International Journal of Scientific Research & Engineering Trends
Volume 1, Issue 4, July-2015, ISSN (Online): 2395-566X

Artificial Neural Network Approach to Distribution Transformers Maintenance

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Abstract **– Distribution Transformers (DTs) are important equipment in distribution network and system reliability largely depends on them, hence the requirement for proper and accurate maintenance procedure which is based on foreknowledge of intending faults. DTs, during operational lifetime are subjected to internal fault due to stress, thus generating abnormalities in electrical parameters, degradation of oil and cellulose insulations etc. These lead to overheating, partial discharge or corona which causes fault related gases such as hydrogen (H_2), carbon monoxide (CO), carbon-dioxide (CO_2,), methane (CH_4), acetylene (C_2H_2), ethane (C_2H_6), and ethylene (C_2H_4) to dissolve in the oil insulation. In this paper, concentrations of fault related gases obtained from Dissolved Gas Analysis (DGA) coded by Roger's ratio method were used to develop a model of Artificial Neural Network (ANN) in MatLab (2013a) to diagnose incipient faults in distribution transformers. The proposed network which was trained with back-propagation algorithm was use to satisfactorily predict faults in distribution transformers.**

Keywords **– ANN, DTs, DGAs, Rogers Ratio.**

I. INTRODUCTION

Electricity distribution is the final stage in electricity delivery to end users. The modern distribution system begins as the primary circuit leaves the sub-station and ends as the secondary service enters the customer's meter. (Uhunmwangho R and Omorogiuwa Eseosa 2014) Distribution transformers (DTs) are very important equipment in power distribution networks. DTs provide voltage transformation by reducing high voltage of 33kV from transmission lines to a lower voltage of 11kV and 415V for power distribution to industries and buildings. DTs are classified mainly into two: liquid immersed and dry type. The former uses oil while the later uses air for cooling. Liquid immersed transformers are further classified as Oil Natural-Air Natural, Oil Natural-Air Force, Oil Force-Air Force, or Oil Force-Oil Directed (Joe Perez, 2010). According to the method of installation, it can be grouped as overhead and pad mount. Their capacities range from 15kVA to 500kVA for three phase overhead type and 75kVA to 2500kVA for three phase pad-mounted type. By method of construction, DTs can be a core or shell type.

When an oil-filled or oil-immersed transformer is subjected to thermal and electrical stress condition, certain gases dissolve in the insulating oil due to degradation in its insulation properties. Major diagnostic gases have been identified as Hydrogen (H_2), Carbon Monoxide (CO), Carbon-Dioxide (CO_2,), Methane (CH_4), Acetylene (C_2H_2), Ethane (C_2H_6), and Ethylene (C_2H_4) (Zhenyuan, 2000). Dissolved Gas Analysis (DGA) includes detection, quantification and characterization of the Gases. The nature and amount of individual component gases extracted from oil may be indicative of the type and degree of abnormality (Naveen Kumar Sharma, 2011) in distribution transformer. Transformer incipient fault can be classified as electrical arcing, electrical corona, overheating of cellulose, overheating of oil (Zhenyuan Wang, 2000).

There are two major classes of DTs failures: internal and external faults (Nadirah, 2010). Examples of internal faults include Core Fault, LV Ratio Link Fault, Phase winding Faults, or OLTC Fault. External faults include overloads, over-current, over-voltage, reduced system frequency, and external short circuits such as short circuit created on the secondary windings (Xujia, 2006). Transformer failure could be as a result of Overloading and imbalance loading, Low transformer oil level, low breakdown value of transformer oil, poor insulation resistance, Poor earthing or absence of earthing etc.

Under stresses from high voltage, current bypasses the conductor through insulators as gradual deterioration of insulation progresses, leading to short circuit and eventually, transformer failure (Willis et al, 2001). Whenever an incipient or internal fault is present, abnormalities in voltage, current and other electrical parameters will be detected (M. Mir, 1999) resulting to overheating, corona or partial discharge. Recent record has suggested that about 70% to 80% of transformer failures are due to internal winding faults (Palmer-Buckle, 1999), hence this paper focuses on internal faults of DTs.

According to Ahmed in 2011, conventional maintenance approach which is corrective in nature is carried out upon occurrence of failure can lead to repeated failures that cannot be maintained and finally to loss of asset. So transformer failures become very costly to maintain. DGA is one of the most recent techniques adapted for fault condition diagnostic of oil-filled transformers. An important problem with conventional DGA methods, however, is over reliance on experts (Zhenyuan, 2000). This leads to variations in conclusions on the conditions of transformers. Therefore, Artificial Intelligent (AI) systems are applied to interpret its data using methods such as Roger ratio, IEC ratio, Doernenburg, Duval triangle or key gas as approach to distribution maintenance. Thus the most identified problems associated with transformers maintenance include: Ambiguity and inconsistency in fault diagnosis and prediction due to variations in experts' experiences (Zhenyuan, 2000). Also, the conventional maintenance approach is not accurate and cost effective, and can lead to more failures or loss of DTs (Ahmed, 2011).

This paper aim to develop ANN based technique for diagnosing and predicting internal fault conditions of oil-filled distribution transformers. Maintenance approach that is accurate, efficient and cost effective using ANN will also be formulated

In this study, ANN is used to interpret DGA data using key gas to diagnose and predict internal faults as an approach to condition based preventive maintenance of oil-fill distribution transformers. This study does not cover dry-type distribution transformers and the reliability and accuracy of this approach is limited to the correctness of DGA data.

II. Literature Review

As stated by Ahmed in 2011, conventional maintenance approaches like corrective and time-based have several disadvantages which include cost and regular system shutdown etc, because of inability to monitor and predict fault. The researcher proposed a reliability centered maintenance technique which optimizes maintenance plan based on risk analysis. Despite the advantages of this technique the complexity of building the model and need for enormous data about failure rate, mode and consequences, are major challenges. In recent times, several methods have been used to monitor and diagnose fault conditions in transformers as an approach to maintenance. Commonly use methods include Dissolved gas analysis (DGA), Oil quality factor, Furfural Factor (FF), Load Tap changer factor, Load history and Maintenance data (Priyesh et al, 2014).

2.1 Dissolved Gas Analysis (DGA)

DGA is an established technique to detect presence of fault in transformers (Young Zaidey et al, 2009). It is a well-known tool for preventive maintenance (condition based) and its interpreted results may indicate active incipient faults or abnormalities within the transformer tank (Priyeshetal, 2014). DGA is based on routine oil sampling, and the modern technology of on-line gas monitors (Zhenyuan Wang, 2000). Typical gases revealed by this method are Hydrogen, H_2, Methane, CH_4, Ethane, C_2H_6, Ethylene, C_2H_4, Acetylene, C_2H_2, Carbon Monoxide, CO, and Carbon Dioxide, CO_2. These gases are extracted from the oil under high vacuum and analyzed by Gas Chromatograph to get each gas concentration separately (V.Gomathy, and S.Sumathi, 2013).

2.2 Oil Quality Analysis (OQA)

In OQA, oil samples were tested for breakdown voltage, water content, acidity and power factor. These tests are the basic routine tests for mineral insulating oil in accordance with IEC 60422:2005, and are sufficient to indicate the condition of the insulating oil. Limits and interpretation of test results in accordance with IEC 60422:2005 were used (Young Zaidey Yang Ghazali et al, 2009).

2.3 Furfural Analysis (FFA)

As the life of the cellulosic material is directly related to the life of the transformer, analysis of the furanic compound in oil or FFA was performed. By measuring the quantity and types of furans present in a transformer oil sample, the insulation's overall assessment and remaining life estimation can also be inferred with a high degree of confidence since it is not practical to obtain a paper sample from de-energized distribution power transformers (Young Zaidey Yang Ghazali et al, 2009).

2.4 Load Tap Changer (LTC) Condition

Insulation of tap changer basically depends upon the insulation in the tap changer. i.e. oil, epoxy resin, fibre glass, pressboard etc. Therefore individual diagnostics test can give cumulative idea about the condition of Tap changer. DGA for oil in LTC can give an idea about the condition of insulation integrity of LTC (Priyesh Kumar Pandey et al, 2014)

2.5 Fault Interpretation Using DGA

DGA is one of the most recent techniques developed to diagnose the fault condition on oil filled insulation transformers (Ali SaeedAlghamdi et al 2012) and methods such as Roger's ratio, IEC basic ratio, Duval triangle, Key gas analysis or Doernenburg Ratio are used to interpret its results.

Roger's ratio method is a four ratios method that utilizes the following ratio of gases: CH4/H2, C2H6/CH4, C2H4/C2H6 and C2H2/C2H4. Realization of fault diagnosis is by a simple coding. Another method is **IEC Basic Ratio Method** and it is similar to Roger's Ratio method, except that the ratio C_2H_6/CH_4 was dropped since it only indicated a limited temperature range of decomposition (S.Saranya, Uma Mageswari, 2013). **Doernenburg Ratio Method** uses the gas concentration from ratio of CH_4/H_2, C_2H_2/CH_4, C_2H_4/C_2H_6 and C_2H_2/C_2H_4. The value of gases must exceed the concentration when there is fault at the unit. (Saranya et al, 2013)

Duval Triangle Method developed by M. Duval in 1960 (Saranya et al, 2013) has proven to be accurate and dependable over many years and is now gaining popularity. It determines whether a problem exists. *(*Ali Saeed Alghamdiet al, 2012.).

According to (S. Saranya et al, 2013) once a problem has been detected, fault diagnosis can be obtained as thus:

- Sum the concentrations of Duval triangle gases (CH_4, C_2H_2, C_2H_4)
- Divide each gas by the result of 1 and multiply by 100 to get the percentage concentration of each gas
- Plot the obtained percentage of the total on the triangle. This gives the diagnosis

2.6 Need For Artificial Intelligence (AI) Interpretation Technique

Conventional DGA is a successful technique for power transformer incipient fault diagnosis, but the knowledge and experiences (in interpretation) require expertise (Zhenyuan Wang, 2000). Therefore application of AI to general maintenance has suggested the possibility of learning directly from raw data.

From (Ali SaeedAlghamdi et al, 2012) explanation, since there are many different methods of DGA fault interpretation techniques, likelihood of variations in interpretation is inevitable and this could lead to inconsistent conclusions on the conditions of the transformer. Another drawback of conventional methods of DGA data interpretation as presented by R. E James and Q. Su, in 2008, is inability to correctly interpret DGA result collected from a single transformer with multiple faults. Combined technique that uses conventional ratio methods and fuzzy-logic was proposed.

A completely automated system can be the final goal of AI based techniques. With the popularity of Internet based applications, it could be a server-based abnormal detection and fault diagnosis system without the need of an administrator. The oil sampling, testing, and the AI diagnostic modules can be developed separately but must be reliable. It is a challenge in all aspects if the complexity of the problem is investigated (Zhenyuan Wang, 2000).

Many AI techniques exist today for interpreting DGA data and diagnosing incipient faults in distribution transformers. Examples include; Artificial Neural Network (ANN), Fuzzy, Interface System (FIS), Genetic Algorithm (GA), Extended Relation Function (ERF), Bayesian Network (BN), Self Organizing Map (SOM) and Discrete Wavelet Network (WNs) Transforms (Naveen Kumar Sharma, 2011). The researcher concluded that these methods are better than classical methods particularly for interpretation of DGA results.

2.7 ANN

ANNs are tools particularly adapted to help specialist in maintenance in terms of the activities of classification, diagnosis and decision making, prediction etc (PallaviPatil and Vikal Ingle, 2012). With the powerful learning ability, excellent generalization capability and infinite non-linear approximation characteristic, Neural Network (NN) has become a valid method for fault diagnosis (Yu Xu, et al, 2010). The highly non-linear mapping capability of the neurons of ANN-based fault diagnosis provides a comparable and often superior performance over fuzzy system solutions (Zhenyuan Wang 2000). Stating that one drawback of fuzzy system is that it is bonded with conventional DGA methods, and cannot learn directly from data samples.

According to PallaviPatil and Vikal Ingle, in 2012, application of ANN makes it possible to reduce considerably the laboratory experiment time while networks learn how to predict properties of insulation for duration longer than those of the test, thus, constituting a tool making more economical, the tests of high voltage in general. The researcher further explained that ANN method is more accurately used for DGA as it has hidden layers which have the ability to learn the relationship between the DGA result and fault type through training.

Emphasizing on the importance of ANNs, (Maitha H. Al Shamisi, Ali H. Assi and Hassan A. N. Hejase, 2011) concluded that ANNs have the ability to model linear and non-linear systems without the need to make assumptions implicitly as in most habitual statistical approaches. ANNs can be classified as feed-forward and feedback (recurrent) networks. In the former network, no loops are formed by the network connections, while one or more loops may exist in the latter. The most commonly used family of feed-forward networks is multi-layer NN.

III. METHODOLOGY

The methods adopted for this paper are stated as follows:

- An overview of DTs fault conditions.
- A study of Roger's method of interpreting DGA data for diagnosing internal faults on transformers
- Modeling a feed forward Artificial Neural Network for fault diagnosis of DTs in MatLab (2013a) based on DGA results using Roger's ratio method

Roger's ratio with ANN method is adopted for diagnosis and classification in this paper because of its accuracy and ability to classify incipient fault into many categories.

3.1 MODELING OF FEED FORWARD ANN

ANN for fault diagnosis and classification based on DGA result using Roger's redefined ratio code is modeled in MatLab(2013a). It was developed using table 3.1

CH_4/H_2	C_2H_6/CH_4	C_2H_4/C_2H_6	C_2H_2/C_2H_4	Diagnosis	Output/ Diagnosis Code
0	0	0	0	Normal deterioration	1 0 0 0 0 0 0 0 0 0 0 0
5	0	0	0	Partial discharge	0 1 0 0 0 0 0 0 0 0 0 0
1 or 2	0	0	0	Slight overheating–below 150 °C	0 0 1 0 0 0 0 0 0 0 0 0
1 or 2	1	0	0	Slight overheating –150-200 °C	0 0 0 1 0 0 0 0 0 0 0 0
0	1	0	0	Slight overheating– 200-300 °C	0 0 0 0 1 0 0 0 0 0 0 0
0	0	1	0	General conductor overheating	0 0 0 0 0 1 0 0 0 0 0 0
1	0	1	0	Winding circulating currents	0 0 0 0 0 0 1 0 0 0 0 0
1	0	2	0	Core and tank circulating currents, overheated joints	0 0 0 0 0 0 0 1 0 0 0 0

0	0	0	1	Flashover without power follow through	0 0 0 0 0 0 0 0 1 0 0 0
0	0	1 or2	1 or 2	Arc with power follow through	0 0 0 0 0 0 0 0 0 1 0 0
0	0	1 or2	1 or 2	Arc with power follow through	0 0 0 0 0 0 0 0 0 1 0 0
0	0	2	2	Continuous sparking to floating potential	0 0 0 0 0 0 0 0 0 0 1 0
5	0	0	1 or 2	Partial discharge with tracking	0 0 0 0 0 0 0 0 0 0 0 1

The ratios of gases were inputs to the ANN to give the corresponding output codes. In the output code, the digit 1 represents the type of fault condition.

Modeling of ANN requires series of training. Technique called back-propagation algorithm (BPA).Itwas used to train and retrain the network until the relation between the input and target output is linear (or almost). It involves performing computations backward through the network.

3.2 ANN Development Analysis

In a multi-layer feed forward NN, the artificial neurons are arranged in layers, and all the neurons in each layer have connections to all the neurons in the next layer. Associated with each connection between these artificial neurons, a weight value is defined to represent the connection weight. Figure 3.1 shows architecture of a multi-layer feed forward NN with input layer, output layer, and hidden layers. The operation of the network consists of a forward pass through the network (KhaledShaban, Ayman El-Hag and Andrei Matveev, 2009)

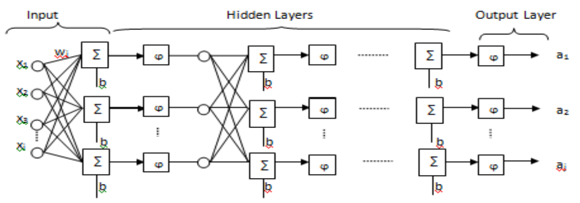

Fig.3.1. An architecture of multilayer feed forward neural network

3.3 Operation of ANN

The operation of ANN can be understood using a simple neuron.

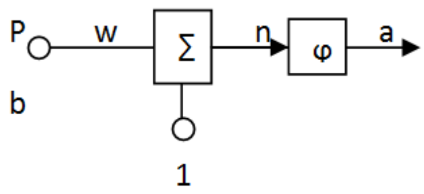

Fig.3.2.A. Simple Neuron

In the figure 3.2, the input p is multiplied by the weight, w and then summed to b to give the network function, n. the transfer function is applied to n to produce a, which is the output of the network. This is mathematically stated as

$$n = \sum pw + b \qquad (1)$$

3.4 Analysis Of Multilayer NN

The error at the output of neuron i at iteration n is given as

$$e_i(n) = y_i(n) - t_i(n) \qquad (2)$$

wherey_i and t_i are the output and target of the neuron, i.

The sum of square errors of all the output neurons for n iterations

$$\varepsilon(n) = \frac{1}{2} \sum e_i^2(n) \qquad (3)$$

The objective of learning process is to adjust the weights in order to minimize the average square error, H given as

$$H = \frac{1}{2Z} \sum e_i^2(n) \qquad (4)$$

where Z is the size of training set.

The adjustment of the weights is made in accordance with the respective error made for each input presented to the network.

For a two-layer NN, (assuming b = 0), the update of the weight, $w^{(2)}$ of the output layer is obtained by using Chain rule to differentiate the gradient, (This represents a sensitive factor determining the direction of search of the weight, $w_{ij}^{(2)}$).

$$\frac{\partial \varepsilon(n)}{\partial W_{ij}^{(2)}(n)} \partial \varepsilon(n) = e_i(n)\varphi'(v_i(n))h_j(n) \qquad (5)$$

The correction factor is defined by Delta Rule as

$$\Delta w_{ij}^{(2)}(n) = -\eta \frac{\partial \varepsilon(n)}{\partial W_{ij}^{(2)}(n)} \; e_i(n)\varphi'(v_i(n))h_j(n) \qquad (6)$$

where η is the learning rate

The updated weight matrix elements of the output layer is therefore,

$$w_{ij}^{(2)}(n+1) = w_{ij}^{(2)}(n) + \Delta w_{ij}^{(2)}(n) \qquad (7)$$

For the next layer the weight matrix, $w_{ji}^{(1)}(n)$ is similarly updated using the gradient

$$\frac{\partial \varepsilon(n)}{\partial W_{ij}^{(1)}(n)} = \sum \delta_k^{(2)}(n) w_{kj}^{(2)}(n)\varphi'(u_j(n))x_i(n) \qquad (8)$$

The correction factor is defined by Delta Rule as follows;

$$\Delta w_{ji}^{(1)}(n) = -\eta \frac{\partial \varepsilon(n)}{\partial W_{ij}^{(1)}(n)} = -\eta\, \delta_j^{(1)}(n)\, x_i(n) \qquad (9)$$

Where

$$\delta_j^{(1)}(n) = \sum_{i=1}^{z} \delta_k^{(2)}(n)\, w_{kj}^{(2)}(n)\varphi'(u_j(n))$$

The update of weight matrix elements of the input layer is

$$w_{ji}^{(1)}(n+1) = w_{ji}^{(1)}(n) + \Delta w_{ji}^{(1)}(n) \qquad (10)$$

This process is continued for the number of layers until $e_i(n) = y_i(n) - t_i(n)$ becomes zero or a value near zero.

3.5 Software Design

The ANN model for diagnosing fault conditions in DTs maintenance in this paper is designed using MATLAB 2013a toolbox. Design process involves the following steps;

Data Collection: Data collected for this design are: concentration of key gases such as H_2, CH_4, C_2H_4, C_2H_4, and C_2H_6 in part per million (ppm) obtained from DGA.

Network creation:This requires choosing the number of hidden layers and their associated number of neurons.

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Network Configuration: This specifies the number of input and output layers neuron based on the number of input and the needed output categories, and also initializes the network adjustable parameter (weights and bias)
Network Training: The weights and bias are adjusted such that the outputs are approximately equal to the target or known output of the network.
Network Testing: The performance of the network developed is tested using a part of the input data randomly selected by the application software.

3.6 Design Flow Chart

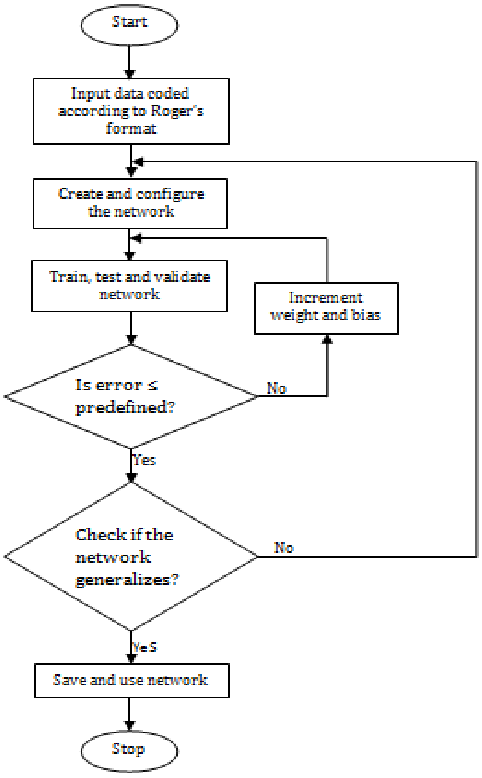

Fig.3.4. Software design flow chart

3.7 Software Development for Training the Network

```
clc
InputData=xlsread('INPUT')';    %reads the various gas concentrations and the ratios from Excel spreadsheet
target=xlsread('TARGET')';    % reads the target from Excel spreadsheet
network=feedforwardnet([20 20]);    %creates the network with two hidden layers; one having 20 neurons and the other 20 neurons
network=configure(network,InputData,target);
%configures the network to 4 inputs and 12 ouputs
network=train(network,InputData,target);    %trains the network
```

The program starts by loading input, 'InputData', and target, 'target' from MS Excel files, 'INPUT' and 'TARGET' respectively. The command
net=train (net,InputData,target)
displays the training window shown in figure 3.5a as it trains the network.

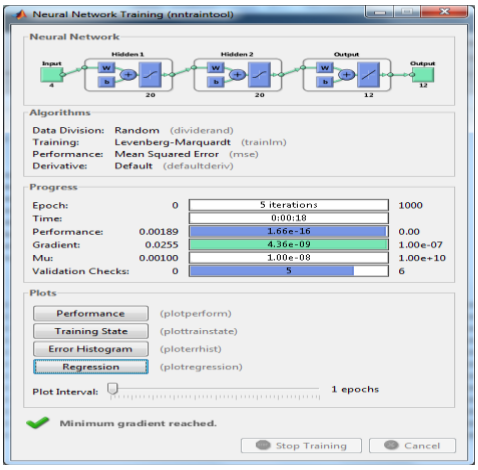

Fig.3.5a. Network training window

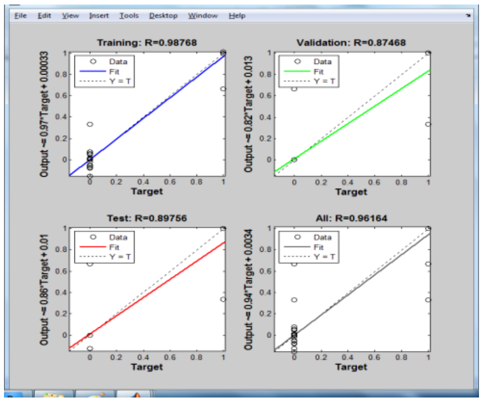

Fig.3.5b. Output-Target relationship

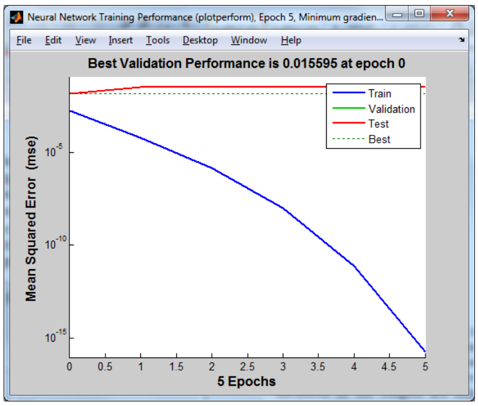

Fig.3.5c. Network training performance

During the training process which involves, training, validation and testing, the proposed network tries to match its outputs with targets. This goes for several iterations as the weights are adjusted to reduce the error between the output and the target to develop a linear relationship between inputs and outputs. Click on Regression button to view the relationship between target and output in figure 3.5b and on Performance button to view network performance in figure 3.5c. The closer the value, R is to 1 (as shown in figure 3.5b) the more linear the relationship. As shown in figure 3.5c, the similarity between the test curve and the validation curve reveals that the network is

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Volume 1, Issue 4, July-2015, ISSN (Online): 2395-566X

well trained. Had there been a significant increase of validation curve before the test curve, over fitting could be assumed. Training and retraining continues until the network is able to generalize. As shown in figure 3.6, the proposed network topology has four inputs, two hidden layer with logsig transfer function in each and twelve outputs.

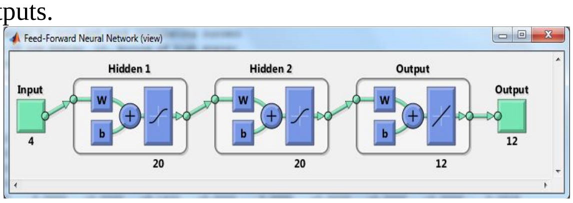

Fig.3.6. Proposed Network Topology

3.8 Developed Software Applied to the Network

Using the software requires that the raw data from DGA be converted into Roger's ratio code. This is done by the following software code.

```
clc
InputTestData1=xlsread('predictiput')';
% loads data to be tested
InputTestData2=InputTestData1(6:9,:);%ratio values from raw data
p=input('number of transformers =');% requests for the number of sample data to be tested
y=p;
n=1;
for i=1:y
if InputTestData2(n,i)<=0.1   %the loops convert ratio values int Roger's codes
InputTestData2(n,i)=5;

elseif InputTestData2(n,i)<1
InputTestData2(n,i)=0;

elseif InputTestData2(n,i)<3
InputTestData2(n,i)=1;
else
InputTestData2(n,i)=2;

end
end
   n=2;
for i=1:y
if InputTestData2(n,i)<1
InputTestData2(n,i)=0;
else
InputTestData2(n,i)=1;

end
end
   n=3;
for i=1:y
if InputTestData2(n,i)<1
InputTestData2(n,i)=0;

elseif InputTestData2(n,i)>=3
InputTestData2(n,i)=2;
else
InputTestData2(n,i)=1;

end
end
   n=4;
for i=1:y
if InputTestData2(n,i)<0.5
InputTestData2(n,i)=0;

elseif InputTestData2(n,i)>=3
InputTestData2(n,i)=2;
else
InputTestData2(n,i)=1;
end
end
InputTestData2=InputTestData2
disp('COLUMN NUMBER AND FAULT TYPE')
disp('1. Normal   2. Partial Discharge of low Energy')
disp('3. Overheating <150  4. Overheating 150-200')
disp('5. Overheating 200-300  6. Conductor Overheating')
disp('7. Overheating by winding circulating current')
disp('8. Overheating by core and tank circulating current ')
disp('9. Arcing of low energy  10. Arcing of high energy')
disp('11. Continous sparking to floating potential')
disp('12. Potential Discharge with high energy')
RESULT=network(InputTestData2)    %displays the diagnosis
```

IV. Results and Discussion

Ten (10) samples of DTs (T1 to T10) with known faults where taken from Port Harcourt distribution network. Each transformer has the same type of oil insulation. The concentrations of H_2, CH_4, C_2H_2, C_2H_4 and C_2H_6 obtained from DGA carried out on each transformer oil sample are tabulated in table 4.1. The actual transformers faults are also shown in the table.

Variations observed in the tabulated quantity/ concentration of gas generated or dissolved in oil is as a result of type and duration of fault as well as temperatures reached during fault conditions. The relationship between temperature, gas types, and quantities generated, is understood using gas generation chart (Hydroelectric Research and Technical Services Group, 2000)

Table 4.1: DGA Data of Ten (10) Distribution Transformers

Transformers	Gas Concentrations (In Ppm) From Dga					Actual Fault
	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	
T1	10	21	0.3	3	7	Normal
T2	1034	993	1	21	1129	Overheating 200-300^{0}C
T3	34	57	0.2	1	300	Overheating 150-200^{0}C
T4	8093	1045	8013	4732	997	Arcing of high energy
T5	10031	2503	11033	6314	1094	Arcing of high energy
T6	23	53	0.2	6	78	Overheating 150-200^{0}C
T7	130	98	0.1	9	103	Overheating by winding circulating current
T8	114	301	0.1	0.5	337	Overheating 150-200^{0}C
T9	1704	1511	0.3	1634	1473	Overheating 200-300^{0}C
T10	2751	153	5735	73	97	Potential Discharge with high energy

The gas ratios for each transformer are coded according to Roger's redefined code in table 4.2a. The coded ratios are as shown in table 4.2b

Table 4.2a: Roger's redefined ratio codes(Saranya et al 2013)

Ratio	Range Of Ratio	Code	Ratio	Range Of Ratio	Code
CH_4/H_2	≤0.1	5	C_2H_4/C_2H_6	<1	0
	>0.1<1	0		≥1<3	1
	≥1<3	1		≥3	2
	≥3	2	C_2H_2/C_2H_4	<0.5	0
C_2H_6/CH_4	<1	0		≥0.5<3	1
	≥1	1		≥3	2

Table 4.2b: Gas ratios and Roger's code

Transformers	Ratio Of Gases				Roger's Ratio Codes			
	CH_4/H_2	C_2H_6/CH_4	C_2H_4/C_2H_6	C_2H_2/C_2H_4				
T1	2.1	0.333333	0.428571429	0.1	1	0	0	0
T2	0.960348	1.136959	0.018600531	0.047619048	0	1	0	0
T3	1.676471	5.263158	0.003333333	0.2	1	1	0	0
T4	0.129124	0.954067	4.746238716	1.693364328	0	0	2	1
T5	0.249526	0.437076	5.771480804	1.74738676	0	0	2	1
T6	2.304348	1.471698	0.076923077	0.033333333	1	1	0	0
T7	0.753846	1.05102	0.087378641	0.011111111	0	1	0	0
T8	2.640351	1.119601	0.00148368	0.2	1	1	0	0
T9	0.886737	0.974851	1.109300747	0.000183599	0	0	1	0
T10	0.055616	0.633987	0.75257732	78.56164384	5	0	0	2

The results generated by inputting the coded ratios to the proposed ANN model, are shown in table 4.3. In each column of table 4.3, take the row number of the value closest to 1 (highlighted in the table), and relate it to the same row number of table 4.4, the corresponding fault represents the prominent fault type for the transformer.

Table 4.3: Output of the proposed ANN

ROW NUMBER	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
1	0.0000	0.0000	-0.0029	0.0000	0.0000	-0.0029	0.0000	-0.0029	0.0000	0.0000
2	0.0000	0.0000	-0.0060	0.0000	0.0000	-0.0060	0.0000	-0.0060	0.0000	0.0000
3	**1.0000**	0.0000	0.0029	0.0000	0.0000	0.0029	0.0000	0.0029	0.0000	0.0000
4	0.0000	0.0000	**1.0046**	0.0000	0.0000	**1.0046**	0.0000	**1.0046**	0.0000	0.0000
5	0.0000	**1.0000**	-0.0019	0.0000	0.0000	-0.0019	**1.0000**	-0.0019	0.0000	0.0000
6	0.0000	0.0000	0.0075	0.0000	0.0000	0.0075	0.0000	0.0075	**1.0000**	0.0000
7	0.0000	0.0000	0.0019	0.0000	0.0000	0.0019	0.0000	0.0019	0.0000	0.0000
8	0.0000	0.0000	-0.0020	0.0000	0.0000	-0.0020	0.0000	-0.0020	0.0000	0.0000

9	0.0000	0.0000	-0.0055	0.0000	0.0000	-0.0055	0.0000	-0.0055	0.0000	0.0000
10	0.0000	0.0000	0.0104	**1.0000**	**1.0000**	0.0104	0.0000	0.0104	0.0000	0.0000
11	0.0000	0.0000	-0.0026	0.0000	0.0000	-0.0026	0.0000	-0.0026	0.0000	0.0000
12	0.0000	0.0000	0.0421	-0.0016	-0.0016	0.0421	0.0000	0.0421	0.0000	**1.0000**

Table 4.4: Typical faults

Row Number	Faults
1	Normal
2	Partial Discharge of low Energy
3	Overheating <150
4	Overheating 150-200
5	Overheating 200-300
6	Conductor Overheating
7	Overheating by winding circulating current
8	Overheating by core and tank circulating current
9	Arcing of low energy
10	Arcing of high energy
11	Continuous sparking to floating potential
12	Potential Discharge with high energy

Relating table 4.3 with table 4.4 as explained, diagnosed faults are shown in table 4.5.

Table 4.5: Interpretation of output of the proposed ANN

Transformer	Actual Fault	Diagnosed Fault
T1	Normal	Overheating <150^{0}C
T2	Overheating 200-300^{0}C	**Overheating 200-300^{0}C**
T3	Overheating 150-200^{0}C	**Overheating 150-200^{0}C**
T4	Arcing of high energy	**Arcing of high energy**
T5	Arcing of high energy	**Arcing of high energy**
T6	Overheating 150-200^{0}C	**Overheating 150-200^{0}C**
T7	Overheating by winding circulating current	**Overheating by winding circulating current**
T8	Overheating 150-200^{0}C	**Overheating 150-200^{0}C**
T9	Overheating 200-300^{0}C	Conductor Overheating
T10	Potential Discharge with high energy	**Potential Discharge with high energy**

The highlighted faults in table 4.5 are correctly diagnosed faults while the non-highlighted once are wrongly diagnosed. 8 out of 10 faults were correctly diagnosed and classified by the proposed ANN.

The error of the network,

$$\alpha = \frac{\text{number of incorrectly predicted faults}}{\text{number of correctly actual faults}}$$

= 2/10=0.2

V. Conclusion

In this paper, ANN was used to successfully diagnose and classify incipient faults of DTs. This provides DTs maintenance engineer with necessary information required to effect adequate maintenance procedures.

Recommendation

The proposed ANN is recommended for maintenance engineers and adoption into on-line monitoring and diagnosis of DTs incipient faults. It is also recommended for further study for fault localization.

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