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Neural Fuzzy Approach for incipient faults for Fault Diagnosis of Transformers

P. Lakshmi Supriya, Assistant Professor, Dept. of EEE, M.G.I.T, Hyderabad, India, plsupriya18@gmail.com,

P.Ram Kishore Kumar Reddy, Professor, Dept. of EEE, M.G.I.T, Hyderabad, India, prkkreddy252@gmail.com,

P.Sujatha, Professor, Dept. of EEE, JNTUCEA, Anantapuramu, India, psujatha1993@gmail.com.

Abstract **The promising diagnosis method for power transformer incipient faults is the dissolved gas in analysis (DGA). certain strategies are developed to illustrate DGA outcomes viz. key gas method, and roger's ratio method. The described approach utilizes ratio method to discriminate fault in transformers. Few concentrations of gases by using the DGA were mismatched by the existing codes, making the diagnosis failure in incipient faults. To overcome failure in diagnosis, the fault data is trained with neural networks and is applied to compute membership function parameters of fuzzy inference system. The Proposed work is focused on development of Neuro-Fuzzy technique for Transformer internal faults prediction. It predicts incipient faults such as arcing, corona, Partial discharge and overheating accurately. Tests using this technique have given promising results in comparison with neural approach.**

Keywords* — *Dissolved Gas Analysis, Doernenberg's ratio method, transformer, neural-fuzzy model

I. Introduction

Power transformers are undoubtedly the primary energetic device in an electrical power network. Incipient faults are effervescent inside the chamber of transformer. Faults origin overheating, discharge and arcing corona. Their Precise identification is essential for protection and reliability of an electrical network. Due to which Power transformer in operation undergoes electrical and thermal stresses. Numerous interpretive techniques based on DGA method have been developed to diagnose transformer deterioration.

Even if DGA analysis has been used broadly in the industry, in few instances, the classical approaches fail to identify type of incipient faults in transformer. Diagnostic approaches with ratio of gases of single or multiple faults are dominant in a transformer analysis. Generated gases creates complex environment inside the transformer [1], which mismatches Pre-defined codes.

The originated gaseous state inside the chamber due to incipient faults contain hydrogen (H2), acetylene (C2H2), ethylene (C2H4), ethane (C2H6), methane (CH4), carbon monoxide (CO) and carbon dioxide (CO). An ANSI/IEEE standard and IEC publication 599 [2], describes three DGA approaches: i) key gas method; ii) Roger's ratio method; and iii) the Doernenberg ratio method, and recently, the artificial intelligent methods which were developed from rigorous studies on gases generated from incipient faults and all three methods are computationally straightforward.

The key gas method relates "key gases" to "fault types" and aims to recognize four types of fault (arcing, corona, Partial discharge and overheating). The ratio methods use coding approach that consigns specific combination of codes to a incipient fault type[3]. The codes are formed by computing gas ratios and associating the ratios to pre-defined ratio intervals. The two widely used ratio methods are the Dornenberg Ratio Method and the Rogers Ratio Method. The latter can distinguish between low temperature, <700°C and >700°C in thermal faults.

Several soft computing strategies have been presented in the literature for exact diagnosis and they are typically adequate for transformers with a single fault or a dominant fault. In general, each strategy is still attributed to particular set of codes specified from reliable gas ratios. Moreover the deficiencies in the earlier fuzzy diagnosis methods [4] such as application of the simple trapezoidal membership function may not be proper choice for the illustration of the boundary of IEC codes. Ultimately, no presentation was highlighted in the examination of condition monitoring of insulation. The above problems can be tackled with a new strategy that has been developed by employing Neuro fuzzy boundaries [5-9] to key gases. The fuzzy inference method is employed for modeling the boundaries and shape of the membership functions depends on level of gas. The fault prediction inside the transformer chamber can be accurately

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done by the fuzzy vector. The strategy is useful to monitor rise in concentrations of gases when two or more faults occurred simultaneously. The local insulation deterioration may also be determined. The Neuro fuzzy diagnosis method [10-12] computational characteristics are fast and appropriate for practical solution.

The paper description is as follows. In Sections II and III, we take a short review of proposed neuro-fuzzy model. Then, fault diagnosis of power transformer based on neuro-fuzzy is analyzed in Section IV. Finally, in Section V concludes the proposed work.

II. NEURO-FUZZY APPROACH

Adaptive Neuro-fuzzy inference system (ANFIS) integrates Sugeno fuzzy inference models with multilayer feed-forward neural networks utilizing the properties of logical capability from fuzzy systems and computation capability from artificial neural network. Neuro-Fuzzy modeling uses input/output data for establishing the fuzzy model.

Application of back-propagation or steepest descent takes long time to identify parameters in adaptive network. Thus hybrid leaning approach combining linear least square estimator and steepest descent is used for fast identification of parameters. Computational complexity of least square estimator is higher than steepest descent. But LSE is much faster. In Hybrid learning each epoch composed of forward pass and backward pass and its procedure is described in Table 1

Table 1 Hybrid Learning Procedure

	Forward pass	Backward pass
Premise Parameters	Fixed	Gradient descent
Consequent Parameters	Least square estimator	Fixed
Signals	Node outputs	Error Signals

A hybrid learning algorithm, which is the combination of least square method and back propagation gradient decent method, is applied to compute membership function parameters of fuzzy inference system.

ANFIS has advantage of both ANN and fuzzy logic, and defuzzification is not needed for its output. Consequently, ANFIS has been widely utilized in different fields. In addition, fault diagnosis accuracy of ANFIS is superior to that of fuzzy logic, thus ANFIS is adopted to set up fault diagnosis models instead of fuzzy logic.

III. NEURO-FUZZY MODELING

The ANFIS network is composed of several nodes connected by directional links, and the network structure is shown as Figure 1. Nodes for input and output membership function are adaptive (represented by squares), while other nodes are fixed (represented by circles). The links indicate directions of signals between nodes and no weights are associated with the links. The characteristics of variables associated with nodes are going to be modified as per its learning rule which determines its output. ANFIS Model has fixed or adaptive characteristic nodes. Adaptive node output is absolutely depends on node characteristics. The basic structure of ANFIS is composed of five layers: input membership function layer, rule layer, normalization layer, output membership function layer and output layer. The input membership function layer has adaptive nodes and performs fuzzification of the inputs. The layered outputs signify the membership grade of inputs.

Layer 1 is named as input layer that comprises of m^2 nodes where m is number of inputs. Fig.1 shows simple ANFIS Architecture. It is described as follows

i) two inputs x and y

ii) 4 nodes in First layer (A1, A2, B1, B2) each node constitutes a fuzzy set. The output of each node signifies membership of corresponding fuzzy set.

iii) Second Layer is named as input membership function layer. It comprises fixed nodes that are conditioned to carry out multiplication of incoming signal. Here the output w1=A1×B1 and w2=A2×B2.

iv) Third layer is named as rule function layer. It has two fixed nodes and by performing normalization the outputs w_1^* and w_2^* are computed which are given by

$$W_1^* = \frac{w_1}{w_1 + w_2} \ \& \ W_2^* = \frac{w_2}{w_1 + w_2}$$

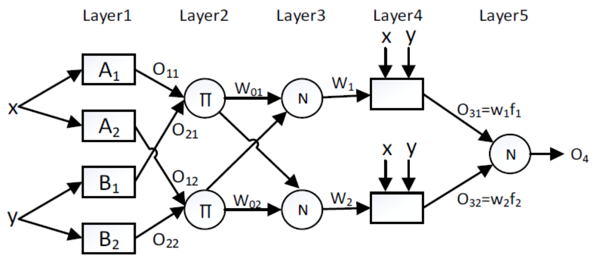

Fig.1 ANFIS Architecture

v) Fourth layer in named as membership function output layer. The output is subjected to adaptive parameter nodes. Sugeno Fuzzy inference output is determined with subsequent parameter nodes. Outputs of layer 4 are denoted as O_{31} and O_{32}

vi) Fifth layer is named as output layer where in only node labeled Σ that executes the addition of all incoming signals.

IV. FAULT DIAGNOSIS

The diagnosis of several kinds of faults in a transformer can be improved by using ANFIS structure. The limitations of standard approaches can overcome by means of ANFIS.

Initially the model is trained precisely based on data of faulty gases and then trained model is used to detect various

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faults of transformer. The ANFIS structure of proposed method is shown in Fig.2.

During the training process, each type of fault is trained with set of input and output data exemplars. Once the training process of ANFIS Model is accomplished, its feasibility is tested with test data. The ANFIS model of fault diagnosis is represented in Fig.3

The present is focused on Sugeno Fuzzy Inference system. The gaseous concentrations CH4, H2, C2H2, C2H4, and C2H6, denoted from Fig 4 to 8, are used as inputs. Each input has 3 membership functions. The state of transformer is represented with 12 membership functions subjected to different gaseous concentrations. The developed ANFIS Rule base is presented in Fig.9.

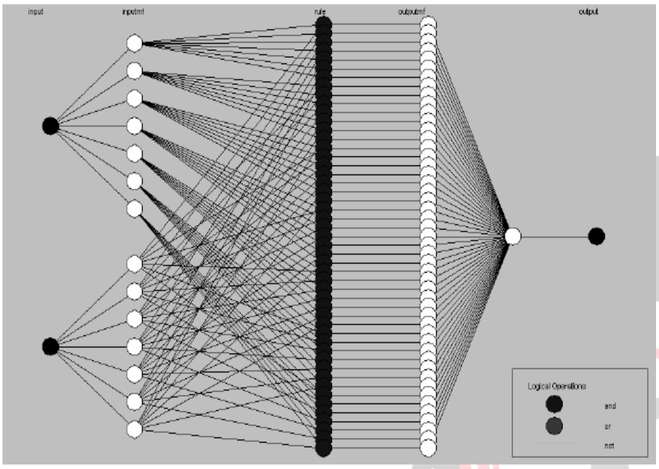

Fig.2 ANFIS structure of proposed method

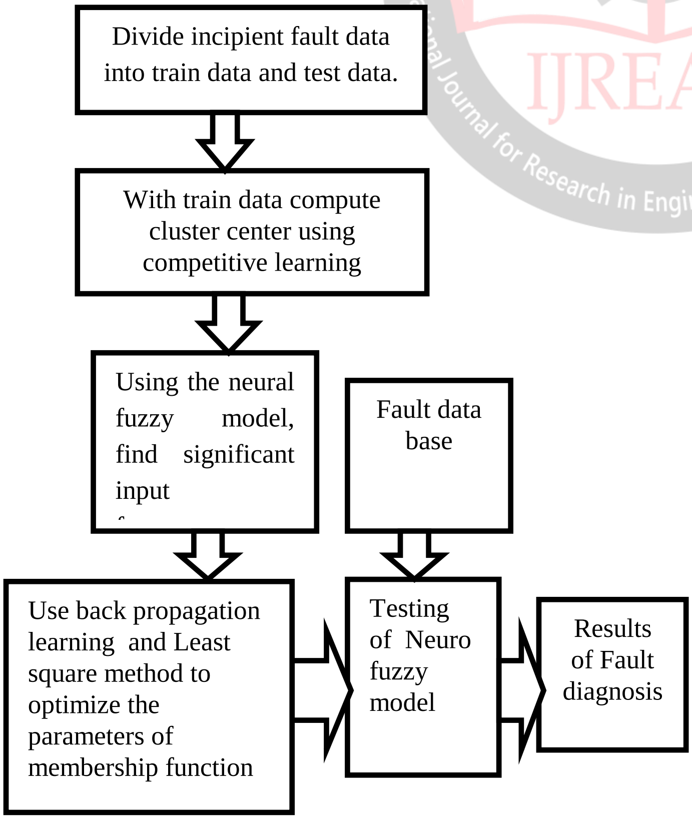

Fig.3 ANFIS Model of fault diagnosis

Incipient faults used in the proposed method are classified in to the following types

PD=Partial Discharge
LED=Low Energy Discharge
HED=High Energy Discharge
LTF=Low Temp Thermal Faults (<700°C)
HTF= High Temp Thermal Faults (>700°C)
ND=No Diagnosis

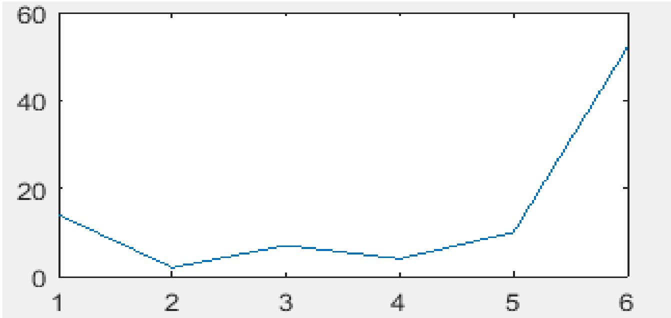

Fig. 4. Input data for H2

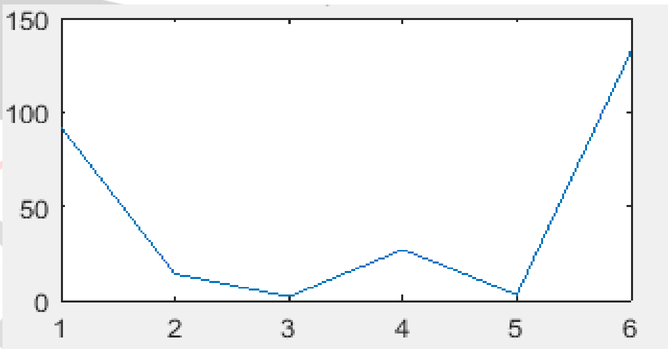

Fig. 5. Input data for CH4

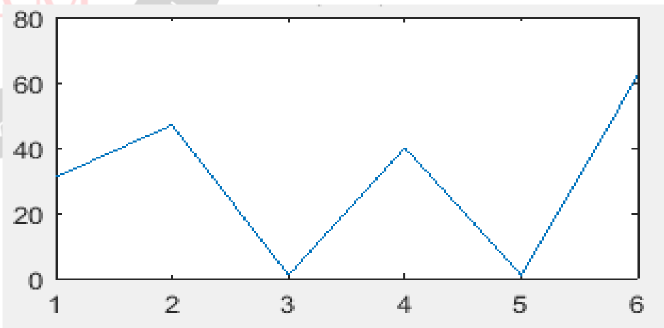

Fig.6. Input data for C2H6

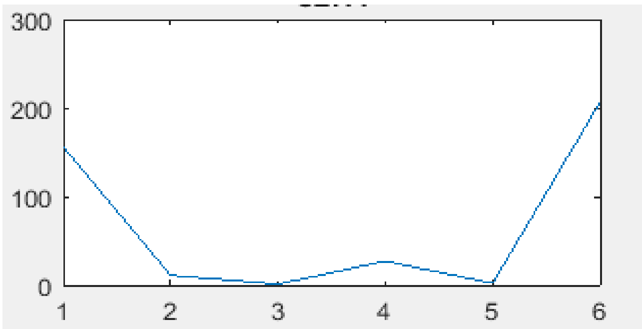

Fig. 7. Input data for C2H4

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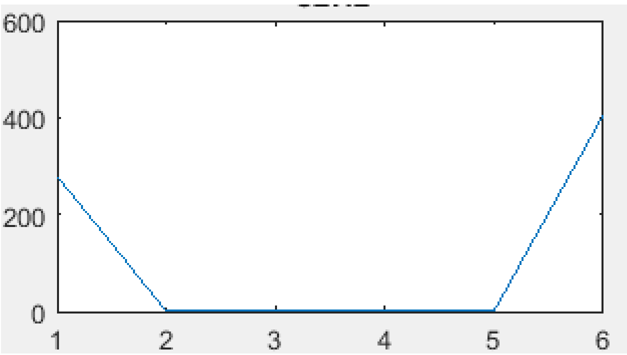

Fig. 8. Input data for C2H2

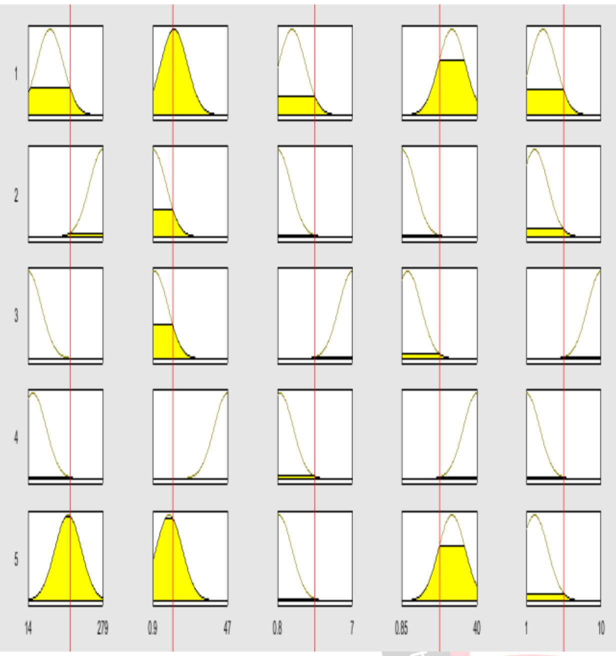

Fig.9 Fuzzy Rules of Fault gases

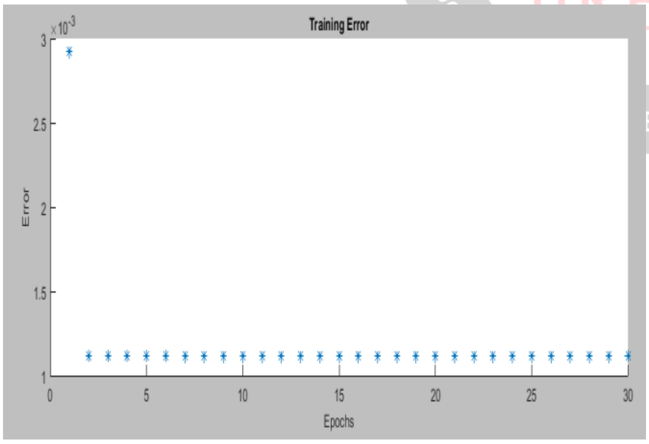

Fig.10 Training Error

The dissolved gaseous concentration data can be resolved in to two groups as shown in Table 2. One group is used to train the ANFIS structure and the other group data is used to test the results. Results acquired states that ANFIS structure exhibits better interpretation in predicting faults. The proposed integrated neural fuzzy network, 96.67% accuracy has been achieved and .Minimal training RMSE is 0.000278 which is shown in Fig.10.

Table 2 Dissolved Gases Concentration

Dissolved gases in PPM					Group
H2	CH4	C2H2	C2H6	C2H4	
46	60	1	15	104	Training Group
10	10	0.01	8	28	
980	73	0.01	41	384	
180	182	6	45	916	
1607	615	1294	80	519	
123	188	3	77	28	
173	334	0.01	41	699	
103	199	3	145	154	
127	107	224	11	110	
60	40	70	6.9	12	
980	73	0.01	58	6	
22	40	1	36	0	
86	30	29	10	35	Testing Group
121	261	0	121	781	
12	8	0.01	40	5	
1770	3630	78	1070	8480	
33	26	0.2	6	53	

V. CONCLUSION

The Neuro fuzzy adaptive learning method developed has been successfully used for the diagnosis of transformer incipient faults. It has been proved that using the Neuro fuzzy diagnosis method, more detailed information about rise in gas concentrations during the faults inside a transformer can be obtained. Prediction of gases mainly depends on the natural behavior patterns of the fault and the parameters of membership functions of gas levels. This has been used for training and testing to identify the incipient faults and determine their severity in comparison to each other. The trend of development of each fault in a transformer can also be determined from its Neuro fuzzy diagnostic vector after certain period of monitoring. The statistics of proposed method are significant with minimal training error and better accuracy in predicting faults. It concerns the transformer replacement or/and refurbishment.

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