Artificial Intelligence Solution For Incipient Faults Diagnosis Of Oil-Filled Power Transformers

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Abstract: *Power transformers are high cost important equipment used in the transmission and distribution of the electric energy. A power transformer in operation is subjected to different stresses such as electrical stress and thermal stress due to natural ageing and loading regime which lead to liberation of gases from the hydrocarbon mineral oil. Dissolved gas analysis (DGA) has been widely used as an effective technique to detect the incipient fault of the transformer. There are different conventional DGA methods developed for analyzing these gases such as key Gas, Rogers Ratio, Doernenburg, International Electrotechnical Commission (IEC) Ratio, and Duval triangle. Artificial Intelligence (AI) can be also used to detect power transformers incipient faults. In this paper, the applications of two AI approaches have been presented based on IEC standard which is fuzzy logic approach (FLA) and artificial neural network approach (ANNA). Each approach is used to get the correct diagnosis of the incipient faults and the accuracy is then calculated.*

Key words: *Dissolved gas analysis, fuzzy logic, neural network, power transformer incipient faults, and transformer oil.*

1. Introduction

In today's competitive energy market, power utilities wish to have sustainable operation of all assets with minimum cost of the existing equipment over their life span. The current trend is to utilize existing equipment at ever-higher capacity levels in order to defer the capital investment in new facilities or in refurbishment of the existing facilities [1]. Power transformers are one of the most expensive and important equipments in power systems. Any fault in power transformers may lead to the interruption of the power supply to consumers [2]. Consequently, it is very important to detect power transformers incipient faults as early as possible. Also, System power reliability improves when incipient faults in power transformers are identified and eliminated before they deteriorate to a critical operation condition. Dissolved gas analysis (DGA) is one of the most useful methods to detect power transformers incipient faults. DGA periodically samples and tests the insulation oil of transformers to obtain dissolved gases in the oil that form due to deterioration of internal insulation materials [3-4]. The main advantage of this method is that the sampling and analyzing processes are simple and inexpensive and can be performed without de-energizing the power transformer from service. The majority of faults are slow to develop, which can be detected by DGA monitoring. However, instantaneous faults are rapid and sometimes cannot be predicted by DGA. The main gases formed as a result of electrical and thermal faults in power transformers are Hydrogen (H_2), Ethane (C_2H_6), Methane (CH_4), Ethylene (C_2H_4), Acetylene (C_2H_2), Carbon dioxide (CO_2), Carbon monoxide (CO). In the past years, different conventional fault diagnosis techniques have been proposed based on DGA such as key Gas, Rogers Ratio, IEC Ratio [5] and Duval triangle. In some cases, conventional fault detection methods fail to give diagnosis due to the no matching codes for diagnosis because of the coding boundary and the sharp codes change. Recently, artificial intelligence techniques have been used to get the correct diagnosis based on DGA data [6-7]. The present paper is aimed at applying fuzzy logic system and artificial neural network based on IEC standard to determine the incipient fault of power transformers. The paper is organized as the following; Section 2 provides a brief explanation on dissolved gas analysis. Section 3 presents the details of the Fuzzy Logic approach. Section 4 presents the details of the artificial neural network approach. Section 5 provides the simulation results of the tests. Finally, the conclusions are discussed in section 6.

2. Dissolved Gas Analysis

Transformer oil is prone to undergo irreversible changes in its chemical and dielectric properties due to aging. Consequently, transformer oil may act as an information carrier whose condition may be related to condition of the power transformer and as a result can determine the incipient fault in the power transformer. Dissolved gas analysis (DGA) is a sensitive and reliable technique to identify the power transformers incipient faults. By using this technique, it is possible to discriminate fault in a great variety of oil-filled equipment. Various techniques have been reported in the literature to predict the incipient faults such as IEC ratio codes, IEEE standard's Roger's and Doernenburg's ratio codes, Key gas method and Duval triangle. Table 1 shows the fault types and the codes addressed in this paper based on IEC standard.

Table 1: Fault types used in the analysis

Fault Type	Code
Partial discharge	PD
Discharges of low energy	D1
Discharges of high energy	D2
Thermal faults T<300 °C	T1
Thermal faults 300<T<700 °C	T2
Thermal faults T>700 °C	T3

The proposed approaches are built using IEC ratios method which uses five gases H_2, CH_4, C_2H_2, C_2H_4 and C_2H_6. These gases are used to produce a three gas ratios: (C_2H_2/C_2H_4), (CH_4/H_2) and (C_2H_4/C_2H_6). Table 2 gives the IEC standard for interpreting fault types of a power transformer and shows the values for the three key-gas ratios corresponding to the suggested fault diagnosis.

Table 2: Diagnosis using IEC ratio method

Fault type	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
PD	<0.1	<0.1	<0.2
D1	>1	0.1 – 0.5	>1
D2	0.6 – 2.5	0.1 - 1	>2
T1	<0.1	>1	<1
T2	<0.1	>1	1 - 4
T3	<0.2	>1	>4

Besides the conventional methods used to detect power transformers incipient faults, the Artificial Intelligence (AI) could also be used to solve this problem. Advances in AI techniques have improved transformer incipient faults diagnosis. Many practical transformer operation problems can now be solved by AI-based condition monitoring and assessment systems [8-9]. In this paper, two different AI techniques are used to get the correct diagnosis of the incipient faults of power transformers which are fuzzy logic (FL) and artificial neural network (ANN).

3. Fuzzy Logic Technique Applied To DGA

There are lots of indeterminate factors in process of transformer incipient fault diagnosis whose influence to the transformer operation status is usually fuzzy and uncertain. Ratio codes are quantized to define the crisp boundaries which are non crisp (fuzzy). These codes may lead to errors in diagnosis process moving across the crisp boundaries from one fault to another. To avoid this problem, fuzzy system for fault diagnosis is used. Table 3 shows the properties of the inputs and the outputs of the developed fuzzy inference system (FIS) which was performed by using MATLAB software.

Table 3: Properties of inputs and outputs of the FIS

Inputs	Outputs
1- C_2H_2/C_2H_4 2- CH_4/H_2 3- C_2H_4/C_2H_6	1- No fault 2- Partial discharge 3- Discharges of low energy 4- Discharges of high energy 5- Thermal faults T<300 °C 6- Thermal faults 300<T<700 °C 7- Thermal faults T>700 °C

The fuzzy logic analysis consists of three successive processes which are fuzzification, fuzzy inference and defuzzification. Fuzzification converts crisp data into a fuzzy input membership. The Gaussian membership function has been used in the analysis. Fuzzy inference draws conclusions from if-then linguistic statements. The fuzzy inference system that has been used is Mamdani type. The Max-Min composition technique has been used. The logical (AND) is used as the minimization operator and logical (OR) is used as the maximization operator. Defuzzification then converts the fuzzy output back into crisp outputs. The aggregation of the outputs is `max` and the defuzzification process is done by using the middle of maximum method [10]. The basic structure of the fuzzy inference system is shown in Figure 1.

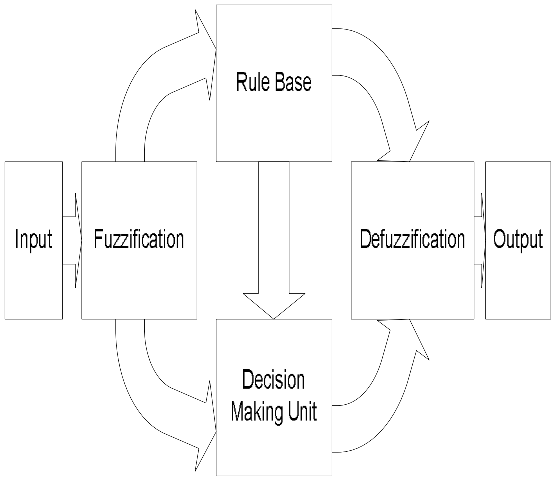

Fig. 1: The basic structure of the fuzzy inference system

The structure of the fuzzy diagnosis system based on IEC standard is shown in Figure 2.

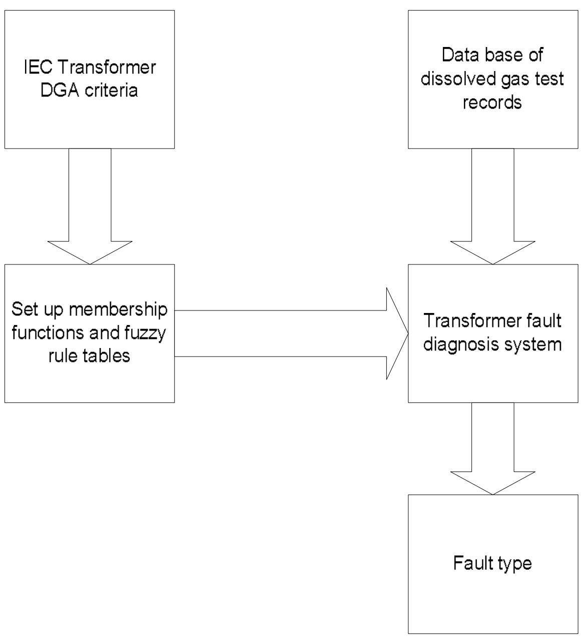

Fig. 2: The structure of the fuzzy diagnosis system based on IEC standard

For each of the gas ratios there are three membership functions that are classified as low, medium and high. The mean and standard deviation of the Gaussian membership functions are selected by integrating IEC standard, relationship between type of incipient faults of transformers and quantity of oil dissolved characteristic gases and other human expertness. The numbers of possible rules are twenty Seven. Each rule consists of two components which are the antecedent (If part) and the consequent (Then part). The design of the fuzzy membership functions of gas ratios are illustrated in figures 3, 4 and 5.

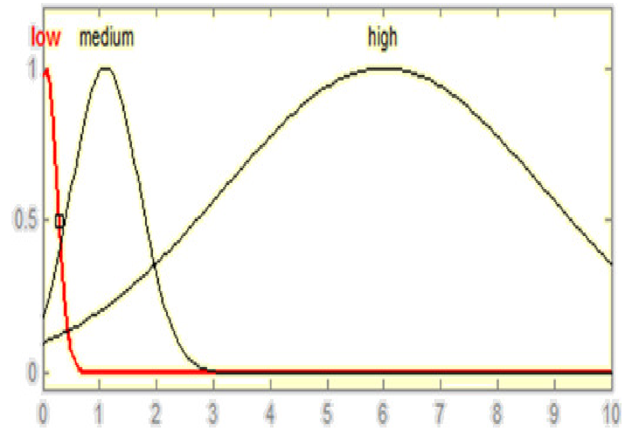

Fig. 3: Membership function of (C_2H_2/C_2H_4)

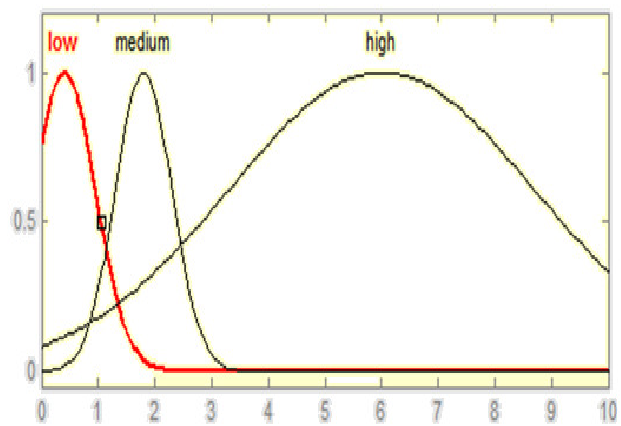

Fig. 4: Membership function of (CH_4/H_2)

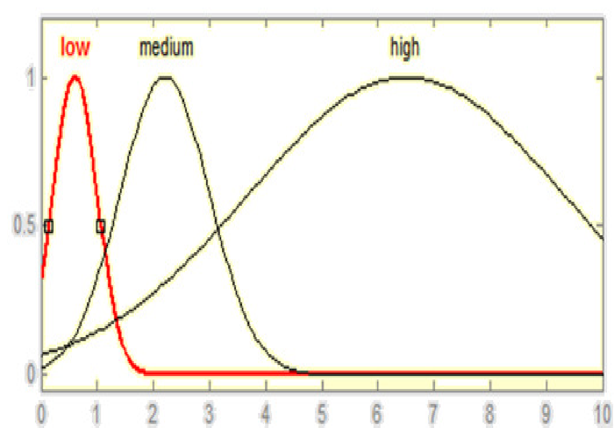

Fig. 5: Membership function of (C_2H_4/C_2H_6)

After implementing fuzzy inference system based on DGA using Mamdani method. A simulink model is then developed in MATLAB using the previous fuzzy inference system in order to ease model testing. The structure of the simulink model is shown in Figure 6.

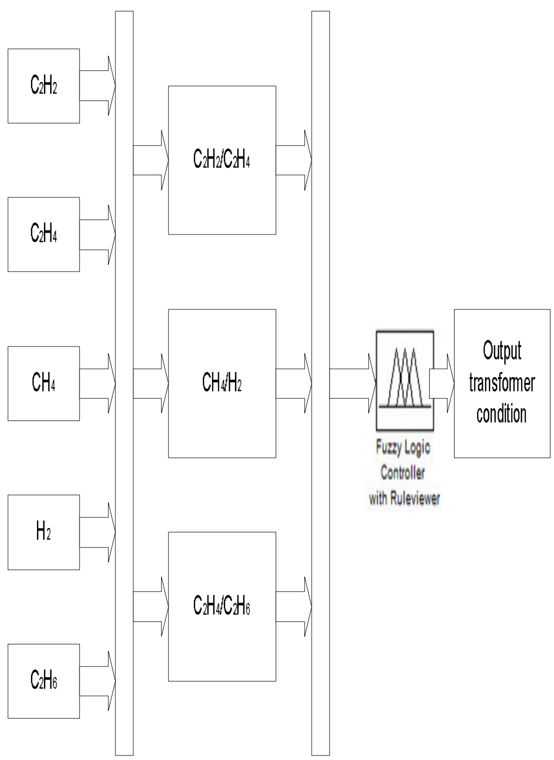

Fig. 6: Simulink model for the fuzzy system

4. Neural Network Technique Applied To DGA

Artificial neural network model is constructed by using MATLAB software. Multilayer feed forward neural network (MLFFNN) is chosen as the network architecture because it is the most popular ANN architecture and applicable to this kind of work. Also, Multiple-layer networks are quite powerful. For instance, a network of two layers, where the first layer is sigmoid and the second layer is linear, can be designed to approximate any function. An MLFFNN contains multiple layers of nodes in a directed graph. Each layer is fully connected to the next layer. Constructing an ANN model requires choosing the best network configuration and parameters such as the number of neurons in the hidden layers and the transfer function in each layer. This network has three gas ratios according to IEC standard as inputs and seven transformer conditions as outputs as shown in table 3. The work involves constructing a two layer network which consists of inputs of the system, two hidden layers and system output. The first hidden layer was designed with three neurons and the transfer function used in this layer is tangent sigmoid as shown in figure 7.

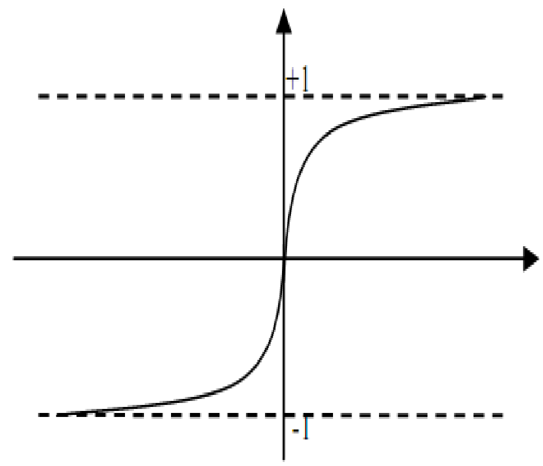

Fig. 7: Tangent sigmoid transfer function

The main aim of this layer is to determine the general condition of the transformer which may be (No fault condition) or (Thermal fault condition) or (Electrical fault condition). The parameters of the weight matrix are chosen to achieve this aim. The second hidden layer was designed with three neurons and the transfer function used in this layer is linear transfer function. The main aim of this layer is to determine the exact condition of the transformer which may be No fault or Partial discharge or Discharges of low energy or Discharges of high energy or Thermal fault ($T<300°C$) or Thermal fault ($300°C<T<700°C$) or Thermal fault ($T>700°C$). The initial values of weight matrices elements are selected by integrating IEC standard, relationship between type of incipient faults of transformers and quantity of oil dissolved characteristic gases and other human expertness. The training process is performed using old laboratory available data. The input and output patterns are determined and the network is then fed with them. If the patterns are selected appropriately, the fault diagnosis will be efficient. The architecture of the proposed ANN in this research is shown in figure 8.

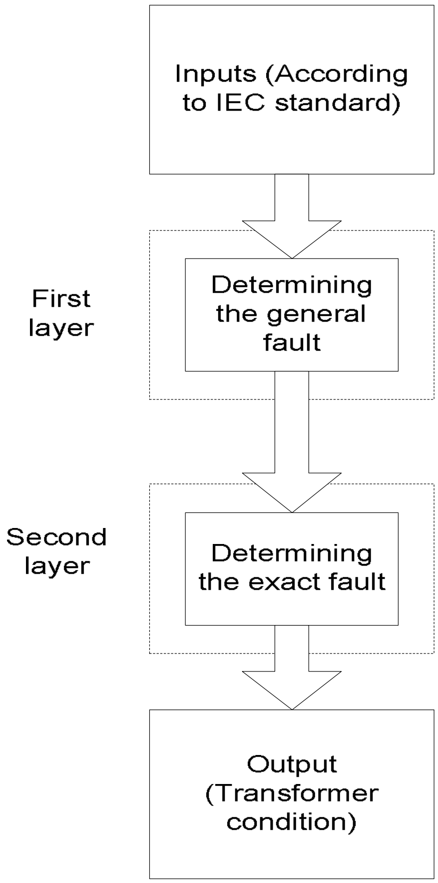

Fig. 8: The architecture of the proposed ANN

5. Tests and Results

In order to examine the accuracy of the proposed approaches, different power transformers DGA results are tested. The detailed gas data are taken from previous research work. The detailed gas data are shown in APPENDIX A [11], where the AFC expresses the actual fault type, the FLA expresses the fuzzy logic approach result and the ANNA expresses the artificial neural network approach result. For each case the measured quantity of gases is mentioned in p.p.m. The tested data contains 30 oil samples. The proposed fuzzy logic approach is able to classify correctly 25 cases of the 30 test cases with accuracy of 83.33% but the proposed artificial neural network approach is able to classify correctly 23 cases of the 30 test cases with accuracy of 76.66%. According to test results, the FLA has higher accuracy since the coding boundary and the sharp codes changes make the determination of transformer status non crisp (fuzzy). This reason makes the use of fuzzy logic with Gaussian membership functions more appropriate for this problem. On the contrary, the ANNA has lower accuracy since the determination of high accuracy ANN model which contains network parameters, configuration and architecture require large number of training data which was not available for the authors.

6. CONCLUSION

Dissolved Gas Analysis (DGA) is the most effective technique used for power transformer incipient faults detection. Many conventional DGA schemes have been developed to estimate transformer condition. But, these schemes cannot consider all possible combinations of gas ratios, which results in inconsistencies and ambiguities. In this paper, two AI techniques based on IEC standard are used in order to make a decision on the power transformer state. The proposed approaches were fast and implemented easily by software. The first technique is the fuzzy logic approach (FLA). It is noted that appropriate membership functions and rules are necessary to obtain high accuracy. The second technique is the artificial neural network approach (ANNA). It is noted that determination of elements in each weight matrix requires high experience about the relation between each fault type and the dissolved gases in the insulating oil. According to test results, it is found that the FLA has a better performance and a higher accuracy than the ANNA. The next proposed step by the authors is to combine together more than one AI technique to improve the accuracy.

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APPENDIX A. Tested gas data of transformer and diagnosis by FLA and ANNA

No.	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	AFC	FLA	ANNA
1	19.3	103	159	19	0.6	**T1**	**T1**	T3
2	497	230	51	151	122	**D2**	**D2**	**D2**
3	615	200	42	102	68	**D2**	**D2**	**D2**
4	594	230	44	130	102	**D2**	**D2**	**D2**
5	27	30	23	2.4	0.1	**No Fault**	**No Fault**	**No Fault**
6	38	55	22	28	0.1	**T2**	**T2**	**T2**
7	30	22	14	4.1	0.1	**No Fault**	**No Fault**	**No Fault**
8	23	63	54	10	0.3	**T1**	**T1**	D1
9	2.9	2	1.5	0.3	0.1	**No Fault**	PD	**No Fault**
10	4	99	82	4.2	0.1	**T1**	**T1**	**T1**
11	56	286	96	928	7	**T3**	**T3**	**T3**
12	78	161	86	353	10	**T3**	**T3**	**T3**
13	21	34	5	47	62	**D2**	D1	T3
14	50	100	51	305	9	**T3**	**T3**	**T3**
15	120	17	32	23	4	**No Fault**	**No Fault**	**No Fault**
16	172	335	171	812	37.8	**T3**	**T3**	**T3**
17	181	262	41	28	0.1	**T1**	**T1**	**T1**
18	27	90	42	63	0.2	**T2**	**T2**	**T2**
19	160	130	33	96	0.1	**No Fault**	D2	D2
20	180	175	75	50	4	**No Fault**	**No Fault**	**No Fault**
21	127	107	11	154	224	**D2**	**D2**	**D2**
22	32.4	5.5	1.4	12.6	13.2	**D2**	**D2**	**D2**
23	345	112.3	27.5	51.5	58.8	**D1**	D2	D2
24	980	73	58	1.2	0.1	**PD**	No Fault	No Fault
25	74	142.2	41.8	324.9	5.3	**T3**	**T3**	**T3**
26	76	140	40.8	317	5.2	**T3**	**T3**	**T3**
27	30.4	117	44.2	138	0.1	**T2**	**T2**	**T2**
28	30.8	149	47.9	146	0.1	**T2**	**T2**	**T2**
29	27	136	46.9	131	0.1	**T2**	**T2**	**T2**
30	1607	615	80	916	1294	**D2**	**D2**	T3