnostic system routines for an integral condition, it has the following results:

- Quantitative key of the criticality of occurrence of the failure mode under analysis.
- Key indicators, how do they evolve key variables describing predictive failure mode study? (Increasing, decreasing, stable, pick-up).
- Nature evolution of the failure mode (Thermal, dielectric, mechanical, chemical, etc.)

According to the PCA, it obtains the variables in the Table 2, with understanding on the two procedures proposed for inductive equipment, the variables has been shown in this section.

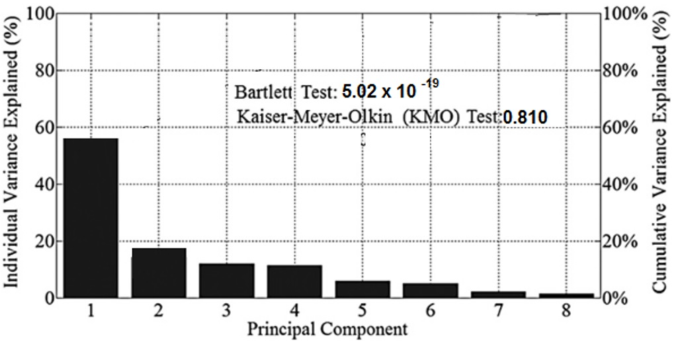

Fig. 3: PCA assessment

In the Fig.3, the suitability of applying PCA, Kaiser-Meyer-Olkin (KMO) test and Bartlett test are useful. Briefly KMO test is a measure of sampling adequacy with values closer to 1 desirable and any value below 0.5 suggesting inadequacy for PCA. Bartlett test evaluates the presence of correlation among the original variables with values lower than a 0. 0 significance level desirable for PCA. Both test statistics as see in the Fig.3 suggest suitability for applying PCA on the original dataset. After performing PCA, eight PCs were obtained which individually explain different percentages of the variance in the original data set.

In Fig.3, the knowledge of each routine is based on rules of IF $\cdots$ THEN type and method of unfuzzy used for the quantifiable calculation of output (criticality index) was that of the method centroid center as Fig. 2. It is describing in detail the development of one subroutines of the main routine for analyzing DGA, which follows all steps of development of a fuzzy inference system (FIS) described above, other subroutines maintain the same scheme with the failure modes and variables.

2.6 Subroutine Fuzzy Result

2.6.1 Subroutine for Thermal Oil Failure

For the development of the subroutine diagnosis of thermal failure it is very important to the method of key gas described in the IEC-60599 standard and to define the ranges of the membership functions from databases of historical DGA, the methodology was proposed by Michel Duval in the reference [5], it was adopted for the subroutine.

Generally, the evolution of a thermal fault in oil is associated with localized overheating problems, due to the presence of hot spots either connections, OLTC selector or failures in the core contacts. When this happens the thermal energy associated with the fault causes the breakdown of the oil (pyrolysis) generating combustible gases. In this case the predominant gases generated are ethylene (C2H4) and ethane (C2H6) whose dates of analysis and concentrations in ppm will be the input variables to the subroutine. The values of the gas concentrations in ppm are applied to the diffuser (fuzzy set) finding the degree of belonging to linguistic set of concentration levels, which in this case were defined in five curves according to Fig.4, as follows: Normal, Low, Medium, High and significant, it is indicated in the Fig.3, with the membership functions for the concentrations of ethylene (C2H4) and ethane (C2H6):

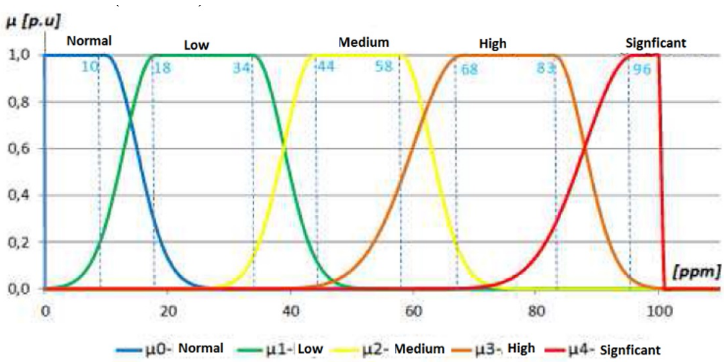

Fig. 4: Member function for output thermal oil failure

With this Fig.4, the Table 3 can be done.

2.6.2 Subroutine for Thermal Kraft (paper) Failure

Carbon Monoxide (CO) and Carbon Dioxide (CO2) are generated when there is pyrolysis of cellulose paper of the internal insulators in the transformer and therefore the dates and concentrations in ppm of these gases are input variables for subroutine fuzzy criticality assessment.

In the Table 2, the limits membership functions for concentrations of Carbon Monoxide (CO) and carbon dioxide (CO2). According to Fig. 5, all stages of these subroutine FIS were performed following the same procedure outlined in the preceding paragraph. Unfortunately, Carbon Monoxide (CO) is not generated within the transformer exclusively, by pyrolysis of cellulose, but their generation is also associated with chemical reactions between the insulating oil and materials used within the separate transformer cellulose, such as nitrile elastomers based, certain paints and phenolic synthetic fibers, among others. This unwanted source of CO distorts the diagnosis of thermal failure modes associated with the role.

Table 3 : Diagnosis result for thermal oil failure.

Element	High C_2H_6	Low C_2H_6	Medium C_2H_6	Low C_2H_6	Normal C_2H_6
C_2H_4 Significative	Signif.	Signif.	Signif.	Signif.	Signif.
C_2H_4 High	Signif.	Signif.	High	High	High
C_2H_4 Medium	Signif.	High	Medium	Medium	Medium
C_2H_4 Low	Signif.	High	Medium	Low	Low
C_2H_4 Normal	Signif.	High	Medium	Low	Normal

Therefore, it is important to write that this routine was necessary to end cross-check with the rate of increase in the total concentration of Combustible Gases (TC-CG) for the purpose of discriminating that the generation of combustible gases CO and CO2 are associated with a failure mode which involves heating the interior of the power transformer.

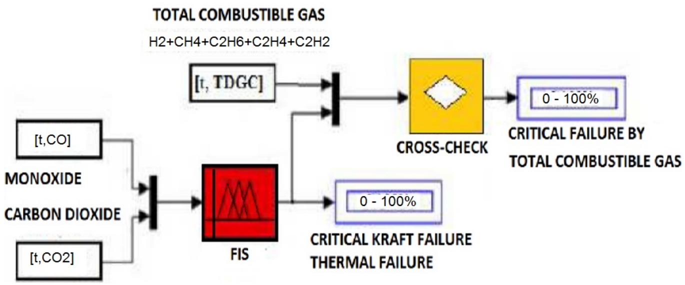

Fig. 5: Cross-check for verify unwanted carbon monoxide generation

2.6.3 Subroutine for General Thermal Failure

To evaluate a criticality index General Thermal Failure a fuzzy subroutine that combines the results of the subroutines for Thermal Oil Failure and Thermal Kraft Paper Failure was developed. The criticality index of these subroutines are the entries of this routine, and the development of FIS for the General Thermal Failure mode follows the same procedure.

The overall thermal criticality gives us an idea of what the thermal performance of the transformer and allows to focus the maintenance actions on those items of equipment that are associated with temperature such as for example: connections, contacts

OLTC, core, flow control dispersion performance cooling system, the management of chargeability of the unit, between others.

2.6.4 Failure Subroutine Partial Discharge Electrical Fault

The partial discharge (PD) activity in the transformer produces a high level of generation of hydrogen (H2) and also a considerable level of methane (CH4). Higher ppm concentrations of these gases are used as input for the fuzzy model developed to measure PD criticality in electric transformer and we have called Partial Discharge Failure.

2.6.5 Failure Subroutine Electric Arc Failure

Arcing is considered one of the most serious concerns in power transformers and more severe failure mode. Both hydrogen (H2) and as acetylene (C2H2) gas are the main indicators for the activity of arcing. The FIS for diagnosing criticality index for the failure mode Fault Electric Arc is developed using these gases as inputs to the model in which the output is the criticality arc.

2.6.6 Integrator Diagnosis General Electric Failure

To evaluate a criticality index General Electric Failure, it was developed for a fuzzy subroutine that combines the results of the subroutines for Thermal Oil Failure and Thermal Kraft Failure. Electric criticality index provides the dielectric condition of the transformer, which is closely linked to the condition of isolation both the solid and the liquid, the effects are: Particulate contamination of insulation parts, moisture, polar substances and the presence of bubbles. Also problems equipotential internal parts of the transformer and high dielectric presence of stress in localized areas of the active part.

2.6.7 Integrator Diagnosis: DGA Criticality

Finally, once assessed and quantified each of the four levels of criticality for failure modes to be detected by analysis of dissolved gases, it is necessary to quantify in a single indicator the condition of the power transformer.

The information used for the assessment is actually in a competition of failure modes because it is not possible to say: It does not happen at this moment, that on a transformer only acted one failure mode at time, and therefore it is necessary to develop a fuzzy routine that integrates all failure modes that can be detected by the DGA, monitoring, power factor, 2FAL test. So, in this way can be quantified in a general index of criticality of 0 to 100% the condition of the transformer, to this indicator we call criticality index integral diagnosis – DGA in Fig. 6 the general scheme of the whole routine for comprehensive diagnosis of the condition of the transformer is shown using information provided by dissolved gas analysis DGA. It is noted as the various subroutines are intertwined together to go systematically developed a unique indicator of the criticality condition.

3. Diagnosis System for Power Transformer

The general outline of the entire system comprehensive diagnosis of the condition of transformers was developed and implemented at Fig.6 and framework at Fig.7, where all subroutines and routines created to diagnose each possible fault all that can be seen affect the capacity of a transformer and therefore possible loss of their duties.

The diagnosis knowledge is represented as the production rule, Fig.7. It followed

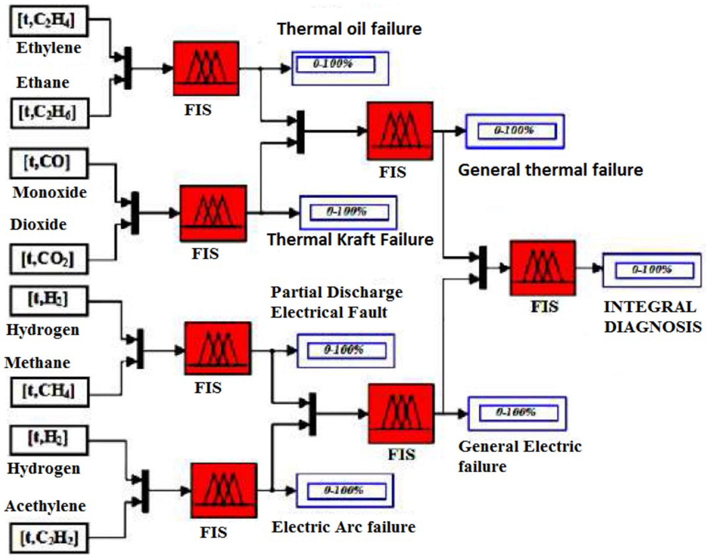

Fig. 6: General outline of the routine for comprehensive diagnosis

the object – attribute – value (O-A-V) knowledge representation method [12], [14]. The conditions of each rule is connected with other rule by conjunction or disjunction based on our newly experiment rule fuzzy logic. This makes the decision – making process more efficient. The system extracts some more logical questions stored in the form of rules in the knowledgebase and prompts the user to select from it. The system then tries to reach the final inference. The intelligent inference model is developed using object – oriented technology based C++ programming language provided in Microsoft Visual Studio. The various components of inference model are discussed below in the case study and conclusions. This new method for condition monitoring and early fault diagnosis of electric power transformers has been introduced. The paper has proposed to use intelligence fuzzy logic for modeling the oil, kraft behavior of an electric power transformer and particularly the variations of a parameter known as DGA and 2FAL with the temperature. To use a statistical fault diagnosis method (Local Statistical Approach to Fault Diagnosis) that enables the early detection of failures (changes) in the transformer's model. A fuzzy model was extracted from data which were obtained from the operation of a real power transformer. Next, the efficiency of the proposed method was tested through the statistical processing according Fig. 7.

4. Case Study

The case study was performed in a real power reactor installed at Trujillo Nueva substation, R -24 phase S, it has anomalies in the power system. The samples taken

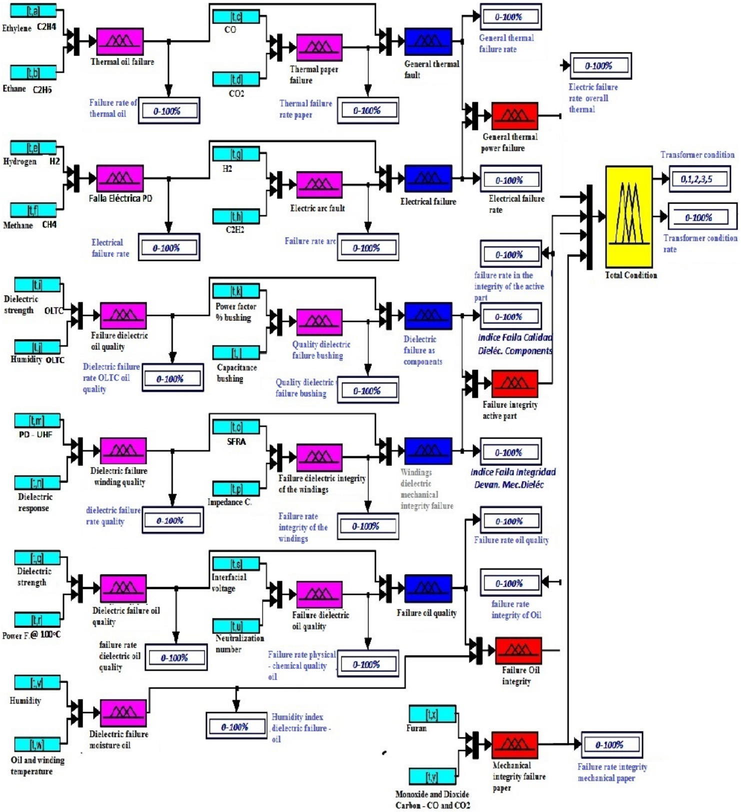

Fig. 7: Framework of the routine for comprehensive diagnosis

after commissioning test. First of all, in the Fig.8, the membership functions are used to translate verbal judgments or linguistics into numeric expressions, a fuzzy membership function is constructed to describe the factor layer of evaluation model. With fuzzy algorithms, you can determine the condition team on the following scale, Table 4.

Fuzzy logic being a logical system provides a very convenient method to map the input to the output through linguistic rules formed from human understanding rather than stringent mathematical models. The fuzzy logic based evaluation is a three step process involving fuzzification, fuzzy inference and defuzzification. Fuzzification involves in assigning a degree of membership to a rather crisp value while fuzzy inferencing makes some conclusions based on the defined linguistic if-then rules.

Defuzzification is the reconversion of the fuzzified outputs corresponding to the fuzzy rules back to a crisp value following a chosen defuzzification method. Each model is trained appropriately using the training dataset to develop its diagnostic capability to identify its own fault type accurately. While training for a particular fault type the output corresponding to that fault is given a value 1 while all the other faults have output value 0.The training is done for sufficient number of epochs so as to keep the training error to less than 0.001.

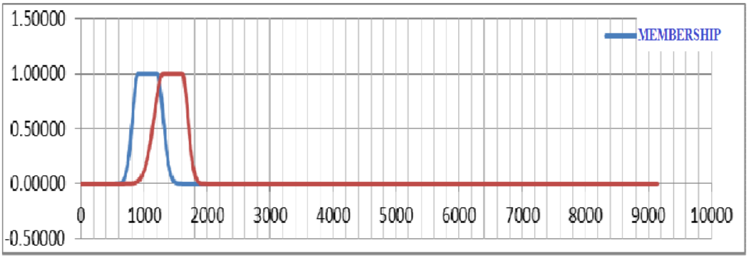

Fig. 8: Membership for calculation

Table 4 : Condition scale

Condition	Value
Out service	0
Risk	1
Low risk	3
Monitoring	4
Normal	5

With the theory, it can be applied in the Table 5, insulating materials within transformers and electrical equipment break down to liberate gases within the unit. The distribution of these gases can be related to the type of electrical fault, and the rate of gas generation can indicate the severity of the fault. The identity of the gases being generated by a particular unit can be very useful information in any preventative maintenance program. Many years of empirical and theoretical study have gone into the analysis of transformer fault gases.

Table 5 : Component values for oil.

Component	Before Value 12/12/2014	After Value 06/04/2015
H_2	15.00	2,475.00
CO	100.00	355.00
C_2H_2	0.00	1,911.00
CH_4	12.00	1,057.00
C_2H_4	1.00	2,396.00
C_2H_6	4.00	233.00
N_2	59,632.00	10,764.00
O_2	9,251.00	114.00
CO_2	1,127.00	5,734.00

DGA usually consists of sampling the oil and sending the sample to a laboratory for analysis. Mobile DGA units can be transported and used on site as well; some units can be directly connected to a transformer. Online monitoring of electrical equipment is an integral part of the smart grid. The DGA technique involves extracting or stripping the gases from the oil and injecting them into a gas chromatograph (GC). Detection of gas concentrations usually involves the use of a flame ionization detector (FID) and a thermal conductivity detector (TCD). Most systems also employ a methanizer, which converts any carbon monoxide and carbon dioxide present into methane so that it can be burned and detected on the FID, a very sensitive sensor. With the Table 5, the condition of the equipment is 1, it is generated by electrical arc in oil with gas, the cellulose degradation is due to overheating, all reliable data. When transformer suffers from mechanical force caused by through fault current (TFC), the insulation system suffers the impact as well in the form of overheating. The overheating is caused by thermal stress during fault and will reduce the dielectric strength of the insulation. As the overheating proceeded, a chemical reaction (pyrolysis oxidative reaction) takes place. This reaction produces combustible gases (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2) in transformer oil and CO and H_2O in paper insulation. As the overheating sustains the gasses amount will grow. It results in paper insulation deterioration. This condition can be known by doing Dissolved Gas Analysis (DGA). Besides, Oil characteristic test need to be done to monitor the physical and chemical characteristic of insulation. The mechanical impact due to the resulted vertical and axial force gives high impacts to the current carrying unit subsystem. The impacts are taking form in direct winding deformation, loose connector, or spacer deformation that will cause indirect winding deformation. The form of impacts depends on the amplitude and duration of fault. As the most severe impact, the transformer will breakdown. Before winding deformation occurs, there are many symptom can be monitor, they are noise level increasing, voltage asymmetry, impedance changing and change of frequency response.

Table 6 : Normativity international vs diagnosis proposal using DGA class.

Method	Criteria	Cal.	Comment
Laboratec Method	Very important-Arc Arc oil or gas LTC (D8)	1	
Dornembur IEC 60599	Low energy discharge (D1)	3	
Dornembur IEC 60599	Fully method reliable (IEEE C57.104)	––	At least one of the gases of each ratio exceeds the normal values
Duvai IEC 60599	Low energy discharge (D1)	3	
ABNT Method	Overheating of oil.	3	
IEC 599/78	Continuous heating oil for poor connection different powers fluctuating dielectric breakdown oil between solids		
IEC 60599	Low energy discharge	3	
IEC 60599	Oil oxidation and aging paper detected through consumption excessive O_2	3	
IEC 60599	Pollution OLTC	3	If there is no connection between tanks, or leaks this criterion often determining pollution cuba oil by contact between oils
IEC 60599	$H > 50 * 10$	––	Reliable analysis by high level of gas oil
IEC 60599	C_2H_2	––	Reliable analysis by high level of gas oil
IEC 60599	C_2H_4	––	Reliable analysis
CIGRE CS 15	Key ratio 1	3	Discharge
CIGRE CS 15	Key ratio 3	2	Oil Thermal failure
CIGRE CS 15	Key ratio 4	2	Degradation of cellulose by overheating.

With the international normativity, our proposal for intelligent diagnosis will present the followings results: The reactor has presented an evolutionary failure associated with oil and gas arc, verified with the drive Buchholz relay. The degraded oil and Kraft equipment, it was installed in 2014 with a reduced service life. According to the document CIGRE [5] regarding the life of inductive equipment, power reactor, is 41 years in the first year after commissioning, according to Table 7 concludes that the associated equipment had an aging 33 years after the above events.

Table 7 : Physical and Chemical deterioration.

Equipment	Dielectric strength [kV]	Power factor 100 degree	Mx Total	Ax Total	Rate of chemical deterioration
1059211	51	0.839	314.113	25.3196	12.406

The Kraft remaining life is indicated in the Table 8.

Table 8 : Kraft remaining life.

Equipment	Rate of physical chemical deterioration [years]	Remaining life assigned [years]	Mx Total	Ax Total	Remaining life [years]
1059211	12.406	38.763	1107.93	33.1527	33.4

After the intervention in April 2015, the analysis confirms the release of high voltage connection in the power transformer under the bushing, in the hub of the reactor, which caused low energy arc, until disconnect the unit.

With the Table 8, in this paper, we can demonstrate the impact in the physical asset management, with the deterioration of the equipment a value of 12% represent a physical problem on a connection, and with the Table 6 and 7, confirm an Arc on Oil problem based on low energy discharge, it causes a continuous overheating with a reliable analysis. Finally, the Table 8 presents a reduction of the remaining life: Estimated 60 years [5] to 33.4 years.

5. Diagnosis Performance

The correct intelligent diagnosis was performance on 107 samples at Peruvian power electrical system for inductive equipment, the results are the followings in the Table 9.

In the Table 9, the new proposal is better than Laboratec Method and ABNT Method for accuracy, and it is easier than Duvai and IEC 60599-2015, because it compares many perspectives and knowledge to obtain a result for normal behavior in power transformers. If we apply this method, on the Table 9, the results can demonstrate a high level of effectiveness with 97.2% according to Duvai 60599-2007 Method and IEC 60599-2015 method for normal condition.

In the Table 10, our proposal has a better accuracy than ABNT Method and IEC 60599; besides, the effectiveness of the Intelligent Diagnosis is 98.13% with the Laboratec Method and Duvai IEC 60599-2007 for a diagnosis on a failure event, we can conclude the new proposal using PCA and fuzzy logic is a good parameter in the electrical assessment.

Table 9 : Effectiveness of the method in normal event.

Method	Correct diagnosis	Incorrect diagnosis	Incorrect diagnosis [percent]	Correct diagnosis [percent]
Intelligent diagnosis	104	3	0.972	0.028
Laboratec	101	6	0.9439	0.0561
Duvai IEC 60599	104	3	0.972	0.028
ABNT IEC 599/78	100	7	0.9346	0.0654
IEC 60599	104	3	0.972	0.028

Table 10 : Effectiveness of the method in failure event.

Method	Correct diagnosis	Incorrect diagnosis	Incorrect diagnosis [percent]	Correct diagnosis [percent]
Intelligent fuzzy diagnosis	105	2	0.9813	0.0187
Laboratec	105	2	0.9813	0.0187
Duvai IEC 60599-2015	105	2	0.9813	0.0187
ABNT IEC 599/78	102	5	0.9533	0.0467
IEC 60599-2015	103	4	0.9626	0.0374

Although DGA has widely been used in the industry, in some cases, the conventional methods fail to diagnosis. This normally happens for those transformers which have more than one type of fault. Actually, the conventional diagnostic methods are based on the ratio of gases generated from a single fault or from multiple faults but with one of dominant nature in a transformer. When gases from more than one fault in a transformer are collected, the relation between different gases becomes too complicated which may not match the codes pre-defined. Now with the new proposal, a intelligent fuzzy diagnosis has been implemented with more accuracy and effectiveness.

6. Conclusion

Systems condition assessment based on fuzzy logic, allows the development of mathematical models and algorithms for knowledge management for the condition analysis, it permits to obtain the linguistic and subjective parameters of technical experts and normativity, as well it use knowledge and experience. Therefore, they are very effective in capturing and documenting know how.

In the Fig.8 a fuzzy membership function is constructed to describe the factor layer of assessment model. According to the fuzzy evaluation results, the original basic probability assignment, which is used for decision-making model of evidential reasoning, is determined with high accuracy, it is shown in the Table 9 for normal condition and Table 10 for failure event.

Intelligent diagnostic systems should be focused on detecting possible failure modes evolving in a transformer, rather than worry indicate whether any variable measured in predictive maintenance is or not offset from some reference value. Thus the basic probability assignment is obtained by evidence reasoning, and finally the assessment results are determined based on the decision rules of the maximum basic probability assignment function, it has been realized case study, Table 5, and the results in the Tables 7 and 8; it can not only determine the remaining life for oil, but also five out the remaining life for Kraft: General thermal failure failure integrity active part, failure oil integrity, mechanical integrity failure paper and total condition . Thus this research provides a new method for oil and Kraft remaining life and conditions for inductive equipment. The method has obtained 12 check points: Failure rate of thermal oil, thermal failure rate paper, electrical failure rate, failure rate arc, dielectric failure rate OLTC oil quality, quality dielectric failure bushing, dielectric failure quality, failure rate integrity of the windings, failure rate dielectric oil quality, failure rate physical - chemical quality oil, humidity index dielectric failure oil and failure integrity mechanical paper.

It is vitally important that the design of intelligent diagnostic systems will stay in harmony with studies of maintenance strategy, to detect failure modes and to establish these, to use predictive maintenance, whether the objective function of these and can be given to the appropriate maintenance process that require maintenance actions signal equipment. Another advantage of the fuzzy diagnosis method is its quantitative indication of the fault likelihood dominance by means of fuzzy diagnostic vector. This has been used to identify the main faults and determine their severity in comparison to each other. It has been found from our experience that the larger is the fuzzy component, the more dominant, active and severe the fault will be. The trend of development of each fault in a transformer can also be determined from its fuzzy diagnostic vector after certain period of monitoring. This information is important for any decision regarding the transformer replacement or refurbishment.

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