APPLICATION OF ARTIFICIAL NEURAL NETWORK-BASED FAULT DIAGNOSIS ON 330kV TRANSMISSION LINES:

(A CASE STUDY OF GWAGWALADA-KATAMPE TRANSMISSION LINE)

BY

SUBERU, Momoh Bello

M.Eng/SEET/2018/8446

A THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF ENGINEERING (MENG) IN ELECTRICAL AND ELECTRONICS (POWER SYSTEMS ENGINEERING OPTION).

SEPTEMBER, 2023

DECLARATION

I hereby declare that this thesis titled: "Application of artificial neural network-based fault diagnosis on 330kV transmission lines (a case study of Gwagwalada-Katampe transmission line)" is a collection of my original research work and it has not, to the best of my knowledge, been presented for any other qualification anywhere. All resources of information (published and unpublished) have been duly acknowledged by mean of references.

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SUBERU, Momoh Bello **SIGNATURE/DATE**
MENG/SEET/2018/8446
FEDERAL UNIVERSITY OF TECHNOLOGY
MINNA, NIGERIA

CERTIFICATION

The thesis titled: "Application of artificial neural network-based fault diagnosis on 330kV transmission lines (a case study of Gwagwalada-Katampe transmission line)" by: Suberu Momoh Bello (MENG/SEET/2018/8446) meets the regulations governing the award of the degree of (MEng) of the Federal University of Technology, Minna and it is approved for its contribution to scientific knowledge and literary presentation.

ENGR. PROF. BABATUNDE A. ADEGBOYE **……………………......**
MAJOR SUPERVISOR **Signature and Date**

ENGR. DR. ODUNAYO IMORU **…………………………...**
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ENGR. DR. L. OLATOMIWA **...……………………...**

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DEAN OF POSTGRADUATE **Signature and Date**
SCHOOL

DEDICATION

This thesis is dedicated to The Almighty God for His everlasting love and mercies.

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ABSTRACT

This research focuses on stimulating an intelligent fault detection system to detect and classify multiple faults on the 330 kV Gwagwalada-Katampe transmission lines. The study employs a feed-forward neural network with a back-propagation algorithm in training the system. The transmission lines were modeled using the SimPowerSytems toolbox in Simulink and simulation was done within the MATLAB environment. The

instantaneous voltages, currents, and settling time values were extracted and used to train the model. Different fault types were considered for detection. These are the single phase-to-ground faults (C-G, B-G, A-G), double phase-to-ground faults (B-C-G, A-C-G, A-B-G), three phase-to-ground faults (A-B-C-G), phase-to-phase fault (B-C, A-C, A-B) and three phaseto-phase faults (A-B-C). Simulation results show 91.5% accuracy of the artificial neural network technique for fault diagnosis on the transmission line. Hence, the technique proposed in this research is recommended for use in fault diagnosis of similar transmission systems.

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GLOSSARY AND LIST OF ABBREVIATIONS

GLOSSARY

ELECTRICAL FAULT A fault in electrical equipment or apparatus is defined as an imperfection in the electrical circuit by which current is deflected from the intended path. In other words, the fault is the abnormal condition of the electrical system which damages the electrical equipment and disturbs the normal flow of the electric current.

LEARNING Learning is using a set of observations to find a function that solves the task in some optimal sense. Or Learning involves the adjustment of synaptic connections that exist between neurons.

NEURONS These are a large number of simple processing units.

SYNAPSE Synapse is a connection between two nerve cells.

TRANSMISSION LINE

The transmission line is the material medium or structure that forms all or part of a path from one place to another for directing the transmission of energy, such as electromagnetic waves or acoustic waves, as well as electric power transmission. Its components are wires, coaxial cables, dielectric slabs, optical fibers, and electric power lines.

WEIGHTS these are the values that are multiplied by each neuron through the process of giving a desired output.

LIST OF ABBREVIATIONS

ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
BP	Back-Propagation

BPSCG	Back-Propagation Scale Conjugate Gradient
CB	Circuit Breaker
DNN	Deep Neural Network
DWT	Discrete Wavelet Travelling
LLG	Double Line-to-Ground Faults
EST	Expert System Techniques
FFNN	Feed Forward Neural Network
FDS	Fast Diagnostic System
FFNNA	Feed Forward Neural Network Algorithm
LTM	Long Term Memory
FLS	Fuzzy Logic Systems
GIS	Global Information Systems
IMFCM	Intelligent Multi-Fault Classification Model
LP	Learning Paradigms
LL	Line-to-Line Faults
MC	Markov Chain
MDP	Markov Decision Process
MSE	Mean Square Error
STM	Short Term Memory
LG	Line-to-Ground Fault
SL	Supervised Learning
TCN	Transmission Company of Nigeria
TL	Transmission Lines
UL	Unsupervised Learning

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

With about half of Nigeria's rural population having little or no access to electricity, the need for a reliable electricity supply is steadily increasing (Alao and Awodele, 2018). There are several ways to generate electricity. This can be divided into two main categories: conventional and non-conventional power generation. In some cases, generation options can be classified as renewable and non-renewable (Sivadanam, Nagu, and Sydulu, 2020). In Nigeria, all grid-connected power plants are conventional power plants, essentially gas turbine-based power plants, and hydro-power plants. (Saturday, 2021). The world's power grid is growing rapidly, eventually resulting in the installation of a large number of new transmission and distribution lines. But that request has many limitations. The introduction of new marketing concepts such as deregulation has increased the need for a reliable and uninterrupted supply of electrical energy to end users who are highly sensitive to power outages. Adequate electricity supply is, therefore, an inescapable requirement for the development of every country, and generation, transmission, and distribution are capital-intensive and require enormous resources, both financially and in capacity (Sambo *et al.*, 2010).

Nigeria's energy sector is split into policy, regulatory, customer, and operational (Alao and Awodele, 2018). In addition, the operations department will uncover the activities of the Transmission Company of Nigeria (TCN), which manages the supply of highvoltage power from power plants to substations for transmission to distribution substations. The

Transmission Company of Nigeria (TCN) manages a 330 kV system capacity of 12,522 MW of electricity from existing power plants over a total distance of

5650 km, which is insufficient for a country of over 200 million people (Hatata *et al.*, 2016). Their focus is on maintaining power system stability, reliability, and sustainability. One of the most important factors preventing continuous power supply is a fault. Abnormal currents flowing through power system components can cause faults in network systems. These faults cannot be eliminated by the main protection systems currently in use. Since distance protection is dominant, it is subject to inaccuracies due to relay limitations on protection schemes that is, settings. These faults can also occur for natural reasons that are always beyond human control (Okwudili *et al.*, 2019).

In this regard, it is very important to have a well-coordinated protection system that detects any kind of abnormal flow of current in the power system, identifies the type of fault, and then accurately locates the position of the fault in the power system. The faults are usually taken care of by devices that detect the occurrence of a fault and eventually isolate the faulted section from the rest of the power system (Mbamaluikem *et al.*, 2018).

Therefore, the identification of faults on Transmission Lines (TL) plays an essential role in power system operation and control. It fulfills an important function in maintaining power system health and promotes the safety of power system operations. Furthermore, the accurate identification of faults forms the basis of power system protection along the transmission line, facilitates the speedy prognosis of power system faults, and ensures the diagnosis of failures related to power system components (Alayande, Okakwu, Olabode, and Nwankwoh, 2021).

Some of the important challenges for the incessant supply of power are the detection, classification, and location of faults. Faults can be of various types, namely transient, persistent, symmetrical, or asymmetrical faults and the fault detection process for each of these faults is distinctly unique in that, there is no one universal fault location technique for all these types of faults (Okwudili *et al.*, 2019). The High Voltage Transmission Lines are more prone to the occurrence of a fault than the

local distribution lines; thus, there are no insulators around the transmission line cables, unlike the service lines (Swain, Abdellatif, Mousa, & Pong, 2022). The fault on the power transmission line occurs due to the following interferences, such as thunderstorms, lightning strikes, heavy rains, heavy winds, and salt deposition on overhead lines and conductors (Su, Yaakob, and Ariffen, 2023). The automatic location of faults can greatly enhance the system's reliability because the faster we restore power, the more money and valuable time we save. Hence, many utilities are implementing fault location devices in their power quality monitoring systems that are equipped with Global Information Systems (GIS) for easy location of these faults.

This work brings to view the application of artificial neural networks for fault diagnosis of transmission lines with regards to fault detection, fault location, and application of the schemes as opposed to conventional approaches such as traveling wave approach and synchronous compensators (Yadav and Goad, 2021).

In this regard fault location techniques can be broadly classified into the following categories:

i. Impedance measurement-based methods ii. Traveling-wave phenomenon-based methods iii. High-frequency components of currents and voltages generated by faults-based methods

iv. Intelligence-based methods

Intelligent-based methods are being used in the process of fault detection and location. The three major artificial intelligence-based techniques that have been used in the power and automation industries are (Madueme and Wokoro, 2015):

i. Expert System Techniques ii.
Artificial Neural Networks iii.
Fuzzy Logic Systems

Among the intelligent-based techniques, Artificial Neural Networks (ANN) will be used vastly in this proposed work on fault diagnosis and maintenance of electric power transmission lines. These ANN-based methods do not require a knowledge base for the location of faults, unlike the other artificial intelligence-based methods. For this reason, the application of artificial neural networks to transmission lines is to ensure a steady supply of electric power and fault diagnosis in power systems to maximize the continuity of power supply (Okwudili *et al.*, 2019).

The identification of faults on Transmission Lines (TL) plays an essential role in power system operation and control. It fulfills an important function in maintaining power system health and promotes the safety of power system operations.

1.2 Statement of the Research Problem

Power system failure has been a critical problem in Nigeria as a result of faults along the transmission lines. The effect of the population increase in the country has increased commercial, industrial, and residential load outputs. Therefore, it is important to reduce the economic and social costs of any power outages and strengthen Nigeria's economic and development system.

1.3 Aim and Objectives of the Study

The aim of the research study is to conduct fault diagnosis using the Artificial Neural Network (ANN) approach to determine the application of artificial neural networkbased fault diagnosis on 330kv transmission lines: (a case study of the Gwagwalada-Katampe transmission line)

To achieve this aim, the following objectives are outlined:

i. To simulate the 330kV Gwagwalada-Katampe transmission line parameters to obtain fault data using Simulink; ii. To develop an intelligent single multi-fault classification model capable of detecting different kinds of faults in the 330kV Gwagwalada-transmission line; iii. To evaluate the performance of the artificial neural network-based fault diagnosis method.

1.4 Significance of the Research Study

This study is very significant because it develops an intelligent measure of detecting and classifying different kinds of faults in the 330KV transmission line. This will help power system engineers and distribution companies to prevent or minimize frequent power outages thereby improving stability.

1.5 Scope of the Research Study

This research work is centered on the Gwagwalada-Katampe transmission line power system.

CHAPTER TWO

2.0 LITERATURE REVIEW

This section presents the literature survey that provides an overview of the relevant areas and theoretical background to the work and reviews some literature relevant to transmission line faults.

2.1 Representation of Power Systems

A complete diagram of the power system representing all the three-phases becomes too complicated and cumbersome for a system of practical size, so much so that it may no longer convey the information it is intended to convey. It is much more practical to represent a power system using simple symbols for each component resulting in what is called a single-line diagram.

2.1.1 Single line diagram

A one-line diagram of a power network shows the main connections and layout of system components with data such as output power, voltage, resistance, and reactance. In additional case of transmission lines sometimes the conductor size and spacing are given to maintain electrical and mechanical integrity. Adequate spacing ensures that electrical insulation requirements are met and minimizes the potential for arcing and short circuits that would help to prevent corona discharge. It is not necessary to show all the components of the system on a single-line diagram, for example, Circuit breakers need to be shown in a load flow study but are required for a protection study. In a single-line diagram, the system components are usually drawn in the form of their symbols. Generators and transformer connections-star, delta, and neutral earthing are indicated by symbols drawn by the side of the representation of these elements. Circuit breakers are represented by rectangular blocks Figure 2.1 shows a one-line diagram of a typical power system. The ratings of generators, motors, and transformers are given below the diagram (Madueme and Wokoro, 2015).

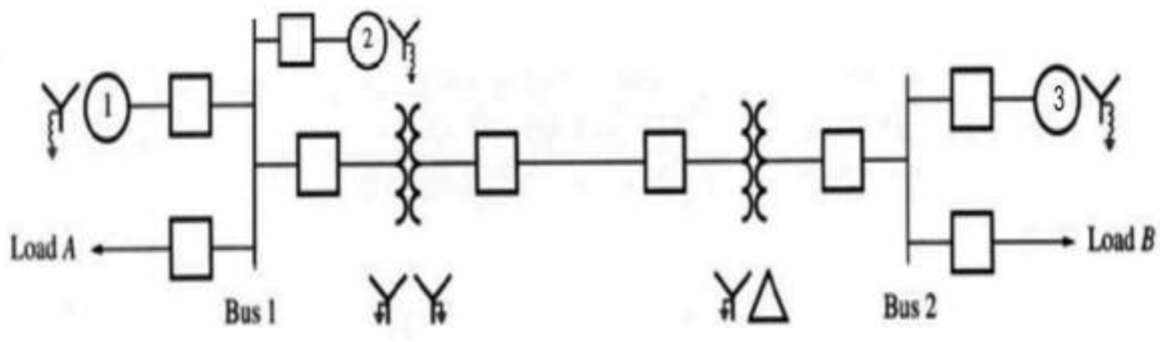


Figure 2.1: Single Line Diagram of a Power System

(Madueme and Wokoro, 2015).

2.1.2 Impedance diagram representation of a power system

Another simplification of the one-line diagram using symbols for the various components is to draw the diagram in terms of impedance only. The impedance diagram of the power system is shown in Figure 2.2. In the impedance diagram, each component is represented by its equivalent circuit, for example, the synchronous generator at the generating station by a voltage source in series with a resistance and reactance, the transformer by its equivalent circuit, and the transmission line by nominal-equivalent circuit. The load is assumed to be passive, contains no rotating machinery, and is represented by series resistance and inductive reactance. The neural ground impedance is not shown in the figure, as symmetrical conditions as assumed. (Madueme and Wokoro, 2015).

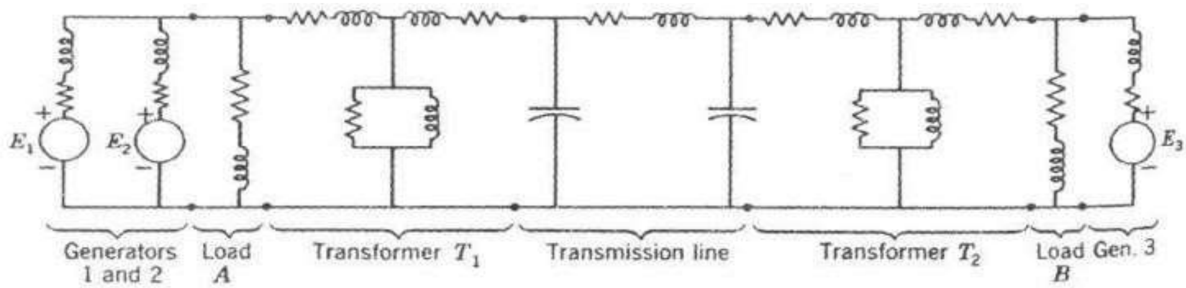


Figure 2.2: Impedance Diagram Representation of a Power System (Madueme and Wokoro, 2015).

The impedance diagram shown in Figure 2.2 is known as a positive sequence diagram since it is drawn for a balanced 3-phase system.

2.2 Artificial Neural Network

Artificial Neural Networks (ANNs) are mathematical computational models inspired by structural and/or functional aspects of biological neural networks. A neural network consists of a group of interconnected artificial neurons that process information using a connectionist computational approach. They are mostly adaptive systems that change their structure based on external or internal information flowing through the network during the learning stage (Kalu and Madueme, 2018). It is a system that closely models the human brain and attempts to achieve performance similar to that of humans in solving problems.

Breaking down what it is made up of, it is seen as a computational system made of a large number of simple and highly connected processing elements that process information by its dynamic state response to external inputs. Computational elements in ANN are non-linear and so the result that comes out through non-linearity can be more accurate than other methods of computation (Okwudili *et al.*, 2019). These nonlinear computational elements will be working in unison to solve specific problems. It is configured for specific applications such as data classification or pattern recognition through a learning process.

In other words, one type of network sees nodes as "artificial neurons" and is called an artificial neural network (ANN). An artificial neuron is an emulation of the biological nervous system. It is inspired by the natural neurons which receive signals through the synapse located on the dendrites or membrane of the neuron. When the received signal is strong enough to exceed a certain threshold, the neuron is activated and sends a signal to the axon. This signal is sent to another synapse and may activate other neurons. The complexity of real neurons is highly abstracted when modeling artificial neurons. These consist of inputs that are like synapses, which are multiplied by weights which are the strength of the respective signals, and then computed by a mathematical function that determines the activation of the neuron. Another function which may be the identity computes the output of the artificial neuron, sometimes dependent on certain thresholds of artificial neurons in the order confirmation.

The more weight of the artificial neuron, the stronger the input multiplied by it. But note that weights can also be negative, so we can say the signal is inhibited by the negative weight. And by adjusting the weights of an artificial neuron we can obtain the desired output of a specific input. This adjustment is done by algorithms designed to handle a large number of inputs in the network because it will be difficult to calculate weights of hundreds of thousands by hand in a particular network to get the desired output. This process of adjusting the Weight is called learning or training. Note that the various inputs to the network are represented by the mathematical symbols X(n). Each input is multiplied by the connection weights and these weights are denoted by W(n). In the simplest case, these products are simply summed, and fed through a transfer function to generate a result and then the output. Even though all artificial neural networks are constructed from these basic building blocks, the fundamentals may vary in these building blocks and there are differences in their performance behaviour (Kalu and Madueme, 2018).

2.2.1 Neural network design

A neural network element is the smallest processing unit of the whole network essentially forming a weighted sum and transforming it by the activation function to obtain the output. To gain sufficient computing power, several neurons are interconnected together. The manner in which the neural is connected together depends on the classes of neural networks. Basically, neurons are arranged in a parallel distributed architecture with many nodes and connections (Hatata *et al.*, 2016).

2.2.2 ANN architecture

The construction of neural Networks involves the following tasks.

i. Determination of network topology ii. Determination of system (activation and synaptic) dynamics

2.2.2.1 *Determination of the network topology*

A neural network's topology is related to both its framework and its connectivity scheme. The number of layers and the number of nodes per layer often specify the framework. The types of layers include (Hatata *et al.*, 2016):

Input Layer, where the nodes are called input units, which do not process information but distribute information to other units.

Hidden Layer(s), where the nodes are called hidden units, which are not directly observable. They provide the networks with the capability to map or classify nonlinear problems.

The Output Layer, where the nodes are called output units, encodes possible concepts (or values) to be assigned to the instance under consideration. For example, each output unit represents a class of objects. Another main important concept is the weight age for the connected unit. It can be real or integer numbers. They can be restricted to areas and adjusted during network training. When training is completed, all of them attain fixed values.

2.2.2.2 *Determination of systems (activation and synaptic) dynamics*

Network dynamics determine its behavior. ANNs can be trainable nonlinear dynamical systems. Neural dynamics consists of two parts one which corresponds to the dynamics of activation states and the other corresponding to the dynamics of synaptic weights.

The activation dynamics determine the time evolution of the neural activations. Synaptic activation determines the change in the synaptic weights. The synaptic weights form Long Term Memory (LTM) whereas the activation's state forms Short Term Memory (STM) of the network. Synaptic weights change gradually, whereas the neuron's activations fluctuate rapidly. Therefore, while computing the activation dynamics, the system weights are assumed to be constant. The synaptic dynamics dictate the learning process(Kalu and Madueme, 2018).

2.2.3 Features of artificial neural networks over other techniques

There are several attractive features of artificial neural networks over other techniques and they are mentioned below.

i. Their ability to represent non-linear relations makes them well-suited for nonlinear modeling in control systems.
ii. The adaptation ability and learning of artificial neural networks in uncertain systems through offline and online weight adaptation is highly remarkable.
iii. Parallel processing architecture allows fast processing for large-scale dynamic systems.

iv. A neural network can handle a large number of inputs and can have many outputs
v. Artificial neural networks can store knowledge in a distributed fashion and consequently have a high fault tolerance.

2.2.4 Advantages of artificial neural networks (ANNs)

i. A neural network can perform tasks that a linear program cannot.

ii. When an element of the neural network fails, it can continue without any problem of its parallel nature.

iii. A neural network learns and does not need to be reprogrammed iv. It can be implemented in any application

v. It can be implemented without any problem.

2.2.5 Disadvantages of artificial neural networks (ANNs)

i. The neural network needs training to operate.

ii. The architecture of a neural network is different from the architecture of microprocessors therefore needs to be emulated.

iii. Requires high processing time for large neural networks.

2.2.6 Learning paradigms (LP)

The main learning paradigms are reinforcement learning, unsupervised learning, and supervised learning corresponding to a specific abstract learning task.

2.2.6.1 *Supervised learning (SL)*

Supervised learning is a process that incorporates external guidance. In supervised learning, a training pair consists of an input vector and a desired target vector. The difference constitutes an error that is used to modify network weights in a manner that reduces the error in subsequent training cycles. These techniques include deciding when to turn off the learning, how long and how often to present each association for training, and supplying performance error information. Supervised learning is further classified as Structural learning / temporal learning. Structural learning encodes correct autoassociations (single-pattern vectors) or hetero-association vectors of pattern pairs that map onto the weight matrix W. Temporal learning encodes a sequence of patterns necessary to achieve the fit come.

2.2.6.2 *Unsupervised learning*

In unsupervised learning, there is no target vector. Input vectors are applied to the network and the system "organizes itself" to produce consistent outputs (presumably unpredictable before training). During the training phase, the weights of the ANN stabilize and testing an unknown pattern yields an output without the time lag of the learning phase. Recall or test depends on network interconnection. In a feed-forward network, the network provides a single-pass output, allowing signal flow in only one direction from the input to the hidden and output layers. In feedback networks, signals can flow bidirectionally or recursively between neurons. The most commonly used rules for learning include Hebb's rule and delta rule for single-layer (perceptual) ANNs and the back-propagation algorithm for multi-layer (perceptual) ANNs.

Thus, its architecture, its processing algorithm, and its learning algorithm characterize a neural network. The architecture specifies the way the neurons are connected. The processing algorithm specifies how the neural network with a given set of weights calculates the output vector for any input vector (Rathore, Mahela, Khan, Alhelou, and Siano, 2020). The learning algorithm specifies how the network adapts its weights for all given vectors.

2.2.6.3 *Reinforcement learning*

In reinforcement learning, data is usually not given but is generated by the interaction of the agent with the environment. At each point in time, the agent acts and the environment generates an observation and an instantaneous cost, according to some (usually unknown) dynamics. The aim is to discover a policy for selecting actions that minimize some measure of a long-term cost; that is., Expected total cost. The environment's dynamics and the long-term cost of each policy are usually unknown but can be estimated.

More formally, the environment is modeled as a Markov decision process (MDP) with states and actions with the following probability distributions: the instantaneous cost distribution P(ct |st), the observation distribution P(tx |st), and the transition P(c_(t+1) |st, at), while a policy is defined as a conditional distribution over actions given the observations. Taken together, the two define a Markov chain (MC). The goal is to find a policy that minimizes the cost; that is., the MC for which the cost is minimal. ANNs are frequently used in reinforcement learning as part of the overall algorithm (Udofia and Nnekwukalu, 2020).

2.3 Faults in the Power System

Faults are inevitable in the electrical power system. They can be detected and cleared very fast if the system has a good protection scheme to avoid damage to the electrical equipment (Thwe and Oo, 2016) . The probability of fault occurring on a transmission line is quite large as it is exposed to environmental conditions. The various types of faults occurring on a transmission line are single line-to-ground faults (L-G), double line-to-ground faults (LL-G), line-to-line faults (L-L), and triple lines-to-ground faults (three phases) (Olutoye and Ezechukwu, 2019). These faults are divided into two main types namely, unbalanced and balanced faults.

2.3.1 Symmetrical fault condition

Balanced fault or symmetrical fault is a fault that occurs in the power system and gives rise to a symmetrical current or short circuit current. A typical scheme is shown in Figure 2.3.

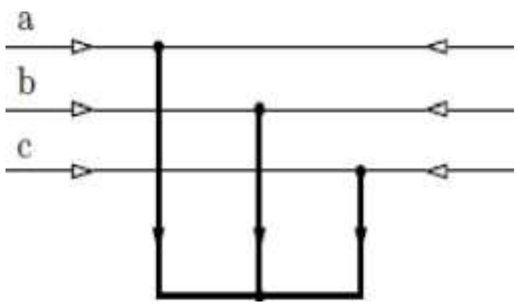


Figure 2.3: Balanced Three-Phase Faults

(Olutoye and Ezechukwu, 2019)

This type of fault occurs when all three conductors' three-phase currents are shorted simultaneously. Because of the balanced nature of this type of fault, only one phase will be considered in the calculation since the phase fault currents are equal in magnitude with 120° displacement among them (Alayande *et al.*, 2021).

The most important parameters needed for the symmetrical fault calculation, the setting of the protective relays and circuit breakers responsible for the tripping, isolation of the faulted line, and for regular operational planning are; the symmetrical fault current (short circuit current, I) and fault impedance, Zf To avoid damage to equipment, the short circuit current has to be reduced by increasing the impedance on the line between the feeder and point of location of the fault (Ogboh and Madueme, 2015).

2.3.1.1 ***Symmetrical component analysis***

The phasors of an unbalanced three-phase system are described by their equilibrium components as shown in the following equations.

$$= {}_1 + {}_2 + {}_0 \tag{2.1}$$

$$= {}_1 + {}_2 + {}_0 \tag{2.2}$$

$$= {}_1 + {}_2 + {}_0 \tag{2.3}$$

Then the phasors of the symmetrical system in terms of phase 'A' symmetrical component are:

$$= {}_1 + {}_2 + {}_0 \tag{2.4}$$

$$= {}^2{}_1 + {}_2 + {}_0 \tag{2.5}$$

$= {}_1 + {}^2{}_2 +$ (2.6)

Matrix $\left| \quad \right| = \left| \begin{matrix} 1 & 1 & 1 \\ 1 & {}^2 & \\ & & {}^2 \end{matrix} \right| \left| \begin{matrix} {}_0 \\ {}_0 \end{matrix} \right|$ form,(2.7) 1 $\quad {}_0$

However, these symmetrical component values of currents and voltages are the solution to the unsymmetrical fault problems on the transmission line.

1 1 [1 1 1] (2.8) [0 1 2]

= 2] 2

01 1 $\frac{1}{3}$ [1 2] [ ]

1 = 1] 2 (2.9)

21

V1] 1 [1 1 1] [0 1 2]

V_b = 2 (2.10)

V_c 2

] = $\frac{1}{3}$ [01 1 1 2] [V V_b V_c]

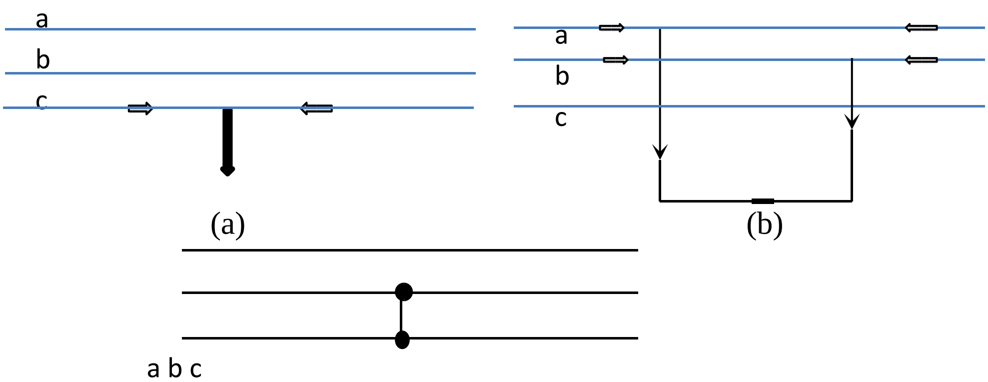
11 (2.11)

21 2

Henceforth, the symmetrical components of the unsymmetrical fault currents and voltages can be determined using equations 2.8 to 2.10.

2.3.2 Unsymmetrical fault conditions

The symmetrical component condition is used for unsymmetrical (unbalanced) fault analysis on power systems. The majority of faults in the power system are asymmetrical in nature. These include; one-line-to-ground, double-line-to-ground, and line-to-line faults. Figure 2.4 shows these types of unsymmetrical faults (Phyu, 2019).



(a) (b)

(c)

Figure 2.4: Unsymmetrical Fault Type (a) Single line-to-ground fault

(b) Double line to-ground fault (c) Line-to-Line fault

When unsymmetrical faults occur on the transmission line, it gives rise to an unsymmetrical current. This means that the magnitude of fault currents in the three lines are different, having unequal phase displacement.

To calculate and find the line parameters (unsymmetrical fault currents, impedance fault, line currents, and voltages) both before and after the fault, the symmetrical component method is used.

Every unbalanced system of three-phase currents and voltages is regarded as composed of three separate sets of balanced vectors.

This means that;

i. A balanced three-phase sequence current has a positive phase sequence component.

ii. A balanced three-phase sequence current has a negative phase sequence component.

iii. A system of three-phase currents equal in magnitude has zero phase displacement and is called zero phase sequence components. The positive, negative, and zero sequences components are the symmetrical components of the original unbalanced system (Ogboh and Madueme, 2015).

2.3.2.1 *Single line-to-ground fault*

In general, single-phase-ground faults occur transmission lines when the conductor falls to earth or touches the neutral conductor. These types of failures can occur in power systems for many reasons, including B. High winds, falling of trees, lightning strikes, etc.

Suppose phase **a** is connected to the ground at the fault point F as shown in Figure 2.5 below. I_a, I_b, and I_c are current, and V_a, V_b, and V_c are the voltage across the three-phase lines a, b, and c respectively. The fault impedance of the line is Z_f.

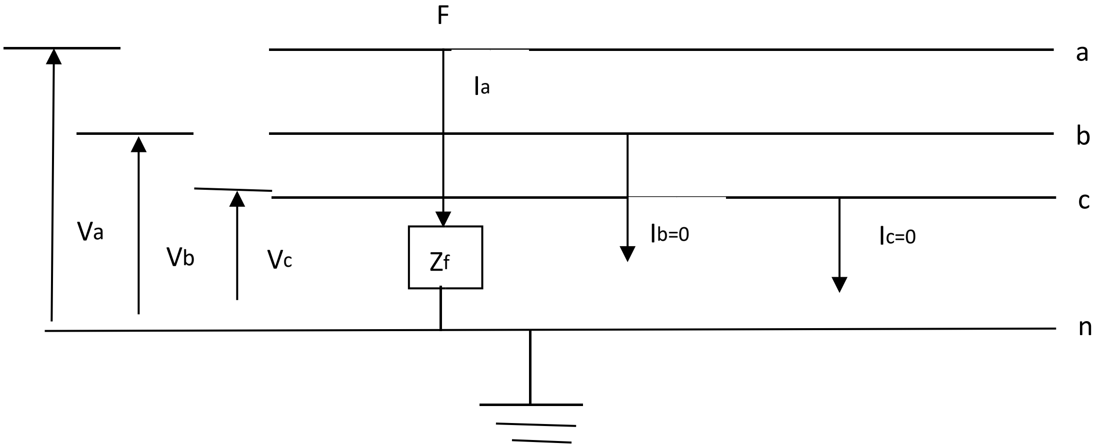


Figure 2.5: Single Line-to-Ground Fault

Since only phase a is connected to the ground at the fault, phases b, and c are opencircuited and carry no current; that is fault current is I_a and $I_b = 0$, $I_c = 0$. The voltage at the fault point F is $V_a = Z_f I_a$.

The symmetrical component of the fault current in phase "a" at the fault point can be written as

$a = 13 \mp (+ = 13 + 0) + 0 - (\quad) = 13$ (2.12)

$1 = 31 \mp (+ 2 = 13 \quad) \quad - (\quad + 0 + 0 \quad) = 13$ (2.13)

1 (2.14)

$2 = 3 \mp 2 + 1 = 13 + 0 + 0 \quad - (\quad) = 13$

$$\begin{bmatrix} \\ \\ \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} {}_0 \\ {}_1 \\ {}_2 \end{bmatrix} = \frac{1}{3}\begin{bmatrix} \\ \\ \end{bmatrix}$$

$$\Big]\begin{bmatrix} {}_0 \\ {}_1 \\ {}_2 \end{bmatrix}$$

$$1\ {}_2\Big]\begin{bmatrix} \\ \\ \end{bmatrix}$$

(2.15)

$a = {}_1 = {}_2 = 13$

This relation can also be found by matrix method as follows: -

$$1 \quad 1 \quad {}_2 \quad {}_2 \qquad (2.16)$$

$$1 \quad 1 \quad 1 \quad 1 \quad {}_2 \qquad (2.17)$$

$$1\begin{vmatrix} {}_0 \\ {}_1 \end{vmatrix} = {}_3\begin{vmatrix} 1 \\ 1 \end{vmatrix} a = {}_1 = {}_2 = {}_3 \qquad (2.18)$$

$${}_2 \quad 1$$

In the case of a single line-to-ground fault, the sequence currents are equal.

The sequence voltage at the fault point is determined by the equations:

$$_0 = _0 - _0 _0 \quad (2.19)$$

$$_1 = _1 - _1 _1 \quad (2.20)$$

$$_2 = _2 - _2 _2 \quad (2.21)$$

Where, E_{a0}, E_{a1}, and E_{a2} are the sequence voltages of phase a, and Z_{a0}, Z_{a1}, and Z_{a2} are the sequence impedances to the flow of currents I_{a0}, I_{a1}, and I_{a2} respectively. For a balanced system

$_0 = 0$, $_2 = 0$, $_1 =$ (2.22) We know that:

$$= _0 + _1 + _2 \quad (2.23)$$

$$_0 = _0 - _0 _0 \quad (2.24)$$

$$_1 = -_0 + - _1 _1 - _2 _2 \quad (2.25)$$

On substituting the $_a = _1 = _2 =$ in above equation we get,

$$= - 3 (_0 + _1 + _2) \quad (2.26)$$

$$= + 3 (_0 + _1 + _2)$$

$$= + \frac{1}{3} \left[_0 + _1 + _2 \right]$$

$$= \frac{1}{\left[+ 3 (_0 + _1 + _2) \right]} \quad (2.27)$$

The sequence current is given by the equation,

$$3_a = 3_1 = 3_2 = \frac{1}{\left[+3\ 0+ -\left(1+2\qquad\right)\right]} \tag{2.28}$$

$$_a = _1 = _2 = \frac{1}{3\times\left[+3\ 0+ -\left(1+2\qquad\right)\right]}$$

$$_a = _1 = _2 = \overline{\left[3+\ 0+\left(1+2\qquad\right)\right]} \tag{2.29}$$

2.3.2.2 ***Line-to-line fault (L-L)***

A line-to-line fault or unsymmetrical fault occurs when two conductors are shortcircuited. Figure 2.6 shows a three-phase system with line-to-line fault phases b and c. where the fault impedance is Zf. The LL fault is placed between lines b and c so that the fault is symmetrical with respect to the reference phase a which is un-faulted.

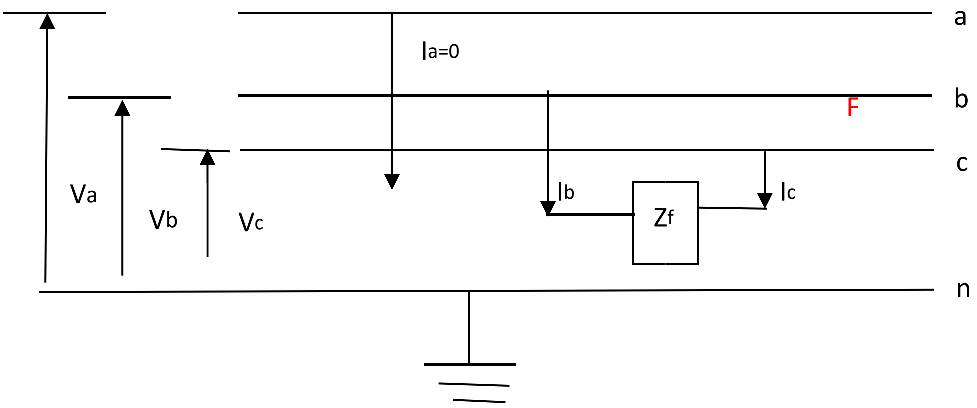


Figure 2.6: Line-to-Line Fault

The symmetrical components of a fault current in phase **‘a’** at the fault point can be divided into three components. The zero-sequence component of current at phase a is

$$_a = \frac{1}{3}\left(\ + +\ 0\right) = \frac{1}{3}\left(\ + -\right) \tag{2.30}$$

For the Positive sequence component of phase a, I_b = -I_c is expressed as

$$-(\quad {}_1 = {}^1{}_3 + + {}_2) = \frac{1}{3}(0 + - {}_2) = \frac{1}{3}(- {}_2) \qquad (2.31)$$

and the negative sequence component of phase a is given by the equation,

$$-(\quad) \quad -(\quad {}_2 = {}_{13} + {}_2 +) = \frac{1}{3}(0 + {}_2 - = {}_{31}\,{}_2 -) \qquad (2.32)$$

The sequence current can also be found by matrix method

$$\begin{bmatrix} {}_0 \\ {}_1 \end{bmatrix} = {}_1 1 \tfrac{}{2} {}_2\, {}_3 \begin{bmatrix} 1 & 1 & 1 \\ 1 & {}^2 & \end{bmatrix} \begin{bmatrix} \\ \end{bmatrix}$$

$$\begin{bmatrix} {}_0 \\ {}_1 \\ {}_2 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \\ 1 & & {}_2 \\ 1 & & \end{bmatrix} \begin{bmatrix} 0 \\ \\ \end{bmatrix} \qquad {}^2(2.33)$$

Therefore, we get

$${}_a = 0 \quad \text{and} \quad {}_1 = - {}_2 \qquad (2.34)$$

Expressing V_a, V_b and V_c regarding voltages at the fault point are found by the relations given by

$$({}_0 + {}_{21} + {}_2 - \quad) \quad (\quad {}_0 + {}_1 + {}_{22}) = ({}_0 + {}_{21} + {}_2) \qquad (2.35)$$

Combination of equation (2.30), (2.34) and (2.35) gives

$$({}_2 -)_1 - ({}_2 -)_2 = ({}_2 -)_1 \qquad (2.36)$$

$${}_1 - {}_2 = {}_1 \qquad (2.37)$$

The sequence current of voltage at the fault point are determined by the relations shown below

$$\begin{vmatrix} 0 \\ 1 \\ \end{vmatrix} = \begin{vmatrix} 0 \\ 1 \\ \end{vmatrix} - \begin{vmatrix} 0 & & \\ 0 & 1 & 0 \\ 0 & 0 & \end{vmatrix} \begin{vmatrix} 0 \\ 1 \\ \end{vmatrix} \begin{vmatrix} 0 \\ 1 \\ \end{vmatrix} \quad 0 \quad 0 \qquad (2.38)$$

$$2 \quad 2 \quad 2 \quad 2 \quad 2$$

$$0 = - \ 00 \qquad (2.39)$$

$$1 = - - \ 11 \qquad (2.40)$$

$$2 = - \ 22 \qquad (2.41)$$

From equation (2.40) and (2.41) we get

$$1 - 2 = - \ 11 + 22 \qquad (2.42)$$

Combination of equation (2.34), (2.41) and (2.42) gives

$$1 = - \ 11 + 22$$

$$= 11 + 21 + 1 = (1 + 2 +)1$$

$$1 = \frac{}{(1+2+)} \qquad (2.43)$$

The fault current is given by the equation

$$= \frac{(2 -)}{(1+2+3)} \qquad (2.44)$$

From equation (2.30) it is clear that the line-to-line fault the zero-sequence component of current I_{a0} is equal to zero. Equation (2.34) shows that the positive-sequence component of current is opposite in phase to the negative-sequence component of current.

2.3.2.3 ***Double line-to-ground fault (LLG):***

Figure 2.7 shows a Double Line-to-Ground Fault at *F* in a power system. The fault may in general have an impedance Z^f as shown.

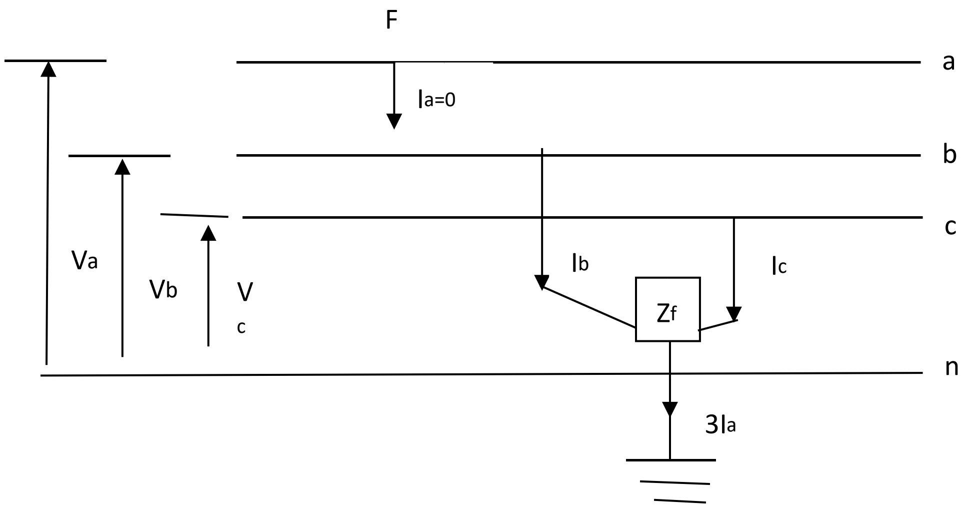


Figure 2.7: Double Line-to-Ground (LLG) Fault Through Impedance Z_f

The current and voltage (to ground) conditions at the fault are expressed as

$$= 0, \qquad {}_1 + {}_2 + {}_0 = 0 \tag{2.45}$$

$$= = (+) = 3_0 \tag{2.46}$$

The symmetrical components of voltages are given by

$$\begin{bmatrix} 0 \\ 2_1 \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \; V \\ 1 & 1_2 & ^2 VV_{bc} \end{bmatrix}\begin{bmatrix} \\ \end{bmatrix} \tag{2.47}$$

from Equation 2.11 it follows that:

$1 = 2 = 13 - [\quad (\quad + 2) \quad]$ (2.48a)

$_0 = \frac{1}{}[3 + 2]$ (2.48b)

From Equations. 2.48a and 2.48b

$0 - 1 = 13\,2 - [- 2] = 3_0.$

$_0 = 3_0 + 1$ (2.49)

From Equations. 2.45, 2.48a, and 2.49, we can draw the connection of sequence networks as shown in Figures. 2.8 a and b. The reader may verify this by writing mesh and nodal equations for these Figures.

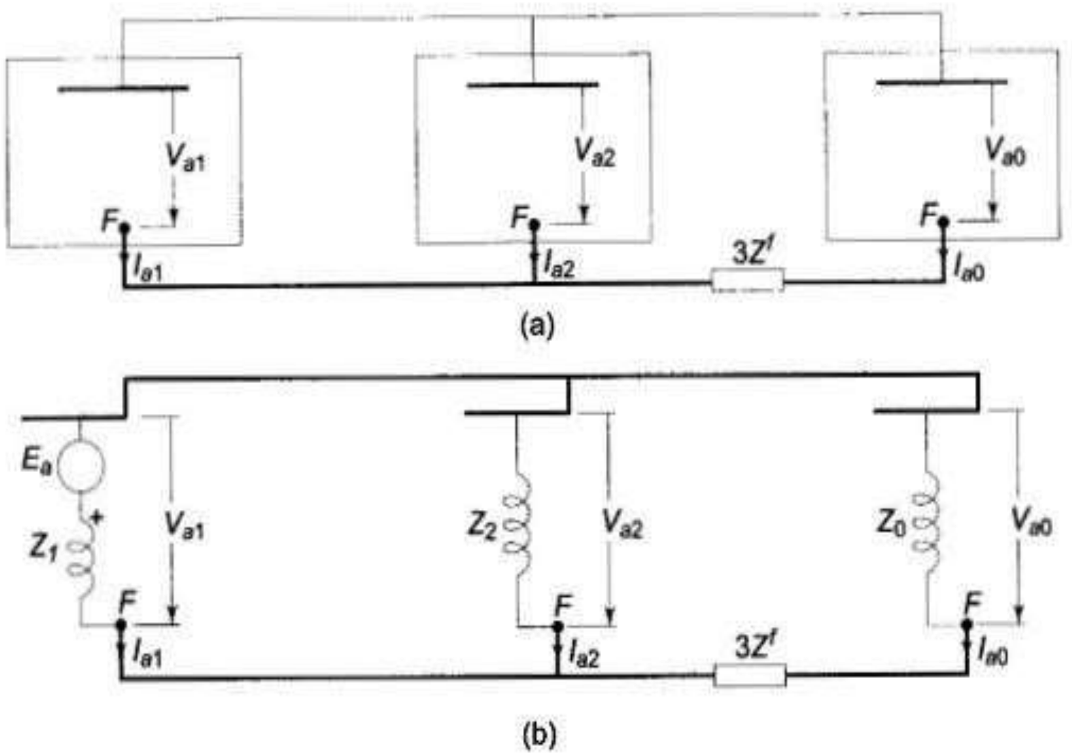


Figure 2.8: Connection of Sequence Networks for a Double Line-to-Ground (L-L-G) Fault

In terms of the Thevenin equivalents, we can write from Figure. 2.8b

$$1 = \overline{\qquad\qquad} 1+2//(0+3) \qquad (2.50)$$

$$1 = \overline{1+2(+3)/(2+0+3)} \qquad (2.51)$$

The above result can be obtained analytically as follows:

Substituting for V_{a1}, V_{a2}, and V_{a0} in terms of E_a in Equation 2.37 and pre-multiplying both sides by Z^{-1} (inverse of sequence impedance matrix), we get

$$0\begin{vmatrix} 1 & 0 & 0 \\ 0 & -21 & 0 \\ 0 & 0 & -1 \end{vmatrix} \begin{vmatrix} -11 \\ -11 \\ -11+30 \end{vmatrix} = \begin{vmatrix} -1 & -11 & \\ 0 & -21 & \\ 0 & 0 & -010 \end{vmatrix} \begin{vmatrix} 0 \end{vmatrix} - \begin{vmatrix} 1 \\ 2 \end{vmatrix} \; 0 \; 0 \qquad (2.52)$$

Pre multiplying both sides by row matrix [1 1 1] and using Equations 2.45 and 2.46, we get

$$\frac{-3}{0}0 \left(+1+\frac{1}{0}\right)\frac{11}{20}\left(-\frac{1}{2}\right)+1= + \qquad (2.53)$$

From Equation (2.48a), we have

$$-11 = -22. \qquad (2.54)$$

Substituting $\quad 2 = -(1+0).$ $\qquad (2.55)$

$$-11 = -2(1+0). \qquad \text{Or} \qquad 0 = \frac{2}{-}\left(\frac{1}{1+2}\frac{2}{1}\right). \qquad (2.56)$$

Substituting this value of I_{a0} in Equation 2.53 and simplifying, we finally get

$$1 = \overline{1+2(+3)/(2+0+3)}. \qquad (2.57)$$

2.4 Review of Related Works

There are different methods which can be employed for fault diagnosis on the power system transmission lines. Among these methods, the use of Artificial Intelligence is prevalent, accurate and fast. Among the artificial intelligence systems is the Artificial Neural Network (ANN), whose its application diagnosis is in three categories, fault detection, fault classification, and fault isolation (Ogboh and Madueme, 2015).

(Akhikpemelo *et al.*, 2019) performed fault detection on 132 kV transmission lines using ANNs. The system was examined by a feed-forward network with a backpropagation algorithm in the recognition process for the Uyo to Eket 132kV transmission line using MATLAB software. The result obtained showed that the trained network with hidden layers architecture (15 15 10 5) has the best performance with mean square error (MSE) value of 0.000145 and correlation coefficients for validation and testing of 0.99998 and 0.99953 respectively (Akhikpemelo *et al.*, 2019). However, the result did not reveal the point at which the fault in the transmission line occurred.

(Ferdous, 2018), examined the zone protection system of a transmission line by distance relay using MATLAB/SIMULINK. The digital computation of impedance uses symmetrical components of three-phase currents and voltages measured at the local end only based on MATLAB and Simulink. The study revealed that the impedance of the faulty line reduces to a zero value approximately where the impedance of the remaining healthy lines B and C was 103Ω while the impedance of the faulty line A from 91Ω to a lower value of 38 Ω due to the fault and impedance of line B and C remain same (Ferdous, 2018). However, the study did not use a single multi-fault classifier model.

(Hatata *et al.*, 2016) studied the transmission line protection scheme for fault detection, classification, and location using Artificial Neural Network. The authors utilized a multi-layer feed-forward neural network algorithm (MFFNN), which is based on MATLAB. The results demonstrate the ability of MFFNN to generalize the situation from the provided patterns and accurately indicate the presence of the fault and locate it (Hatata *et al.*, 2016). However, the study failed to show the time at which the MFFNN indicated the presence of a fault and where it was located.

(Jamil *et al.,* 2015) examined fault detection and classification in electrical power transmission systems using the Artificial Neural Network (ANN) system. The simulation method based on neural networks is efficient in detecting and classifying faults in the transmission by measuring voltage, current, and the processing of data. The simulation results concluded that the method based on the neural network is efficient in detecting and classifying the faults on transmission lines with satisfactory performances (Jamil *et al.*, 2015). However, the study considered only line-ground transmission networks, while other classifications were not considered.

(Madueme and Wokoro, 2015) utilised a cascade, multi-layer ANN structure using the back-propagation (BP) learning algorithm, the findings indicated that the fault diagnostic system accurately identifies high impedance faults, which are relatively difficult to identify with other methods. However, the study failed to use an intelligent single multi-fault classification model for accuracy and a fast diagnostic system (FDS).

(Mbamaluikem *et al.*, 2018) carried out an intelligent fault classification system for the 33-kV Nigerian transmission line using an artificial neural network. The simulation results have been provided to demonstrate the efficiency of the developed intelligent systems for fault detection and classification on the lines. The performance of the detector-classifier is evaluated using mean square error (MSE) and the confusion matrix; the systems achieved an acceptable MSE of 0.00004279. Showing that the performance of the developed intelligent system is satisfactory and better in comparison with other systems in the literature concerning Nigeria transmission lines (Mbamaluikem *et al.*, 2018). However, an intelligent multi-fault classification model for fault classification occurrence was not considered.

(Udofia and Nnekwukalu, 2020) works on fault detection, classification, and location on 132kV transmission line based on discrete wavelet transform (DWT) and adaptive neuro-fuzzy inference system (ANFIS). The system used simulation investigations and the result revealed that the fault classifications scheme was able to discriminate between actual fault cases from the normal condition in a maximum time of eight milliseconds after fault inception (Udofia and Nnekwukalu, 2020); however, the study did not show the faults at different phases of the fault scenario.

(Ogboh and Madueme, 2015) used artificial neural networks (ANNs) to investigate transmission line faults in the Nigerian power system. He used the ANN method for fault diagnosis on the 132kV transmission line from Enugu - Otukpo - Yandev. The results indicate that three lines – ground, three lines – lines, three double lines – ground, and one three-phase fault occurred in the system. Performance graphs and the regression analysis graphs of output versus target were used to test the accepted ANN. They also show the convergence of the network output with respect to the target values, the best line of fitting for fault detection, and the best pattern recognized for fault classification of the network (Ogboh and Madueme, 2015). However, an intelligent multi-fault classification model was not used to reveal the faults at the time.

(Okwudili *et al.*, 2019) examined the fault diagnosis using an artificial neural network method for fault detection on transmission. Two versions of parameters were used to train and simulate the ANN network architecture selected for each stage of the detection.

The simulation results show that the demonstrated ANN-based methods are efficient in detecting faults on the transmission lines and the three-line-ground, three-line-line, three double line-ground, and one three-phase fault in the transmission lines diagnosed satisfactorily (Okwudili *et al.*, 2019). However, the inter-fault distance was not considered.

(Padhy *et al.*, 2018) employed Artificial Neural Network (ANN) in a transmission line and for the fault detector and classifier, a back-propagation algorithm was used. The modeling of the transmission line was done by using MATLAB and Simulation result showed the efficiency of the proposed method in a transmission line (Padhy *et al.*, 2018). However, the study did not disclose the estimated level of efficiency in each of
the fault classifications.

(Resmi *et al.*, 2019) examined the detection, classification, and zone location of faults in transmission lines using the Artificial Neural Network (ANN) algorithm. The power system study was simulated using load flow analysis and short circuit analysis to detect unsymmetrical faults, classify the fault type and locate the fault zone in the transmission lines, the system was capable of identifying line-to-ground faults, line-to-line faults, and double-line-to-ground faults, and indicating the zone in which the fault has occurred. By obtaining the regression plot of the ANN classifier, there is a very good relationship established between the output and the target, only after 6500 epochs this, shows that the developed algorithm is able to locate and detect the fault in the system accurately (Resmi *et al.*, 2019). However, the findings did not consider the distance between each
fault classification detected.

(Rosle *et al.*, 2020) carried out fault detection and classification in three-phase series compensated transmission lines using Artificial Neural Network (ANN). The ANN model was successfully developed to localize and classify the fault in the three-phase power transmission line. The results obtained show that ANN can accurately detect the different types of faults and classify them into the respective category even if the random vectors on the system are used (Rosle *et al.*, 2020). However, the study did not consider the distance along the transmission line.

The authors carried out fault detection, classification, and estimation of fault location on an overhead transmission line using an S-transform and neural network. The features extracted from ST were given to ANN for training, and subsequently, it is tested for effective classification. The results obtained show satisfactory accuracy and the effect of noise on both the current and voltage signals was investigated (Roy and Bhattacharya, 2015). However, the study did not consider all fault scenarios such as line-line fault, line-line-ground fault, and three-phase fault.

The authors examined the transmission line fault analysis, using artificial neural networks for fault detection, classification, and location of faults in an interconnected power system. The network was modeled and simulated in the MATLAB/Simulink environment and revealed that: the operation of ANN shows proficiency as its capability to classify fault type and architecture of ANN is found to be accurate, reliable, and effective for the problem of detection, classification, and location of the faults. Thus, the performance of the detector and classifier was evaluated using a regression plot and error histogram from the system (Sidhu *et al.*, 1995). However, the study did not use an intelligent Single multi-fault classification model to examine the distance of the fault along the transmission line.

The authors study the detection and classification of transmission line fault using Discrete Wavelet Transform (DWT) and Artificial Neural Networks as classifiers, the study made use of Wavelet Toolbox of MATLAB software for acquiring the various parameters like the presence of harmonic and over-voltage, the results showed that the faulted waves of current and voltages can be observed during line to a fault (Taywade and Ghute, 2016). However, the study did not consider other power system protection such as a differential relay.

The authors examined the fault detection and classification for transmission line protection systems using Artificial Neural networks (ANN). The study employed a feed-forward neural network along with a back-propagation algorithm. The ANN was trained and tested using various sets of field data, which was obtained from the simulation of faults at various fault scenarios (fault types, fault locations, and fault resistance) of 230kV, 193.2km in length “Mansan-Shwesaryan, Mandalay Region, Myanmar” transmission line using a computer program based on MATLAB/Simulink. Simulation results confirm that the proposed method can efficiently be used for accurate fault classification on the transmission line (Thwe and Oo, 2016). However, the study examined fault scenarios, such as fault types, fault locations, and fault resistance without reference to the computational speed as an index of the ANN performance.

The authors examined the fault classification for protective relaying, using Artificial Neural Network (ANN) via wavelet analysis; the proposed algorithm was tested on 400kV two-terminal transmission lines simulated using MATLAB/SIMULINK. The PSO-based multi-layer perceptron neural network fault classification is capable of producing fast and more accurate results taken from the simulation studies when combined with a wide area monitoring system that would be an effective tool for detecting and identifying the faults in any part of the system. The performance of the proposed technique is analyzed by comparing the fault classification results with the original Back-Propagation Neural Network (BPNN) method for the same test data considering wide variations in the operating conditions (Upendar *et al.*, 2010). However, the results did not consider using an intelligent multi-fault classification model for each fault classification.

The authors examined the detection, classification, and transmission line's fault using Wavelet Transform and Artificial Neural Network, the study used the Wavelet Transform two types of neural network architectures as analysis tools, and the results obtained showed the validity of the proposed methodology (Wani *et al.*, 2018). However, the study did not disclose the nature of the fault type that was detected.

(Warlyani *et al.*, 2011) carried out fault classification and faulty section identification in Teed transmission circuits using Artificial Neural Network (ANN). The algorithm uses the voltage and current signals of each section measured at one end of the teed circuit to detect and classify double-line to ground faults. The result shows better performance indicating that the neural networks-based approach is an improvement on the conventional fault selection algorithm (Warlyani *et al.*, 2011). However, the study did not reveal the other faults for the different scenarios to be detected.

The authors examined transmission line fault distance and direction estimation using Artificial Neural networks (ANN). The study used the voltage and current available at only the local end of the line based on simulation using MATLAB and the results showed that single phase-to-ground faults (both forward and reverse) can be correctly detected and located one cycle after the inception of fault (Yadav and Thoke, 2011).

However, the study did not consider double-line to ground.

2.5 Summary of the Literature Review

Among the gaps established from the literature are non-consideration of fault occurrence time, inter-fault distance, intelligent single multi-fault classification model for all faults, and evaluation of the performance accuracy of the artificial neural network-based fault diagnosis method. It is pertinent to address these gaps in order to achieve very fast and accurate fault diagnostic processes. It is on this premise that the present work considers an intelligent single multi-fault model for all faults detection, classification, and conceptualization of the artificial neural network for the applications to the 330kV transmission line. This will be made possible through the use of the artificial neural network approach.

CHAPTER THREE

3.0 MATERIALS AND METHOD

This chapter describes the Gwagwalada 330kV Transmission Line and its Parameters, the development and utilization of algorithms of ANN that make predictions based on input data obtained from the simulations carried out using Simulink in the MATLAB environment. This powerful tool proved effective in predicting various fault detection, classification and optimal performance evaluation of the Gwagwalada-Katampe transmission lines power network.

3.1 Materials (The Gwagwalada 330kV Transmission Line and its Parameters)

Transmission Company of Nigeria 330/132/33***k*** substation Gwagwalada, Abuja is one of the most important components of the power substation, which connects the generating station with the distribution system. It has four transmission lines LokojaGwagwalada line 1 and line 2, Shiroro-Gwagwalada line 3, and Gwagwalada-Katampe line 4 that are all connected with turn-in and turn-out bus-bar arrangement as shown in the schematic representation of the single-line diagram of Figure 3.1.

The Gwagwalada-Katampe 330kV line was considered in this study due to the availability of data. The various types of faults occurring on this transmission line are single line-to-ground faults (L-G), double line-to-ground faults (L-L-G), line-to-line faults (L-L), and triple line-to-ground faults (Three-phase).

The purpose of a protective relay is to clear the fault as quickly as possible by opening and closing contacts electrically or mechanically**,** minimizing the damage caused by the fault, and restoring the line quickly. As a result of this, it is important to understand the nature of the fault that occurred in the line and its exact location.

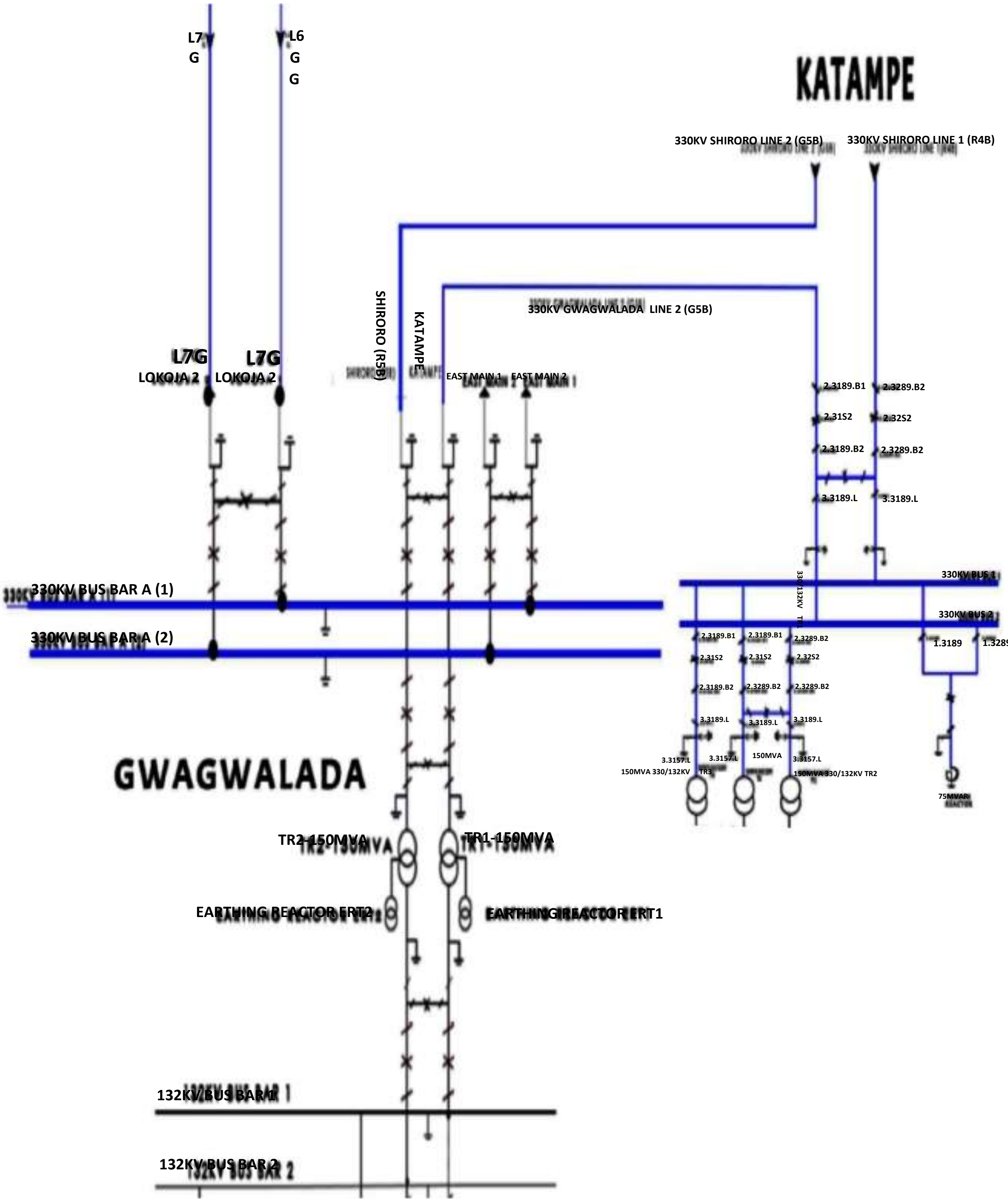


Figure 3.1: Single Line Diagram of the 330kV Gwagwalada Transmission Company

3.2 Method

Due to the variety of fault scenarios imminent in power systems, the artificial neural network (ANN)-based fault diagnosis of 330kV transmission lines performed in this study is summarized as represented by the flow diagram shown in Figure 3.2.

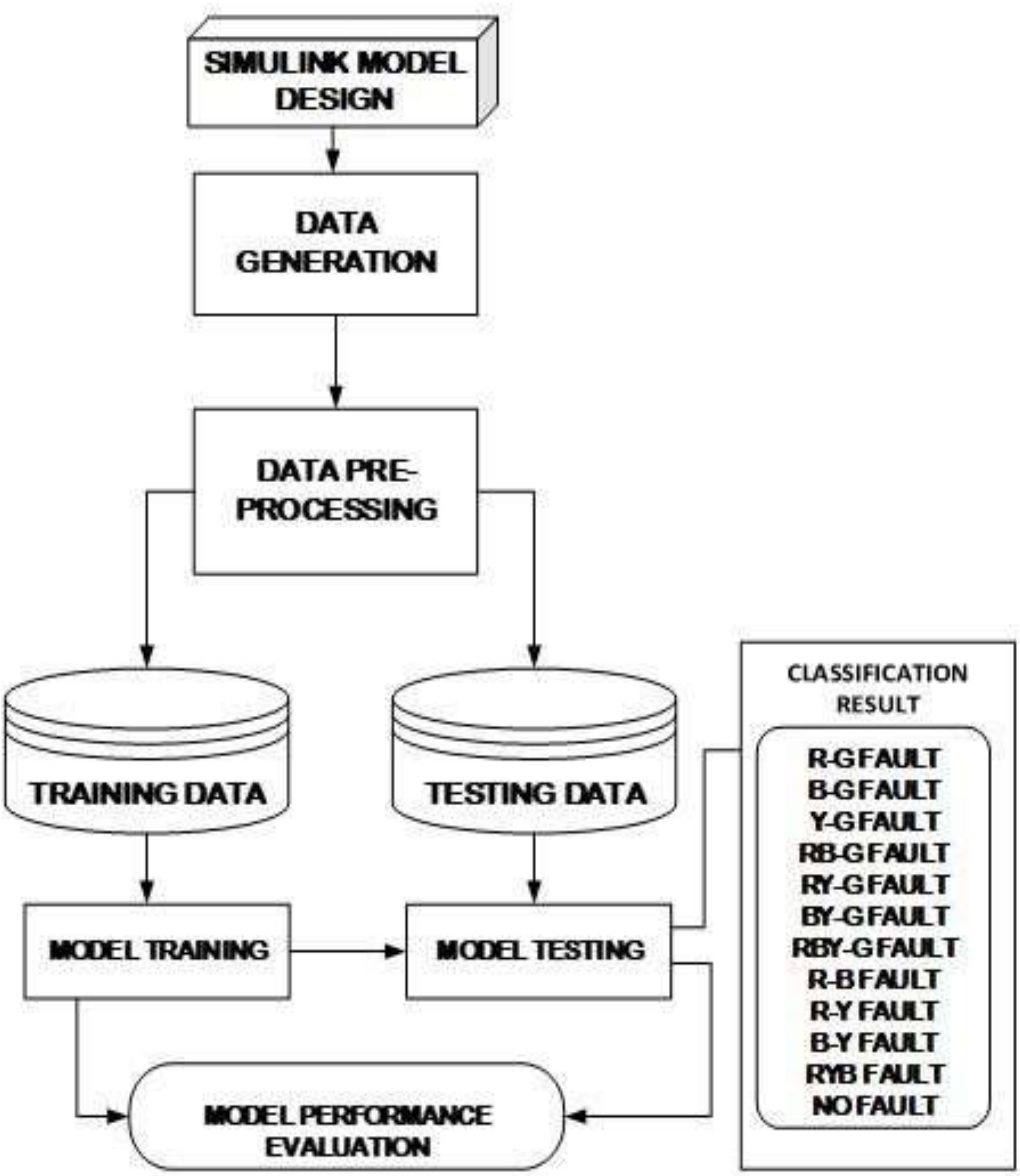


Figure 3.2: Implementation Flow Diagram

(Madueme and Wokoro, 2015).

3.2.1 Simulink model design for fault detection

The three-phase power system network model is simulated in MATLAB/Simulink software. It is a 330kV, 50 Hz, 140 km transmission line power system. It consists of Voltage and current measurements, circuit breakers, transmission line, and load which are shown in Figure 3.3. The main purpose of the transmission lines is to supply power to the load. The power supply generated by the Generator is supplied to the load through the transmission line network. The load is the feeder of the load, the load that the load supplies and the kVA are unbalanced, the ANN can see faults such as overload current. Traditional algorithms are based on Kirchhoff voltage and current laws for well-defined transmission line protection models.

Conventional distance relays consider the power swing of voltage and current as a fault and tripping mechanism. Such faulty components would lead to severe consequences and contribute to power system instability. The application of Artificial Neural

Networks to transmission line faults gives accurate results.
A Simulink model of the one-line diagram in Figure 3.1 is shown in Figure 3.3.

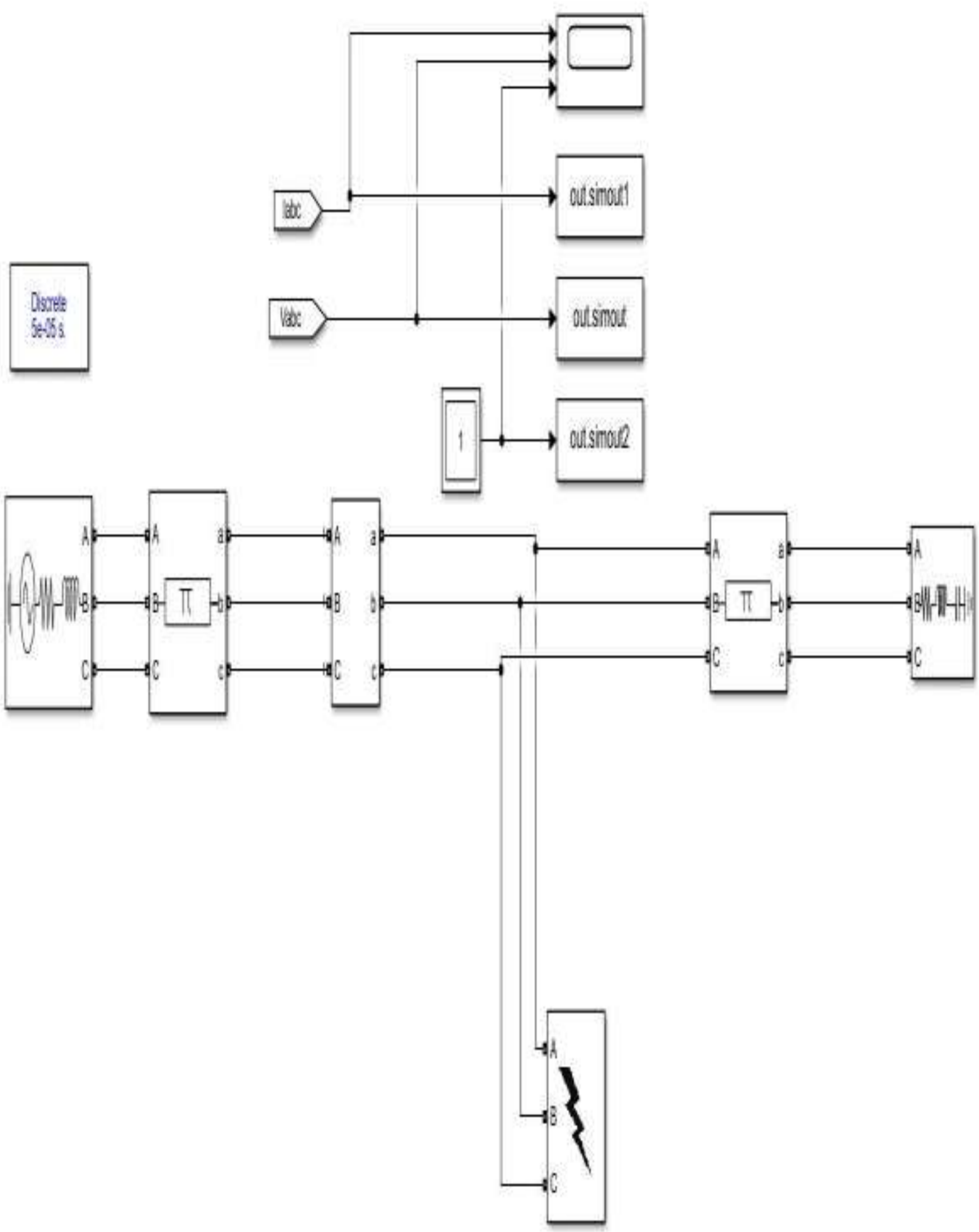


Figure 3.3: Simulink Model

Transmission Line parameters are shown in Table 3.1

Table 3.1: Transmission Line Parameters

Line Parameters	Values
Line Length	140 km
Positive- and zero-sequence resistances (Ohms/km):	[0.01273 0.3864]
Positive- and zero-sequence inductances (H/km):	[0.9337e-3 4.1264e-3]
Positive- and zero-sequence capacitances (F/km)	[12.74e-9 7.751e-9]
Fault Resistance	0.001

Source: 330/132/33kV Transmission Substation Gwagwalada.

3.2.2 Data generation

A Simulink model is shown in Figure 3.3. was used to generate the data required to train and test the intelligent model for fault classification: Simulations were carried out for different fault scenarios in order to get various fault patterns. Six features corresponding to the number of phase voltages and currents were generated for each
fault scenario.

The faults scenarios considered were:

For each fault scenario, the six-input data/features were generated after simulating the model and combining the features for all the fault scenarios. A total of 12,201 input data were generated.

Similarly, the target data were generated using the encoding scheme shown in the Appendix B. The encoding scheme was designed for a multi-fault scenario having 12 inputs each.

From Appendix B, the No-fault case has a class value of 0000000000001, the C-G fault has 100000000000, the B-G fault has 01000000000, the A-G fault has 001000000000, the B-C-G fault has 000100000000, the A-C-G fault has 000010000000, the A-B-

G fault has 000001000000, the A-B-C-G fault has 000000100000, the B-C fault has 000000010000, the A-C fault has 000000001000, the A-B 000000000100 while the AB-C fault has 000000000010. A total of 12,201×12 target samples were generated.

3.2.3 Data pre-processing

The data-set generated was pre-processed and partitioned into training and testing data. The pre-processing was carried out to normalize the input to match the ANN input pattern from 0's to 1's. this presents bias and improved the classification rate.

3.2.4 Training and testing data

Several different training algorithms for ANN are available (Madueme and Wokoro, 2015). All of these algorithms use the gradient of the power function to determine how to adjust the weights to minimize power. Gradients are determined using the backpropagation technique. This involves performing computations backward through the network. Taking speed and memory allocation into account, many algorithms are available for implementing the back-propagation method. Over the years, different popular, improved variations of BPNN have been proposed to specifically address several important issues, namely, reduction in convergence time, ease of computational burden, reduced memory requirement, and so on (Okwudili *et al.*, 2019).

The training and testing data used for the training and testing of the intelligent model are shown in Table 3.4. A total of 8,541 samples for both input and target were selected for training, while 1,220 for validation and 2,440 samples were selected for testing which were obtained from the training confusion matrix and testing confusion matrix in Figure 4.8 and Figure 4.9 respectively.

Table 3.4: Training and Testing

Models	Number of samples	Percentage (%)
Training	8541	70
Validation	1220	10
Testing	2440	20

3.2.5 Model training

The ANN model was designed to train the data generated, pre-processed, and partitioned as earlier discussed. The training parameters are shown in Table 3.5. For each parameter, the decision/ reason for the selection of such parameter was given. It can be seen that the feed-forward neural network (FF-NN) model was selected on its efficiency and excellent in classification tasks, the three layers (input-hidden-output) were selected for its requirement, back-propagation scale conjugate gradient (BP-SCG) was considered for the training algorithm on its fast speed and accuracy, the 40 neurons in the hidden layer were considered for the experiment to be adequate while 6 input-output neurons were considered for the multi-fault scenario.

Table 3.5: The Model Parameters

	Model parameter	Reason
Model Type	FF- Neuron	Excellent for classification problem
Number of layers	Three layers (input-hidden output)	Required
Training algorithm	Back-propagation scale conjugate gradient (BP-SCG)	Very fast and accurate
Number of Neurons input	6	Number of inputs for multifault scenario

Number of Neurons hidden layer	40	Experiment to be adequate
Number of Neurons output layer	12	Number of outputs for multi-fault scenario

3.2.6 Model testing

The trained model was tested using the 20% data which is 2,440 samples from the different fault scenarios as discussed earlier. For each sample, the ANN model detected the fault type and produced an output corresponding to the fault type given in the target vector.

After testing all 2,440 samples, the performance of the model was measured by comparing the model output with the target output.

3.2.7 Performance evaluation

The model performance was evaluated after testing the model using the following performance matrices calculated from the confusion matrices:

Accuracy: This measures the ability of the model to find the correct fault types. It is given as, Accuracy $= \frac{T+T}{T+T+T+T}$ (3.1)

Where:

TP is the true positive, FP is the false positive, TN is the true negative and FN is false negative.

Sensitivity: This measures the ability of the model to detect positive faults. It is represented as, Sensitivity $= \frac{T}{T+T}$ (3.2)

Specificity: This measures the ability of the model in detecting negative faults

$$\text{Specificity} = \frac{T}{T+T} \tag{3.3}$$

3.3 ANN Structures

A brief overview of the application of NNs to power systems can be found in (Roy and Bhattacharya, 2015). An Artificial Neural network (ANN) is a massively parallel distributed processor made up of processing units that have the capacity for storing experimental knowledge and making it available for use. Similar to the functional behaviour of the human brain, the network receives input signals and internal processing takes place through the activation of neurons to yield output signals (Kalu and Madueme, 2018). An ANN consists of a massively parallel distributed processing system made of highly interconnected neural computing elements called “Neurons”, which have the ability to learn and thereby acquire knowledge. ANN comprises a number of neurons that forms the basic processing unit. Each neuron is also connected to other neurons by connections. Every neuron receives a number of inputs which are modified by 'weights'. The synaptic weights would either strengthen or weaken the signal which is processed further (Okwudili *et al.*, 2019). One particular structure, based on multi-layer perceptron, called back-propagation neural network (BPNN), is the most popular neural network architecture, which uses supervised learning to determine a complex, nonlinear, multidimensional mathematical fitting. Artificial neurons are used to transmit signals from one layer to the other, its complex network of interconnected neurons is analogous to the firing of electrical pulses via its connections that lead to information propagation. An artificial neural network consists of three layers, the input layer, hidden layer, and output layer having a number of neurons present in it (Hatata *et al.*, 2016).

To generate the final output the sum of the weighted output will be passed on to a nonlinear filter called "activation function" plus a threshold value called 'bias' which will release the output.

Although the basic concept behind relays remains the same, digital technology has had a significant influence on the way relays operate and have offered several improvements over traditional Electro-Mechanical relays (Yadav and Goad, 2021).

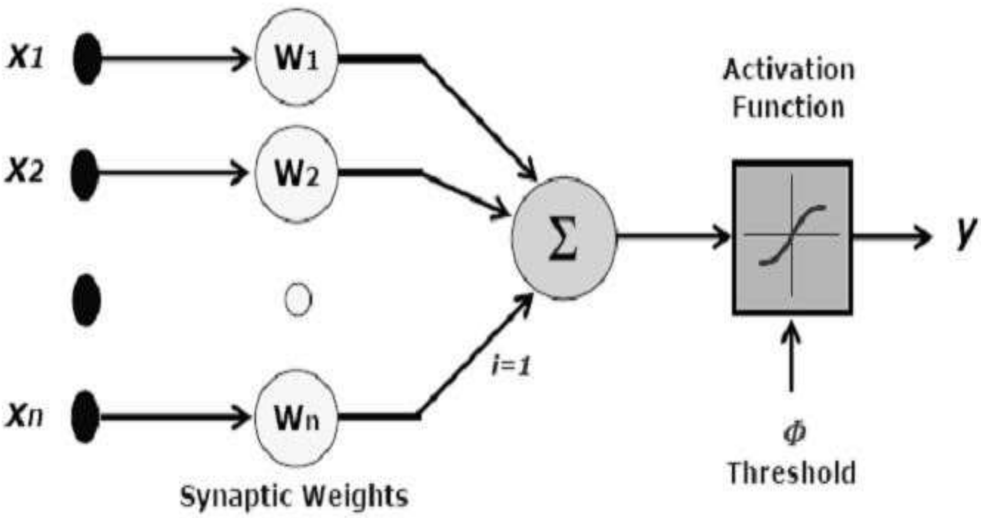


Figure 3.4: artificial neural network model

$$= f(_{11} + _{22} + ... + + = f \sum_{11} + +) \tag{3.4}$$

The work is to design, develop, test, and implement a complete strategy for the transmission line's fault diagnosis as shown in Figure 3.5.

First, all collected data is split into two sets, a training data set, and a test data set. The first step in this process is fault detection. Once we know that a fault has occurred on the transmission line, the next step is to classify the fault into different categories based on the phases that are faulted (Yadav and Goad, 2021). Then, the third step is to pinpoint the position of the fault on the transmission line. A back propagation-based neural network has been used for the purpose of fault detection and another similar one for fault classification. For each of the different kinds of faults, A single multi-fault neural network model was employed for the detection and classification of faults.

Each of these steps has been depicted in the flowchart shown in Figure 3.5

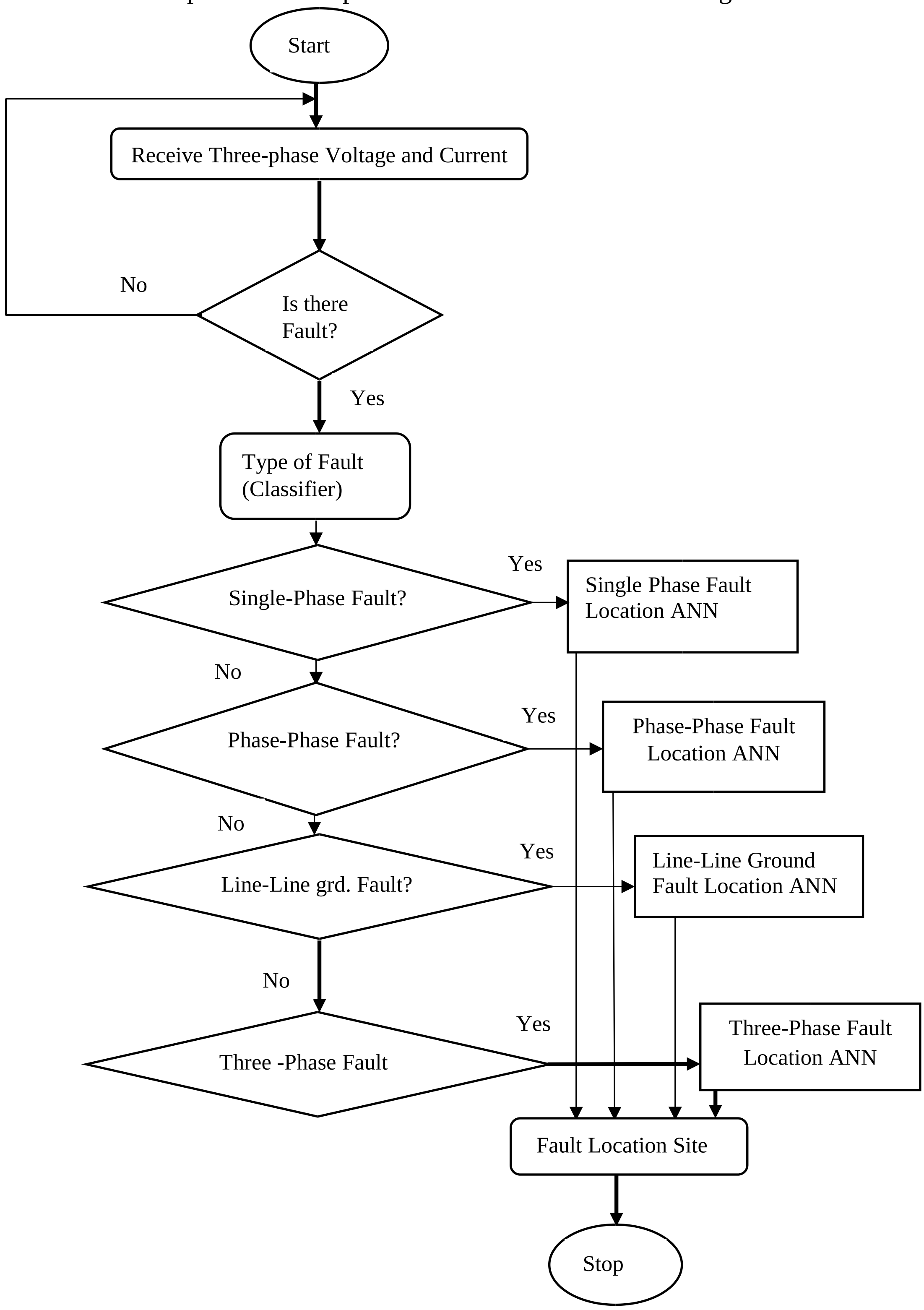


Figure 3.5: Flow Chart of the Fault Diagnosis Process

CHAPTER FOUR

4.0 RESULTS AND DISCUSSIONS

In order to achieve fault diagnosis of the 330 Gwagwalada-Katampe transmission line using the Artificial Neural Network approach, simulations were carried out using Simulink in the MATLAB environment. In addition, a classification model for different faults detected was developed with the performance of the approach evaluated.

This chapter presents results of various faults identified and classified on the 330 Gwagwalada-Katampe transmission line and as well provide an extensive discuss of the various results obtained.

4.1 Results

This section presents all results obtained on diagnosis of various fault scenario. At the first instance, the no-fault scenario was considered. This is followed by Single Phase-toGround Fault Scenario, Double Phase-to-Ground Fault Scenario, Three Phase-toGround Fault Scenario and Phase-to-Phase Fault Scenario.

4.1.1 No-fault scenario

The no-fault scenario result is shown in Figure 4.1. It should be noted that I_a, I_b, and I_c represent current in the yellow, blue and red phases respectively, while V_a, V_b and V_c represent the voltages on the yellow, blue and red phases respectively.

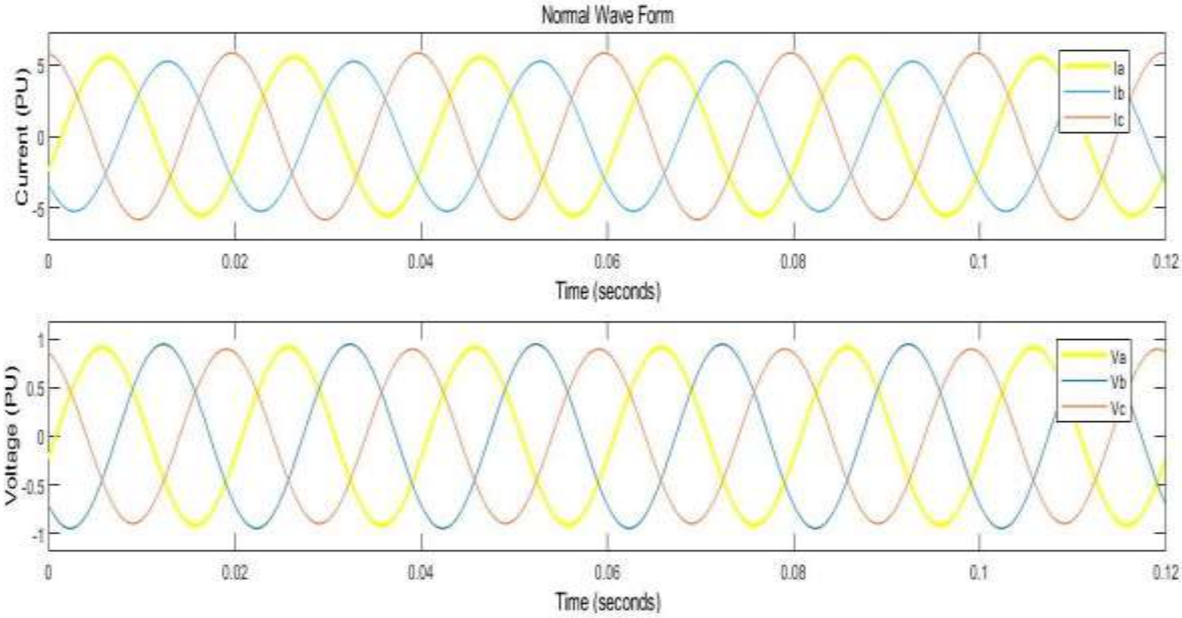


Figure 4.1: Normal Waveform for Three-Phase Voltage (V_{abc}) and Current (I_{abc})

4.1.2 Single phase-to-ground fault scenario

The results of the single phase-to-ground fault is presented in Figure 4.2. There are three possible single line to ground faults exist (A-G, B-G,C-G), corresponding to each of the three phases (A, B or C) being faulted

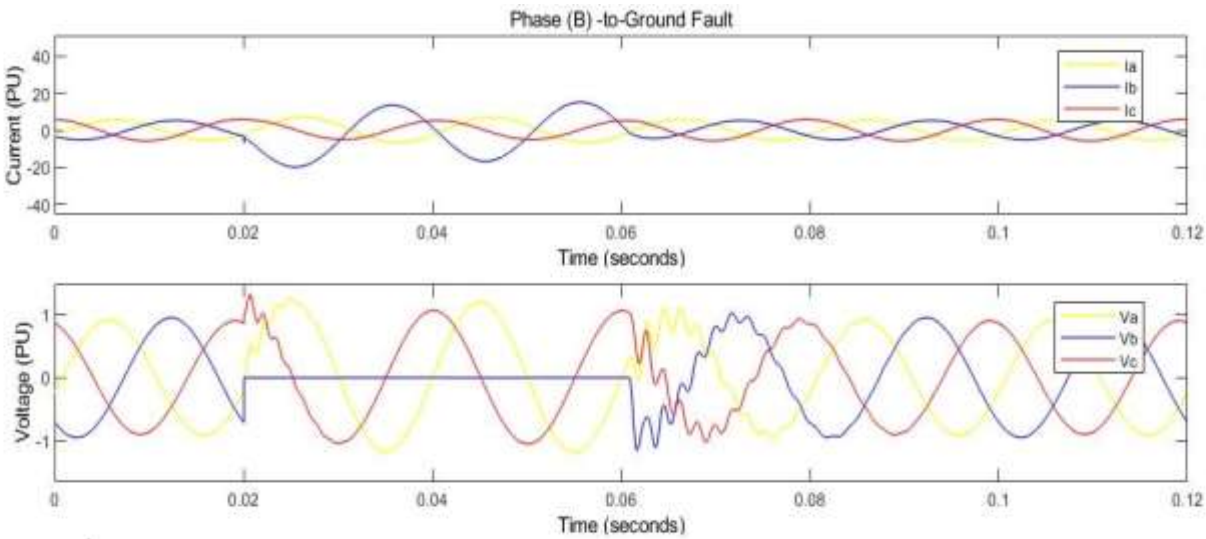


Figure 4.2: B-G Fault Waveform for Three-Phase Voltage (V_{abc}) and Current (I_{abc})

4.1.3 Double phase-to-ground fault scenario

The result of the double phase-to-ground fault case is shown in Figure 4.3., The third category of faults is the double-line-ground fault, there are three possible double-lineground faults exist which are A-B-G, B-C-G, and A-C-G (based on which two of the three phases A, B, and C are faulted)

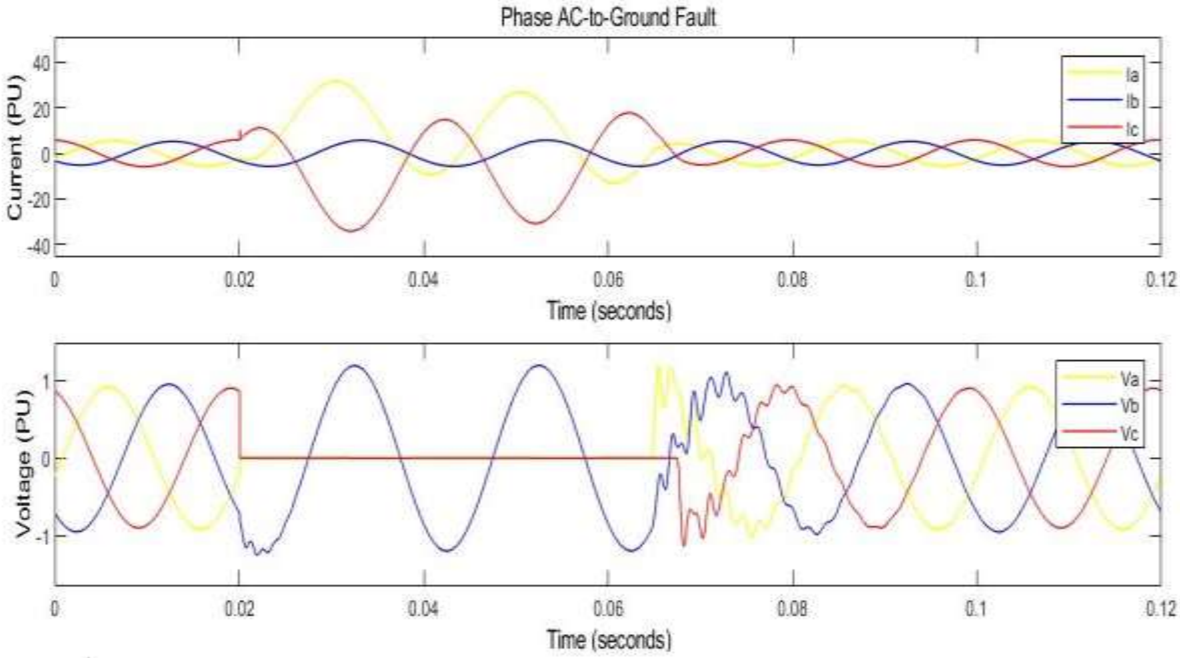


Figure 4.3: A-C-G Fault Waveform for Three-Phase Voltage (V_{abc}) and Current (I_{abc})

4.1.4 Three phase-to-ground fault scenario

The results of the Three Phase-to-Ground Fault are presented in Figure 4.4, this is a category of faults that exists only one kind of three-phase fault thus, A-B-C-G fault where all the phases A, B, and C are faulted to the ground.

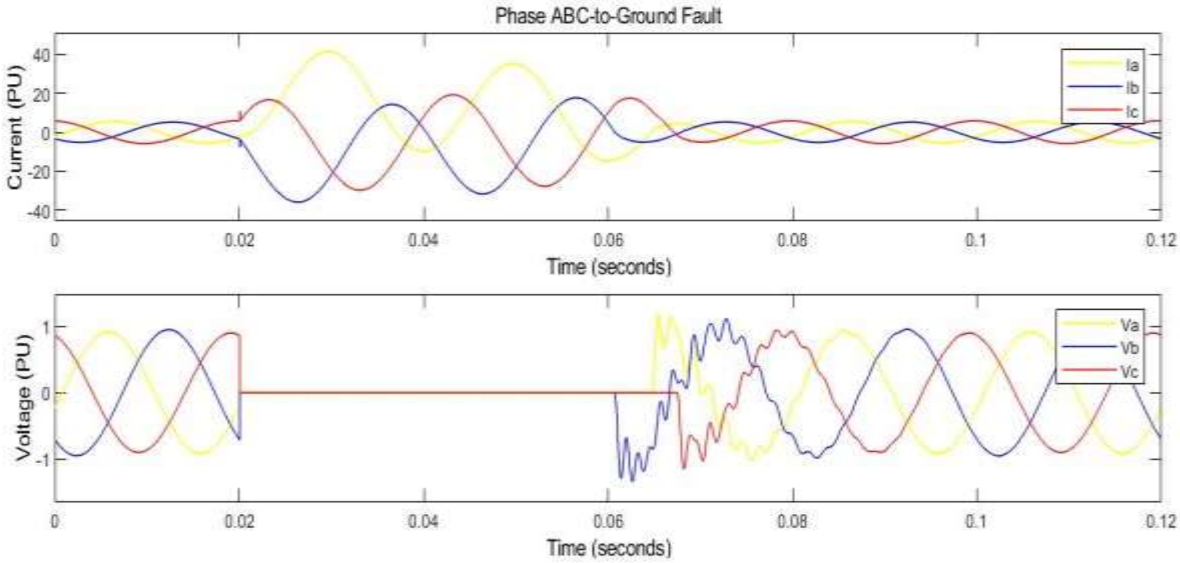


Figure 4.4: A-B-C-G Fault Waveform for Three-Phase Voltage (V_{abc}) and Current (I_{abc})

4.1.5 Phase-to-phase fault scenario

The result of the Phase-to-Phase Fault scenario is presented in Figure 4.5, There are three possible line-line faults exist (A-B, B-C, C-A), corresponding to each of the three (A, B, or C) being faulted.

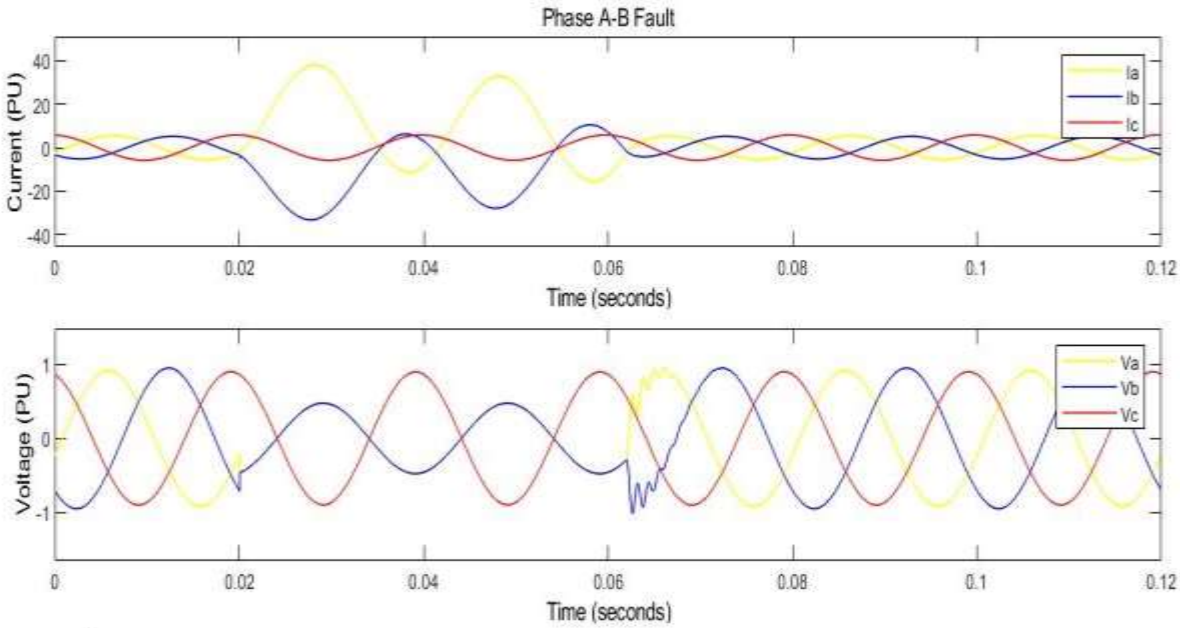


Figure 4.5: A-B Fault Waveform for Three-Phase Voltage (V_{abc}) and Current (I_{abc})

These faults were used to generate the data set for training the intelligent system. The waveform of other faults is described in the Appendix of the research work.

4.1.6 Faults classification results

The results obtained from the intelligent multi-faults classification model are presented in this section as shown in Figure 4.6 and Figure 4.7 respectively.

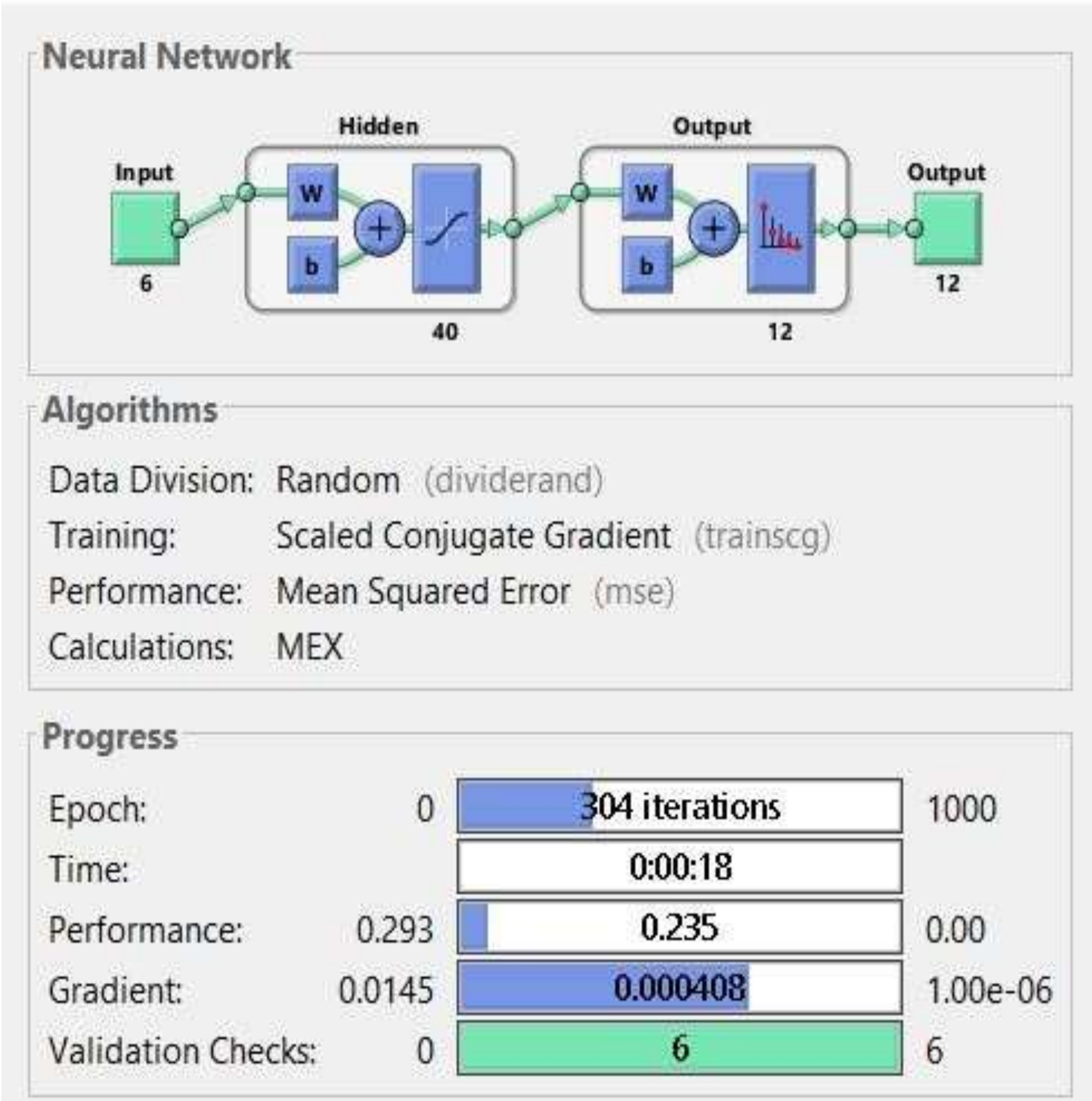


Figure 4.6: Training Performance of the Process

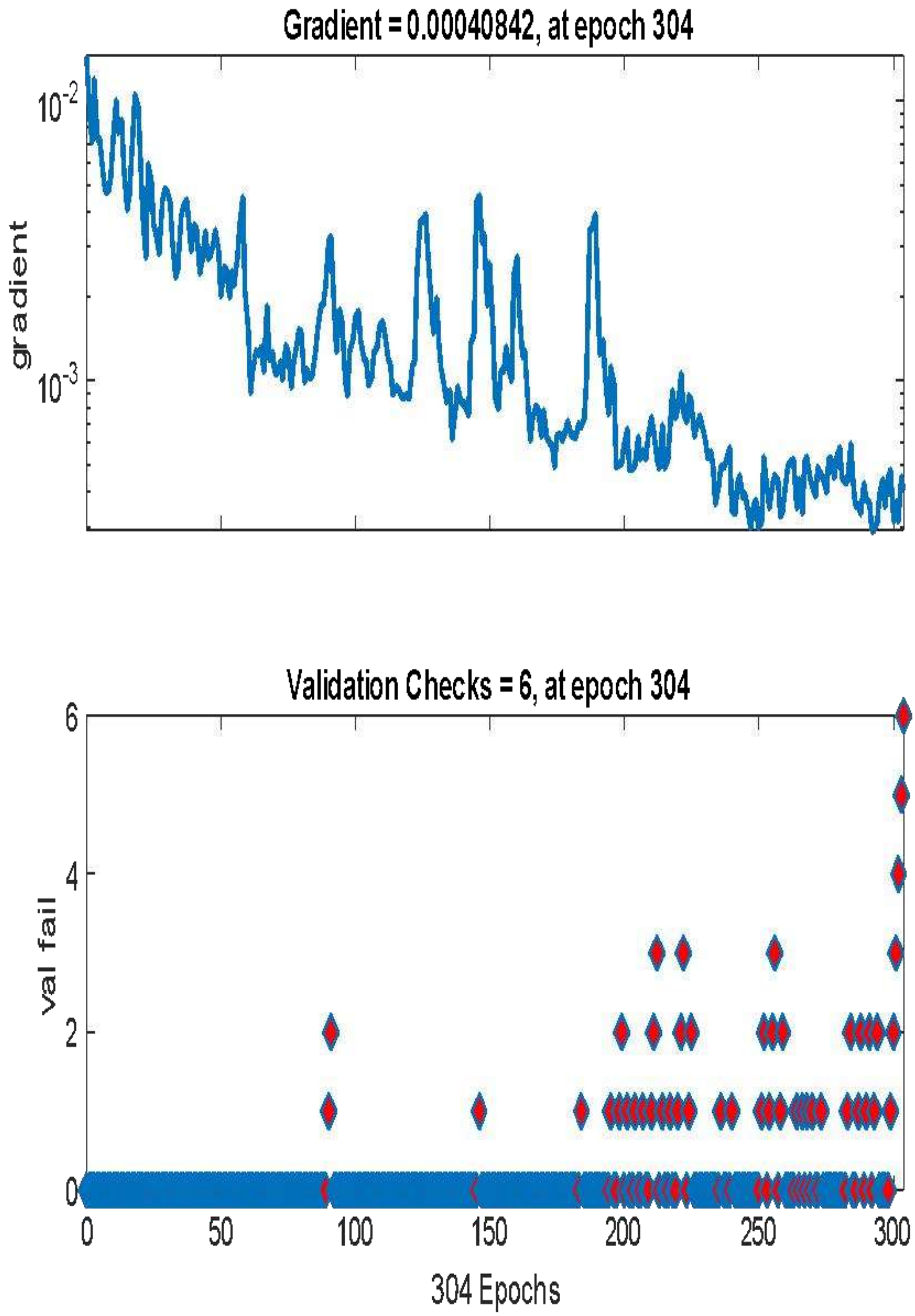


Figure 4.7: Training/Validation States

4.1.7 Training and testing confusion matrix results

The results obtained from the training and testing confusion matrix of multi-faults classification models are presented in this section as shown in Figure 4.8 and Figure 4.9 respectively. It provides a summary of the predicted and actual fault classifications, allowing us to analyze the accuracy and effectiveness of the fault classification system.

These confusion matrices are represented in Figure 4.8 and Figure 4.9 as a table with rows and columns for both training and testing. The rows represent the actual fault classifications, while the columns represent the predicted fault classifications. Each cell in the matrix represents the number of instances where a particular fault classification was predicted (column) for a given actual fault classification (row). The diagonal line of the confusion matrix represents the correct predictions, where the predicted fault classification matches the actual fault classification. The values on this diagonal line indicate the number of corrected predictions for each fault type.

The colours in the confusion matrix were used to visualize and represent the performance of the classification system. For example, the cells on the diagonal line, representing correct predictions, were highlighted in green indicating accuracy. Cells off the diagonal line, representing incorrect predictions, were highlighted in red to indicate errors. It helps in evaluating the accuracy of the classification model by summarizing the results of classification tasks.

From the right-hand side column, sensitivity represents the ability of the system to correctly identify the presence of a fault. It is calculated by dividing the number of true positive predictions by the sum of true positive and false negative predictions while from the bottom row the specificity, on the other hand, measures the true negative rate, which is the ability of the system to correctly identify negative instances.

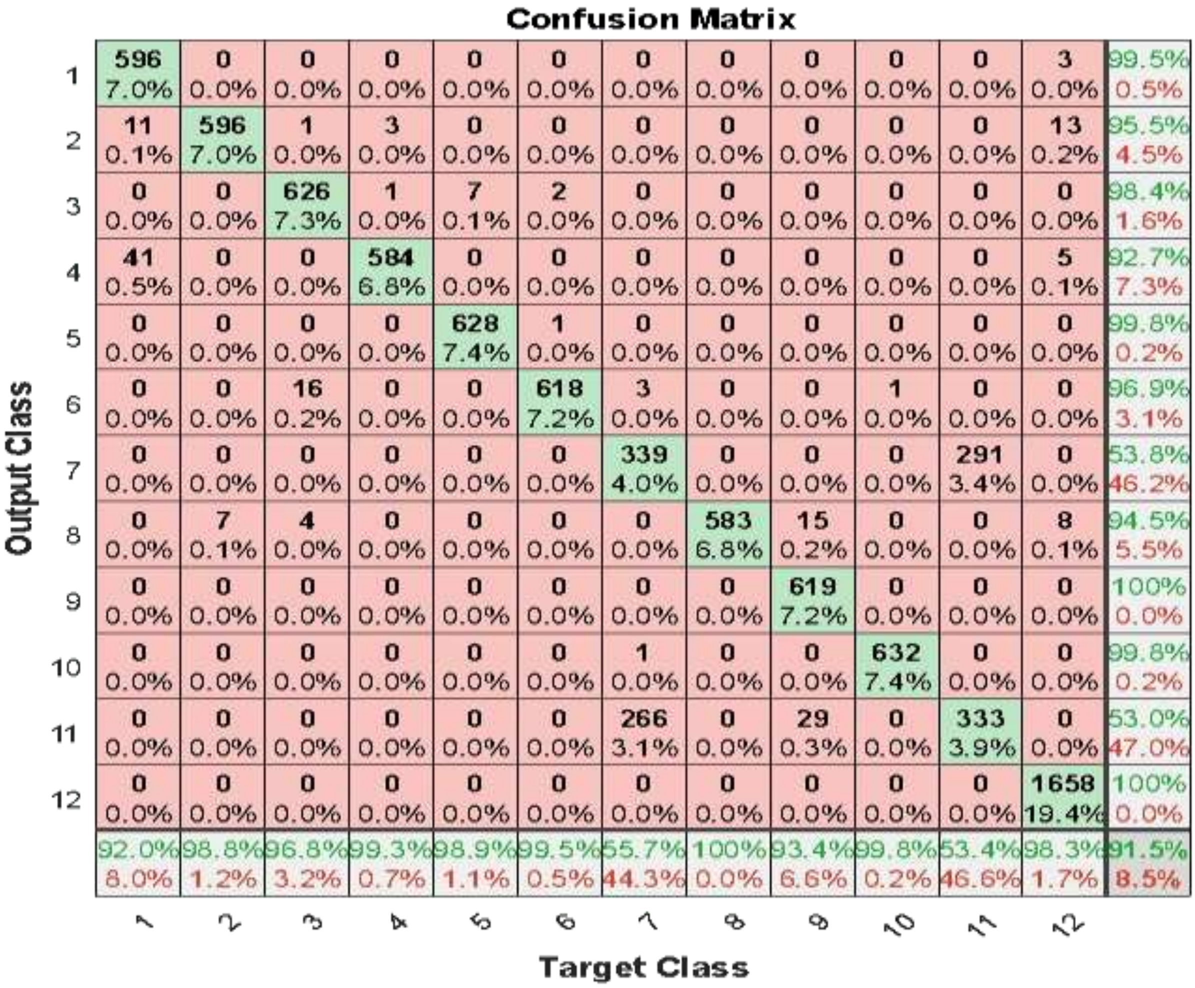
From equation (3.2) sensitivity of faults C-G that were correctly classified in the row 1

$= \frac{T}{T+T} = \frac{596}{596+3} = \frac{596}{599}$ 0.99499 = 99.5%

While the corresponding specificity of faults C-G that were correctly classified in the column 1 $= \frac{T}{T+T} = \frac{596}{596+52} = \frac{596}{648}$ 0.9197 = 92%.

Subsequently, other rows and columns are thus computed to obtain those results in the confusion matrix.

Overall, the confusion matrix, along with sensitivity, specificity, and the diagonal line, provides a comprehensive evaluation of the fault diagnosis model classification tasks system's performance in the 330kV transmission line.



Confusion Matrix

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	11	12	
1	596 7.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	3 0.0%	99.5% 0.5%
2	11 0.1%	596 7.0%	1 0.0%	3 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	13 0.2%	95.5% 4.5%
3	0 0.0%	0 0.0%	626 7.3%	1 0.0%	7 0.1%	2 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	98.4% 1.6%
4	41 0.5%	0 0.0%	0 0.0%	584 6.8%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	5 0.1%	92.7% 7.3%
5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	628 7.4%	1 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	99.8% 0.2%
6	0 0.0%	0 0.0%	16 0.2%	0 0.0%	0 0.0%	618 7.2%	3 0.0%	0 0.0%	0 0.0%	1 0.0%	0 0.0%	0 0.0%	96.9% 3.1%
7	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	339 4.0%	0 0.0%	0 0.0%	0 0.0%	291 3.4%	0 0.0%	53.8% 46.2%
8	0 0.0%	7 0.1%	4 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	583 6.8%	15 0.2%	0 0.0%	0 0.0%	8 0.1%	94.5% 5.5%
9	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	619 7.2%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
10	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1 0.0%	0 0.0%	0 0.0%	632 7.4%	0 0.0%	0 0.0%	99.8% 0.2%
11	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	266 3.1%	0 0.0%	29 0.3%	0 0.0%	333 3.9%	0 0.0%	53.0% 47.0%
12	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1658 19.4%	100% 0.0%
	92.0% 8.0%	98.8% 1.2%	96.8% 3.2%	99.3% 0.7%	98.9% 1.1%	99.5% 0.5%	55.7% 44.3%	100% 0.0%	93.4% 6.6%	99.8% 0.2%	53.4% 46.6%	98.3% 1.7%	91.5% 8.5%

Figure 4.8: Training Confusion Matrix

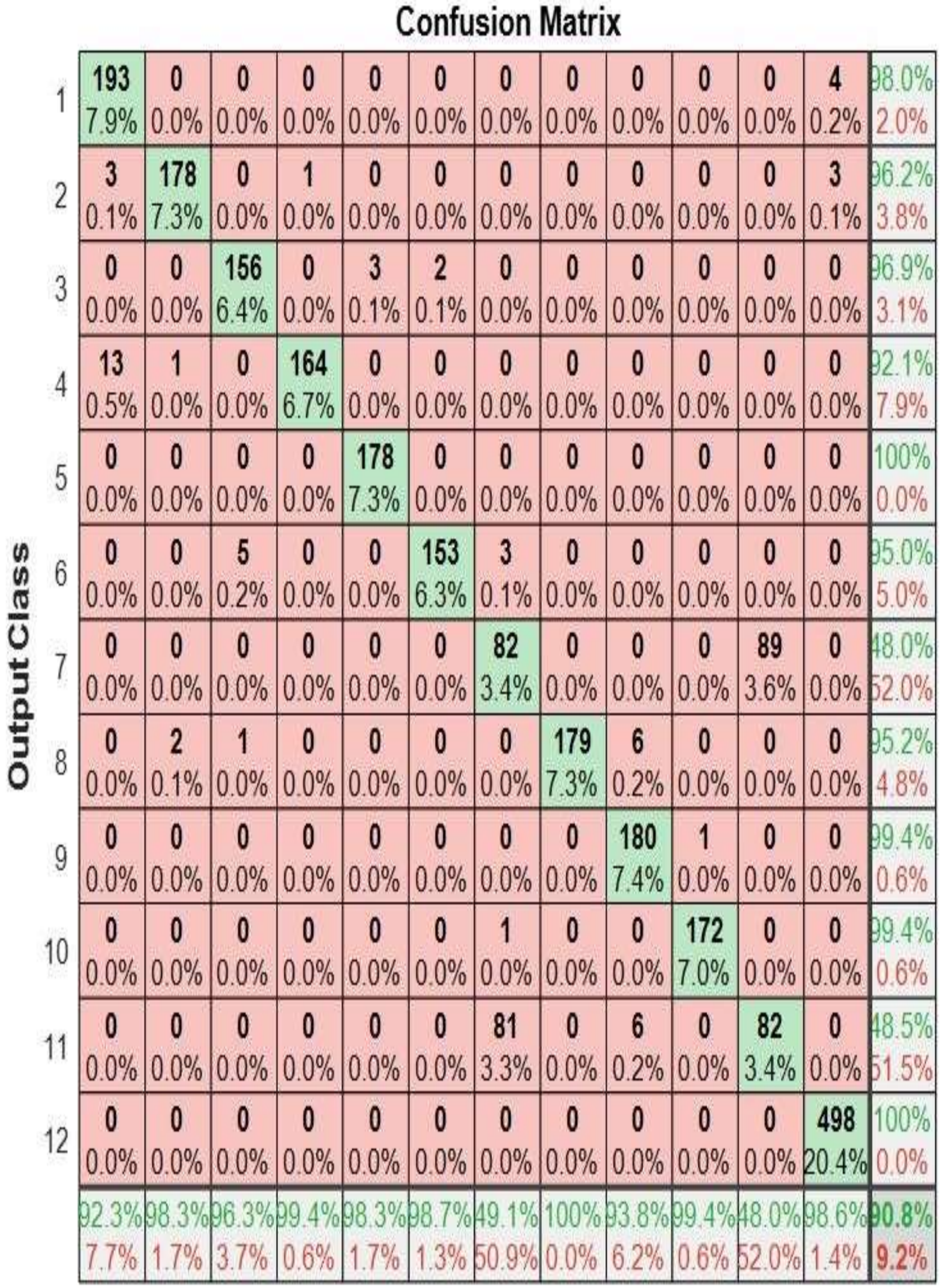


Figure 4.9: Testing Confusion Matrix

4.2 Discussion of Results

This section presents the discussions of the results obtained from the diagnosis of fault scenarios in sequential order. The sensitivity and specificity from the testing and training confusion matrix for the various faults in the Figure 4.8 and Figure 4.9. At the first instance, the no-fault scenario was discussed. This is followed by Single Phase-toGround Fault Scenario, Double Phase-to-Ground Fault Scenario, Three Phase-to-Ground Fault Scenario, Phase-to-Phase Fault Scenario, Fault Classification Results, Training Fault Detection Result Summary, Testing Fault Detection Result Summary, Summary of Results for Intelligent Multi-Fault Classification Model (IMFCM).

4.2.1 No-fault case

The no-fault scenario result is shown in Figure 4.1. it can be seen that the magnitude of the three-phase voltage and current are the same for the red, blue, and yellow phases. This implies that in the testing and training confusion matrix for the no-fault scenario, the sensitivity and specificity are 100%, 98.6%, and 100%, 98.3% as shown in Figures 4.7 and 4.8 respectively.

4.2.2 Single phase-to-ground fault

The results of the single phase-to-ground fault (B-G) are presented in Figure 4.2. From the graph, it can be seen that the magnitude of the faulty line (blue) deviated from the other lines from 0.02s to 0.06s which gives a higher voltage and zero current at that time. This implies that for a single phase-to-ground fault scenario, the sensitivity and specificity obtained for testing and training confusion matrix is 96.2%, 98.3%, and 95.5%, 98.8% as shown in Figures 4.7 and 4.8 respectively.

4.2.3 Double phase-to-ground fault

The results of the double phase-to-ground fault (A-C-G) scenario is presented in Figure 4.3. From the graph, it can be seen that the magnitude of the faulty line (red and yellow) deviated from the other lines from 0.02s to 0.04s which gives a higher voltage and zero current at that time. This implies that for the double phase-to-ground (A-C-G) fault scenario the sensitivity and specificity for testing and training confusion matrix is 100%, 98.3%, and 99.8%, 98.9% as shown in Figures 4.7 and 4.8 respectively.

4.2.4 Three phase-to-ground fault

The result of the three phase-to-ground fault (A-B-C-G) scenario is shown in Figure 4.4. The graph in Figure 4.4 shows the voltage and current waveform of a three-phase-toground (A-B-C-G) fault. It can be seen that the magnitude of the faulty line (red, blue, and Yellow) deviated from the normal lines from 0.02s to 0.06s at that time. This implies that for three phase-to-ground faults (A-B-C-G) scenarios, the sensitivity and specificity for testing and training confusion matrix is 48.0%, 49.1%, and 53.8%, 55.7% as shown in Figures 4.7 and 4.8 respectively.

4.2.5 Phase-to-phase fault

The results of the phase-to-phase fault (A-B) scenario are presented in Figure 4.5 shows the voltage and current waveform of phase to phase (A-B) fault. From the graph, it can be seen that the magnitude of the faulty line (blue and yellow) deviated from the other lines from 0.02s to 0.06s which gives a higher voltage and zero current at that time. This implies that for the phase-to-phase fault (A-B) scenario, the sensitivity and specificity for testing and training confusion matrix are 99.4%, 99.4%, and 99.8%,
99.8% as shown in Figures 4.7 and 4.8 respectively.

4.2.6 Faults classification results

The results obtained from the intelligent multi-faults classification model are described in this section. Figure 4.6 shows the trained model, algorithms, and training progress. From the Figure, it can be seen that 6 inputs were used, 40 hidden, and 12 outputs. The algorithm converges at 304 iterations with a performance of 0.293 and a gradient of 0.0145 with 6 validation checks. As also shown in Figure 4.7, The graph shows the training and validation state of the model. With a minimum gradient of 0.00040842.

Figure: 4.6, shows an artificial neural network (ANN) classifier as can be seen, it has six (6) inputs, namely, Voltages (Va, Vb, Vc) and Currents (Ia, Ib, Ic), as processed in Figure 4. The ANN consists of 40 hidden layers and 12 output layers. Its objective (based on its training) is to identify faults in the Gwagwalada-Katampe transmission line. The output is trained to give a response to any of the fault conditions presented and thus represents a Common Fault Alarm (or Trip). This means that the performance of the ANN to identify the faults correctly is good and acceptable.

Figure 4.8 shows the training confusion matrix of multi-faults classification models. From the Figure, the green diagonal boxes indicate the faults that were correctly classified while the red boxes show the faults that were wrongly classified. The results show that 596 faults were correctly classified as C-G. 596 faults were correct as B-G faults, 626 faults were correctly classified as A-G faults, and 584 faults were correctly classified as B-C-G. 628 faults were correctly classified as A-C-G. 618 faults were correctly classified as A-B-G, 339 faults were correctly classified as A-B-G, 339 faults were correctly classified as A-B-C-G. 583 faults were correctly classified as B-C, and

619 faults were correctly classified as A-C faults. 632 faults were correctly classified as A-B faults, 333 faults were classified as A-B-C, and 1,658 were correctly classified as No-fault.

Table 4.1 shows the sensitivity and specificity of training fault detection. From the table, the No-Fault has the highest sensitivity value of 100 followed by A-B-C and A-C-G with a sensitivity value of 99.8 and A-B-C obtained the lowest sensitivity of 53. In terms of specificity, B-C obtained the value of 100 which indicate the highest specificity, this is followed by A-B with a sensitivity value of 99.8, and A-B-C having the value of the lowest specificity of 53.4. The graph in Figure 4.9 Indicates the relationship between sensitivity and specificity with the blue line indicating sensitivity and the red line indicating specificity. A-B-C-G has the lowest sensitivity peak and A-

B-C-G with A-B-C are having the lowest specificity peak.

Table 4.1: Training Fault Detection Result Summary

Faults	Sensitivity	Specificity
C-G	99.5	92
B-G	95.5	98.8
A-G	98.4	96.8
B-C-G	92.7	99.3
A-C-G	99.8	98.9
A-B-G	96.9	99.5
A-B-C-G	53.8	55.7
B-C	94.5	100
A-C	100	93.4
A-B	99.8	99.8
A-B-C	53	53.4
No-Fault	100	98.3

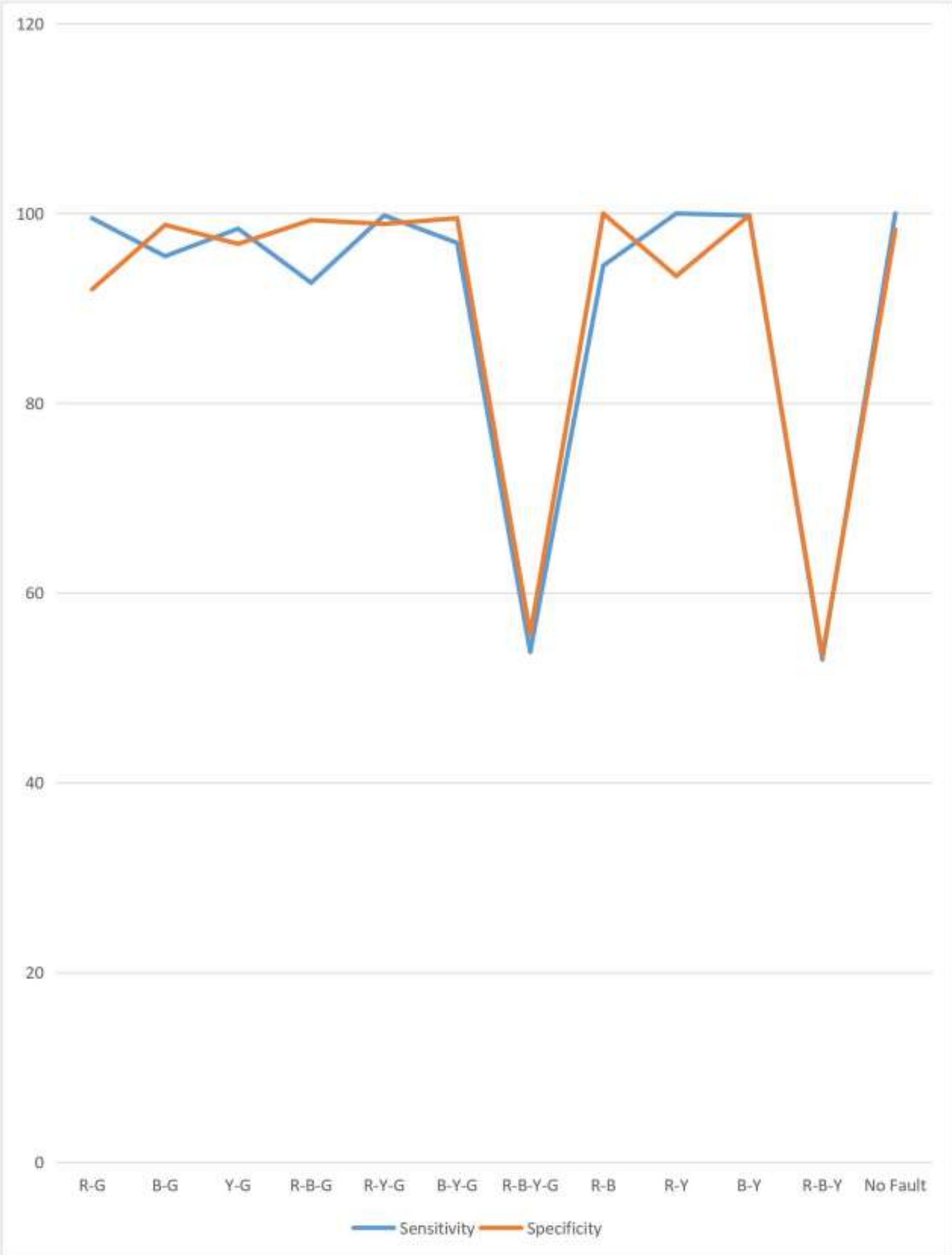


Figure 4.10: Relationship Between Sensitivity and Specificity of Training Fault

Table 4.2 indicates the sensitivity and specificity of testing fault detection. In the table, the No-Fault and A-C-G have the highest sensitivity value of 100 followed by A-B and A-C with a sensitivity value of 99.4 and A-B-C obtained the lowest sensitivity of 48.5. In terms of specificity, A-B obtained a value of 100 which indicates the highest specificity, this is followed by B-C-G and A-B with a sensitivity value of 99.4, and AB-C having the value of the lowest specificity of 48.5, The graph in Figure 4.11 indicates the relationship between sensitivity and specificity with the blue line indicating sensitivity and the red line indicating specificity. A-B-C and B-G have the highest specificity peak.

Table 4.2: Testing Fault Detection Result Summary

Faults	Sensitivity	Specificity
C-G	98.0	92.3
B-G	96.2	98.3
A-G	96.9	96.3
B-C-G	92.1	99.4
A-C-G	100	98.3
A-B-G	95.0	98.7
A-B-C-G	48.0	49.1
B-C	95.0	100
A-C	99.4	93.8
A-B	99.4	99.4
A-B-C	48.5	48.0
No-Fault	100	98.6

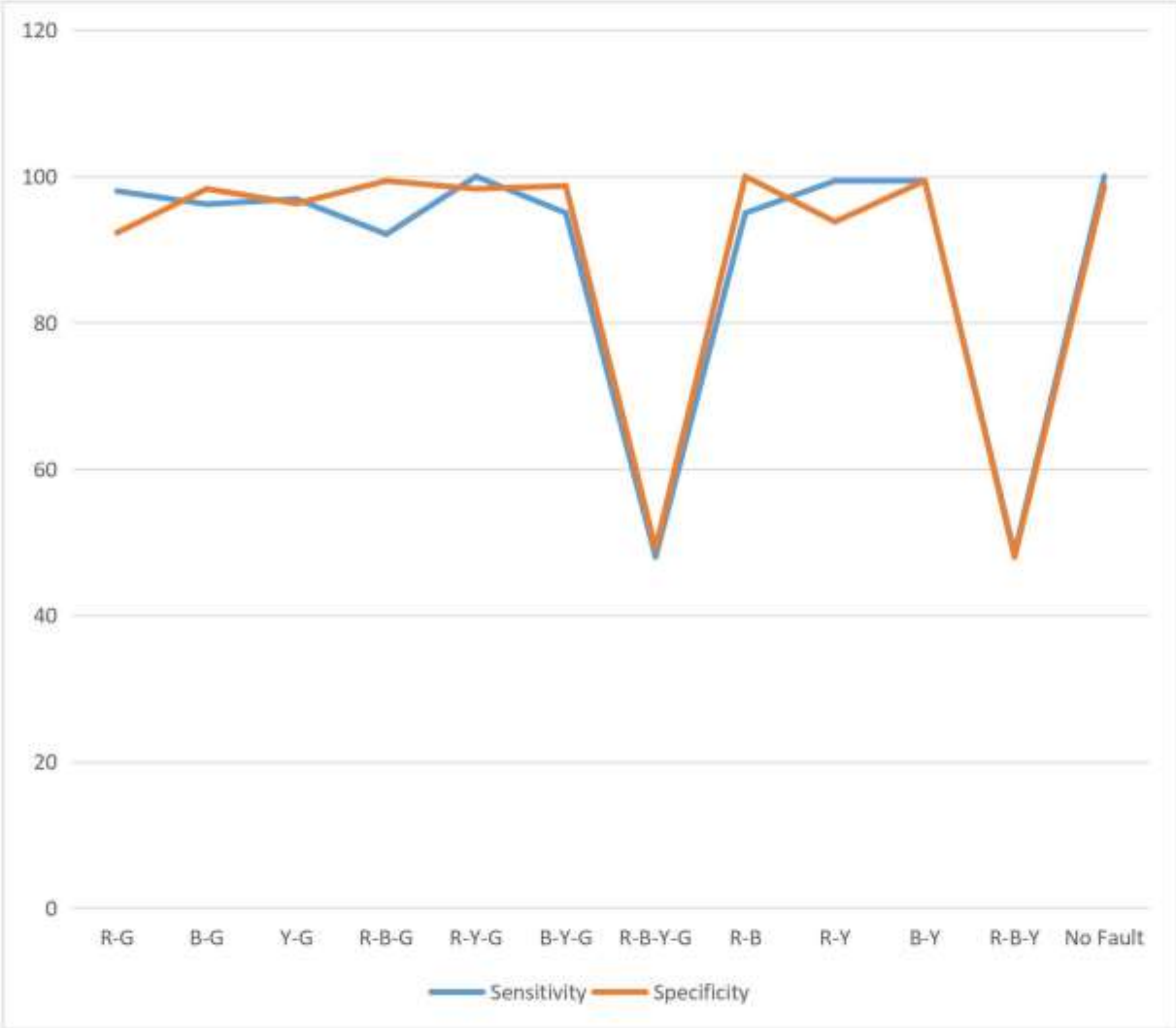


Figure 4.11: Relationship Between Sensitivity and Specificity of Testing Fault

Table 4.3: Summary of Results for IMFCM

	Accuracy (%)	Sensitivity	Specificity
Training	91.500	90.6583	90.4917
Testing	90.800	89.0416	89.3500

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This research work proposed the application of an Intelligent multi-fault classification model using an artificial neural network on the 330kV Gwagwalada-Katampe transmission line for various possible faults namely single line-to-ground, line-to-line, double line-to-ground, and three-phase faults have been taken into consideration. The data set used for training the intelligent model was first extracted by simulating the network fault conditions. For each fault type, six features were collected including the type of fault as the class. The data set was then pre-processed, partitioned, and used to train the model. The model was trained and validated using training and testing data.

Therefore, the work proved that an average of 91.5% model accuracy can be achieved for fault and no-fault conditions. The results of the work also showed the sensitivity and specificity of the sample of three-phase faults which produced the lowest values of 48%.

From the foregone, it can be deduced that: (i) An intelligent multi-fault detection and classification model can be simulated to detect faults and classify the nature of the faults. (ii) Among all the faults considered, the three-phase faults were the most difficult to classify. Their detection rates were the lowest compared to other faults. (iii) The simulated model produced high detection rates for single phase-to-ground and double phase-to-ground and phase-to-phase faults. (iv) The low detection rates of the threephase faults may be attributed to the similarities between the features of the three-phaseto-ground faults and three-phase faults.

5.2 Recommendations

i. The detection and classification of three-phase to ground and three-phase faults be improved to enhance the overall network performance.

ii. More machine learning models like deep neural networks (DNN) can be investigated for performance comparison.

iii. Some data filtering techniques be applied to the data to improve detection rates.

iv. This model can also be added with distance location for a prompt response.

5.3 Contribution to knowledge

This research work contributed to the body of knowledge in the following ways:

The artificial neural network model was applied with 70%, 20%, and 10% of the data used for training, testing, and validation respectively, the training and testing were achieved with an accuracy of 91.5% and 90.8% respectively and a total of eleven (11) different faults were successfully classified as single phase-to-ground faults, double phase-to-ground faults, three phase-to-ground faults, phase-to-phase faults, and threephase faults finally, this can be deployed to detect and classify the types of faults in the Gwagwalada-Katampe transmission lines.

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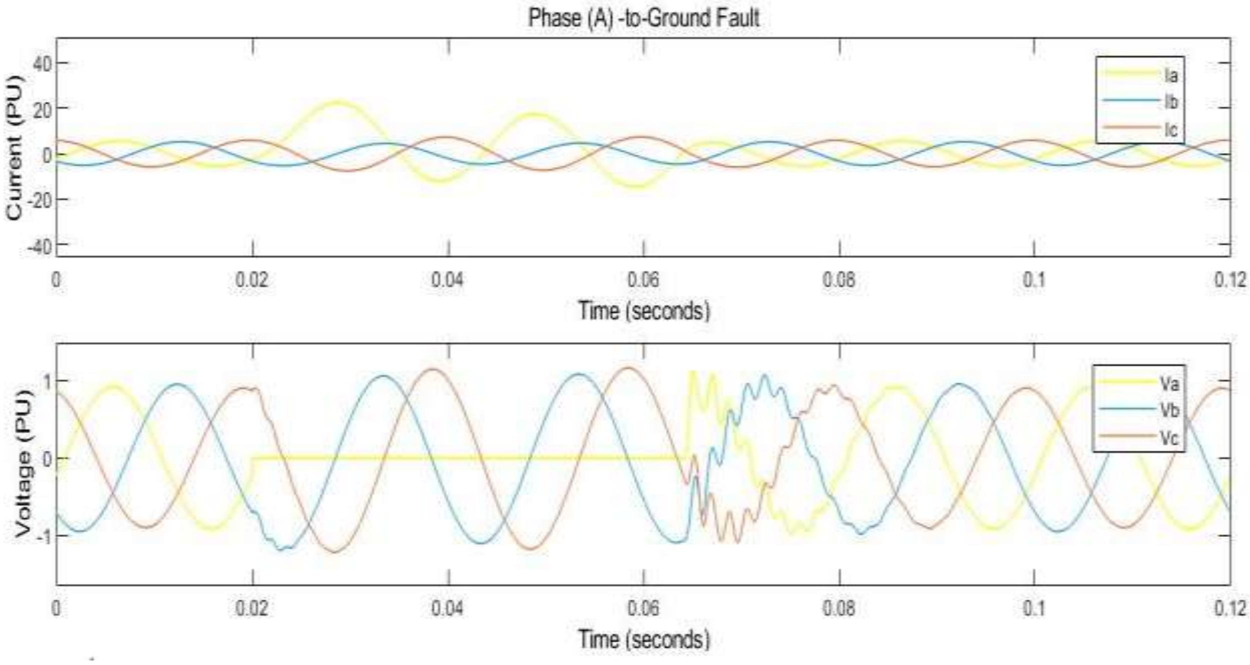
Appendix A:

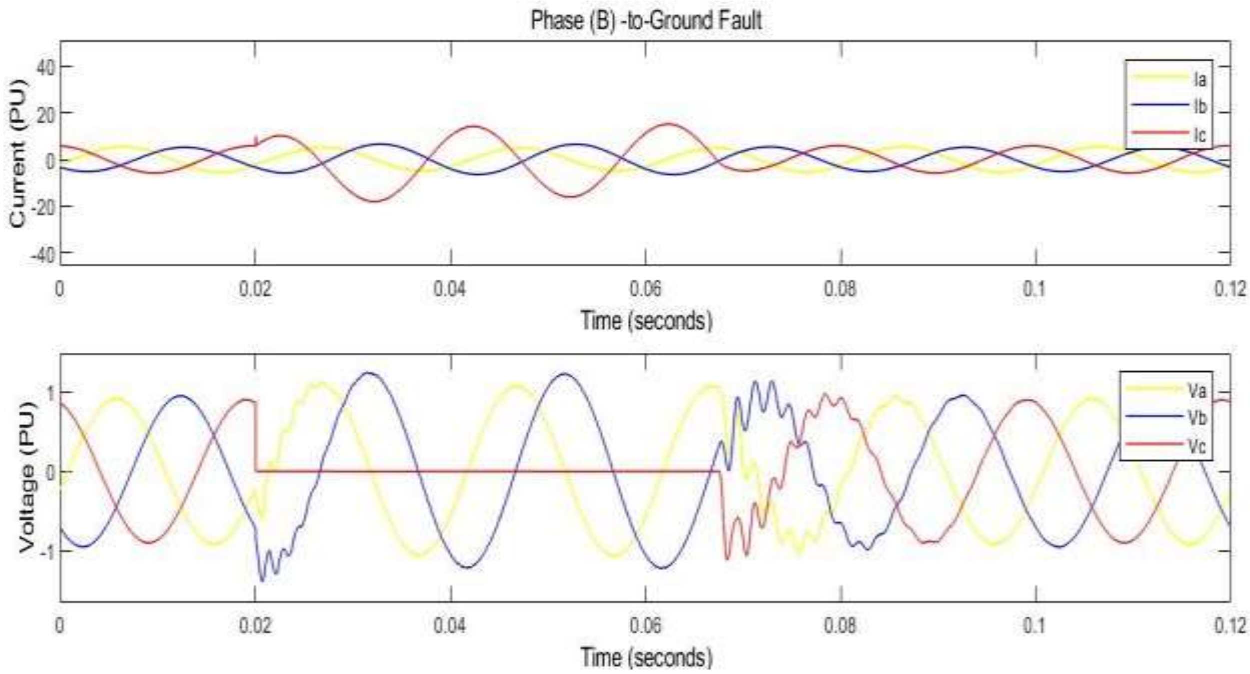
The waveform of other faults in the research work.

Appendix A1:



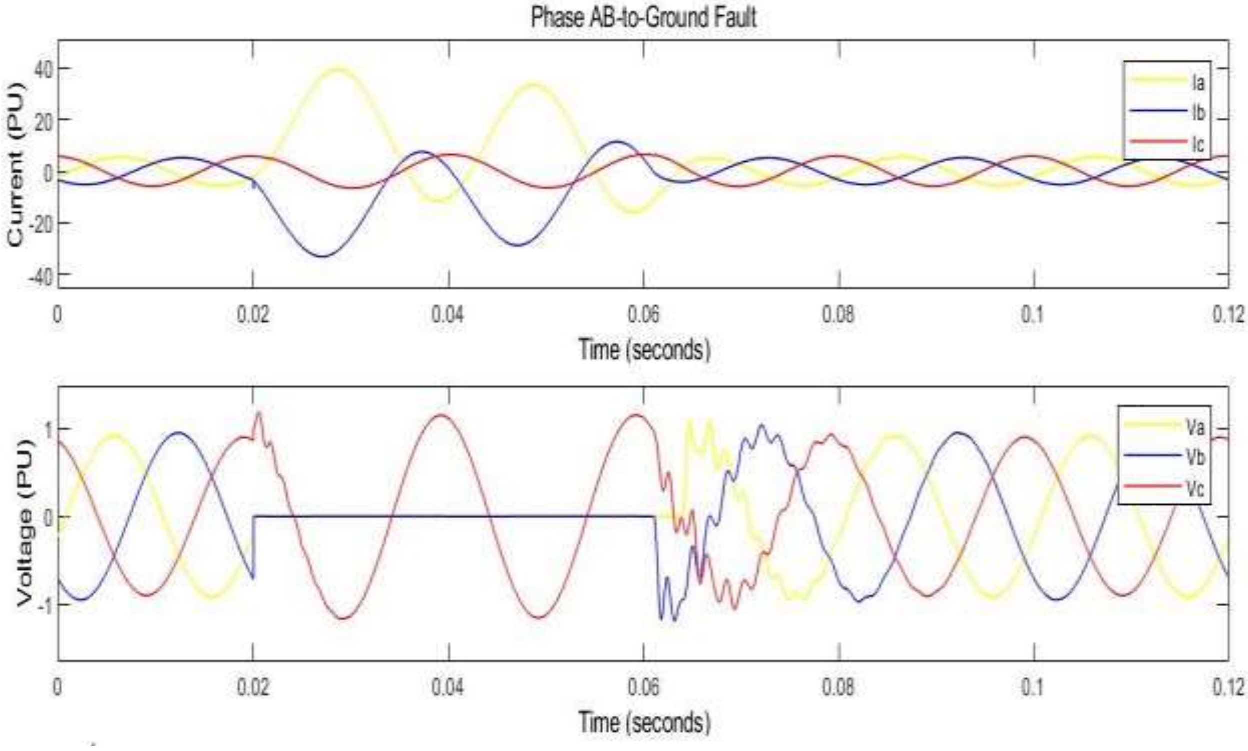
The Single Phase-to-Ground fault A-G **Appendix**

A 2:



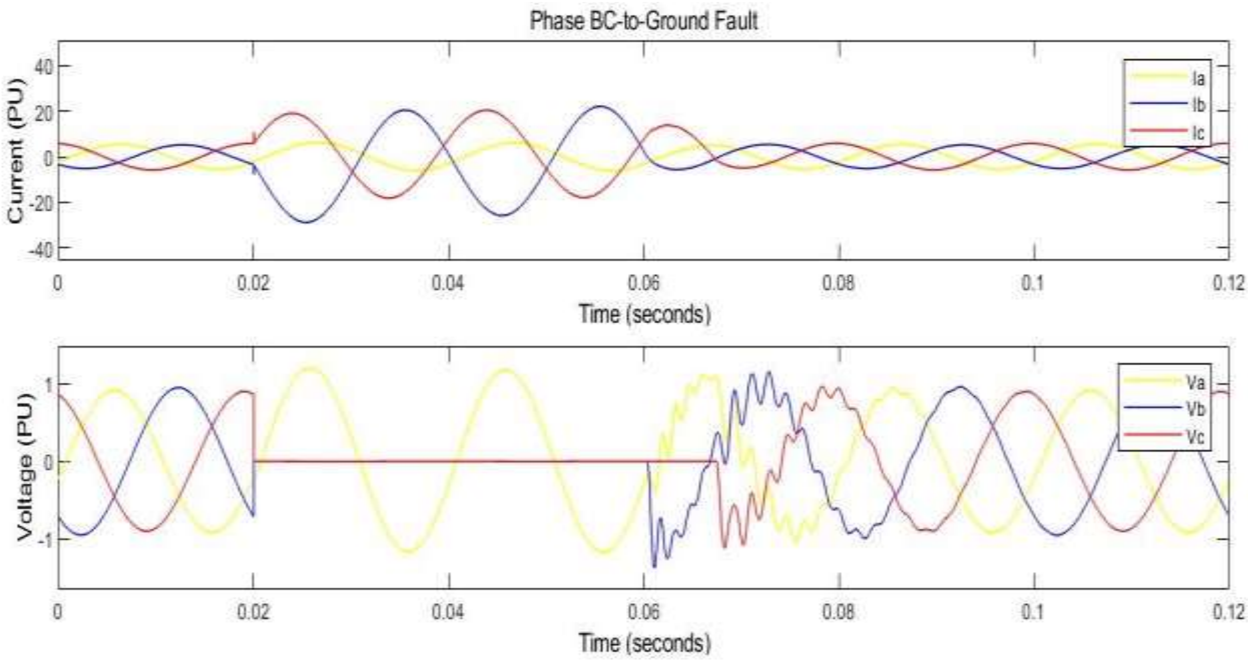
The Single Phase-to-Ground fault C-G

Appendix A3:

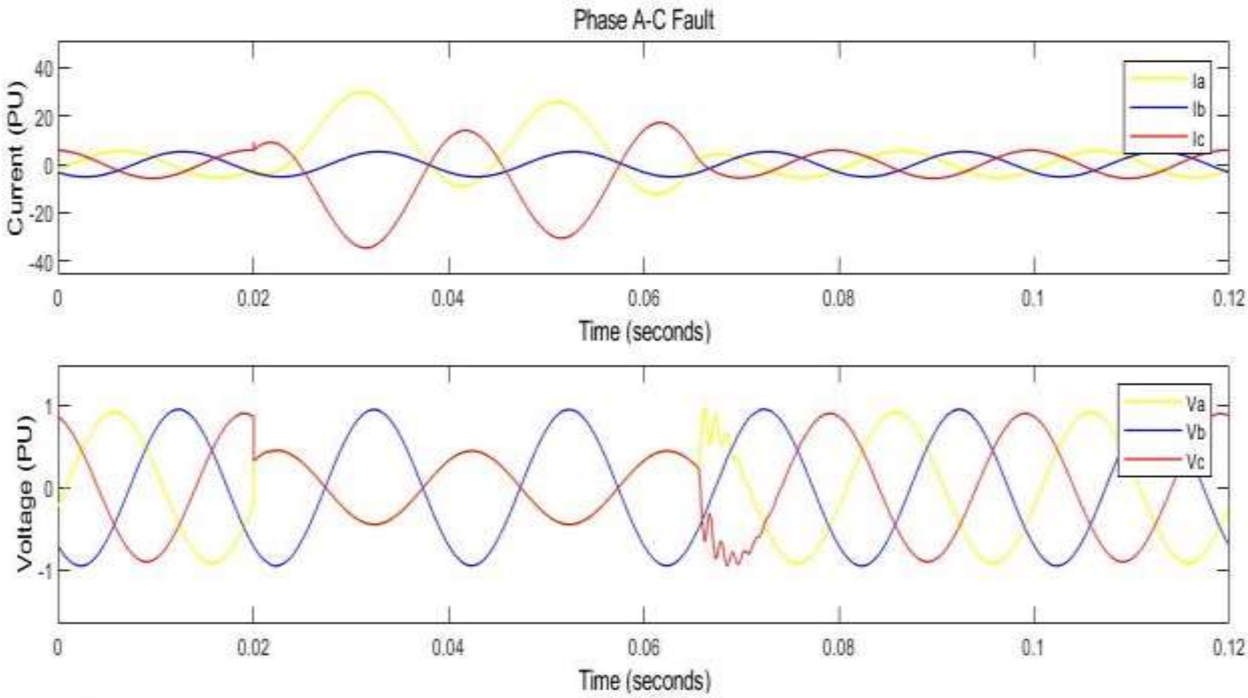


The Double Phase-to-Ground faults A-B-G **Appendix**

A4:

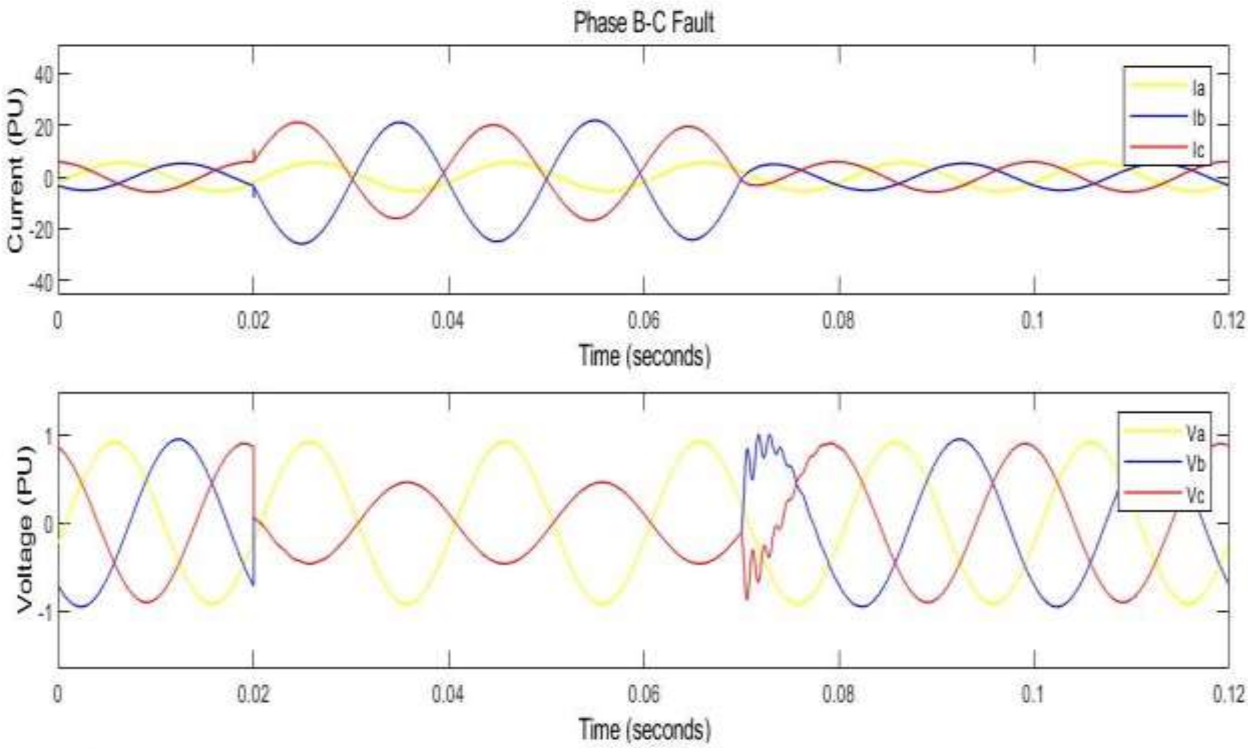


The Double Phase-to-Ground Faults B-C-G

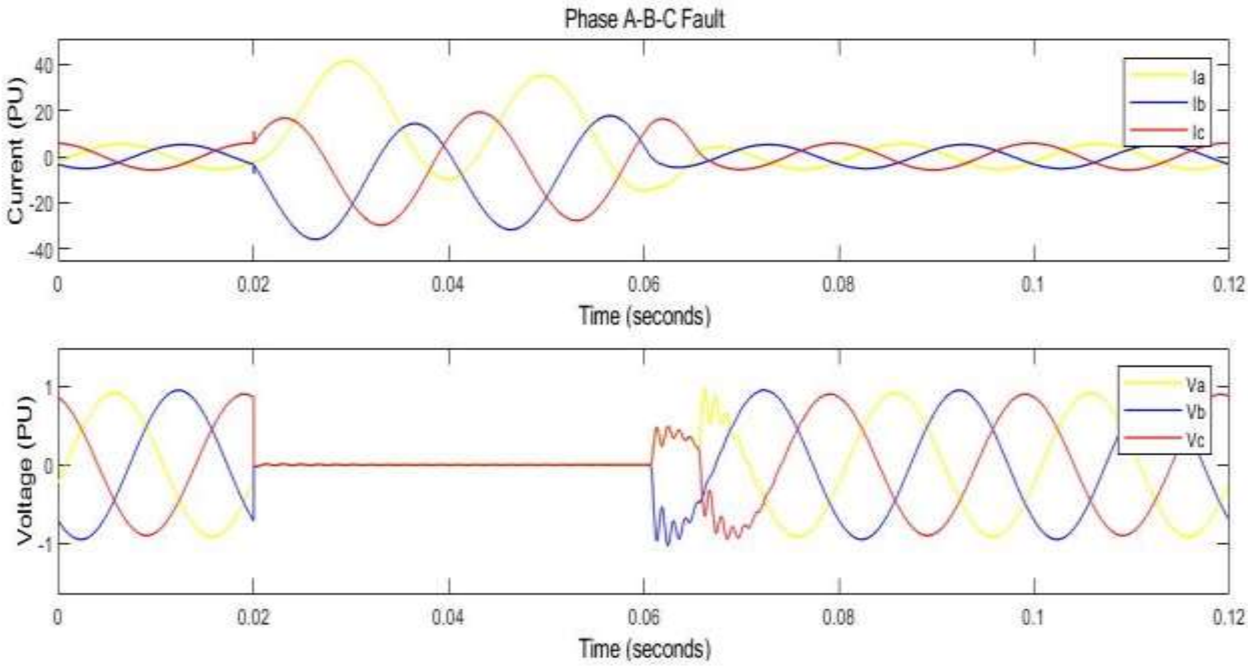


The Phase-to-Phase Fault A-C

Appendix A5:



The Phase-to-Phase Fault B-C **Appendix A6:**



Three Phase-to-Phase Faults (A-B-C)

Appendix B:

Table 3.2: Shows sample of generated data for each fault type

Fault Type	V_c	V_b	V_a	I_c	I_b	I_a
	0	0.38360	0.51380	5.47450	0	0
	0	0.36990	0.52540	5.48410	0	0
C-G	0	0.35610	0.53680	5.49220	0	0
	0	0.34220	0.54810	5.49910	0	0
	0	0.32820	0.55930	5.50450	0	0
	0.00017	0	0.46914	0	5.00560	0
	0.00019	0	0.45790	0	5.03020	0
B-G	0.00021	0	0.44499	0	5.05252	0
	0.00229	0	0.43059	0	5.07311	0
	0.00025	0	0.41480	0	5.09288	0
	0.11549	0.00024	0	0	0	5.22471
	0.13358	0.00019	0	0	0	5.23339
A-G	0.15309	0.00147	0	0	0	5.24052
	0.17363	0.00104	0	0	0	5.24397
	0.19441	0.00006	0	0	0	5.24256
B-C-G	0	0	0.00062	4.48697	1.25122	0

	0	0	0.00065	4.45212	1.34788	0
	0	0	0.00069	4.41532	1.44322	0
	0	0	0.00073	4.37822	1.53881	0
	0	0	0.00077	4.34217	1.63603	0
	0	0.00017	0	13.8188	0	4.364322
	0	0.00014	0	13.9743	0	4.442191
A-C-G	0	0.00011	0	14.131	0	4.520082
	0	0.00008	0	14.2864	0	4.596287
	0	0.00005	0	14.4361	0	4.669349
	0.00020	0	0	0	3.59342	0.41790
	0.00020	0	0	0	3.52247	0.76713
A-B-G	0.00020	0	0	0	3.45269	1.12862
	0.00020	0	0	0	3.38345	1.49605
	0.00020	0	0	0	3.31359	1.861530
	0	0	0	-5.76198	20.4036	-14.9839
	0	0	0	-5.79205	20.4269	-14.8596
A-B-C-G	0	0	0	-5.8212	20.4447	-14.7304
	0	0	0	-5.84931	20.4408	-14.5804
	0	0	0	-5.87608	20.4050	-14.4000
B-C	0.000010	0.320228	0.320218	0	4.932641	-4.932641

	0.000020	0.313605	0.313603	0	3.733939	-3.733939
	0.000023	0.306666	0.306664	0	3.904537	-3.904537
	0.000030	0.299418	0.299415	0	4.066464	-4.066464
	0.000036	0.291823	0.291820	0	4.221701	-4.221701
	0.044984	0.045004	0.044985	5.341208	0	-5.341208
A-C	0.059489	0.059491	0.059499	2.452453	0	-2.452453
	0.073726	0.073730	0.073728	2.579165	0	-2.579165
	0.087742	0.087746	0.087742	2.675997	0	-2.675997
	0.101598	0.101598	0.101600	2.748055	0	-2.748055
	0.275229	0.00003	0.00003	-8.042600	8.042600	0
	0.254194	0.00004	0.00004	-4.034505	4.034505	0
A-B	0.233254	0.00006	0.00006	-4.411748	4.411748	0
	0.212601	0.00008	0.00008	-4.751151	4.751151	0
	0.192395	0.00009	0.00009	-5.059980	5.059980	0
	0	0	0	-4.74760	-4.37941	9.36949
	0	0	0	-4.51378	-4.35701	9.11614
A-B-C	0	0	0	-4.28141	-4.33586	8.86539
	0	0	0	-4.04639	-4.31314	8.61034
	0	0	0	-3.80457	-4.28651	8.34449

Appendix C:

Table 3.3: Target Encoding Scheme for IMFCM

Fault Type	**Line Fault Type**											
	C-G	B-G	A-G	B-C-G	A-C-G	A-B-G	A-B-C-G	B-C	A-C	A-B	A-B-C	No Fault
C-G	1	0	0	0	0	0	0	0	0	0	0	0
B-G	0	1	0	0	0	0	0	0	0	0	0	0
A-G	0	0	1	0	0	0	0	0	0	0	0	0
B-C-G	0	0	0	1	0	0	0	0	0	0	0	0
A-C-G	0	0	0	0	1	0	0	0	0	0	0	0
A-B-G	0	0	0	0	0	1	0	0	0	0	0	0
A-B-C-G	0	0	0	0	0	0	1	0	0	0	0	0
B-C	0	0	0	0	0	0	0	1	0	0	0	0
A-C	0	0	0	0	0	0	0	0	1	0	0	0
A-B	0	0	0	0	0	0	0	0	0	1	0	0

A-B-C	0	0	0	0	0	0	0	0	0	0	1	0
No-Fault	0	0	0	0	0	0	0	0	0	0	0	1