APPLICATION OF AI TECHNIQUES FOR NON-DESCTRUCTIVE EVALUATION OF POWER TRANSFORMERS USING DGA

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ABSTRACT

Non-Destructive Evaluation of Power transformer by monitoring various parameters, to predict its in-service behaviour, is very much necessary for operating engineer to avoid catastrophic failures and costly outages. Dissolved Gas Analysis (DGA) is an important tool for transformer fault diagnosis. The ratio methods used in the DGA have an advantage that they are independent of volume of gases involved. But the main drawback of the ratio methods is that they fail to cover all ranges of data and ambiguity about the boundaries of gas ratios in diagnosing the fault. In this paper Artificial Intelligence techniques like Artificial Neural Network (ANN), Fuzzy Logic (FL) and Extension Neural Network (ENN) are used to overcome the above drawbacks, and the results of various methods are compared.

1. INTRODUCTION

Transformers, traditionally highly reliable and efficient equipment used for bulk transfer of power from one voltage level to another, are always under the influence of electrical, mechanical, thermal and environmental stresses which cause the degradation of insulation quality and ultimate failure of transformer leading to major breakdown of the power system itself. To avoid such a scenario, it is very much necessary to periodically monitor the health of transformers to keep them in satisfactory working condition. The benefits of condition monitoring include reducing of maintenance costs, limiting probability of destructive failures, helping the maintenance engineer to plan the maintenance schedule, etc.

Some of the faults like partial discharges, overheating, winding circulating currents, arcing, and continuous sparking will cause the deterioration of the insulation. Therefore, periodic monitoring will help to identify and foresee the trend of insulation degradation and prevent possible failures in the transformer and enable to undertake corrective action well in advance to minimize the unplanned outages. Hence the continuous monitoring of service parameters of insulation system is the basic prerequisite of preventive remedial measures, to ensure reliable services for sufficiently predictable long period under continuous service stresses.

Oil insulation is very effective in HV power apparatus. However, such insulating oil suffers from deterioration, which can become fatal for the apparatus. Also, discharge in oil can cause serious damage to the other insulating materials. For this reason, condition monitoring of HV power apparatus insulation has become an important task.

There are many methods available for diagnosis of oil. Those are Dissolved Gas Analysis (DGA), breakdown voltage test, the water content test, the tan (delta) test, resistivity test, acidity test, sludge test and interfacial tension test. Among these, Dissolved Gas Analysis (DGA) has gained more popularity as it shows the present status of the transformer and provides the information regarding the faults that are growing inside the transformer [1].

Dissolved Gas Analysis (DGA) methods have been widely used [2-4] to detect incipient faults in transformers. DGA approaches identify faults by considering the ratios of specific dissolved gas concentrations. But the actual diagnosis must also consider other information of transformer such as size, volume of oil, type of transformer etc. Therefore a fuzzy expert system [5-6] has been suggested. However, the fuzzy expert system could not learn from previous diagnosis results because the membership functions and diagnostic rules were determined by practical experience or trial and error methods. Neural Networks has been used for this purpose since the hidden relationships between the fault types and dissolved gases can be recognized by NN through training process [7].

2. DISSOLVED GAS ANALYSIS

Like a blood test or a scanner examination of the human body, DGA can warn about an impending problem, give an early diagnosis, and increase the chances of finding the appropriate cure. There are many methods in DGA. Some, among them are Norms Method, Gas Ratio Method, and Key Gas Analysis. The detection of incipient faults in oil immersed transformers by examination of gases dissolved in oil, is developed from original Buchholz relay application. The Gas Chromatograph (GC) is the most practical method available to identify combustible gases. GC involves both a qualitative and quantitative analysis of gases dissolved in transformer oil.

2.1 Gas Ratio Methods

In condition monitoring, the advantage of using ratio methods is that, they overcome the issue of volume of oil in the transformer by looking into the ratio of gas pairs rather than absolute values. But the drawback of the ratio methods is that, they fail to cover all ranges of data and quite often ratios fall outside the scope of the tables. Also, there is an ambiguity about the boundaries of gas ratios in diagnosing the fault. The ratio method considered in this paper is IEC Method. Table I shows the codes allocated for different gas ratios.

Table I: Gas Ratio Codes

Gas Ratios	Ratio Codes
CH_4/H_2	i
C_2H_4/C_2H_6	k
C_2H_2/C_2H_4	l

3. IEC METHOD

Fault diagnosis scheme recommended by IEC originated from Rogers' method, except that the ratio C_2H_6/CH_4 was dropped since it only indicated a limited temperature range of decomposition. Four conditions are detectable, i.e. normal ageing, partial discharge of low and high energy density, thermal faults and electrical faults of various degrees of severity. However, no attempt is made to identify both thermal and electrical faults into more precise subtypes.

In this method three gas ratios are used to interpret the faults. Table I shows codes for gas ratios used in this method. Tables II & III show the codes and linguistic variables for different gas ratios depending on the range of gas ratios and their interpretation. In this paper, Artificial Intelligent techniques are used to overcome the drawbacks of conventional DGA.

4. APPLICATION OF FUZZY LOGIC TO DGA

Fuzzy logic, unlike Boolean or crisp logic, deals with problems that have vagueness, uncertainty and use membership functions with values varying between 0 and 1. Fuzzy logic tends to mimic human thinking that is often fuzzy in nature. In conventional set theory based on Boolean logic, a particular object or variable is either a member (logical 1) of a given set or it is not (logic 0). On the other hand, in fuzzy set theory based on fuzzy logic, a particular object has a degree of membership in a given set, which is the range of 0 (completely not in the set) to 1 (completely in the set). This property allows fuzzy logic to deal with uncertain situations in a fairly natural way. Fig. 1 shows the basic block diagram of a fuzzy logic control block.

Fuzzy logic uses the gas ratios directly. Since there is still an ambiguity about the boundaries of gas ratios in diagnosing the fault, Fuzzy Logic was implemented for this application. In this paper, trapezoidal membership function is considered. The values of membership functions used in IEC Method are given in Table IV and Fig. 2. The IEC method matches certain combinations of input classifications with diagnostic outcomes as shown in Table V.

Table II: IEC Ratio Codes

Ratio code	Range	Code	Linguistic Variables
l	<0.1	0	LOW(L)
	0.1-1.0	1	MEDIUM(M)
	1.0-3.0	1	MEDIUM(M)
	>3.0	2	HIGH(H)
i	<0.1	1	LOW(L)
	0.1-1.0	0	MEDIUM(M)
	1.0-3.0	2	HIGH(H)
	>3.0	2	HIGH(H)
k	<0.1	0	LOW(L)
	0.1-1.0	0	LOW(L)
	1.0-3.0	1	MEDIUM(M)
	>3.0	2	HIGH(H)

Table III: IEC Fault Diagnosis Table

l	i	k	Characteristic fault	Code
0	0	0	Normal ageing	a
*	1	0	Partial discharge of low energy density	b
1	1	0	Partial discharge of high energy density	c
1->2	0	1->2	Discharge of low energy (Continuous sparking)	d
1	0	2	Discharge of high energy (Arc with power flow through)	e
0	0	1	Thermal fault <150°C	f
0	2	0	Thermal fault 150° - 300°C	g
0	2	1	Thermal fault 300°- 700°C	h
0	2	2	Thermal fault >700°C	m

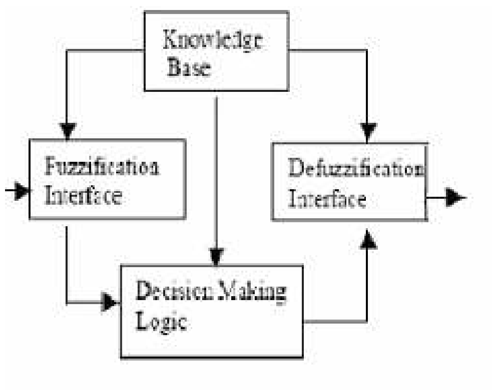

Fig. 1 Basic Fuzzy Logic Control

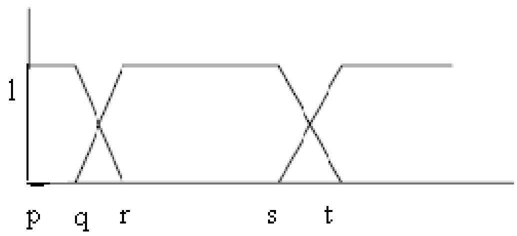

Fig. 2 Membership function used in IEC Method

Table IV: Values of Member ship functions used in IEC Method

	p	q	r	s	t
l	0	0	0.2	2.9	3.1
i	0	0	0.2	0.9	1.1
k	0	0.9	1.1	2.9	3.1
o/p	0	0.05	0.15	0.85	0.95

Table V: IEC Method Diagnosis Rules

i		L			M			H		
k		L	M	H	L	M	H	L	M	H
l	L	b	-	-	a	f	-	g	h	m
	M	c	-	-	-	d	d,e	-	-	-
	H	-	-	-	-	d	d	-	-	-

5. APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO DGA

Artificial Neural Networks is a massively parallel-distributed processor as shown in Fig. 3, having a natural tendency to acquire sufficient experimental knowledge and making it available for use.

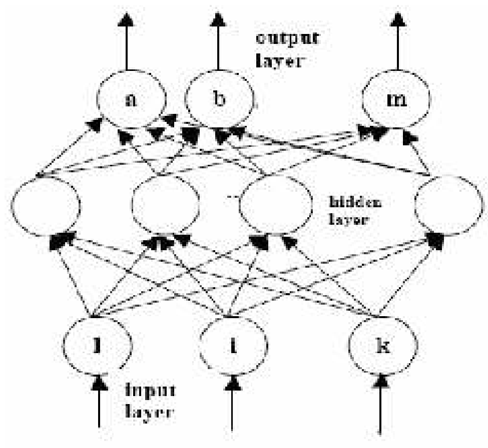

Fig. 3 Artificial Neural Network

The ANN used in this method is trained by Back Propagation Algorithm (BPA) with sigmoid function as non-linearity. Back Propagation Algorithm propagates the output error backward through the connections to the previous layer until the input layer is reached. The training patterns for IEC Method are shown in Table VI.

Table VI: Training patterns for IEC Method

Input pattern			Output pattern								
1	i	k	a	b	c	d	e	f	g	h	m
0	0	0	1	0	0	0	0	0	0	0	0
0	1	0	0	1	0	0	0	0	0	0	0
1	1	0	0	0	1	0	0	0	0	0	0
0.5	0	0.5	0	0	0	1	0	0	0	0	0
1	0	2	0	0	0	0	1	0	0	0	0
0	0	1	0	0	0	0	0	1	0	0	0
0	2	0	0	0	0	0	0	0	1	0	0
0	2	1	0	0	0	0	0	0	0	1	0
0	2	2	0	0	0	0	0	0	0	0	1

6. APPLICATION OF EXTENSION NEURAL NETWORKS TO DGA

Traditional neural networks can directly acquire experience from the training data, and overcome some of the shortcomings of the expert system. However, the traditional neural networks present difficulties in deciding upon the number of neurons in hidden layers and are time consuming in training. To overcome the drawbacks of traditional neural networks, Extension neural networks are used as they do not possess any hidden layer and training time is quite economical and mapping capability is high.

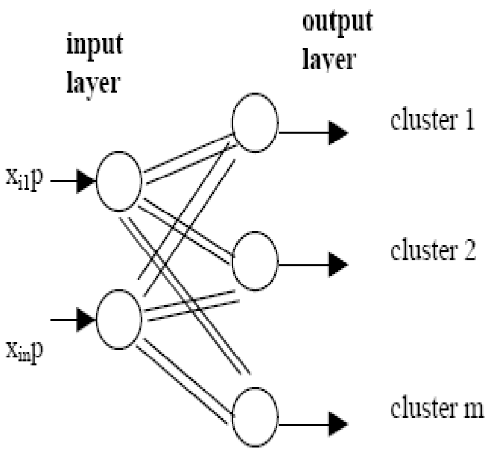

Fig 4: Extension Neural Networks

Fig. 4 shows the typical structure of extention neural network. This new neural network is a combination of the extension theory and the neural network. The Extension Neural Network uses a modified extension distance to measure the similarity between data and cluster center; it permits adaptive process for significant and new information, and gives shorter learning times than traditional neural networks [8]. This Extension Neural Network shows higher accuracy and less memory consumption in application.

Defining the name of matter as N, one of characteristics of the matter as C, and the value of C as V, a matter-element in extension theory can be described as R = (N, C, V), where N, C, and V are called the three fundamental elements of the matter-element. Assuming R = (N, C, V) to be a multi-dimensional matter-element, C = [c1, c2, …..,cn] to be a characteristic vector and V = [v1, v2,…,vn] to be a value vector of C, then a multidimensional matter-element is defined as

$$R = (N, C, V) = \begin{bmatrix} R_1 \\ R_2 \\ \cdots \\ R_n \end{bmatrix} = \begin{bmatrix} N, & c_1, v_1 \\ & c_2, v_2 \\ \cdots\cdots & \\ & c_n, v_n \end{bmatrix}$$

where R1= (N,c,v) (i=1,2,...n) is defined as the sub matter-element of R.

6.1 Supervised learning algorithm of the ENN is given below:

Step 1**:** Set the connection weights between input nodes and output nodes by the matter-element model:

$$R_k = \begin{bmatrix} \text{cluster } k, & c_1, V_{k1} \\ & c_2, V_{k2} \\ \cdots\cdots & \\ & c_n, V_{kn} \end{bmatrix}$$

k = 1, 2,…,m where c_j is the j-th characteristic (feature) of the cluster k, and $V_{kj} = (w_{kj},u_{kj})$ are the classical domains of cluster k.

Step 2: Calculate the initial cluster centers of every cluster.

$Z_k = \{z_{k1}, z_{k2},\ldots,z_{kn}\}$

$z_{kj} = (w_{kj}+u_{kj})/2$

For k = 1,2,…,m; j=1,2,….n;

Step 3: Read the i-th training patterns and its cluster number p

$Xip = \{ x_{i1}p, x_{i2}p, \ldots, x_{in}p\}$

Step 4: Using the proposed Extension Distance (ED), calculate the distance between the training pattern Xip and cluster k as follows:

$ED_{ik} = \|X_{ip}-Z_k\| = \Sigma\ EDj_k$

for $j = 1,2,\ldots n$; $k = 1,2,\ldots m$

where

$ED_{jk} = (|x_{ij}p-z_{kj}| - (w_{kj}-u_{kj})/2) / (|(w_{kj}-u_{kj})/2|)$

Step 5: Find the k*, such that $ED_{ik}^* = \min\{ED_{ik}\}$. If k* = p then go to Step 7; otherwise go to Step 6.

Step 6: Update the weights of cluster p and cluster k* as follows:

$z_{pj}new = z_{pj}old + \eta(x_{ij}p-z_{pj}old)$

$Z_{K*J}^{NEW} = Z_{K*J}^{OLD} + H(X_{IJ}^{P}-Z_{K*J}^{OLD})$

update the weights of cluster p and k* as

$w_{pj}new = w_{pj}old + \eta(x_{ij}p-z_{pj}old)$

$u_{pj}new = u_{pj}old + \eta(x_{ij}p-z_{pj}old)$

$w_{k*j}\ new = w_{k*j}old + \eta(x_{ij}p-z_{k*j}old)$

$u_{k*j}new = u_{k*j}old + \eta(x_{ij}p-z_{k*j}old)$

Where η is learning rate. In this step, the learning process is only to adjust weights of clusters p and k, and other weights do not change in the learning. Thus, the proposed ENN has a speed advantage over other neural networks, and can quickly adapt processes to significant new information.

Step 7: Repeat Step 3-Step 6 until the entire pattern has been through the clustering process, then the learning epoch is finished.

6.2 The fault diagnosis method using Extension neural network is described below:

Step 1: Build the matter-element models of every fault type according to IEC codes. The matter-element model as shown in Table VII, where Ri is the matter-element of nine fault types, I={ I1, I2, I3, I4, I5, I6, I7, I8, I9 } is the fault set, I, is an I-th fault type, and C = { C1, C2, C3 } is a characteristic set in which C1-> C_2H_2/C_2H_4, C2-> CH_4/H_2, and C3-> C2H2/C2H6.

Step 2: Set up the diagnosis ENN. According to matter-element models, the structure of the ENN for transformer fault diagnosis includes nine nodes in the output layer and three nodes in the input layer.

Step 3: Input a set of field test data and use the supervised learning algorithm to train the diagnosis ENN.

Step 4: Input the data of the tested transformer.

Step 5: Employ the trained ENN to diagnose the tested transformer.

Step 6: Go back to Step 4 for the next transformer when the diagnosis of one has been completed, until all have been done.

Table VII: Fault matter-element model of IEC Method

Fault No.	1	2	3
Matter element	R_1={ I_1,C_1,{0,0,1} C_2,{0,1,1} C_3,{0,1} }	R_2={ I_2,C_1,{0,0,1} C_2,{0,1,1} C_3,{1,3} }	R_3={ I_3,C_1,{0,0,1} C_2,{1,3} C_3,{0,1} }
Fault No.	4	5	6
Matter element	R_4={ I_4,C_1,{0,0,1} C_2,{1,3} C_3,{1,3} }	R_5={ I_5,C_1,{0,0,1} C_2,{1,3} C_3,{3,10} }	R_6={ I_6,C_1,{0,0,1} C_2,{0,0,1} C_3,{0,1} }
Fault No.	7	8	9
Matter element	R_7={ I_7,C_1,{0,1,3} C_2,{0,0,1} C_3,{0,1} }	R_8={ I_8,C_1,{0,1,3} C_2,{0,1,1} C_3,{1,3} }	R_9={ I_9,C_1,{0,1,3} C_2,{0,1,1} C_3,{3,10} }

7. RESULTS

In order to test the accuracy of diagnosis by various AI techniques, 30 test samples given in Table VIII were considered with a known cause of fault. The results obtained during testing are presented in Table IX. From Table IX it is observed that the Fuzzy Logic and Artificial Neural Network made a correct diagnosis in 27 out of 30 cases and Extension Neural Network made a correct diagnosis in 29 out of 30 in IEC method.

8. CONCLUSIONS

DGA has been recognized as an important tool in condition monitoring of power transformer. The main advantage of using ratio methods is that, volume of oil involved in the dissolution of gas is not required as only ratios of gases are involved. But the main drawback of the ratio methods is that they fail to cover all ranges of data and ambiguity about the boundaries of gas ratios in diagnosing the fault. Therefore, Artificial Intelligent techniques are used as a remedy to overcome the above drawbacks. From the results obtained, it is observed that ENN is highly reliable as it exhibits higher accuracy, less training time and less memory consumption.

Table VIII: Sample Data

H_2	CH_4	C_2H_4	C_2H_6	C_2H_2	Known fault
24	13	43	5	319	Arcing
266	584	862	328	1	Overheating
160	10	1	3	1	Discharges
80	619	2480	326	0	Severe Overheating
231	3997	5584	1726	0	Severe Heating
127	24	32	0	81	Arcing
9474	4066	6552	353	12997	Arcing
507	1053	1440	297	17	Severe local Overheating
416	695	867	74	0	Heating and Arcing
441	207	224	43	261	Arcing
65	61	143	16	3	Overheating
16	87	395	75	30	Overheating
212	38	47	15	78	Arcing
800	1393	2817	304	3000	Arcing
199	770	1508	217	72	Overheating
4906	8784	9924	1404	9671	Arcing
425	1742 4	37043	7299	158	Overheating
1076	95	71	4	231	Partial Discharges
244	754	1281	172	27	Overheating
117	167	481	48	7	Overheating
858	1324	2793	208	7672	Arcing
137	369	1242	144	16	Overheating
274	27	33	5	97	Arcing
1249	370	606	56	1371	Arcing
240	20	28	5	96	Partial Discharges
33	79	215	30	5	Overheating
307	22	33	2	109	Arcing
60	144	449	67	9	Overheating
2004	9739	5113	2750	0	Overheating
127	107	154	11	224	Arcing

Table IX: Results of DGA by AI Techniques

Test Code	Known fault	Diagnosis results obtained from IEC Method using		
		Fuzzy logic	ANN	ENN
1	Arcing	√	√	√
2	Overheating	√	√	√
3	Discharges	√	√	√
4	Severe Overheating	√	√	√
5	Severe heating	√	√	√
6	Arcing	√	√	√
7	Arcing	√	√	√
8	Severe local overheating	√	√	√
9	Heating and arcing	√	√	√
10	Arcing	√	√	√
11	Overheating	√	√	X
12	Overheating	√	√	√
13	Arcing	√	√	√
14	Arcing	X	X	√
15	Overheating	√	√	√
16	Arcing	X	X	√
17	Overheating	√	√	√
18	Partial Discharges	√	√	√
19	Overheating	√	√	√
20	Overheating	√	√	√
21	Arcing	X	X	√
22	Overheating	√	√	√
23	Arcing	√	√	√
24	Arcing	√	√	√
25	Partial discharges	√	√	√
26	Overheating	√	√	√
27	Arcing	√	√	√
28	Overheating	√	√	√
29	Overheating	√	√	√
30	Arcing	√	√	√

REFERENCES

1. “IEEE Guide for the Detection and Determination of Generated Gases in Oil-Immersed Transformers and their Relation to the Serviceability Equipment,” *ANSI/IEEE* C57.104-1978.

2. R. R. Roger, “IEEE and IEC Codes to Interpret Incipient Faults in Transformers Using Gas in Oil Analysis,” *IEEE Transactions on Electrical Insulation,* vol. 13, No. 5, pp. 348-354, 1978.

3. Duval. M, “Dissolved gas analysis: It can save your transformer,” *IEEE Electrical Insulation Magazine,* vol. 5, No .6, pp. 22-27, 1989

4. T. O. Rose, “Mineral Insulating Oil in Transformers”, *IEEE Electrical Insulation Magazine,* vol. 14, No. 3, pp .6-28, May/June, 1998.

5. C. E. Lin, J. M. Ling and C. L. Huang, “An expert system for transformer fault diagnosis system through evolutionary fuzzy logic”, IEEE Transactions on Power delivery, vol. 8, pp. 231-238, Jan 1993.

6. James U. Dukarm, “Transformer oil diagnosis using fuzzy logic and neural networks”, *IEEE Transactions on Power Delivery*, vol. 8, pp. 329-332, 1993.

7. O.Vanegas, Y.Mizuno and K.Naito, “Diagnosis of Oil-insulated Power Apparatus by using Neural Network Simulation”, *IEEE Transactions on Dielectrics and Electric Insulation*, vol.4, No.3, pp.290-299, June, 1997.

8. M. H. Wang, “Extension Neural Network for power transformer incipient fault diagnosis”, *IEE Proceedeings, Generation, Transmission, Distribution*, vol.150, No.6, Nov,2003.

BIBLIOGRAPHIES

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