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Dissolved Gas Analysis of Transformer oil using Adaptive Neuro-Fuzzy Inference System

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Abstract—In this paper, Adaptive Neuro-Fuzzy Inference System (ANFIS) has been developed for analysing various incipient faults occurring in oil immersed transformer. By using dissolved gas analysis (DGA) we can effectively monitor condition of oil immersed transformer. Various standards have been already developed for analysing faults on basis of dissolved gases in oil. But these standards fails in diagnosing some faulty conditions, therefore here ANFIS is implemented in accordance with DGA interpretation standard IEC-60599. Proposed model of diagnosing fault has been trained and tested by using sample of faulty transformers from various utilities and literature. From results obtained it can be seen that proposed system is more reliable than that of conventional standards.

Index Terms— ANFIS, DGA, IEC-60599, incipient faults.

1 INTRODUCTION

In electrical power system, transformer is one of the major equipment, which operates continuously. Due to continuous operation, transformer undergo various mechanical, thermal and electrical stresses, these stresses leads to failure of the transformer. On occurrence of failure of transformer we have to either replace or repair transformer which is highly uneconomical. Thus it is important to keep a track of the health of the transformer and also develop a diagnosis system. The condition of oil immersed transformer depends directly on the condition of insulating liquid (the transformer oil) and solid impregnated insulation cellulose. DGA (Dissolved Gas Analysis) of the transformer oil, degree of polymerization measurements, furan analysis of the paper, power factor testing, winding resistance and etc.[1] are methods which can used for the evaluating the ageing process and the deterioration of cellulose material. Among all these methods, for evaluating fault in transformer, DGA is a method widely used by utilities and researchers for fault diagnosis as it is most sensitive and reliable technique.

For dissolved gas analysis various standards are explained in [2-4]. But these standards cannot analyse all faults accurately, this happens when more than one fault occurs in transformer or when concentration of gases are near to the threshold. To deal with this problem i.e. to further improve the reliability of fault diagnosis various intelligent algorithms like wavelet analysis [10], ANN (artificial neural network) [12, 13], FIS (fuzzy inference system) [14-16], neuro-fuzzy system [17] are developed [5]. Even though these techniques have improved the reliability of the standards by improving the accuracy of fault detection, there are some drawbacks such as, wavelet network has higher efficiency but low degree of convergence, ANN require huge data for developing fault detection capability and FIS may present difficulty in deriving rules to classify the faults in transformer.

Here in this paper, ANFIS is developed in accordance with IEC-60599 standards so as to identify incipient faults in oil immersed transformer such as partial discharge, electrical discharge, overheating (<300°C, 300°C-700°C, >700°C). Developed system has been tested for its fault identification capability and results are presented. In section 2 conventional DGA standards are presented, basic architecture of ANFIS is explained in section 3. How proposed ANFIS is developed and applied for DGA is explained in section 4, results are given in section 5 and paper is concluded in section 6.

2 DISSOLVED GAS ANALYSIS

Under normal operating condition various gases like C_2H_4, C_2H_2, CH_4, N_2 and O_2 are present in small quantity in transformer oil. When fault occurs in transformer, concentration of these gases varies depending on type of faults. Level of gases generated in oil filled transformer in service is frequently the first available indication of malfunctioning. The gases used for DGA are H_2 (Hydrogen), CH_4 (Methane), C_2H_4 (Ethylene), C_2H_6 (Ethane), C_2H_2 (Acetylene), CO (Carbon monoxide), and CO_2 (Carbon dioxide). Standards for analysing faults on basis of dissolved gases in oil are key gas analysis, Dornenburg's ratio method, Roger's ratio method, IEC standards and Duval's triangle [1-4].

In key gas analysis concentration of key gases like C_2H_6, C_2H_4, C_2H_2, CO, CO_2 and H_2 are used for analysing faults like overheating of oil, overheating of cellulose, corona (pd), arcing[11]. In Dornenburg's ratio method thermal and electrical faults are differentiated by comparing pairs of deterioration gases with approximately equal solubility and diffusion coefficient. Therefore ratios of gases chosen are CH_4/H_2, C_2H_2/C_2H_4, C_2H_6/C_2H_2 and C_2H_2/CH_4. In Roger's ratio method depending on sequence of attaining maxima with increase in temperature, the choice of four ratios for fault diagnosis are CH_4/H_2, C_2H_6/CH_4, C_2H_4/C_2H_6, C_2H_2/C_2H_4. This method identifies faults like normal aging, overheating, partial discharge, circulating current in winding, general con-

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ductor overheating, flashover, arcing and sparking are diagnosed. IEC-60599 ratio method is similar to that of Roger's ratio method, the ratio of C_2H_6/CH_4 is eliminated, since this only indicates the limited temperature range of decomposition and cannot assist in further identifying the fault. By using IEC ratio method faulty condition like partial discharge, energy discharge, and thermal faults [6] can be detected. Duval's triangle method uses concentration of CH_4, C_2H_2, C_2H_4 gases. The gas concentration reduces to ppm v/v are graduated from 0 to 100% and marked along the side of equilateral triangle, this triangle is called as Duval's Triangle. This triangle is divided in several parts and each part represents particular fault. Using Duval's triangle method partial discharge, energy discharge, thermal fault, and some electrothermal faults can be determined [7].

3 Adaptive Neuro Fuzzy Inference System

ANFIS combines the benefits of two powerful models (i.e. FIS and ANN) into a single system. In ANFIS neural learning rules are applied to identify and tune the parameters and structure of a fuzzy inference system (FIS). The network of ANFIS can be regarded as an adaptive fuzzy inference system with the capability of learning fuzzy rules from data or as a connectionist architecture provided with some linguistic meaning. Figure-1 shows five layer architecture of ANFIS, for two input and single output in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

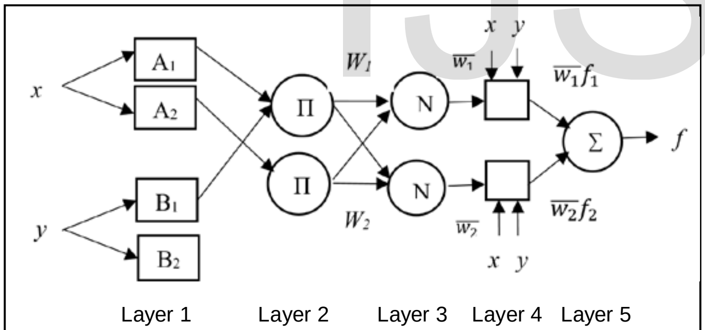

Fig. 1. Architecture of ANFIS.

Here x and y are the two crisp inputs, and A_1 and B_1 are the linguistic labels associated with the node function. This five layer architecture of ANFIS [8,9] is explained below

3.1 Layer 1(Input node)

Nodes in layer 1 consist of membership functions, parameters in this layer are called as premise parameters. Every node i in this layer is adaptive node, with a node function given as,

$$O_i^1 = \mu_{A_i}(x) \qquad i=1, 2 \qquad (1)$$

Where O_i^1 is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i.

3.2 Layer 2(Rule nodes)

Output of layer 2 represents a firing strength of a rule, every node in this layer is fixed node. This layer chooses the minimum value of two input weights. In this layer, the AND/OR operator is applied to get one output that represents the firing strength. The node generates the output (firing strength) by cross multiplying all the incoming signals given as,

$$O_i^2 = w_i = \mu_{A_i}(x) * \mu_{B_i}(y) \qquad i=1, 2 \qquad (2)$$

3.3 Layer 3 (Average nodes)

Every node in this layer is a fixed node, labelled N. The i^{th} node calculates the ratio between the i^{th} rule's firing strength to the sum of all rules firing strengths. Every node of these layers calculates the weight, which is normalized. Outputs of this layer are called normalized firing strengths.

$$\overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad i=1, 2 \qquad (3)$$

3.4 Layer 4 (Consequent nodes)

This layer includes linear functions, which are functions of the input signals. This means that the contribution of i^{th} rules towards the total output or the model output and/or the function defined is calculated. Every node i in this layer is adaptive node with a node function represented as,

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(r_i) \qquad (4)$$

Where $\overline{w}_i$ is the output of layer 3, and (r_i) is the parameter set of this node. These parameters are referred to as consequent parameters.

3.5 Layer 5 (Output node)

The single node in this layer is a fixed node labelled $\sum$, which computes the overall output by summing all incoming signals given as,

$$O_i^5 = \sum w_i f_i = \sum \overline{w} i f_i \Big/ \sum w_i \qquad (5)$$

4 Application of ANFIS for DGA

Before applying ANFIS available data has been normalised so that it can be used for proper training of the system. Process of fault diagnosis by ANFIS can be mainly classified in two stages i.e. training stage and testing stage. Data required in both of these stages should be different, to avoid overfitting problems during the estimation, the data set has been randomly splited into two sets, a training set (about 70% of the data), and a

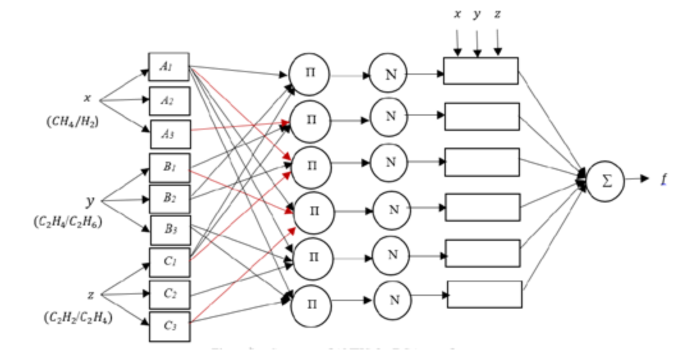

Fig. 2.Structure of ANFIS for DGA.

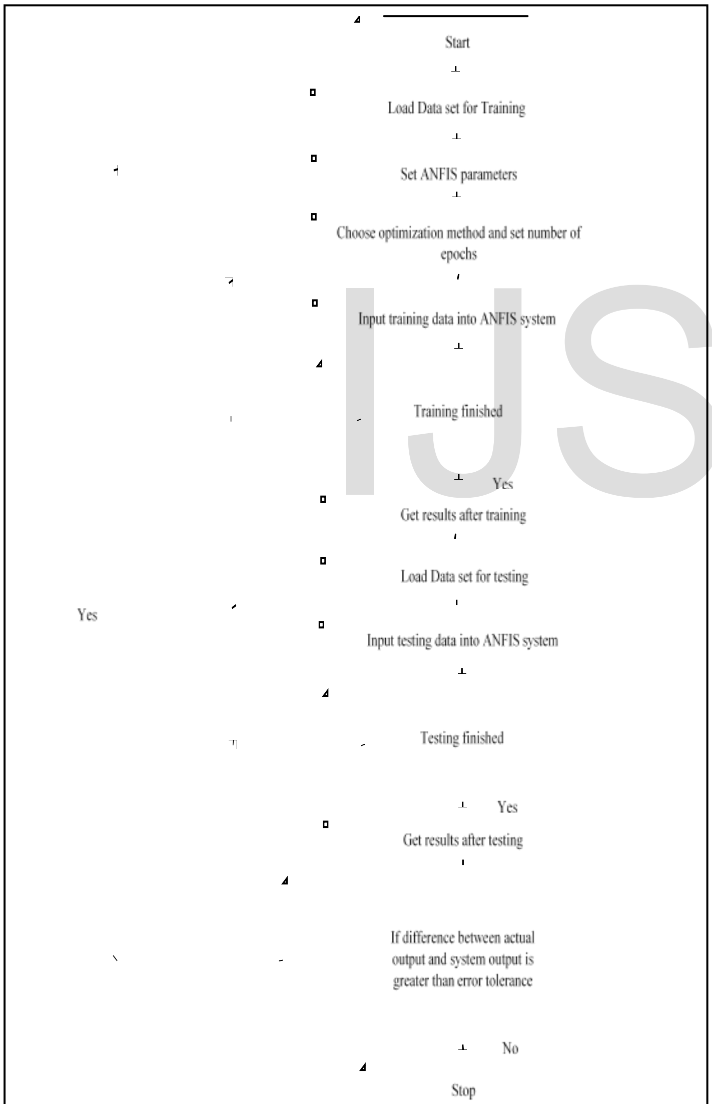

Fig. 3. Flow Chart of ANFIS for DGA of Transformer Oil.

testing set (about 30% of the data).

4.1 Training Stage

Initially dataset for training the system has been loaded, system has been trained for various faults listed by IEC-60599 standards therefore input datasets consists of ratio of gases according to standards i.e. C_2H_2/C_2H_4 CH_4/H_2, C_2H_4/C_2H_6, and output consists of various fault codes for faults like partial discharge, electrical discharge, overheating (<300°C, 300°C-700°C, >700°C). After loading training data initial parameter settings have been done. Type of Tagaki- Sugeno Fuzzy inference System (TSK FIS) is chosen, initial parameters of input and output for system have been inserted and proper set of fuzzy IF-Then rules have been derived. Then proper optimization method has been used with such a number of epochs or iteration so that the error between the actual fault in transformer and fault indicated by ANFIS system is limited to 0.001. ANFIS structure obtained after training system is shown in Figure-2. Where red arrows between layer 1 and layer 2 shows logical not relation in rules, three inputs x, y and z are three ratios C_2H_2/C_2H_4 CH_4/H_2, C_2H_4/C_2H_6, respectively and output f gives the fault code.

4.2 Testing Stage

While testing of the ANFIS testing set from the samples has been loaded to the system and the system has been tested. This stage of testing is carried out because, if training data is noisy or insufficient for certain fault then after number of iterations it is possible that error in output may increase. This leads to get inappropriate output of the system. Therefore in such condition modifiable parameters are changed and system is trained again with different parameter settings. Therefore testing data is loaded and the proposed system is tested. Flow chart of ANFIS for fault diagnosis is shown in Figure-3.

After training and testing of the ANFIS, this system has been implemented for diagnosing the fault in 12 different transformers. Details of these transformers including location of transformer, rating of transformer, voltage ratio and testing date are given in Table-1 concentration of dissolved gases (in ppm) in all these transformers are given in Table-2.

5 Results & Discussion

Sample of DGA are obtained from various utilities and literature for training and testing of the system. About 70% samples of dissolved gas in oil are used for training of the network and remaining samples are used for testing the network. Dataset of faulty samples obtained from utilities as specified in Table-2 has been provided to the system so as to detect the fault in transformer. Comparing faults detected by system for these samples with actual faults identified after inspection in that cases, it is observed that faults for 11 samples are detected accurately by the system and one sample (sample number 2) is detected inaccurately. In sample number 2 ANFIS system in dicates partial discharge whereas the actual fault is thermal fault of range 300°-700°. It can be seen from table-3 that conventional IEC standards cannot determine fault in transformer-2 and transformer-4. This comparison of fault diagnosed by conventional IEC-60599 standard, proposed ANFIS and actual

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inspection are given in Table-3.

TABLE 1
DETAILS OF TRANSFORMERS

Trans-former No.	Name of Substation	MVA Rating	Voltage Ratio	Date of test
1	220kV Alephata	50	220/33kV	9/2/2003
2	220kV Alephata	50	220/33kV	18/7/2003
3	132kV Kamthadi	10	33/22kV	16/10/2005
4	132kV Kurunda	50	132/33kV	9/4/2010
5	400kV Waluj	167	400/220/33kV	6/5/2011
6	400kV Waluj	167	400/220/33kV	6/5/2011
7	132kV Shirur	50	132/33kV	23/12/2011
8	220kV Alephata	50	220/33kV	23/12/2011
9	132kV Jintur	50	132/33kV	19/4/2012
10	220kV Alephata	50	220/33kV	31/8/2013
11	400kV Waluj	315	400/220/33kV	31/5/2014
12	400kV Waluj	315	400/220/33kV	31/5/2014

TABLE 2
CONCENTRATION OF DISSOLVED GASES IN TRANSFORMER OIL IN PPM

Trans-for-mer No.	CO_2	CO	CH_4	C_2H_4	C_2H_6	C_2H_2	H_2
1	3801	401	63	21	30	1	4
2	2926	430	226	230	90	1	201
3	2073	290	328	978	401	8	154
4	1878	165	25	5	5	0	564
5	3506	228	516	878	90	1081	1601
6	9500	573	15	29	43	22	40
7	603	34	25	45	30	1	8
8	2930	428	225	228	31	1	203
9	1815	236	58	5	8	0	915
10	3806	405	65	23	32	1	6
11	3019	314	72	46	34	4	21
12	3681	452	93	38	36	0	28

TABLE 3
COMPARISON BETWEEN ACTUAL FAULTS, FAULT INDICATED BY ANFIS & FAULT BY CONVENTIONAL IEC METHOD

Transformer No.	Fault by IEC Standards	Fault by IEC standards with ANFIS	Fault identified after inspecation of transformer
1	TF(<300)	TF(<300)	TF
2	TF(300-700)	TF(300-700)	TF
3	TF(300-700)	TF(300-700)	TF
4	**UD**	**PD**	**PD**
5	ED	ED	ED
6	**UD**	**TF(<300)**	**PD**
7	TF(300-700)	TF(300-700)	TF
8	TF(>700)	TF(>700)	TF
9	PD	PD	PD
10	TF(<300)	TF(<300)	TF
11	TF(300-700)	TF(300-700)	TF
12	TF(300-700)	TF(300-700)	TF

ED means electric discharge, PD means partial discharge, TF means thermal fault, UD means undetected fault.

6 CONCLUSION

Here ANFIS is developed to reveal the condition of transformer and classification of different incipient faults according to IEC-60599 standards. The proposed method has been extensively tested and evaluated for the oil samples collected from 12 transformers at various electric utilities. Proposed system can detect the faults in transformer even when the concentration of gases is near threshold which remains undetected by conventional method. Results shows that performance of proposed ANFIS is superior then conventional standards.

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