National Institute of Technology, Hamirpur (HP), India

EXTENDED ABSTRACT OF THE M.TECH DISSERTATION

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Application of Artificial Intelligence in Incipient Fault diagnosis and Condition Assessment of Power Transformer

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1. Introduction

This dissertation presents a systematic study of artificial intelligence (AI) applications for the incipient fault diagnosis and condition assessment of power transformer. The AI techniques include fuzzy-logic systems and artificial neural networks (ANN, or probabilistic neural networks - PNN).

The fault diagnosis is based on dissolved gas-in-oil analysis (DGA). A literature review [1-3] showed that the conventional fault diagnosis methods, i.e. the ratio methods (Rogers, Dornenburg and IEC) and the key gas method [4-6], have limitations such as the "no decision" problem. Various AI techniques may help solve the problems and present a better solution [7-11] when implemented for fault diagnosis of power transformers.

Based on the IEC 60599 standard and industrial experience, a knowledge-based inference engine for fault detection was developed. Using historical transformer failure data from [12] and an industrial partner, a multi-layer perceptron (MLP) modular neural network was identified as the best choice among several neural network architectures. Subsequently, the concept of a hybrid diagnosis was proposed and implemented, resulting in a combined neural network and fuzzy expert system tool for power transformer incipient diagnosis. The abnormal condition screening process, as well as the principle and algorithms of combining the outputs of knowledge based and neural network based diagnosis, were proposed and implemented in the ANN and Fuzzy-Logic. Methods of fuzzy logic based transformer oil/paper insulation condition assessment, and estimation of oil sampling interval and maintenance recommendations, were also proposed and implemented in the present dissertation works.

Several methods of power transformer incipient fault location were investigated, and a MLP network and Fuzzy-Logic were identified as the best choice. Several methods for on-load tap changer (OLTC) coking diagnosis were also investigated, and a MLP based modular network Fuzzy-Logic were identified as the best choice. Logistic regression analysis was identified as a good auditor in neural network input pattern selection processes.

The above results can help developing better power transformer maintenance strategies, and serve as the basis of on-line DGA transformer monitors.

2. Materials and Methodology

2.1 Transformer Units

Ten transformers from seven substations of the Himachal Pradesh Electricity Board (HPSEB), Shimla, India are used for the purpose of data. The data is collected from the transformer's maintenance records of the operation and maintenance department and oil samples are collected as per ASTM standard. The transformers have different service periods and aging conditions. The transformers ratings ranges from 6.3-52MVA and their rating voltage ratios are 132/33/11 KV.

2.2. Methods

There are several conventional methods for transformer fault diagnosis and condition assessment using DGA on which AI techniques can be applied, out of theme some methods have been taken for the dissertation work as follows:

2.2.1. Possible Fault Diagnosis Using Key Gas Method

Incipient faults of power transformers can be classified into the following major categories [C57.125, C57.104]: electrical arcing, electrical corona, overheating of cellulose, overheating of oil. These faults may due to one or more of the causes shown in Table 2.1. This classification is a standard but not the only one that is being used in practice. For example, Doble Engineering Company used a different classification system. According to Table 2-1, one fault type may have more than one cause. This makes fault location very difficult.

Table 2.1: Correlation between Power Transformer Incipient Faults and Causes

Causes	**Faults Type**			
	Arcing	Corona	Overheating of cellulose	Overheating of oil
Winding turn-to-turn short-circuit	X		X	
Winding open circuit	X		X	
Operation of build-in LTC	X			
Winding distortion or displacement		X	X	
Lead distortion or displacement		X	X	
Loose connection to bushing terminals, tap leads, terminal boards	X	X	X	
Free water or excessive moisture in oil	X	X		
Floating metal particles	X	X		
Loose connection to corona shields		X		
Loose collars, spacers, core ground straps, core hold down angle (Braces)		X		
Through fault			X	
Overloading			X	X
Damaged yoke bolt insulation				X
Rust or other damage on core				X
Damaged shunt packs of tank				X
Jammed oil circulating path				X
Cooling system malfunction				X

An ANSI/IEEE standard describes key gas method approach. This method is computationally straightforward. However, this method, in some cases, provides erroneous diagnoses as well as no conclusion for the fault type. The key gas method based on the determination of the key gas provides the basis for qualitative determination of fault types from the gases that are typical or predominant at various temperatures. Now, if the fault is very severe, then all of the gas concentrations will be high, yet insufficient to register a fault when using the values specified in IEEE standard [11].

Table 2.2: Key Gases for DGA and Their Faults

Key Gases	**Symbol for Key Gases**	**Type of Fault**
Hydrogen	H_2	Corona

Carbon-Dioxide Carbon-Monoxide	CO_2 CO	Cellulose Insulation Break Down
Methane Ethane	CH_4 C_2H_6	Low Temperature Oil Break-Down
Ethylene	C_2H_4	High Temperature Oil Break-Down

2.2.2. Incipient Fault Diagnosis Using IEC Roger's Ratio Method

The typical faults in power transformers are classified as partial discharges, discharges of low and high energy, and thermal faults of three degrees of severity depending upon the temperature of the fault. Many countries have adopted this standard as a reference standard like India. The individual gases used to determine each ratio and its assigned limits are shown in Tables 2.3 and 2.4.

Table 2.3. IEC Ratio Codes [5]

Ratio ⇔ Codes	**0**	**1**	**2**
$X_1=C_2H_2/C_2H_4$	<0.1	0.1-3	>3
$X_2=CH_4/H_2$	0.1-1	<0.1	>1
$X_3=C_2H_4/C_2H_6$	<1	1-3	>3

Table 2.4. Classification of Faults according to the IEC gas ratio codes [5]

No.	**Fault Type**	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
0	No fault	0	0	0
1	Partial discharges of low energy density	0	1	0
2	Partial discharges of high energy density	1	1	0
3	Discharge of low energy	1 or 2	0	1 or 2
4	Discharge of high energy	1	0	2
5	Thermal fault of low temperature, <150 ^oC	0	0	1
6	Thermal fault of low temperature, 150-300 ^oC	0	2	0
7	Thermal fault of medium temperature, 300-700 ^oC	0	2	1
8	Thermal fault of high temperature, >700 ^oC	0	2	2

The gases are analysed to diagnose the incipient fault more accurately in a transformer, so that individual faults could be determined. These could be achieved by the fuzzy-logic method presented in this paper. It employs fuzzy boundaries between different IEC codes that are called the fuzzy IEC code with demi-Cauchy distribution function. Each fault in a transformer can be assessed by the fuzzy vector and the trend of fault development with time can be closely monitored. This technique can be used to monitor for multiple faults in a transformer.

2.2.3. Transformer Paper Deterioration Condition Estimation

2.2.3.1) CO_2 and CO Accumulated Total Gas Values

CO_2 and CO total gas values are obtained as a part of DGA. The status conditions based on accumulated values of CO_2 and CO is given as per the IEEE Standard C57.104™ *Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers* [4]. These accumulated dissolved gas levels provide four status conditions for estimation the paper deterioration: Normal Operation, Modest Concern (investigate), Major Concern (more investigation), and Imminent Risk (nearing failure). For each status condition, the CO_2 and CO levels in ppm are given as below:

Table 2.5. Paper Status Condition Using CO and CO_2 [4]

CO_2	CO	Condition
X_1=0-2500	Y_1=0-350	Normal Operation (NO)
X_2=2500-4000	Y_2=351-570	Modest Concern (MCI)
X_3=4001-10,000	Y_3=571-1400	Major Concern (MCMI)
X_4=>10,000	Y_4=>1400	Imminent Risk (IRF)

2.2.3.2) CO_2/ CO Ratio

CO_2/CO ratio test is conducted as a part of DGA. It gives an indication of the paper insulation involvement in faults and carbonization, thus, the deterioration of cellulose. According to the IEC 60599, if the CO2/CO ratio is less than 3, this indicates cellulose deterioration involvement. An off line oil sample is taken from the transformer main tank and the chromatographic analysis is performed to analyze the dissolved gases in the transformer.

2.2.4. Transformer Diagnosis Using Total Dissolved Key Gas Concentration

Total Dissolved Combustible Gas (TDCG) in transformer fault detection concept is useful in finding out the suitable oil-sampling interval based on the health condition of the transformer so as to compensate the conflict between excessive cost due to over sampling and neglected danger owing to long sampling period. In general, TDCG uses the sum of the 6 key gas values (as formula 1) and the TDCG gas generation rate to determine the operating procedure and predict suitable oil sampling interval as shown in Table 1 [4].

$TDCG = C_2H_2 + C_2H_4 + H_2 + CH_4 + C_2H_6 + CO$ *(1) and*

$TDCG\_Rate = (St-So)/T$ *(2)*

Where *St* = Current TDCG; *So* = Previous TDCG; and T = Time duration in days.

Table 2.6: Action Based on Dissolved Combustible Gas as per [4]

Status/ TDCG (ppm)	**TDCG_Rates (ppm/day)**	**Sampling Intervals and Operating Procedures for Gas Generation Rates**	
		Sampling Interval (SI)	**Operating Procedure (OP)**
Condition 1 <720	<10	6 Monthly (SIA)	Continue normal operation (OPA)
	10-30	Quarterly (SIQ)	
	>30	Monthly (SIM)	Exercise caution; Analise individual gases to find cause. Determine load dependant (OPB)
Condition 2 721-1920	<10	Quarterly (SIQ)	Exercise caution. Analise individual gases to find cause. Determine load dependant (OPB)
	10-30	Monthly (SIM)	
	>30		
Condition 3 1921-4630	<10	Monthly (SIM)	Exercise caution. Analise individual gases to find cause. Plan outage. (OPC)
	10-30	Weekly (SIW)	
	>30		
Condition 4 >4630	<10	Weekly (SIW)	Exercise caution. Analise individual gases to find cause. Plan outage. (OPC)
	10-30	Daily (SID)	
	>30		Consider removal from service

Although the TDCG method is widely used in solving fault diagnosis problem, but in the certain cases, it is very hard to determine the correct group of the TDCG value especially when the TDCG value falls near the boundary line as shown in the TDCG rules set in Table 2.6. The fuzzy logic technique is advantageous in solving this problem, which is explained in section 3.

3. Artificial Intelligence (AI) Based Methodology

3.1. Fuzzy-Logic Based Methodology

All Fuzzy-Logic (FL) is a relatively new artificial intelligence technique. FL means approximate reasoning, information granulation, computing with logical words and so on. Fuzzy systems are rule-based systems that are constructed from a collection of linguistic rules. FL is a convenient way to map an input space to an output space. It provides mathematical strength to the emulation of certain perceptual and linguistic attributes associated with human cognition. The theory of fuzzy logic provides an inference mechanism under cognitive uncertainty. This view of network as a parameterized function will be the basis for applying standard function optimization methods to solve the problem of neural network training.

The schematic diagram of fuzzy logic based transformer diagnostic expert system (FLTDS) is shown in Fig.1. FLTDS is a novel fuzzy-based approach that deals with heterogeneous data of both linguistic and numeric types, imprecise, vague in-formation, and concepts encountered in the mechanical-fit process and facilitate the expression of the reasoning process of an experienced observer with minimal rules.

The Fuzzy Logic Transformer fault diagnosis process represents a fuzzy-logic-based complete transformer diagnosis process comprising the following three phases:

phase I: tentative selection of Key-Gases or Three ratio (X_1, X_2, X_3) for incipient fault diagnosis; CO_2, CO for paper deterioration condition estimation; and TDCG, TDCG_Rate for SI, OP estimation.

phase II: mechanical-fit process;

phase III: estimation and optimization of insulation paper status conditions or faults type.

A general schematic of FLTDS representing the second phase is shown in Fig. 1. It involves the following phases:

1) Fuzzification; 2) Knowledge representation; 3) Inference scheme; 4) Defuzzification.

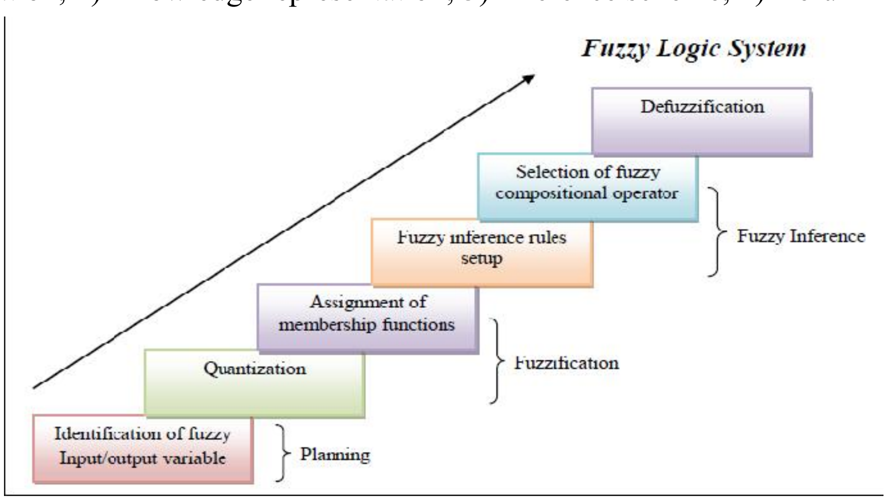


Fig. 1: Design Methodology for Fuzzy Diagnostic System with Matlab

3.1.1 Fuzzy-Logic Based System for Transformer's Incipient Fault Diagnosis

In this section, a novel fuzzy logic model is developed to detect the incipient fault of power transformer using oil DGA response. Based on these results, a fuzzy model is developed to estimate the expected transformer fault using its input variable, X_1, X_2 and X_3. Fig. 2 shows the fuzzy block diagram to detect the transformer incipient faults, where variables X_1, X_2, and X_3 represent the C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6 respectively, as an input data to the fuzzy model. Membership functions (MF) for input variables are established based on the variation of C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6 as shown in Fig. 3 and Fig. 4. The membership functions for the output variables (expected fault) are shown in Fig 3(d) and Fig. 4(d).

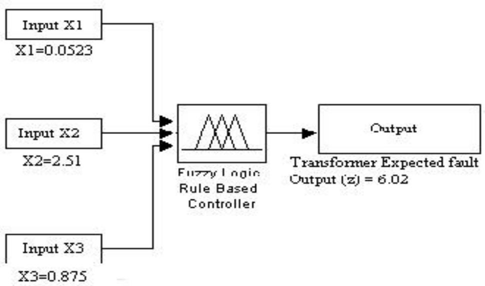
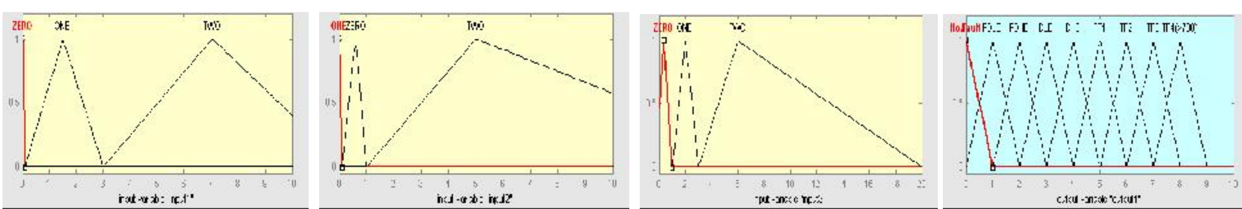


Fig. 2: Block diagram for fault analysis

Table 3.1: Fuzzy logic rules for transformer fault diagnosis

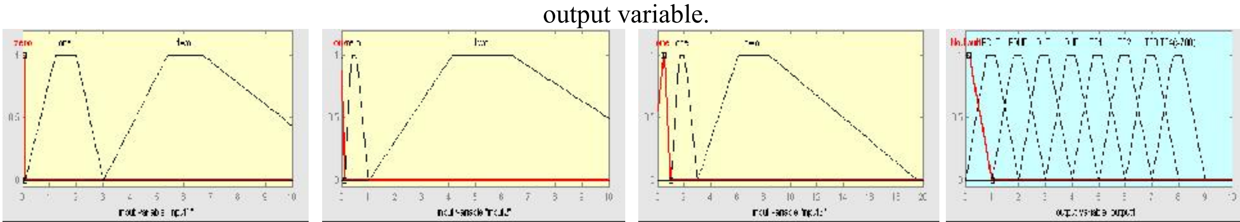
	$X_2=0$			$X_2=1$			$X_2=2$		
	$X_3=0$	$X_3=1$	$X_3=2$	$X_3=0$	$X_3=1$	$X_3=2$	$X_3=0$	$X_3=1$	$X_3=2$
$X_1=0$	0	5	N	1	N	N	6	7	8
$X_1=1$	N	3	4	2	N	N	N	N	N
$X_1=2$	N	3	N	N	N	N	N	N	N

Where; X_1, X_2 and X_3 are the fuzzy input variables and ZERO, ONE and TWO are the fuzzy codes. N denotes the Null (no match) condition.



(a) (b) (c) (d)

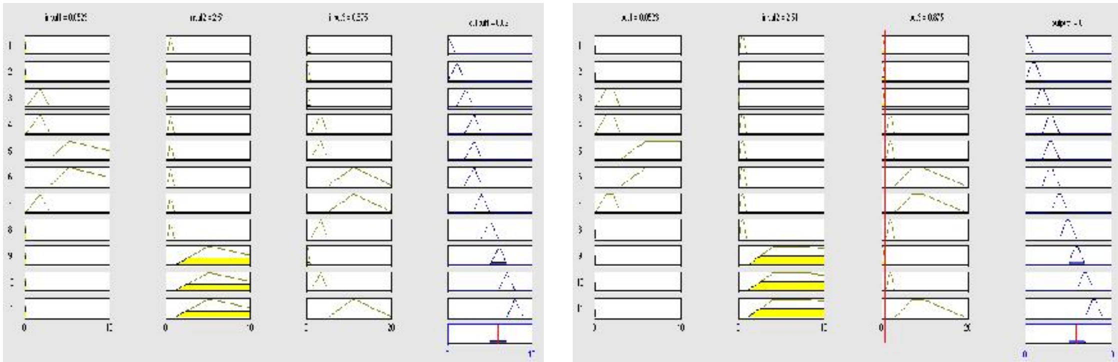
Fig. 3: Triangular membership functions: (a) input variable X_1; (b) input variable X_2; (c) input variable X_3; (d) output variable.



(a) (b) (c) (d)

Fig. 4: Trapezoidal membership functions: (a) input variable X_1; (b) input variable X_2; (c) input variable X_3; (d) output variable.

Based on the experimental results, a set of fuzzy rules relates the input variables to the output are developed as shown in Fig. 5(a) and Fig. 5(b). The expected faults using fuzzy logic model is tested with inputs; X_1, X_2 and X_3. The model result different type of faults which is depends upon input variable.



(a) (b)

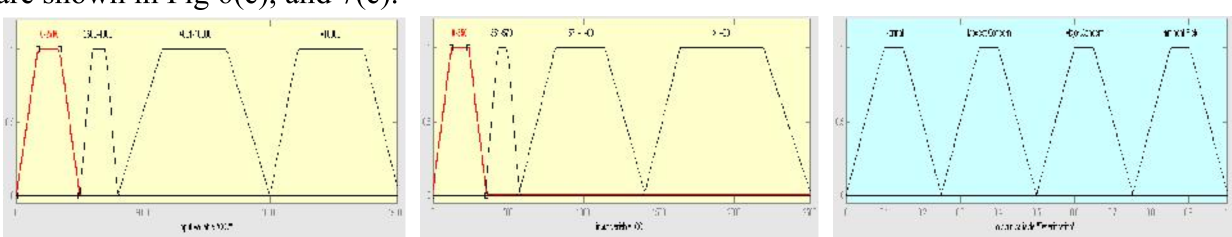
Fig. 5: Test results of fuzzy fault diagnosis (a) with triangular membership function and (b) with trapezoidal membership function

3.1.2 Fuzzy-Logic Based System for Transformer's Oil-immersed paper Deterioration Estimation

CO_2 and CO in transformer is useful in finding out the suitable oil-sampling interval based on the health condition of the transformer so as to compensate the conflict between excessive cost due to over sampling and neglected danger owing to long sampling period.

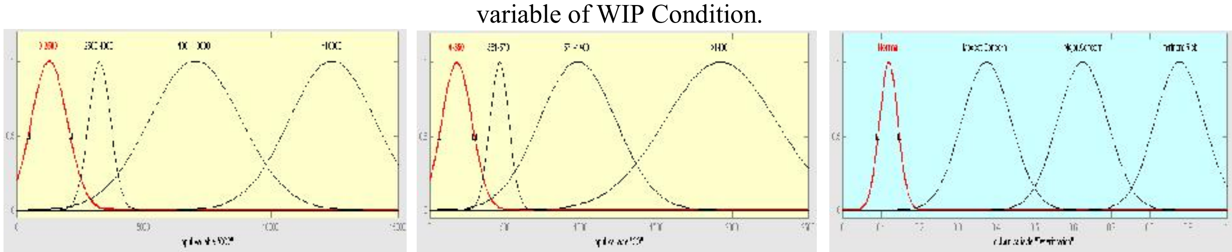
Although "CO_2 and CO accumulated total gas values" and "CO_2/CO ratio" methods are widely used in solving insulation deterioration diagnosis problem, but in the certain cases, it is very hard to determine the correct group of the CO_2 and CO values especially when the CO_2 and CO value fall near the boundary line as shown in the CO_2 and CO rules set in Table 2.5. The fuzzy logic technique is advantages in solving this problem.

For the insulation paper diagnostic method, Membership functions (MF) for input variables are established based on the variation of CO_2, and CO as shown in Fig. 6(a-b), and 7(a-b). The membership functions for the output variables (expected insulation paper deterioration condition) are shown in Fig 6(c), and 7(c).



(a) (b) (c)

Fig. 6: Trapezoidal membership functions (trapmf): (a) input variable of CO_2; (b) input variable of CO; (c) output variable of WIP Condition.



(a) (b) (c)

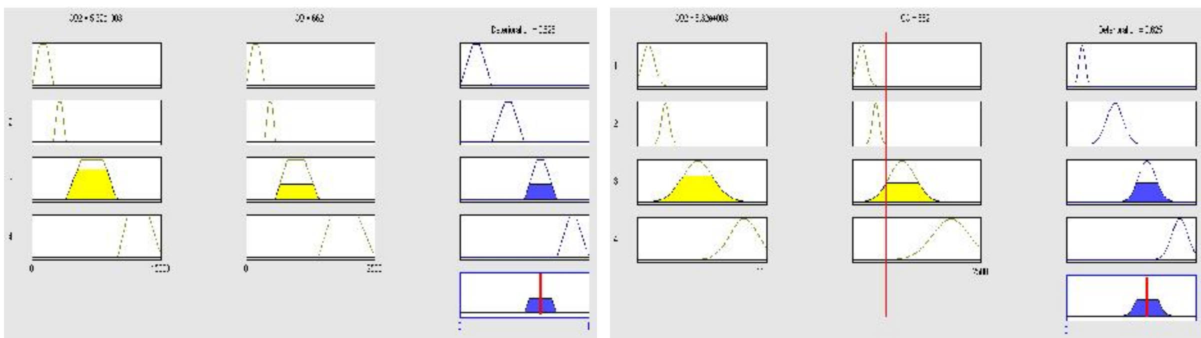
Fig. 7: Gaussian membership functions (gauss): (a) input variable of CO_2; (b) input variable of CO; (c) output variable of WIP Condition.

Table 3.2: Fuzzy logic rules for transformer insulation paper deterioration condition estimation

	Y_1	**Y_2**	**Y_3**	**Y_4**
X_1	NO	N	N	N
X_2	N	MCI	N	N
X_3	N	N	MCMI	N
X_4	N	N	N	IRF

Where; X_1, X_2, X_3, X_4 and Y_1, Y_2, Y_3, Y_4 are the fuzzy input variables. N denotes the Null condition.

Based on the experimental results, a set of fuzzy rules relates the input variables to the output are developed as shown in Table 3.2. The expected health condition for transformer insulation paper using input variables is shown in Fig. 8.



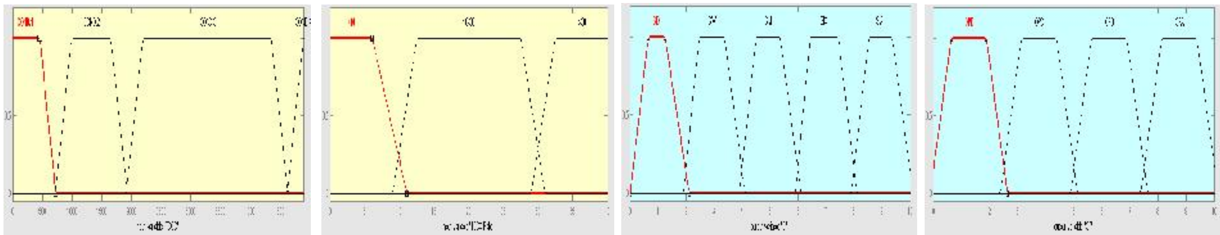
(a) (b)

Fig. 8: Test results of fuzzy based WIP deterioration conditions with (a) triangular membership function; (b) Gaussian membership functions (gauss)

3.1.3 Fuzzy-Logic Based System for Transformer's Sampling Interval (SI) and Operating Procedure Estimation

Total Dissolved Combustible Gas (TDCG) in transformer fault detection concept is useful in finding out the suitable oil-sampling interval (SI) based on the health condition of the transformer so as to compensate the conflict between excessive cost due to over sampling and neglected danger owing to long sampling period. In general, TDCG uses the sum of the 6 key gas values (formula 1) and the TDCG gas generation rate (formula 2*)* to determine the operating procedure (OP) and predict suitable oil sampling interval as shown in Table 2.6 [4].

For the TDCG diagnostic method, the sum of the six fault gases and the gas generation rate are required to determine the health condition of a power transformer. Based on these results, a fuzzy model is developed using its input variable, TDCG, and TDCG_Rate. Membership functions (MF) for input variables are established based on the variation of TDCG, and TDCG_Rate as shown in Fig. 9(a-b). The membership functions for the output variables (expected diagnosis such as SI and OP) are shown in Fig 9(c-d).



(a) (b) (c) (d)

Fig. 9: Trapezoidal membership functions: (a) input variable of TDCG; (b) input variable of TDCG_Rate; (c) output variable of SI; (d) output variable of OP.

Based on the experimental results, a set of fuzzy rules relates the input linguistic variables to the output are developed as shown in Table 3.3. The expected diagnosis for transformer using input variables is shown in Fig. 10.

Table 3.3: Fuzzy inference rules for Transformer Health

Rule 1	If (TDCG is COND.1) and (TDCG_Rate is <10) then (SI is SIA)(OP is OPA)
Rule 2	If (TDCG is COND.1) and (TDCG_Rate is 10-30) then (SI is SIQ)(OP is OPA)
Rule 3	If (TDCG is COND.1) and (TDCG_Rate is >30) then (SI is SIM)(OP is OPB)
Rule 4	If (TDCG is COND.2) and (TDCG_Rate is <10) then (SI is SIQ)(OP is OPB)
Rule 5	If (TDCG is COND.2) and (TDCG_Rate is 10-30) then (SI is SIM)(OP is OPB)
Rule 6	If (TDCG is COND.2) and (TDCG_Rate is >30) then (SI is SIM)(OP is OPB)
Rule 7	If (TDCG is COND.3) and (TDCG_Rate is <10) then (SI is SIM)(op is OPC)
Rule 8	If (TDCG is COND.3) and (TDCG_Rate is 10-30) then (SI is SIW)(OP is OPC)
Rule 9	If (TDCG is COND.3) and (TDCG_Rate is >30) then (SI is SIW)(OP is OPC)
Rule 10	If (TDCG is COND.4) and (TDCG_Rate is <10) then (SI is SIW)(OP is OPC)
Rule 11	If (TDCG is COND.4) and (TDCG_Rate is 10-30) then (SI is SID)(OP is OPC)
Rule 12	If (TDCG is COND.4) and (TDCG_Rate is >30) then (SI is SID)(OP is OPD)

However, this method can not specify the type of fault that occurs in the transformer. This method is only able to detect whether the transformer is in good or bad condition which is imported for maintenance scheduling.

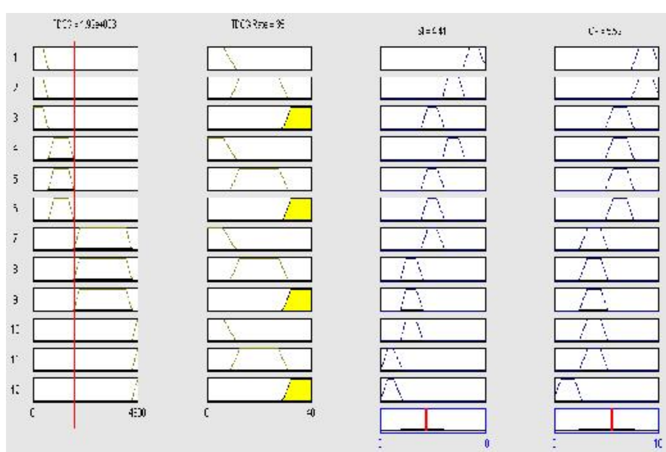


Fig. 10: Test results of fuzzy transformer diagnosis with trapezoidal membership function

3.2. Artificial Neural Network (ANN) Based Methodology

Knowledge based power transformer fault diagnostic become popular because of its simplicity, but application of these standards requires experience. Most of the time this involves an extensive examination of gases in oil concentrations and compare the results of different methods. This section describes neural network based technique for 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. Back propagation is a systematic method for training multilayer ANN. It has a strong mathematical foundation. Back propagation networks often use the log-sigmoid and tansigmoid transfer functions. The tan-sigmoid function is considered for training and testing.

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 [14]. 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.

To find the validation error, view the **Performance** graph. A plot of the training errors, validation errors, and test errors appears.

The **error histogram** represents additional verification of network performance. The blue bars represent training data, the green bars represent validation data, and the red bars represent testing data. The histogram can give us an indication of outliers, which are data points where the fit is significantly worse than the majority of data. In this case, we can see that most data fall on zero error line. It is a good idea to check the outliers to determine if the data is bad, or if those data points are different than the rest of the data set. If the outliers are valid data points, but are unlike the rest of the data, then the network is extrapolating for these points.

Plot fit response displays the inputs, targets and errors versus time. It also indicates which time points were selected for training, testing and validation.

Regression graph is used to validate the network performance. The following regression plots display the network outputs with respect to targets for training, validation, and test sets. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. For this problem, the fit is excellent for all data sets, with R values in each case of 1.

3.2.1 ANN Based System for Transformer's Incipient Fault Diagnosis

Five key gases (H_2, C_2H_2, C_2H_4, CH_4, and C_2H_6) are chosen as inputs. Nine output codes representing the different type of faults such as PD of low energy, PD of High energy, Low energy discharge, High energy discharge, thermal fault (<150^{O}C), thermal fault of 150-300^{O}C, thermal fault of 300-700^{O}C, thermal fault (>700^{O}C) and No fault condition are considered.

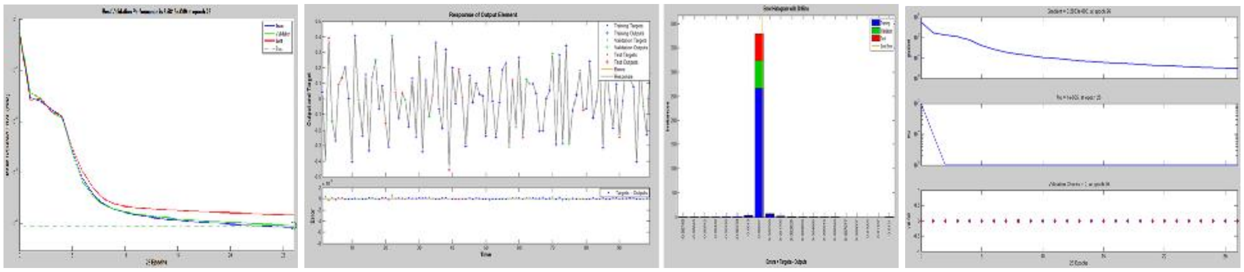
The neural network (5x29x9) is implemented using the back propagation algorithm and the hidden layer neurons are chosen from trial and error method.

Network parameters:

- gradient=9.29e-006 and Mu=1.00e-006, at epoch 26
- the learning rate = 0.025; momentum factor = 0.8;
- no of hidden layer neurons = 29;

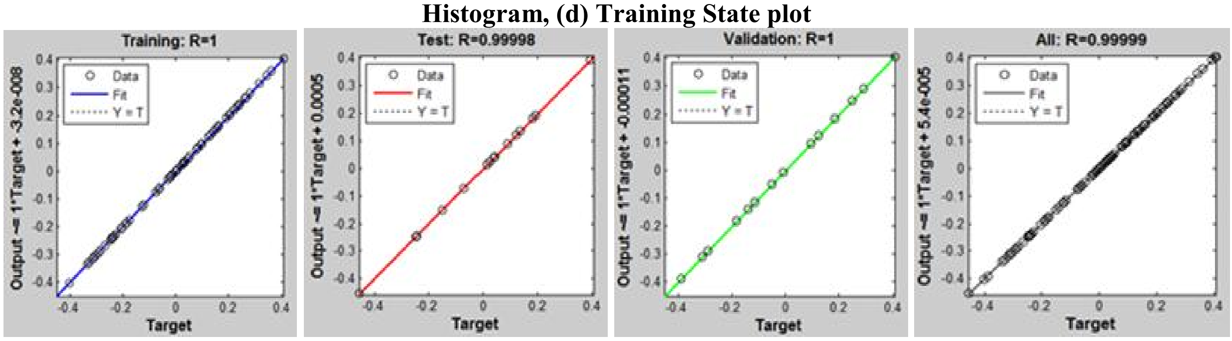
- Tolerance = 0.0008.

As examples of the kind of graphical results for oil-immersed paper deterioration condition that are estimated by ANN using matlab simulation tool box [13] are shown in Fig. 11-12.



(a) (b) (c) (d)

Fig. 11 (a) Performance graph based on Mean Square Error (mse) algorithm, (b) Fit plot, (c) Error Histogram, (d) Training State plot



(a) (b) (c) (d)

Fig. 12 Prediction of paper deterioration condition during (a) training analysis, (b) validation analysis, (c) test analysis, (d) over all Regression plot

3.2.2 ANN Based System for Transformer's Oil-immersed paper Deterioration Estimation

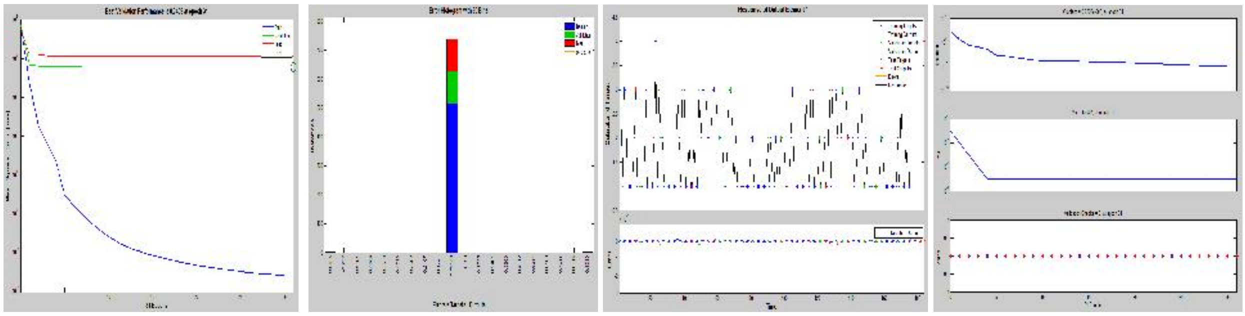
Two key gases CO_2 and CO are chosen as inputs. Four output codes representing the different oil-immersed paper insulation conditions such as modest concern (investigate), major concern (more investigate), imminent risk (nearing failure) and normal operating condition are considered.

An important advantage of ANN based paper insulation condition detection is that it can learn directly from the training samples, and update its knowledge when necessary. The highly non-linear mapping capability of the neurons provides a comparable performance over fuzzy system. ANN computational complexity is not too high, especially in the testing (diagnosis) process [15]. The neural network (2x10x4) is implemented using the back propagation algorithm and the hidden layer neurons are chosen from trial and error method.

Network parameters:

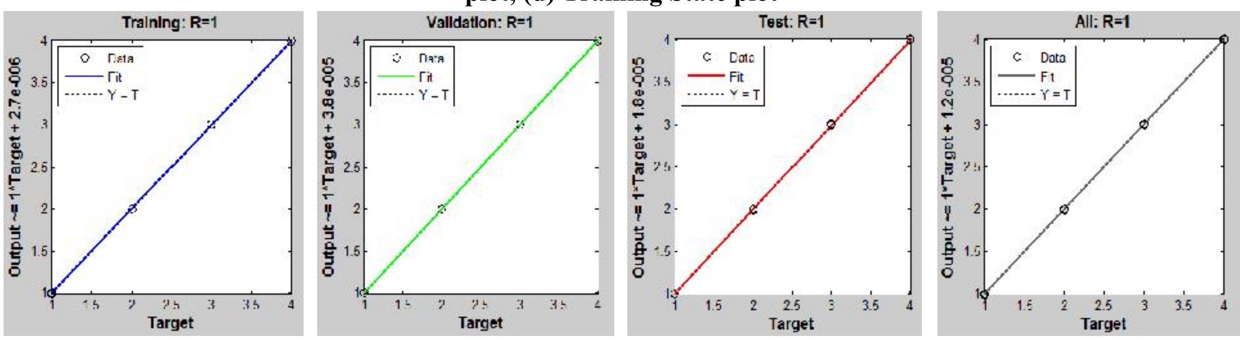
- gradient=9.2202e-006 and Mu=1e-007, at epoch 31
- the learning rate = 0.025; momentum factor = 0.8;
- no of hidden layer neurons = 10;
- tolerance = 0.0009.

As examples of the kind of graphical results for oil-immersed paper deterioration condition that are estimated by ANN using matlab simulation tool box [13] are shown in Fig. 13-14.



(a) (b) (c) (d)

Fig. 13 (a) Performance graph based on Mean Square Error (mse) algorithm, (b) Error Histogram, (c) Fit plot, (d) Training State plot



(a) (b) (c) (d)

Fig. 14 Prediction of paper deterioration condition during (a) training analysis, (b) validation analysis, (c) test analysis, (d) over all Regression plot

4. Result and Discussion

Using the Neuro-Fuzzy scheme, 10 number of 11–132 kV power transformers of Himachal Pradesh State Electricity Board (HPSEB), India were diagnosed and some typical results are given in Table 3(experiment data). These results are taken by using Kalman Transport-X DGA analyzer. For this method, four status conditions of paper deterioration and type of faults are determined by choosing the highest degree of membership value obtained from the fuzzy inference rules and low mean squire error (mse) in neural network.

In fuzzy-logic system, the status conditions of paper deterioration can be classified into the linguistic variable based on the degree of membership function as shown as Table 4.1 and for SI, OP is shown in Table 4.2.

Table 4.1: Four Estimated Condition by Fuzzy Logic for transformer diagnosis

Degree of Membership of Fuzzy output Result for status condition	
Normal Operation (NO)	<0.20
Modest Investigate (MCI)	0.30-0.45
Major Investigate (MCMI)	0.61-0.68
Nearing Failure (IRF)	>0.7

Table 4.2: degree of membership function for SI and OP

Membership Degree (out of 10) of Fuzzy output Result for SI		Membership Degree (out of 10) of Fuzzy output Result for OP	
SIA	>8		
SIQ	6.0-7.84	OPA	>7.45
SIM	4.97-5.85	OPB	6.25
SIW	2.96-3.84	OPC	3.75
SID	<1.9	OPD	<1.29

It can be seen from some samples that the new method is generally in agreement with ANSI/IEEE method for transformers of fault diagnosis. Compared with ANSI/IEEE C57.104

method, the Neuro-Fuzzy method also has some advantages. For example, due to no matching condition, five transformers could not be diagnosed by the ANSI/IEEE method but are diagnosed by the Neuro-Fuzzy method, as shown in Table 4.3-4.5.

Table 4.3.AI Based Incipient Fault Estimation

S. N	Fault Estimation as per IEC Method		Incipient Fault Estimation as per AI Method			
	IEC code	Type of Fault	Fuzzy fault components	ANN fault components	PNN fault classification	Actual Fault
1	020	(6)Thermal fault of low temperature (150-300^{o}C)	F(6)=5.98	F(6)=5.99998	Fault 6	Thermal fault (150-300^{o}C)
2	022	(8)Thermal fault of high temperature (>700^{o}C)	F(8)=8.0	F(8)=8.00000	Fault 8	Thermal fault (>700^{o}C)
3	021	(7)Thermal fault of medium temperature (300-700^{o}C)	F(7)=6.99	F(7)=6.99999	Fault 7	Thermal fault (300-700^{o}C)
4	120	**No match**	**F(N)=5.0**	**F(N)=4.99995**	**Fault 5**	**Thermal fault (<150^{o}C)**
5	101	(3)Discharge of low energy	F(3)=3.0	F(3)=3.00000	Fault 3	Discharge of low energy
6	212	**No match**	**F(N)=5.0**	**F(N)=4.99995**	**Fault 5**	**Thermal fault (<150^{o}C)**
7	000	(0)No fault	F(0)=0.387	F(0)=0.00001	Fault 0	No fault
8	001	(5)Thermal fault of low temperature (<150^{o}C)	F(5)=4.99	F(5)=4.99999	Fault 5	Thermal fault (<150^{o}C)
9	102	(4)Discharge of high energy	F(4)=4.0	F(4)=4.00000	Fault 4	Discharge of high energy
10	010	(1)Partial discharge of low energy density	F(1)=0.99	F(1)=0.99999	Fault 1	PD of low energy

Table 4.4. AI Based Oil-Immersed Paper Deterioration Condition Estimation

Sample No.	DGA Test Results		Paper Deterioration Condition as per IEEE Std. C57.104	AI Based 4 Condition Estimation			Actual Paper Deterioration Condition
	CO_2	CO		Paper Deterioration Condition as per Fuzzy-Logic	Paper Deterioration Condition as per PNN	Paper Deterioration Condition as per ANN	
1	5315	662	Major Concern	C(3)=0.626	Condition 3	3	3
2	198	06	Normal Condition	C(1)=0.125	Condition 1	1	1
3	3089	405	Modest Concern	C(2)=0.375	Condition 2	2	2
4	1178	193	Normal Condition	C(1)=0.125	Condition 1	1	1
5	3141	158	**No match**	**C(N)=0.25=2**	**Condition 2**	**2**	**2**
6	4811	480	**No match**	**C(N)=0.5=3**	**Condition 3**	**3**	**3**
7	1936	97	Normal Condition	C(1)=0.125	Condition 1	1	1
8	433	42	Normal Condition	C(1)=0.125	Condition 1	1	1
9	5004	935	Major Concern	C(3)=0.626	Condition 3	3	3
10	229	10	Normal Condition	C(1)=0.125	Condition 1	1	1

Table 4.5. AI Based Sampling Interval (SI) and Operating Procedure (OP) Estimation

TRF.No.	TDCG	TDCG _Rate	Action for Gas Generation Rate as per IEEE Std. C57.104		Action for Gas Generation Rate as per Fuzzy Logic		Action for Gas Generation Rate as per ANN	
			Sampling Interval **(SI)**	Operating Procedure **(OP)**	Sampling Interval **(SI)**	Operating Procedure **(OP)**	Sampling Interval **(SI)**	Operating Procedure **(OP)**
1	544	<10	SIA	OPA	8.98-8.99	8.75	1	1
		10-30	SIQ		6-7.84	7.9-8.75	2	1
		>30	SIM	OPB	4.98	6.25	3	2
2	280	<10	SIA	OPA	8.98-8.99	8.75	1	1
		10-30	SIQ		6-7.84	7.49-8.75	2	1
		>30	SIM	OPB	4.97-4.98	6.25	3	2
3	506	<10	SIA	OPA	8.98-8.99	8.75	1	1
		10-30	SIQ		6-7.84	7.79-8.75	2	1

		>30	SIM	OPB	4.97-4.98	6.25	3	2
4	1337	<10	SIQ		6.97-6.99	6.25	2	2
		10-30	SIM		4.97-5.85	6.25	3	2
		>30			4.97-4.98	6.25	3	2
5	1026	<10	SIQ		6.97-6.99	6.25	2	2
		10-30	SIM		4.97-5.85	6.25	3	2
		>30			4.97-4.98	6.25	3	2
6	3318	<10		OPC	4.97-4.99	3.75	3	3
		10-30	SIW		2.96-3.84	3.75	4	3
		>30			2.96-2.98	3.75	4	3
7	2477	<10	SIM		4.97-4.99	3.75	3	3
		10-30	SIW		2.96-3.84	3.75	4	3
		>30			2.96-2.98	3.75	4	3
8	2881	<10	SIM		4.97-4.99	3.75	3	3
		10-30	SIW		2.96-3.84	3.75	4	3
		>30			2.96-2.98	3.75	4	3
9	4705	<10			2.99	3.75	4	3
		10-30	SID		1.03-1.9	2.51-3.75	5	3
		>30		OPD	1.03	1.26	5	4
10	4885	<10	SIW	OPC	2.96-298	3.75	4	3
		10-30	SID		1.01-1.9	2.51-3.75	5	3
		>30		OPD	1.01-1.02	1.25	5	4

5. Conclusions

DGA is a very efficient tool for diagnosing incipient failure condition in oil-filled electrical equipment. The gas ratios and relative proportions of gases can be used to diagnose the failure condition and improve the accuracy of insulation deterioration diagnosis. This dissertation has been described the oil-immersed paper deterioration condition assessment, incipient fault diagnosis and SI-OP estimation for transformer using Neuro-Fuzzy and ensemble technique. The effectiveness of the proposed method has been shown by numerical simulation using actual measured data. The authors have estimated the insulation paper deterioration condition, incipient faults and SI-OP using proposed method for 10 transformers or more. As a result, appropriate replacement time of transformer and appropriate maintenance scenario can be planned.

References

[1] Jashandeep Singh, Yog Raj Sood,and **R.K. Jarial**, "Condition Monitoring of Power Transformers-Bibliography Survey", IEEE Electrical Insulation Magazine, vol. 24, no. 3, pp. 11-25, 2008.

[2] Tapan K. Saha, "Review of Modern Diagnostic Techniques for Assessing Insulation Condition in Aged Transformers" IEEE Transactions on Dielectrics and Electrical Insulation Vol. 10, No. 5; Pp. 903-917,Oct.2003.

[3] M.Wang and A.J. Vandermaar, "Review of Condition Assessment of Power Transformer in Service", IEEE Electrical Insulation Magazine, vol. 18, no. 6, pp. 12-25, 2002.

[4] IEEE Standard Guide C57.104.2008, "Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers", 2009.

[5] IEC International Standard 60599, "Mineral oil-impregnated electrical equipment in service -Guide to the interpretation of dissolved and free gases analysis" 2007.

[6] Facilities Instructions, Standards, and Technologies, "Transformer Diagnostics", US Dept. of Interior Bureau of Reclamation, Vol. 3-31, June 2003.

[7] Q.Su, C.Mi, L.Lai, and P.Austin, "A Fuzzy Dissolved Gas Analysis Method for the Diagnosis of Multiple Incipient Fault in a Transformer", IEEE Transactions on Power Systems Vol.15, No.2, Pp.593-598, May 2000.

[8] M. Duval, "Dissolved gas analysis: A powerful maintenance tool for transformers," presented at the TechCon, San Antonio, TX, Jan. 25–29, 2004.

[9] D. R. Morais and J. G. Rolim, "A hybrid tool for detection of incipient faults in transformers based on the dissolved gas analysis of insulting oil," *IEEE Trans. Power Del.*, vol. 21, no. 2, pp. 673–680, Apr. 2006.

[10] Y.-C. Huang, "Evolving neural nets for fault diagnosis of power transformers," *IEEE Trans. Power Del.*, vol. 18, no. 3, pp. 843–848, Jul.2003.

[11] R. R. Rogers, "IEEE and IEC codes to interpret incipient faults in transformers, using gas in oil analysis," *IEEE Trans. Elect. Insul.*, vol. EI-13,no. 5, pp. 348–354, Oct. 1978.
[12] M. Duval, "Interpretation of gas-in-oil analysis using new IEC publication 60599 and IEC TC 10 databases," *IEEE Elect. Insul. Mag.*, vol.17, no. 2, pp. 31–41, Mar/Apr. 2001.
[13] MATLAB R2009b, Fuzzy Logic Toolbox version 7.9.0.529, 32-bit, The Mathworks.
[14] Y.-C. Huang, "Evolving neural nets for fault diagnosis of power transformers," *IEEE Trans. Power Del.*, vol. 18, no. 3, pp. 843–848, Jul.2003.
[15] K. Tomsovic, M. Tapper, and T. Ingvarsson, "A fuzzy information approach to integrating different transformer diagnostic methods", *IEEE Trans. Power Del.*, vol. 8, no. 3, pp. 1638–1646, Jul. 1993.

List of Publications

INTERNATIONAL JOURNAL PUBLICATIONS (2)

- **Hasmat Malik**, Tarkeshwar Mahto and R.K.Jarial, *"Fuzzy-Logic Applications in Transformer Diagnosis Using Individual and Total Dissolved Key Gas Concentrations", in* International Journal of Electrical Engineering (IJEE) ISSN 1582-4594.
- **Hasmat Malik**, Abdul Azeem and Amit Kr.Yadav, *"Condition Assessment of Power Transformer by Swift Frequency Response Analysis"* in International Journal of Electrical Engineering (IJEE) ISSN 0974-2158, Vol. 4, No. 2(2011), pp. 199-207.

Elsevier/ScienceDirect PUBLICATIONS (2)

- **Hasmat Malik**, Tarkeshwar and R.K.Jarial, "Make Use of DGA to Carry Out the Transformer Oil-Immersed Paper Deterioration Condition Estimation with Fuzzy-Logic", in **Elsevier/ScienceDirect** Procedia Engineering, **ISSN: 1877-7058, Vol. 30,** December 2011, pp. 587-595.
- **Hasmat Malik**, Surinder Singh, Mantosh Kr and R.K..Jarial "UV/VIS Response Based Fuzzy Logic for Health Assessment of Transformer Oil", in **Elsevier/ScienceDirect** Procedia Engineering, **ISSN: 1877-7058, Vol. 30,** December 2011, pp. 932-939.

IEEE INTERNATIONAL CONFERENCE PUBLICATIONS (4)

- **Hasmat Malik**, Tarkeshwar and R.K.Jarial, "*An Expert System for Incipient Fault Diagnosis and Condition Assessment in Transformers*", in **IEEE** International Conference on Computational Intelligence and Communication Networks (CICN-2011), pp. 138-142.
- **Hasmat Malik**, R.K.Jarial, Amit Kr.Yadav and Abdul Azeem, "*Application of Modern Technology for Fault Diagnosis in Power Transformer Energy Management*", in **IEEE** International Conference on Communication System's Network Technologies CSNT-2011. Pp.376-381.
- **Hasmat Malik**, Amit Kr.Yadav, Tarkeshwar and R.K..Jarial *"Make Use of UV/VIS Spectrophotometer to Determination of Dissolved Decay Products in Mineral Insulating Oils for Transformer Remnant life Estimation with ANN",* in **IEEE** International Conference on Engineering Sustainable Solutions **(INDICON-2011)**, Pp.1-6.
- **Hasmat Malik**, Mantosh Kr. and R.K..Jarial *"Application Research Based on Modern Technology to Investigating Causes and Detection of Failures in Transformers on the Bases of Importance Level,"* in **IEEE** International Conference on Engineering Sustainable Solutions **(INDICON-2011)**, Pp.1-6.