Artificial Neural Network Based Fault Diagnostic Tools of Power Transformer in Bauchi 132/33 kV Substation

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Abstract- to ensure a reliable operation of power system, power transformers' health condition must be continuously monitored and assessed for appropriate operation and maintenance decisions. Currently, there are various insulation condition monitoring of powertransformers. Such as dissolved gas analysis (DGA), Duval Triangular Method (DTM) and Rogers Ratio Method (RRM) Artificial neural network (ANN) etc. In the paper, 132/33 kV Bauchi substation was used as the study system and a selected injection feeder simulated for fault impact tests using Power System Computer Aided Design (PSCAD). The results which emanate from the study revealed that the current magnitude of bus voltage was 7.472%, bus voltage drop below 5% recommended while the oil and impregnated paper insulation degradation characterized with Kelman Transport X test equipment and MATLAB based ANN fault detection and classification jointly correlated that the sample oil only suffered for thermal faults greater 700^{0}C but other characteristics such as arc faults, water contents were 73 ppm etc remained satisfactory for in the reference substation. Therefore, this paper has demonstrated detection, location and restoration of faults in the installed transformers.

Indexed Terms- Power Transformer, Dissolved Gas Analysis, Fault Diagnosis Tools, Artificial neural network

I. INTRODUCTION

A fault diagnostic tool is needed to facilitate alarge analysis, visual inspection, testing and robust maintenance of power transformers. The maintenance planners can reduce the increasing rate of internal faults. Accurate diagnostic can also improve the service reliability of this important asset whose optimal conditions largely depend upon the state of the oil-paper insulation. A power transformer is one of the most important and expensive assets in a power system. The reliable operation of transformers has a significant impact on the availability of electricity supply to customers [1]-[2]. Power transformer has a number of subsystems including winding, On Load Tap Changer (OLTC), bushing, cooling systems and other peripherals. Transformers both power and distribution in the power station operate to ensure the transmission and the distribution of the electrical energy. The power transformer works without several moving components; the only component moving in the power transformers is the OLTC [3]. The integrity of transformer must be continuously monitored for appropriate operational decisions and maintenance schedules. Effective methodologies and innovative techniques need to be developed to pave way for comprehensive condition monitoring and diagnosis of power transformers. The conditions of the cooling system used in a power transformer have significant impacts on the overall reliability and service ability of the apparatus [4]**.** The faults diagnosis is a powerful tool that carries out a large analysis; visual inspection; test and the maintenance of the power transformer to prevent faults and ensure normal operating conditions.

II. RELATED WORK

Diagnostic tools to detect some latent faults in transformer are based upon the study of characteristic nature of the insulating materials used for cooling the device during normal or abnormal operation. The nature of the insulating materials involved in the fault and the fault itself affect the distribution of dissolved gases monitored in the transformers. [5].

Dissolved Gas analyser (DGA) is a tool which allows diagnosis of insulation oil for power equipment. It has been used several decades in transformer oil condition test to monitor the operating conditions of the unit and to detect the early faults aimed at avoiding failures and serious damage of transformer [6].

Safe and reliable operation of the power transformer play major role in the stability of the power system and relevant apparatus. Since any fault in the transformers influences some sections of powersystem, the precise diagnosis of the faults and quick interruption of the faulty transformers from the rest ofthe power system is essential to reduce damage caused by the high fault current that cause instability of the power system and/or fire outbreak. A numberof articles involving several subjects about power transformer faults diagnosis have been documented. It has been confirmed that the conventional fault diagnosis methods such as the ratio methods (Rogers, Dornenburg, Duval triangle and IEC) and the key gas methods involving the quantity of hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO), carbon dioxide (CO_2) have limitations in giving actionable alerts on the real problem of the transformers [7]. The Duval triangle dissolved gas analysis tool has also been proven to be helpful in interpreting possible faults within a transformer. It uses the proportions of the three key gases acetylene, ethylene, and methane to determine what type of fault might have occurred in the transformer. However, Duval's triangle should be used with caution because it will always indicate that there is some kind of faults in the transformer even if it is operating normally. In most cases, thistool is used after a fault has been determined by some other methods as validating tool. More specifically, the benefit of DTM is that it is not only useful in determination of the types of fault but also gives its severity. Therefore, this is a need to reassess the set ofdiagnostic methods to develop the compendium of the causes, effects and remedy catalogue in powerdiagnosis.

Also, the diagnosis of electrical and thermal faults in vegetable-insulating oils require some modifications. Refs. [10, 11] proposed modified Duval triangle method referred to as DTM type 3 to diagnose the thermal and electrical fault. This method has the advantages of high diagnostic accuracy and consistency.

Incipient faults can also be diagnosed using on DGA tools to identify dissolved gases in power transformer under diagnostic themes of key gas methods, Rogers's ratio methods, Duval triangle method, Doernenburg Ratio method, Basic Gas Ratio, and artificial intelligence based methods.

For key gas method applicable in incipient faults diagnosis, the key gas identifies each type of fault and uses the percent of this gas to determine faults by IEEE standard C57.104. The percent of gas is then obtained in terms of the total combustible gases (TCG). The main disadvantage of this method is that the interpretation by the individual gases is difficult in practice since each incipient fault produces traces of other gases in addition to the key gas of such fault.

The ratio methods for fault diagnosis use certain ratios of dissolved gas concentrations according to combinations of codes. An incipient fault is detected when a code combination matches with the code pattern of the fault. The most widely used ratio methods are the Doernenburg Ratio Method, Rogers Ratio Method, and IEC standard.

Various AI techniques include artificial neural networks (ANN) may help solve the problems and present a better solution [8]. In paper, artificial intelligence technique is used as a diagnostic tool for diagnosing the power transformer health. By using artificial intelligence, the rule can be generated automatically and the decision could be made with high assurances. In fact, one of the benefits of artificial intelligence is to minimize the subjective rules in perspective diagnostic techniques. Fuzzy logic and artificial neural network are the most commonly used artificial intelligence techniques for power transformer diagnosis [9]. The ratio methods for fault diagnosis use certain ratios of dissolved gas concentrations according to combinations of codes. An incipient fault is detected when a code combination matches with the code pattern of the fault. The most widely used ratio methods are the Doernenburg ratio method, Roger's ratio method, and IEC standard. Six gas ratios have been used by different researchers [12].

III. METHODOLOGY

3.1 Complete transformer fault diagnosis

The complete flowchart for determining the faults of power transformer based on lab fault diagnosis and neural network techniques from Matlab is presented in Figure 1. The first step in fault diagnosis for detecting the faults of power transformer is to take oil sample specimen from the transformer and then processed in the laboratory using optical gas analyser described in section 3.3.4. Following the analysis of the samples from the laboratory, the concentrations of dissolved gases are obtained using some standard DGA ratios such as KGM: DTM and RRM methods. The alternative method to the aforementioned classical ratio tests is toinput the oil concentrations into the NN (Neural Network) to identify the types of faults

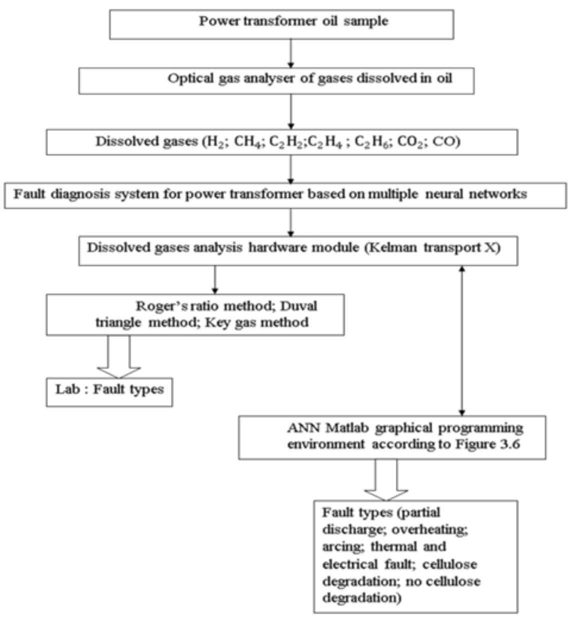


Figure 1. Flowchart for determining the faults of powertransformers based on neural networks.

3.2 Transformer diagnosis case study of Bauchi – Nigeria substation

DGA samples of transformer T3 in Bauchi-Nigeria with nameplate information is shows in table 1 was sampled for routine testing on the 04-September-2021. Figure2. Shows the summary of the procedure invoked when using ANN as an alternative tool for DGA analysis.

TABLE 1. NAME PLATE INFORMATION

Bauchi T/S 132/33 kv 30/40 MVA, transformer T3		
Name plate data		
Manufacturer	*Transformers &electicals telk kerala limlited,India*	
Serial n°	*120345-1*	
Type	*SOLOCR*	
Year of manufacture	*1995*	
From	*3NYCP*	
Stardand(specifications)	*IEC 76 [part1&2]-1993,[part3]-1980&[part5]-1976*	
Rated power	*30/40MVA*	
Cooling method	*ONAN/ONAF*	
Volume of oil in litres	*17950L*	
Frequency	*50 Hz*	
Masse of oil in Kg	*16160Kg*	
Phase	*3*	
Masse of core & winding in Kg	*38000Kg*	
Air circulation M3/mm	*6*90*	
Connection symbol	*YNd11*	
Guaranteed max temp rise of oil	*50°C*	
Winding	*55°C*	
Winding	*Impulse test voltage Kv peak*	*Power frequency test voltage Kv rms*
HV line	*650*	*275*
HV neutral	*95*	*35*
LV line	*170*	*75*

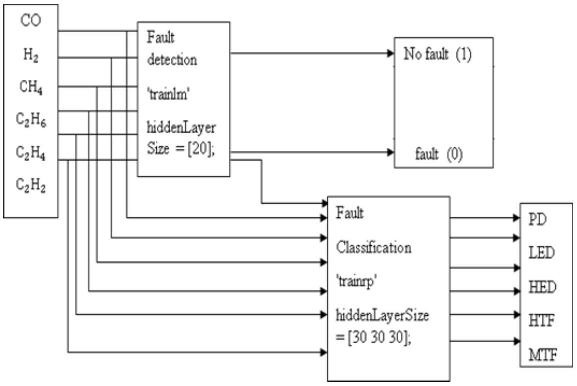


Figure 2. Fault diagnosis model

3.3 63-Bus bank road distribution network

In this research the virtual lab. Simulator developed by [13] has been adopted. for the study of the causes and impacts of faults on power transformer failures in the network. Herein, the Bauchi-Nigeria 63-bus, 33/11 kV Bank Road feeder was used as the candidate feeder; analysed using PSCAD. PSCAD model is shown in Figure 3.

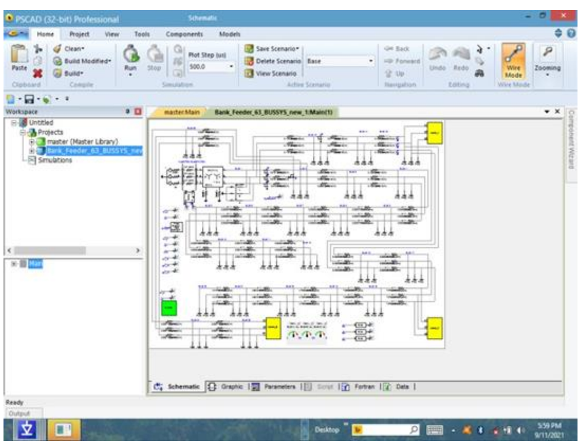


Figure 3. PSCAD Model of 63-Bus Distribution Bauchi-Nigeria Bank Road network

3.4 Transformer oil sample

The transformer oil sample was collected from the Bauchi-Nigeria 132/33 kV substation power transformer. In the transformer under maintenance about 60 cl of the oil was scooped for DGA analysis.

3.5 Kelman transport X DGA

Kelman transport X DGA was used to measure all seven (7) critical faults one after the other. The gases as well as water content (moisture) were determined. The oil sample manually obtained from Bauchi 132/33/11KV sub-transmission station were analysed. Plate I shows the Kelman Transport X DGA instrument available in Gombe TCN. The equipment was used to analyse the oil sample according to the operating procedure summarized in the salient steps:

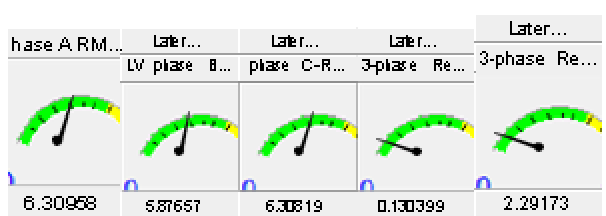
i. Boot the equipment and then follow the onscreen menu drive instructions of the machine
ii. Inject 50 ml of the oil sample using the plunger apparatus and insert magnet into the bottle
iii. Print the test results:

Plate I kelman transport X

IV. RESULTS AND DISCUSSION

4.1 Causes and Impacts of faults on power transformers

Faults in power systems can be initiated by transient operations such as switching of large loads, short circuit or open circuit of lines. The protective schemes should guarantee quick detection and location of the faults so as to safeguard all other essential equipment particularly transformers. Herein, the results are presented for short circuit of the main 15MVA, 33/11 kV substation transformer at Bank Road, Bauchi. Figure 4 shows the inception fault



(a) (b) (c) (d) (e)

Main ...	Main ...	Main ...	Later...	Later...
BUS B Volta...	BUS A Volta..	BUS C Volta...	3-phase Re...	3-phase Re...

5.91114	6.31683	6.27204	0.130399	2.29173
(f)	(g)	(h)	(i)	(j)

Figure 5. Substation Meters for Fault Analysis: Lateral (a-e) and main (f-h)

occurring at the substation upstream few meters away with the circuit breaker simulating the fault from 6s to 6.5s. Also, there was another downstream short circuit fault initiated after 2s up to 10s with the system responses shown in Figure 5 (a-l) representing three sinusoidal waveforms phase voltages A to C, RMS voltage oscillograph of phase A, three sinusoidal waveforms phase current A to C, RMS voltage oscillograph of phase B, three real power signals at A, B & C and RMS voltage oscillograph of phase C respectively. In this situation the percentage voltage regulation of the line is computed as in Equation (4.1) yielded 0.115%, 0.584% and - 0.576% for phases A, B and C respectively in the lateral bus numbers 13 to 22.

$$\%\text{voltage regulation} = \frac{v\text{sending end} - v\text{receving end}}{2av\text{sending end}} \times 100 \qquad (1)$$

The positive regulation indicates volt drop and negative indicates rise in voltage. These results were obtained from PSCAD described in the previous section

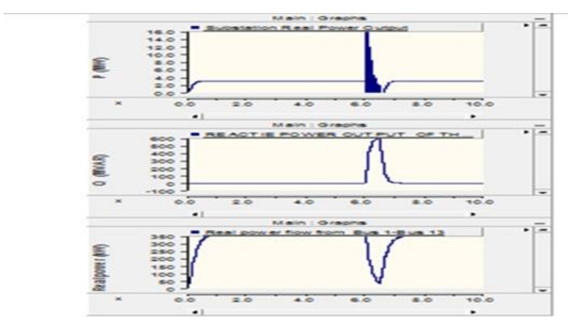


Figure 4. The inception fault at bus 1-13.

The causes and impact of fault on transformer failure are simulated in PSCAD corresponding to commonly experienced abnormalities in the power system. Analytic failure tests are carried out to establish the tolerable limits of power systems apparatus particularly power transformers in terms of insulation degradation or breakdown. These tests are divided in two groups: Low Voltage (LV) and High Voltage (HV) tests where the limit is set at 1 kV. Most HV tests, such as induced voltage tests, partial discharge (PD) test or lightning impulse test, require the usage of heavy or highly specialised test devices and the appropriate expertise to interpret the results. Those tests are mostly carried out in the factory and rarely onsite. On the other hand, LV tests, like winding resistance, insulation resistance, tangent delta and voltage ratio, are relatively easy to perform in the factory as well as onsite.

In the research work both HV and LV tests were simulated in the study distribution network. In Figure 4 the incoming voltage phases A to C under normal and abnormal conditions were measured while in Figure 5 the normal voltage profile is monitored.

i. The lowest normal voltage of the incoming feeder for one of the laterals injected power at bus 13 was found to be 5.9114× √3 = (10.238 kV) which is 6.927% slightly above the 5% specification in NEC 210-19 FPNNo: 4. In the farthest receiving end of the lateral, the voltage drop was 7.472%.
ii. Under fault condition, the inception power grew up 16 MW and 600 kvAr far above the normal rate of 15 MW and 3.75MVAr which is 5.5% and 84% respectively.

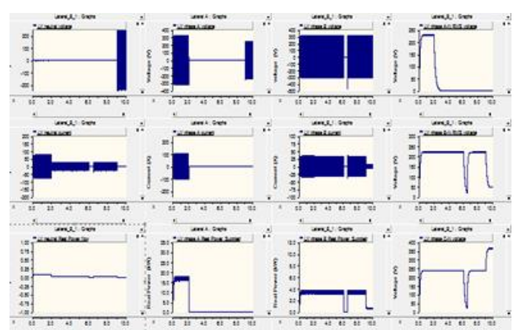


Figure 6. Downstream short circuit fault at the lateral between bus 13 and 22

4.2 Fault detection and prediction

The ANN fault detection and prediction are considered with the standard DGA data adopted for validation [14] while the oil specimens analysed with KTX equipment are compared appropriately.

4.2.1 Optimal neural network architecture forDGA fault detection

Table 2 Shows the various network architectures tested. It can be seen that thearchitecture with [30 30 30] obtained the best performance of lowest error of 3.41% classification architecture and therefore the lowest error percentage. Single layer networks with 10 neurons performed poorly. But as the number of neurons was increased the performance improved. The best performance of 78% for single layer was obtained at around 30 Neurons. Increasing the number did not improve the performance. For two layers architecture, the best results obtained was with [20 20]. For three layers the best architecture obtained was [30 30 30]. It had a performance of 91%. Increasing the number of layers beyond three layers did not result to any significant increase in performance. As the number of neurons and layers increased it was noticed that the training time also increased. Figure 7 showsthe optimal neural network architecture selected. The iteration curve for DGA fault detection is shown in figure 8 and The ROC curve is shown in figure 9

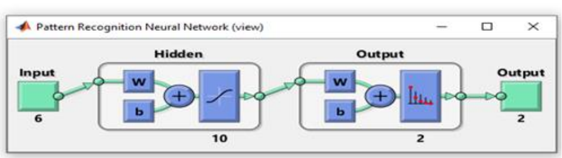


Figure 7. Neural network architecture for DGA fault detection

TABLE 2. OPTIMAL NEURAL NETWORK ARCHITECTUREFOR DGA FAULT DETECTION

Architecture	% Error	Train (RMSE)	Test (RMSE)	Validation (RMSE)
10	17.06	0.65	0.71	0.33
20	16.24	0.23	0.73	0.43
30	13.67	0.25	0.01	0.04
20-20	15.41	0.56	0.23	0.10
30-30	17.20	0.17	0.33	0.27
10-10-10	15.74	0.00	0.44	0.95
20-20-20	29.71	0.18	0.29	0.71
30-30-30	3.41	0.29	0.91	0.21
30-20-10	11.16	0.88	0.05	0.45
25-25-25	17.41	0.97	0.38	0.53
40-40-40	17.17	0.52	0.21	0.83

4.2.2 Optimal neural network training algorithm for DGA fault detection

Table 3. Shows the various training algorithms tested. The various training algorithms are Trainscg, Trainbfg, Traincbg, Traingda, Trainrp and Trainlm. From this table its seen that Trainscg had 17.11%, Trainbfg 23.04%, Traincbg 0.54%, Traingda 13.98%, Trainrp 0.19% and Trainlm 0.19%. The best training algorithm is trainlm and trainrp which both had percentage error of 0.1.

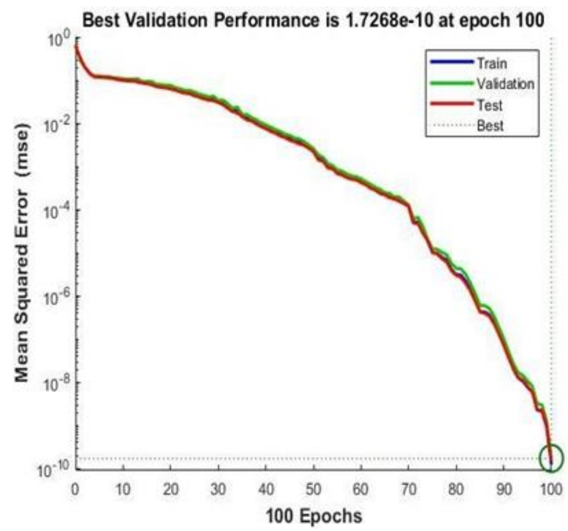


Figure 8. Iteration curve for DGA faultdetection

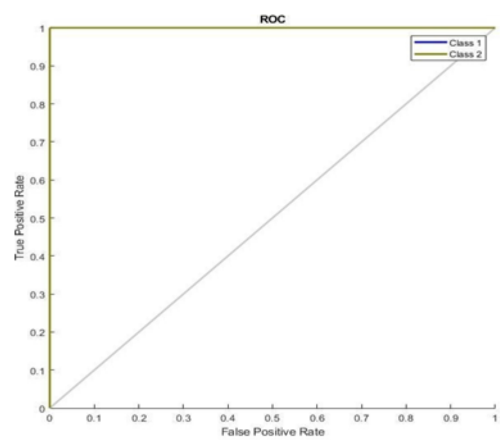


Figure 9. ROC curve for DGA fault detection

TABLE 3. OPTIMAL NEURAL NETWORK TRAININGALGORITHM FOR DGA FAULT DETECTION

Algorithm	% Error	Train	Test	Validation

Trainscg	17.11	0.82	0.77	0.49
Trainbfg	23.04	0.66	0.02	0.66
Traincbg	0.54	0.92	0.64	0.80
Traingda	13.98	0.05	0.64	0.24
Trainrp	0.19	0.74	0.64	0.60
Trainlm	0.19	0.12	0.11	0.27

4.3 Fault classification

4.3.1 Optimal neural network architecture for DGAfault classification

Table 4 shows the various network architectures tested. It can be seen that the architecture with [30 30 30] obtained the lowest error percentage. The plot showing the performance of tested architectures is shown in figure 10 figure 11. Shows the network architecture with 3 layers and 30 neurones in each layer.

TABLE 4. OPTIMAL NEURAL NETWORK ARCHITECTURE FOR DGA FAULT CLASSIFICATION

Architecture	% Error	Train (RMSE)	Test (RMSE)	Validation (RMSE)
10	34.87	0.67	0.18	0.02
20	22.37	0.21	0.47	0.44
30	42.53	0.65	0.18	0.35
20-20	16.14	0.06	0.92	0.50
30-30	16.73	0.20	0.04	0.78
10-10-10	29.76	0.16	0.24	0.73
20-20-20	32.41	0.59	0.20	0.43
30-30-30	11.39	0.20	0.42	0.64
30-20-10	43.20	0.60	0.21	0.14
25-25-25	28.00	0.72	0.71	0.18
40-40-40	21.08	0.05	0.30	0.50

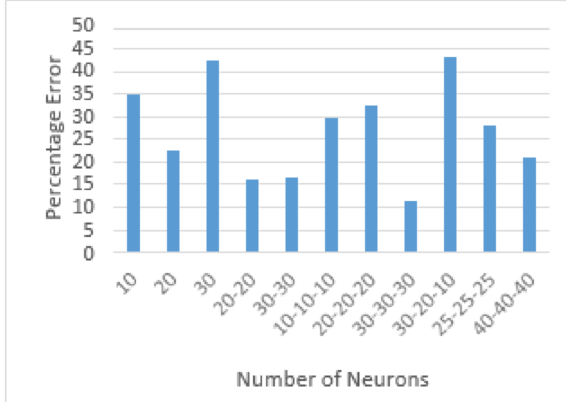


Figure 10. Performance of network architecture for DGA fault classification

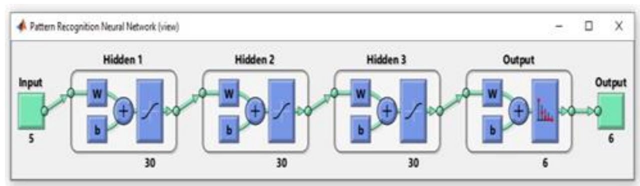


Figure 11. Neural network architecture for DGA fault detection

4.3.2 Optimal neural network training algorithm for DGA fault classification

The results obtained for the training algorithms tested during the determination of the best training algorithm for fault classification show that trainscg, trainbfg, traincbg, traingda, trainrp and trainlm obtained a training percentage of 91%, 58%, 46%, 67%, 58%, and 78% respectively. This is shown in Table 5 and it can be seen that trainlm obtained the best results and therefore it was chosen as the algorithm to be used. Figure 12 shows the receiver operating characteristic (ROC) curve for fault classification. ROC provides model prediction for true positive equivalent to hitting the target, true negative which is clear rejection and their opposite: false positive and false negative. It is the plot of true positive rate against the false positive rate at various threshold settings. The statistical representation of the ROC is established from the confusion matrix. The confusion matrix for the fault classification in power transformers is shown in figure 13. The diagonal cells show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified cases. The blue cell in the bottom right shows the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red). The results show very good recognition. Out of the six classes considered, class four outperformed the other five counterpart yielding positive classifier of 97.4%.

TABLE 5. OPTIMAL NEURAL NETWORK TRAINING ALGORITHM FOR DGA FAULT CLASSIFICATION

Algorithm	% Error	Train	Test	Validation
trainscg	17.01	0.82	0.56	0.60
trainbfg	11.31	0.73	0.45	0.37
traincbg	28.29	0.73	0.22	0.89
traingda	65.72	0.52	0.54	0.65
trainrp	8.01	1.00	0.61	0.87
trainlm	5.25	0.24	0.13	0.53

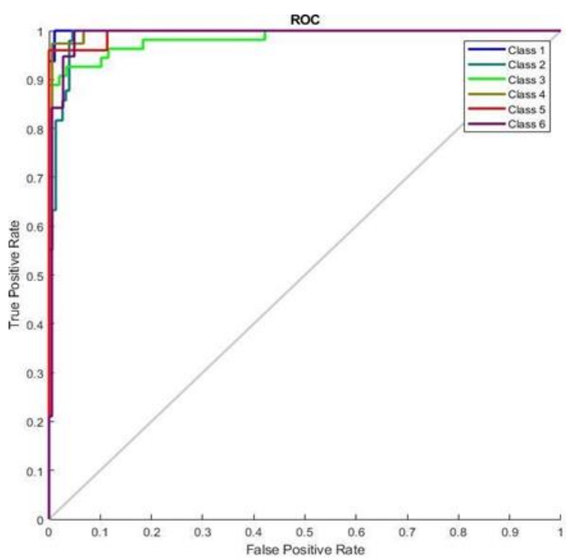


Figure 12. ROC curve for fault classification

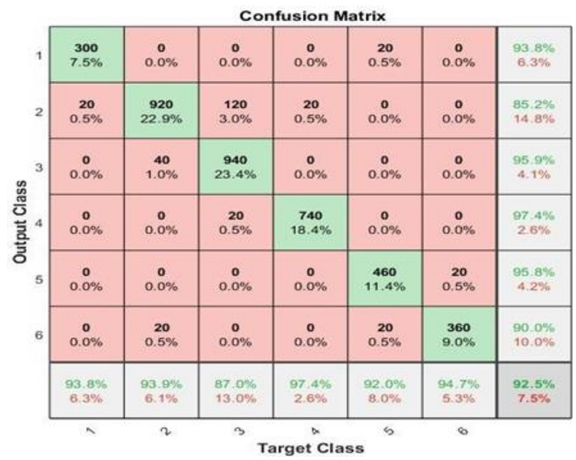


Figure 13. Confusion matrix for fault classification

CONCLUSION

Three different tests namely Roger's ratio method, Duval triangle method and Key gas method have been studied and reported in this research. Thesetests are conducted to reveal the degradation in oil and impregnated paper used in power transformer for cooling and insulation. The insulation oil and paper characteristics of the transformer were determined based on the three ratio test methods. After running the diagnostics using there classical dissolved gas analytical tools with samples data taken from the power transformer, two of the models DTM, RRM indicated that there was a thermal fault with high energy. Other specific observations from each analytical tool are considered in sequel.

The ANN optimally tested with DGA data has shown the effect of various network architectures for detection of transformer faults. It has been observed that performance of ANN architecture is a function numbers of neurons and levels of hidden layers. For instance, with [30 30 30] which signifies 3 levels of hidden layers, each level having 30 neurons has been adjudged the best performed ANN architecture with the lowest error of 3.41%: Other conclusions can be drawn from the research as follows:

i. Single layer networks with 10 neurons performed poorly. But as the number of neurons increased the network performance improved. The best performance of 78% for single layer was obtained at around 30 Neurons. Increasing the number did not improve the performance.

ii. For two layers architecture, the best results obtained was with [20 20].

iii. For three layers the best architecture obtainedwas [30 30 30] with accuracy of 91%. Increasing the number of layers beyond three layers did not result to any significant increase in performance.

iv. As the number of neurons and layers increased it was noticed that the training time also increased. The final iteration was 100 and out of the six classes considered, class four outperformed the other five counterpart yielding positive classifier of 97.4%.

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