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Expert System for Health Index Assessment of Power Transformers

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Abstract: A fuzzy logic based technique using dissolved gas analysis to determine the health index of the oil in a power transformer is proposed in the present paper. The proposed fuzzy model integrates the DGA standards and the practical knowledge of transformer diagnostics experts in making a consistent decision on the health condition of the transformer oil. Twenty different transformer oil samples of a power utility validate the reliability of the proposed diagnostic models. Furthermore, a fuzzy logic based overall transformer health assessment model has been proposed in this paper. This model uses several diagnostic tests data of transformers including water content, break down voltage, interfacial tension. It is envisioned that the proposed fuzzy models will prove very convenient even for inexperienced engineers to determine the health index of the transformers. This shall help in initiating suitable action for proper maintenance of the transformers and enhancing their remnant life.

Keywords: Transformer, attribute, fuzzy logic, health index, diagnosis.

1. Introduction

Power transformers are very vital components of power systems and need to be monitored continuously throughout their life span [1], [2]. It has been reported in the literature that the service lifetime of power transformers is determined mainly by the lifetime of their insulation [3]. During normal operation, electrical and thermal stresses cause deterioration of the transformer oil and paper insulation, leading to accumulation of gases within the transformer oil. These gases have been studied by researchers to assess the condition of the oil, expressed as a health index [4], [5]. Over the past two decades dissolved gas analysis (DGA) has also proved to be useful as an early indicator of transformer incipient faults [6]. Incipient faults are internal faults which constitute no immediate hazard to the transformer [5], but could eventually lead to major failure if ignored.

Commonly occurring gases in the transformer oil are acetylene (C_2H_2), ethylene (C_2H_4), ethane (C_2H_6), methane (CH_4), hydrogen (H_2), carbon monoxide (CO) and carbon dioxide (CO_2). The concentrations of these gases are dependent on temperature [7]. Overheating, partial discharge and arcing are the three primary causes which give rise to the generation of these gases within the transformers. These gases are indicative of faults present in the transformers and their concentrations identify the severity of the fault as well. Changes in the individual concentration of the gases serve as an indicator for the identification of various types of faults. During the past few decades, several diagnostic methods such as Key gas [6], Rogers ratios [7], [8], Duval Triangle [9], [10], Dornenburg ratios [11], [12], modified Rogers ratios [10], [11] and IEC/IEEE ratio code methods [12], [13] based on the concentration of gases have been developed. These methods use the ratios of the concentrations of specific pairs of gases to identify a specific fault condition [14]–[16]. However, none of these techniques is based on a mathematical model, and therefore very often interpretations are not accurate [17]. Other methods based on gas concentration ratios and fuzzy logic have been developed for transformer fault diagnosis [17], [18]. These techniques are heuristic in nature and may vary from utility to utility [19]. Confident fault diagnosis using the diagnostic methods enlisted above sometimes proves difficult, if not impossible, particularly when two or more faults are present simultaneously in a transformer [17]. Consequently, there is a need to develop a method which is able to determine the health index for transformers. This problem has been

addressed in the present work.

In this article we proposed a method to determine the health index of transformer oil, based on fuzzy logic (FL). It utilizes the concentrations of five gases dissolved in the transformer oil to provide an accurate health index assessment of the oil. In addition, an overall health assessment model has also been proposed. The proposed method has proved to be more convenient than conventional DGA interpretation methods. Twenty transformer oil samples collected by Himachal Pradesh State Electricity Board (HPSEB) were tested to prove the reliability of the method.

2. The Proposed Fuzzy Logic Based Oil Health Index Method

The proposed FL based oil health index method has four stages, namely determination of membership functions, fuzzification, fuzzy inference and defuzzification. Various aspects of the method are discussed below.

GA Data

Dissolved gas analysis is the most widely used method to determine the health index of transformer oil, and to identify incipient faults present within transformers. It uses the concentrations of various gases dissolved in the oil. As per IEEE standard C57.104–2008 [12], the gas concentrations are divided into four ranges, as shown in Table 1, where ranges 1, 2, 3 and 4 indicate excellent, good, poor and bad oil health respectively. The overall condition of the transformer is determined by the total dissolved combustible gas (TDCG) concentration [12], which is the sum of the concentrations of all the gases excluding CO₂. CO₂ is excluded because it is incombustible [19].

Table 1. Gas Concentrations (in ppm) Divided into Four Ranges.

Gas	Range Number			
	1	2	3	4
H ₂	0–100	101–700	701–1800	>1800
CH ₄	0–120	121–400	401–1000	>1000
C ₂ H ₂	0–35	36–50	51–80	>80
C ₂ H ₄	0–50	51–100	101–200	>200
C ₂ H ₆	0–65	66–100	101–150	>150
CO	350	351–570	571–1400	>1400
CO ₂	2500	2500–4000	4001–10000	>10000
TDCG	720	721–1920	1921–4630	>4630

It is often observed in oil samples that the concentration of a particular gas lies in range 1, but the concentrations of one or more of the remaining gases lie in other ranges. In such cases it is difficult to determine the overall condition of a transformer using TDCG data alone [12]. Identification of incipient faults present in transformers is usually carried out using one of the transformer diagnostic methods [7]–[13], e.g., the IEC ratio code method [7]. However, this method fails when two or more incipient faults exist simultaneously in a transformer [15], [16]. In recent years, various FL models have been developed to determine the overall health of transformers [5], [14]–[19]. These models use the results of various tests, e.g., breakdown voltage, degree of polymerization of the transformer insulation paper, furan content, water content and TDCG of the oil. Although each of these models has its own particular strengths, none of them considers the concentrations of the individual dissolved gases. However, it is important to consider the individual concentrations. H₂ is generated by all incipient faults present in the transformers including corona discharges in the oil [15]. C₂H₄, H₂, CH₄ and C₂H₆ are generated in oil at high temperatures, CH₄ and C₂H₆ are also generated at low oil temperatures, and C₂H₂ is generated only at very high oil temperatures in the presence of an arc

[15]. Thus, in order to extract as much detailed information as possible, it is important to consider the individual gas concentrations.

Our proposed oil health index FL model uses the concentrations of H_2 , CH_4 , C_2H_4 , C_2H_6 and C_2H_2 , which are generated at high oil temperatures ($> 700^\circ C$). These gases cause rapid deterioration of the transformer oil, and therefore strongly influence the oil health index. The concentrations of CO and CO_2 are not taken into account in our model, because these gases are generated only by cellulosic decomposition at low temperature and have little influence on the oil health index [12].

Membership Functions and Degrees of Membership

Following established practice [12] we have divided the concentrations of the five dissolved gases listed above into five groups (or fuzzy sets), namely Very Low (VLow), Low, Medium, High and Very High (VHigh). The concentration limits or boundaries of these sets (a and b) are given in Table 2. These limits are based on the recommendations of transformer diagnosis experts [8]–[12], [20], [21]. We determined the values of a and b through repeated trials, the final values being chosen on the basis of an accurate oil health index output [20]. Our values of a and b differ from those quoted in [6] and [20] by 5-10%. This variation is within the expected ranges [12], [20].

A membership function (MF) is a curve that defines how a given dissolved gas concentration is mapped to a degree of membership (DOM), between 0 and 1, of any one of the five fuzzy sets (Figure 1). A MF can take various shapes, e.g., triangular, Gaussian, sigmoidal or trapezoidal [22], [23]. A widely-used MF is the so-called Gauss2 [22], shown in Figure 1. It is the product of two Gaussian functions given in (1).

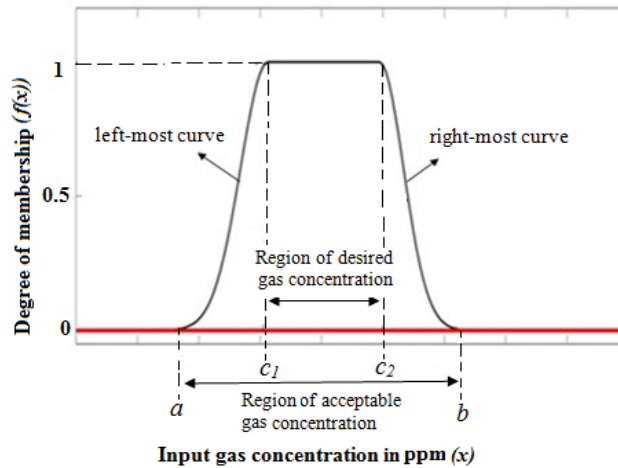


Figure 1. A Gauss2 membership function.

$$\text{Membership Function} = \exp\left[\frac{-(x-c_1)^2}{2\sigma_1^2}\right] \times \exp\left[\frac{-(x-c_2)^2}{2\sigma_2^2}\right] \quad (1)$$

where x is the input gas concentration, c_1 and c_2 are the centers of the two exponential functions, and σ_1 and σ_2 are their standard deviations [23]. The gas concentration region between c_1 and c_2 shown in Figure 1, and the other two regions between a and c_1 , and

between c_2 and b , vary between input MFs. If the input gas concentration lies between c_1 and c_2 for any of the five MFs, then the corresponding MF attains the maximum DOM of unity.

Gas concentrations between a and c_1 , and between c_2 and b , will have DOMs less than unity. The five MFs for hydrogen are shown in Figure 2. Similar plots of MFs were obtained for each of the other four gases.

σ_1 and σ_2 were set equal within each MF, and were the same for all MFs for a given gas. The reason is that unequal σ_1 and σ_2 lead to asymmetrically-shaped MFs, which in turn yield inaccurate and unreliable outputs [22]. σ_1 and σ_2 were set at 50 ppm for all MFs of hydrogen, and at 25, 2, 6 and 5 ppm for all MFs of CH_4 , C_2H_2 , C_2H_4 and C_2H_6 respectively. These values lead to an overlap of 25% between adjacent MFs, as seen in Figure 2, and yield more accurate oil health indexes than MFs based on precise sets [3], [8]–[12], [20]. Additional information on MFs and degrees of membership can be found in [22] and [23].

Table 2. Lower and upper dissolved gas concentration limits a and b (in ppm) for each of the five input Membership Functions, and for each dissolved gas, for transformers rated 5-50 MVA and voltage 6-220 kV [6], [20].

Gas	VLow		Low		Medium		High		VHigh	
	a	b	a	b	a	b	a	b	a	b
H_2	0	200	50	600	450	1200	1050	1700	1550	1800
CH_4	0	100	50	400	350	700	650	950	900	1000
C_2H_2	0	30	25	50	45	70	65	95	80	80
C_2H_4	0	40	20	100	80	140	120	200	180	200
C_2H_6	0	70	55	95	80	130	115	145	130	150

The range of hydrogen covered by each MF, and the DOM of each MF in the range 0–1, are shown in Figure 2.

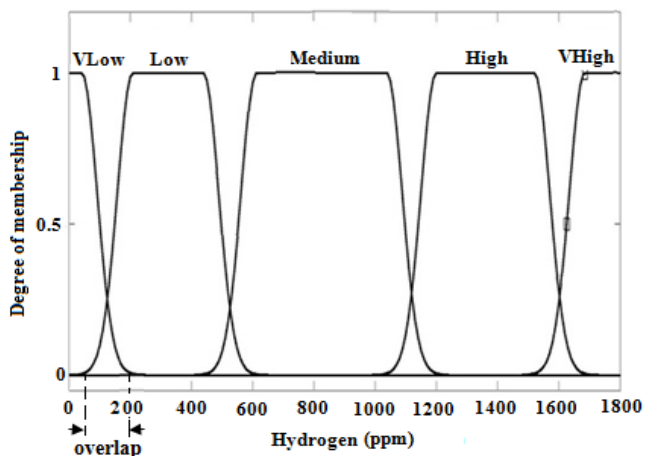


Figure 2. Five membership functions and degrees of membership for hydrogen.

The output of our FL method, i.e., the oil health index, covers the range 0–1, and is divided into five Gauss2 type MFs, as shown in Figure 3. The limits of each output MF are in accordance with [21]. σ_1 and σ_2 were set at 0.025 for each output MF, following the same 25% overlap requirement as for the input MFs. Oil with an Excellent health index does not require filtering, one with a VGood index requires single filtration, while that with a Good

health index requires double filtration. Similarly, oil with a Bad health index requires reclamation, while a VBad index oil should be replaced immediately [20], [21].

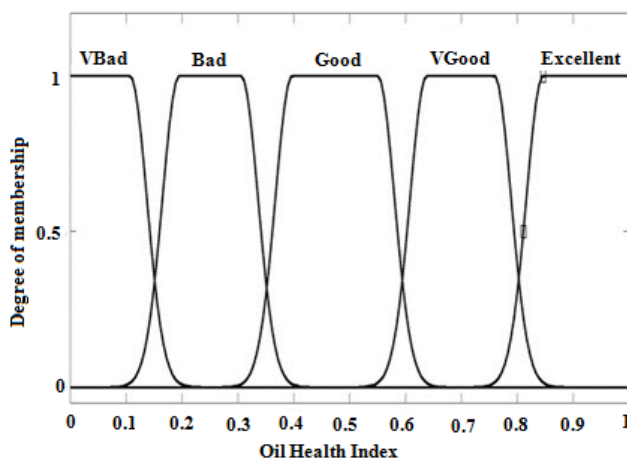


Figure 3. Membership functions and degrees of membership for the output oil health index.

3. Fuzzification

Fuzzification converts the measured gas concentrations from precise form to fuzzy (imprecise) form. The process of fuzzification may be understood from Figure 4 respectively, which relates to one of the samples considered later (sample 1). The dissolved gas concentrations (in ppm) in this sample were $H_2=925$, $CH_4=525$, $C_2H_2=50$, $C_2H_4=110$ and $C_2H_6=90$. $H_2=925$ corresponds to a DOM of 1 within the Medium MF (Figure 4(a)). DOMs of 1 within the Medium MF were also found for CH_4 , C_2H_2 and C_2H_4 . However, in the case of C_2H_6 , with a concentration of 90 ppm, there are two possible DOM values, namely 0.953 and 0.075, within the Medium MF (Figure 4(b)). In such a case, priority is usually given to the higher DOM, since it has a greater impact on the health index [22]. Sometimes the DOMs of two adjacent MFs are equal for a given gas concentration; in that case the two MFs are given equal weight in the fuzzy design process, leading to equal impact on the output health index [23].

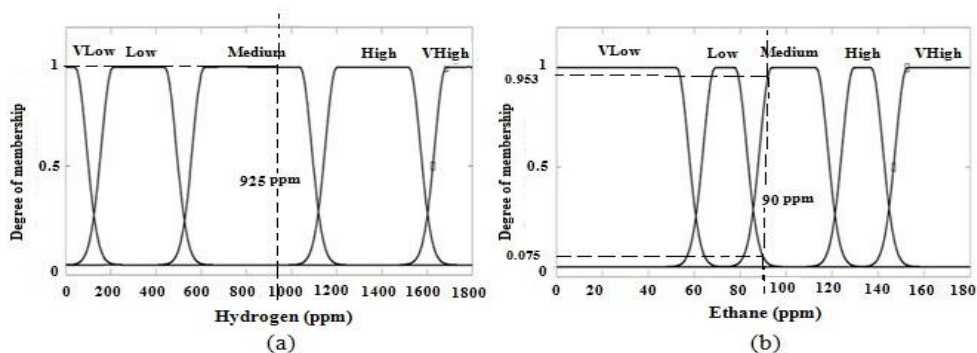


Figure 4. Fuzzification of the input dissolved gas concentrations of an oil sample. (a) hydrogen, (b) ethane.

Fuzzy Inference

Fuzzy inference is the process through which the input dissolved gas concentrations are mapped into the output oil health index, using a number of specifically designed fuzzy rules. A fuzzy rule is a conditional statement connecting the experimental data inputs and the output [22]. In the present work, each of the five inputs (dissolved gas concentrations) contains five

MFs, i.e., a total of 25 MFs [24]. In the design of every fuzzy rule, at least one MF from each of the five inputs has been considered because every input has its own impact on the oil health index. Having such combinations, every input MF generates 125 combinations with the MFs of the other four inputs, without repetitions [23], [24]. Thus, in total $25 \times 125 = 3125$ combinations, yielding 3125 fuzzy logic rules, are possible [25]. Additional information on the total possible combinations of input MFs, and the generation and reduction of fuzzy logic rules can be found in [23]–[25]. Making use of each of these 3125 fuzzy rules would be very time consuming. Therefore, we adopted a much smaller number (31) of fuzzy rules based on an analysis of several transformers having Excellent, VGood, Good, Bad and VBad conditions, as specified in Figure 3.

It is reasonable to discuss here why using only 31 of the 3125 possible fuzzy logic rules would not be expected to lead to inaccurate oil health indexes. This is because of the following reasons:

(i) It is generally accepted that hydrogen is generated (in the oil) by nearly all transformer faults [6], [20]. This is not true of the other four dissolved gases whose concentrations are used in our method [15]. There are five possible concentration ranges (from VLow to VHigh) for each of the five gases, but in order to simplify the fuzzy logic procedure we decided to use only the most commonly reported concentration ranges for each of the other four non-hydrogen gases. For different health conditions of transformer oil (from Excellent to Worst), these ranges were determined based on the literature and the recommendations of transformer diagnosis experts [8]–[12], [20], [21], given in Table 3. This decision reduced the number of possible fuzzy logic rules from 3125 to 25.

Table 3. The five concentration ranges of Hydrogen and the commonly reported concentration ranges of the other four gases for different output ranges.

Input 1 (H ₂)	Input 2 (CH ₄)	Input 3 (C ₂ H ₂)	Input 4 (C ₂ H ₄)	Input 5 (C ₂ H ₆)	Output
VLow	VLow	VLow	VLow	VLow	Excellent
VLow	Low	Low	Low	Low	VGood
VLow	Medium	Medium	Medium	Medium	Good
VLow	High	High	High	High	Poor
VLow	VHigh	VHigh	VHigh	VHigh	Worst
Low	VLow	VLow	VLow	VLow	Excellent
Low	Low	Low	Low	Low	VGood
Low	Medium	Medium	Medium	Medium	Good
Low	High	High	High	High	Poor
Low	VHigh	VHigh	VHigh	VHigh	Worst
Medium	VLow	VLow	VLow	VLow	Excellent
Medium	Low	Low	Low	Low	VGood
Medium	Medium	Medium	Medium	Medium	Good
Medium	High	High	High	High	Poor
Medium	VHigh	VHigh	VHigh	VHigh	Worst
High	VLow	VLow	VLow	VLow	Excellent
High	Low	Low	Low	Low	VGood
High	Medium	Medium	Medium	Medium	Good
High	High	High	High	High	Poor
High	VHigh	VHigh	VHigh	VHigh	Worst
VHigh	VLow	VLow	VLow	VLow	Excellent
VHigh	Low	Low	Low	Low	Vgood
VHigh	Medium	Medium	Medium	Medium	Good
VHigh	High	High	High	High	Poor
VHigh	VHigh	VHigh	VHigh	VHigh	Worst

(ii) It is also accepted that low level partial discharge (LPD) fault within the transformer oil generates H_2 and low concentrations of CH_4 (nearly equal to 20% of H_2) [15]. Further, this fault accelerates to high level partial discharge, and then gets transformed to low level and high level arcs respectively. Finally, these high level arcs suddenly explode the transformers and create a huge revenue loss to the utilities. Also the degradation rate of transformer oil from low level partial discharge to high level arcs is very high as compared to that of the other incipient faults of transformers. Thus, low level partial discharges (i.e. preliminary arc formation stage) have higher impact on the oil health condition as compared to the other incipient faults [7]. Hence, we incorporated the valuable information of such low level partial discharges in the fuzzy rules between 26 and 31. In these 6 rules, the most acceptable combinations generated by VLow and Low MFs of CH_4 were considered as per the criterion followed for the above 25 rules. The reason for considering VLow and Low MFs of CH_4 is that only these two MFs represent low concentration of CH_4 (i.e.20% of H_2 concentration) under the low partial discharge fault. The combinations generated by H_2 MFs were already adopted in the earlier 25 rules. Thus, in total 31 fuzzy logic rules were designed in the present work, shown in Figure 5. The representation of various shapes seen in Figure 5 is detailed in Table 4.

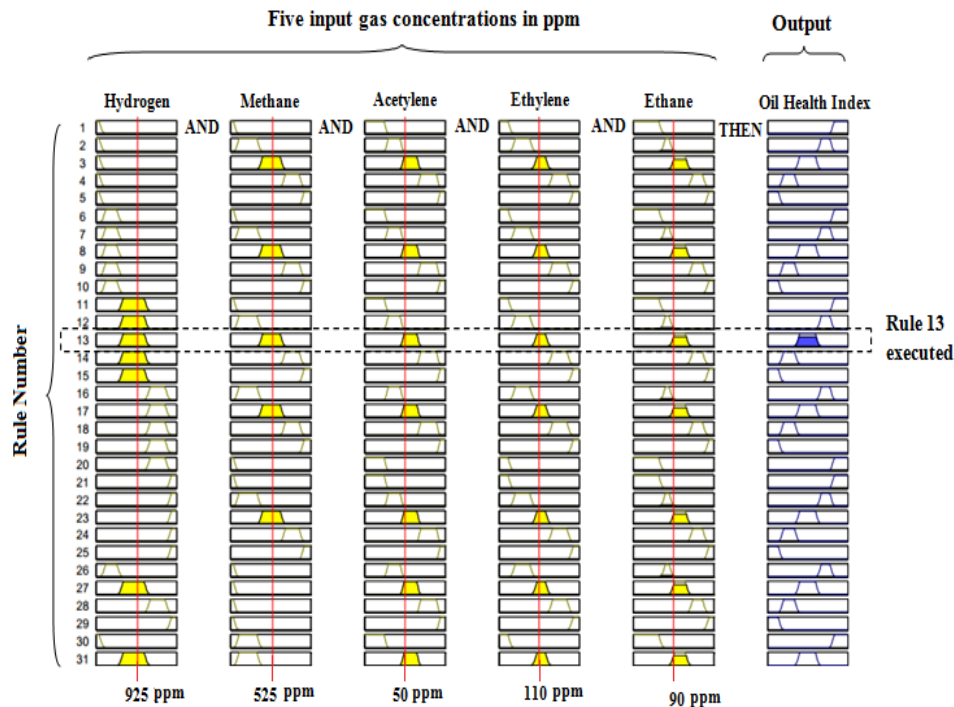


Figure 5. Graphical representation of the 31 fuzzy rules developed to determine the oil health index, applied to oil sample 1.

In Figure 5, the limits of all unfilled areas as well as yellow and blue filled areas specify the lower and the upper limits of the MFs in the designed fuzzy rules. The interpretation of five of the 31 rules in Figure 5 is given below to aid understanding of the rules.

Table 4. Symbols in Figure 5 and their meanings.

Symbol	Meaning
	VLow input MF. In general it starts from a gas concentration of 0 ppm having a maximum DOM of unity. Such starting MFs in the inputs of the proposed FL model provide more accurate output [23], [24].
	Input MF in the relevant fuzzy rule
	Input MF corresponding to specific gas concentration
	VHigh input MF. It ends at deterioration level of gas concentration having a maximum DOM of unity. Such ending MFs of the inputs in the proposed fuzzy model provide the more accurate output health index of oil [23]-[25].
	Output MF in the relevant fuzzy rule
	Output MF corresponding to specific set of input gas concentrations
	Input dissolved gas concentration value

Rule 1: *IF (each of the five inputs is VLow) THEN (the health condition of the transformer oil is Excellent).*

Rule 2: *IF (input1 is VLow) AND (each of the other four inputs is Low) THEN (the health condition of the transformer oil is VGood).*

Rule 3: *IF (input1 is VLow) AND (each of the other four inputs is Medium) THEN (the health condition of the transformer oil is Good).*

Rule 4: *IF (input1 is VLow) AND (each of the other four inputs is High) THEN (the health condition of the transformer oil is Poor).*

Rule 5: *IF (input1 is VLow) AND (each of the other four inputs is VHigh) THEN (the health condition of the transformer oil is Worst).*

In our model, the Mamdani maximum–minimum fuzzy inference method is used to determine the output MF from the set of input gas concentrations. It truncates the output MF at its minimum DOM value [22]. Such a truncation is shown in Figure 6 in relation to rule 13 applied to sample 1. Rule 13 agrees the given set of input gas concentrations (oil sample 1). The input MFs are shown in the first five yellow boxes, and the output MF is shown by the hatched part in the blue box. The output MFs for hydrogen, methane, acetylene and ethylene for this sample were Good with a DOM of 1, but for ethane the output MF was Good with a DOM of 0.953. The fuzzy inference method therefore truncates the output at the lower DOM value of 0.953. Consequently, the output of the proposed model in accordance to the remaining thirty fuzzy rules depicted in Figure 5 is zero, for the same set of input gas concentrations (oil sample 1). The reason is that one or more input gas concentrations in sample 1 did not lie within the ranges specified in these 30 rules. Thus, in relation to rule 3, the methane, acetylene, ethylene and ethane input concentrations lie within the specified limits of Medium MF shown by the yellow-coloured bands in Figure 5. However, the hydrogen concentration does not do so. Thus, it was not highlighted by a yellow-coloured band, but shown by a black slanted line. To satisfy rule 3 the hydrogen concentration must lie in the VLow range, i.e., 0 to 100 ppm, and not in the Medium range. Therefore, the output corresponding to rule 3, and for each of the other rules except rule 13, was zero. The final precise output from the truncated output MF is determined using the defuzzification stage of the model.

Defuzzification

Defuzzification is the process of producing a precise quantitative value from the truncated output MF according to an executed rule [22]. In our work defuzzification was performed using the popular center of gravity method. This method determines the center of gravity or the centroid (Z_0) of the area bounded by the truncated output MF [23], as shown in Figure 7. It is given by

$$Z_0 = \frac{\int z \cdot \mu(z) dz}{\int \mu(z) dz} \quad (2)$$

where $\mu(z)$ is the DOM of the truncated output MF and z is the oil health index variable. The truncated output MF is determined from the set of five gas concentrations in sample 1. Its centroid is the quantitative oil health index (OHI) value, and its value was 0.446, which indicates that the health condition of this oil sample is Good. However, it requires double filtration to improve its dielectric properties.

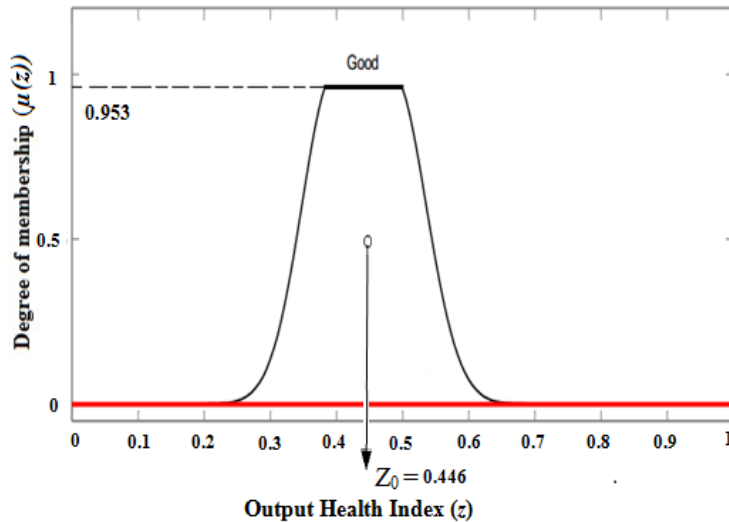


Figure 7. Determination of oil health index (precise quantitative output) using the center of gravity defuzzification method.

Table 5. Dissolved gas concentrations (in ppm) and the resulting oil health indexes.

Sample No.	H ₂	CH ₄	C ₂ H ₂	C ₂ H ₄	C ₂ H ₆	Oil Health Index	Oil Health Condition (OHC)	OHC in accordance to Diagnostic Experts
1	925	525	50	110	90	0.446	G	G
2	42	123	190	145	33	0.490	G	G
3	99	128	0	285	18	0.882	E	G
4	15	12	0.2	1.5	1.6	0.940	E	E
5	34	109	0	250	17	0.878	E	E
6	60	144	9	440	67	0.825	E	G
7	532	119	850	135	29	0.445	G	E
8	79	75	118	73	5	0.648	VG	G
9	112	108	134	87	30	0.629	VG	G
10	65	215	0	450	54	0.759	VG	G
11	49	45	83	76	8	0.676	VG	E
12	751	101	340	98	14	0.685	VG	E
13	9	20	0	10	5	0.929	E	E
14	60	340	10	391	43	0.627	VG	G
15	816	187	999	250	17	0.349	G	G
16	201	780	76	1508	217	0.127	VB	B
17	268	586	22	861	324	0.389	G	G
18	509	1121	32	1444	298	0.273	B	B
19	809	1400	3012	2819	305	0.075	VB	VB
20	9478	4066	1298	663	351	0.048	VB	VB

Similarly, the health indexes of the remaining oil samples collected from various transformers operated by HPSEB, India were determined using the proposed FL method. The MVA ratings of the transformers were in the range 5–50 MVA, and their kV ratings in the range 6–220 kV. The experimental DGA results for the twenty oil samples and their health indexes obtained using the proposed FL method are given in Table 5. The health conditions of the transformer oils obtained from the proposed oil HI model have been compared with the health condition derived by the transformer diagnostic experts based on conventional test methods. Outputs obtained from both the methods are given in Table 5, columns 8 and 9 respectively.

4. Transformer Diagnostic Tests

Breakdown Voltage

Voltage at which breakdown occur between two electrodes when oil is subjected to an electric field under prescribed conditions is called breakdown voltage (BDV) [23]. Electric strength is the basic parameter for insulation system design of a transformer which serves to indicate the presence of contaminants like moisture, perceptible sludge and sediment [24].

Dissipation Factor

Dissipation factor (DF) is numerically equal to sine of the loss angle and is good tool to indicate the quality of insulation [13]. A high value of dissipation factor is an indication of the presence of contaminants such as water, oxidation products or de-polymerization of paper insulation etc. [24].

Water Content

The amount of dissolved and free water present in the oil is its water content. It is expressed in ppm (parts per million by weight) [15]. Moisture in the oil is harmful since it adversely affects the electrical characteristics of oil and accelerates deterioration of insulating materials [16].

Acidity

Acidity is defined as the measure of free organic and inorganic acids present in the transformer oil, and is expressed in terms of milligrams of potassium hydroxide required to neutralize the total free acid in one gram of oil [25].

Dissolved Combustible Gases

When abnormal thermal and electrical stresses are not very high, the gasses generated as a consequence of decomposition of insulating oil will get enough time to dissolve in the oil. In dissolved gas analysis of transformer oil, the gases in oil are extracted and analyzed [26]. Using percentages of different gasses present in the oil, the internal condition of transformer can be predicted [26].

2-Furaldehyde (2-FAL)

Two major parts of transformers i.e. core and winding have solid dielectric. It is made of cellulose. Cellulose consists of a structure of long chain of molecules [27]. These long chains are normally broken into large number of shorter parts, as per the aging. When the transformer oil is soaked into solid dielectric, it is damaged by heat, and dissolved in the oil along with CO₂ and CO. These compounds belong to the fur-furaldehyde group. Among all Furfurals compounds, 2-Furfural is the most predominant. The rate of rise of degree of Furfurals products in oil, with respect to time, is used for assessing the condition and life cycle of paper insulation in power transformer. Fur-furaldehyde analysis is very sensitive as because damage of few grams of paper can be detected in the oil even of a very large size transformer [27].

Proposed Fuzzy Logic Model

Six inputs namely water content, acidity, BDV, DF, DCG, and 2-Furfuraldehyde were considered in the present proposed model in determining the overall health index of the transformers. Higher number of inputs increases the reliability of the overall health assessment model. Three sub-fuzzy models viz. F_1 , F_2 and F_3 were developed separately. F_1 consist of water content and acidity as inputs, whereas BDV and DF are for F_2 . Similarly F_3 is developed with DCG and 2-FAL as inputs. Furthermore, the outputs of these three sub-models have been evaluated through a single fuzzy model called F_4 which determines the final output health index of transformers. The input MFs used in F_1 , F_2 and F_3 were designed in accordance to [28]. Trapezoidal shaped MFs (Figure 8) were used for all the inputs, and the limits of these MFs were also selected according to [28]. These limits for MFs of water content input in F_1 are shown in Fig. 2. Similar shapes were obtained for the MFs of the remaining inputs. The lower and the upper limits, and the two centers of these MFs are specified in Table 6.

However, input 2-FAL in F_3 consists of 5 MFs as per [26]. These MFs are Good, Low-moderate, High-moderate, Bad and Very bad. The lower and upper limits of these MFs, and their centers are [0 0 0.2 0.2], [0.2 0.2 0.9 1.3], [1 1.4 2.8 3.7], [3 3.7 6.2 7.5] and [6 7.5 10 10] respectively. In case of F_4 , the output MFs used in each of the three sub-models were used as input MFs. The corresponding input and output MFs are same as described in Figure 8.

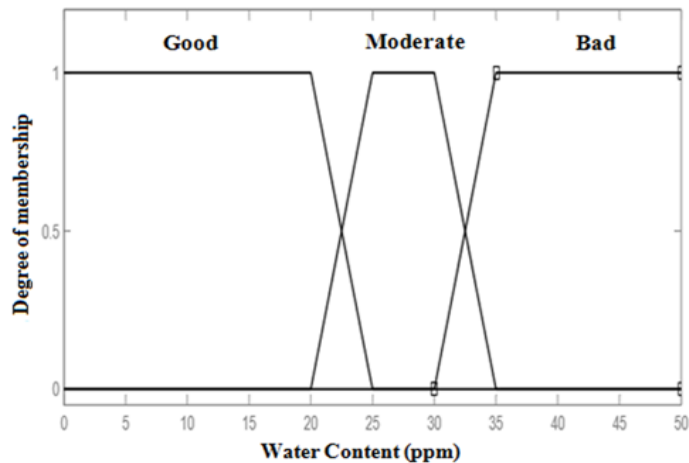


Figure 8. Membership functions for water content input in F_1 .

Table 6. Lower and upper limits for input membership functions

Input MF ranges	Good				Moderate				Bad			
	a	c_1	c_2	b	a	c_1	c_2	b	a	c_1	c_2	b
BDV	1	1	22	23	22	23	23	24	23	24	0	0
DF	0	0	0.05	0.1	0.05	0.1	0.8	1	0.8	1	1.5	1.5
DCG	0	0	300	400	300	400	1100	1400	1100	1400	2000	2000
Acidity	0	0	0.03	0.05	0.03	0.05	0.15	0.2	0.15	0.2	0.3	0.3

The output for each of the three models F_1 , F_2 and F_3 was divided in to 4 MFs as specified in Figure 9. The limits and centers for these MFs were selected in accordance to [29].

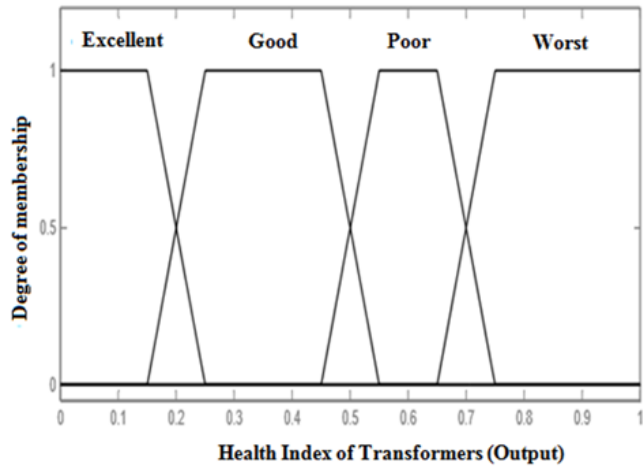


Figure 9. Membership functions of input F4.

Initially the inputs are fuzzified, further the truncated output from each of the three models can be obtained based on the fuzzified inputs and the specially designed expert fuzzy rules. In the present work, the fuzzy rules possible between the inputs of F₁ are as shown in Figure 10, two inputs each with three MFs generate a total of 9 combinations. Similar combinations are also obtained for F₂.

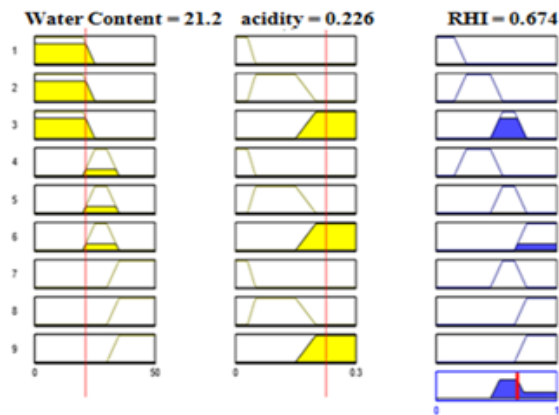


Figure 10. Rule base of F1 fuzzy logic model.

In case of F₃, the three input MFs in DCG, and five MFs in 2-FAL make a total of fifteen fuzzy rules. The corresponding output according to each of these rules is detailed in Figure 11. Similarly, all the possible combinations of input MFs in case of F₄ were generated. These rules are shown in Figure 12.

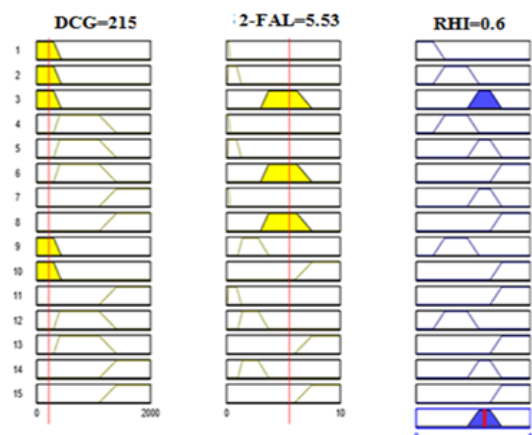


Figure 11. Rule base of F3 fuzzy model.

6. Results and Discussion

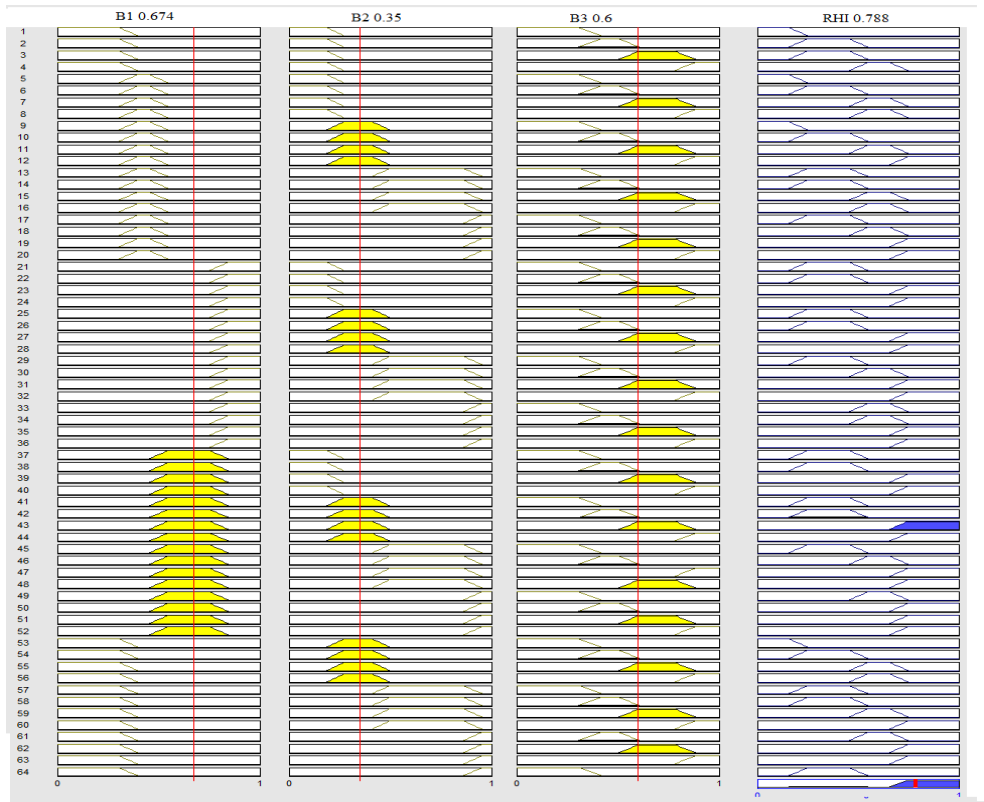


Figure 12. Rule Base of Fuzzy Logic Model F4.

In order to understand proposed methodology, sample 1 detailed in Table 7 has been evaluated. In sample 1, 21.2 ppm of water content, 0.226 mgKOH/g of acidity, 48.7 KV of BDV, 0.424 of DF, 215ppm of DCG and 5.53ppm of 2-FAL were initially fuzzified in the present proposed model. The corresponding input MFs for the given set of inputs for sample 1 can be identified from figures 10 to 12. The corresponding outputs can also be obtained from the same figures.

After defuzzification, the output obtained from F_1 (i.e. B_1) is 0.674, F_2 (i.e. B_2) is 0.35, and F_3 (i.e. B_3) is 0.6. And based on these three outputs final outcome from F_4 (i.e. B_4 or RHI) is 0.788. Similarly the health index for the remaining samples of different transformers was determined and given in Table 7 (column 8). In the proposed model, four output membership functions have been considered whereas in case of reference model five membership functions are there.

Table 7. Health indices calculated for 20 test case transformers

Sample Number	WC	Acidity	BDV	DF	DCG	2-FAL	Health Index obtained using Present Proposed Method	Health Condition of Transformers	Transformer HC According to Diagnostic Experts
1	21.3	0.026	29	0.077	489	0.85	0.35	G	G
2	26.1	0.092	56	0.892	292	0.61	0.413	G	G
3	13.6	0.038	53	0.147	77	0.22	0.236	E	G
4	21.8	0.227	47.7	0.431	215	5.54	0.788	W	W
5	8	0.016	73	0.118	127	0.01	0.0995	E	E
6	15.4	0.071	73	0.145	38	0.52	0.248	E	G
7	16.1	0.165	70.5	0.261	147	0.74	0.236	E	E
8	13	0.083	67.2	0.219	28	0.65	0.248	E	E
9	19	0.038	64.5	0.182	8	0.31	0.236	E	E
10	27	0.091	39.5	0.357	194	0.21	0.35	G	G
11	15.2	0.172	22.7	0.217	38	8.56	0.776	W	W
12	14	0.136	36.5	0.192	51	7.45	0.601	P	G
13	15.3	0.128	26.6	0.189	76	9.34	0.622	P	P
14	17	0.41	55.2	0.267	51	6.62	0.851	W	W
15	25.8	0.069	31.4	0.131	321	5.35	0.851	W	W
16	23.5	0.109	43.8	0.216	33	0.344	0.256	E	E
17	27.9	0.021	27.9	0.061	501	1.24	0.245	E	E
18	26.3	0.063	37.2	0.213	25	0.57	0.267	E	E
19	31	0.069	29.7	66	32	15.543	0.843	W	W
20	19.4	0.064	61.5	0.245	61	0.134	0.11	E	E

7. Conclusion

The paper presents a new fuzzy logic interpretive approach for dissolved gas analysis of transformer oil based on the concentrations of dissolved gases namely CH_2 , CH_4 , C_2H_2 , C_2H_4 and C_2H_6 . The proposed health index fuzzy logic model determines the health index of the transformer oil. The proposed fuzzy model integrates the DGA standards and the practical knowledge of transformer diagnostics experts in making a consistent decision on the health condition of the transformer oil. Further, a new FL based overall health assessment model has been proposed in the present paper. Twenty different transformer oil samples of a power utility validate the reliability of the proposed diagnostic models. It is envisioned that the proposed models will prove very convenient even for inexperienced engineers to determine the oil health index and the incipient faults of the transformers. This shall help in initiating suitable action for proper maintenance of the transformers and enhancing their remnant life.

8. References

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