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Application of Adaptive Neuro-Fuzzy Inference System Based on IEC Method for Transformer Fault Diagnosis

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Abstract: Power transformer is one of the most important components in a power system. It experiences thermal and electrical stresses during its operation. The insulation system consisting of mineral oil and the insulation paper used in transformer undergoes chemical changes under these stresses and gases are generated. These gases dissolve in oil. The dissolved gases are extracted in the laboratory using gas chromatograph. The dissolved gases are used for fault identification. The fault identifications in a transformer are based on certain key-gas ratios. International standards such as IEEE and ASTM are used for fault identification. However, these standards are not able to diagnose the faults under certain conditions. Hence, there is a need to improve the diagnostic accuracy. This study attempts to diagnose the faults in a power transformer using adaptive Neuro-Fuzzy Inference System. Simulation model is developed using MATLAB™ Software and trained using the IEC TC 10 database of faulty equipments inspected in service. The outputs of the adaptive Neuro-Fuzzy Inference System based model are compared with the Roger's Ratio Method. The comparison shows that the condition assessments offered by the adaptive Neuro-Fuzzy Inference System based model is capable of predicting the transformer faults with higher accuracy.

Key words: Dissolved gas analysis, IEC TC 10 database, artificial intelligence, transformer fault diagnosis, chromatograph

INTRODUCTION

Reliability of the transformer is very important considering its cost and long gestation time for replacement. It requires very high cost in diagnosing and correcting faults in a transformer. In order to reduce the risk of failure, condition monitoring has been practised to assess the health of a transformer. There are several methods available for diagnosing power transformer. Sweep Frequency Response Analysis, Frequency Domain Spectroscopy, Recovery Voltage Method, Thermography, Acoustic Emission Method and Dissolved Gas Analysis (DGA) are some of the methods for transformer fault diagnosis. DGA is commonly used to detect faults in transformers.

There are several diagnostic methods available for transformer fault diagnosis based on DGA. Some of the diagnostic methods include Neuro-Fuzzy (Naresh *et al*., 2008), Association Rule Mining (Yang *et al*., 2009), Wavelet Networks (Chen *et al*., 2009), Active Diverse Learning Neural Network Ensemble (Xu *et al*., 2010), Reduced Multivariate Polynomial Based Neural Network (Wu *et al*., 2011) and Particle Swarm Optimization-Support Vector Machine (Liao *et al*., 2011a, b), etc. This study describes Adaptive Neuro-Fuzzy Inference System (ANFIS) based on IEC Method for transformer fault diagnosis applied to data published in IEC TC 10 database of faulty equipments inspected in service.

TRANSFORMER FAULT DIAGNOSIS

Review of artificial intelligence techniques: Artificial intelligence techniques are extensively applied for transformer fault diagnosis. They are adaptive, capable of dealing with non-linear relationships and are able to generate solutions for a new group of data (Morais and Roblim, 2005). Morais and Roblim (2005) proposed a hybrid tool for the diagnosis of faults in transformers through analysis of dissolved gases in oil. The results obtained with this tool in the diagnosis of incipient faults achieved a success rate of 80%.

Richardson *et al.* (2008) presented a Parsen-Windows (PW) based classifier for transformer fault diagnosis. Particle swarm optimizer is used to optimize the parameters of PW. This method is able to interpret transformer dissolved gas analysis with a probabilistic scheme. An accuracy achieved was 80.2%. Naresh *et al.* (2008) used neural fuzzy approach for transformer fault diagnosis. The

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proposed approach formulates the modelling problem of higher dimensions into lower dimensions by using the input feature selection based on Competitive Learning and Neural Fuzzy Model. The neural fuzzy approach achieved 96.67%.

Association Rule Mining (ARM) based dissolved gas analysis approach was used by Yang *et al.* (2009). The basic idea of implementing ARM is to generate association relationships between a set of key gas values and transformer working states. ARM-based approach got an accuracy of 65.85%.

A comparative study of Genetic algorithm evolving Wavelet network approach was presented by Chen *et al.* (2009). In this study, a three layer structure with an input layer, hidden layer and an output layer are used. The method was tested on 700 practical DGA data and compared with each other.

Xu *et al.* (2010) presented an ensemble learning algorithm. The method was applied to dissolved gas analysis based fault diagnosis of power transformer. It is shown to have an achievement of 86.67% for independent learning and 93.33% for Diverse Ensemble Learning Method.

Wu *et al.* (2011) applied Reduced Multivariate Polynomial based Neural Network (RMP-NN) for interpretation of DGA. Six inputs to the RMP-NN with three layer structure are made up of five gases. The effect of the order of RMP NN on diagnosis accuracy was analysed in the study. According to the results, 5-7 orders of RMP NN are shown as good selection for DGA.

The interpretation scheme by Li *et al.* (2011) diagnosed five types of faults using seven gas concentration levels. The rules and the method for DGA, derived based on case study have been presented. The method was compared with Dual Triangle Method. Five types of faults were diagnosed using four steps and obtained 93.37% accuracy.

A two level assessing model including Fuzzy Model and Evidential Reasoning Decision-Making Model was developed by Liao *et al.* (2011a, b) to facilitate the assessing process. A decision making procedure for condition assessment presented to illustrate how to use the model to deal with an assessing problem. Samples from abnormal ageing transformers and normal transformers were selected. The assessing procedure gave an overall accuracy of 92.98%.

A Fuzzy Information Granulated Particle Swarm Optimisation-Support Vector Machine Regression Model was proposed by Liao *et al.* (2011a, b). A procedure is put forward to serve as an effective for the trend forecasting of transformer gas contents. Results show that this model

Table 1: Comparison of published results

References	No. of samples	Content
Morais and Roblim (2005)	431	Data from TC 10 and CELPA Training data: 292 Testing data: 139 Accuracy: 97.84%
Naresh *et al.* (2008)	117	Data from HPSEB Training data: 87 Testing data: 30 Accuracy: 96.67%
Chen *et al.* (2009)	700	Training data: 400 Testing data: 300 Accuracy: 91.67%
Wu *et al.* (2011)	173	Training data: 156 Testing data: 17 Accuracy: 94.2%

is capable of forecasting the gas development trend accurately. The summary of of results published by various researchers over the years along with the sample size is listed in Table 1. The data used for training and testing is also given.

From the Table 1, the comparison is difficult as the source of data is not the same for all the four cases. Further, the percentage of samples used for training and testing are not the same. The work reported in this study is based on the data published by Duval and de Pablo (2001) comprising of IEC TC 10 database of faulty equipment inspected in service. Fault diagnosis based on IEC Ratio Method and Adaptive Neuro-Fuzzy Inference Systems applied to IEC Ratio Method are reported.

Fault diagnosis based on key gas: The detection of certain gases generated in an oil filled transformer in service is frequently the first available indication of a malfunction that may eventually lead to failure if not corrected at right time. Arcing, partial discharge, low energy sparking, severe overloading, pump motor failure and overheating in the insulation system are some of the possible mechanisms (IEEE, 2009).

The TC 10 database of faulty equipments inspected in service contains 151 data. Gases produced under partial discharge are shown in Fig. 1. Partial Discharge (PD) is a fault involving low energy content which can occur in oil filled transformer containing gas in the oil impregnated paper insulation system.

PD is a localized dielectric breakdown in a transformer insulation system under high electric stress. This is due to the stress enhancement in gas bubbles surrounding oil insulation system. It results in ionic bombardment of the oil molecules.

A large amount of hydrogen is produced and a comparatively small quantity of methane is also produced. Most of the transformers can generate gases in small quantities even at normal operating temperatures. However, as temperature increases, methane (CH_4) is

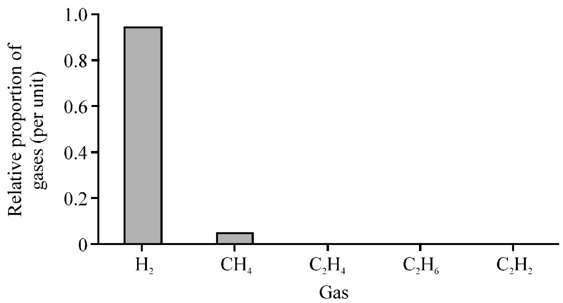

Fig. 1: Gas pattern under partial discharge in oil

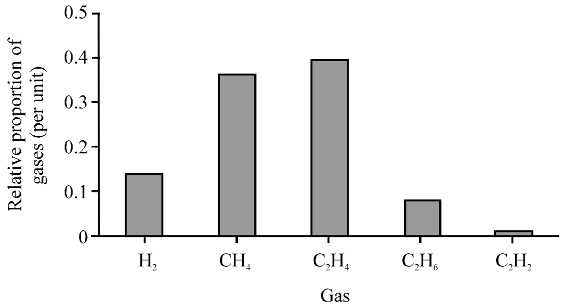

Fig. 2: Gas pattern under thermal faults

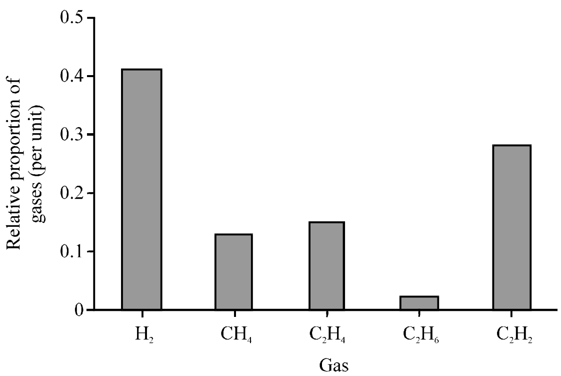

Fig. 3: Gas pattern under electrical arcing

produced. At high temperatures, ethane (C_2H_6) and ethylene (C_2H_4) are produced. The gases produced under thermal faults are given in Fig. 2. Electrical arcing involves high energy discharge in Transformer Insulation System. Acetylene gas is produced during electrical arcing as in Fig. 3. It occurs as a flow of current between line to ground or line to line, etc. This results due to the presence of contaminations, ageing of insulation, etc.

FAULT DIAGNOSIS BASED ON IEC RATIO METHOD

According to IEC, the extended Rogers Method is used to produce a three digit code. The code is

Table 2: IEC standard 599/78

C_2H_2/ C_2H_2	CH_4/ H_2	C_2H_4/ C_2H_6	Diagnosis
<0.1	0.1-1.0	<0.1	Normal ageing
<0.1	<0.1	<0.1	Low intensity Partial Discharge (PD)
0.1-3.0	<0.1	<0.1	High intensity Partial Discharge (PD)
>0.1	0.1-1.0	>1.0	Arc-low Intensity Discharge (D1)
0.1-3.0	0.1-1.0	>3.0	Arc-high intensity Discharge (D2)
<0.1	>1.0	<1.0	Thermal fault (150°C<t<300°C) (T1)
<0.1	>1.0	0.1-3.0	Thermal fault (300°C<t<700°C) (T2)
≤0.1	>1.0	>3.0	Thermal fault (t>700°C) (T3)

Table 3: Diagnosis using IEC Ratio Method

No. of samples	Fault type	Right Diagnosis	Right diagnosis (%)
9	Partial discharge	4	44.4
74	Arc-low intensity, high intensity	68	91.8
34	Thermal faults-T1, T2, T3	16	47.0

Mean of right diagnosis (%) = 75.2

determined based on three gas ratios C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6. Table 2 shows the values of the three key gas ratios corresponding to transformer fault diagnosis. From the 117 data samples, faults are analysed using IEC ratio code and the results are tabulated in Table 3. The right diagnosis by applying IEC ratio code for 117 data corresponding IEC TC 10 data base of faulty transformers inspected in service is 75.2%.

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

Takagi-Sugeno Model: Adaptive Neuro Fuzzy Inference System (ANFIS) is one of the Hybrid Neuro-Fuzzy Inference Expert Systems and it works based on Takagi-Sugeno type Fuzzy Inference System. ANFIS provides a method for a fuzzy modelling procedure to learn information about a data set. This learning method works similar to that of neural networks.

ANFIS Toolbox in MATLAB environment performs the membership function parameter adjustments. Based on the input-output data set, ANFIS toolbox builds a Fuzzy Inference System whose membership functions are adjusted either using Back Propagation Network Training algorithm or adaline network algorithm which uses least mean square learning rule. This makes the fuzzy system to learn from the data they model.

This adaptive network is functionally equivalent to Sugeno-Fuzzy Model. ANFIS uses a strategy of Hybrid Training algorithm to tune all parameters. It takes a given input/output data set and constructs a fuzzy inference system whose membership function parameters are tuned or adjusted using either a Back Propagation algorithm in combination with a least squares type of method.

Application of ANFIS to IEC Method: IEC extended Roger's Method uses three ratios. They are determined from the gas ratios C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6. These three ratios form the input vectors for the ANFIS.

Pre-processing: Each sample data is pre-processed by normalization process which is necessary to standardize all the features to the same level. Further data containing null is replaced by insignificant value to avoid divide by zero.

Fault classification using ANFIS: The Neuro Adaptive Learning Method works similarly to that of neural networks. Neuro-adaptive learning techniques provide a method for the fuzzy modelling procedure to learn information about a data set. Fuzzy Logic Toolbox Software computes the membership function parameters that allow the associated Fuzzy Inference System to track the input/output data. The fuzzy logic Toolbox function that accomplishes this membership function parameter adjustment is called ANFIS. The membership function parameters are tuned using either a back propagation algorithm alone or in combination with a least squares type of method. This adjustment allows the fuzzy systems to learn the data they are modelling (Sivanandam and Deepa, 2011).

An ANFIS based classifier is used as a diagnostic tool to diagnose transformer faults. The ANFIS network outputs are defined as PD, D1, D2, T1/T2 and T3 and the corresponding output vector are specified as 0.2, 0.4, 0.6, 0.8 and 1.0, respectively.

RESULTS

The ANFIS uses Takagi-Sugeno type model and has three inputs and one output and a total of 27 fuzzy rules. The transformer fault diagnosis based on ANFIS was performed using MATLAB™ Software. IEC TC 10 database of faulty equipments in service contains 117 data related to various faults. The data given in the database are used in the analysis. ANFIS Model is trained using 59 data sets. The remaining 58 data set is used for testing. Every data set is replicated 10 times and the average output value is taken. The results are shown in Table 4.

The method developed based on ANFIS using MATLAB™ Software diagnoses transformer fault with 100% accuracy for partial discharge, discharge of high energy and thermal faults involving temperature >700°C. However, the accuracy is 92.3% for discharge of low energy and 62.5% for T1 and T2 type of fault involving temperature <700°C.

Table 4: Fault diagnosis using ANFIS

No. of test samples	Fault	Correct diagnosis
4	Partial Discharges (PD)	4.0
13	Discharge of low energy (D1)	12.0
24	Discharge of high energy (D2)	24.0
8	Thermal faults <700°C (T1 and T2)	5.0
9	Thermal faults >700°C (T3)	9.0
Total data = 58	Right diagnosis	54.0

Overall diagnosis accuracy (%) = 93.1

CONCLUSION

ANFIS Software is tested using IEC TC 10 database of faulty equipment in service. The test results are analysed for crisp logic and fuzzy logic. The diagnostic accuracy obtained is 75.2% in case of crisp logic and 93.1% for ANFIS Method. In future, it is proposed to improve the diagnostic accuracy by using ANFIS Software based on ASTM and CEGB standards.

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