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FORECASTING THE NATURE OF POWER TRANSFORMER INSULATION OIL USING CHEMICAL PROPERTIES OF DISSOLVED GASES

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ABSTRACT

The life expectancy of transformers at various operating conditions is not accurately known. Deterioration of power transformer insulation is a function of time and temperature. Since in power transformer, the temperature distribution is not uniform, the part which is operating at the highest temperature will ordinarily undergo the greatest deterioration. Therefore, it is usual to consider the effects produced by the highest temperature hottest spot. The hottest-spot winding temperature is the principal factor in determining life due to loading. The temperature cannot be measured directly because of the hazards in placing a temperature detector at the proper location because of voltage. In this paper a neural network based regression analysis was done to forecast the nature of power transformer insulation oil and life time of transformer including loading conditions.

Key words: Dissolved gas analysis, Levenberg algorithm, Regression analysis.

INTRODUCTION

The largest portion of capital investment in transmission and distribution substations represented by power transformers. A lose in a single unit can have a multimillion dollar impact on financial consequences. But a failing transformer removed from service in time can usually be economically reconditioned. Fault conditions in a power transformer are detected in several ways. One of the methods is based on detection of the degradation products in the insulating oil. The degradation of insulating oil occurs due to abnormal dissipation of energy within the transformer. This causes carbon by products dissolved in the insulating oil[1]. However, the energy released through fault processes such as overheating, partial discharge and arcing, is often sufficient to generate the fault gases initially in the form of bubbles. Also high moisture conditions and sudden overloads can cause the inception of moisture vapor bubbles released from conductor insulation. When abnormal

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gassing from dissolved gas analysis results, the transformer is subjected to frequent testing weekly or even daily to understand, what is happening inside the transformer and to prevent a catastrophic failure.

Table 1: Fault with dissolved gases

H_2 (Hydrogen)	Exposed to partial discharge or corona in the transformer also created with excessive moisture
CH_4 (Methane)	Exposed to excessive heat from an intimate contact with a hot metal
C_2H_6 (Ethane)	Exposed to excessive heat from a hot metal. Heat required is greater than heat required for methane
C_2H_4 (Ethylene)	Exposed to excessive heat from a hot metal. Heat required is greater than heat required for ethane
C_2H_2 (Acetylene)	Typically associated with electrical arcing.
CO_2 (Carbon dioxide)	Exposed, when cellulose insulation is exposed to excessive heat, such as during period of over loading.

When a transformer's insulating oil exposed to excessive heating under normal or abnormal operating conditions, the heat is transformed to the oil and if sufficient amount of heat is present, combustible gases are created. Since the decomposition of oil indicates a threat to the operational safety of expensive machines, electrical engineers focus attention on the amount and nature of the gas evolved. Based on the result of DGA and the potential cause of such differences, appropriate preventive measures are taken to protect the transformer. Measuring the levels of the light gases found in an electrical transformers insulating oil is one way to monitor the health of a transformer[1,2]. A gas sample is extracted from the oil and nine key gas components-namely hydrogen, oxygen, nitrogen, methane, carbon monoxide, carbon dioxide, ethane, ethylene and acetylene are analyzed. When a transformer is failing, the chemical compounds in the oil break down to give off these gases. If analyzed on a routine basis, a failing transformer can be identified and replaced without a power loss or the potential of a serious explosion.

Interpretation of dissolved gas analysis

The main difficulty in making use of dissolved gas analysis results is that it is not easy to draw the line between normal and abnormal results. So in[4] interpretation schemes include a normal condition as one of the diagnostic outcomes, but have not been particularly effective in reliably identifying a normal condition. There are three most important discussions needed from user point of view in power transformer.

(i) Normal condition

(ii) Transformer needs immediate breakdown maintenance

(iii) Condition demands continuous monitoring with period

If there is no appreciable rise in concentration of various gases then transformer is healthy as in first two cases and if the rise in concentration is in the order of hundreds or thousands of ppm every week or at lesser intervals, then transformer needs immediate breakdown maintenance[5]. For the third question, the interpretation given in Table 1 will have to be further simplified and made applicable to those cases of condition monitoring, where rise in concentration of one or more individual gases is being observed. The simplified approach forms the new method of interpretation, applicable to all the cases of condition monitoring as in Table 2.

Table 2: Interpretation result of dissolved gas analysis

Rise in gas concentration	Key gas method	Ratio method	As per IS : 10593
Nil	Normal aging	Normal aging	Normal aging
CH_4	----	Thermal fault below 150°C	Thermal fault from 150°C to 300°C
C_2H_4	Over heating	General conductor over heating	Thermal fault of low temperature upto 150°C
CH_4 & C_2H_6	---	Fault from 150°C to 300°C	----
CH_4 & C_2H_4	----	Circulating currents and/or over heated joints	Thermal fault of 300°C to 700°C or above
C_2H_2	----	Flash over without power flow through	----
C_2H_2 & C_2H_6	----	Tap changer selector breaking current	----

Drawbacks from the conventional DGA interpretation schemes are –

- Mainly developed based on human judgment and no systematic attempt has been made. High degree of inconsistency and ambiguity.
- Unable to detect with high confidence multiple faults that occur concurrently within the transformer

- Unable to detect new or unknown faults owing to lack of expert knowledge in them.

Proposed work

In this paper, we use regression method of Artificial Neural Network to overcome the above drawbacks. The problem of neural network learning can be seen as a function optimization problem, where we are trying to determine the best network parameters (weights and biases) in order to minimize network error[6]. This said several function optimization techniques from numerical linear algebra can be directly applied to network learning, one of these techniques being the Levenberg-Marquardt algorithm. The Levenberg Marquardt algorithm provides a numerical solution to the problem of minimizing a nonlinear function over a space of parameters for the function. It is a popular alternative to the Gauss-Newton method of finding the minimum of a function. As our problem related to Fault Diagnosis by Dissolved Gas Analysis of a Power Transformer, the neural can be viewed as highly nonlinear functions[7]. From this perspective, the training problem can be considered as a general function optimization problem[8,9], with the adjustable parameters being the weights and biases of the network, and the Levenberg-Marquardt can be straight forward applied in this case. For training the neural network, we consider the DGA data with corresponding load for a power transformer in an electrical utility in India rated as 105 MVA, 400/230KV, BHEL make transformer in an substation with serial No. 6006653.

Table 3: DGA data of a 400/230 KV Transformer

Date of test	Hydrogen (H_2)	Methane (CH_4)	Ethane (C_2H_6)	Ethylene (C_2H_4)	Acetylene (C_2H_2)	Carbon dioxide (CO_2)	Load (MW)	Current (A)
26.7.11	4	1	1	0.1	0.1	947	100	439.17
30.9.11	5	2	1	1	1	1150	120	527
30.11.11	6	2	1	2	1	1120	110	483.091
30.1.12	11	1	2	0.1	0.1	1478	100	439.17
29.3.12	12	1	1	0.1	0.1	1560	120	527
21.7.12	5	1	2	0.1	1	1152	120	527
20.9.12	3	1	0.1	0.1	0.1	441	110	483.09
27.2.13	34	10	5	5	2	2345	170	746.59
29.4.13	62	32	46	15	10	2654	170	746.59
21.6.13	71	43	49	32	5	2763	160	702.67

Tables 3 and 4 show the dissolved gas value in ppm with variable load for a 400/230 KV transformer. Figs. 1 and Fig. 2 show that variation of acetylene with respect to load and variation of hydrogen with respect to load. The inference from the Fig. 1 is, when sudden increase in acetylene gas level in transformer oil from 2 ppm to 10 ppm shows that there is increase in load hence load, current. Also from Fig. 2, we conclude that as load increases, due to thermal effect the hydrogen value in ppm also get increased[10]. As per the standard, sudden increase in hydrogen leads thermal fault. Due to this thermal effect, cellulose degradation will occur and acetylene gas level also get increased, which leads to arcing fault. This data is used to train the neural network using Levenberg algorithm and the fault of that transformer was predicted.

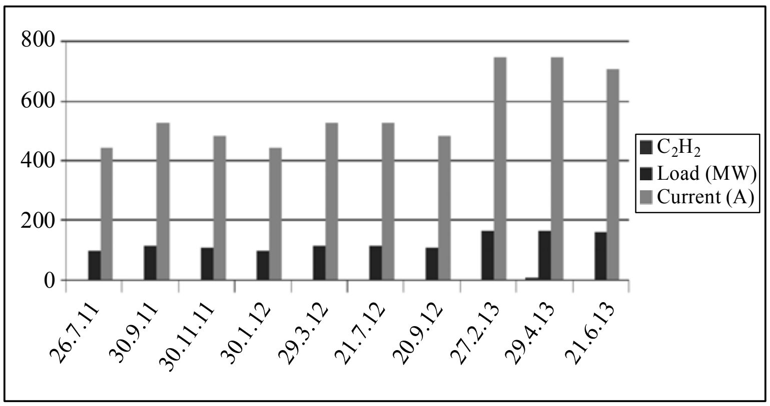

Fig. 1: Load influence in acetylene formation in insulating oil

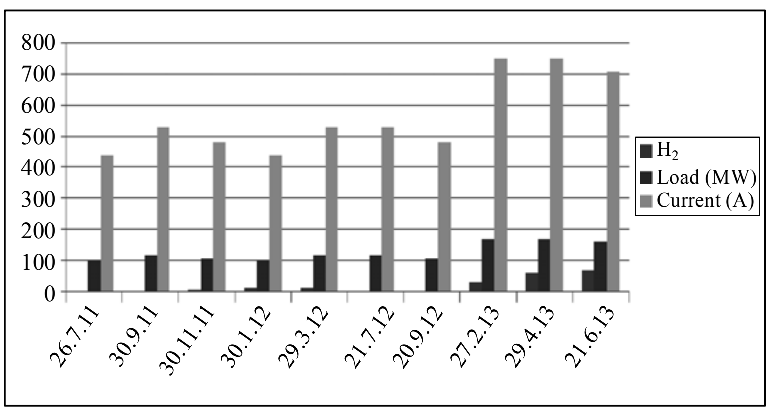

Fig. 2: Load influence in hydrogen formation in insulating oil

Levenberg's main contribution to the method was the introduction of the damping factor λ. This value is summed to every member of the approximate Hessian diagonal before the system is solved for the gradient. Typically λ would start as a small value such as 0.1. Then the Levenberg-Marquardt equation is solved commonly by using LU decomposition. After the equation is solved, the weights w are updated using δ and network errors for each entry in the training set are recalculated. If the new sum of squared errors has decreased, λ is decreased and the iteration ends. If it has not, then the new weights are discarded and the method is repeated with the higher value of λ.

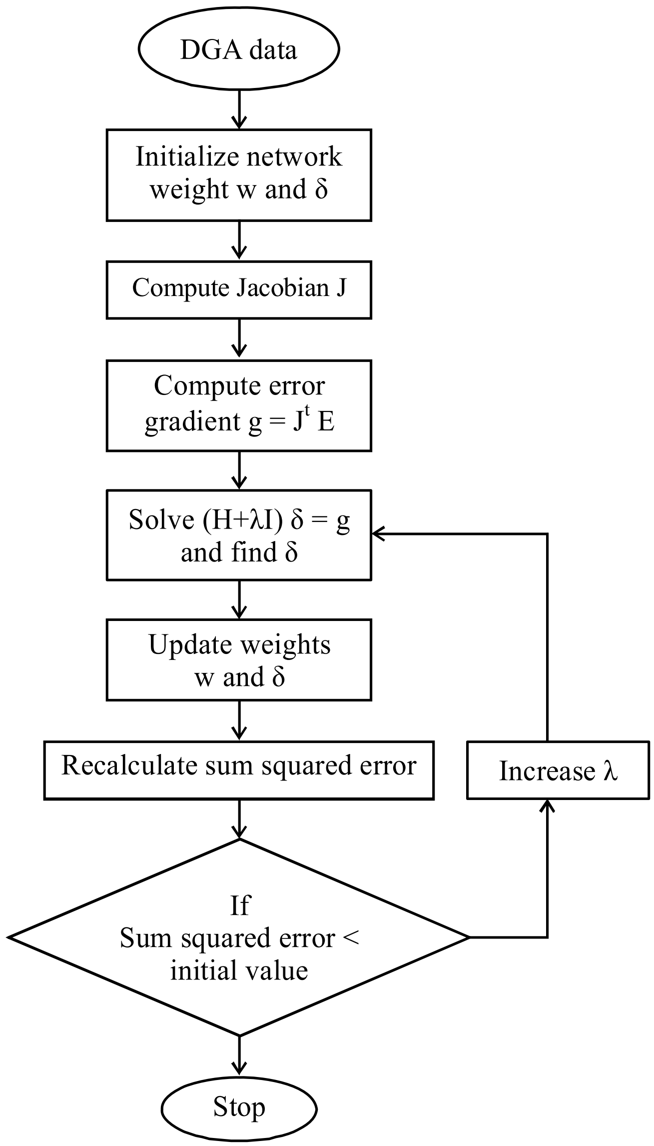

Fig. 3: Algorithm flow chart

Variations of the algorithm may include different values for v, one for decreasing λ and other for increasing it. Others may solve $(H + \lambda \text{ diag } (H)) \delta = g$ instead of $(H + \lambda I) \delta = g$, while others may select the initial λ according to the size of the elements on H, by setting $\lambda_o = t_{max}$ (diag (H)), where t is a value chosen by the user. We have chosen the identity matrix equation because it is the same method implemented internally by the Neural Network Tool Box in MATLAB.

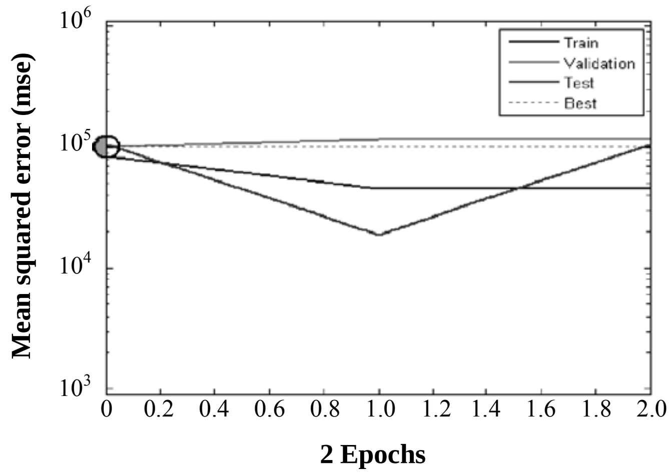

Fig. 4: Performance plot of developed NN

The above performance plot shows, how the network performance improved during training. It shows the value of the performance function verses the iteration number. The network performance is measured in terms of mean squared error, shown in log scale. It rapidly decreased as the network was trained. The performance plot doesn't indicate any major problems with training because the validation and test curves are very similar at both ends. If the test curve increased, then it is possible that some over fitting might have occurred. Performance is shown for each of the training, validation and test sets. The version of the network that did best on the validation set was after training. The mean squared error of the trained neural network can now be measured with respect to the training samples. This will give us a sense of how will the networks will do, when data applied from real world. The average squared error is the difference between the network outputs (a) and the target outputs (t). It is defind as –

$$\text{mse} = \frac{1}{N}(C_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \quad \ldots(1)$$

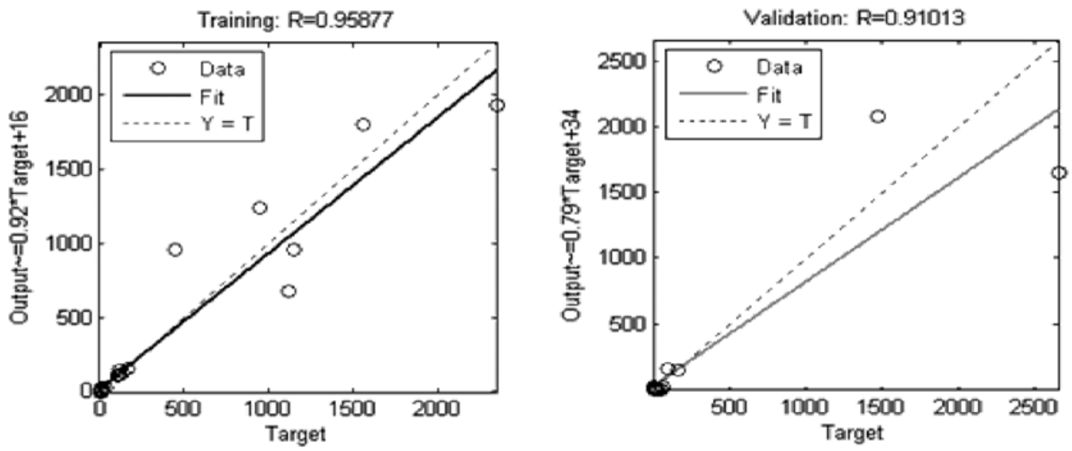

Fig. 5: Regression plot of developed NN

The regression plot represents the training, validation, testing and all data. The dashed line in each axis represents the perfect result. i.e. Output = Target. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. From the above regression, plot training data indicates a good fit. The scatter plot is helpful in showing that certain data points have poor fit. If it is, it would investigate this data point to determine, if it represents extrapolation. If so, then it should be included in the training set and additional data should be collected to be used in the test data.

Table 4: Predicted diagnosis

Predicted testing year	Predicted fault	Approximated load in MW
2014	Normal ageing	132.8
2016	Arc or flashover along with over heating	165.9
2019	Arc or flashover along with over heating	160.3
2020	Arc or flashover along with over heating	162.9

Table 4 shows that when sudden increase is there in load, beyond the rating due to utility, the thermal stress get increased, which lead degradation of insulation and possibility of arcing fault. When the loading reaches 50% of nameplate, the hot metal gases ethylene, ethane and methane starts increases. If it was unpredicted, it leads to thermal fault of 300^{o}C to 700^{o}C with high and low energy discharges. When the temperature is greater than 700^{o}C, the breakdown of oil occurs and produces acetylene. It causes a sustained arcing, a more serious operational issue that can lead transformer failure, if left unpredicted. So by predicting the dissolved gas data by regression method using Neural Network, we can deduce the health of the transformer by finding the type of fault will occur in future.

CONCLUSION

The important need for condition evaluation is that there is an aging problem of transformers installed in industries and transmission and distribution of power system network. Most of the transformers were installed 20 to 30 years ago, when large investments were made in expanding electrical power system network. These transformers have been exposed to various accumulative worsening stresses and these are in high risk of failure. So there is increase in need of reburshment, repair and replacement. Based on this view, the predictive analysis of transformer will enable the power system network to give reliable availability of power supply.

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