Design of potential faults diagnosis system of transformers based on fuzzy logic combined with hedge algebras

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***Abstract*—In the process of a transformer working, under the effect of heat, the hydrogen-carbon element of the mineral oil is broken down to hydrogen and produces components of hydrogen gas, such as methane, ethane, ethylene, acetylene and some other gases. The density of these gas components may indicate some states of working and potential faults of the transformer. Based on the diagnostic method according to the codes of IEC-599 standard, this paper proposes diagnostic model based on fuzzy logic combine with hedge algebra. The designation of membership functions for fuzzy sets are based on the semantic of the linguistic terms in hedge algebras. From the results of the analysis of density of oil gas components (DGA - Dissolved Gas Analysis), the inference system calculate the total gas content, total flammable gas content and determine 8 cases fault diagnosed and a case is normal (no fault). Along with the conclusions about faults, corresponding reliability is calculated as a percentage. The diagnostic software has been coded completely on the web environment and has been tested with many actual data sets. The diagnosis results are reliable.**

Keywords—Diagnose Transformer Faults; Dissolved Gas Analysis; Hedge Algebra; Fuzzy Logic

I. INTRODUCTION

Transformers are a major device in the energy system. Their reliability not only change the ability to supply electricity but also affect the economic performance of an any customer (for example furnaces, production lines, etc. in factories). For example, a fault of a distribution transformer can cause thousands of households to lose power. A fault of a voltage increase transformer may cause a power outage of adjacent areas in that grid system.

Diagnosing the potential faults of a pressure transformer in the electrical system is a problem of concern to many scientists. In order to be able to provide information on possible future faults (potential faults) of transformers, in some published, diagnostic methods based on dissolved gas analysis in oil. There are also diagnostic methods based on frequency spectrum response of the transformer, diagnostic based on vibration of transformer. The method of dissolved gas analysis in oil requires to be specialized measuring devices and requires high accuracy. Based on these techniques, there are many modern techniques that allow better diagnostics [1], [2], [3], [4], [5] but a common point of these methods is to rely on accurate measurement techniques. Therefore, the diagnostic results also depend heavily on the accuracy of the measurements. Another diagnostic method that can inherit expert knowledge in the form of statistic rules has been introduced [6], [7], [8], [9], [10]. This method was developed based on the use of artificial neural networks. In order to get accurate diagnosis results, it is necessary to have an experiment data set large enough to train the network and select a reasonable network structure. In fact, according to this approach, there are many network structures that can be selected with diversification diagnostic results. Large network training time is also a disadvantage of this method. Methods for using fuzzy logic are also proposed [11], [12], [13], [14], [15]. The common point of these methods is to inherit expert knowledge based on the rule base system. However, how to build a membership function for fuzzy sets is an issue to be studied. In the same diagnostic rule base system, the building of different fuzzy sets makes the diagnostic results are not the same.

This paper proposes to build a membership function for fuzzy sets based on the semantics of the linguistic terms in hedge algebras. According to this proposal, the change of the degree of fuzzy dependence is more reasonable.

II. DIAGNOSE POTENTIAL FAULTS OF TRANSFORMERS BASED ON DGA RESULTS

A. Characteristics of generate gas and dissolved gas analysis

In the progress of a transformer working, under the effect of electricity and heat, the hydrogen-carbon element ($H-C$) of mineral oil can be broken down into hydrogen and $H-C$ fragments, which can be combined to create gases are hydro hen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), CO

and CO_2. The amount of gas of each individual gas depends on the temperature near the point of effect.

Dissolved gas analysis in the transformer oil aims to detect soon local overheating, discharge of low energy, etc. The increase in these processes will lead to incident. The incident generated during this period is not detected by the gas relay. A small a number of gases formed continuously through small decomposition in oil or insulating material. To analyze dissolved gas in transformer oil, need to use a system of analyzers called TOGAS (Transformer Oil Gas Analysis System). From the results of dissolved gas analysis in transformer oil we can diagnose the damaged forms of transformers. The analysis of dissolved gas in oil without the need to disconnect the transformer power is called the online diagnostic method. This type of analysis includes conventional DGA, which is based on periodic oil sampling and modern techniques of online gas monitoring.

A type of fault can be caused by many reasons. This makes partitioning very difficult. Therefore, the actual operation usually only uses DGA to diagnose the original fault, not the final conclusion. Other tests and even the opening of the transformer may be necessary to localize the error and find the cause more accurately.

However, fault diagnosis by DGA is good enough to provide information on maintenance schedules and act as a preventive maintenance strategy. For this purpose, DGA has become a major tool for diagnosing potential faults of transformer. It includes much successful research in three main areas: ratio method, main gas method and artificial intelligence methods.

For the proportional method, many researchers have proposed many methods to diagnosis potential faults in transformers such as Dornemburg ratio, Roger ratio, main gas method and IEC-599 standard [1], [2].

B. Diagnose potential faults based on ratios according to IEC-599 standard

The Dornemburg and Rogers methods use four ratios, the ratio C_2H_6/CH_4 represents only the limited temperature range of cellulose disintegration without any help with fault detection. Therefore, in the IEC-599 standard and the proportion of Rogers method development later were abolished.

An improvement of IEC-599 standard was launched in 1996 (IEC-599/2). It has become perfect at this time. Rogers ratio method and IEC-599 standard have been developed commonly in industry. However, in some cases, it does not give a final conclusion, meaning there are faults that these methods cannot be identified.

TABLE I. RATIO OF GAS COMPONENTS AND CORRESPONDING FAULTS ACCORDING TO IEC-60599 (2015)

Faults		R1 (CH_4/H_2)	R2 (C_2H_2/C_2H_4)	R5 (C_2H_4/C_2H_6)
Normal		< 0.1	< 0.1	< 0.1
Partial discharges		< 0.1	NS(a)	< 0.2
Discharges of low energy		0.1 – 0.5	> 0.1	> 1
Discharges of high energy		0.1 – 1	0.6 – 2.5	> 2
Thermal fault	t < 300 °C	> 1, NS(a)	NS(a)	< 1
	300 °C < t < 700 °C	> 1	< 0.1	1 – 4
	t > 700 °C	> 1	< 0.2(b)	> 4

Note:
(a) NS: Non-Significant whatever the value
(b) If C_2H_2 increases strongly, it may overheat t > 1000 °C

From **Error! Reference source not found.**, according to IEC-599 standard, ranges were coded and represent faults according to diagnostic rules such as TABLE II. and TABLE III. .

TABLE II. TABLE 1. CODES OF RATIOS AND CORRESPONDING RANGES ACCORDING TO IEC-599 STANDARD

Ranges of ratios	Codes of ratios		
	R1=$\frac{C_2H_2}{C_2H_4}$	R2=$\frac{CH_4}{H_2}$	R3=$\frac{C_2H_4}{C_2H_6}$
<0.1	0	1	0
0.1 – 1.0	1	0	0
1.0 – 3.0	1	2	1
>3.0	2	2	2

Note: denote R3 instead of the ratio of R5 in **Error! Reference source not found.**.

TABLE III. RULE DIAGNOSIS OF FAULTS BY CODE ACCORDING TO IEC-599 STANDARD

Rule no	R1=$\frac{C_2H_2}{C_2H_4}$	R2=$\frac{CH_4}{H_2}$	R3=$\frac{C_2H_4}{C_2H_6}$	Decision
1	0	0	0	Normal ageing
2	0 (*)	1	0	Partial discharge of low energy density
3	1	1	0	Partial discharge of high energy density
4	1 or 2	0	1 or 2	Discharge of low energy
5	1	0	2	Discharge of high energy
6	0	0	1	Thermal fault <150 °C
7	0	2	0	Thermal fault 150° – 300 °C
8	0	2	1	Thermal fault 300° – 700 °C
9	0	2	2	Thermal fault > 700 °C

* insignificant

III. INTRODUCTION TO HEDGE ALGEBRA

Hedge algebra is an algebraic structure on the linguistic value domain introduced in [17] and the application to solve fuzzy problem classes that are stated based on linguistic information [18], [19], [20]. With the hedge algebra approach gives us many advantages in calculating on the linguistic terms. This article has used hedge algebra to build fuzzy computational model for approximate system of reasoning, diagnose potential faults of transformers.

Consider an ordered language value set on the domain of the linguistic variable including the following words:

$\mathcal{T} = \{Very\ Very\ low < More\ Very\ low < Very\ low < Rahter\ Very\ low < Little\ Verry\ low < Very\ More\ low < More\ More\ low < More\ low < Rather\ More\ low < Little\ More\ low < low < \cdots < Medium < Very\ Little\ high < More\ Little\ high < \cdots < high < Very\ high < Very\ Very\ high \ldots\}$.

It can be seen that the ordered set *T* contains the linguistic terms that they can appear in language rules. Calling $\{low\ < high\}$ is two primitive elements that are opposite, impact on them by words such as *Very*, *Little*, *Rather*, *More*, we will get ordered linguistic terms as in *T*. We have an algebraic structure on the specified domain of the linguistic variable defined as follows.

Definition 1. [17]. The hedge algebra of the linguistic variable $\mathcal{T}$ is a set of 5 components $\mathcal{AT} = (T, G, C, H, \leq)$, where:

- T: Is the base set of AT, includes the elements in $\mathcal{T}$.
- $G = \{c^-, c^+\}$, $c^- \leq c^+$, is called the generating elements (the original words, for example $low < hight$).
- $C = \{\mathbf{0}, \boldsymbol{W}, \mathbf{1}\}$ is a set of the constants, $\mathbf{0} \leq c^- \leq \boldsymbol{W} \leq c^+ \leq \mathbf{1}$, which show the elements with the smallest semantics, neutral elements, and elements with the greatest semantics.
- H: A set of singular operators, called hedges (emphasizing adverbs). $H = H^- \cup H^+$, where $H^- = \{h_j\!: -q \leq j \leq -1\}$ is the set of negative hedges, $H^+ = \{h_j\!: 1 \leq j \leq p\}$ is a positive hedges.
- $\leq$: is the expression of the order relationship on the linguistic words (fuzzy concepts) in *T*, which is “induced” from the natural semantics of language.

From the properties of hedge algebras, the authors in [17], [18], [19] the authors have developed the measurement functions, in which the semantic quantitative function - SQMs [21] allows to quantify from the linguistic terms into their corresponding semantic values. It is easier to calculate for speech problems in language.

IV. DEVELOP THE DIAGNOSTIC TOOL FUZZY LOGIC COMBINED WITH HEDGE ALGEBRA

A. *Build the fuzzy diagnostic model based on Hedge Algebra*

Suppose there are 2 fuzzy intervals corresponding to *u* and *v* linguistic terms. For each semantic value *x* in the range of $fm(v) < x < fm(u)$, x has a “close” semantic relationship with the parts from *u* and *v*. Assume the semantic “equilibrium” point for *u* and *v* elements through the fuzzy distance and their semantic value by expression:

$$\boldsymbol{w} = \frac{\boldsymbol{v(v)*fm(v)+v(u)*fm(u)}}{\boldsymbol{fm(v)+fm(v)}} \qquad (1)$$

Expression (1) indicates that the semantic value *w* has a “close” (or “characteristic”) is the same for *u* and *v* elements. The semantic value nearer *v(v)* the more “close” *v* and the “difference” *u* and vice versa.

The new proposal is to find the *w'* point so that we can determine a linear function where the characteristic point w is the horizontal axis value of the *G* center point of fuzzy sets *Su* and *Sv* (See Fig. 1). Thus, we need to determine the point *w' ≠ w* at which, its dependence on fuzzy sets *u* and *v* is equal to 0.5. *G* center point is calculated by the formula:

$$\boldsymbol{G} = \frac{\boldsymbol{Gu*Su+Gv*Sv}}{\boldsymbol{Su+Sv}} \qquad (2)$$

Where *Gu*, *Gv* are the center points of fuzzy set with area *Su*, *Sv* respectively. With a value $v(v) \leq x \leq v(u)$), the total degree of $\mu_v(x) + \mu_u(x) = 1$.

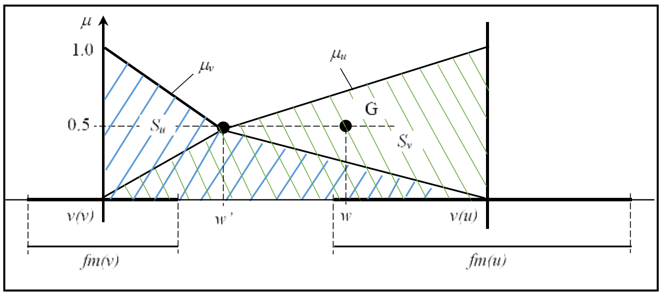

Fig. 1. *Design membership functions between 2 semantic values with “characteristic” point*

From that point of view, it can state in the form of a postulate:

Postulate 1. (New proposal) Let the linguistic terms $u, v \in T$, $v(v) \leq x \leq v(u)$.

The linear function is determined through the *w'* point so that horizontal axis value of the *G* center point is the center of the fuzzy set *u*, *v* has the area *Su*, *Sv* is the “characteristic” point w satisfies the condition $\mu_v(w') = \mu_u(w') = 0.5$ và $\mu_v(x) + \mu_u(x) = 1$

$$\boldsymbol{w'} = \frac{\boldsymbol{v(v)*fm(u)+v(u)*fm(v)}}{\boldsymbol{fm(v)+fm(v)}} \qquad (3)$$

The construction of the membership function for fuzzy sets by linear transitions of the semantic weight of this postulate let to describe the membership degree between linguistic terms is quite reasonable.

The fuzzy diagnostic model is built through 2 steps as follows:

1) Step 1: Design fuzzy sets

Based on the ranges in IEC-599 standard, We choose linguistic terms to replace the codes for each ratio as in TABLE IV. :

TABLE IV. LINGUISTIC TERMS REPLACE FOR CODES

Codes / Ratios	0	1	2
R1	*vvvL*	*M*	*vvvH*
R2	*vL*	*vvvL*	*H*
R3	*vL*	*lH*	*vvvH*

There are symbols: *L – Low, H – High, v – very, l – litle*

The variable range of these quantities is [0.3]. Therefore, from semantic range, we have to scale with a coefficient, r = 3.

- Define the structure of hedge algebra and the fuzzy parameters:

$$\mathcal{AT} = (T, G, C, H, \leq)$$

$$G = \{L(Low) < H(High)\}$$

$$H = \{l(litle), v(very)\}, \mu(l) = \alpha = \mu(v) = 0.5$$

Select *M* (*Medium*) is the neutral element W. $v(M) = v(W) = fm(L) = 0.5$, This value is selected qualitatively by the designer.

- Calculate the semantic value of linguistic terms and points $v(x_i) \cup w' = \{a, b, c, d, e\}$ for ratios according to (3):

The ratio R1:

$$a = v(vvvL) = \mu(v) * \mu(v) * \mu(v) * fm(L) * \alpha * range = 0.09375$$

$$c = v(M) * range = w * range = 1.5$$

$$e = v(vvvH) = (1 - \mu(v) * \mu(v) * \mu(v) * fm(L) * \alpha) * range = 2.90625$$

$$b = \left(\frac{v(vvvL) * fm(M) + v(M) * fm(vvvL)}{fm(M) + fm(vvvL)}\right) * range$$

$$= \left(\frac{0.03125 * 0.5 + 0.5 * 0.0625}{0.5 + 0.0625}\right) * 3 = 0.25$$

$$d = \left(\frac{v(M) * fm(vvvH) + v(vvvH) * fm(M) +}{fm(M) + fm(vvvH)}\right) * range$$

$$= \left(\frac{0.5 * 0.0625 + 0.96875 * 0.5}{0.5 + 0.0625}\right) * 3 = 2.75$$

The set of points for the ratio R1: {0.09375, 0.25, 1.5, 2.75, 2.90625}

The ratio R2 and R3: Calculating similarly with semantic equilibrium points according to (3), we get the coordinate parameters of points {a, b, c, d, e} determine the fuzzy set for the ratios as:

R2: {0.09375, 0.15, 0.375, 1.0, 2.25} and R3: {0.375, 1.125, 1.875, 2.7, 2.90625}

The membership function for fuzzy sets corresponds to linguistic terms of the ratios as shown in Figure 2.

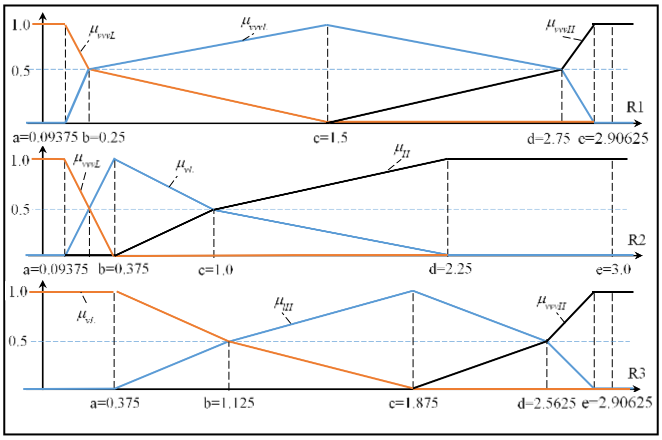

Fig. 2. *Fuzzy set of ratios*

Membership degrees are calculated according to the following formulas:

$$\mu_{vvvL}(x), \mu_{vL}(x) = \begin{cases} 1, x < a \\ \frac{2b-a-x}{2(b-a)}, a < x \leq b \\ \frac{1}{2}\frac{(c-x)}{(c-b)}, b < x \leq c \\ 0, c < x \end{cases} \quad (4)$$

$$\mu_{M}(x), \mu_{vL}(x), \mu_{lH}(x) = \begin{cases} 0, x < a \\ \frac{1}{2}\frac{(x-a)}{(b-a)}, a < x \leq b \\ \frac{x+(c-2b)}{2(c-b)}, b < x \leq c \\ \frac{2d-c-x}{2(d-c)}, c < x \leq d \\ \frac{1}{2}\frac{(e-x)}{(e-d)}, d < x \leq e \\ 0, e < x \end{cases} \quad (5)$$

$$\mu_{vvvH}(x), \mu_{H}(x) = \begin{cases} 0, x < c \\ \frac{1}{2}\frac{(x-c)}{(d-c)}, c < x \leq d \\ \frac{x+(e-2d)}{2(e-d)}, d < x \leq e \\ 1, e < x \end{cases} \quad (6)$$

Calculation for example, with the set of values calculated from experimental data:

$R1 = \frac{C_2H_2}{C_2H_4} = 0.393$, this value is in the range, [b, c] = [0.25, 1.5]

$R2 = \frac{CH_4}{H_2} = 0.5$, this value is in the range, [c, d] = [0.375, 1.0]

$R3 = \frac{C_2H_4}{C_2H_6} = 0.667$, this value is in the range, [a, b] = [0.375, 1.125]

- Calculate the membership function of the ratio variable R1:

We get the vector $\mu^{R1} = (0.4428, 0.5572, 0)$,

Total membership degree = $\mu^{R1}_{vvvL} + \mu^{R1}_{M} + \mu^{R1}_{vvvH} = 1$

- Calculate the membership function of the ratio variable R2:

$\mu^{R2}_{vvvL}(0.5) = 0$

$$\mu^{R2}_{vL}(0.5) = \frac{2d-c-x}{2(d-c)} = \frac{2*1\text{-}0.375\text{-}0.5}{2(1\text{-}0.375)} = 0.9$$

$$\mu^{R2}_{H}(0.5) = \frac{1}{2}\frac{(x-c)}{(d-c)} = \frac{1}{2}\frac{(0.5-0.375)}{(1-0.375)} = 0.1$$

We get the vector $\mu^{R2} = (0, 0.9, 0.1)$,

Total membership degree = $\mu^{R2}_{vvvL} + \mu^{R2}_{vL} + \mu^{R2}_{H} = 1$

- Calculate the membership function of the ratio variable R3:

$$\mu^{R3}_{vL}(0.667) = \frac{2b-a-x}{2(b-a)} = \frac{2*1.125-0.375-0.667}{2(1.125-0.375)} = \frac{1.208}{1.5} = 0.805$$

$$\mu^{R3}_{lH}(0.667) = \frac{1}{2}\frac{(x-a)}{(b-a)} = \frac{1}{2}\frac{(0.667-0.375)}{(1.125-0.375)} = \frac{1}{2}\frac{0.292}{0.75} = 0.195$$

$\mu^{R3}_{vvvH}(0.667) = 0$

We get the vector $\mu^{R3} = (0.805, 0.195, 0)$,

Total membership degree = $\mu^{R3}_{vL} + \mu^{R3}_{lH} + \mu^{R3}_{vvvH} = 1$

2) Step 2: Convert the diagnostic rule system from classic logic to fuzzy logic

From the diagnostic rule table according to the IEC-599 standard (TABLE III.) and the linguistic term were chosen to replace the codes as shown in TABLE IV. , we get the diagnostic rule table in the linguistic terms as in TABLE V.

TABLE V. THE DIAGNOSTIC RULE TABLE FOR 8 FAULTS IS REWRITTEN ACCORDING TO THE LANGUAGE LABEL

Rule no	R1=$\frac{C_2H_2}{C_2H_4}$	R2=$\frac{CH_4}{H_2}$	R3=$\frac{C_2H_4}{C_2H_6}$	Decision
1	*vvvL*	*vL*	*vL*	Normal ageing
2	*	*vvvL*	*vL*	Partial discharge of low energy density
3	*M*	*vvvL*	*vL*	Partial discharge of high energy density
4	*M or vvvH*	*vL*	*lH or vvvH*	Discharge of low energy
5	*M*	*vL*	*vvvH*	Discharge of high energy
6	*vvvL*	*vL*	*lH*	Thermal fault <150 °C
7	*vvvL*	*H*	*vL*	Thermal fault 150° – 300 °C
8	*vvvL*	*H*	*lH*	Thermal fault 300° – 700 °C
9	*vvvL*	*H*	*vvvH*	Thermal fault > 700 °C

In the above table, each line of diagnostic rule is interpreted as follows:

Rule 1: if (R1=vvvL)and(R2=vL)and(R3=vL) then "Normal ageing"

Rule 3: if (R1=M)and(R2=vvvL)and(R3=vL) then "Partial discharge of low energy density"

Rule 4: if ((R1=M)or(R1=vvvH))and(R2=vL)and((R3=lH)or(R3=vvvH)) then "Discharge of low energy"

Where (R1=M) ⇔ µM(x), x∈R1 (the membership degree of x in the R1 into M).

B. Algorithm for diagnostic model

From the model of the above reasoning system, the calculation steps of the algorithm are described in detail as in the following algorithm:

Fuzzy_ Hedge_Algebra_Diagnosis_Algorithm()

Input: Gas components [ppm]: H_2 (hydrogen), CH_4 (methane), C_2H_2 (acetylen), C_2H_4 (ethylen), C_2H_6 (ethane); O_2, N_2, CO, CO_2 [ppm].

Output: Conclude the status of the transformer according to the diagnostic rule system and corresponding diagnostic reliability

Method:

*1) **If** all values of gas components do not exceed the L1 threshold (TABLE VI.) **Then** the conclusion is "Normal" (return).*

TABLE VI. THRESHOLD L1 ACCORDING TO IEC-599

Key gas	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO
Threshold L1 (concentration [ppm])	100	120	35	50	65	350

***Else** // One of the gas components exceeds the L1 threshold, next to step calculation*

2) Calculate the value of the ratios $x = \frac{C_2H_2}{C_2H_4}$, $y = \frac{CH_4}{H_2}$, $z = \frac{C_2H_4}{C_2H_6}$

3) Calculate the membership degree vectors corresponding to each Ri (i = 1..3) according to formula (4) - (6)

The result is:

$$\mu^{R1} = [\mu_{vvvL}(x), \mu_{M}(x), \mu_{vvvH}(x)], x \in R1$$

$$\mu^{R2} = [\mu_{vvvL}(x), \mu_{vL}(x), \mu_{H}(x)], y \in R2$$

$$\mu^{R3} = [\mu_{vL}(x), \mu_{lH}(x), \mu_{vvvH}(x)], z \in R3$$

*4) **For** each rule in the rules table calculates the reliability of the decision as follows (see TABLE VII.):*

$r_i = min(\mu^{R1}_X, \mu^{R2}_Y, \mu^{R3}_Z)$, $X, Y, Z \in \{vvvL, vL, M, lH, vvvH\}$, i is the index of the rule line.

For example, with the rule line *i=4*, the left is calculated by the following formula:

$$r_4 = max\begin{pmatrix} min(\mu_M^{R1}, \mu_{vL}^{R2}, \mu_{lH}^{R3}), \\ min(\mu_M^{R1}, \mu_{vL}^{R2}, \mu_{vvvH}^{R3}), \\ min(\mu_{vvvH}^{R1}, \mu_{vL}^{R2}, \mu_{lH}^{R3}), \\ min(\mu_{vvvH}^{R1}, \mu_{vL}^{R2}, \mu_{vvvH}^{R3}) \end{pmatrix}$$

TABLE VII. CALCULATION OF DECISION RELIABILITY OF FUZZY DIAGNOSTIC RULE

R	$\frac{C_2H_2}{C_2H_4}$	$\frac{CH_4}{H_2}$	$\frac{C_2H_4}{C_2H_6}$	Reliability
1	*vvvL*	*vL*	*vL*	$r_1 = min(\mu_{vvvL}(x), \mu_{vL}(y), \mu_{vL}(z))$
2	*	*vvvL*	*vL*	$r_2 = min(\mu_{vvvL}(y), \mu_{vL}(z))$
3	*M*	*vvvL*	*vL*	$r_3 = min(\mu_M(x), \mu_{vvvL}(y), \mu_{vL}(z))$
4	*M or vvvH*	*vL*	*lH or vvvH*	$r_4 = max\begin{pmatrix} min(\mu_M(x), \mu_{vL}(y), \mu_{lH}(z)), \\ min(\mu_M(x), \mu_{vL}(y), \mu_{vvvH}(z)), \\ min(\mu_{vvvH}(x), \mu_{vL}(y), \mu_{lH}(z)), \\ min(\mu_{vvvH}(x), \mu_{vL}(y), \mu_{vvvH}(z)) \end{pmatrix}$
5	*M*	*vL*	*vvvH*	$r_5 = min(\mu_M(x), \mu_{vL}(y), \mu_{vvvH}(z))$
6	*vvvL*	*vL*	*lH*	$r_6 = min(\mu_{vvvL}(x), \mu_{vL}(y), \mu_{lH}(z))$
7	*vvvL*	*H*	*vL*	$r_7 = min(\mu_{vvvL}(x), \mu_H(y), \mu_{vL}(z))$
8	*vvvL*	*H*	*lH*	$r_8 = min(\mu_{vvvL}(x), \mu_H(y), \mu_{lH}(z))$
9	*vvvL*	*H*	*vvvH*	$r_9 = min(\mu_{vvvL}(x), \mu_H(y), \mu_{vvvH}(z))$

5) Calculate the total amount of gas dissolved in the oil (total gas components in ppm)

$$Total = O_2 + N_2 + CO + CO_2 + H_2 + CH_4 + C_2H_2 + C_2H_4 + C_2H_6 \text{ [ppm]}$$

6) Display the results on the screen

a) Display on the screen the decisions and corresponding reliability.

*b) **If** $Total > 10000$ notice "The total amount of dissolved gas in oil is not up to standard";*

***Else** notice "Total amount of dissolved gas in oil meets standard".*

7) Report: Print out the summary report of the diagnosis in standard format.

8) Save to Data base.

End Fuzzy_Hedge_Algebra_Diagnosis_Algorithm

V. EXPERIMENTAL RESULTS

The diagnostic software has been fully installed and runs on the web environment, at http://mba.hopto.org/. The software is highly compatible, can run on many operating system platforms. Specifically, it can run on PC with Windows, iOS operating system of Mac; Can run with the appropriate interface on SmartPhone with both iOS and Android. Experiment with the data set [15], we get the diagnostic results as shown in TABLE VIII. .

TABLE VIII. DGA SAMPLE AND DIAGNOSIS RESULTS BY DIFFERENT METHOD

No.	H2	CH4	C2H4	C2H6	C2H2	Actual fault number	IEC method	Fuz_HA method	Reliability [%]
1	200	700	740	250	1	8, 9	8	9	100
2	300	490	360	180	95	8	N	4, 6, 8	24.7, 24.7, 49.4
3	56	61	32	75	31	3	N	1, 7	21.3, 21.3
4	33	26	5.3	6	0.2	1	1	1, 4, 6	66.1, 33.9, 33.9
5	176	205.9	75.7	47.7	68.7	4	N	4, 6	43.2, 23.7
6	70.4	69.5	241.2	28.9	10.4	9	N	4, 9	49, 51
7	162	35	30	5.6	44	5	5	5	57.6
8	345	112.25	51.5	27.5	58.75	4	4	4	85.6
9	181	262	528	210	0	8	8	8, 9	53.5, 46.5
10	172.9	334.1	812.5	172.9	37.7	9	9	9	87.3
11	2587.2	7.882	1.4	4.704	0	2	2	2	100
12	1678	652.9	1005.9	80.7	419.1	5	5	5	56.7
13	206	198.9	612.7	74	15.1	9	N	9	47.32
14	180	175	50	75	4	7	1	1, 7	52.2, 47.8
15	34.45	21.92	44.96	3.19	19.62	5	5	4, 5	57.5, 57.5
16	51.2	37.6	52.8	5.1	51.6	5	5	5, 9	71.3, 20.9
17	106	24	28	4	37	5	5	4, 5	60.4, 60.4
18	180.85	0.574	0.188	0.234	0	2	2	2	71.4
19	27	90	63	42	0.2	8	8	7, 8	25, 75
20	138.8	52.2	62.8	6.77	9.55	5	5	4, 5	18.7, 81.3

Note: N – No decision

Observe the results on TABLE VIII. shows that IEC method (IECM) has 5 cases where the fault cannot be determined, whereas with Fuzzy_Hedge_Algebra method (FHA) there are no cases. It came up conclusion with fault number for all cases. With the 2nd, 5th, 6th and 13th data sets, IECM cannot decision, but FHA has made faults conclusions the same actual fault with the highest reliability. In addition, it also offers other faults with lower reliability. Similarly, with the 9th, 14th, 16th, 19th, and 20th data sets, FHA has come up with faults conclusions the same actual faults with the highest reliability and other faults with lower reliability. In general, highly reliable conclusions are the same actual faults.

However, there is only one case of FHA that gave inaccurate conclusions. At the 3rd set of data, the actual fault is 3 but FHA makes the conclusions of faults are 1 and 7 but with very low confidence level. That means it is necessary to pay attention to the fault 7 than the 1, which is Thermal fault 150 oC – 300 oC. The cause of this overheating is usually caused by the fault 2 or 3.

The remaining results show that FM is well-diagnostic system, accompanied by information on diagnostic reliability. This is the advantage of FM compared to IECM. That information also indicates the degree of development of the corresponding fault. Based on that, the operators have specific plans in the maintenance of transformers.

VI. CONCLUSION

In this paper, we have proposed a new diagnostic model and algorithm to diagnosis potential faults of transformers. The diagnostic system is made based on DGA results and the ratio method. Specifically, we have built a diagnostic model based on fuzzy logical approach combined with hedge algebras, developed from diagnosis rules according to IEC-599 standard. Fuzzy sets are designed based on the semantics of the linguistic terms in hedge algebras. This fuzzy diagnostic model overcomes the limitations of IEC-599 when representing the value of ratios based on fuzzy sets. It allows describing the density of gas components to be consistent with reality. With this fuzzy model calculation, potential faults are diagnosed with a degree of reliability. The diagnostic software has been coded completely and running on the web environment. It has been tested with many actual data sets and has the necessary corrections to make the diagnosis more reliable.

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