International Journal of Scientific & Engineering Research, Volume 3, Issue 7, July-2012 1
ISSN 2229-5518

Diagnosis of Transformer Faults Based on Adaptive Neuro-Fuzzy Inference System

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Abstract— Transformer fault diagnosis is an interesting subject for plant operators due to its criticality in power systems. There are several international standards available to interpret power transformer faults based on dissolved gas analysis. In certain cases these standards are not able to provide correct diagnosis. There are several soft computing techniques available for modelling transformer faults. Adaptive Neuro-Fuzzy Inference System (ANFIS) modelling technique emerges as one of the soft computing modelling technique for power transformer. The objective of this paper is to obtain an ANFIS model from DGA system stimulus and response data of power transformers. The prediction ability of the ANFIS is also tested using limited data set for model training. Results show that ANFIS model is able to estimate the transformer faults with high level of accuracy.

Index Terms— Transformer, DGA, ANFIS, MATLAB, IEEE method, IEC method

1 Introduction

TRANSFORMER experiences electrical, mechanicalmand thermal stresses during its service. It also experiences electrical faults such as partial discharge, low and high energy discharges and thermal faults. This results into decomposetion of mineral oil used in the power transformer and liberates gases. The gases dissolve in oil and the dissolved gases in oil are extracted using gas chromotograph and analysed in the laboratory. Dissolved gas analysis is a technique used to assess the health of the transformer. IEC/IEEE standard, Roger's ratio, Dual triangle etc are some of the DGA interpretation methods. In spite of various diagnostic methods, still there is no universally accepted method for DGA interpretation. A lot of money is spent on diagnosing and correcting transformer faults. Developing a transformer fault diagnosis system is proposed in this paper.

2 Generation of Fault Gases

2.1 Feault Gases

All transformers generate gases to some extent [1]. Internal faults in oil produce gaseous by- products hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), and ethane (C_2H_6). When cellulose is involved, the faults produce methane, hydrogen, carbon monoxide and carbon dioxide.

2.2 Partial Discharges

About 150 transformer data [2] was analysed. Partial discharges (D1) due to electrical stresses occur inside a transformer. In service, detectable amounts of gases and damage might possibly be produced by a large number of Partial Discharges (PD) of smaller magnitude occurring over a longer period of time [3]. Fault gases distribution Fault gases distribution (in per unit) under PD is shown in Fig.1.

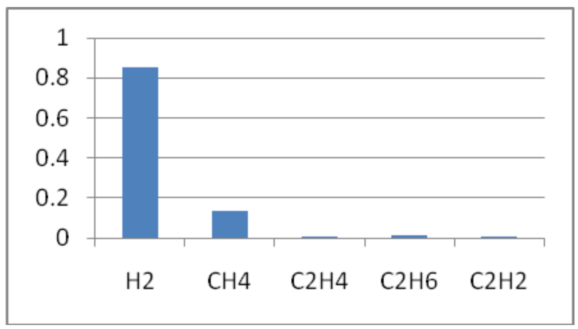

Fig. 1 Fault gases under PD

Monitoring the fault by acoustic and electrical techniques is thus more useful at this stage.

2.3 Electrical discharges D1 and D2

Discharges of low energy (D1) and discharges of high energy (D2) are due to tracking and arcing behavior inside a transformer. Distribution of gases generated under low energy discharge is shown in Fig.2.

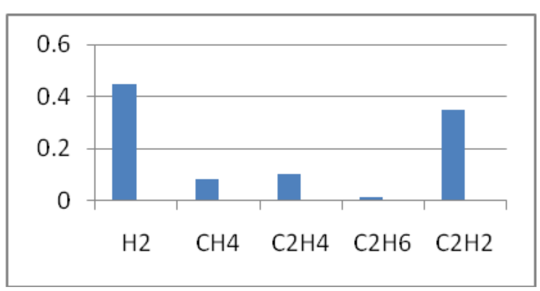

Fig.2 Fault gases under D1 type of fault

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ISSN 2229-5518

As the discharge energy increases, D2 type of faults are developed and the corresponding distribution of gases are as shown in Fig.3

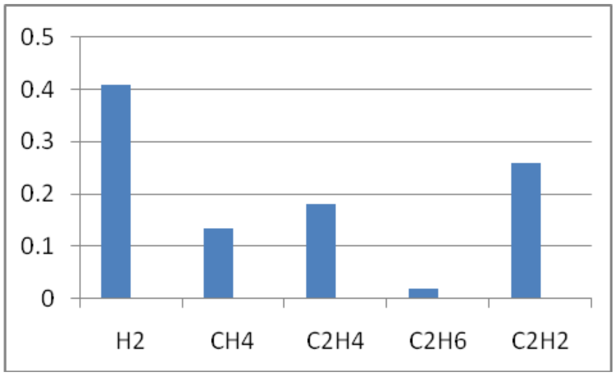

Fig.3 Fault gases under D2 type of fault

C_2H_2 gas is formed during severe arcing type of fault involving low energy as well as in high energy.

2.4 Thermal Faults

A DGA results for those in the T2/T1 type of fault correspond in general to a thermal fault in paper and those in T3 type of fault represents a thermal fault in oil. Presence of ethane indicates local over heating and the fault gases pattern as in Fig.4

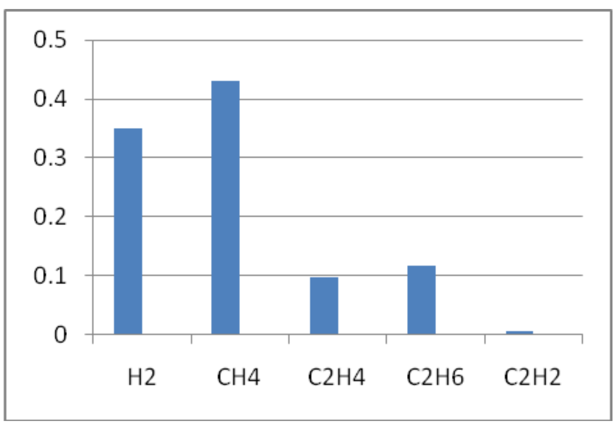

Fig.4 Fault gases under T1/T2 type of fault

As the severity of the thermal fault increaes, it leads to generation of ethylene as shown in Fig.5. Thermal faults are generally due to loose connections, circulating currents in strands and in the core etc.

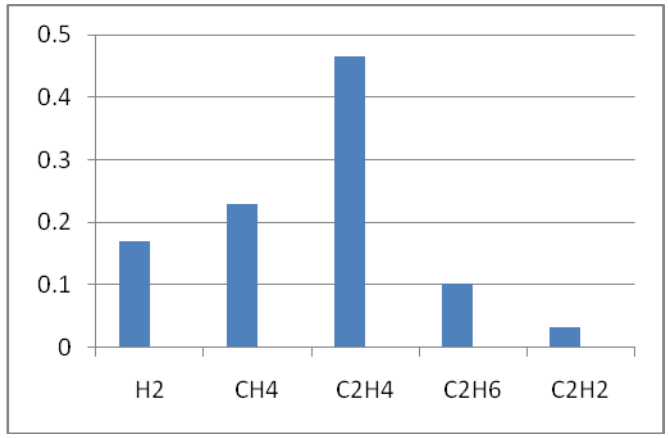

Fig.5 Fault gases under T3 type of fault

3 Adaptive Neuro-fuzzy Inference System

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a class of adaptive networks that is functionally equivalent to fuzzy inference system. Sugeno type ANFIS [4] uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference system. It applies a combination of the least squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set.

An ANFIS works [5] by applying neural learning rules to identify and tune the parameters and structure of a Fuzzy Inference System (FIS). There are several features of the ANFIS which enable it to achieve great success in a wide range of scientific applications. The attractive features of an ANFIS include: easy to implement, fast and accurate learning, strong generalization abilities, excellent explanation facilities through fuzzy rules, and easy to incorporate both linguistic and numeric knowledge for problem solving.

According to the neuro-fuzzy approach, a neural network is proposed to implement the fuzzy system, so that structure and parameter identification of the fuzzy rule base are accomplished by defining, adapting and optimizing the topology and the parameters of the corresponding neuro-fuzzynetwork. The network can be regarded both as an adaptive fuzzy inference system with the capability of learning fuzzy rules from data, and as a connectionist architecture provided with linguistic meaning.

The H_2, CH_4, C_2H_4, C_2H_6 and C_2H_2 gas concentrations are the input vectors for the network as shown in Table 1

TABLE 1
INPUT VECTOR FOR ANFIS

Input Vector	Input Parameter
1	H_2
2	CH_4
3	C_2H_4
4	C_2H_6
5	C_2H_2

The IEC Publication 60599 [6] provides codes for different type of faults as shown in Table 2. The IEC TC 10 databases relates to faults identified by visual inspection of faulty transformers in service.

TABLE 2
TRANSFORMER FAULT CLASSIFICATION

Sr.No	Fault classification	Number of data
1	Partial Discharge (PD)	9
2	Discharge of low energy (D1)	26
3	Discharge of High Energy (D2)	48
4	Thermal faults <700 °C (T1 and T2)	16
5	Thermal faults >700 °C (T3)	18
6	Normal (NF)	34

The network output is defined as PD, D1, D2, T1/T2, T3 and NF and the corresponding output vector is as shown in Table 3.

TABLE 3
OUTPUT VECTOR FOR ANFIS

OUTPUT VECTOR					
PD	D1	D2	T1 and T2	T3	NF
0.2	0.4	0.6	0.8	1.0	0

An output value of 0.2 signifies the type of fault PD and a value of 0 indicates that the transformer is healthy (NF – No fault).

4 MATHEMATICAL MODELLING

4.1 Plot of Fuzzy Inference System

The MATLAB function plotfis(fismat) displays a high level diagram of a FIS, fismat. Inputs and their membership functions appear to the left of the FIS structural characteristics, while outputs and their membership functions appear on the right as in Fig. 6

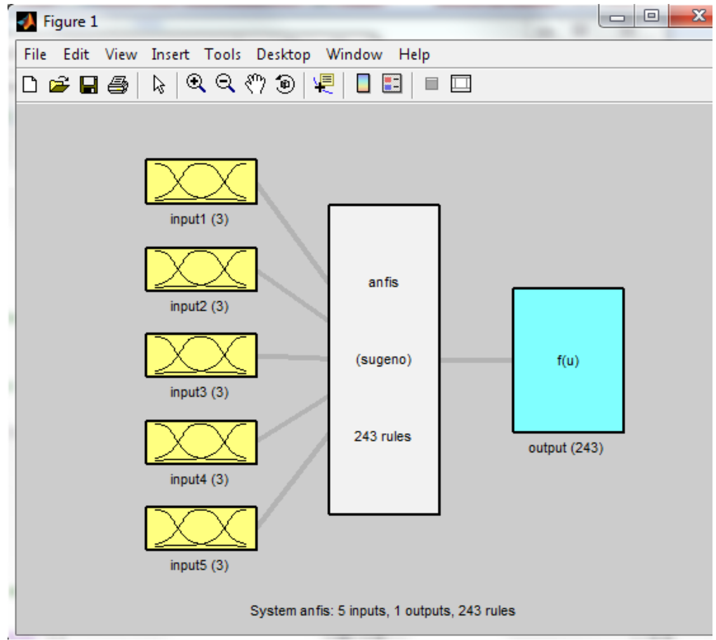

Fig.6 Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System uses 5 inputs with one output and 243 rules.

4.2 Computation of Error

The network is trained using 150 data sets. Out of 150 data sets 34 contain data for healthy transformers. The error computed is shown in Fig.7.

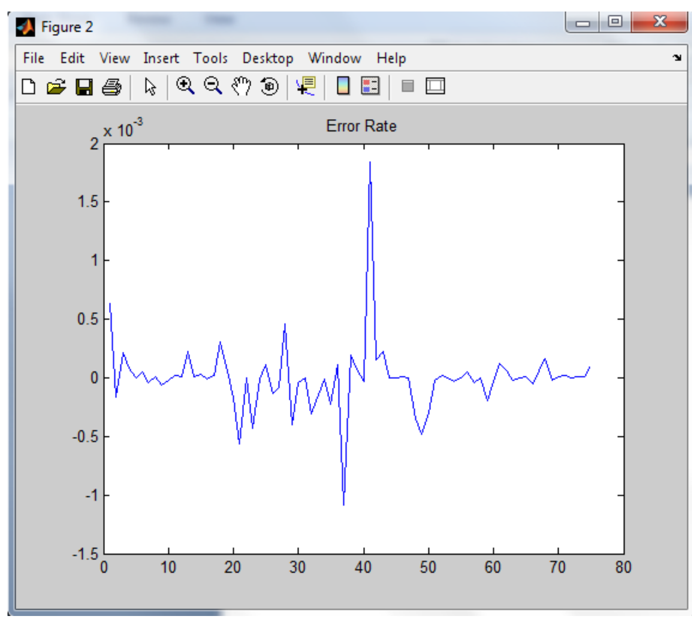

Fig.7 Error in Computation

The error is the difference between desired response and the ANFIS response.

4.3 Display of Rule Viewer

The Rule Viewer invoked using the MATLAB command ruleview('nfis') depicts the fuzzy inference diagram for a FIS stored in a file, nfis.fis. The Fig.8 shows the Rule Viewer for the ANFIS model.

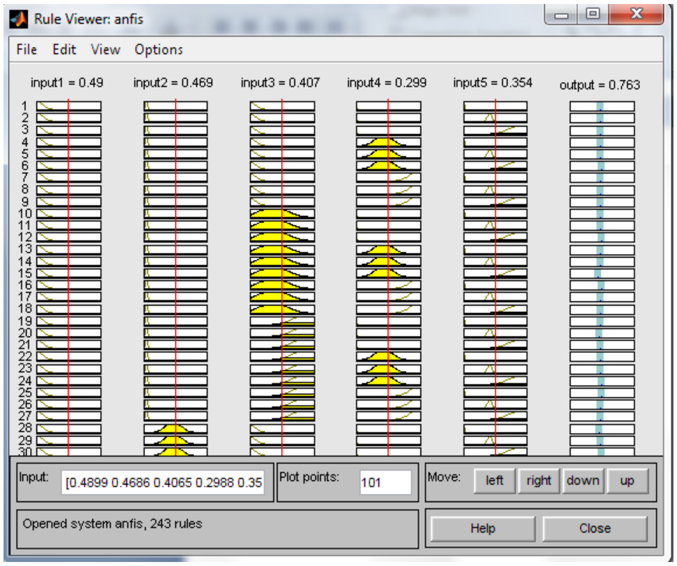

Fig. 8 Rule Viewer for the ANFIS Model

The ANFIS system uses 5 inputs and 1 output with 243 rules.

4.4 Analysis of Results

From the published literature, 150 transformers data are taken up for analysis. Fault types of partial discharge, electrical discharges and thermal faults are analysed in detail. Table 4 shows close correlation between desired responses (actual fault) reported in the literature and the fault diagnosis by the adaptive neuro-fuzzy inference system.

TABLE 4
PERFORMANCE COMPARISON

Fault	Desired Response	ANFIS Response	
		Low	High
PD	0.2	0.1998	0.2006
D1	0.4	0.3999	0.4002
D2	0.6	0.5994	0.6018
T1	0.8	0.7995	0.8002
T2	1.0	0.9998	1.0001
NF	0	0.0001	0.0002

The ANFIS response obtained by the model varies from low to high as given in the table. From the performance comparison table it is clear that the system can be effectively used to diagnose transformer faults.

5 Scope For Further Work

Extended Neural Network, Evolutionary Fuzzy Logic and Support Vector Machine can be used to diagnose transformer faults [7].

Extended NN uses the concept of extension set to extend the fuzzy logic values from limited range of [0, 1] to an infinitely wide range. It allows for simpler definition of NN that has no hidden layer.

Evolutionary fuzzy logic method allows for updating to new test data. It also has a provision to update the probability of fault identification.

SVM is based on statistical learning theory and works using feature space of the measured data. Unlike ANN, SVM can learn the non-linear high dimensional space of variables using small number of samples to classify them or to find the multivariate relation between them using regression.

6 Conclusions

In this paper Adaptive Neuro-Fuzzy inference system is developed. The MATLAB toolbox is used to develop transformer fault diagnosis system. The software model is validated using the data on IEC TC 10 databases of faulty equipments in service. The software can be used to diagnose the transformer fault accurately.

Acknowledgment

The authors wish to thank Dr.K.Ramar, Principal, Einstein College of Engineering, for supporting this research. The authors are also thankful to Shri.A.Amudhavanan, Chairman, and Einstein College of Engineering for granting permission to publish this paper.

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