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Condition Monitoring of Power Transformer Using ANN for IEC based on DGA

Priyam Kumari[1], Kulraj Kaur[2] and Jagdeep Singh[3]

ABSTRACT

Power transformer plays a vital role for transmission and distribution of electric power. It is a most essential and costly element so its safety from different types of faults are critical. Many techniques are there for diagnosis of transformer's fault in which DGA is most famous and effective technique. In this paper, ANN method for IEC code have been implemented for diagnosis of fault using MATLAB software and been tested using test data sets. It has been coded by using pattern recognition. It has been shown that result of ANN has overcome the disadvantage of conventional IEC method.

Keywords: Dissolved Gas Analysis (DGA), Power Transformer, pattern recognition, Fault Diagnosis, interpretation, Artificial Intelligence, ANN

1. INTRODUCTION

The transformer plays a key part in power system as it transforms electricity from one circuit to other circuit. It changes the level of voltage and current for power supply so we can't imagine our power system without considering transformer. Mechanical or electrical stress in transformer may interrupt power supply and cause of outage of power system. As transformer is very costly element in power system so faults in it will cause of great financial loss. It is necessary to protect transformer from different type of faults. Many devices such as differential relay, buchholz relay, thermal relay etc are used in transformer as protective device which protects the transformer at severe fault condition only. Insulation of transformer constitute of mineral oil and cellulose material. Even in normal condition, internal stress like mechanical and electrical stress takes place during operation of transformer which deteriorates its insulation and generates some harmful gases. Evolve gases get dissolve in transformer insulating oil and subsequently the oil gets damaged. By using DGA technique, concentration of gases can easily be detected at parts per million (PPM) level. Depending on the concentration of the dissolved gases, transformer's condition can be determined. frequency response analysis, partial discharge, thermal modelling, dissolved gas analysis etc are techniques used for condition monitoring of transformer in which DGA is most effective and famous technique for fault diagnosis of transformer. Thermal and electrical stress causes Incipient faults and decompose the mineral oil into hydrocarbon gases like hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane(C_2H_6), carbon monoxide (CO), carbon dioxide (CO_2) etc.[1, 3] Various conventional and non conventional methods are applied on the basis of DGA for fault diagnosis. Different conventional Dissolved Gas Analysis methods such as Roger's ratio method, Dornenburg's method, Duval's triangle method and key gas ratio methods are used to determine the exact amount of evolved gases to know the condition of transformer. An ANSI/IEEE standard and IEC publication 599 describes three DGA conventional approaches i.e. key gas method; Rogers ratio method; and Doernenburg ratio method. [12] Conventional methods have some drawbacks as

[1,2,3] School of Electrical and Electronics Engineering, Lovely Professional University, Punjab, India, *Emails: priyamkumari1072@gmail.com, kulraj.15720@lpu.co.in, jagdeepsinghnukera@outlook.com*

they fail to identify the type of fault in case of multiple fault condition and generate invalid codes which give no conclusion for some faults. We can say that conventional methods are not very much efficient. So mostly researchers use artificial intelligence techniques to detect and diagnose transformer faults based on Dissolved Gas Analysis methods. Artificial intelligence techniques includes fuzzy logic, artificial neural network, neuro-fuzzy method, expert method, wavelet network, Genetic Algorithm Approach etc. all soft computing techniques have their own advantages and disadvantages. [14]

This paper deals with artificial neural network for fault diagnosis. ANN model have been implemented for IEC interpretation method with the help of MATLAB. After comparison of results of ANN and IEC, it has been proved that ANN is better than conventional method IEC. Artificial method ANN overcomes from limitation of conventional IEC methods.

2. DISSOLVED GAS ANALYSIS

It is a routine technique by which we come to know about the quantity of evolve gases present in transformer insulating oil. It is used to assess the health condition of transformer. During normal condition, gases like hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane(C_2H_6), carbon monoxide (CO), carbon dioxide (CO_2) etc gets release. Due to thermal and electrical stresses, the quantity and rate of evolve gases increases. These gases gets more dissolve to oil result in damage of insulating oil. Further, it will decline the performance of transformer. To prevent the insulating oil from damage, it is very important to know the exact quantity of dissolved gases in oil.DGA is best way to know the amount of dissolve gases. Conventional techniques used under DGA are key gas method, Doernenberg ratio method, Rogers's ratio method, Logarithmic ratio method and Duval triangle.

3. FAULTS DETECTED BY DGA

IEC Publication 60599 has provided a list of detected faults by DGA in transformer as [8]

- Partial discharge (PD): Sparking occurs in the gas bubbles results to generation of large amount of hydrogen.
- Low energy discharge (D1): This fault causes tracking, arcing, large puncture through papers and carbonization of oil and paper.
- High energy discharge (D2): This fault is most dangerous fault as it causes extensive destruction because of flashover and short circuit, carbonization, metal fusion and tripping of equipment.
- Thermal faults T <300 ° C (T1): it causes the paper insulation to turn brownish in color.
- Thermal faults 300 ºC <T< 700 ºC (T2): Carbonization of insulation takes place at this level of thermal fault.
- Thermal faults T > 700 ºC (T3): it includes large amount of formation of carbon particles in oil and metal fusion.

4. INTERPRETATION METHODS OF DGA

Key gas method: Principle of key gas method depends on the quantity of evolved gases and their generation rates after occurring of fault in transformer. The generated gas having higher concentration (ppm) is referred as key gas which defines the type of fault in transformer. it is used to identify basically four types of faults such as pyrolysis in oil, pyrolysis in cellulose, partial discharge and arcing. Key gases and its relative proportions for fault type are shown in table 1. [10]

IEC method: it is a kind of conventional ratio method which is originated from roger's ratio method without considering ratio C_2H_6/CH4. It uses only three key gas ratios unlike roger's ratio method which

Table 1
key gas interpretation

Fault type	*Characteristic fault condition*	*Key gas*
1	Pyrolysis in oil	C_2H_4
2	Pyrolysis in cellulose	CO
3	corona	H_2
4	arcing	C_2H_2

Table 2
Generated codes for IEC

Gas ratio	*values*	*code*
X1 = C2H2/C2H4	X1< 0.1	0
	0.1 ≤ X1 ≤ 3	1
	X1 > 3	2
X2 = CH4/H2	X2 < 0.1	1
	0.1 ≤ X2 ≤ 1	0
	X2 > 1	2
X3 = C2H4/C2H6	X3 < 1	0
	1 ≤ X3 ≤ 3	1
	X3 > 3	2

Table 2
Diagnosis on the basis of IEC ratio method

C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6	DIAGNOSIS
0	0	0	No fault
0	1	0	Low intensity partial discharge (PD)
1	1	0	High intensity partial discharge (PD)
1	0	1	Arc-low intensity discharge(D1)
1 or 2	0	1 or 2	Arc-high intensity discharge(D2)
0	0	1	Thermal fault of temperature <150° C
0	2	0	Thermal fault (150° C <t<300° C) (T1)
0	2	1	Thermal fault (300° C <t<700° C) (T2)
0	2	2	Thermal fault (t>700°)(T3)

gives it the advantage of saving computation time as well as enhanced efficiency. The defined generated code for IEC method is shown in table 2. Interpretation based on IEC method is given in table 3. [4]

5. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural network gives accurate performance because of using mathematical modelling which computes output from input using interconnected neurons. It is adaptive in nature which acquires experiences from training data. Multilayer perception neural network with feed forward back propagation for classification of faults has been widely used in transformer. The goal of this type of network is to make a modal which can maps the input to the output using historical data. It can have three or more than three layers in which one will be input layer, one will be output layer and one or more than one can be hidden layers depending on complexity of problem. The neural network structure is shown as in figure 1. [3]. Here it can be shown

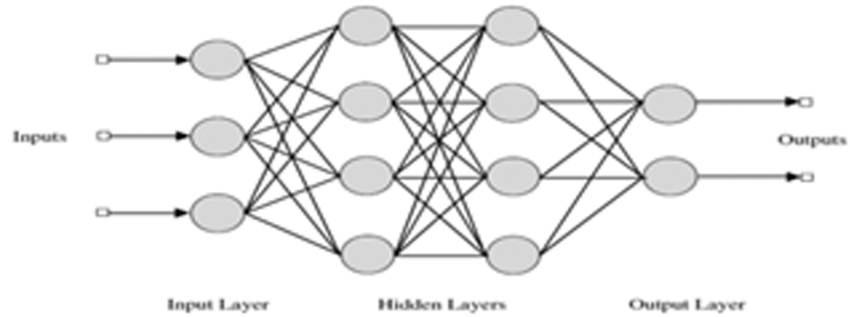

Figure 1: General Architecture of Artificial Neural Network

that each neuron of one layer in connected with each neuron of next layer. Neuron number in input layer will be equal to the number of input data and number of neurons in the output layer will be dependent upon number of variables that user wants. [8]

Set of inputs which are applied from outside is multiplied by corresponding weight '*w*'. The Sum of weighted inputs and the bias '*b*' acts as input for activation function. Activation function will process it further and transform it to an output signal to the next neuron model. [10]. for each hidden layer in the network, output is calculated by [5]

$$a_{ij} = f_j(w_{ij} * p_i + b_i) \tag{1}$$

and output of the previous layer is computed by

$$a_{jk} = f_k(w_{jk} * a_{ij} + b_j) \tag{2}$$

Where w_{ij} and w_{jk} are the weight of the hidden layer and output layers respectively, p_i is the input of i^{th} neuron, f_i and f_k activation function of the hidden layer and output layer respectively and b_i, b_j are bias of hidden layer and output layer respectively. [5]

6. IMPLEMENTATION OF ANN TO IEC CODE INTERPRETATION METHOD

In this paper, ANN has been implemented for IEC Standard code using MATLAB software. So the three inputs are C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6. feed forward back propagation architecture with is used. Sigmoid function is used as activation function in which output lies in range of 0 to 1. Number of layers Levenberg-marquardt algorithm as it is the fastest algorithm and consumes less memory. It has been coded by using pattern recognition which is a branch of machine learning. The network is trained to associate outputs with input patterns during training. Number of layers used in this implementation is four (one input layer, one output layer and two are hidden layers). The number of neurons used in input layer is 3, in first hidden layer it is 10, in second hidden layer it is 5 and at output layer number of neuron is 1. The structure of proposed ANN is shown in figure 2

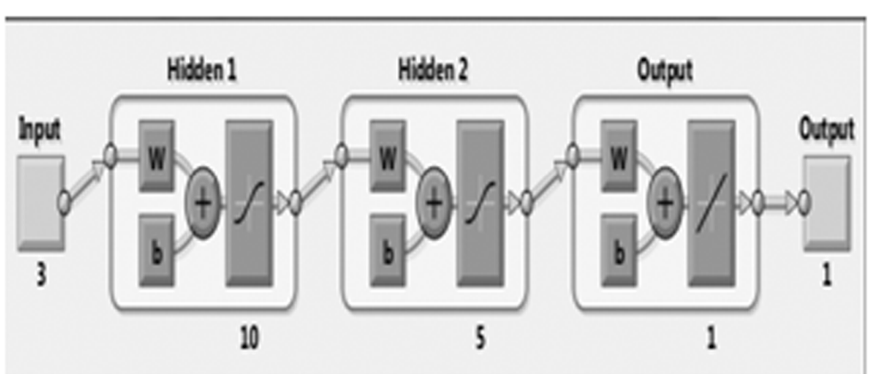

Figure 2: Proposed structure of neural network

Coding for ANN has been developed on MATLAB. After execution of command gensim(net) the simulink model opened is shown in figure 3. We can try with different test gas ratios and view result with help of this Simulink. In figure 3, ratio of $C_2H_2/C_2H4 = 0.04$, $CH_4/H2 = 0.4$ and $C_2H_4/C_2H6 = 0.2$ has taken than the output of network is 1 it means there is no fault. We can try with different test gas ratios. The output will be ranged from 1 to 9 which represent different type of faults. If 0 comes it means fault was not detected. ANN will detect most of the gas ratios and gives higher efficiency.

The designing of ANN crosses two stages to be developed i.e. training stage and testing stage. The flowchart of developed ANN is shown in figure 4

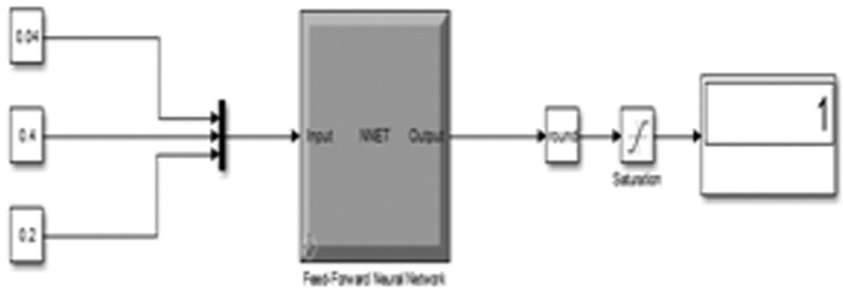

Figure 3: Constructed model for IEC using MATLA B

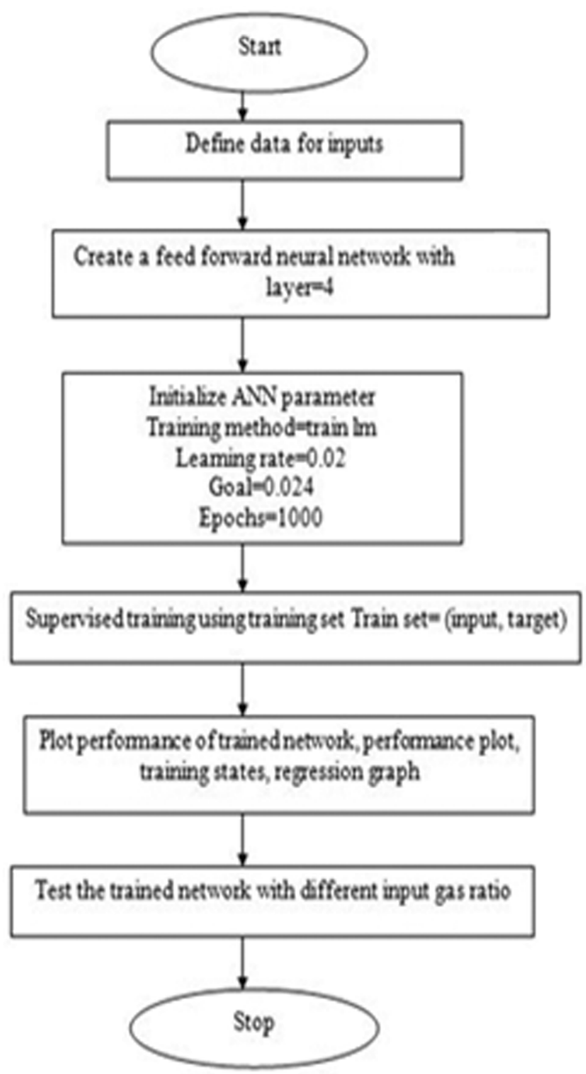

Figure 4: Flowchart of ANN algorithm

7. RESULT AND DISCUSSION

The proposed ANN network has been trained by using 300 data samples on basis of particle recognition machine learning and 50 samples have been used for its testing purpose. Training set is used to calculate the gradient and improves the network's biases and weight on that basis. After training, ANN model have been checked with different test data. Results obtained shows that ANN has good performance in fault classification. Training performance curve for ANN is shown in figure 5 which shows that mean square error is decreased to 0.0020004. The regression plot of the network used in this work is given in the Figure 6 having regression coefficient R=0.99983 which is very much accurate. It has mapped almost all the input data into output.

Some test data for comparing the results of ANN is shown in table 3.

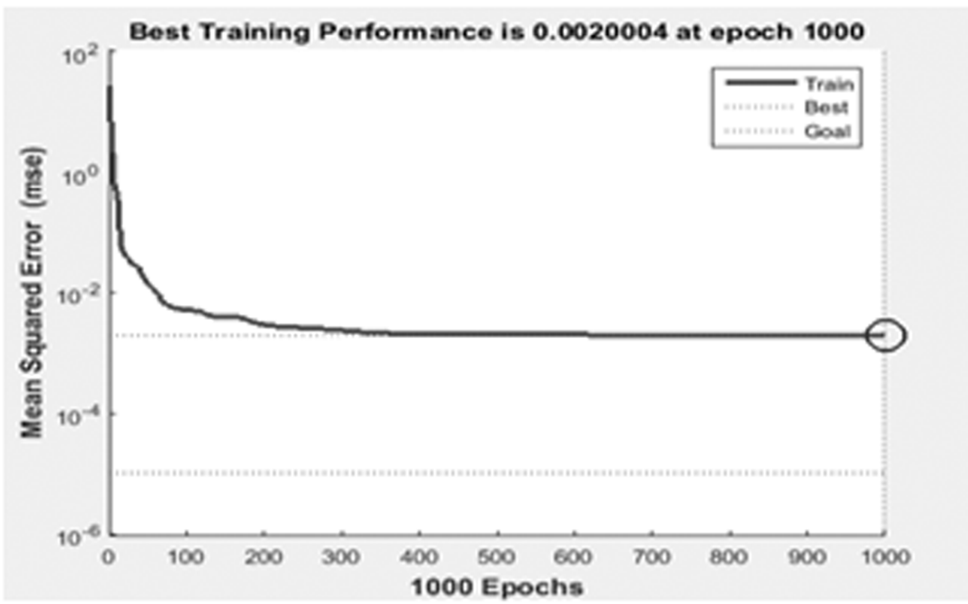

Figure 5: Performance Curve for Ann

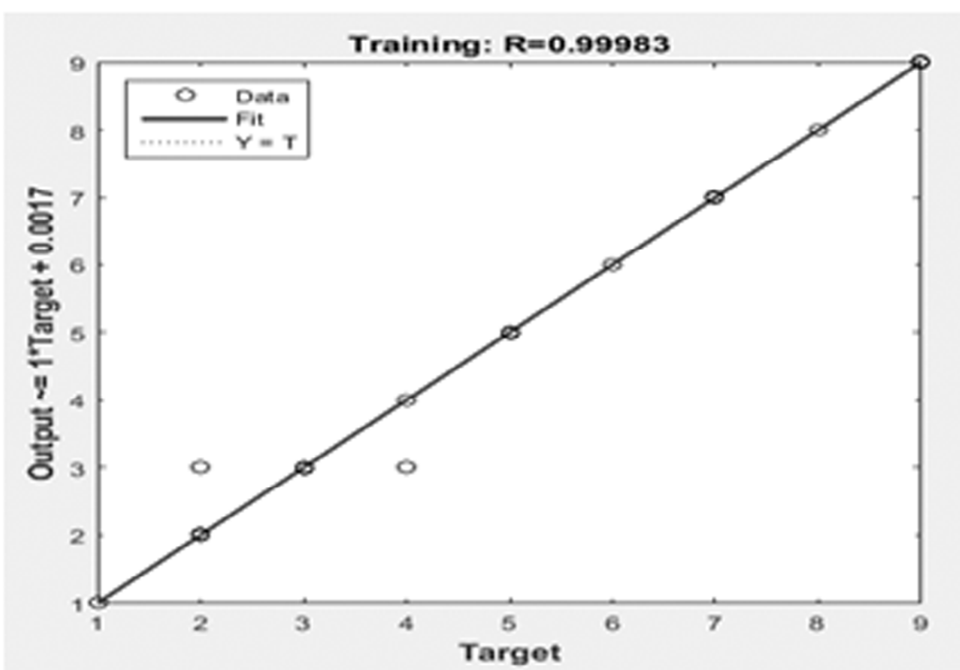

Figure 6: Regression plot for ANN

Table 3
Result of ANN on different gas ratios of testing data

Sr no	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6	Actual output	ANN
1	0.16	1.81	0.16	T2	T2
2	1.32	0.22	7	PD-H	PD-H
3	0	0.002	0.76	PD-L	PD-L
4	0	0.66	0.12	NF	NF
5	0.04	1.93	4.69	T3	T3
6	0	1.56	2.05	T2	T2
7	0.41	0.38	12.4	PD-L	PD-L
8	0.02	0.96	8.27	T3	T3
9	0	0.16	1.3	T1	T1
10	0	0.003	0.29	D1	D1
11	0.01	3.5	2.96	T2	T2
12	0.96	1.08	0.42	D2	ND
13	0.03	0.787	0.88	NF	NF
14	0.90	1.16	1.58	D1	D1
15	0.04	0.987	8.34	T3	T3
16	1.46	0.216	0.53	D2	PD-H
17	1.14	0.325	1.87	D2	D2
18	1.57	0.14	9.54	D2	D2
19	1.59	0.33	78.8	T3	T3
20	0.01	1	0.12	T2	T2
21	0.33	0.68	0.2	PD-H	PD-H
22	0.99	0.819	1.68	D1	D1
23	0.12	4	0.02	D2	D2

ND-Not detected

NF-No fault

PD-H-partial discharge with high intensity

PD-L-partial discharge with low intensity

8. CONCLUSION

In this paper, artificial neural (ANN) model is implemented using MATLAB to overcome the limitation of IEC standard and has been proved as successful tool to identify transformer's fault. ANN has shown correct result for 46 of the testing data. Some test data results are shown in table 3. The Results of ANN shows that ANN is better than conventional IEC method for diagnosis of faults in the transformer.

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