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Hybrid diagnosing techniques for analyzing dissolved gases in power transformers

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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 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 Andhra Pradesh State Transmission Corporation (APTRANSCO) in the form of required transformer analysis data and expert opinion for validation of the tool.

Key words: Transformer faults, expert system, Matlab, graphical user interface (GUI), fuzzy, artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS), genetic algorithm- artificial neural networks (GA-ANN).

INTRODUCTION

Dissolved Gas Analysis (DGA) has been used for more than 30 years (Duval and dePablo, 2001; Duval, 1989; IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers, 2009) for the condition

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assessment of functioning electrical transformers. DGA measures the concentrations of hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO) and carbon dioxide (CO_2) dissolved in transformer oil. CO and CO2 are generally associated with the decomposition of cellulose insulation; usually, small amounts of H_2 and CH_4 would be expected as well. C_2H_6, C_2H_4, C_2H_2 and larger amounts of H_2 and CH_4 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 (IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers, 2009) and IEC 60599 (1999) use threshold values for gas levels.

Other methods make use of ratios of gas concentrations (Duval, 1989; Rogers, 1978) 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 (1999) 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, 300ºC < T < 700ºC) and T3 (Thermal fault of high temperature range, T >700ºC) (Zhang et al., 1996). 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 (Dukarm, 1993; Zhang et al., 1996; Yang and Huang, 1998; Wang et al., 1998; Guardado et al., 2001; Huang, 2003; Miranda and Castro, 2005; Naresh et al., 2008; Chen et al., 2009) built around a feed-forward neural-network classifier, that is also called Multi-Layer Perceptron (MLP) and that will be explained in the paper. Some of these papers introduce further enhancements to the MLP: in particular, neural networks that are run in parallel to an expert system in Wang et al. (1998), Wavelet Networks (that is, neural nets with a wavelet-based feature extraction) in Chen et al. (2009), Self-Organizing Polynomial Networks in Yang and Huang (1998) and Fuzzy Networks in Dukarm (1993), Huang (2003), Miranda and Castro (2005), and Naresh et al. (2008). Several studies (Dukarm, 1993; Huang et al., 1997; Huang, 2003; Miranda and Castro, 2005; Naresh et al., 2008; Chen et al., 2009) resort to fuzzy logic **(**Huang, 2003**)** 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 Huang et al. (1997), Huang (2003), Hao and Cai-Xin (2007), Chen et al. (2009), and Shintemirov et al. (2009). Finally, Shintemirov et al. (2009) 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 a comprehensive tool which incorporates both traditional methods and tools based Artificial Intelligence has been designed. After an introduction and motivation for the paper along with a brief survey of literature, the problem statement was briefly described, followed by a description of approaches for dissolved gas analysis. An insight into the GUI tool was provided, the results presented and the study concluded.

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 genetic algorithm- artificial neural networks

(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.

ANALYSIS METHODS INCORPORATED IN THE AUTOMATE 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.

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.

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.

Quantization

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 (Med), High (Hi) and Very High (Vhi) term set according to their membership intervals as defined below:

AE = {Lo, Med, Hi}
MH = {Lo, Med, Hi, Vhi}
EE = {Lo, Med, Hi}
EM = {Lo, Hi }

Assignment of membership functions

This approach is using the membership functions of type Triangular, Trapezoidal, L-function and Γ-function. The fuzzy membership function for the Roger 4 ratio input classifications for Acetylene / Ethane (AE), Methane / Hydrogen (MH), Ethane / Ethylene (EE) and Ethane / Methane (EM). Figure 1 depicts the structure of membership function used for Ethylene / Ethane (EE)

Fuzzy inference rules setup

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, the fuzzy logic techniques which allow partial membership may improve the number of matched cases as compared to the ordinary crisp set theory.

Antecedent:

Rule 1 = Min{MH=L, AE=L,EE=L, EM=L}
Rule 2 = Min{MH=L, AE=L,EE=L, EM=H}
Rule 3 = Min{MH=L, AE=L, EE=M, EM=L}
Rule 4 = Min{MH=L, AE=M, EE=L, EM=L}
Rule 5 = Min{MH=M, AE=L, EE=L, EM=L}
Rule 6 = Min{MH=M, AE=L, EE=L, EM=H}
Rule 7 = Min{MH=M, AE=L, EE=M, EM=L}
Rule 8 = Min{MH=M, AE=L, EE=M, EM=H}
Rule 9 = Min{MH=M, AE=M, EE=L, EM=L}
Rule 10 = Min{MH=M, AE=M, EE=L, EM=H}
Rule 11 = Min{MH=M, AE=M, EE=M, EM=L}
Rule 12 = Min{MH=M, AE=M, EE=H, EM=L}
Rule 13 = Min{MH=M, AE=H, EE=L, EM=L}
Rule 14 = Min{MH=M, AE=H, EE=M, EM=L}
Rule 15 = Min{MH=M, AE=H, EE=H, EM=L}
Rule 16 = Min{MH=H, AE=L, EE=L, EM=L}
Rule 17 = Min{MH=H, AE=L, EE=L, EM=H}
Rule 18 = Min{MH=H, AE=L, EE=M, EM=L}
Rule 19 = Min{MH=H, AE=L, EE=H, EM=L}
Rule 20 = Min{MH=H, AE=M, EE=L, EM=L}
Rule 21 = Min{MH=VH, AE=L, EE=L, EM=H}
Rule 22 = Min{MH=VH, AE=L, EE=H, EM=L}

The output of the fuzzy inference can be obtained using the Mamdani’s Max-Min composition technique and the

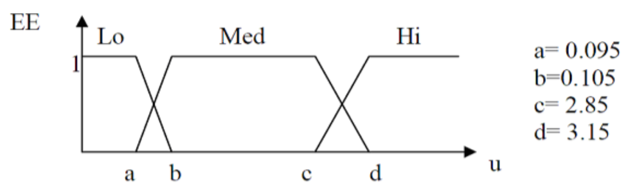


Figure 1. Structure of membership function used for Ethylene / Ethane (EE).

Table 1. Quantification for different key gases.

Gas	High	Medium	Low
H_2	105	100	95
C_2H_2	36.75	35	33.25
C_2H_4	52.5	50	47.5
C_2H_6	68.25	65	47.5
CH_4	126	120	114
CO	367.5	350	332.5
CO_2	2625	2500	2375

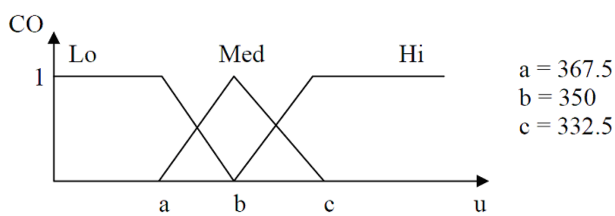


Figure 2. Structure of membership function used for CO.

consequent are computed as follows:

Condition A = Max {rule 5}
Condition B = Max {rule 1}
Condition C = Max {rule 4}
Condition D = Max {rule 3}
Condition E = Max {rule 2}
Condition F = Max {rule 9, rule 13}
Condition G = Max {rule 11, rule 14}
Condition H = Max {rule 12, rule 15}
Condition I = Max {rule 7}
Condition J = Max {rule 8}
Condition K = Max {rule 10, rule 20}
Condition M = Max {rule 16}
Condition N = Max {rule 6, rule 17, rule 21}
Condition O = Max {rule 18}
Condition P = Max {rule 19, rule 22}

Fuzzy key gas method

A set of rules to diagnose abnormalities such as Thermal, Corona or Arcing problems is employed in The Key Gas method. It is a reliable diagnostic method because it can be used to diagnose the condition of the transformer even though 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.

Quantization

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% more or 5% less than the medium term set respectively as defined in Table 1.

For the Fuzzy Key Gas fault diagnostic method, the appropriate types of membership function are Triangular, L-function and Γ-function. The fuzzy membership function for the Key Gas input for H_2, CO, CO_2, C_2H_2, C_2H_4, C_2H_6, CH_4 and the Figure 2 depicts the structure of membership function used for Carbon Monoxide (CO).

Selection of fuzzy compositional operator

The output of the fuzzy inference can be obtained using the Mamdani's Max-Min composition technique shown as follows:

Antecedent:

Rule 1 = Min{ H_2=Hi }
Rule 2 = Min{ H_2=Med }
Rule 3 = Min{ H_2=Lo }
Rule 4 = Min{ CO=Hi and CO_2=Hi }
Rule 5 = Min{ CO=Hi and CO_2=Med }
Rule 6 = Min{ CO=Hi and CO_2=Lo }
Rule 7 = Min{ CO=Med and CO_2=Hi }
Rule 8 = Min{ CO=Med and CO_2=Med }
Rule 9 = Min{ CO=Med and CO_2=Lo }
Rule 10 = Min{ CO=Lo and CO_2=Hi }
Rule 11 = Min{ CO=Lo and CO_2=Med }
Rule 12 = Min{ CO=Lo and CO_2=Lo }
Rule 13 = Min{ C_2H_2=Hi }
Rule 14 = Min{ C_2H_2=Med }

Rule 15 = Min{ C_2H_2=Lo }
Rule 16 = Min{ C_2H_4=Hi }
Rule 17 = Min{ C_2H_4=Med }
Rule 18 = Min{ C_2H_4=Lo }
Rule 19 = Min{ CH_4=Hi and C_2H_6=Hi }
Rule 20 = Min{ CH_4=Hi and C_2H_6=Med }
Rule 21 = Min{ CH_4=Hi and C_2H_6=Lo }
Rule 22 = Min{ CH_4=Med and C_2H_6=Hi }
Rule 23 = Min{ CH_4=Med and C_2H_6=Med }
Rule 24 = Min{ CH_4=Med and C_2H_6=Lo }
Rule 25 = Min{ CH_4=Lo and C_2H_6 =Hi }
Rule 26 = Min{ CH_4=Lo and C_2H_6=Med }
Rule 27 = Min{ CH_4=Lo and C_2H_6=Lo }

The consequent are 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.

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 (Huang, 2003). 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 H_2, 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 of training and adaptation of the network is used. 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.

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 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 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, CO_2 and CO gas concentrations are the input vectors for the network.

ANFIS can also be invoked using an optional argument 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.

The accuracy of any Neuro Fuzzy system is influence by its inference rules and how many possible conditions these inference rules may represent positively; the higher the representation higher the accuracy. These input parameters are classified as High, Medium and Low as described in 'Fuzzy Key Gas Method'. The faults that are classified are CN, CIB, LTOB, HTOB, and ARC. A representation of the rules are given below

Rule 1: If $H_{2\,=}$ LOW and CH_4, =LOW and C_2H_4 =LOW and C_2H_6 =LOW and $C_2H_{2\,=}$ LOW, and CO_2=LOW and CO =LOW Fault = 0 (No Fault)

Rule 2: If $H_{2\,=}$ MEDIUM and CH_4, =LOW and C_2H_4 =LOW and C_2H_6 =LOW and $C_2H_{2\,=}$ LOW, and CO_2=LOW and

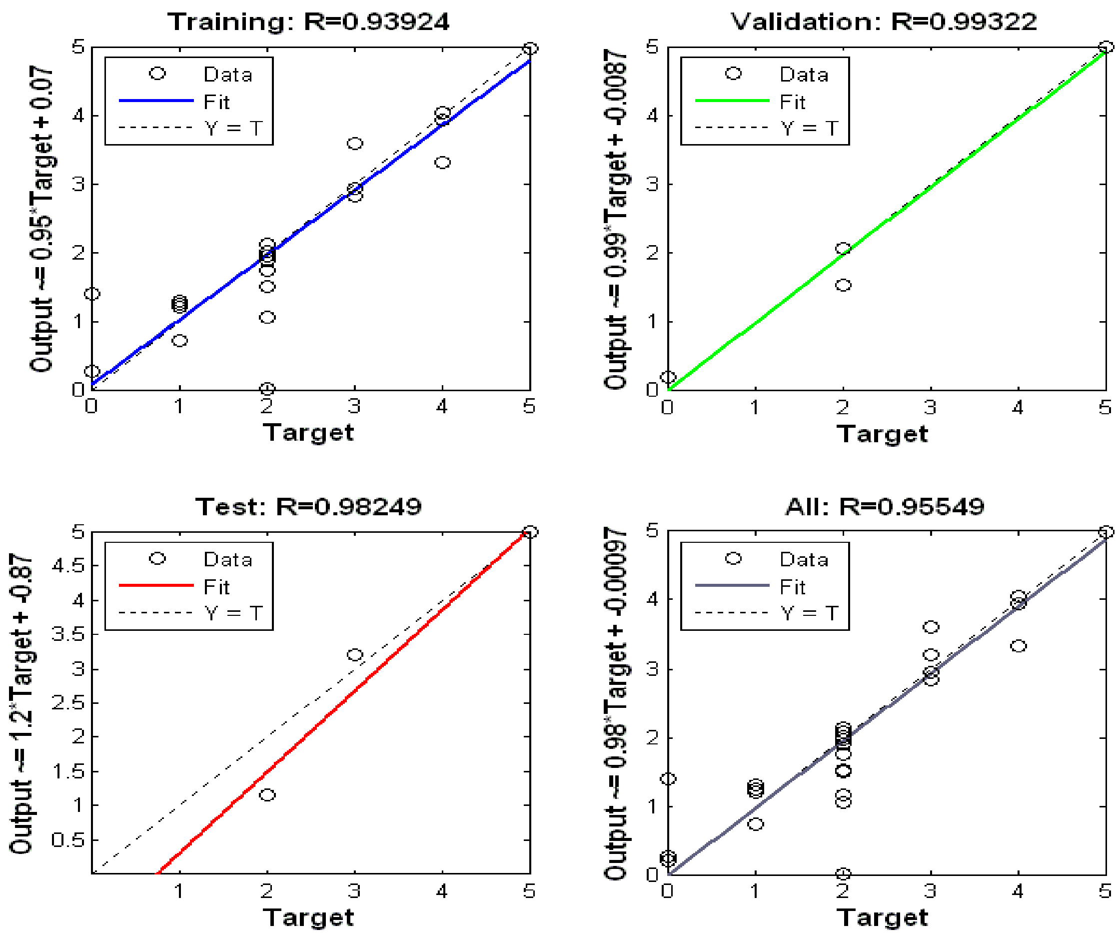


Figure 3. Regression plot of the ANN used in analysis.

CO =LOW Fault = 0 (No Fault)
Rule 3: If H_2 = HIGH and CH_4, =LOW and C_2H_4 =LOW and C_2H_6 =LOW and C_2H_2 = LOW and CO_2=LOW and CO =LOW Fault = 1 (CN Fault)
Rule 4: If H_2 = LOW and CH_4, =LOW and C_2H_4 =LOW and C_2H_6 =LOW and C_2H_2 = MEDIUM, and CO_2=MEDIUM and CO =LOW Fault = 0 (No Fault)
Rule 5: If H_2 = LOW and CH_4,=LOW and C_2H_4 =LOW and C_2H_6 =LOW and C_2H_2 = MEDIUM, and CO_2=HIGH and CO =LOW Fault = 2 (CIB)
Rule 6: If H_2 = LOW and CH_4, =LOW and C_2H_4 =LOW and C_2H_6 =LOW and C_2H_2 = MEDIUM, and CO_2=MEDIUM and CO =LOW Fault = 0 (No Fault)
Rule 7: If H_2 = LOW and CH_4, =LOW and C_2H_4 =LOW and C_2H_6 =LOW and C_2H_2 = MEDIUM, and CO_2=LOW and CO =MEDIUM Fault = 2 (No Fault).

Rule 177: If H_2 = HIGH and CH_4, =HIGH and C_2H_4 =HIGH and C_2H_6 =HIGH and C_2H_2 = HIGH, and CO2=HIGH and CO =HIGH Fault = 5 (HTOB).
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.

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

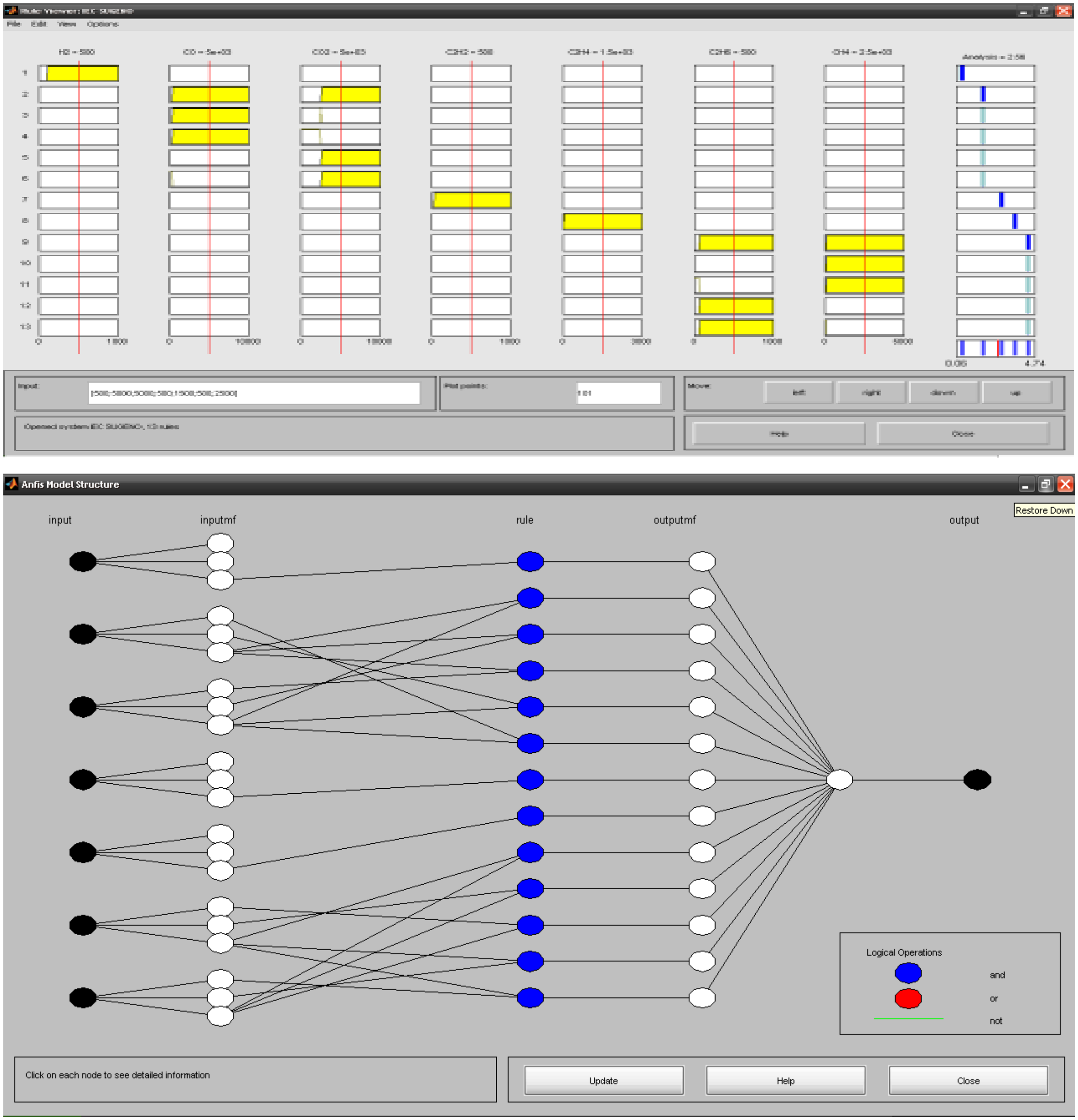


Figure 4. Rule base of Sugeno System to Model and ANFIS model structure.

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 (Pandey et al., 2010). 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” (Pandey et al., 2010). 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 (Rajasekaran and Pai, 2006). 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.

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.

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 5.

1- Functional icon used to load the data for analysis through a Excel spread sheet
2- The Transformer location and other particulars like rating are displayed here.
3- The Concentration of dissolved gases being analyzed is displayed here
4- Functional icons used to execute different methods of analysis
5- Results of the diagnosis are displayed here.

Whenever the value of the gas being analyzed is in excess of a 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 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 two Substations of Kurnool and Ananthapur as Sample Cases like 220/KV Transformer - AP CARBIDES (KURNOOL) and 220/KV Transformer - SS Ananthapur (Tables 2 and 3). In Table 2, analysis report as given by the testing station [220/KV Transformer - AP CARBIDES (KURNOOL)], with results being within limits is presented. In Table 3, analysis report as given by the testing station (220/KV Transformer - SS Ananthapur), with dissolved gases increased is presented, with one more sample to be sent after 3 months.

The analysis with respect to the ANFIS 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

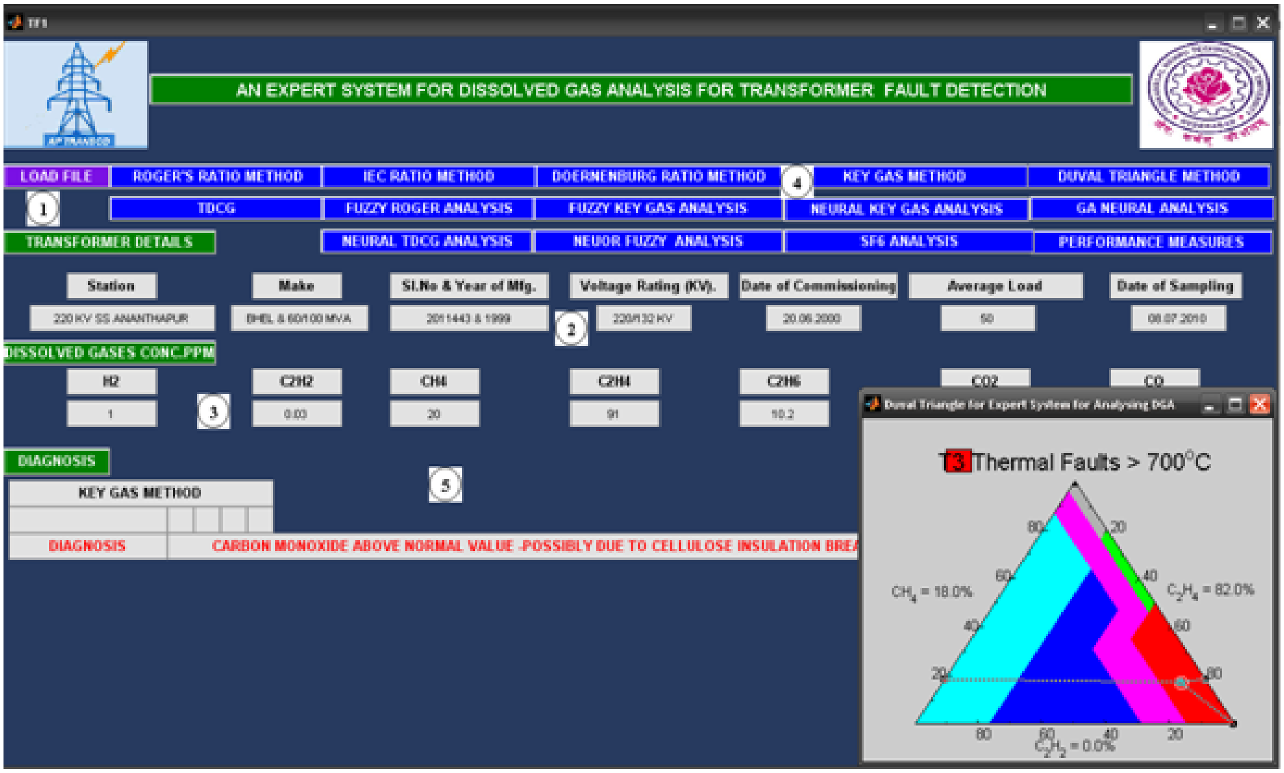
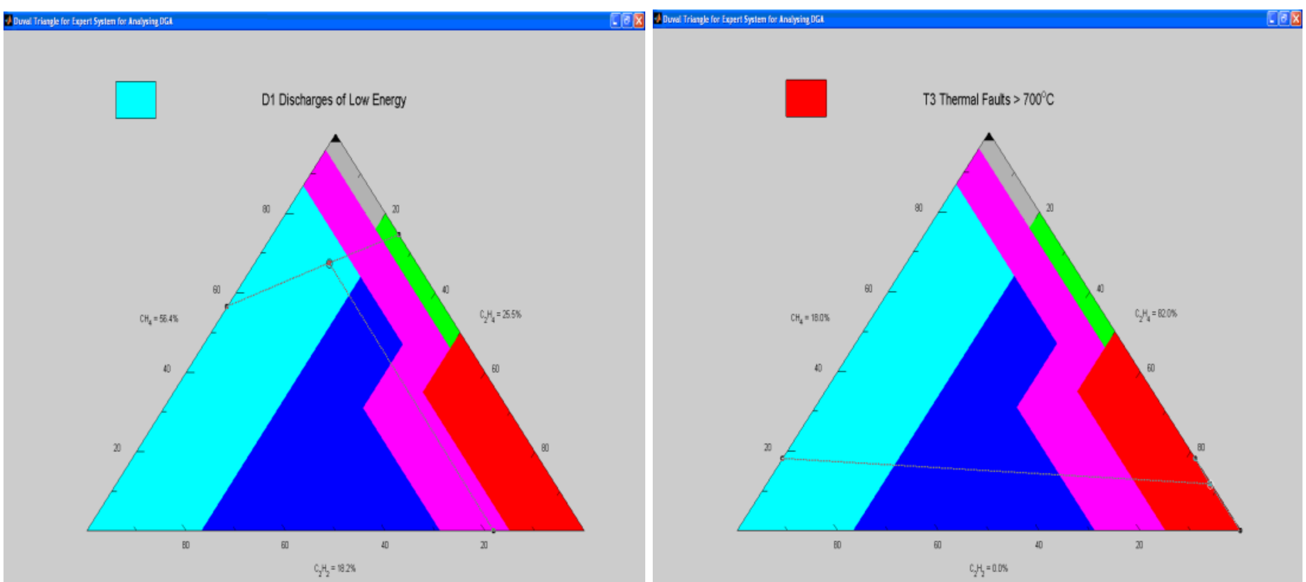


Figure 5. Snap shot of graphical user interface.



(Case 1) (Case 2)

Figure 6. Snapshots of Duval triangle for Cases 1 and 2 diagnoses as plotted by the tool.

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

Table 2. Case 1 [220/KV Transformer - AP CARBIDES (KURNOOL)] analysis as obtained through the proposed work.

S/No	Type of diagnosis	Result
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 6)
6	TDCG Method	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

Table 3. Case 2 (220/KV Transformer - SS Ananthapur) analysis as obtained through the proposed work.

S/No	Type of diagnosis	Result
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 -300 to 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 6)
6	TDCG Method	TDCG Value: 3721 – High Level of Decomposition-Immediate Action suggested
7	Fuzzy Rogers Analysis	Thermal Fault of High Temperature Range 300 – 700°C
8	Fuzzy Key Gas Analysis	High Temperature Oil Break Down (HTOB)
9	ANN Analysis	High Temperature Oil Break Down (HTOB)

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 4. The table consists of data of dissolved gases and the diagnosis provided by different methods.

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 5 indicates the performance in comparison with the training data and Table 6 the performance against the test data.

The performances of the proposed GA- ANN and conventional DGA techniques for detecting corona-type PDs are illustrated in Table 7. This confirms the appropriate ability of the proposed systems for detecting PDs of the corona type which occur in the gas phase of voids or gas bubbles and are very different from PDs of the sparking type occurring in the oil phase.

Tables 4 to 7 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.

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. 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

Table 4. Diagnosis from different methods in the proposed tool.

H_2	CH_4	C_2H_4	C_2H_6	C_2H_2	CO	CO_2	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.

Table 5. Diagnostic accuracy (%) of GA- ANN compared with other methods for 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 6. Diagnostic accuracy (%) of GA- ANN compared 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

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.

Table 7. 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

Conflict of Interest

The authors have not declared any conflict of interests.

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