DEVELOPMENT OF AN INTELLIGENT NOVEL ALGORITHM FOR TRANSFORMER FAULT DETECTION USING VARIOUS EMISSION SIGNALS

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CERTIFICATE

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DECLARATION

I hereby declare that the research work presented in this thesis entitled **"Development of an Intelligent Novel Algorithm for Transformer Fault Detection using various emission signals"** submitted for the award of the degree of Doctor of Philosophy in the Department of Electrical and Instrumentation Engineering, Thapar University, Patiala is an authenticated record of my own research work carried out under the supervision of Dr. B. N. Chudasama (School of Physics and Materials Science) and Prof. (Dr.) Yadwinder Singh Brar (Department of Electrical Engineering) and refers other researcher's work are duly listed in the reference section.

The matter presented in this thesis has not previously been submitted in part or full to any other University or institution for the award of any degree in India or abroad.

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ABBREVIATIONS

ANN	-	Artificial Neural Network
AAF	-	Accelerated Aging Factor
ANOVA.	-	Analysis of Variance
ASTM	-	American Society for Testing and Materials
ANFIS	-	Adaptive Network-based Fuzzy Inference System
AI	-	Artificial Intelligence
AE	-	Acoustic Emission
BPN	-	Back Propagation Neural Network
BP-ALM	-	Back Propagation with Adaptive Learning Rate and Momentum coefficient
CW	-	Circulating Water
CIGRE	-	Council on Large Electric System
CMAC	-	Cerebeller Model Articulation Neural Network
DGA	-	Dissolved Gas Analysis
DP	-	Degree of Polymerization
EEMF	-	Excitation Emission Matrix Fluorescence
FWNN	-	Fuzzy Wavelet Neural Network
FCM	-	Fuzzy c-means
FMM	-	Fuzzy Min–Max
FIS	-	Fuzzy Inference System
FA	-	Factor Analysis
FRA	-	Frequency Response Analysis
FDR	-	Frequency Dielectric Response

GIS/GITL	-	Gas-insulated Switchgear/transmission lines
GIS	-	Gas Insulated Substations
GBP	-	General Back-propagation Artificial Neural Network
HV	-	High Voltage
HRPNN	-	Heteroscedastic Probabilistic Neural Network
HST	-	Hot Spot Temperature
LS	-	Least Square
LVQ	-	Learning Vector Quantization
MLP	-	Multi-layer Perceptron
MMF	-	Magnetomotive Force
NN	-	Neural Network
OLTC	-	On-load Tap Changer
PD	-	Partial Discharge
PSO	-	Particle Swarm Optimization
PNN	-	Probabilistic Neural Network
PDC	-	Polarization and Depolarization Current
PPM	-	Parts Per Million
QPSO	-	Quantum-inspired Particle Swarm Optimization
RS	-	Rough Set
RecBFN	-	Rectangular Basis Function Network
RTR	-	Refined Three-Ratio method
RBF	-	Radial Basis Function
RVM	-	Recovery Voltage Measurement

SLT	-	Statistical Learning Theory
SVM	-	Support Vector Machine
SVMG	-	Support Vector Machine with Genetic Algorithm
SFS	-	Synchronous Fluorescence Spectroscopy
SOM	-	Self-Organizing Map
TLM	-	Transmission Line Method
TDCG	-	Total Dissolved Combustible Gas
TPSW	-	Two Pass Split Window
T2-FLS	-	Type-2 Fuzzy Logic System
TS	-	Transformer Station
UCI	-	University of California at Irvine
WT	-	Wavelet Transform

SYMBOLS

C_2H_2	-	Acetylene
C_2H_6	-	Ethane
C_2H_4	-	Ethylene
H_2	-	Hydrogen
CH_4	-	Methane
CO	-	Carbon Monoxide
CO_2	-	Carbon Dioxide
N_2	-	Nitrogen
Φ	-	Flux
VA	-	Volt-Amperes
kVA	-	Kilo Volt-Amperes
%	-	Percentage

LIST OF PUBLICATIONS FROM PRESENT WORK

A. Papers in SCI journals

1. **Tapsi Nagpal**, Yadwinder Singh Brar, Expert System based Fault Detection of Power Transformer, Journal of Computational and Theoretical Nanoscience. (Accepted) IF: 1.03
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ABSTRACT

Transformers are an essential part of the electrical power system because they have the ability to change voltage and current levels, which enables the transformers to generate the electric power, to transmit and distribute electric power and utilize the power at economical and suitable levels. In electrical power system, voltage of electricity generated at the power plant is increased to a higher level with step-up transformers. A higher voltage reduces the energy lost during the transmission process of the electricity. After electricity has been transmitted to various end points of the power grid, voltage of the electricity is reduced to a usable level with step- down transformer for industrial customers and residential customers. Since power transformer is vital equipment in any electrical power system, so any fault in the power transformer may lead to the interruption of the power supply and accordingly, the financial losses will also increase. 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. To monitor the service ability of power transformer, many devices have been evolved such as buchholz relay, differential relay, over current relay, thermal relay etc. which are part of protection in terms of determination of faults in the transformer. But the main shortcoming of these devices is that they only respond to the severe power failures which require removal of equipment from the service.

Even in normal operation, a power transformer is subjected to internal stresses that often, in time affect the performance and reliability of the transformer through the steady breakdown of its insulating materials. These materials include paper and oil. Such insulating materials after being subjected to a variety of stressful conditions that occur in a transformer, have been found to deteriorate, which results in generation of gases which are often combustible or harmful. During the operation of transformers, they are subject to electrical and thermal stresses, which can cause the degradation of the insulating materials. Stability and reliability of a power system in many respects depends on the condition of power transformers. Essential devices as power transformers are in a transmission and distribution system, a wide variety of electrical and thermal stresses often age the transformers and subject them to incipient faults. Being one of the most expensive and important elements, a power transformer is a

highly essential element, whose failures and damage may cause the outage of a power system. Thus, techniques for early detection of the faults would be very valuable to avoid outages. The degradation of the insulating materials produces the degradation products, which are gases, which entirely or partially dissolve in the oil where they are easily detected at the parts per million (PPM) level by dissolved gas analysis. The transformer faults can be differentiated for their energy, localization and occurrence period. There are increased oil temperatures and generation of certain oxidation products such as acids and soluble gases, associated with the occurrence of the fault.

In case of thermal and electrical stress condition caused by fault current in the transformers, the hydrocarbons molecules of mineral oil can decompose and form active hydrogen and hydrocarbon fragment can combine with each other to form gases like hydrogen (H_2) , methane (CH_4), acetylene (C_2H_2) ,ethylene (C_2H_4) , ethane (C_2H_6) , carbon monoxide (CO), carbon dioxide (CO_2) etc. Such gases are considered as fault indicators and can be generated in certain. The deterioration of the insulation accompanies incipient faults, in the form of arcs or sparks resulting from dielectric breakdown of weak or overstressed parts of the insulation, or hot spots due to abnormally high current densities or due to high temperature in conductors. Irrespective of the cause, these stresses result in the chemical breakdown of oil or cellulose molecules constituting the dielectric insulation.

Different conventional Dissolved Gas Analysis methods such as Roger's ratio method, Dornenburg's method, Duvel's triangle method and key gas ratio methods are used to ascertain the exact amount of harmful gases dissolved in the transformer oil. The conventional methods have some drawbacks like some time the method is inconclusive on the specific fault-type and other time, it gives a false fault type.

The present research work utilizes artificial intelligence techniques to detect, diagnose and classify transformer faults based on Dissolved Gas Analysis methods. The Dissolved Gas Analysis dataset encapsulates the data of gas concentration in ppm, collected from Punjab State Electricity Board, Patiala. The four different Back Propagation Learning Algorithms i.e. gradient descent method, gradient descent with adaptive learning method and Levenberg-Marquardt method have been designed and compared amongst themselves for their performance in transformer fault diagnosis and classification. The performance comparison has also been carried out between

Back Propagation Neural Network classifier and Probabilistic Neural Network classifier, which show that the later outperforms the former, for transformer fault classification. Additionally, a hybrid system i.e. Adaptive Neuro Fuzzy Inference System (ANFIS) has also been constructed to diagnose incipient transformer faults. It has been found that ANFIS outperforms the Artificial Neural Network (ANN) and Fuzzy Inference System (FIS) since it integrates the best features of both the expert systems. Entire thesis is divided into six chapters. Summary of each of them is provided here.

Chapter 1 describes the significance of power transformer condition monitoring and fault analysis. Basic idea about research problem, the origin of transformer failure, transformer fault types and fault detection methods is given in this chapter.

Chapter 2 delineates the basic construction of the transformer. It also describes the various types and properties of transformer insulating materials like mineral oil and cellulose paper. The significance of transformer condition monitoring and its advantages have also been described shortly.

Chapter 3 summarizes the Dissolved Gas Analysis based techniques used for the power transformer incipient fault diagnosis. This chapter discusses the methodology and detailed operating procedure of Dissolved Gas Analysis.

Chapter 4 focuses the implementation of artificial neural network based algorithms to classify different types of faults in a power transformer, meant particularly for Non-Destructive Testing of transformer fault classification. In this chapter, a knowledge based inference engine has been developed for transformer fault diagnosis, based on IEC 60599 ratio method (Dissolved Gas Analysis Technique).

Chapter 5 employs the two soft computing techniques namely fuzzy logic and Adaptive Neuro-fuzzy Inference System (ANFIS), for detecting the faults in a power transformer.

Chapter 6 summarizes all the major findings of the work. Future prospective and scope in field is also included in this chapter.

CONTENTS

Certificate ii

Declaration iii

Acknowledgement iv

List of Abbreviations vi

List of Symbols ix

List of Publications x

Abstract xi

1 Introduction and Literature Survey …....………………………………. 1-22

1.1 Transformer Condition Monitoring ………………………………….. 2

1.2 Life Assessments and Fault Types of Power Transformers ...……….... 3

1.3 Literature Review …….……………………………………………..... 7

1.4 Objectives of the proposed research …………………………………. 21

2 Transformer Basics ……………………………………………………... 23-38

2.1 Basic Concepts of Transformer……………………...…….................. 23

2.2 Transformer Construction ……...…………….………………….. 27

2.3 Transformer Condition Monitoring …...……………………………. 29

2.4 Transformer Insulating Materials ……………….…………………... 31

2.4.1 Transformer Oil …………………………………………......... 31

2.4.1.1 Insulating oil quality ……………………………………………. 32

2.4.2 Paper insulation……………………………...………………. 33

2.5 Methods of Monitoring and Diagnosis of Power Transformers ……. 33

2.5.1 Visual inspection…………………………...…………………. 34

2.5.2 Chemical procedures……………….……...…………………. 35

2.5.3 Electrical procedures……………………...……………………. 36

3 Dissolved Gas Analysis Techniques …………………………………… 39-58

3.1 Introduction……………………………………………………….. 39

3.2 Methodology……………………………………..………………... 42

3.2.1 Operating Procedure….…………………………………………. 43

3.3 Transformer Faults………………………………………………… 43

3.4 Significance……………………………………………………….. 44

3.5 Mechanism of Gas Formation ……………………………………… 45

3.6 Faults Detectable using Dissolved Gas Analysis ………………………. **45**
3.7 Dissolved Gas Analysis in Oil …………………………………………. 46
3.8 Methods for Diagnosing Transformer Faults using Dissolved Gas Analysis………………………………………………………………. 47
3.8.1 Methods of Analyzing Dissolved Gases in Oil ………………………. 47
4 Artificial Intelligence Techniques……………………………………… 59-82
4.1 Introduction…………………………………………………………... 59
4.2 Back propagation Training Algorithm ………………………………. 63
4.3 Probabilistic Neural Network ………………………………….………. 65
4.4 Probabilistic Neural Network (PNN) Algorithm ……………………. 66
4.5 Proposed Work …..…………………………………………………… 67
4.5.1 Defining the Inputs and Outputs ………………………………… 67
4.5.2 ANOVA Plot of DGA Database ………………………………… 68
4.5.3 Training the Neural Network ……………………………………. 70
4.5.4 Choosing the Architecture of Neural Network …………………. 71
4.5.5 Receiver Operating Characteristics ……………………………… 72
4.5.6 Comparative Analysis of Various Intelligent Techniques ……… 73
5 Fuzzy Logic and Adaptive Neuro Fuzzy Inference System …............. 83-136
5.1 Fuzzy Logic………………………………………………………….. 83
5.1.1 Introduction ……………………………..…………………….. 83
5.1.2 Proposed Fuzzy Structure…………………………..…………. 83
5.2 Adaptive Neuro-Fuzzy Inference System …………………………… 129
6 Conclusion and Future Scope ………………………………………….. 137-138
6.1 Conclusion…………………………………………………………… 137
6.2 Future Scope………………………………………………………..... 138
References …………………………………………………………… **139**

LIST OF TABLES

1 Introduction and Literature Review ..……………………................	**1**
Table 1.1 Relation between Fault Type and Fault Gases …………..........	6
3 Dissolved Gas Analysis Techniques …...……………………………….	**39**
Table 3.1 Dissolved Gases Groups …..………………………………...........	41
Table 3.2 Relation between Fault Type and Fault Gases …..…………………	42
Table 3.3 Temperature limits of Gases …..………………………………….....	45
Table 3.4 Solubility of gases in percent by volume (Static equilibrium at 760 mm Mercury and 25^0C) …………………………….......................	46
Table 3.5 Roger's Ratio Code determination values ...……………………...	49
Table 3.6 Fault Diagnosis Table using Roger's Ratio Codes ...…………..….	50
Table 3.7 Violation limit of gases according to IEEE Gas Guide ...………...	51
Table 3.8 Diagnosis using the IEC 60599 ratio method ....………………	52
Table 3.9 Fault Diagnosis Table using IEC/IEEE Codes ………………..	53
Table 3.10 CEGB Code determination values ....…………..……………..	54
Table 3.11 Fault Diagnosis Table using CEGB Codes …..…………………	55
Table 3.12 ASTM Code determination values …..………………………….	56
Table 3.13 Concentration L_1 for Doernenburg Method ...………………..	56
Table 3.14 Fault Diagnosis Table using ASTM Codes …...……………...	57
Table 3.15 Fault Diagnosis for Doernenburg Method …..……………….	58
Table 3.16 Fault Diagnosis for Duval Triangle Method …..……………..	58
4 Artificial Intelligence Techniques ……………………………………...	**59**
Table 4.1 Diagnosis using the ratio method (IEC 60599) …..…………………	68
Table 4.2 ANOVA Table …...…………………………………………......	70
Table 4.3 Comparison of weight update rule indifferent BPN Learning Methods ………………………………………………………………..	75
Table 4.4 Comparison amongst different Back Propagation (BPN) learning Methods ……………..	76
Table 4.5 Confusion Matrix of Back Propagation Neural Network showing Fault classification results of different algorithms …………….	79

Table 4.6 Classification results for Probabilistic Neural Network using Confusion Matrix …………..……………………………..…................. 80
Table 4.7 Comparison of root mean square (RMSE) values for training, and validation samples for Back Propagation Network (BPN) and Probabilistic Neural Network (PNN) ………………………..…............... 80
Table 4.8 Diagnostic accuracy comparison of fault-type classification (according to IEC 60599) between Back Propagation Neural Network (BPN) and Probabilistic Neural Network (PNN) 81
Table 4.9 Comparison of Regression and Accuracy amongst different intelligent methods ……………………………………..……............ 81
Table 4.10 Testing the classification results with actual faults ………….. 82
5 Fuzzy Logic and Adaptive Neuro Fuzzy Inference System …………. 83
Table 5.1 Comparison between different types of membership functions.. 109
Table 5.2 Comparison between IEC 60599, Back Propagation Neural Network (BPNN), Fuzzy logic and Adaptive Neuro-Fuzzy Inference System (ANFIS) ………..…………….……………………………………...... 133

LIST OF FIGURES

1 Introduction and Literature Review ………………………………………. 1

Figure 1.1 Transformer Service Life……………………………………... 3

Figure 1.2 Transformer Fault-Type Classification Scheme ………………… 4

2 Transformer Basics ………………………………………………………… 23

Figure 2.1 A step-down transformer ……………………………………... 24

Figure 2.2 Phasor diagram of transformer ………………………………….. 24

Figure 2.3 Equivalent Circuit of Transformer ……………………………… 25

Figure 2.4 IT Visual inspection components (Clockwise direction: Terminals, membranes, bolts and sparkgaps) ………….....………………… 34

Figure 2.5 Key gas method charts ………………………………………….. 35

Figure 2.6 Capacitance and power factor measurement ……………………. 37

Figure 2.7 Artificial climate chamber ……………………………………… 37

3 Dissolved Gas Analysis…………………………………………………….. 39

Figure 3.1 Working process of Dissolved Gas Analysis (DGA) ………………. 42

Figure 3.2 Relative Solubilities of gases as a function of Oil Temperature ... 46

Figure 3.3 Dissolved Gas Analysis (DGA) based Fault Interpretation Scheme ……………………………………………………………………… 48

Figure 3.4 Fault Types as per IEC 60599 Ratio Method …………………… 51

Figure 3.5 The Duval Triangle ……………………………………………… 58

4 Artificial Intelligence Techniques………………………………………….. 59

Figure 4.1 Structure of a single neuron …………………………………... 60

Figure 4.2 Different types of nonlinear activation functions(a) Signum function or hard limiter (b) Threshold function (c) Sigmoid function (d) Piecewise Linear …………...……………………...................................... 60

Figure 4.3 General Architecture of Artificial Neural Network (ANN) …….. 62

Figure 4.4 General flow chart of Back Propagation Neural Network ……… 64

Figure 4.5 Flow chart of the proposed Fault Classification Scheme ……….. 67

Figure 4.6 ANOVA plot of raw data collected from different transformers... 69

Figure 4.7 Receiver Operating Characteristics for Probabilistic Neural Network (PNN) ……..……………………………………………………. 72

Figure 4.8 Error and epoch graph of (a) Gradient Descent Method. Best Training Performance is 0.0099 at epoch 66. (b) Levenberg-Marquardt Method. Best Training Performance is 0.099 at epoch 5. (c) Conjugate Gradient Descent Method. Best Training Performance is 0.0087 at epoch 16. (d) Resilient Method. Best Training Performance is 0.0097 at epoch 35.. 77

Figure 4.9 Regression Plot of (a) Gradient Descent Method. R= 0.97. Output =0.94$\times$Target + 0.0022. (b) Levenberg-Marquardt Method. R= 0.99. Output = 0.95$\times$Target + 0.032. (c) Conjugate Gradient Descent Method. R= 0.96. Output = 0.89$\times$Target + 0.020. (d) Resilient Method.R= 0.95. Output = 0.86$\times$Target + 0.004. ..…………………………………... 78

5 Fuzzy Logic and Adaptive Neuro Fuzzy Inference System………………. 83

Figure 5.1 Structure of Fuzzy Diagnosis System …………………………… 84

Figure 5.2 Different types of Membership Functions ………………………. 84

Figure 5.3 Gaussian membership functions : (a) R1=input variable = C_2H_2/C_2H_4; (b) R2 = input variable = CH_4/H_2; (c) R3 = input variable = C_2H_4/C_2H_6;(d) faults = output variable ………...………………... 89

Figure 5.4 Triangular membership functions : (a) R1=input variable = C_2H_2/C_2H_4; (b) R2 = input variable = CH_4/H_2; (c) R3 = input variable = C_2H_4/C_2H_6; (d) faults = output variable ……………….……..………………... 91

Figure 5.5 Trapezoidal membership functions : (a) R1=input variable = C_2H_2/C_2H_4; (b) R2 = input variable = CH_4/H_2; (c) R3 = input variable =C_2H_4/C_2H_6; (d) faults = output variable ………..…………………. 93

Figure 5.6 Gbell membership functions : (a) R1=input variable = C_2H_2/C_2H_4; (b) R2 = input variable = CH_4/H_2; (c) R3 = input variable = C_2H_4/C_2H_6; (d) faults = output variable …………………………. 95

Figure 5.7 Sigmoidal membership functions : (a) R1=input variable = C_2H_2/C_2H_4; (b) R2 = input variable = CH_4/H_2; (c) R3 = input Variable = C_2H_4/C_2H_6; (d) faults = output variable ……………….……………...….. 97

Figure 5.8 Pi-shaped membership functions : (a) R1=input variable = C_2H_2/C_2H_4; (b) R2 = input variable = CH_4/H_2; (c) R3 = input variable = C_2H_4/C_2H_6; (d) faults = output variable …………………………………….. 99

Figure 5.9 S-shaped membership functions : (a) R1=input variable = C_2H_2/C_2H_4; (b) R2 = input variable = CH_4/H_2; (c) R3 = input variable = C_2H_4/C_2H_6; (d) faults = output variable ………………………… 101
Figure 5.10 Z-shaped membership functions : (a) R1=input variable = C_2H_2/C_2H_4; (b) R2 = input variable = CH_4/H_2; (c) R3 = input variable = C_2H_4/C_2H_6; (d) faults = output variable ………………………… 103
Figure 5.11 Gauss2mf membership functions : (a) R1=input variable = C_2H_2/C_2H_4;(b) R2 = input variable = CH_4/H_2; (c) R3 = input variable =C_2H_4/C_2H_6; (d) faults = output variable ……….………………… 105
Figure 5.12 Probability Density Curves for the fault type Partial Discharge . 111
Figure 5.13 Probability Density Curves for the fault type Low energy discharge ………………………………………………………………… 112
Figure 5.14 Probability Density Curves for the fault type High energy discharge ………………………………………………………………… 114
Figure 5.15 Probability Density Curves for the fault type Thermal faults < 300°C……………………………………………………………….. 115
Figure 5.16 Probability Density Curves for the fault type Thermal faults < 700°C……………………………………………………………….. 117
Figure 5.17 Probability Density Curves for the fault type Thermal faults > 700°C……………………………………………………………….. 118
Figure 5.18 Probability Density Curves for the fault type Partial Discharge.. 120
Figure 5.19 Probability Density Curves for the fault type Low energy Discharge ……………………………………………………………… 121
Figure 5.20 Probability Density Curves for the fault type High energy discharge ……………………………………………………………........ 123
Figure 5.21 Probability Density Curves for the fault type Thermal faults < 300°C…………………………………………………….................... 124
Figure 5.22 Probability Density Curves for the fault type Thermal faults < 700°C…………………………………………………….................... 126
Figure 5.23 Probability Density Curves for the fault type Thermal faults < 700°C…………………………………………………….................... 127
Figure 5.24 General Architecture of Adaptive Neuro-Fuzzy Inference System (ANFIS) ..……………………………………………………… 129

Figure 5.25 Training Error versus epochs plot ……………………………... 131
Figure 5.26 Testing Error versus epochs plot ………………………………. 132
Figure 5.27 Schematic structure of the proposed Adaptive Neuro-Fuzzy
Inference System ………………………………………………………………. 132

Chapter 1: Introduction and Literature Review

Transformers constitute a vital part in electrical utilities asset base. With the development and expansion of electrical systems, a fleet of transformers have been installed. Most of these transformers are on the verge of ageing. In many cases, the operation of these transformers is being carried out beyond their predicted functional life of 25 - 40 years. In order to fulfill the increasing electricity supply demands, transformers in few regions are being operated above their rated capacity. To maximize the profits and to cope up with the supply demands, the operators are operating generator transformers on heavy loads. Transformers are significant part of the industries which include aluminium smelting industry and steel plants. Failure of a transformer in a generation plant or industry can outlay many millions of dollars, depending upon its outage tenure. To replace a transformer is a very costly and time-consuming affair. Currently, the outlay and lead time to deliver a new transformer is very large. This is because of the increasing supply demand of transformers and raw materials [Domun et al. 1991; Breen et al. 1992; Pahlavanpour et al.1994; Steed et al. 1995].

Since 1950's, the transformer monitoring and diagnostics has been developing. In order to avert catastrophic losses and curtail the outages, many transformer monitoring techniques (off-line and on-line) are being utilized. Many organizations have introduced Condition-based maintenance (CBM) to mitigate maintenance costs, by carrying out maintenance as and when necessary. CBM necessitates the awareness of the condition of transformer and its parts, and the knack to forecast when maintenance will be necessary [Pahlavanpour et al. 1997; Leemans et al. 1998; Basak 1999; Leibfried et al. 1999].

In operation, the transformers are subjected to combined stresses (electrical, thermal, mechanical and environmental), leading to the decreased life and appearance of faults with irreversible evolution. Taking into account the fact that most transformers are in operation for more than 20 years, they need to be fitted with systems for monitoring and diagnosing [Harley et al. 2000; Thomas et al. 2001; Lundgaard et al. 2005; Gasser et al. 2006].

1.1 Transformer Condition Monitoring

Condition Based Maintenance (CBM) is an advanced maintenance policy developed in recent years. CBM is mainly based on the condition information obtained from equipments, it uses the information by the data analysis and diagnostic techniques to forecast the residual life of equipment or failure rate, then makes decisions to equipment maintenance by optimizing their reliability index, namely whether the equipment needs prevention maintenance, if needed, when the equipment should be repaired. This idea has been widely accepted in the field of maintenance, the current urgent problem needed to solve is how to use the condition information in the process of the scientific decision-making for device maintenance [Verma et al. 2005; Stephen et al. 2004].

The initial CBM decision-making depends on the measure and test of condition signal of devices. When the monitored value exceeds the threshold, the maintenance decision has to be timely executed. This maintenance policy is easy and simple, but for a system with multiple state variables, it is difficult to read exact health of the transformers. Therefore, the key of Condition Based Monitoring decision-making is to establish a precise and reasonable functional relation between their health levels and their condition parameters [Verma et al. 2004; Fuhr et al. 2004; Saha 2003].

In power transformer, the insulation consists of liquid insulation (mineral oil) and solid impregnated insulation (cellulose). The transformer oil is obtained by fractional distillation of crude petroleum and it consists of hydrocarbon compounds namely paraffin, naphthenes, aromatics and olefins. This oil has low density, low viscosity and is colourless. Transformer oil not only provides liquid insulation, but also dissipates heat of the transformer.In addition to these; this oil helps to preserve the core and winding as these are fully immersed inside oil and prevents direct contact of atmospheric oxygen with cellulose made paper insulation of windings [Garnitschnig et al. 2002; Han et al. 2003; Huang et al. 2003].

1.2 Life Assessments and Fault Types of Power Transformers

Determination of effective working life of a transformer is a very difficult task. Different international councils have suggested different failure models of transformer. International Council on large electric system (CIGRE) developed a well-known failure model shown in Figure 1.1 [Qun et al. 2001; Chang et al. 2002]. Transformer can be unserviceable due to variety of reasons. Most common reason is the aging and faults

Figure 1.1 clearly shows that the transformer insulation possesses sufficient strength in the initial stages (with some spare margin to withstand maximum operational stresses), but this margin decreases with aging and faults. Figure 1.2 shows the transformer fault-type classification scheme [Hassig et al. 2001].

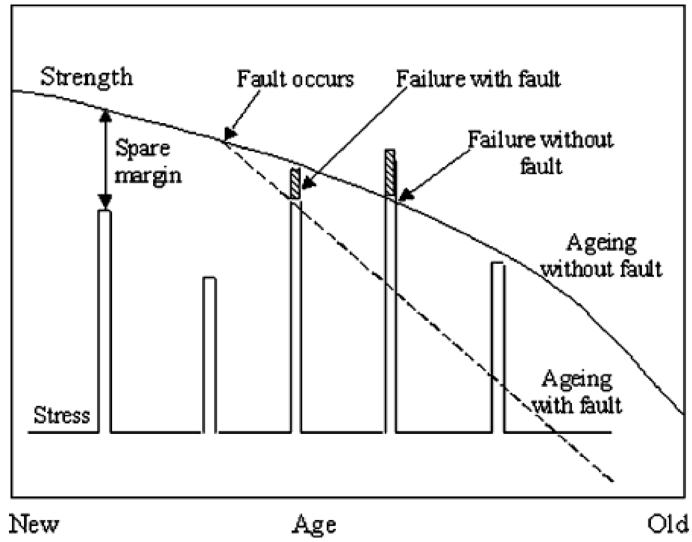

Figure 1.1 Transformer Service Life

Most of the transformers placed in the outdoor are oil cooled. Other methods of cooling are forced air cooling, forced oil cooling, water cooling etc. These transformers are filled with transformer oil which is a dielectric fluid. The main function of the transformer oil is to insulate and cool the windings. Transformer oil is made up of highly refined mineral oil. A brand new power transformer has a life of 50 years. According to Montsinger's rule, life expectancy of transformer reduces by 50% for each 10º C rise in temperature of insulation. Accelerated aging factor (AAF) of a transformer can be calculated as follows [Wang et al. 2000]:

$$AAF = e^{\left[\frac{15000}{383} - \frac{15000}{HST+273}\right]} \tag{1.1}$$

where HST is the hottest spot temperature in degree Celsius and AAF is unity at 110ºC. Equivalent aging factor can be calculated as follows:

$$AAF_{eqv} = \frac{\sum_{i}^{N} AAF_i \Delta t_i}{\sum_{i}^{N} \Delta t_i}$$

(1.2)

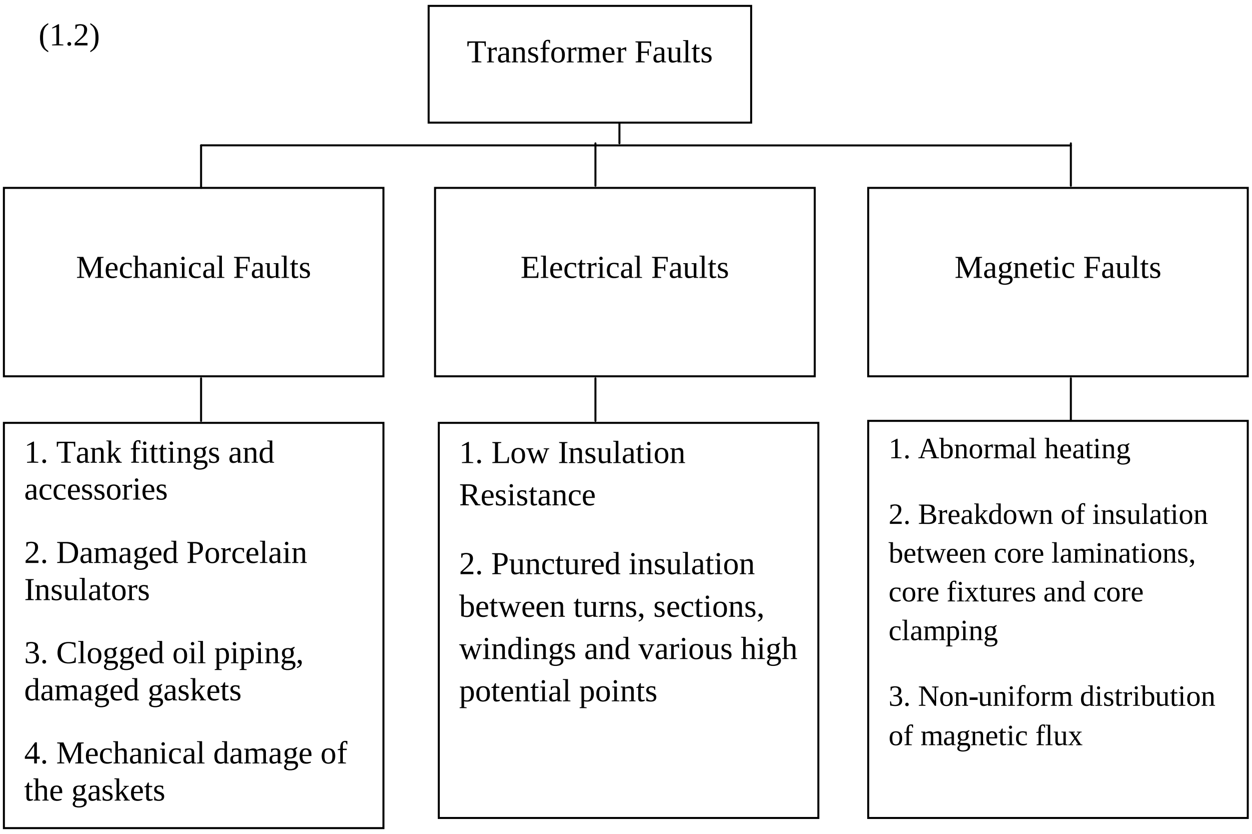

Figure 1.2 Transformer Fault-Type Classification Scheme

Life of transformer also depends on transformer paper (solid impregnated insulation). An empirical formula used to calculate the life expectancy (elapsed life) of transformer with the help of degree of polymerization (DP) of insulation paper is given by [Darveniza et al. 1998]:

$$\text{Elapsed life} = 20.5 \ln\left(\frac{1100}{DP}\right) \tag{1.3}$$

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 [Morais et al. 2006; Singh et al. 2007]. In general, TDCG uses the sum of the 6 key gas values and the TDCG gas generation rate to determine the operating procedure and predict suitable oil sampling interval as follows:

$$TDCG = C_2H_2 + C_2H_4 + H_2 + CH_4 + C_2H_6 + CO \tag{1.4}$$

Rate of TDCG = (Current TDCG- PrevTDCG/Time (days)) (1.5)

TDCG generation rate must be less than 30 ppm/month and all individual combustible gas generation rate less than 10 ppm/month, CO generation less than 70 ppm/month and acetylene generation equal to 0 ppm/month. Different security features are employed in the transformer for protection and condition monitoring purpose. These security features include fixed or portable thermography, on line gas in oil monitor, fibre optic temperature devices, moisture in oil sensor, partial discharge monitor, online bushing power factor sensor and vibration sensors [Duval et al. 2005; Huang et al. 2012].

Whenever power transformer goes under severe thermal and electrical stress, the transformer oil decomposes and emits some harmful gases (emission signals). With the passage of time, the harmful gases get dissolved in the transformer oil and subsequently the oil gets damaged. Due to damaged oil, the performance of insulating material also declines and hence, the performance of power transformer. To prevent the insulation failure, it is required to know the exact amount of harmful gases dissolved in the transformer oil. Dissolved gas analysis (DGA) is a routine technique which is carried out to know the exact amount of gas dissolved. This method has been used for more than 30 years. Generally in oil filled transformers, the following gases are dissolved in transformer oil, Hydrogen (H_2), Methane (CH_4), Acetylene (C_2H_2), Ethylene (C_2H_4), and Ethane (C_2H_6). Different conventional methods such as Roger's ratio method, Dornenburg's method, Duval's triangle method and key gas ratio methods are used to ascertain the exact amount of harmful gases dissolved in the transformer oil [Mosinski et al. 2003; Kim et al. 2005].

Depending on the concentration of the dissolved gases, the condition of the transformer can be determined. This is because each type of fault burns the oil in a different way which correspondingly generates different pattern of gases. This makes it possible for the experts to identify the nature of the fault type based on the gas type and its concentration. For example, arcing may cause high concentration of acetylene dissolved in the oil. The details of fault type and the relation with the fault gases have been seen in Table 1.1 [Zylka et al. 2002].

Table 1.1 Relation between Fault Type and Fault Gases

Fault Type	Fault Gas	Chemical Symbol
Corona	Hydrogen	H_2
Arcing	Acetylene	C_2H_2
Low Temperature Oil Breakdown	Methane	CH_4
	Ethane	C_2H_6
High Temperature Oil Breakdown	Ethylene	C_2H_4
Cellulose Insulation Breakdown	Carbon Monoxide	CO
	Carbon Dioxide	CO_2

Benefits of using DGA as transformer fault diagnostic technique include advanced warning of developing fault, detection of fault during warranty period, status checks on new and repaired units, convenient scheduling of repairs, monitoring of units under overload and essential information of asset management programme [Mollmann et al. 1999; Chatterton et al. 2000].

Conventional DGA methods rely on personnel experience more than mathematical formulation. The Ratio Methods including Roger, Doerenenburg IEEE std. C 57.104:1991 and IEC std. 60599:1999, CIGRE method are only valid if a significant amount of the gas used in the ratio is present otherwise the method will not be able to identify the type of fault and will lead to invalid code. Key gas method is not widely accepted as an effective tool to evaluate the health condition of in-oil immersed transformers as it is considered very conservative [Sparling et al. 1999].

To deal with the uncertainties arising from fault diagnosis, based on gas contents extracted from transformer oil samples (DGA), various soft computing techniques have been developed by many researchers. In these soft computing techniques, fault types are classified based on on-site experience. Subsequently, various soft computational methods are employed to reveal the relationships between fault symptoms and malfunction types found on gas-fault mapping schemes.

1.3 Literature Review

A brief insight to the previous work done related to the research problem under consideration is provided as follows:

Booth *et al.* (1998) covered the generic capabilities of artificial neural networks, for condition monitoring applications, in estimation mode as well as classification mode. The authors have carried out the monitoring of a power transformer using the examples based on the above criterion.

Patricia *et al.* (1998) successfully applied a combinatorial intelligent system based on neuro-fuzzy, neuro-expert and fuzzy-expert algorithms in the detection of a number of faults in a range of equipment.

Wang *et al.* (2000) proposed an artificial intelligence approach in order to detect incipient faults in On-load tap changers (OLTCs) i.e. one of the most problematic components of power transformers. The authors utilized neural networks to find the principal gases related to the fault conditions in oil-immersed power transformers and to improve the performance efficacy of transformer fault diagnosis.

Su *et al.* (2000) proposed fuzzy logic technique for multiple fault detection in power transformers. This technique aims at quantitatively indicating the likelihood/severity of each fault thereby monitoring the insulation deterioration at each fault location, closely according to its trend. The authors also tested proposed technique on a number of transformers and achieved satisfactory results.

Gupta *et al.* (2001) developed a model for the propagation of electrically induced acoustic waves through gaseous medium. The authors also studied their effect on the walls of the Gas Insulated Substations (GIS), representing fluid structure coupling. The robust strategies to locate the source of the discharge can also be designed using such kind of simulation technique.

Metwally *et al.* (2004) focused on the measurement techniques to present a review on the insulation and Partial Discharge (PD) monitoring for gas-insulated switchgear/transmission lines (GIS/GITL). The authors also discussed the computer-aided interpretation and classification of defects considering large amount of data generated by PD monitoring systems.

Kuo *et al.* (2004) presented a fuzzy-neural transformer diagnostic system (SE-FNTDS) for oil-immersed power transformers based on symbiotic evolution. For input/output rule generation and training data for the fuzzy-neural network, an expert database has been applied, upon the database collected from real-time transformer records.

Peng *et al.* (2004) summarized the application of wavelet technique in machine fault diagnostics, including the main aspects such as time–frequency analysis of signals, the fault feature extraction, the singularity detection for signals, the de-noising and extraction of the weak signals, the compression of vibration signals and system identification.

Hung *et al.* (2004) developed a method for transformer fault diagnosis, using cerebeller model articulation neural network (CMAC) method. The authors utilized the self-learning and generalization characteristics, like the cerebellum of human being and enabled a powerful, straight forward and efficient fault diagnosis system. They also tested the proposed scheme on published transformer data and achieved high accuracy and high noise rejection ability.

Ganyun *et al.* (2005) presented a statistical learning theory (SLT) based machine learning method i.e. Support vector machine (SVM). This method is powerful for the problem with small sampling, nonlinear and high dimensions. A special data processing technique pre-processed the content of five diagnostic gases dissolved in oil, obtained by dissolved gas analysis (DGA). Consequently, six features have been extracted for SVMs, followed by the training of the multi-layer SVM classifier, using the training samples, extracted by the above data processing. Finally, the trained classifier identified the four fault types of the transformer.

Lin *et al.* (2005) presented a computer-based on-line partial discharge (PD) monitoring and diagnostic system for transformers. The system used wide-band active transducers and a data acquisition unit with modularized and exchangeable components. With the help of seven experimental models for simulating PDs in transformers and three models for simulating interfering discharges in air, the statistical characteristics of PDs in power transformers were studied.

Miranda *et al.* (2005) described that mapping of a neural network into a rule-based fuzzy inference system, leads to knowledge extraction. They used the mapping to explicit the knowledge implicitly captured by the neural network during the learning stage, by transforming it into a set of rules and then applied it to transformer fault diagnosis using dissolved gas-in-oil analysis.

Karthikeyan *et al.* (2005) considered Partial Discharge (PD) patterns as an important tool for diagnosis of High Voltage (HV) insulation systems. The authors also explored that how probabilistic neural networks fit into the earlier framework of pattern recognition of partial discharge patterns. A complex probabilistic neural network system has been used to describe a method for the automated recognition of phase resolved PD (PRPD) patterns, for the purpose of classification.

Adriana *et al.* (2005) developed a new methodology for transformer fault diagnosis, with the combination of neural network and rule–based inference system. The authors captured the knowledge by using neural network during the learning stage and made it explicit, by converting the same into Fuzzy Inference System.

Garcia *et al.* (2005) proposed a transformer condition monitoring technique, using vibration model. The authors also discussed the benefits of incipient failure diagnosis including the savings in investments and availability of enough time to plan for transformer outage, if required. They also reviewed the basic theory of transformer vibration.

El-Zonkoly *et al.* (2006) formulated an optimization problem i.e. the problem of simultaneous and coordinated tuning of stabilizers parameters and automatic voltage regulators (AVRs) gains in multi-machine power systems. The authors solved this problem using particle swarm optimization technique. In order to represent the allowable region of the system parameters, the parameters optimization problem was formulated as nonlinear problem with constraints.

Jardine *et al.* (2006) emphasized on models, algorithms and technologies for data processing and maintenance decision-making. The authors also presented a summary and review of the recent research and developments in diagnostics and prognostics of mechanical systems implementing CBM (Condition based maintenance). Different techniques for multiple sensor data fusion, their current practices and future trends have been also discussed.

Ngaopitakkul *et al.* (2006) presented an algorithm based on a combination of Discrete Wavelet Transforms and neural networks for detection and classification of internal faults in a two-winding three-phase transformer.

Morais *et al.* (2006) presented computational system approach, having the integrated approach of dissolved gas analysis published in standards, fuzzy logic and artificial neural network systems. The authors not only discussed the authenticity of such tools, that has been written in technical literature over last 20 years but also proved that these tools provide promising results, reaching success levels of 80%.

Deepa *et al.* (2006) monitored the transformer oil degradation by evaluating synchronous fluorescence spectroscopy (SFS) and excitation emission matrix fluorescence (EEMF) spectroscopy. The onset of degradation of transformer oil on 17th day and transformer oil with polypropylene and cellulosic paper on 23rd and 27th days respectively, has been sensitively reflected in the above spectral characteristics (SFS and EEMF), using the accelerated thermal ageing method.

Monsef *et al.* (2007) proposed a novel approach for power transformer differential protection, using wavelet transform (WT) and adaptive network-based fuzzy inference system (ANFIS), in order to distinguish internal faults from inrush currents. The design of the developed method is based on the differences between amplitudes of wavelet transform coefficients, in a specific frequency band, which has been generated by faults and inrush currents. The authors also carried out the simulation of different faults and switching conditions, using PSCAD/EMTDC software, in order to demonstrate the performance of the proposed algorithm.

Kuo *et al.* (2007) utilized Acoustic Emission (AE) technique for defect type recognition of epoxy-resin transformers by Partial Discharge (PD). High voltage test has been conducted for pre-faulty transformers and PD signals measured for the required recognition. Afterwards, from these collected PD signals, the proposed selected features have been extracted. Consequently, the effective fault type identification has been done using the proposed particle swarm optimization combined with neural network, according to the above features.

Tan *et al.* (2007) applied a hybrid neural network model, to a fault detection and diagnosis task in a power generation station. The proposed hybrid network was based on the integration of fuzzy ARTMAP (FAM) and the rectangular basis function network (RecBFN). With the help of a set of real sensor measurements collected from the power station, the efficiency of the network in monitoring the operating conditions of circulating water (CW) system was evaluated.

Sun *et al.* (2007) developed a transformer fault diagnosis system using training patterns, selected from the results of a Refined Three-Ratio method (RTR). An efficient BP-ALM (BP with Adaptive Learning Rate and Momentum coefficient) algorithm has been proposed to reduce the training time and avoid being trapped into local minima.

Babnik *et al.* (2007) developed a data mining technique known as Self-organizing Map (SOM) for the analysis and interpretation of captured partial discharge (PD) data obtained by radiometric measurements performed on a power transformer.

Duraisamy *et al.* (2007) utilized the fuzzy system and neural network approaches for transformer fault identification using dissolved gas analysis (DGA) method (IEC/IEEE DGA criteria and the gas concentration values as references). The practical data has been collected from Electricity Board and the proposed systems were verified.

Quteishat *et al.* (2008) developed a fuzzy min–max (FMM) network in order to improve its classification performance during the formation of large hyperboxes in the network. The authors also evaluated out fault detection and classification with the help of a set of real sensor measurements collected from a power generation plant, using FMM.

Dong *et al.* (2008) utilized a rough set (RS) as a front of fuzzy wavelet neural network (FWNN), for transformer fault diagnosis. The proposed diagnosis system has been integrated with Least Square (LS) weighted fusion algorithm in order to simplify the input of FWNN and mine the rules whose "confidence" and "support" satisfy preset criteria. The FWNN input was simplified by rough set reduction, and its learning rate got improved greatly.

Karthikeyan *et al.* (2008) utilized two versions of Probabilistic Neural Network and developed a Composite Probabilistic Neural Network Inference System. This inference system was obtained based on the outcome to innovatively conceived fourteen unique characteristic vector inputs. Such systems enabled an accurate and reliable decision in the classification of complex stochastic Partial Discharge patterns, thereby, obviating the necessity of skilled operators.

Ozgonenel *et al.* (2008) obtained residuals by comparing real system currents and calculated Transmission Line Method (TLM) observer currents. Consequently, the authors performed continuous wavelet transform on these residuals, in order to extract the features for fault identification.

Kundu *et al.* (2008) utilized three different electrode systems to report and analyze the classification of partial discharges in oil press-board insulation system. The authors carried out this classification with the help of laboratory simulated partial discharges, obtained through acoustic emission signal method.

Flores *et al.* (2009) presented a novel methodology to assess the risk of power transformer failures caused by external faults. The authors utilized Monte Carlo simulation to find the survival function of the currents flowing through the transformer winding during a single-phase or a three-phase short-circuit. The Roy Billinton Test System, a real power system had been used to test the results.

Satish *et al.* (2009) demonstrated the introduction of localized faults at different transformer winding positions. The authors carried out sweep frequency measurements to determine open-circuit and short-circuit natural frequencies, terminal effective resistance, shunt capacitance and inductance. Corresponding to each set of measurement, a lumped-parameter ladder network has been synthesized. A comparison of such synthesized circuits with a reference (or fault-free) circuit has also been carried out, which reveals the location, quantum, and nature of fault.

Zhang *et al.* (2009) proposed support vector machine with genetic algorithm (SVMG) to detect the power transformer failures related with key-gas ratios i.e. C_2H_2/C_2H_4, CH_4/H_2 and C_2H_4/C_2H_6. The authors utilized genetic algorithm to determine free parameters of support vector machine. The proposed method when tested, achieved greater accuracy than artificial neural network and gray model, under the conditions of small training data available.

Su *et al.* (2009) utilized waveguide for the partial discharge measurement in a cast-resin dry-type transformer. In order to improve the propagation of the partial discharge acoustic signals occurring in the high voltage winding to the used acoustic sensors of the transformer, the waveguide has been placed atop the high voltage winding of the said transformer.

Fei*et al.* (2009) applied support vector machine with genetic algorithm (SVMG) for power transformer fault detection. The authors utilized genetic algorithm to select appropriate free parameters for SVM. They also compared the performance of the proposed scheme with that of Grey model, normal SVM classifier and artificial neural network; the outcome being the higher diagnostic accuracy of the proposed scheme.

Kuo *et al.* (2009) collected Acoustic Emission (AE) signals for fault recognition system of a power transformer, through a series of high voltage tests, conducted on pre-faulty transformers. The authors utilized these experimental AE signals for the input characteristic of recognition system. The proposed recognition system combined particle swarm optimization with an artificial neural network for more effective fault-type identification.

De Souza *et al.* (2009) developed a neural tool utilizing the wave front time, the wave tail time and the voltage variation rate, as inputs to Artificial Neural Networks (ANN) while the maximum current in the secondary of the transformer has been taken as the output variable. The authors developed this neural tool to estimate the currents related to lightning in a transformer.

The proposed tool minimized empirics and evaluation errors, thereby, contributing to the minimization of the failure rate of transformers.

Beniwal *et al.* (2010) presented an algorithm to estimate the life and switching withstand capability of the distribution transformers considering creep. The authors achieved success to develop guidelines to select creep resistant material, to be used in power deficient areas, poorly designed and haphazardly expanded power distribution networks, in order to design and produce reliable distribution transformers.

Meng *et al.* (2010) proposed a new hybrid self-adaptive training approach-based radial basis function (RBF) neural network, as a fault diagnostic tool for power transformer. The proposed tool, which is based upon fuzzy c-means (FCM) and quantum-inspired particle swarm optimization (QPSO), is equipped with the benefit to automatically configure network structure and obtain model parameters. This learning method, when tested upon five benchmark testing data sets, proved to be a significantly reliable diagnostic tool for power transformers.

Bhalla *et al.* (2010) proposed a sequential hybrid system, after reviewing the previously applied Artificial Intelligence techniques, thoroughly. The proposed synergy of Artificial Neural Network (ANN) and Fuzzy Inference System (FIS) by the authors provided considerably better results for power transformer fault detection, than using both ANN and FIS, as a single fault detection tool.

Che *et al.* (2010) presented a cost estimation approach called FAPSO-TBP, using the combination of factor analysis (FA), particle swarm optimization (PSO) and artificial neural network with two back-propagation networks as well as a single back-propagation network, termed as FAPSO-SBP. The authors verified the proposed FAPSO-TBP approach by comparing it with the FAPSO-SBP and general back-propagation artificial neural network (GBP).

Pamuk *et al.* (2010) discussed the failure of insulating oil in power transformers. The authors also analyzed the electrical and thermal effects of cellulose materials, when subjected to degradation. In addition, the authors also developed fuzzy logic computer program to evaluate the probable causes of transformer failures.

Beniwal *et al.* (2011) presented an experimental study related to the axial fatigue behaviour of loose winding conductors of aluminium and copper wound distribution transformers. The proposed algorithm paved the way to frequently energized distribution transformers with trivial protection against cold load pick up and inrush current.

Venkatesh *et al.* (2011) implemented a Robust Heteroscedastic Probabilistic Neural Network (RHRPNN), for the classification of multi-source partial discharge (PD) patterns. The authors also developed a Two Pass Split Window (TPSW) scheme, to study and compare the classification capability of the RHRPNN with that of Heteroscedastic Probabilistic Neural Network (HRPNN).

Rao *et al.* (2011) developed a novel system based on fuzzy logic considering prevailing transformer conditions i.e. electrical and mechanical conditions. The proposed system provided an insight to the critical conditions of paper thermal and oil thermal. Diagnostic techniques such as Dissolved Gas Analysis, Partial Discharge, Break down voltage and Sweep Frequency response Analysis have been discussed individually, in order to take the necessary preventive actions by the technologists.

Isa *et al.* (2011) developed a Clustered-Hybrid Multilayer Perceptron (Clustered-HMLP) network , which was trained using modified training algorithm called Clustered-Modified Recursive Prediction Error (Clustered-MRPE).The authors demonstrated the capability of the Clustered-HMLP network with Clustered-MRPE training algorithm, using seven benchmark datasets from the University of California at Irvine (UCI) machine learning repository (i.e. Iris, Ionosphere, Pima Indian Diabetes, Wine, Lung Cancer, Hayes-Roth and Glass).

Venkatesh *et al.* (2011) utilized Radial Basis Probabilistic Neural Network (RBPNN) with Forward Orthogonal Least Square Algorithm (FOLS) centre selection algorithm to compare the performance of standard version of Probabilistic Neural Network (PNN) and Heteroscedastic PNN (HRPNN), for classification of multiple PD sources. The authors also discussed the advantages of the hybrid technique of Radial Basis Function Neural Network (RBFNN) and PNN, in classifying multiple PD sources.

Ning *et al.* (2011) introduced a delayed semi-Markov process that incorporates real-time data from advanced sensors, as a means of efficiently calculating time-varying or condition-based failure probabilities.

Flores *et al.* (2011) developed an efficient expert system using Duval's triangle, key-gas ratio and IEC 60599 method, for the power transformer condition monitoring. The authors performed a knowledge mining procedure, by feeding into a first Type-2 Fuzzy Logic System (T2-FLS), the results of conducted surveys. As an input to a second T2-FLS, the output of this first T2-FLS has been taken into consideration, which subsequently updated the weights to improve the condition of paper-oil insulation system.

Barakat *et al.* (2011) developed an adaptive intelligent technique based on artificial neural networks combined with advanced signal processing methods. The authors applied discrete wavelet transform and training techniques based upon locating and adjusting the Gaussian neurons in activation zones of training data, in order to classify mechanical faults of rotary elements and to detect and isolate disturbances for a chemical process.

Sood *et al.* (2011) described the application of artificial intelligence techniques, Bayesian Classifier, Self Organizing Map and Discrete Wavelet Network Transforms, to increase the efficiency and accuracy of diagnosis, during off-line and on line monitoring of power transformers.

Yadaiah *et al.* (2011) presented both off-line and on-line methodologies for transformer incipient fault detection. The authors utilized dissolved gas analysis reports of transformer for off-line transformer fault detection using an artificial neural network while wavelet transforms have been used for on-line transformer fault detection.

Liao *et al.* (2011) presented a forecasting model using the hybrid-model of least squares support vector machine and particle swarm optimization algorithm. The authors applied the developed model on actual transformer gas data, in order to forecast the gas contents in transformer oil and found the promising results.

Huang *et al.* (2012) reviewed fuzzy logic approaches to give a significant overview of fuzzy logic applications in transformer fault diagnosis, taking the help of dissolved gas analysis. The authors provided the conclusions to be further used as an important measure, by various researchers as well as field engineers, for transformer fault diagnosis.

Bhalla *et al.* (2012) utilized the concentration of dissolved gases in oil, as inputs to Artificial Neural Network, for transformer incipient fault diagnosis. The authors split the input space into sub-regions and consequently derived linear equation for each sub-region. The rule sets extracted from function approximating Artificial Neural Network, proved to be accurate for predictions, when applied to many case studies.

Bacha *et al.* (2012) proposed a novel extension method consisting of an input vector established by the combination of ratios and graphical representation (two DGA methods proposed by IEC 60599 method) to resolve the problem of uncertainty of results caused by the two representations for the same input data. The authors applied support vector machine (SVM) to classify the power transformers faults and to choose the most appropriate gas signature between the DGA traditional methods and the proposed method.

Sun *et al.* (2012) reviewed computational intelligence approaches including fuzzy logic, neural networks and evolutionary optimization techniques; for oil-immersed power transformer. The authors also discussed historical developments and presented state-of-the-art of fault diagnosis methods.

Silva *et al.* (2012) presented a transformer failure diagnosis system, based on Dissolved Gas Analysis. The authors developed a new methodology by extracting fuzzy rules from Kohonen Self-Organizing Map. The validity of this methodology was tested on a dataset of faulty transformers, which proved the proposed technique to be more accurate than the conventional dissolved gas analysis techniques.

Seifeddine *et al.* (2012) presented a comparative study for the choice of the most appropriate DGA method. The authors also compared the various Multi-layer Perceptron (MLP) architectures by comparing two output data types and three hidden layer types with the aim to develop the most suitable MLP model.

Pallavi *et al.* (2012) proposed a neuro-fuzzy method for transformer condition monitoring. The proposed method includes the benefits such as self-learning and auto rule adjustment, in order to produce best results. The authors also briefed Dissolved Gas Analysis (DGA) as an effective tool for transformer condition monitoring, in addition to the multiple DGA techniques for transformer fault diagnosis.

Huang *et al.* (2012) discussed that Dissolved gas analysis (DGA) of oil-immersed transformers, diagnosis incipient transformer faults, which helps to prevent further damage. The authors also discussed many DGA techniques to analyze the dissolved gases and to interpret their significance, such as Key Gas, Dornenburg Ratio, Rogers Ratio, Nomograph, IEC Ratio, Duval Triangle and CIGRE. They also compared the effectiveness of various DGA techniques to interpret transformer conditions.

Nandy *et al.* (2012) presented an improved back propagation algorithm using steepest descent method. The authors carried out the optimization using multilayer neural network, by Gauss-Newton numerical optimization method, taking into consideration the benefit of fast convergence.

Malik *et al.* (2012) proposed an artificial intelligence (AI) approach to encode the power transformer fault diagnostic techniques such as liquid chromatography, acoustic analysis, and transformer function techniques. Additionally, the authors presented an expert system using AI techniques to diagnose multiple faults in a transformer theoretical and practical fuzzy-logic information model and validated the same using more than seventy power transformers.

Olga *et al.* (2012) analyzed few forms of preventive maintenance of power transformers, considering superposition of failures and planned maintenance. The authors applied the proposed technique to one transformer station (TS) 110/10kV with $2 \times$ 31500 kVA – 110 kV Star – 10 kV Delta transformers, in two cases; the first one being radial supplying of customers and the second one when outage of one power transformer does not affect the power supply to customers.

Ji *et al.* (2012) proposed a hybrid model of a disc-type transformer winding for frequency response analysis (FRA) of winding deformation and measurement parameter influence. Additionally, the authors carried out simulation studies using two statistical indicators for result analysis. The authors achieved success to prove that if certain parameters of the proposed hybrid model are changed, winding deformation and measuring connection variation can be reflected in frequency response analysis.

Paidarnia *et al.* (2013) utilized wavelet transform to extract main features from primary and secondary three phase currents and search coils differential voltage. Consequently, dimensionally reduced data obtained with the help of principal component analysis has been used as inputs to probabilistic neural network classifier.

Hormatollah *et al.* (2013) developed the application of transfer function method during the manufacturing process of transformer so as to evaluate the drying quality of active part. Consequently, the features extracted from the measured transfer functions have been given as inputs to artificial neural network (ANN), to estimate the required time in drying process.

Dash *et al.* (2013) provided a comprehensive overview of various existing methods from 1970's to the present. Additionally, the authors identified four steps of a typical feature selection method, categorized the various existing methods in terms of generation procedures and evaluation functions, such that these methods divulge previously unattempt combinations of generation procedures and evaluation functions.

Jianqing *et al.* (2013) utilized Matlab programming to study and compare the power fault diagnosis performance of three kinds of neural networks viz. Radial Basis Function (RBF) neural network, Learning Vector Quantization (LVQ) neural network and Probabilistic Neural Network (PNN). Subsequently, the authors proved that PNN is the best diagnostic tool, amongst the three neural network architectures, owing to its best diagnosis identification ratio and the fastest fault identification rate.

Srinivasan *et al.* (2013) proposed a new semi-physical model, to estimate hot spot temperature (HST) in transformer, constituting the environment variables. Additionally, the authors also proposed a Matlab/ Simulink based valid model to estimate HST, under varying environment conditions. The authors also compared the estimated HST with the measured data of an operating power transformer.

Bhalla *et al.* (2013) utilized Dempster-Shafer Evidential Theory (DST) to combine the results of incipient fault diagnosis of back propagation neural network and fuzzy logic, in order to overcome the conflicts in the fault type diagnosed. The authors applied the proposed approach to different transformer datasets and achieved success in identifying transformer fault-types, even in case of conflicting results of Intelligent Systems applied to DGA datasets.

Konstanttinos *et al.* (2014) proposed a hybrid support vector fuzzy inference system, as a fault classification tool. This system comprised of fuzzy logic, genetic algorithms and support vector machines. The authors also produced a set of fuzzy rules based upon which, the fault classification has been done, in addition to the comparison with the previously applied classification tools on the same dataset.

Wei *et al.* (2014) proposed three different Support Vector Machine (SVM) fault classifiers, first time ever in the area of dissolved gas analysis. The authors compared the performance of these three SVM fault classifiers and also provided an in-depth understanding of the performance of each classifier with clear apprehensible figures. The authors concluded that least-square support vector machine considerably improves the diagnostic accuracy of dissolved gas analysis.

1.4 Objectives of the proposed research

Based upon literature survey, following lacunae are unidentified with the conventional DGA Ratio Methods:

- Failure to identify fault types in case of multiple fault conditions
- Various DGA techniques are not consistent and they may lead to different interpretation for the same oil sample
- Significant number of DGA results fall outside the proposed codes of ratio-based methods
- Fault diagnosis using DGA requires manual extraction of an oil sample and delivery to laboratory for analysis thereby adding the time-factor to the process
- The more is the sample data collected; higher will be the accuracy of the fault diagnosis. This will further result in an increase in the network degree and computational difficulty.

By considering the lacunae, following objectives were undertaken:

1. To acquire various signals from large number of transformers located at different sites at rated and other than rated voltage.
2. To develop a new hybrid algorithm for data processing and condition monitoring for various transformers.
3. To validate the results of the developed models by comparing them with standard results.

In order to achieve the first objective, transformers from ten substations of Punjab State Electricity Board have been used to collect gas samples. The data is collected as per the ASTM standards. The transformer rating ranges from 52 MVA to 63 MVA. The range of voltage level is 132/33/11 KV. After the data is collected, it is pre-processed by removing linear trends, removing outliers, etc. Using MATLAB programming, this processed data has been used to train different neural network architectures and to design fuzzy inference system (FIS). The expert system (neural network and FIS) has been further used as a diagnostic tool for the fault detection of transformer, using dissolved gas analysis method. To cover the second objective, a hybrid algorithm, Adaptive Neuro-Fuzzy Inference System (ANFIS) has been developed for transformer fault diagnosis. This algorithm integrates the best characteristics of both the fuzzy inference system and neural network. The third objective has been covered by validating the results obtained with the already established standards.

Chapter 2: Transformer Basics

2.1 Basic Concepts of Transformer

A transformer is a static device which transfers electrical energy from one circuit to another through magnetic coupling. It usually consists of two or more coupled windings and a core to concentrate magnetic flux. An alternating source voltage when applied to one of the windings will create a time-varying magnetic flux in the core, which, in turn, induces a voltage in the other winding. If the relative number of turns between primary and secondary windings is varied, the ratio of the input and output voltages can be determined, resulting in voltage transformation, by stepping it up or down between the circuits. Faraday demonstrated the transformer principle in 1831, although its practical design did not exist until the 1880s.Within less than ten years, the transformer got instrumental during the "War of current" in seeing alternating current systems conquer over direct current, a position in which the former ones have always remained dominant [Daniels et al. 1985].

By converting electrical power into a high voltage, low current form and back to low voltage, high current form, the transformer significantly mitigates energy losses and also leads to the economic transmission of power over remote areas. With the help of transformer, transmission of power can be carried out from remotely located generating stations to the points of demand. The transformer is one of the simplest and most efficient electrical machines, with its large units achieving performance more than 99.75%. The range of the size of transformer varies from a thumb nail sized coupling transformer hidden inside a stage microphone to huge Giga VA-rated units, applied to interconnect parts of national power grids. All these applications work on the same basic principles, with various similarities in their portions. There exists a diversity of transformer designs which perform specific roles in home as well as in industry [Flanagan et al. 1993; Gottlieb et al. 1998; Tawadros et al. 2009].

A source voltage fed to the primary winding causes a current to flow, which, in turn, develops a magneto motive force (MMF) inside the core. In an ideal transformer, the magnetizing current i.e. the current required to create the MMF, is considered to be insignificant, though its presence is still vital to cause the flow of flux around the magnetic circuit of the transformer core. This results in an induced EMF across each winding of the transformer, an effect being termed as mutual inductance. Figure 2.1 depicts an ideal step down transformer. The transformer operation at higher frequencies, paves the way to its more compact size without reaching saturation, and more power transfer for a given core. The drawbacks of higher frequency operation include an increase in core loss and conductor skin effect, which result in comparatively poor efficiency of the transformer. Aircraft and military equipment employ 400 Hz power supplies because decrease in efficiency is more than offset by reduction in core and winding weight [Hindmarsh et al. 1977; Heathcote et al. 1998; Harlow et al. 2004; Kulkarni et al. 2004].

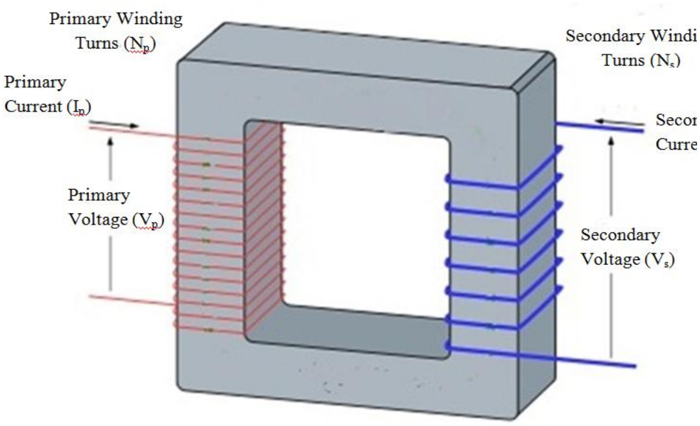

Figure 2.1 A step-down transformer

An ideal transformer is equipped with zero energy loss features and is therefore 100% efficient. Transformer is considered to be one of the most efficient electrical machines. The experimental models using superconducting windings possess efficiency of 99.85% along with the energy loss in the windings, core and surrounding structures. Larger transformers are usually more efficient. Those transformers, rated for electricity distribution, generally have efficiency more than 95%. On the other hand, the efficiency of a small transformer such as plug-in power brick applied in low-power consumer electronics, may be lower than 85%

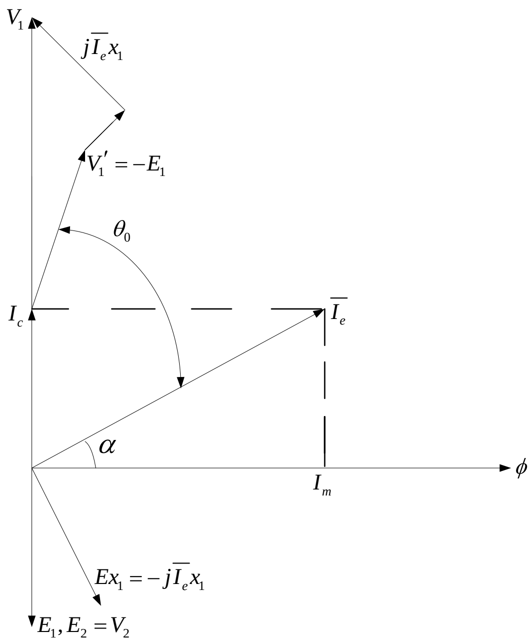

Figure 2.2 Phasor diagram of transformer

Figure 2.2 depicts that I_e (no-load primary current, called exciting current of the transformer) which has been shown leading Φ (magnetic flux), can be resolved into two components [McLaren et al. 1984].The component I_m along Φ is called the reactive or magnetising current, since its function is to provide the required magnetic flux (Φ).The second component along V_1' is I_c and this component is called the core-loss component or power component, of I_e [McLyman et al. 2004].

$$V_1' I_c = P_c \text{ and } \quad I_c = \frac{P_c}{V_1'} \tag{2.1}$$

The primary voltage of transformer can be given by

$$\overline{E_1} = \overline{V_1'} + (r_1 + jx_1) \tag{2.2}$$

The secondary voltage of transformer can be given by

$$\overline{E_2} = \overline{V_2'} + (r_2 + jx_2) \tag{2.3}$$

where E_1 and E_2 are induced emfs of primary and secondary windings respectively; I_1 and I_2 are primary and secondary winding current respectively; r_1 and r_2 are primary and secondary resistance respectively; x_1 and x_2 are primary and secondary reactance respectively; V_1' and V_2 are primary terminal voltage and secondary terminal voltage, respectively.

Figure 2.3 shows the equivalent circuit of the transformer drawn with the help of the equations (1) and (2).

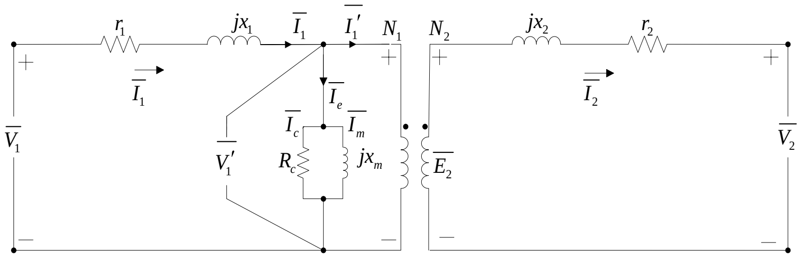

Figure 2.3 Equivalent Circuit of Transformer

Numerous causes lead to transformer losses, those arising in the windings, known as copper losses while the ones originating from the magnetic circuits are called iron losses. The copper losses occur in the transformers, during resistive heating of the conductors, when the current flows through the windings. During transformer operation at higher frequencies, an additional winding resistance and losses occur, due to skin effect and proximity effect. The core losses include various types of losses viz. hysteresis losses which occur due to the magnetic field reversing; eddy current loss, a complex function of the square of supply frequency and inverse square of the material thickness; magnetostriction losses due to physical expanding of the core material, making the buzz sound; mechanical losses due to fluctuation of electromagnetic forces between primary and secondary windings of transformer; stray losses which are associated with the transformer's support structure. Apart from these losses, cooling system for the big transformers is generally included in the losses [Pansini et al. 1999].

When a transformer is supplied with a constant voltage, the terminal voltage changes due to voltage drop in the internal parameters of the transformer i.e. primary and secondary resistances and inductive reactance. The internal voltage drop depends upon the load and its power factor. The algebraic difference between the no-load and full-load terminal voltage is measured in terms of voltage regulation which is defined as the change in secondary terminal voltage from no-load to full-load with respect to no load voltage (at constant supply voltage) [Ryan et al. 2004].

Let E_2 be the secondary terminal voltage at no-load and V_2 be the secondary terminal voltage at full-load.

Then, voltage regulation = $\frac{E_2 - V_2}{E_2}$ (2.4)

In the form of percentage,

%regulation = $\frac{E_2 - V_2}{E_2} \times 100$ (2.5)

When all the quantities are referred to the primary side of the transformer,

% regulation = $\frac{V_1 - E_1}{E_1} \times 100$ (2.6)

The load on certain transformers fluctuates throughout the day. The distributions transformers are energized for 24 hours, but such transformers deliver very light loads. Hence, the performance of such transformers cannot be adjudged on the basis of commercial efficiency, but it can be judged by all-day efficiency, which is defined as the ratio of output in kWh (or Wh) to the input in kWh (or Wh) of a transformer over 24 hours [Sayet al. 1983].

All day efficiency = $\eta_{\text{all day}}$ = Output in KWh /Input in KWh (24 hours) (2.7)

A diversity of specific transformer designs have been developed to perform certain engineering applications, though they share various similarities. An autotransformer is the one which has only one winding having two end terminals, in addition to a third winding, at an intermediate tap point. The primary voltage is applied across these two terminals, while secondary voltage is taken from one of these windings and third terminal. Few more types of transformers include Poly phase Transformers such as three-phase units, where the magnetic circuits are linked together and the core contains a three-phase flux-flow, numerous winding configurations are possible, giving rise to different features and phase shifts; Resonant Transformer that uses the inductance of its primary winding in series with a capacitor to form a tuned resonant circuit such as Tesla coil used to develop very high voltage and provide much higher current than electrostatic machines; Instrument Transformers such as current and voltage transformers utilized for measurements purposes [Winders et al. 2002].

2.2 Transformer Construction

Basically, transformer consists of core, windings and shielding. Transformer core is made up of highly permeable material, for power frequency applications. The high value of permeability paves the way to a low reluctance path for the flux such that the flux lines almost confine themselves to the iron core. Present day materials provide the relative permeability μ_r above 1000. Thin laminations, utilized for the core material are generally made up of silicon steel. Over the successive years, better magnetic properties are achieved by shifting from Hot rolled non-oriented to Hot rolled grain oriented steel. Presently, much better laminations in the form of cold rolled grain oriented (CRGO), high B (HiB) grades are easily available. The thickness of the laminations successively got decreased from more than 0.5mm to the present 0.25mm per lamination. A thin layer of insulating varnish, oxide or phosphate is coated over such laminations. The magnetic material must be equipped with the characteristics such as high permeability, high saturation flux density, very low permanence and a small area under the B-H loop, in order to allow operation with high flux density, small magnetizing current and small hysteresis loss. The resistivity of the iron sheet must be high enough to decrease the eddy current losses. The eddy current can be highly reduced by using very thin laminations. But, extra thin lamination increases the production cost of steel laminations. The steel should be annealed after cutting and stacking, in order to avoid the residual mechanical stresses which, in turn, decrease their magnetic properties [Enokizono et al. 1990; Joon et al. 2011].

Very small transformers (ranging from a few VA to a few kVA) comprise of hot rolled silicon steel laminations, either E and I, C and I or O while the core cross is section either a square or a rectangle. The silicon steel contains about 3.5% of steel. This is due to the reason that the higher percentage makes the steel very brittle and very hard to cut. Currently, the steel laminations used, carry the saturation flux density about 2 Tesla [Enokizono et al. 1993].

Windings constitute another vital part of the transformers. A two winding transformer comprises of two windings. The winding to which a voltage source is applied, which creates the flux is known as primary winding. The winding where the voltage gets induced through induction is termed ad secondary winding. If the secondary voltage is lower than the primary voltage, the transformer is known as step down transformer. If the secondary voltage is greater than the primary voltage, then it is called as step up transformer. A step down transformer can be transformed into a step up transformer by taking the low voltage winding of the transformer, as its primary winding. Therefore, it is always preferred to designate the transformer windings as High Voltage (HV) and Low Voltage (LV) windings. The winding having greater number of turns is considered to be a HV winding. The current on the HV side is lower as V-I product is constant and taken as VA rating of the transformer. The HV winding is required to carry more insulation, in order to withstand the higher voltage across it. The clearance to the core, yoke or the body is also more, in case of

HV winding. These factors decide the type of the winding utilized for the HV or LV windings [Enokizono et al. 1998].

A broad classification of transformer coils can be concentric coils and sandwiched coils. The concentric coils are generally used with core type transformers while the sandwich coils with shell type transformers. In concentric coil arrangement, depending upon the lower insulation and clearance requirements, the Low Voltage winding is placed near the core, the latter one being at ground potential. The High Voltage winding surrounds the Low Voltage winding. Whenever the change of voltage is required, the taps are provided on HV winding. This requirement justifies the location of High Voltage winding as the outer winding [Suzuki et al. 1972].

Small signal transformers do not produce considerable quantity of heat. Power transformers having the range up to a few kilowatts depend upon natural convective air-cooling. On the other hand, high power transformers must be equipped with appropriate cooling systems. The transformer cooling systems for dry- type transformers of small rating include Air Natural and Air Forced Type cooling while the cooling systems for oil-filled transformers include Oil Natural Air Forced, Oil Forced Air Natural, Oil Forced Air Forced and Oil Immersed Water Cooling Type [McLyman et al. 2004].

Transformer oil is a highly refined mineral oil, which inherits the characteristic to remain stable at high temperatures, works as an insulator as well as coolant for high power transformers. The windings of these transformers remain immersed in transformer oil. Superconducting windings, which help to reduce the copper losses, but not the iron losses, have been used to build the power transformers having the range of 2MVA. These transformers are cooled by the use of liquid nitrogen or helium [Wang et al. 2008].

2.3 Transformer Condition Monitoring

A technique to monitor the operating features of a physical asset is termed as Condition monitoring (CM). The alteration in the monitored feature can be utilized to plan maintenance before the occurrence of any severe damage or break-down. CM encompasses the information of loss mechanisms of individual accessories or the combined system, sensor technologies, data acquisition and analysis, and the knack to predict the health condition of the asset [Vandermaar et al. 1995].

Recently, an advanced maintenance policy has been developed called Condition based maintenance (CBM). The basis of CBM is the knowledge of health condition obtained from equipment. This knowledge is further utilized by the data analysis and diagnostic techniques to predict the remaining life of equipment or loss rate. Subsequently, the decisions are made related to equipment maintenance by optimizing their reliability index, namely whether the equipment requires preventive maintenance, if required, when the equipment must be repaired. This scheme has been widely acknowledged in the area of maintenance, the current critical problem required to resolve is how to utilize the health condition information during technical decision-making for device maintenance [Leibfried et al. 1998].

The initial CBM decision-making depends on the measure and test of condition signal of devices. When the monitored value exceeds the threshold or the trend occurs to change, the maintenance decision should be timely decided according to pre-set threshold value. This maintenance policy is easy and simple, but for a system with multiple state variables tested it is difficult to reflect the combined effect on a variety of factors. Therefore, the key of CBM decision-making is to establish a precise and reasonable functional relation between their health levels and their condition parameters [Leibfried et al. 1998].

Condition monitoring embraces the benefits i.e. reduced maintenance costs, provision of a quality control feature, reduction in the probability of destructive failures, improvements in operator’s safety, quality of supply, mitigation in the severity of any loss incurred, eliminating further repair activities, identification of the root causes of losses and knowledge of the transformer operating life. These benefits enable business decisions to be taken either on plant revamping or on equipment replacement [Gockenbach et al. 1998].

During operation, the transformers get subjected to various stresses i.e. electrical, thermal, mechanical and environmental. These stresses further pave the way to occurrence of some internal faults in transformers with irreversible evolution, thereby, reducing their operating life; taking into consideration the fact that most of the transformers have been in operation since more than two decades. Thus, it becomes imperative to fit the transformers with monitoring and diagnosing systems [Lapworth et al. 1998].

All the units undergo through routine tests based on a periodic scheme, for screening to diagnose initial failure and indicate normal condition. Special tests are carried out only as needed for further diagnosis and detailed assessment [Donald et al. 1999].

2.4 Transformer Insulating Materials

The insulating materials inherit the properties including resistivity, breakdown voltage, permittivity and dielectric loss, etc. An ideal insulating material retains its dielectric properties at high temperature i.e. high resistivity, good thermal conductivity, and shear strength of solid insulation. The mechanical properties that a material should possess include ability to withstand moisture, vibration, abrasion and bending. It should also be able to bear chemical attack, heat and other worse conditions [Saha et al. 2003; Verma et al. 2005].

2.4.1 Transformer oil

After refining crude petroleum, mineral oil is obtained and that oil is used for the insulation in a transformer. Other oils like animals and vegetable oil can't be used for the insulation purpose as these form fatty acids after heating, which corrode the cellulose paper that is used for insulation. In electrical equipment, mineral oils were used as liquid dielectric for over hundred years. Variety of other synthetic oils with more superior properties is available even then mineral oils are preferred due to plentiful availability and economy [Fofana et al. 2006].

The properties of mineral oil i.e. high insulating, good oxidative, aging stability and heat transferability make it convenient, to be used as a dielectric. The good performance of mineral oil as an insulator depends on basic oil characteristics that will affect the overall performance of an electrical equipment such as adequate low temperature properties down to the extreme of climatic conditions expected at the installation site, high electric strength to withstand the stresses in service, sufficiently low viscosity so that its ability to circulate and transfer heat, is not impaired and free from corrosive sulphur which corrodes metal parts and insulation, good resistance to emulsion to prevent holding water in the suspension in it, free from inorganic acid, alkali and accelerate the production of sludge, free from sludge under normal separating conditions, low water content, low pour point and high flash/fire points[Pradhan et al. 2006; Verma et al. 2005].

2.4.1.1 Insulating oil quality

The performance and the service of a transformer mostly depend upon the condition of the oil used. The quality of the oil is determined by performing various tests like electrical, physical and chemical tests, to determine whether there is any change in electrical properties and what is the level of impurities and degree of retrogression [Duval et al. 2005].

With the help of these test results, various maintenance procedures are developed to avoid shut down and early equipment failure. This will extend the life of equipment. Number of tests is available for the insulating oil. ASTM D3487, specifies threshold level for new oils, while IEEE Guide 637-1985, and determines the threshold level for service oils. A specific number of furanic compounds are formed and dissolved in oil, as and when the insulation paper deteriorates. The strength of the paper is determined by the degree of polymerization which is related to the presence of these furanic compounds. The condition of the paper insulation in oil can be accessed with Furan and Phenol value in oil, which is an appropriate non-invasive method [Pahlavanpour et al. 1998].

Furans and phenols are analyzed in the transformer oil sample, when any of the condition occurs such as increase in CO or CO_2, transformer overheating or overloading, gradual decrease of interfacial tension without increase in acid number, sudden rise in the moisture content, change in color of oil suddenly for transformers over 25 years old [Verma et al. 2005].

2.4.2 Paper insulation

With the help of Kraft process wood pulps are removed to make insulating paper. It contains about 90% cellulose, 6-7% lignin and, the balance is hemi cellulose. The natural humidity of paper is 4-5% by weight and the insulation is dried after winding, to less than 0.5%. To increase the dielectric strength of the dried paper, it is soaked in insulating oil. It is also used to cool the windings of the transformer. The cellulose gets depolymerised in the presence of heat, water and oxygen. Subsequently, the polymer molecular chain gets reduced, thereby, decreasing the mechanical strength of the material [Verma et al. 2005; Prevost et al. 2006; Oommen et al. 2006].

Local mechanical failure corresponds to short the turns or paper fragments or fibres in oil vessels and this will lead to thermal or dielectric failure of the insulating system. Changes in the compliance and tension of the windings with time could lead to distortion and an enhanced susceptibility to short-circuit, force failure of the aged insulation or even of the winding itself. Water is a by-product of ageing process. Its availability in the dielectric enhances conductivity and the possibility of gas bubble formation, reducing the thermal stability of the insulation system during overload conditions [Hill et al. 1995].

Paper insulation is equipped with all the features of a good insulator like high resistivity, good breakdown voltage, and low conductivity of extract, low cost, high degree of polymerization, low dissipation factor and good tensile strength. Table 2.3 shows the characteristics features and the specific values of the electrical grade paper according to the guidelines of various DGA Interpretative Standards viz. IEC 554-3-5 1984 [Emsley et al. 2000; Heywood et al. 1997].

2.5 Methods of Monitoring and Diagnosis of Power Transformers

There exist many tools and methods for monitoring and diagnosis of high voltage power transformers. These tools and methods are traditional ones and have been utilized since many years. Such traditional diagnosis methods give valuable results, which in many cases are insufficient to diagnose the transformer condition. The traditional methods may provide significant results using soft computing tools.

The use of software techniques considerably improves the reliability and gives facilities to analyze the test data, collected from Dissolved Gas Analysis (DGA) method, a traditional transformer fault diagnosis method. Advanced informative technology methods like Data Mining, provide information and knowledge which is neither available nor visible directly from the data. This advancement in artificial intelligence (AI) modelling techniques has empowered power engineers and researchers to develop and implement valuable artificial intelligent software for transformer fault diagnosis.

Intelligent techniques support the data interpretation. A computer program which accomplishes a complex decision-making task within a specific narrow problem area which is generally performed by a human expert is known as expert system. Such systems acquire the knowledge from an expert and express it in a suitable representation to exploit the information in a similar way, as the human specialist performs with the same results. The application of intelligent techniques for transformer diagnosis offers the potential of mitigating the overhead expense borne by substations for transformer maintenance.

Contrary to laboratory measurements, on-site measurements get repeatedly disturbed by noise caused by electromagnetic waves and stern environmental conditions. However, on-site monitoring provides actual data, which permits rapid reaction and measures to be taken. Moreover, the data shows the actual service condition and can be utilized for further assessment, in case this data has been recorded over a specific time to detect the trend in the parameter development. Thus, gradual changes can be detected and an alarming message or command can be given, to immediately disconnect the system, in case the prescribed limits get crossed [Lachman et al. 2000; Strachan et al. 2008].

Figure 2.4 IT Visual inspection components (Clockwise direction: Terminals, membranes, bolts and spark gaps)

2.5.1 Visual inspection

During the conditions, when the expansion membrane gets damaged and the module's disassemble becomes essential, the diagnostic technique applied has to interrupt the services of the system. A 22-item checklist is prepared to carry out terminal check, oil leakage detection, expansion membrane check and mechanical integrity evaluation. Figure 2.4 shows details of these activities. During this process of inspection, root cause is find-out, because a breathing hole always remains there for a high Partial Discharge reading IT [Azcarraga et al., 2006].

2.5.2 Chemical procedures

Some of the failures in the transformer insulation can be detected by utilizing chemical procedures. Dissolved Gas Analysis (DGA) is one of the well-known chemical procedures, in which a sample of the insulating liquid is extracted from the transformer and evaluated. After a vacuum extraction, this sample has to undergo an analysis process using gas chromatography to find out the dissolved gases in transformer oil. In order to determine the failure, various quotients of low-molecular hydrocarbon connections have to be critically analyzed. Figure 2.5 shows four characteristic Key Gas Method (KGM) charts which represent specific relative gas concentrations for the most commonly observed, four fault- types i.e. overheating of cellulose, overheating of oil, partial discharge and arcing.

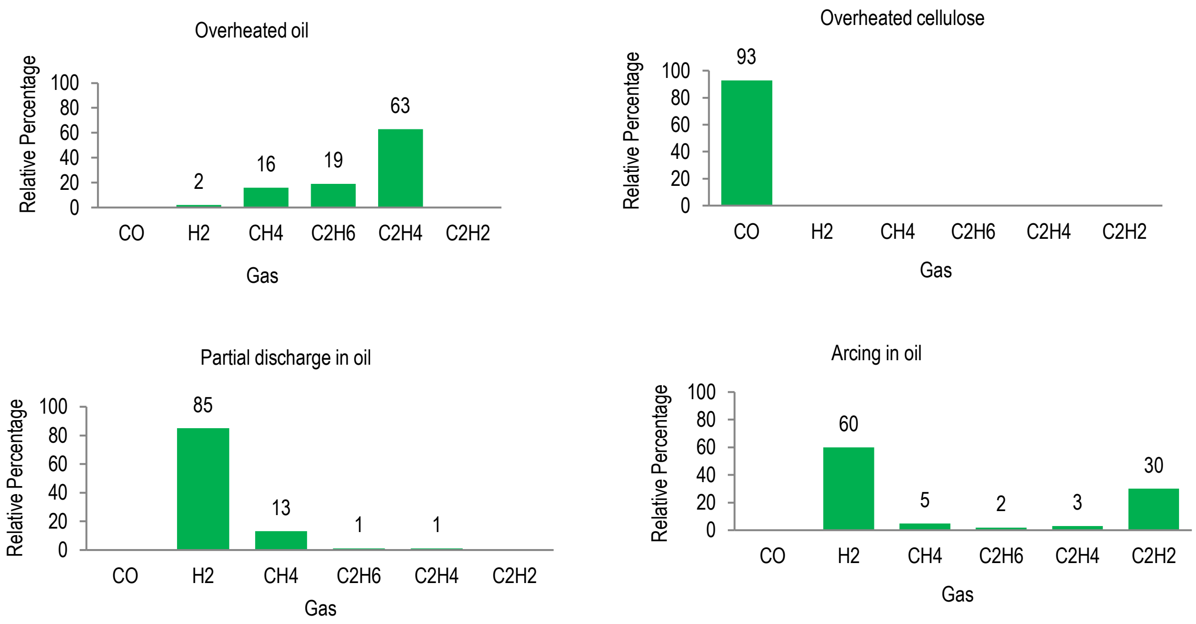

Figure 2.5 Key gas method charts

Other chemical procedures for transformer incipient fault diagnosis have been developed by Duval, Dornenburg, Roger’s, Mueller, Schliesing and Soldner (MSS). The drawback of these chemical procedures lies in the fact that these permit only one integral analysis to the insulation. Additionally, sampling and further treatment of the sample may affect the measurement.

Furan analysis (HPLC) and the analysis of the collection of free gases in Buchholz relay are another chemical procedure carried out to detect transformer faults. While the furan analysis, involves the extraction of the fundamental knowledge of the quality of the solid insulation, the analysis of the free gases collected in Buchholz relay gives knowledge related to the range of an existing fault [Duval et al. 2005; Fallou 1975].

In order to improve the evaluation of the existing fault, it is imperative to find out the gas rate. This purpose is solved by using Electronic Buchholz relay, an extension for Buchholz relay, without restraining its function. The Electronic Buchholz relay determines the past history of the gas evolution, during instantaneous recording of the transformer operating conditions, which provides additional conclusions on an existing fault.

2.5.3 Electrical procedures

While the chemical procedures provide a cumulative knowledge related to the time-period passed since last evaluation, the electrical procedures provide information related to the current position of the transformer. The main electrical procedures include the partial discharge measurement (on-line) and the transfer function measurement (off-line) [Wang et al. 2001].

2.5.3.1 Capacitance and tan-delta measurements

Power factor is related to Watt losses and Volt-Ampere load. For convenience, this ratio is generally represented as a percentage value. Power factor value depends upon the range of moisture, temperature and ionization, instead of insulation area or thickness [Huang et al. 1998].

From the point of view of electrical engineering, there exists an equivalence factor between tan delta measurements and power factor measurements for low angles; the latter gets increased with an increase in the value of electrical conduction across the dielectric. The expected value of the readings of insulation oil gets increased (above 0.5 %.) with the presence of water in insulation oil. Figure 2.6 depicts the capacitance and tan delta measurements using a 12 kV commercial system. An artificial climate chamber is shown in Figure 2.7. It is encapsulated in a small area in North China Electric Power University, within the network of a diversity of simulated environment conditions (like temperature, humidity, pressure, filthy and other factors). It is an electrical instrument for the electrical features to generate a test with the actual condition similar to the environment. The height of the insulation of the whole artificial climate chamber is 4 meters while the diameter is 2.3 meters [Azcarraga et al. 2006; Wang et al. 2009].

Figure 2.6 Capacitance and power factor measurement

Figure 2.7 Artificial Climate Chamber

2.5.3.2 Partial Discharge Measurement

The properties of the dielectric materials in transformers get curtailed with the occurrence of Partial Discharge and can lead to gradual failures. In order to detect Partial Discharge directly in transformers, two types of measurements are carried out i.e. acoustic signals and electrical signals. The Partial Discharge detection can also be done by utilizing chemical techniques, through the measurement of decomposition products by Partial Discharge. The permissible range of Partial Discharge varies from less than100 to 500 pC.

The detection of acoustic stress waves within the range of 100 to 300 kHz can be done by mounting acoustic emission sensors on the transformers. In case of multiple sensors, the location of the partial discharge can be determined based on the onset time of the pulses received at the sensors. Such type of instrument is available commercially to constantly monitor and assess the value of internal partial discharge (on-line) taking the help of the two methods i.e. acoustic method and electrical method. Current research depicts that optical sensors have a much higher potential sensitivity than regular tank-mounted piezoelectric sensors, for the detection of Partial Discharge. Such equipments are also available which can be used to measure electrical Partial Discharge signals, bushing tap current or voltage and neutral current, at a number of different locations [Duet al. 2005].

2.5.4 Dielectric procedures

The dielectric methods being utilized as offline procedures, allow a more accurate analysis of the insulating system, if a comprehensive statement about the condition of the dielectric is required. Such dielectric procedures embody the methods such as Recovery Voltage Measurement (RVM), Polarization and Depolarization Current (PDC) and Frequency Dielectric Response (FDS) [Saha et al. 2004].

Discharge and locate the origin of the discharge utilizing acoustic emission sensors along with specialized software. Power engineers and researchers have developed flexible Artificial Intelligence (AI) software to detect and diagnose transformer faults. This curtails the requirement of manpower and financial overhead by utilities, to carry out transformer condition monitoring, with greater accuracy and improved efficiency [Rosa et al. 2005].

Chapter 3: Dissolved Gas Analysis

3.1 Introduction

Thermal and electrical distributions in the operating transformer are two most important causes of dissolved gases in oil. The gases produced from thermal decomposition of oil and solid insulation are because of the losses in conductors due to loading. Also, decomposition occurs in oil and solid insulation and produces harmful gases. In case of electrical disturbances, the gases are formed principally by ionic bombardment. The gases are generated mainly because of cellulose and oil insulation deterioration. During the normal operation of the transformer, gases such as Hydrogen (H_2), Methane (CH_4), Ethylene (C_2H_4), Acetylene (C_2H_2), Ethane (C_2H_6), Nitrogen (N_2) and Oxygen (O_2) are released. In the existing methods, parts per million (PPM) values are determined for each gas in the oil along with a total value of combustible gases. When there is an abnormal situation such as a fault occurrence, some specific gases are produced in greater quantity than in the normal operation. Thus, the amount of these gases in the transformer oil increases. The increase in the amount of gases results in saturation of the transformer oil and no further gas can be dissolved in oil. Therefore, when the oil is saturated, the gases get released from the oil. The transformer oil gets damaged due to these dissolved gases. Due to damaged oil, the performance of insulating material as well as the performance of power transformer declines. To prevent the insulation failure, it is required to know the exact amount of harmful gases dissolved in the transformer oil. The amount of the dissolved gas is related to the temperature of the oil and the type of gas. Dissolved gas analysis (DGA) is a routine technique which is carried out to know the exact amount of the gas dissolved. This method has been used for more than 30 years [Abu-Siada et al. 2012; Agou 2000].

The gases which are produced by the degradation of oil as a result of elevated temperatures may be caused by several factors as listed below:

a) Severe overloading
b) Lighting
c) Switching transients

d) Mechanical flaws
e) Chemical decomposition of oil or insulation
f) Overheated areas of the windings
g) Bad connections which have a high contact resistance

The type of gases present in an oil sample makes it possible to determine the corresponding type of fault that occurs in the transformer. This is usually done by analyzing the type and amount of the gases that are present when abnormality occurs or during routine maintenance [Cordomi et al. 2008; Almas et al. 2009].The characteristics of the transformer faults are described as below:

(a) Arcing

Arcing is the most severe of all fault types. Large amount of Hydrogen and Acetylene are produced, with minor quantities of Methane and Ethylene. Arcing occurs in high current and high temperature conditions. Carbon Dioxide and Carbon Monoxide may also be formed if the fault involves cellulose. In some instances, the oil may become carbonized.

(b) Thermal heating / Pyrolysis

Thermal heating leads to the decomposition products including Ethylene and Methane, together with smaller quantities of Hydrogen and Ethane. Traces of Acetylene may be formed if the fault is severe or involves electrical contacts.

(c) Corona

Corona is a low-energy electrical fault. Low-energy electrical discharges produce Hydrogen and Methane, with small quantities of Ethane and Ethylene. Comparable amounts of Carbon Monoxide and Carbon Dioxide may result from discharge in cellulose.

(d) Overheated Cellulose

Large quantities of Carbon Dioxide and Carbon Monoxide are evolved from overheated cellulose. Hydrocarbon gases, such as Methane and Ethylene, will be formed if the fault is involved with an oil-impregnated structure.

Table 3.1 Dissolved Gases Groups

Group →	Hydrocarbons and Hydrogen	Carbon Oxides	Non-Fault Gases
Gases →	CH_4,C_2H_6,C_2H_4,C_2H_2	CO,CO_2	N_2,O_2

The Dissolved Gas Analysis method involves sampling of the oil inside the transformer at various locations. Then, chromatographic analysis is carried out on the oil sample to measure the concentration of the dissolved gases. The extracted gases are then separated, identified and quantitatively determined such that the DGA method can then be applied in order to obtain reliable diagnosis. The extracted gases meant for analysis purpose are 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), Nitrogen (N_2) and Oxygen (O_2). These dissolved gases can be classified into 3 groups which are shown in Table 3.1 [Arakelian et al. 2002].

Depending on the concentration of the dissolved gases, the condition of the transformer can be determined. This is because each type of fault burns the oil in a different way which correspondingly generates different pattern of gases. This makes it possible for experts to identify the nature of the fault type based on the gas type and its concentration. For example, arcing may cause high concentration of acetylene dissolved in the oil. The detail of fault type and the relation with the fault gases can be shown in Table 3.2 [Aschwanden et al. 1998].

Table 3.2 Relation between Fault Type and Fault Gases

Fault	Insulation Involved	Fault Gases Present
Corona/Partial Discharge	Oil	H_2
	Cellulose	H_2,CO,CO_2
Thermal Heating/Pyrolysis	Oil-Low Temperature	CH_4,C_2H_6
	Oil-High Temperature	C_2H_4,H_2 (CH_4,C_2H_2)
Arcing	Cellulose-Low Temperature	CO_2 (CO)
	Cellulose-High Temperature	CO (CO_2)
	Oil/Cellulose	C_2H_2,H_2 (CH_4,C_2H_6,C_2H_4)

3.2 Methodology

A sample of the oil is carefully drawn from the bottom of the unit, using a specially prepared glass syringe. Extreme care is taken to ensure that the oil is not exposed to the atmosphere. After drawing the oil, any air bubbles that remain in the syringe are purged and the syringe is sealed. Glass is used to prevent the gases from being absorbed into the walls of a plastic sampling device. After sampling, complete nameplate data is recorded to be used for identifying the sample and for diagnostic purposes. After receipt of the transformer oil sample at the laboratory, the oil is subjected to a very high vacuum that extracts the gas from the oil molecule. The amount of gas extracted per millilitre is carefully recorded. The extracted gases are passed through a highly accurate gas chromatograph. The amount of each gas is recorded in parts per million [Bengtsson 1996; Bouvier 1970].

Figure 3.1 Working process of Dissolved Gas Analysis (DGA)

A report has been prepared showing the amount of each gas in proportion to the total amount of gas contained in the oil sample. The numbers are entered into a computer program that performs different ratio comparisons as described by ANSI and other accepted methods. The output of the program identifies any fault conditions that exist inside the transformer; and in some cases, even pinpoints the actual source area of the fault [Cardoso et al. 1999].

3.2.1 Operating Procedure

The following major steps are undertaken to analyze the Dissolved Gas Analysis [Duval 2003]:

(a) Detection: The generation of any gas above the normal level is detected first and then appropriate guidelines are utilized so that possible abnormality can be recognized at the earliest in order to minimize the damage to the transformer.

(b) Evaluation: The impact of the abnormality or fault on the serviceability is evaluated by using a specified set of guidelines and recommendations.

(c) Action: Lastly, the action is recommended, which begins with increased surveillance and confirming a supplementary analysis and leads to either a determination of load sensitivity, reducing the load on the transformer or actually removing the unit from service.

3.3 Transformer Faults

All transformers generate gases to some extent at normal operating temperatures. But, occasionally a gas generation does occur within an operating transformer during occurrence of the abnormalities such as local overheating, dielectric problems, or a combination of these. In electrical equipment, these abnormalities are called faults and faults may be thermal, corona and arcing. Internal faults in oil produce the gaseous by products such as Hydrogen (H_2), Methane (CH_4), Ethane (C_2H_6), Ethylene (C_2H_4) and Acetylene (C_2H_2). When cellulose is involved, the faults produce Hydrogen, Methane Carbon Monoxide and Carbon Dioxide. Each of these types of faults produces certain gases that are generally combustible [Gibeault et al. 1995]. The total of all combustible gases may indicate the existence of anyone type of fault or a combination of thermal, electrical or corona faults. From the gases dissolved in the transformer oil, following types of faults are interpreted:

(a) Thermal Faults

The decomposition of oil takes place above the temperature ranging from 150°C to 500°C which produces relatively large quantities of low molecular weight gases, such as H_2, $CH_4$and trace quantities of the higher molecular weight gases such as Ethane, Ethylene and Acetylene. As the fault temperature in mineral oil increases, the hydrogen concentration exceeds that of methane, accompanied by significant quantities of higher molecular weight gases, first ethane and then ethylene. At the upper end of the thermal fault range, increasing quantities of hydrogen and ethylene and traces of acetylene may be produced. In contrast with the thermal decomposition of oil, the thermal decomposition of cellulose and other solid insulation produces CO, Carbon Dioxide (CO_2) and water vapour at temperature much lower than that for decomposition of oil and at rates exponentially proportional to the temperature. Since the paper begins to degrade at normal operating temperature in the transformer, the ratio of CO_2 / CO is sometimes used as an indicator for the thermal decomposition of cellulose. This ratio is normally more than seven. As the magnitude of CO increases, the ratio CO_2 / CO decreases. This may indicate an abnormality i.e. degradation of cellulose insulation.

(b) Low Intensity Discharges

Low intensity discharges such as partial discharge and very low level intermittent arcing produce mainly hydrogen, with decreasing quantities of methane and trace quantities of acetylene. As the intensity of the discharge increases, the acetylene and ethylene concentrations rise significantly.

(d) High Intensity Discharges

It is also referred as arcing. As the intensity of electrical discharge reaches arcing or continuing discharge proportion that is produced at the temperature range between 700°C to 1800°C, the quantity of acetylene becomes pronounced.

3.4 Significance

Dissolved gas analysis method has been equipped with a multiple number of the significant advantages, few of which have been listed below [Guardado et al. 2001]:

a) Advance warning of developing fault
b) Detection of fault during warranty period
c) Status checks on new and repaired units
d) Convenient scheduling of repair
e) Monitoring of units under overload
f) Essential information for asset management program

3.5 Mechanism of Gas Formation

Gases in oil always result from the decomposition of the electrical insulation material (oil or paper), as a result of faults or chemical reaction occurring in the equipment. For example, oil is a molecule of hydrocarbons i.e. containing hydrogen and carbon atoms linked by chemical bond (C-H, C-C). Some of these bonds may dissociate and form H_2, CH_4, C_2H_6 radicals. All these radicals then recombine to form fault gases observed in oil i.e. H_2, CH_4, C_2H_6, C_2H_2, and C_2H4 [Ding et al. 2011; Cavallini 2005].

In addition to above, the decomposition of paper also produces CO_2, CO and water (H_2O). The production rate of gases of all types is closely linked to rate of energy liberation. Low rate of energy liberation in partial discharge and thermal fault will cause gases to evolve slowly and dissolve in oil. The higher rate of energy liberation of high temperature core fault can cause an evolution of fault gas rapid enough to result in gas bubbles. Some of the gases may dissolve in oil and some gases reach buchholz relay. Table 3.3 shows the allowable temperature (in °C) for the fault gases [Hohlein et al. 2010; Augusta 2012].

Fault Gas	Temperature
Methane	>120°C
Ethane	>120°C
Ethylene	>150°C
Acetylene	>700°C

Table 3.3 Temperature limits of Gases

3.6 Faults Detectable using Dissolved Gas Analysis

Four basic types of fault detectable by DGA have been listed below [Ivanka et al. 2010; Hejazi et al. 2011]:

1. Partial discharge of corona type (PD) - Discharge in gas bubbles or voids trapped in paper, as a result of poor drying.

2. Discharge of low energy (D1) – It includes visual marks of tracking, small arcing, sparking, carbonized pinholes in paper or carbon particles in oil.

3. Discharge of High energy (D2) – It includes high energy arcing, flashover and short circuit resulting in damage of paper, large formation of carbon particles in oil, tripping of the equipment used for gas alarm.

4. Thermal fault of temperature > 700°C- It includes extensive formation of carbon particles in oil and metal fusion. It is due to large circulating current in tank and core and short circuit in laminations.

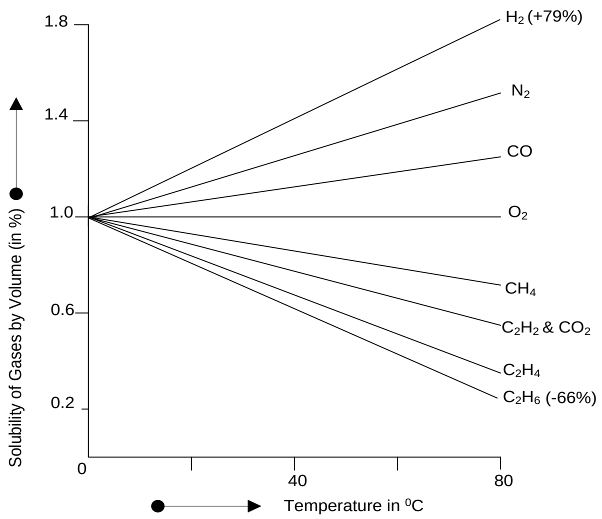

Figure 3.2 Relative Solubilities of gases as a function of oil Temperature

3.7 Dissolved Gas Analysis in Oil

Table 3.4 Solubility of gases in percent by volume (Static equilibrium at 760 mm Mercury and 25^0C)

Gas	Percent by volume
Hydrogen	7
Nitrogen	8.6
Carbon Monoxide	9
Oxygen	16
Methane	30
Carbon Dioxide	120
Ethane	280
Ethylene	280
Acetylene	400

Dissolved gas in oil analysis or gas chromatography is a cyclic process of detecting concentrations of various gases that may remain soluble in oil. Electrical and thermal stresses generated by arcing and PD in the transformer, result in decomposition of its insulation, which is oil-impregnated paper and oil. The decomposition products from oil are mainly hydrocarbon gases (hydrogen, oxygen, nitrogen, methane, ethane, ethylene, acetylene, carbon monoxide and carbon dioxide). When the fault gas analysis is being considered, it is important to take into account, the solubility of fault gases in mineral oil as well as their temperature dependence. In general, the fault gases (key gases) are those which are more soluble in oil. Additionally, the solubility of the mineral oil must be taken into consideration as a function of oil temperature (Figure 3.2) [Molton et al. 1977; Hohlein et al. 2002].

The saturation solubility of the gases has been listed in Table 3.4. This table clearly shows that the hydrogen is the least soluble while acetylene being the most soluble gas. The dissolved gas samples taken must be scaled carefully and analyzed quickly to minimize loss of hydrogen. Due to normal and natural ageing of insulation, some gases are always found in oil. However, incipient and active faults tend to generate a substantial increase in one or more gas concentrations, gassing rate and total combustible gases. Several techniques have been developed in the past to analyze the results of gas chromatography and infer faults in a transformer [Hui 2003].

3.8 Methods for Diagnosing Transformer Faults using Dissolved Gas Analysis

3.8.1 Methods of Analyzing Dissolved Gases in Oil

In DGA, at first, a sample of the transformer oil is taken. Then, the dissolved gases are extracted, separated, and measured by means of chromatography. In order to interpret the results of the experiment, data has been produced in a suitable form to diagnose the fault [Jarman et al. 2009]. Figure 3.3 shows the flow chart used to interpret results [Singh et al. 2007]. Following sub-sections describe the various DGA methods to interpret transformer fault types based on different standards.

A. Key Gas Method

The dependence on temperature of the types of oil and cellulose decomposition gases provides the basis for the qualitative determination of fault types from the gases that are typical, or predominant, at various temperatures. These significant gases and their proportions are called key gases. The principle of the Key Gas method is based on the quantity of fault gases released from the insulating oil when a fault occurs which in turn increases the temperature in the power transformer.

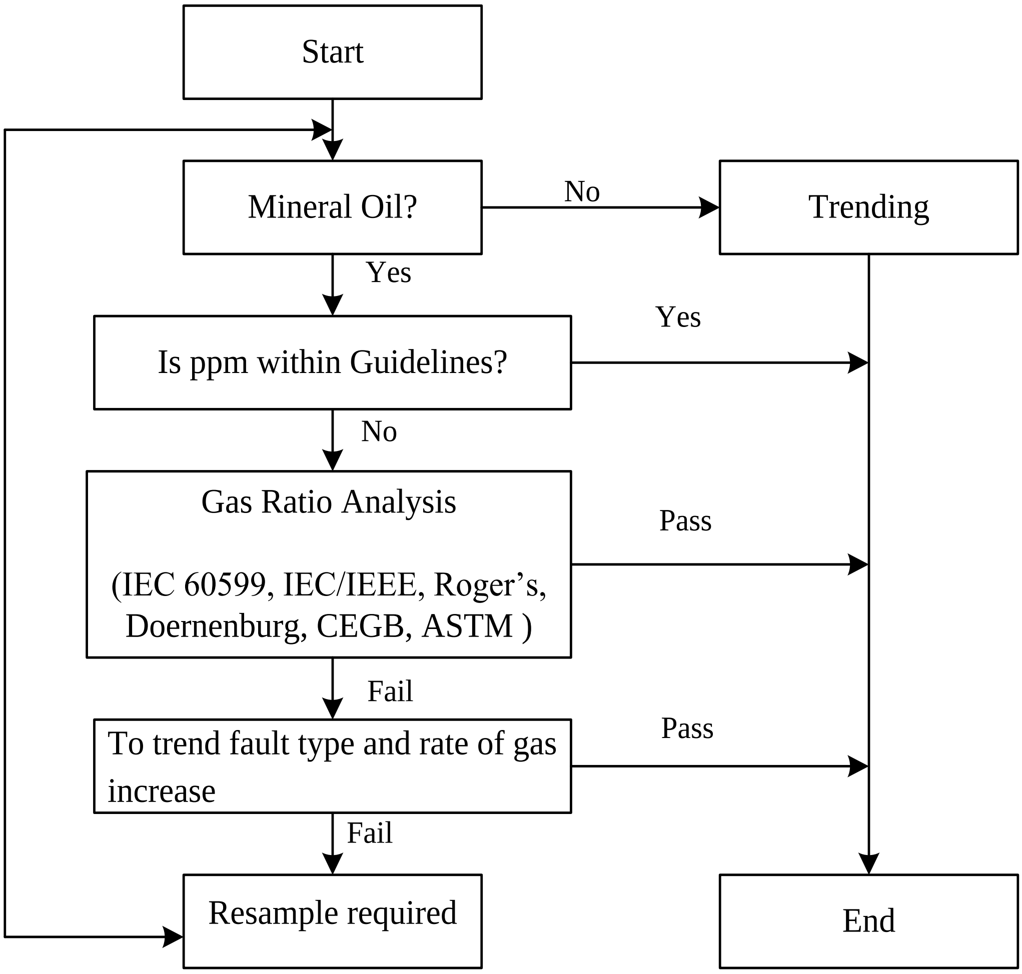

Figure 3.3 Dissolved Gas Analysis (DGA) based Fault Interpretation Scheme

The presence of the fault gases depends on the temperature or energy that will dissociate the links of the insulating oil chemical structure. This method uses the individual gas rather than the calculation of gas ratios for detecting fault. The Key Gas Method gives basically four types of faults such as Pyrolysis in Oil, Pyrolysis in Cellulose, Partial Discharge and Arcing as explained below [Lin et al. 2011]:

B. Rogers Ratio Method

This method utilizes the four digit ratio-code that has been generated from the five key (fault) gases (H_2, CH_4, C_2H_4, C_2H_6, C_2H_2), to interpret the transformer fault type based on the related diagnostic code as shown in Table 3.5 and 3.6.

Table 3.5 Roger's Ratio Code determination values

Gas Ratios	Ratio Code
CH_4/H_2	W
C_2H_6/CH_4	X
C_2H_4/C_2H_6	Y
C_2H_2/C_2H_4	Z

This method is based on the thermal degradation principles. The validity of this method is based on correlation of the results of a much large number of failure investigations with the gas analysis for each case. The value for the three key gas ratio corresponding are given in the Table 3.6. These ratios according to Roger's are applicable to both the gases taken from the gas space as well as extracted from the oil. The fault type is decided by combining some cases from the number of fault types originally suggested by Rogers [Mollmann et al. 1999].

C. IEEE Gas Guide

Mineral oil and paper at higher temperature and during electrical faults liberate fault gases. Distribution of gases can be related to the type of the fault and the rate of gas generation indicates the severity of fault. Table 3.7 shows the violation limit of gases (fault and non-fault) in ppm as per IEEE Gas Guide [Shroff et al.1985; Kachler et al. 2005].

D. IEC Standard

IEC 60599 ratio method is an improvement over the Rogers ratio method. Instead of using four gas ratios, ratio C_2H_6/CH_4 was dropped because it indicated only a limited temperature range of decomposition. Therefore, this method gains the advantage to discriminate faults by reducing the computation time thereby enhancing the efficiency of transformer fault diagnosis.

Table 3.6 Fault Diagnosis Table using Roger's Ratio Codes

Gas Ratios	Value	Code
$W=CH_4/H_2$	< = 0.1	5
	> 0.1, < 1.0	0
	> = 1.0, < 3.0	1
	> = 3.0	2
$X=C_2H_6/CH_4$	< 1.0	0
	> = 1.0	1
$Y=C_2H_4/C_2H_6$	< 1.0	0
	> = 1.0, < 3.0	1
	> = 3.0	2
$Z=C_2H_2/C_2H_4$	< 0.5	0
	> = 0.5, < 3.0	1
	> = 3.0	2

A generally accepted ppm concentration typical values range of the fault gases, observed in power transformers according to IEC 60599 is as follows [Sayed 2003]:

a) Hydrogen (H_2): 60-150 ppm
b) Methane (CH_4): 40-110 ppm
c) Ethane (C_2H_6): 50-90 ppm
d) Ethylene (C_2H_4): 60-280 ppm
e) Acetylene (C_2H_2): 3-50 ppm
f) Carbon monoxide (CO): 540-900 ppm
g) Carbon dioxide (CO_2): 5100-13000 ppm

Table 3.7 Violation limit of gases according to IEEE Gas Guide

Gas	Symbol	Violation limit (in ppm)
Hydrogen	H_2	100
Methane	CH_4	120
Ethylene	C_2H_4	50
Ethane	C_2H_6	65
Acetylene	C_2H_2	1
Carbon Monoxide	CO	350
Carbon Dioxide	CO_2	2500
Nitrogen	N_2	-
Oxygen	O_2	-

Table 3.8 shows the IEC 60599 standard for interpreting fault types and gives the values for the three key-gas ratios corresponding to the suggested fault diagnosis. A fault type can be deduced by checking the three ratio ranges. When key gas ratios exceed specific limits; incipient faults can be expected in the transformer. The ratios are significant only if at least one of the gases is above the typical value.

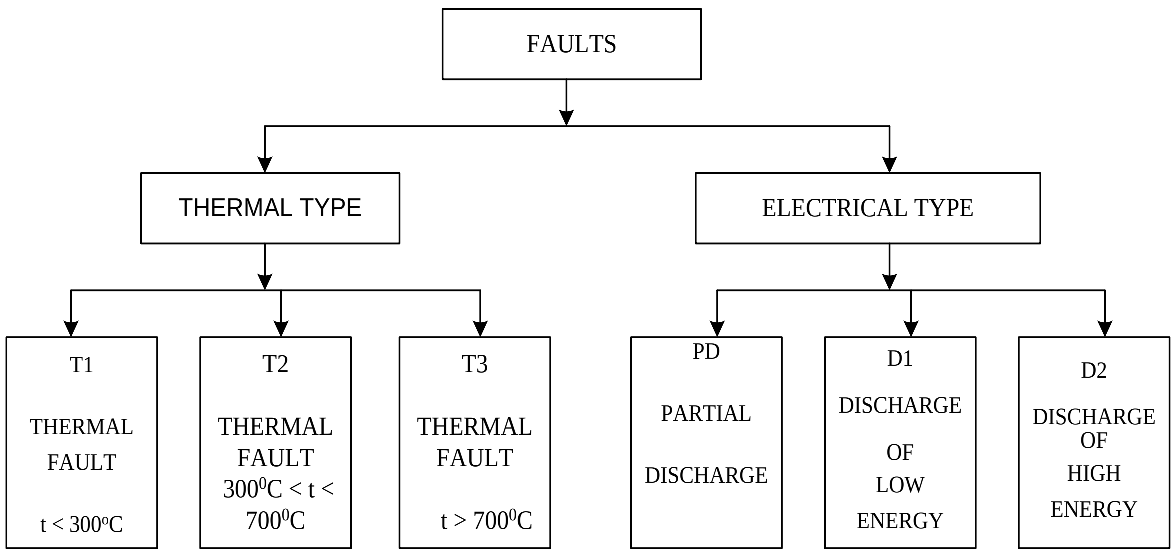

Figure 3.4 Fault Types as per IEC 60599 Ratio Method

The limitations are that it is only able to detect a single fault type and calculated ratios may fall outside the ratio ranges. Figure 3.4 describes the fault types (electrical and thermal) as interpreted using IEC 60599 ratio method [Seyed et al. 2012].Table 3.9 shows the fault diagnosis table using IEC/IEEE Codes [Seyed et al. 2012].

Table 3.8 Diagnosis using the IEC 60599 ratio method

Fault Type	**C_2H_2/ C_2H_4**	**CH_4/H_2**	**C_2H_4/C_2H_6**
Partial Discharge (PD)	<0.1	<0.1	<0.2
Low Energy Discharge (D1)	>1	0.1-0.5	>1
High Energy Discharge (D2)	0.6-2.5	0.1-1	>2
Thermal faults < 300^0C (T1)	<0.1	>1	<1
Thermal faults < 700^0C (T2)	<0.1	>1	1-4
Thermal faults > 700^0C (T3)	<0.1	>1	>4

E. CEGB Standard

In this standard, a four digit code is created using the Rogers method and four gas ratios of CH_4/H_2, C_2H_6/CH_4, C_2H_4/C_2H_6, and C_2H_2/C_2H_4.Regarding the obtained codes and data in Table 3.10, the faults are diagnosed (using CEGB code). Table 3.11 gives the list of different faults which match the relative code as described (using CEGB code) [Sifeddine et al. 2011].

F. ASTM Standard

In this standard a four digit code is generated based on the codes given in using the Rogers method and the four gas ratios of C2H4/C2H6, C2H6/CH4, C2H2/C2H4, and CH4/H2. The faults are diagnosed corresponding to the obtained codes and data given in Table 3.12 and 3.14. The ratio of CO2/CO (Carbon Dioxide/Carbon Monoxide) is used in diagnosing fault location (in oil and cellulose).

Table 3.9 Fault Diagnosis Table using IEC/IEEE Codes

S.No.	Code			Kind of Fault	Fault Code
	X	Y	Z		
1	0	0	0	No Fault	F0
2	0	1	0	Partial Discharge with Low Energy Density	F1
3	1	1	0	Partial Discharge with High Energy Density	F2
4	1 or 2	0	1 or 2	Partial Discharge with Low Energy Density	F3
5	1	0	2	Partial Discharge with High Energy Density	F4
6	0	0	1	Thermal fault with temperature less than 150^0C	F5
7	0	2	0	Thermal fault with temperature between 150^0C to 300^0C	F6
8	0	2	1	Thermal fault with temperature between 300^0C to 700^0C	F7
9	0	2	2	Thermal fault with temperature greater than 700^0C	F8
10	Code other than above			Unidentified Fault	-

In general, if the ratio of CO_2/CO is greater than 11 (or in many cases less than 3) it indicates that in the vicinity of the cellulose insulation, the temperature is higher than the normal operating temperature [De Pablo et al. 1996]. Despite the fact that the Rogers method is useful for assessing the quality of the transformer insulation, no quantitative criterion is provided for the possibility of occurrence of each fault in the insulation.

Table 3.10 CEGB Code determination values

Gas Ratios	Value	Code
	W<=0.1	5
	0.1<W<1	0
$W=CH_4/H_2$	1<=W<3	1
	W>=3	2
$X=C_2H_6/CH_4$	X<1	0
	X>=1	1
	Y<1	0
$Y=C_2H_4/C_2H_6$	1<=Y<3	1
	Y>=3	2
	Z<0.5	0
$Z=C_2H_2/C_2H_4$	0.5<=Z<3	1
	Z>=3	2

In the case of the occurrence of multiple faults, the gases from different faults get mixed together. As a result, the code matching between the gas ratios and code is improper, thereby, resulting in an uncertainty in fault diagnosis [Neyertz et al. 2008].

Table 3.11 Fault Diagnosis Table using CEGB Codes

S. No.	Code				Kind of Fault
	W	X	Y	Z	
1	0	0	0	0	No Fault
2	5	0	1	0	Partial Discharge
3	1 or 2	0	0	0	Increase in temperature greater than 150^0C
4	1 or 2	1	0	0	Increase in temperature 150^0C – 200^0C
5	0	1	0	0	Increase in temperature 200^0C – 300^0C
6	0	0	1	0	Increase in overall temperature in conductive parts
7	1	0	1	0	Circulating current in winding
8	0	0	0	1	Spark with low energy density
9	0	0	1	1 or 2	Spark with high energy density
10	0	0	2	2	Continuous spark
11	5	0	0	1 or 2	Partial discharge with tracking
12	1	0	2	0	Circulating current between core and tank

Once an abnormality has been determined to exist, to obtain fault diagnosis, the total accumulated amount of the three Duval Triangle gases (CH_4, C_2H_2 and C_2H_4) has been calculated. Each gas has been divided by the total amount of gases to determine the percentage of each gas of the total amount [Sabau et al. 2000]. Finally, the percentage of the total amount of gases has been plotted on the triangle to arrive at the diagnosis result (Figure 3.5).

Table 3.12 ASTM Code determination values

Gas Ratios	Value	Code
$W=CH_4/H_2$	0<W<0.1	1
	0.1<W<1	2
	1<=W<3	3
	W>3	4
$X=C_2H_6/CH_4$	X<1	0
	X>1	1
$Y=C_2H_4/C_2H_6$	Y<1	0
	3<Y<1	1
	Y>3	2
$Z=C_2H_2/C_2H_4$	Z<0.5	0
	3<Z<0.5	1
	Z>=3	2

Table 3.13 Concentration L_1 for Doernenburg Method

Key Gas	Concentration L_1 (in ppm)
Hydrogen	100
Methane	120
Carbon Monoxide	350
Acetylene	35
Ethylene	50
Ethane	65

Table 3.14 Fault Diagnosis Table using ASTM Codes

S. No.	Code W	X	Y	Z	Kind of Fault
1	2	0	0	0	Normal
2	1	0	0	0	Partial Discharge
3	3	0	0	0	Increase in temperature less than equal to 150^0C
4	4	0	0	0	Increase in temperature less than equal to 150^0C
5	3	1	0	0	Increase in temperature from 150^0C – 200^0C
6	4	1	0	0	Increase in temperature from 150^0C – 200^0C
7	4	1	0	0	Increase in temperature from 200^0C – 300^0C
8	2	0	1	0	Increase in temperature in all conductors
9	3	0	1	0	Circulating current in winding
10	3	0	2	0	Circulating current between core and tank
11	2	0	0	1	Spark with low energy density
12	2	0	1	1	Spark with high energy density
13	0	0	1	2	Spark with low energy density
14	0	0	2	1	Spark with low energy density
15	2	0	2	2	Continuous spark
16	1	0	0	1	Partial discharge with tracking
17	1	0	0	2	Partial Discharge

G. Doernenburg Method

This method utilizes the four gas ratiosi.e.CH_4/ H_2, C_2H_2/CH_4, C_2H_4/C_2H_6 and C_2H_2/ C_2H_4. The gas values at first exceed the concentration value L_1, to confirm whether there is really an abnormality within the unit and then whether the generation of each gas is sufficient enough for the ratio analysis to be applicable [Perrier et al. 2012]. The key gases and their concentration L_1 has been tabulated in Table 3.13.

If all the succeeding gas ratios for a particular fault-type lie within the values in the given, the suggested diagnosis is valid.

Table 3.15 Fault Diagnosis for Doernenburg Method

Gas	L_1 limit	G_1 limit (PPM per month)	G_2 limit (PPM per month)
H_2	100	10	50
CH_4	75	8	38
C_2H_2	3	3	3
C_2H_4	75	8	38
C_2H_6	75	8	38

Table 3.16 Fault Diagnosis for Duval Triangle Method

Suggested Fault Diagnosis	Ratio R_1 CH_4/H_2 M	Ratio R_2 C_2H_2/C_2H_4 N	Ratio R_3 C_2H_6/C_2H_2 O	Ratio R_4 C_2H_2/CH_4 P
Thermal Decomposition	>1,0	<0.75	<0.4	<0.3
Corona (Low intensity Partial Discharge)	<0.1	Not Significant	<0.4	>0.3
Arcing (High intensity Partial Discharge)	>0.1 <1.0	<0.75	>0.4	<0.3

Once an abnormality has been determined to exist, to obtain fault diagnosis, the total accumulated amount of the three Duval Triangle gases (CH_4, C_2H_2 and C_2H_4) has been calculated. Each gas has been divided by the total amount of gases to determine the percentage of each gas of the total amount [Sabau et al. 2000]. Finally, the percentage of the total amount of gases has been plotted on the triangle to arrive at the diagnosis result (Figure 3.5).

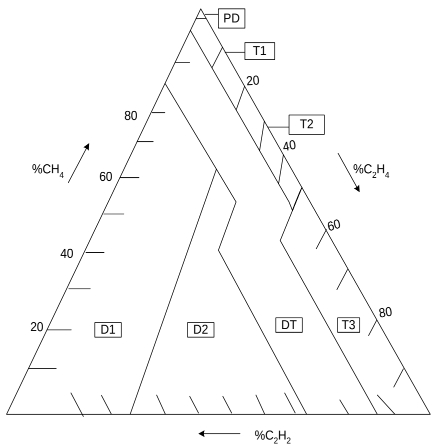

Figure 3.5 The Duval Triangle

Chapter 4: Artificial Intelligence Techniques

4.1 Introduction

For an intelligent fault detection based on Dissolved Gas Analysis (DGA), many researchers have used neural network concepts. Multilayer perception neural network has been widely used for prediction, classification, regression, time series prediction etc. An Artificial Neural Network (ANN) is trained to detect the faults of the transformer. Artificial neural networks (ANNs) have been used to deal with the transformer fault diagnosis, due to their accurate and efficient performance in numerical modeling problems. The ANNs can acquire new experiences by incremental training from newly obtained samples. Moreover, they can interpolate and extrapolate from their experiences, yielding at least a best guess of the fault. The ANNs trained by an error back-propagation algorithm have great diagnostic capabilities. However, certain issues, such as local convergence, determination of the network configuration and control parameters (learning rate and momentum constant), must be resolved before the ANNs can become a practical tool. Furthermore, the error back-propagation algorithm is based on a gradient descent technique using classification errors to modify connection weights and bias terms in the ANNs. The gradient descent technique may stagnate at the potentially local optimal solutions, reducing the performance of the ANNs, because the typical search space frequently includes local minima [Angeli et al. 2001; Balasubramaniam et al. 2007, Behjat et al. 2012; Javed et al. 2012 ; Qianjin et al. 2014].

Artificial neural network (ANN) is named after the network of nerve cells in the human brain. McCulloch and Pitts have developed the neural networks for different computing machines. There are extensive applications of all kinds of ANN in the field of communication, control, instrumentation and forecasting. The ANN is capable of performing on nonlinear input and output systems in the workspace due to its large parallel interconnection between different layers and its nonlinear processing characteristics. An artificial neuron basically consists of a computing element that performs the weighted sum of the input signal and the connecting weight. The sum is added with the bias or threshold and the resultant signal is then processed for nonlinear function of sigmoid or hyperbolic tangent type [Candela et al. 2001; Farag et al. 2001; Balasubramaniam et al. 2006; Joshi et al. 2010; Singh et al. 2011]. Every neuron is associated with three parameters whose learning can be adjusted. These parameters are as follows the connecting weights, the bias and the slope of the nonlinear function

The structure of a neural network (NN) may be single layer or it may be multilayer. In multilayer structure, there can be one or many artificial neurons in each layer. In the practical cases, there may be a number of layers to each and every parameter under consideration. Each neuron of one layer is connected to each neuron of the next layer. The functional-link ANN is another type of single layer NN. In these networks, the input data is allowed to pass through a functional expansion block where the input data are nonlinearly mapped to more number of points. This is achieved by using trigonometric functions, products or power terms of the input. The output of the functional expansion is then passed through that single neuron.

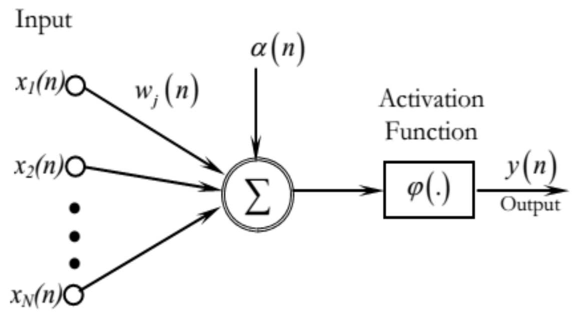

Figure 4.1 Structure of a single neuron

The basic structure of an artificial neuron is presented in figure 4.1. The neuron is involved in the computation of the weighted sum of inputs and threshold. The resultant signal is then passed through a nonlinear activation function. This is also known as a perceptron. Different types of nonlinear functions are shown in the figure 4.2.

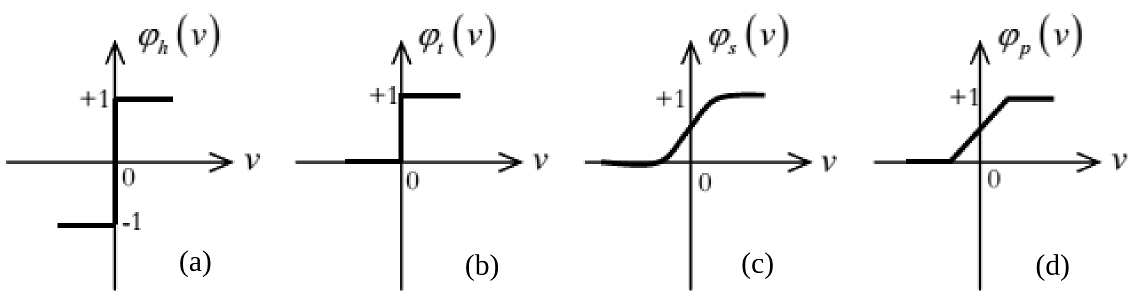

Figure 4.2 Different types of nonlinear activation functions, (a) Signum function or hard limiter, (b) Threshold function, (c) Sigmoid function, (d) Piecewise Linear

The various types of activation functions have been described as follows:

(a) **Signum Function:** The signum function returns one of the two-states (corresponding to neuronal firing and non-firing states) depending on the input parameter and the threshold parameter. This two-state neuron is suited to address binary information. This function is also termed as Hard Limiter Function because it can be implemented in an Op-Amp without feedback. The Signum Function is represented as below:

$$\varphi^{h\lim}\ v\ = \begin{cases} 1 & v > 0 \\ 0 & v = 0 \\ -1 & v < 0 \end{cases} \tag{4.1}$$

where $\varphi^{h\lim}$ is the Signum Function or Hard Limiter Function and v is the input to the Signum or Hard Limiter Function.

(b) **Threshold Function:** This function is represented as below:

$$\varphi^{thr}\ v\ = \begin{cases} 1 & v \geq 0 \\ 0 & v < 0 \end{cases} \tag{4.2}$$

where φ^{thr} is the Threshold Function and v is the input to the Threshold Function.

(c) **Sigmoid Function:** This function is S-shaped and is the most common form of the activation function used in artificial neural network. It is the most common form of activation function used in the Artificial Neural Network architecture. Such type of function exhibits a graceful balance between linear and nonlinear behaviour. The Sigmoid Function is represented as below:

$$\varphi^{sig}\ v\ = \frac{1}{1 + \exp\ -a_p} \tag{4.3}$$

Where φ^{sig} is the Sigmoid Function and v is the input to the Sigmoid Function, a is the slope of the sigmoid function. For the steady convergence, a proper choice of a is very important. A Threshold Function assumes the value of 0 or 1, whereas a sigmoid function assumes a continuous range of values form 0 and 1. The Sigmoid function is differentiable, which is an important characteristic feature of neural network theory.

The derivative of the sigmoid function can be easily calculated as follows:

$$\frac{\partial \varphi(v)}{\partial v} = \varphi(v)\left(1-\varphi(v)\right) \tag{4.4}$$

(d) **Piecewise - Linear Function:** The Piecewise - Linear Function is represented as:

$$\varphi^{pwl}(v) = \begin{cases} 1, & v \geq 1/2 \\ v+1/2, & -1/2 < v < 1/2 \\ 0, & v \leq -1/2 \end{cases} \tag{4.5}$$

Where φ^{pwl} is the Piecewise - Linear Function and v is the input to the Piecewise - Linear Function.

The amplification factor inside the linear region is assumed to be unity. The following two situations may be viewed as special forms of the piecewise linear function:

a) A linear combiner arises if the linear region of operation in maintained without running into saturation.
b) The piecewise-linear function reduces to a threshold function if the amplification factor of the linear region in made infinitely large.

In the neural network the most basic information - processing unit is the neuron model. The neural model organized in three or more layers, such as input layer (one or more), hidden layer (one or more) and single output layer, use a back-propagation for training, presented in Figure 4.3. The number of neurons in the hidden layer remains variable for each diagnosis criterion, depending upon the complexity. Each neuron

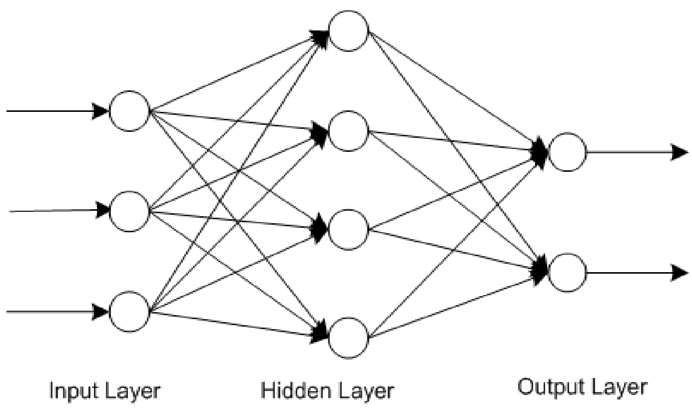

Figure 4.3 General Architecture of Artificial Neural Network (ANN)

model receives input signals, which are multiplied by synaptic weights. An activation function transforms these signals into an output signal to the next neuron model and so on [Moravej et al. 2001; Kuo et al. 2007].

In neural network, training algorithm plays a very important role. The training algorithm adjusts the weights, biases in such a manner that the input-output mapping is done in a minimum amount of time. Back propagation (BPN) algorithm is one of the age old learning algorithms and is used for multi-layer feed forward neural network for a supervised training. The central idea behind the term back-propagation is that the errors for the units of the hidden layer are determined by back propagating the errors of the units of the output layer [Pugh et al. 1961; El-Arroudi et al. 2007; Upender et al. 2010; Zakaria et al. 2014]. Figure 4.4 shows the general flow chart of BPN.

4.2 Back propagation Training Algorithm

Given a set of training pairs $(x^1, d^1), ..., (x^i, d^i)$

STEP 1 Initialize weights and thresholds. Initialize the weights and thresholds to small random values.

STEP 2 Present new input vectors and desired output. Present the new input vector x^i and the corresponding desired output d^i. Calculate actual outputs.

STEP 3 Calculate error gradients.

STEP 4 Adapt weight vectors and thresholds:

$$w(k+1) = w(k) - \alpha \nabla_w E(w(k), t(k)) \quad (4.6)$$

$$t(k+1) = t(k) - \alpha \nabla_t E(w(k), t(k)) \quad (4.7)$$

STEP 5 Repeat by returning to Step 2.

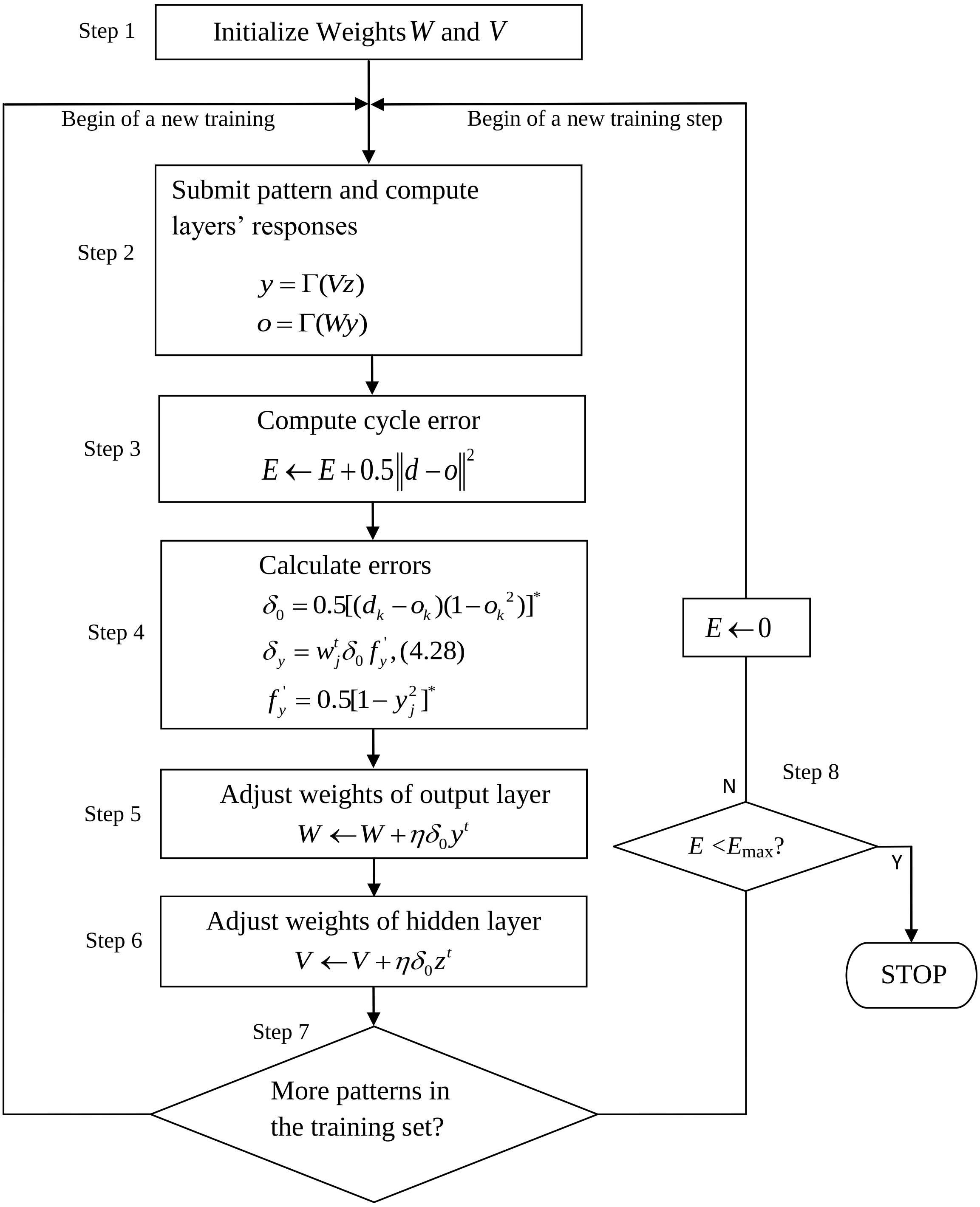

Figure 4.4 General flow chart of Back Propagation Neural Network

The ANNs can acquire new experiences by incremental training from newly obtained samples. Moreover, they can interpolate and extrapolate from their experiences, yielding at least a best guess of the fault. The ANNs trained by an error back-propagation algorithm have great diagnostic capabilities. However, certain issues, such as local convergence, determination of the network configuration and control parameters (learning rate and momentum constant), must be resolved before the ANNs can become a practical tool. Furthermore, the error back-propagation algorithm is based on a gradient descent technique using classification errors to modify connection weights and bias terms in the ANNs. The gradient descent technique may stagnate at the potentially local optimal solutions, reducing the performance of the ANNs, because the typical search space frequently includes local minima. Additionally, this algorithm is mainly dependent on learning rate and momentum factor. To remove this kind of bottle neck, conjugate gradient methods and scaled conjugate gradient methods are widely used. In the conjugate gradient algorithms, a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions.The Levenberg-Marquardt (LM) algorithm is an approximation to the Newton method used also for training NNs. LM is popular in the NN domain, although it is not that popular in the meta-heuristics field.

4.3 Probabilistic Neural Network

There are some drawbacks of back propagation training algorithm. It is too slow for practical applications, especially when too many hidden layers are employed. An appropriate selection of training parameters in the back propagation algorithm is difficult and purely based on trial and error. There are many learning algorithms or modifications of the back propagation algorithm in the literature but none of these methods are able to completely solve the problems associated with the back propagation algorithm [Upender et al. 2008; Samantaray et al. 2011; Manjula et al. 2013].

To overcome these drawbacks of back propagation algorithms, another type of neural network called Probabilistic Neural Network (PNN) classifier is used in this present research work. In1990, Specht introduced PNN architecture as a three layer feed forward neural network architecture [Specht et al. 1990; Huang et al. 2007; Mohammed et al. 2009,Balaga et al. 2010; Javed et al. 2012; Agrawal et al. 2012; Chenxi et al. 2014]. The layers in PNN are input layer, pattern layer and summation layer.

PNN is the neural network implementation of Parzen window kernel discrimination analysis. PNN is implemented using probabilistic model. Unlike back propagation algorithm, it is bound to converge. No learning process is required for PNN, and there is no need to set weight.

Output of pattern layer is calculated as

$$\varphi_{ki}(x) = \frac{1}{(2\pi)^{\frac{d}{2}}\sigma^d}\exp\left[-\frac{(x-x_{ki})^T(x-x_{ki})}{2\sigma^2}\right] \tag{4.8}$$

where x_{ki} is the neuron vector, σ is the smoothing parameter, d is the dimension of pattern vector x, φ_{ki} is the output of pattern layer.

Output of summation layer of kth input is given as

$$p_k(x) = \frac{1}{(2\pi)^{\frac{d}{2}}\sigma^d N_i}\exp\left[-\frac{(x-x_{ki})^T(x-x_{ki})}{2\sigma^2}\right] \tag{4.9}$$

The output of decision layer is given by

$$c(x) = \arg\max(p_k(x)) \quad k = 1,2,3----m$$

4.4 Probabilistic Neural Network (PNN) Algorithm

PNN training algorithm is given as follows:

Begin procedure

Mark all patterns as unused

While training set contains unused

Patterns and cost(p) < C_{th}

Repeat

Set l = random number (1,N) and set k = class(x(l))

Until x (l) used, mark x(l) used

Compute the class probability values

Choose class c with max probability

Choose class c' with the second max probability

If $\frac{f^c(x(l))}{f^{c'}(x(l))} < r$ and $n < n_{max}$, then add a new pattern unit centred on x(l)

While number of iterations<= I_{max}, select new p = optimize (p)

End while

End if

4.5 Proposed Work

Figure 4.5 shows the flow chart for the proposed fault classification algorithm where the raw data is collected and data is pre - processed. After that, the dimension reduction and feature selection is performed and the last step of the classification flow chart is neural network based classification to determine different faults.In this proposed research, different topologies of back propagation learning algorithm i.e. gradient descent method, gradient descent with adaptive learning method and Levenberg-Marquardt method have been proposed for transformer fault diagnosis.

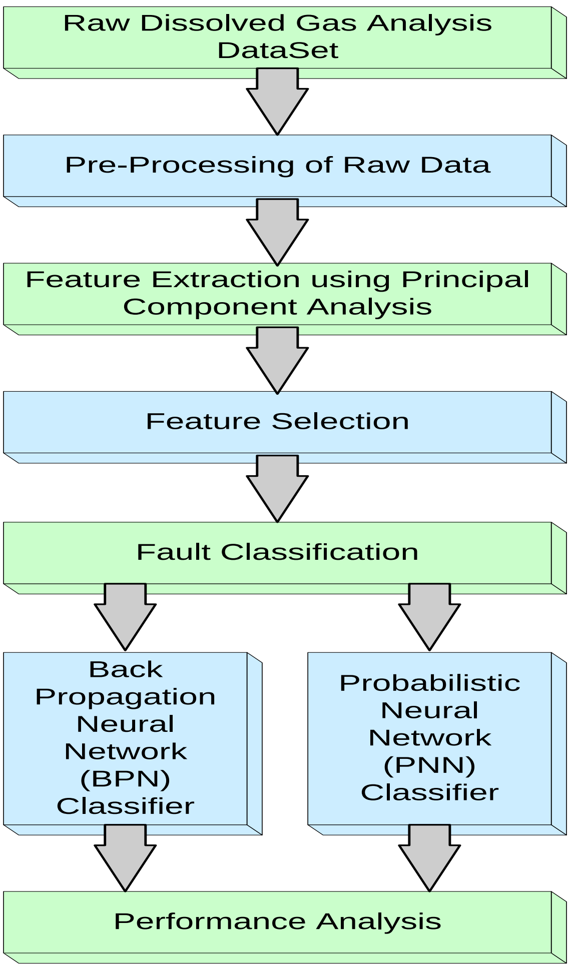

Figure 4.5 Flow chart of the proposed Fault Classification Scheme

4.5.1 Defining the Inputs and Outputs

Each configuration accepts the ratio of the concentration (ppm) of the gases (C_2H_2, C_2H_4, C_2H_6, H_2 and CH_4) i.e. $R_1(C_2H_2/C_2H_4)$,$R_2(CH_4/H_2)$ and R_3 (C_2H_4/C_2H_6) as input and predicts all the fault types in IEC 60599 ratio method (Table 4.1) as output, as shown in Figure 4.3.

Table 4.1 Diagnosis using the ratio method (IEC 60599)

Fault Type	R_1	R_2	R_3
Partial discharge (PD)	<0.1	<0.1	<0.2
Low energy discharge (D_1)	>1	0.1-0.5	>1
High energy discharge (D_2)	0.6-2.5	0.1-1	>2
Thermal faults < 300^0C (T_1)	<0.1	>1	<1
Thermal faults < 700^0C (T_2)	<0.1	>1	1-4
Thermal faults > 700^0C (T_3)	<0.1	>1	>4

The historical DGA database (raw) based on actual gas records collected from Punjab State Electricity Board was used for the training and testing purpose of the neural network. The 500 DGA samples were collected, 250 of which have been used for training purpose while 250samples have been used for testing and validation purpose. These DGA samples associated with their real fault types have been classified with the help of various DGA interpretative techniques, by the Electricity Board experts, after internal examination of the suspected transformers and the subsequent analysis.

4.5.2 ANOVA Plot of DGA Database

The DGA data has been normalized before training. ANOVA plot of normalized DGA data is shown in Figure 4.6.

The standard ANOVA table has six columns:

1. The source of the variability.
2. The sum of squares (SS) due to each source.
3. The degrees of freedom (df) associated with each source.
4. The mean squares (MS) for each source, which is the ratio SS/df.
5. The F-statistic, which is the ratio of the mean squares.
6. The p value, which is derived from the Cumulative Distribution Function of F.

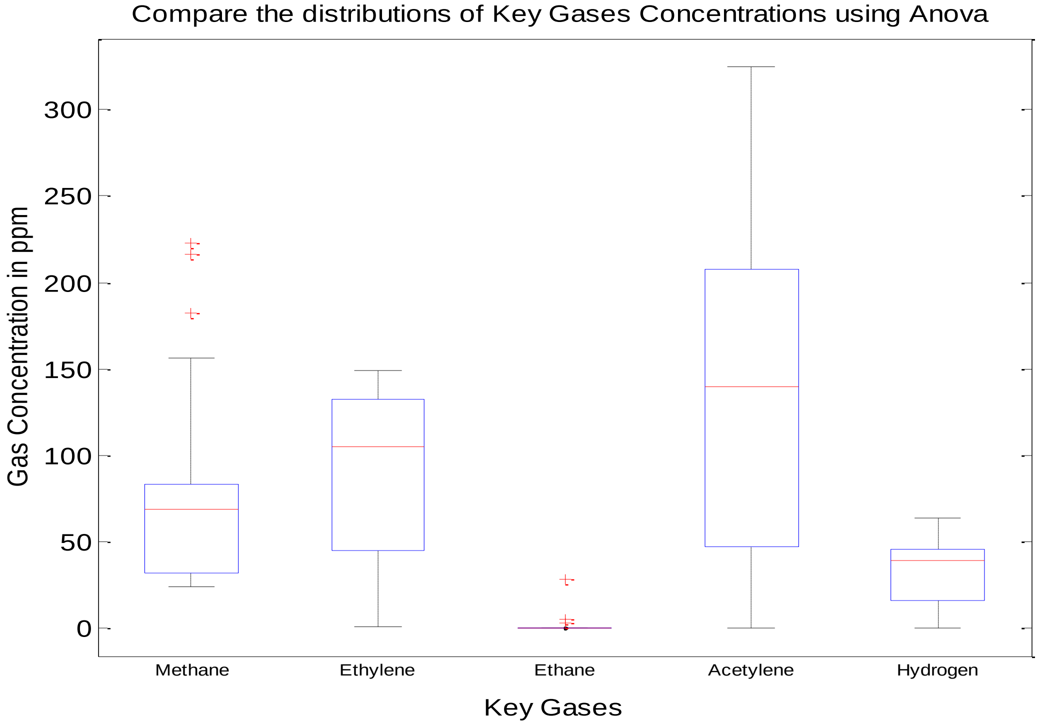

Figure 4.6 ANOVA plot of raw data collected from different transformers

The ANOVA parameters have been calculated as follows:

(a) Sum of squares (SS) is calculated by:

$$SST = \sum x^2 - \frac{\sum x^2}{n} \tag{4.10}$$

$$SSTR = \sum \frac{T_j^2}{n_j} - \frac{\sum x^2}{n} \tag{4.11}$$

$$SSE = SST - SSTR$$

(b) Mean squares (MS) is calculated by:

$$MSTR = \frac{SSTR}{k-1} \tag{4.12}$$

(c) Degree of freedom (df) is calculated by:

$$df = n-1 \tag{4.13}$$

(d) Test statistic for one-way ANOVA (independent samples, normal populations, and equal population standard deviations) is calculated by:

$$F = \frac{MSE}{MSTR} \tag{4.14}$$

where $x = 1,2,3,....,n;$ number of observations

T_j = Sum of sample data from population

n_j = Size of sample from population

k = Number of populations

SST = Total sum of squares

$SSTR$ = Sum of squares for treatment

SSE = Sum of squares due to error

$MSTR$ = Mean square between treatment

Table 4.2 ANOVA Table

Source	SS	df	MS	F	Prob > F
Columns	640911.1	4	160227.8	48.65	6.4435e-31
Error	905716.9	275	3293.5		
Total	1546627.9	279			

Table 4.2 shows the ANOVA parameters calculated using the collected DGA data, which shows the skew ness of the data and it also shows that there are very less outliers.

4.5.3 Training the Neural Network

The encoding of the proposed neural network output has been done using binary encoding i.e. if any of the fault type occurs, as described in IEC 60599 method (Table 4.1), the corresponding output is one and in the absence of a particular fault, the corresponding output is zero.The Back Propagation Network has been trained using the following network parameters:

Gradient = 9.29e-006, μ= 1e-006, Learning Rate = 0.02, Momentum Factor = 0.8, Number of Neurons in hidden layer = 18, Tolerance = 0.005

4.5.4 Choosing the Architecture of Neural Network

Different back propagation learning algorithms, namely, Gradient Descent, Levenberg-Marquardt, Conjugate Gradient and Resilient back-propagation algorithms have been compared for transformer fault classification. Five key gas ratios are considered as input to the neural network and six output codes are treated as the output of the neural network. An Artificial Neural Network of (5x18x6) is designed and back propagation algorithm is used to train the neural network. The dataset is divided in to two categories such as training set (50%) and testing set (50%). The six output codes, to be treated as output of the neural network includes all thefault types in IEC 60599 ratio method (Table 4.1).There are many learning algorithms associated with the back propagation. The most commonly used is steepest descent algorithm also called as gradient descent algorithm. The idea is to make a change in the weight proportional to the negative of the derivative of the error as measured on the current pattern with respect to each weight:

$$\Delta_p w_j = -\gamma \frac{\partial E^p}{\partial w_j} \tag{4.15}$$

where γ is the constant of proportionality known as learning rate. But the limitation of steepest descent algorithm is slow convergence rate. To counter this slow convergence, many methods were developed. These methods include momentum based back propagation algorithm, variable learning back propagation algorithm, Levenberg – Marquard at back propagation, conjugate back propagation (Quasi-Newton method).In case of variable learning back propagation algorithm, the learning rate is adapted after every learning pattern in order to minimize the error on the training set [Angeli et al. 2004; Georgilakis et al. 2006]. Levenberg-Marquardt algorithm was designed to attend second order training speed without calculating Hessian Matrix. It has been proved that Levenberg-Marquardt training algorithm provides superior performance than conventional gradient descent algorithm. In conjugate gradient descent algorithm, the step size is adjusted in every iteration. In resilient back propagation algorithm, only the sign of the derivative is used to update the weight [Rao et al. 2008; Sharma et al. 2010; Joshi et al. 2010]. The magnitude of the derivative has no effect on the weight update.

4.5.5 Receiver Operating Characteristics

Receiver Operating Characteristics (ROC) shows the trade-off between sensitivity and specificity [Erkel et al. 1998; Tang et al. 2004; Shrivastava et al. 2010]. In other words, ROC curves provide a visual tool to examine the trade-off between the ability of a classifier to correctly identify positive fault cases and the number of negative fault cases that are incorrectly classified.Any increase in sensitivity will result in decrease in specificity. The closer the curve is to the left hand margin, the more accurate the test is. The slope of the tangent line at a cut-point gives the likelihood ratio for that certain value. ROC for Probabilistic Neural Network (PNN) based fault analysis has been shown in Figure 4.7. Class 1 and Class 2 represent the healthy and faulty state of transformer. It clearly indicates that PNN is a better fault classifier, as it is closer to the zero false positive axis.

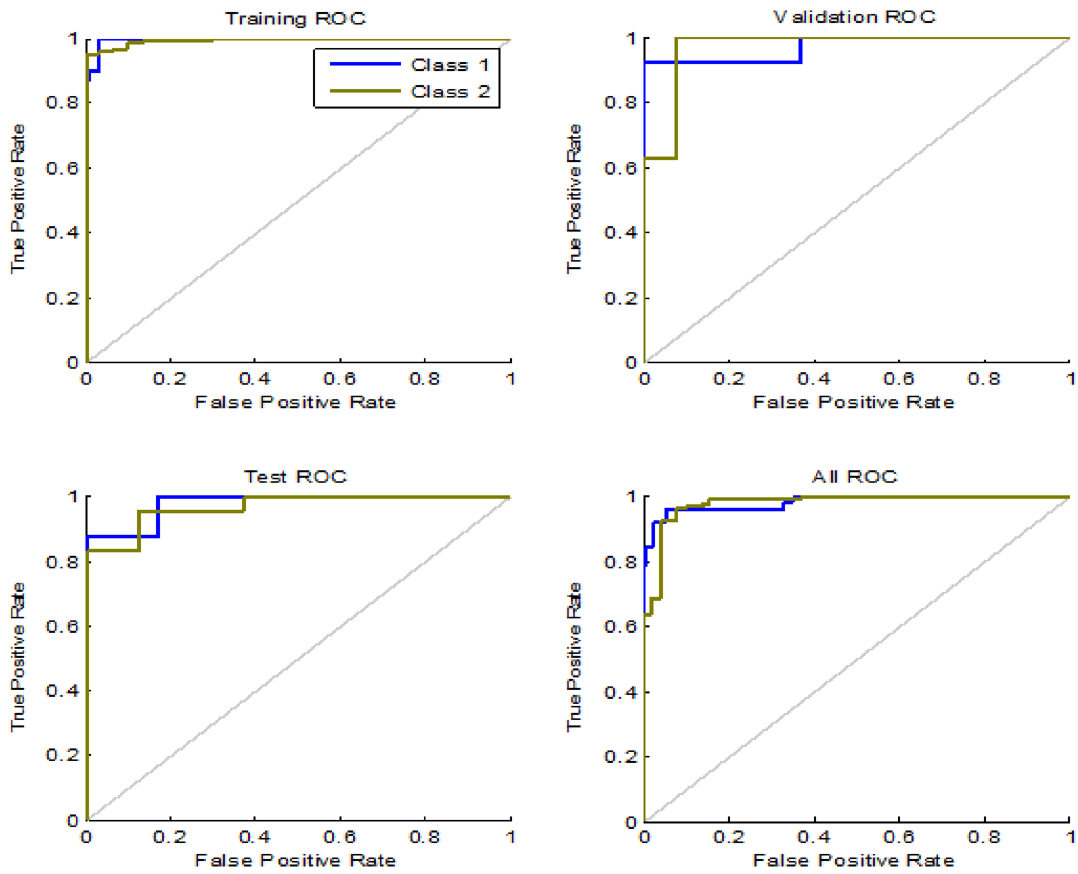

Figure 4.7 Receiver Operating Characteristics for Probabilistic Neural Network (PNN)

4.5.6 Comparative Analysis of Various Intelligent Techniques

A) Table 4.4 shows the comparison of weight update rule in different BPN Learning Methods.

B) Table 4.3 shows the comparative analysis of the four different back propagation learning algorithms on the basis of CPU Time, Regression, Train Recognition Accuracy, Sensitivity and Specificity and it is seen that Levenberg-Marquardt method outperforms the other back propagation learning algorithms.

The configuration of the system used for the simulation process is as follows:

(a) Processor: Intel(R) Core(TM) i3 CPU
(b) Processor Speed: 2.27 GHz
(c) Installed Memory(RAM): 3.00 GB (2.86 GB usable)
(d) System type: 64-bit Operating System (Window7 Professional N)

The value of sensitivity and specificity for different back propagation learning algorithms can be calculated as follows:

Sensitivity is the ratio between the correctly classified data of a particular class to the total data of that particular class i.e.

$$\text{Sensitivity } S_e \ \% = \frac{TP}{TP+FN} \times 100, \tag{4.16}$$

where TP is true positive i.e. fault correctly classified as fault, TN is true negative absence of fault correctly classified as absence of fault, FP is false positive i.e. absence of fault incorrectly classified as presence of fault and FN is false negative i.e. presence of fault incorrectly classified as absence of fault.

Specificity is the measure of the ability of the classifier to reject the non-events i.e.

$$\text{Specificity } S_p \ \% = \frac{TN}{TP+FP} \times 100 \tag{4.17}$$

C) Figure 4.8 shows the error and epoch graph for different back propagation learning algorithms. This figure gives a plot between the error values i.e. the difference between the desired output and actual output, and the number of iterations it takes to reach to minimum error. From this figure, it is clear that Levenberg-Marquadt algorithm takes less number of iterations to converge to the required tolerance level.

D) Figure 4.9 shows the regression (R) plot of different learning algorithms. It is plotted to measure the correlation between outputs and targets. An R value of one means a close relationship, zero a random relationship. The Regression plot drawn in this figure shows that the value of R is closest to one which indicating that output of the training network is quite close to the targets, when the dataset was trained with Levenberg-Marquardt.

E) Table 4.5 shows the confusion matrix for back propagation neural network and its various learning algorithms. Let a, b, c and d be the entities of a 4x4 matrix, respectively. Then, a represents true positive data i.e. particular fault classified correctly as fault, b represents false negative data i.e. particular fault present incorrectly classified as absence of fault, c represents false positive rate i.e. particular fault not present incorrectly classified as fault and d represents absence of fault correctly identified as absence of fault. Keeping, this in mind, a confusion matrix has been created for all the fault-types. Accuracy percentage classifies different transformer fault type of the fault classification algorithms i.e. Gradient Descent Algorithm, Levenberg Marquardt algorithm, Gradient Descent Scaled Conjugate and Resilient, is 88.3%, 93.6%, 93.5% and 93%, respectively.The accuracy percentage is higher, when LM method is used to classify different fault-types of power transformer.

Table 4.6 shows the confusion matrix for probabilistic neural network and accuracy of fault classification using PNN comes out to be 95.6% which is an improved accuracy than back-propagation learning algorithms. The accuracy of PNN learning algorithm has been checked using confusion matrix. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. The name stems from the fact that it makes it easy to see, if the system is confusing two classes (i.e. commonly mislabelling one as another).

Table 4.3 Comparison amongst different Back Propagation (BPN) learning methods

BPN Learning Methods	CPU Time (in seconds)	Regression (R)	Test Recognition Accuracy (in %)	Sensitivity (in %)	Specificity (in %)
Gradient Descent	11.84	0.97322	92.72	95.6	73.1
Levenberg-Marquardt	5.28	0.98072	98.42	98.3	89.2
Conjugate Gradient	9.40	0.97793	85.27	96.2	76.5
Resilient	3.92	0.97641	92.57	92.4	78.8

A comparison of root mean square (RMSE) values for training, testing and validation samples for Back Propagation Network (BPN) and Probabilistic Neural Network (PNN) has been carried out in Table 4.7. As clearly evident from the table, the value of RMSE is lower for PNN, indicating that PNN is a better fault classifier when compared to BPN.

G) Table 4.8 shows the diagnostic accuracy comparison of fault-type classification (according to IEC 60599) using BPN and PNN. It reveals that PNN outperforms in fault-type classification task when compared to BPN.

Table 4.4 Comparison of weight update rule in different BPN Learning Methods

BPN Learning Methods	**Weight Update Rule**
Gradient Descent	$\Delta w_p = -\frac{\partial E}{\partial w_p} = \sum_{k=1}^{n} (z_{pk} - z'_{pk}) \cdot \frac{\partial z'_{pk}}{\partial w_p}$ where w_p is network weight, E is error, z_{pk} is be the value of the k^{th} observed variable in the p^{th} training sample and z'_{pk} is the corresponding ANN approximation.
Levenberg - Marquardt	$w_{i+1} = w_i - (H - \lambda I)^{-1} d$ where w_{i+1} is updated weight, w_i is network weight, H is Hessian Matrix, λ is the blending factor which will determine the mix between steepest descent and quadratic approximation and d is the steepest descent.
Resilient	$\Delta w_p = \begin{cases} -\Delta_{ij}^{(t)}, if \frac{\partial E^{(t)}}{\partial w_{ij}} > 0 \\ +\Delta_{ij}^{(t)}, if \frac{\partial E^{(t)}}{\partial w_{ij}} < 0 \\ 0, else \end{cases}$ and $w_{ij}^{t+1} = w_{ij}^{(t)} + \Delta w_{ij}^{(t)}$ where w_{ij} is weight update from i^{th} to j^{th} neuron, E is error, t is the step time, and Δ_{ij} is individual update-value for each connection, which solely determines the size of the weight update

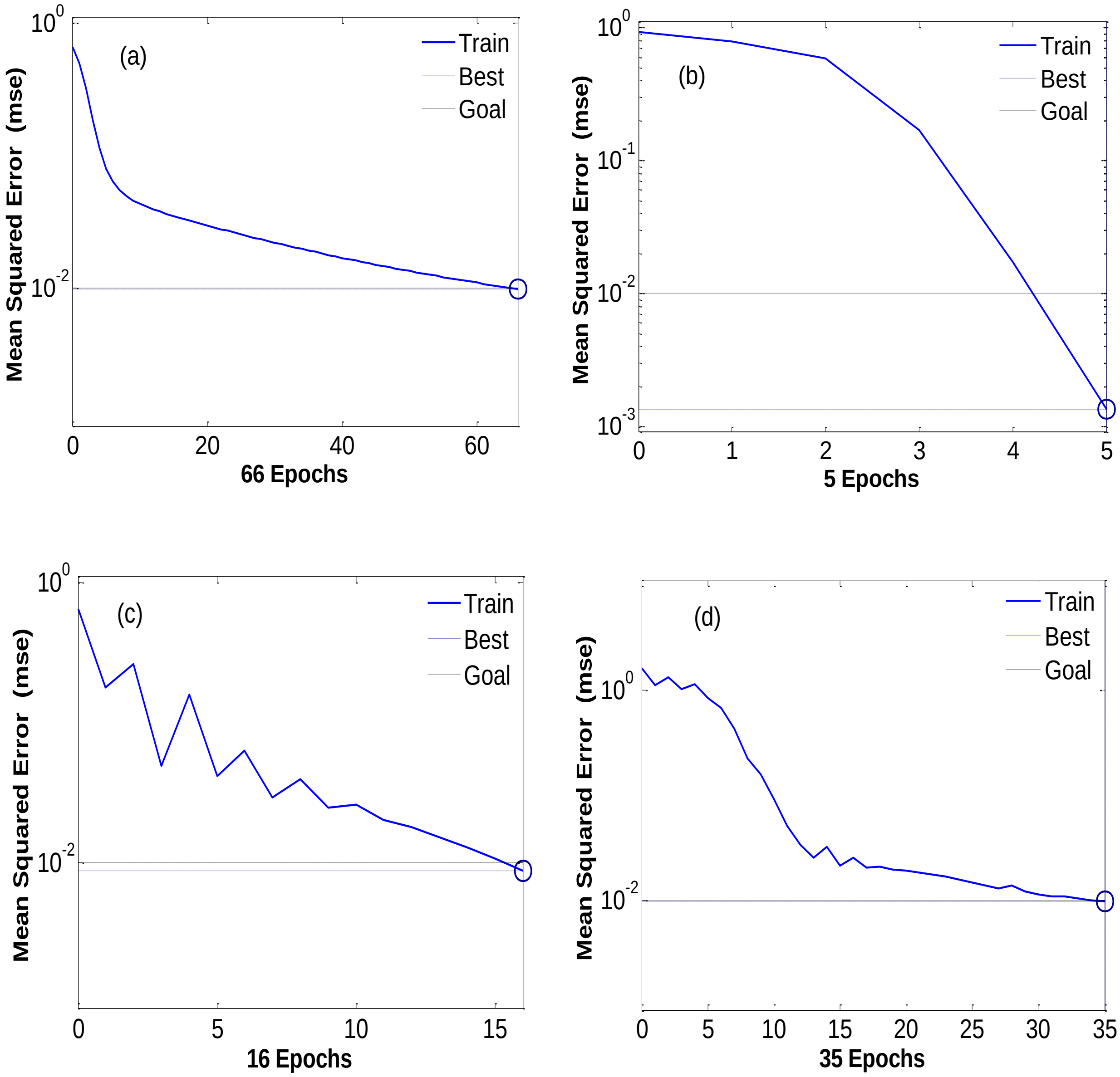

Figure 4.8 Error and epoch graph of (a) Gradient Descent Method. Best Training Performance is 0.0099 at epoch 66. (b) Levenberg-Marquardt Method. Best Training Performance is 0.099 at epoch 5. (c) Conjugate Gradient Descent Method. Best Training Performance is 0.0087 at epoch 16. (d) Resilient Method. Best Training Performance is 0.0097 at epoch 35.

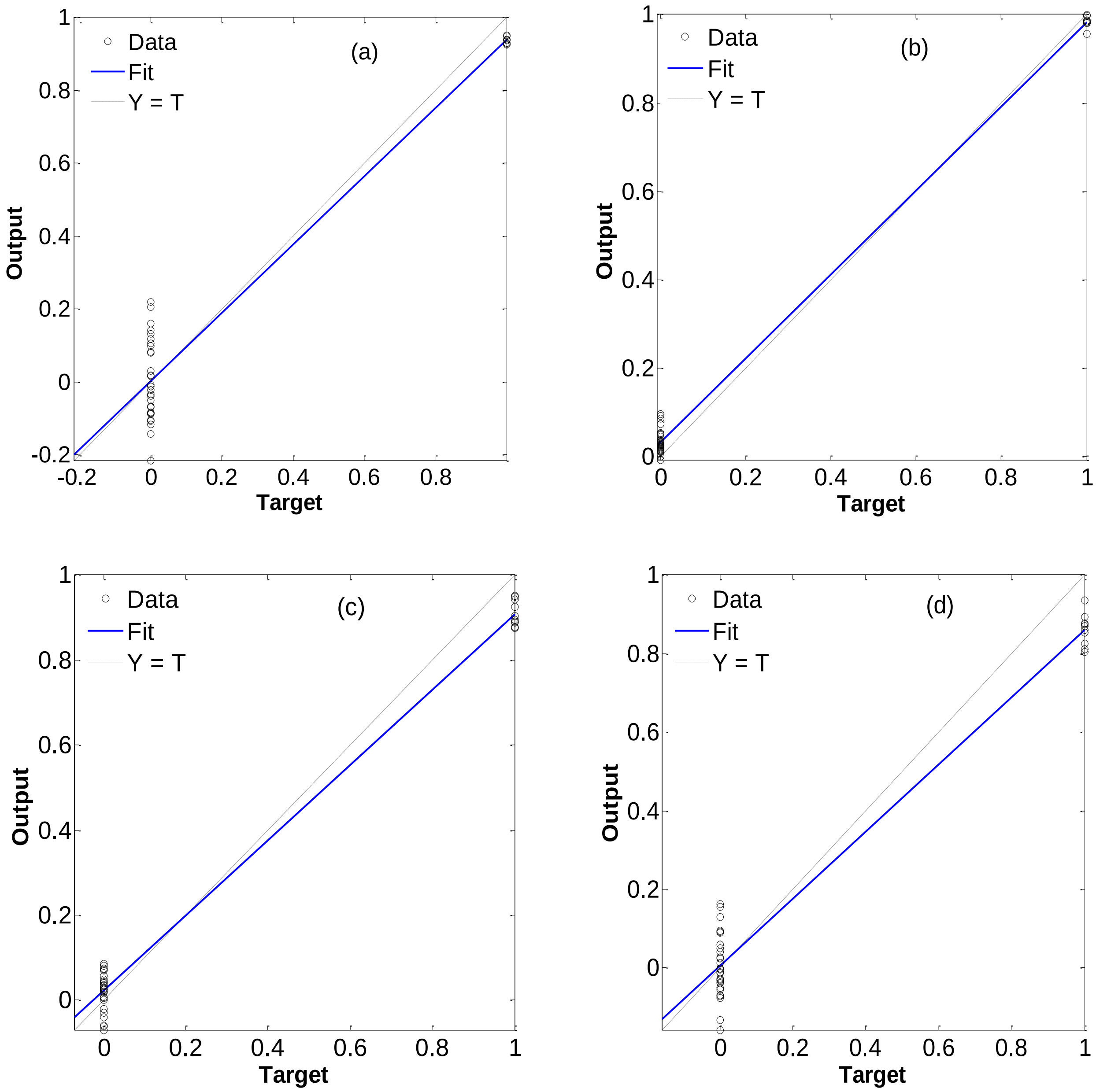

Figure 4.9 Regression Plot of (a) Gradient Descent Method. R= 0.97. Output = 0.94 × Target + 0.0022. (b) Levenberg-Marquardt Method. R= 0.99. Output= 0.95 × Target + 0.032. (c) Conjugate Gradient Descent Method. R= 0.96. Output = 0.89 × Target + 0.020. (d) Resilient Method. R= 0.95. Output = 0.86 × Target + 0.004.

Table 4.5 Confusion Matrix of Back Propagation Neural Network showing fault classification results of different algorithms. GD = Gradient Descent Algorithm, LM = Levenberg Marquardt algorithm, CGD = Gradient Descent Scaled Conjugate, RA = Resilient, PD = Partial Discharge, D1 = Low energy discharge, D2 = High energy discharge, T1 = Thermal faults < 300^0C, T2 = Thermal faults < 700^0C, T3 = Thermal faults > 700^0C.

Algorithms ↓	Fault Type →	PD	D1	D2	T1	T2	T3
GD	PD	89	0	11	0	0	0
LM		100	0	11	0	0	0
CGD		100	0	0	0	0	0
RA		100	0	0	1	1	0
GD	D1	0	99	0	0	0	0
LM		0	97	0	0	0	0
CGD		0	84	0	4	0	0
RA		0	95	0	0	0	0
GD	D2	0	0	75	0	2	0
LM		0	0	98	2	4	0
CGD		9	0	85	0	1	1
RA		0	0	98	2	4	0
GD	T1	0	0	2	95	0	0
LM		0	0	0	95	0	0
CGD		2	0	0	98	0	0
RA		0	0	0	92	0	0
GD	T2	0	0	2	1	87	0
LM		0	0	0	0	90	1
CGD		0	0	1	0	95	0
RA		0	0	0	0	88	1
GD	T3	0	2	0	0	0	88
LM		0	0	0	0	1	88
CGD		1	0	0	0	0	99
RA		0	0	0	0	1	85

Table 4.6 Classification results for Probabilistic Neural Network using Confusion Matrix

Fault Type	Accuracy of PNN: 95.6%					
	PD	**D1**	**D2**	**T1**	**T2**	**T3**
Partial discharge (PD)	89	0	0	0	0	0
Low energy discharge (D_1)	0	99	0	0	0	0
High energy discharge (D_2)	0	0	98	0	0	0
Thermal faults < 300^0C (T_1)	0	0	0	95	0	0
Thermal faults < 700^0C (T_2)	0	2	0	0	96	0
Thermal faults > 700^0C (T_3)	1	0	0	0	0	97

F) The Artificial Neural Network (ANN) algorithms in the proposed research were compared by computing root mean square error (RMSE). RMSE is defined as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} y_t - y_a^{\ 2}} \quad (4.17)$$

Here N is number of samples, y_t is target value, y_a is actual value and y is average value of N observations. RMSE indicates the residual errors, which give a global idea of the difference between the observed and predicted values. The smaller the RMSE value, the better the forecasting model.

Table 4.7 Comparison of root mean square (RMSE) values for training, and validation samples for Back Propagation Network (BPN) and Probabilistic Neural Network (PNN)

Process	**Samples**	**RMSE for BPN**	**RMSE for PNN**
Training	300	4.489*10^-2	2.41*10^-2
Validation	300	9.918*10^-2	4.279*10^-2

Table 4.8 Diagnostic accuracy comparison of fault-type classification (according to IEC 60599) between Back Propagation Neural Network (BPN) and Probabilistic Neural Network (PNN)

Fault Type	**Accuracy (in %)**	
	BPN	**PNN**
Partial discharge (PD)	80.23	83.25
Low energy discharge (D_1)	84.89	87.52
High energy discharge (D_2)	86.9	91.58
Thermal faults < 300^0C (T_1)	78.5	90.2
Thermal faults < 700^0C (T_2)	77.6	85.5
Thermal faults > 700^0C (T_3)	81.5	79.8

H) To evaluate the performance of the classifiers to classify six fault classes, PNN is compared with different learning algorithms of back-propagation algorithm. The neural network is trained for 500 samples of training data (100 samples of each class). The network is further tested with 500 samples (100 samples of each class). Table 4.9 gives a comparative analysis of accuracy and regression among different learning algorithms of back propagation method and PNN. From this table, it is seen that PNN is a better classifier than others.

Table 4.9 Comparison of Regression and Accuracy amongst different intelligent methods

Learning Methods	**Regression (R)**	**Train Recognition Accuracy for six classes of faults (in %)**
Gradient Descent	0.98128	88.3
Levenberg-Marquardt	0.98232	93.6
Conjugate gradient	0.97905	93.5
Resilient BPN	0.97544	93
PNN	0.9875	95.6

To validate the simulated results with practical results, practical values of samples are taken. Electricity Board experts (from ten substations) and conventional DGA methods classified the faulty type of transformers which was eventually cross checked by the simulated result as shown in Table 4.9.

I) Table 4.10 gives the classification results and compares the actual fault with the simulated fault and from the comparison it is seen that PNN is a better classifier.

Table 4.10 Testing the classification results with actual faults where BPN- Back propagation neural network, GD- Gradient Descent, LM- Levenberg Marquardt, SCD- Gradient Descent Scaled Conjugate, RBP- Resilient Back-propagation, √- Fault classified properly and × - Fault not classified properly

Sample No.	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	Actual Fault	BPN				PNN
							GD	LM	SCD	RBP	
1	336	419	105	1074	21	High temp. overheat	×	√	×	√	√
2	160	130	33	96	0	Low temp. overheat	×	√	√	×	√
3	57	77	58	21	0	Low temp. overheat	√	×	√	√	√
4	565	93	34	47	0	Partial discharge	×	√	×	√	√
5	650	53	34	20	0	Partial discharge	√	√	×	×	×

Chapter 5: Fuzzy Logic and Adaptive Neuro-Fuzzy Inference System

5.1 Fuzzy Logic

5.1.1 Introduction

Fuzzy Logic offers a better way of representing imprecision and uncertainties in data. In fuzzy logic, a statement is true to various degrees, ranging from completely true through half-true to completely false. The principal objective is the treatment of inaccuracy and uncertainty of diagnosis (due to the values close to the limit values of classification procedures) by defining a fuzzy set. The fuzzy set comprises of the membership functions representing possibilities of degree of belonging to the set. The fuzzy logic systems are very helpful to approximate the relation between the measured values and the faults causing the different gas combinations [Anderson et al. 1998; Islam et al. 2000; Bansal et al. 2003; Arshad et al. 2005; Prabhakar et al. 2008; Ibrahim et al. 2014].

5.1.2 Proposed Fuzzy Structure

Figure 5.1 shows the structure of fuzzy diagnosis system. Fuzzy analysis consists of three parts viz. fuzzification, fuzzy inference and de-fuzzification. Fuzzification is the process of transforming crisp input values into grades of membership for linguistic terms of fuzzy sets. The membership function is used to associate a grade to each linguistic term. In practice, membership functions may have numerous different types, such as the triangular wave-shape, trapezoidal wave-shape, Gaussian wave-shape, bell-shaped wave-shape, sigmoidal wave-shape and S-curve wave-shape. The exact type of the wave-shape depends on the actual applications under consideration. For the systems which require considerable dynamic deviation in a small period of time, a triangular or trapezoidal wave-shape must be utilized. For the systems which require very high controlled accuracy, a Gaussian or S-curve wave-shape must be selected. Figure 5.2 (a) to (h) depict the shapes of different types of membership functions.

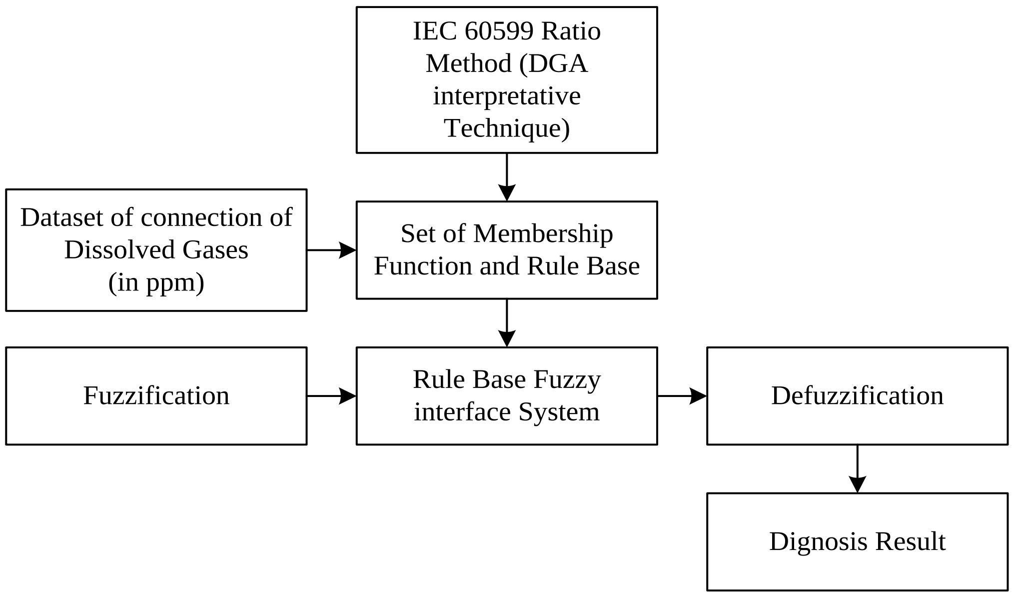

Figure 5.1 Structure of Fuzzy Diagnosis System

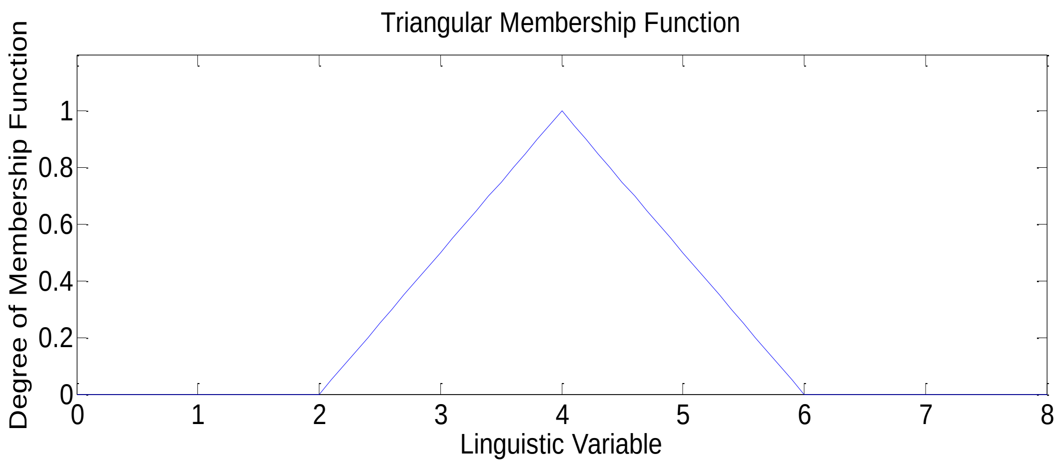

Figure 5.2(a) Triangular Membership Function

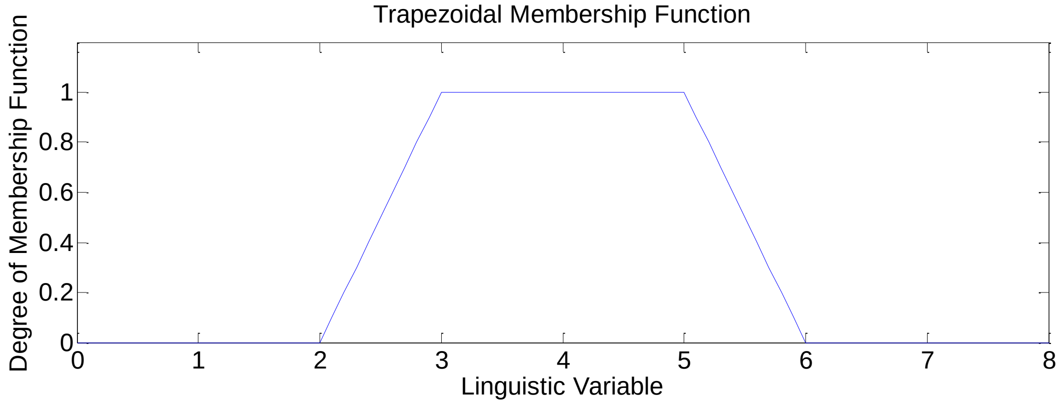

Figure 5.2(b) Trapezoidal Membership Function

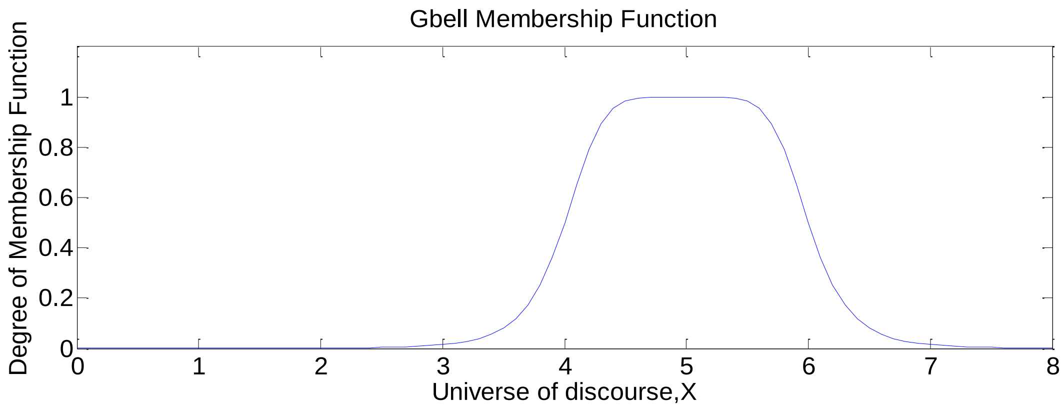

Figure 5.2(c) Gbell Membership Function

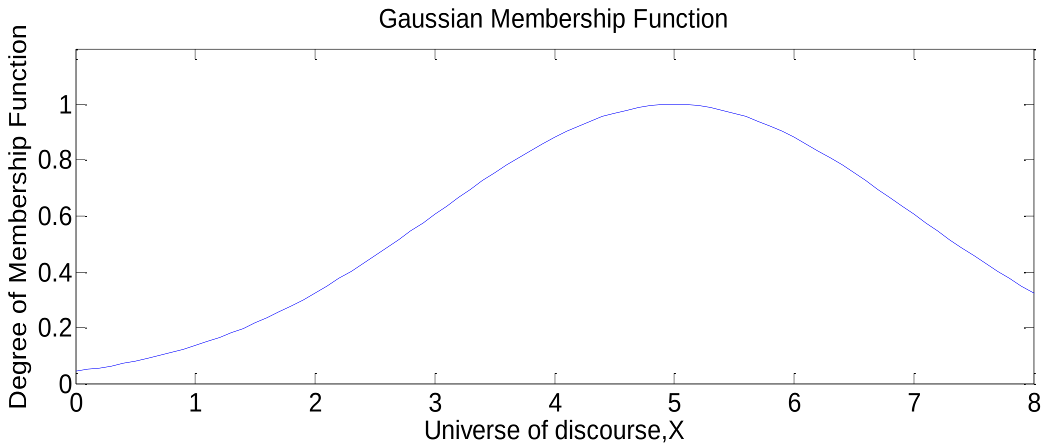

Figure 5.2(d) Gaussian Membership Function

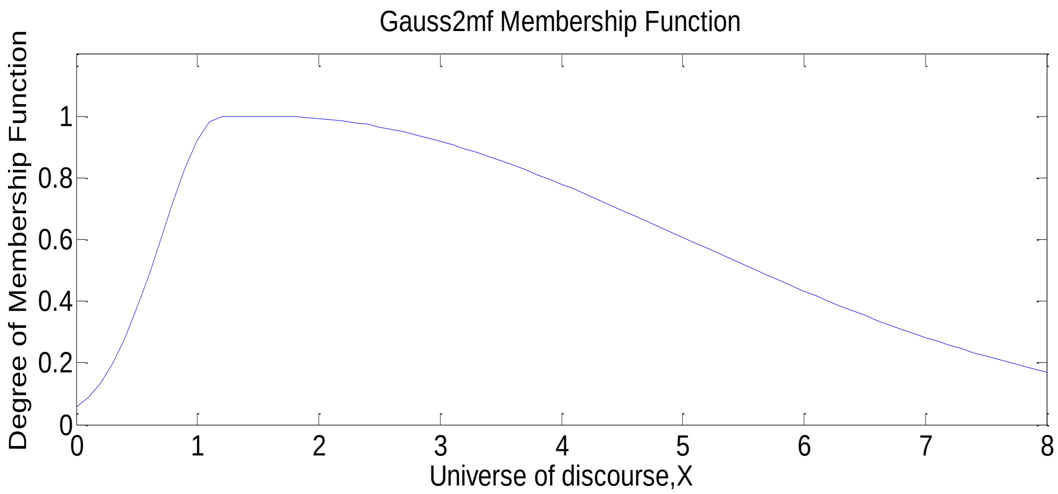

Figure 5.2(e) Gauss2mf Membership Function

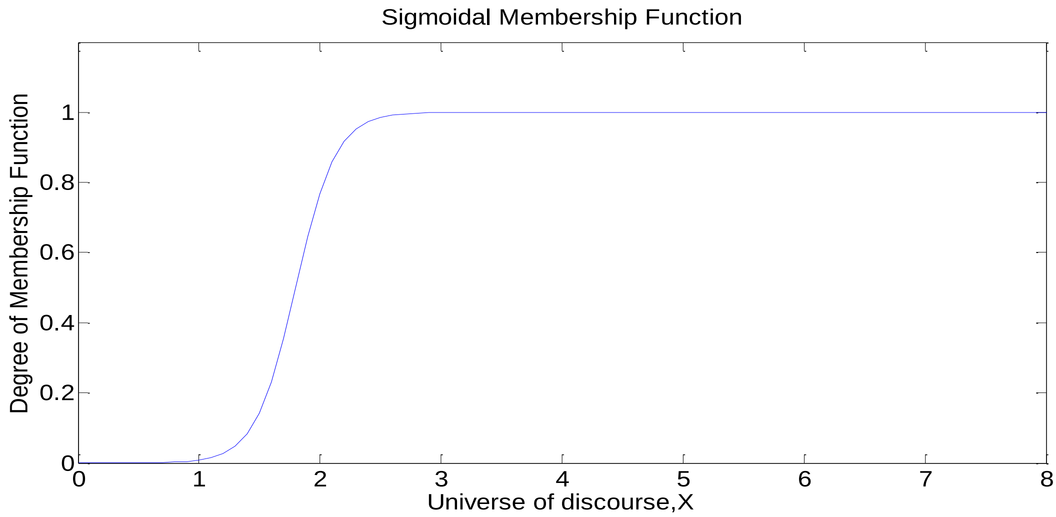

Figure 5.2(f) Sigmoidal Membership Function

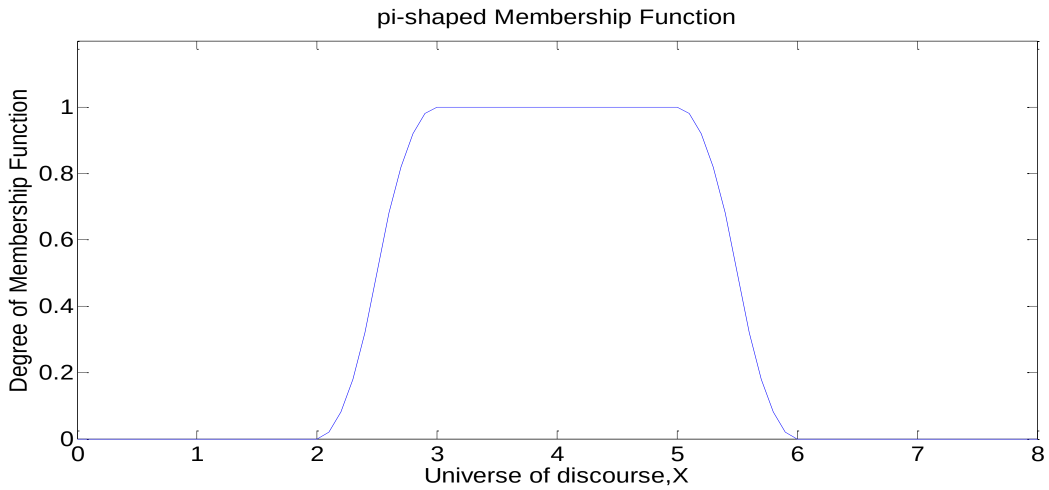

Figure 5.2(g) Pi-shaped Membership Function

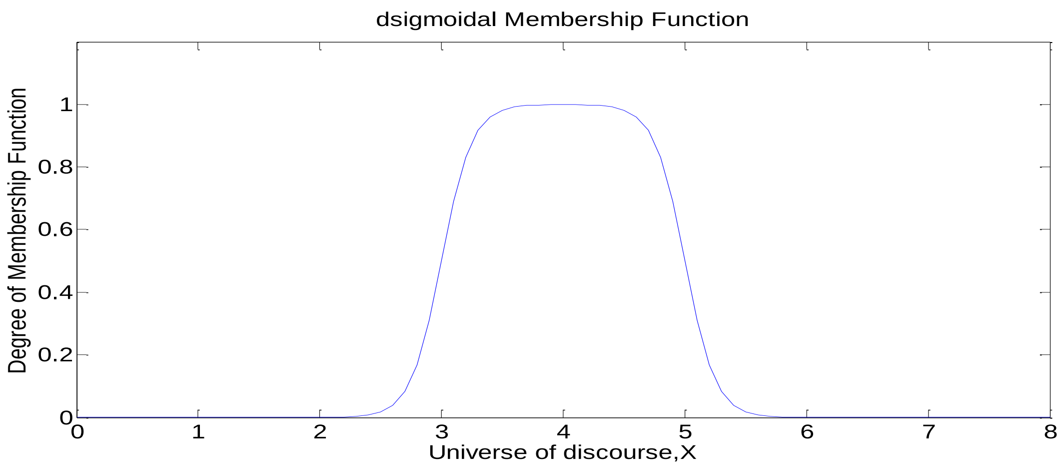

Figure 5.2(h) dsigmoidal Membership Function

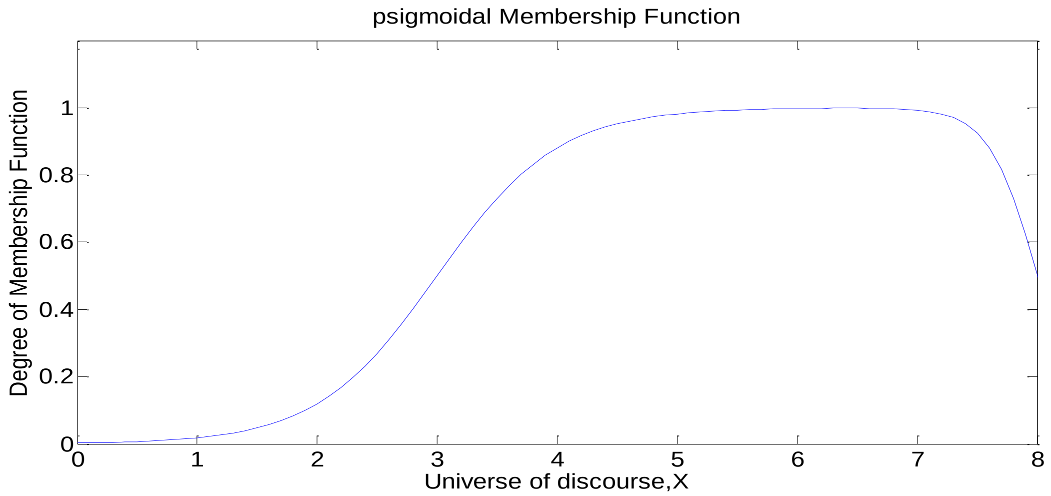

Figure 5.2(i) psigmoidal Membership Function

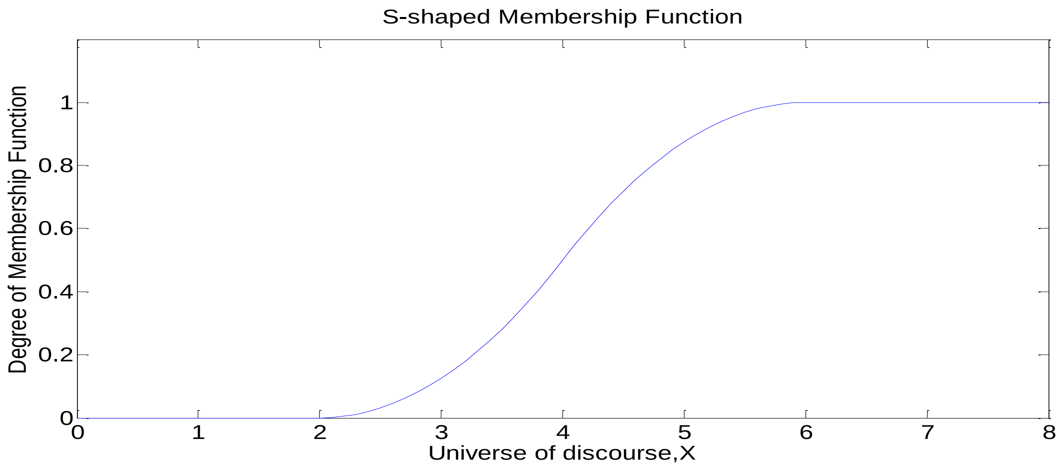

Figure 5.2(j) S-shaped Membership Function

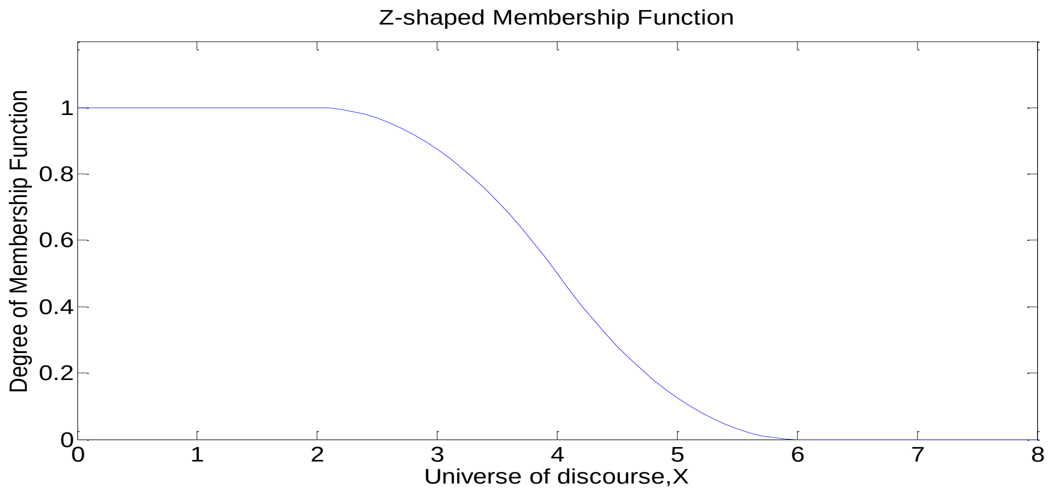

Figure 5.2(k) Z-shaped Membership Function

A chosen Fuzzy Inference System is responsible for drawing conclusions from the knowledge based fuzzy rule set of if-then linguistic statements [Hosseinzadeh et al. 1999, Aragon-Patil et al. 2007; Markus et al. 2009; Németh et al. 2009]. Fault types indicated with the help of IEC 60599 ratio method form the fuzzy rule set of the diagnosis system. Defuzzification then converts the fuzzy values back into crisp output actions.

There are two important differences between the fault gas analysis using IEC 60599 ratio method and fault gas analysis using fuzzy logic [Afiqah et al. 2010; Németh et al. 2010; Albakry et al. 2011, Ahmed et al. 2013; Abu-Siada et al. 2013]. The first one is the application of fuzzy membership functions for the classification of fault gas ratios. The second difference is that by the use of these functions, an upper and a lower limit is calculated for the specific fault. The classification of faults using the gas ratio codes (IEC 60599) as inputs can be done by the following characteristic parameters:

(i) Three linguistic variables are the three ratios : C_2H_2/ C_2H_4 (R1) , CH_4/H_2 (R2) , C_2H_4/C_2H_6 (R3)

(ii) Three linguistic values are : low, medium, high

(iii) Three sets of reference, for the three inputs have been taken such asforR1, U_1 is having range of [0.08-2.5], U_2 is having range of [0.08-2.0] for R2 and for R3, U_3 is having range of [0.1-5]; where U_1, U_2 and $U_3$are three sets of decompositions for three linguistic variables (input).

(iv) Six sets of reference, for the six outputs have been taken such as for partial discharge, U4 is having range [0-2], U_5 is having range of [1.2-3] for low energy discharge, U_6 is having range of [2-4] for high energy discharge, U_7 is having range of [3-5] for thermal faults $T<300^0C$, U_8 is having range of [4-6] for thermal faults $300^0C<T<700^0C$, U_9 is having range of [5-7] for thermal faults $T>700^0C$; where U_4, U_5 and U_6, U_7, U_8 and U_9 are six sets of decompositions for six output variables.

(v) Membership Function : Gaussian

(vi) Fuzzy rules : $3^3 = 27$

It is important to remark that while setting the crossing of membership functions, the degree of uncertainty can be taken into consideration [David et al. 2011].

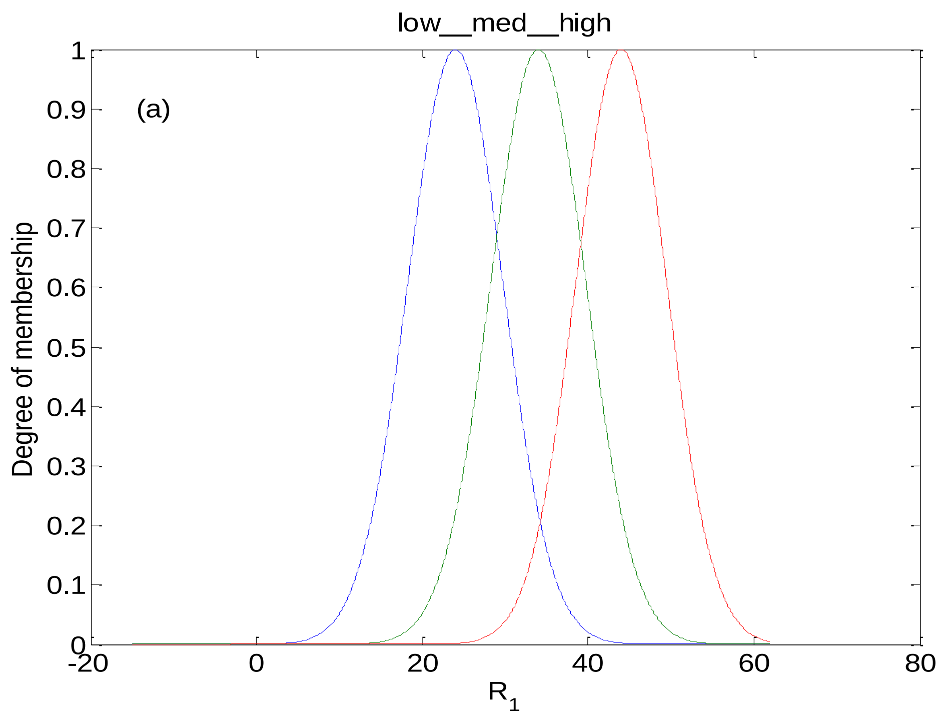

Figure 5.3(a) Gaussian membership function: R_1=input variable = C_2H_2/C_2H_4

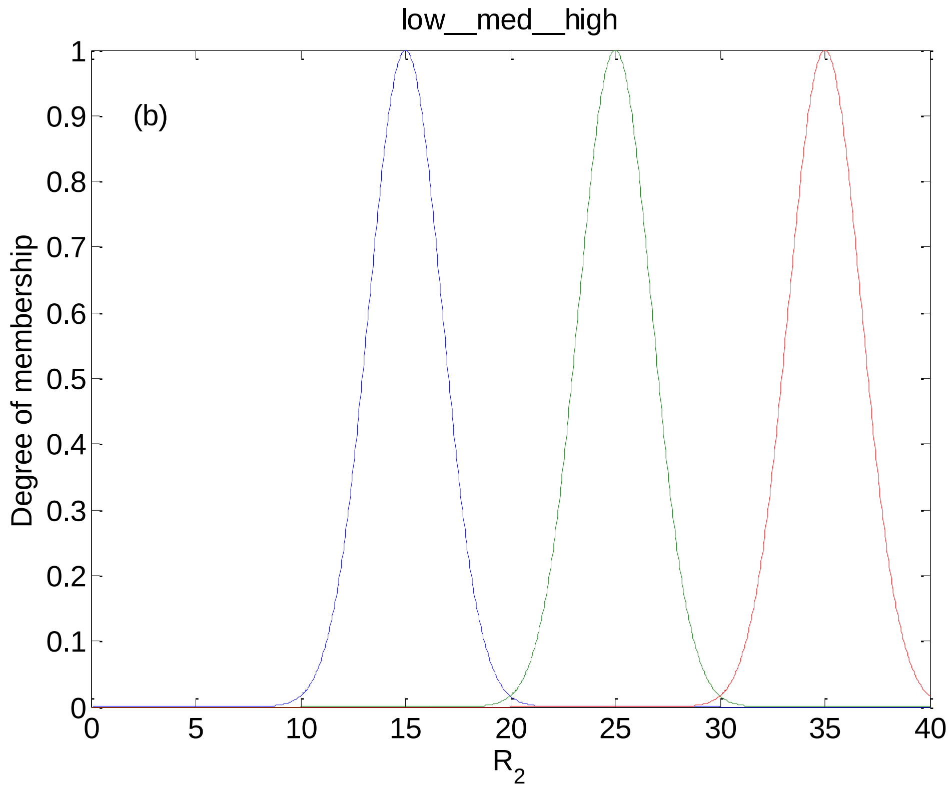

Figure 5.3(b) Gaussian membership function: R_2 = input variable = CH_4/H_2

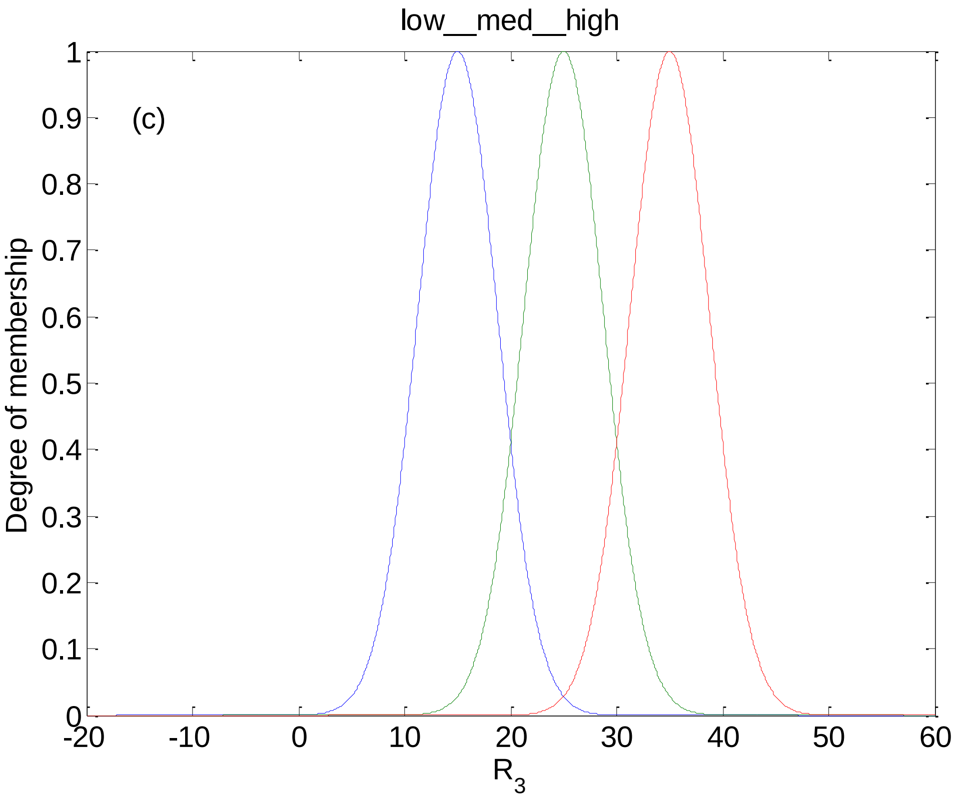

Figure 5.3(c) Gaussian membership function: R_3 = input variable = C_2H_4/C_2H_6

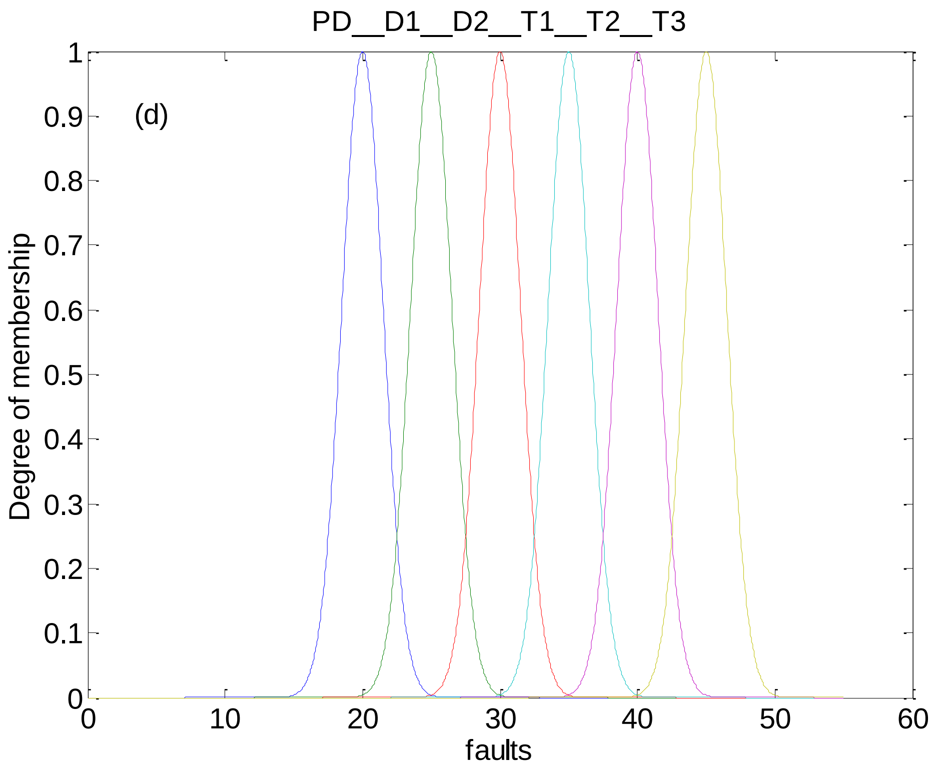

Figure 5.3(d) Gaussian membership function: faults = output variable

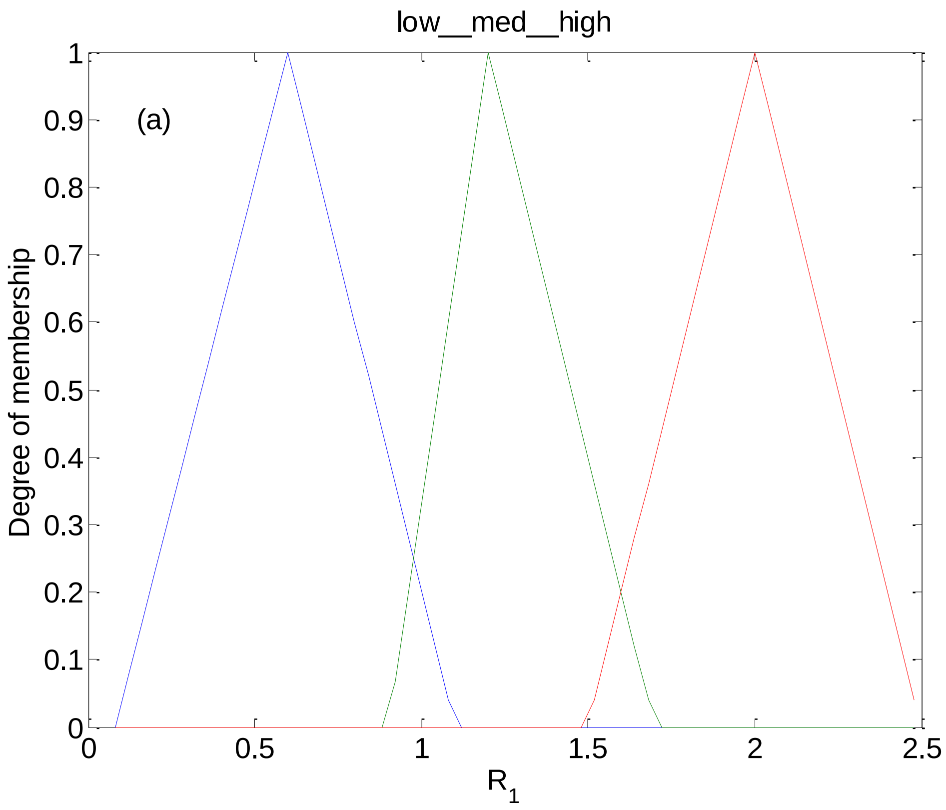

Figure 5.4(a) Triangular membership function: R_1=input variable = C_2H_2/C_2H_4

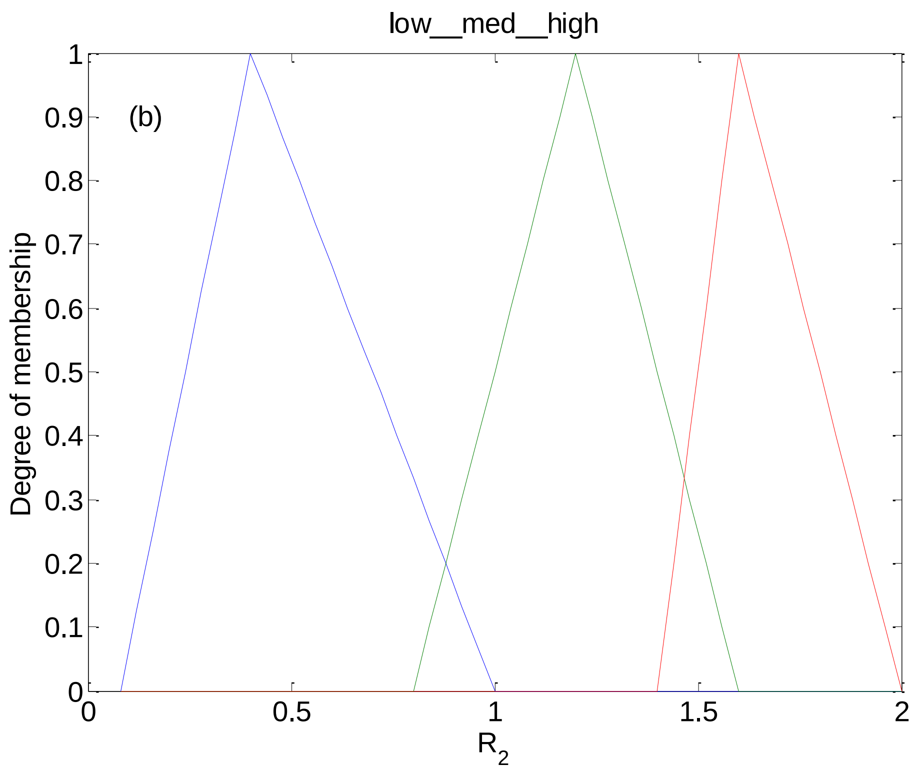

Figure 5.4(b) Triangular membership function: R_2 = input variable = CH_4/H_2

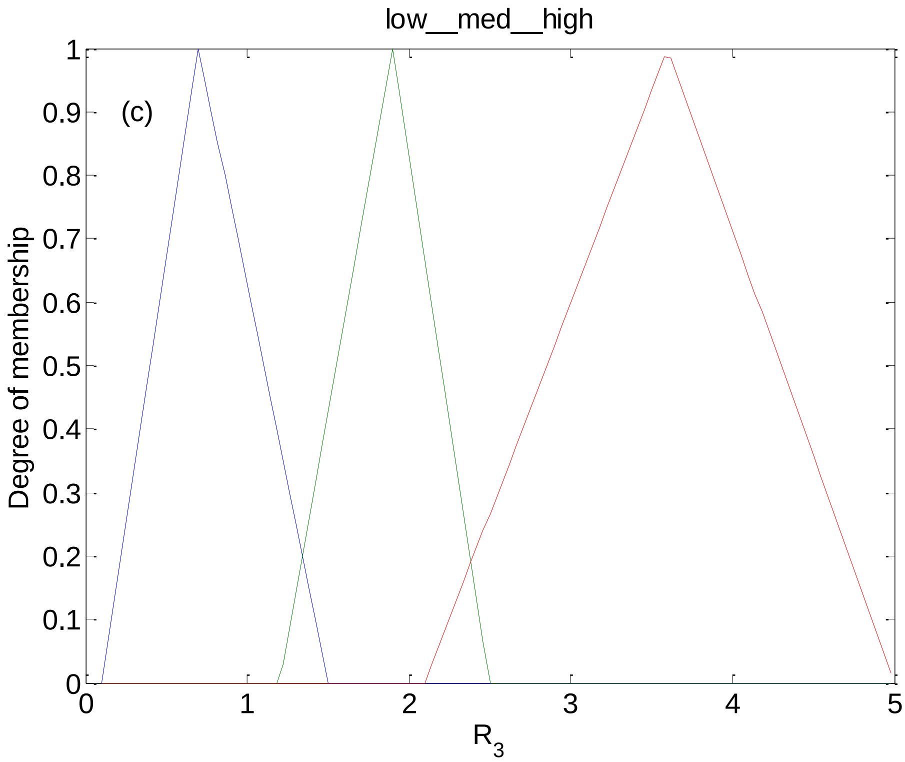

Figure 5.4(c) Triangular membership function: R_3 = input variable = C_2H_4/C_2H_6

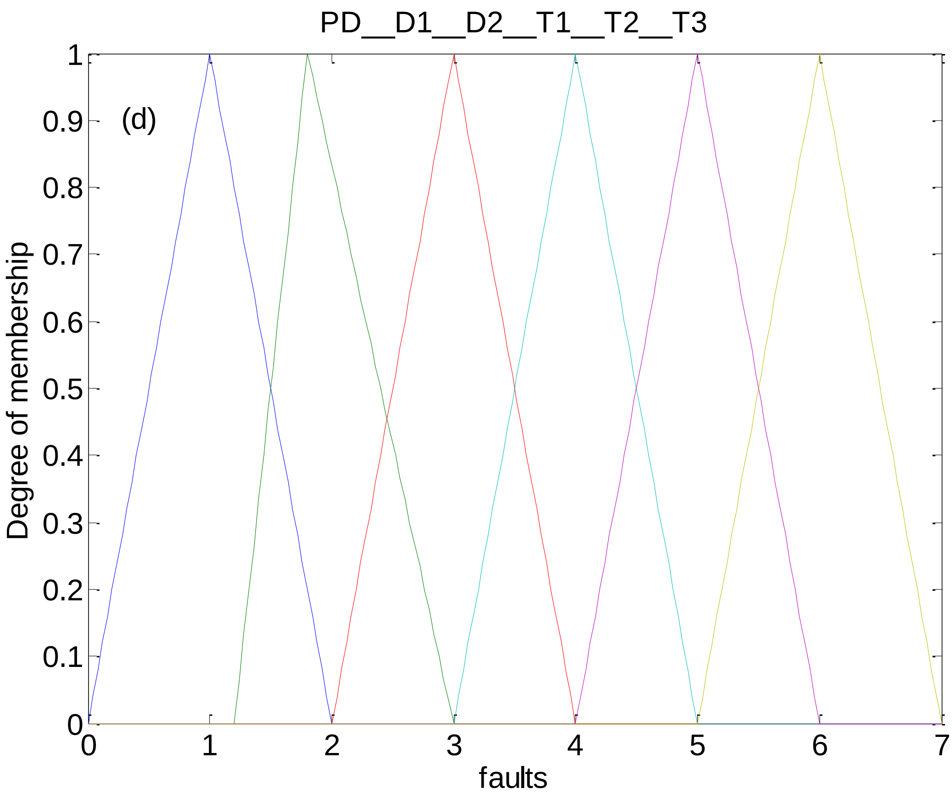

Figure 5.4(d) Triangular membership function:faults = output variable

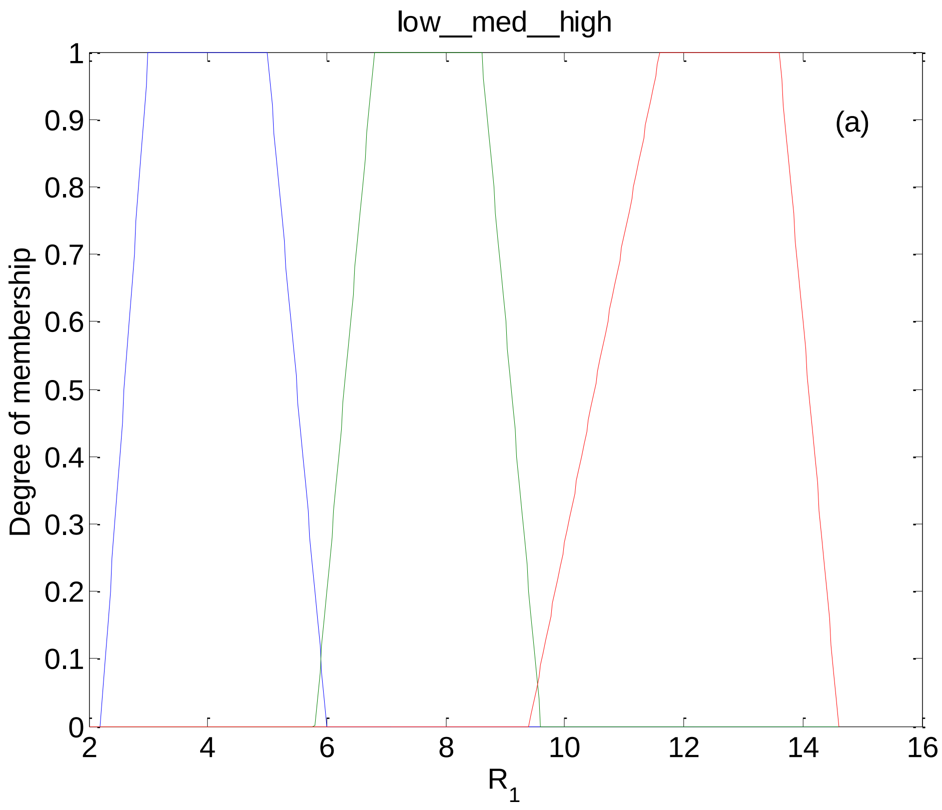

Figure 5.5(a) Trapezoidal membership function: R_1=input variable = C_2H_2/C_2H_4

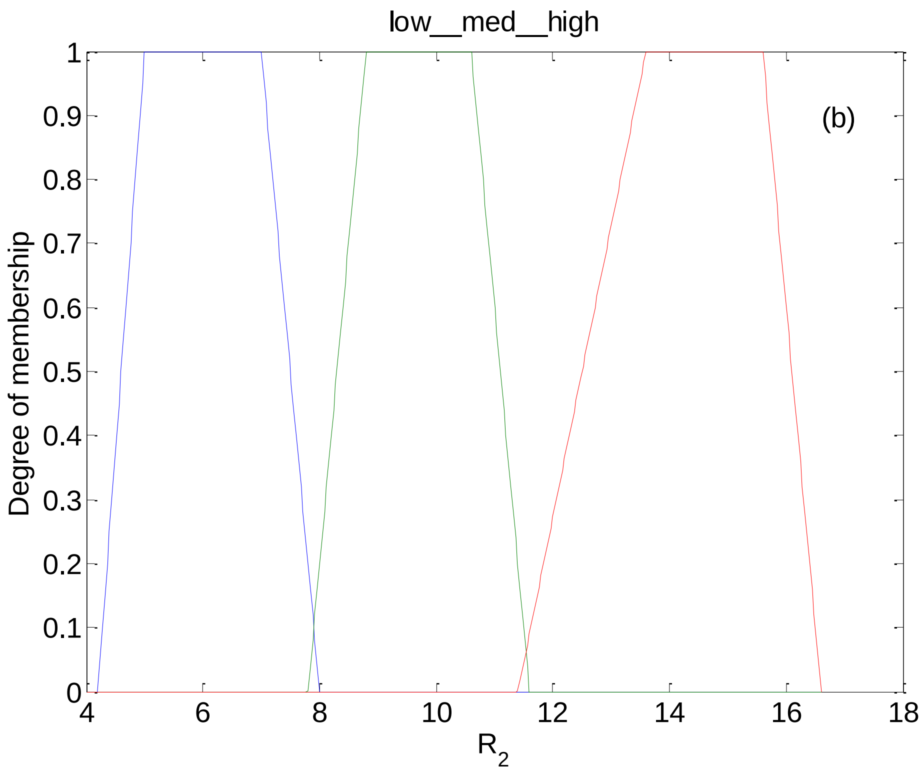

Figure 5.5(b) Trapezoidal membership function:R_2 = input variable = CH_4/H_2

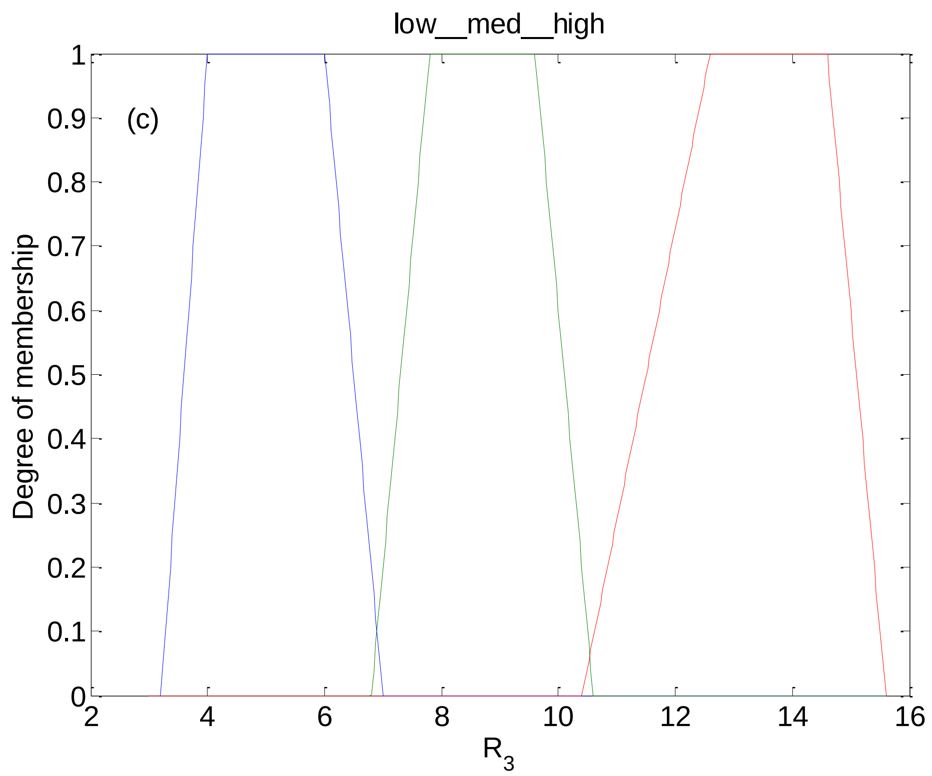

Figure 5.5(c) Trapezoidal membership function: R_3 = input variable = C_2H_4/C_2H_6

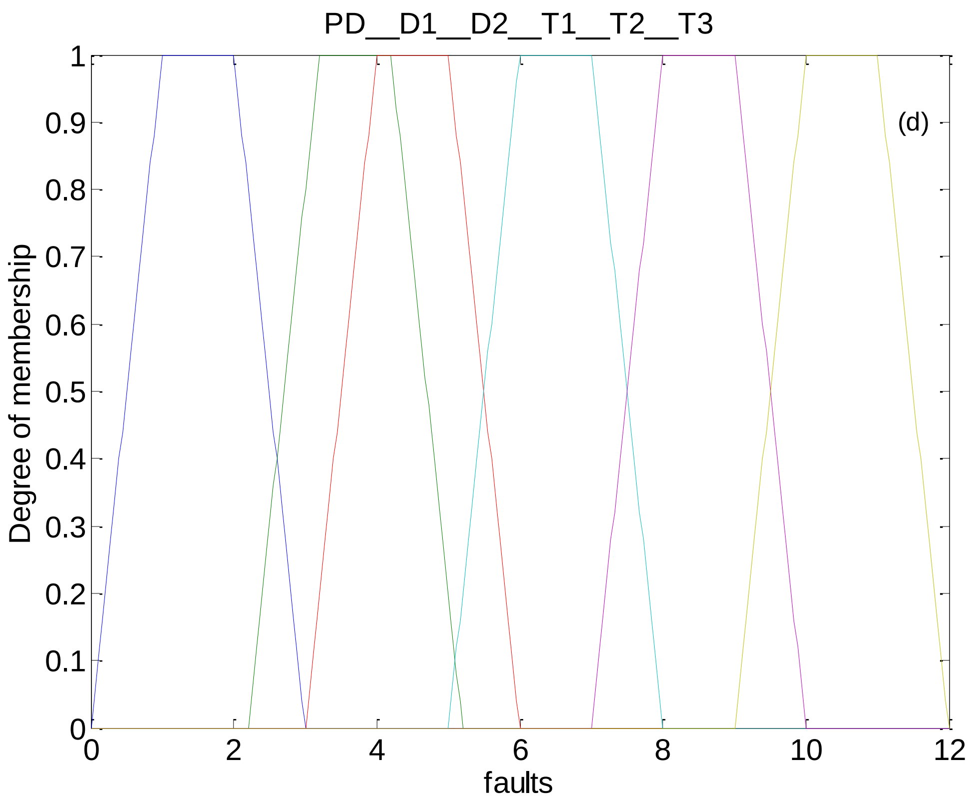

Figure 5.5(d) Trapezoidal membership function:faults = output variable

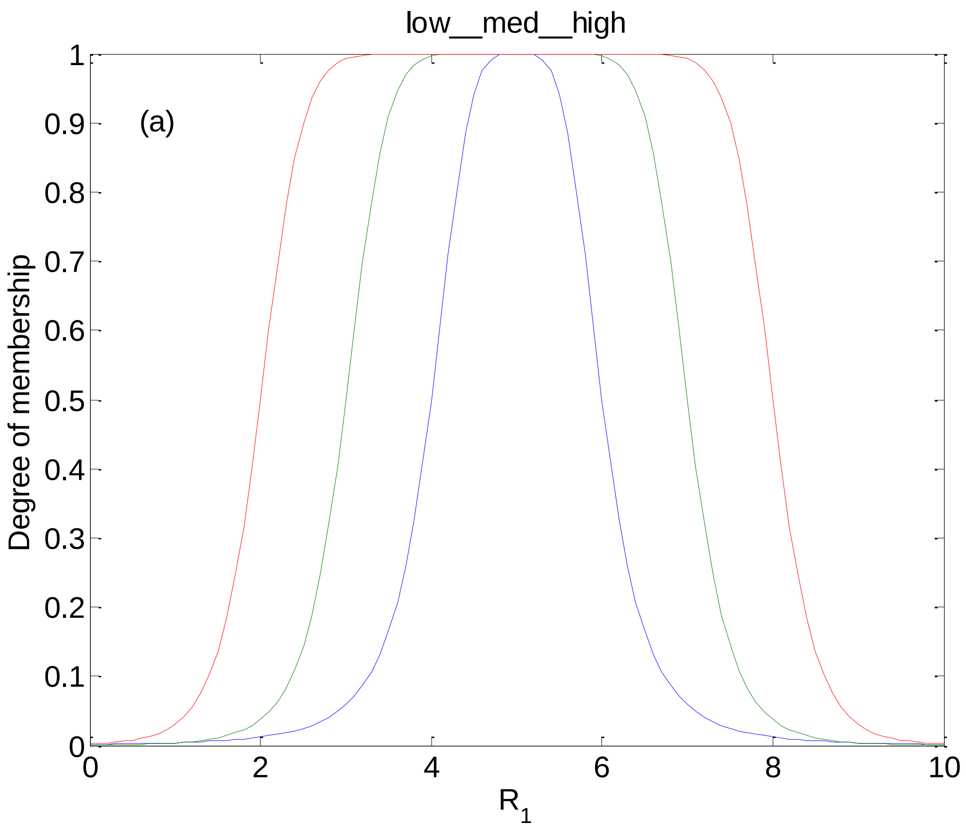

Figure 5.6(a) Gbell membership function: R_1=input variable = C_2H_2/C_2H_4

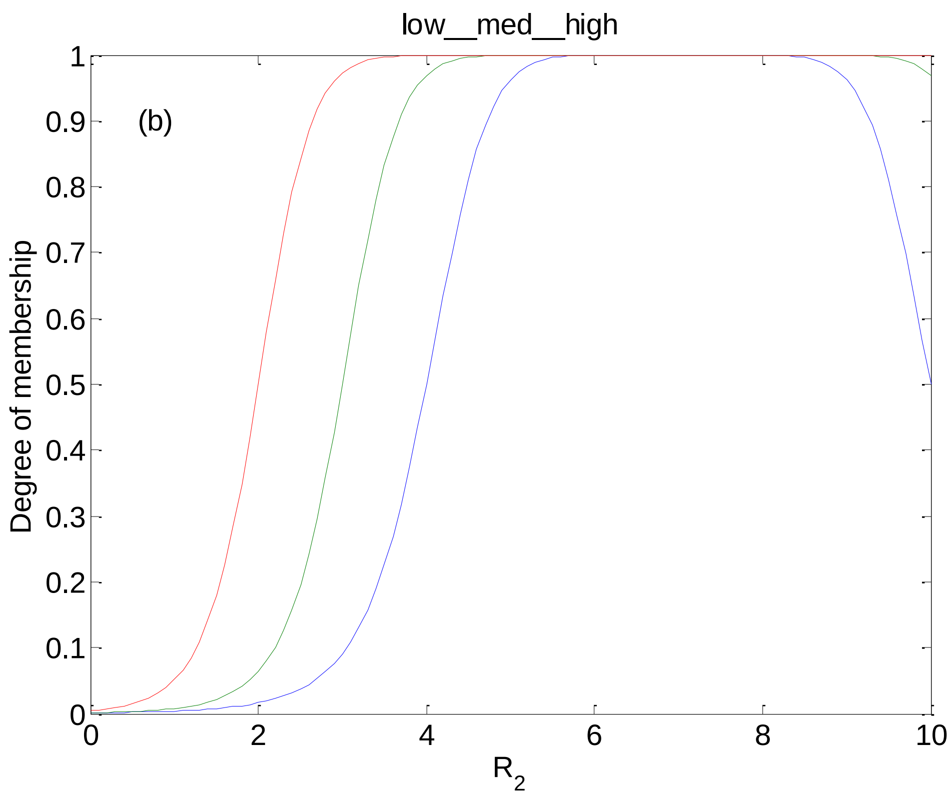

Figure 5.6(b) Gbell membership function: R_2 = input variable = CH_4/H_2

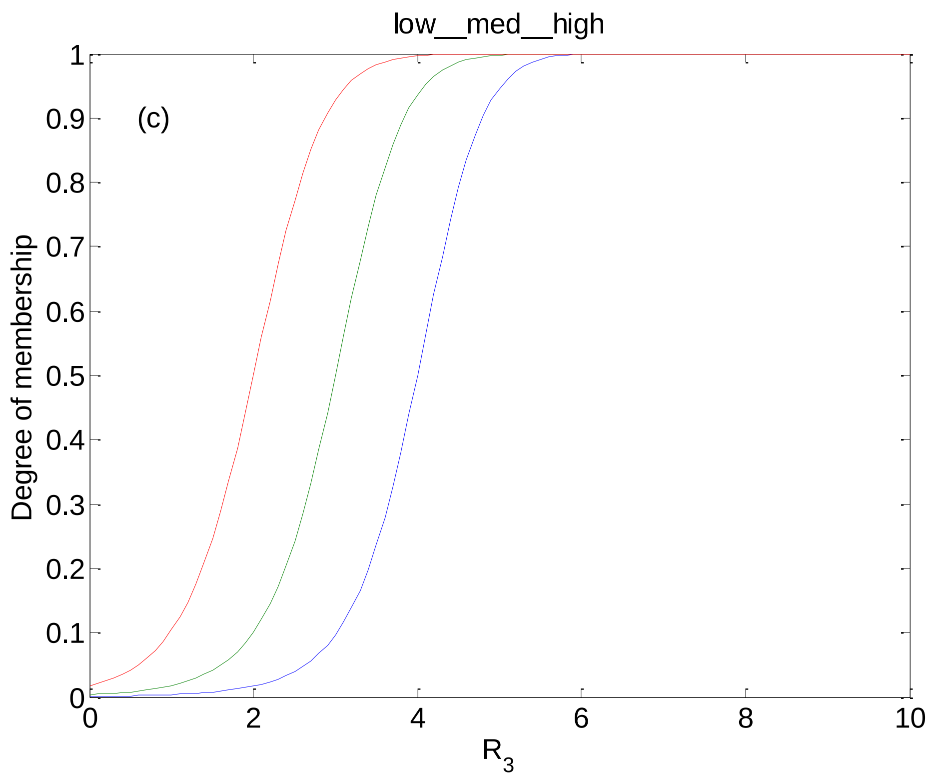

Figure 5.6(c) Gbell membership function: R_3 = input variable = C_2H_4/C_2H_6

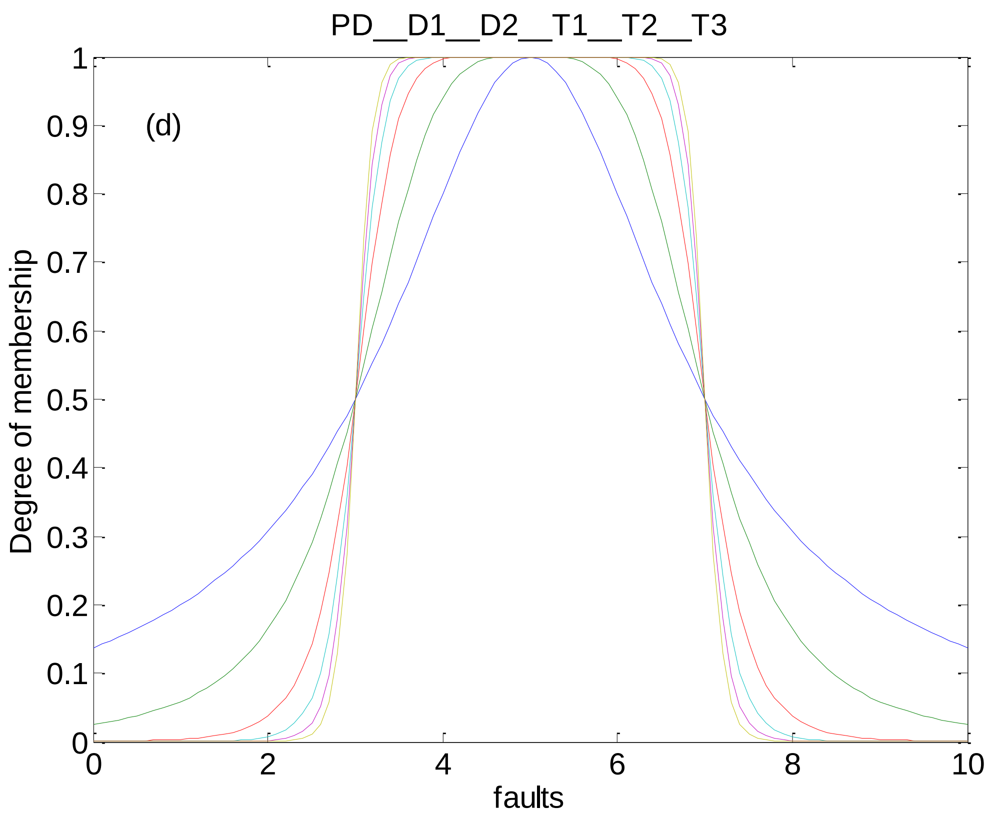

Figure 5.6(d) Gbell membership function: faults = output variable

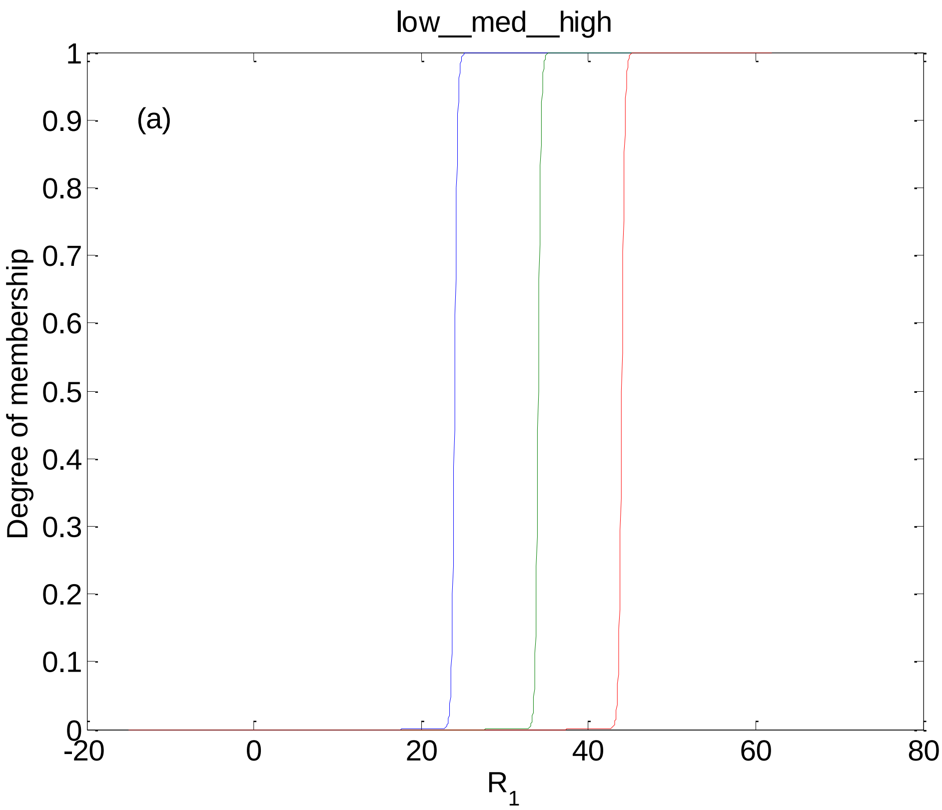

Figure 5.7(a) Sigmoidal membership function: R_1=input variable = C_2H_2/C_2H_4

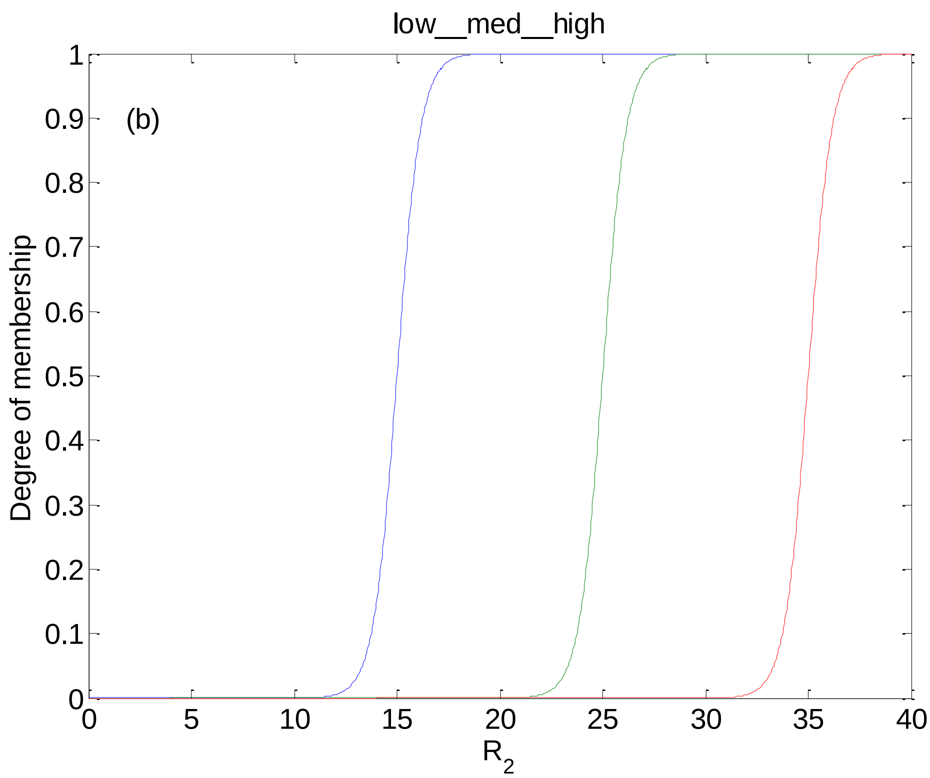

Figure 5.7(b) Sigmoidal membership function: R_2 = input variable = CH_4/H_2

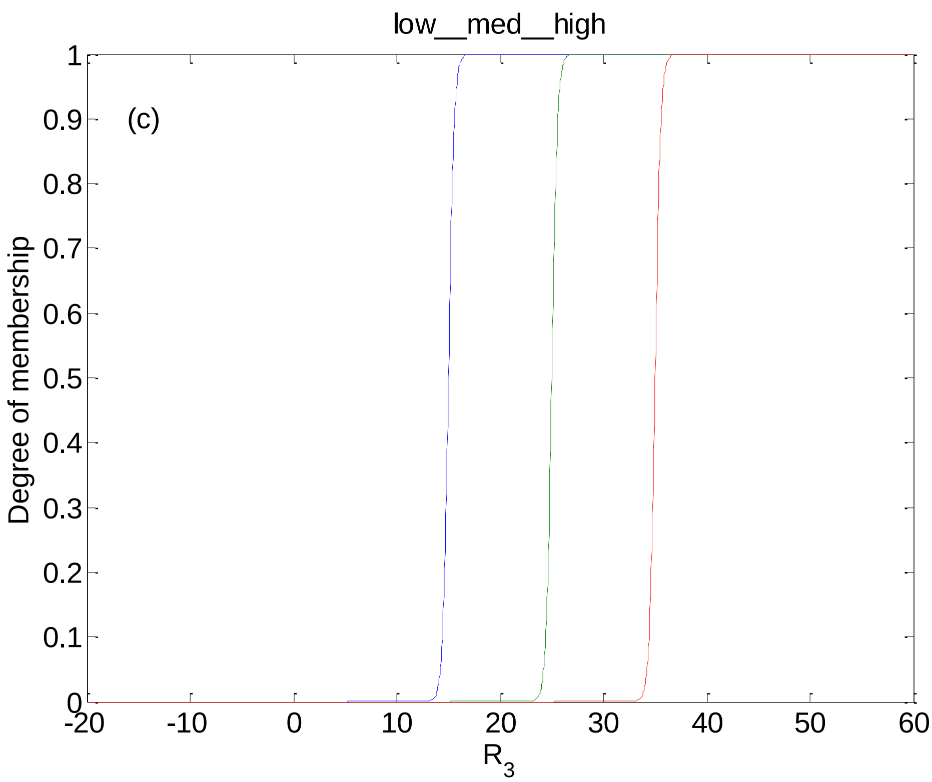

Figure 5.7(c) Sigmoidal membership function: R_3 = input variable = C_2H_4/C_2H_6

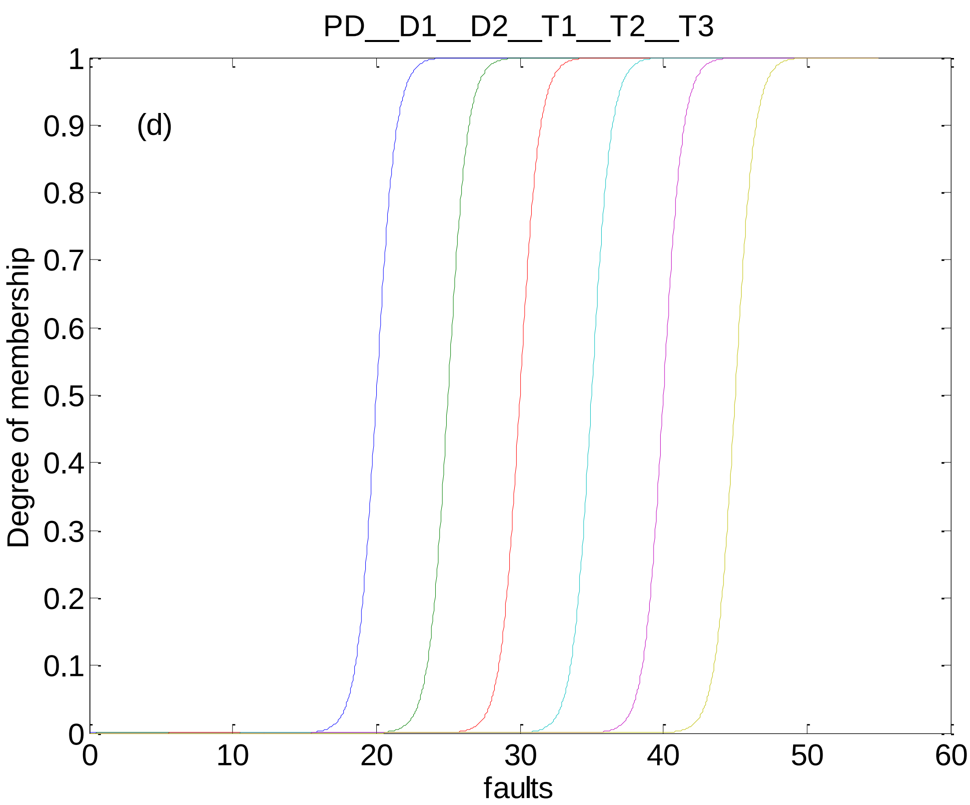

Figure 5.7(d) Sigmoidal membership function: faults = output variable

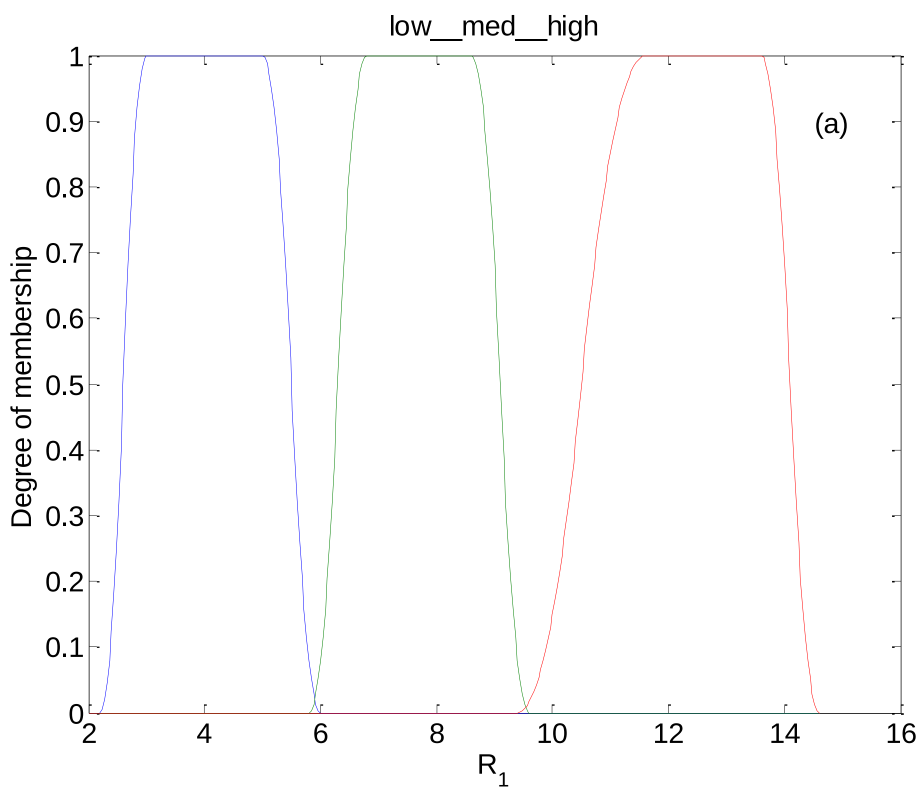

Figure 5.8(a) Pi-shaped membership function: R_1=input variable = C_2H_2/C_2H_4

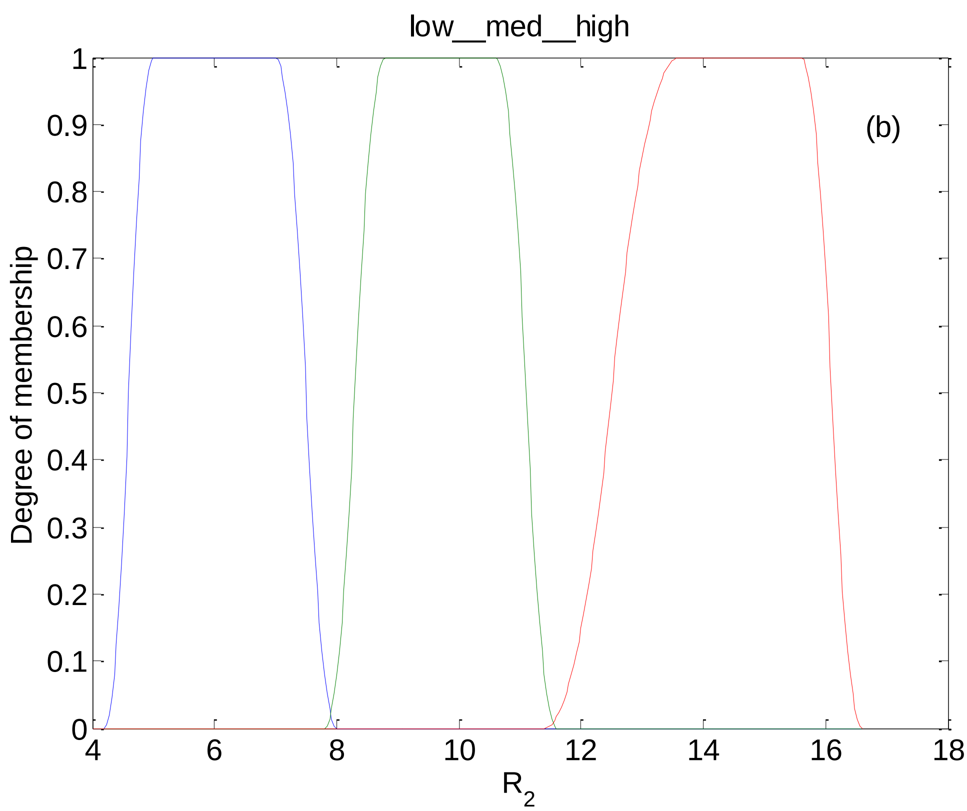

Figure 5.8(b) Pi-shaped membership function:R_2 = input variable = CH_4/H_2

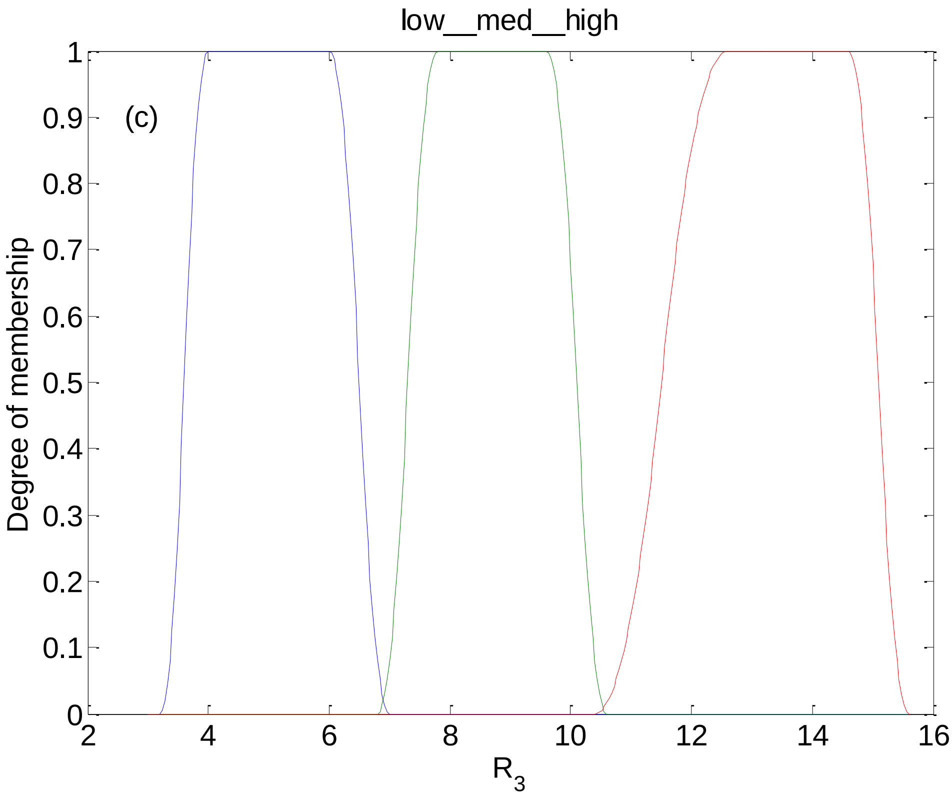

Figure 5.8(c) Pi-shaped membership function: R_3 = input variable = C_2H_4/C_2H_6

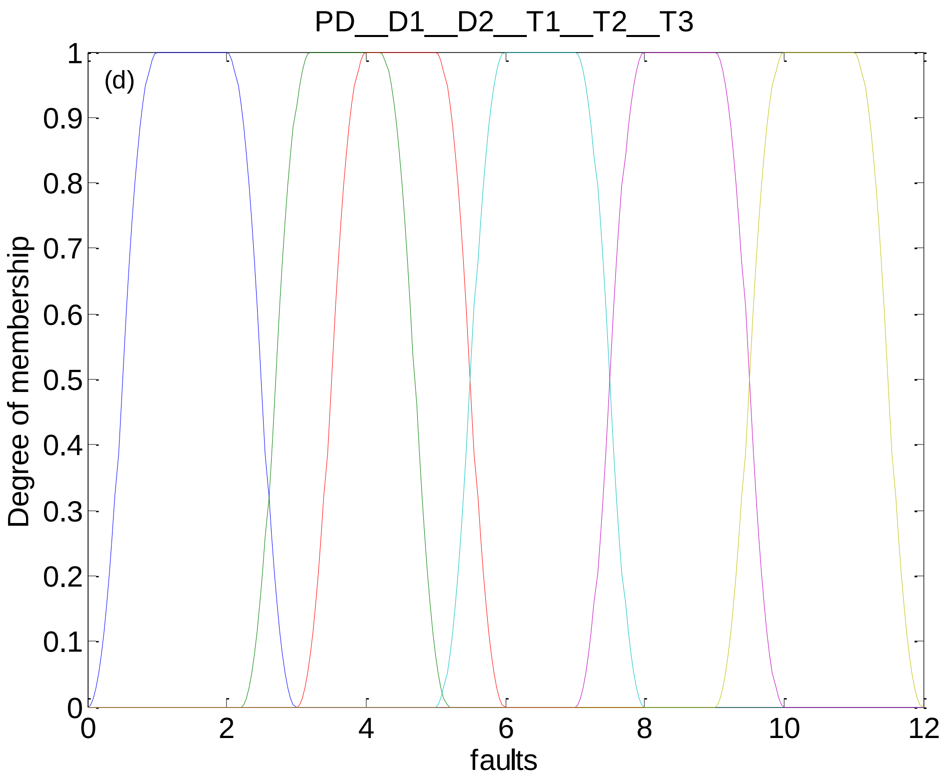

Figure 5.8(d) Pi-shaped membership function: faults = output variable

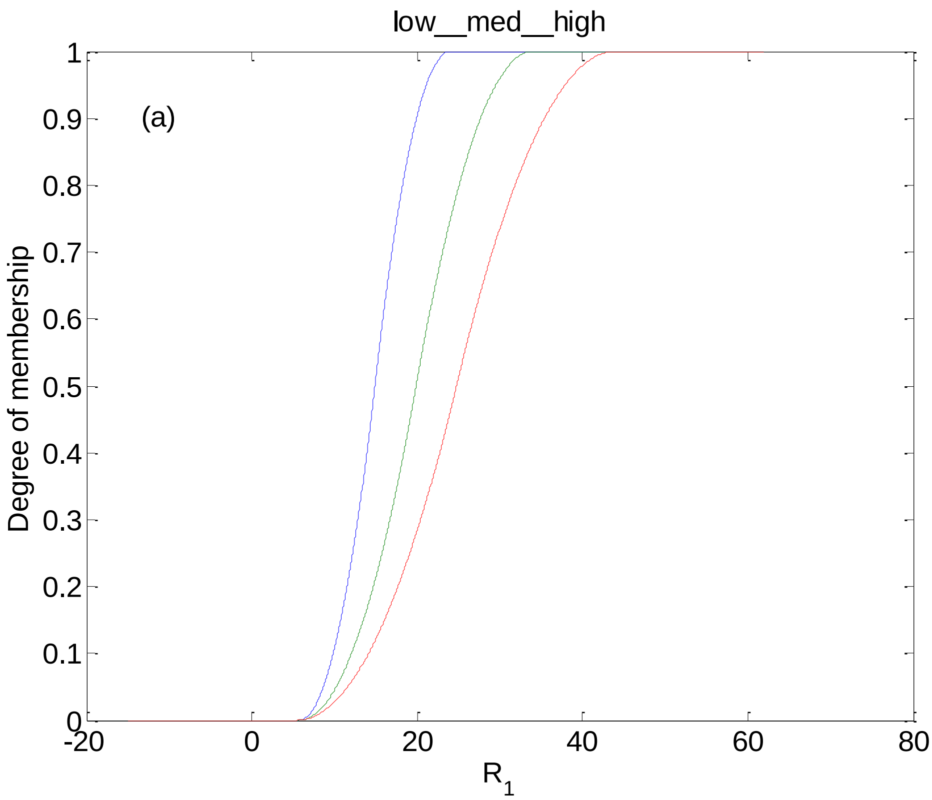

Figure 5.9(a) S-shaped membership function: R_1=input variable = C_2H_2/C_2H_4

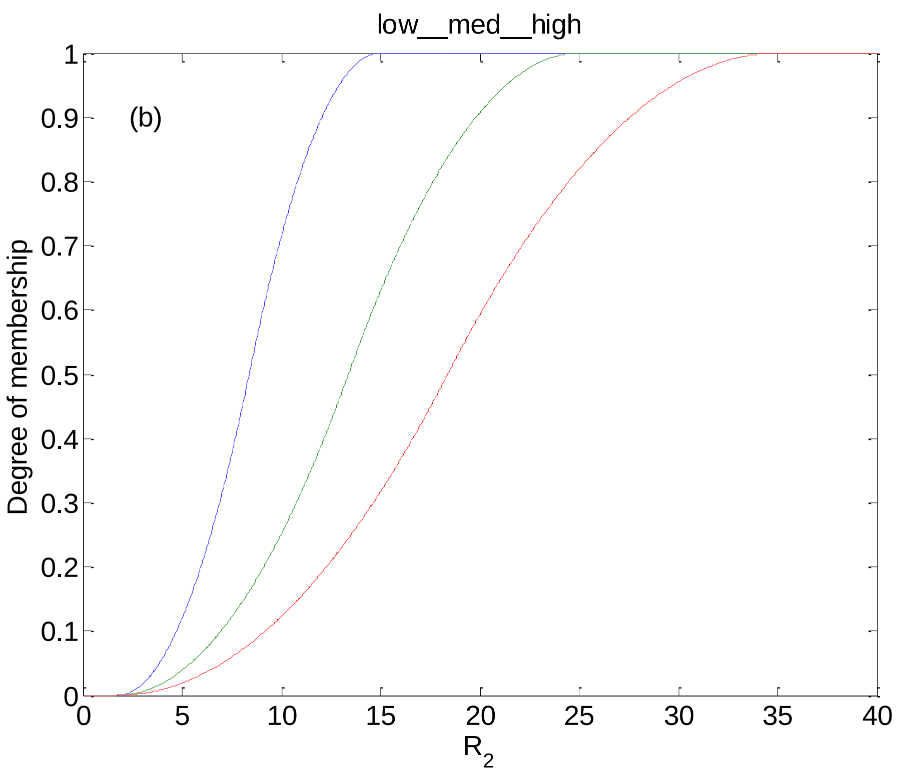

Figure 5.9(b) S-shaped membership function: R_2 = input variable = CH_4/H_2

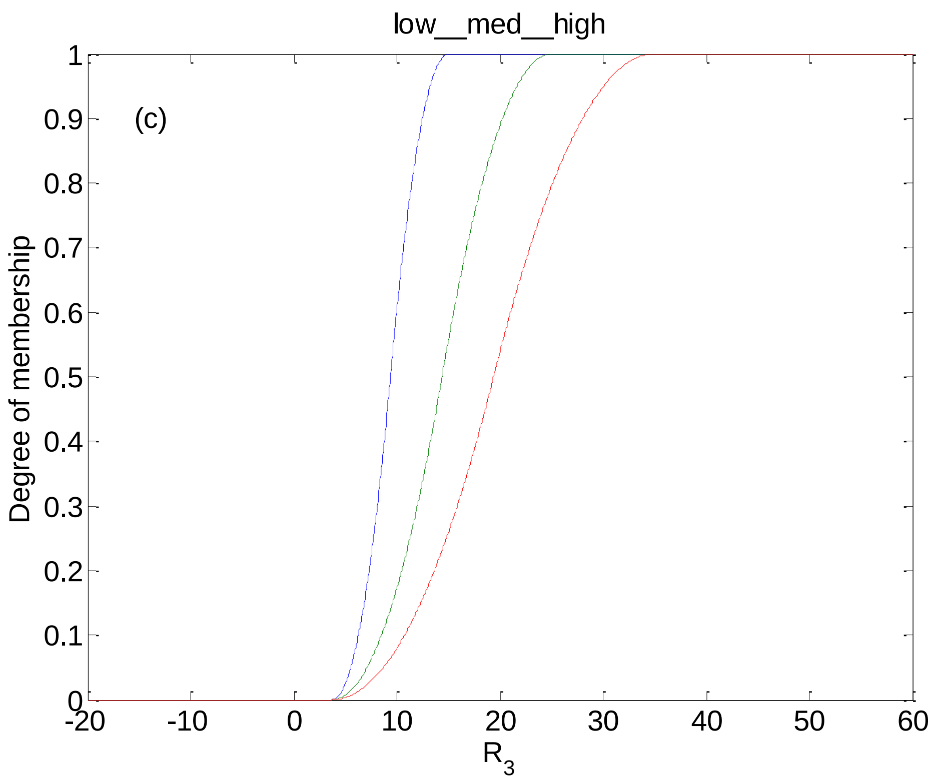

Figure 5.9(c) S-shaped membership function: R_3 = input variable = C_2H_4/C_2H_6

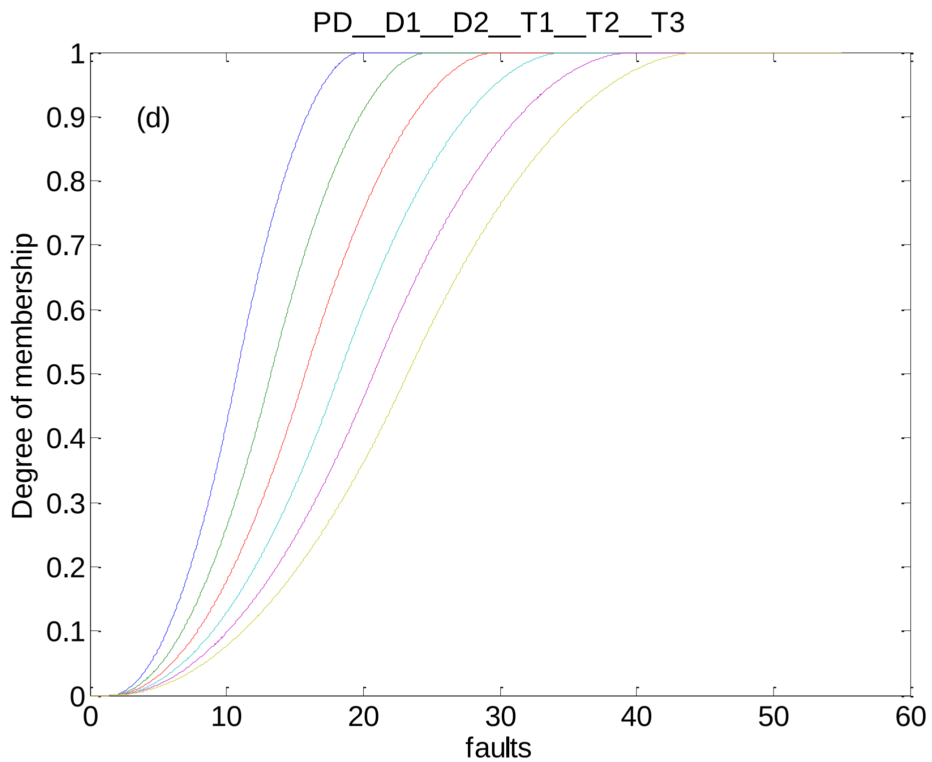

Figure 5.9(d) S-shaped membership function: faults = output variable

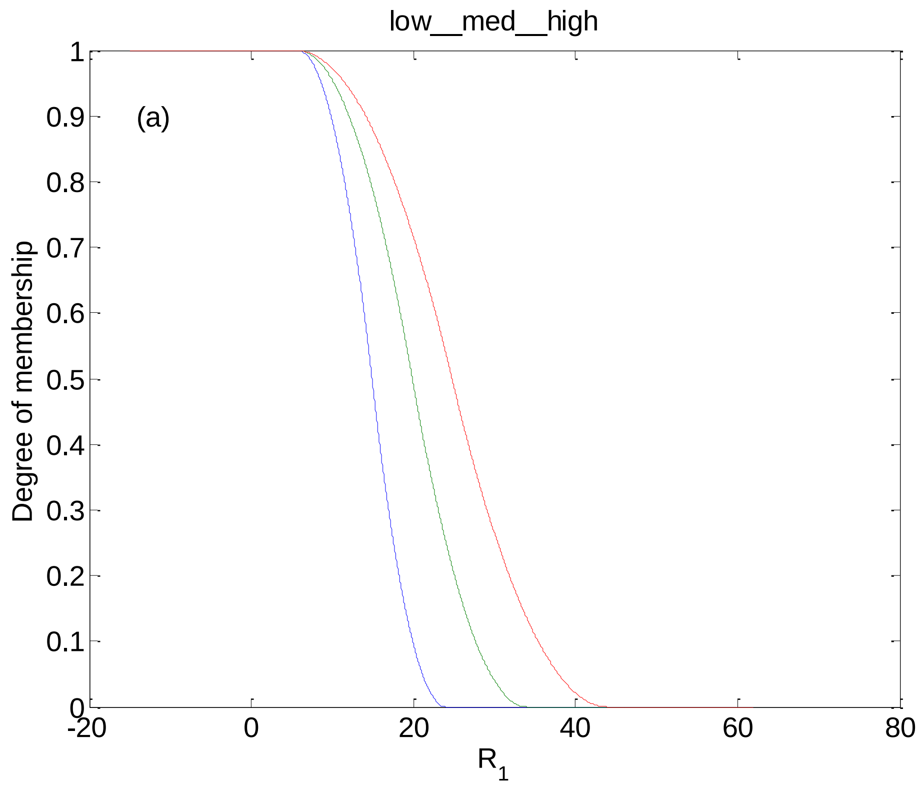

Figure 5.10(a) Z-shaped membership function: R_1=input variable = C_2H_2/C_2H_4

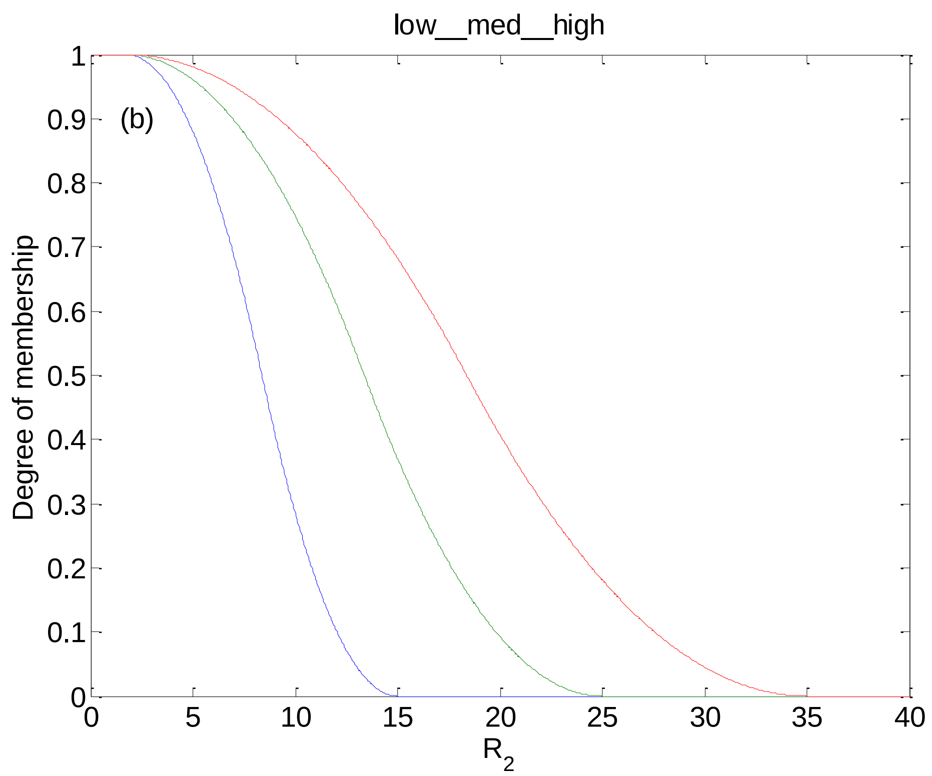

Figure 5.10(b) Z-shaped membership function: R_2 = input variable = CH_4/H_2

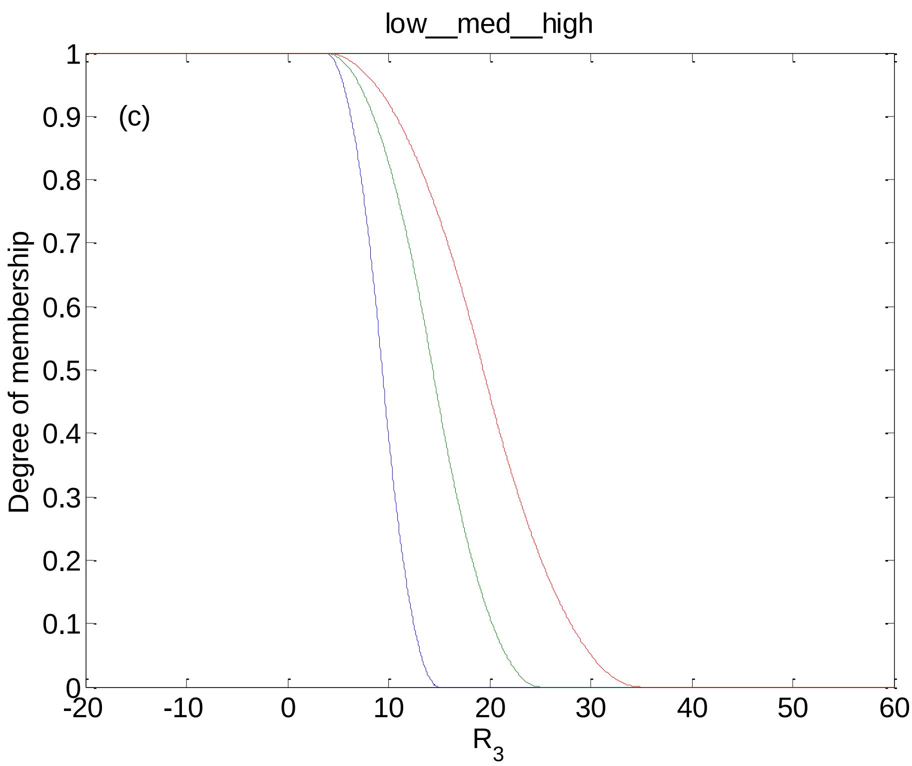

Figure 5.10(c) Z-shaped membership function:R_3 = input variable = C_2H_4/C_2H_6

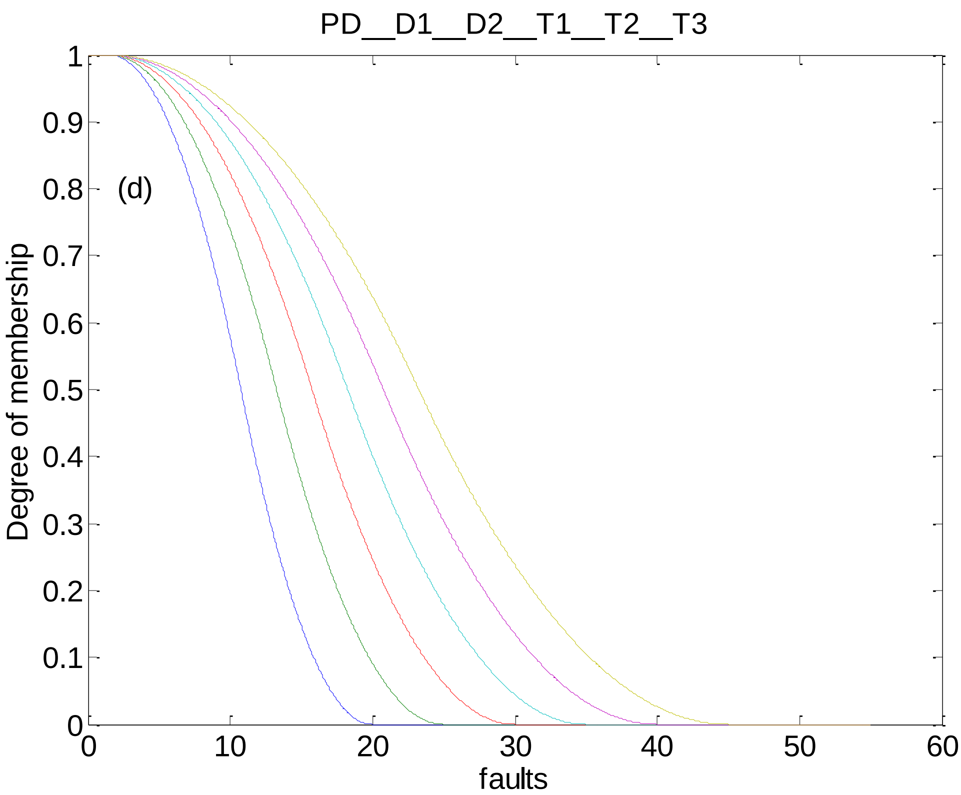

Figure 5.10(d) Z-shaped membership function: faults = output variable

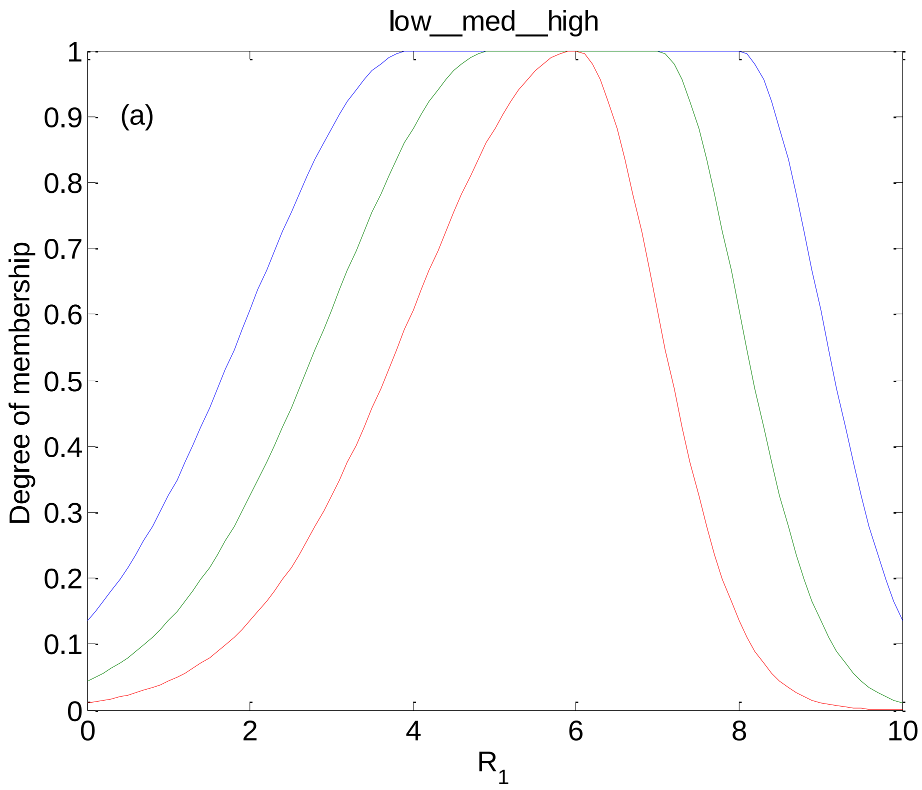

Figure 5.11(a) Gauss2mf membership function: R_1=input variable = C_2H_2/C_2H_4

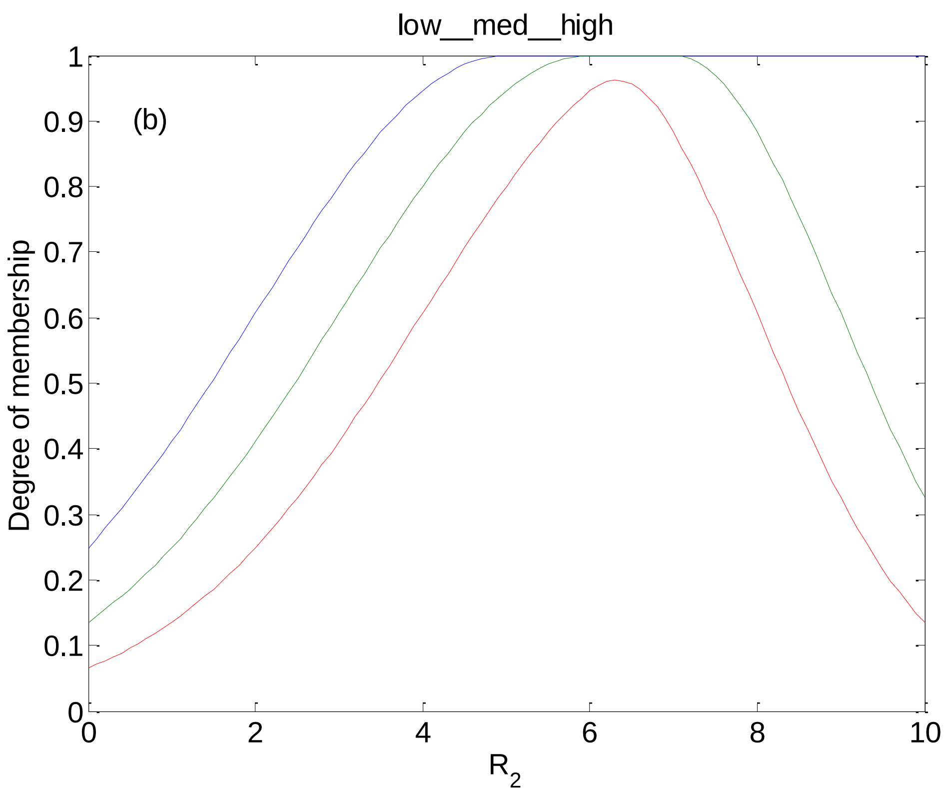

Figure 5.11(b) Gauss2mf membership function: R_2 = input variable = CH_4/H_2

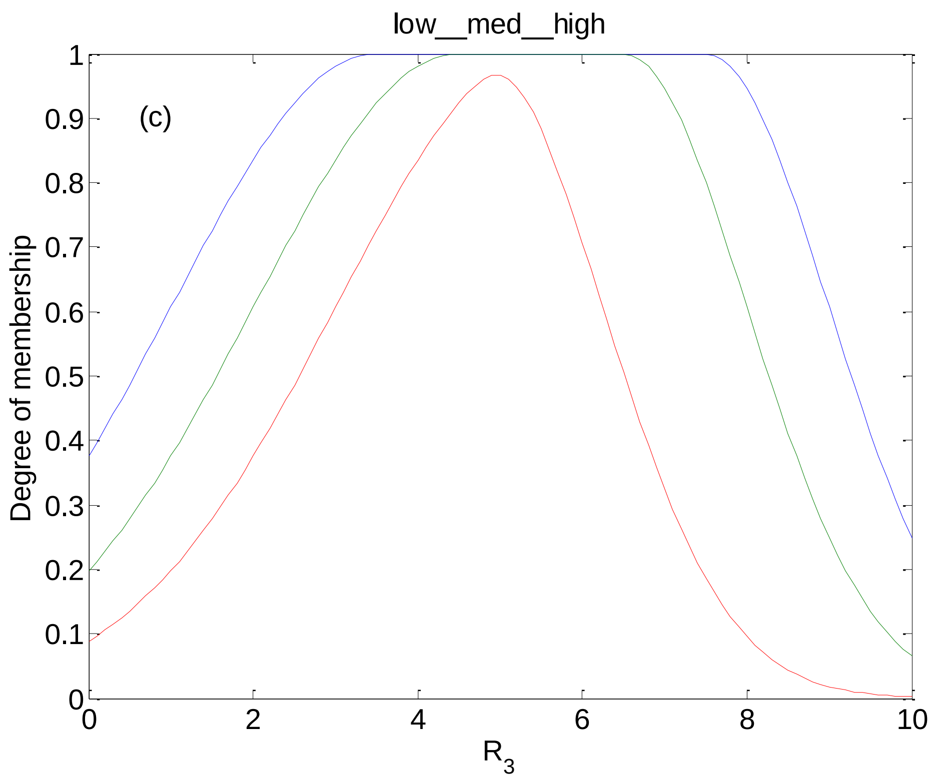

Figure 5.11(c) Gauss2mf membership function: R_3 = input variable = C_2H_4/C_2H_6

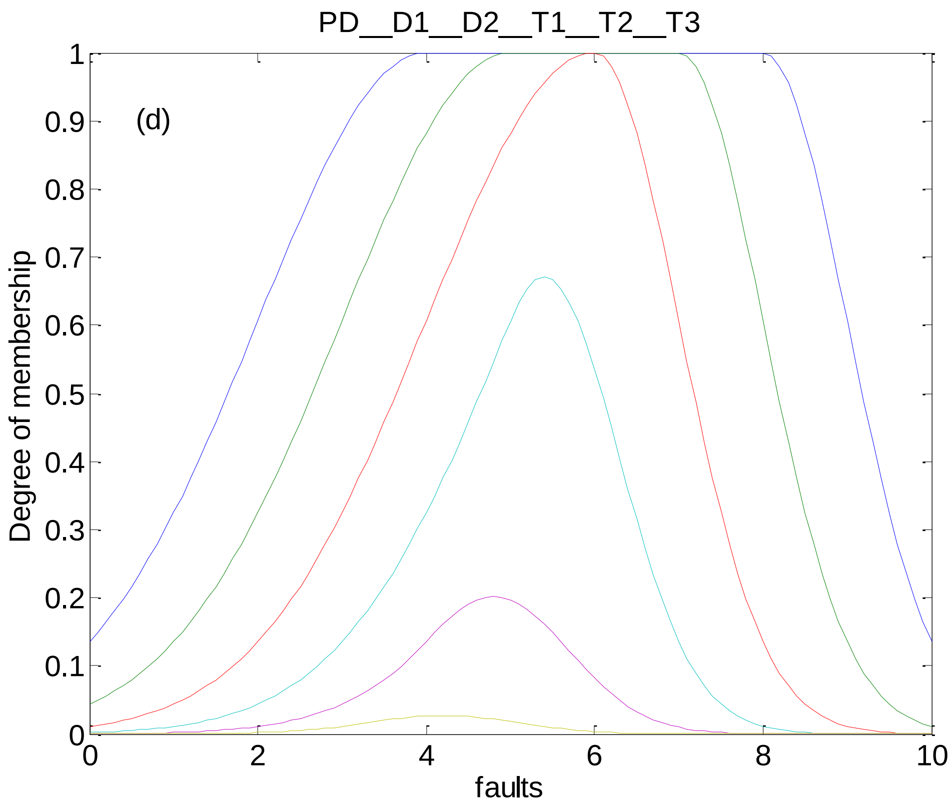

Figure 5.11(d) Gauss2mf membership function: faults = output variable

The fuzzy rules have been listed below:

1. If all the three ratios; R1, R2 and R3 are low, then the fault is PD.
2. If R1, R3 are medium and R2 is low, then the fault is D1.
3. If R2, R3 are medium and R1 is high, then the fault is D2.
4. If R1 is low, R2 is high and R3 is medium, then fault is T1.
5. If R2, R3 are medium and R1 is low, then the fault is T2.
6. If R1 is low, R2 is medium and R3 is high, then fault is T3.
7. If R2, R3 are low and R1 is medium, then the fault is PD.
8. If all the three ratios; R1, R2 and R3 are medium, then the fault is D1.
9. If R1, R3 are low and R2 is medium, then the fault is D2.
10. If R1, R3 are low and R2 is high, then the fault is T1.
11. If R1, R3 are high and R2 is medium, then the fault is T2.
12. If all the three ratios; R1, R2 and R3 are high, then the fault is T3.

Expression low means that the particular value is not involved to the fault calculation of the maximal degree of existence while it is involved to the calculation of minimal one. It is assumed that the appearance of fault gases and the any not low ratio of the gases (according to IEC 60599 method) is a symptom, that is caused by the fault at the end of the rule. A specific rule contains the fuzzy AND connection between the symptoms connected to a given fault. The fuzzy fault diagnosis (FFD) system is tested with different membership functions such as Gaussian, triangular, trapezoidal, Gbell, Sigmoidal, pi-shaped, S-shaped, Z-shaped and gauss2mf as shown in Figure 5.3, Figure 5.4, Figure 5.5, Figure 5.6, Figure 5.7, Figure 5.8, Figure 5.9, Figure 5.10 and Figure 5.11, respectively. These membership function types have been compared on the basis of the performance and analysis of Fuzzy Fault Diagnosis by calculating average error for the membership functions i.e. Gaussian, Triangular, Trapezoidal, Gbell, Sigmoidal, pi-shaped, S-shaped, Z-shaped and gauss2mf, as shown in Table 1.

Table 5.1 shows a very lucid comparison amongst various types of fuzzy membership functions.The calculated average error is minimum in case of Gaussian membership function, paving the way to the selection of this membership function for the proposed research problem. During the process of fuzzy based reasoning, it is imperative that membership functions be chosen in a manner that it reflects the inherent statistical properties (such as skewness , kurtosis etc.) of the data in the input and output feature space. According to Central Limit Theorem, a normal distribution is obtained by repeatedly computing arithmetic average of large number of mutually independent observed values of a sample. The normal from variate, having a limiting cumulative function, which is approximately a normal distribution, is given by:

$$X_{norm} \equiv \frac{\sum_{i=1}^{N} x_i - \sum_{i=1}^{N} \mu_i}{\sqrt{\sum_{i=1}^{N} \sigma_i^2}} \tag{5.1}$$

where x_i is the set of independent random variates with mean μ_i and a finite variance σ^2. X_{norm} is the normal form variate.

In the proposed research, in case of fuzzy membership functions, a large number of mutually independent fuzzy rules have been generated whose repeatedly computed arithmetic average leads to the distribution curve which is actually a normal distribution curve i.e. a bell-shaped curve. This has served as a motivation to select the membership function as a Gaussian one. In order to study the statistical properties, the paper by Duval et al. 2001 has been referred and appropriate modifications to the membership functions have been incorporated in the solution of the proposed problem. Thirty six probability density curves have been generated using the rules generated in the proposed fuzzy inference system. These curves have been generated by writing a code in Matlab 2011b platform. From these curves, it is clearly evident that the fuzzy output i.e. the various fault types, is having bell shaped membership function, which properly reflects the statistical properties of the data. Figure 5.12 to 5.23 depict the probability density curves for the various fault types, as described in the above mentioned fuzzy rules.

Table 5.1. Comparison between different types of membership funcions

Type of Membership Function	Expected Output	Observations		
		FFD Output	Error	Average Error
Gaussian	0	0.013	0.013	0.0926
	5	4.91	0.09	
	6	6.16	0.16	
	8	7.9	0.1	
	9	8.9	0.1	
Triangular	0	0.011	0.011	0.1922
	5	4.89	0.11	
	6	6.14	0.14	
	8	7.6	0.4	
	9	8.7	0.3	
Trapezoidal	0	0.014	0.014	0.1728
	5	4.92	0.08	
	6	6.17	0.17	
	8	7.8	0.2	
	9	8.6	0.4	
Gauss2mf	0	0.012	0.012	0.1524
	5	4.9	0.1	
	6	6.15	0.15	
	8	7.7	0.3	
	9	8.8	0.2	
Gbell	0	0.015	0.015	0.2550
	5	4.87	0.13	
	6	6.13	0.13	
	8	7.5	0.5	
	9	8.5	0.5	
Sigmoidal	0	0.017	0.017	0.3674
	5	4.76	0.24	
	6	6.18	0.18	
	8	7.3	0.7	
	9	8.3	0.7	
Pi-shaped	0	0.016	0.016	0.3552
	5	4.68	0.32	
	6	6.15	0.15	
	8	7.45	0.55	
	9	8.26	0.74	
S-shaped	0	0.018	0.018	0.4358
	5	4.54	0.46	
	6	6.19	0.19	
	8	7.389	0.611	
	9	8.1	0.9	
Z-shaped	0	0.016	0.016	0.4832
	5	4.2	0.8	
	6	5.8	0.2	
	8	7.4	0.6	
	9	8.2	0.8	

Figure 5.12 clearly depicts that when all the three inputs i.e. R1, R2 and R3 are low, then the output i.e. the fault type is Partial Discharge (Rule 1). Figure 5.13 clearly describes that when the two inputs i.e. R1, R3 are medium and R2is low, then the output i.e. the fault type is Low energy discharge (Rule 2). Figure 5.14 clearly shows that when the two inputs i.e. R2, R3 are medium and R1ishigh, then the output i.e. the fault type is High energy discharge (Rule 3).Figure 5.15 clearly delineates that when input R1 is low, R2 is high and R3 is medium, then the output i.e. the fault type is Thermal faults < 300°C (Rule 4). Figure 5.16 clearly describes that when the two inputs i.e. R2, R3 are medium and R1islow, then the output i.e. the fault type is Thermal faults < 700°C (Rule 5). Figure 5.17 clearly reveals that when input R1 is low, R2 is medium and R3 is high, then the output i.e. the fault type is Thermal faults > 700°C (Rule 6). Figure 5.18 clearly depicts that when two inputs i.e. R2, R3 are low and R1ismedium, then the output i.e. the fault type is Partial Discharge (Rule 7). Figure 5.19 clearly delineates that when all the three inputs i.e. R1, R2 and R3 are medium, then the output i.e. the fault type is Low energy discharge (Rule 8).Figure 5.20 clearly shows that when two inputs i.e. R1, R3 are low and R2ismedium, then the output i.e. the fault type is High energy discharge (Rule 9). Figure 5.21 clearly describes that when two inputs i.e. R1, R3 are low and R2ishigh, then the output i.e. the fault type is Thermal faults < 300°C (Rule 10).Figure 5.22 clearly delineates that when all two inputs i.e. R1, R3 are high and R2ismedium, then the output i.e. the fault type is Thermal faults < 700°C (Rule 11). Figure 5.23 clearly reveals that when all the three inputs i.e. R1, R2 and R3 are high, then the output i.e. the fault type is Thermal faults > 700°C (Rule 12). In all these figures, Linguistic Values are Low, Medium and High. Reference sets for Linguistic Variables are: U = [5.25 44] for R_1, U = [1.75 35] for R_2, U = [3.75 45] for $R_{3,}$ Reference sets for Linguistic Values of R_1 are: U = [5.25 24] for Low, U = [3.25 34] for Medium, U = [3.25 44] for High, Reference sets for Linguistic Values of R_2 are: U = [1.75 15] for Low, U = [0.75 25] for Medium, U = [0.75 35] for High, Reference sets for Linguistic Values of R_3 are: U = [3.75 25] for Low, U = [2.75 35]for Medium, U = [2.75 45] for High and the Membership Function is Gaussian.

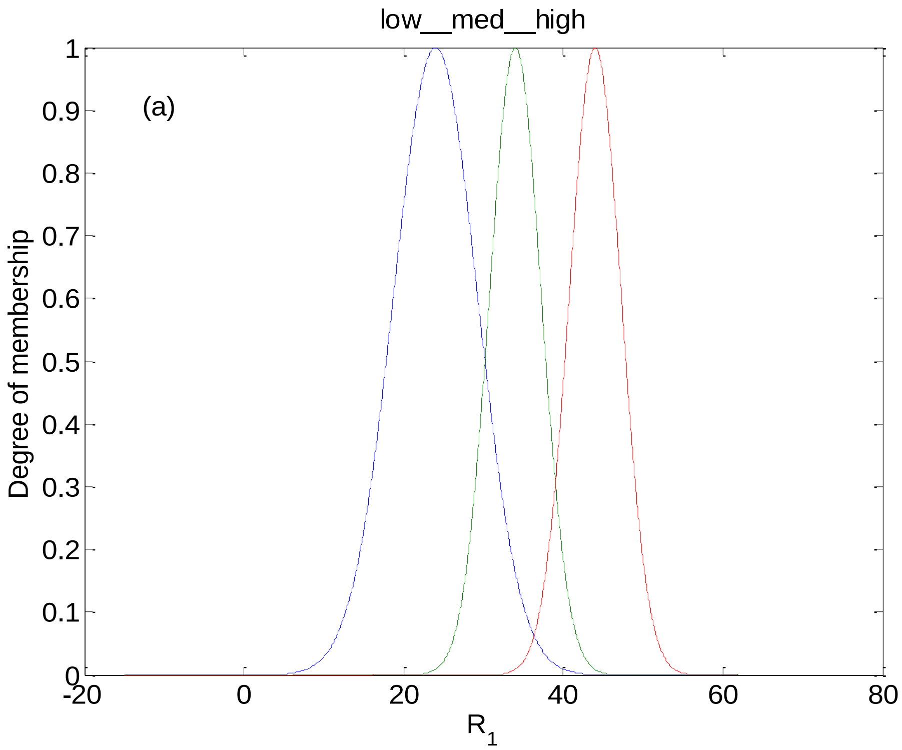

Figure 5.12(a) Probability Density Curves for the fault type Partial Discharge. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4;

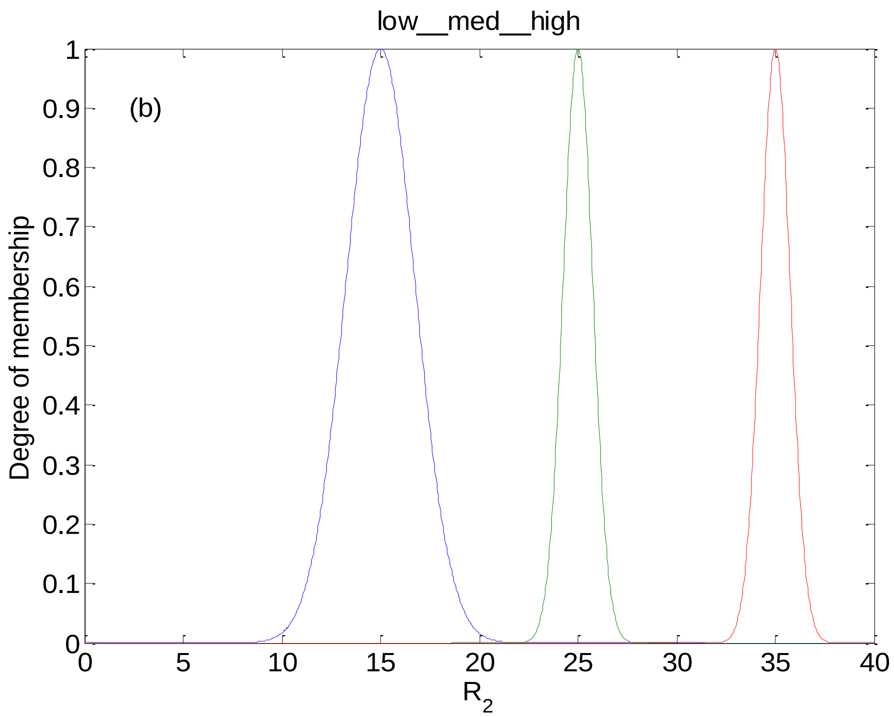

Figure 5.12(b) Probability Density Curves for the fault type Partial Discharge. Linguistic Variable: R_2 = input variable = CH_4/H_2

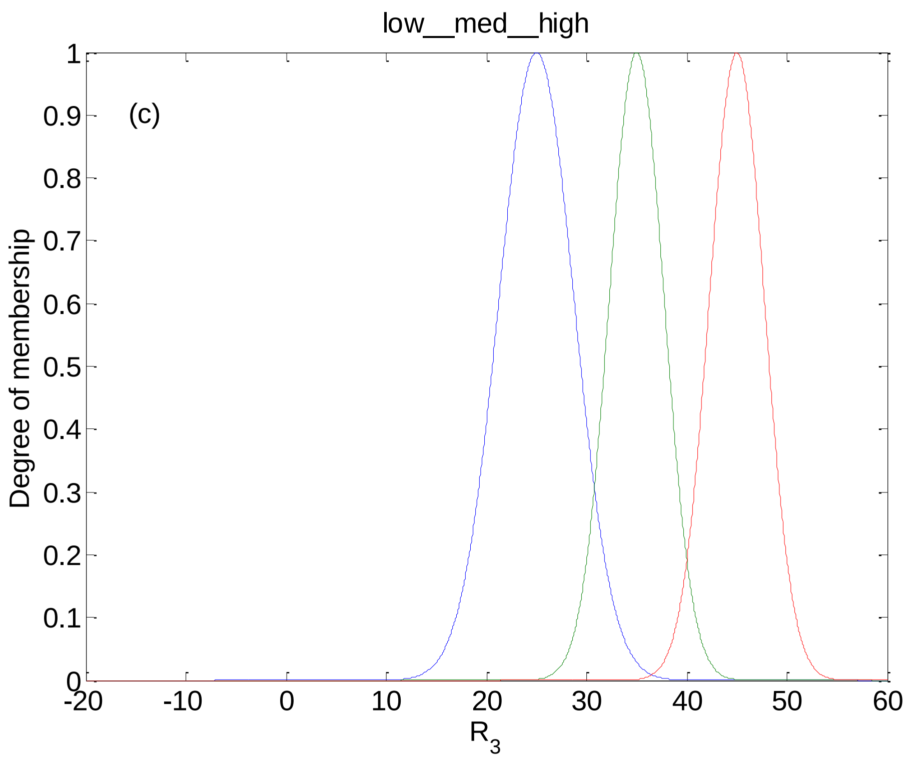

Figure 5.12(c) Probability Density Curves for the fault type Partial Discharge. Linguistic Variable: R_3 = input variable = C_2H_4/C_2H_6

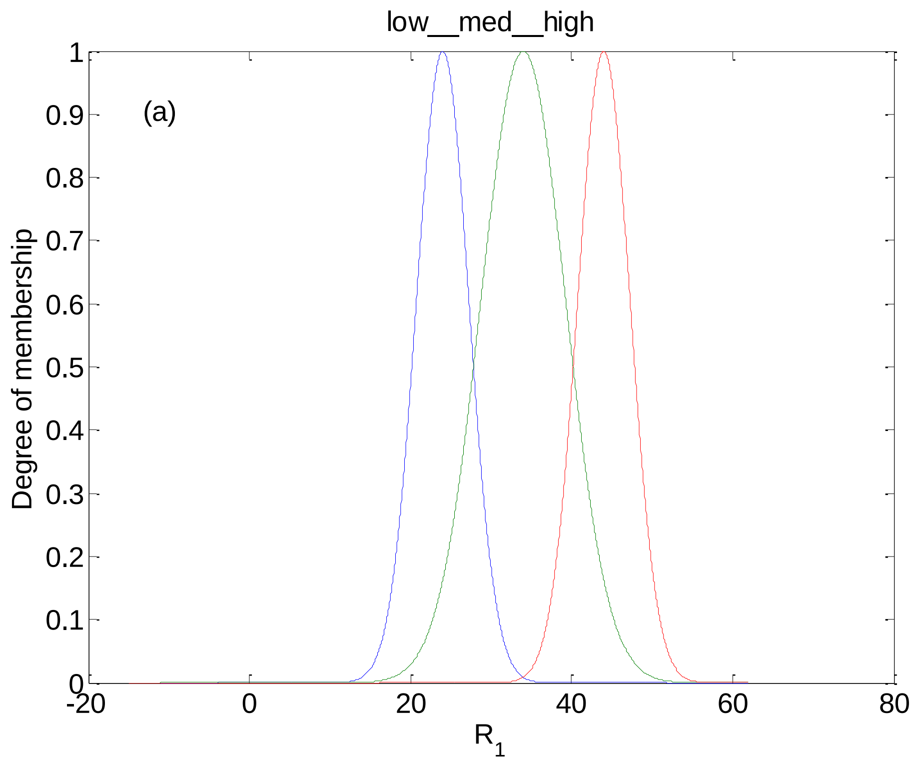

Figure 5.13(a) Probability Density Curves for the fault type Low energy discharge. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

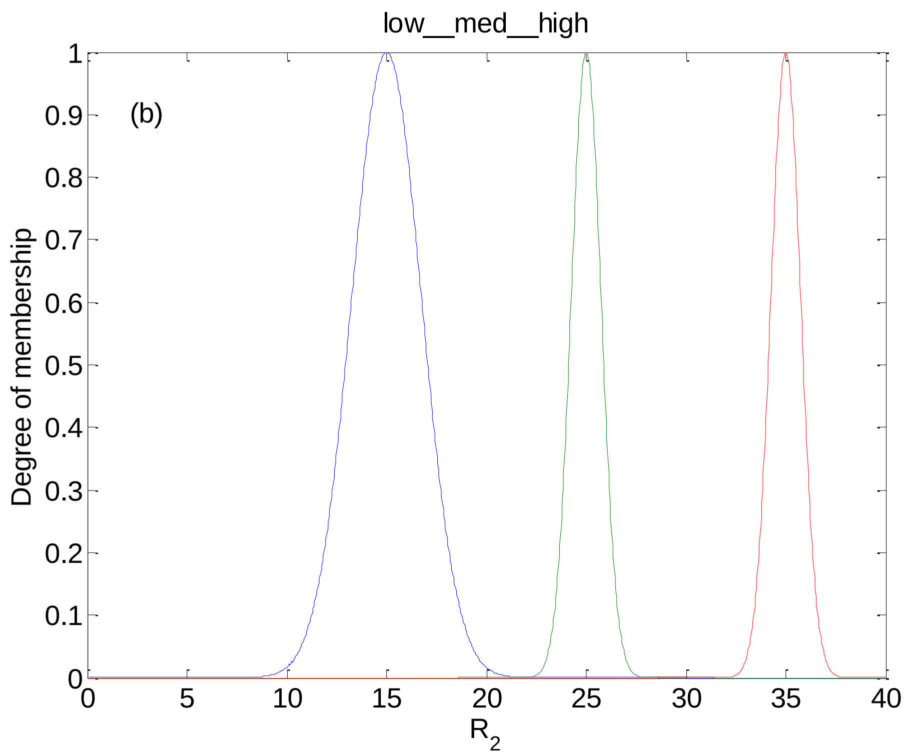

Figure 5.13(b) Probability Density Curves for the fault type Low energy discharge. Linguistic Variable: R_2 = input variable = CH_4/H_2

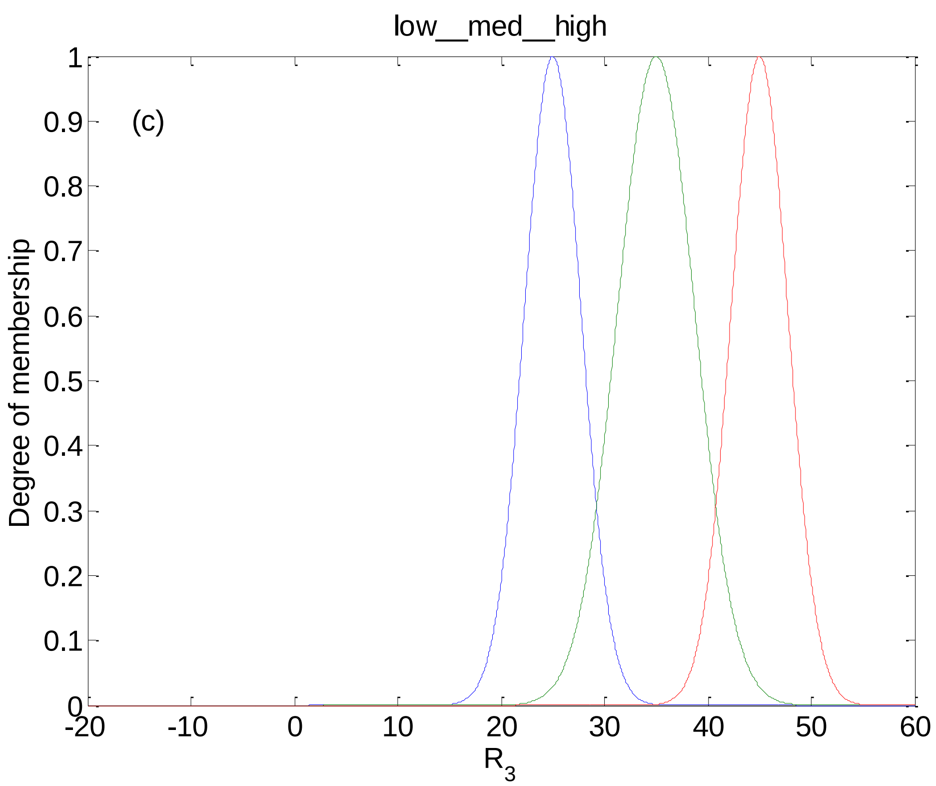

Figure 5.13(c) Probability Density Curves for the fault type Low energy discharge. Linguistic Variable: R_3 = input variable = C_2H_4/C_2H_6

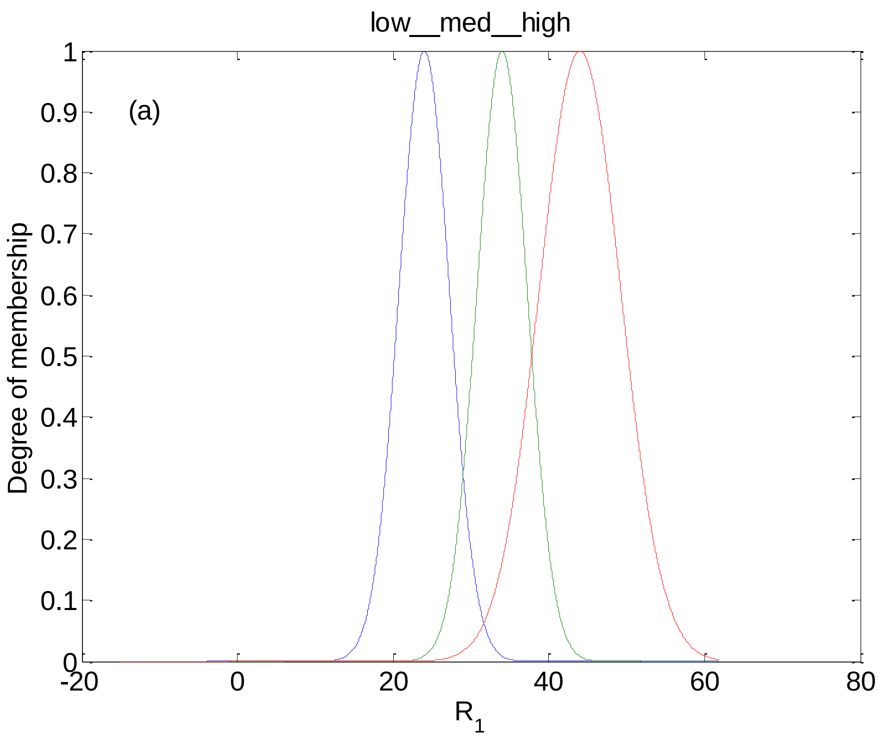

Figure 5.14(a) Probability Density Curves for the fault type High energy discharge. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

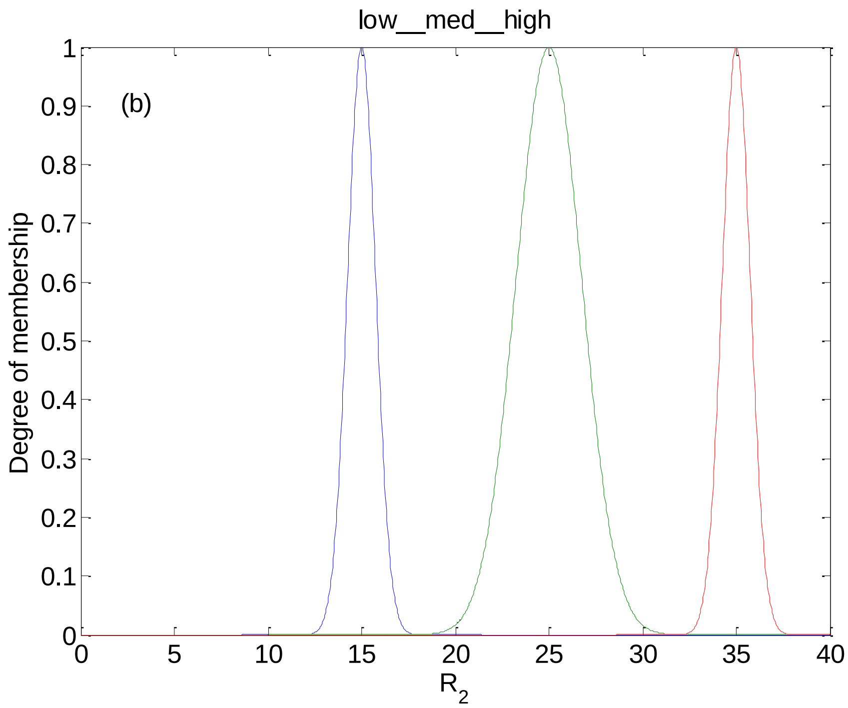

Figure 5.14(b) Probability Density Curves for the fault type High energy discharge. Linguistic Variable: R_2 = input variable = CH_4/H_2

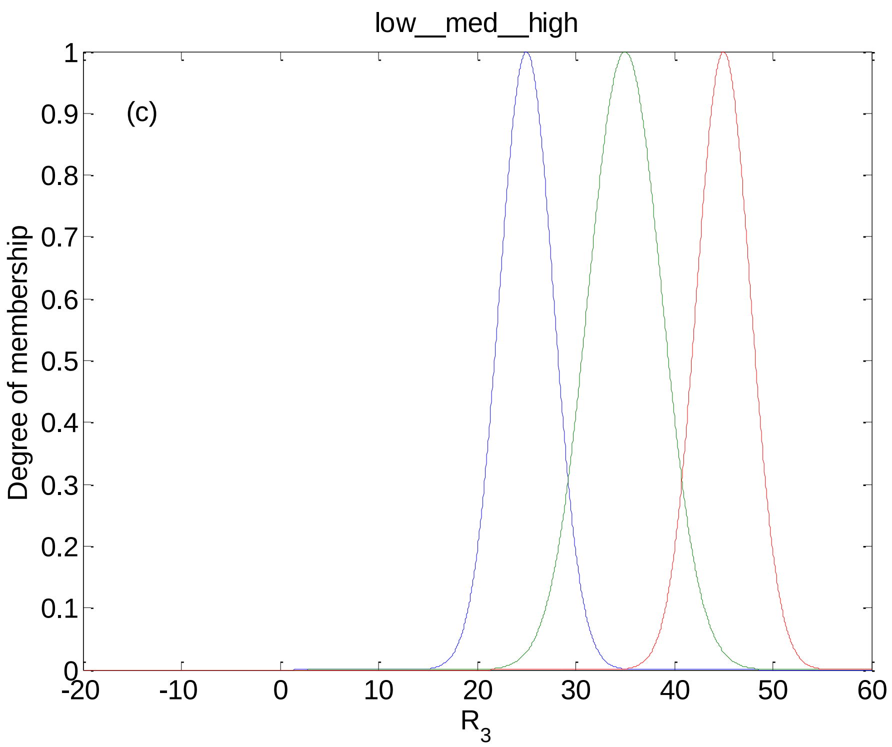

Figure 5.14(c) Probability Density Curves for the fault type High energy discharge. Linguistic Variable: R_3 = input variable = C_2H_4/C_2H_6

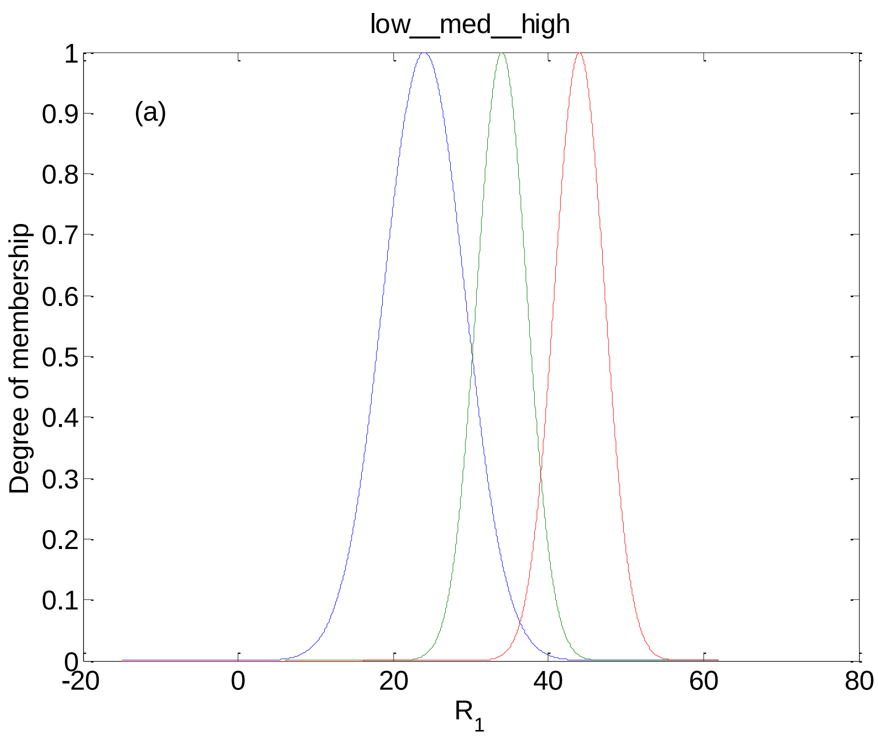

Figure 5.15(a) Probability Density Curves for the fault type Thermal faults < 300°C. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

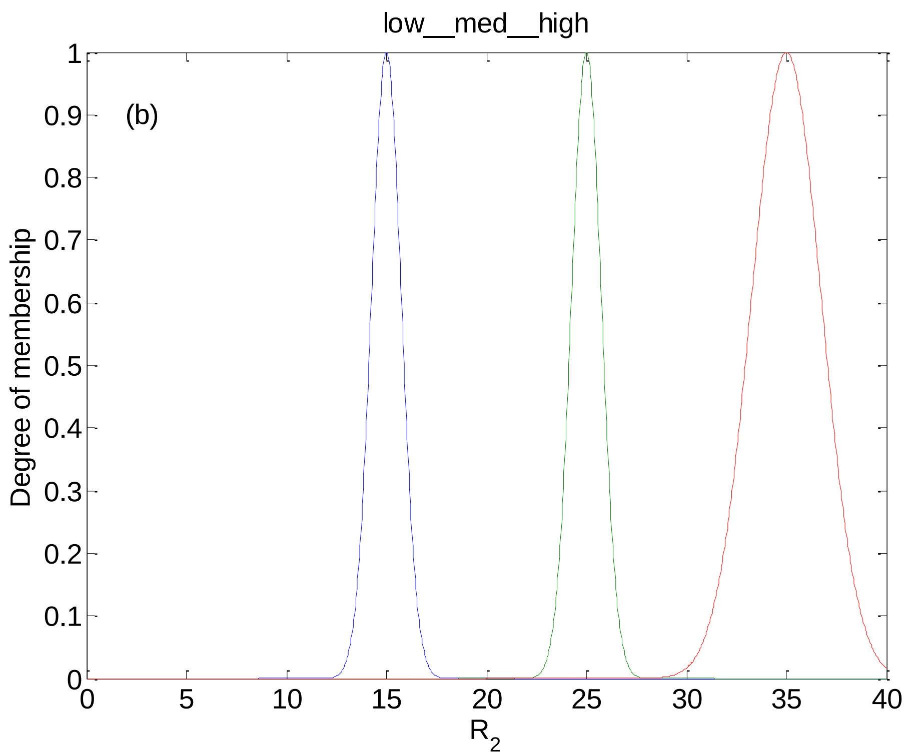

Figure 5.15(b) Probability Density Curves for the fault type Thermal faults < 300°C. Linguistic Variable: R_2 = input variable = CH_4/H_2

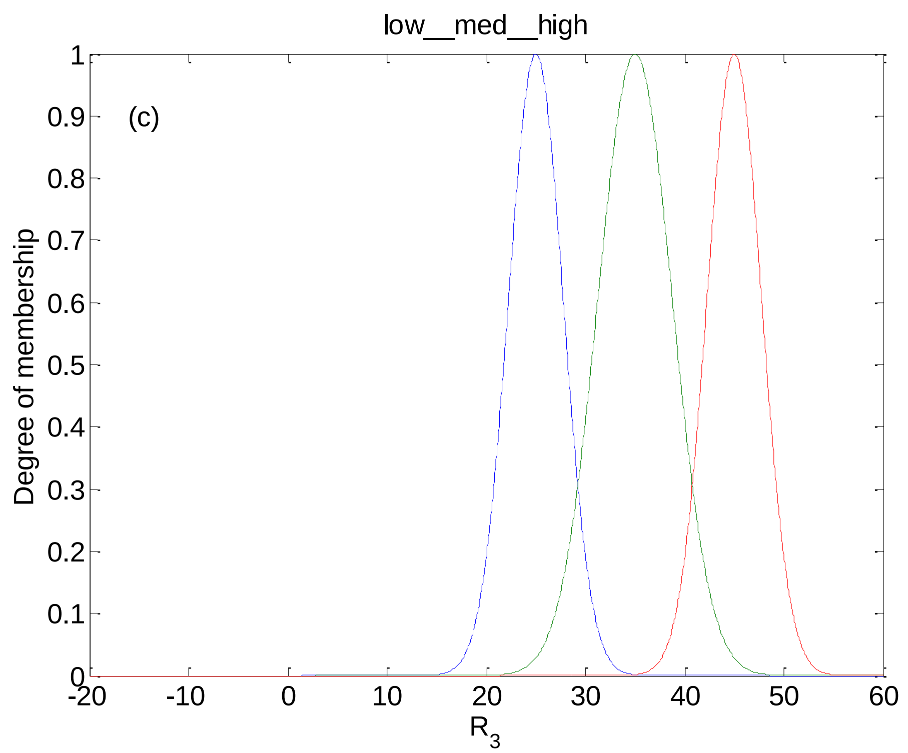

Figure 5.15(c) Probability Density Curves for the fault type Thermal faults < 300°C. Linguistic Variable: R_3 = input variable = C_2H_4/C_2H_6

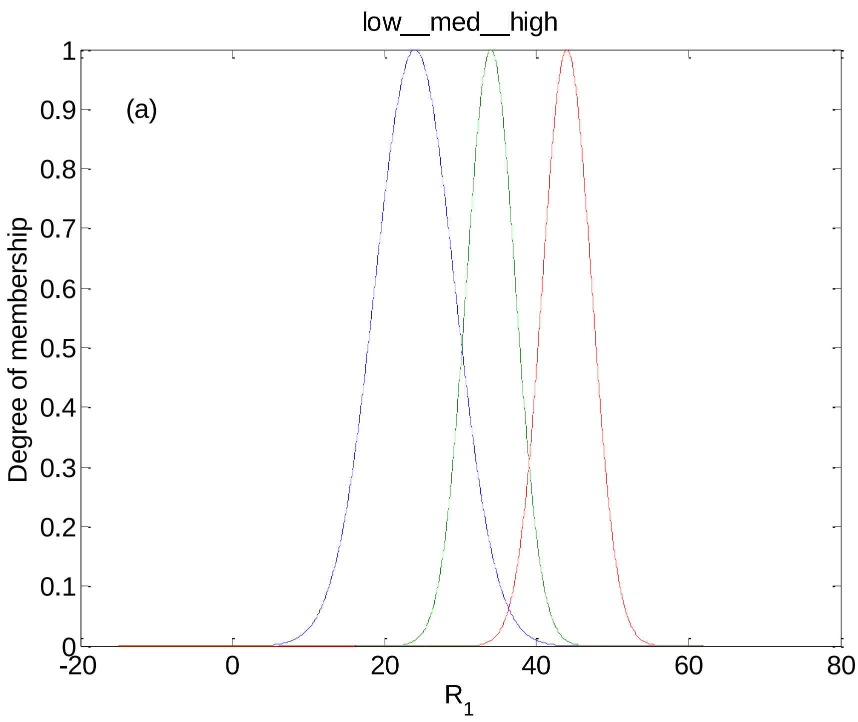

Figure 5.16(a) Probability Density Curves for the fault type Thermal faults < 700°C. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

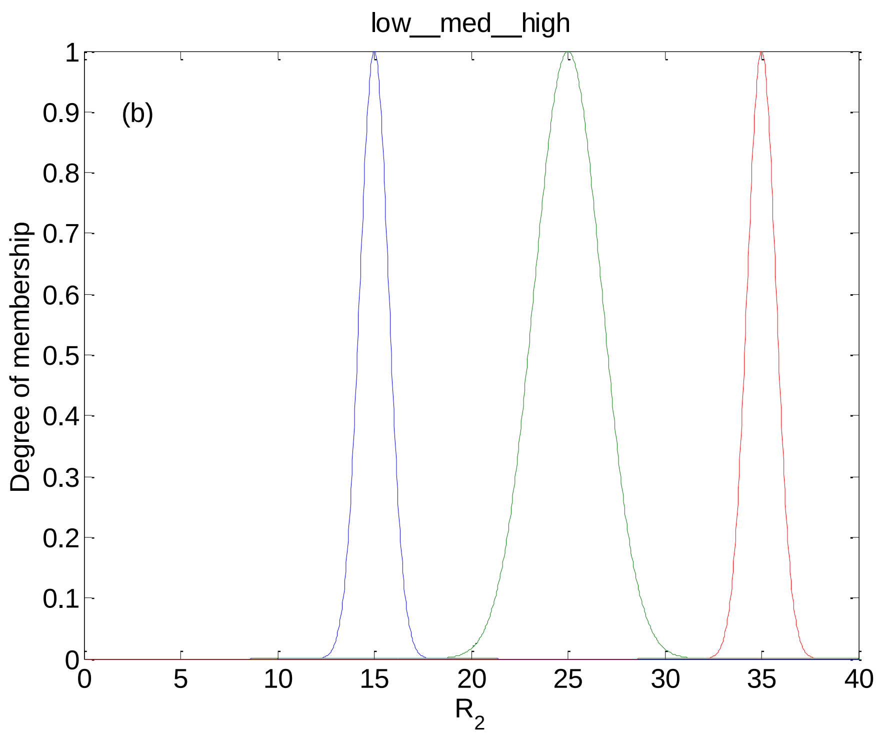

Figure 5.16(b) Probability Density Curves for the fault type Thermal faults < 700°C. Linguistic VariablesR_2 = input variable = CH_4/H_2

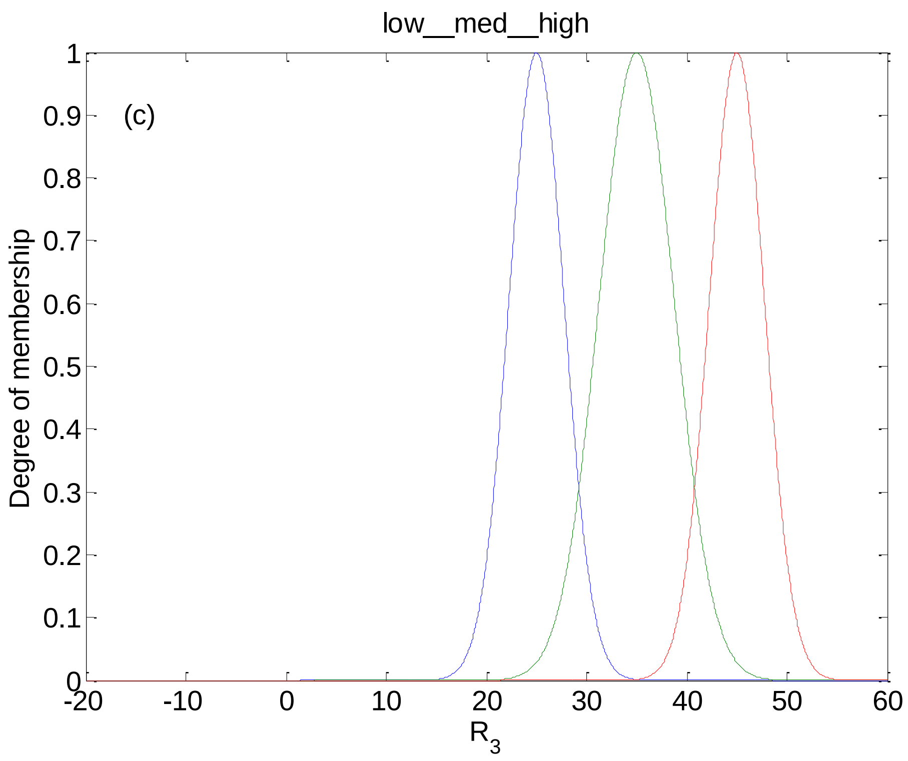

Figure 5.16(c) Probability Density Curves for the fault type Thermal faults < 700°C. Linguistic VariablesR$_3$ = input variable = C_2H_4/C_2H_6

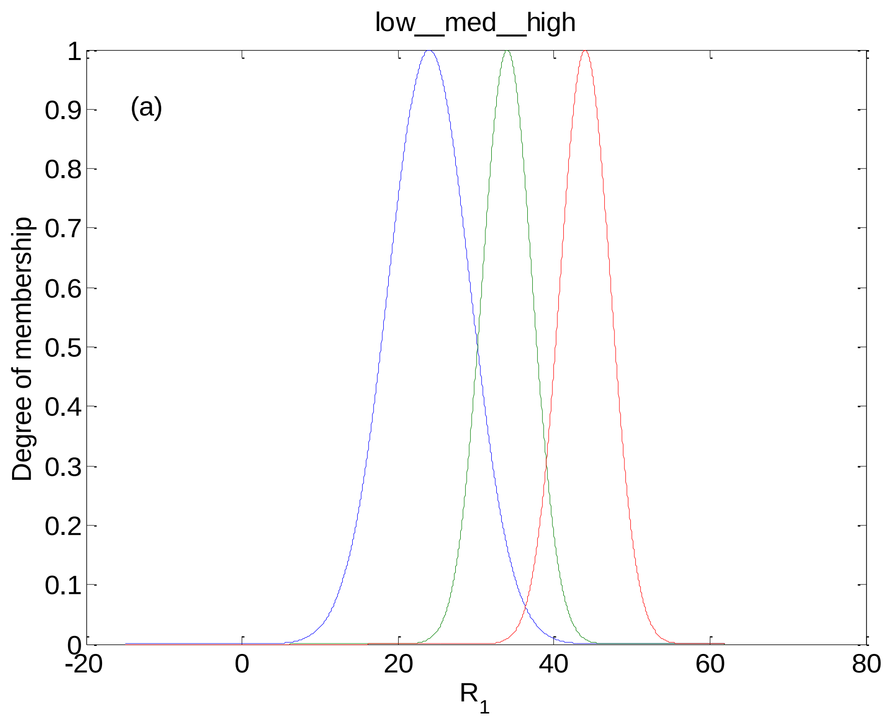

Figure 5.17(a) Probability Density Curves for the fault type Thermal faults > 700°C. Linguistic Variables: R$_1$=input variable = C_2H_2/C_2H_4

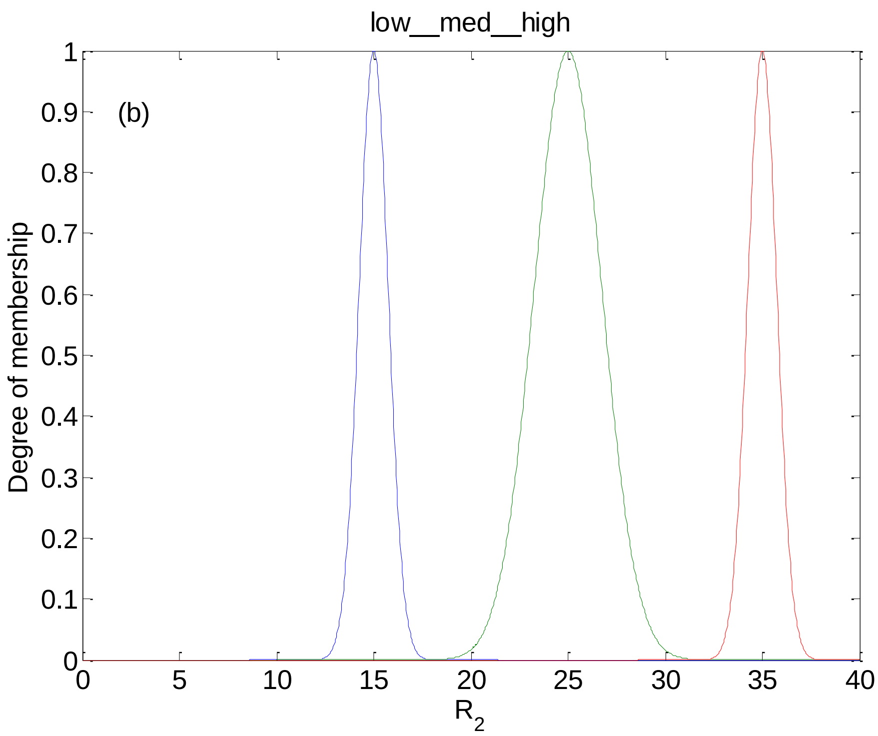

Figure 5.17(b) Probability Density Curves for the fault type Thermal faults > 700°C R_2 = input variable = CH_4/H_2

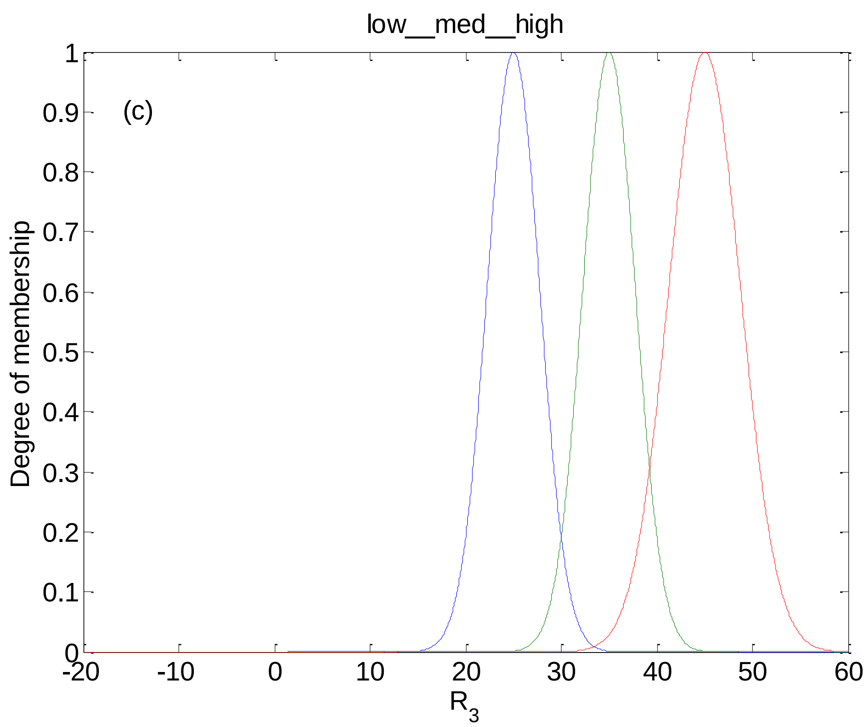

Figure 5.17(c) Density Curves for the fault type Thermal faults > 700°C+ R_3 = input variable = C_2H_4/C_2H_6 Linguistic Values: Low, Medium and High

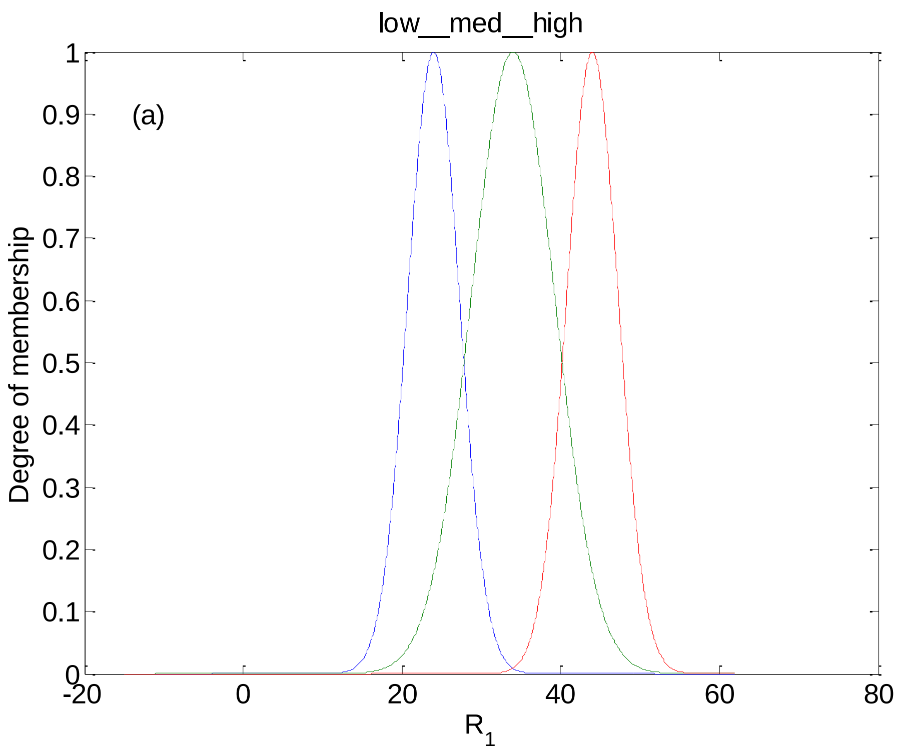

Figure 5.18(a) Probability Density Curves for the fault type Partial Discharge. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

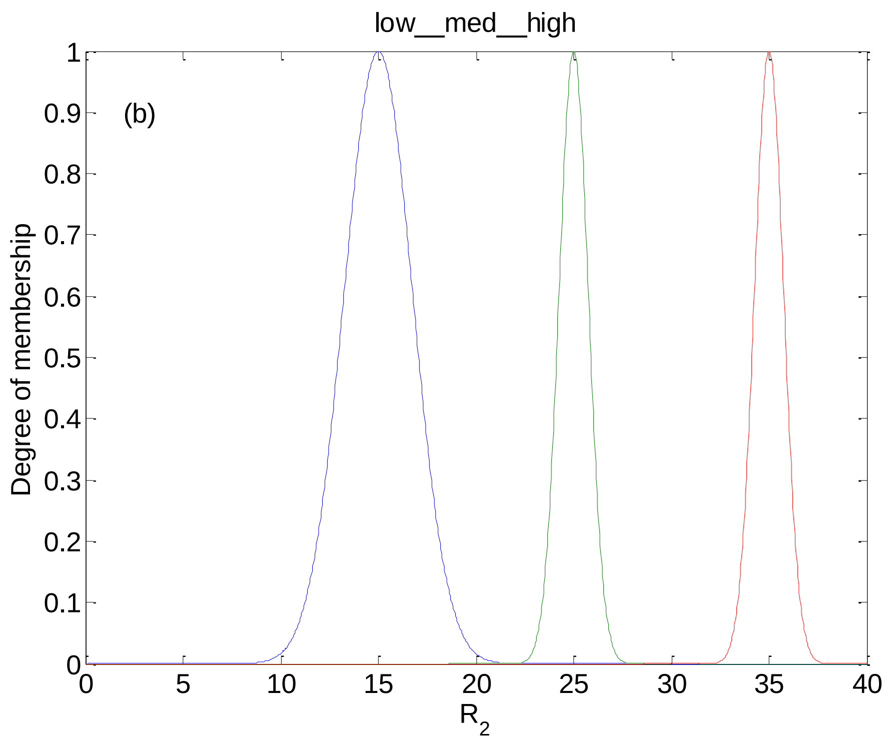

Figure 5.18(b) Probability Density Curves for the fault type Partial Discharge. Linguistic Variable: R_2 = input variable = CH_4/H_2

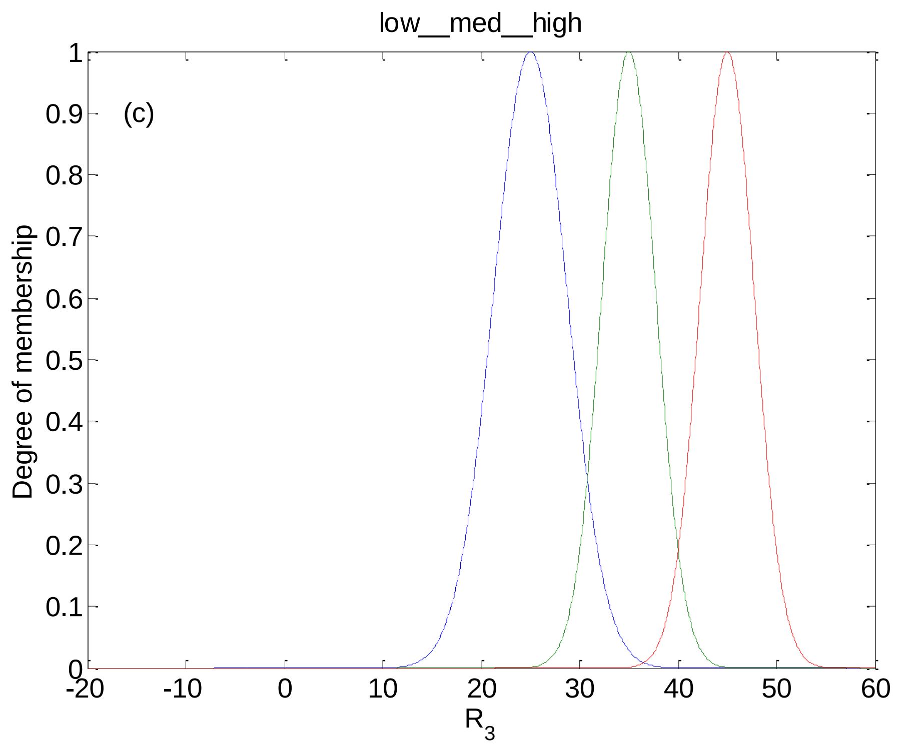

Figure 5.18(c) Probability Density Curves for the fault type Partial Discharge. Linguistic Variable: R_3 = input variable = C_2H_4/C_2H_6

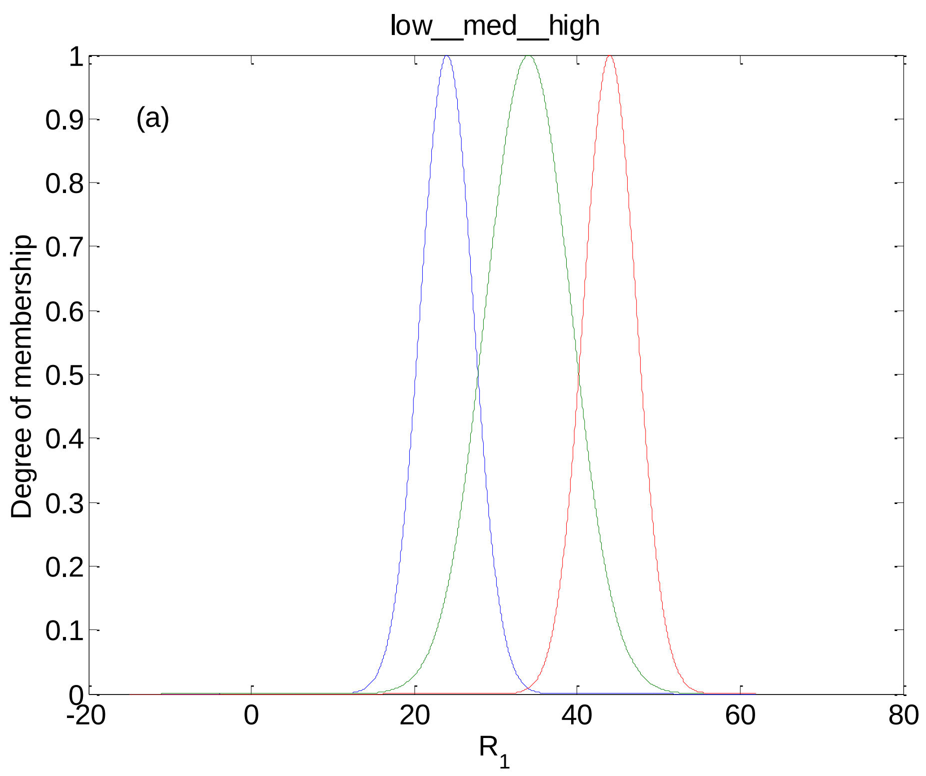

Figure 5.19(a) Probability Density Curves for the fault type Low energy discharge. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

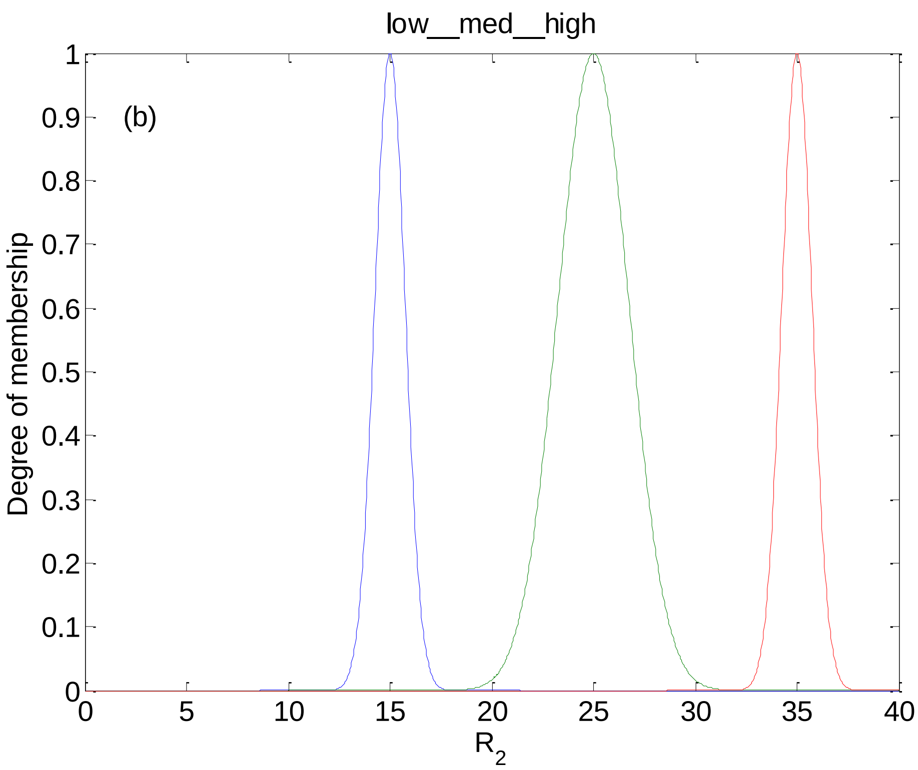

Figure 5.19(b) Probability Density Curves for the fault type Low energy discharge. Linguistic Variable: R_2 = input variable = CH_4/H_2

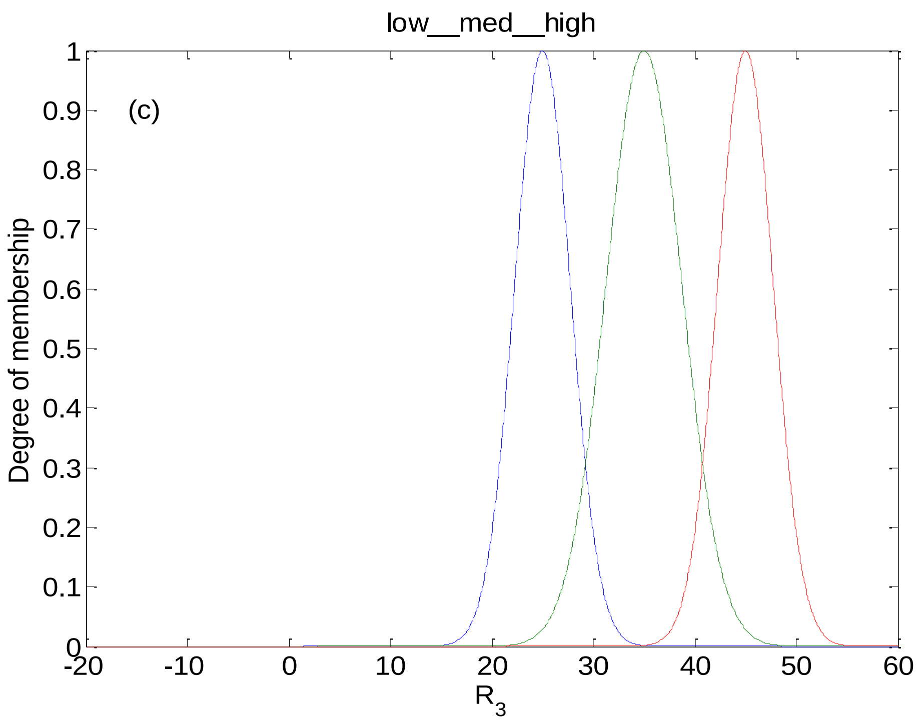

Figure 5.19(c) Probability Density Curves for the fault type Low energy discharge. Linguistic Variable: R_3 = input variable = C_2H_4/C_2H_6

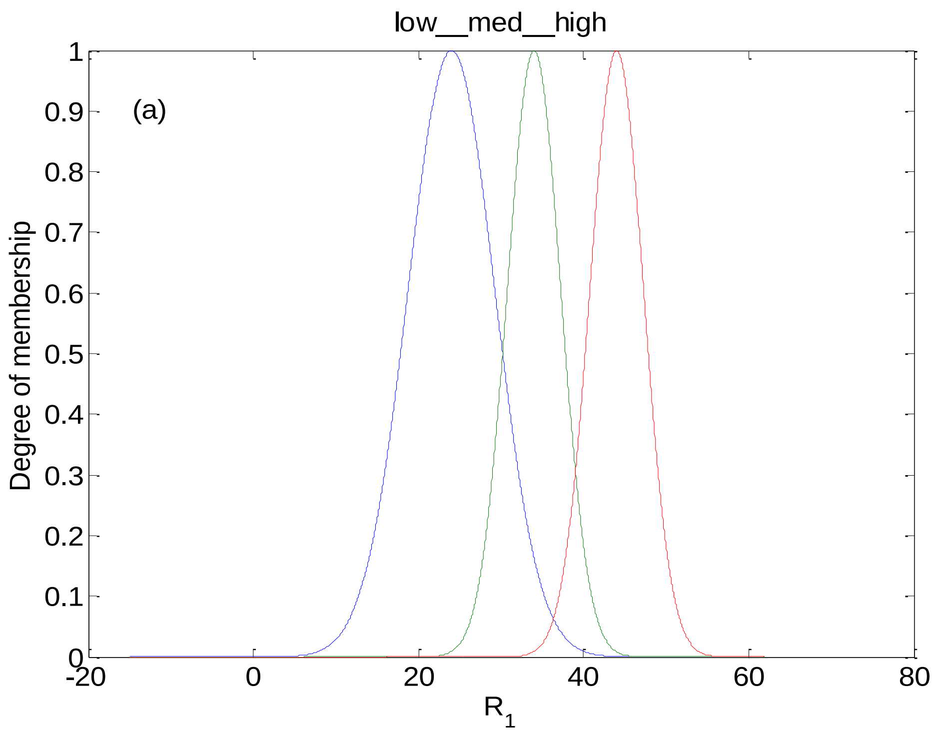

Figure 5.20(a) Probability Density Curves for the fault type High energy discharge. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

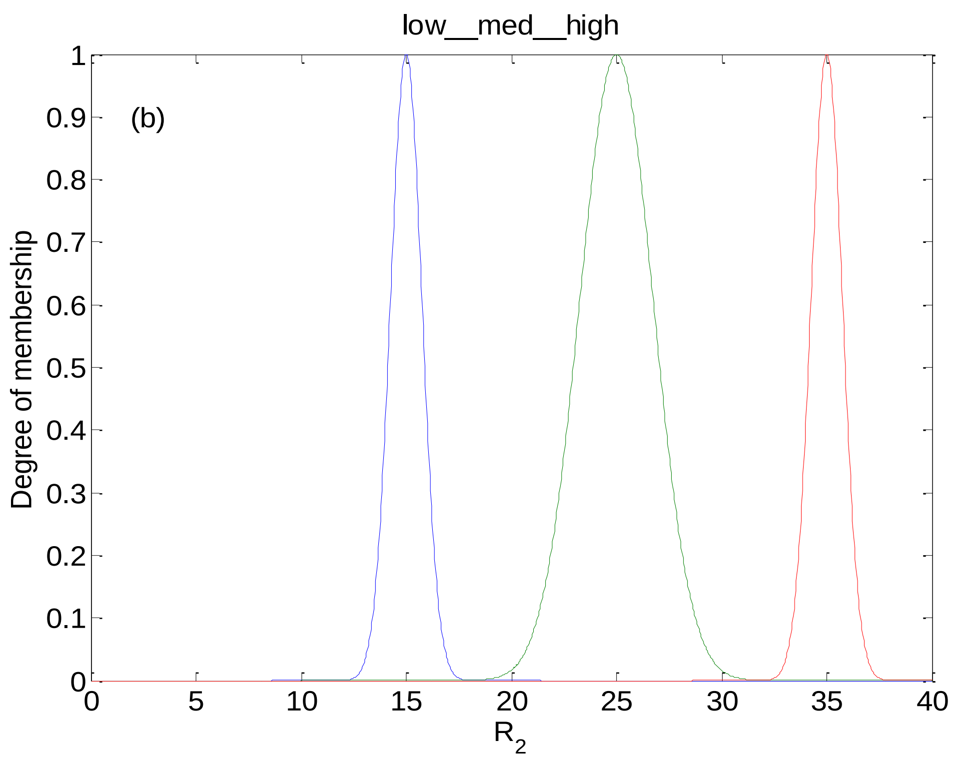

Figure 5.20(b) Probability Density Curves for the fault type High energy discharge. Linguistic Variable: R_2 = input variable = CH_4/H_2

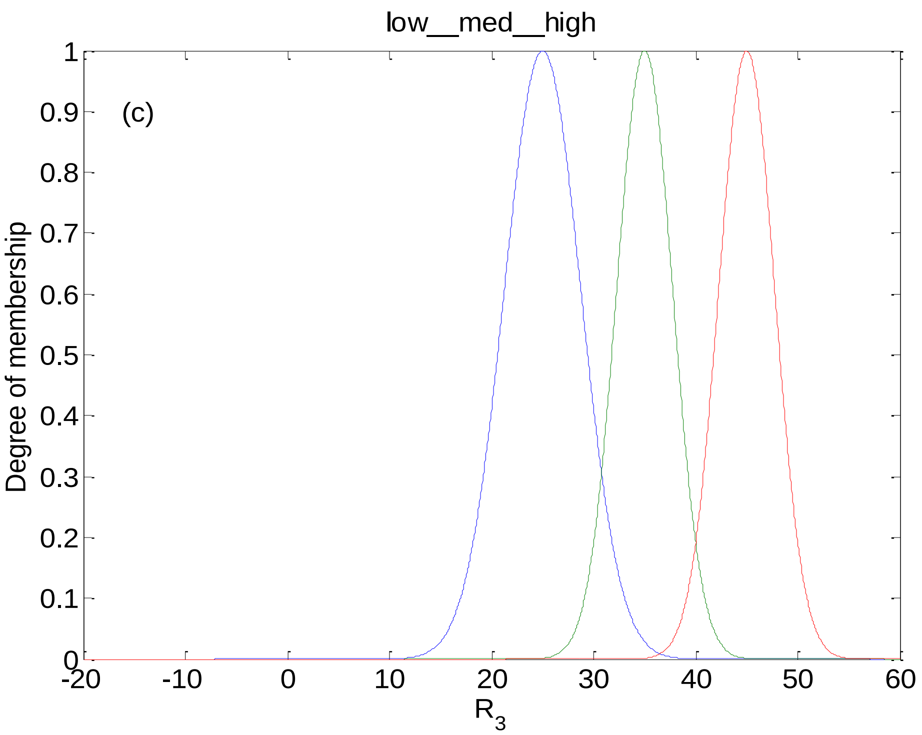

Figure 5.20(c) Probability Density Curves for the fault type High energy discharge. Linguistic Variable: R_3 = input variable = C_2H_4/C_2H_6

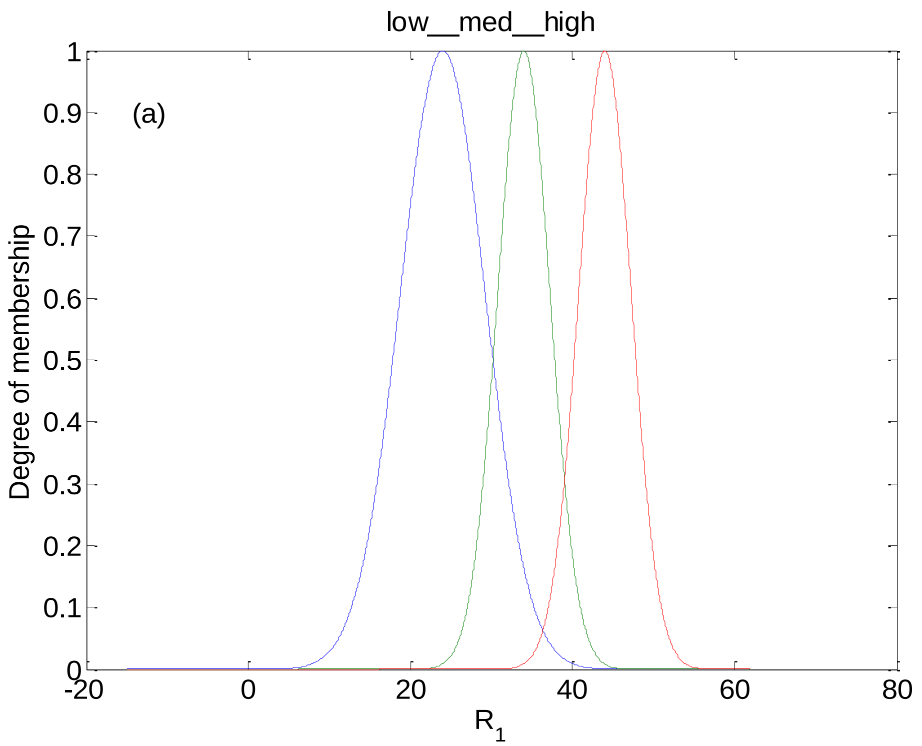

Figure 5.21(a) Probability Density Curves for the fault type Thermal faults < 300°C. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

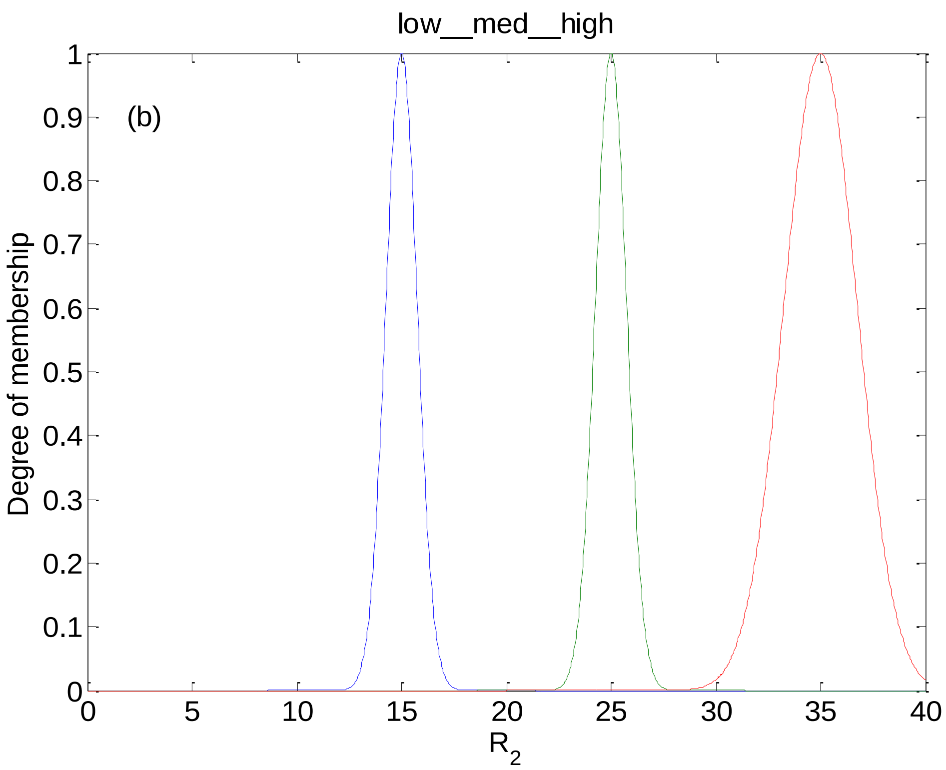

Figure 5.21(b) Probability Density Curves for the fault type Thermal faults < 300°C. Linguistic Variable: R_2 = input variable = CH_4/H_2

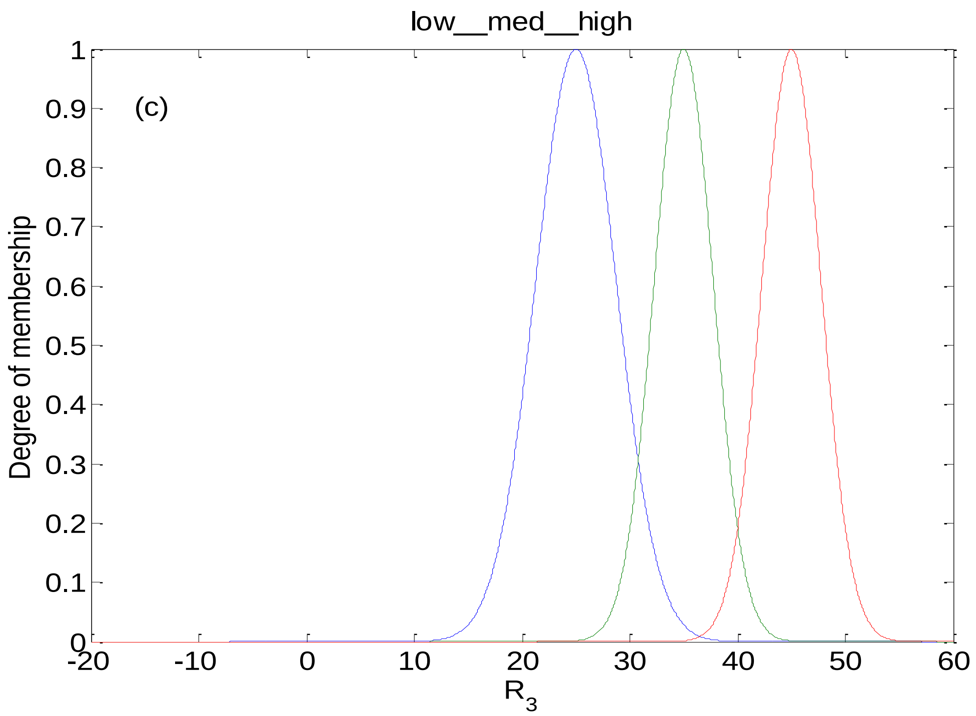

Figure 5.21(c) Probability Density Curves for the fault type Thermal faults < 300°C. Linguistic Variable: R_3 = input variable = C_2H_4/C_2H_6

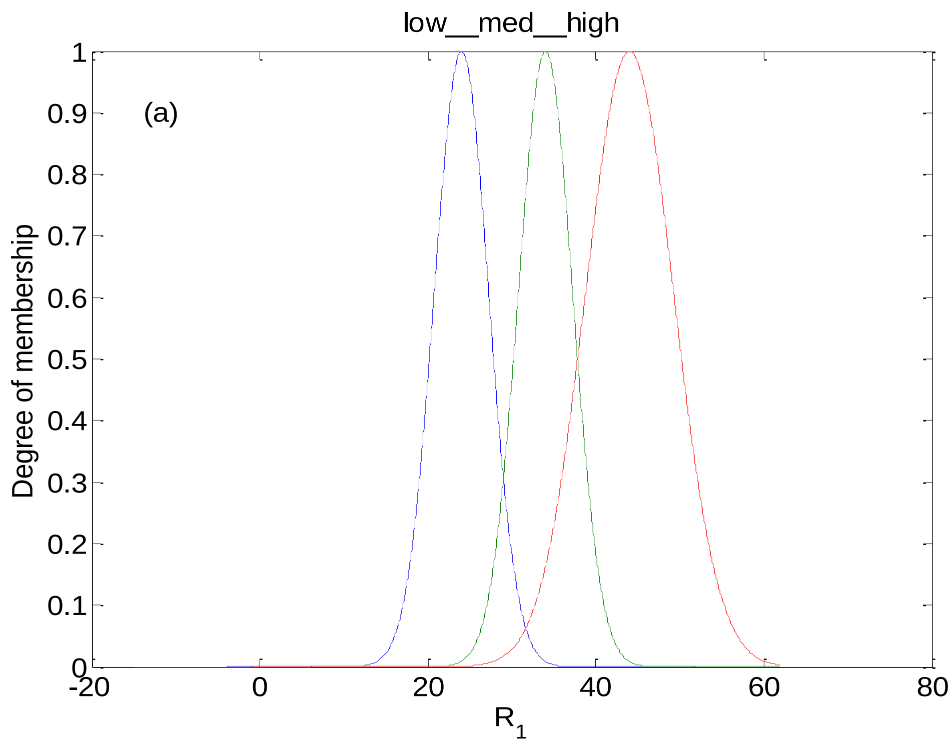

Figure 5.22(a) Probability Density Curves for the fault type Thermal faults < 700°C. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

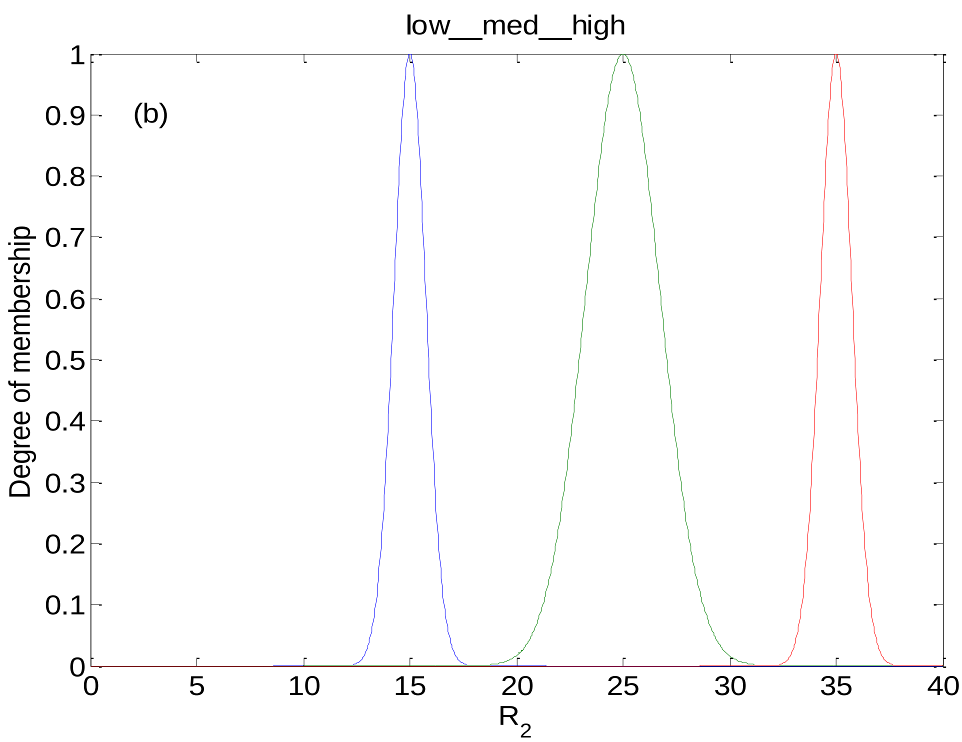

Figure 5.22(b) Probability Density Curves for the fault type Thermal faults < 700°C. Linguistic Variable: R_2 = input variable = CH_4/H_2

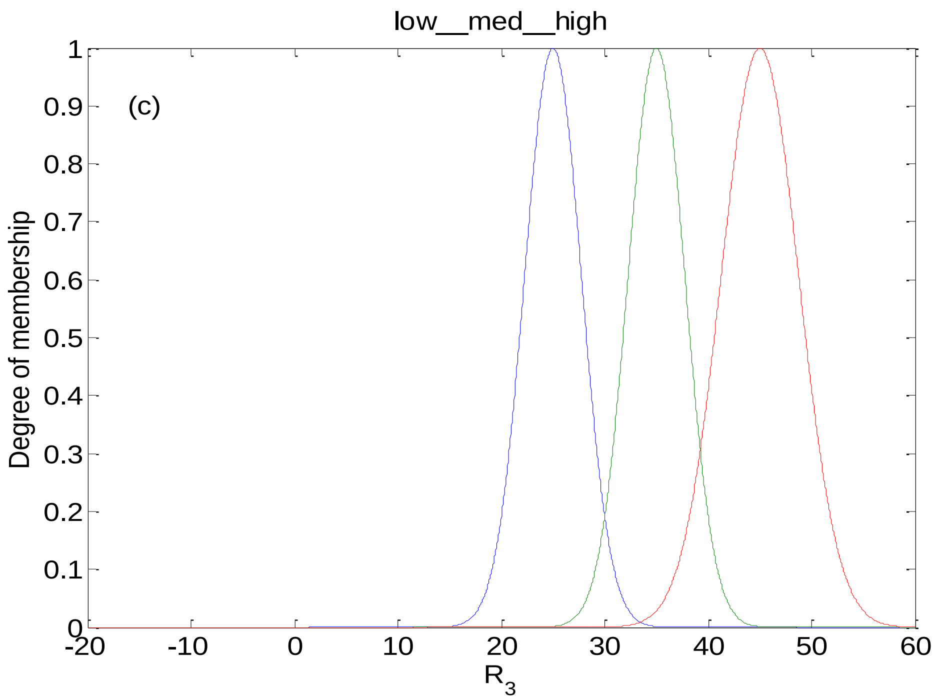

Figure 5.22(c) Probability Density Curves for the fault type Thermal faults < 700°C Linguistic Variables: R_3 = input variable = C_2H_4/C_2H_6

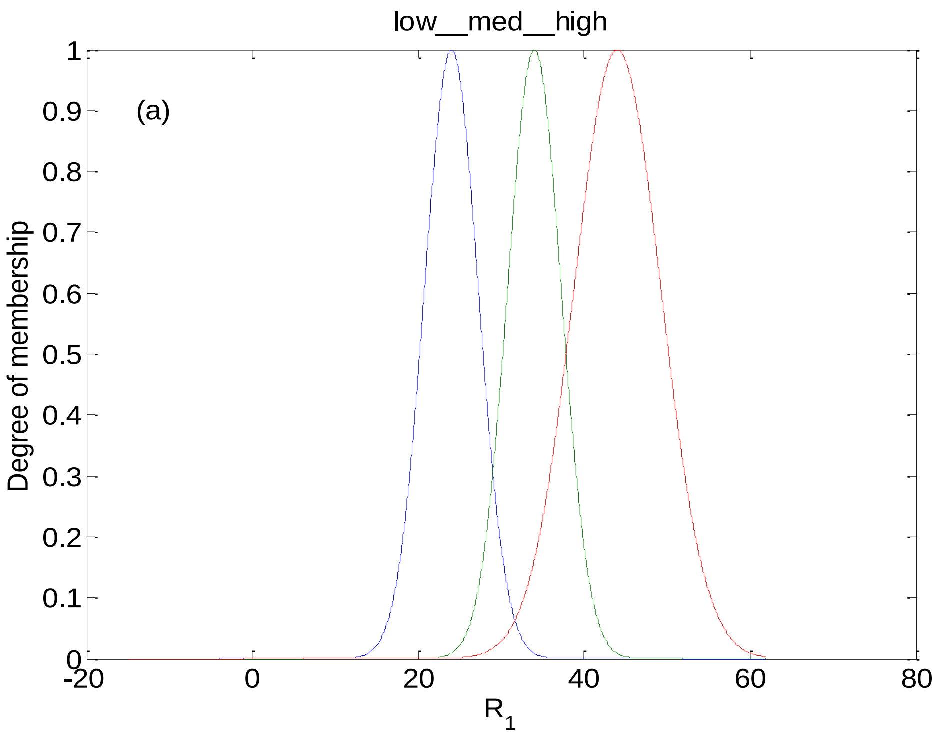

Figure 5.23(a) Probability Density Curves for the fault type Thermal faults < 700°C. Linguistic Variable: R_1=input variable = C_2H_2/C_2H_4

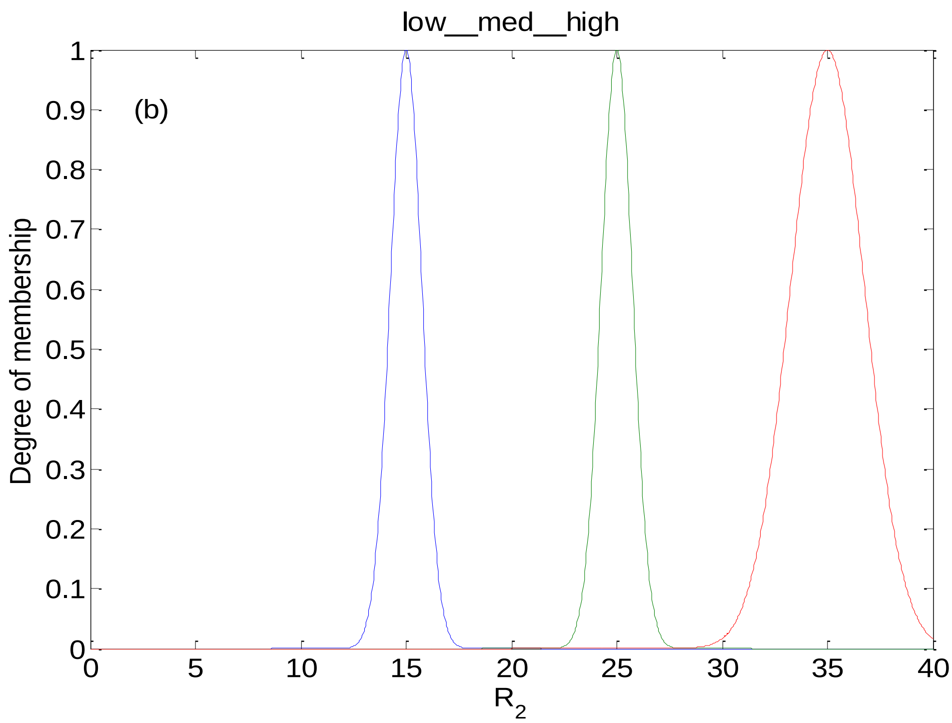

Figure 5.23(b) Probability Density Curves for the fault type Thermal faults < 700°C Linguistic Variables: R_2 = input variable = CH_4/H_2

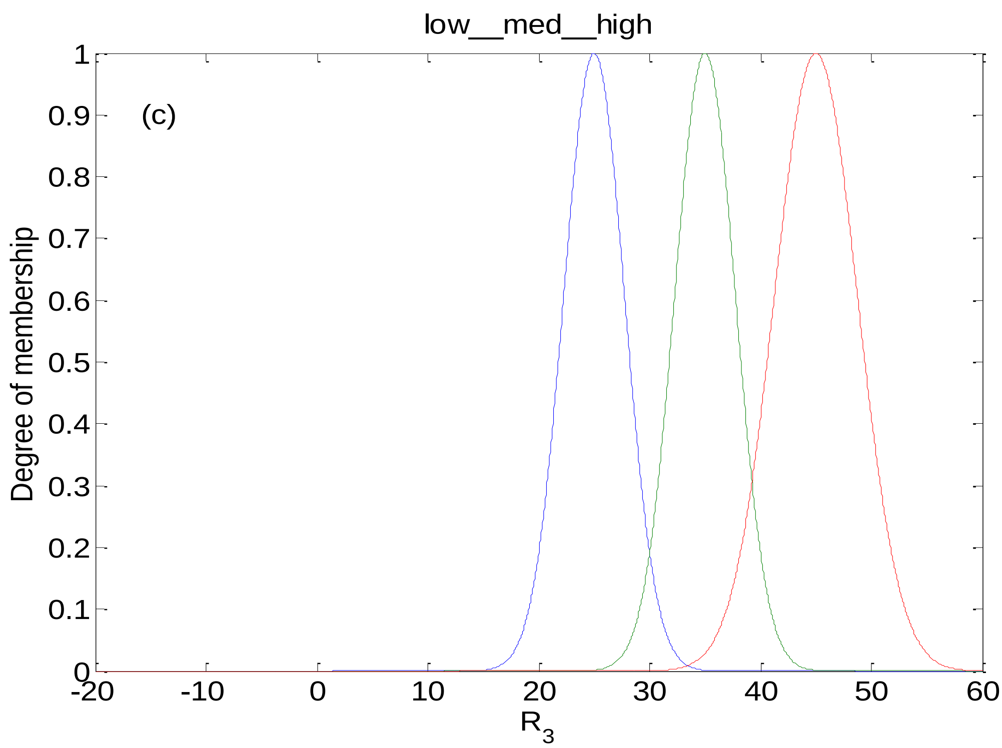

Figure 5.23(c) Probability Density Curves for the fault type Thermal faults < 700°C. Linguistic Variable: R_3 = input variable = C_2H_4/C_2H_6

5.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The combination of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS) has drawn the attention of several researchers in various scientific and engineering fields due to the rising needs of intelligent systems to solve the real world complex problems. ANN learns the presented inputs from the base by updating the interconnections between layers. FIS is a most common computation model based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. ANFIS is one of the best trade off between neural and fuzzy systems providing smoothness due to Fuzzy Control interpolation and adaptability due to Neural Network back propagation. The general ANFIS structure is presented in Figure 5.24. This structure consists of five layers. Layer 1 is a transparent layer. It just transmits input values to the next level. Layer 2 calculates the membership degrees. Layer 3 finds out the matching degrees for any rule. Layer 4 integrates the rule strengths and layer 5 calculates the outputs [Jang et al. 1993; Rojas et al. 2000; Joshi et al. 2003].

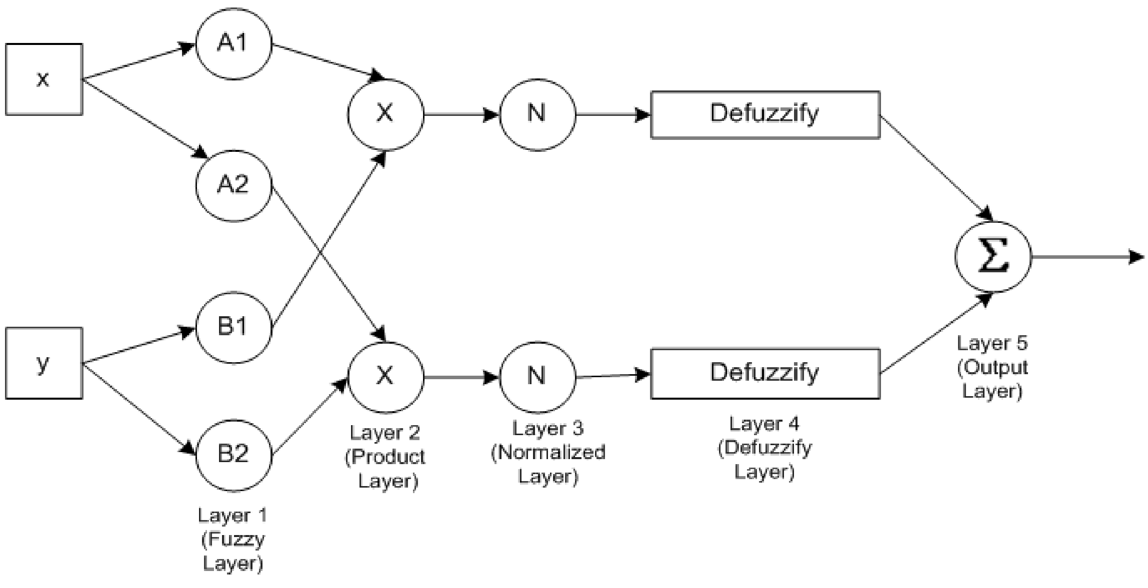

Figure 5.24 General Architecture of Adaptive Neuro-Fuzzy Inference System(ANFIS)

The algorithm of the proposed training methodology of Adaptive Neuro-Fuzzy Inference System (ANFIS) system is given below [Hongsheng et al. 2007; Tag et al. 2010; Hooshmand et al. 2012]:

1. Load the training/testing data and generate initial fuzzy inference system (FIS) model.

2. Set initial parameters and membership functions.

3. Choose FIS model optimization method (hybrid method).

4. Define training and testing parameters (number of training/testing epochs).

5. Input training data into ANFIS system.

6. Check out, if the training finished. If yes, go to step 7, else go to step 5.

7. Get the results after training.

8. Input testing data into ANFIS system.

9. Check out, if the testing finished. If yes, go to step 10, else go to step 8.

10. View FIS structure for the output surface of FIS, generated rules and adjusted membership functions.

The collected DGA database, has been taken to build an Adaptive Neuro-Fuzzy Inference System (ANFIS), to predict various fault types as interpreted by the international standard IEC 60599 (Table 4.1). The three gas ratios R1 (C_2H_2 /C_2H_4), R2 (CH_4/H_2) and R3 (C_2H_4/C_2H_6) have been taken as inputs while various fault types have been taken as output of the ANFIS network. The Gaussian membership function has been taken into consideration for both the inputs and outputs. The ANFIS network has been has been trained in MATLAB 2011b environment, to detect the various fault types. During training, 110 sets of DGA data have been taken while the testing dataset number equals 150.

The proposed ANFIS network configuration includes the following parameters:

Number of nodes - 78

Number of linear parameters - 108

Number of Non-Linear Parameters - 18

Total number of Parameters - 126

Numbers of training data pairs - 110

Number of checking data pairs - 150

Number of fuzzy rules – 27

The ANFIS training gets completed at epoch 2 for the proposed system. The average training and testing error for the proposed system are 0.23 and 0.20, respectively. Figure 5.25 and 5.26 show the plots of training and testing error versus epochs, respectively. In figure 5.25, the blue asterisks (*) represent the training error while the blue dots (·) represent the testing error. In figure 5.26, the actual values have been represented by the blue color dots while the red dots represent the output values calculated from the existing membership functions. Figure 5.27 shows the schematic structure of the proposed ANFIS network.

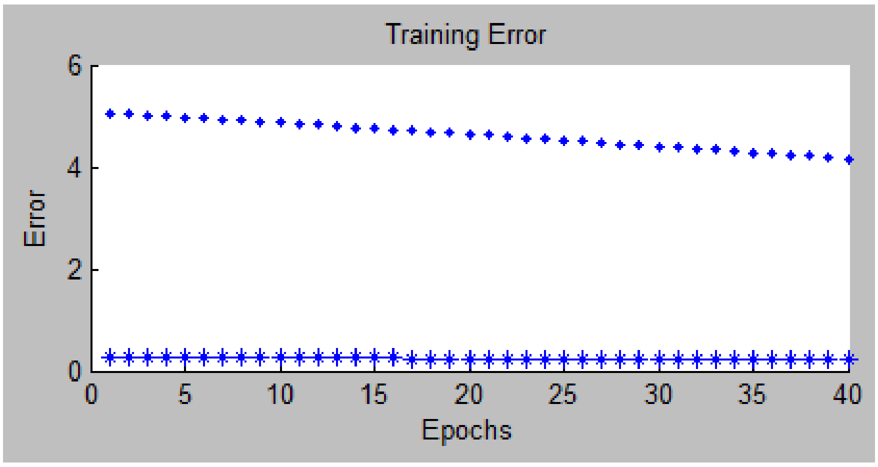

Figure 5.25 Training Error versus epochs plot

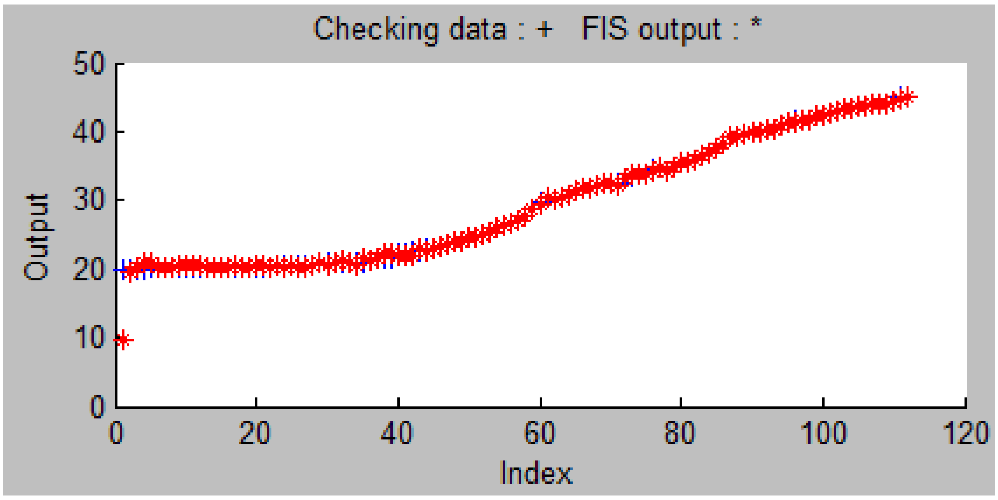

Figure 5.26 Testing Error versus epochs plot

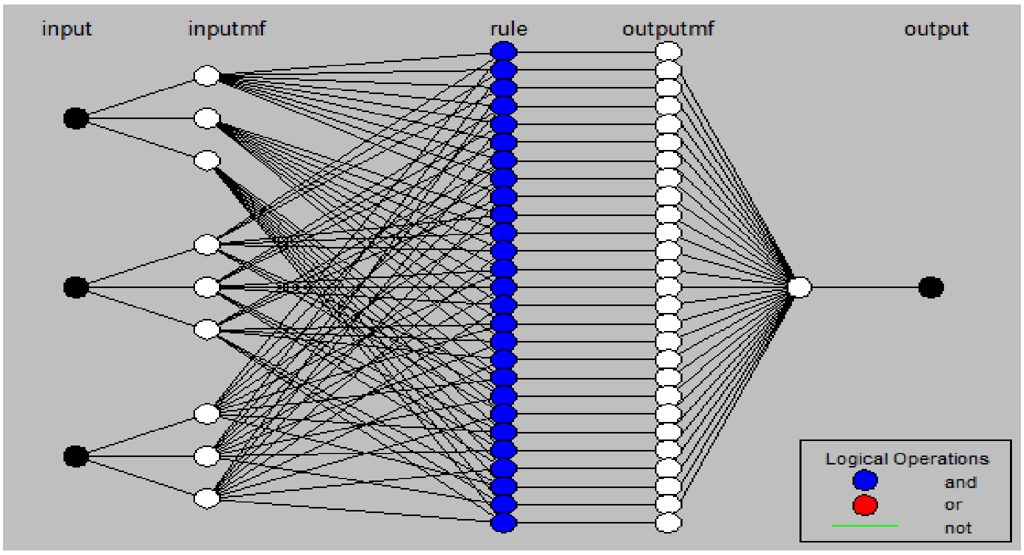

Figure 5.27 Schematic structure of the proposed Adaptive Neuro-Fuzzy Inference System

Figure 5.27 shows ANFIS structure, developed for the condition monitoring of power transformer using MATLAB. Here, the dataset of dissolved gases in oil is used as input to ANFIS where as the fuzzy inference mechanism is used for detection of faults.

Table 5.2 gives a comparative analysis of classification accuracy amongst different learning algorithms of back propagation method, conventional DGA method (IEC 60599 ratio method), Fuzzy Logic and ANFIS. From this table, it is seen that ANFIS is a more accurate learning algorithm than the rest ones.

Table 5.2 Comparison between IEC 60599, Back Propagation Neural Network (BPNN), Fuzzy logic and Adaptive Neuro-Fuzzy Inference System (ANFIS) where PD- Partial Discharge, D1- Low energy discharge, D2- High energy discharge, T1- Thermal faults < 300°C, T2- Thermal faults < 700°C, T3- Thermal faults > 700°C

Sample	Transformer Rating	R1	R2	R3	IEC 60599 Method	BPNN	Fuzzy based Fault Detection	ANFIS	Actual fault
1	115 kV & 20 MVA	1	0.05	0.03	PD	PD	PD	PD	PD
2	68 kV & 30 MVA	0.04		12.64	Not Identified	Not Identified	T3	Not Identified	T3
3	69 kV & 25 MVA	3.36	0.26	1.18	Not Identified	D1	Not Identified	D1	D1
4	220 kV & 100 MVA	0.08	29.82	3.45	T2	T2	T2	T2	T2
5	210 kV & 120 MVA	0.94	0.65	3.13	D2	D2	D2	D2	D2
6	65 kV & 35 MVA	0.03	2.25	0.2	T1	T1	Not Identified	T1	T1
7	70 kV & 40 MVA	1.17	0.11	0.10	PD	Not Identified	Not Identified	PD	PD
8	78 kV & 45 MVA	0.01	1.45	9.10	T3	T3	T3	T3	T3
9	85 kV & 50 MVA	2.88	0.13	8.63	D1	D1	D1	D1	D1
10	125 kV & 25 MVA	0.02	1.25	2.98	Not Identified	T2	T2	T2	T2
11	135 kV & 35 MVA	1.03	1.00	14.96	Not Identified	D2	D2	D2	D2
12	150 kV & 50 MVA	0.01	1.11	0.55	T1	T1	T1	T1	T1
13	215 kV & 125 MVA	2.00	0.13	0.01	Not Identified	PD	PD	PD	PD
14	205 kV & 95 MVA	0.18	0.15	6.67	T3	T3	Not Identified	T3	T3
15	220 kV & 120 MVA	5.78	6.68	11.39	D1	Not Identified	D1	D1	D1

Sample	Transformer Rating	R1	R2	R3	IEC 60599 Method	BPNN	Fuzzy based Fault Detection	ANFIS	Actual fault
16	215 kV & 120 MVA	0.05	2.68	2.08	T2	T2	T2	T2	T2
17	200 kV & 120 MVA	2.31	0.20	11.3	D2	D2	D2	Not Identified	D2
18	220 kV & 125 MVA	0.05	2.00	0.18	Not Identified	T1	T1	T1	T1
19	210 kV & 125 MVA	0.12	0.68	0.01	PD	PD	PD	PD	PD
20	135 kV & 95 MVA	0.03	2.35	3.9	Not Identified	T3	T3	T3	T3
21	205 kV & 120 MVA	5.29	0.54	12.26	Not Identified	D1	D1	D1	D1
22	200 kV & 125 MVA	0.04	3.27	2.56	T2	Not Identified	Not Identified	T2	T2
23	220 kV & 95 MVA	1.16	0.46	21.95	D2	D2	D2	D2	D2
24	210 kV & 95 MVA	0.04	3.4	0.16	T1	Not Identified	T1	T1	T1
25	205 kV & 125 MVA	1.10	0.03	0.01	Not Identified	Not Identified	PD	PD	PD
26	135 kV & 50 MVA	0.06	8.00	12.50	T3	D2	T3	T3	T3
27	225 kV & 95 MVA	1.84	0.48	2.13	D1	Not Identified	D1	D1	D1
28	115 kV & 20 MVA	1	0.05	0.03	PD	PD	PD	PD	PD
29	68 kV & 30 MVA	0.04	1.57	12.64	Not Identified	Not Identified	T3	Not Identified	T3
30	69 kV & 25 MVA	3.36	0.26	1.18	Not Identified	D1	Not Identified	D1	D1
31	220 kV & 100 MVA	0.08	29.82	3.45	T2	T2	T2	T2	T2

Sample	Transformer Rating	R1	R2	R3	IEC 60599 Method	BPNN	Fuzzy based Fault Detection	ANFIS	Actual fault
32	210 kV & 120 MVA	0.94	0.65	3.13	D2	D2	D2	D2	D2
33	65 kV & 35 MVA	0.03	2.25	0.2	T1	T1	Not Identified	T1	T1
34	70 kV & 40 MVA	1.17	0.11	0.10	PD	Not Identified	Not Identified	PD	PD
35	78 kV & 45 MVA	0.01	1.45	9.10	T3	T3	T3	T3	T3
36	85 kV & 50 MVA	2.88	0.13	8.63	D1	D1	D1	D1	D1
37	125 kV & 25 MVA	0.02	1.25	2.98	Not Identified	T2	T2	T2	T2
38	135 kV & 35 MVA	1.03	1.00	14.96	Not Identified	D2	D2	D2	D2
39	150 kV & 50 MVA	0.01	1.11	0.55	T1	T1	T1	T1	T1
40	215 kV & 125 MVA	2.00	0.13	0.01	Not Identified	PD	PD	PD	PD
41	205 kV & 95 MVA	0.18	0.15	6.67	T3	T3	Not Identified	T3	T3
42	220 kV & 120 MVA	5.78	6.68	11.39	D1	Not Identified	D1	D1	D1
43	215 kV & 120 MVA	0.05	2.68	2.08	T2	T2	T2	T2	T2
44	200 kV & 120 MVA	2.31	0.20	11.3	D2	D2	D2	Not Identified	D2
45	220 kV & 125 MVA	0.05	2.00	0.18	Not Identified	T1	T1	T1	T1
46	210 kV & 125 MVA	0.12	0.68	0.01	PD	PD	PD	PD	PD
47	135 kV & 95 MVA	0.03	2.35	3.9	Not Identified	T3	T3	T3	T3
48	205 kV & 120 MVA	5.29	0.54	12.26	Not Identified	D1	D1	D1	D1

Sample	Transformer Rating	R1	R2	R3	IEC 60599 Method	BPNN	Fuzzy based Fault Detection	ANFIS	Actual fault
49	200 kV & 125 MVA	0.04	3.27	2.56	T2	Not Identified	Not Identified	T2	T2
50	220 kV & 95 MVA	1.16	0.46	21.95	D2	D2	D2	D2	D2

Chapter 6: Conclusions and Future Scope

6.1 Conclusions

Oil filled power transformers are the backbone of electrical transmission and distribution system. During operation, the thermal and mechanical stress leads to incipient faults in the transformers. Harmful gases produced by the overheating of cellulose and transformer oil result in the degradation of transformer performance. Expert system based schemes have been proposed to diagnose the faults in transformers through the analysis of dissolved gases in oil. The following conclusions highlight the results:

- Literature study shows that the limitation of conventional methods (the ratio methods and key gas method) is that they rely too much on human experts and Artificial Intelligence based techniques could be a solution.
- There are two important differences between the fault gas analysis using IEC 60599 ratio method and fault gas analysis using fuzzy logic. The first one is the application of fuzzy membership functions for the classification of fault gas ratios. The second difference is that by the use of these functions, an upper and a lower limit is calculated for the specific fault. It may conclude that the intelligent techniques are much better than the conventional DGA methods.
- Such expert schemes are advantageous when compared to conventional Dissolved Gas Analysis (DGA) Methods, since in case of multiple fault diagnosis by DGA, the gases from different faults get mixed up resulting in such gas ratio, which cannot be matched by the existing codes thereby reducing the accuracy.
- In this proposed research, DGA dataset has been collected from the experts of Punjab State Electricity Board, Patiala, for various ratings of transformers. This dataset has been divided into training and testing sets (50:50). Different topologies of back propagation learning algorithm i.e. gradient descent method, gradient descent with adaptive learning method and Levenberg-Marquardt method have been proposed to train and test the neural network architecture, for transformer fault diagnosis.

- A comparative study of back propagation algorithm and probabilistic neural network algorithm reveals that probabilistic neural network is more accurate fault classifier than the back propagation method.
- Additionally, a hybrid tool, adaptive neuro-fuzzy inference system (ANFIS) has been implemented, in the proposed scheme, to diagnose the faults in power transformers through the analysis of dissolved gases in oil.
- ANFIS is advantageous when compared to neuro-fuzzy schemes in single since it provides faster convergence rates than typical feed-forward neural networks, its ability to create non-linear mapping, utilizes smaller size of training set, automatic fuzzy logic control (FLC) parametric tuning and smoothness guaranteed by interpolation (caused by FLC interpolation mechanism to interpolate among rules).
- Testing results proved that the performance of the hybrid diagnosis is better than that of the Conventional DGA methods, Fuzzy Logic and neural network based diagnosis works alone.

6.2 Future Scope

Despite being a relatively new technique with added advantages, the Adaptive Neuro-Fuzzy Inference System (ANFIS) creates a multitude of negative results such as surface oscillations around points (caused by high partition number), coefficients signs not always consistent with underlying monotonic relations (caused by partial loss of "locality"), symmetric error treatment and great outlier's influence (caused by Back propagation Network to tune fuzzy partitions) etc.

The incompleteness of ANFIS can be addressed by implementing techniques such as Support Vector Machine (SVM), Wavelet transform, Unsupervised and reinforced learning rules, Elman neural network, cascaded neural network etc.

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