UNIVERSITY GRANTS COMMISSION

ज्ञान-विज्ञान विमुक्तये

MINOR RESEARCH PROJECT

“FAULT DIAGNOSIS OF POWER TRANSFORMER USING SOFT COMPUTING TECHNIQUES”

PRINCIPAL INVESTIGATOR

Mrs. Nisha Divya

(Asst. Professor, Mathematics)

Dr. Radhabai Govt. Navin Kanya Mahavidyalaya, Raipur (C.G.)

Annexure -III

UNIVERSITY GRANTS COMMISSION
BAHADUR SHAH ZAFAR MARG
NEW DELHI – 110 002.

Final Report of the work done on the Minor Research Project.

1. Project report No. : Final Report
2. UGC Reference No. : MS-19/202057/XII/14-15/CRO
3. Period of report : from 01 July 2015 to 30 June 2017
4. Title of research project : **"Fault Diagnosis of Power Transformer Using Soft Computing Techniques"**
5. (a) Name of the Principal Investigator: : **Mrs. Nisha Divya**

   (b) Deptt. and College where work has progressed : Mathematics : Government Navin Kanya Mahavidyalaya, Mathpuraina, Raipur (C.G.)
6. Effective date of starting of the project : 01 July 2015
7. Grant approved and expenditure incurred during the period of the report:

a. Total amount approved Rs. : **55,000/-**

b. Total expenditure Rs. : **55,217/-**

c. Report of the work done: (Please attach a separate sheet)

(i) Brief objective of the project : Report attached

(ii) Work done so far and results achieved and publications, if any, resulting from the work (Give details of the papers and names of the journals in which it has been published or accepted for publication. : Work done and result achieved is attached in separate sheet.

(iii) Has the progress been according to original plan of work and towards achieving the objective. if not, state reasons : Yes

(iv) Please indicate the difficulties, if any, experienced in implementing the project - None

(v) If project has not been completed, please indicate the approximate time by which it is likely to be completed. A summary of the work done for the period (Annual basis) may please be sent to the Commission on a separate sheet : The project is completed, report is attached.

(vii) Any other information which would help in evaluation of work done on the project. At the completion of the project, the first report should indicate the output, such as (a) Manpower trained (b) Ph. D. awarded c) Publication of results (d) other impact, if any : Ph.D. awarded

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Annexure -IV

UNIVERSITY GRANTS COMMISSION
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Utilization certificate

Certified that the UGC approved grant of Rs. **55000.00** (Rupees Fifty Five Thousands only) for research project and grant being received **50000.00** (Rupees Fifty Thousand Only) from the University Grants Commission under the scheme of support for Minor Research Project entitled **"Fault Diagnosis of Power Transformer Using Soft Computing Techniques"** vide UGC letter No.- MS-19/202057/XII/14-15/CRO dated 20 Feb.2015 has been fully utilized for the purpose for which it was sanctioned and in accordance with the terms and conditions laid down by the University Grants Commission.

SIGNATURE OF THE
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SIGNATURE OF THE
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PRINCIPAL

CHARTERED ACCOUNTANT

Annexure -V

UNIVERSITY GRANTS COMMISSION
BAHADUR SHAH ZAFAR MARG
NEW DELHI – 110 002.

STATEMENT OF EXPENDITURE IN RESPECT OF MINOR RESEARCH PROJECT

1. Name of Principal Investigator : Mrs. Nisha Divya
2. Deptt. Of College : Department of Mathematics, Govt. Navin Kanya Mahavidyala, Raipur (C.G)
3. UGC approval No. and date : MS-19/202057/XII/14-15/CRO
4. Title of research project : **"Fault Diagnosis of Power Transformer Using Soft Computing Techniques**
5. Effective date of starting of the project : 01 July 2015
6. (a) Period of Expenditure : From 01 July 2015 to 30 June 2017
   (b) Details of Expenditure : Enclosed

S.N.	Item	Amount Approved	Amount Released	Expenditure Incurred(Rs.)
1	Book & Journals	10000.00	10000.00	10056.00
2	Equipment	35000.00	35000.00	35000.00
3	Travel, Field work	5000.00	2500.00	5161.00
4	Contingency	5000.00	2500.00	5000.00
5	Chemical & Glassware	0.00	0.00	0.00
6	Special Needs	0.00	0.00	0.00
	Total	**55000.00**	**50000.00**	**55217.00**

Total Amount Approved = 55000.00
Total Amount Released from UGC = 50000.00
Total Expenditure = 55217.00

SIGNATURE OF THE
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PRINCIPAL

Annexure -VI

UNIVERSITY GRANTS COMMISSION
BAHADUR SHAH ZAFAR MARG
NEW DELHI – 110 002.

STATEMENT OF EXPENDITURE INCURRED ON FIELD WORK

Name of the Principal Investigator : Mrs. Nisha Divya

Date of Journey		Place of Journey		Name of the Place visited	Mode of Journey	Expenditure Incurred (Rs.)
From	To	From	To			
13.11.15	13.11.15	Raipur	Korba	NTPC, Korba	Car	2500/-
13.11.15	13.11.15	Korba	Raipur		Car	2500/-
					Total	**5000/-**

Certified that the above expenditure is in accordance with the UGC norms for Minor Reserch Projcect.

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SIGNATURE OF THE
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/PRINCIPAL

Annexure -VII

UNIVERSITY GRANTS COMMISSION
BAHADUR SHAH ZAFAR MARG
NEW DELHI – 110 002.

ACCEPTANCE CERTIFICATE FOR RESEARCH PROJECT

1. Name : Mrs. Nisha Divya
2. File No. : MS-19/202057/XII/14-15/CRO
3. Title of research project : **"Fault Diagnosis of Power Transformer Using Soft Computing Techniques**

1 The research project is not being supported by any other funding agency.

2 The terms and conditions related to the grant are acceptable to the Principal Investigator and University/College/Institution.

3 At present, I have no research project approved by UGC and the accounts for the provious project, if any have been settled.

4 The College/University is fit to receive financial assistance from UGC and is included in the list prepared by the UGC.

5 The Principal Investigator is a retired teacher and eligible to receive honorarium as he/she is neigher getting any honorarium from any agency nor is he/she gainfully employed anywhere. N.A.

6 His / Her date of birth is : 28.11.1983

7 The date of implementation of the project is : 01 July 2015

SIGNATURE OF THE
PRINCIPAL INVESTIGATOR

SIGNATURE OF THE
COINVESTIGATOR/REGISTRAR
/PRINCIPAL

Annexure -VIII

UNIVERSITY GRANTS COMMISSION
BAHADUR SHAH ZAFAR MARG
NEW DELHI – 110 002.

PROFORMA FOR SUBMISSION OF INFORMATION AT THE TIME OF SENDING THE FINAL REPORT OF THE WORK DONE ON THE PROJECT

1. NAME AND ADDRESS OF THE PRINCIPAL INVESTIGATOR : Smt. Nisha Divya
2. NAME AND ADDRESS OF THE INSTITUTION : Govt. Navin Kanya Mahavidyalaya, Raipur (C.G.)
3. UGC APPROVAL NO. AND DATE : MS-19/202057/XII/14-15/CRO & 20 Feb. 2015
4. DATE OF IMPLEMENTATION : 01 July 2015
5. TENURE OF THE PROJECT : 01 July 2015 to 30 June 2017
6. TOTAL GRANT ALLOCATED : 55000.00
7. TOTAL GRANT RECEIVED : 50000.00
8. FINAL EXPENDITURE : 55217.00
9. TITLE OF THE PROJECT : **" Fault Diagnosis of Power Transformer Using Soft Computing Techniques"**
10. OBJECTIVE OF THE PROJECT : Mentioned In Encloser 1
11. WHETHER OBJECTIVES WERE ACHIEVED (GIVE DETAILS) : Yes ,Mentioned In Encloser 1
12. ACHIEVEMENT FROM THE PROJECT : Mentioned In Encloser 2
13. SUMMARY OF THE FINDINGS (IN 500 WORDS) : Mentioned In Encloser 1
14. CONTRIBUTION OF THE SOCIETY : 1. The major outcome of the works is the industries dealing with power transformers will be capable to design new power transformers for improving reliability and controllability of power system as well as its performance, which will avoid the unnecessary power cut in the Chhattisgarh state.

    2. The results of this works will be more useful for the management to manage and rectify the power system problems more effectively and

economically and study will enable the power utility companies for their effective expansion planning of power plants.

15. WHETHER ANY PH.D. ENROLLED PRODUCED (OUT OF THE PROJECT) : No

16. NO. OF PUBLICATIONS OUT OF THE PROJECT (PLEASE ATTACH RE - PRINT) : 2

SIGNATURE OF THE
PRINCIPAL INVESTIGATOR

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COINVESTIGATOR /REGISTRAR
/PRINCIPAL

DETAILS OF EXPENDITURE STATEMENT

1. NAME OF THE PRINCIPAL INVESTIGATOR : Smt. Nisha Divya
2. UGC APPROVAL NO. : MS-19/202057/XII/14-15/CRO
3. PERIOD OF UTILIZATION : 01 July 2015 to 30 June 2017

Books and Journals:-

S.No.	**Name of the Firm**	**Bill.No.**	**Date**	**Amount**
1.	Central Book House	IN-4070	13.09.2016	4048=00
2.	Central Book House	IN-4065	20.07.2016	6008=00
			Total	**10056=00**

Details of Equipments :-

S.No.	Name of the Firm	Bill.No.	Date	Amount
1.	Compact Computer	CC-1443	10.08.2016	35000=00
			Total	**35000=00**

Details of Contingency :-

S.No.	Name of the Firm	Bill.No.	Date	Amount
1.	Alpha Stationers	5324	10.10.2015	2586=00
2.	Laxman Stationary Mart	1723	12.07.2106	2575=00
			Total	**5161=00**

SIGNATURE OF THE
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SIGNATURE OF THE
COINVESTIGATOR /REGISTRAR
/PRINCIPAL

Details of Travel and Field Work:-

Date of Journey		Place of Journey		Name of the Place visited	Mode of Journey	Expenditure Incurred (Rs.)
From	To	From	To			
13.11.15	13.11.15	Raipur	Korba	NTPC, Korba	Car	2500/-
13.11.15	13.11.15	Korba	Raipur		Car	2500/-
					Total	**5000=00**

SIGNATURE OF THE
PRINCIPAL INVESTIGATOR

SIGNATURE OF THE
COINVESTIGATOR /REGISTRAR
/PRINCIPAL

Enclosure - 2

1.	NAME OF THE PRINCIPAL INVESTIGATOR	:	Smt. Nisha Divya
2.	UGC REFERENCE NO.	:	MS-19/202057/XII/14-15/CRO
3.	PERIOD OF UTILIZATION	:	01 July 2015 to 30 June 2017
4.	ACHIEVEMENT	:	PH.D. enrolled Titled **" Fault Diagnosis of Power Transformer Using Soft Computing Techniques"**

5. NO OF PUBLICATION

❖ Barle Nisha, sarojinee R., Jha M., (2016) "Fault Developed in Power Transformer: A review" IJESRT, 5(1), 2277-9655.

❖ Jha M., Barle Nisha, Trivedi R., (2015) "Application of Artificial Intelligence Techniques For Dissolved Gas Analysis of Transformer – A review" IJISET Journal, vol.2, Issue 12, 2348-7968. (Reprint Attached)

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Enclosure – 1

Summary

1. Title of Thesis:

"Fault Diagnosis of Power Transformer using Soft computing Techniques"

2. Introduction:

The basic function of power distribution system is to supply customers with electric energy as economically as possible and with an acceptable degree of reliability and quality. System reliability depends on components' reliability. The condition of components and the environment directly affects system condition resulting in equipment failures.

Power transformers are essential devices in a transmission and distribution system. As a major apparatus in a power system, the power transformer is vital to system operation. Failure of a power transformer may cause a break in power supply and loss of profits. Failure of these transformers is very costly to both the electrical companies and customers. Therefore, it is of great importance to detect incipient failures in power transformers as early as possible, so that we can switch them safely and improve the reliability of power systems.

To prevent the failures and to maintain transformers in good operating condition is a very important issue for utilities. Traditionally, routine preventative maintenance programs combined with regular testing were used. With deregulation, it has become increasingly necessary to reduce maintenance costs and equipment inventories. This has led to reductions in routine maintenance. The need to reduce costs has also resulted in reductions in spare transformer capacity and increases in average loading.

Neuro-Fuzzy were studied worldwide recently for pattern recognition such as fault diagnosis. In addition, ANFIS has also been successfully applied to a number of real-world problems such as handwritten characters recognition, face detection, and medical diagnosis. The approach is systematic and properly motivated by statistical learning theory. In this study, fault diagnosis in power Transformers using Adaptive Neuro-Fuzzy Inference System (ANFIS) is presented. Three DGA criteria commonly used in industry was trained and tested with ANFIS classifier. The results of this study are useful in development of a reliable transformer automated diagnostic system. We determined best model choosing and reached 76.0 % diagnostic success.

The learning rules of ANFIS only deals with parameter identification (J.Vieira et al 2004). A method for structure identification is needed here to determine an initial ANFIS architecture (M.F.Qureshi et al 2008) before any parameter tuning procedures can take over. By having solid methods for both structure and parameter identification ANFIS methods is used for performance modeling of superheater system of a power plant. Structure identification in fuzzy modeling involves some primary issues i.e. (1) selection of relevant input variables (2) determining an initial ANFIS architecture including input space partitioning, number of membership functions for each input, Number of fuzzy IF-Then rules, Antecedent (premise) parts of fuzzy rules and consequent (conclusion) parts of fuzzy rules, (3) choosing initial parameters for membership functions. Moreover the resulting ANFIS architectures are more efficient in both training and application.

The ANN-based methods have been successfully used in various disciplines for modeling; however, the lack of interpretation is one of the major drawbacks of their utilization. Wieland et al. reported that one of the major shortcomings of ANNs is that they do not reveal causal relationships between major system components and thus are unable to improve the explicit knowledge of the user. Another problem is due to the fact that reasoning is only done from the inputs to the outputs. In cases where the opposite is requested (i.e., deriving inputs leading to a given output), neural networks can hardly be used. There are also some basic aspects of fuzzy inference system that are in need of better understanding. In order to overcome the problematic combinations of ANNs and fuzzy systems, a new system combining ANN and the fuzzy system, called the adaptive network-based fuzzy inference system (ANFIS), was proposed by Jang. However, even before Jang published his paper, Lin and Lee and Wang and Mendel had already published their respective works on adaptive neuro-fuzzy inference systems. Jang and Sun expressed that adaptive neuro-fuzzy inference systems and the adaptive network-based fuzzy inference systems have the same aim. Therefore, they used adaptive neuro-fuzzy inference systems (ANFIS) to stand for adaptive network-based fuzzy inference systems.

The conventional control and operating devices are based on hard bound computational criteria, for incorporating human reasoning using FIS and computational power of ANN in fault diagnosis of power transformer ANFIS is proposed for the following purposes or objectives of research which are highlighted below:-

1. The purpose of this piece of research work is implementation of soft computing tools (Fuzzy Logic, Neural Network and Genetic Algorithm) for fault diagnosis of power transformer.
2. Exploiting the reasoning capability of fuzzy Logic, computational capability of Neural Network and optimization capability of Genetic Algorithm in fault diagnosis of power transformer.
3. The primary objective of this research is modeling and simulation of soft computing tools using MATLAB 6.5 version software for fault diagnosis of power transformer.

2.1 A brief Review of the work Already done in the field:

Farag AS, Mohandes M, Al-Shaikh A. (2001) presented diagnosing Failed Distribution Transformers Using Neural Networks, United States Department of the Interior Bureau of Reclamation (2000) worked on Transformer Maintenance: Facilities Instructions, Standards and Techniques. Wang MH. (2003) Investigated A Novel Extension Method for Transformer Fault Diagnosis, Saha TK. (2003) Discussed Review of Modern Diagnostic Techniques for Assessing Insulation Condition in Aged Transformers, Zhang Y, Ding X, Liu Y, Griffin PJ. (1996) presented An Artificial Neural Network Approach to Transformer Fault Diagnosis, J.-S.R. Jang, (1993) Worked on ANFIS: Adaptive-network based fuzzy inference system, Wang Z, Liu Y, Griffin PJ. (2000) investigated Neural Network and Expert System Diagnose Transformer Faults, Wang M, Vandermaar AJ, Srivastava KD. (2002) discussed Review of Condition Assessment of Power Transformers in Service, IEC Publication 60599. (1999) presented Mineral oil impregnated electrical equipment in service-Guide to the interpretation of dissolved and free gases analysis, C.-T. Sun, (1994) presented Rule base structure identification in an adaptive-network-based fuzzy inference system, Ubeyli ED, Guler I., (2005) investigated Automatic detection of erythemato-squamous diseases using adaptive neuro-fuzzy inference systems Computers In Biology And Medicine, Bersini H., Bontempi G. (1997) investigated Now comes the time to defuzzify neuro-fuzzy models, Purwanto E., Arifin S. and Bian-Sioe So. (2001) investigated Application of adaptive neuro fuzzy inference system on the development of the observer for speed sensor less induction motor, Ali Akaayol. (2004) discussed Application of adaptive neuro-fuzzy controller for SRM.

2.1.1. Noteworthy Contribution in the field of proposed Work:

Wang Z, Liu Y, Griffin PJ. (2000) investigated Neural Network and Expert System Diagnose Transformer Faults,Wang M, Vandermaar AJ, Srivastava KD. (2002) discussed Review of Condition Assessment of Power Transformers in Service,IEC Publication 60599. (1999) presented Mineral oil impregnated electrical equipment in service-Guide to the interpretation of dissolved and free gases analysis,J.-S.R. Jang, (1992) worked on Self-learning fuzzy controllers based on temporal backpropagation, M. Sugeno and G.T. Kang,(1988) discussed Structure identification of fuzzy model,C.-T. Sun, (*1994)* presented Rulebase structure identification in an adaptive-network-based fuzzy inference system,Takagi T, Sugeno M., (1983) worked on Derivation of fuzzy control rules from human operator's control actions,Ubeyli ED, Guler I., (2005) investigated Automatic detection of erythemato-squamous diseases using adaptive neuro-fuzzy inference systems Computers In Biology And Medicine, Takagi T, Sugeno M., (1985) discussed Fuzzy identification of systems and its applications to modeling and control,J. S. Bridle , (1990) presented “Probabilistic Interpretation of Feedforward Classification Network

Outputs with Relationships to Statistical Pattern Recognition,D.S. Broomhead and D. (1988) worked on Low Multivariable functional interpolation and adaptive networks,Bersini H., Bontempi G. (1997) investigated Now comes the time to defuzzify neuro-fuzzy models.

2.1.2 Proposed Methodology during the tenure of the Research Work

The proposed method during the tenure of this piece of research work is application of soft computing tools i.e. fuzzy logic, neural network and genetic algorithm in fault diagnosis of power transformer. The Soft computing Diagnosis Model will be developed to detect and diagnose the fault in power Transformer. The results and outcomes of the above models will be analyzed and compared for useful study. The data acquired from the existing industries of power transformer repair and maintenance wing will be used to design the Soft computing Diagnosis Model using MATLAB 6.5 Software and validate the above-proposed Soft computing Diagnosis Model of fault diagnosis of power transformer. Before using the raw data available from the power plant, it will be normalized for mapping in 0,1 range.

3. Expected Outcome of the proposed Work:

Such kind of study has not been conducted in Chhattisgarh region earlier and will open new vistas in knowledge and trigger many research works. The expected major outcome of the works will be:

a. The power utility and industries dealing with power transformers will be capable to design new power transformers for improving reliability and controllability of power system as well as its performance, which will avoid the unnecessary power cut in the Chhattisgarh state.
b. The results obtained using Soft computing Diagnosis Tools which incorporates the human reasoning using FIS, the computational power of ANN and optimization power of Genetic Algorithm will be more useful for the management to manage and rectify the power system problems more effectively and economically.
c. This study will enable the power utility companies for their effective expansion planning of power plants.

In chapter 1 Different types of faults developed in the transformer has been discussed External Faults in Power Transformer

3.1 External Short - Circuit of Power Transformer

The short - circuit may occur in two or three phases of electrical power system. The level of fault electric current is always high enough. It depends upon the voltage which has been short - circuited and upon the impedance of the circuit up to the fault point. The copper loss of the fault feeding transformer is abruptly increased. This increasing copper loss causes internal heating in the transformer. Large fault electric current also produces severe mechanical stresses in the transformer. The maximum mechanical stresses occur during first cycle of symmetrical fault current.

3.2 High Voltage Disturbance in Power Transformer

High Voltage Disturbance in Power Transformer is of two kinds,

(1) Transient Surge Voltage

(2) Power Frequency over Voltage

3.3 Transient Surge Voltage

High voltage and high frequency surge may arise in the power system due to any of the following causes,

(a) Arcing ground if neutral point is isolated.

(b) Switching operation of different electrical equipment.

(c) Atmospheric Lightening Impulse.

Whatever may be the causes of surge voltage, it is after all a traveling wave having high and steep wave form and also having high frequency. This wave travels in the electrical power system network, upon reaching in the power transformer, it causes breakdown the insulation between turns adjacent to line terminal, which may create short circuit between turns.

3.4 Power Frequency over Voltage

There may be always a chance of system over voltage due to sudden disconnection of large load. Although the amplitude of this voltage is higher than its normal level but frequency is same as it was in normal condition. Over voltage in the system causes an increase in stress on the insulation of transformer. As we know that, voltage $V = 4.44\Phi.f.T \Rightarrow V \propto \Phi$, increased voltage causes proportionate increase in the working flux. This therefore causes, increased in iron loss and dis - proportionately large increase in magnetizing current. The increase flux is diverted from the transformer core to other steel structural parts of the transformer. Core bolts which normally carry little flux may be subjected to a large component of flux diverted from saturated region of the core alongside. Under such condition, the bolt may be rapidly heated up and destroys their own insulation as well as winding insulation.

3.5 Under Frequency Effect in Power Transformer

As, voltage $V = 4.44\Phi.f.T \Rightarrow V \propto \Phi.f$ as the number of turns in the winding is fixed. Therefore, $\Phi \propto V/f$ From, this equation it is clear that if frequency reduces in a system, the flux in the core increases, the effect are more or less similar to that of the over voltage.

Internal Faults in Power Transformer

The principle faults which occurs inside a power transformer are categorized as,

(1) Insulation breakdown between winding and earth

(2) Insulation breakdown in between different phases

(3) Insulation breakdown in between adjacent turns i.e. inter - turn fault

(4) Transformer core fault

3.6 Internal Earth Faults in Power Transformer

Internal Earth Faults in a Star Connected Winding with Neutral Point Earthed through an Impedance

In this case the fault electric current is dependent on the value of earthing impedance and is also proportional to the distance of the fault point from neutral point as the voltage at the point depends upon, the number of winding turns come under across neutral and fault point. If the distance between fault point and neutral point is more, the number of turns come under this distance is also more, hence voltage across the neutral point and fault point is high which causes higher fault current. So, in few words it can be said that, the value of fault electric current depends on the value of earthing impedance as well as the distance between the faulty point and neutral point. The fault electric current also depends up on leakage reactance of the portion of the winding across the fault point and neutral. But compared to the earthing impedance, it is very low and it is obviously ignored as it comes in series with comparatively much higher earthing impedance.

Internal Earth Faults in a Star Connected Winding with Neutral Point Solidly Earthed

In this case, earthing impedance is ideally zero. The fault electric current is dependent up on leakage reactance of the portion of winding comes across faulty point and neutral point of transformer. The fault electric current is also dependent on the distance between neutral point and fault point in the transformer. As said in previous case the voltage across these two points depends upon the number of winding turn comes across faulty point and neutral point. So in star connected winding with neutral point solidly earthed, the fault electric current depends upon two main factors, first the leakage reactance of the winding comes across faulty point and neutral point and secondly the distance between faulty point and neutral point. But the leakage reactance of the winding varies in complex manner with position of the fault in the winding. It is seen that the reactance decreases very rapidly for fault point approaching the neutral and hence the fault electric current is highest for the fault near the neutral end. So at this point, the voltage available for fault electric current is low and at the same time the reactance opposes the fault electric current is also low, hence the value of fault electric current is high enough. Again at fault point away from the neutral point, the voltage available for fault electric current is high but at the same time reactance offered by the winding portion between fault point and neutral point is high. It can be noticed that the fault electric current stays a very high level throughout the winding. In other word, the fault electric current maintain a very high magnitude irrelevant to the position of the fault on winding.

3.7 Internal Phase to Phase Faults in Power Transformer

Phase to phase fault in the transformer are rare. If such a fault does occur, it will give rise to substantial electric current to operate instantaneous over electric current relay on the primary side as well as the differential relay.

3.8 Inter Turns Fault in Power Transformer

Power Transformer connected with electrical extra high voltage transmission system, is very likely to be subjected to high magnitude, steep fronted and high frequency impulse voltage due to lightening surge on the transmission line. The voltage stresses between winding turns become so large, it can not sustain the stress and causing insulation failure between inter - turns in some points. Also LV winding is stressed because of the transferred surge voltage. Very large number of Power Transformer failure arise from fault between turns. Inter turn fault may also be occurred due to mechanical forces between turns originated by external short circuit.

3.9 THE LEAKAGE FLUX IN THREE-PHASE TRANSFORMERS

`In power transformers, not all the flux produced by the primary winding passes through the secondary winding, nor vice versa. Instead, some of the flux lines exit the iron via the air. The portion of magnetic flux that goes through one of the transformer windings but not the other is called *leakage flux* [27], and the amount of leakage flux mainly depends on the ratio between the reluctance of the magnetic circuit and the reluctance of the leakage path [28]. Leakage °ux lines in transformers are curved at the ends of the coils and °ow through the air almost parallel to the winding axis [29]. The degree of curvature of the lines is affected by the distance between the coils and the machine's shield and the latter's distribution in the air is in°uenced by the type of winding used in the machine's construction [29]. Leakage °ux lines in a healthy transformer have a horizontal axis of symmetry that passes through the middle of the magnetic core of the machine. When a short- circuit, or even a strong deformation, of one or several turns occurs, this symmetry is lost, therefore leakage °ux can be used for the early diagnosis of insulation faults. Below, a simple theoretical approach for the analysis of the leakage °ux in the windings of a power transformer is presented. This approximate analysis will show the symmetrical nature of leakage °ux and will allow the establishment of the foundations for a diagnosis procedure. Theoretical results will be complemented with ¯nite element models of transformers with different type of windings where the actual distribution of leakage °ux will also be analyzed.

3.9.1 Faults - Types and their Effects

It is not practical to design and build electrical equipment or networks so as to completely eliminate the possibility of failure in service. It is therefore an everyday fact of life that different types of faults occur on electrical systems, however infrequently, and at random locations. Faults can be broadly classified into two main areas which have been designated “Active” and “Passive”.

3.9.2 Active Faults

The “Active” fault is when actual current flows from one phase conductor to another (phase-to-phase) or alternatively from one phase conductor to earth (phase-to-earth).

This type of fault can also be further classified into two areas, namely the “solid” fault and the “incipient” fault.

The solid fault occurs as a result of an immediate complete breakdown of insulation as would happen if, say, a pick struck an underground cable, bridging conductors etc. or the cable was dug up by a bulldozer. In mining, a rock fall could crush a cable as would a shuttle car. In these circumstances the fault current would be very high, resulting in an electrical explosion.

This type of fault must be cleared as quickly as possible, otherwise there will be:

- Greatly increased damage at the fault location. (Fault energy = 1^2 x Rf x t where t is time).
- Danger to operating personnel (Flash products).
- Danger of igniting combustible gas such as methane in hazardous areas giving rise to a disaster of horrendous proportions.
- Increased probability of earth faults spreading to other phases.

 Higher mechanical and thermal stressing of all items of plant carrying the current fault. (Particularly transformers whose windings suffer progressive and cumulative deterioration because of the enormous electromechanical forces caused by multi-phase faults proportional to the current squared).
 Sustained voltage dips resulting in motor (and generator) instability leading to extensive shut-down at the plant concerned and possibly other nearby plants.

The “incipient” fault, on the other hand, is a fault that starts from very small beginnings, from say some partial discharge (excessive electronic activity often referred to as Corona) in a void in the insulation, increasing and developing over an extended period, until such time as it burns away adjacent insulation, eventually running away and developing into a “solid” fault.
Other causes can typically be a high-resistance joint or contact, alternatively pollution of insulators causing tracking across their surface. Once tracking occurs, any surrounding air will ionise which then behaves like a solid conductor consequently creating a “solid” fault.

3.9.3 Passive Faults

Passive faults are not real faults in the true sense of the word but are rather conditions that are stressing the system beyond its design capacity, so that ultimately active faults will occur.
Typical examples are:
 Overloading - leading to overheating of insulation (deteriorating quality, reduced life and ultimate failure).
 Overvoltage - stressing the insulation beyond its limits.
 Under frequency - causing plant to behave incorrectly.
 Power swings - generators going out-of-step or synchronism with each other. It is therefore very necessary to also protect against these conditions.

3.9.4 Transient & Permanent Faults

Transient faults are faults which do not damage the insulation permanently and allow the circuit to be safely re-energized after a short period of time.

A typical example would be an insulator flashover following a lightning strike, which would be successfully cleared on opening of the circuit breaker, which could then be automatically reclosed. Transient faults occur mainly on outdoor equipment where air is the main insulating medium.

Permanent faults, as the name implies, are the result of permanent damage to the insulation. In this case, the equipment has to be repaired and reclosing must not be entertained.

In chapter 2 Fault diagnosis in power transformer has been discussed in detail. Fault diagnosis (FD) plays a crucial role in power system monitoring and control that ensures a stable electrical power supply to consumers. FD involves identifying the location and nature of faults occurring on power system due to different disturbances [1,2]. FD function is the most basic fault handling function of power system supervisory control and data acquisition (SCADA) systems. Figure 1 shows the different blocks that configure a protective relay, based on which the FDS module is the most important one.

Fault type classification is an essential protective relaying feature due to its significant effect on the enhancement of relaying operation. Correct operation of major protective relays may be depending on fault classification [3]. Faulted phase selection is as important as fault detection. It would lead to increasing the system stability and system availability by allowing single pole tripping. Single pole tripping has many benefits like improving the transient stability and reliability of the power system, reducing the switching over-voltages and shaft torsional oscillations of large thermal units.

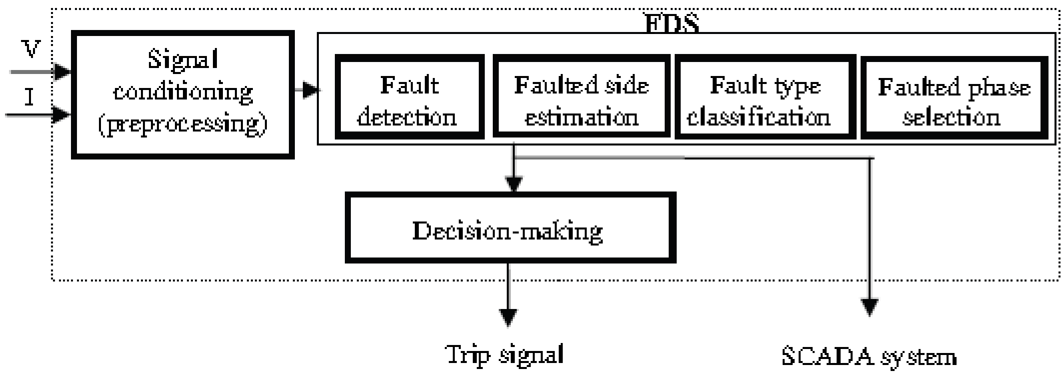

Fig. 1. FDS blocks in a transformer protective relay.

Large power transformers are considered important equipment in power systems. If a transformer experiences a fault, it is necessary to take it out of service as soon as possible in order to minimize the expected damage. The cost associated with repairing a damaged transformer is very high. An unplanned outage of a power transformer can cost electric utilities millions of dollars. Consequently, it is of great importance to minimize the frequency and duration of unwanted outages of power transformers. Accordingly, high demands are imposed on transformer protective relays. The protection degree of a power transformer is assessed according to its importance and rating [1].

Conventional approaches are: relying on system operating conditions, consuming large time, and failing to perform faulted phase selection [5,6]. ANN's provide a very interesting and valuable alternative because they can deal with most complex situations, which are not defined sufficiently for deterministic algorithms. They are robust with respect to incorrect or missing data. Protective relaying based ANN is not affected by system operating conditions. It also has high computation rates, large input error tolerance and adaptive capability [7]. Many literatures concerned with the application of ANN-based protection algorithm for power transformers have been reported [8-11]. Most of these literatures are relying on experimental transformer model. However, small size transformers usually behave differently compared with large power transformers during inrush and fault periods. Also, the evaluation of ANN relay sensitivity and stability boundaries has not been addressed. In Ref. [12], a transformer model during energization and fault periods is developed using the (EMTP). The training sets for the ANN are formulated considering various conditions including different fault classes. The response of the proposed ANN relay was measured and compared with the differential relay. It was found that the proposed relay was more efficient regarding the speed of detection, sensitivity, and stability boundaries. In this paper, an ANN based FDS, for power transformer external-faults, has been developed. The functions of the proposed FDS are to: detect the fault, localize the faulted side, classify the fault type and determine the faulted phase as well. The required specifications of the FDS should prove high reliability, and fast response.

4. Power System Simulation Using EMTP

The EMTP [13] is used for simulating the transients of power system elements including transformers. EMTP transformer model, implemented here, does not handle winding internal faults and inrush current cases, but it gives the ability to adapt the model for the transformers equivalent circuit.

The power system considered for this study is the Upper Egypt Power System (UEPS), Fig. 2. It consists of two generating stations, transformer substations, power lines, and loads. The power line from High-Dam 500 kV power station "HD500" to Cairo 500 kV power station "CA500" is, a double circuit line each of length 788 km. The present study is interested in the protection of the High-Dam 15.75/500 kV transformer substation. This system is selected, as an application example, to design and evaluate (test) the proposed approach. Figure (2) shows not only the system arrangement but also the location of the

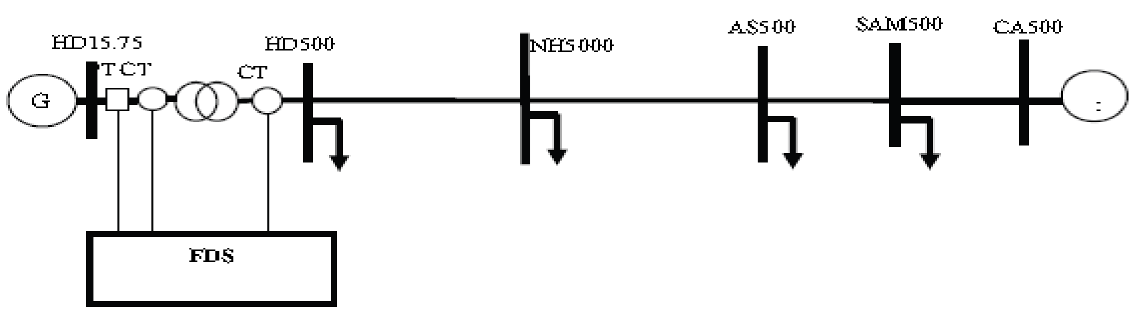

Fig.2 System under study

FDS. The UEPS system has been simulated under the following assumptions:

1- An infinite bus at the CA500 substation was considered.

2- No protection system was activated on the simulated system.

3- Generators were operating at one loading level.

4- No machine controllers existed.

5- Static loads were modeled as constant impedances.

5. ANN Design

The error back-propagation technique with adaptive learning rate and momentum is used (Appendix B). The three-layer feed-forward ANN is satisfactory for most power applications [14]. The tan-sigmoid and log-sigmoid functions are differentiable as well as monotonic functions. Therefore, selected design will have one hidden layer with tan-sigmoid neurons followed by an output layer with log-sigmoid neurons. Since, the proposed FDS would determine the faulted side, fault type and faulted phase, it was decided to choose three phase voltage and current samples as input signals. This selection is based on the fact that the three-phase current and voltage capture all the required information about the fault (as side, type and incipient time). A sampling rate of 800 Hz (16 samples per cycle for 50 Hz power frequency) is used. This sampling rate satisfies the feature space requirements and gives optimal conversion performance [14]. On the other hand, one output neuron with multi-level is used in this research. There are 11 ANN’s constructing the proposed FDS, therefore, it will be a tedious work to design each ANN individually. One ANN is, therefore, selected as model. After selecting the number of inputs and # of neurons in the hidden layer for the model, these selections were then applied to the other ten. Therefore, the input to each of these ANN’s may contain one or more samples. The set of samples which are used as inputs to the ANN will be called a pattern. A sample means a vector of three phase primary voltages and primary & secondary currents, sampled at a certain instant. Thus the number of inputs of a certain pattern is defined as follows:

Number of input patterns = 9 x number of samples composing the pattern = 9 x 4 = 36. Different configurations of ANN’s were tested. It was found that, ANN with 36 neurons in one hidden layer has resulted in a good performance.

In chapter 3 Several soft-computing tools and techniques have been discussed.

5.1 FDI VIA NEURAL NETWORKS

To overcome some of the difficulties of using mathematical models, and make FDI algorithms more applicable to real systems, the neural network can be used to both generate residuals and isolate faults (Chen & Patton, 1999). A neural network is a processing system that consists of a number of highly interconnected units called neurons. The neurons are interconnected by a large number of ‘weighted links’. Each neuron can be considered as a mathematical function that maps the input and output space with several inputs. The inputs are connected to either the inputs of the system or the outputs of the other neurons in the system. The output of one neuron affects the outputs of other neurons and all neurons connected together can perform complex processes. Indeed, one of the main features of neural networks is their ability to learn from examples. Hence, they can be trained to represent relationships between past values of residual data (generated by another neural network) and those identified with some known fault conditions.

5.2 FAULT DIAGNOSIS VIA FUZZY LOGIC

Since Zadeh (1965) introduced the theory of the fuzzy sets – manipulating data that were not precise, but rather “fuzzy” and since the work of Mamdani (1974), industrial application studies using fuzzy logic controllers have reached a major position in systems engineering. Fuzzy Systems are useful in any situation in which the measurements taken are imprecise or their interpretation depends strongly on the context or on human opinion. Complying with the practical gas records and associated fault causes as much as possible, a fuzzy reasoning algorithm is presented to establish a preliminary fuzzy diagnosis system. In this system, an evolutionary optimization algorithm is further relied on to fine-tune the membership functions of the if then inference rules. Lu et al (1998) described a fuzzy diagnostic model that contains a fast fuzzy rule generation algorithm and a priority rule based inference engine.[10] The advantage of the fuzzy approach is that it supports, in a natural way, the direct integration of the human operator into the fault detection and supervision process. By avoiding an incorrect decision that can cause false alarms the aim of the FDI decision making (for fault diagnosis) is to decide whether and where the fault in the system has occurred Fuzzy decision making objectives are very similar to expert systems and supervisory control. Expert Systems are used to simulate the problem-solving and decision making processes of a human expert within a relatively narrow domain. This is done using special computer packages along with knowledge, information and databases In recent years the application of fuzzy logic to model-based fault diagnosis approaches has gained increasing attention in both fundamental research and application. Symptoms can be generated using observers based on the estimation of the output from the system. The first methods used fuzzy set theory to express cause-effect relations in expert systems. The key idea of model-based methods is the generation of signals, termed residuals. These are usually generated using mathematical methods (based on state observers, parameter estimation or parity equations). The models correspond to the monitored system Residuals are signals representing inconsistencies between the model and the actual system being monitored, but the deviation between the model and the plant is influenced not only by the presence of the fault but also modeling uncertainty. One solution is for the observer and controller parameters to be tuned via estimation from the real system for fault isolation and threshold adaptation. The introduction of fuzzy logic can improve the decision-making, and in turn will provide reliable and sufficient FDI.[3,10]

5.3. DGA METHODS

The detection of certain level of gases generated in oil filled transformer in service is frequently the first available indication of malfunctioning that may lead to ultimate failure of a transformer, if not corrected. Arcing, corona discharge, low energy sparking, overheating of insulation due to severe overloading, failure of forced cooling systems are some of the possible mechanism for gas generation. The gases generated in oil filled transformers that can be used for qualitative determination of fault type, based on which gas is typical or predominant at various temperatures. These gases are hydrogen (H2), methane (CH4), ethylene (C2H4), ethane (C2H6), acetylene (C2 H2), carbon monoxide (CO), and carbon dioxide (CO2).

5.4. ARTIFICIAL INTELLIGENCE TECHNIQUES APPLIED TO DGA

Data of the dissolved gas in oil can be incorporated into expert systems to facilitate decision making. There also exists certain amount of uncertainty in the data concerning dissolved gas analysis due to generation, sampling, and chromatography analysis. There is thus variation in interpreting the variation of the gases by the utilities. Due to the diverse gas content of the insulating oil of transformers many AI techniques have been presented. The AI techniques studied and used by the researches for application to DGA are Expert Systems , Fuzzy Inference Systems (FIS) and various type of Artificial Neural Networks (ANN), Genetic Algorithm (GA)and even Novel Cerebellar Model Articulation Controller based method for off line and on line monitoring and Discrete Wavelet Transforms for on line monitoring.

A. Expert Systems

The expert system is decision support systems that have been applied for fault diagnosis and maintenance to advance the DGA information and incorporate it to build diagnostic rules [9]. The effectiveness of the knowledge expert systems depends on the precision and knowledge base, which is usually very complicated and must be constricted carefully. Such an expert system can neither acquire knowledge from new data samples through self-learning process and nor can it adjust its diagnostic rules automatically. C. F. Lin et al. [9] developed an expert system to diagnose transformer faults using DGA and also suggested proper maintenance. Data of 251 samples from transformers of Taiwan Power Company were used; three cases are discussed in details for the last five to six tests carried out. For the first two samples the diagnostic results agreed with the actual fault type causes and appropriate maintenance was suggested. For the third case the transformer unit after more than seventeen years of operation suffered an arc tracing fault. After repairing and degassing the transformer oil a gas fingerprint of this transformer was developed.

B. Fuzzy Inference System

K. Tomsovic et al. [10] proposed a fuzzy information approach to integrate different transformer diagnostic methods. Five gases were considered and detailed analysis of four transformers had been carried out. A fault tree was proposed and there was a framework for performing diagnosis using fuzzy information system. The fuzzy relations were combined with the fault tree to provide best analysis possible. The fact that an older or a heavily loaded transformer will have high concentration of gases that have built up over a time was taken into account. The proposed framework could provide a good foundation for providing diagnosis on variety of power system equipment. Yann-Chang Huang et al. [11] used Evolutionary Fuzzy Logic to develop a diagnostic system. The DGA method considered were Rogers Ratio, Doernenburgs' & IEC method. All the seven gases were considered. N.A Muhamad et al. [14] made a comparative study & analysis using fuzzy logic for six DGA methods namely Key Gas, Rogers Ratio, Doernenburg's, Logarithmic Nonograph, Duval Triangle, and IEC Method. 69 samples were used and a MATLAB program was developed to automate the evaluation of the methods. Some basic coding and construction of simulink block diagram was carried out. It was found that the accuracy gets reduced with fuzzy logic this was because the no of predictions when using fuzzy system is increased and this increases the possibility of incorRect prediction.

C. Artificial Neural Network

Diego Roberto Moaris et al. proposed an ANN approach for Transformer Fault Diagnosis. Forty sample sets from different transformers are used for training and testing of major fault type diagnosis. A two step Back Propagation Algorithm ANN approach was used. One ANN was used to classify the major fault type and the second ANN focused on determining in case cellulose is involved. The two step approach made ANN easier to train and more accurate in detecting faults. For diagnosis of oil-insulated power apparatus using neural network simulation O. Vanegas et al. used real data from 26 samples [15]. NN Back propagation technique algorithm was used. In the NN the input features (or variables) selected were the ratios while in the second SOPN the input features (or variables) selected were the gases H2, CH2, C2H6, C2H4, and C2H2. Two ANN- were built as well using the same sample data by error back propagation training algorithm. J. L. Guardado et al. [17] made a comparative study of Neural Network Efficiency in Power Transformer Diagnosis using DGA.

A feed forward neural network was trained to diagnose reasons for failure of distribution transformers. The training algorithm used was back propagation assuming initially a sigmoidal transfer function for networks processing unit. After the network was trained the units' transfer function was changed to hard limiters with thresholds equal to the biased obtained for the sigmoids during training. Six individual ANN were used for six important factors that were; age of the transformer, the weather conditions, damaged bushings, damaged bodies, oil leakage, and winding faults. The six ANN's are combined to one ANN to give recommendations complete diagnosis for working transformers to avoid possible failures. The developed ANN could give complete diagnosis of working transformer and be used as a decision support facilities to the companies for planning and maintenance schedule.

D. Artificial Neural Network & Fuzzy Logic

Transformer oil diagnosis using fuzzy logic and NN was proposed by James J. Dukaram using 150 real and synthetic examples [23]. Fuzzy was applied to Key gas analysis, Rogers' ratio method, and nomographs. Feed forward neural network were used. It was concluded that fuzzy logic can be used to automate standard methods of transformer oil DGA. In some cases NN could be used in combination with fuzzy logic to implement more complex diagnostic methods while maintaining a straightforward relation between the enhanced method and the original one. The main obstacle to developing a real diagnostic rule is the lack of sufficient high quality examples with which to train and validate a network. Jingen Wang et al. applied fuzzy classification by Evolutionary Neural Network [24]. The method models the membership functions of all fuzzy sets by utilizing a three layer feed forward network, trains a group of neural networks by combining the modified evolutionary strategy with Levenberg-Marquardt optimization method in order to accelerate convergence and avoid falling into local minima.

M. A. Izzularab et al. [26] developed an on line method for diagnosis of incipient faults and cellulose degradation using neuro-fuzzy. Records of six gases were considered and for the cellulose degradation the ratio of CO2/CO was used. A combination of neural networks and fuzzy sets was proposed to enhance the diagnostic system. Multilayered perceptron with sigmoidal activation function and error back propagation algorithm for training was used for 160 data samples of Egyptian Electricity Network. 75% for the data was used for training and remaining 25 % for testing. Three cases were considered and discussed in detail. Total combustible gases (TGC) was used to decide the normal and abnormal condition in a transformer. A comparison of the proposed technique and reported methods were carried out. The test results reveled that the proposed system had the highest reported classification capability. Adriana Rosa et al [27] made an attempt on knowledge discovery in NN with application to transformer failure diagnosis. A new methodology for mapping a neural network into a rule based fuzzy inference system. The maping makes explicit the knowledge implicitly captured by the neural network during the learning stage, by transforming it into a set of rules. 292 training and 139 testing patterns were used. The control of convergence of ANN has been taken into account not only the mean square error (MES) but also the success in classification. The classification of transformer faults has been done as onto three type only namely thermal faults, discharges and partial discharges. This is applied to transformer fault diagnosis using DGA. Good results were achived and knowledge discovery was made possible.

F. Genetic Algorithm Approach

Yann-Chang Huang used a new data mining approach to dissolved gas analysis of oil-insulated power apparatus [29] using 820 actual gas records of Taipower Company from 172, 68 kV transformers. The Genetic Algorithm (GA) and ANN (back-propagation) has been compared with Genetic Algorithm Tunes Wavelet Networks (GAWN) for data mining of dissolved gas analysis records and incipient fault detection of oil insulated power transformers. The GAWN's have been tested using four diagnosis criteria, and compared with ANN and conventional methods. The GAWN's have remarkable diagnosis accuracy and require far less learning time than ANN's for different diagnosis criteria. Wavelet network for power transformers diagnosis using DGA was proposed by Weigen Chen et al. [30]. 700 samples were used; 400 training samples and 300 testing samples. Wavelet Networks (WN's) are an efficient model of nonlinear signal processing developed in recent years. The training and testing samples are processed by fuzzy logic technology comparison and analysis of network training process and simulation results of five WN's. The proposed approach had many important advantages over traditional methods of analysis and interpretation of DGA data. The novel approach does not depend upon any actual fault cases for its modeling, hence it is easy and cost effective to implement. It provides more consistent and convincing diagnosis as the revealed structure actually originates from the real measured DGA records. The feed forward wavelet network used is divided into two types based on different activation functions of the wavelet nodes applied in fault diagnosis of power transformer. A GA base on real-encoded method of optimization in WN, was put forward (WN_GA) which is used to optimize the structure and parameters of the training process. The training process, diagnostic results and reasons for the difference in diagnosis are compared and analyzed. The Gauss activation function used achieve higher diagnostic accuracy because it can capture, the non-linear relationship among dissolved gas contents and corresponding fault information. The WN-GA had higher fault reorganization as compared the two other WN.

G. Discrete Wavelet Transform Method

Karen L. Butler-Purry et al. for identifying transformer incipient events for maintaining distribution system reliability have used Discrete Wavelet Transform (DWT) [31]. The approach has been applied to investigate the characteristics of incipient events in single phase transformer. MATLAB program was used to calculate the DWT of the signals. The Daubechies Db-4 type wavelet was used as a mother wavelet. On line incipient fault detection technique for distribution transformer was based on signal analysis. The method used discrete wavelet transform to identify incipient faults in single phase distribution transformers. The simulation method is based on Finite Element Methods (FEM) and ANSOFTs' Maxwell software was used for the circuit analysis. The simulation method takes into account the aging phase and the arcing phase. An experimental setup was made and the simulation methodology was tested. Time-domain results and frequency-domain results were compared for single phase transformer. The data obtained from tests and computer simulations were used to observe the variation. The results show the potential of using DWT-based method for fault prediction, maintenance and maintaining reliability of transformer.

In chapter 4 Artificial intelligence based Fault Diagnosis of Power Transformer-A Probabilistic Neural Network and Interval Type-2 Support Vector Machine Approach has been discussed. Power transformer has an important role in electrical network. This equipment is a main element in electrical power transmission, because of power source, transmission and distribution lines and consumer in different voltage levels are connected by transformer. Much kind of faults damage it. Most of them are short circuit winding faults and tab changer fault. Internal fault generates heat that causes deterioration insulation and decomposes oil and releases various gases such as hydrogen (H_2), methane (CH_4), ethane (C_2H_6),ethylene(C_2H_4), acetylene(C_2H_2),carbon monoxide (CO),carbon dioxide(CO_2). Winding fault, overheating and partial discharge is detected through the dissolved gas analysis (DGA). Released gas ratio is used as a fault indicator. DGA results that are combined with probability neural network classifier are widely used for fault detection. Other signals - used for fault detection is electrical signals such as three phase currents and if search coils are installed, their voltages. Search coils differential voltages are used for early detection and location of internal winding of transformer. Wavelet results are as probabilistic neural network inputs in order to detect inrush current. Interval type-2 Fuzzy SVM classifier is used for fault detection. Key point for fault detection is the feature extraction from raw signals. The wide varieties of electrical and thermal stresses often age the transformers and subject them to incipient faults. If an incipient failure of a transformer is detected before it leads to a catastrophic failure, predictive maintenance can be deployed to minimize the risk of failures and further prevent loss of services. In industrial practice, dissolved gas analysis (DGA) is a very efficient tool for such purposes since it can warn about an impendent problem, provide an early diagnosis, and ensure transformers' maximum uptime. The DGA methods ana1yse and interpret the attributes acquired: ratios of specific dissolved gas concentrations, their generation rates and total combustible gases are used to conclude the fault situations. Recently, artificial intelligence techniques have been extensively used with the purpose of developing more accurate diagnostic tools based on DGA data. R. Naresh, et al (2008) presents a new and efficient integrated neural fuzzy approach for transformer fault diagnosis using dissolved gas analysis. The proposed approach formulates the modeling problem of higher dimensions into lower dimensions by using the input feature selection based on competitive learning and neural fuzzy model. Then, the fuzzy rule base for the identification of fault is designed by applying the subtractive clustering method which is efficient at handling the noisy input data. V.Miranda (2005) et al describes how mapping a neural network into a rule-based fuzzy inference system leads to knowledge extraction. This mapping makes explicit the knowledge implicitly captured by the neural network during the learning stage, by transforming it into a set of rules. This method is applied to transformer fault diagnosis using dissolved gas-in-oil analysis. A.Shintemirov (2009) et al presents an intelligent fault classification approach to power transformer dissolved gas analysis (DGA), dealing with highly versatile or noise-corrupted data. Bootstrap and genetic programming (GP) are implemented to improve the interpretation accuracy for DGA of power transformers. Bootstrap pre-processing is utilized to approximately equalize the sample numbers for different fault classes to improve subsequent fault classification with GP feature extraction. GP is applied to establish classification features for each class based on the collected gas data. The features extracted with GP are then used as the inputs to artificial neural network (ANN), support vector machine (SVM) and K-nearest neighbor (KNN) classifiers for fault classification. The aim of this paper is to present a new method for detection and classification of power transformers faults by using a dissolved gas analysis and an artificial intelligence technique for decision with a maximal classification rate. Here we use probabilistic neural network and interval type-2 fuzzy support vector machine for classification and detection of power transformer fault profile. This paper is organized as follows: Section 2 introduces the PNN architecture and theory of operation. Section 3 presents interval type-2 fuzzy support vector machine (IT2SVM) technique. Section 4 presents probabilistic neural network plus interval type-2 fuzzy SVM Fusion Model. Section 5 presents Simulation of Transformers Faults Classification. The simulation results are presented in Section 6. Finally, the conclusion is provided in Section 7.

6. PNN Architecture and Theory of Operation

The probabilistic Neural Network used in this paper is shown in Fig.1. The first (leftmost) layer contains one input node for each input attribute in an application. All connections in the network have a weight of 1, which means that the input vector is passed directly to each hidden node. In PNN, there is one hidden node for each training instance i in the training set. Each hidden node h_i has a center point y_i associated with it, which is the input vector of instance i. A hidden node also has a spread factor, s_i, which determines the size of its respective field. There are a variety of ways to set this parameter. s_i is equal to the fraction f of the distance to the nearest neighbor of each instance i. The value of f begins at 0.5 and a binary search is performed to fine tune this value. At each of five steps, the value of f that results in the highest average confidence of classification is chosen (HongYu et al. 2010). A hidden node receives an input vector x and outputs an activation given by the Gaussian function g, which returns a value of 1 if x and $y_i$are equal and drops to an insignificant value as the distance grows (HongYu et al. 2010):

$$g(x, y_i, s_i) = \exp(-D^2(x, y_i)/2s_i^2)$$

The distance function D determines how far apart the two vectors are. By far the most common distance function used in PNNs is Euclidean distance. However, in order to appropriately handle applications that have both linear and nominal attributes, a heterogeneous distance function HVDM is used to normalize Euclidean distance for linear attributes and the Value Difference Metric (VDM) for nominal attributes.

Interval Type-2 Fuzzy Support Vector Machine (IT2SVM)

SVM is a powerful and promising machine learning tool, support vector machines (SVMs) employ Structural Risk Minimization (SRM) principle to achieve better generalization ability than traditional machine learning algorithms, such as decision trees and neural networks. SVM classification aims to construct an optimal separating hyper plane in a higher transformed feature space by maximizing the margin between the separating hyper plane and classification data. The transformation of feature spaces from input spaces can be made through kernel trick, which allows every dot-product to be replaced simply by a kernel function. Kernel functions play an essential role in the SVM classification since they determine feature spaces in which data examples are classified and can directly affect SVM classification results and performances. A less time-consuming way is to randomly choose several SVMs with different kernels and construct an ensemble model to combine the different SVM classifiers and generate a hybrid classifier. This paper proposes an ensemble model to combine multiple SVM classifiers by applying the knowledge of interval type-2 fuzzy logic system (IT2FLS). Interval type-2 fuzzy sets and IT2FLS can better handle uncertainties and imprecision in classification data such as noise or outliers. Unlike type-1 FLS, MFs of type-2 fuzzy sets themselves are fuzzy such that membership grades of type-2 fuzzy sets are fuzzy sets in [0, 1]. This basic characteristic of type-2 fuzzy sets makes type-2 FLS especially useful to handle situations where shapes, positions or other parameters of MFs are uncertain. The proposed interval type-2 fuzzy ensemble model takes consideration of the classification results of data examples from different SVMs and generates outputs indicating whether data examples belong to positive or negative class.

In this chapter, the artificial intelligence techniques are implemented for the faults classification using the dissolved gas analysis for power transformers. The DGA methods studied are key gas, graphical representation and ratios method. The fault diagnosis models performance was analyzed with interval type-2 fuzzy logic (using Gaussian, trapezoidal and triangular membership functions), probabilistic neural network (PNN) and Support Vector Machine (with polynomial and Gaussian kernel functions). The real data sets are used to investigate the performance of the DGA methods in power transformer oil. In this paper, we propose an interval type-2 SVM fusion model to combine multiple individual SVM classifiers. The experimental results show that interval type-2 FLS is a suitable and feasible way to implement ensemble approaches in terms of performance and computational complexity. The proposed type-2 SVM fusion system demonstrates more stable and more robust generalization ability than individual SVMs. The experimental results show that the interval type-2 fuzzy logic classifier with triangular membership presents the best result in comparison with the other two membership functions. The classification accuracies of PNN are superior to RBF, MLP NN and the SVM with Gaussian kernel function has more excellent diagnostic performance than the SVM with polynomial kernel function. According to test results, it is found that the ratios method is more suitable as a gas signature. The IT2SVM with the Gaussian kernel function has a better performance than the other AI methods in diagnosis accuracy. The proposed method can be applied to online diagnosis of incipient faults in transformers. Proposed approach for fault classification is presented. IT2SVM combined with PNN has a good efficiency in transformer fault classification.

In chapter 5 Dissolved Gas Analysis of Power Transformer using AUROCC-based Genetic Fuzzy SVM fusion model has been discussed. In extended power systems, substation facilities have become both too complex and too large. Customers require the high quality offered by an electrical power system. However, some facilities have become old and often break down unexpectedly. Such unexpected failure may cause a break in the power system and result in loss of profits. Therefore, it is important to prevent abrupt faults by monitoring the condition of power systems. Among the various power facilities, power transformers play an important role in transmission and distribution systems. At present, it has been proven that the dissolved gas analysis (DGA) is the most effective and convenient method to diagnose the transformers. Under normal conditions, the insulating oil and the organic insulating material in oil-filled equipment generate a small amount of gas caused by the gradual degradation and decomposition. The DGA approach identifies faults by considering the ratios of specific gas concentration. There are various methods based on DGA such as Dornenburg ratios, Roger ratios, IEC ratios, and etc. The DGA is a simple, inexpensive, and non-intrusive technique. The transformer oil provides both cooling and electrical insulation. It baths every internal component and contains a lot of diagnostic information in the form of dissolved gases. Since these gases reveal the faults of a transformer, they are known as Fault Gases. The DGA is the study of dissolved gases in transformer oil. The concentration of the different gases provides information about the type of incipient-fault condition present as well as the severity. Different methods Rogers, fuzzy, neural, key gas method, duval, dornenburg ratio etc. are available for fault detection using DGA data.

Under the abnormal condition in transformers, the insulation oil and the organic insulation material in oil filled equipment generate several gases such as hydrogen (H_2), carbon monoxide (CO), acetylene

(C_2H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), carbon dioxide (CO_2), and etc. The quantity of the dissolved gas depends fundamentally on the types of faults occurring within power transformers. By considering these characteristics, DGA methods make it possible to detect the abnormality of the transformers.

Table 1 shows decision criteria according to quantity of each dissolved gas in transformers, which means the standard considered in NTPC Korba India (National Thermal Power Development Corporation Korba, India). More specifically, this method determines incipient faults in transformers according to the amount of gasses acquired from DGA. Here, the incipient faults include normal, alarm, fault, and danger. Also, this method makes it possible to identify the causes of faults represented as partial discharge, insulator degradation, arc discharge, low overheat and high overheat according to the concentration of special gasses.

This diagnosis technique based on these categories has certain limitations. For example, in case of exceeding 400 (ppm) for the concentration of hydrogen, this method determines the fault as an alarm condition and identifies the cause of the fault as partial discharges. However, the transformer is assumed to be operating normally in case of 399 (ppm). Even though the difference between the two data is only 1 (ppm), the interpretations are completely different. This indicates a very crisp interpretation with respect to the boundaries.

On the other hand, a specific gas is generated and accumulated in the oil as time goes on in spite of the normal condition. Therefore, the potential possibility and the degree of aging could be different even to transformers that are in normal condition. In fact, the amount of these gases indicates the potential for seeking a method for finding a faulted condition. This fault detection should be made periodically by means of DGA to maintain reliable operation of the transformers. Therefore, the variation of the existence and the concentration of the gasses with time must be taken into account for an accurate identification of the fault evolution and the aging reasons.

The soft computing techniques like Fuzzy, Neural and Neuro-fuzzy utilizes limited parameters where as the parameters are not compressive, hence resulted into inaccurate classification of it. Support Vector Machines is a powerful methodology for solving problems in nonlinear classification. The advantage of DGA is that the operation and test are performed at the same time, in addition to the fact that it is a simple and inexpensive diagnosis process. However, much uncertainty exists in the data with respect to the dissolved gas. For example, the amount of special gas in normal condition could vary according to the characteristics of the transformer. Furthermore, the DGA method cannot provide accurate diagnosis without the help of experienced experts.

The proposed SVM classifiers are applied to solve the practical problems of small samples and non-linear prediction better and it is suitable for the DGA in power transformers. The accuracy of an SVM model is largely dependent on the selection of the model parameters. This paper uses genetic algorithm to optimize the parameters of AUROCC-based genetic fuzzy SVM fusion model. Genetic algorithm uses selection, crossover and mutation operation to search the model parameter. Classifier fusion is to combine a set of classifiers in a certain way so that the combined classifier can receive a better performance than its composing individual classifiers. The reason that the combined classifier could outperform the best individual classifier is because the data examples misclassified by the different classifiers would not necessarily overlap, which leaves the room for the classifier complementariness. A fuzzy logic system (FLS) is constructed to combine multiple SVM classifiers in the light of the performance of each individual classifier. The memberships of the fuzzy logic system are tuned by genetic algorithms (GAs) to generate the optimal fuzzy logic system. One question here is how to evaluate classifier performance in the fusion model. Typically, *accuracy* is the standard criterion to evaluate a classifier performance. The Receiver Operating Characteristics (ROC) and the area under an ROC curve (AUC) have been shown to be statistically consistent with and more discriminating than accuracy empirically and theoretically. This paper will use AUC as the evaluation of classifier performance to build the genetic fuzzy fusion model to enhance the performance of SVM classifiers. Then proposed method is applied to measure the possibility and degree of aging as well as the faults occurred in the transformer. To demonstrate the validity of the proposed method, various experiments are performed and their results are presented. To demonstrate the validity of the proposed method, an experiment is performed and its results are illustrated. The objective of this paper is to develop a AUROCC-based genetic fuzzy SVM fusion model and then this model is used for Dissolved Gas analysis (DGA) in power transformer. The results compare diagnostic performance according to normal, care and healthy conditions with respect to our method and expert's decision are discussed. Also aging degree of power transformer for insulation degradation and CO_2 excess for good, medium and low conditions are demonstrated.

In this chapter while developing AUROCC-based genetic fuzzy SVM fusion model, we will first introduce the Proposed Diagnosis System using AUROCC-based genetic fuzzy SVM fusion model in Section 2. Then we will discuss Genetic Fuzzy SVM Fusion Based on AUROCC in Section 3. The Tuning Fuzzy System Using GA's will be proposed in Section 4 and Experimental Result and Analysiswill be discussed in Section 5. Finally in Section 6, conclusions will be drawn.

In this paper, we proposed a method of power transformer diagnosis using AUROCC-based Genetic Fuzzy SVM fusion model. Here, we propose a genetic fuzzy SVM classifier fusion model to combine multiple SVM classifiers. Individual SVMs are combined in a genetic fuzzy system and GAs is applied to tune the fuzzy MFs based on AUROCC measure. The experimental results show that the proposed genetic fuzzy system is more stable and more robust than individual SVMs. Moreover, the combined SVM classifier from the genetic fuzzy fusion model accomplishes more accurate ranking of data examples which provides valuable interpretation of the real-world data and may help dissolve gas analysis (DGA). From various experimental results, we conclude that the proposed method is efficient in estimating the aging degree for normal transformers as well as the cause of transformers in care conditions. The objective of this paper is to develop an AUROCC-based genetic fuzzy SVM fusion model and then this model is used for Dissolved Gas analysis (DGA) in power transformer. The results compare diagnostic performance according to normal, care and healthy conditions with respect to our method and expert's decision are discussed. Also aging degree of power transformer for insulation degradation and CO_2 excess for good, medium and low conditions are demonstrated

7. Result Discussion

Artificial intelligence based Fault Diagnosis of Power Transformer-A Probabilistic Neural Network and Interval Type-2 Support Vector Machine Approach

Simulation of Transformers Faults Classification

Transformer Fault Types: IEC Publication 60599 provides a coded list of faults detectable by dissolved gas analysis (DGA):

• Partial discharge (PD): PD occurs in the gas phase of voids or gas bubbles. It is usually easily detectable by DGA, however, because it is produced over very long periods of time and within large volumes of paper insulation. It often generates large amounts of hydrogen.

• Low energy discharge (D1): D1 such as tracking, small arcs, and uninterrupted sparking discharges are usually easily detectable by DGA, because gas formation is large enough.

• High energy discharge (D2): D2 is evidenced by extensive carbonization, metal fusion and possible tripping of the equipment.

• Thermal faults T <300 ° C (T1): T1 evidenced by paper turned brownish.

• Thermal faults 300 <T< 700 ºC (T2): T2 evidenced when paper carbonizes.

• Thermal faults T > 700 ºC (T3): T3 evidenced by oil carbonization, metal coloration or fusion.

***Diagnosis and Interpretation Methods**:*

The DGA methods have been widely used by the utilities to interpret the dissolved gas. According to the pattern of the gases composition, their types and quantities, the interpretation approaches below for dissolved gas are extensively followed: Key gas method; Ratios method; The graphical representation method. In this key gas method, we need five key gas concentrations H_2, CH_4, C_2H_2, C_2H_4 and C_2H_6 available for consistent interpretation of the fault. Table 1 shows the diagnostic interpretations applying various key gas concentrations. The results are mainly adjectives and provide a basis for further investigation.

Classification by Interval Type-2 Fuzzy Logic

For The fuzzy logic faults classification is performed using several DGA methods as gas signature. ***Fuzzy key gas:*** Firstly, we will classify the faults using key gas as input data with: •5 linguistic variables are the 5 gas: H2, CH4, C2H2, C2H4 and C2H6; •3 linguistic values: small, medium and high; •5 sets of reference: U = [0, 650] for H2, U = [0, 550] for CH4, U = [0, 450] for C2H2, U = [0, 750] for C2H4 and U = [0, 370] for C2H6; •7 outputs, the reference sets are : U = [0, 1] for the non-fault, U = [0, 2] for the PD, U = [1, 3] for the D1, U = [2, 5] for the D2, U = [3, 6] pour for the T1, U = [4, 7] for the T2 and U = [5, 8] for the T3 ; •3 membership functions: triangular, trapezoidal and Gaussian; •35 = 251 fuzzy rules; •Defuzzification by the centroid method.

Classification by SVM

As shown in Fig.6, the diagnostic model includes six IT2FSVM classifiers which are used to identify the seven states: normal state and the six faults (PD, D1, D2, T1, T2 and T3). With all the training samples of the states, IT2FSVM1 is trained to separate the normal state from the fault state. When input of IT2FSVM1 is a sample representing the normal state, output of IT2FSVM1 is set to +1; otherwise -1. With the samples of single fault, IT2FSVM2 is trained to separate the discharge fault from the overheating fault. When the input of IT2FSVM2 is a sample representing discharge fault, the output of IT2FSVM2 is set to +1; otherwise-1. With the samples of discharge fault, IT2FSVM3 is trained to separate the high-energy discharge (D2) fault from the partial discharge (PD) and low energy discharge (D1) fault. When the input of IT2FSVM3 is a sample representing the D2 fault, the output of IT2FSVM3 is set to +1; otherwise -1. With the samples of overheating fault, IT2FSVM4 is trained to separate the high temperature overheating (T3) fault from the low and middle

The performance of key gas method is analyzed in terms false alarm rate and non-detection rate for triangular, trapezoidal and Gaussian membership functions as shown in Table 5. According to the results, we find that the triangular membership function is more efficient for system fault diagnosis, but this method does not give excellent results. So, we must propose an alternative method. All the six IT2FSVMs adopt polynomial and Gaussian as their kernel function. In IT2FSVM, the parameters σ and C of IT2FSVM model are optimized by the cross validation method. The adjusted parameters with maximal classification accuracy are selected as the most appropriate parameters. Then, the optimal parameters are utilized to train the IT2FSVM model. So the output codification is presented in Table 6.

Firstly, we will classify the faults by SVM with the polynomial kernel. To select more efficient kernel between the two cores used (polynomial and Gaussian), we compare the false alarm rate and non-detection rate given in Table 7. The results in Table 7 show that the Gaussian kernel gives the best performance for the test.

Dissolved Gas Analysis of Power Transformer using AUROCC-based Genetic Fuzzy SVM fusion model

7.1 Experimental Result and Analysis

Historical data

To evaluate the proposed method, we use the dataset acquired by NTPC-Korba India. It includes the records for 345kV and 154kV transformers operated in two different areas during 1992-1997. These patterns are acquired from transformers in two regions in Korba. There are 963 DGA patterns acquired from 177 transformers in 64 substations located in the same region and 471 patterns acquired from 98 transformers in 38 substations in another region. Each pattern consists of H_2, O_2, N_2, CO_2, C_2H_4, C_2H_6, C_2H_2, CH_4, CO, and T.C.G. Among these gases, we chose 963 patterns for the training purpose, while the rest of the data were used for testing.

Fig.6 shows Output of SVM classifiers fusion model i.e. Amount of specific Gas. Here, we consider the 7 specific gases such as H_2, CO, C_2H_2, CH_4, C_2H_6, C_2H_4, and CO_2, which are described from number 1 to 7 in this Fig.6. From this Fig.6, we see that each condition has the characteristics according to the amount of specific gas. For example, care condition for insulator degradation has more CO gas than the other conditions. Otherwise, the amount of CO gas is less than 0.7 under normal conditions. Here the number of inputs equals the kinds of specific gases considered in this architecture. Also, the number of outputs equals the kinds of care conditions plus the normal condition. Care conditions include the six types such as insulator degradation, CO_2 excess, arc discharge, low overheat and high overheat. Therefore the numbers of input and output are 7 and 6, respectively.

Diagnosis performance

Fig.7 presents the output value for the normal condition among the output units in SVM classifiers fusion model according to the normal and care dataset determined by experts for normal mode. The values of most of the normal data are higher than 0.4. Otherwise, the output unit corresponded for normal state has the value less than 0.25 for care data.

Table 2 shows the diagnosis results with respect to normal and care conditions. From this table, the result by our method is equal to the expert’s decision. However, the result for normal data is slightly different from the decisions made by the experts. The reason for this could be well explained by Fig.7.

According to the decision rule performed by NTPC-Korba, if the amount of gas for CO (described as number 2 in the fig.7) is less than 300, the transformer is determined as normal. Also, if the amount of gas for CO_2 (described as number 10 in the fig.7) is less than 4000, the transformer is determined as normal. More specifically, the values of gases are 287 and 3460 for CO and CO_2, respectively. By considering these relations, our method concludes that this transformer is in care condition. Table 2 indicates the diagnosis performance according to care conditions. As seen in Table 3, the diagnosis performance by our method shows the same decision criteria comparing with the determination by expert's except for insulation degradation.

8. Conclusions

In this thesis, the artificial intelligence techniques are implemented for the faults classification using the dissolved gas analysis for power transformers. The DGA methods studied are key gas, graphical representation and ratios method. The fault diagnosis models performance was analyzed with interval type-2 fuzzy logic (using Gaussian, trapezoidal and triangular membership functions), probabilistic neural network (PNN) and Support Vector Machine (with polynomial and Gaussian kernel functions). The real data sets are used to investigate the performance of the DGA methods in power transformer oil. In this paper, we propose an interval type-2 SVM fusion model to combine multiple individual SVM classifiers. The experimental results show that interval type-2 FLS is a suitable and feasible way to implement ensemble approaches in terms of performance and computational complexity. The proposed type-2 SVM fusion system demonstrates more stable and more robust generalization ability than individual SVMs. The experimental results show that the interval type-2 fuzzy logic classifier with triangular membership presents the best result in comparison with the other two membership functions. The classification accuracies of PNN are superior to RBF, MLP NN and the SVM with Gaussian kernel function has more excellent diagnostic performance than the SVM with polynomial kernel function. According to test results, it is found that the ratios method is more suitable as a gas signature. The IT2SVM with the Gaussian kernel function has a better performance than the other AI methods in diagnosis accuracy. The proposed method can be applied to online diagnosis of incipient faults in transformers. Proposed approach for fault classification is presented. IT2SVM combined with PNN has a good efficiency in transformer fault classification.

In this chapter, we proposed a method of power transformer diagnosis using AUROCC-based Genetic Fuzzy SVM fusion model. Here, we propose a genetic fuzzy SVM classifier fusion model to combine multiple SVM classifiers. Individual SVMs are combined in a genetic fuzzy system and GAs is applied to tune the fuzzy MFs based on AUROCC measure. The experimental results show that the proposed genetic fuzzy system is more stable and more robust than individual SVMs. Moreover, the combined SVM classifier from the genetic fuzzy fusion model accomplishes more accurate ranking of data examples which provides valuable interpretation of the real-world data and may help dissolve gas analysis (DGA). From various experimental results, we conclude that the proposed method is efficient in estimating the aging degree for normal transformers as well as the cause of transformers in care conditions. The objective of this paper is to develop an AUROCC-based genetic fuzzy SVM fusion model and then this model is used for Dissolved Gas analysis (DGA) in power transformer. The results compare diagnostic performance according to normal, care and healthy conditions with respect to our method and expert's decision are discussed. Also aging degree of power transformer for insulation degradation and CO_2 excess for good, medium and low conditions are demonstrated

9. Outcome of the proposed Work:

Such kind of study has not been conducted in Chhattisgarh region earlier and will open new vistas in knowledge and trigger many research works. The expected major outcome of the works will be:

d. The power utility and industries dealing with power transformers will be capable to design new power transformers for improving reliability and controllability of power system as well as its performance, which will avoid the unnecessary power cut in the Chhattisgarh state.

e. The results obtained using Soft computing Diagnosis Tools which incorporates the human reasoning using FIS, the computational power of ANN and optimization power of Genetic Algorithm will be more useful for the management to manage and rectify the power system problems more effectively and economically.

f. This study will enable the power utility companies for their effective expansion planning of power plants.

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