Application of Physical-Chemical Data in Estimation of Dissolved Gases in Insulating Mineral Oil for Power Transformer Incipient Fault Diagnosis with ANN

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ABSTRACT
In this paper, Artificial Neural Networks are used to solve a complex problem concerning to power transformers and characterized by non-linearity and hard dynamic modeling. The operation conditions and integrity of a power transformer can be detected by analysis of physical-chemical and chromatographic isolating oil, allowing establish procedures for operating and maintaining the equipment. However, while the costs of physical-chemical tests are smaller, the chromatographic analysis is more informative. This work presents an estimation study of the information that would be obtained in the chromatographic test from the physical-chemical analysis through Artificial Neural Networks. Thus, the power utilities can achieve greater reliability in the prediction of incipient failures at a lower cost. The results show this strategy to be a promising, with accuracy of 100% in best cases. The authors have estimated the dissolved gases in insulating mineral oil using proposed method for 185 transformers. As a result, appropriate maintenance scenario can be planned.

Keywords
Aging, Artificial Neural Network (ANN), Incipient Fault, UV/VIS, Transformer Diagnosis.

1. INTRODUCTION
The dielectric quality of the transformer insulating oil, and the incipient failures of thermal and electrical type of this equipment, can be determined from physical-chemical and chromatograph tests [1-4, 6]. These tests are important to keep the integrity of the transformers. In the meantime, while the costs of the physical-chemical tests are lower, the chromatograph one is more informative [1-4]. There are, in the technical literature, papers which point to the correlation between these two types of tests. [5-7], and this article aims at methodology to explore this co-relation when estimates the concentration of gases dissolved in insulating oil (normally obtained by chromatograph test) in function of physical-chemical characteristics of the sample. This proposal, thus, brings economic reduction in the information extractions relevant to foresee incipient failures of transformers.

The relation between the physical-chemical measures and the gases concentration is set in this paper through Artificial Neural Networks (ANN) which from example for learning how to make linear or non-linear mappings, considered universal approximators.

This document is organized as it follows. The Section 2 makes comments about the material and methodology used. The Section 3 talks about ANN and section 4 deals the estimative proposal of dissolved gases using ANN. The Section 5 deals with the calculated result verification using IEC method [8]. The results obtained are analyzed in Section 6, and the conclusions in Section 7.

2. MATERIAL AND METHODOLOGY

2.1 Power Transformer Units
Twenty five transformers from seven substations of the Himachal Pradesh Electricity Board (HPSEB), India have been used. The data is collected from the transformers maintenance records of the operation and maintenance department and oil samples were collected as per ASTM standard. The transformers have different service periods and aging conditions. The transformers ratings ranges from 6.3-52MVA and their rating voltage ratios are 132/33/11 KV.

2.2 Power Transformer Units
Available data selected from [16], it is observed that for the major five fault types, the gases dissolved in the oil are hydrogen, methane, acetylene, ethylene, ethane, and for the decomposition of cellulosic insulation, the gases dissolved in the oil are carbon monoxide and carbon dioxide. The first step for developing the neural model is feature selection. In feature selection the gases which are most important for the diagnosis of the major faults are obtained using physical-chemical data through the ANN model.

Table 1: Test Results of Some Samples Using DGA

S..N	H_2	CO_2	CO	C_2H_4	C_2H_6	CH_4	C_2H_2
1	<5	12850	283	7	8	10	<O.5
2	7	9320	726	327	106	171	<O.5
3	<5	3705	592	21	12	30	<O.5
4	1879	198	6	36	5	29	521
5	<5	1245	77	1	1	2	<O.5
6	14840	433	42	485	17	290	4895
7	16	5004	935	28	6	12	29
8	<5	442	18	2	3	1	1
9	<1	1542	103	8	8	3	8
10	1866	229	10	111	2	64	1265
11	<5	51	<1	<1	<1	<O.5	<O.5

The chromatographic analysis is sensitive to atmospheric condition; therefore, it is highly recommended to perform such test away from interfering conditions like sources of CO_2. The DGA is performed using the IEC 567 method.

3. ARTIFICIAL NEURAL NETWORK

Neural networks are a relatively new artificial intelligence technique. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. The learning procedure tries is to find a set of connections '***w***' that gives a mapping that fits the training set well. Furthermore, neural networks can be viewed as highly nonlinear functions with the basic the form

$$F(x, w) = y$$

Where '***x***' is the input vector presented to the network, '*w*' are the weights of the network, and ***y*** is the corresponding output vector approximated or predicted by the network. The weight vector '*w*' is commonly ordered first by layer, then by neurons, and finally by the weights of each neuron plus its bias. This view of network as a parameterized function will be the basis for applying standard function optimization methods to solve the problem of neural network training.

3.1 ANN Structure

A neural network is determined by its architecture, training method and exciting function. Its architecture determines the pattern of connections among neurons. Network training changes the values of weights and biases (network parameters) in each step in order to minimize the mean square of output error.

Multi-Layer Perceptron (MLP) has been used in load forecasting, nonlinear control, system identification and pattern recognition, thus in this paper multi-layer perceptron network (with two inputs, one outputs and a hidden layer) with Levenberg-Marquardt training algorithm have been used.

In general, on function approximation problems, for network that contain up to a few hundred weights, the Levenberg-Marquardt algorithm has the fastest convergence. This advantage is especially noticeable if very accurate training is required. In many cases, *'trainlm'* is used to obtain lower mean square error (MSE) than any other algorithms tested. As the number of weights in the network increases, the advantage of *'trainlm'* decreases. In addition *'trainlm'* performance is relatively poor on pattern recognition problems. The storage requirements of *'trainlm'* are larger than the other algorithm tested.

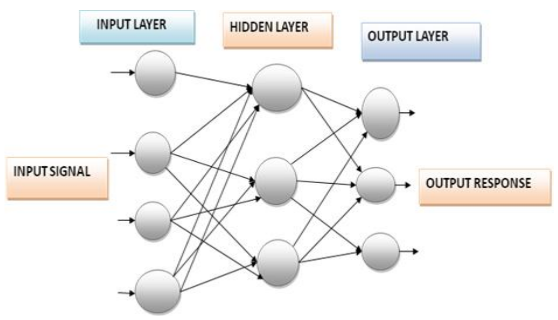


Fig. 1: Artificial Neural Network

3.2 Input and Output of ANN

A neural network is a data modeling tool that is capable to represent complex input/output relationships. ANN typically consists of a set of processing elements called neurons that interact by sending signals to one another along weighted connections. The required data are the data which have been accumulated by physical-chemical and chromatographic test results. In last recent four years, conventional methods are used for estimating the dissolved gases in oil of transformers and consequently transformer operating condition is estimated by proposed method. The schematic of the presented method can be shown by Fig. 2.

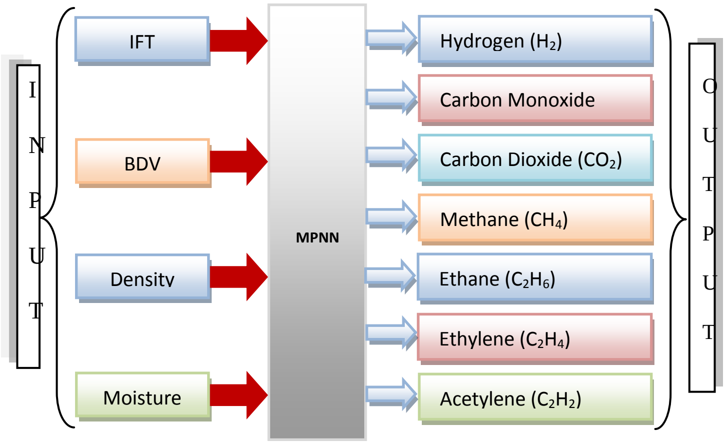


Fig. 2: Schematic Scheme for Inputs and Outputs

3.3 Training of ANN

The major justification for the use of ANNs is their ability to learn relationships in complex data sets that may not be easily perceived by engineers. An ANN performs this function as a result of training that is a process of repetitively presenting a set of training data (typically a representative subset of the complete set of data available) to the network and adjusting the weights so that each input data set produces the desired output.

The back propagation training algorithm is a method of iteratively adjusting the neural network weights until the desired accuracy level is achieved. It is based on a gradient-search optimization method applied to an error function.

3.4 Applying the ANN for the Dissolved Gases Estimation

As already mentioned, the ANN are applied in the stages of the estimation of dissolved gasses where the relationships among the variables are not well defined and where the empirical knowledge is otherwise the only way to get the desired parameters. It is the case of, for example, getting the dissolved gasses initial parameters or the prediction of the dissolved gasses.

The methodology presented in this work applies multilayer perceptron neural networks in seven different stages of the seven gases, as detailed in Table 2. The purpose of the procedure is to use the ANN to identify the relationships among the several variables involved in estimating the dissolved gasses in oil. The systems that correspond to specific application aspects of this methodology are presented in the next section.

Table 2: PHASES OF THE GAS ESTIMATION PROCEDURE WHERE THE ANN APPROACH IS APPLIED AND THE RESPECTIVE NETWORKS

Network	Stage of the project
I	Prediction of the hydrogen (H_2)
II	Prediction of the carbon dioxide (CO_2)
III	Prediction of the carbon monoxide (CO)
IV	Prediction of the ethylene (C_2H_4)
V	Prediction of the Ethane (C_2H_6)
VI	Prediction of the methane (CH_4)
VII	Prediction of the acetylene (C_2H_2)

4. Estimation of Dissolved Gases Using ANN

Considering the results obtained in [14], were definite the physical-chemical characteristics which influence in the quality of insulating oil. The vector of input to be applied to ANN is constituted by the certain elements: Acidity, Breakdown Voltage, Water Content, Interfacial Tension, Density and Oil Power Factor.

The estimation of dissolved gases is obtained in the output of the neural network. The estimated gases are necessaries to make the diagnostic of incipient failures in transformers [1-4, 11]. Thus, the concentrations of the followed gases were estimated: Hydrogen (H_2), Carbon Monoxide (CO), Carbon Dioxide (CO_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4) and Acetylene (C_2H_2).

It was conceived one ANN to each gas to be estimated with just one neuron of output. Therefore, the seven neural networks give the associate linking between the physical-chemical measures of input and the dissolved gases in oil of output. Tests were done to the estimation of gases dissolved in the oil of the transformer from physical-chemical analyze with one architecture of ANN: (i) Network MLP (Multi Layer Perceptron), with algorithm of training Levenberg-Marquardt with incremental strategy of increase of new neurons in the hidden layer to better mapping.

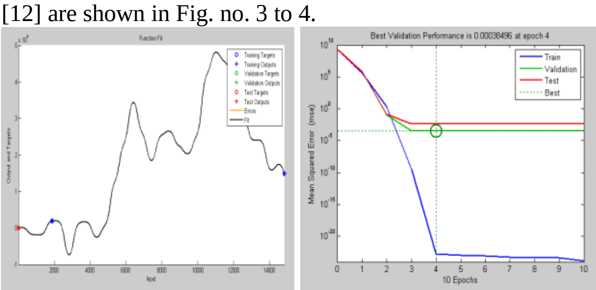
4.1 Estimation of Hydrogen (H_2)

In this specific calculation process, the input variables for the network I are the wished final parameters. The output variable (to be estimated by the network) is first dissolved gas parameter. The proposed simulation model developed was able to estimate hydrogen (H_2) with more than 99.999% accuracy compared to the measurement result from Kalman Transport-X DGA analyzer as per ASTM D3612. Summary of the percentage of error for the simulation model compared to spectrophotometer measurement result is shown in table 3.

Table 3: Comparison between simulation and field measurement results

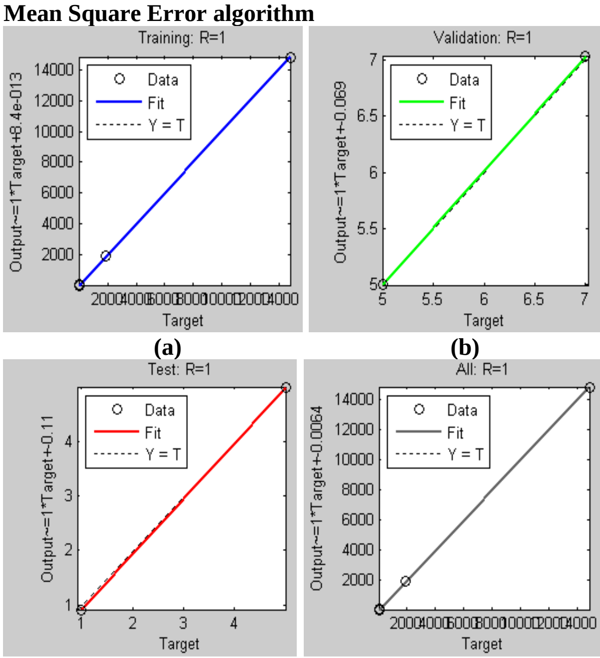
Sample No	Input				Output		(%) age of error
	IFT	MOISTURE	BDV	DENSITY	DGA Based H_2	ANN Based H_2	
1	26.1	5.7	61.62	0.813	<5	4.999	0.0
2	43.7	9.43	44.14	0.823	7	7	
3	21.9	49.49	37.6	0.866	<5	4.999	
4	29.6	35	23.2	0.81	1879	1879	
5	33.8	5	85.1	0.81	<5	4.999	
6	38.9	18	68.1	0.82	14840	14840	
7	38.7	3	68	0.81	16	16	
8	23.4	9	61.44	0.81	<5	4.999	
9	34.8	18	46.36	0.81	<1	0.999	
10	26.8	12	69.22	0.81	1866	1866	
11	32.7	3	48	0.816	<5	4.999	

As examples of the kind of graphical results for H_2 that are estimated by ANN network I using matlab simulation tool box [12] are shown in Fig. no. 3 to 4.



(a) **(b)**

Fig. 3: (a) Data fit plot, (b) Performance graph based on Mean Square Error algorithm



(a) **(b)**

(c) **(d)**

Fig. 4 Prediction of H_2 in mineral insulating oil of transformer during (a) training analysis, (b) validation analysis, (c) test analysis, (d) Regression plot

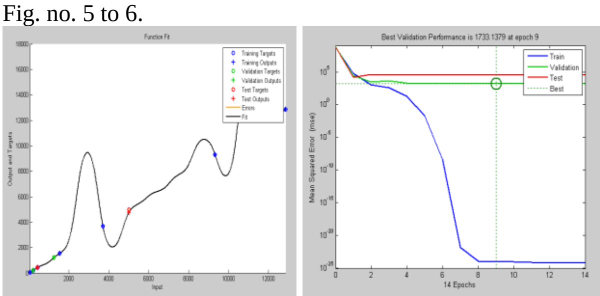
4.2 Estimation of Carbon Dioxide (CO_2)

The simulation model developed was able to estimate carbon dioxide (CO_2) with more than 99.98% accuracy compared to the measurement result from ASTM D3612. Summary of the percentage of error for the simulation model compared to spectrophotometer measurement result is shown in table 4.

Table 4: Comparison between simulation and field measurement results

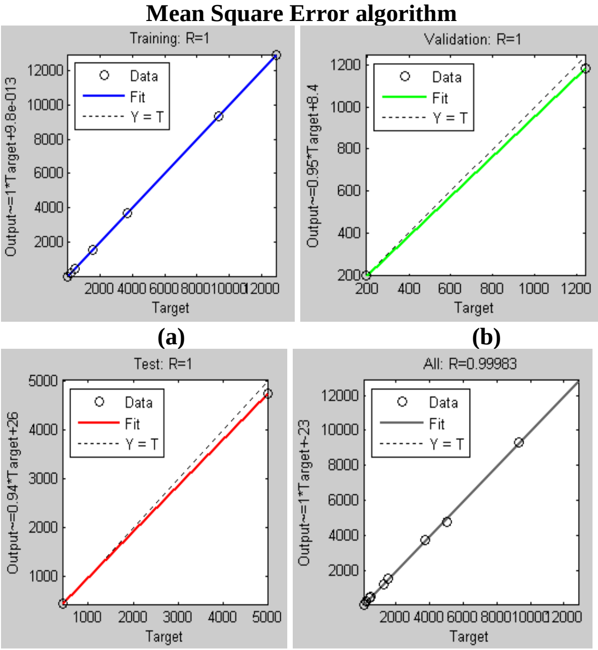
Sample No	Input				Output		(%) age of error
	IFT	MOISTURE	BDV	DENSITY	DGA Based CO_2	ANN Based CO_2	
1	26.1	5.7	61.62	0.813	12850	12847.8	-0.017
2	43.7	9.43	44.14	0.823	9320	9318.41	
3	21.9	49.49	37.6	0.866	3705	3704.37	
4	29.6	35	23.2	0.81	198	197.96	
5	33.8	5	85.1	0.81	1245	1244.78	
6	38.9	18	68.1	0.82	433	432.9	
7	38.7	3	68	0.81	5004	5003.14	
8	23.4	9	61.44	0.81	442	441.92	
9	34.8	18	46.36	0.81	1542	1541.73	
10	26.8	12	69.22	0.81	229	228.96	
11	32.7	3	48	0.816	51	50.99	

Obtained ANN based graphical results for CO_2 by ANN network II from matlab simulation tool box [12] are shown in Fig. no. 5 to 6.



(a) (b)

Fig. 5: (a) Data fit plot, (b) Performance graph based on Mean Square Error algorithm



(a) (b)

(c) (d)

Fig. 6 Prediction of CO_2 in mineral insulating oil of transformer during (a) training analysis, (b) validation analysis, (c) test analysis, (d) Regression plot

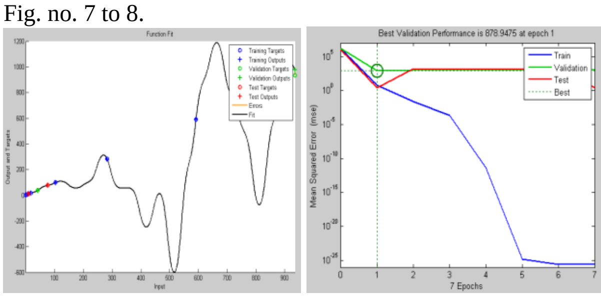
4.3 Estimation of Carbon Monoxide (CO)

Developed simulation model was able to estimate carbon monoxide (CO) with more than 99.99% accuracy compared to the measurement result from ASTM D3612. Summary of the percentage of error for the simulation model compared to spectrophotometer measurement result is shown in table 5.

Table 5: Comparison between simulation and field measurement results

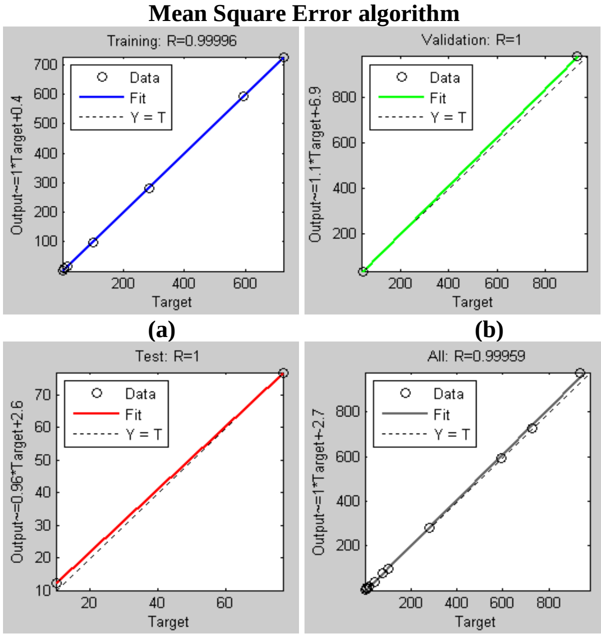
Sample No	Input				Output		Percentage of error
	IFT	MOISTURE	BDV	DENSITY	DGA Based CO	ANN Based CO	
1	26.1	5.7	61.62	0.813	283	282.88	-0.041
2	43.7	9.43	44.14	0.823	726	725.70	
3	21.9	49.49	37.6	0.866	592	591.75	
4	29.6	35	23.2	0.81	6	5.9975	
5	33.8	5	85.1	0.81	77	76.968	
6	38.9	18	68.1	0.82	42	41.98	
7	38.7	3	68	0.81	935	934.61	
8	23.4	9	61.44	0.81	18	17.99	
9	34.8	18	46.36	0.81	103	102.95	
10	26.8	12	69.22	0.81	10	9.9959	
11	32.7	3	48	0.816	<1	0.9994	

Obtained ANN based graphical results for CO by ANN network III from matlab simulation tool box [12] are shown in Fig. no. 7 to 8.



(a) (b)

Fig. 7: (a) Data fit plot, (b) Performance graph based on Mean Square Error algorithm



(a) (b)

(c) (d)

Fig. 8 Prediction of H_2 in mineral insulating oil of transformer during (a) training analysis, (b) validation analysis, (c) test analysis, (d) Regression plot

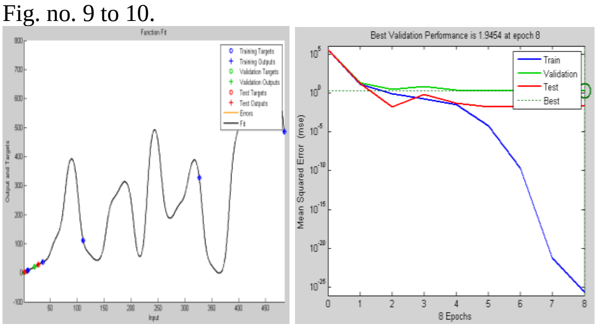
4.4 Estimation of Ethylene (C_2H_4)

The simulation model developed was able to estimate ethylene (C_2H_4) with more than 99.99% accuracy compared to the measurement result from ASTM D3612. Summary of the percentage of error for the simulation model compared to spectrophotometer measurement result is shown in table 6.

Table 6: Comparison between simulation and field measurement results

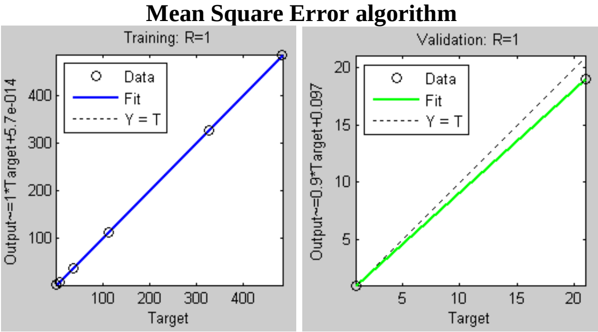
Sample No	Input				Output		Percentage of error (%)
	IFT	MOISTURE	BDV	DENSITY	DGA Based C_2H_4	ANN Based C_2H_4	
1	26.1	5.7	61.62	0.813	7	6.999	-0.001
2	43.7	9.43	44.14	0.823	327	326.99	
3	21.9	49.49	37.6	0.866	21	20.999	
4	29.6	35	23.2	0.81	36	35.999	
5	33.8	5	85.1	0.81	1	0.9999	
6	38.9	18	68.1	0.82	485	484.99	
7	38.7	3	68	0.81	28	27.999	
8	23.4	9	61.44	0.81	2	1.9999	
9	34.8	18	46.36	0.81	8	7.9999	
10	26.8	12	69.22	0.81	111	110.99	
11	32.7	3	48	0.816	<1	0.9998	

Obtained ANN based graphical results for C_2H_4 by ANN network IV from matlab simulation tool box [12] are shown in Fig. no. 9 to 10.

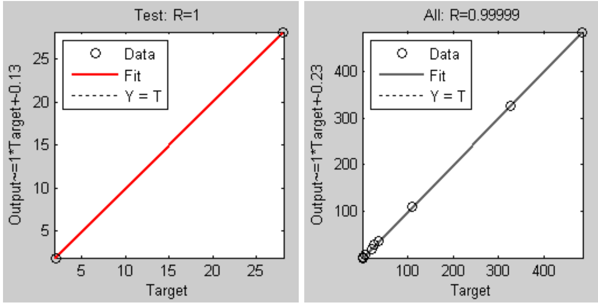


(a) **(b)**

Fig. 9: (a) Data fit plot, (b) Performance graph based on Mean Square Error algorithm



(a) **(b)**



(c) **(d)**

Fig. 10 Prediction of H_2 in mineral insulating oil of transformer during (a) training analysis, (b) validation analysis, (c) test analysis, (d) Regression plot

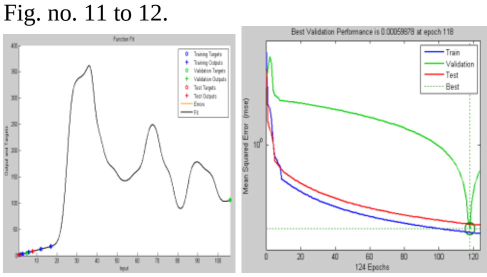
4.5 Estimation of Ethane (C_2H_6)

The simulation model developed was able to estimate ethane (C_2H_6) with more than 99.999% accuracy compared to the measurement result from ASTM D3612. Summary of the percentage of error for the simulation model compared to spectrophotometer measurement result is shown in table 7.

Table 7: Comparison between simulation and field measurement results

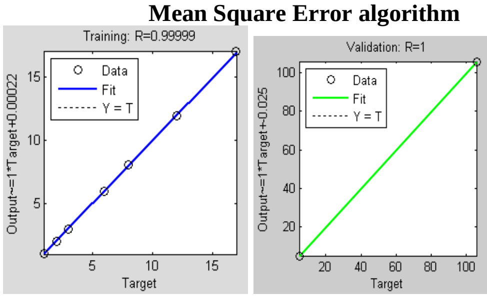
Sample No	Input				Output		Percentage of error
	IFT	MOISTURE	BDV	DENSITY	DGA Based C_2H_6	ANN Based C_2H_6	
1	26.1	5.7	61.62	0.813	8	8	0.0
2	43.7	9.43	44.14	0.823	106	106	
3	21.9	49.49	37.6	0.866	12	12	
4	29.6	35	23.2	0.81	5	5	
5	33.8	5	85.1	0.81	1	1	
6	38.9	18	68.1	0.82	17	17	
7	38.7	3	68	0.81	6	6	
8	23.4	9	61.44	0.81	3	3	
9	34.8	18	46.36	0.81	8	8	
10	26.8	12	69.22	0.81	2	2	
11	32.7	3	48	0.816	<1	0.9999	

Obtained ANN based graphical results for C_2H_6 by ANN network V from matlab simulation tool box [12] are shown in Fig. no. 11 to 12.

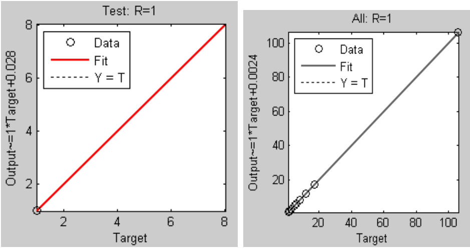


(a) **(b)**

Fig. 11: (a) Data fit plot, (b) Performance graph based on Mean Square Error algorithm



(a) **(b)**



(c) (d)

Fig. 12 Prediction of H_2 in mineral insulating oil of transformer during (a) training analysis, (b) validation analysis, (c) test analysis, (d) Regression plot

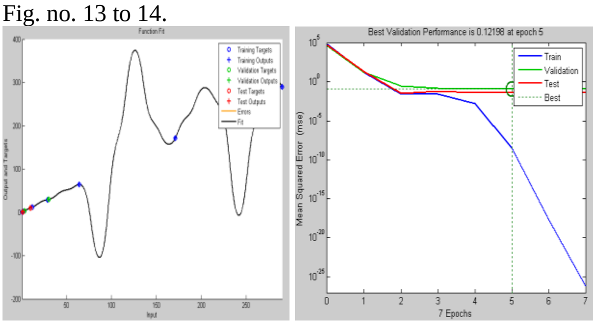
4.6 Estimation of Methane (CH_4)

The simulation model developed was able to estimate methane (CH_4) with more than 99.999% accuracy compared to the measurement result from ASTM D3612. Summary of the percentage of error for the simulation model compared to spectrophotometer measurement result is shown in table 8.

Table 8: Comparison between simulation and field measurement results

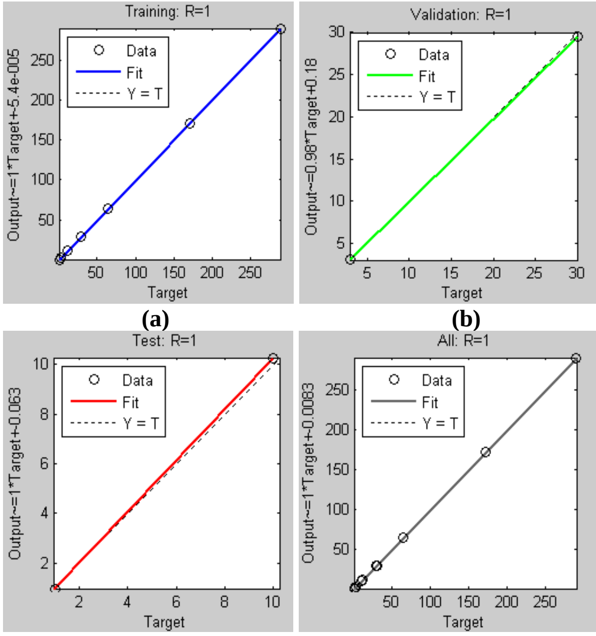
Sample No	Input				Output		Percentage of error
	IFT	MOISTURE	BDV	DENSITY	DGA Based CH_4	ANN Based CH_4	
1	26.1	5.7	61.62	0.813	10	10	
2	43.7	9.43	44.14	0.823	171	171	
3	21.9	49.49	37.6	0.866	30	30	
4	29.6	35	23.2	0.81	29	29	
5	33.8	5	85.1	0.81	2	2	
6	38.9	18	68.1	0.82	290	290	0.0
7	38.7	3	68	0.81	12	12	
8	23.4	9	61.44	0.81	1	1	
9	34.8	18	46.36	0.81	3	3	
10	26.8	12	69.22	0.81	64	64	
11	32.7	3	48	0.816	<O.5	0.4999	

Obtained ANN based graphical results for CH_4 by ANN network VI from matlab simulation tool box [12] are shown in Fig. no. 13 to 14.



(a) (b)

Fig. 13: (a) Data fit plot, (b) Performance graph based on Mean Square Error algorithm



(a) (b)

(c) (d) **Fig. 14 Prediction of H_2 in mineral insulating oil of transformer during (a) training analysis, (b) validation analysis, (c) test analysis, (d) Regression plot.**

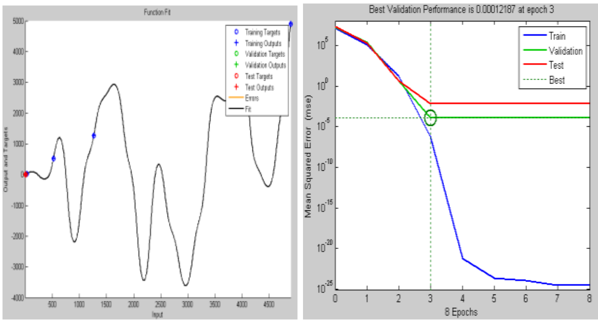
4.7 Estimation of Acetylene (C_2H_2)

The simulation model developed was able to estimate acetylene (C_2H_2) with more than 99.99% accuracy compared to the measurement result from ASTM D3612. Summary of the percentage of error for the simulation model compared to spectrophotometer measurement result is shown in table 9.

Table 9: Comparison between simulation and field measurement results

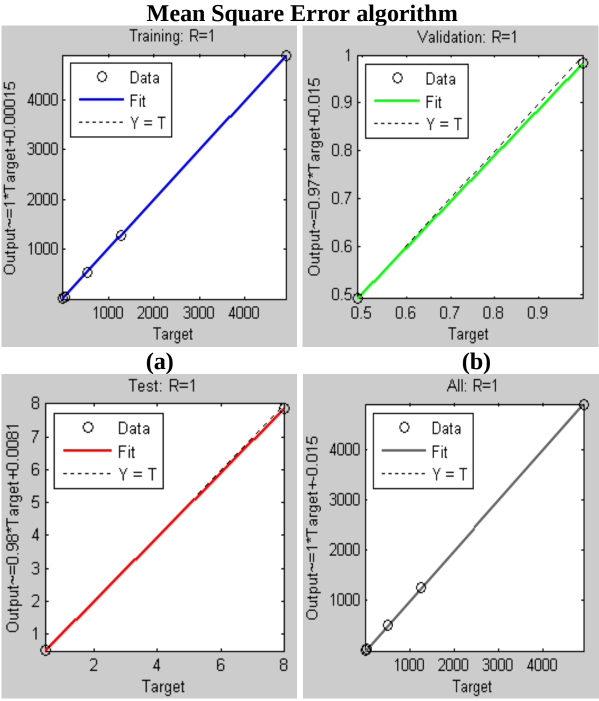
Sample No	Input				Output		age of (%)
	IFT	MOISTURE	BDV	DENSITY	DGA Based C_2H_2	ANN Based C_2H_2	
1	26.1	5.7	61.62	0.813	<O.5	0.4999	
2	43.7	9.43	44.14	0.823	<O.5	0.4999	
3	21.9	49.49	37.6	0.866	<O.5	0.4999	
4	29.6	35	23.2	0.81	521	521	
5	33.8	5	85.1	0.81	<O.5	0.4999	
6	38.9	18	68.1	0.82	4895	4895	0.0
7	38.7	3	68	0.81	29	29	
8	23.4	9	61.44	0.81	1	1	
9	34.8	18	46.36	0.81	8	8	
10	26.8	12	69.22	0.81	1265	1265	
11	32.7	3	48	0.816	<O.5	0.4999	

Obtained ANN based graphical results for C_2H_2 by ANN network VII from matlab simulation tool box [12] are shown in Fig. no. 15 to 16.



(a) (b)

Fig. 15: (a) Data fit plot, (b) Performance graph based on Mean Square Error algorithm



(a) (b)

(c) (d)

Fig. 16 Prediction of H_2 in mineral insulating oil of transformer during (a) training analysis, (b) validation analysis, (c) test analysis, (d) Regression plot

5. CALCULATED RESULT VALIDATION BY FAULT DIAGNOSIS TECHNIQUE

According to the different faults, transformer faults are classified into five types using fault classification method of IEC60599 for oil-immersed transformer as shown in table no. 10.

The fault diagnosis method of gases dissolved in transformer oil can reflect the latent failure in transformer. The accuracy of modified three-ratio method is the highest in various diagnostic methods, so the three characteristic values (CH_4/H_2, C_2H_2/C_2H_4 and C_2H_4/C_2H_6) of gases dissolved in transformer oil are taken for estimation of fault type Based on Obtained Dissolved Gases By DGA and Fault type Based on calculated Dissolved Gases by ANN. As per reference [20], some analytical comparison is shown in table no.11.

Table 10: Classification of Transformer Fault

Nature of Fault	**Expression of set of fault**
Low-energy discharge	1
High-energy discharge	2
General superheating	3
Serious superheating	4
Partial discharge	5

After analysis of the actual fault based on obtained dissolved gases by DGA and based on calculated dissolved gases by ANN, we conclude that faults are same in both conditions. TABLE 11 lists actual faults data detected by sampling and purposed method.

Table 11. Sample Data of Tran sformer Fault

Sample No.	**Fault type Based on Obtained Dissolved Gases By DGA**				**Fault type Based on calculated Dissolved Gases by ANN**			
	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6	Fault type	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6	Fault type
1	<0.071429	>2	0.875	3	0.071424	2.0004	0.874875	3
2	<0.001529	24.42857	3.084906	4	0.001529	24.4285	3.084811	4
3	<0.02381	>6	1.75	3	0.023806	6.0012	1.749917	3
4	<14.4722	0.015434	7.2	3	14.72624	0.015434	7.1998	3
5	0.5	>0.4	1	1	0.49995	0.400008	0.9999	1`
6	10.09278	0.019542	28.529412	3	10.092992	0.019542	28.52882	3
7	1.035714	0.75	4.66666	2	1.035751	0.75	4.6665	2
8	0.5	>0.2	0.6666	3	0.500025	0.20004	0.666633	3
9	1	>3	1	3	1.000013	3.003003	0.999987	3
10	11.396396	0.034298	55.5	3	11.397423	0.34298	55.495	3
11	0.5	0.1	1	1	0.5	0.1	0.9999	1

6. RESULT AND DISCUSSION

From the database of chromatography and physicalchemical analyzes were used 190 samples, extracted from TIFAC-CORE Lab, NIT Hamirpur, India and [18] to fulfill the training stages, validation and developed Neural Networks.

In purposed ANN model, the samples of training, validation and test present, 132, 29 and 29 samples respectively for dissolved gases in oil estimation. Samples taken from TIFAC-CORE Lab are used as testing data, some of them are shown in table no.1.

Proposed simulation model was able to estimate the dissolved gases using physical-chemical data with more than 99.9% accuracy compared to the measurement result from Kalman Transport-X DGA analyzer. Summary of the percentage of error for the simulation model compared to chromatographic (DGA-Analyzer) measurement result is shown in table 3-9.

7. CONCLUSIONS

A reliable and efficient neural dissolved gases estimation approach has been developed and implemented in this paper. This ANN model was formulated by applying the feature selection concept on the training data and thereafter on the selected input features, which were further optimized using the neural-network back propagation algorithm. After completion of training, testing data were applied. The results obtained from the proposed ANN model were then compared with the chromatographic method and both results were also compared by IEC-60599 fault diagnosis three ratio method. The comparison with the different chromatographic results leads to the observation that the proposed approach was successfully tested and provided similar results.

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