DURBAN UNIVERSITY OF TECHNOLOGY

MODELING AND RECOGNITION OF FAULTS IN SMART DISTRIBUTION GRID USING MACHINE INTELLIGENCE TECHNIQUE

by

Adeniyi Kehinde ONAOLAPO

Student Number: 21649264

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Faculty of Engineering and the Built Environment

Durban University of Technology, Durban, South Africa

Supervisor: Mr K. T. Akindeji

Co-Supervisor: Prof E. Adetiba

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ABSTRACT

Electrical power systems experience unforeseen faults attributable to diverse arbitrary reasons. Unanticipated failures occurring in power systems are to be prevented from propagating to other parts of the protective system to enhance economic efficacy of electric utilities and provide better service to energy consumers. Since most consumers are directly connected to power distribution networks, there is an increasing research efforts in distribution network fault recognition and fault-types identifications to solve the problem of outages due to faults. This study focuses on fault recognition and fault-types identification in electrical power distribution system based on the Design Science Research (DSR) approach. Diverse simulations of fault types at different locations were applied to the IEEE 13 Node Test Feeder to produce three phase currents and voltages as data set for this study. This was realized by modelling the IEEE 13-node benchmark test feeder in MATLAB-Simulink R2017a. In order to achieve intelligent fault recognition and fault-type identification, different Multi-layer Perceptron Artificial Neural Networks (MLP-ANN) models were designed and subsequently trained using the generated dataset with the Neural Network toolbox in MATLAB R2017a. The fault recognition task verifies if a fault occurs or not while the fault-types identification task determines the fault class as well as the faulty phase(s). Results obtained from the various MLP-ANN models were recorded and statistically analyzed. Acceptable performances were obtained for fault recognition with the 6-25-20-15-1 MLP-ANN architecture, for fault-types identification with the 6-40-4 MLP-ANN architecture and for fault location with the 6-30-15-5-4 MLP-ANN architecture. Given the result obtained in this study, MLP-ANN is adjudged suitable for intelligent fault recognition and fault-types identification in power distribution systems. The trained MLP-ANNs in this study could ultimately be incorporated in power distribution networks within South Africa and beyond in order to enhance energy customers' satisfaction.

DECLARATION OF ORIGINALITY

I, Adeniyi Kehinde ONAOLAPO declare that this dissertation is a representation of my own work, written and executed by me. Partial or complete submission of this dissertation into any University or institution of higher learning for the award of a masters' degree has never taken place. All information cited from published or unpublished works have been acknowledged.

This research was conducted at the Durban University of Technology under the supervisions of Mr. K.T. Akindeji and Prof. E. Adetiba.

Submitted By:

....

Adeniyi Kehinde ONAOLAPO

Student number: 21649264

APPROVED FOR FINAL SUBMISSION

Supervisor …………………………… ..………………………..

Mr. Kayode Timothy AKINDEJI Date

(MSc Electrical Engineering)

Co-Supervisor …………………………… ..………………………..

Prof. Emmanuel ADETIBA Date

(PhD Information and Communications Engineering)

DEDICATION

This dissertation is dedicated to the Almighty God who made all grace abound unto me from the beginning to the completion of this study. To Him alone be all the glory and honour.

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Acronyms

ACSR	Aluminium Conductor Steel Reinforced
ANN	Artificial Neural Network
ART	Adaptive Resonance Theory
ASAI	Average Service Availability Index
ASIDI	Average System Interruption Duration Index
ASIFI	Average System Interruption Frequency Index
ASUI	Average Service Unavailability Index
BP	Back-Propagation
BPA	Back-Error-Propagation Algorithm
CAIDI	Customer Average Interruption Duration Index
CAIFI	Customer Average Interruption Frequency Index
CIM	Computational Intelligence Methods
CTs	Current Transformers
CWT	Continuous Wavelet Transform
DA	Distribution Automation
DAPFA	Distributed Architecture for Power Network Fault Analysis
DCE	Data Communication Equipment
DCG	Development Coordination Group
DFR	Digital Fault Recorder
DG	Distributed Grid
DN	Distribution Networks
DSLI	Distribution Supply Loss Index
DSR	Design Science Research
DTE	Data Terminal Equipment
DWT	Discrete Wavelet Transform
EMTP	Electromagnetic Transients Program
EMTP-RV	Electro-Magnetic Transients Program-Restructured Version
ENS	Energy Not Supplied Index
EPR	Ethylene Propylene Rubber

ES	Expert System
FCI	Faulted Circuit Indicators
FDIR	Fault Detection, Isolation, Location and Recovery
FL	Fuzzy Logic
FMEA	Failure Mode Effect Analysis
FT	Fourier Transform
GA	Genetic Algorithm
HIFs	High Impedance Faults
HFCs	High Frequency Components
HV	High Voltage
ICT	Information and Communication Technology
IEDs	Intelligent Electronic Devices
IEEE	Institute of Electrical and Electronic Engineers
KBM	Knowledge Based Methods
KPI	Key Performance Index
LIFs	Low Impedance Faults
LSM	Least Squares Method
LV	Low Voltage
LVQ	Learning Vector Quantization
MAIFI	Momentary Average Interruption Frequency Index
MIT	Machine Intelligent Technique
MLPNN	Multi-Layer Perceptron Neural Network
MQS	Minimum Qualification Score
MRA	Multi-Resolution Analysis
MSE	Mean Square Error
MV	Medium Voltage
NN	Neural Network
OC	Over-Current
O&M	Operational and Maintenance
PC	Personal Computers
PCA	Principal Component Analysis

PLC	Programmable Logic Controller
PNN	Probabilistic Neural Network
PQ	Power Quality
RBF	Radial Basis Function
ROC	Receiver Operating Characteristics
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SCADA	Supervisory Control and Data Acquisition
SDG	Smart Distribution Grid
SDN	Smart Distribution Network
SG	Smart Grid
SOM	Self-Organizing Map
STFT	Short-Time Fourier Transform
SVCs	Support Vector Classifiers
SVMs	Support Vector Machines
TW	Travelling Wave
VTs	Voltage Transformers
WFNN	Wavelet Fuzzy Neural Network
WP	Wavelet Packets
WT	Wavelet Transform
XLPE	Cross-Linked Polyethylene

CHAPTER 1

Introduction

1.1 Background

Smart Grid (SG) is a power system, that is more dependable, cost-effective, eco-friendly, with better safety and security features. It is an innovative form of power grid, given its upgraded energy efficacy, controlled emission, optimized utility, outlined demand and decreased cost. The smart grid was defined by the European Regulators Group for Electricity and Gas as "*an energy system that can competently incorporate the performance and activities of all users joined to it –generators and or consumers – so as to make provision for a power system that can be sustained and also efficient – economic wise; having losses that are reduced to the barest minimum and quality, security and safety that are extraordinary".*[1]. Smart grid is likewise famous for its self-healing abilities. Grid self-healing embraces the skills of self-detection, self-identification, self-decision and self-restoration; and makes the operations of distribution systems in diverse conditions - safe and reliable. Under extreme situations, separation from the main grid is achievable via self-healing. In this situation, continuous operation with a distributed power and power storage scheme is realized [2].

Faults in Distribution Network (DN) cause outages and bring about Power Quality (PQ) and reliability issues such as momentary and prolonged interruptions, voltage sags and increased costs of operation [3]. The management and detection of outage has been an established problem in power distribution systems. The societal and economic costs owing to loss of loads from distribution outages have been progressively severe. Nevertheless, a number of methods have been proposed for fault detection, identification and location. Fault detection, identification, and location typically needs to be treated as an integrated problem in power systems. It could be predicted that a multifunctional method, which could do fault recognition, identification and location, would have an extensive array of applications in SG systems [4].

The introduction of Intelligent Electronic Devices (IEDs) and Information and Communication Technology (ICT) into the DN has revolutionized the network into a smarter one, making it better and safer. ICT defines the essence of unified communications [5] and the incorporation of telecommunications (wireless signals and telephone lines), computers, innovative software, middleware, audio-visual and storage systems, which allow users to receive, transmit, manipulate and store information [6]. ICT is so broad and covers any product that will receive, transmit, operate, or store information in an electronic or digital form, e.g. e-mail, computers, digital television as well as robots. An IED is a power system controller based on microprocessor, such as circuit breaker, transformer and capacitor bank. IEDs receive information from power equipment and sensors, and can give commands for control purposes such as toggling circuit breakers if they perceive current, voltage or frequency abnormalities, raise or reduce voltage levels in order to achieve the preferred level [7]. Examples of IEDs are protective relaying devices, circuit breaker controllers, On Load Tap Changer (OLTC) controllers, recloser controllers, capacitor bank switches, voltage regulators etc. A typical IED contains up to 5-12 protection functions, an auto-reclose function, 5-8 control functions, communication functions, self-monitoring function and etc. Hence, the name - Intelligent Electronic Devices.

Recently, there have been much research works on the recognition, identification and location of faults, and a range of techniques, algorithms, and models have been suggested [8]. This thesis focuses fault recognition, fault-type identification and recovery (FRIR), regularly considered “self-healing” ability [9, 10]. Although both series and shunt faults were discussed in the literature, this research work is limited to shunt faults; hence, shunt faults are the only ones considered in the proposed flowchart (Figure 3.3).

1.2 Problem Statement

When fault occurs in a distribution network, it often takes time to detect the location of the fault. This delay may lead to major or multiple faults. When the location is finally known, isolating the fault is another challenge. Most often, an entire network is shut down in order to isolate a minor fault. This impacts negatively on the supplier as well as the consumers.

Faults in power distribution network occur as a result of aging of network equipment; adverse weather situations such as storms, lightning, snow and freezing rain, insulation breakdown, short circuits by birds and other external objects [11]. In many fault cases, mechanical damages to the network equipment need to be repaired before restoring the system into service. Therefore, accuracy and speed in detecting and locating faults along distribution networks are vital.

1.3 Research Aim and Objectives

The main aim of this research is to implement a model for monitoring, recognition and identification of faults in smart distribution networks.

The objectives of this study are to:

1. Model a distribution network based on the IEEE 13 Node Test Feeder as a test case.
2. Simulate and analyze different types of electrical faults in the model.
3. Apply machine intelligence algorithm to recognize faults in the modelled distribution network.
4. Evaluate the performance of the recognition algorithm.

1.4 Research Methodology

Design Science Research (DSR) approach was adopted for this study. The DSR originates from the sciences and engineering [12]. It is a model essentially created to solve problems. It pursues innovative means that outline the designs, practices, technical abilities and products through which the examination, strategy, application, organization and utilization of ICT can be excellently and proficiently realized [13]. Over the years, DSR has been engaged in fields like computer science, software engineering and information systems [14]. Chapter three of this dissertation provides a comprehensive description of DSR’s application for recognition of faults in power distribution system.

The software MATLAB-Simulink v2017a was used to simulate and analyze the steady state operation of an electric power distribution system. A test system consisting of 1-generator, 13 buses, overhead and underground lines with variety of phasing, in-line transformer and distributed loads was studied. The system was first simulated and analyzed without faults and then with different types of faults at different locations. To recognize the presence of faults and identify different types of faults in power distribution system, Artificial Neural Network (ANN) algorithms were used.

1.5 Contributions

The main contributions of this study are as follows:

a. Development of a smart distribution network model based on IEEE 13 Node Test Feeder and machine intelligence. This provides a reliable basis for practitioners to develop and deploy systems for fault recognition.

b. This dissertation and other publications from the study add to the Body of Knowledge (BoK) on the use of ICT for fault recognition in power systems engineering.

1.6 Outline of the Thesis

This dissertation consists of five chapters. The first chapter presents a brief introduction of the study. It also described the problem statement, research aim and objectives, research methodology and contributions. Furthermore, this chapter presents the outline of the dissertation as well as the research output. Chapter two presents a comprehensive review of existing literature on location of faults in smart distribution systems. Chapter three describes the application of the DSR approach, employing Machine Intelligent Technique (Artificial Neural Network in particular) to realize the aim and objectives of this research study. Chapter four presents the evaluation of results while chapter five, which is the final chapter of the dissertation presents the conclusion and recommendations for future works.

1.7 Research Outputs

1. **A.K. Onaolapo,** K. T Akindeji and E. Adetiba: "Faults Recognition, Identification And Localization In Smart Distribution Networks – A Review". Paper presented at

Protection, Automation and Control (PAC) World Conference, Raleigh, North Carolina, USA, 29 – 31 August 2017.

2. **A.K. Onaolapo,** K.T. Akindeji, E. Adetiba. Faults Recognition and Identification in Smart Distribution Networks using Machine Intelligent Technique (ongoing).

CHAPTER 2

Literature Overview

A review of relevant literature to the study in this thesis is presented in this chapter. Published works were obtained from knowledge bases such as Institute of Electrical and Electronic Engineers (IEEE) Xplore, Google Scholar, ScienceDirect and Web of Science. The chapter begins with an overview of electric power system in general and narrowed down to power distribution systems and its various components. The chapter further examined fault categories, types and causes. Various fault recognition techniques in the literature were discussed in the last part of this review.

2.1 Overview of Electric Power System

An electric power system is a network of electrical mechanisms used for the generation, transportation, delivery and eventually, the consumption of electric energy. This can be largely divided into the generator that serves as the source of the power, the transmission system that transports the power from the generating centers to the load centers and the distribution system that distributes the power to domestic, commercial and industrial consumers.

Electric power systems consist of other subsystems; in a deregulated market, different subsystems are managed by different companies and free competition is allowed in each of them. The main subsystems in electric power system are presented in the following sub-sections. Figure 2.1 shows the general structure of power systems [15-18].

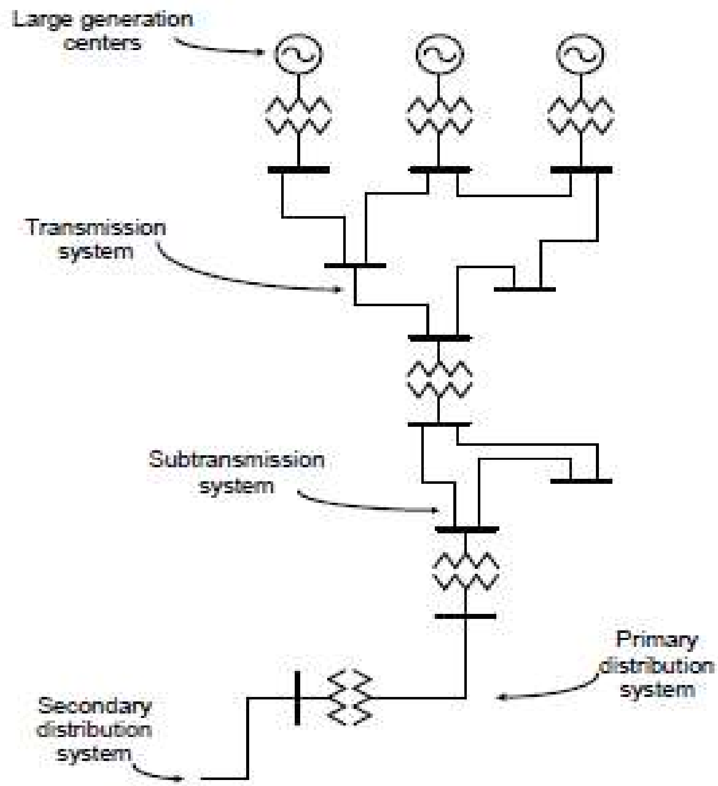


Figure 2.1 Power delivery system structure [15, 18]

2.1.1 Generation System

Diverse technologies have been employed to generate electrical energy in a large scale, such as hydro, nuclear, coal, natural gas, etc. Usually, using large generation units, major electrical energy is generated in isolated sites, which are several kilometers away from final consumption points [19].

2.1.2 Transmission System

The transmission system is the link between the generating unit and the consumption points. It is made up of a set of lines, substations and equipment designed to link large generation plants and consumption centers [19]. Transmission lines typically, span over several kilometers and transport large quantities of energy at high-voltage levels (e.g. 400 and 220 kV) in order to cater for losses.

2.1.3 Sub-transmission System

The sub-transmission system is a connection in-between the transmission and the distribution system. The sub-transmission lines extend over shorter distances than those in the transmission system; as a result, they operate at lower voltage levels (e.g. 132, 66, and 45 kV). High consumption facilities such as industries (constituting large loads) can be directly fed by the sub-transmission system [18].

2.1.4 Primary Distribution System

Energy coming from the sub-transmission system is received at the substation of the primary distribution system where the voltage is further stepped down to medium-voltage levels (e.g. 25 and 11 kV). Similar to sub-transmission system, primary distribution system can feed large loads [18].

2.1.5 Secondary Distribution System

Low power customers, such as commercial and residential loads are fed by the secondary distribution system. The system is made up of step-down Medium Voltage/Low Voltage (MV/LV) distribution transformers and low-voltage lines (e.g. 400 and 230 V) [18].

2.2 Power Distribution System

2.2.1 Overview of a Distribution System

The interface between power distribution system and upstream power delivery system is the distribution substation. Various equipment are installed at the substation to ensure accurate measurement, switching operations and protection purposes [20]. The transformer (HV/MV) at the substation steps down the sub transmission voltage level to a suitable value for primary distribution lines, which are also referred to as feeders. This voltage is finally stepped down by the distribution transformer (MV/LV) to a level acceptable for final consumption (400V/230V). The secondary distribution lines, low voltage (mostly single phase with few three phase circuits) feed the energy to the consumers. Figure 2.2 represents the configuration of a typical power distribution system.

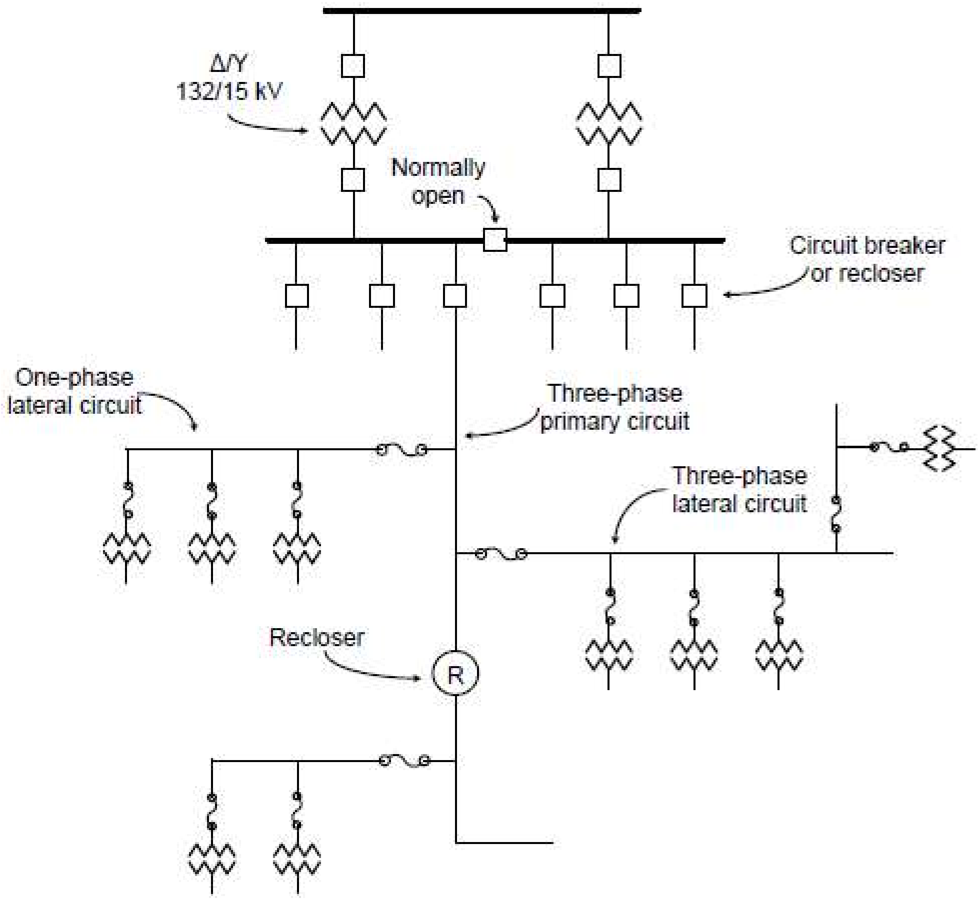


Figure 2.2 Typical distribution system configuration [15]

2.2.2 The Substation of a Distribution System

In designing a distribution substation, certain important factors are taken into consideration; such as load level, auxiliary equipment required, anticipated reliability and the type of system (urban, suburban or rural) [16].

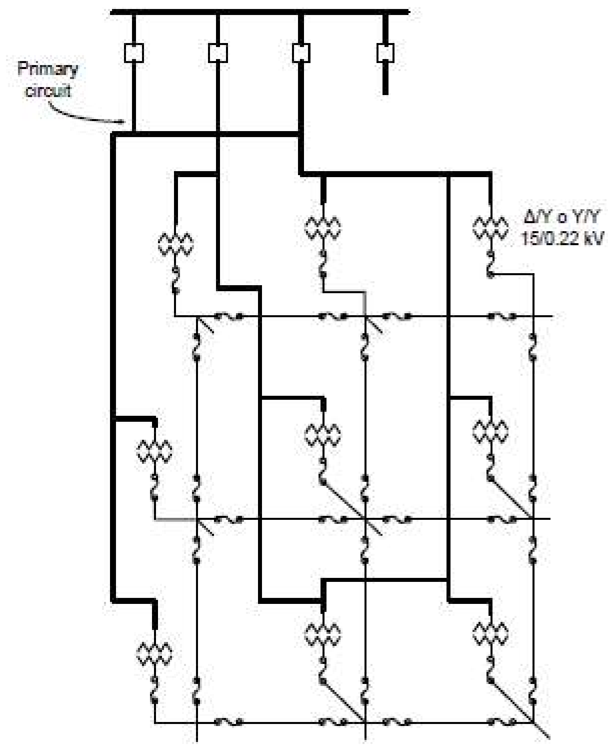


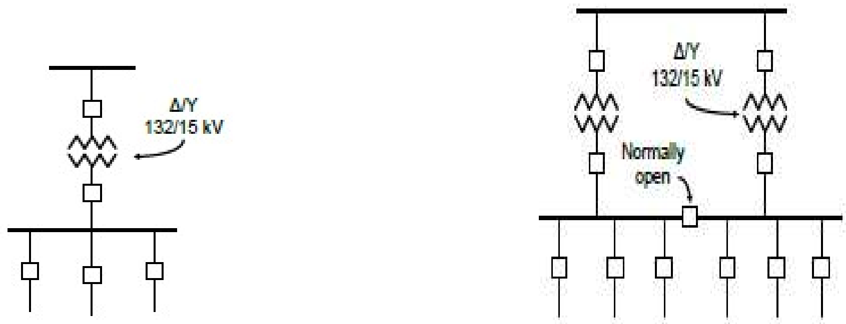
Figure 2.3 Network configuration [16]

a) Rural Substation

The configuration of a rural substation is made up of a single high-voltage (HV) and medium-voltage (MV) bus. One transformer, whose protection depends on its rated power, is sufficient to supply the entire power demand because of the low load level of the rural environment (Figure 2.4a). Primary distribution lines, which are protected by either overcurrent relays or recloser, are connected to the medium voltage [16].

b) Suburban Substation

The configuration of a sub-urban substation is made up of a single high-voltage bus and one medium-voltage bus for each substation transformer. Due to the advantage of a more uniform load distribution among transformers, preference is given by some utilities to the use of a single medium-voltage bus for all substation transformers. Because of the requirement of higher load level than rural substation, more than one transformer is required for suburban system. The medium voltage buses are connected to one another via a normally-open tie-switch (Figure 2.4b). When a transformer fails, the tie switch is operated, and the load served by the failed transformer would be supplied by another in-service transformer(s). This split bus configuration prevents the presence of circulating currents, encourages voltage control and reduces fault level [16].

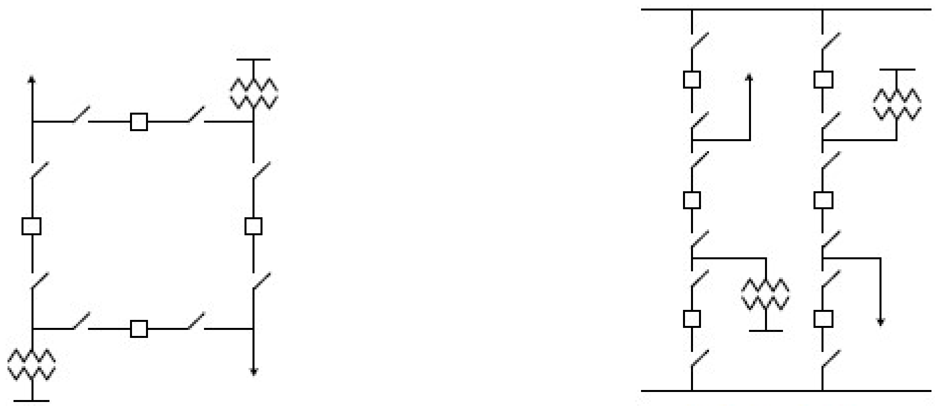


a) Rural substation b) Suburban substation

Figure 2.4 Distribution substation configuration [16]

c) Urban Substation

Two of the common designs of an urban substation are the ring-bus and breaker-and-a-half configurations. In ring-bus design, the buses of the medium-voltage are in a closed loop and separated by circuit breakers. The substation transformers' secondary side and the distribution feeders can be connected to the mid-point of any section of the bus, in-between two circuit breakers (Figure 2.5a). In breaker-and-a-half design, one or more branches are connected between two medium-voltage buses and each branch consists of three circuit breakers. The primary distribution lines or secondary side of a substation transformer can be connected between any two adjacent circuit breakers (Figure 2.5b). For the purpose of load transfer or maintenance, modifications could be done on either configuration [21].



a) Ring-bus b) Breaker-and-a-half

Figure 2.5 Urban substation configuration [16]

2.2.3 Distribution System Components

Components are installed in power distribution network for efficiency and safe operations of the system. Some of the components are listed and described briefly in this section.

2.2.3.1 Transformer

A transformer is a device consisting of a primary winding and a secondary winding connected by their electromagnetic fields. It carries power from a winding to another without changing the frequency and steps-up or steps-down voltage level. To provide appropriate voltage level needed by every section of the distribution system, transformers carry out voltage reduction successively [15, 22]. Transformer operation is illustrated by equation (2.1).

$$\frac{V_p}{V_s} = \frac{n_p}{n_s} \tag{2.1}$$

Where V_p = potential difference (voltage) input on the primary coil, V_s = potential difference (voltage) output on the secondary coil, n_p = number of turns (coils) of wire on the primary coil and n_s = number of turns (coils) of wire on the secondary coil

a) Potential Transformer

Potential transformers are used to step down the voltage of the primary circuit to a safe value (120 V), to serve as input signal for protection and monitoring devices. They are designed to serve low rating meters and relays. Standard potential transformers are single-phased, with primary and secondary windings on common core and the secondary voltage maintains a fixed relationship with primary voltage [15, 22]. The secondary terminal voltage and voltage ratio error are given by equations (2.2) and (2.3) respectively.

$$V_s = V_p x \frac{C_p}{C_p + C_s} \tag{2.2}$$

$$RatioError = \frac{K_n I_s - I_p}{I_p} \tag{2.3}$$

Where K_n is the nominal ratio, i.e., the ratio of the rated primary voltage and the rated secondary voltage; V_s – secondary terminal voltage, V_p – primary terminal voltage, I_s – secondary terminal current, I_p – primary terminal current, C_s – secondary capacitor and C_p – primary capacitor.

b) Current Transformer

The primary winding of a current transformer is insulated from its secondary winding. Its secondary winding supplies current at a fixed relationship that is directly proportional to that of its primary current. Line current is converted by current transformer into values appropriate for protection and monitoring devices and isolates the relays from line voltages. The primary winding is in series with the circuit of the line current to be measured while the secondary winding is in series with protection and monitoring devices [15, 22]. A current transformer, like any other transformer, must satisfy the amp-turn equation. The turns-ratio (T.R.) is given by equation (2.4).

$$T.R. = \frac{n_p}{n_s} = \frac{I_s}{I_p} \tag{2.4}$$

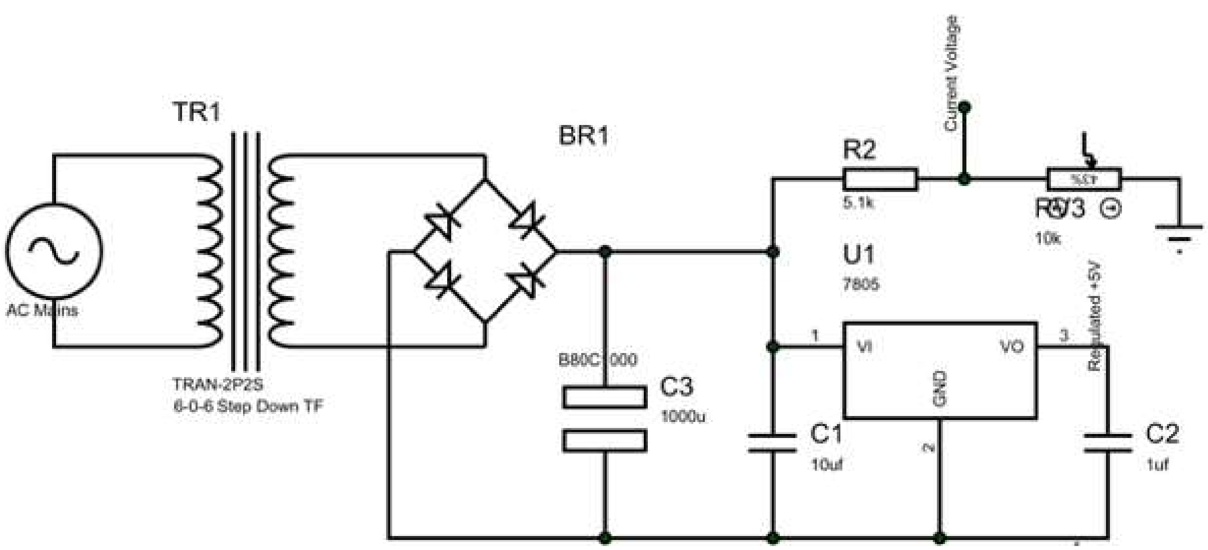
Where I_s – secondary terminal current, I_p – primary terminal current, n_p = number of turns (coils) of wire on the primary coil and n_s = number of turns (coils) of wire on the secondary coil.

2.2.3.2 Lines

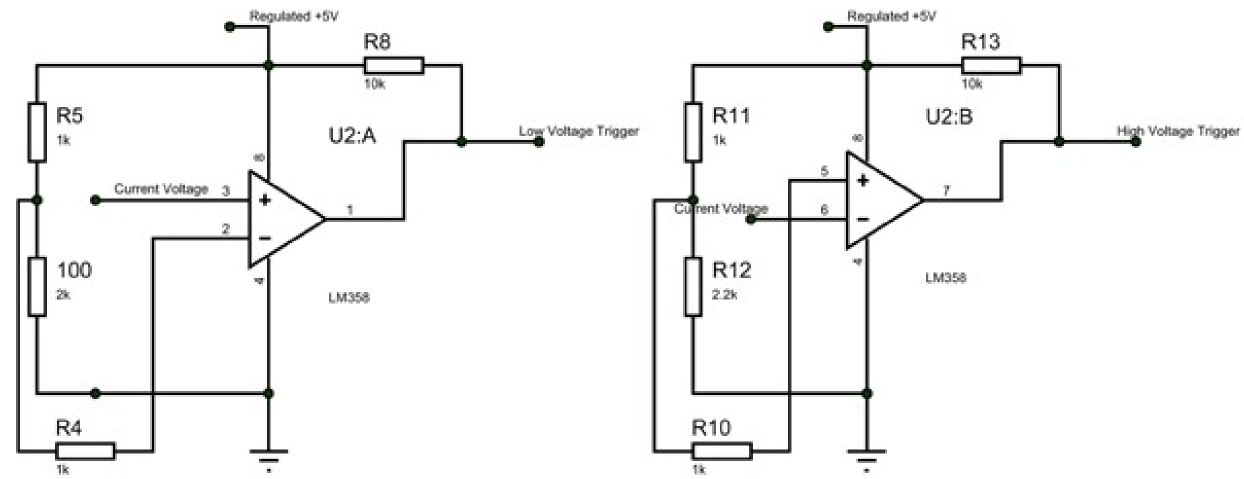
A line is a medium through which electrical energy is transferred from one point to the other. This could be in overhead or underground form. Overhead lines are usually made of bare aluminum, commonly Aluminium Conductor Steel Reinforced (ACSR) type while underground lines are usually cables made of polymer-insulation, such as Cross-Linked Polyethylene (XLPE) and Ethylene Propylene Rubber (EPR). Distribution lines are characterized by their rated voltage and current carrying capacity [15, 18].

2.2.3.3 Circuit Breaker

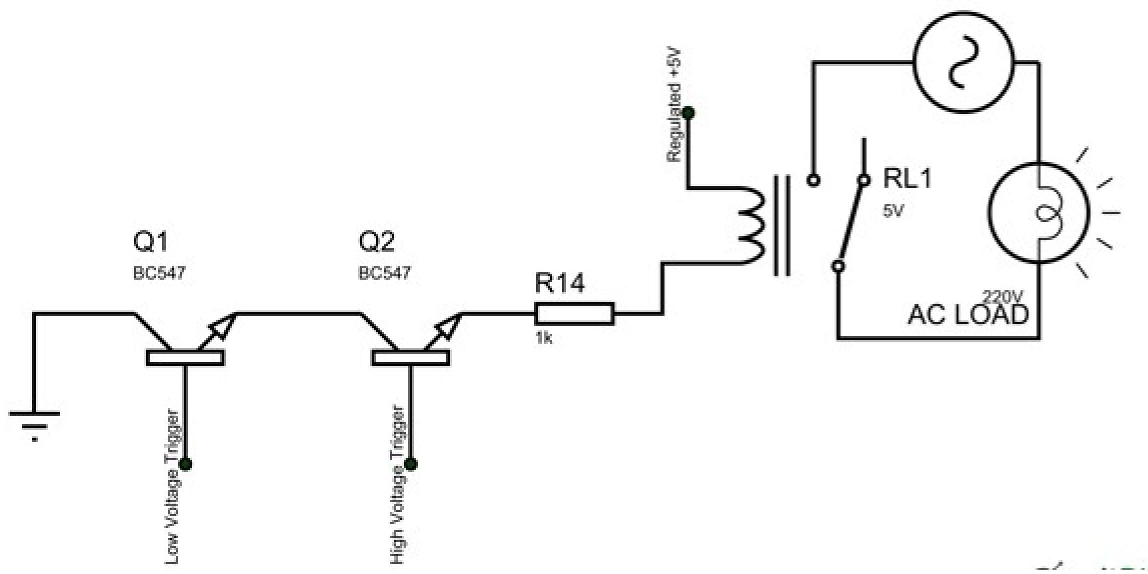
A circuit breaker is designed to isolate a circuit automatically at a particular overcurrent value in order to protect itself and other equipment. It is simply a switching component designed to close and open a circuit by non-automatic measures [18, 22, 23]. It is divided into the power, op-amp and relay sections respectively. Figure 2.6 shows a schematic diagram of a circuit breaker.



a. Power Section



b. Op-Amp Section



c. Relay Section

Figure 2.6 Schematic Diagram of a Circuit Breaker [22]

2.2.3.4 Relay

In distribution systems, relays are low-powered switching devices used to activate high-powered devices. Relay protects feeders and equipment by giving tripping commands to the corresponding circuit breakers to interrupt the current produced by a fault [22, 23].

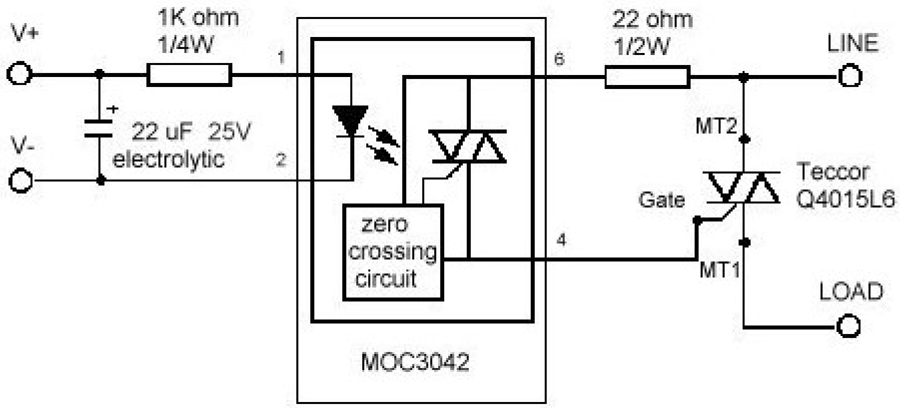


Figure 2.7 Solid State Relay [22]

2.2.3.5 Recloser

A recloser is an intelligent switching device that can sense overcurrent, interrupt fault current and re-energize the line by re-closing automatically. When permanent fault occurs, after about three or four operations (usually preset), the recloser locks open thereby isolating the faulted section from the rest of the system [23, 24].

2.2.3.6 Fuse

A fuse contains a strip of wire that melts when an overcurrent or short-circuit current passes through it. The fuse's time-current curves determine the melting and clearing times. A fuse, usually K and T types, is used in distribution systems to protect laterals, secondary circuits, and low power transformers [22, 23].

2.2.3.7 Sectionalizer

A sectionalizer is a protective device used together with source-side protective devices to automatically isolate faulted sections of electrical distribution systems. Such source-side protective devices could be reclosers or circuit breakers. When current flow above a preset value is sensed by the sectionizer, the source-side protective device opens to de-energize the circuit, then the sectionalizer counts the overcurrent interruption [23, 24].

2.2.3.8 Capacitor Bank

A capacitor bank is generally three-phase, installed in the substation or at mid-point of a primary circuit line of a distribution system. It performs voltage regulation and reduce system losses by correcting power factor. It is a local source of reactive power [22, 24].

2.2.3.9 Switch

A switch is a device used for isolating a system element for repair or maintenance. It must be able to carry and break currents during normal operating conditions. A switch is not designed to break fault current, although it may have a fault making capacity. It may have definite operating overload conditions and carry currents under specified abnormal conditions such as those of a short circuit for certain time [23, 24].

2.2.3.10 Voltage regulator

A voltage regulator is a transformer with an on-load tap changer having a nominal transformation of ratio 1:1. Voltage regulators are installed, to compensate the voltage drop produced, at the mid-point of long primary lines[22, 23].

2.2.3.11 Supervisory Control and Data Acquisition (SCADA)

SCADA is a communication system used for real-time monitoring of the distribution network. SCADA stores information collected throughout the system in a database that can be accessed by users and applications. SCADA is capable of operating circuit breakers and switches remotely; thereby making system operations to be flexible and reducing switching actions' response time [22, 23].

Figure 2.8 Supervisory Control and Data Acquisition [23]

2.3 Distribution Automation

Automation refers to doing a particular task automatically in a specific array and at a faster degree [25, 26]. The influence of Information and Communication Technology (ICT) on power system is changing the traditional grid into a smart grid through automation. A smart grid is an electrical power grid, which embraces diverse energy and operational means including smart appliances, smart meters, energy efficiency resources and renewable energy resources [27]. IEEE defined Distribution Automation (DA) as *"a system that allows an electric utility to observe, manage and control components of a distribution system in a real-time mode from remote locations"* [28]. DA permits utilities to put into operation, an easy control of the distribution network, which in turn boosts the supply in terms of reliability, effectiveness and quality [28]. Automation is employed in power distribution system to automatically monitor and switch devices to isolate the part of the network that is faulty or restore supply so that customers can enjoy the benefit of continuity of supply as much as possible. In addition, automation permits real time monitoring of network and implements predefined contingency switching plans based on current fault locations and feeder loadings. The system may be partly automated depending on how many contingency switching levels has been pre-programmed in its automation functionality. Consequently, the down-time of supply is reduced by isolating the locations that are faulty and restores supply to customers via an alternative available power source. There are instances where operators have to fix faulty devices manually, therefore, automation is not an absolute substitute for manual measures but enables the electricity system to function optimally, as a result of accurate information fed into the decision-making applications and devices at the right time [23]. The investment of utilities in DA is borne from the realities of its boost on the efficacy, quality and dependability of supply to maximize profits and prevent incurring penalties by performing beyond Minimum Qualification Score (MQS) targets. This also inspires the customer to transfer premium quality contracts with the power utility, thereby serving as extra revenue streams for the utility. Distribution automation (DA) has enhanced utilities businesses because of improved efficiency in restoring outage and reduced downtime thereby enhancing their reliability, improved safety to operating personnel and quality of supply to customers [23]. In most cases, implementation of DA takes place in the upstream of the network. However, implementation of DA in the downstream, close to customers site, is done if it is commercially viable or as a stiff contract obligation, for instance, if a large utility is required by contract to supply a big consumer of power such as Oil and Gas or mine company. DA is nowadays, not limited to substations only, but it has been extended to devices along the feeders and even meters. DA was not widely accepted in the past because it was seen as not making good investment sense as a result of cost; but recently, the rise in cost-efficient control systems and deregulations within the industry has solved this problem [23]. Table 2.1 summarizes the key automation benefits by control hierarchy layer.

Table 2.1 DA Benefit Classification by Control Hierarchy Layer [23]

Control Hierarchy Layer	Reduce Costs on O&M	Capacity Project Deferrals	Improved Reliability	New Customer Services	Power Quality	Better Info for Engr. & Planning
1.Utility	√	---	---	√	---	√
2.Network	√	√	√	---	√	√
3.Substation	√	√	√	---	√	√
4.Distribution	√	√	√	---	√	√
5.Customer	√	√	√	√	√	√

1). Reduced Costs on Operation and Maintenance

DA reduces Operational and Maintenance (O&M) costs in many ways. Rapid response time is required for service restoration after outage at High Voltage (HV) level; meanwhile if a fault, such as insulation breakdown, occurs on HV lines, locating such fault may impose some difficulties and take time because of the height and length of the overhead lines or night time visibility factor. Fast fault location considerably reduces crew travel time at substation and distribution levels. Traditional fault location practices of line patrols and manual operation of switches are eradicated because DA helps to dispatch the crews directly to the area of the network that is faulty. The same applies to long Medium Voltage (MV) lines that require many operating staff to do manual switching sectionalization to locate faulty area [23].

2). Capacity Project Deferrals

Real-time monitoring of transformer loading and transferring of excess short-term loading from one transformer to another, located in another substation by switching open points automatically. This ensures that substation transformers are optimally loaded, and their thermal levels do not exceed the limit stipulated by the manufacturers thereby enhancing their lifespan [23].

3). Improved Reliability

Installation and remote monitoring of equipment improves reliability in distribution network. Such equipment as reclosers, circuit breakers and fault indicators are connected over the network to the management system in the control room thereby enabling the control room personnel to guide the operators on the field to the areas where the fault occurred. Installation of these equipment could reduce the number of outages and cause average down-time duration to reduce by between 20 – 30% per annum for an overhead feeder that is sustained with adequate maintenance. To make this improvement, it is assumed that temporary outages that can be attributed to the actions of auto-recloser are acceptable. Auto-reclosers automatically reclose for nuisance tripping activities which averts needless interruption to customers' supply and consequently results in reliability improvements [23].

4). New Customer Services

The improvement in reliability and power quality, an enhancement of supplies and a reduction in outage times as a result of the instrumentality of DA contribution to power system is a boost to servicing customers. DA engenders improved supply quality, reduced cost of interruption for Industrial and Commercial customers and improved package dependability [23].

5). Power Quality

Though many electronic gadgets, particularly the expensive ones like medical appliances and laptops are produced with in-built protection circuits or passive elements such as fuses so that they could be protected from power supplies that are of poor quality; utility performance could be enhanced by distribution automation by ensuring that the supply is of good quality by conforming to standards (such as NRS 048-2:2007) on power quality. Active control of voltage regulation via the control of capacitor banks and voltage regulators remotely is also possible by automation [23].

6). Better Information for Engineers and Planners

DA delivers better visibility to planners and network operators due to availability of real-time data. The optimization of communication infrastructures is a vital facet that would ensure that essential data are sent to suitable application in the implementation of automation. Such data is essential to asset management and improved planning [23].

2.4 Smart Distribution System

Smart Grid (SG) is referred to as the new generation of energy grid, for its controlled emission, outlined demand, enhanced energy efficiency, optimized efficacy and reduced cost. It is more dependable, makes more economic sense, friendly to the environment, safer and secure than the traditional energy grid. [29, 30]. The European Regulators Group for Electricity and Gas defines SG as *"a power system that can effectively coordinate the conduct and activities of all stakeholders linked to it – generators and/or consumers – to ensure commercially viable, workable energy system with commensurate quality levels and less losses with a safe and secure supply"* [1, 31, 32]. Smart grids with automatic diagnostic, monitoring, and repairing features are used to achieve an advanced power system [33-41]. Smart grid is renowned for its outstanding self-healing abilities which is a significant characteristic of intelligent distribution systems. "Self-healing" originates from the biomedical field. It is attributed to a system having a self-awareness of its state which can take suitable actions to return to the usual state automatically after self-assessment without operator's physical intervention. Self-healing of the grid implies that little or no human intervention is required; instead, enhanced monitoring devices for the actions and processes of the power-grid are employed to allow non-stop online analysis and examinations. This allows quick recognition and timely intervention of faults as well as eradication of unseen issues. Grid self-healing abilities encompasses self-observation, self-analysis, self-verdict and self-recovery; and makes possible, diverse kinds of activities that are dependable and safe in distribution system. The procedure of self-healing of the smart grid can regulate the different conditions of the network, leading to optimization and caution under normal conditions and fault analysis under faulty conditions; hence, resulting in reconfiguration of the network and restoration of the power supply. Self-healing also gives room for isolation from the main grid under life-threatening circumstances. In this circumstance, continuity of supply is achieved with a distributed generation and power storage equipment [2]. The vision of smart grid distribution system is graphically illustrated in Figure 2.9

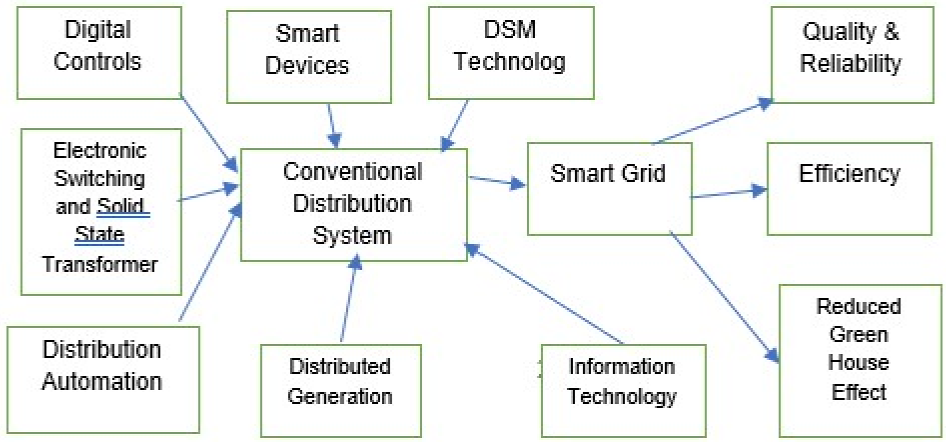


Figure 2.9 Smart Grid Distribution System's Vision [42].

Faults in distribution networks are either temporary or permanent. If the fault is permanent, the identified faulty sections or equipment are disconnected permanently by the appropriate protective relays. Thus, it is important that the location of a fault is either known or can be projected with rationally high precision. This decreases the cost and time for the scrutiny and restoration and also provide better services as a result of faster power supply restoration.

In modern societies and with the introduction of 'smart power grid', customers are more sensitive to the power outages. Therefore, more effective and accurate approaches of fault monitoring, recognition and location are required. These will result in improved power supply restoration process, reduction in the overall power outages time, enhancement of customer satisfaction and reduction in operational cost [43]. The variations between the smart grid and conventional distribution system are shown in Table 2.2

Table 2.2 Differences Between Conventional And Smart Grid Distribution System [42]

S/N	Conventional Distribution Systems	Smart Grid Distribution Systems
1	One-Way Distribution: Power can only be distributed from the main plant using traditional energy infrastructure.	Two-Way Distribution: While power is still distributed from the primary power plant, in a smart grid system, power can also go back up the lines to the main plant from a secondary provider. An individual with access to alternative energy sources, such as solar panels, can actually put energy back on to the grid.
2	Controls are electromechanical	Controls are digital
3	Generations are centralized	Distributed generations are accommodated
4	Restoration is manual	Restoration is by self-healing
5	No or few sensors are utilized	Advanced sensors are utilized for monitoring throughout the system
6	Committee takes emergency decisions using phone	Predictive reliability and Decision support systems are used.
7	Price information is limited or none	Price information is fully available
8	Control over power flows is limited	Full control over power flows
9	It is a blind system	The system is self-monitoring.
10	Communication is one-way	Communication is two-way
11	Susceptible to failures and blackouts	Possibility of adaptive protection and islanding.
12	Equipment are tested and operated manually.	Equipment are tested and operated remotely.
13	The choice of limited customers	The choice of many customers
14	Switches used are manual operated disconnecting ones.	Switches used are high rated power electronic ones.

2.5 Reliability in Distribution Systems and Power Systems Reliability Indices

Reliability in distribution system centers on customers interruptions and equipment outages. Every equipment (excluding standby) is energized and all customers are supplied in normal operating conditions. Planned and unplanned events interrupt normal operating conditions and can result in power failure. The purpose of assessing, designing and enhancing reliability in distribution networks is to ensure incessant supply of power to customers, decrease the rate of recurrence and outage period, minimize the impact of outages, ensure standards are complied with, evaluate and improve system performance as well as to find out the causes of outages so as to take corrective action to reduce them considering its huge cost to customers [20].

Power Systems Reliability Indices are measures of the dependability and accessibility of power supply from the utility in relation to the experience of outages suffered by different customers. The performance reliability indices measure interruptions with respect to the frequency, duration, number of customers affected and that of the installed plant (transformers) impacted by the events on the network. Each index is defined by different equations as described in the following subsections:

2.5.1 Reliability Indices for Sustained Interruption (≥ 2 minutes window)

Various Key Performance Index (KPI) applies to continuous outages (i.e. having a window of ≥ 2-minute). The customers and installed loads are the factors of the indices (i.e. customers and load affected. The former expressed in their numbers and the latter expressed in KVA) [3].

a). System Average Interruption Frequency Index

System Average Interruption Frequency Index (SAIFI) is a measure of the frequency of an average customer on the network experiencing a continuous outage in a year not including repeat outages. It can be stated as [44]:

$$SAIFI = \frac{Total\ number\ of\ customer\ \text{int}\, erruptions\ p.a.}{Total\ number\ of\ customers\ served}$$

(2.5)

For certain numbers of customers, the amount of continuous interruptions experienced has to reduce so as to improve SAIFI [17].

b). System Average Interruption Duration Index

System Average Interruption Duration Index (SAIDI) is a measure of the length of a continuous outage experienced by the average customer in a year excluding repeat outages. The unit is in interruption's customer minutes or customer hours [44].

$$SAIDI = \frac{\sum Customer\ \text{int}\, erruptions\ durations\ p.a.}{Total\ number\ of\ customers\ served} \tag{2.6}$$

For a certain quantity of customers, the amount or duration of interruptions experienced by customers has to reduce so as to improve SAIDI. A reduction in SAIDI signposts a good development in reliability [17].

c). Customer Average Interruption Duration Index

Customer Average Interruption Duration Index (CAIDI) is a measure of the average period of a continuous outage that would be experienced by only the customers affected in a year excluding repeat outages. The unit is in interruption's customer minutes or customer hours [3]. The difference between CAIDI and SAIDI is that the total number of customers interrupted is considered in the case of the latter's denominator as against the total number of customers served considered in the former's case. CAIDI is also expressed as the ratio of SAIDI to SAIFI.

$$CAIDI = \frac{\sum Customer\ \text{int}\, erruptions\ durations\ p.a.}{Total\ number\ of\ customers\ \text{int}\, errupted} \tag{2.7}$$

Or alternatively:

$$CAIDI = \frac{SAIDI}{SAIFI} \tag{2.8}$$

Generally, CAIDI ≥ SAIDI, because CAIDI is only interested in the number of customers affected. CAIDI also measures the re-energized time of the average customer. CAIDI measures the time it takes for an average outage to persist, and also measures the time it takes for utility respond to system emergencies. To improve CAIDI, the length of interruptions must be reduced; and to reduce CAIDI, the number of short interruptions must be increased. Therefore, a reduction in CAIDI does not signpost a good development in reliability [17].

d). Customer Average Interruption Frequency Index

Customer Average Interruption Frequency Index (CAIFI) is a measure of the average rate annually at which the outage affected customers experience such outages in a sustained manner. The customer, irrespective of the number of times interrupted is counted only once in this calculation [44]. The difference between CAIFI and SAIFI is that the total number of customers served is considered in the case of the latter's denominator as against the total number of customers interrupted considered in the former's case. It is expressed mathematically as:

$$CAIFI = \frac{Total\ number\ of\ customers\ \mathrm{int}\,erruptions\ p.a.}{Total\ number\ of\ customers\ \mathrm{int}\,errupted} \tag{2.9}$$

e). Average System Interruption Frequency Index

Average System Interruption Frequency Index (ASIFI) and SAIFI are alike; nonetheless, while the former considers the load affected, the latter considers the number of customers interrupted [17].

$$ASIFI = \frac{Load\ \text{interrupted}}{Total\ load\ connected} = \frac{\sum \lambda_i L_i}{\sum L_i}\ \text{int}/KW \quad (2.10)$$

where, *Li* stands for the load interrupted at load point *i*.

f). Average System Interruption Duration Index (ASIDI)

Rather than duration of interruption that certain quantities of customers experienced, Average System Interruption Duration Index (ASIDI) measures the period of the load interrupted [17].

$$ASIDI = \frac{Duration\ of\ load\ \text{interrupted}}{Total\ load\ connected} = \frac{\sum U_i L_i}{\sum L_i}\ hr/KW \quad (2.11)$$

where, *Li* stands for the load interrupted at load point *i*.

g). Average Service Availability/Unavailability Index

Average Service Availability/Unavailability Index (ASAI/ASUI) signifies the portion of time (usually stated in percentage) that power supply has been made to a customer in a year. ASAI is a measure of how available stable supplies has been to customers with firm supplies [17]. It is stated mathematically as:

$$ASAI = \frac{Customer\ hours\ service\ availability\ p.a.}{Customer\ hours\ service\ demand\ p.a.} \quad (2.12)$$

Since a leap year and a non-leap year contain 8784 and 8760 hours respectively, ASAI can alternatively, be expressed as:

$$ASAI = 1 - \frac{SAIDI}{8760} \qquad (2.13)$$

$$ASUI = 1 - ASAI$$

h). Energy not supplied index, ENS

Energy Not Supplied (ENS) is a measure of non-delivered energy [17]. ENS is a reliability index used for power systems and usually has the unit kWh . The index can be used to calculate historical events or to simulate future scenarios (e.g. compare different investment options).

$$ENS = Total\,energy\,not\,\mathrm{sup}\,plied\,by\,the\,system = \sum L_{a(i)} U_i \qquad (2.14)$$

where *Ui* represents interruption time in a year while *La(i)* stands for the load connected (on average) to load point *i.*

i). Distribution Supply Loss Index

Distribution Supply Loss Index DSLI is the measure of the loss of high voltage (HV) supply (HV/MV transformers and bulk loads) triggered by continuous outages [17]. DSLI is stated in minutes per month or hours per month. The index gives a KPI for assessing how a system performs due to outages in distribution systems only (HV supply) [44]. It is expressed as:

$$DSLI = \frac{\sum MVA.Hours.lost("O"+"E"+"F")\,per\,month}{Installed\ HV\ Transformer\ MVA\,base + Bulk\ load\ MVA\,base} \qquad (2.15)$$

Where “O”, “E”, and “F” are notified outage, unplanned emergency outage and unplanned fault respectively.

j). MV Supply Loss Index

Reticulation Supply Loss Index (RSLI) measures the average duration of the medium-voltage network unavailability per month. This does not include the low-voltage customers. It is a measure of the loss of medium voltage supply (MV/LV transformers and bulk loads) triggered by continuous outages [44]. It is expressed as:

$$Faults/100km = \frac{\sum Total\ number\ of\ sustained\ interruptions\ p.a.x100}{Total\ line\ length\ (km)} \tag{2.16}$$

k). Momentary Average Interruption Frequency Index

Momentary Average Interruption Frequency Index (MAIFI) represents temporary outages (< 2 minutes) in a system where the supply voltage is ≥ 1 kV. The indices measure the temporary outage performance in a system. MAIFI measures the average rate at which the customers served would experience a momentary outage annually [44]. It can be expressed as:

$$MAIFI = \frac{Total\ number\ of\ customer\ momentary\ interruptions\ p.a.}{Total\ number\ of\ customers\ served} \tag{2.17}$$

MAIFI is attractive to utilities because it is easy to calculate from the counters of recloser and breaker [17].

2.5.2 Load Point Reliability Indices

The three-elementary load point reliability indices are (failure rate (λ), mean repair (or outage) time (r) and annual unavailability (U)).

a). Failure Rates

A distribution feeder is a radial system comprising of a series of sets of devices; each device, such as cable, line, recloser, fuse and interruption device has its failure rate (λ) [45], often represented as:

$$\lambda = \frac{Number\ of\ failures\ per\ unit\ time}{Number\ of\ components\ exposed\ to\ failure} \tag{2.18}$$

Failure rate (λ) in distribution feeders is directly proportional to the features used in constructing the device and the area (or locality) where the device is installed. Therefore, the use of more reliable component (lower λ) or amendment of physical location of the feeder is required to improve the failure rate *(λ).* In design, the acceptable number of faults expected on a network depends on environmental condition, quality of construction and maintenance, equipment quality, specification and application, the failure rate per device that is acceptable for that link and the count of devices such as length of the line, type of structure and number of transformers [46]. Failure rate changes during the life of a component, the change in failure rate is expressed in Figure 2.7.

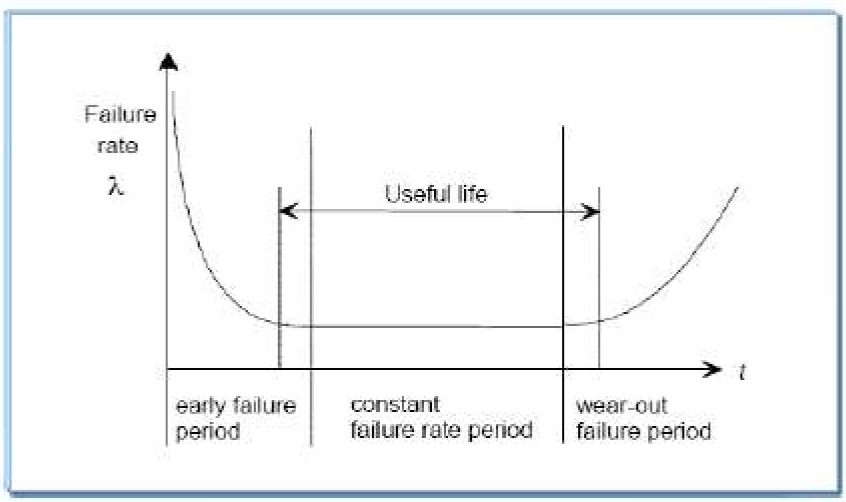


Figure 2.10 The Bathtub Curve [46]

Component failures could be categorized as either teething failures, random failures or ageing failures in reference to the bathtub curve. Teething failures occur when the components are first connected to the network and are detected by onsite test [29]. The random failure rate is constant over time. External factors like weather conditions or bulldozer work causes random failures. Ageing failures occur as a result of accumulated electrical, mechanical, thermal, manufacturing and environmental stress as the component ages. Over time, as the component ages, there is a corresponding increase in the ageing failure rate as well [29]. Our interest is in the failure rate over the useful life of the component i.e. failure rate is constant.

b). Mean Repair (or Outage) Time

Mean Time Between Failures (MTBF) or outage time (*r*) of a component is a distribution system reliability index, which is directly proportional to the period of supply outages and to how the utility company is to address failures in the system [45]. The implication of this is that adequate preparation for interruption restoration is essential for reducing the duration of an interruption. r is expressed mathematically as:

$$r = \frac{1}{\lambda} = \frac{T}{R} \tag{2.19}$$

Where R is the number of failures and T is total time.

c). Annual Unavailability

Availability, an essential part of reliability (expressed in per cent or per unit) is the probability of getting something energized. Unavailability is the complement of availability. That is; Availability is the possibility of becoming energized while Unavailability is the possibility of not becoming energized [17].

2.6 Analysis of Reliability

2.6.1 Engaging Load Point Reliability Indices

The average reliability indices are computed using analytical methods by employing a mathematical equation set, thus engaging an easy and fast step. The analytical method takes into cognizance, the assumptions of statistical distributions of failure rates and repair times [38]. Analytical methods focus on the index calculations and the effect of the failure of a particular device on the load points. Failure mode analysis and minimum cut set analysis are the most common evaluation techniques. For load point *i,* the three basic load point indices can be calculated using the following formulae [47]:

$$\lambda s = \sum \lambda_i \tag{2.20}$$

$$rs = \frac{U_s}{\lambda_s} = \frac{\sum \lambda_i r_i}{\sum \lambda_i} \tag{2.21}$$

$$U_s = \sum \lambda_i r_i \tag{2.22}$$

Hence, from equations (2.20) to (2.22) we can derive reliability indices such as SAIFI and SAIDI; resulting in equations (2.23) to (2.25) below [47]. These indices relay to either how often or the period of the supply outages.

$$SAIFI = \frac{\sum \lambda_i N_i}{\sum N_i} \tag{2.23}$$

$$SAIDI = \frac{\sum U_i N_i}{\sum N_i} \tag{2.24}$$

$$CAIDI = \frac{SAIDI}{SAIFI} = \frac{\sum U_i N_i}{\sum \lambda_i N_i} \tag{2.25}$$

Where the failure rate is represented by λi, Ni stands for the number of customers at load points i. and the unavailability is expressed as Ui.

2.6.2 Failure Mode Effect Analysis

The Failure Mode Effect Analysis (FMEA) which is one of the easiest techniques for assessing reliability; is hinged on the failure mode of devices in a distribution network affected by interruptions due to a specified load. The FMEA reviews several components, subsystems and assemblies to detect failure modes, what causes them and the impact they have. FMEA categorizes the failure state of a single device occurring separately and gets fixed before the occurrence of another. It can be employed in other methods such as cut set and fault tree analysis to calculate the failure behavior of the devices. The failure modes could be expressed in a table featuring the quantity of devices impacted and the period of the impact. FMEA has the merit of providing full details of network failure behaviors while assessing the consequences of failure states of all devices but the demerit is that examining multiple failures is difficult [48].

2.7 Faults

It is not feasible to design and implement electrical network or equipment to eliminate the likelihood of failure in service. It is a fact of life that diverse kinds of faults happen on electrical systems at random locations, however infrequently. Faults are unwanted but inevitable events which can temporarily or permanently disrupt the stable condition of the power system. Whitaker [49] defines fault in an electrical power system as *"the unplanned and unwanted event along a conductor or an obstruction to the flow of electricity".* The causes of faults are many, they include trees collapsing on power lines, wind damage, vehicles or aircraft colliding with the electric poles, lightning, birds shorting lines or vandalism [50]. These faults take lengthier period to clear in the traditional grid but are rapidly cleared in the smart grid by employing intelligent electronic devices (IED) and algorithms. Faults in Distribution Network (DN) result in interruptions and bring about dependability and power quality (PQ) challenges such as voltage sags, momentary or continuous interruptions and astronomical costs of operation [3]. In traditional distribution systems, fault-location methods depend on labor-intensive interruption survey using calls across to customers. Furthermore, the basic voltage and current data and electrical parameters of the system are taken only at the substation. Fault location and management has been an established challenge in power distribution networks. The more the society becomes dependent on energy supply, the more the economic loss due to outages from distribution system interruptions becomes severe.

2.7.1 Categories of Fault

Faults could be grouped under different categories using various parameters, but the sub-categories are similar; some are discussed as follows.

i). Active and passive faults

ii). Transient & Permanent faults

iii). Symmetrical & Asymmetrical faults

iv). Short circuit or Shunt faults and Open Circuit or Series faults.

A) Active and Passive Faults

Active Faults:

The “Active” fault occurs when there is a phase-to-phase flow of current i.e. real flow of current from a conductor (one phase) to another conductor (another phase) or on the other hand, when there is a phase-to-earth flow of current (i.e. actual current flow between a conductor and ground or earth). Active fault can be further categorized into two, namely the “solid” fault and the “incipient” fault. The solid fault is caused as a result of a sudden total collapse of insulation. For instance, in such situation whereby an excavator struck a cable buried under the ground, causing conductors to bridge or a rock fall, in mining, crushes a cable. In such scenarios the fault current is expected to be so high and could lead to an electrical explosion [4, 51].

Conversely, the “incipient” fault, is a fault that begins in a small way, for instance, an incomplete discharge (from an extreme electronic action known as corona) in a void in the insulation, growing and evolving for a longer duration, and gradually burning nearby insulation and eventually evolving into a “solid” fault. Additional reasons could basically be an insulation’s pollution or high-resistance contact triggering tracking along their surface. Tracking reacts with air to ionize thereby behaving like a solid conductor and eventually resulting into a solid fault [4, 51].

Passive Faults:

In the factual sense of the word, passive faults imply no faults in real sense but are rather circumstances that exerts pressure on the system more than its design ability that eventually leads to active faults. Cases of such are as follows:

i). Overloading – causing insulation to be overheated (quality deteriorates, lifespan reduces and failure results eventually).

ii). Overvoltage - exerting pressure on the insulation above its limits.

iii). Under frequency – leading to incorrect behavior of plants.

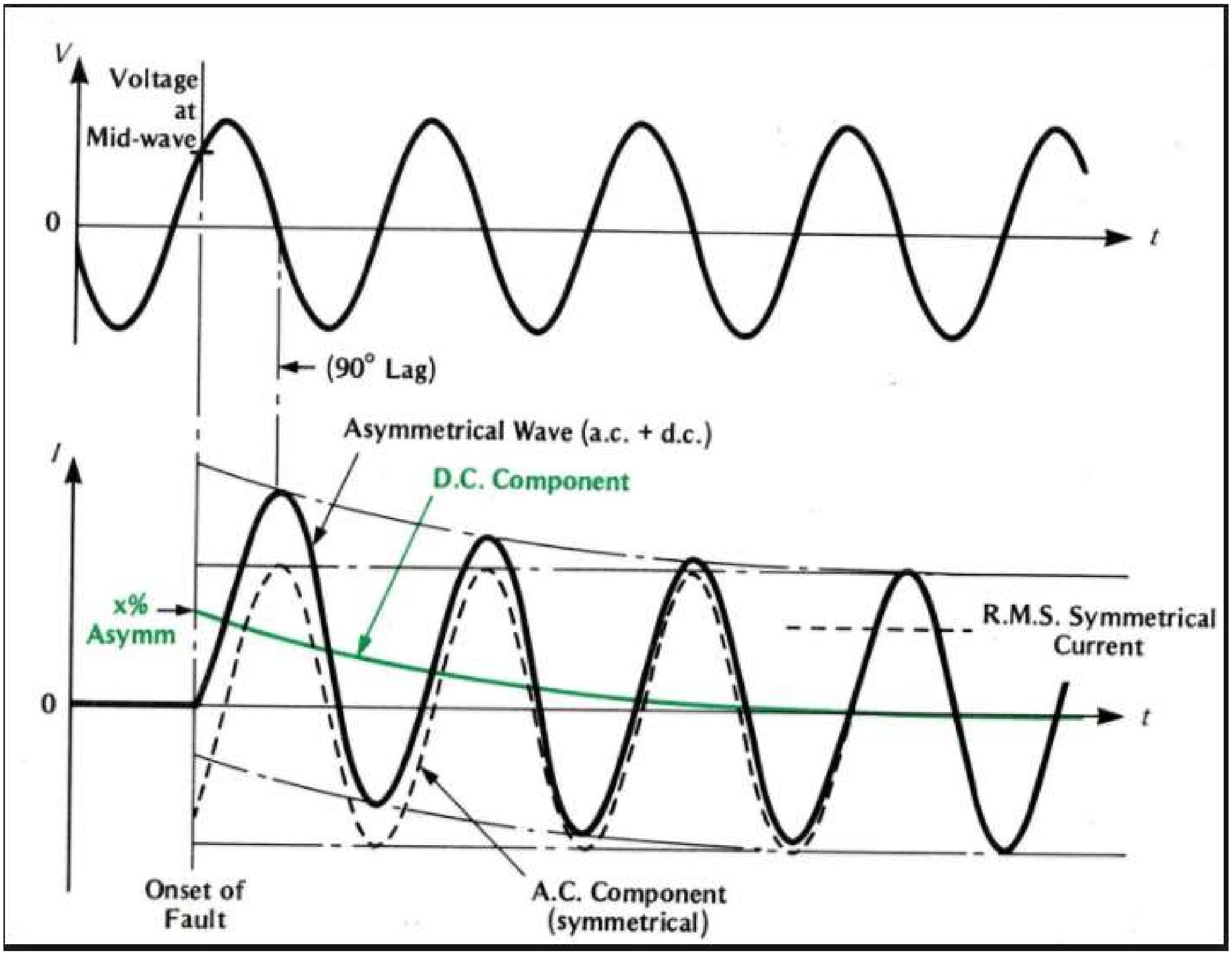
iv). Power swings - out-of-step workings of generators or not synchronizing with one another [4, 51].

B) Transient and Permanent Faults

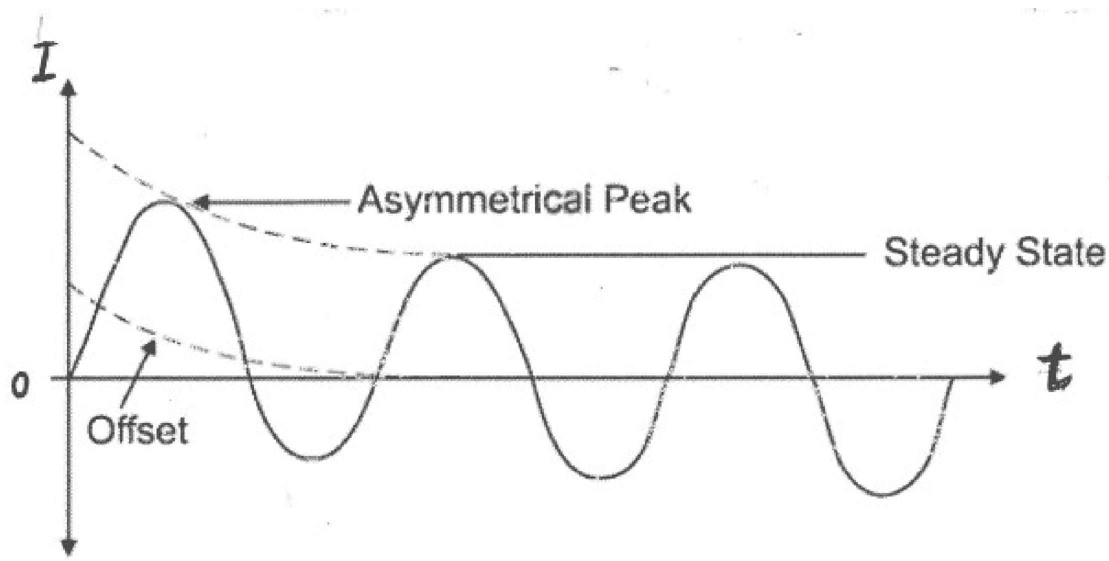
Faults that do not wreck permanent damage on the insulation but allows the network to safely come alive in a short while after occurrence is referred to as transient fault. A usual instance is an insulator flashover after a strike of lightning, which when circuit breakers are opened, could be cleared successfully and then be reclosed automatically. Transient faults take place primarily on equipment installed outdoor where the core-insulating channel is the air. When there is a permanent damage on the insulation, permanent fault occurs. When this happens, room must not be given to reclosing and necessary repair has to be carried out on the equipment [29].

C) Symmetrical & Asymmetrical Faults

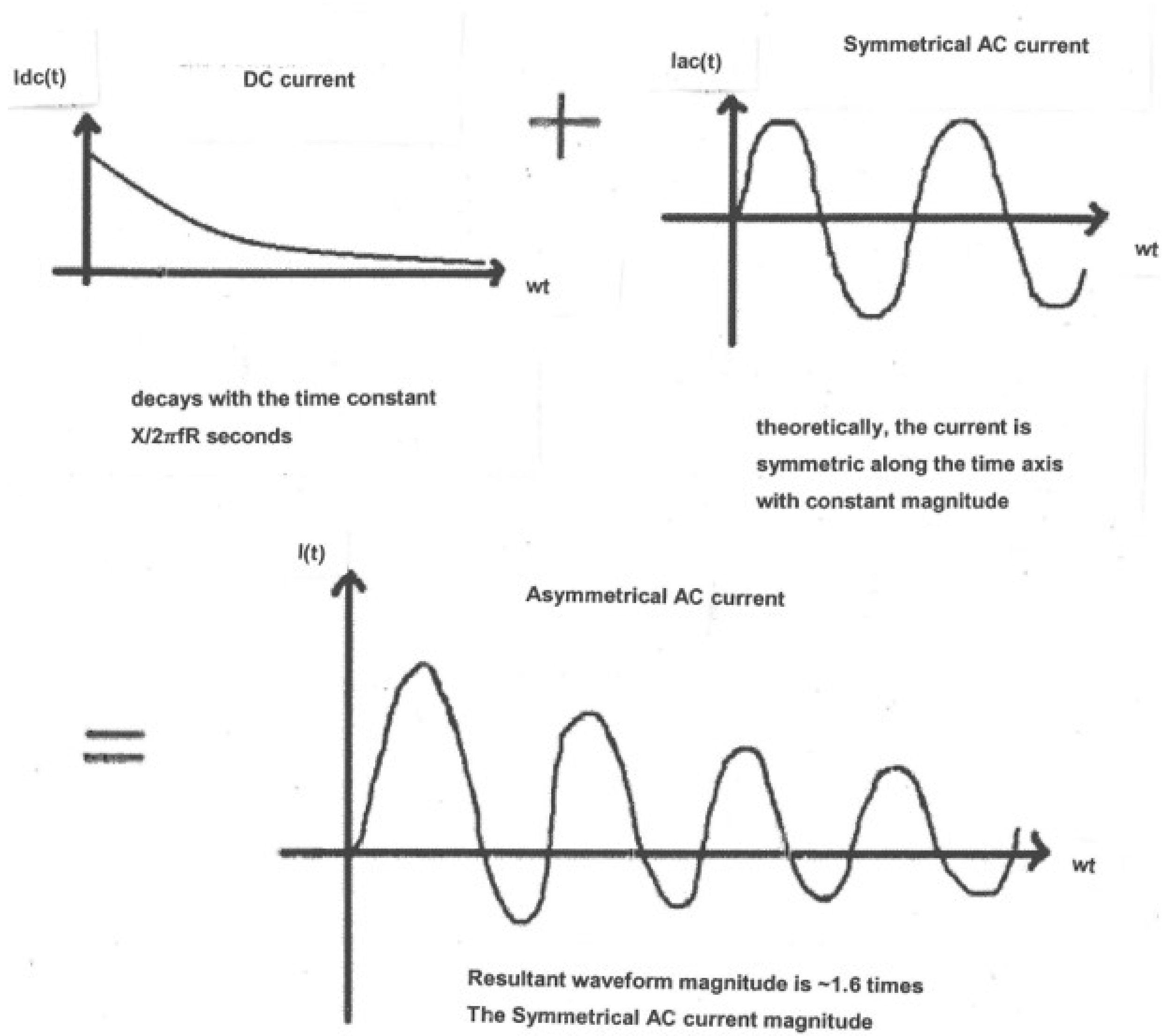
A symmetrical fault is referred to as a balanced fault having sinusoidal waves being equivalent around their axes and signifies a steady state condition. A symmetrical fault has same and equal impact on each of the three phases. An asymmetrical fault is an unbalanced fault, which is momentary in nature, exhibits a d.c. offset and decomposing to the steady state of the symmetrical fault after certain time duration. An asymmetrical fault does not have same and equal impact on each of the three phases. Offset quantity depends on the X/R (power factor) of the electric system and the ratio of the first peak to that of steady state could be as much as 2.55 (i.e. 2.55 times steady state value) [52, 53]. Figure 2.11 contains diagrams which further explain symmetrical and asymmetrical faults.



(a) Symmetrical and Asymmetrical Currents in Short Circuit Faults [52]



(b) Symmetrical and Asymmetrical Faults [4]



(c) Composition of Fault Current (as seen on 1-Phase) [53]

Figure 2.11: Diagrams Explaining Symmetrical and Asymmetrical Faults

D) Short Circuit or Shunt Faults and Open Circuit or Series Faults

Short circuit or shunt fault:

Distribution feeder short circuit or shunt faults can further be sub-divided into two major categories vis; the high impedance faults and the low impedance faults:

i) High Impedance Faults (HIFs):

HIF occurs when there is an electrical contact between a naked conductor (carrying current) and an insulated object i.e. when a conductor (carrying current) breaks and makes physical contact with a surface having high impedance. Such surface could be grass, sand or road and could constitute a hazard to human being and his surroundings. Or alternatively, the conductor (having flow of current) may not break but makes contact with an insulated object that is grounded. [54].

ii) Low Impedance Faults (LIFs)

LIF includes conventional short circuit or shunt faults like:

1. Single line-to-ground (L-G) fault
2. Line-to-line fault
3. Double line-to-ground fault
4. Three phase fault
5. Balance 3 phase-to-ground fault

With a single line-to-ground (L-G) fault, only one phase (either phase A, B or C) has non-zero fault current (see figure 2.12). This could take the form A-G or B-G or C-G fault. Single-line-to-ground fault occurs most frequently in the power system. Its probabilities of appearance in the power system is 70% [52].

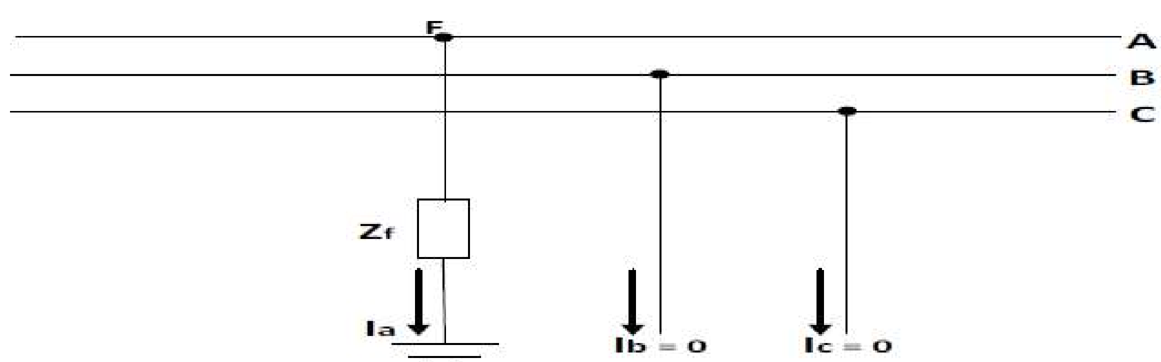


Figure 2.12: A single line-to-ground fault [55]

When a phase comes in contact physically with another phase and the ground, a double line-to-ground (L-L-G) fault results. (see figure 2.13). i.e. short-circuit occurs between two phases and the ground. This could take the form A-B-G or B-C-G or C-A-G fault. Its probabilities of appearance in the power system is about 10% [52].

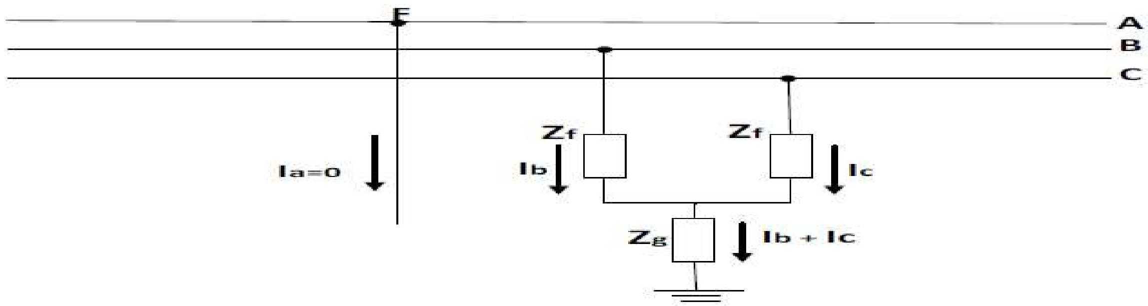


Figure 2.13: A double line-to-ground fault [55]

Line-to-line(L-L) faults occur when two of the conductors come in contact physically with each other i.e. when two phases are short-circuited (see figure 2.14). This could take the form A-B or B-C or C-A fault. Its probabilities of appearance in the power system is about 15% [52].

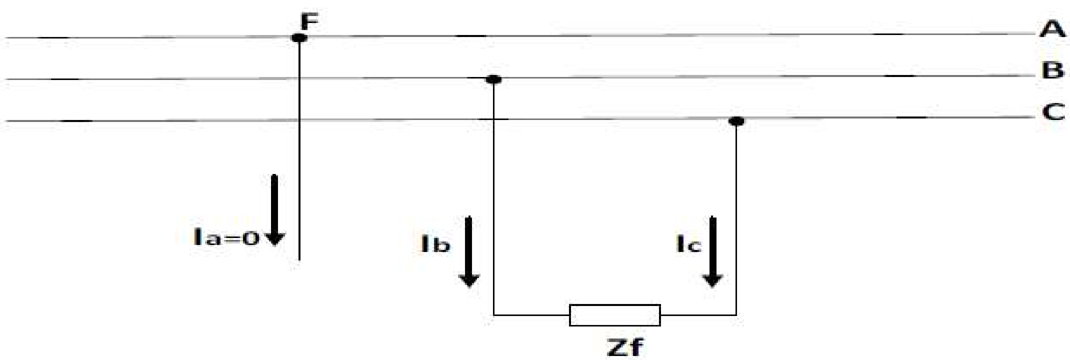


Figure 2.14: A line-to-line fault [55]

Three phase (L-L-L) fault occur when all the three conductors come in contact with one another i.e. when three phases are short-circuited (see Fig. 2.15). This could be expressed in the form A-B-C fault. Its probabilities of occurrence in the power system is about 2% - 3% [52].

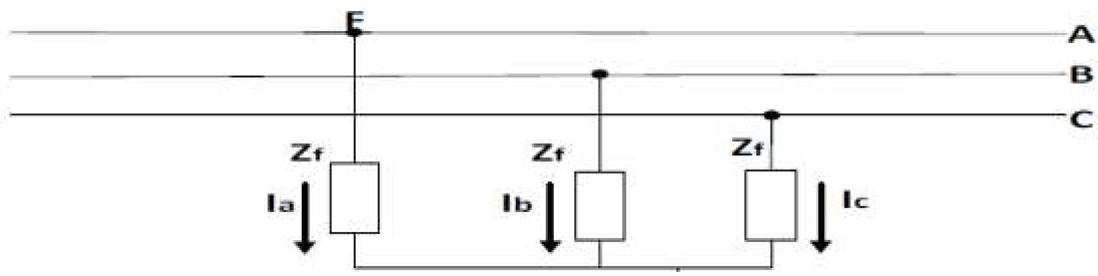


Figure 2.15: A three phase fault [55]

Three phase-to-ground (L-L-L-G) fault is the least likely faults but yet the most severe [56]. This could be expressed in the form A-B-C-G fault (see Fig. 2.16). Its probabilities of occurrence in the power system is hardly 2% - 3% [52].

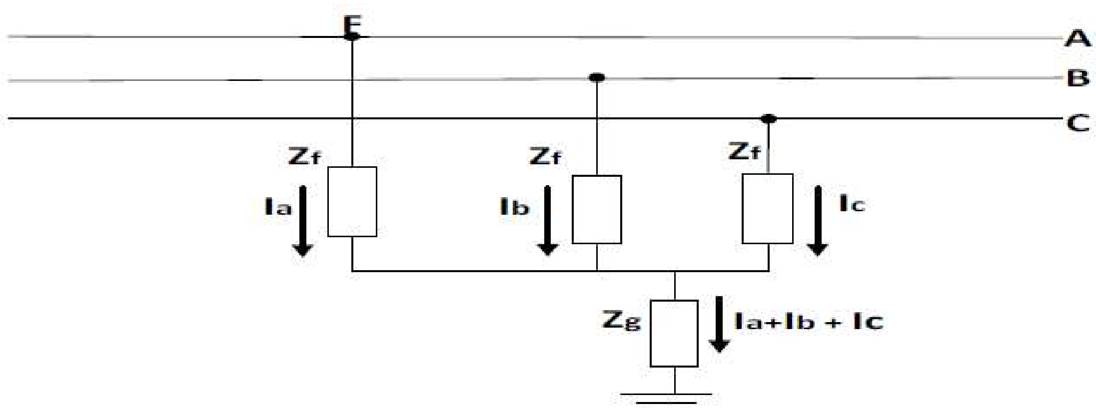


Figure 2.16: A three phase-to-ground fault [55]

Figures 2.12 - 2.16 show some typical forms of shunt faults at position '*F*' in a particular power distribution system. Using the three-component technique, the zero, positive (+ve) and negative (-ve) sequence i.e. I_{a0}, I_{a1} *and* I_{a2} respectively, the fault currents at fault position '*F*' of phase A could be calculated [57]. If a fault occurs at position '*F*', the flow of the fault current could be via any system feeder and if I_{ia0}, I_{ia1} and I_{ia2}, represent the zero, +ve and -ve sequence fault currents of phase A respectively at a specific feeder *i*, the currents were calculated by [55] as expressed in equations (2.26) – (2.31) relying on zero, positive and negative sequence networks [55].

$$\begin{cases} I_{ia0} = K_{i0} I_{a0} \\ I_{ia1} = K_{i1} I_{a1} \\ I_{ia2} = K_{i2} I_{a2} \end{cases} \tag{2.26}$$

In equation (2.26), K_{i0}, K_{i1} and K_{i2}, are the feeder coefficients of feeder *i for* zero, positive and negative sequence respectively with respect to fault position '*F*'. Assuming the fault current is so great compared to the load current at a particular location in a network, the load current could be ignored. Hence, for a specific feeder in the system linked to a specific fault position, these three feeder coefficients are constants and were calculated in [55] by employing circuit theory and three sequence networks. Feeder coefficient varies from locations and feeders and for a specific feeder *i*, the coefficient of the feeder may differ for various fault locations. Diverse feeders may possess diverse feeder coefficients for a fault position.

From equation (2.26), if $K_{i0} = K_{i1} = K_{i2} = K_i$, then:

$$\begin{cases} I_{ia0} = K_i I_{a0} \\ I_{ia1} = K_i I_{a1} \\ I_{ia2} = K_i I_{a2} \end{cases} \tag{2.27}$$

where *ki* represents the feeder coefficient of feeder *i* with respect to fault position *'F'*. Hence, the currents of 3-phase fault at feeder *i* were calculated using Equation (2.27) [55, 58].

$$\begin{bmatrix} I_{ia} \\ I_{ib} \\ I_{ic} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \begin{bmatrix} I_{ia0} \\ I_{ia1} \\ I_{ia2} \end{bmatrix} \tag{2.28}$$

$$\begin{bmatrix} I_{ia} \\ I_{ib} \\ I_{ic} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \begin{bmatrix} K_i I_{ia0} \\ K_i I_{ia1} \\ K_i I_{ia2} \end{bmatrix} \tag{2.29}$$

$$\begin{bmatrix} I_{ia} \\ I_{ib} \\ I_{ic} \end{bmatrix} = K_i \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \begin{bmatrix} I_{ia0} \\ I_{ia1} \\ I_{ia2} \end{bmatrix} = K_i \begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \tag{2.30}$$

where a is an operator giving a phase shift of 120º clockwise and a^2, a phase shift of 240º. Hence,

$$\begin{bmatrix} |I_{ia}| \\ |I_{ib}| \\ |I_{ic}| \end{bmatrix} = |K_i| \begin{bmatrix} |I_a| \\ |I_b| \\ |I_c| \end{bmatrix} \tag{2.31}$$

Equation (2.31) reinstates that the magnitude of the fault current at feeder *i* in a specific fault position is in a multiple of K_i. Therefore, for a feeder *i at a* fault location '*F*', K_i is a constant. When there is an occurrence of fault, the distribution of fault current in the faulty system is signified by the feeder coefficients of all the feeders in the system.

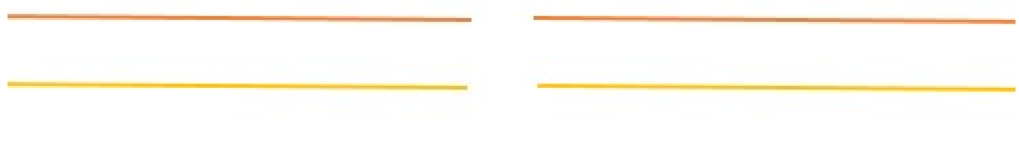
Open circuit or series fault: Open circuit faults, which are also referred to as series faults, are the unbalanced or unsymmetrical fault types with the exception of three-phase open fault. Typical examples are single phase, two phase and three phase open circuits (see Figure 2.17). These faults are mostly caused by the failure of one or more cables, melting of a conductor or fuse in one or more phases, failure of the circuit breaker of one or more phases, joint failures of conductors and overhead lines.

If one of the phases of a transmission line, working with a balanced load at an open-circuit pre-fault stage melts, there occurs a reduction of the actual loading of the alternator thereby causing an increase in the acceleration of the alternator; running at a speed slightly greater than synchronous speed. This over-speed results in over-voltages in other transmission lines.

Thus one or two phase open circuit scenario could result in the unbalance of the power system voltages and currents thereby causing enormous damage to the equipment [52]

(a) Single-phase open-circuit [52]

(b) Two-phase open-circuit [52]



(c) Three-phase open-circuit [52]

Figure 2.17 Open-circuit Faults

2.7.2 Causes of Faults

The factors responsible for interruptions of power supply to customers are classified into different categories namely, natural factors, human factors and equipment factors [59]:

i) Natural Factors

Natural factors are such events like hostile climatic conditions, vegetations and animals making physical contact with current-carrying conductors. These are termed as an act of nature and are outside the human control [52].

ii) Human Factors

Human factors are such events like theft and vandalism. Practically speaking, it is impossible for utilities to disallow human beings from interfering with all the apparatuses of the distribution system. The main targets of the vandals are copper, aluminium and transformer oil. Theft and vandalism is largely driven by increased world market demand for these products leading to the increasing markets for aluminium and copper in the international metals market powered by the growth of China and India in industrialization [17].

iii) Equipment Factors

Equipment factor refers to failure of any equipment at the substation or on the feeder leading to supply interruption. The malfunctioning component can be discovered by naked eyes if the defect is glaring or by an elimination procedure if the defect is not glaring. The effect of failure of any component depends on the distance from the end of the feeder where the component has malfunctioned. If a component close to substation on a feeder fails, leading to supply interruption, the impact would be experienced by several customers and the loss in revenue is generally considerable including personnel overhead, transportations, cost of repairs or replacing defective component to restore the power. Efforts must be made by power utilities to implement capital projects to bring down the failure rates of equipment to bearable economic levels. Such capital projects may include condition monitoring systems strategies, preventive maintenance and reliability centered maintenance. Equipment factors include, but are not limited to failure of any of the following components: transformer, switchgear, cable circuit, overhead line, reactive control devices (reactors, capacitors), terminal equipment (busbars, instrument transformers, lightening arresters), control system (SCADA) and protection system (fuse, relays) [59]:

2.7.3 Effects of Faults on Power Distribution System

When fault occurs, heavy short circuit current flows in the circuit. The flow of this current could lead to the following consequences:

a. If the short circuit current takes the form of an arc, it could cause significant havoc to the element of the power system.
b. Due to overheating or abnormal mechanical forces, it may result to damage of other apparatus in the system.
c. The heavy current as a result of the fault causes excessive heating which may result in fire and probably explosion.
d. It may lead to distribution system stability problem or even a complete shutdown of the power system.

Many unsymmetrical faults are momentary in nature and may vanish within a few cycles, for instance, when a twig stem falls across a line, it burns itself out within seconds or just fall. The symmetrical three-phase faults, commonly occur as a result of operating personnel's carelessness.

2.8 Review of Distribution Line Fault Location Techniques

The distribution line fault location techniques could be categorized into the following sub-headings

2.8.1 Impedance and Fundamental Frequency Based Methods

A). Impedance Based Method

The impedance-based method of fault recognition and identification involves the basic approach of measuring current and voltage before and after the occurrence of fault, at one terminal of the feeder or at both terminals. The parameters measured are then employed through mathematical equations in computing the features of the line. The fault location is calculated using line impedance per unit length. The simple reactance method determines fault distance using equations (2.32) - (2.34).

$$V_s = (x.Z_l..I_s) + R_F.I_F \tag{2.32}$$

$$I_{m\left(\frac{V_s}{I_s}\right)} = I_m\left(x.Z_l\right) = x.x_l \tag{2.33}$$

$$x = \frac{I_m\left(\frac{V_s}{I_s}\right)}{X_l} \tag{2.34}$$

Where *x* represents the distance to the fault position, *Is* and *Vs* are the current and voltage of the generating terminal of the line, *I"s* is the difference in current between the pre-fault and post-fault (fault component current), and I_F stands for fault current. X_l represents power line reactance per unit length, *Im* denotes imaginary component and * signifies conjugate component. Takagi [60] proposed an improvement over the reactance method for fault location in a single-end approach, employing both pre-fault and fault data. The method reduces the effect of load flow and fault resistance; this is an upgrade on the simple reactance method [61].

$$x = \frac{I_m\left(V_s.I_s^{"*}\right)}{I_m\left(Z_l I_s.I_s^{"*}\right)} \tag{2.35}$$

Where x represents the distance to the fault point, *Vs* and *Is* signify the voltage and current of the sending terminal respectively. *I"s* stands for the difference between the post-fault and the pre-fault current values, the impedance per unit length of the electric network is Z_l, the imaginary component is *Im* and * represents the conjugate component. The modified Takagi technique is another impedance-based method, it uses zero sequence current and therefore, needs no pre-fault data.

$$x = \frac{I_m\left(V_s.\left(3.I_{0s}\right).e^{-jT}\right)}{I_m\left(\left(Z_l.I_s.I_s^{"*}\right).e^{-jT}\right)} \tag{2.36}$$

Equations for different categories of fault taking place at the main feeder and at a single phase, lateral line in distribution networks was presented in Girgis, (1993). Discrete Fourier Transform (DFT) was employed by applying modest calculation to filter harmonics while issue of multiple fault locations derived from mathematical calculations was resolved by updating the voltage and current vectors applying the model of static impedance load. In [62], faulty feeder current, symmetrical components network impedance and 3-phase voltage values taken at the supply busbar (pre-calculated after every alteration of the system parameters and recorded in the databank) of a 16-feeder medium voltage (MV) system were used to find the locations of single-line-to-ground (SL-G) and 3-phase (3-Ph) faults. Three test networks were utilized to identify the faulted lateral in [63] in order to eradicate the challenge of multiple estimation in fault location common to impedance techniques applying voltage and current parameters measured at one terminal of the power substation. The method revealed that by recognizing only one faulty terminal, the multiple estimation issue is eradicated. In [64] an iterative algorithm was used to pay off for the capacitive current of the underground cables and posited this algorithm for SL-G and 3-Ph faults for a distribution system using apparent impedance computed from the local current and voltage. The performance of this method does not depend on the fault distance and resistance values. Although the accuracy of the calculated fault distance may be affected by existence of laterals. In [65] two equation techniques were recommended for distance estimation of fault. Technique number one formed two linear equations from the apparent impedance equation, while technique number two posited the distance equation as dependent on fault resistance. Although the former give result that is more accurate when the fault was with zero resistance, the latter produced better results than the former. In [66] a SL-G faults method utilized voltage and current phasors taken at the level of the substation, and the magnitudes of voltage taken at the buses of feeder. It possesses a databank which comprised of topology of the distribution network's operational and electrical parameters. By verifying the method on an actual 13.8 kV, 238 nodes overhead feeder, it was discovered that it could be executed using Power Quality (PQ) quantity components attached to the feeders. The PQ components carry out the task of analyzing the quality of power and position of fault. Also, in [67] an algorithm for fault location (using PQ meters and other devices) to measure voltage sag on the feeders was proposed. Input data to the algorithm were produced by simulations of Alternative Transient Program (ATP). Senger *et al.,* [68] posited a technique utilizing measurements from IEDs fitted to the substation and implemented with a databank containing the parameters and topology of the network. Single-phase-to-ground, phase-to-phase, phase-to-phase-to-ground, three-phase and three-phase-to-ground faults were considered. Salim *et al.*[69] talked about a fault-location which is an extension of impedance-based design for distribution network considering unbalanced distribution feeders wherein input data were voltages and currents measurements, and considered different fault types and load variation effects. Simulations results of a distribution system in Southern Brazil were obtained; presenting a commendable technique but the software has not been used to analyze any fault scenario in real life.

An improvement on impedance-based technique was proposed by De Almeida *et al.* [70] whereby indicators (Faulted Circuit Indicators, FCI) were installed along the feeder to eradicate the ambiguity about fault position. The Chu–Beasley Genetic Algorithm (GA) was employed by the method to assign along the feeders of a distribution system, a specific number of FCIs. Simulation and real-life results of the IEEE 34-bus system and a 475-bus system respectively were presented. In [71] an impedance based technique employing the impedances, relay event reports, FCIs and length of the feeder sections to calculate fault locations in a distribution network was proposed. Dashti and Sadeh [72] likewise developed a scheme which classifies the network into zones using impedances, time comparison, installing fuse links in the feeder and detecting fuse operation. It compares the impedance, voltage and current pre-fault and post-fault values. The faulty zone is detected using the impedance measured, analysis is conducted on the fault duration; the cut-out fuse that operated is determined and the zone that is faulty is identified.

B). Fundamental Frequency Based Methods

The fundamental frequency-based method for fault recognition and identification depends on measurements of power frequency quantities taken from protection devices such as relays, voltage transformers (VTs) and current transformers (CTs) located at zone substations, terminal stations or in the field. Sequence components analysis is then employed on the quantities obtained to determine fault types and location estimates. In [73], a C-programming language fault diagnosis and location scheme, that employed in its calculation, the load current and fault current simulations values attained from Electromagnetic Transients Program (EMTP) was developed. The interrupted load current waveform was compared with that of real-life load and the precise position of the fault was thereby diagnosed. Authors in [74] developed a matrix algorithm (of three sub-routines vis network matrix, fault information matrix and the fault detection matrix) for distribution network (with DGs based) fault section location using current inputs from feeder terminal units. In [75], a recursive charging current and least-squares based technique was recommended. A method using fundamental frequency of voltage and current values before and after fault considering only SL-G faults and hinged on the assumption that loads past the faulty node are integrated into one at the other terminal was described in [76]. In [77] a scheme considering faults in the form of both open and short circuits, treated concurrently in a 11kV distribution system that was fully automated was described. The load current is denoted by 0 during normal operation while the faulty sections (in fault mode) is denoted by 1. The fault current is very high relative to normal load current. Fault detections occur in sections having 1 and 0 status while the status in non-faulty sections is either 1 and 1 or 0 and 0. Saha *et al* [78] presented an algorithm (examining Line-to-Line (L-L) and SL-G faults) for fault location estimation on a radial MV system by evaluating the calculated feeder impedance with the measured impedance. In [79] an algorithm (embedded into microprocessors and connected to substations) using line currents and voltages (in RMS form) at the MV/LV substations in the location of various types of fault was developed.

2.8.2 High Frequency Components (HFC) and Travelling Wave (TW) Methods

The investigation of higher frequency signals other than the fundamental frequency, such as natural oscillating frequency, harmonic and travelling wave is referred to as high frequency components and travelling wave schemes. Because of their overwhelming effect of background noise and low magnitudes, they could pose a problem while making efforts to excerpt them from the fault composite signal. The application is using either the travelling wave technique or as natural oscillating frequencies and harmonics analysis technique.

In the technique of analyzing the harmonics, the higher harmonic currents are analyzed to distinguish the features peculiar for capacitor switching, load switching and devices that produces arc from those of faults surges. These frequency features propagate in both directions from the point of fault. These waves come across disturbances as they move along the feeder and as such, reflected back to the point of fault and converge at the relay terminal producing a vastly interrelated signal. The original values of the waves are functions of the fault's path resistance, instance of occurrence and position on the feeder. The fault distance (*x*) based on the travelling wave technique for a double ended line [80] is expressed in equation (2.37).

$$x = \frac{l + k_c(t_a - t_b)}{2} \tag{2.37}$$

The length of the cable is *l* while the propagation speed of the travelling wave is *kc;* the difference between the arrival times of the travelling waves of each side is $t_a - t_b$.
Linear mixtures of wavelets possessing similar features of their parent wavelets are called Wavelet Packets (WP) while the decomposition of signals into consecutive wavelet components conforming to a signal in a time-domain over a range of frequency is referred to as Wavelet Transform (WT). The initial signal could be portrayed relative to a wavelet extension using the quantities of the wavelet functions.

A proposed Short-Time Fourier Transform (STFT) technique (based on the signal division appointing a window which is time-confined and subjecting each division to analysis) was employed to find the phase content and sinusoidal frequency of local signal sections taking its variation with time into consideration. The Short-Time Fourier Transform employs similar time-window size for each and every frequency. This shortcoming is overcome by wavelet analysis employing a windowing procedure of flexible-size sections with time intervals long enough for accurate signals with low-frequency, and the smaller sections that demands the use of signals with high frequency; thus, allowing a signal depicted in time-frequency. Several wavelets can be constructed from a function, ψ(t) referred to as "mother wavelet" which is limited to a finite interval i.e. WT disintegrates a specified signal into frequency bands, before subjecting them to time-analysis. WT are generally categorized into Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT). The CWT of a signal *x(t)* is explained as the product of the summation over all time of the signal to be analyzed, the graded and shifted forms of the wavelet function ψ [65, 81].

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t)_{\psi_{a,b}}(t)dt \qquad (2.38)$$

ψ(t) represents the mother wavelet, *a* stands for the scale factor, *b* signifies the translation factor, *R* is a real continuous number system and *a*, *b*∈*R, a*≠0 are the scaling and shifting parameters, respectively. $|a|^{-1/2}$ stands for the normalization value of $\psi_{a,b}(t)$ so that if $\psi(t)$ has a unit length, its scaled version of $\psi_{a,b}(t)$ also has a unit length. CWT is used to divide a continuous-time function into wavelets which are highly localized in time. The CWT, unlike the Fourier Transform (FT) can construct a time-frequency depiction of a signal which produces excellent time and frequency localization and is a good instrument for plotting the varying features of signals that are not stationary. DWT subjects' specific signals with diverse resolutions into varying frequency band analyses. This is achieved by disintegrating the signal into detail coefficients and coarse approximation using the wavelet functions and scaling. DWT varies from WT in that its analysis scale changes by a factor of two [82-84].

$$DWT(m.n) = \frac{1}{\sqrt{2^m}} \sum_k f(k)\psi\left(\frac{n-k2^m}{2^m}\right) \qquad (2.39)$$

Where *f*(*k*) represents a discrete signal, ψ(*n*) signifies the mother wavelet (window function), *m* and *n* are discrete time scale parameters, *k* denotes the number of coefficients, 2^m is the variable for scale, $k2^m$ stands for the variable for shift, and $1/2^m$ is the energy stabilization factor to allow an equivalent scale as the mother wavelet.

Öhrström *et al.* [85] proposed a technique making use of principles' adaptations established for HV transmission network in MV distribution system whereby diverse travelling wave algorithms were appraised employing directional wave, correlation and wavelets test schemes. Yang *et al.*[86] presented a paper which focused on Multi-Resolution Analysis (MRA) of measurement features. This scheme discovered High Impedance Faults (HIFs) by employing the output of MRA whereby the current and voltage signals of the distribution feeder were culled-out even when the signals were not strong. The technique based on extraction and identification of features focused on DWT and arithmetical assurance respectively were utilized for efficient discrimination between the switch operations and the HIFs. In [87] a MATLAB implemented algorithm was developed and verified by means of simulation gotten from Development Coordination Group's (DCG) Electro-Magnetic Transients Program-Restructured Version (EMTP-RV) employing an adapted IEEE 13-Node Test Feeder to evaluate the faulty region of an unbalanced network in a noisy setting. The scheme appointed travelling wave scheme and the procedure employed was the theory of autocorrelation and the input data contains the local voltage only. Another technique for fault recognition and identification in underground distribution system employing DWT was suggested in [88]; an ATP-EMTP simulation of 400-kV underground cable system for 3-phase of different balanced loads networks and fault situations using Daubechies db-8 wavelet transform for fault transient's analysis. Apisit and Ngaopitakkul [89] developed a method for diagnosing the fault in a particular phase in an underground system simulating different faults in ATP-EMTP. High Frequency Components (HFC) was extracted using WT and superimposed on the fault signals. The quantities of current signals for positive sequence were found and used for fault recognition resolution algorithm. Magnago and Abur [90] investigated a technique employing the high frequency features obtained at the substation. The technique recognized the fault pathway based on the information of fault transient signals and derived the fault position along the recognized pathway by means of the power frequency signals. A fault localization scheme built on high frequency signals was proposed in [91], the scheme recognized the faulty section using the wavelet decomposition of the transient signals and voltage signal decomposition in a frequency spectrum of 12.5 kHz to 25 kHz. The scheme rode on the benefit of the distinct qualities of the WT to discriminate between faults taking place in main feeder's various sections, with equal distance away from the main substation. In [92] a technique where voltage and current features (in high frequency mode) were taken at one point was suggested. The signals were evaluated by relating the distance between the travelling waves peaks with the known feeder distance. Akorede and Katende [93] proposed a WT technique for the recognition of HIF activities in distribution system. Electrical models were developed in MATLAB for a capacitor switching event and HIF in an electrical system. The classifier algorithm hinged on a moving window tactic in which one sample is used to move DWT outputs' one-cycle window continuously.

In [94] a method hinged on the differences between the terminal voltage magnitudes of the devices having fault indicators all along the feeders to recognize the areas that are faulty was suggested. A distribution networks fault location algorithm was proposed in [95]; the algorithm relied on WT evaluation of the voltage waveforms documented during fault. Execution of the process was done using CWT while the performance of the method was analyzed using the IEEE 34-node standard test distribution system. In [96] a fault classification and localization technique with the simulations of diverse fault classes employing parameters of fault resistances, and fault inception angles using 7-node and 19-node three-phase test systems adopting wavelet multi-resolution approach. Butler-Purry and Cardoso [97], proposed an on-line method for fault recognition and forecast of the remaining life expectancy of the cable. In an on-line monitoring of underground cable lateral for recorded data, a setup of two experiments were designed and implemented. The recorded data was investigated with the help of a time-frequency multi-resolution method using ANN for pattern recognition of the recorded data. Authors in [98] presented a preliminary research work carried out in a 23.8 kV distribution system. Transient current events measurements obtained at the substation and voltage values projected with the use of the transmission line modelling method followed by a cross-correlation parameter allowed to detect the transient travelling waves and the fault distance computed. Adopting an extended correlation window as a means for eradicating breaks in single-end technique was suggested. Salim *et al.* [99], used the WT through the multi-resolution scrutiny of the current signals obtained at the point of the relay for single-line-to-ground fault recognition in primary distribution systems. Authors in [89] worked on a travelling wave algorithm based on DWT to recognize the HFC and determine the position of fault in underground system of the distribution network. From transmitting terminal, fault distance was calculated using the first peak time attained from the bus at fault. The proposed technique's validity was confirmed with various fault types, locations and inception angles. Fault signals were simulated at a sampling rate of 200 kHz using ATP/EMTP. In [100] an algorithm that uses transient signals and steady state signals for the recognition of faulty feeder was developed. The two signals were compared for a Peterson-coil-grounded system. It extracts the fundamental and HFC using wavelet packet analysis thereby determining the faulty feeder.

2.8.3 Knowledge Based Methods

Knowledge Based Methods (KBM) comprise of distributed devices methods, computational intelligence and mathematical methods as well as hybrid methods.

A) Distributed Device Based Methods

The distributed device methods rely on the idea based on the combination of extra factors such as network data scheme and distribution automation into the prevailing context of a protection system of the distribution network i.e. rather than installing new device and developing new network models, only the existing components and data are used. The distributed device techniques offer brilliant setting for data to be well processed and makes possible the integration of Graphical User Interfaces (GUI) for weather conditions, fault management and terrain information into the system.

A preliminary research work in [101] defined a system for wholly computerized procedure and analysis of substation disturbance data but having the settings for the IEDs, binary data from the IEDs and Circuit Breakers (CBs), channel assignments, and power network features as a necessity. In [102] a scheme for integrating distribution automation and network information systems into the infrastructures on ground was proposed. This encompassed a databank of the needed data for real-time topology information and distribution network fault current investigation and possibly incorporating weather conditions and fault detector information with fuzzy logic utilized for additional processing. Kezunovic [103] matched measured data with historical fault data that was stored in a databank containing previous records of fault measurements of voltage sag. Whenever a fault occurs, the databank values are compared with the voltage sags measured. Nevertheless, this method would not be applicable peradventure the fault is yet to occur at that position or was not stored in the databank. In [104] a mathematical technique making use of matrices formulation was designed between the sections and the voltage sensors and also between the nodes and the sections in the electric network. Hence, employing mathematical procedures, faulty regions are identified using matrices.

B) Computational Intelligence and Mathematical Methods

The Computational Intelligence methods encompasses the Expert System (ES), the Optimization methods, the Fuzzy Logic (FL) and Machine Learning (ML) methods such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree (DT) and etc [11, 105, 106]. The mathematical methods depend on statistics and probabilities to solve the problems of fault position for single-phase earth faults with very high resistance. In addition, matrix could be designed to denote similarities among nodes, sections and voltage sensors that are installed in a distribution system.

An expert system is a computational scheme exhibiting a skillful depth of knowledge in a particular area [11, 105, 106]. An expert system employs an information domain and an inference apparatus to solve problems. The inference apparatus employs an exploration space tree to decide the experimental exploration arrangement while the information domain comprises of production rules and facts. Fuzzy logic systems also try to proffer approximate solution to problems just like human beings, by representing knowledge with approximate terms, thus representing inaccurate human knowledge in a natural and reasonable way which is neither 1 nor 0 (true nor false) [11, 105, 106].

An Artificial Neural Network (ANN) is a pattern that processes signal and designed like the biological nervous systems comprising of several highly interrelated processing components called neurons and in similar manner like human beings, learns by example [105, 107-109]. Neurons are interlinked via biases and synaptic weights and training is implemented by modifying the connected biases and weights. ANNs decide on the basis of information stored beforehand. Optimization techniques such as genetic algorithms are computational techniques that imitate natural procedure of evolution in finding universal best solution [11].

A fault section location method in an electric power system was developed in [110]; the estimation of the faulted section was based on ANN employing binary information from circuit breakers and protection relays. Martins *et al.* [111] posited that the Clark's line currents transformation into the alpha, beta, and zero sequence (αβ0) space vector (an adjusted form of Clarke-Concordia transformation) can help in detecting and classifying different types of fault. The methodology used acquired data, application of mathematics by Clarke-Concordia transformation, fault recognition by comparing the characteristic curves of fault and pre-fault values; and finally, fault position which is derived from the correlation between distance and the eigen value of the line currents matrix. In [112] the ability of Support Vector Machines (SVMs) to predict fault in power systems employing values of voltage and power as inputs and IEEE 118 test feeder as model. SVMs model was developed and compared with Learning Vector Quantization (LVQ) and ANN models; resulting in the development of an equation for forecasting fault in a power system. Fulczyk *et al.*[113] proposed a scheme applied with 3-phase voltage and current from all (*n*) ends and formulated subroutines using the universal fault loop and fault models. The process of Multi-criteria collection was used in choosing the effective subroutine that specifies the section of the faulty line. A technique comprising three different processes was presented in [114]; the fault recognition and identification method used the wavelet technique, while the fault-location method was impedance based and fundamental phasors of local voltage and current. Faulty area identification employed ANN using the local voltage and current data to approximate the faulty area. Rayuda, [115] suggested a distributed diagnostic algorithm, already executed on a sub-system in New Zealand. Distributed Architecture for Power Network Fault Analysis (DAPFA) is a model-based, smart analytical procedure, which integrates a graded power system depiction and model built on implementation standards of substation automation. The model depicting the structure and function is a multi-level one whereby each level represents a combination of devices that is simpler than its successor in the hierarchy. The distributed functional depiction comprises the behavioral information linked to the devices of that level in the structural model. The DAPFA analytical algorithm, which integrates knowledge-based and model-based cognitive machineries was applied to analyze fault in pre-diagnostic and diagnostic levels. Real-time analysis and final diagnostic analysis respectively were provided by these two phases. In [116] an ANN method built on clustering algorithm for line faults detection and classification in a power distribution system was introduced. Chan and Lu, [58] suggested a system applying the notion of a representative vector employing digital Over-Current (OC) relays for fault-location. This system was able to locate faults in both feeder and bus by plotting consistent characteristic vectors with fault current vector in a databank pre-built for this purpose. By bringing up-to-date the databank of the characteristic vector, the suggested technique could be useful to the altered scheme also, thus realizing adaptive characteristics. In [117] a distribution system (with DG) fault identification method which applied RBF neural network and employed current as inputs to train the four neural networks for four different fault types was discussed. The approach in [118] was established on the statistical modelling and data extraction from databases linked to fault recording. The selection of the original values essential for the algorithms, the number of groups and the share of models in respective group were the potential limitations for the proposed practice. An application that applied a *N*-ary tree structure which automatically computed the faulty position in a power distribution network was developed. In [119] a fault pattern recognition using machine learning algorithm applying capturing mechanism of a network state; a fault recognition scheme for power distribution networks was discussed while Al-Shaher *et al.* [120] presented an ANN method in a multi-ring distribution structure utilizing the circuit breaker status, feeders' fault voltage and real power (to train the ANN) for finding the positions of 3-phase faults during the normal and short circuit situations. This technique was used in an existing 13.8kV distribution system. A technique that involves the simulation of a 25kV power distribution network and protective relaying using ATP and MATLAB to acquire a meaningful fault database was described in [121] and the database containing 930 fault scenarios was employed to achieve various forms of system analysis. A neural network fault type and location determination method based on Radial Basis Function (RBF) was described in [122]. This method used normalized fault current of the main source in distribution network with DGs for determining fault category, whereas the 3-phase short circuit current of all the network sources were employed as input to two RBF neural networks for fault location; also, a differential current ratio technique was described by Guo-fang and Yu-ping in [123] to be applied in distribution networks with DGs. A technique proficient in HIF and LIF detection was proposed and executed with a cascaded multilayer ANN configuration employing the Back-Propagation (BP) algorithm by Mohamed & Rao [124]; Wen and Chang [125], presented a fault identification scheme for distribution system using frugal set casing theory and Genetic Algorithm (GA) while Lee *et al.* [73], developed scheme which depends on the estimate of load and fault current for finding fault position. A statistical method built on finite mixture produced a statistical model found by extracting the magnitude of the voltage sag recorded when a fault occurred, together with the topology and parameters in the network [126]. The disadvantages of the offered method are the choice of the quantity of clusters, the ratio of samples in each cluster and the preliminary values essential for the algorithms. These limitations were overcome by presenting theoretical and heuristic measures.

C) Hybrid Methods

In fault recognition and location methodologies, the hybrid scheme is embraced to generate a new structure that couples the benefits presented by the integration of more than one techniques. The core aim is to advance the precision and dependability of the resultant method, as well as decreasing or eradicating the restrictions of the different techniques. In [52] a smart scheme based on intelligent agent theory, knowledge discovery theory, and rough set theory using threshold pickups and a logic table using as inputs, the ratios of the zero sequence, negative sequence, and positive sequence phase angles depending on the fault type was proposed. An approach employing innovative signal-processing coupled with NN was discussed by Samantaray *et al* [127]; time-frequency and time-time distributions of the HIF and No-Fault (NF) data are culled separately. A probabilistic neural network (PNN) was trained and tested on the features extracted for a correct grouping of HIF from no fault. A rule dependent algorithm derived from three phases and zero sequence currents using wavelet energy spectrum entropies was presented by Adewole and Tzoneva, [128] for fault recognition and identification in distribution network. In Adewole and Tzoneva, [55], they further compared how the wavelet entropy dependent algorithms performed with respect to others relying on statistical techniques such as standard deviation and mean absolute deviation. A fault diagnostic technique containing an Expert System (ES), Artificial Neural Networks (ANNs), and a fault examination array employing as inputs, the fault current and voltage signals, binary data from protection relays, and CBs was developed in [129]. The ES was responsible for the faulty position approximation mission, while the ANN was responsible for the fault recognition and single or multiple faults decisions.

The decision made by the ANNs is verified by the fault analysis package. An ANN and Support Vector Classifiers (SVCs) distribution systems fault location scheme employing as inputs, the substation measurements and binary statuses from circuit breakers and relays and a real-life 52-bus distribution network with loads as model was discussed in [130]. Principal Component Analysis (PCA) was adopted for analyzing the data. A hybrid method of WT and ANNs for taking care of the challenges of HIFs recognition in power distribution feeders was suggested in [131]. The variation in the signals of phase current triggered by normal switching events and faults was employed. The DWT disintegrates the current signals of the time domain into different harmonics in time-frequency domain, take out the essential constituents for the training of the ANNs thereby reducing the quantity of inputs to the ANN, and increases the convergence of the training. Data of several HIFs, LIFs and common switching measures were used, the multilayer perceptron network and Levenberg–Marquardt back-propagation algorithm of SimPowerSystem in MATLAB were employed for the implementation. In [132], a technique based on recursive wavelet and Kohonen NN for distribution network whereby the inputs to the NN were the wavelet coefficients from the residual current and voltage in the faulty feeder was presented. Ziolkowski *et al.* [133], suggested a technique built on smart scheme and statistical techniques with phase voltages and line currents as inputs while Martins *et al.,* [111] suggested another method which adopted the Eigen value and an ANN dependent learning algorithm. The technique recognized the presence of fault, classified the fault category and unraveled the faulty area. In [134] a method employing neural network and Fuzzy theory to fuzzify the extracted information. An integration of wavelet and fuzzy neural network yielded the Wavelet Fuzzy Neural Network (WFNN). The limitations of this fault location method are that it comprises numerous calculations and the training procedure is rather slow. Barros *et al*, [135] suggested a method based on STFT and Kalman filters for the recognition of Power Quality (PQ) disturbance. Aslan and Türe, [136] discussed a scheme using Programmable Logic Controller (PLC) which employs the post-fault and pre-fault voltage and current signals. Also, the travelling wave technique is limited by the discontinuities produced by the several sub-feeders typical of a radial distribution network. The discontinuities might occur between the line terminal and the fault position, thereby summing up the reflections to the transient waves from the fault. Moreover, current measurement was shifted from the lateral to the substation, thereby eradicating the problem of multiple locations of fault point. The collected data was processed offline to locate the shunt faults on the main feeder or in the laterals. The fault location algorithm was subjected to full automation whereby the faulty lateral or overhead feeder was scanned at 10m intervals. An initial assumption of a fault is made at the sub-feeder point; when a detection of fault occurs at the sub-feeder, then follows a data update of the pre-fault and post-fault signals at the Digital Fault Recorder (DFR) to the tap of the prospective feeder for fault location investigation. The fault path currents attained for each assumed fault location are then stored into an output file for additional examination. The point along the path of the minimum fault currents is taken as the fault location.

2.8.4 Discussions of Reviews

This review of literature in distribution system fault recognition, identification and location started with a survey on the various techniques vis: the impedance and fundamental frequency; high frequency components and travelling waves; and Knowledge Based Methods (KBM). The impedance and fundamental frequency dependent techniques are easy to apply but are limited by some factors such as multiple estimations, load imbalance, measurement error, line loading, the current source parameters’ harmonic components, resistance of the fault path, etc. Hence, the obtainable accuracy of the total line length is about 2-3% and any significant future improvement is unlikely [94]. Fault location using the high frequency components and travelling wave techniques is with high accuracy but with limitations like the requirement of high sampling rate, complexity, implementation costs, and the necessity of sophisticated measuring equipment. Knowledge based techniques are viewed as complicated and may require high computational costs in applications, coupled with a characteristic challenge related to the upgrading of trained neural networks. A thorough comparison of the methods show that KBM is fast, cheaper, scalable, adaptable, the most accurate and remains the best alternative among all! Computational Intelligence Methods (CIMs), out of various KBM techniques, have garnered more applications as a result of their success in fault recognition, identification and location in recent years [137]. As illustrated in the foregoing review, ANN among CIMs has attracted a lot of attentions for power systems' fault identification, recognition and location in the literature because of its many outstanding features such as [27, 138, 139]:

i) It is able to solve non-linear problems with ease.
ii) The problem containing massive information can be solved easily.
iii) It is capable of learning by examples and with experiences.
iv) There are several algorithms in ANN to simulate the network in a fast and reliable manner with different power system conditions.
v) If condition of the distribution system changes after successive disturbance; an ANN is proficient in incorporating the dynamic fluctuations in the distribution system.
vi) ANN mechanism depends on a series of very simple operation, and has outputs that are reliable, fast and accurate depending on the training.
vii) ANN is flexible, fast, resistant to errors in the training data and admits any real values (highly interrelated or otherwise) as an input.
viii) ANN possesses outstanding pattern recognition abilities.
ix) It is adaptable to parallel computing.

A problem in the development of ANN dependent application is how to synthesize the algorithm for the adaptive learning process. Another weakness is that there is neither a well-structured guide for choosing the ideal number of hidden layers nor the neuron numbers per each hidden layer. From another observation, this is an advantage, bearing in mind the capability to generalize [140]. Hence, it is able to generate an accurate output conforming to any input; though the input might not be fed into the ANN in the process of training.

This research work therefore endeavours to fill some of the gaps in the literature by modifying Suhaas B. A. architecture for fault recognition [141] and adapting it for distribution systems. The modification largely involves the use of MLP-ANN models for fault recognition.

2.8.5 Artificial Neural Network

Artificial Neural Network (ANN) is an information dispensation expertise which derived its inspiration from the data processing technique of human brain [142]. It is defined as a combination of basic neurons which are typically linked in organically stimulated manners and arranged in numerous layers [140, 143]. The structure of a basic three-layer architecture of a feed-forward ANN, also known as the perceptron is shown in Figure 2.18. Each ith layer contains Ni neurons and the set of inputs to the ANN is a1, a2 … aN0; the inputs to these neurons are linked to the neurons of the preceding layer. Similar to a processor, a neuron produces an output by carrying out on its inputs, a modest and non-linear procedures [144]. Training a NN is the procedure of fine-tuning different weights, attached to the neurons and tailored to the training set. ANN learns to produce a response by adjusting the node weights based on the inputs given. i.e. a combination of data, known as the training data set, employed in training the NN.

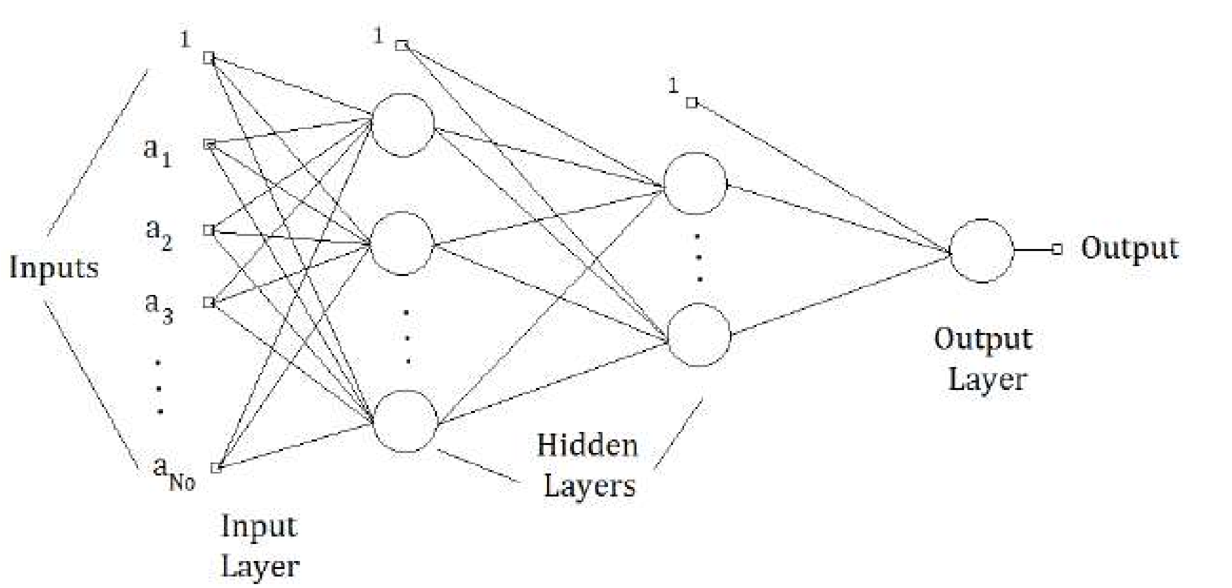


Figure 2.18 Basic Architecture of a Feedforward ANN [141]

The back-error-propagation algorithm (BPA) is an elementary algorithm whereby the weights of the neuron are adjusted in successive stages in order to reduce the error between the real and the targeted outputs [141]. This procedure is also referred to as supervised learning. A basic neuron model (Figure 2.19) could be defined by a function which computes the output as a function of N_0 inputs to it [145].

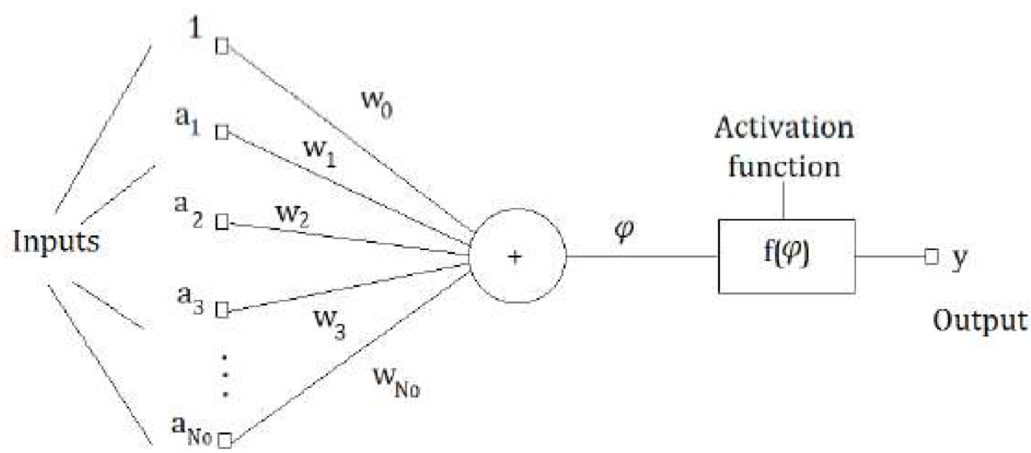


Figure 2.19 Representative Model of a Neuron [141]

The output of the neuron is expressed as:

$$y = f(\varphi) = f\left(\sum_{i=0}^{N_0} w_i a_i\right) \tag{2.40}$$

Where: w0a0 represents the threshold value (polarization), f (φ) stands for the neuron activation function, φ depicts the summation output signal and y is the neuron output.

$$\varphi = W^T A \tag{2.41}$$

Where:

$$W = \left[w_0 w_1 \ldots w_{K_0}\right], \quad A = \left[a_0 a_1 \ldots a_{N_0}\right]^T. \tag{2.42}$$

The appropriate activation function, f (φ), is selected based on the application's requirements. Based on the sum of the inputs, the f (φ) depicts how strong the output by the neuron would be. The f (φ) can be in diverse forms, some examples are as follows:

Step Activation Function

$$f(\varphi) = \begin{cases} 1 & if\ \varphi \geq 0 \\ 0 & if\ \varphi \lhd 0 \end{cases} \tag{2.43}$$

Piecewise Linear Activation Function

$$f(\varphi) = \begin{cases} 1 & if\ \varphi \rhd 1 \\ -1 & if\ \varphi \lhd -1 \\ \varphi & if\ |\varphi| \lhd 1 \end{cases} \tag{2.44}$$

Sigmoid Unipolar Activation Function

$$f(\varphi) = \frac{1}{1 + e^{-\beta\varphi}} \tag{2.45}$$

Sigmoid Bipolar Activation Function

$$f(\varphi) = \tanh(\beta\varphi) = \frac{1 - e^{-2\beta\varphi}}{1 + e^{-2\beta\varphi}} \tag{2.46}$$

NNs can generally be classified into two (with respect to how the neurons are interconnected in a model) vis: feedforward and feedback or recurrent neural networks. Brief discussions of the latter before the former are as follows:

2.8.6 Feedback or Recurrent Neural Networks

Feedback neural network has at least a feedback link connected back into the system together with the input [146, 147]. There could be neurons with self-feedback connection. i.e. the output of a neuron is fed back into itself as input (as shown in Figure 2.20).

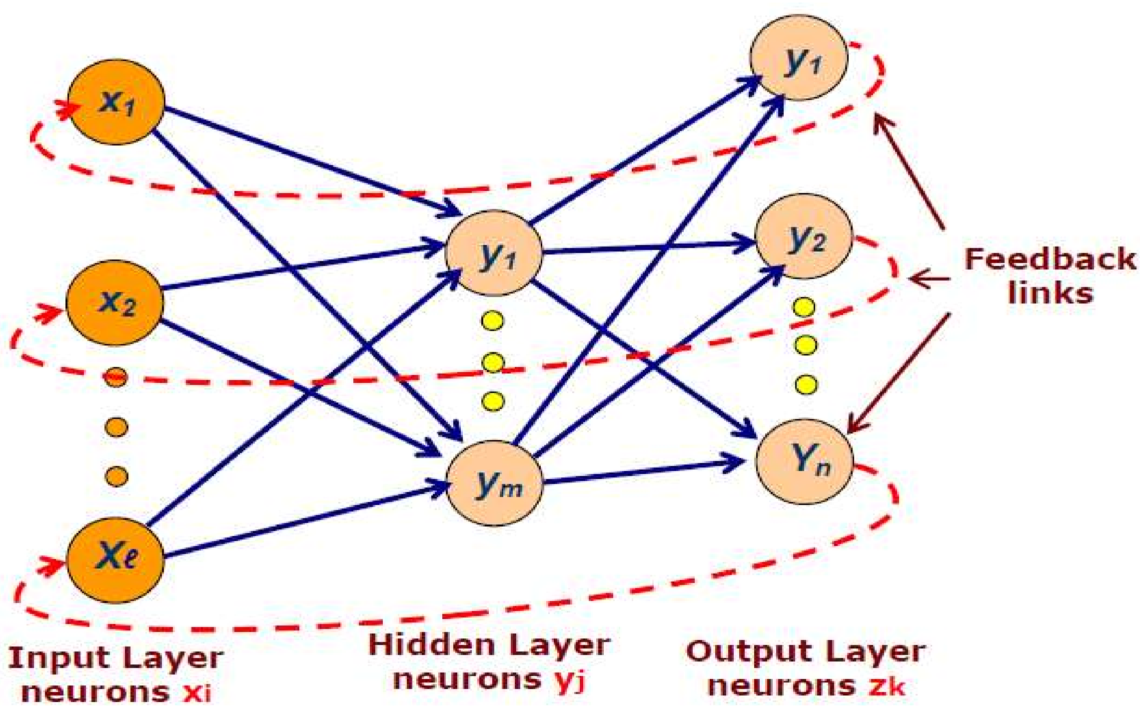


Figure 2.20 Structure of a Feedback Network [148].

2.8.7 Feedforward Neural Networks

Due to the presence of well-defined learning algorithms and their simplicity, only feedforward neural network is employed for simulation in this study. Feedforward neural network is a simple network in which the information move in a single direction and requires no feedback link [109]. Figure 2.21 shows a feedforward network. The ith layer computation procedure can be described by equation (2.47)

$$p^{(i)} = f^{(i)}\left(W^{(i)} g^{(i-1)}\right) \tag{2.47}$$

Where N_0 is the input signals, K_R is the output signals;

$$p^{(i)} = \left[p_1^{(i)} p_2^{(i)} \dots p_{N_i}^{(i)}\right]^T \tag{2.48}$$

is the signal vector at the *i*th layer output; and

$$W^{(i)} = \begin{pmatrix} w_{10}^{(i)} & w_{11}^{(i)} & \cdots & w_{1N_{i-1}}^{(i)} \\ w_{20}^{(i)} & w_{21}^{(i)} & & w_{2N_{i-1}}^{(i)} \\ \vdots & & \ddots & \vdots \\ w_{N_i 0}^{(i)} & w_{N_i 1}^{(i)} & \cdots & w_{N_i N_{i-1}}^{(i)} \end{pmatrix} \tag{2.49}$$

is the weighing matrix between the (*i*-1)th and the *i*th layer.

$$g^{(i-1)} = \begin{cases} A & for \quad i = 1 \\ \begin{bmatrix} 1 \\ p^{(i-1)} \end{bmatrix} & for \quad i = 2,3,....,R \end{cases} \tag{2.50}$$

Where *f*(*i*)(.) stands for the activation function of the neurons in the *i*th layer, **A** represents the vector containing the input signals, and *R* is the number of processing layers. The assumption is that in a layer, all the neurons are similar in all facets and the number of hidden layers (usually determined by the purpose of the NN) can be more than one. The processed NN's output is expressed by the output vector as:

$$y = p^{(R)} = \begin{bmatrix} y_1 & y_2 & \dots & y_{N_R} \end{bmatrix}^T \tag{2.51}$$

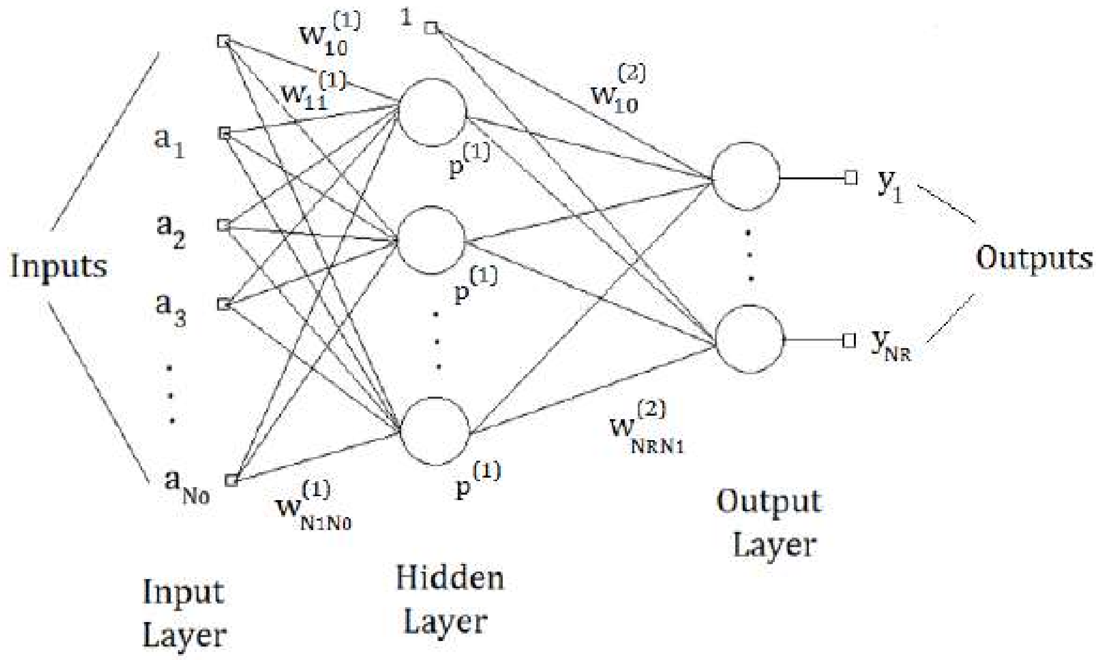


Figure 2.21 Structure of a Multilayer Feedforward Network [141].

2.8.8 Learning Techniques in Neural Networks

Learning or training in NN is the process of determining the weights in order to achieve the desired target [149-151]. The learning strategy adopted is dependent on the architecture of the NN. The different learning methods in NN are classified into three types vis the supervised learning, unsupervised learning and the reinforced learning (Figure 2.22). The classification is done based on the presence or absence of teacher and the information provided for the teacher to learn. They are further categorized based on the rules used.

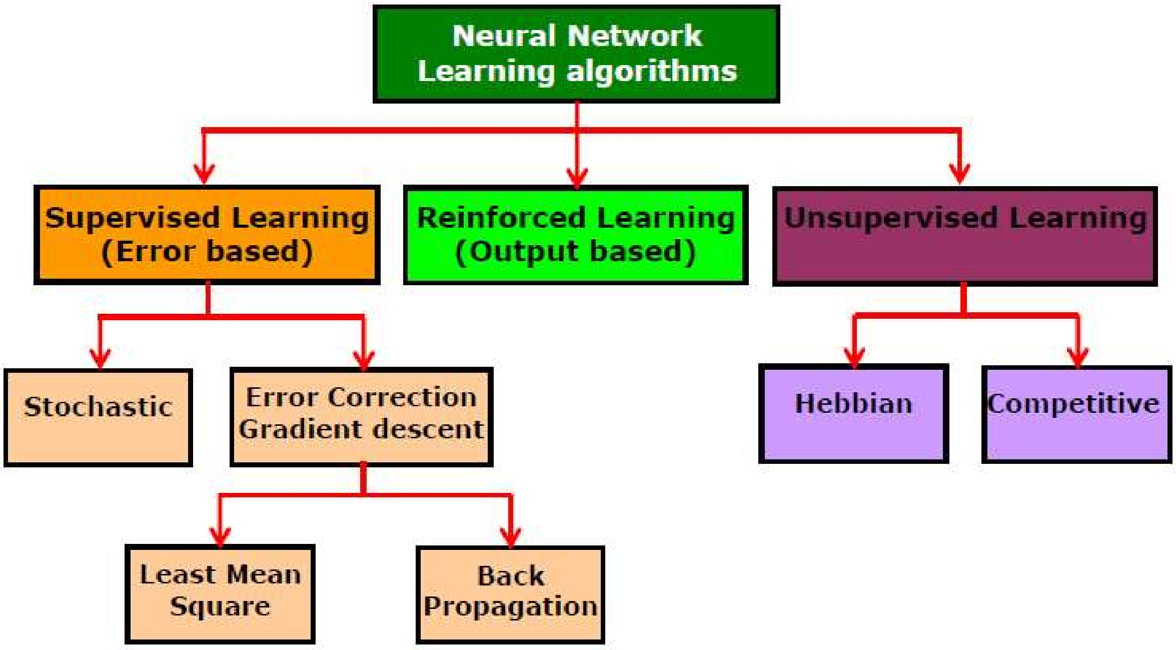


Figure 2.22 Classifications of Learning Algorithms [148].

In the case of supervised learning, a teacher, who presents expected output, is present during the learning process and the weights of the network are adapted with the utmost goal of reducing the error between a specific collection of inputs and their equivalent target values to the barest minimum [140]. Hence, before ANN's training both the inputs and the expected target values are known. In the case of unsupervised learning, a teacher is not present, and the expected output is not presented to the network i.e. the relationship between the inputs and the target values is not present prior to the training. The neural network with a training data set in which only the input values are known is trained. Here, choosing the right set of examples; using some sort of a similarity principle, is very important for efficient training [109]. The most frequently used unsupervised learning algorithms are the Adaptive Resonance Theory (ART) and the Self-Organizing Map (SOM). In reinforced learning, a teacher is present, but the desired output is not presented; he simply shows whether the computed output is right or not.

Supervised learning approaches are used in training Feedforward networks. The input-output sets employed in training the NN are collected before the training process either through simulations or by physical measurements. Figure 2.23 reveals that weights are modified with respect to the error 'e' in-between the outputs and the expected through the teachings of the teacher. Iterative modification of the weights is then performed (see equation (2.52)) [11].

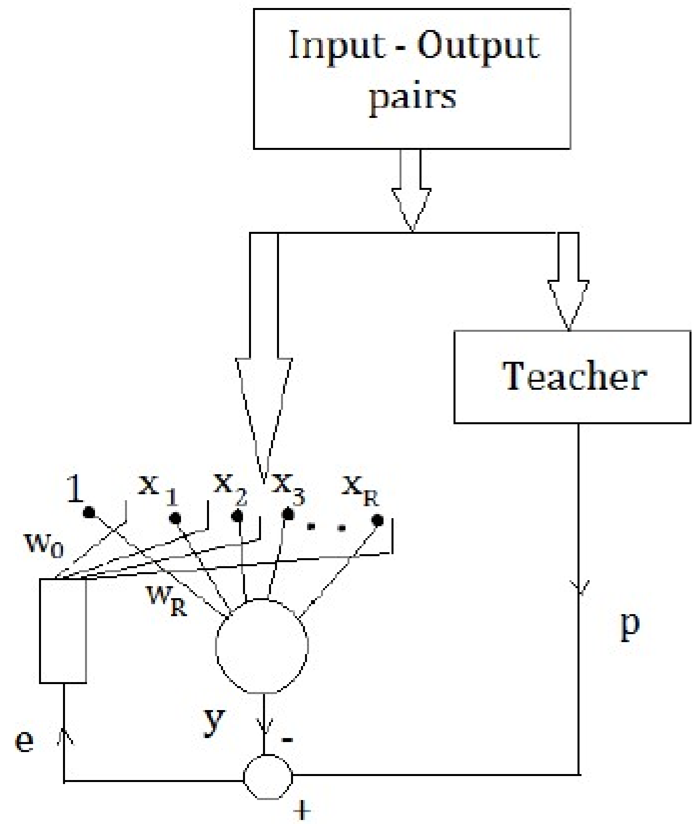


Figure 2.23 Supervised Learning Scheme [140].

$$w_{ji}(n+1) = w_{ji}(n) + \Delta w_{ji}(n) \tag{2.52}$$

Where: wji(n) represents the previous weights and wji(n+1) is the altered weights coupled between the ith and the jth connecting layers. Δwji(n) is the alteration factor and 'n' represents the number of iterations. Considering the jth neuron in one-layer NN, the training effectiveness is boosted by error minimization between the actual and targeted output of the jth neuron. Let the jth neuron's actual and the targeted outputs in the nth iteration be represented by yj(n) and pj(n). Then the iteration's error value is expressed in equation (2.53) as:

$$e_j(n) = p_j(n) - y_j(n) \tag{2.53}$$

The correction factor i.e. the quantity owing to the changes by weighing coefficients is given by the following equation (2.54). The vector **e**(n) storing all error values is likewise a function of the weights **w**(n) for the inputs of the corresponding layers.

$$\Delta w_{ji}(n) = \eta e_j(n) x_i(n) \tag{2.54}$$

Where: η is the learning process rate and xi is the ith input signal.

Learning process, as mentioned previously, aims at minimizing the error function; so also, by employing a Least Squares Method (LSM). Therefore, if a network contains L neurons, equation (2.55) gives the cost function for minimization.

$$S_2(w) = \frac{1}{2}\sum_{j=1}^{L}\left(p_j - y_j\right)^2 \tag{2.55}$$

If the number of learning pairs of the (x(n), d(n)) form in the training set are P; with input and output vectors x(n) and d(n) respectively, then during the learning process' nth iteration, it gives equation (2.56).

$$S_2(w(n)) = \frac{1}{2}\sum_{n-1}^{p}\ \sum_{j=1}^{L}\left(p_j(n) - y_j(n)\right)^2 \tag{2.56}$$

Minimization of equation (2.43) is a non-linear problem because the often-employed activation functions are non-linear. Quite a few mathematical approaches that can take care of non-linear functions efficiently are obtainable and are built on the steepest-decent technique which is a form of Laplace's system of integral estimation where in a complex plane, the contour integral is deformed to approach a stationary point in the steepest decent direction. The learning technique of back-error-propagation, typically used as the Levenberg-Marquardt algorithm is built on this steepest-decent technique [152]. Random weights are chosen by the back-error-propagation algorithm (BPA) for the NN nodes, input pair is fed, result is obtained, hence, each node error is calculated by backward propagation of errors beginning from the last stage. Then, the weights are updated, and the process repeated; with the availability of the input-output pairs' entire set in the training data set; till the convergence of the network with reference to the anticipated targets. The structure of BPA is shown in Figure 2.24. The BPA method is extensively employed in many applications including its error functions application (other than the sum of squared errors) and for Jacobian and Hessian matrices evaluation. The correction values, estimated from the minimization of equation (2.43), are calculated as functions of errors. This procedure is performed layer by layer in the backward path throughout the network.

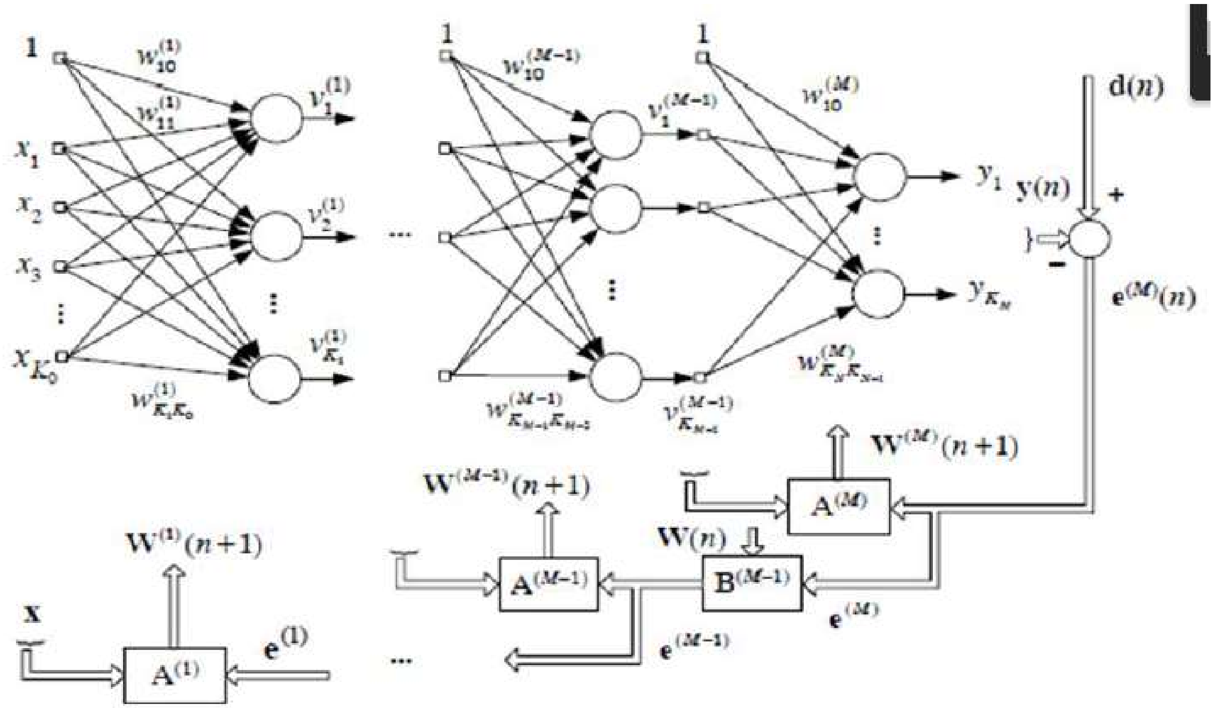


Figure 2.24 Back-Error-Propagation Algorithm's Structure [11]

The blocks A(M), A(M-1),…, A(1) show equivalent weighing vectors and the lower layers propagated errors are calculated and kept in the blocks B(M-1), B(M-2),…, B(2). The BPA has been applied in several forms, but the elementary principle has not changed; what varies in each implementation is the technique applied in calculating the weights that are iteratively upgraded layer by layer in the backward path in the NN. The adjustments employed are also utilized in the repeated networks' training process. The rate of occurrence of the learning process could be assessed by checking the correction values in successive stages. To achieve satisfactory convergence rate, the total number of iterations essential depends on the size and structure of the neural network; the problem in the study; the learning strategy used and the learning or training set size. The effectiveness of a preferred NN and the learning strategy applied could be assessed by applying the trained NN on some test scenarios with expected output values. This test set is a subset of the learning data set. The training data set is employed in training the NN and the testing data set is employed in evaluating the performance of the NN that was trained [141].

2.8.9 Framework of Fault Recognition Scheme

The focus of this scheme is to design, develop, test and implement a strategy for fault recognition, fault-type identification and fault location. Although the fundamental principle for relays remains unchanged, the smart grid technology has had a substantial impact on the mode of operations of relay and have presented numerous developments over traditional electromechanical relays. The entire data generated is further divided into two sets namely the testing and the training data sets. The first stage in the procedure is fault recognition, followed by identification of the fault-type depending on the faulty phases on the distribution line and finally location of the fault. The focus of this research is to recommend a technique to achieve these tasks by means of ANNs. A back-propagation based NN has been employed for fault recognition and other comparable ones for fault-type identification and fault location.

2.9.0 The Neural Network Training Process

Training is the procedure by the NN of learning from given input sets and updating its weights in accordance [153]. Training of the NN requires feeding the training data set (i.e. a set of input output pairs) into the neural network, thereby, teaching the neural network what output is expected, when feeding the input into it. The training data set is slowly learnt, a capability to generalize on the data is slowly developed, and an output is eventually produced when it received a new data. While training, the NN's update their weights with the goal of diminishing the performance function, which is user defined; but typically feedforward networks engage Mean Square Error (MSE) as the performance function. MSE is adopted as performance function in this research work. Sequential feeding of input and output pair is adopted for the purpose of training the neural networks for various steps

2.9.1 The Neural Network Testing Process

In neural networks application, testing the neural network is the next procedure to perform after training. Testing the ANN is necessary to ensure that the trained data set generalizes well and produces the expected outputs when it receives new data. Several methods are available for testing the trained network's performance, one such method is plotting of the best linear regression fit between the real NN's outputs and the expected targets [154]. Subjecting the slope of this line to analysis will generate a clue of the training process. The best regression fit gives the slope that equals 1. The correlation coefficient (r) is another method; the 'r' of the outputs and the targets depicts how accurate the output desired is tracked by the ANN's output. The farther r's value is to 1, the worse the NN's performance. Another method for testing the NN is plotting the confusion matrix which will show the actual number of scenarios that have been classified positively by the NN [154]. Ideally, a hundred percentage (100%) depicts a situation of zero confusion in the classification process. Thus, when the positive classification rate is very low, it means that the confusion matrix performance would be low. A further testing method for NN is by presenting a whole new data set with known inputs and targets to it and compute the percentage error in the NNs output. The NN is adjudged to have passed the test if the ANN's output has an acceptable average percentage error and is readily applicable in the future.

The whole set of data provided for the MATLAB Simulink neural network toolbox is divided into three separate sets vis the training, the validation and the testing data sets. Training of the network is done using the training data set which computes the gradient and updates the weights of the network. The network is provided with the validation set (the inputs only, without the outputs) during the training process and throughout the training process, the validation data set error is monitored. When the overfitting of data starts occurring in the network, the error in validation increases and when the increment in the number of validation fails is beyond certain value, the training process halts so as not to overfit the data further and at the smallest number of validation errors the network is returned [154]. The test data set is not used during the process of training but used to assess the performance of the trained network. If the minimum value of MSE is achieved by the test set at a meaningfully separate iteration than the validation set, then, satisfactory performance will not be provided by the NN.

CHAPTER 3

Research Methodology

This chapter discusses the employment of Design Science Research (DSR) method for evolving the architecture for fault recognition in smart distribution network. DSR fundamentals and how its guidelines are accustomed to this research work are briefly presented so as to serve as the basis for the rest of the chapter.

3.1 Design Science Research

DSR originates from engineering and the applied sciences [12]. It encompasses the development and evaluation of artefacts envisioned to unravel acknowledged organizational and societal problems. Such artefacts consist of models, constructs, algorithms, implemented and prototyped systems [155-157]. The scientific basis for design gives room for several numerical assessments of the artefact as well as optimization evidences and logical simulations [156, 158]. By applying DSR, engineers have developed new algorithms, simulation models, prototypes, computer architectures, and various other types of systems [159]. Grounded on the principle that knowledge is formed in the creation and application of artefacts, Hevner *et al.* [160] outlined seven guidelines for DSR. Those guidelines offer a pattern to achieving the aim and objectives of this study [161]. Sub-sections 3.1.1 – 3.1.7 describe the guidelines and how they are adapted to this research work. Thus, this chapter describes the application of the different guidelines in DSR approach for the development of Machine Intelligence based Technique (Artificial Neural Network in particular) for fault recognition and location in a power distribution system.

3.1.1 Design as an Artefact

This involves the formulation of a resolute and innovative problem solving. An approach involving multiple methodology including theory building, observation, system development and experimentation was proposed [162]. Peffers *et al* [163] also discussed that requirements analysis and design specification are also essential stages for developing an artefact. This research work is in tandem with DSR's first guideline by evolving an architecture for fault recognition in a smart distribution system. A model was simulated in line with the developed architecture. Hence, in this work, the architecture and the model are the developed artefacts.

3.1.2 Problem Relevance

DSR ensures that developed artefact delivers solutions that are technology-oriented to relevant societal problems. Steps are taken to solve the problems creatively by drawing the solutions from the existing body of knowledge [164]. This study, in alignment with this guideline, addresses the delay in recognition and location of fault in distribution networks. Detecting the location of fault in a distribution system often takes time and this delay usually aggravates the faults. When the location is eventually known, isolating the fault becomes a difficult task. Repeatedly shutting down an entire network in order to clear a minor fault thereby impacting negatively on the consumers. The developed model, which is an artefact will help to address these problems of delay and location of faults in distribution systems.

3.1.3 Design Evaluation

This third guideline in DSR encompasses the formation of design substitutes against requirements until the realization of an acceptable design. The efficiency of a designed artefact is established via carefully chosen evaluation methods [160]. Prevailing DSR evaluation metrics comprise of observation, testing, experiments, description and analysis. A combination of evaluation metrics, as suggested by Karmokar *et al.* [165], were employed from machine intelligence, software engineering and electrical engineering knowledge domains to analyze different aspects of this research work. For instance, machine intelligence evaluation metrics such as accuracy and mean square error were employed in choosing appropriate pattern classifier for the model.

3.1.4 Research Contributions

DSR is expected to supply proven and explicit contributions in the areas of *methodologies, foundations* and *artefacts* [160]. *Methodologies* involve the development and employment of new evaluation metrics and methods; *foundations* infer the knowledge base of the discipline around which the research is taking place [161] while *artefacts* are explained in Section 3.1.1. Research contributions should not be simple alterations of an existing product but innovative additions of context, user need, theory and technology [166]. The proposed architecture of fault recognition in this research is adapted from the architecture by Suhaas B. A. [141] and modified for distribution systems. The proposed architecture; which is a modest addition to existing power distribution architectures, is an artefact contribution by this study. The model simulated in line with the architecture is also an artefact contribution.

3.1.5 Research Rigor

The application of rigorous techniques in constructing and evaluating the designed artefacts is canvassed in the fifth DSR's guidelines. The active employment of engineering knowledge base and theoretical foundations and methodologies is rigorous [160]. Notwithstanding, while applying the DSR's required rigor, other crucial features must not be relegated. Such features include the possibility of applying, generalizing and making relevant the designed artefacts [167]. Identification of gaps in the existing fault recognition architectures was achieved through rigorous review of literatures. The development of an appropriate model, and the evaluation of the simulated results also engender DSR's rigor requirement [168, 169].

3.1.6 Design as a Search Process

DSR as a search process solves problems by breaking them down into sub-problems; the sub-problems are subjected further to iteration and refinement, thereby yielding a designed artefact that is significan and appropriate [160]. This study developed an architecture and model via autonomous and iterative refinement, simulation and testing.

3.1.7 Communication of Research

Communication of research in DSR is expected to address both professionals and the academia for respective applications and extensions [160]. The researcher has both published and ongoing articles on the review of the subject matter and the results of the developed model. This dissertation will also be a tremendous treasure to the engineering body of knowledge.

3.2 Architecture for Fault Modelling, Recognition and Location in a Smart Distribution Grid

Several multi-tier fault recognition and location architectures have been proposed by numerous authors [55, 141, 170-175]. A number of fault recognition and location architectures in the literature contains power grid components, microcontroller and sensors, along with service-oriented information systems as their respective first, second and third layers. Absence of intelligent data processing in the service–oriented information system layer is a major hole in the previous architectures. Many professionals who embarked on executing most of the topologies also found them cumbersome and complex for implementation. These holes are responsible for the drive to design an architecture of a fault recognition and location in smart grid in this study; hence fulfilling the DSR's design as an artefact (i.e. guideline 1). The proposed architecture (see Figure 3.1) is an extension of Suhaas B. A. [141] generic fault location reference flowchart. It addresses pattern recognition techniques for power distribution system while that of Suhaas B. A. addresses pattern recognition techniques for transmission system. The proposed architecture is also more compact thereby making it easy to implement.

In engaging research as a search process (i.e. the DSR guideline 6), the proposed architecture is made up of three layers which are the Power Grid Components Layer (PGCL), the Fault Data Acquisition Layer (FDAL) and the Machine Intelligent Layer (MIL). Each of these layers (PGCL, FDAL and MIL) suggests a template for the development of the functional units of the simulation model in this study. Hence, the explanations of the proposed architecture and the account of the model designs for the PGCL, FDAL and MIL are contained in the successive sections.

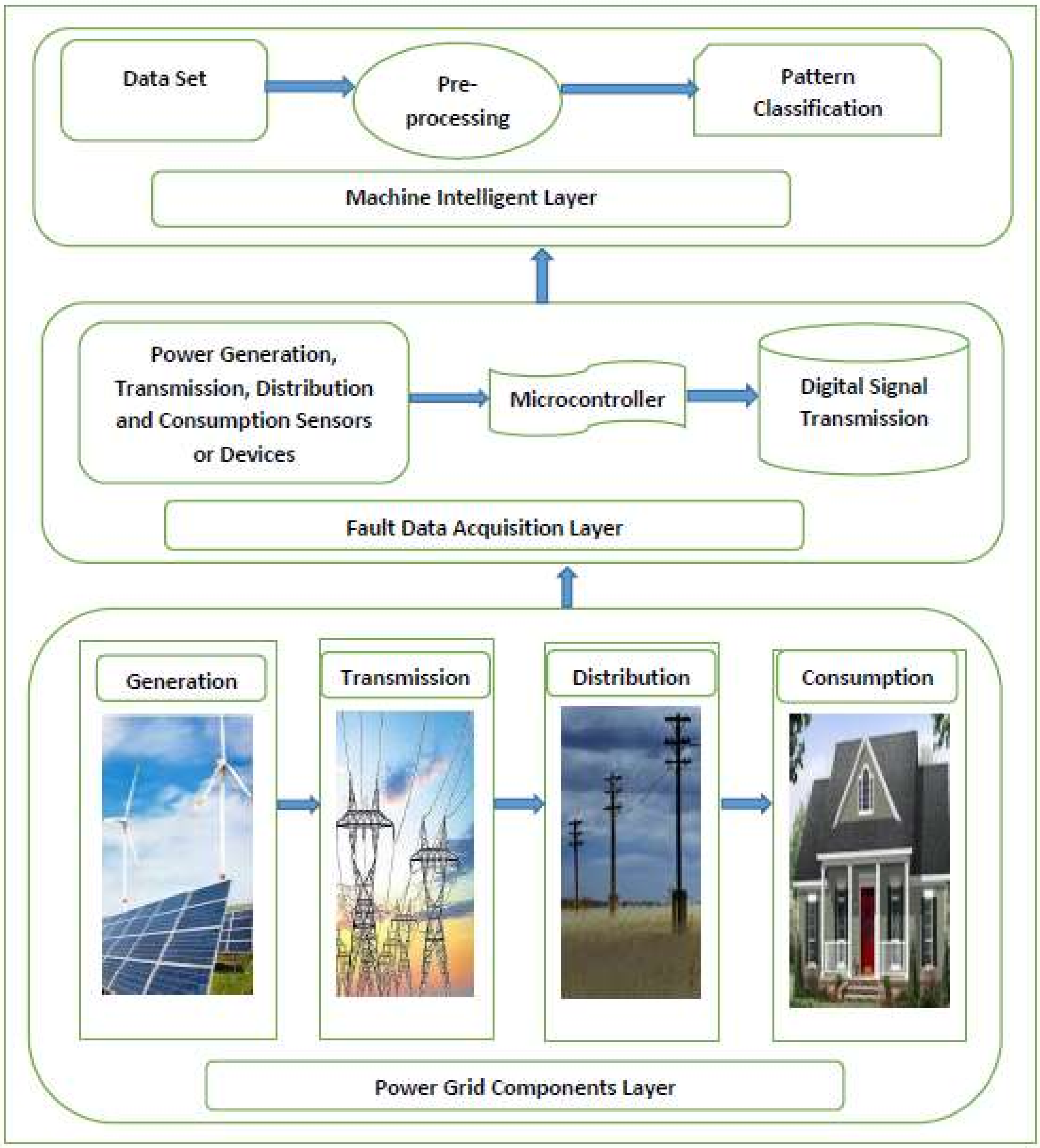


Figure 3.1 Proposed Architecture of a Machine Intelligent based Fault Recognition and Location in the Smart Grid.

3.3 Power Grid Components Layer

The PGCL (see Figure 3.1) comprises of the Generation, Transmission, Distribution and Consumption blocks. As explained in section 2.1, the Electrical Power System is made up of the Generation which is the source of power, a high voltage Transmission Grid which connects the generators to substations and transports power to the 'Consumers' via the Distribution Systems (Figure 2.1). In this research work, the focus is on fault recognition and location in the Distribution System unit of the generic architecture in Fig. 3.1 using Machine Intelligence Technique (i.e. ANN).

3.3.1 Modelling of the Power Distribution Network

A 13 Node IEEE Test Feeder is utilized for the model. IEEE 13 Node Test Feeder is valuable in the evaluation of common structures of power distribution system. Operating at 4.16 kV, it has the properties of being short and relatively highly loaded. The system comprises of a single voltage regulator located at the substation, overhead and underground lines, an inline transformer, 2 shunt capacitors, and 9 unbalanced loads [176]. Figure 3.2 depicts a one-line diagram of the 13 Node IEEE Test Feeder. This distribution network model is simulated by means of the SimPowerSystems toolbox accessible in Simulink in MATLAB® setting. A picture of the model is shown in Figure 3.4. The data sets are trained and tested using the data obtained from the model. The 3-phase currents and voltages samples were taken using the 3-phase V–I measurement blocks. Various fault types at different locations and values of the fault resistances were simulated on the model. 60Hz was the considered frequency for this research work. Six hundred (600) fault cases were simulated for the purpose of each of fault recognition, fault-type identification and fault location respectively.

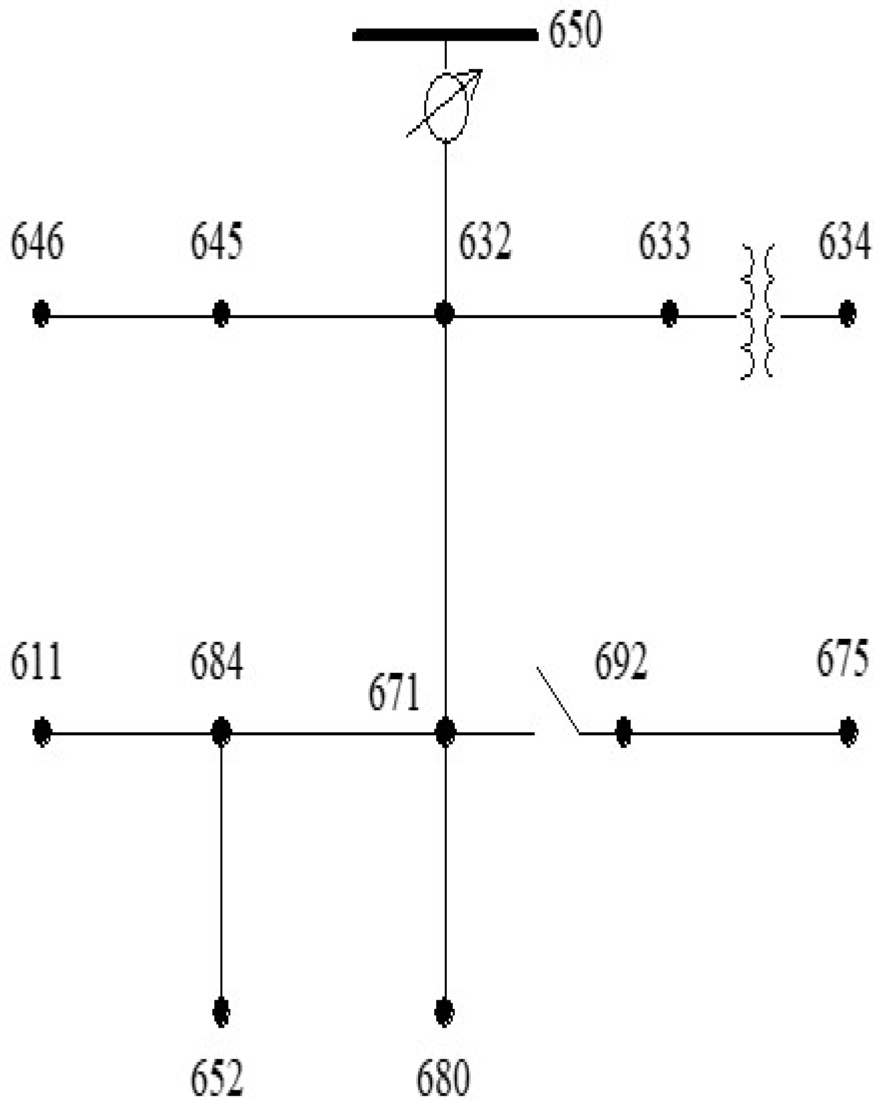


Figure 3.2 One-line diagram of the 13 Node IEEE Test Feeder [176]

The 13 Node IEEE Test Feeder Line Parameter Specifications and Power Flow Results could be found in Appendix 1 and 2 respectively.

3.3.2 Simulation of the Models

Fig. 3.3 shows a proposed flowchart for fault recognition, identification and location scheme. Initially, the entire data collected was subdivided into the training and the testing data sets. The first step in the process is fault recognition. Once we confirm that a fault has occurred on the distribution network (Figure 3.3), then we proceed to identify the fault-type. The third stage is to locate the zone or branch of the distribution network where the fault occurred. It should be noted that the fault types employed in this research work are shunt faults (section 2.7.1.D); hence, the reason why they (shunt faults) are considered in the proposed flowchart (Figure 3.3).

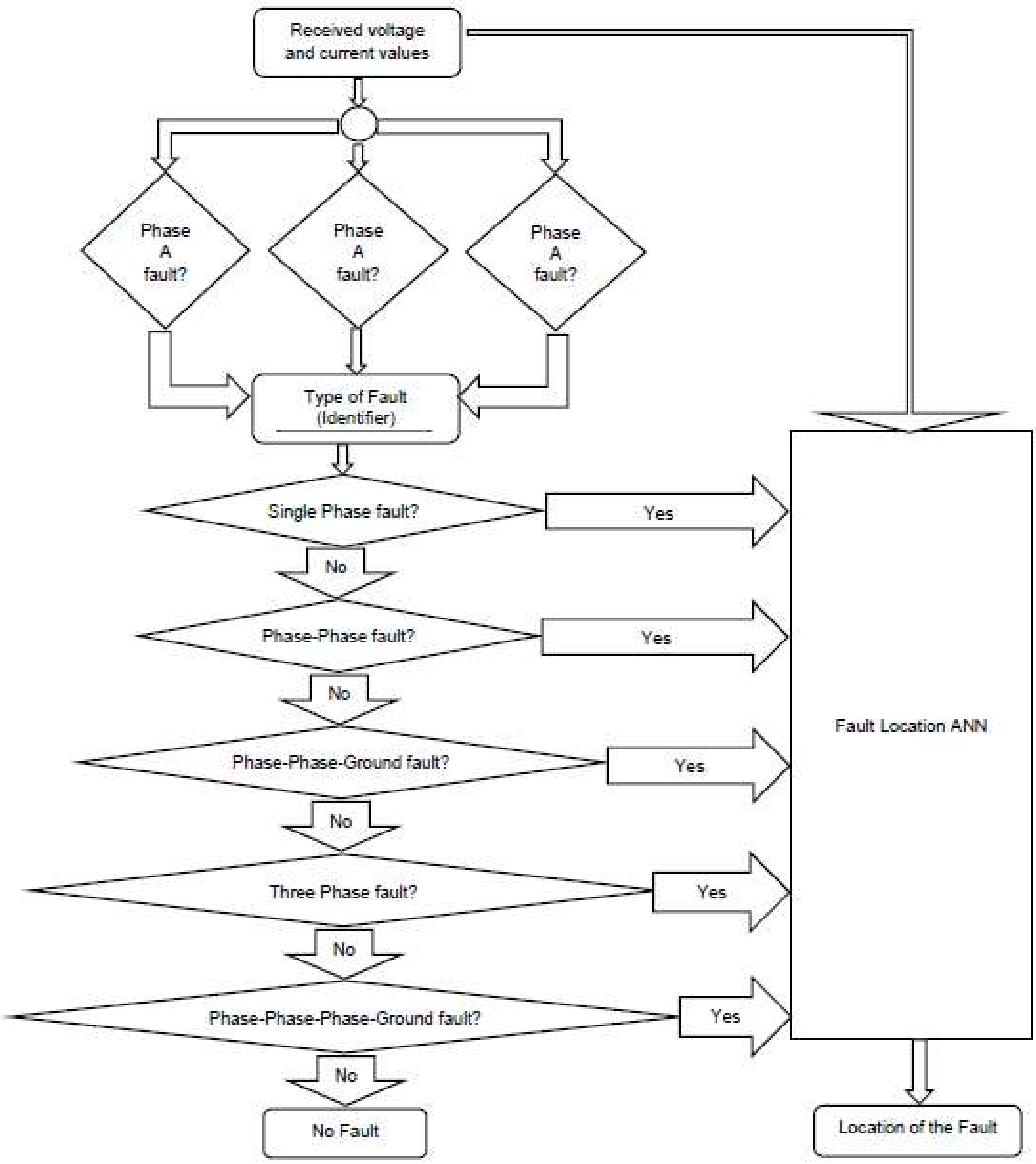


Figure 3.3 Proposed flowchart for fault recognition, identification and location scheme.

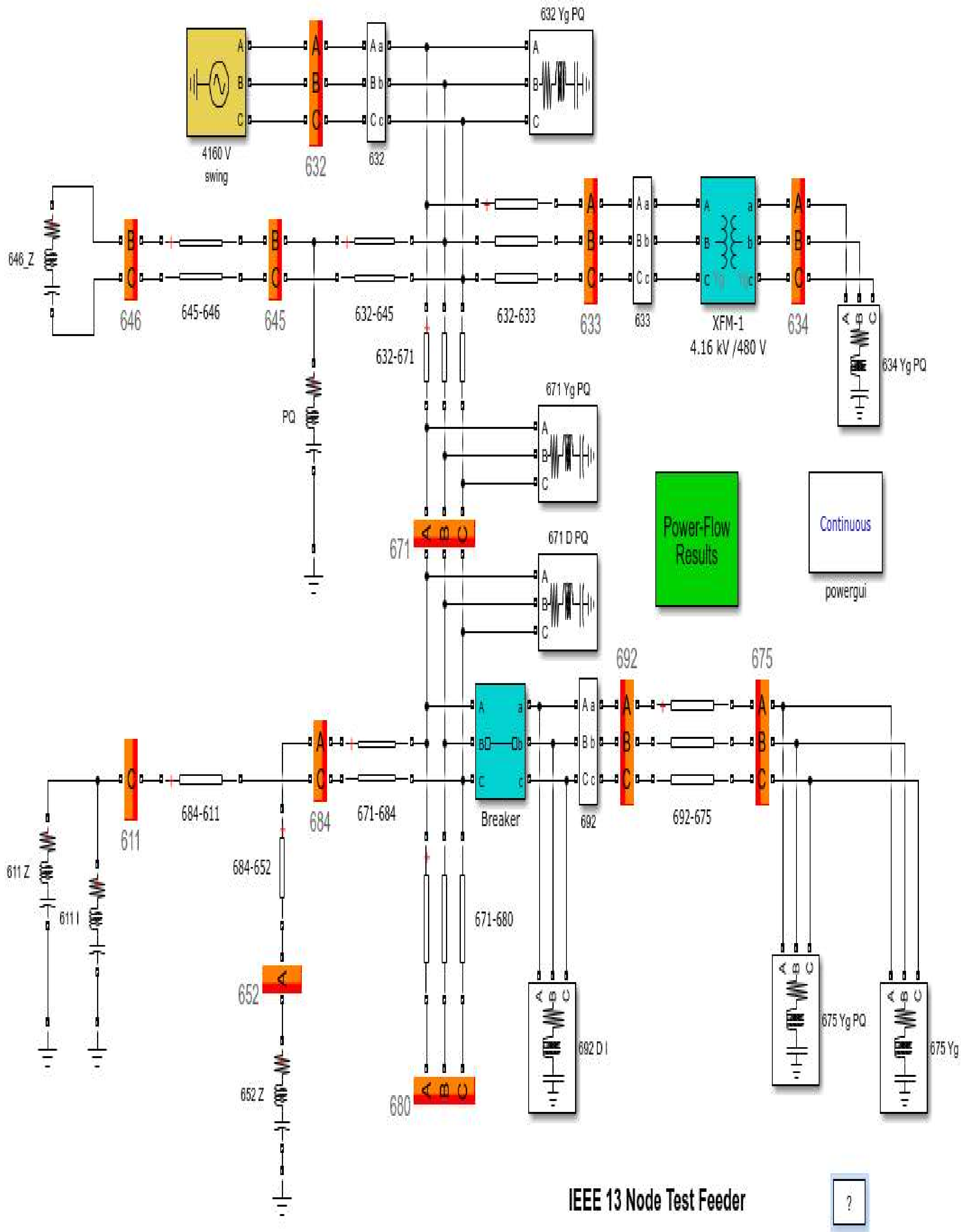


Figure 3.4 Simulation Diagram for the 13 Node IEEE Test Feeder in MATLAB Simulink

This study purposes to propose an integrated techniques, employing artificial neural networks in performing the stated tasks. Similar back-propagation dependent neural networks were used for the purpose of fault recognition, fault-type identification and fault location respectively.

To acquire a robust training set for effective performance, eleven (11) classes of faults were simulated at different locations and fault resistances along the employed distribution line. About fifty (50) different scenarios for each of the eleven (11) classes of faults were simulated. Fault was introduced at different locations on the three-phase lines of the distribution model i.e. lines 632-633, 631-671, 671-680 and 692-675 (as shown in Figure 3.4) of the model while the fault resistance was varied as follows: 0.001-ohm, 0.0025 ohm, 0.005 ohm, 0.0075 ohm, 0.01 ohm, 0.025 ohm, 0.05 ohm, 0.075 ohm and 0.1 ohm.

3.4 Fault Data Acquisition Layer

The FDAL comprises of the Power Generation, Transmission, Distribution and Consumption Sensors or Devices (PGTDCS) and the microcontroller as shown in Fig. 3.1. The electronic sensors receive signals from the network and transmit them to the microcontroller. The sensors work by detecting magnetic fields generated by electricity and converting them into electrical current and voltage signals. In the FDAL, the microcontroller contains the processor, Input/Output (IO) pins, timers, memory interface controllers and the interrupt controller. The electronic sensors interfaces with the appropriate IO pins on the microcontroller to receive the captured signals and send same over the Digital Signal Transmission Unit. This study focuses on Power Distribution Unit (PDU), which is described in details in subsequent subsections.

3.4.1 Fault Sensing and Modelling in the Power Distribution Network

Magnetic field sensors are reliable in fault recognition and location schemes due to the relationship between current and magnetic field intensity [177, 178]. Many sets of magnetic field intensity sensors could be installed on a single transmission or distribution line as suggested by a patent [177, 178]. Recognition of Phase to ground faults is achieved by deploying magnetic sensors around the ground conductors; phase to phase faults are recognized by using a sensor which detects orthogonal fields due to arcing. Fault would most likely occur between the first two poles at which it is detected. So, minimum synchronization among the multiple sensors is required because fault location does not depend on the exact time of the fault incidence but on the first locations where the fault was detected [177].

To analyse a three-phase system, the vertical and horizontal magnetic field intensities are detected and the waveforms compared to the expected results [179]. A general system for analysis is shown in Figure 3.5.

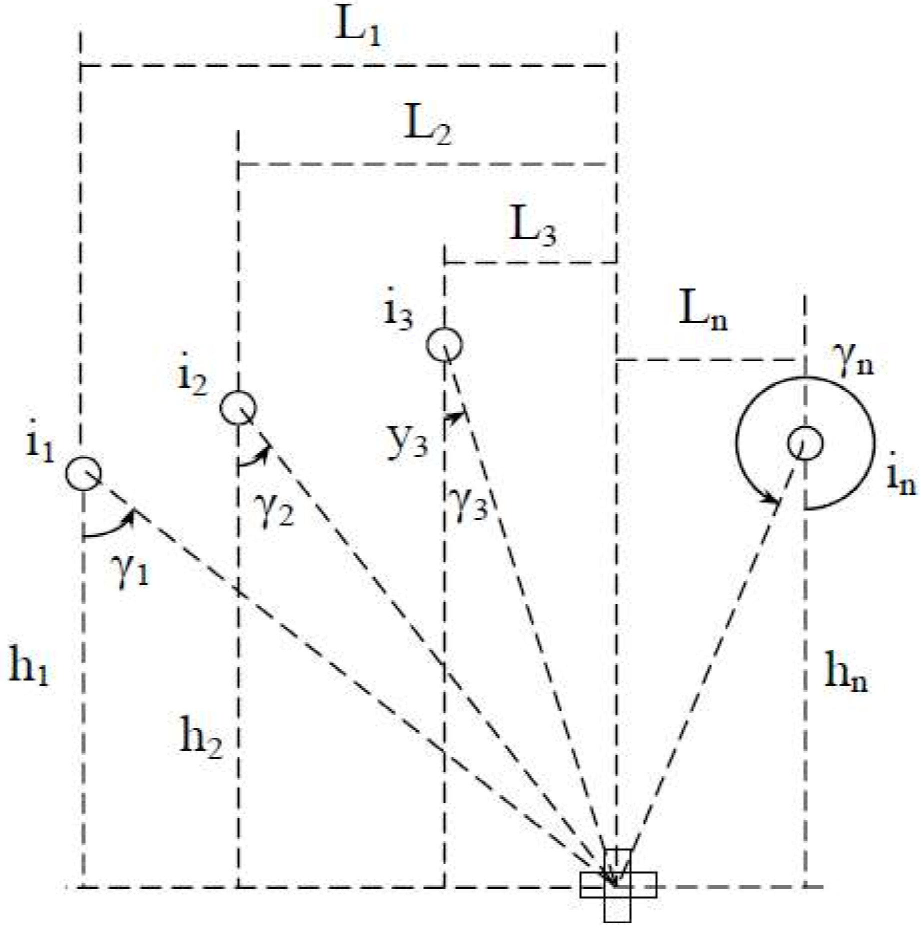


Figure 3.5 – Magnetic field analysis for any system [177]

For any given conductor k, the magnetic fields are:

$$\left.\begin{aligned} H_{x,k} &= D_k i_k \\ H_{y,k} &= Q_k i_k \end{aligned}\right\} \tag{3.1}$$

Where

$$\left.\begin{aligned} D_k &= \frac{\cos^2 \gamma_k}{2\pi h_k} \\ Q_k &= \frac{\sin \gamma_k \cos \gamma_k}{2\pi h_k} \end{aligned}\right\} \tag{3.2}$$

As derived in [177], the currents and their coefficients are therefore

$$[i] = \begin{bmatrix} i_1 \\ i_2 \\ i_3 \\ \vdots \\ i_n \end{bmatrix} and [XY] = \begin{bmatrix} I_1 & 0 \\ X_2 & Y_2 \\ X_3 & Y_3 \\ \vdots & \vdots \\ X_n & Y_n \end{bmatrix} \tag{3.3}$$

The magnetic field due to all of the currents is then given by

$$[H] = [P][i] \tag{3.4}$$

where the magnetic field matrix is

$$[H] = \begin{bmatrix} H_x \\ H_y \end{bmatrix} \tag{3.5}$$

and the position matrix is

$$[P] = \begin{bmatrix} D_1 & D_2 & D_3 & \cdots & D_n \\ Q_1 & Q_2 & Q_3 & \cdots & Q_n \end{bmatrix} \tag{3.6}$$

Fault recognition is dependent on two variables – rho and theta when analysed in polar coordinates rather than cartesian coordinates, but only one of the two is used per algorithm. Rho and theta are expressed as [177]

$$\rho = \sqrt{H_x^2 + H_y^2} \tag{3.7}$$

$$\theta = \tan^{-1}\left(\frac{H_y}{H_x}\right) \tag{3.8}$$

where the result of the inverse tangent has been corrected if H_x is negative.

Accuracy of fault recognition could be affected by magnetic interference, and sometimes raise false faults alarms. To reduce such effects, the sensors should be installed fairly close to the distribution lines vertically [177].

Two search coils designs are suggested for magnetic field sensors one such that its induced voltage is proportional to the vertical magnetic field and the other such that its induced voltage is proportional to the horizontal magnetic field [177].

The voltages induced in the coils are

$$v_x = \mu_0 NA \frac{\delta H_x}{\delta t} = K\omega \hat{H}_x \cos(\omega t + \theta_x) \tag{3.9}$$

and

$$v_y = \mu_0 NA \frac{\delta H_y}{\delta t} = K\omega \hat{H}_y \cos(\omega t + \theta_y) \tag{3.10}$$

where the coil constant is

$$K = \mu_0 NA \tag{3.11}$$

and

$\mu_0 = 4\pi \, x \, 10^{-7} \; H/m$ is the permeability of free space.

3.4.2 Microcontroller and Digital Signal Transmission Units

Several microcontroller boards could be employed for this application and Arduino Uno is suggested for its ease of programming, reliability and because it is an open-source based hardware. The Arduino Uno's operating microcontroller is ATmega328 as shown in Figure 3.6. It has an operating voltage of 5V and 14 digital input and output pins on the microcontroller. Some of the pins could be programmed to provide Pulse Wave Modulation (PWM) output and analog inputs from the connected sensors respectively. The sensors could be connected to the analog input pins. The ATmega328 microprocessor converts the information from the sensors from electrical signals to digital data employing a program developed and embedded in the memory of the microcontroller.

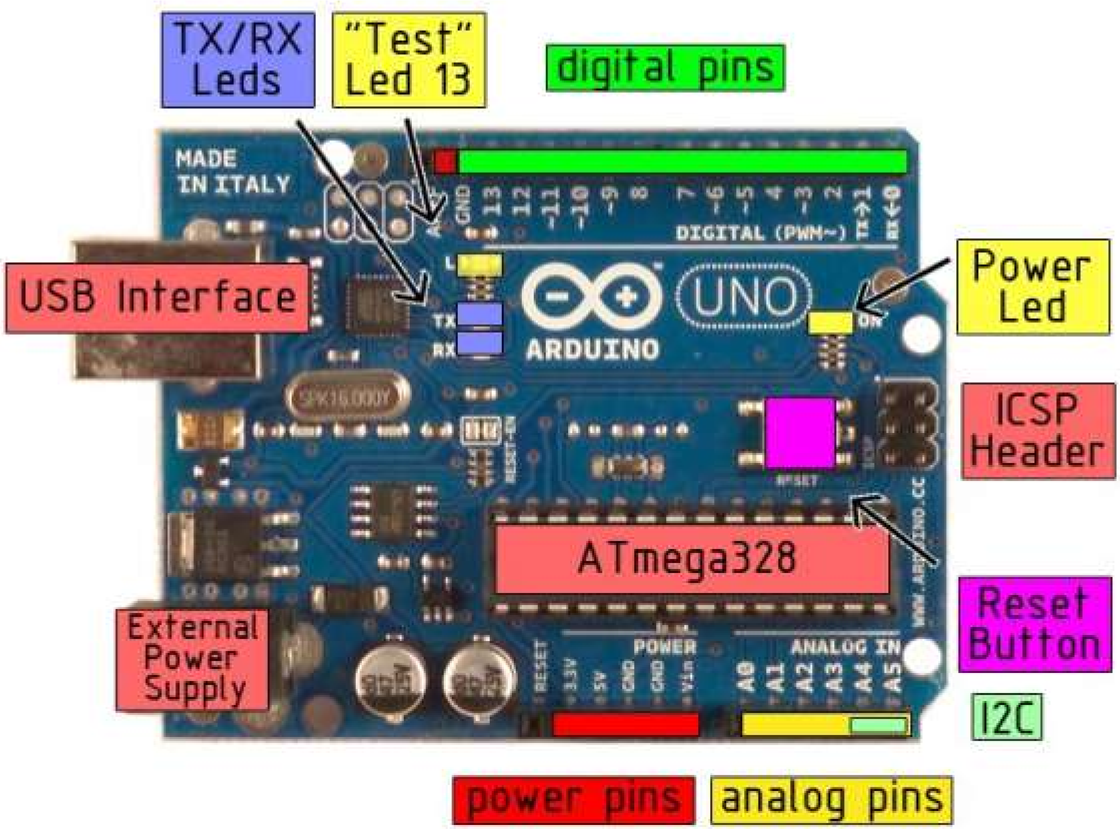


Figure 3.6 The Arduino Uno Microcontroller Unit [180]

Varieties of connectivity alternatives are available to network devices. Some network involves the use of cables, servers, routers, modems, bridges and Personal Computers (PCs); and sometimes the network services are bundled in a black-box manner with few device. Common serial data exchange interfaces employed in connecting two or more devices together are RS-232, RS-422, and RS-485. All three interfaces use Data Communication Equipment (DCE) and Data Terminal Equipment (DTE) terminologies (as shown in Figure 3.7). The DTE is the device communicating with another device somewhere else while the DCE is the device essentially performing the communicating, or acting as generator or receiver. For instance, a DTE is like a PC communicating with another PC while an example of the DCE is a modem. The Digital Signal Transmission Unit (DSTU) receives the digital signal from the Microcontroller Unit and transmits it via the DCE to the database of the Data Set (DS) located in the Machine Intelligent Layer (MIL). However, the implementation of the Microcontroller and Digital Signal Transmission Units of the architecture in Figure 3.1 is beyond the scope of the current study.

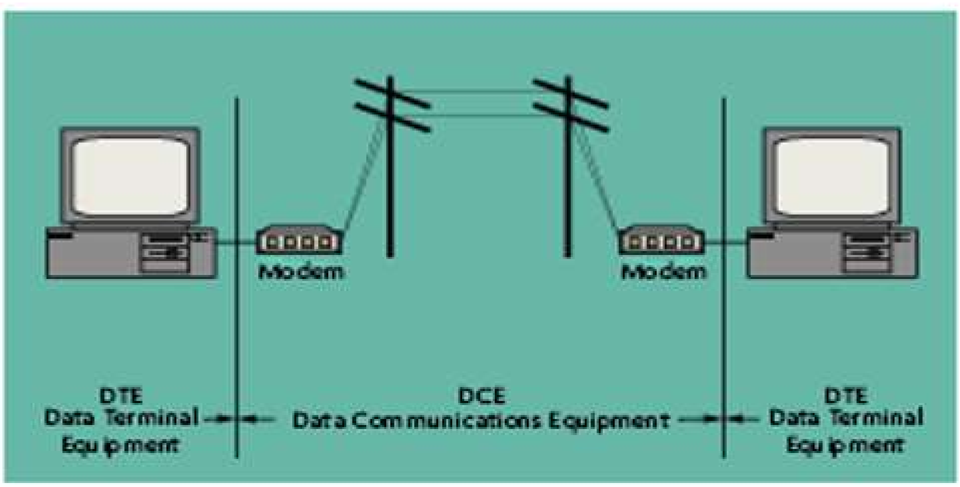


Figure 3.7 Serial Data Transmission **[181]**

3.5 Machine Intelligent Layer

The MIL is the last layer in the hierarchy. It is made up of the Data Set (DS), Pre-processing and Pattern Classification (PC) units. These are discussed further in this section.

3.5.1 Data Set

To acquire a robust training set for effective performance, eleven (11) classes of faults were simulated at different locations and fault resistances along the employed distribution line. The classes of faults are Phase A to Ground, Phase B to Ground, Phase C to Ground, Phase A to B, Phase B to C, Phase C to A, Phase A to B to Ground, Phase B to C to Ground, Phase C to A to Ground, Phase A to B to C and Phase A to B to C to Ground. About fifty (50) different scenarios for each of the eleven (11) classes of faults were simulated. Fault was introduced at different locations on the three-phase lines of the distribution model i.e. lines 632-633, 631-671, 671-680 and 692-675 (as shown in Figure 3.9) of the model while the fault resistance was varied as follows: 0.001-ohm, 0.0025 ohm, 0.005 ohm, 0.0075 ohm, 0.01 ohm, 0.025 ohm, 0.05 ohm, 0.075 ohm and 0.1 ohm.

3.5.2 Pre-processing

The performance of the NN is greatly enhanced by a reduction in its size and this is achievable by carrying out feature extraction thereby utilizing effectively, all the significant and pertinent information available in the current and voltage waveforms.

Standard deviation also expressed as Mean Square Error (MSE) is a parameter employed in this thesis for feature extraction (as shown in equation 3.13).

$$\mu = \frac{x_1 + x_2 + x_3 + \cdots + x_N}{N} \tag{3.12}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \mu)}{N}} \tag{3.13}$$

The standard deviation 'σ' shows the degree of how a set of data deviates from its mean 'μ'. A high value of standard deviation implies that the data values spread over a wide range while a low value of standard deviation implies otherwise.

Current and voltage waveforms of all the three phases were obtained, sampled at a frequency of 60 Hertz and were noted along with their equivalent pre-fault values. The inputs to the NN are the ratios of the 3-phase voltages and 3-phase currents before and after the occurrence of fault, forming a set of six inputs [182] (as shown in Table 3.1).

In Table 3.1, Va, Vb , Vc and Ia, Ib, Ic are the values of post-fault voltage and current samples respectively while Va(bf), Vb(bf), Vc(bf) and Ia(bf), Ib(bf), Ic(bf) are the

Table 3.1 Sample of Inputs to the neural network.

Case No	Input Vector						Fault Type
	$\frac{Va}{Va(bf)}$	$\frac{Vb}{Vb(bf)}$	$\frac{Vc}{Vc(bf)}$	$\frac{Ia}{Ia(bf)}$	$\frac{Ib}{Ib(bf)}$	$\frac{Ic}{Ic(bf)}$	
1	0.9806	1.0543	0.9761	1.0000	1.0005	0.9997	No fault
2	0.0041	1.2246	1.2465	9.0700	1.0468	0.9837	A to Ground
3	1.2951	0.0041	1.2130	1.0473	13.3108	1.0616	B to Ground
4	1.2214	1.2335	0.0043	1.0862	0.9230	9.0326	C to Ground
5	0.5198	0.4784	0.9902	13.9979	18.1890	0.9805	A to B
6	0.9941	0.4858	0.5193	0.9978	17.5978	11.8259	B to C
7	0.4948	1.0198	0.5024	12.1060	1.0207	12.2577	C to A
8	0.0038	0.0037	1.2489	14.1228	19.2454	1.0167	A to B to Ground
9	1.3019	0.0038	0.0036	1.0942	18.5760	12.0910	B to C to Ground
10	0.0035	1.2865	0.0039	12.4090	0.9851	12.8013	C to A to Ground
11	0.0513	0.0535	0.0531	15.2494	21.4537	13.2423	A to B to C
12	0.0033	0.0035	0.0034	15.0310	21.5561	13.4356	A to B to C to Ground

respective pre-fault values. The specified table denotes the values for the different classes of faults and during the pre-fault scenario.

3.5.3 Pattern Classifier

A Multilayer Perceptron Artificial Neural Network (MLP-ANN) pattern classifier was explored for the classification of the features in this study. Although, it has its merits and demerits. It has the advantage of satisfactory performance, the ability to discover complex non-linear relationships among variables and of largely very fast. But suffers the disadvantage of multiple local minimal and overfitting, because it relies on the old experimental principle of risk minimization. Exploring the DSR guidelines 3, 5 and 6 (design evaluation, research rigor and design as a search process), simulation was employed to evaluate the classifier’s performance on the problem in this study.

CHAPTER 4

Results and Discussion

4.1 Fault Recognition

Diverse topologies of Multi-Layer Perceptron Neural Network (MLPNN) were researched for recognition of the presence of fault in a network. Key factors such as the learning strategy used, the network size and the size of the training data set are considered in determining an ideal topology. The back-propagation algorithm was resolved as the ideal topology; although comparatively slow because of the small learning rates utilized, such strategy as Levenberg-Marquardt optimization method can significantly boost the performance of the algorithm. Network size selection is so important as it enhances the capability of the NN to characterize the problem at hand as well as reduces the training time. Although, no rule of thumb to determine the number of hidden layers as well as the number of neurons per hidden layer in a particular problem.

4.1.1 Pattern Classifiers' Training and Performance Evaluation for Fault Recognition

The motivation for choosing MLP-ANN and its basic configurations have been presented in Chapter 3. The MLP-ANN target output were encoded using the one-per-class coding method [183, 184] as shown in Table 4.1. The MLP-ANN was trained and the training results were evaluated using the Mean Square Error (MSE) metric. Several MLP-ANN were trained out of which the training performance for six were reported in Table 4.2 and it could be seen that the ANN with configuration (6-25-20-15-1) produced the most satisfactory result among others with a MSE of 3.601e-10.

Table 4.1 Target output of the MLP-ANN for Fault Recognition

S/N	Type of Fault	MLP-ANN Target Output
1	No fault	100000000000
2	A-G	010000000000
3	B-G	001000000000
4	C-G	000100000000
5	A-B	000010000000
6	B-C	000001000000
7	C-A	000000100000
8	A-B-G	000000010000
9	B-C-G	000000001000
10	C-A-G	000000000100
11	A-B-C	000000000010
12	A-B-C-G	000000000001

Table 4.2 Performance result of the MLP- ANN pattern classifier for Fault Recognition

ANN Type	Number of Hidden Layers	ANN Configuration	MSE
ANN 1	1	6-20-1	7.5108e-10
ANN 2	1	6-40-1	4.0748e-09
ANN 3	2	6-20-10-1	9.9678e-10
ANN 4	2	6-25-15-1	2.8649e-09
ANN 5	3	6-20-15-10-1	1.2819e-09
ANN 6	3	6-25-20-15-1	3.6010e-10

For the purpose of training for fault recognition, the network is presented with six inputs of the three phases' current and voltage values (expressed as the ratio of their pre-fault values) for no-fault and eleven different fault types. The training data set is made up of about 576 input output sets (48 for each of the eleven faults and 48 for the no fault scenario) with each input-output pair containing a set of six inputs and one output. A 1 or 0 (i.e. a yes or a no) is the output of the NN depending on whether a fault has been recognized or not. Thorough simulations using diverse neural network configurations were conducted. For necessary illustrations Figures 4.1 – 4.5 show NN with different numbers of hidden layers and neurons per hidden layer that attained reasonable performance. The training performance plot of the NN 6-20-1 (i.e. 6 neurons in the input layer, 1 hidden layer containing 20 neurons and 1 neuron in the output layer) is shown in Figure 4.1. The network's best validation performance (i.e. the Mean Square Error, MSE) after the training process is 7.5108e-10 at Epoch 14.

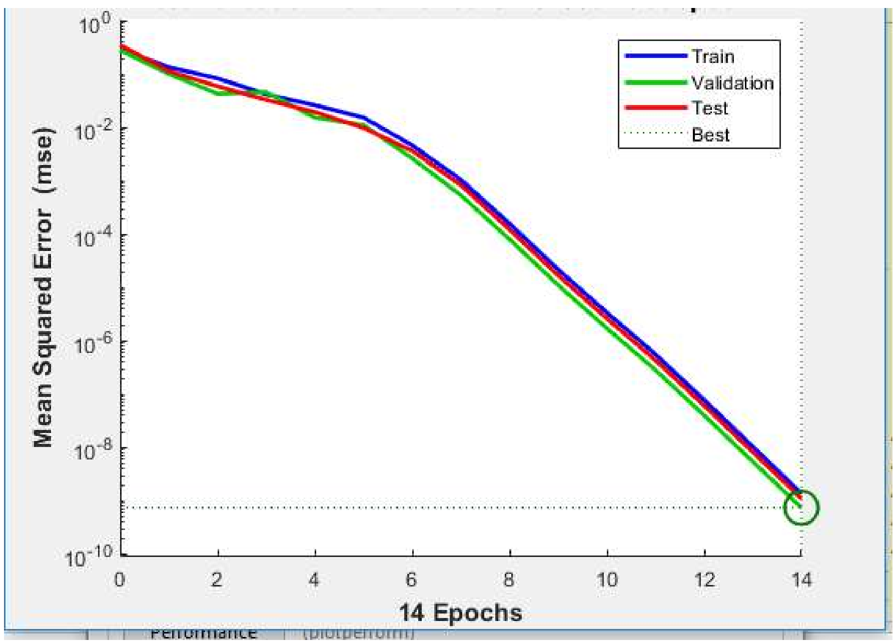


Figure 4.1 Network (6-20-1) MSE performance

The training performance plot of the NN 6-40-1 (i.e. 6 neurons in the input layer, 1 hidden layer containing 40 neurons and 1 neuron in the output layer) is shown in Figure 4.2. The network's best validation performance (i.e. the MSE) after the training process is 4.0748e-9 at Epoch 24.

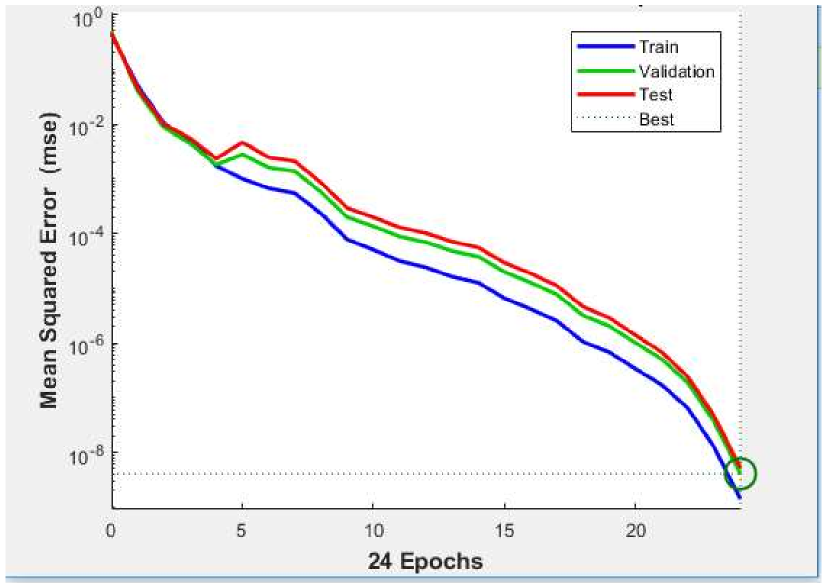


Figure 4.2 Network (6-40-1) MSE performance

The plot of the training performance of the NN 6-20-10-1 (i.e. 6 neurons in the input layer, 2 hidden layers containing 20 and 10 neurons respectively and 1 neuron in the output layer) is shown in Figure 4.3. The network's best validation performance (i.e. the MSE) after the training process is 9.9678e-10 at Epoch 17.

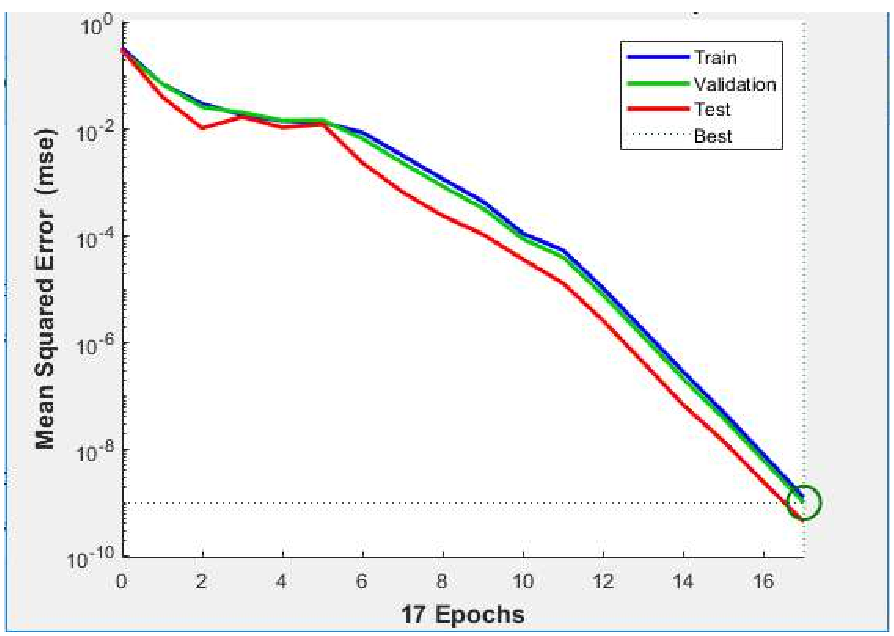


Figure 4.3 Network (6-20-10-1) MSE performance

The plot of the training performance of the NN 6-25-15-1 (i.e. 6 neurons in the input layer, 2 hidden layers containing 25 and 15 neurons respectively and 1 neuron in the output layer) is shown in Figure 4.4. The network's best validation performance (i.e. MSE) after the training process is 2.8649e-9 at Epoch 13.

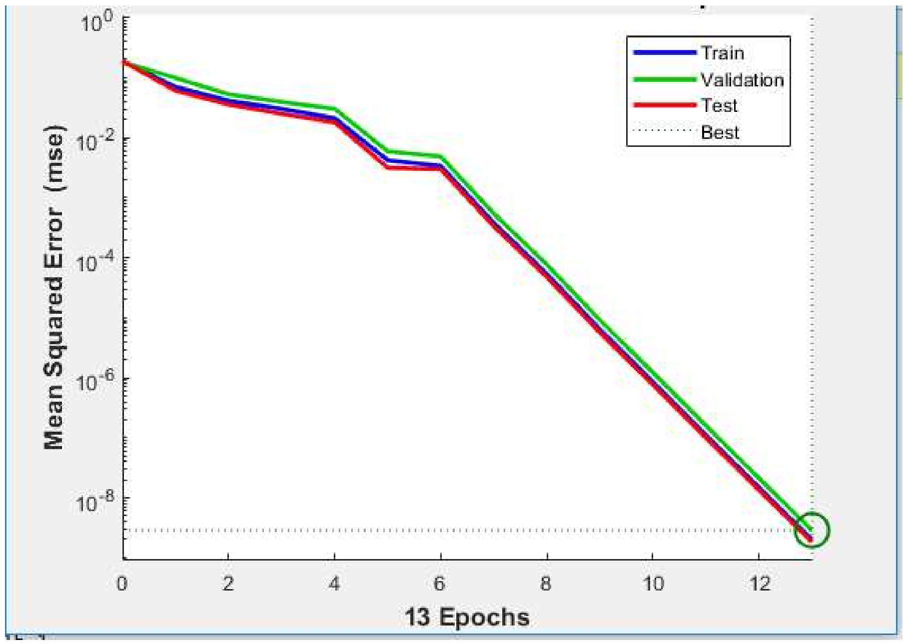


Figure 4.4 Network (6-25-15-1) MSE performance

The plot of the training performance of the NN 6-20-15-10-1 (i.e. 6 neurons in the input layer, 3 hidden layers containing 20, 15 and 10 neurons respectively and 1 neuron in the output layer) is shown in Figure 4.5. The network's best validation performance (i.e. the MSE) after the training process is 1.2819e-9 at Epoch 10.

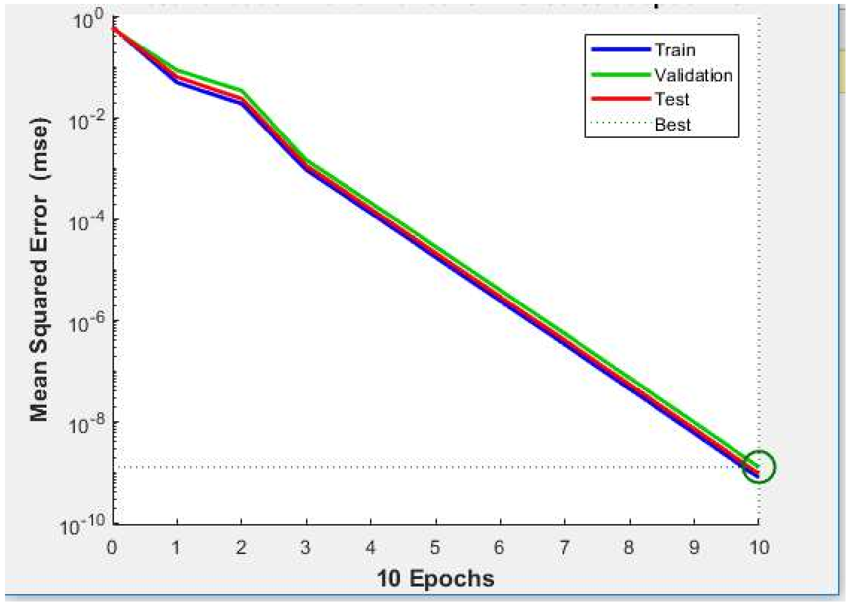


Figure 4.5 Network (6-20-15-10-1) MSE performance

The training performance plot of the NN 6-25-20-15-1 (i.e. 6 neurons in the input layer, 3 hidden layers containing 25, 20 and 15 neurons respectively and 1 neuron in the output layer) is shown in Figure 4.6. The network achieved very satisfactory performance. The network's best validation performance (i.e. the MSE) after the training process is 3.601e-10 at epoch 16.

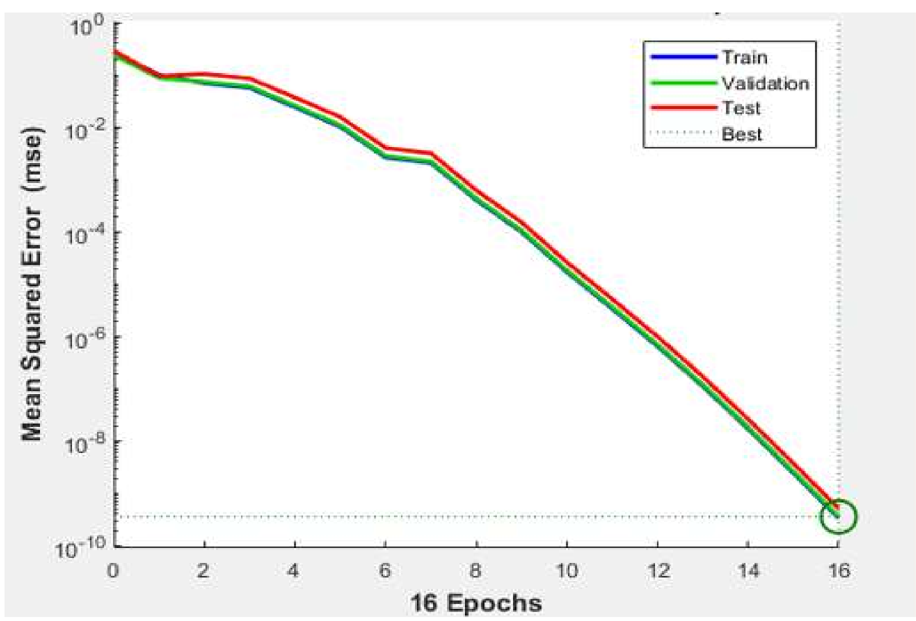


Figure 4.6 Network (6-25-20-15-1) MSE performance

Hence, the 6-25-20-15-1 neural network architecture has been selected (i.e. having three hidden layers with 25, 20 and 15 neurons respectively) as the network with the best performance. Figures 4.7 – 4.10 illustrate further, the various error performance plots and architecture of the best (chosen) network.

4.1.2 Testing for Fault Recognition

Three different factors are employed in testing the performance of the trained NN. The first is by plotting the best linear regression that relates the targets to the outputs as shown in Fig 4.7. The correlation coefficient (r) measures how accurate the output desired is tracked by the ANN's output (0 is zero correlation while 1 is full correlation). In this case, the correlation coefficients for the three phases of training, testing and validation is 1 indicating excellent correlation.

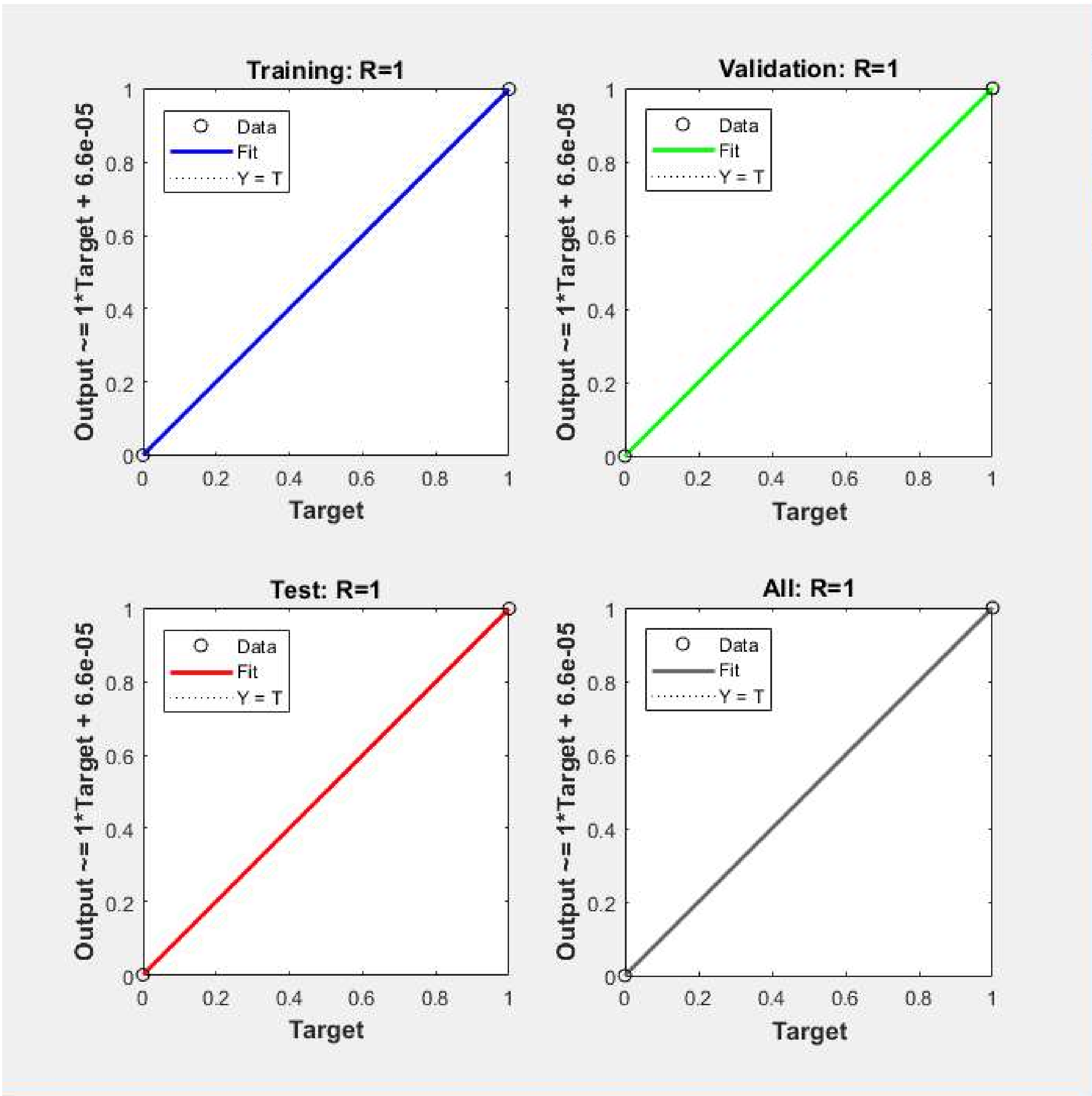


Figure 4.7 Regression FIT for Training, Testing and Validation phases.

The second factor employed to test the performance of the trained NN is the plotting of the confusion matrix for the different kinds of errors occurring for the trained neural network (Figure 4.8). The green diagonal cells represent the number of cases that have been classified correctly by the neural network and the red off-diagonal cells represent the number of cases that have been classified wrongly by the ANN. The last blue cell in the matrix indicates the total percentage of scenarios of correct classification in green and the vice-versa in red. The selected neural network has 100% accuracy in fault recognition.

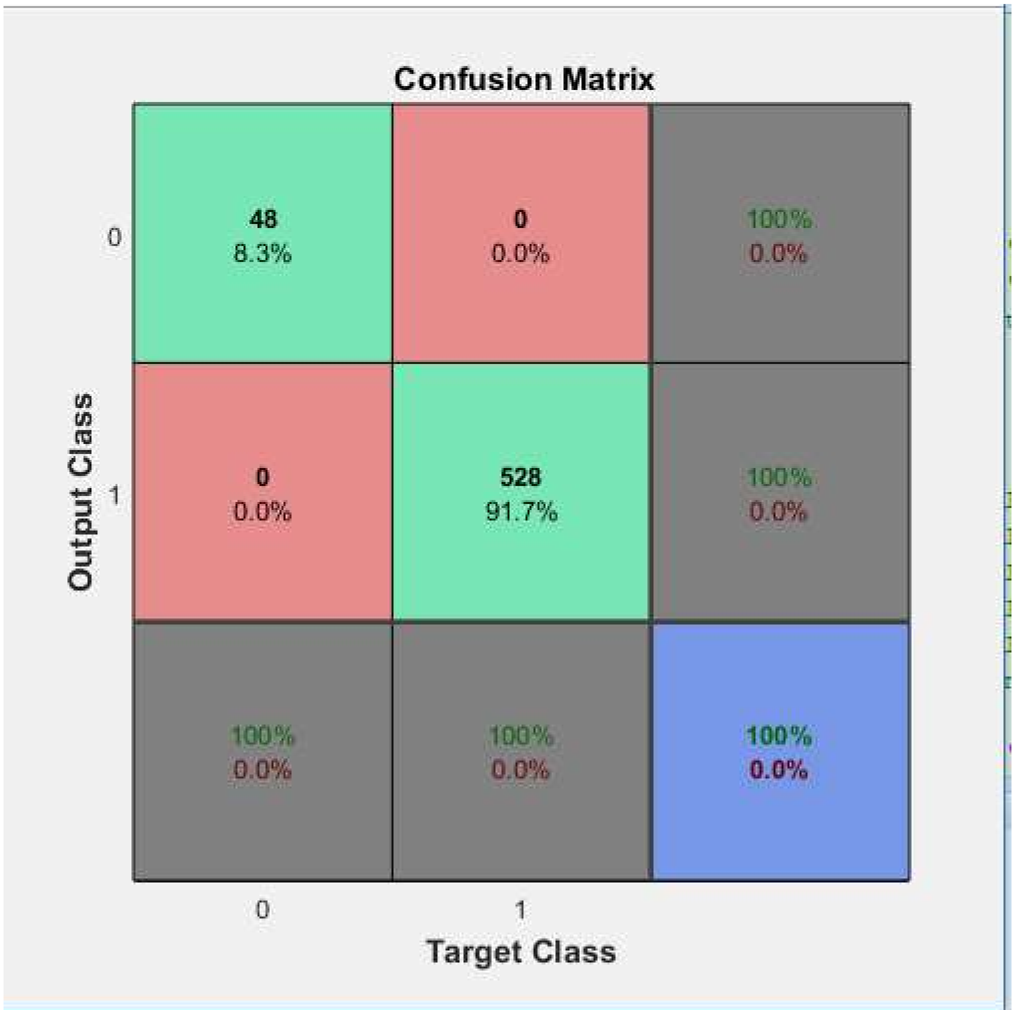


Figure 4.8 Confusion matrix for the network (6-25-20-15-1).

The third factor employed in testing the performance of the trained NN is to generate a separate data set known as the test set to evaluate the performance of the trained NN. The test data set is made up of about 24 input output sets (2 for each of the eleven faults and 2 for the no fault case) with each input-output pair containing a set of six inputs and one output. The neural network is made to absorb the test set and yielded its result which has an efficiency of 100% in fault occurrence recognition ability. Therefore, the neural network can recognize a normal condition from a faulty one with excellent accuracy.

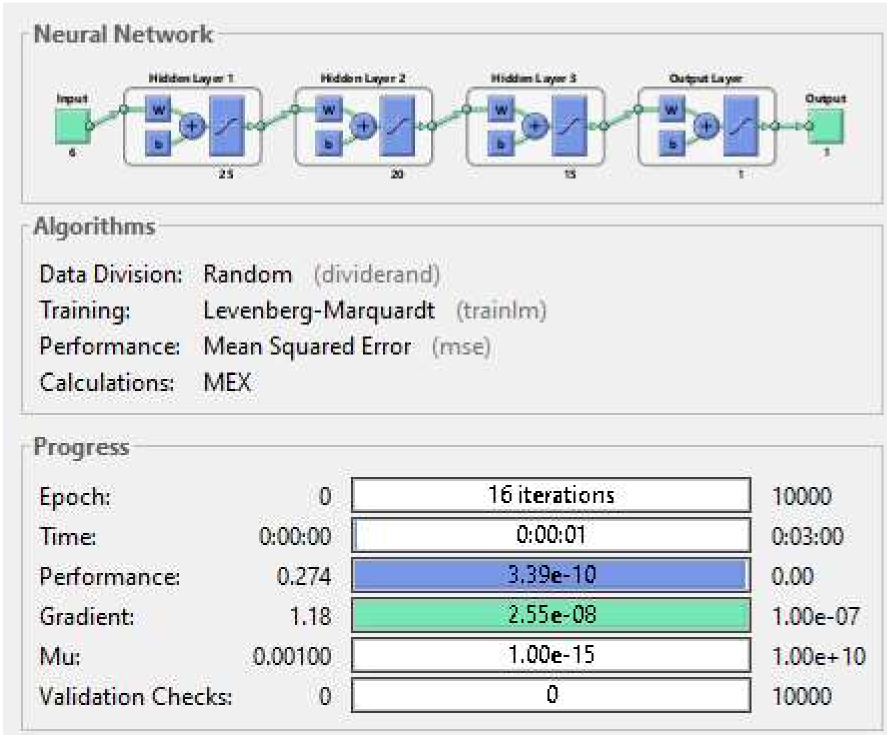


Figure 4.9 Overview of the ANN with configuration (6-25-20-15-1) chosen for fault recognition.

A snapshot of the trained ANN with the configuration 6 – 25 – 20 – 15 – 1 is presented in Figure 4.9. The mean square error (MSE) in fault recognition achieved was 3.39e-10 and the number of validation check fails were 0 after the training process. The chosen NN's structure for fault recognition with the configuration 6 – 25 – 20 – 15 – 1 (i.e. 6 neurons in the input layer, 3 hidden layers with 25, 20 and 15 neurons respectively and 1 neuron in the output layer) is shown in Figure 4.10.

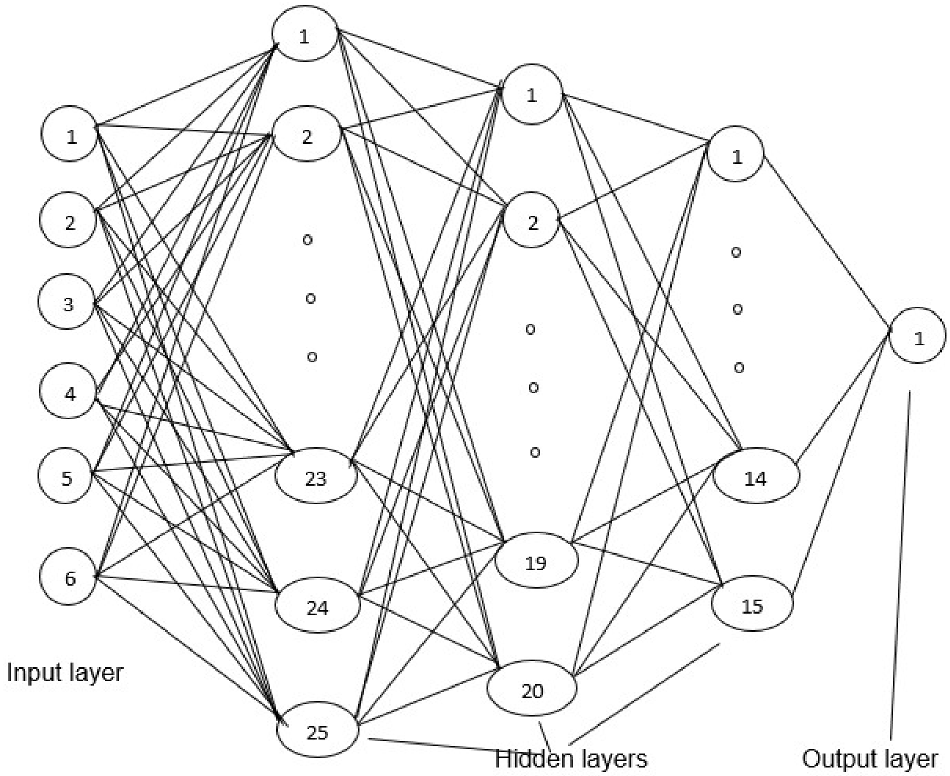


Figure 4.10 Chosen ANN for Fault Recognition (6 – 25 – 20 – 15 – 1)

4.2 Fault-Type Identification

Identifying the fault-type is the next stage after the recognition of fault in a distribution system. The multilayer perceptron neural network employing the back-propagation learning strategy is used. Though backpropagation technique is characteristically slow in learning and proves difficult when selecting the optimal size of the network, it is notwithstanding, the ideal strategy to be used when a large training set is involved because back-propagation algorithm gives a well compacted distributed depiction of complex data sets.

4.2.1 Pattern Classifiers' Training and Performance Evaluation for Fault-Type Identification

The MLP-ANN target output were encoded using the one-per-class coding method [183, 184] as shown in Table 4.3. The MLP-ANN was trained and the training results were evaluated using the Mean Square Error (MSE) metric. Several MLP-ANN were trained out of which the training performance for six were reported in Table 4.4 and it could be seen that the ANN with configuration (6-40-4) produced the most satisfactory result among others with a MSE of 3.0073e-03.

The fault-type identification's training network is fed with sets of six inputs (the three-phase current and voltage values expressed as a fraction of their respective no-fault values) and produces four outputs. Each of the outputs corresponds to the fault circumstance of each of the three phases (represented as A, B or C) and one output for the ground line (represented as G). Therefore, the outputs are either a 1 or 0 signifying the presence or absence of a fault on the equivalent line. Hence, the probable permutations can denote each of the different faults accordingly. The posited NN configuration should be capable of differentiating between the eleven possible types of faults precisely. Table 4.3 is the output table representing the target output for each type of fault.

Table 4.3 Target output of the MLP-ANN for Fault-Type Identification

Type of Fault	Network Output			
	A	B	C	G
A-G	1	0	0	1
B-G	0	1	0	1
C-G	0	0	1	1
A-B	1	1	0	0
B-C	0	1	1	0
C-A	1	0	1	0
A-B-G	1	1	0	1
B-C-G	0	1	1	1
C-A-G	1	0	1	1
A-B-C	1	1	1	0
A-B-C-G	1	1	1	1

Table 4.4 Performance result of the MLP- ANN pattern classifier for Fault-Type Identification

ANN Type	Number of Hidden layers	ANN Configuration	MSE
ANN 1	3	6-30-20-10-4	5.5445e-03
ANN 2	3	6-30-15-5-4	6.6771e-03
ANN 3	2	6-50-25-4	4.5066e-03
ANN 4	2	6-30-15-4	4.0764e-03
ANN 5	1	6-60-4	3.9336e-03
ANN 6	1	6-40-4	3.0073e-03

The training data set is made up of about 576 input-output sets (48 for each of the eleven faults and 48 for the no fault case) with each input-output pair containing a set of six inputs and one output. A number of back-propagation networks (with different numbers of hidden layers and different numbers of neurons per hidden layer were analyzed and their performance are shown in Figures 4.11 – 4.15; followed by the best neural network depicted in Figure 4.20 and described further in detail in various error performance plots in Figures 4.16 – 4.21.

The training performance plot of the NN 6-30-20-10-4 (i.e. the input layer containing 6 neurons, 3 hidden layers containing 30, 20 and 10 neurons respectively and output layer containing 4 neurons) is shown in Figure 4.11. The network's best validation performance (i.e. MSE) after the training procedure is 5.5445e-3 at Epoch 20.

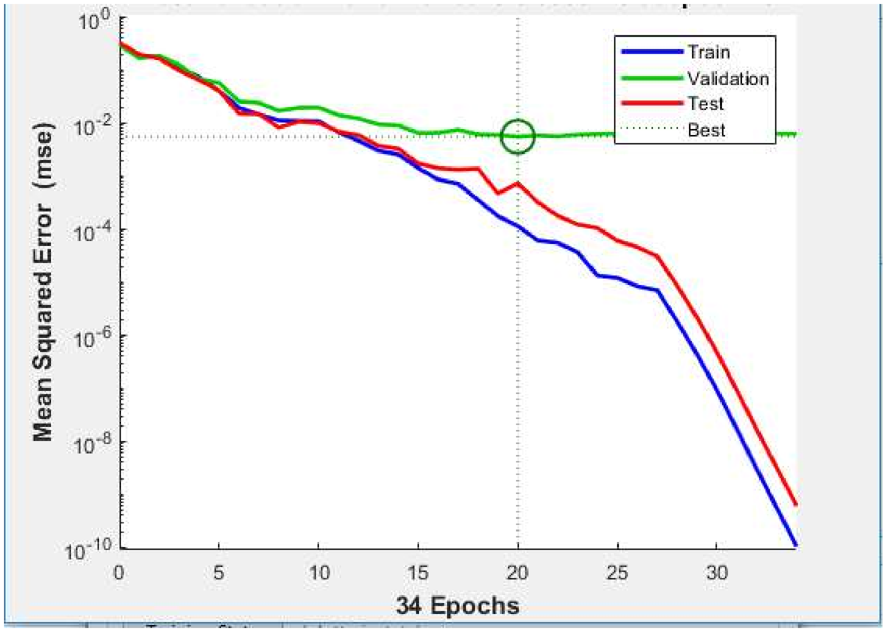


Figure 4.11 Mean-square error performance of the network (6-30-20-10-4).

The training performance plot of the NN 6-30-15-5-4 (i.e. the input layer containing 6 neurons, 3 hidden layers containing 30, 15 and 5 neurons respectively and output layer containing 4 neurons) is shown in Figure 4.12. The network's best validation performance (i.e. MSE) after the training procedure is 6.6771e-03 at Epoch 23.

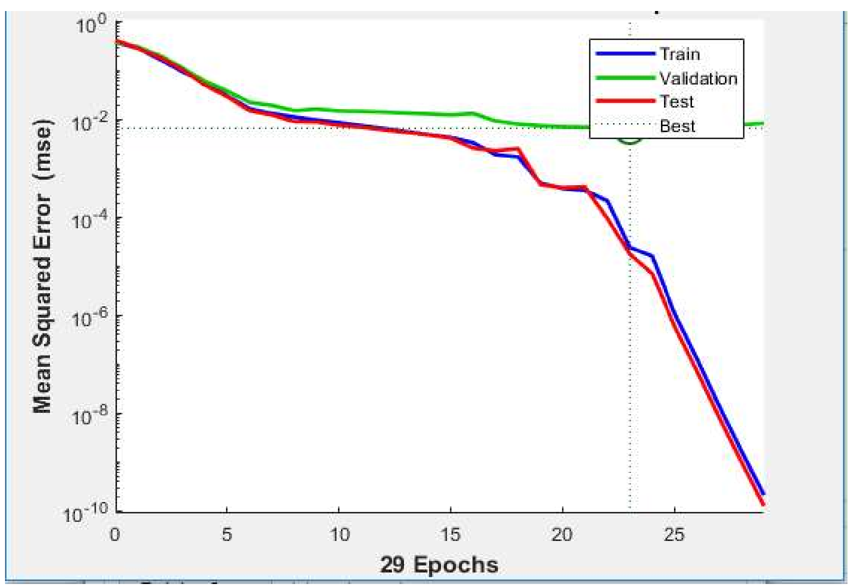


Figure 4.12 MSE performance of the network (6-30-15-5-4).

The training performance plot of the NN 6-50-25-4 (i.e. the input layer containing 6 neurons, 2 hidden layers containing 50 and 25 neurons respectively and output layer containing 4 neurons) is shown in Figure 4.13. The network's best validation performance (i.e. MSE) after the training procedure is 4.5066e-03 at Epoch 46.

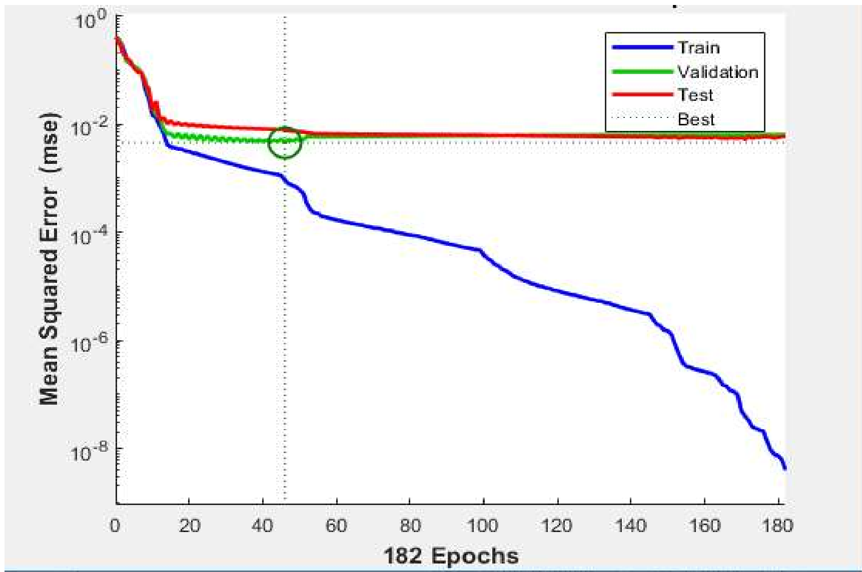


Figure 4.13 MSE performance of the network (6-50-25-4).

The training performance plot of the NN 6-30-15-4 (i.e. the input layer containing 6 neurons, 2 hidden layers containing 30 and 15 neurons respectively and output layer containing 4 neurons) is shown in Figure 4.14. The network's best validation performance (i.e MSE) after the training procedure is 4.0764e-03 at Epoch 127.

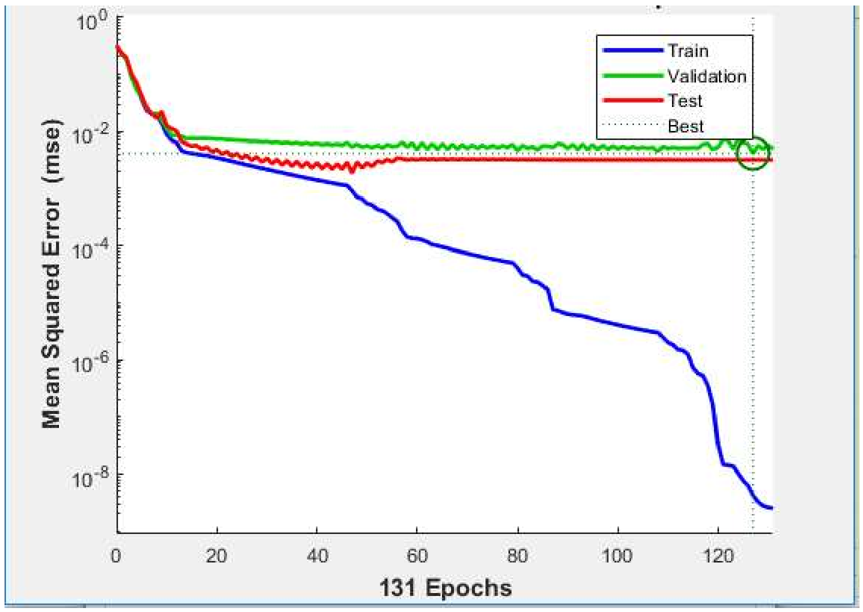


Figure 4.14 MSE performance of the network (6-30-15-4).

The training performance plot of the NN 6-60-4 (i.e. the input layer containing 6 neurons, 1 hidden layer containing 60 neurons and output layer containing 4 neurons) is shown in Figure 4.15. The network's best validation performance (i.e. MSE) after the training procedure is 3.9336e-03 at Epoch 36.

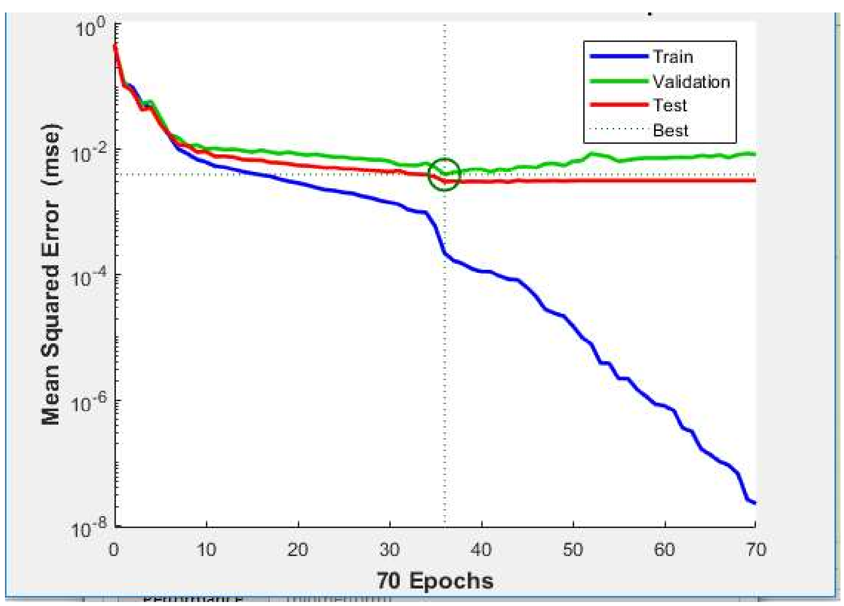


Figure 4.15 MSE performance of the network (6-60-4).

The training performance plot of the NN 6-40-4 (i.e. the input layer containing 6 neurons, 1 hidden layer containing 40 neurons and output layer containing 4 neurons) is shown in Figure 4.16. The network achieved very satisfactory performance. The network's best validation performance (i.e. MSE) after the training procedure is 3.0073e-03 at Epoch 98.

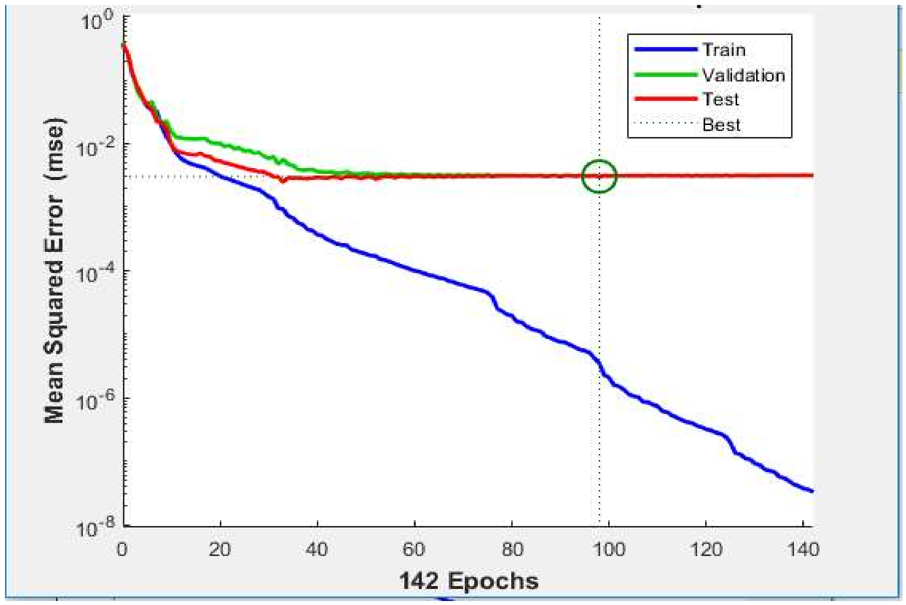


Figure 4.16 MSE performance of the network (6-40-4).

It could be observed from Fig 4.16 that the testing and the validation curves possess similar characteristics which is an indication of efficient training. Hence, this network has been chosen as the ideal ANN for fault-type identification purposes.

4.2.2 Testing for Fault-Type Identification

Testing for fault-type identification was done by taking three diverse factors into consideration. The first factor is by plotting the best linear regression of the outputs and the targets for the 3 phases of training, validation and testing (see Figure 4.17). The correlation coefficient (r) here gives 0.98943 which implies satisfactory correlation between the outputs and the targets. The dotted line and the solid lines in the figure indicate the ideal and actual regression fit of the neural network respectively. The two lines trail each other very closely signifying an excellent performance by the neural network.

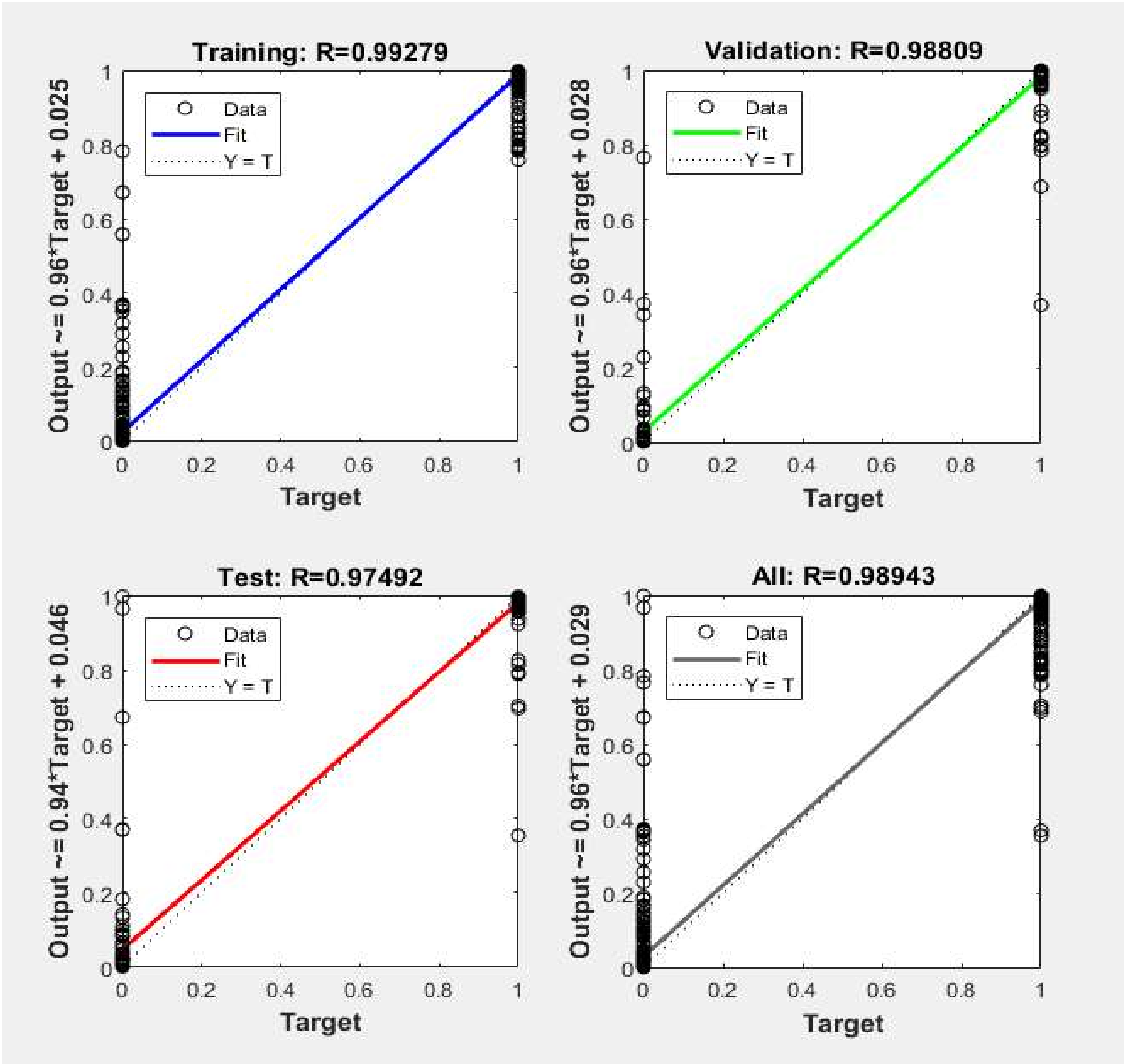


Figure 4.17 Regression FIT for Training, Testing and Validation phases.

The second factor for testing is by plotting the Receiver Operating Characteristics curve (ROC) as shown in Figure 4.18. The ROC curves are plots of the rates of positive sorting (true positive rates) and rate of incorrect sorting (the false positive rates) of the neural network fault-type identifiers. An ideal ROC curve would, therefore, display points only in the upper-left corner because that is what indicates an excellent true positivity in the identification. Fig 4.18 shows an ROC curve for this network which is nearly perfect because it has all the lines in the upper-left corner.

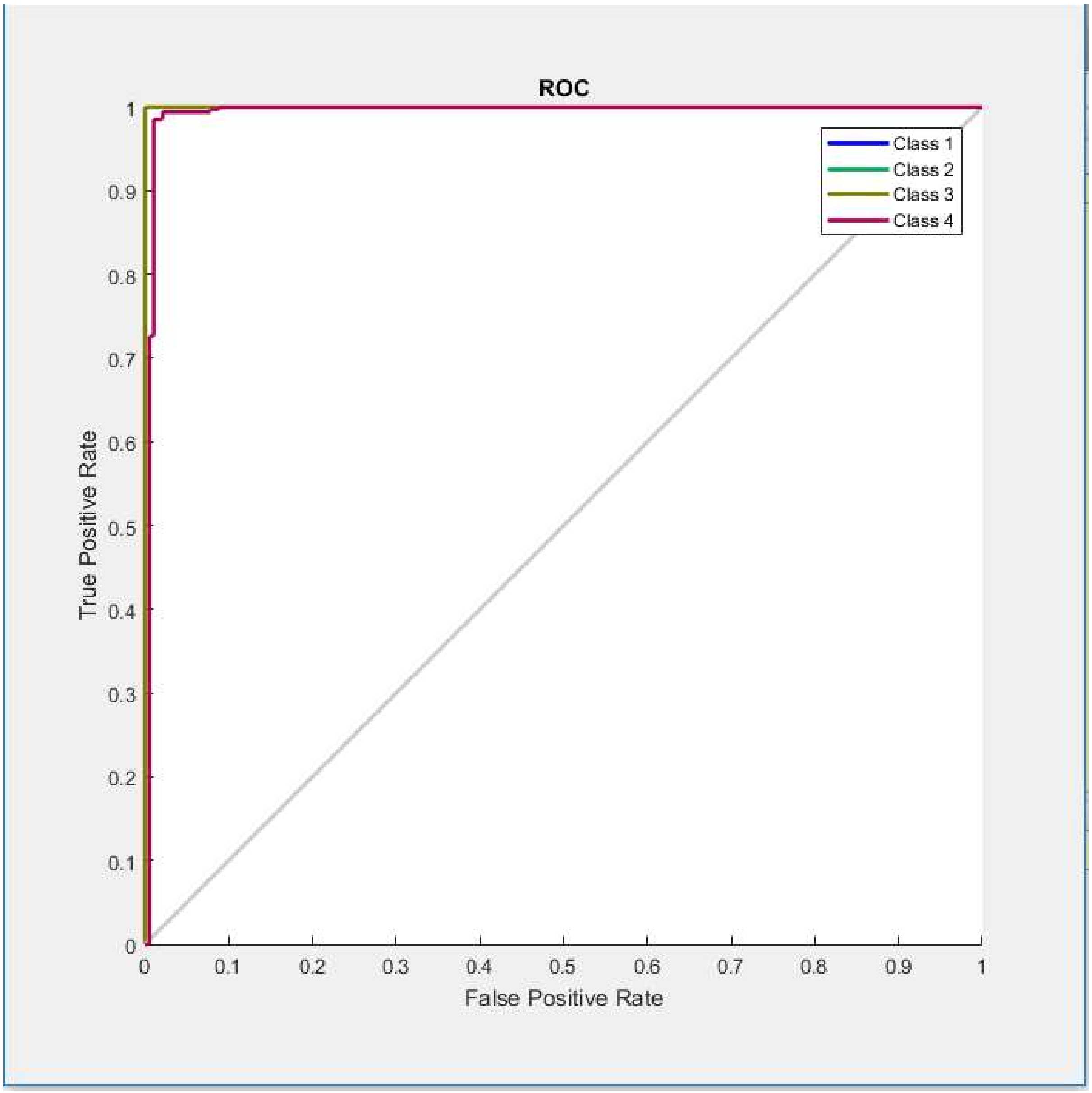


Figure 4.18 ROC curve of the network (6-40-4).

The third factor in the testing procedure is the creation of a distinct data set known as the test set to evaluate how the trained neural network performs. The test data set is made up of about 24 input-output sets (2 for each of the eleven faults and 2 for the no fault case) with each input-output pair containing a set of six inputs and one output. The neural network received the test set and yielded the results; the neural network's efficiency with respect to its aptitude in identifying the fault-type is 100%. Therefore, the neural network can identify each of the eleven possible types of faults, with excellent accuracy. A snapshot of the chosen ANN for fault type identification with the configuration 6 - 40 - 4 (i.e. the input layer containing 6 neurons, 1 hidden layer containing 40 neurons and output layer containing 4 neurons) is presented in Figure 4.19 while its structure is shown in Figure 4.20.

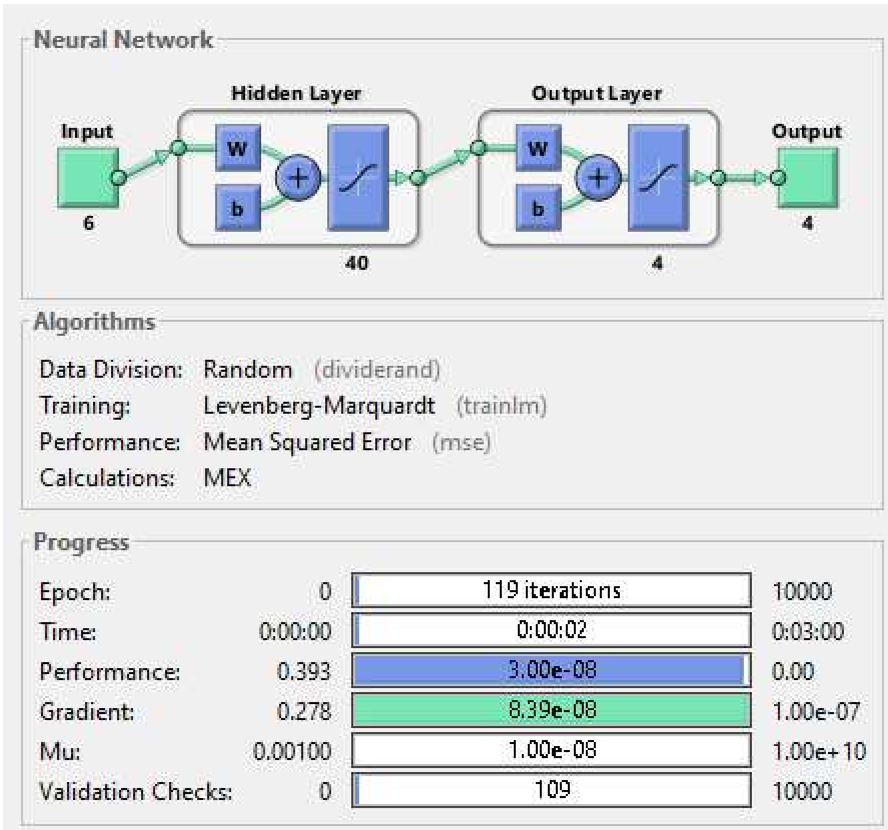


Figure 4.19 ANN with configuration (6-40-4) chosen for fault type identification

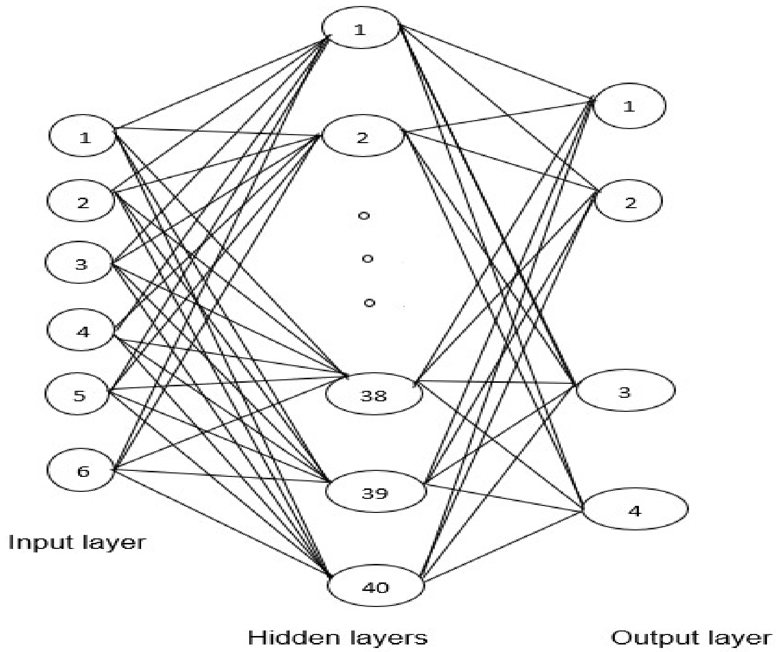


Figure 4.20 Structure of chosen ANN for Fault Type Identification (6 – 40 – 4)

4.3 Fault Location

Locating the fault is the last stage after the recognition and identification of fault in a distribution system. Like in previous stages, the multilayer perceptron neural network employing the back-propagation learning strategy is used considering its effectiveness when a large training set is employed because back-propagation algorithm gives a well compacted distributed depiction of complex data sets.

4.3.1 Pattern Classifiers' Training and Performance Evaluation for Fault Location

The MLP-ANN target output were encoded using the one-per-class coding method [183, 184] as shown in Table 4.5. The MLP-ANN was trained and the training results were evaluated using the Mean Square Error (MSE) metric. Several MLP-ANN were trained out of which the training performance for six were reported in Table 4.6 and it could be seen that the ANN with configuration (6-30-15-5-4) produced the most satisfactory result among others with a MSE of 5.4033e-11.

The fault location's training network is fed with sets of six inputs (the three-phase current and voltage values expressed as a fraction of their respective no-fault values) and produces four outputs. Each of the outputs corresponds to the fault circumstance of each of the four zones. The four three-phase lines of IEEE 13 Node Test Feeder were divided into four zones as illustrated in table 4.5. Therefore, the outputs are either a 1 or 0 signifying the presence or absence of a fault on the equivalent line. Hence, the probable permutations can denote each of the different faults accordingly. Table 4.2 is the output table representing the target output for fault location.

Table 4.5 Target output of the MLP-ANN for Fault Location

Fault Location	Line	Network Output			
		Zone 1	Zone 2	Zone 3	Zone 4
Zone 1	632-633	1	0	0	0
zone 2	632-671	0	1	0	0
Zone 3	671-680	0	0	1	0
Zone 4	692-675	0	0	0	1

Table 4.6 Performance result of the MLP- ANN pattern classifier for Fault-Type Identification

ANN Type	Number of Hidden layers	ANN Configuration	MSE
ANN 1	1	6-20-4	3.0911e-02
ANN 2	1	6-40-4	8.9914e-10
ANN 3	2	6-20-10-4	1.1921e-09
ANN 4	2	6-25-15-4	2.3397e-10
ANN 5	3	6-20-15-10-4	1.3366e-02
ANN 6	3	6-30-15-5-4	5.4033e-11

The training data set is made up of about 550 input-output sets (50 for each of the eleven faults-type) with each input-output pair containing a set of six inputs and one output. A number of back-propagation networks (with different numbers of hidden layers and different numbers of neurons per hidden layer were analyzed and their performance are shown in Figures 4.21 – 4.25; followed by the best neural network depicted in Figure 4.31 `and described further in detail in various error performance plots in Figures 4.26 – 4.30.

The training performance plot of the NN 6-20-4 (i.e. the input layer containing 6 neurons, 1 hidden layer containing 20 neurons and output layer containing 4 neurons) is shown in Figure 4.21. The network's best validation performance (i.e. MSE) after the training procedure is 3.0911e-2 at Epoch 19.

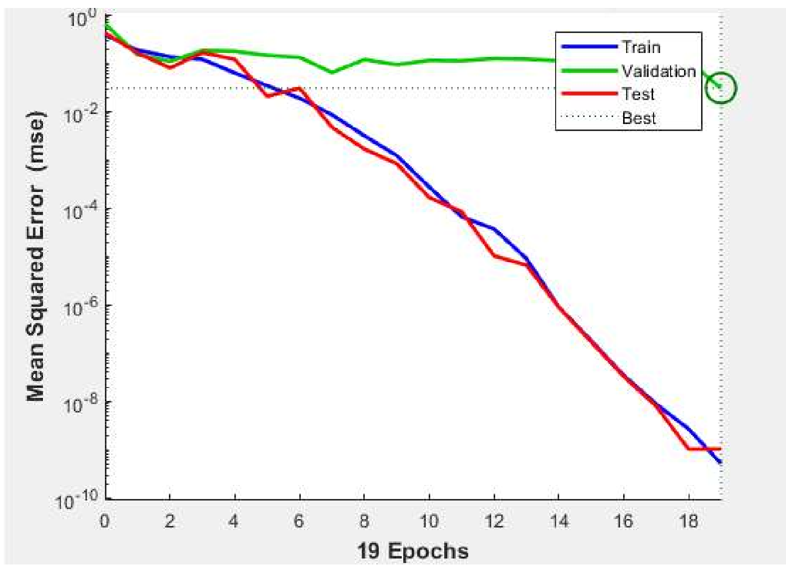


Figure 4.21 Mean-square error performance of the network (6-20-4).

The training performance plot of the NN 6-40-4 (i.e. the input layer containing 6 neurons, 1 hidden layer containing 40 neurons and output layer containing 4 neurons) is shown in Figure 4.22. The network's best validation performance (i.e. MSE) after the training procedure is 8.9914e-10 at Epoch 12.

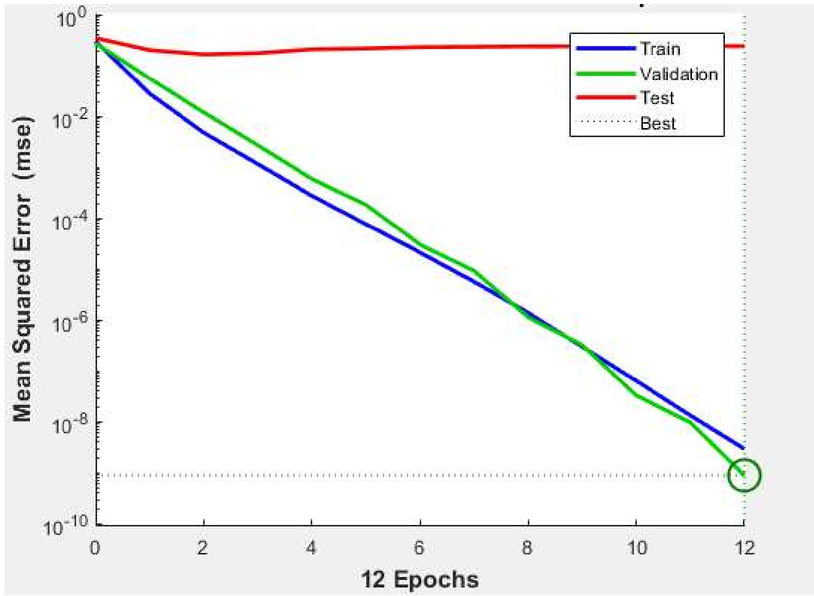


Figure 4.22 MSE performance of the network (6-40-4).

The training performance plot of the NN 6-20-10-4 (i.e. the input layer containing 6 neurons, 2 hidden layers containing 20 and 10 neurons respectively and output layer containing 4 neurons) is shown in Figure 4.23. The network's best validation performance (i.e. MSE) after the training procedure is 1.1921e-09 at Epoch 16.

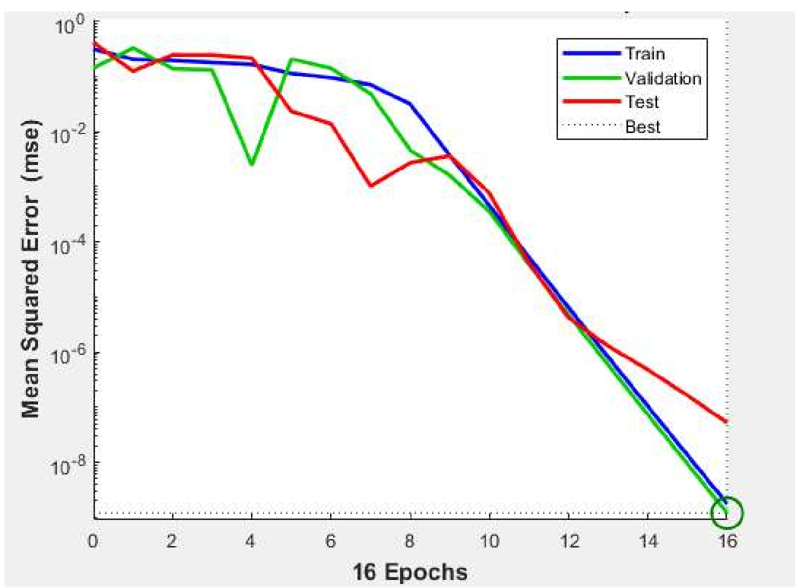


Figure 4.23 MSE performance of the network (6-20-10-4).

The training performance plot of the NN 6-25-15-4 (i.e. the input layer containing 6 neurons, 2 hidden layers containing 25 and 15 neurons respectively and output layer containing 4 neurons) is shown in Figure 4.24. The network's best validation performance (i.e MSE) after the training procedure is 2.3397e-10 at Epoch 12.

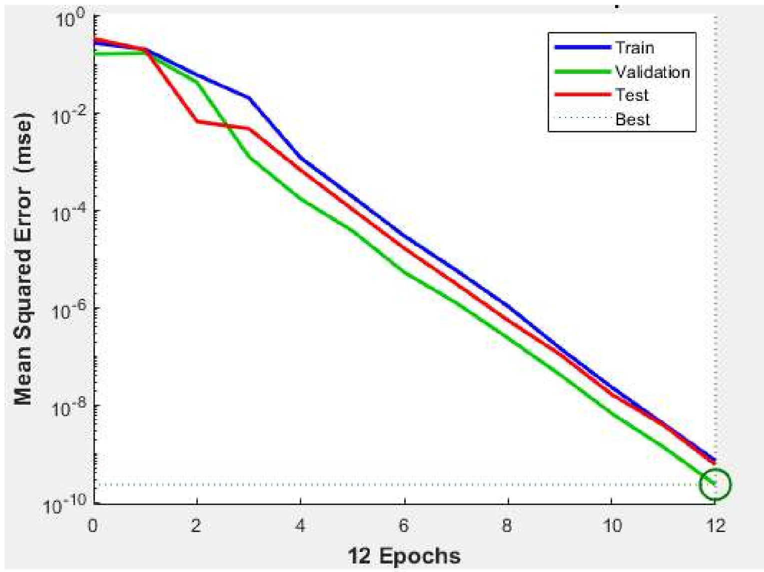


Figure 4.24 MSE performance of the network (6-25-15-4).

The training performance plot of the NN 6-20-15-10-4 (i.e. the input layer containing 6 neurons, 3 hidden layers containing 20, 15 and 10 neurons respectively and output layer containing 4 neurons) is shown in Figure 4.25. The network's best validation performance (i.e. MSE) after the training procedure is 1.3366e-02 at Epoch 15.

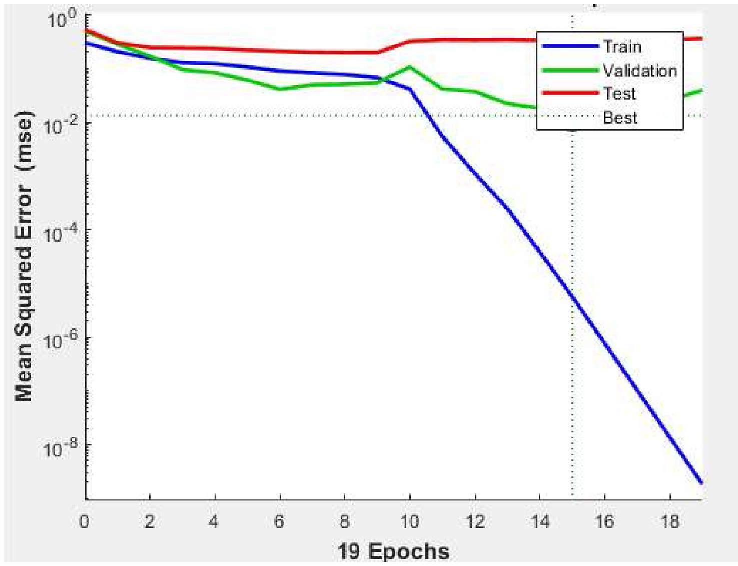


Figure 4.25 MSE performance of the network (6-20-15-10-4).

The training performance plot of the NN 6-30-15-5-4 (i.e. the input layer containing 6 neurons, 3 hidden layers containing 30, 15 and 5 neurons respectively and output layer containing 4 neurons) is shown in Figure 4.26. The network achieved very satisfactory performance. The network's best validation performance (i.e. MSE) after the training procedure is 5.4033e-11 at Epoch 17. Hence, this network has been chosen as the ideal ANN for fault location purposes.

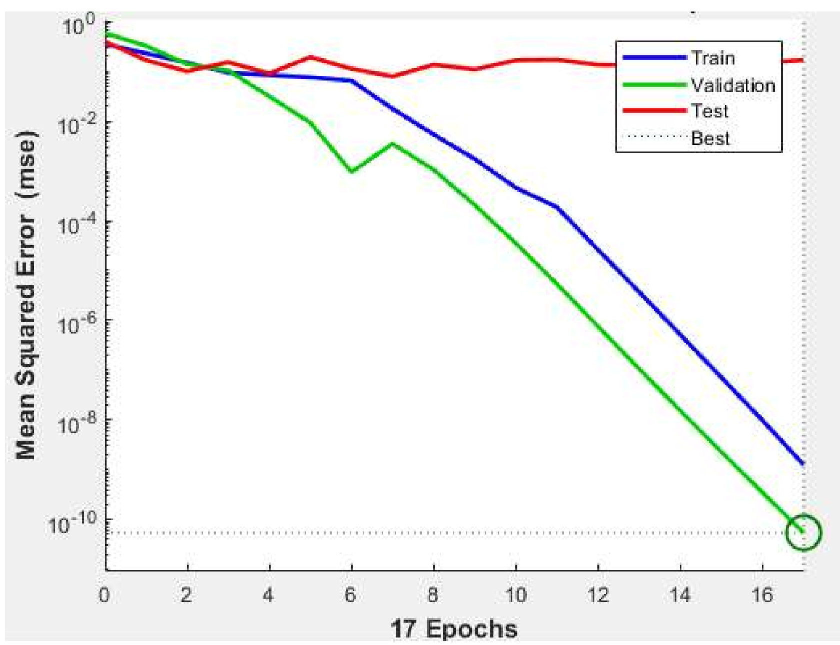


Figure 4.26 MSE performance of the network (6-30-15-5-4).

4.3.2 Testing for Fault Location

Testing for fault-type identification was done by considering three diverse factors. The first factor is by plotting the best linear regression of the outputs and the targets for the 3 phases of training, validation and testing (see Figure 4.27). The correlation coefficient (r) here gives 0.94485, which implies satisfactory correlation between the outputs and the targets. The dotted line and the solid lines in the figure indicate the ideal and actual regression fit of the neural network respectively. The two lines trail each other very closely signifying an excellent performance by the neural network.

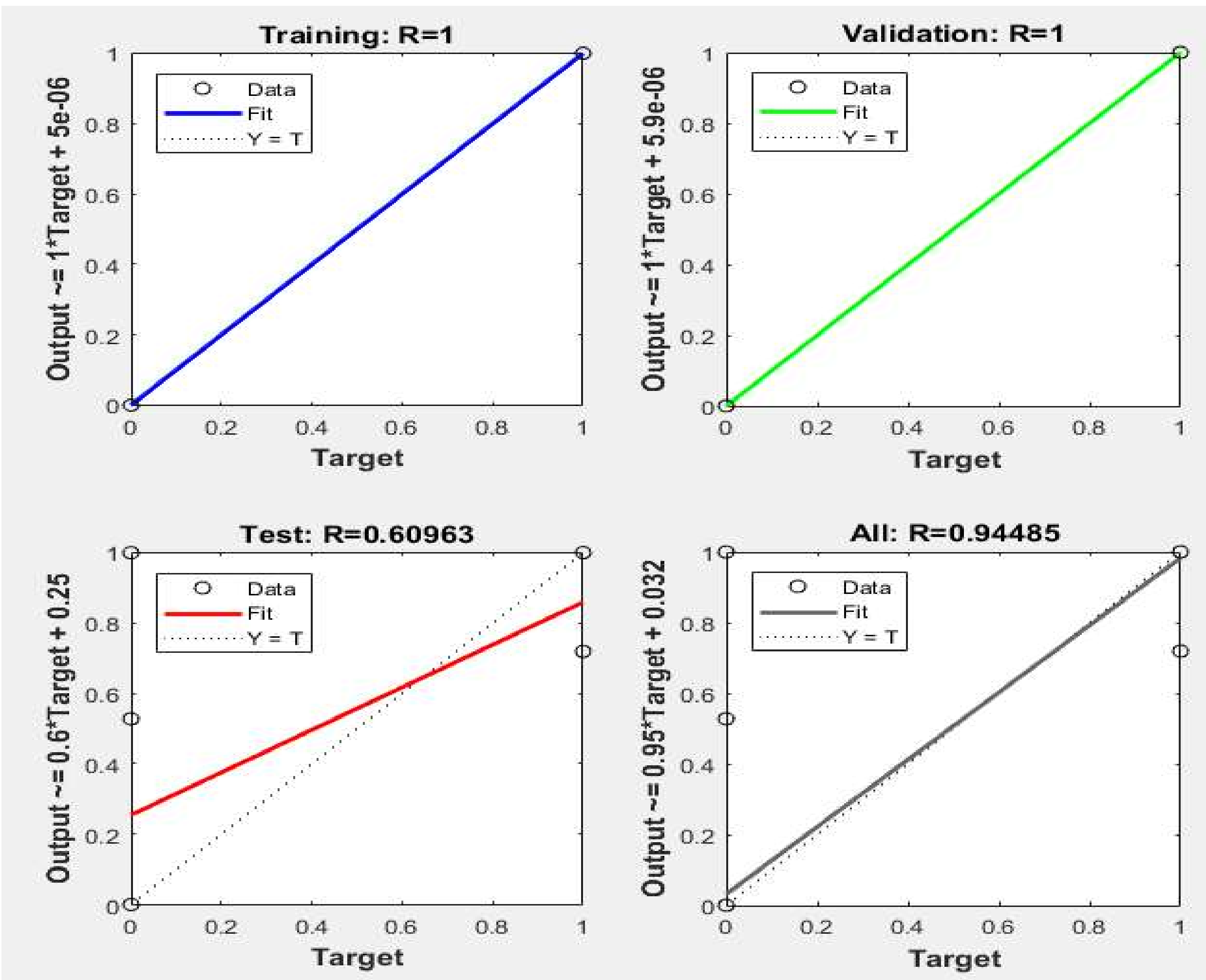


Figure 4.27 Regression FIT for Training, Testing and Validation phases.

The second factor for testing is by plotting the Receiver Operating Characteristics curve (ROC) as shown in Figure 4.28. The ROC curves are plots of the rates of positive sorting (true positive rates) and rate of incorrect sorting (the false positive rates) of the neural network fault-type identifiers. An ideal ROC curve would, therefore, display points only in the upper-left corner because that is what indicates an excellent true positivity in the identification. Fig 4.28 shows an ROC curve for this network which is nearly perfect because it has all the lines in the upper-left corner.

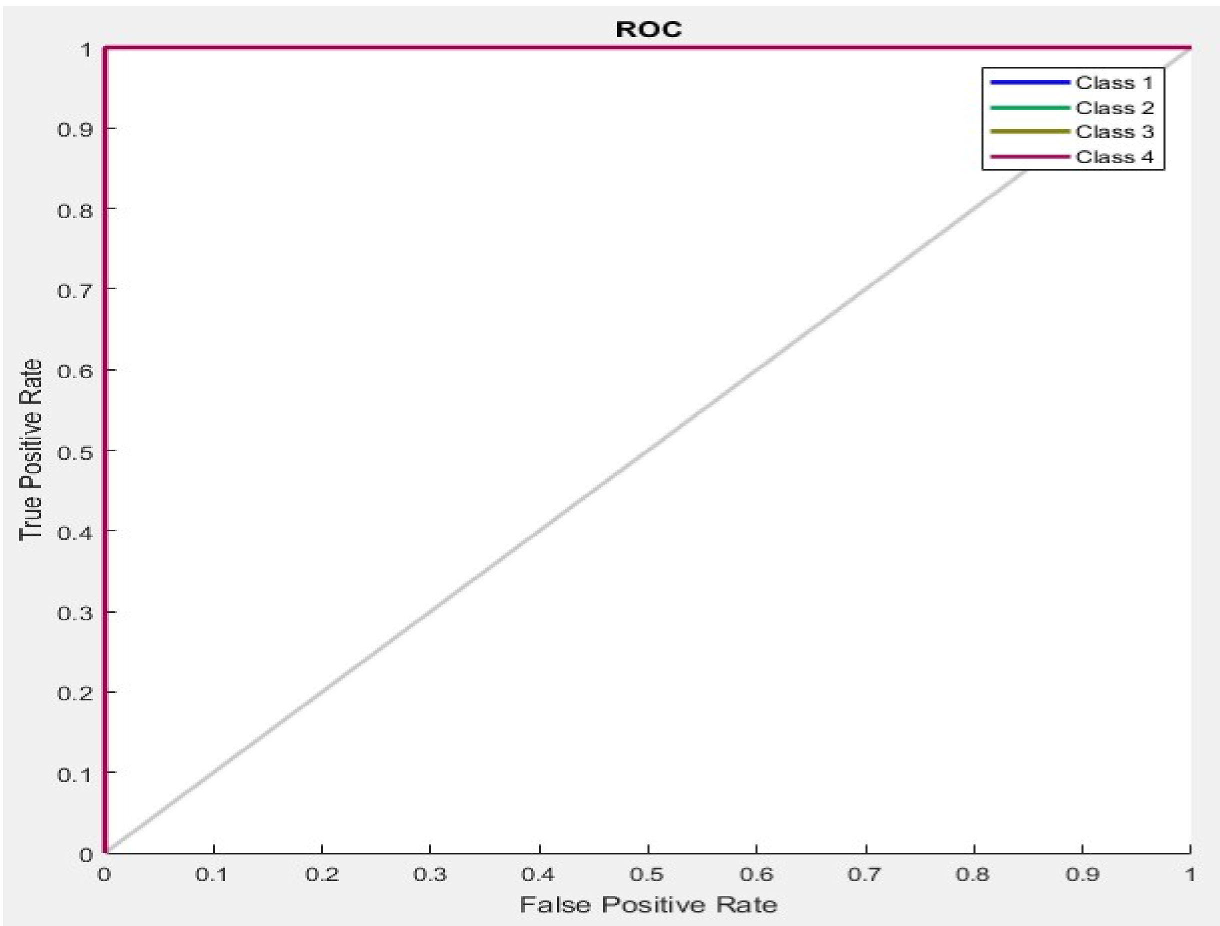


Figure 4.28 ROC curve of the network (6-30-15-5-4).

The third factor in the testing procedure is the gradient and validation performance plot. It can be seen in Figure 4.29 that there is a steady decrease in the gradient and also that the number of validation fails are 0 during the entire process which indicates smooth and efficient training.

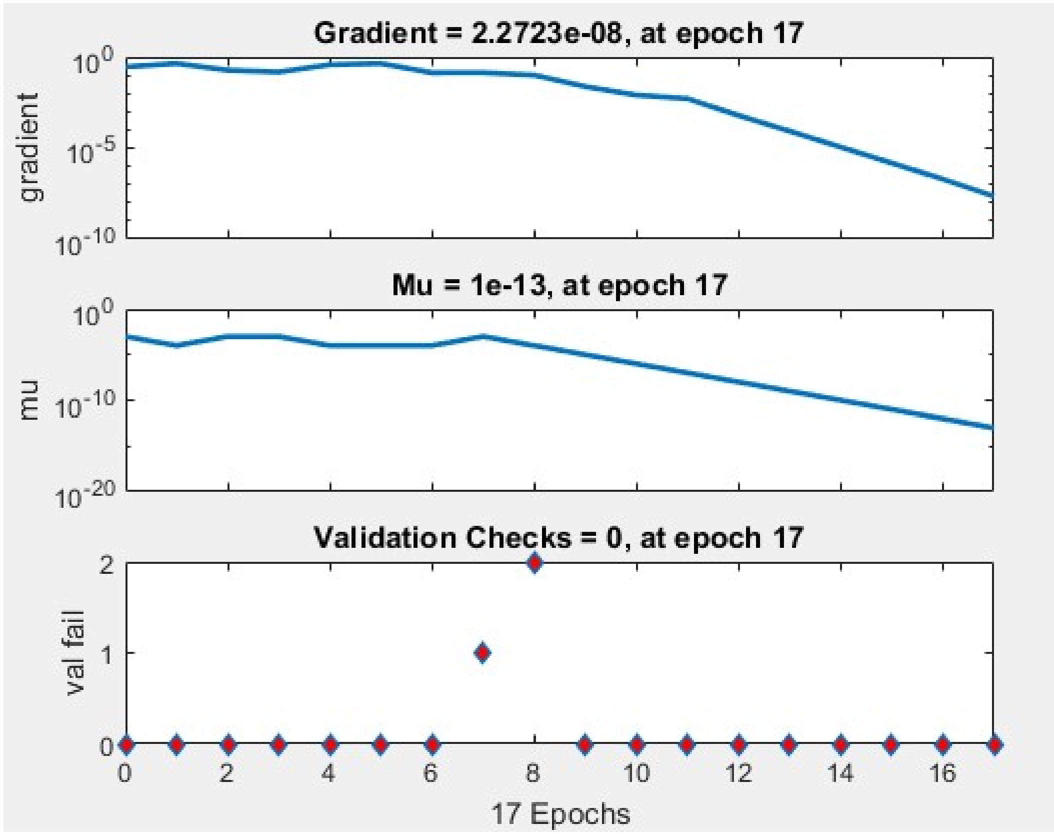


Figure 4.29 Gradient and validation performance of the NN (6-30-15-5-4).

A snapshot of the chosen ANN for fault location with the configuration 6-30-15-5-4 (i.e. the input layer containing 6 neurons, 3 hidden layers containing 30, 15 and 5 neurons respectively and output layer containing 4 neurons) is presented in Figure 4.30 while its structure is shown in Figure 4.31.

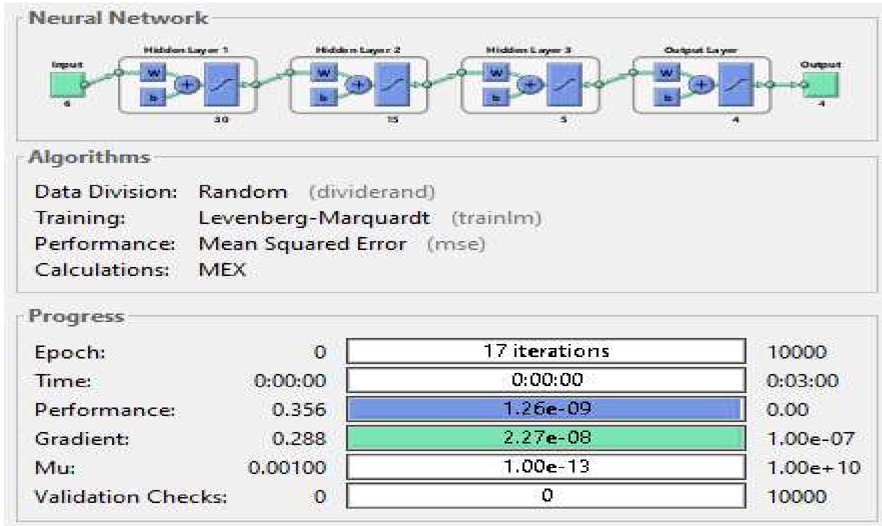


Figure 4.30 ANN with configuration (6-30-15-5-4) chosen for fault location

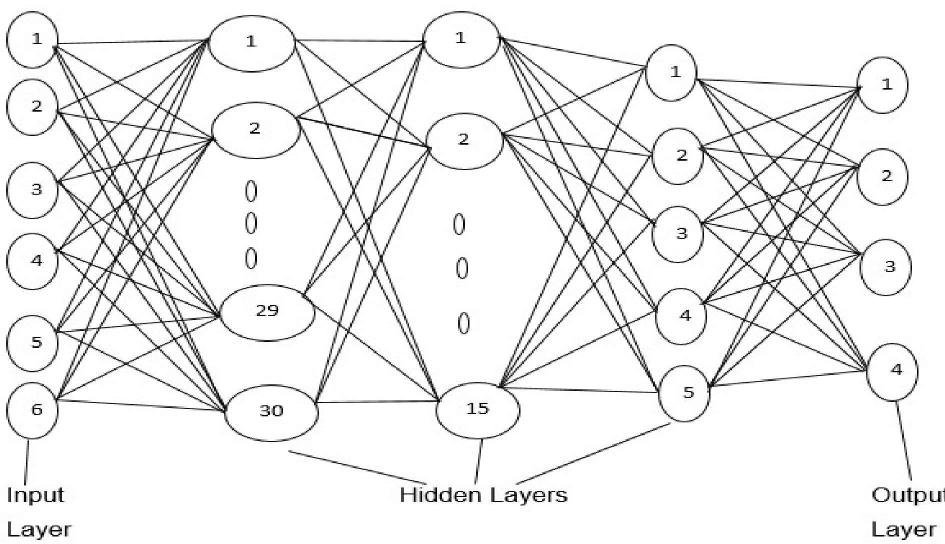


Figure 4.31 Structure of chosen ANN for fault location (6-30-15-5-4)

CHAPTER 5

Conclusions and Recommendation

5.1 Conclusions

In this thesis, the application of neural networks for the recognition of faults, identification of fault-types and location of faulty zone in the distribution system has been studied. The technique utilizes the 3-phase currents and voltages (expressed as a ratio of their no-fault values) as inputs to the neural networks. In this work, different types of faults such as single line-ground, line-line, double line-ground, three-phase and three-phase to ground faults have been taken into consideration and separate artificial neural network configurations were utilized for each of the faults. Every neural network configuration adopted in this dissertation employed the back-propagation neural network architecture. By the instrumentality of artificial neural networks, a scheme for the distribution system, from fault recognition to fault-type identification and fault location stages was developed effectively. The results obtained from simulations confirm that satisfactory performance has been attained by each and every proposed neural networks. The size of the ANN (the number of hidden layers and number of neurons per hidden layer) varies constantly based on how the neural network is applied and the size of the training data set. In this work, emphasis has been laid on how significant it is to choose the most suitable ANN configuration, so as to derive the utmost performance from the network.

MATLAB R2017a together with the SimPowerSystems toolbox in Simulink has been employed in simulating the distribution system model and obtaining the training data set while the Artificial Neural Networks Toolbox has been used in training and analyzing the performance of the neural networks. Some significant conclusions that can be drawn from this work are:

- Artificial Neural Networks are efficient and dependable techniques for an electrical power distribution system's fault recognition scheme particularly due to the increase in the sophistication of the recent power distribution systems.

The performance of the structure and learning algorithm of a particular artificial neural network should be analyzed thoroughly before it is chosen for practical applications.

Back Propagation Neural Networks (BPNN) have been chosen for all the processes of fault recognition, fault-type identification and fault location in this thesis. BPNNs are very effective when complex or large training data sets are involved.

5.2 Recommendation

This research study has showcased the effectiveness of artificial neural network in recognizing faults, identifying different types of faults in a distribution system and locating the distribution zone or branch where the fault occurs. Future work may consider how to identify the exact location of the faults in the distribution systems. Also, testing of the techniques on a real-life distribution system would provide a basis for confirming its effectiveness.

It would be quite useful, as a possible extension to this work, to analyze all the other neural network architectures, apart from back propagation neural networks (BPNN) such as radial basis neural network (RBF) and support vector machines (SVM) networks, to provide a comparative analysis on each of the architectures and their performance characteristics.

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APPENDIX 1

13 Node IEEE Test Feeder Line Parameter Specifications [176]

(a). Line Segment Data:

Node A	Node B	Length(ft.)	Config
632	645	500	603
632	633	500	602
633	634	0	XFM-1
645	646	300	603
650	632	2000	601
684	652	800	607
632	671	2000	601
671	684	300	604
671	680	1000	601
671	692	0	Switch
684	611	300	605
692	675	500	606

(b). Overhead Line Configuration Data:

Config.	Phasing	Phase	Neutral	Spacing
		ACSR	ACSR	ID
601	B A C N	556,500 26/7	4/0 6/1	500
602	C A B N	4/0 6/1	4/0 6/1	500
603	C B N	1/0	1/0	505
604	A C N	1/0	1/0	505
605	C N	1/0	1/0	510

(c). Underground Line Configuration Data:

Config.	Phasing	Cable	Neutral	Space ID
606	A B C N	250,000 AA, CN	None	515
607	A N	1/0 AA, TS	1/0 Cu	520

(d). Transformer Data:

	kVA	kV-high	kV-low	R - %	X - %
Substation:	5,000	115 - D	4.16 Gr. Y	1	8
XFM -1	500	4.16 – Gr.W	0.48 – Gr.W	1.1	2

(e) Regulator Data:

Regulator ID:	1		
Line Segment:	650 - 632		
Location:	50		
Phases:	A - B -C		
Connection:	3-Ph,LG		
Monitoring Phase:	A-B-C		
Bandwidth:	2.0 volts		
PT Ratio:	20		
Primary CT Rating:	700		
Compensator Settings:	Ph-A	Ph-B	Ph-C
R - Setting:	3	3	3
X - Setting:	9	9	9
Volltage Level:	122	122	122

(f). Capacitor Data:

Node	Ph-A	Ph-B	Ph-C
	kVAr	kVAr	kVAr
675	200	200	200
611			100
Total	200	200	300

(g). Distributed Load Data:

Node A	Node B	Load	Ph-1	Ph-1	Ph-2	Ph-2	Ph-3	Ph-3
		Model	kW	kVAr	kW	kVAr	kW	kVAr
632	671	Y-PQ	17	10	66	38	117	68

(h). Spot Load Data:

Node	Load	Ph-1	Ph-1	Ph-2	Ph-2	Ph-3	Ph-3
	Model	kW	kVAr	kW	kVAr	kW	kVAr
634	Y-PQ	160	110	120	90	120	90
645	Y-PQ	0	0	170	125	0	0
646	D-Z	0	0	230	132	0	0
652	Y-Z	128	86	0	0	0	0
671	D-PQ	385	220	385	220	385	220
675	Y-PQ	485	190	68	60	290	212
692	D-I	0	0	0	0	170	151
611	Y-I	0	0	0	0	170	80
	TOTAL	1158	606	973	627	1135	753

APPENDIX 2

13 Node IEEE Test Feeder Power Flow Results

632	----------A--------		--------B--------		--------C------------		---V1-----PQtotal------	
V (pu deg.)	1.0210	-2.49	1.0420	-121.72	1.0174	117.83	1.0268	-2.12
Gen (kW kvar)	1230.42	607.00	981.18	343.04	1307.14	590.11	3518.74	1540.14
PQ load (kW kvar)	8.50	5.00	33.00	19.00	58.50	34.00	100.00	58.00
Z shunt (kW kvar)	0.00	0.00	0.00	-0.00	-0.00	0.00	-0.00	0.00
-> 633 (kW kvar)	163.23	115.48	121.91	93.21	122.16	93.30	407.30	301.99
-> 671 (kW kvar)	1058.69	486.52	491.99	102.90	1046.82	324.82	2597.50	914.24
-> 645 (kW kvar)			334.28	127.93	79.65	137.99	413.93	265.92

633	-------A--------		--------B--------		--------C------		---V1--PQtotal---	
V (pu deg.)	1.0178	-2.56	1.0402	-121.77	1.0148	117.83	1.0243	-2.16
Gen (kW kvar)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PQ load (kW kvar)	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
Z shunt (kW kvar)	-0.00	0.00	-0.00	0.00	0.00	0.00	0.00	0.00
-> 632 (kW kvar)	-162.86	-114.93	-121.78	-92.95	-121.84	-93.07	-406.48	-300.95
-> 634 (kW kvar)	162.86	114.93	121.78	92.95	121.84	93.07	406.48	300.95

692	-------A--------		--------B--------		--------C------		---V1--PQtotal---	
V (pu deg.)	0.9871	-5.53	1.0519	-122.41	0.9780	116.00	1.0054	-3.94
Gen (kW kvar)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PQ load (kW kvar)	42.83	122.30	0.00	-0.00	125.48	27.20	168.31	149.50
Z shunt (kW kvar)	0.00	-0.00	-0.00	-0.00	0.00	-0.00	0.00	0.00
-> 671 (kW kvar)	-531.02	-121.99	-68.34	161.79	-416.10	-48.57	-1015.46	-8.77
-> 675 (kW kvar)	488.19	-0.30	68.34	-161.79	290.62	21.37	847.15	-140.72

Series RLC Load 611 I
P 611_c = 170*0.9741 = 165.6 kW
Q 611_c = 80*0.9741 = 77.92 kW

Three-Phase Series RLC Load 692 D I
Vca = 0.9780*exp(1i* 116.00*pi/180)-0.9871*exp(1i*-5.53*pi/180)
abs(Vca)/sqrt(3) = 0.9900
P 692_c = 170*0.9900 = 168.3 kW
Q 692_c = 151*0.9900 = 149.5 kW

Three-Phase Series RLC Load 671 671 D PQ
[385 385 385] kW
[220 220 220] kW