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Expert system for the assessment of power transformer insulation condition based on type-2 fuzzy logic systems

Wilfredo C. Flores [a,*], Enrique E. Mombello [b], José. A. Jardini [c], Giuseppe Rattá [a], Antonio M. Corvo [d]

[a] *Instituto de Energía Eléctrica, National University of San Juan, Av. Libertador San Martín, 1109 (oeste), J5400ARL San Juan, Argentina*
[b] *CONICET, At Instituto de Energia Electrica, National University of San Juan, Ave. Libertador San Martin, 1109 (oeste), J5400ARL San Juan, Argentina*
[c] *University of São Paulo, Department of Engineering of Energy and Electric Automation, Brazil*
[d] *CTEEP, Companhia de Transmissão de Energía Elétrica Paulista, Rua Casa do Ator, 1.155-04546-004, Villa Olimpica, São Pablo, Brazil*

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ABSTRACT

An efficient expert system for the power transformer condition assessment is presented in this paper. Through the application of Duval's triangle and the method of the gas ratios a first assessment of the transformer condition is obtained in the form of a dissolved gas analysis (DGA) diagnosis according IEC 60599. As a second step, a knowledge mining procedure is performed, by conducting surveys whose results are fed into a first Type-2 Fuzzy Logic System (T2-FLS), in order to initially evaluate the condition of the equipment taking only the results of dissolved gas analysis into account. The output of this first T2-FLS is used as the input of a second T2-FLS, which additionally weighs up the condition of the paper-oil system. The output of this last T2-FLS is given in terms of words easily understandable by the maintenance personnel. The proposed assessing methodology has been validated for several cases of transformers in service.

1. Introduction

Power transformers are the most complex and strategically important components of any power transmission system. For this reason, their condition monitoring is crucial. At the present time, one of the most used on-line methods of power transformers monitoring is the dissolved gas analysis (DGA). The method using gas ratios according to IEC 60599 Standard is widely used to evaluate the condition of the paper-oil system of power transformers. Nevertheless, doing an evaluation of the isolation of a transformer using this method requires expert knowledge, with which not always it is counted. Besides, when different kinds of faults appear simultaneously, the system of diagnosis could fail. In order to try to solve these problems, methodologies which consider the fuzzy nature of the gas ratio boundaries using the fuzzy set theory have been suggested (Islam, Wu, & Ledwich, 2000; Su, Mi, Lai, & Austin, 2000). An efficient expert system, which uses the expert knowledge in the diagnosis results, it is proposed in this work. This expert system uses the gas ratios defined in IEC 60599 standard, and eventually also the Duval's triangle (Duval, 2002), as well as other parameters suggested recently (Duval et al., 2004). Moreover, the annual growth of the carbon monoxide (CO) is taken into account, which indicates the possible decomposition of solid insulation. Once this diagnosis is obtained, its interpretation is necessary. For this purpose, it is feasible to consult either a data base, tables of codes, (such as suggested by IEC, Su et al., 2000), or experts. The use of the expert opinions in diagnostic problems has been widely implemented (Peng & Reggia, 1990). In addition, type-2 fuzzy systems have been recently used in decision-making problems to handle the uncertainty associated with words, as well as the uncertainty in the opinion of experts (Liang, Karnik, & Mendel, 2000; Romero, 2005).

This work presents an expert system for the assessment of power insulation based on on-line tests like DGA and some off-line tests like oil and solid insulation tests, and using an approach based on two T2-FLS. The T2-FLS takes into account the uncertainty associated to the meaning of words and to the opinion of experts. The diagnostic system implemented in this manner can be used in the sense of "perceptual computation" (Mendel, 2001), by which people are allowed to interact with devices using a natural language. In the case of diagnostics of power transformer insulation, the proposed diagnostic system allows to readily establish the condition of the paper-oil insulation system.

The structure of this work is as follows: a brief explanation about the diagnostics of the paper-oil system of a power transformer using the suggested gas ratio defined in the IEC 60599 standard and the Duval's triangle is given in Section 2. In Section 3, the algorithm combining both DGA diagnostics methods is shown. A brief review about oil and solid insulation test parameters related to power

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[*] Corresponding author. Address: Faculty of Science, School of Physics, Universidad Nacional Autónoma de Honduras, Tegucigalpa, MDC, Honduras, Central America. Tel.: +504 2396566.

E-mail address: wilfredo.flores@gmail.com (W.C. Flores).

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transformers insulation is also given. In Section 4, a description of the construction of type-1 fuzzy sets used to include the oil and solid insulation test values in the diagnosis is shown. Section 5 contains a summary about the logical type-2 fuzzy systems. In Section 6, the knowledge system based on surveys for the evaluation of equipment condition is presented. Section 7 is related to the application of the methodology. The conclusions are given in Section 8.

It is assumed that the studied transformers do not have access to the load tap changer.

2. Diagnostics by DGA

2.1. Gas ratios: IEC 60599 standard

IEC 60599 standard establishes a classification by which five different types of faults can be detected by means of dissolved gas analysis. These faults are classified in the following way:

(a) Partial discharge (PD): cold plasma (corona) type fault, resulting in possible X-wax deposition (polymer of hydrocarbon not saturated: by-products of degradation).
(b) Discharges of low energy (*D*1): in oil or/and paper, evidenced by larger perforations in paper, tracking, or carbon particles in the oil.
(c) Discharges of high energy (*D*2): in oil or/and paper, evidenced by extensive carbonization of paper, metal fusion and possible tripping of the equipment.
(d) Thermal faults: Below 300 °C if the paper has turned brownish (*T*1), and above 300 °C if it has carbonized (*T*2).
(e) Thermal faults above 700 °C (*T*3): evidenced by the carbonization of the oil, metal coloration or metal fusion.

The three basic gas ratios used by IEC are: $r_1 = C_2H_2/C_2H_4$ = acetylene/ethylene, $r_2 = CH_4/H_2$ = methane/hydrogen and $r_3 = C_2H_4/C_2H_6$ = ethylene/ethane. Additionally, the r_4 ratio ($r_4 = CO_2/CO$ = carbon dioxide/carbon monoxide < 3) is used, which indicates the possible participation of paper insulation in the fault, but not always (Duval, 2002). For this reason, this ratio must be used with caution. Other typical gas limits are shown in Table 1, which also shows the logic rules used in the DGA diagnostic algorithm.

Since the r_4 ratio is not absolutely reliable, and with the aim of detecting a possible degradation of paper, three additional types of faults have been considered:

(a) Excessive degradation of insulation paper (EDI): it occurs when the ratio r_4 is smaller than 3 or the CO level is greater than 600 ppm. This last restriction is specified according to the limits proposed by Duval et al. (2004), in relation to the values of typical gas concentration and to the key gas criterion.
(b) Cellulose overheating (COV): this happens when the r_4 ratio is greater than 10 or the CO level is greater than 600 ppm. This last restriction is specified as in paragraph a.
(c) Continuous degradation of cellulose (CDC): evidenced when the typical value of the increase rate of CO (TRGI, ppm/year) rises beyond the values proposed by Duval et al. (2004) (Table A.2 – rank of values). The age of the equipment is taken into account. In addition, the condition CO > 600 ppm must be met (see Table 1).

Table 1
Types of failures detected by dissolved gas analysis.

Fault	Ratio	Causality
PD	$r_2 < 0.1$ (A_1); $r_3 < 0.2$ (A_2); pC $\geqslant$ 10–30[a] (A_3)	$(A_1 \cap A_2) \cup A_3$
D_1	$r_1 > 1$ (B_1); $0.1 < r_2 < 0.5$ (B_2); $r_3 > 1$ (B_3); $H_2 > 150$[b] (B_4); $CH_4 > 130$ (B_5)	$(B_1 \cap B_2 \cap B_3) \cup (B_4 \cap B_5)$
D_2	$0.5 < r_1 < 2.5$ (C_1); $0.1 < r_2 < 1$ (C_2); $r_3 > 2$ (C_3); $H_2 > 150$ (C_4); $C_2H_2 > 20$ (C_5)	$(C_1 \cap C_2 \cap C_3) \cup (C_4 \cap C_5)$
T_1	$r_1 < 0.1$ (D_1); $r_2 > 1$ (D_2); $r_3 < 1$ (D_3)	$D_1 \cap D_2 \cap D_3$
T_2	$r_1 < 0.1$ ($E1$); $r_2 > 1$ (E_2); $r_3 < 4$ (E_3); $C_2H_4 > 280$ (E_4); $CH_4 > 130$ (E_5)	$(E_1 \cap E2 \cap \mathrm{E3}) \cup (\mathrm{E4} \cap \mathrm{E5})$
T_3	$r_1 < 0.2$ (F_1); $r_2 > 1$ (F_2); $r_3 > 4$ (F_3)	$F_1 \cap F_2 \cap F_3$
EDI	$r_4 < 3$ (G_1); CO > 600 (G_2)	$G_1 \cup G_2$
COV	$r_4 > 10$ (H_1); CO > 600 (H_2)	$H_1 \cup H_2$
CDC	Rate CO > TRGI[c](I_1); CO > 600 (I_2)	$I_1 \cap I_2$

∩: Interception; ∪: union.
[a] PicoCoulombs (pC).
[b] Parts by million (ppm).
[c] Rate of increase of typical value of CO (ppm/year).

The third column of Table 1 shows the manner to obtain the causality to detect a fault. For instance, the fault *D*1 is detected if conditions B1 AND B2 AND B3 OR B4 AND B5 are present. In this way, a fault is detected as long as the causality is greater or equal than 0.5 and gas ratios indicate the presence of fault. The output of the DGA diagnostic algorithm is a vector having ones and zeros, according to whether the failure is detected or not, respectively.

2.2. Triangle of Duval

The diagnostic method using Duval's triangle is described in Appendix B of IEC 60599:1999 standard. This method is used for diagnostics of high voltage oil-immersed equipment (mainly transformers) and it was developed by Michel Duval at Hydro Quebec Research Institute. Fig. 1 shows the triangle of Duval.

The concentrations (in ppm) of methane (CH_4), ethylene (C_2H_4), and acetylene (C_2H_2) are expressed as a percentage of the total ($CH_4 + C_2H_4 + C_2H_2$) and define a point (%CH_4, %C_2H_4, %C_2H_2) in a coordinate system represented as a triangular diagram, which has been subdivided in different zones. Each zone is related to a certain type of fault.

The fault zone in which the point is located gives the probable type of fault characterized by such combination of gas concentrations. The classification of fault types is the same as that of the IEC 60599 standard.

The method of the Duval's triangle, as well as any other method of DGA diagnostics, must be only applied if at least one gas concentration value is above the typical value and above the typical rate of gas increase.

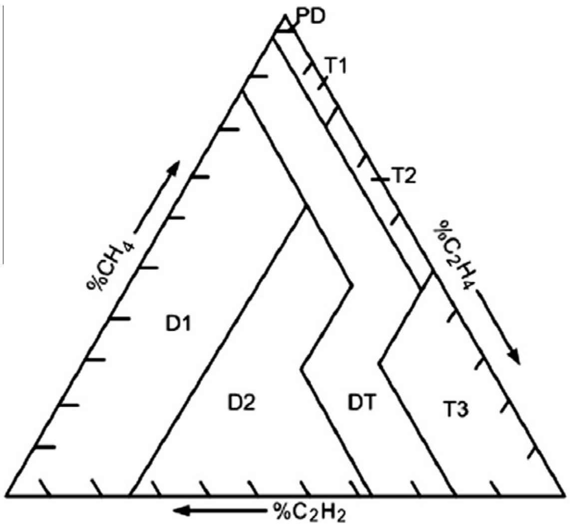

Fig. 1. Coordinates and fault zones of the Duval's triangle.

3. Expert system proposed for diagnostics by dissolved gas analysis and oil test values

3.1. Condition evaluated by dissolved gas analysis

At the present time, the DGA diagnostic methods of better performance are the key gas method using Roger ratios (Roger, 1978) or the key gas method together with the Duval's triangle used as confirmation (Horning, Kelly, Myers, & Stebbins, 2004). In this work, the Duval's triangle is used as confirmation for the IEC method.

It is considered in this work that if all gas concentrations are below their 90% typical values, it is not necessary to calculate the gas ratios and the equipment is considered healthy, and hence the fault probability is low, as stated in Duval et al. (2004). So, the decision triangle shown in Fig. 2 is based on the presence of an abnormal level of gas.

The algorithm finds the possible faults using the Duval's triangle and the IEC method. If the IEC method does not find the fault found by the Duval's triangle, the results of the Duval's triangle are added to the final diagnosis. Following this procedure, the vector of possible disorders detected by DGA diagnostics is obtained, as shown in the lower part of Fig. 2. The remaining blocks of Fig. 2 will be explained in detail in the following sections.

In order to guarantee the correctness of fault detection by means of the DGA diagnostic algorithm, the comprehensive databases proposed in Duval and de Pablo (2001) were used. These databases are composed of data from faulty equipment inspected in service and of typical normal values related to different equipment characteristics such as type, age and type of fault. Table 2 gives some results obtained by applying the algorithm for failure detection using the database mentioned previously. The first column shows the diagnosis obtained by using Duval's triangle in Duval and de Pablo (2001); the second and third columns shows the results of the algorithm by applying IEC 60599 and Duval's triangle, respectively. The fourth column shows the combination of the results of columns two and three. The other columns show the concentration of gases in ppm.

It can be seen from Table 2 that the algorithm is efficient in the detection of incipient failures. It is also able to detect the presence of insulation paper involved in the failure, something that neither IEC nor Duval's triangle do. This fact could be seen during the

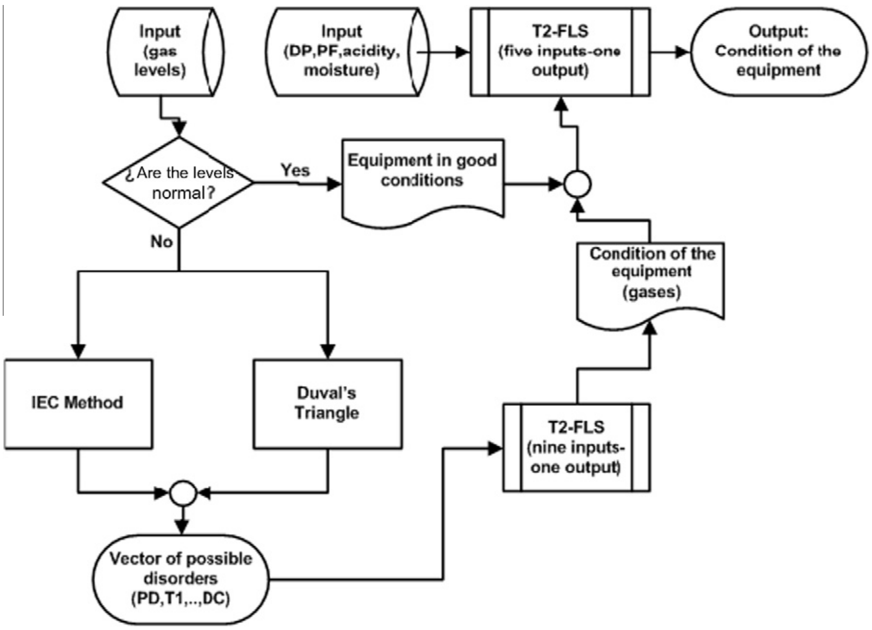

Fig. 2. Algorithm of the expert system for diagnosis by gas and oil test values.

Table 2
Comparisons between the results of Duval and de Pablo (2001) and the proposed algorithm.

Duval[*]	Results from algorithm			H_2[**]	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2
	IEC	Duval	Diagnostic by DGA							
PD[a]	PD, D_1	PD	PD, D_1	37800	1740	8	8	249	56	197
D_1	D_1, D_2	D_1	D_1, D_2	305	100	541	161	33	440	3700
D_1	D_1, D_2	D_1	D_1, D_2	595	80	244	89	9	524	2100
D_2[b]	D_1, D_2, EDI, COV, CDC	D_2	D_1, D_2, EDI, COV, CDC	545	130	239	153	16	660	2850
D_2[c]	D_1, D_2, T_2, EDI, COV, CDC	D_2	D_1, D_2, T_2 EDI, COV, CDC	1820	405	634	365	35	1010	8610
T_1–T_2[d]	D_1, COV	T_2	D_1, T_2, COV	1270	3450	8	1390	520	483	44500
T_3[e]	D_1, D_2, T_2	T_3	D_1, D_2, T_2, T_3	6709	10500	750	17700	1400	290	1500

[*] Results from Duval and de Pablo (2001).

[**] The concentrations of gases in ppm.

[a] The inspection shown corona and x-wax formation.

[b] Short circuit from LV to connector.

[c] Short circuit between conductors.

[d] High circulating currents between conductors with winding damage.

[e] Circulating currents between yoke clamps and connecting bolts.

transformer inspections c and d and from the presence of EDI, COV and CDC.

Furthermore, the algorithm has enough versatility to detect the failures that are also detected by the Duval's triangle. The DGA diagnostics proposed in this work has been proven to be very efficient since the faults in defective transformers have been detected in all cases.

3.2. Physical and chemical factors affecting the state of insulation of power transformers

The paper-oil insulation degrades over time. This process depends on thermal and electrical conditions, water content and oxygen, and other internal conditions in the transformer. The most accepted degradation mechanisms of paper cellulose are pyrolysis, hydrolysis and oxidation.

In the case of pyrolysis, the reaction takes place by means of a dehydrated compound, which produces furans among other byproducts of degradation.

Hydrolysis is considered the most harmful degradation mechanism for the paper. In general, the mechanical life of the insulation is reduced to one-half when the moisture content doubles (Du, Zahn, Lesieutm, Mamishev, & Lindgren, 1999).

The oxidation produces moisture and weakens the unions of glucose molecules of the paper. For this reason, some secondary reactions could cause ruptures in the chain of paper polymer.

In order to establish the state of the paper-oil system, it is necessary monitoring the different parameters involved in the paper-oil degradation.

From the point of view of physical and chemical factors, it has been established in this work that a broad way to know the insulation condition is by means of monitoring four variables: the degree of polymerization (DP), the moisture by dry weight in the paper, the power factor of the winding (PF) and the acidity of the oil. These four variables have been chosen following the guide for diagnosis implemented in Lundgaard and et al. (2007) and the criteria and experience of the authors. The four factors are the inputs of the diagnostic system shown in the upper part of Fig 2. The diagnostics of power transformers proposed in this way is focused to give an idea about the condition of the insulation paper, its ageing level, taking into account some field test used commonly (as PF), using a minimum amount of variables. This approach can provide useful information about the state of the equipment's insulation. Other insulating oil and winding tests such as interfacial tension, dielectric strength in oil, recovery voltage measurement, frequency response analysis, etc. (IEEE Std., 1995; Wang, Vandermaar, & Srivastava, 2002), could be used too, but the approach is oriented to obtain a diagnosis of the insulation paper of power transformers in service using a minimum amount of variables. This is proposed in this way because of two reasons: the first is that it is considered in the industry that *the life of a power transformer is the life of its insulation paper* and the second is that it is necessary to avoid the *course of dimensionality* (Mendel, 2004) in the T2-FLS used in the diagnostic algorithm.

The DP is closely related to the mechanical strength of the paper and there exist several mathematical models that relate the DP to the level of furans in oil. Flores, Mombello, Rattá, & Jardini (2007) show a review of the most commonly models used. Therefore, if the value of DP is unavailable, it is feasible to get it from the furans content. Although it is possible to derive the value of DP from the furans content in this way, it should be noted that the accuracy of this value is low. It should also be considered that some oil treatments performed during transformer service life remove furans, and consequently the calculated DP level has no meaning and should not be used. The algorithm uses the value of DP obtained either by mean of a direct sampling of paper insulation or by mean of oil insulation sampling with the aim of make use of furan contents in oil. The models showed in Flores et al. (2007) are useful for the latter.

Moisture contributes to accelerate the rate of aging of the insulating liquid and of the solid insulation. Solid insulation degradation caused by moisture produces a permanent damage and a premature loss of equipment life. The premature aging of solid insulation is directly related to its percent moisture content (Horning et al., 2004). There is a normal and continual migration of water between the oil and cellulose and this migration occurs at rates dependent on temperature. In spite of that, the moisture in the paper can be calculated from the water levels in an oil sample. A common practice has been to measure the moisture content in oil using the Karl Fischer Titration, IEC 60814. Although the water migrates between the solid and liquid insulation in a transformer with changes in load and temperature (IEEE Std., 1995), it is possible to estimate the moisture in the paper using different equilibrium curves (Du et al., 1999). Finally, the percentage of moisture per dry weight of the paper can be obtained. It is necessary to mention that the use of these equilibrium curves to predict the moisture level in the insulation under non-equilibrium conditions will result in erroneous estimates (Oommen, 1983). It is therefore very difficult to estimate the paper water content from an oil sample. Also, the correct use of the equilibrium curves must be taken into account (Oommen, 2003).

The insulation power factor (PF) is the ratio of the resistive current component to the total leakage current under an applied voltage. PF measurement is an important source of data in monitoring transformers condition. It is used to detect problems with the transformer bushings and to evaluate the condition of the oil/paper insulation structure (Wang et al., 2002). The PF does not depend upon the amount of insulation tested or its configuration, but only upon its condition (Doble Engineering Company, 1993). This is a useful fact as it enables insulation systems of different masses and shapes to be compared directly without the need to apply correction factors. A new transformer should have a PF of 0.5% or less (Horning et al., 2004). While the PF for most older transformers will also be <0.5% (20 °C), PF between 0.5% and 1% (20 °C) may be acceptable; however, PF >1% (20 °C) should be investigated (IEEE Std., 1995). In general, a PF of less than 0.5% is considered good; 1–2% is questionable; and if it exceeds 2%, action should be taken (Wang et al., 2002). The evaluation is not only based on a single power factor data point but is also based on the history of the change in PF. Noonan (2000) categorizes the interwinding PF as the following: dry 0.5%; medium <1.5%; and wet >1.5%.

In the case of aged insulating oil, a way to know the oil condition is by determining the acidity content. Acidity is gauged by a neutralization number (NN), which is expressed in the number of milligrams of potassium hydroxide required to neutralize the acid in a gram of oil (mg KOH/g). A used oil having a high NN indicates that the oil is either oxidized or contaminated with materials such of varnish, paint, or other matter. This condition may be indicative of sludge formation (IEEE Std., 1995).

4. Type-1 fuzzy sets used to evaluate the physical and chemical condition of the liquid and solid insulation

Once the physical and chemical parameters are obtained, these are introduced to the diagnostic system. To do this, the classification of values in service proposed in Horning et al. (2004) is used. They are shown in Tables 3–6. The limits of PF are the ones proposed in IEEE Std. (1995). These tables are the basis for the construction of the type-1 fuzzy sets shown in Figs. 3 and 4.

The moisture levels depend on the equipment rated voltage. Therefore, the intervals represented by type-1 fuzzy sets also depend on the rated voltage. These sets are shown in Fig. 4.

Table 3
Intervals for DP.

	Acceptable	Questionable	Unacceptable
DP	>500	250–500	0–200

Table 4
Intervals for acidity.

	Acceptable	Questionable	Unacceptable
mg KOH/g	0–0.05	0.05–0.10	>0.10

Table 5
Intervals for power factor.

	Acceptable	Questionable	Unacceptable
%	⩽0.5	0.5–1.0	⩾1.0

Table 6
Intervals for moisture by dry weight.

Voltage (Kv)	Acceptable (%)	Questionable (%)	Unacceptable (%)
⩽69	0–2.0	2.51–4.0	⩾4.01
>69 and <230	0–1.35	1.71–2.65	⩾2.66
⩾230	0–0.85	1.06–1.70	⩾1.71

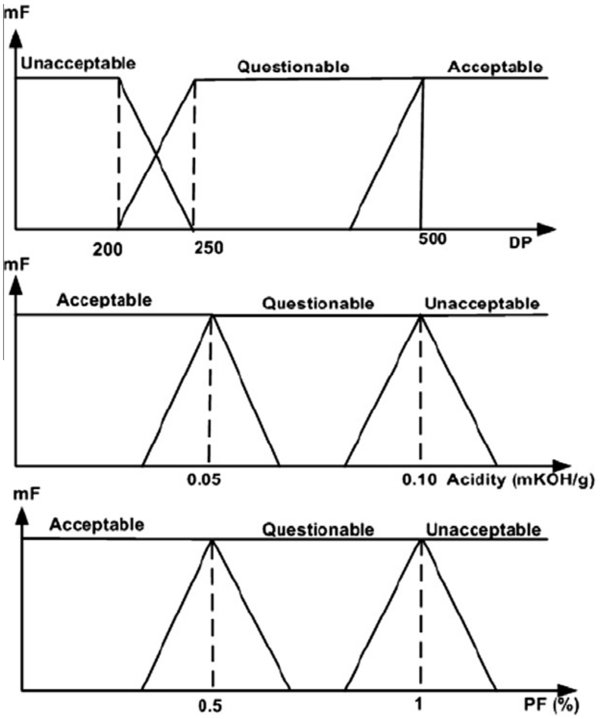

Fig. 3. Type-1 fuzzy sets representing the bounds for DP, Acidity and PF.

At this time, it is necessary to clarify that a type-1 fuzzy set A, defined in the universe of discourse X, handles the uncertainty of the meaning of the words using a two-dimensional membership function which is crisp. This is obtained using (1),

$$A = \int_{x\in X} \mu_A(x)/x \tag{1}$$

where $\mu_A(x)$ is the grade of membership function (a crisp number) for an element $x \in X$ and the symbol $\int$ represents the union over all possible x.

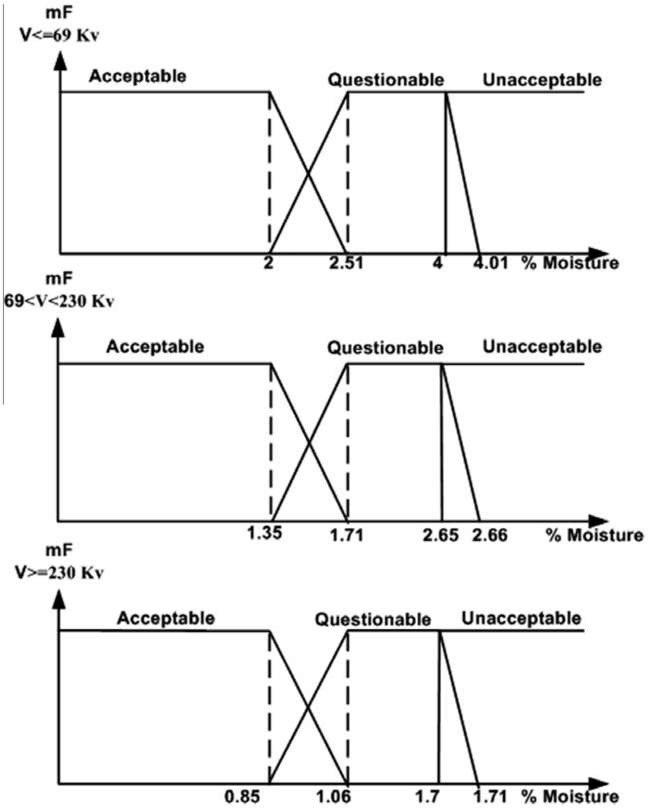

Fig. 4. Type-1 fuzzy sets representing the bounds for % of moisture by dry weight.

5. Type-2 fuzzy logic systems: a brief overview

Because in this work type-2 fuzzy logic systems (T2-FLS) are used as a tool for the diagnostic of power transformers, it is convenient to present a brief introduction to the general outlines of type-2 fuzzy sets and T2-FLS. A rigorous description of their mathematical theory and applications can be found in Mendel (2004).

A type-2 fuzzy set $\widetilde{A}$, can model the uncertainty related to the meaning of words using a function of three-dimensional property, which is fuzzy. This is shown in (2) and (3)

$$\widetilde{A} = \int_{x\in X} \mu_{\widetilde{A}}(x)/x \tag{2}$$

$$\mu_{\widetilde{A}}(x) = \int_{u\in J_x} f_x(u)/u, \quad J_x \subseteq [0, 1] \tag{3}$$

where $\mu_{\widetilde{A}}(x)$ is the *secondary membership function* for an element $x \in X$. The domain (J_x) and the amplitude ($f_x(u)$) of $\mu_{\widetilde{A}}(x)$, are the primary membership of x and secondary grade, respectively.

The union ($\cup$) of all the primary memberships of $\widetilde{A}$ is a region called *fingerprint of uncertainty* (FOU) (4). The upper and lower limits of the FOU are called upper and lower membership functions of $\widetilde{A}$, respectively, and they are represented by (5) and (6).

$$FOU(\widetilde{A}) = \bigcup_{x\in X} J_x \tag{4}$$

$$\overline{\mu}_{\widetilde{A}}(x) = \overline{FOU(\widetilde{A})} = \bigcup_{x\in X} \overline{J_x} \quad \forall x \in X \tag{5}$$

$$\underline{\mu}_{\widetilde{A}}(x) = \underline{FOU(\widetilde{A})} = \bigcup_{x\in X} \underline{J_x} \quad \forall x \in X \tag{6}$$

FLSs are used to represent and numerically manipulate linguistics rules, in a natural way. They are also useful because of their ability to handle problems which the conventional control theory cannot focus successfully, because the latter requires a valid and precise model, which not always exists (Liang et al., 2000).

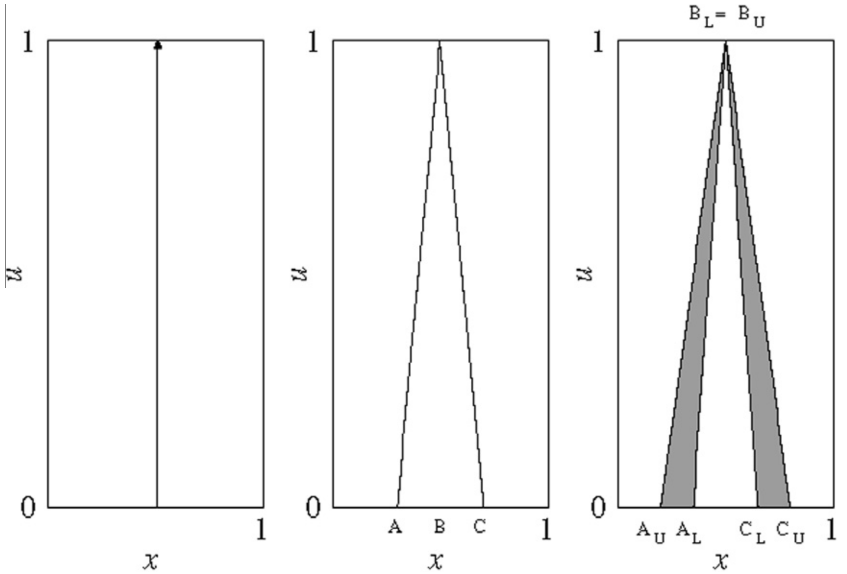

Fig. 5. Memberships functions of type-2 singleton (left), type-1 triangular fuzzy set (middle) and FOU of interval type-2 triangular fuzzy set (right).

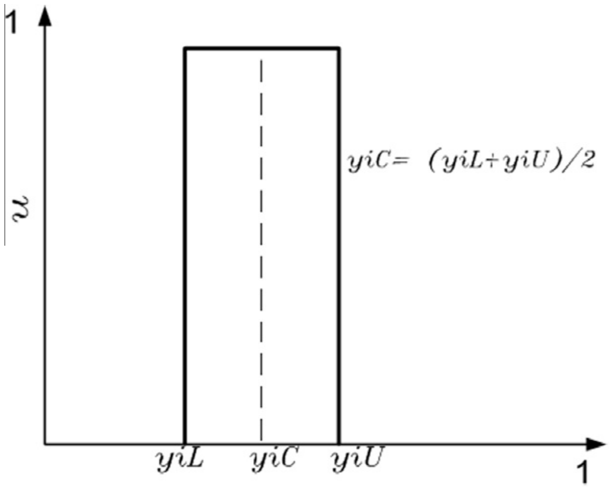

Fig. 6. Type-reduced fuzzy set.

T2-FLSs can be classified into two types: general type and interval type. The former uses fuzzy sets whose secondary grade can take any value in the interval between (0, 1), and the latter uses fuzzy sets whose secondary degrees are equal to 1. In this work only type-2 fuzzy sets of interval type are used, because they are computationally more efficient than those of general type (Mendel, 2004). The inputs of a T2-FLS can be modelled by type-2 singletons, type-1 fuzzy sets or interval type-2 fuzzy sets, depending on the nature of uncertainty. These are shown in Fig. 5.

The shaded area of the FOU models the uniformity of the secondary grades of an interval type-2 fuzzy set ($f_x(u) = 1, \forall u \in J_x$). The output of a T2-FLS is a crisp value (y_{iC}) and a type-1 interval ($y_i = [y_{il}, y_{iU}]$) called *type-reduced fuzzy set* (see Fig. 6). This interval is a measure of the uncertainty of the crisp output, in a similar way that for models based on probability, where the standard deviation is a measure of the uncertainty of the average.

6. Diagnostics of the paper-oil system using T2-FLS

The design process of a survey-based type-2 FLS system requires collecting the knowledge, setting the rules, choosing and defining antecedent and consequent membership functions, choosing type-reduction and extracting decision boundaries (Liang et al., 2000). For this reason, the results of each T2-FLS depend on the rule base designed using expert opinions.

The T2-FLS used for the diagnostic by dissolved gases in oil is of singleton type (the inputs are crisp values) and uses the base of rules of Table 7 (512 rules). Each rule has nine antecedents (PD, $D1$, $D2$, $T1$, $T2$, $T3$, EDI, COV, and CDC) and one consequent (condition of the equipment). For the sake of simplicity, not all rules are shown. Each term in the antecedents is modeled by means of sigmoid-type functions obtained by the conditions of gas ratios showed in the second column of Table 1. An example of the functions for the detection of $T1$ is shown in Fig. 7. In this case, a positive detection of $T1$ is obtained if the causality of the third column of Table 1 ($D1 \cap D2 \cap D3$, see Table 1) is greater or equal than 0.5 and the membership function of the gas ratio is greater than or equal to 0.5. In this example the causality is 0 so that the fault T1 is not detected.

The inputs of the first T2-FLS are binary terms (1–0), which indicate whether the fault exists or not. The consequents are modelled by means of type-2 fuzzy sets, of the interval type, such as the one shown in Fig. 5 (right). The consequents are described by three linguistic terms (unacceptable, questionable, acceptable), whose membership function is obtained by means of the expert's opinion about the value of these linguistic terms in the interval (0–10).

The extreme values (unacceptable and acceptable) are modelled by means of trapezoidal type-2 fuzzy sets. The questionable term is modelled by means of triangular type-2 fuzzy sets. The result of this T2-FLS is an interval similar to the one shown in Fig. 6, which is the input of the second T2-FLS that evaluates the paper-oil insulation on the basis of the oil physical and chemical data and the DGA results. The output is the type-reduced fuzzy set and it is

Table 7
Part of the base of rules from T2-FLS of diagnostics by dissolved gases.

No	Antecedents									Consequent
	PD	D_1	D_2	T_1	T_2	T_3	EDI	COV	CDC	Condition
1	0	0	0	0	0	0	0	0	1	Acceptable
2	0	0	0	0	0	0	0	1	0	Acceptable
3	0	0	0	0	0	0	1	0	0	Questionable
4	0	0	0	0	0	1	0	0	0	Questionable

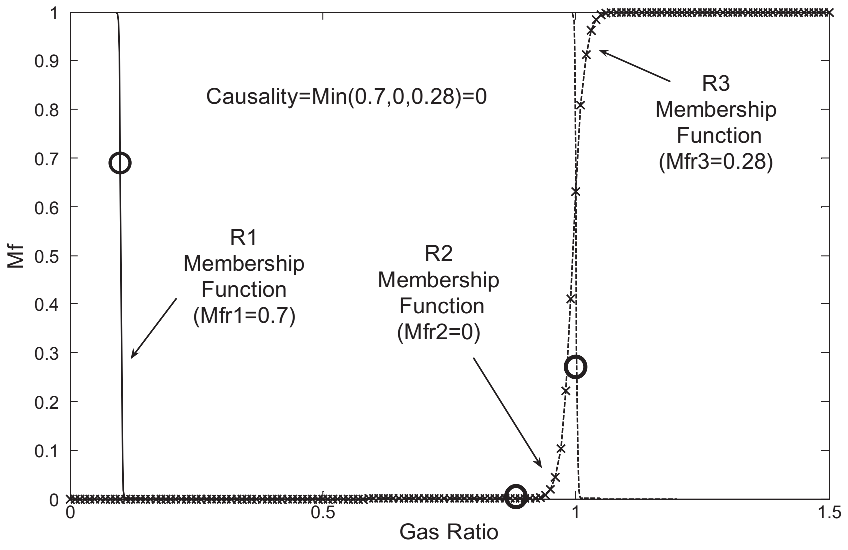

Fig. 7. Example of detection of *T*1 by mean of gas ratios.

Table 8
Part of the base of rules from T2-FLS of diagnosis based on physical and chemical values.

No	Antecedents					Consequent
	DP	Acidity	Moisture	PF	Diag.Gas	Condition
1	U	U	U	U	U	Terrible
2	Q	A	A	A	U	Questionable
3	A	U	U	U	U	Bad
4	Q	A	A	Q	Q	Good

obtained using the extended *sup-star* composition, under maximum-product norms, and centre of sets type- reduction (Mendel, 2004).

The second T2-FLS is of non-singleton type, because the inputs can be fuzzy numbers or crisp values. The base of rules of this *T*2-FLS is shown in Table 8. As in the case of Table 7, the complete rule-base is not shown since there are many rules (243 rules).

Each rule has five antecedents (DP, acidity, moisture, PF, DGA diagnostic results) and one consequent (the condition of the equipment).

The terms in the antecedents are modelled by means of type-1 fuzzy sets. The membership function of each antecedent is found from its value (crisp) and the type-1 fuzzy sets shown in Figs. 3 and 4. The consequents are modelled by means of type-2 fuzzy sets, of the interval type, such as the one shown in Fig. 5 (right). The consequents of this second T2-FLS are described by ten linguistic terms (terrible, very bad, bad, questionable, regular, medium, medium good, very good, excellent, superb), whose membership function is obtained by means of expert's opinion about the value of these linguistic terms in the interval (0–10). The extreme values (terrible and superb) are modelled by means of trapezoidal type-2 fuzzy sets. The remaining terms are modelled by means of triangular type-2 fuzzy sets. The type-2 fuzzy sets of these linguistic terms are shown in Fig. 8. The result of this T2-FLS is an interval similar to the one shown in Fig. 5.

As it can be seen, this procedure works as a translator, which "translates" the values of each variable (DP, PF, gases, etc.) to linguistic values that allow the operator to readily know the equipment condition, so as to make the most suitable decision in each case.

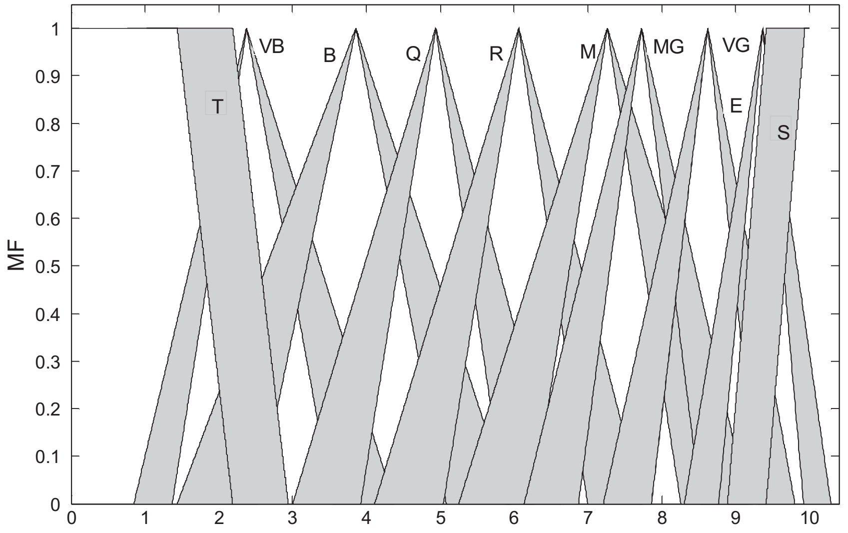

Fig. 8. Type-2 fuzzy sets of linguistic terms used as consequent in the second T2-FLS. (T: Terrible, . . ., S: Superb).

7. Experimental verification

7.1. Case I: using the whole algorithm

The condition of a 28 MVA, 147/11 KV transformer, which presented a fault in the low voltage windings, is analyzed. The transformer was put out of service by the Buchholz relay as a result of the electrodynamics stresses produced by a short circuit near the equipment.

Three weeks before the fault, an oil sample was drawn and the corresponding tests were performed. The results of the dissolved gas analysis and those of the oil tests are shown in Table 9. Using this data as inputs, the diagnosis shown in Fig. 9 can be drawn.

The Fig. 9 shows that the transformer was in a "questionable" condition. The result is consistent with the fact that, although gas levels do not exceed 90% of the typical values (the transformer is in a good condition, as for dissolved gas analysis), the algorithm detects that the values of PF and DP are in the "unacceptable" and "questionable" zones, respectively.

Formally, the centroid of the consequent representing the "questionable" condition is 4.6491 and the solution interval [*Questionable*$_L$, *Questionable*$_R$] is [4.5317, 4.7665].

7.2. Case II: using only the algorithm by dissolved gas in oil

Six months after the fault, the equipment was repaired and put in service. At this time, the DGA shown in Table 10 was made. From these results, the laboratory reported "presence of discharges in the solid isolation". When these data are used as input, the algorithm detects $D1$ (discharges of low energy), $D2$ (discharges of high energy) and EDI (excessive degradation of insulation paper), whose linguistic result is shown in Fig. 10 ("very bad"). The presence of EDI shows that paper insulation is involved in the fault.

Table 9
Gas chromatography and physical–chemical data.

Gas (ppm)						
CH_4	C_2H_4	C_2H_6	C_2H_2	H_2	CO	CO_2
2	8.7	0.5	0	0	198.8	544.2
DP	390					
PF	2.94%					
Moisture	1.2%					
Acidity	0.049 mg KOH/g					
Age of equipment	8 years					
TRGI (CO)	22 ppm/year					

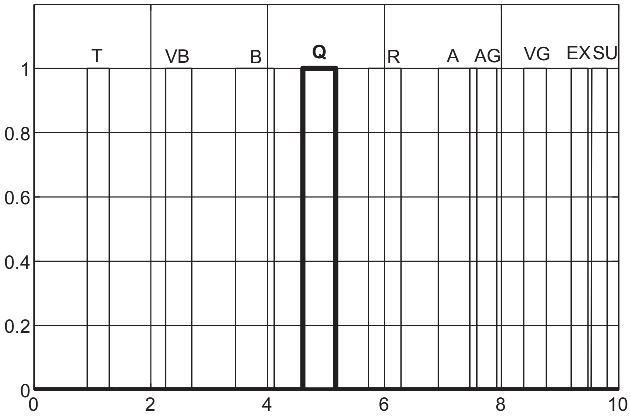

Fig. 9. Output of the diagnostic algorithm from DGA and oil test results.

Table 10
DGA results after failure (ppm).

CH_4	C_2H_6	C_2H_4	C_2H_2	H_2	CO	CO_2
95	6	94	139	345	266	95

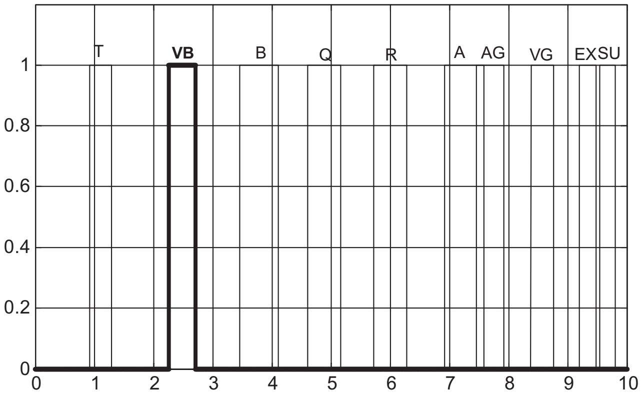

Fig. 10. Output of the diagnostic algorithm obtained from DGA. Post failure.

In spite of the results of the latter DGA, the transformer was kept on line and few days later, it was put out of service due to fault in the paper insulation of the low voltage winding.

Formally, the centroid of consequent representing the "very bad" condition is 2.4813 and the solution interval [very bad$_L$, very bad$_R$] is [2.2552, 2.7075].

7.3. Case III: diagnostics of three single-phase transformers

The condition of three 80 MVA, 345 KV, single-phase transformers of a three-phase transformer bank installed in the transmission system of Brazil is analyzed. The results of the dissolved gas analysis and those of the oil tests are shown in Table 11. These test results were obtained on July 2005. Using this data as inputs, the diagnosis (for the three transformers) shown in Fig. 11 can be drawn. In this case the diagnosis of all three transformers has the same result.

Fig. 11 shows that the transformers were in a "questionable" condition.

For the transformer of phase A the algorithm detects $T3$, thermal fault above 700 °C, and a high level of moisture. Consequently, the final result is a "questionable" condition. For the phase B, the algorithm detects that all gas concentrations are below 90% of their typical values and the equipment is considered to be healthy.

Table 11
Gas chromatography and physical-chemical data.

Gas (ppm)	CH_4	C_2H_4	C_2H_6	C_2H_2	H_2	CO	CO_2
Ph. A	21	133	2	0	20	506	3452
Ph. B	5	59	1	0	16	390	3201
Ph. C	4	105	1	0	22	559	3809
Phase		A		B		C	
Furans[a] (ppm)		0.19		0.03		0.33	
DP		604		879		521	
PF		0.33%		0.35%		0.13%	
Paper moisture		2.5%		2.4%		2.5%	
Acidity (mg KOH/g)		0.01		0.01		0.01	
Age of equipment		10 yr		10 yr		10 yr	
TRGI (CO)[b]		97.12 ppm/yr		67.67 ppm/yr		88.05 ppm/yr	

[a] Total furans.
[b] Average.

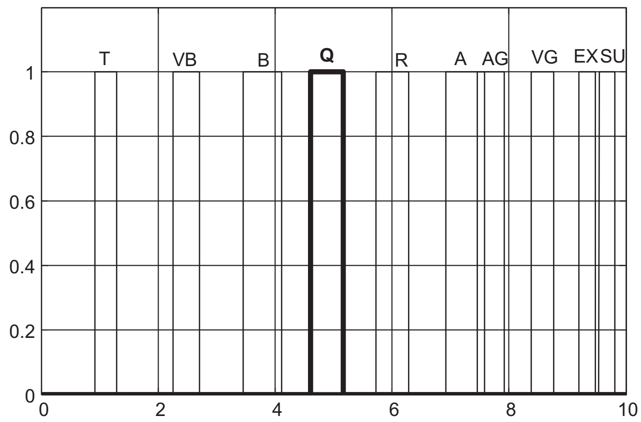

Fig. 11. Output of the diagnostic algorithm from DGA and oil test results.

Nevertheless, because of the high moisture level, the final result is "questionable". For the phase C, the algorithm detects $T3$ and additionally a high level of moisture; therefore the final result is again "questionable".

Formally, the centroids of the consequents representing the "questionable" condition are 5.3790 and the solution interval $[\text{Questionable}_L, \text{Questionable}_R]$ is $[5.2964, 5.4617]$, for the transformers of phase A, B and C, respectively.

8. Conclusions

A new methodology for the assessment of the condition of power transformers has been presented in this paper. The necessary information used includes the chromatographic analysis of dissolved gases in oil and physical and chemical properties of the transformer oil determined by test. The proposed algorithm can be seen as a translator, which translates the diagnostic results to linguistic values that allow the operator to readily know the equipment condition. In this way, the operation and maintenance personnel can establish the condition of the paper-oil insulation system by means of words that are easy to understand.

Also, this translator could be used for training personnel having little experience in transformer diagnostics. The diagnostic algorithm has the versatility to evaluate the equipment condition only using one of the two available data subsets (dissolved gases in oil and oil test results) or using both subsets. The algorithm is also able to detect if paper insulation is involved in the fault. Type-2 fuzzy sets and T2-FLS provide flexibility for modelling the uncertainty of the data and of the meaning of words.

The use of T2-FLS also allows the inclusion of other factors as inputs of the diagnostic algorithm, which could be either new influence factors or a combination of the ones used in this work. This flexibility is very important for the improvement of the algorithm in the future.

The use of expert opinions in the development stage of the diagnostic algorithm makes possible the consideration of years of experience in the diagnostics of power transformers, increasing the robustness of the methodology.

The validation cases show the efficiency of the proposed diagnostic algorithm. In the author's opinion, the proposed method can be a valuable tool for utilities for the assessment of the condition of their transformers.

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