An Automated Tool for Analyzing Dissolved Gases in Power Transformers and Sf6 in Switch Gears Using Artificial Intelligence Approaches including performance measure

Ms. Alamuru Vani.[a,] Dr. Pessapaty Sree Rama Chandra Murthy.[b]

[a] *Associate Professor, Department of Electrical Engineering, VJIT, Hyderabad,*
vanialamuru@gmail.com
[b] *Dean, School of Electrical Engineering, Sreenidhi Institute of Science and Technology, Hyderabad*

Abstract— Safe operation of elements of power systems plays a crucial role in maintaining the reliability and safety of the system. Transformers being a key element in power systems need to be maintained and monitored on a regular basis. Dissolved gas analysis has been used as a reliable tool in maintaining the safe operation of transformers for a long time. Analysis of dissolved gases is analytical and often interpreted differently by different users and methods. The scope of Artificial Intelligence tools in dissolved gas analysis has become critical with increasing number of transformers being used in power systems coupled with rapid expansion of transmission and distribution components. Adaptive Neuro-Fuzzy Inference System (ANFIS) modeling technique has emerged as one of the soft computing modeling technique for power transformer. An ANFIS model for dissolved gas analysis of power transformers is implemented. Similarly the GA-based weight optimization during training of an ANN is employed to improve diagnostic accuracy. A Graphical User Interface (GUI) is designed using Matlab to help in the seamless integration of analysis and decision making. The user interface is simple and easy to use providing the user flexibility and wide options for analysis. Traditional methods like Rogers Ratio, Key Gas Method, IEC Ratio Method, Dorenburg Ratio Method, Total Dissolved Combustible Gases Method and Triangle Method. The tools also incorporate fuzzy based analysis based on Rogers's ratios and Key Gas methods and analysis using Artificial Neural Networks. The tool also has provision for analyzing Sf6 components. The performance of the proposed tool is validated using ROC analysis. The primary motivation for the work is to provide a platform for analysis of dissolved gases to help in the early detection and diagnosis of transformer faults. This work is carried out with assistance from with Andhra Pradesh State Transmission Corporation (APTRANSCO) in the form of required transformer analysis data and expert opinion for validation of the tool.

Index Terms—TRANSFORMER FAULTS, EXPERT SYSTEM, MATLAB, GUI, Fuzzy, ANN, ANFIS, ROC, SF6,GA-ANN.

———————————————— ◆ ————————————————

1 INTRODUCTION

Dissolved Gas Analysis (DGA) has been used for more than 30 years [1]–[3] for the condition assessment of functioning electrical transformers. DGA measures the concentrations of hydrogen (H2), methane (CH4), ethane (C2H6), ethylene (C2H4), acetylene (C2H2), carbon monoxide (CO) and carbon dioxide (CO2) dissolved in transformer oil. CO and CO2 are generally associated with the decomposition of cellulose insulation; usually, small amounts of H2 and CH4 would be expected as well. C2H6, C2H4, C2H2 and larger amounts of H2 and CH4 are generally associated with the decomposition of oil. All transformers generate some gas during normal operation, but it has become generally accepted that gas generation, above and beyond that observed in normally operating transformers, is due to faults that lead to local overheating or to points of excessive electrical stress that result in discharges or arcing. Despite the fact that DGA has been used for several decades and is a common diagnostic technique for transformers, there are no universally accepted means for interpreting DGA results IEEE C57-104 [3] and IEC 60599 [4] use threshold values for gas levels.

Other methods make use of ratios of gas concentrations [2], [5] and are based on observations that relative gas amounts show some correlation with the type, the location and the severity of the fault. Gas ratio methods allow for some level of problem diagnosis whereas threshold methods focus more on discriminating between normal and abnormal behavior. The IEC standard 60599 [18] classifies the DGA detectable transformer faults into 2 categories: the electrical fault and the thermal fault. These two main categories can be further sorted into 6 types of transformer fault, according to the magnitudes of the fault energy: the electrical fault: partial discharge (PD), D1 (discharge of low energy) and D2 (discharge of high energy); the thermal fault: T1 (Thermal fault of low temperature range, T < 300 °C), T2 (Thermal fault of medium temperature range, 300 °C < T < 700 °C) and T3 (Thermal fault of high temperature range, T >700 °C) [7].Many DGA analysis techniques employing Artificial Intelligence can be found in the literature. We briefly review here previous techniques for transformer failure prediction from DGA. All of them follow the methodology consisting in feature extraction from DGA, followed by a classification algorithm. The majority of them are techniques [6],

[7], [9]–[13], [15], [16] built around a feed-forward neural-network classifier, that is also called Multi-Layer Perceptron (MLP) and that we explain in Section IV. Some of these papers introduce further enhancements to the MLP: in particular, neural networks that are run in parallel to an expert system in [10], Wavelet Networks (i.e. neural nets with a wavelet-based feature extraction) in [16], Self-Organizing Polynomial Networks in [9] and Fuzzy Networks in [6], [12], [13], [15]. Several studies [6], [8], [12], [13], [15], [16] resort to fuzzy logic [18] when modeling the decision functions. Fuzzy logic enables logical reasoning with continuously-valued predicates (between 0 and 1) instead of binary ones, but this inclusion of uncertainty within the decision function is redundant with the probability theory behind Bayesian reasoning and statistics. Stochastic optimization techniques such as genetic programming are also used as an additional tool to select features for the classifier in [8], [12], [14], [16], and [17]. Finally, Shintemirov et al. [17] conduct a comprehensive comparison between k-nearest neighbors, neural networks and support vector machines each of them combined with genetic Programming-based feature selection.

In this work we have designed a comprehensive tool which incorporates both traditional methods and tools based Artificial Intelligence.The paper is organized with Section 1 describing the introduction and motivation for the paper along with a brief survey of literature, Section 2 describes the problem statement in brief, followed by description of approaches for dissolved gas analysis in Section 3. Section 4 describes the performance measures required for validating the proposed tool. Section 5provides an insight in to the GUI tool, with Section 6 presenting the results. Section 7 concludes the work with references being cited in section 8.

2 . Problem Statement

The Dissolved Gas Analysis is a diagnostic and maintenance tool used in machinery. Through this method, gases are studied to give an early indication of transformer abnormal behavior. For the last 20 years, this method is widely used for detecting and diagnosing the incipient faults of power transformers. Its effectiveness has been proven by a lot of well known electrical testing laboratories or institutions such as The Institute of Electrical and Electronics Engineers (IEEE), Central Electricity Generating Board of Great Britain (CEGB), International Electro technical Commission (IEC), etc.. Today, numbers of diagnostic methods based on the DGA have been proposed by researchers in the power transmission field from all over the world.

The aim of the proposed work is to design a comprehensive tool for dissolved gas analysis that incorporate artificial intelligence elements to aid in incipient transformer fault detection. The objectives of the proposed tool can be listed as to provide seamless integration between different methods of analysis by enabling flexible and easy use of the tool; use hybrid artificial intelligence elements like Neural Network, Neuro Fuzzy and GA- ANN to improve the diagnostic accuracy of the tool; provide the user with wide variety of options that include traditional methods of analysis like Rogers Ratio, IEC, Duval Triangle etc… to provide a holistic approach in analyzing transformer faults. Similarly the tool also has provision for making

Sf6 analysis.

3. Analysis methods incorporated in the automated tool.

As part of this work different methods of diagnosis of dissolved gases to identify transformer faults are designed and presented. The data for analysis is sourced from AP Transco (Andhra Pradesh Transmission Corporation) after extensive survey and data collection about different transformers located across Andhra Pradesh.

3.1. A Fuzzy Approach for Dissolved Gas Analysis

Fuzzy logic had been applied in various fields such as control system, decision support, fault diagnostics, image processing and data analysis. The fuzzy logic theory was applied in solving nonlinear control problems heuristically and modularly along linguistic lines. The advantages of fuzzy logic are that it exhibits the nature of human thinking and makes decision or judgment using linguistic interpretation. Furthermore, the control rules, regulations and methods based on the perception, experience and suggestion of a human expert were encoded in the meaningful way to avoid mathematical modeling problems.

3.1.1 Fuzzy Rogers Ratio

Rogers Ratio method uses the 4-digit ratio code generated from the 5 fault gases which are Acetylene, Ethylene, Methane, Hydrogen and Ethane to determine 15 transformer conditions. Therefore, the structure for the Fuzzy Rogers Ratio is such that the four ratio codes are identified as the input parameter while the 15 interpretation results based on the difference combination of ratio code are identified as the output parameter. The approach used in fuzzifying the gas ratios according to the method of Roger's Ratio is discussed here. The real variables are converted into the appropriate linguistic variables. The 4 ratios are classified as Low (Lo), Medium
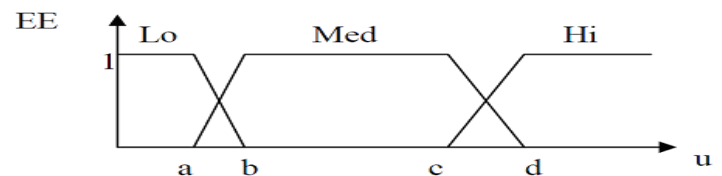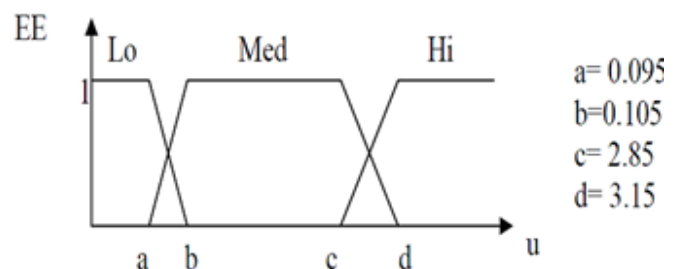

Figure (1): Structure of Membership Function used for Ethylene / Ethane (EE)

a= 0.095
b=0.105
c= 2.85
d= 3.15

Fuzzy inference rules consist of a collection of rules which are extracted from the expert. Normally, fuzzy inference consists of two components which are antecedent (if part) and consequent (then part). For this application, the fuzzy inference rules can be extracted from the Roger's ratio fault interpretation guide. There are a total of 22 fuzzy inference rules that can be derived from Rogers fault interpretation. However, with the fuzzy logic techniques which allow partial member-

ship may improve the number of matched cases as compared to the ordinary crisp set theory. The output of the fuzzy inference can be obtained using the Mamdani's Max-Min composition technique

3.1.2 Fuzzy Key Gas Method

A set of rules to diagnose abnormalities such as Thermal, Corona or Arcing problems is employed The Key Gas method. It is a reliable diagnostic method because it can be used to diagnose the condition of the transformer even there are only a few gases obtained from the oil sample. Comparatively, the Rogers Ratio method requires all 5 necessary ratio gases to be detected correctly earlier to produce satisfactory result. However, there is a possibility that the ratio code cannot provide meaningful information due to the absent of certain gases. In this case, Fuzzy Key Gas method which uses the individual gas rather than the calculation gas ratio for detecting fault condition will be a perfect candidate to offset the limitation of the Rogers Ratio method. The quantization step is to define the threshold values for all the 7 input gases. The international recognized standard can be used to define the threshold value for Key Gas method. Based on the IEEE Standard, 7 input variables have been classified into Low (Lo), Medium (Med) and High (Hi) term set. From the 3 term sets, the IEEE standard value is being used as the medium term set while the high and low term set are being adjusted 5 percent more or 5 percent less than the medium term set respectively.

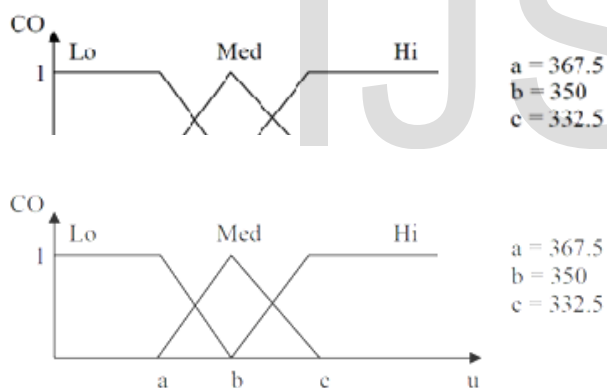For the Fuzzy Key Gas fault diagnostic method, the appropri-

Figure (2): Structure of Membership Function used for CO

The output of the fuzzy inference can be obtained using the Mamdani's Max-Min composition .The consequent is computed as follows:

Corona (CN) = Max {Rule 1}

Cellulose Insulation Breakdown (CIB) = Max {Rule 4, Rule 5, Rule 7, Rule 10}

Low Temperature Oil Breakdown (LTOB) = Max {Rule 19, Rule 20, Rule 21, Rule 22, Rule 25}

High Temperature Oil Breakdown (HTOB) = Max {Rule 16}

Arcing (ARC) = Max {Rule 13

A suitable defuzzification method for fuzzy diagnosis system is the Max-membership defuzzification method where the element that has the maximum degree of membership function is chosen is used

3.2 ANN Based System for Transformer Incipient Fault Diagnosis

The basic idea of neural network based diagnosis is non-linear mapping input and outputs. Both back propagation network (BPN) and probabilistic neural network (PNN) are used to diagnose the transformer faults in its incipient stage. An artificial neural network (ANN) includes selection of inputs, outputs, network topology and weighed connection of node. Input features will correctly reflect the characteristics of the problem [18]. Another major work of the ANN design is to choose network topology. This is done experimentally through a repeated process to optimize the number of hidden layers and nodes according to training and prediction accuracy. In this work 7 key gases namely H2, CO, CO_2, C_2H_2, C_2H_4, C_2H_6, and CH_4 are analyzed to diagnose 5 different fault conditions namely, Corona (CN), Cellulose Insulation Breakdown (CIB), Arcing (ARC), Low Temperature Oil Breakdown (LTOB) and High Temperature Oil Breakdown (HTOB).In this work a Feed – Forward Back Propagation network is used. A TRAINLM training function along with LEANGDM adaptive learning function is used of training and adaptation of the network. MSE is used to compute the performance measure. The total network comprises of 2 layers with layer one having 10 neurons and using a TANSIG transfer function. The regression plot of the regression plot of the network used in the work is given in the Figure (3)
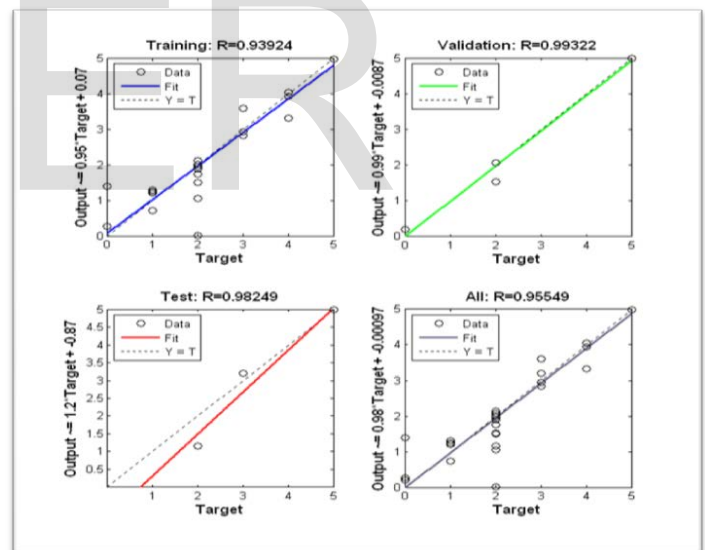

Figure (3) Regression plot of the ANN used in Analysis

3.3 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 [19] 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 [20] 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-fuzzy network. 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, $C2H_6$ and C_2H_2, CO2 and CO gas concentrations are the input vectors for the network. Anfis uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. 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.
Figure (4) Rule base of Sugeno System to Model and ANFIS Model Structure
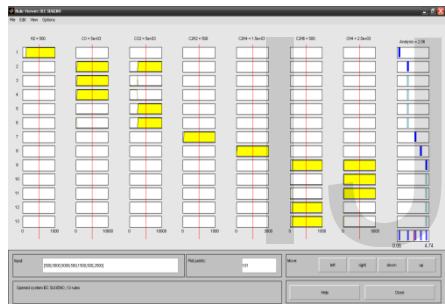
Anfis can also be invoked using an optional argument t for model validation. Anfis only supports Sugeno-type systems. In this work a Sugeno type fuzzy system is initially created with H_2, CH_4, C_2H_4, C_2H_6 and C_2H_2, CO2 and CO gas concentrations as input vectors for the network. Initially the system is trained using a data set which contains around 40 data inputs which has different types of faults and no faults condition represented by them. This data is essential in the generation and training of the ANFIS from the basic fuzzy structure. ANFIS has around 177 rules derived from the basic fuzzy structure. The ANFIS model structure that is generated for the analysis is presented in the figure (4). The above ANFIS system which is conceptually based on KEY gas method is

capable of identifying faults like Corona, Arcing, High Temperature Oil Break Down, Cellulose Insulation Break Down, etc.

3.4 GA Optimized ANN for Incipient Fault Detection

Genetic algorithm is an adaptive search technique used for solving mathematical problems and engineering optimization problems that emulates Darwin's evolutionary theory that is fittest is likely to survive. An important characteristic of GA is that global feature of search is related to the diversity of the initial population: the more diverse the population, the more global the search. From the initial population, selection strategy based on fitness proportion is adopted to select individuals in current population. Higher selective pressure often leads to the loss of diversity in the population, which causes premature convergence but at the same time improves convergence speed. GA is much superior to conventional search and optimization techniques in high-dimensional problem space due to their inherent parallelism and directed stochastic search implemented by recombination operators.

Artificial neural networks and genetic algorithms are both abstractions of natural processes. They are formulated into a computational model so that the learning power of neural networks and adaptive capabilities of evolutionary processes can be combined [21]. Genetic algorithms can help to determine optimized neural network interconnection weights, as well as, to provide faster mechanism for training of the neural network. Training a given neural network generally means to determine an optimal set of connection weights. This is formulated as the minimization of some network error functions, over the training data set, by iteratively adjusting the weights. The mean square error between the target and actual output averaged over all output nodes serves as a good estimate of the fitness of the network configuration corresponding to the current input. Conventionally a back-propagation neural network (BPNN) updates its weights through a gradient descent technique with backward error propagation. This gradient search technique sometimes gets stuck into local minima. Gas, on the other hand, though not guaranteed to find global optimum solution, have been found to be good at finding "acceptably good" solutions "acceptably quickly" [21].The GA-based weight optimization during training of an ANN follows two steps. The first step is encoding strings for the representation of connection weights. The second step is the evolutionary process simulated by GA, in which search operators have to be implemented in conjunction with the representation scheme. The evolution stops when the population has converged. A population is said to have converged when 95% of the individuals constituting the population share the same fitness value [22]. The whole process for neural network training using a genetic algorithm is shown below

Step 1: Decoding each individual in the current population into a set of connection weights and construct a corresponding ANN with the weights.

Step 2: Evaluating the ANN by computing its total mean square error between actual and target outputs.

Step 3: Determining fitness of individual as inverse of error. The higher is the error, the lower is the fitness.

Step 4: Storing the weights for mating pool formation.

Step 5: Implementing search operators such as cross-over/mutation to parents to generate offspring's.

Step 6: Calculating fitness for new population.

Step 7: Repeating steps (3) to (4) until the solution converge.

Step 8: Extracting optimized weights.

3.5 SF6 Analysis

Sulfur Hexafluoride, SF6, is an excellent dielectric with unique arc interruption properties that have led to its successful and widespread use in circuit breakers as well as in gas insulated substations. First introduced in the 1960's, SF6-filled equipment gained substantial popularity by the 1980's. Today as utility infrastructures are reaching middle age and the number of equipment replacements is growing, oil-filled breakers are being replaced almost exclusively with SF6-filled equipment. SF6 now dominates the higher voltage classes, and all indications are that this trend will continue through the lower voltage classes. **Under** ideal circumstances, when a discharge occurs, each fluorine on the SF6 may capture an electron and dissociate from the sulfur [23].When the discharge has ended, each fluorine loses the captured electron and recombines with a sulfur to reform SF6. This is the "self-healing" or regenerative property of SF6. Regardless of circumstances, this is the predominate reaction occurring in SF6-filled high voltage electrical equipment. However, when other species such as oxygen and water from atmospheric contamination, carbon from Teflon interrupter components, copper and tungsten from contacts and aluminum are introduced into the discharge, they can react with the various species that have been created from the dissociation of SF6. **For** all of its advantages, SF6-filled equipment is neither maintenance nor trouble free, and while SF6 may eliminate many of the issues of the oil-filled equipment, many new issues have arisen with its use. Safety and performance concerns about arc by-products, environmental concerns over the greenhouse effect of SF6 as well as the expense of new SF6 are among these issues.

IEC and CIGRE elaborate specific criteria and limits for SF6gas contamination as well as the handling of SF6 gas used in electrical switchgear applications. These criteria are found in IEC 60480 and the "SF6 Recycling & Handling Guide". Over time, the combination of moisture with certain decomposition products (such as SO2 or SOF2) produces acid, corroding the interior of switchgear tanks and creating a dangerous situation that must be avoided. The maximum acceptable impurity levels for used SF6gas (according to IEC 60480)[23]are:

SF 6 percentage: < 3%

Decomposition products: < 50 ppm

Moisture: dew point temperature > -9.4°F (MV) or > -32.8°F (HV

4. Validation and Performance Assessment of the proposed Tool

Any decision making system has to be assessed and validated by comparing it with standards and by soliciting expert clinical opinion. This can be done by having a slew of performance measures and identifying how the proposed fault diagnosis system performs. This is performed when the test results are recorded as dichotomous outcomes (positive/negative results).A diagnostic test result has four possible outcomes. They are:

True Positive (Hit): If a fault is present and it is classified as a fault, it is counted as True Positive (TN).

False Positive (false alarms): If the fault is present and it is not classified as a fault, it is counted as False Positive (FP).

False Negative (Misses): If a fault is not present and it is classified as a fault, it is counted as False Negative (FN).

True Negative (correct rejections): If a fault is not present and it is classified as no fault, it is counted as True Negative (TN).

Any assessments of diagnostic performance require some comparisons of diagnostic decisions with 'truth'. With the above classified values, different performance parameters (Accuracy, Error, Sensitivity, Specificity, Positive predictive value (PPV), Negative predictive value (NPV), False detection rate (FDR), Matthews correlation coefficient (MCC), False prediction rate, False negative rate, Prediction conditioned fallout, Prediction conditioned miss, Rate of positive prediction , Rate of negative prediction, Odds ratio, Likelihood ratio positive, Likelihood ratio negative, Prevalence, Pretest odd, Posttest odds of outcome for given positive test results, Posttest odds of outcome for given negative test results, and Receiver Operating Characteristics (ROC)) are computed. Receiver operating characteristic plots provide a pure index of accuracy by demonstrating the limits of a test's ability to discriminate between alternate states of health over the complete spectrum of operating conditions. ROC plots are fundamental; their pivotal position provides a unifying concept in the process of test evaluation. ROC graphs are two-dimensional graphs in which True positive rate (Sensitivity) is plotted on the Y-axis and False positive rate (1-Specificity) on X-axis. An ROC graph depicts relative tradeoffs between benefits (True positives) and costs (False positives). The general form of the ROC is shown in Figure (5)
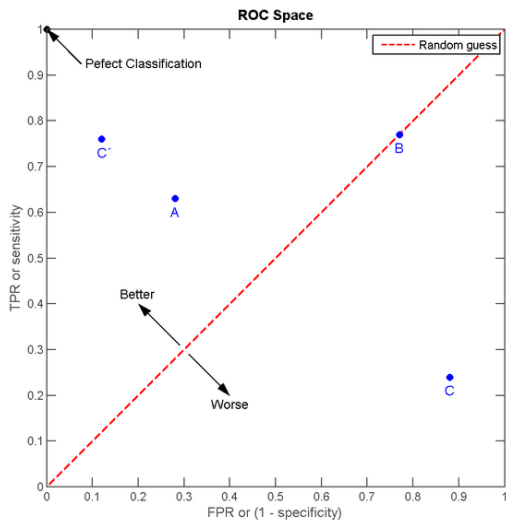
Figure (5) Plot of ROC Space

A move towards the right on an ROC is equivalent to the use of stringent diagnostic criteria (over reading) for determining the outcome of an examination, thereby increasing sensitivity but decreasing specificity. A move towards the left on a ROC increases the specificity but decreases sensitivity of the diagnostic test. The upper right corner of ROC (100% sensitivity and 0% specificity) is formed when all findings are read as abnormal. The lower left corner (0% sensitivity and 100% specificity) is formed when all findings are read as norm. These values can be computed and graphs can be plotted by add on performance measure tool integrated with the GUI-CAD (Figure 6).

Figure (6) : Screen Shot of Performance Tool

5. The Graphical User Interface Tool

A comprehensive tool capable of performing different analysis as required by the user is designed. The tool is coded using Matlab Version 7.1. A Graphical User Interface is designed for to enable the user to have seamless analysis of the data using different methods. Both Traditional Methods and methods based on artificial intelligence are available in the tool. An add on GUI is also incorporated to have an analysis of the performance of the tool in terms of different performance parameters like accuracy, sensitivity, ROC, etc..

Figure (7): Snap Shot of Graphical User Interface
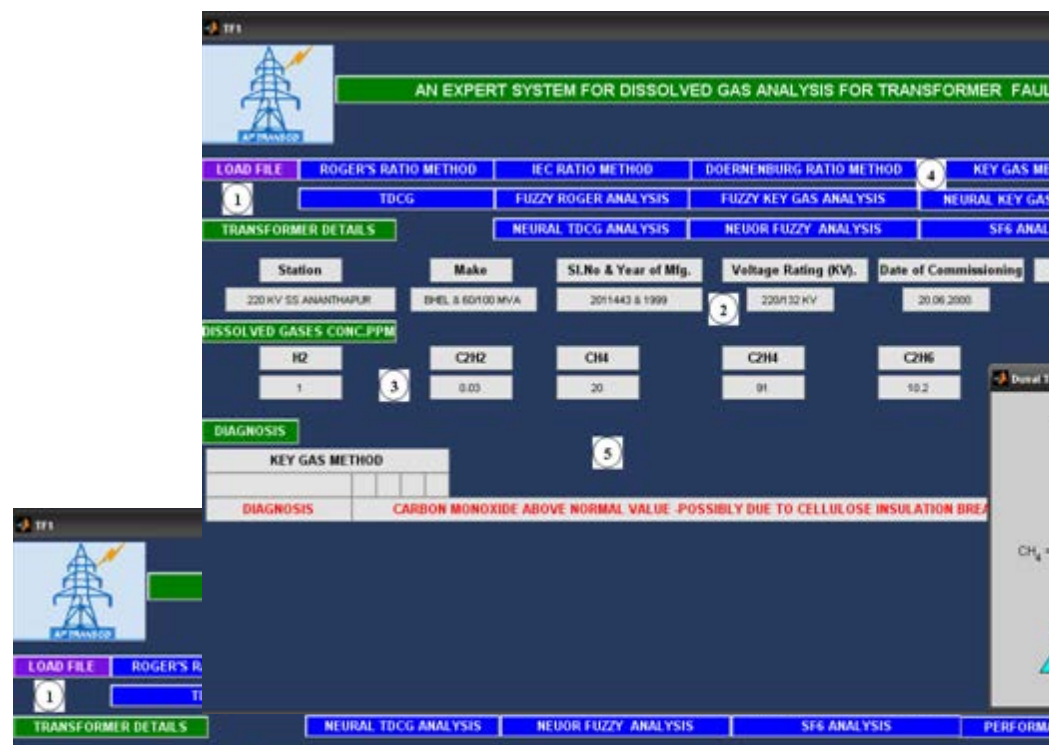
The data required for analysis is fed through an Excel sheet in predefined format. This helps in standardizing the input methods and helps in avoiding user induced error. In this work we have used the data format as used by APTRANSCO for collection of Dissolved Gas Analysis data. Once the Data is loaded the basic information about the transformer like its capacity, location, Make, average, load, date of commissioning are displayed in the GUI. Similarly the concentration of different gases in the sample under study is also depicted .Upon clicking the Load button the user is prompted to select a particular Excel work book and a specific sheet for analysis. Once the data is loaded, the user can select the method for analyzing the Data. The functional icons present in the GUI can be described as below in reference to the Figure (7)

1-
unctional icon used to load the data for analysis through a Excel spread sheet

2-
he Transformer location and other particulars like rating are displayed here.

3-
he Concentration of dissolved gases being analyzed is displayed here

4-
unctional icons used to execute different methods of analysis

5-
esults of the diagnosis are displayed here.

Whenever the value of the gas being analyzed is in excess of stipulated value as specified by that method of analysis, the diagnosis information is depicted in 'RED' otherwise it is depicted in 'GREEN'. Alert Pop –Ups are also generated to warn about a specific Condition as depicted in Figure (7).

6. Results and Discussion

The Data that is used to validate the approaches discussed in this work is obtained from APTRANSCO. To validate our proposed approach we are considering data from 2 Substation of Kurnool and Ananthapur as Sample Cases like 220/KV Transformer - AP CARBIDES (KURNOOL) and 220/KV Transformer - SS Ananthapur.

Case 1: 220/KV Transformer - AP CARBIDES (KURNOOL)

Analysis Report as given by the testing station: Results are within limits

Analysis as Obtained through the Proposed Work

1. Rogers Ratio Method: Rogers Code: 1 0 1 0 - Low Energy Discharge with Continuous Sparking to Floating Potential.

2. IEC Ratio Method : IEC Code: 1 0 1- Low Energy Discharge

3. DorenBurg Analysis Method : Not in the Purview of Dorenburg Analysis

4. Key Gas Method : All the Gases Are With In Permissible Limits-No Fault

5. Duval Triangle Method : Discharge of Low Energy [As indicated in Figure (8)]

6. DCG Method : TDCG Value: 286.69 - All the Gases Are With In Permissible Limits-No Fault

7. Fuzzy Rogers Analysis : Low Energy Discharges

8. Fuzzy Key Gas Analysis :Possible Arcing

9. ANN Analysis : Corona

Case 2: 220/KV Transformer - SS Ananthapur

Analysis Report as given by the testing station: Dissolved gases are increased. Please send one more sample after 3 months.

Analysis as Obtained through the Proposed Work

Analysis Report as given by the testing station: Dissolved gases are increased. Please send one more sample after 3 months.

Analysis as Obtained through the Proposed Work

1. Rogers Ratio Method: Not in the Purview of Analysis

2.

IEC Ratio Method : IEC Code: 0 2 2- Thermal Fault of High Temperature Range -300c t0 700 c

3.

DorenBurg Analysis Method : Not in the Purview of Dorenburg Analysis

4.

Key Gas Method : CO above Normal Value Cellulose Insulation Break Down

5.

Duval Triangle Method :Thermal Faults > 700 C [As indicated in Figure (8)]

6.

DCG Method : TDCG Value: 3721 – High Level of De-composition-Immediate Action suggested

7. Fuzzy Rogers Analysis: Thermal Fault of High Temperature Range 300C – 700C

8. Fuzzy Key Gas Analysis : High Temperature Oil Break Down (HTOB)

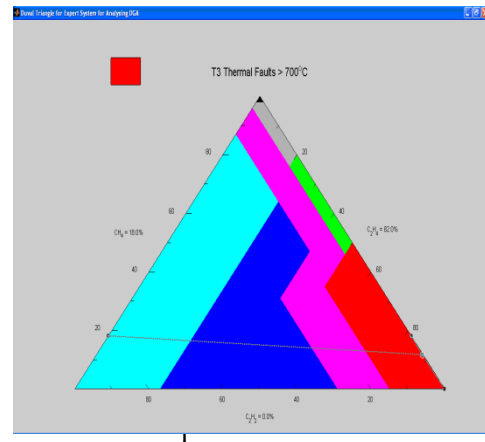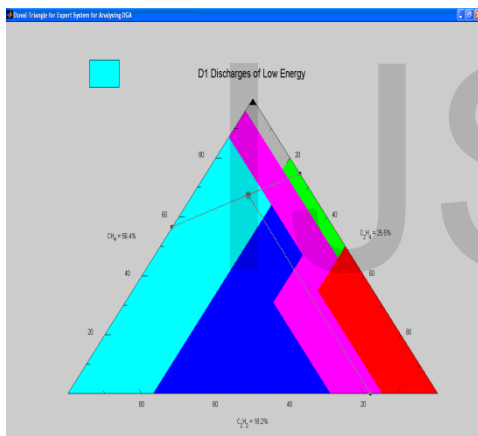9. ANN Analysis : High Temperature Oil Break Down (HTOB)

Figure (8) Snapshots of Duval Triangle for Case 1 & 2 Diagnosis as Plotted by the Tool

The analysis with respect to the NFIS system is primarily based on the values for Key Gas analysis. Based on the relation of fault gases, a decision can be made such as the presence of gas Acetylene which may indicate fault arcing if it is above certain limit in the insulation oil. In addition, the identification of Hydrogen in the presence of Methane may indicate corona or partial discharge. If corona developed into low energy sparking, a higher temperature is detected which lead to the additional presence of Acetylene. On the other hand, if sparking escalates to Arcing, the presence of Ethylene can also be detected. Furthermore, when Arcing takes place in the presence of cellulose, the high temperature deterioration of the solid insulation also releases carbon monoxide and carbon dioxide into the oil. The results of the proposed method are presented in the form of   Table (1.0). The table consists of data of dissolved gases and the diagnosis provided by different methods.

Table (1): Diagnosis from different methods in the proposed tool

Training Data

Method	PD	Thermal Faults	Discharges
Rogers	9.0	61.5	60.8
Doerenburg	42.5	69.2	74.1
Duval	59.9	93.4	95.6
IEC	32.3	79.6	82.7
ANN	74.5	83.6	89.4
GA-ANN	94.5	98.6	99.0

Table (3): Diagnostic Accuracy (%) of GA- ANN compared

H2	CH4	C2H4	C2H6	C2H2	CO	CO2	IEC	IEC	DUVAL	ANN	ANFIS
1.74	0.31	0.14	0.11	0.1	53.31	230.98	101	DL	DL	CN	ARC
0.1	2.13	24.95	8.72	0.1	26.62	169.69	21	TF - 100 - 200C	TF > 700 C	CN	ARC
0.27	17.85	0.96	20.93	0.1	25.39	370.03	-	-	TF<300C	ARC	ARC
145.33	14.11	6.11	4.69	0.1	646.8	5401.06	-	-	DTF	CN	CN
10.11	16.26	26.46	3.96	0.1	1502.54	5275.27	22	TF-300-700C	TF > 700 C	HTOB	CIB
13.2	5.05	52.18	16.81	0.1	339.29	1798.63	-	-	TF > 700 C	CN	ARC
3.74	0.6	0.78	0.22	0.1	24	303	-	-	DTF	ARC	ARC
3.39	13.99	67.64	8.45	0	277.02	2879.82	22	TF-300-700C	TF > 700 C	CN	CIB
0	14	13.6	5.2	0	602	2955	21	TF - 100 - 200C	DT	CIB	CIB
0.0	2.1	13.6	1.1	0.0	176	1694	22	TF-300-700C	TF > 700 C	CN	ARC
0.0	3.6	0.5	1.2	0.0	670	1397	20	TF-100-200C	TF<300C	CN	CIB
1.0	20.0	91.0	10.2	0.03	412	3437	22	TF-300-700C	TF > 700 C	CN	HTOB
0.0	31	2.0	27.6	0.08	90	1605	20	TF-100-200C	TF<300C	CN	ARC
0	0.7	1.2	0	0	69	497	-	-	DL	NF	NF
0	0.9	0.2	0	0	21	248	-	-	DL	NF	NF

Legend : TF- Thermal Faults; DL- Low Energy Discharge; DT-Thermal Discharge; CN-Corona ; ARC- Arcing ;CIB-Cellulose Insulation Break Down;HTOB-High Temperature Oil Break Down;NF-No Fault

It can be observed from the results that the ANFIS system is capable of identifying a wide range of faults in comparison with that of a pure ANN based diagnosis.

The diagnostic accuracy of the GA optimized ANN method in identifying different faults is given in the tables below. Table 2 indicates the performance in comparison with the training data and Table 3 the performance against the test data.

Table (2): Diagnostic Accuracy (%) of GA- ANN compared with Other Methods for

with Other Methods for Test Data

Method	PD	Thermal Faults	Discharges
Rogers	6.5	56.4	58.2
Doerenburg	38.0	64.1	71.7
Duval	55.6	89.7	91.5
IEC	27,8	74.6	79.3
ANN	71.7	79.5	85.3
GA-ANN	89.6	94.3	96.5

The performances of the proposed GA- ANN and conventional DGA techniques for detecting corona-type PDs are illustrated in Table 4. This confirms the appropriate ability of the proposed systems for detecting PDs of the corona type which oc-

cur in the gas phase of voids or gas bubbles and are very different from PDs of the sparking type occurring in the oil phase

Table (4): Positive diagnostics of various DGA techniques and the GA- ANN systems for detecting corona-type PDs

Method	Training Data	Test Data
Rogers	0/15	0/12
Doerenburg	8/15	4/12
Duval	14/15	10/12
IEC	7/15	6/12
ANN	10/15	9/12
GA-ANN	12/15	10/12

The above tables clearly suggest that the proposed method based on GA- ANN is capable of providing much higher accuracy of diagnosis in comparison to the conventional diagnosis method

The Sf6 Analysis is done in regard to the presence of four important components. The Sf6 is analyzed for the presence of SOF_2, SO_2 and SO_2F_2. The dew point is also analyzed for its permissible limits and possible outcomes. The presence of SO_2 above the permissible is a typical indication of occurrence of overheats faults. Similarly the presence of SOF_2 and SO_2F_2 indicates the probable occurrence of arc discharges and spark discharges respectively. The below Table (5) summaries the results of SF6 analysis of a sample test case

Table (5): Sf6 Diagnosis of test Samples

Sample	Diagnosis
Sample 1	
Dew Point : -25 C SOF$_2$: 40 SO$_2$: 100 SO$_2$F$_2$: 400	Over heat fault in excess of 400 c
Sample 2	
Dew Point : -55 C SOF$_2$: 40 SO$_2$: 500 SO$_2$F$_2$: 600	Moisture in Excess of Permissible Limits, Over heat fault in excess of 500 c and possible occurrence of Spark discharges.

The validity of the expert system is tested against an expert clinical opinion and comparative analysis through a set of data which includes gases to indicate the presence and absence of faults. Five sample sets of data are taken. The data is generalized to indicate the presence and absence of a fault without detailing in to the specific kind and type of fault. The decision making ability of the expert system is compared in analysis to any one of the method succeeding in the correct identification of the fault. The tabular column Table (6) gives the different

sample sets used and cumulative number of faults present and absent in that particular data set.

Table (6): Number of Sample gas concentrations indicating fault and no fault.

Data	Number of gas concentrations indicating the presence of faults	Number of gas concentrations indicating the absence of faults
Data set 1	29	17
Data set 2	41	24
Data set 3	48	35
Data set 4	37	36
Data set 5	30	23

When the above data sets were analyzed using the different methods designed in this work, their prediction is presented in the form of results are recorded as dichotomous outcomes (positive/negative results) as describe in section 4.

Table (7): Dichotomous outcomes (positive/negative results)

Data	Number of True Positives (TP)	Number of False Positives (FP)	Number of True Negatives (TN)	Number of False Negatives (FN)
Data set 1	27	2	15	2
Data set 2	38	1	23	3
Data set 3	46	2	33	2
Data set 4	32	1	35	5
Data set 5	28	1	21	2

Different performance parameters (Accuracy, Error, Sensitivity, Specificity, Positive predictive value (PPV), Negative predictive value (NPV), False detection rate (FDR), Matthews correlation coefficient (MCC), False prediction rate, False negative rate, Prediction conditioned fallout, Prediction conditioned miss, Rate of positive prediction , Rate of negative prediction, Odds ratio, Likelihood ratio positive, Likelihood ratio negative, Prevalence, Pretest odd, Posttest odds of outcome for given positive test results, Posttest odds of outcome for given negative test results, and Receiver Operating Characteristics (ROC)) are computed using a built in GUI as described in section 4. Using a built function 'Tabulate Results in Excel' all the

results of the above mentioned performance parameters are directly tabulated and plotted in an Excel work book. This enables the user to have a recorded view and analysis of the performance measures. The below figure (9) give the snapshot of the Excel work book created to store the performance measures of the five different data sets being tested

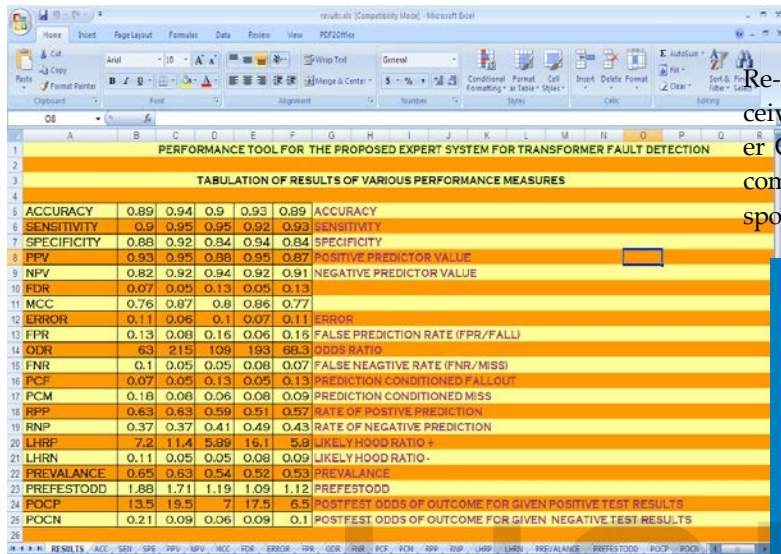| ACCURACY	0.90986	ODR	129.35
SENSITIVITY	0.9310778	FNR	0.0689222
SPECIFICITY	0.8824723	PCF	0.0860267
PPV	0.9139733	PCM	0.09814
NPV	0.90186	RPP	0.5853367
FDR	0.0860267	RNP	0.4146633
MCC	0.814659	LHRP	9.2845981
ERROR	0.09014	LHRN	0.0781038
FPR	0.1175277	PREVALANCE	0.5750006

Figure (10) : Screen Shot of Excel sheet populated automatically for Analysis

A sample plot of accuracy as plotted automatically in the Excel work book is given in the below figure (10)

Receiver Operating Characteristics plot (Sensitivity Vs 1-Specificity) combined for five data sets is shown below and the corresponding area under the ROC in figure (11)

Figure (11): Plot of ROC Space

The data points on the plot indicate the ROC heaven region of ROC space which is desired area on ROC space implying the best diagnosis performance of the proposed tool.
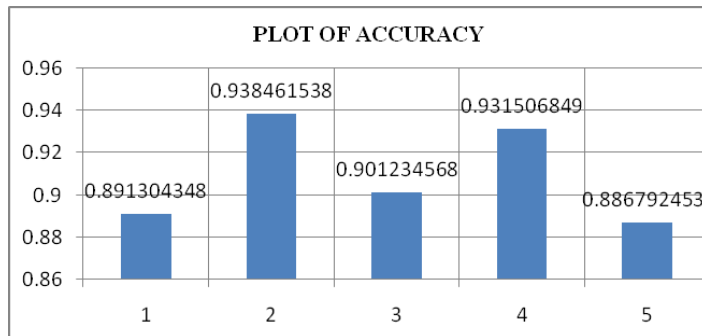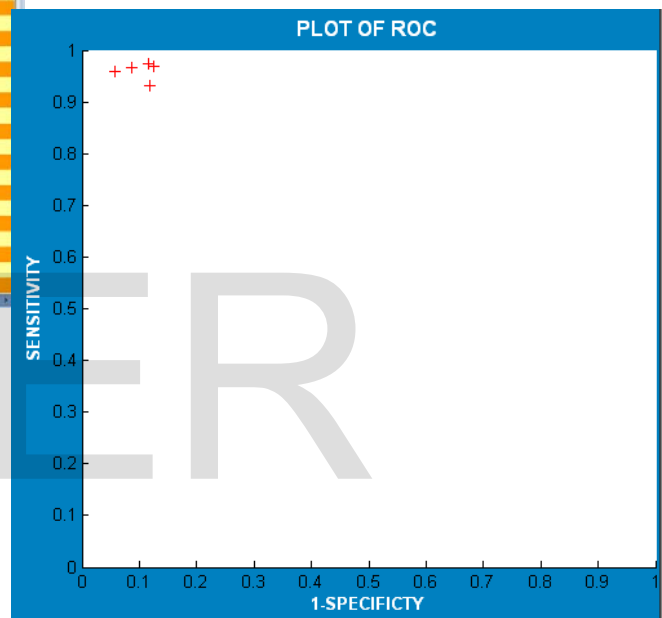
Figure (10): Plot of accuracy for the 5 sample data sets.

The below table (8) tabulates the different performance measures for the 5 sample datasets. The average value of each measure for the five sample sets are presented below.

Table (9): The average performance measures value for different data set.

7. Conclusion

An automated tool using Matlab is designed for analyzing the dissolved gases in transformer oil and subsequent interpretation of possible faults. The tool is configured to be an expert system capable of performing a wide variety of analysis both in the conventional domain and by using AI tools. The comprehensive nature of the tool makes interpretation and decision making an informed one helping in early detection and diagnosis of transformer faults. The tool can also be used for the analysis of Sf6.To validate the performance of the tool data is obtained from APTRANSCO about analysis of dissolved gas done at different transformers spread over entire Andhra Pradesh.

According to the IEEE standard (C57.104-1991) , all the fault gases have their own norm value in normal and in faulty condition and the norm value varies due to different operating conditions, manufacturers and environmental factors such as humidity and weather. Due to this, different institutions from different countries have set their own sets of norm values in fault diagnosis. In this work, the IEEE norm value has been selected for Key Gas fault diagnostic method. It can be observed from the results that the ANFIS system is capable of identifying a wide range of faults in comparison with that of a pure ANN based diagnosis. Similarly the proposed method based on GA- ANN is capable of providing much higher accuracy of diagnosis in comparison to the conventional diagnosis methods. The Sf6 analysis is also capable of giving a wide prediction of the different faults that can be diagnosed and attributed to the impurities present in the Sf6.

The performance measures also indicate that the system is capable of providing a very good convergence in terms of fault detection and diagnosis. It can be observed from the above results that the proposed tool is capable of providing a better opinion in regard to fault detection. Because of this comprehensive approach a conservative opinion can be obtained in the viewpoint of equipment safety and necessary action shall be initiated.

8. References

[1] M. Duval and A. dePablo, "Interpretation of gas-in-oil analysis using new IEC publication 60599 and IEC TC 10 databases," *IEEE Electrical Insulation Magazine*, vol. 17, pp. 31–41, 2001.

[2] M. Duval, "Dissolved gas analysis: It can save your transformer," *IEEE Electrical Insulation Magazine*, vol. 5, pp. 22–27, 1989.

[3] IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers, IEEE Std. C57.104-2008, 2009.

[4] Mineral Oil-Impregnated Equipment in Service Guide to the Interpretation of Dissolved and Free Gases Analysis, *IEC Std. Publication 60 599, 1999.*

[5] R. R. Rogers, "IEEE and IEC codes to interpret incipient faults in transformers, using gas in oil analysis," *IEEE Transactions on Electrical Insulation*, vol. EI-13, pp. 349–354, 1978.

[6] J. J. Dukarm, "Tranformer oil diagnosis using fuzzy logic and neural networks," in *CCECE/CCGEI, 1993*, pp. 329–332.

[7] Y. Zhang, X. Ding, Y. Liu, and P. Griffin, "An artificial neural network approach to transformer fault diagnosis," *IEEE Transactions on Power Delivery*, vol. 11, pp. 1836–1841, 1996.

[8] Y.-C. Huang, H.-T. Yang, and C.-L. Huang, "Developing a new transformer fault diagnosis system through evolutionary fuzzy logic," *IEEE Transactions on Power Delivery*, vol. 12, pp. 761–767, 1997.

[9] H.-T. Yang and Y.-C. Huang, "Intelligent decision support for diagnosis of incipient transformer faults using self-organizing polynomial networks," *IEEE Transactions on Power Delivery*, vol. 13, pp. 946–952, 1998.

[10] Z. Wang, Y. Liu, and P. J. Griffin, "A combined ann and expert system tool for transformer fault diagnosis," *IEEE Transactions on Power Delivery*, vol. 13, pp. 1224–1229, 1998.

[11] J. Guardado, J. Naredo, P. Moreno, and C. Fuerte, "A comparative study of neural network efficiency in power transformers diagnosis using dissolved gas analysis," *IEEE Transactions on Power Delivery*, vol. 16, pp. 643–647, 2001.

[12] Y.-C. Huang, "Evolving neural nets for fault diagnosis of power transformers,"*IEEE Transactions on Power Delivery,* vol. 18, pp. 843–848, 2003.

[13] V. Miranda and A. R. G. Castro, "Improving the IEC table for transformer failure diagnosis with knowledge extraction from neural networks*," IEEE Transactions on Power Delivery*, vol. 20, pp. 2509– 2516, 2005.

[14] X. Hao and S. Cai-Xin, "Artificial immune network classification algorithm for fault diagnosis of power transformer," *IEEE Transactions on Power Delivery*, vol. 22, pp. 930–935, 2007

[15] R. Naresh, V. Sharma, and M. Vashisth, "An integrated neural fuzzy approach for fault diagnosis of transformers," *IEEE Transactions on Power Delivery*, vol. 23, pp. 2017–2024, 2008.

[16] W. Chen, C. Pan, Y. Yun, and Y. Liu, "Wavelet networks in power transformers diagnosis using dissolved gas analysis," *IEEE Transactions on Power Delivery*, vol. 24, pp. 187–194, 2009.

[17] A. Shintemirov, W. Tang, and Q. Wu, "Power transformer fault classification
based on dissolved gas analysis by implementing bootstrap and genetic programming," *IEEE Transactions on Systems, Man and Cybernetic*s, vol. 39, 2009.

[18] Y.-C. Huang, "Evolving neural nets for fault diagnosis of power transformers," *IEEE Trans. Power Del*., vol. 18, no. 3, pp. 843–848, July

[19] Fuzzy Logic Toolbox, MATLAB

[20] Adaptive Neuro-Fuzzy Systems, Azar, Ahmad Taher, Electrical Communications & Electronics Systems Engineering Department, Modern Science and Arts University (MSA),ISBN 978-953-7619-92-3,pp216

[21] S. N. Pandey, S. Tapaswi, and L. Srivastava, "Integrated evolutionary neural network approach with distributed computing for congestion management," Applied Soft Computing Journal, vol. 10, no. 1, pp. 251–260, 2010.

[22] S. Rajasekaran and G. A. V. Pai, Neural Networks, Fuzzy Logic and Genetic Algorithms—Synthesis and Applications, Prentice-Hall Press, New Delhi, India, 2006.

[23] IEC INTERNATIONAL STANDARD-**60480-**Second edition 2004-10