Fault detection in power transformers using random neural networks

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Article Info	ABSTRACT
	This paper discuss the application of artificial neural network-based algorithms to identify different types of faults in a power transformer, particularly using DGA (Dissolved Gas Analysis) test. The analysis of Random Neural Network (RNN) using Levenberg-Marquardt (LM) and Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithms has been done using the data of dissolved gases of power transformers collected from Punjab State Transmission Corporation Ltd.(PSTCL), Ludhiana, India. Sorting of the preprocessed data have been done using dimensionality reduction technique, i.e., principal component analysis. The sorted data is used as inputs to the Random Neural Networks (RNN) classifier. It has been seen from the results obtained that BFGS has better performance for the diagnosis of fault in transformer as compared to LM.

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1. INTRODUCTION

Power transformer is one of the important equipment in power system. The fault in transformer causes breakdown in power system which produces financial losses to power industry and inconvenience to the end user. In power transformers, liquid insulation in the form of mineral oil/transformer oil is being used as cooling agent. An impregnated insulation cellulose/paper is also used as solid insulation in transformer. Transformer oil as liquid insulation is very important as it provides electrical insulation, dissipates heat as cooling agent, protect the core & winding and does isolation and moreover, prevent direct contact of atmospheric oxygen with winding.

Paper insulation of winding deteriorate with time of usage which results in deterioration of solid insulation [1], [2], [3]. The liquid insulation (transformer oil) when heated up due to working of transformer, decomposes and produce gases like hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4) and ethane (C_2H_6). These gases deteriorate the quality of transformer oil and further its properties as coolant and insulator are affected which may result in breakdown of transformer as equipment in power supply. This can be prevented by knowing the amount of gases dissolved in the transformer oil at regular intervals of time of usage. The conventional methods like Roger's ratio method, Dornenburg's method, Duval's triangle method and key gas ratio methods are used to find the fault in respect of amount of harmful gases dissolved in the transformer oil. But, these methods sometimes give a false fault type [4], [5]. To improve these anomalies in conventional methods, various software based intelligent methods such as artificial neural networks [6], [7], [8], [9], [11], Wavelet Analysis, Least Vector Quotient, Probabilistic Neural Network (PNN), fuzzy logic, Support Vector Machine classifiers and Self-Organizing Map classifiers have been

proposed to find faults in transformers, [12], [13], [14], [15], [16]. As this is diagnosis process so neural network can be applied successfully [18].

This paper proposes a new ANN (Artificial neural network) based algorithm Random Neural Network to find faults in power transformers using BFGS (Broyden-Fletcher-Goldfarb-Shanno) and LM (Levenberg-Marquardt). Further, linear regression and Bland Altman techniques are used to compare BFGS and LM algorithm. Also, Receiver Operating Characteristic (ROC) curve is used to validate the results. It has been found out that BFGS outperform the LM algorithm.

2. FAULT CLASSIFICATION ALGORITHM APPROACH

Following are the steps implemented for the proposed transformer fault classification scheme. The raw data are collected from PSTCL (Punjab State Transmission Corporation Ltd.) labs and preprocessed. After that feature selection is performed so that all faults are covered in the data selected and in the last step of the classification, ANN (Artificial neural network) based classifiers have been applied to determine different faults.

3. PROBLEM FORMULATION

3.1. Dissolved gas analysis (DGA)

The DGA (Dissolved Gas Analysis) is the most common techniques used for incipient fault diagnosis. Oil samples are collected to perform DGA and hence gas amount in the oil sample. The level of gases generated in oil-filled transformer provides the first level information for fault detection in transformer based on various conventional methods. Faults in oil-filled transformers can be found out according to the amount and type of gases generated These gases are hydrogen (H_2), methane (CH_4), ethylene (C_2H_4), ethane (C_2H_6), acetylene (C_2H_2), carbon monoxide (CO), and carbon dioxide (CO_2). Various conventional methods generally based on defined principles such as gas concentrations, key gases, key gas ratios, and graphical representations. Under IEEE Standard C57.104- 2008 Key Gas Analysis, Dornenberg and Rogers Ratio Methods, Nomograph, IEC Ratio, Duval Triangle, and CIGRE Method are listed to find out faults in transformers. The DGA can find faults such as partial discharge (corona), overheating, and arcing in many different power transformers. Like a blood test in human body, DGA can provide the early diagnosis to find incipient faults and increase the chance of finding an appropriate maintenance schedule or repair if required. Table 1 shows different faults of power transformer as given by IEC/IEEE. This will be used to train RNN neural network to find fault in transformers. Currently seven methods based on dissolved gas data are used to diagnosis types of faults:

a. Key Gas Method,
b. Dornenburg Ratio Method,
c. Rogers Ratio Method,
d. Nomograph Method,
e. IEC Ratio Method,
f. Duval Triangle Method and
g. CIGRE Method.

Table 1. Faults in Power Transformers

S No	Type of Fault	Short Name	Code used for fault
1	Partial discharge	PD	0
2	Partial discharge with low energy density	D1	1
3	Partial discharge with High energy density	D2	2
4	Thermal fault with temp. less than 300° C	T1	3
5	Thermal fault with temp. between 300° C to 700° C	T2	4
6	Thermal fault with temp. greater than 700° C	T3	5

3.2. Data collection

The gas samples of transformers from various substation of Punjab State Transmission Corporation Ltd (PSTCL), Ludhiana have been used as data for analysis. The data is collected as per the American Society for Testing and Materials (ASTM) standards. After the data collection, data is processed by removing linear trends, outliers, etc. Table 2 shows the data of samples obtained from PSTCL situated in Ludhiana.Total data collected from laboratory are 700 samples. After processing 600 samples are selected and100 sample per fault are used as input data. For reference only 5 samples are shown in Table 2.

Table 2 Samples of Data of Dissolved Gases in Powertransformers

Sample No.	H2 ppm	CH4 ppm	C2H6 ppm	C2H4 ppm	C2H2 ppm
1.	95	10	0	11	39
2.	150	130	55	9	30
3.	75.03	21.99	21.86	132.99	5.56
4.	84.72	2.54	1.05	3.52	1.71
5	150	22	9	16	11

4. RANDOM NUERAL NETWORK

Random Neural Networks (RNNs) are a type of Artificial Neural Networks (ANNs) that could also be specified as type of queuing network. The information is presented as a dataset of labeled samples. The aim is "to learn" the relationship between input and output features. This learning process is done based on a set of examples in order to generate a learning model with the power of "generalising", this is to make "good" predictions for new unseen inputs. This procedure is based on the classical back propagation algorithm [11]. As in practice, the input and output variables in learning problems are bounded with known bounds, the algorithm described in [12] assumes that a (k) ∈ [0..1]I and b (k) ∈ [0..1]O, for all sample k. The RNN model as a predictor is a parametric mapping ν(a, w+, w−, L), where the parameters w+ and w− are adjusted minimizing the loss function. The network architecture is defined with I input nodes and O output nodes. There are no additional constraints regarding the network topology that means the network can be feedforward with one or several layers, or it can be recurrent network. We set the port of the input neurons each time that an input pattern a (k) is offered to the network. The inputs to the positive ports are set with the input pattern: λ+i=a (k) i; the negative ports of input neurons are conventionally set to zero (λ−i=0). The output of the model is a vector of the activity rates produced by the output neurons. The adjustable parameters of the mapping are the weights connections among the neurons. RNN is implemented using two algorithm namely LM (Levenberg-Marquardt)and BFGS(Broyden-Fletcher-Goldfarb-Shanno) algorithms.

5. RESULTS AND DISCUSSION

In LM algorithm, at each epoch μ, the approximation of the Hessian matrix is given by (1).

$$H = H^T * H \tag{1}$$

Where H is hessian matrix. The dumping factor is modified at each epoch. In this case the calculated error E2 decreases, then the dumping factor η is calculated by some constant value β known as dumping constant α ← η/β. Otherwise, the dumping value is increased by a factor of β, α← η β.

The 600 data samples collected from PSTCL lab were used for training the RNN with 100 samples for each fault. After 500 iterations error is reduced to 0.454 from 1038.21. The dumping constant for modifying the dumping factor which is taken as 3, and β=10. The LM algorithm calculate the weight correction as

$$\delta w = -G \times g \tag{2}$$

where g is gradient of input funcion and G is inverse of Hessian matrix. Then, the weights are updated by δw. Error plot as given in Figure 1.

BFGS (Broyden-Fletcher-Goldfarb-Shannon) Algorithm: The Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm for the RNN model was proposed in 2000 by Likas and Stafylopatis [16]. It is an offline algorithm. At each epoch μ approximate Hessian matrix He (τ) is computed. The method starts with Positive definite Hessian matrix, then gradient and cost function are intialised from start point. The weight correction is calculated by using same equation (2) as used for Levenberg-Marquardt function. Gradient and cost function is calculated and change in gradient function is given by the equation.

$$\delta g = g^2 - g \tag{3}$$

Using BFGS algorithm, after 500 iterations error is reduced to 0.166 from 1038.21. Error graph for BFGS is as shown in Figure 2.
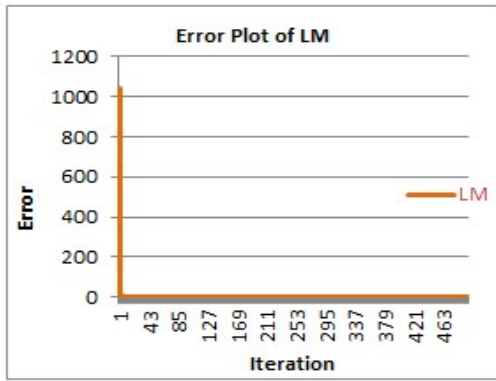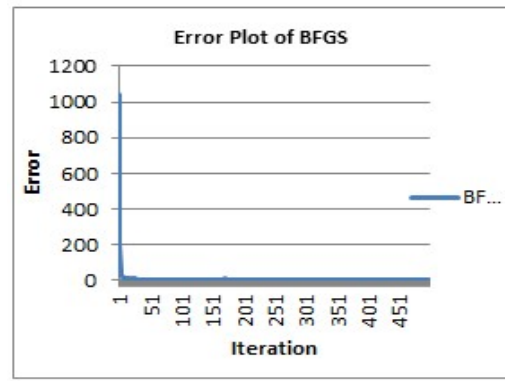
Figure 1. Error plot for LM algorithm   Figure 2. Error plot for BFGS algorithm

After training both the LM and BFGS algorithms were tested for 300 samples with 50 samples per fault. The linear regression and Bland Altman plot are used to compare clinical methods for diagnosis. In linear regression case plot between actual output and output from the proposed algorithm is plotted and gives coefficient of Determination r^2 and SSE denotes the Sum of square error [8]. It is an approach to model the relationship between actual output and output from the proposed algorithm. Regression minimizes the sum of squared differences from each point to the fitted line (or curve).

Bland-Altman plot [9] is a plot for matched pairs analysis which shows the relationship between the differences of actual and predicted output from proposed method versus the means of the these two outputs. RPC denotes reproducibility coefficient, CV is the coefficient of variation. Figure 3 and Figure 4 shows both the plots for LM and BFGS algorithms respectively.
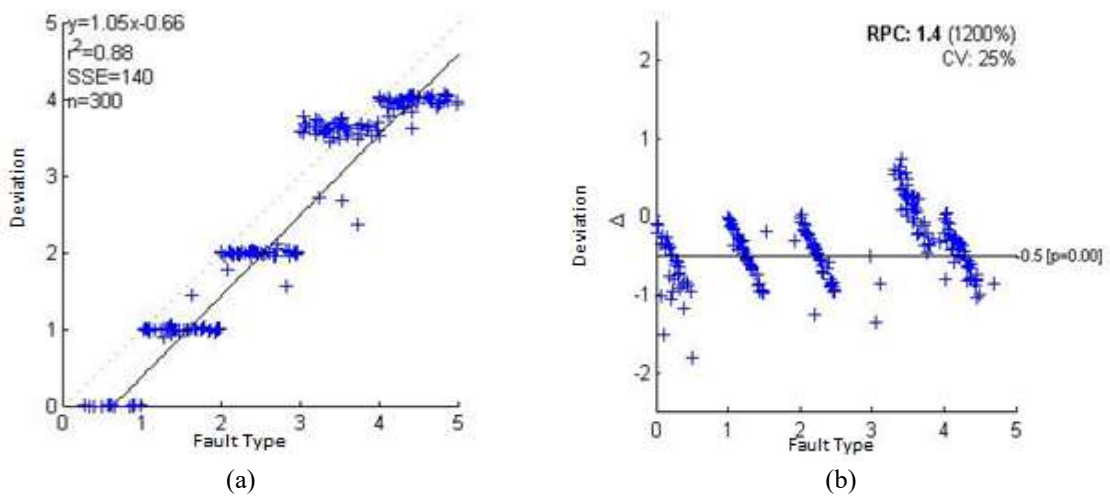

(a)   (b)

Figure 3. (a) Linear regression; (b) Bland altman plot of LM

(a)   (b)
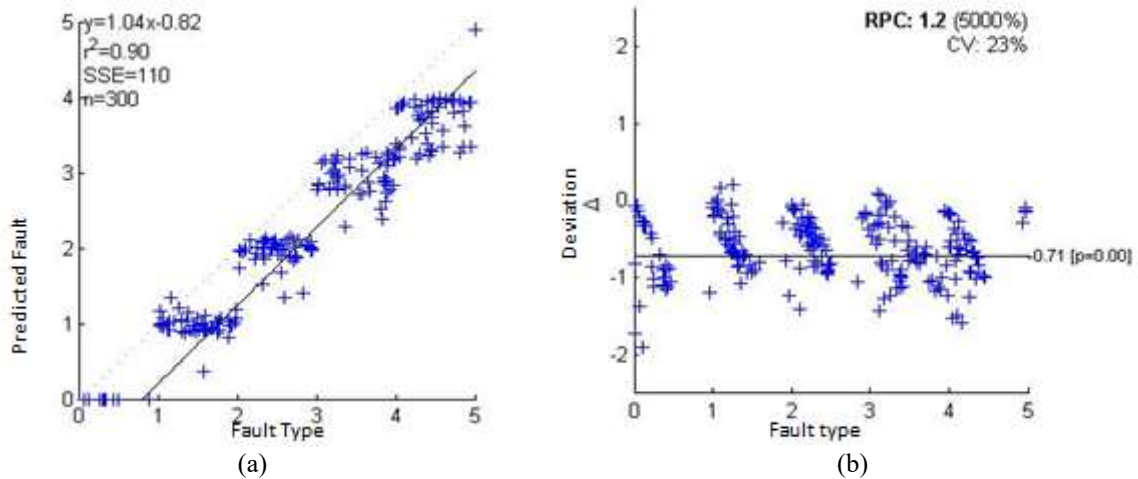
Figure 4. (a) Linear regression; (b) Bland altman plot of BFGS

A confusion matrix, also known as an error matrix is a specific table that is used to visualize the performance of an algorithm, it is usually called a matching matrix. Each row of the matrix represents the output by proposed algorithm while each column represents the actual output. Figure 5 and Figure 6 shows the confusion matrix for Random Neural Network to classify different transformer fault by using LM and BFGS algorithms. The accuracy obtained from these algorithms are 99.33% for BFGS and 94.66% for LM. These accuracies are 95.6 % for Probabilistic Neural Network classifier and 93.6 % for Backpropagation Network classifier (Levenberg–Marquardt Method) [5].

For further validation of results ROC curves [10] are plotted for both the algorithms and shown in Figure 7 and Figure 8. The Receiver Operating Characteristic (ROC) curve is a plot of the true positive rate against the false positive rate for the different possible cutpoints of a diagnostic test. AUC (Area under Curve) is equal to the probability that an algorithm will rank a randomly chosen positive instance higher than a randomly chosen negative one and is measure of test accuracy. Area under the ROC curve is 80.6% for LM algorithm while for BFGs it is 80.3 %. Table 3 shows the comparison of both algorithm based on sensitivity and specificity.
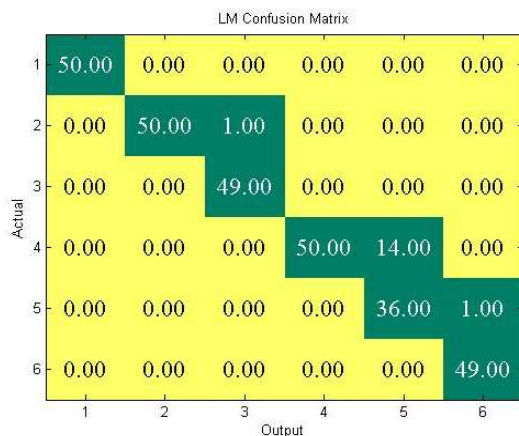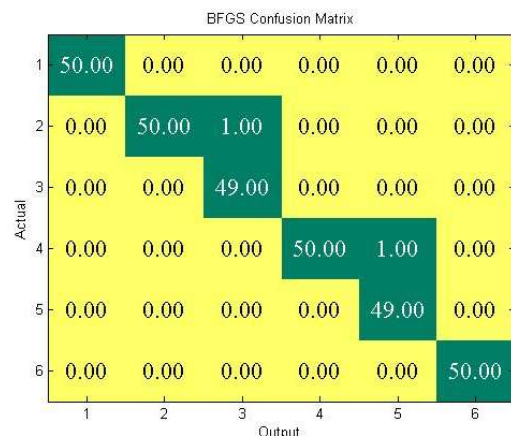

Figure 5. Confusion matrix for LM algorithm

Figure 6. Confusion matrix for BFGS algorithm

Table 3. Comparison of BFGS and LM Training Algorithm for RNN

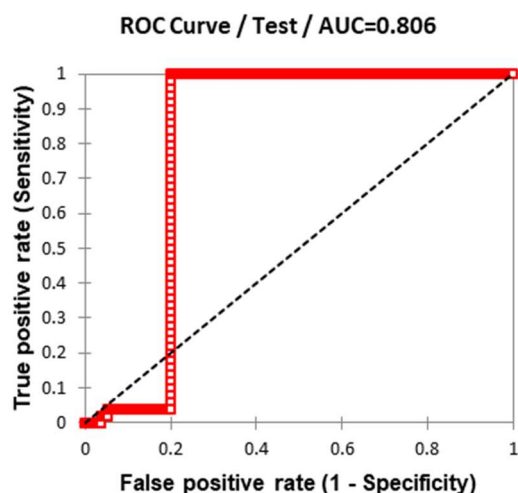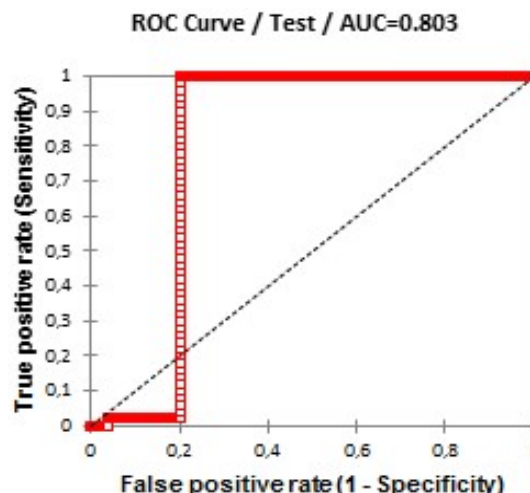| Algorithm	Recognition Rate	Sensitivity	Specificity
LM	95%	0.955	0.99
BFGS	99%	0.993	1

Figure 7. ROC for LM

Figure 8. ROC for BFGS

5. CONCLUSIONS

RNN based Fault Diagnosis method (intelligent method based on AI techniques) is projected for fault recognition in Power Transformers. Based upon the results attained, it is concluded that finding/detection of faults in Power Transformers could be efficiently done using this intelligent method. In this paper, RNN is executed by using two different algorithms i.e. LM and BFGS. Both of these algorithms are compared by using various techniques like Regression Plots, Confusion Matrix and ROC Curve (proven methods to corroborate any diagnosis test/algorithm). It is also distinguished that results from BFGS is augmented in comparison to LM algorithm. Moreover, memory requirement for BFGS is also less as compared to LM algorithm as BFGS is a Quasi-Newton method, and will converge in fewer steps [19]. Hence, proposed RNN with BFGS algorithm could effactually be implemented to diagnose fault in Power Transformers.

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