The Application of Artificial Neural Networks to Transmission Line Fault Detection and Diagnosis

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Dedicated to my children, Omphile, Reneilwe and Palesa Nonyane

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Abbreviations

BPNN	Back Propagation Algorithm
BW	Bias Weights
CB	Circuit Breaker
CT's	Current Transformers
DC	Direct Current
EHV	Extra High Voltage
EPS	Electrical Power System
FD	Fault Detection
FLC	Fuzzy Logic Controller
GU	Generating Unit
IW	Input Weights
L-G	Single Phase to Ground Fault
L-L	Phase to Phase Fault
L-L-G	Two Phase to Ground Fault

L-L-L	Three Phase Fault
LPU	Large Power Users
QoS	Qaulity of Supply
RMS	Root Mean Sqaure
SPU	Small Power User
TL	Transmission Lines
UHV	Ultra High Voltage
VSD	Variable Speed Drive

Declaration

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P. Nonyane

Abstract

Fault Detection on transmission lines forms an important part of monitoring the health of the power plant and is an indicator of when potential faults can lead to catastrophic failure of equipment. This research analyses the early detection of generator, transmission line faults and also researches methods of fault detection via the application of Artificial Neural Network techniques.

The monitoring of the generator voltages and currents, of transmission line performance parameters forms an important monitoring criterion of large power systems. Failures lead to system down time, damage to equipment and it presents a high risk to the integrity of the power system, and affects the operability and reliability of the network.

This dissertation therefore deals with fault detection on the Eskom transmission lines from a simulation perspective. Electrical faults have always been a constant source of conflict between transmission lines and power consumers.

This dissertation presents the application faults detection on the transmission lines using Artificial Neural Networks. The ANN is used to model and to predict the occurrence of a transmission line fault, and classifies faults according to its transient characteristics. Results show that the ANN can be used to accurately identify and to classify faults, given accurate problem set-up and training.

The major contribution of the dissertation is the application of ANNs to predict faults on the transmission lines.

Acknowledgments

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1 Introduction

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, and facilitates the speedy prognosis of power system faults and ensures the diagnosis of failures related to power system components [1].

The importance of accurately identifying power system faults on transmission lines and correctly responding to them through protection, isolation or tripping of electrical devices have become more and more important [2]. This is partly due to the fact that as power systems increases in complexity and size, the need to effectively identify transmission line faults have become more and more important.

Therefore, it is the aim of this dissertation to explore the detection of transmission line faults, through the application of Artificial Neural Networks (ANN). Although there are many possible ways of determining and diagnosing faults on transmission lines, the ANN fault detector forms one method of application, common to the power industry. Its methods and techniques are evaluated, with recommendations made as to future successes.

1.1 Fault Detection and its Importance to Power Systems

In South Africa, electrical consumers use electricity produced by the power utility, Eskom. Systems like the generation plants, transmission lines and distribution networks form major components of the electrical network. Eskom has an obligation to supply electricity to its customers, whether the customer is a Small Power User (SPU), such as domestic consumers, or Large Power Users (LPU) as are found within the mining, municipal loads and other industries where large energy consumption takes place [3].

Therefore, it is important for Eskom to maintain supply of Electricity to all its power users, and hence fault detection becomes one of the important performance indicators of electrical quality, but most importantly it also ensures that the power users and all consumers of electricity have reliable and sustainable energy supply. Figure 1.1 gives an overview of the Power System.

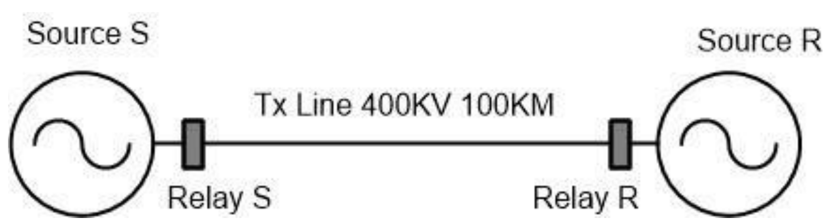

Figure 1.1: A Typical Transmission Line of a Power System

One of the reasons why fault detection is important is that it ensures that electrical consumers receive reliable and good quality of supply (QoS) of electricity at all times. For good QoS the magnitude and frequency of generated voltages and of that on the transmission line must be within the boundaries of voltage or current magnitude, voltage or current phase, frequency and of energy, must be operated within prescribed operational limits [4]. This QoS is then transferred to the electrical customers, who can then reliably utilize the energy for their specific production processes. Each of the aforementioned QoS characteristics can be used for reliably determining transmission line faults through ANN.

A power system therefore, in which the states (voltage, frequency, current, and energy) are operated to within nominal values as far as is practical could then be regarded as a perfect supply system [5]. This ensures that the power system is operated reliably, and that availability of the power system is guaranteed for all possible operating conditions. If the electrical supply system is good, then any loads connected to it will be operating optimally because the QoS is good [6].

Therefore, if the fault detection systems applied to power systems are good and are reliably operating, costs associated to maintenance will be low and the carbon footprint will be low as well. In addition, any unplanned power outages due to faults can and will be minimised [7] because faults are accurately identified allowing speedy recovery of transmission line systems.

However, if the fault detection of the electrical network is not functioning well, then electrical loads connected to the network will fail or will have a reduced lifetime (such as load shedding), and the efficiency of the electrical installation will reduce [8]. Conversely, if the operational and running costs are high, it could be indicative of deteriorating QoS and increasing transmission line cost due to remedial repairs and frequent transmission line faults.

Therefore, this research focuses on identifying faults within a power system that could have a negative impact on the transmission line and the electrical network [9]. Faults within an electrical network can occur often leading to unplanned power outages. In some cases it leads to load shedding, unbalanced supplies and also could cause significant damage to the electrical loads and power system equipment.

By identifying electrical faults accurately, timeously and reliably could improve on the early detection and elimination of faults [10]. This improves electrical network performance and also improves on the QoS [11].

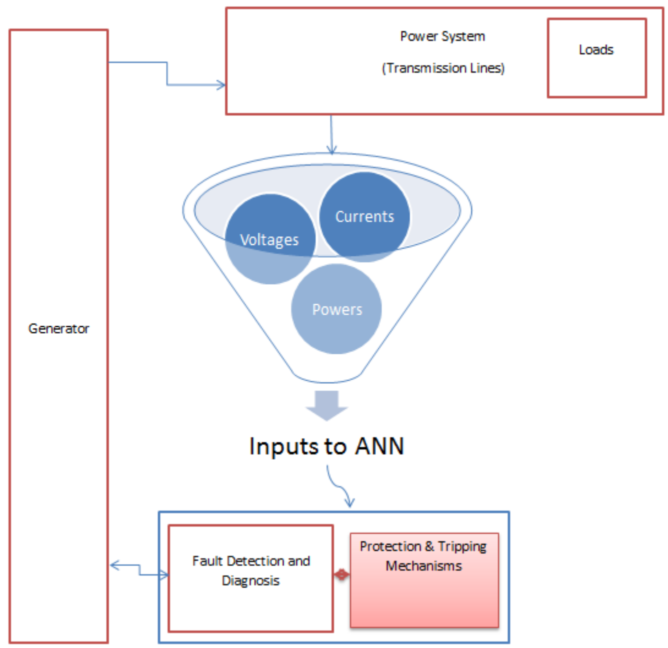

Figure 1.2: The context of fault detection in a power system

Based on several applications of fault detection in the power systems, its methods and techniques have became an important component of power system studies. This chapter provides the basic introduction of fault detection and the rationale of the thesis and its overview.

1.2 Thesis Rationale and Motivation

If fault detection in a power system is compromised then the QoS system is not good, and therefore the electrical loads connected to the power grid will fail [12]. The life span of electrical equipment connected will be reduced which could have a negative impact on its long term operation. In this case, fault detection can help protect electrical equipment by disconnecting affected transmission lines before failure occurs.

The problem of electrical faults can cause severe damages in electrical systems and in the eventuality of a transmission line fault, protective relays will open isolation breakers based upon protective functions. In order to achieve assurance and protection against transmission line faults, alternative methods of fault detection needs to be analyzed and evaluated [13]. Therefore, we considered fault detection through the application of ANN to detect faults quickly.

In addition, electrical faults and their impact on customer loads constitute the most common power quality problem in transmission line systems and distribution systems [14]. Electrical faults can result in the tripping of customers equipment and shutting down of production lines leading to production loss and expensive restart procedures. Examples of electrical faults would include voltage depression, where sensitive electrical equipment such as computer controlled processes, variable speed drives (VSD) and induction motors to name but a few, would deteriorate in performance as result of the voltage depression [15]. In some instances, system modifications can be implemented to minimize the magnitude and the duration of the voltage depression which have a positive impact on the performance of the grid as well.

In other cases, special measures can be implemented at the customers end to reduce equipment sensitivity to electrical faults and the use of Artificial Neural Networks to minimize the impact on equipment. In the processing industry where high reliability of supply of electricity is required, and where the use of motors forms a high component of the industry, the early detection of faults can save on production loss. Lately, attention has been paid to electrical faults in addition to supply interruptions, because of the reduced fault detection times, short recovery time and speedy production normalization is achieved after a fault incident.

According to some estimates electrical faults may cause even more severe problems than interruptions, where a single electrical fault can lead to a shutdown of a production process and thus causes very high recovery costs and revenue lost due to production loss [16]. Because of the importance of fault detection, it has an impact on process industries and also regulatory requirements of QoS conditions, the purpose of this study is to research fault detection of transmission lines faults, its methods of detecting and to analysis different electrical fault of power system. The early detection of faults could improve the QoS and also recommend solutions of prevention catastrophic electrical failures, by the fact of its early detection [17, 18].

1.2.1 Objectives of the Thesis and its Research

The objective of this research is:

1. To measure the amount of electrical faults on the transmission line using ANN.
2. To detect the electrical faults and classify them in real time.
3. To use a power system network model and to simulated it in Matlab Software.

1.2.2 Research Methodology

To achieve the objectives of this study, a section of power system consisting of a transmission line in which an electrical fault is applied is studied, which is based upon a simulation study. In a practical sense, it takes time for Eskom to diagnosis transmission line faults, however by using simulation studies, fault diagnosis and remedial action can be planned more effectively. In this dissertation, the literature has

has been reviewed from conference proceedings, journal papers and certain internet sources and have formed the basis of a literature study.

Comprehensive simulations have been performed to validate the performance of the designed, and trained ANN. In order to achieve this, training data for the ANN is created using models in Simulink, and based upon different operating regimes of the transmission line model. This would include, variations in electrical load, variations in transmission line length and variations in transmission line characteristics. Each of these conditions are simulated and consolidated data is then used to train the ANN.

In order to validate the performance of the trained ANN, the error between the actual transmission line fault and the output of the ANN is measured. If the error is zero, there is a complete match between the actual and simulated fault. Therefore, training of the ANN becomes a minimisation problem.

1.3 Overview of the Thesis

Chapter 1: Presents a background and introduction to the dissertation.

Chapter 2: This chapter focuses on faults detection. It is aimed at presenting a comprehensive study of fault detection methods and application within industry. We specially focus on the power industry and reviews the methods and techniques for transmission lines.

Chapter 3: This chapter presents the methodology of applying ANN to transmission line fault detection. It focuses on understanding the basis of ANN and how it can be applied to fault detection.

Chapter 4: The results are achieved by simulating the model is presented in this chapter. It presents results and shows the effectiveness of the ANN method.

Chapter 5: It concludes the thesis by summarizing its most important results, followed by recommendations.

1.4 Summary of Chapter

This chapter gave an introduction and motivation of the dissertation, with the aim to evaluate methods of fault detection and to analysis the detection of faults through the application of Artificial Neural Networks, it would form the main contribution of this dissertation.

2 A Review of Fault Detection and Diagnosis

2.1 Power Systems

The process of converting mechanical energy to electrical energy is done by the generator of power stations, where energy is supplied to substations via transmission lines. Thereafter, power will be transmitted to the distribution substations before it is transferred to domestic, commercial and industrial consumers [19].

Transmission lines have resistances, capacitances and inductances which varies with the length of the line and has a role to play in the dynamic behavior of the line. Furthermore, transmission lines are modeled as PI - sections along the length of the line [20], where the line is the aggregation of many PI - sections. This makes its easier to model the transmission line.

Power plants generate electricity and they are generally situated far from the electrical consumers due to safety reasons. Therefore electricity is transmitted to the consumers via the long transmission lines and distribution lines. Before the electricity is supplied to consumers, it is necessary for the voltage to be stepped down using transformers [21].

Sub-stations form an important part of power system operation and control. In step-up sub-stations, to operating voltages are 22KV, 400KV or 500KV, and this depends upon the operating parameters of the transmission line. [22, 23].

Therefore, electrical power systems composes of a number of Generation Units (GU), transmission lines, distribution lines, and substations. These systems functions together to form a complete Electrical Power System (EPS). The electrical power generated is rated at about 11KV to 25KV, then it is step up by using the Generator Transformer to 220kV or 500kV, this depends upon the rated transmission voltage parameters, and is required for long distance transmission lines.

Before the power is fed to the grid, it has to be transmitted through the high voltage line as depicts in Figure 2.1. A typical transmission line is divided into three functional sections, as listed below;

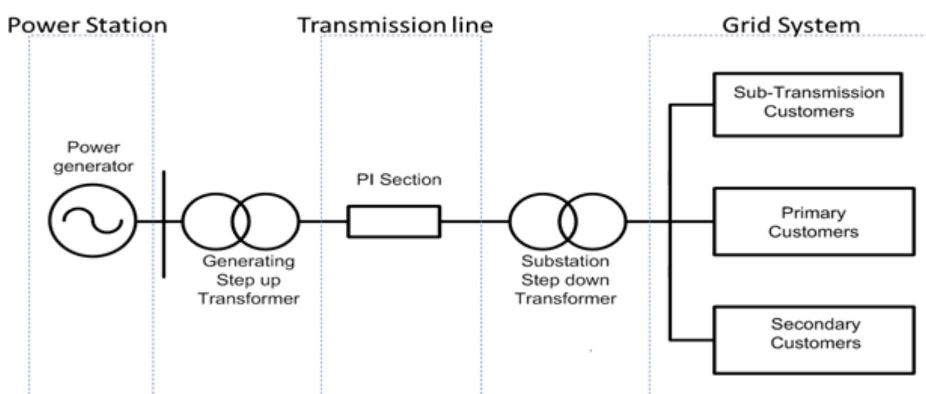

Figure 2.1: A model of a power system

1. The Generation Site,
2. The Transmission Site, and
3. The Distribution or the Grid Site.

Furthermore, the transmission line is a vital part of the Electrical Power System, and plays an important role in the operation and control of the power system [24]. In addition to power system operation and control, is power system protection, and in the context of this dissertation, transmission line protection forms the main focus of this work.

Transmission line protection plays an important part in meeting the stability requirements of Electrical Power Systems, firstly in terms of voltage stability and especially by controlling and protecting against transmission line faults. Furthermore, transmission line protection systems safeguards critical electrical components from damage, separates systems against faults and maintains operational integrity during fault conditions.

2.2 Faults in Power Systems

The rapid growth of electrical power systems in terms of size and complexity implies to a certain extent that power system faults are unavoidable. The complexity and nature of electrical power systems, makes faults to be unavoidable, especially in the transmission line system [25. Faults are an undesired short circuit condition that is observed either between two phases or between a phase and ground.

There are different types of faults that are observed in power systems, and they can be caused by any of the following conditions [26];

1. Lightning,
2. Short Circuits,
3. Faulty Equipment,
4. Miss Operation,
5. Human Errors,

6. Overload, and Aging.

These can be further categorized into three types;

1. Symmetrical Faults,
2. Unsymmetrical Faults and,
3. Open Circuit Faults.

Transmission Line faults are dangerous since it causes overheating or create mechanical forces with the capability to break equipment and other elements of power system [27].

2.2.1 Symmetrical Faults

To have a healthy power system we must ensure that we protect it from the short-circuit faults [28]. Symmetrical faults consist of three types of faults, namely;

- Single Phase Fault - this is where one phase is short circuited while either involving the ground or not,
- Two Phases Fault - this is where two phases are short circuited while either involving the ground or not,
- Three Phases Fault - this is where all three phases are short circuits while either involving the ground or not [29].

Symmetrical fault takes place when all three phases experiences short circuit faults at the same time.

2.2.2 Unsymmetrical Faults

The majority of the faults that take place on power systems are unsymmetrical faults. Unsymmetrical faults can compose of unsymmetrical short circuits, unsymmetrical faults through impedances, or open conductors. The unsymmetrical faults are classified as follows [30]:

1. Single Phase to Ground (L-G) fault - L-G is a short circuit that exists between one of phase conductors and earth. It can be caused either by insulation failure between a phase conductor and earth or breaking and falling of phase conductor to the ground.

2. Two Phases to Ground (L-L-G) Fault - L-L-G is a short circuit between any two phases and earth, where the path of the fault current from line-to-line or line-to-the ground may not contain impedance.

3. Phase to Phase (L-L) Fault - L-L is a short circuit that is found lining whichever two phases of the system.

4. Three-Phase (L-L-L) Fault - L-L-L is a short circuit found linking whichever two phases of the system.

2.2.3 Open Circuit Faults

Open Circuit Faults mostly results from conducting path disconnection. These faults are mostly common in cases when one or more phases of the conductor are disconnected or a cable joint or jumper on an overhead line fails.

These kinds of faults may results from the disconnection of two or more phases which are on the power system and affect the rest of the transmission lines equipment [31]. These faults are mostly common in cases when one or more phases of the conductor are disconnected or a cable joint/jumper on overhead line electrical networks fails. And these types of faults may be happened in cases when the circuit breakers or isolators open while failing to close in one or more phases.

Alternatively, these types of faults may be observed in cases when the circuit breakers or isolators open while failing to close in one or more phases. During the open circuit of one of the two phases, unbalanced current flows in the system, thereby heating rotating machines [32]. Protective schemes must be provided to deal with such abnormal conditions.

On the other hand, it is the transmission line which contributes the most in electric power system instability, which justifies the much focus on protection of transmission lines. On the other hand, there are many different protection solutions for the transmission line offered by different leading transmission line protection companies [33].

However, the solutions provided are not perfect, this leaves a room for more studies to be conducted in order to improve the current solutions. There protection of the transmission line is conducted by devices that can sense the fault and remove it. It is given that random types of faults will occur, in different random location [34].

Hence the importance of fully recognizing the different steps that needs to be done to accomplish this transmission line protection. The protection of transmission lines is categorized into three steps: Fault detection, fault classification, and fault location [35].

2.2.4 Fault Detection

Fault Detection (FD)is a vital objective of power system engineers since the inception of power system technology. Not only does it play an important role in power system operation and control, but accurate Fault Detection enhances operational performance. The accuracy and speed of detection are measures of the effectiveness of the detection mechanism; the faster the detection mechanism the higher the possibility that the equipment can be protected [36].

The significance of damage is directly proportional to the time it takes to detect and correct the fault. Even though fault detection schemes have been developed in the past, a variety of fault detection approaches continue to be developed to enhance the performance and accuracy of fault detection methodologies.

Each fault detection approach detects faults independently and once faults have been detected by one or more detection mechanism, the time at which it occurs is recorded. If abnormalities are observed, then other processes might follow such as fault classification and fault location identification.

However, if the abnormality is recorded at only one end of the transmission line, then the possibility that an error might have occurred is recorded in the microprocessor memory.

The implementation of a fault detector is not a difficult procedure, since high speed electronic microprocessors, advanced digital signal processing techniques and dedicated embedded hardware systems provides sufficient and satisfactory hardware implementation methods. The hardware implementation becomes a challenge because the fields in question are not necessary limited to ellipses in their shapes. These explain the need for more steps to the fault detection procedure to prevent false alarms while improving accuracy.

All the fault detection computations are done identically and independently for both ends of the transmission line. The computation of both ends interacts only if the potential fault is detected [37].

2.2.5 Fault Classification

Transmission line faults can be classified into different types of faults based upon its characteristic fault signature. Transient voltages and currents exhibits different behavior, which allows fault classification methods to be able to accurately identify and to classify faults. Therefore, the fault detection section of any fault protection relay is used to ensure that the classification fault section is initiated and it also ensures that the location of fault section is initiated.

Fault classification is essential for determining the type of a fault occurring in the transmission line. The classification of fault in the transmission line is essential for fault location procedure. Furthermore, the classification section is used to categories phase-to-ground fault, phase-to-phase to ground fault, phase-to-phase to phase-to-ground fault, and the fault on the Transmission Lines [38].

The circuit breaker receive the messages from the fault classifier section and location section fault and check what type of fault and the location that the fault took place, therefore it will decide to open (trip) or close (not trip) [39]. Once the circuit breaker decide to trip therefore there will be no power on the Transmission Lines, but if it decide not to trip therefore the will be the situation will remain the same and the current will be supplied in normal conditions.

2.2.6 Identifying the Fault Location

Most of faults used to occur on the EHV/UHV overhead lines are single phase to ground faults. The protective relays together with the Auto-reclosing were used to monitor the transmission lines and distribution Lines and then if there's a fault it will trip the line and once the fault is cleared it will energize the line immediately [40]. If the fault occurs on the transmission line or distribution line the relay should be capable to detect the any kind of fault that may take place as quick as possible and inform the circuit breaker to trip.

For the worst case scenario, if the If the Location cannot be identifying on time which means there will revenue loses and the situation whereby consumers will not be able to receive electricity in their houses. Some methods used in fault locators are proposed to make distance calculations of the fault as accurate as possible. The fault locator in most of the instances are linked with protection relays and distance relays of the transmission lines shows some indication where the fault is took place, but they are not considered to identify the location [41].

Table 2.1 gives and overview of the characteristics of a Fault Locator and a Protection Relay. If can be seen that the characteristics are dependent upon the type of fault and the equipment used.

2.3 Conventional Fault Detection Mechanisms

There is a high chance of experiencing electrical fault in a Power system, hence Fault Detection was employed to detect if there is no fault on the system [42]. The main objective of this Research is to enhance fault detection methods on the transmission line.

2.3.1 Challenges and Limitations

If there is electrical fault in a power system, it is important to detect it in a short space of time and very accurately, for instance if the power system is swinging the attention of the fault should be taken into a consideration. If the fault happen during power swing and the distance relay cannot figure out that there is electrical

Table 2.1: A comparison between a fault locator and a Protection Relay

Characteristic	Fault Locator	Protective Relay
Speed of Response	Low Speed - Typically fault locators are slow, since it analyses where the faults are located. This takes some time.	High speed operation - A protection relay needs response very fast to transmission line faults, where it serves a protective function.
Accuracy of Detection	Pinpoints the fault position accurately. The aim of the fault locator is to identify the location of the fault along the transmission line.	The protective relay does not pinpoint the fault, but only identifies the fault. Fault clearing time is good
Fast and Reliability	Fast and reliable indication	Fast and Reliable.
Flexibility of Detection	Very specific in its detection mode and fault to be detected. Protection zone to provide back capability. Not that flexible.	Capable to trip any type of fault. More flexible.

fault, therefore the circuit breaker will keep close. The circuit will not be able to trip which means there will be excessive current flowing on the transmission lines that can cause a major power blackout.

Conventional fault detection techniques depend on the input and output current and input and output voltage. For this technique to detect electrical fault, the conventional fault detection techniques it depend on the amount of voltage and voltage also depend on amount of current flowing on the power system [43, 44].

2.4 Other New Fault Detection Methods

2.4.1 Application of Fuzzy Logic Controller

Fuzzy Logic Controller can be used as an effective tool for high speed digital relaying and can be also used as the correct detection is achieved within a cycle of the fault incident.

2.4.2 Fuzzy Logic Controller Techniques

Fuzzy Logic Controller developed with the aid of relational neural networks. Figure 2.2 shows the Fuzzy Logic Controller. Fuzzy Logic Control consists of the Inference Engine, where the decision making of the controller takes place, with Fuzzification and Defuzzification for interacting with the process plant for control.

Fuzzy sets and neural networks deal efficiently with the two very distinct areas of information processing [45]. When we evaluate the FLC and ANN, we found that FLC are good on knowledge representation and ANN has effective structures, reliable, accurate and capable of learning [46]. Both techniques have their advantages and disadvantages.

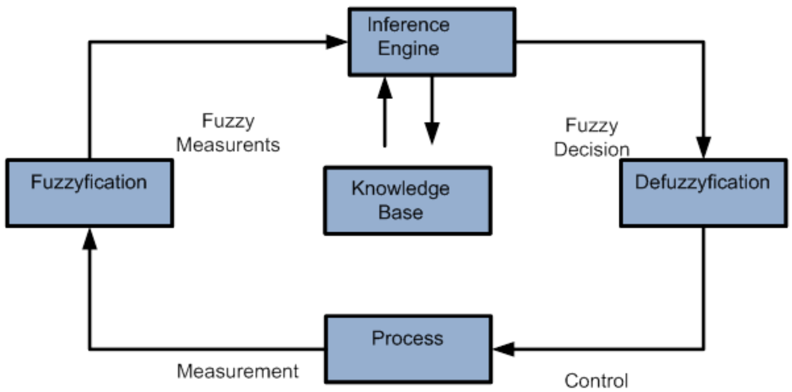

Figure 2.2: Fuzzy Logic Controller block diagram

2.5 ANN Fault Detector

An ANN detector was tested in many types of fault, classify fault, location fault and different fault resistance, it was recommended base on the results that ANN Technique can be applied on the power transmission line to detect the any kind fault. ANN Fault Detector is capable to detect the fault, locate the fault and classify the fault on the transmission lines. ANN has effective structures, reliable, accurate and capable of learning.

2.5.1 Description of Artificial Neural Networks

Is a good technique which works like a brain of human being and also capable of learning. Many training are required by ANN before it can be applied in a particular plant. ANN have set of neurons that are connected and arranged in many layers, its structure consists of inputs layers, hidden layers and output layers [47].

2.5.2 Applications of ANN

The power systems grow very fast and it is important to locate and identify the fault on the system by using techniques which are quicker, reliable and accurate. ANN was proposed in this regard to deal with the classification of faults and location of faults on the transmission line [48].

2.5.3 Testing of ANN

Fault resistances, fault locations and other types of faults were used to test ANN fault detection and fault classifiers [49].

2.5.4 Advantages and Disadvantages of ANN

Table 2.2 below gives an overview of the advantages and disadvantages of ANN, and compares it to the results of Fuzzy Logic Control. It is clear that both methods can solve a vast range of problems, each with their respective advantages and disadvantages.

Each method, namely FLC and ANN can be applied to different problems, each with their specific application focus depending upon the nature and complexity of the problem to be solved. It should be noted that initial analysis, problem formulation and preparation into the problem to be solved must first be performed.

Table 2.2: A comparison between Fuzzy Logic and Artificial Neural Networks

Fuzzy Logic	**Artificial Neural Network**
Advantages	*Advantages*
Fast adaptation to changes	Learning ability via training
High degree of tolerance to uncertainty	Faster detection of faults
Smooth operation over control regimes	Protect power system intelligently
Reduce the effects of non-linearity	Faster computational times necessary
Learning ability limited, requires intelligence	Adaptive features, to learn to new problems
Inherent approximation capability	It detect and classify the fault
High accuracy of tolerance	Noise rejection cababilities via AI
Disadvantages	*Disadvantages*
Difficult to model mathematically, and requires expernt knowledge.	Requires careful analysis

2.6 Summary of Chapter

This chapter presented an overview of the literature. It focused on artificial intelligence techniques such as Artificial Neural Networks and the Fuzzy Logic Controller as new techniques to protect the transmission lines [50]. Several researchers have proposed different techniques for fault classification of transmission lines using different types of neural network topologies. In this research we proposed ANN to the detection of faults, because it gives correct fault type classification however this method does require more training to achieve good results [51].

3 Methodology of Fault Detection

In an Electrical Power System the possibility of an occurrence of a fault is always prevalent and the Network Operator needs to be fully informed on the health and status of the Power System Network. This enables the Network Operator to make an informed decision on the necessary corrective actions needed and also to perform remedial work to clear a fault. Therefore, this section more fully explains the procedures that are necessary to be followed when detecting faults, and also of successfully analyzing and diagnosing transmission line faults [52].

In order to detect faults, it is important to have an understanding on the nature and characteristics of the faults, and of the methods used for its detection. Conventional fault detection relays as applied to power systems have been predominately used for transmission line faults [53].

Conventional fault detection systems have been based upon parameter settings and limiters for different voltage and fault currents settings and can be more accurately described as protection limiters to trip the network accordingly. However, to more intelligently detect faults, Artificial Neural Network (ANN) was introduced as a fault detector.

In this section, the methodology of Fault Detection and Diagnosis is explained, and it shows how ANN can be used as a fault detection tool.

3.1 An Overview of the Model

The system which forms the basis of the present analysis is a 400KV transmission line system. The protection strategy implemented is through the application of Artificial Neural Networks (ANNs), which performs the diagnostic and classification functions of the ANN protection relay.

Figure 3.1 shows a simplified Single Line Diagram of the system. At either end of the transmission lines are Generating Units, or AC Sources, with electrical loads connected. The system is modeled using distributed line parameters (PI Networks). This model is common found within the literature and forms that basis of analysis.

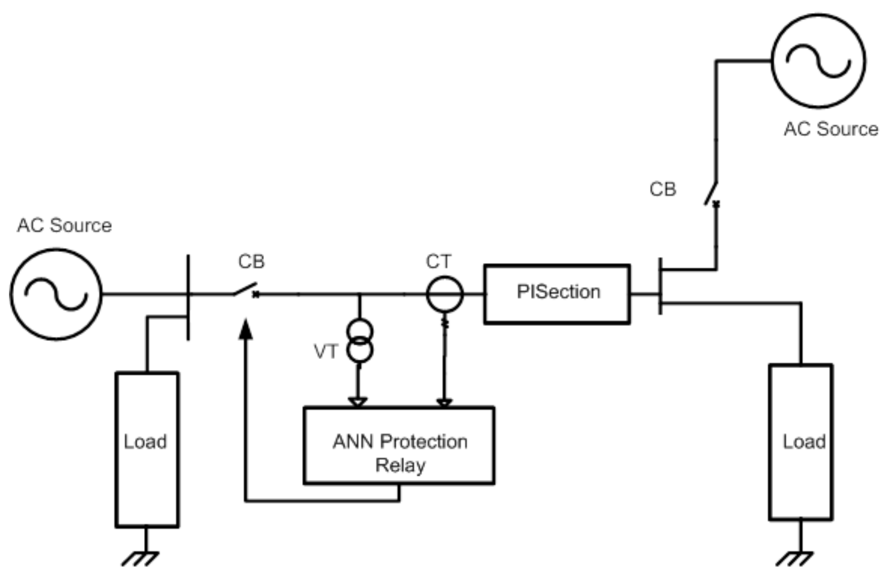

Figure 3.1: A simple block diagram model of a power system

If there is a fault on the Transmission Line, the ANN Relay will sense the presence of the fault and will initiate a tripping command to the Circuit Breaker (CB) to protect the TL from adverse effects and failure as shown in Figure 3.1. The ANN Relay is the protection device of the transmission line network.

Its is the purpose of the ANN Protection Relay to monitor the health of the network and to perform a protective function. Consequently Fault Detection will activate the ANN to determine the type of fault (which is known as Fault Classification), while Fault Locators are used to accurately pin point the position of the fault [54]. In contrast to this, Fault Relays only indicate the general location of the fault [55].

Relevant to the application of ANN to FD, the ANN Fault Detector works online and performs measurements of voltages and currents. It is required that ANN FD perform its calculations at fast as possible [56].

3.2 The ANN Fault Detector

The effectiveness of the ANN fault detector depends upon the accuracy of its input measurements, and upon the effectiveness of the training data.

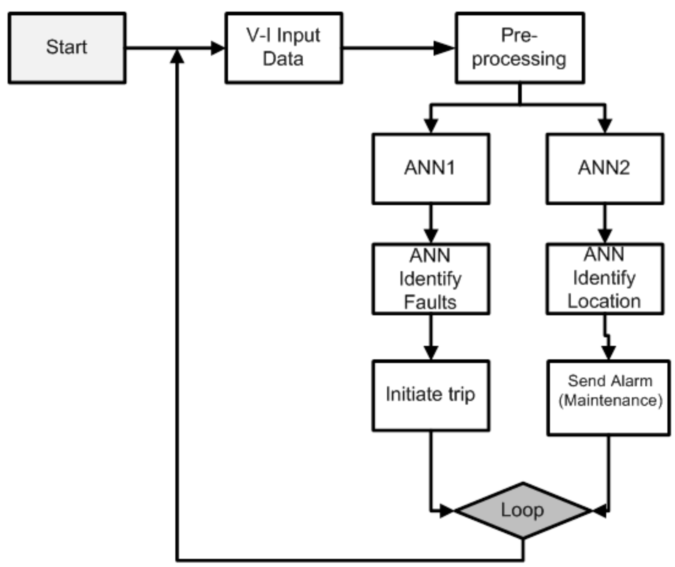

Figure 3.2: Fault-chart showing ANN FD method.

The training data should be well managed, appropriately filtered and scaled, to enable the application of intelligent methods such as ANN [57]. This process is graphically shown in Figure 3.2.

Figure 3.2 show two general approaches, namely Fault Detection (ANN1) and Fault Location Identification (ANN2). Fundamentally, the structure and method training the ANN for each method is the same, however their respective application differs in terms of output and processed information.

Upon successful completion of the ANN, a trip command is given to the circuit breaker to trip the transmission line, and also a signal confirms the location of the fault. This process iteratively performed within the ANN fault detector.

3.3 Method of ANN Training

The training of Neural Networks forms one of the most important steps in the development of ANN fault detectors and fault locators, and therefore training data should be methodically and thoughtfully prepared [58]. In some applications training data is not always available as part of a real system, and therefore the use of a training simulator can be used for generating relevant data for training ANN [59].

When developing training data, the data should be representative of all possible scenarios under which the ANN will be called upon to perform its detection and classification functions. Thus training data can becomes huge sets of data. The Back Propagation Algorithm (BPNN) has been used for training [60]. Figure 3.3 gives an overview of the Training process.

The ANN is an interconnection of neurons, where each layer of neurons form inputs to successive layers. Each layer is adjusted by weights and enhance signal transmission strength. The output that was produced by BPNN is a target output and the output produced by the conventional method is an actual output.

The error makes us to understand the difference between the desired outputs and the actual process outputs. For us to calculate the Least Mean Square Error we used the error. When null error is obtained the BPNN will operates by propagating errors backwards from the output layer [40, 41, 42].

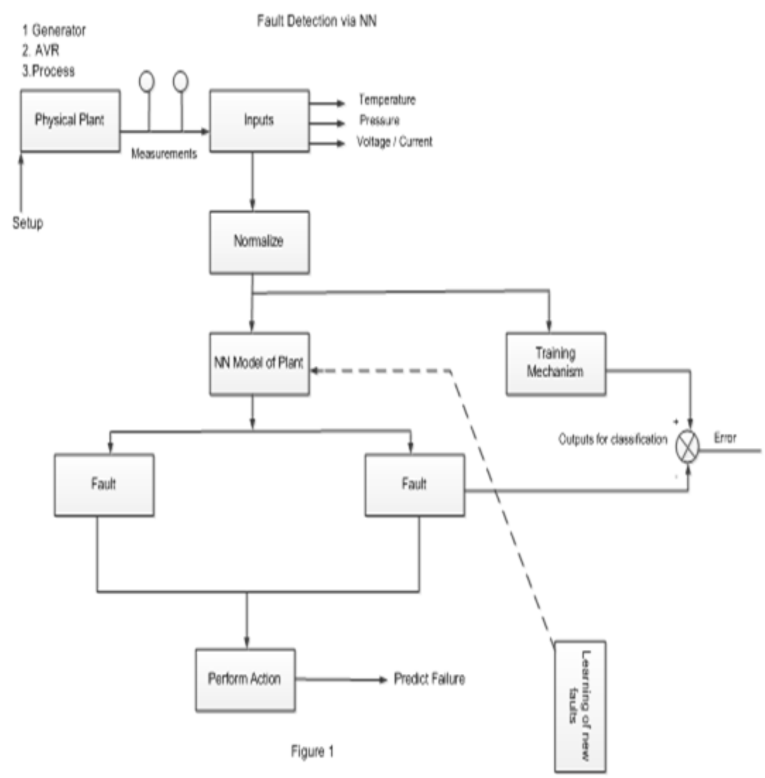

Figure 3.3: Block Diagram of the ANN training process

The ANN Fault Detector experiences training which have many reasons of matching to different kinds of data, of which electrical faults forms the basis of this study. The validation of the trained ANN is performed via simulation, where the accuracy of the results and its performance is verified. Therefore, validation and testing of ANN output to input data is most important.

As can be seen from Figure 3.3, our proposed solution is to use actual data (simulated) for training of the ANN. In addition we apply a learning methodology to learn new faults as the system performs in real time. Simulation would show the feasibility of this research and its application to industry.

To create an ANN, the inputs and outputs of the neural network the pattern recognition must be explained, and correlated to train the ANN. The inputs to the network gives a picture of the condition and transient characteristics of the faults to be detected, and this should carefully taken into a consideration.

The neural detector is designed to indicate the presence of a transmission line fault presence, or the fault absence. The appearance of such a fault is given by identifying directly the power system state starting from the instantaneous voltages and currents. Consequently before that the voltages and the current signals enter to the neural network, a scaling technique (or signal normalization is performed) has a great importance in order to reduce the execution computing time. For this purpose we adopted a scaling technique expressed by the division of the magnitudes of the fundamental voltages and currents.

ANN can be considered as an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to new previously unseen data. This is via training, and it assumes that learning takes place.

3.4 Summary of Chapter

This Chapter presented an overview of the methodology of fault detection, and also showed the approach followed in this dissertation to solve the fault detection and diagnosis problem of transmission lines.

4 The Application of ANN for Fault Detection of Transmission Lines

The importance of Fault Detection is to detect, monitor and protect the transmission lines if theres a fault, irrespective the transmission lines size (short or long) [61]. The proposed method focuses on identification when the fault occurred and pinpointing the type of fault and its location on the transmission lines. The ANN detector and classifier are tested in many fault types, various locations, different fault resistances and various inception angle. The Artificial Neural Networks (ANN) for the fault detection and classification in real time, transmission lines which can be used in the production system digital protection [62].

This approach is based on the action of each phase current and voltage. The outputs of the ANN indicate the fault presence and it type. All the test results show that the fault suggested detector and classifier can be used to support a new system generations of the protection relay at high speed and accurately. Nowadays power system is highly interconnected requires early fault detection and fast isolation to maintain system stability. Faults transmission lines need to be detected, classified and located quickly [63].

There are many reasons why ANN was used for currents as the inputs to the Neural Networks. Current signals measured at one end of the line only have been used as the inputs to the ANN algorithms because Current Transformers (CT's) are always present at each of the line for measurement and protection purposes [63]. VTs may sometimes not been used due to revenue reasons.

Current signals measured at one end of the transmission lines only can be used for fault classification and location. Voltages and currents are utilized as an input to the neural network therefore ANN output will give good results and very fast. ANN method uses these voltages and the currents to obtain the load reactive power.

This Chapter gives an overview of the application of ANN to fault detection for transmission line faults. It is important as described in previous chapters to be able to identify and locate transmission line faults, because faults can cause damage to equipment, outages and shutdown of power system networks. If the faults occur on the transmission lines without noticing them therefore there will be some major breakdown in the entire networks of the power system.

We need to model transmission lines to ensure that if there is a fault it can be detected on time and ANN can give accurate readings. Simulink have been used to simulate three phase transmission lines, where faults have been modeled as ground faults.

4.1 Fault Classification

It is important to classify transmission line faults, since it identifies what type of fault it is and allows for appropriate decision making processes. The following classification is commonly used within the literature, and also shown in Figure 4.2. The more classification rules there are, the more complex the size and design of the ANN is and adds to the complexity of the training of the ANN.

Therefore, we chose to classify ANN out as a common fault detector. Classification rules are as follows.

1. A-G - A Phase A to Ground Fault.
2. B-G - A Phase B to Ground Fault..
3. C-G - A Phase C to Ground Fault.
4. AB-G - A AB Phase to Ground Fault.
5. AC-G - A AC Phase to Ground Fault.
6. BC-G - A BC Phase to Ground Fault.
7. ABC-G - A ABC Phase to Ground Fault.

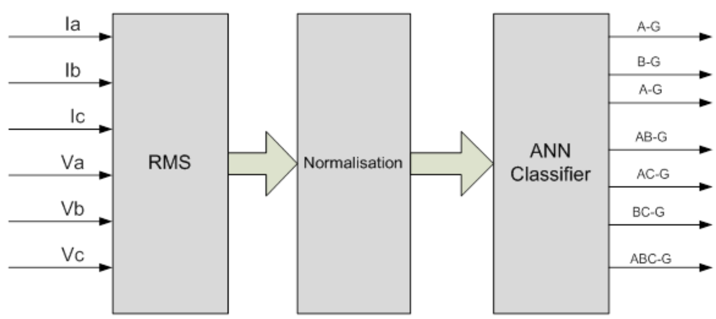

Figure 4.1: Block Diagram of the fault classification process

Input to the ANN fault detector are the three phase voltages (Va, Vb and Vc) and the currents (Ia, Ib and Ic). Initially, both the voltages and currents are converted to RMS values (or DC signal). Filtering of the signals can also be performed to remove unwanted harmonics and signal noise, typically, this function is performed by a Low Pass Filter. See Figure 4.1. The ANN system is capable to describe each type of fault and send it to the output (classification).

4.2 Simulink Model for Fault Detection

The three phase power system network model is simulated in MATLAB/Simulink software. It is a 400kV, 60 HZ, 100km transmission line power system. It consists of Voltage and current measurements, circuit breakers, transmission line and load which are shown in Figure 4.2. The main purpose of the transmission lines is to supply power to the load. The power supply is generated by the Generator is supplied to the load through the transmission line network.

A Circuit Breaker is a device that makes or breaks the electrical connection of a system and it interrupts the flow of current in an electrical circuit. The load is the feeder of the consumers, whereby the consumers fed from it and ANN can be able to detect some faults like overload current if the KVA is imbalanced. The Load may be designed as radial or ring feeders on the power system, the ring feeder has a back-up supply while the radial feeder is a straight line supply to the consumers.

Earlier systems use a conventional method on the transmission lines to detect the fault which takes time to detect the fault and gives inaccurate results [1]. Conventional algorithms are based on upon Kirchhoff Voltage and Current Laws on a well-defined model for transmission line protection.

Conventional distance relays consider power swing of voltage and current as a fault and tripping mechanism. Such faulty components would lead to severe consequences and contributed to power system instability. The application of Artificial Neural Networks to transmission line faults gives accurate results. Transmission Line parameters are shown in Table 4.1.

As shown in Figure 4.2 is a three phase transmission line system. It consists of two three phase sources simulating a synchronized power system. The transmission line includes PI transmission line component, with points for the measurement of voltage and current. In addition, three phase loads are distributed along the length of the transmission line. A three phase fault simulates transmission line ground, phase to phase and phase to ground fault.

Table 4.1: Transmission Line Parameters

	Parameters	
Transmission Line Parameters	Length (m)	100
	Voltage (kV)	400
	Positive Sequence Impedance (Ω/km)	$(0.1273 + j0.352)$
	Zero Sequence Impedance (Ω/km)	$(0.3864 + j1.556)$
	Positive Sequence Capacitance (nF/km)	$12.74nF$

4.2.1 ANN Pre-Processing or RMS

Measurements of Voltage and Current are typically superimposed with noise and spurious harmonics, which can disturb the accuracy of the ANN performance. In a real systems, analogue filtering of signals are used to remove these harmonics, to minimize unwanted signals. In addition to signal filtering, signals are Normalized into a range from 0 to 1 to simplify the range of signal amplitudes (this is shown in Figure 4.3 as the Normalization Gains).

In order to convert the incoming AC voltages and currents to an equivalent DC signal, an RMS conversion is performed. This simplifies the operation of the ANN, and makes the signals easier to work with. See Figure 4.3.

Figure 4.3 shows how the voltages and currents are normalized to per unit values. The use of per unit values simplifies the processing of the simulation data, and performs the calculation for each and every phase. The use of the RMS function effectively filters the normalized voltage and current data to represent an equivalent

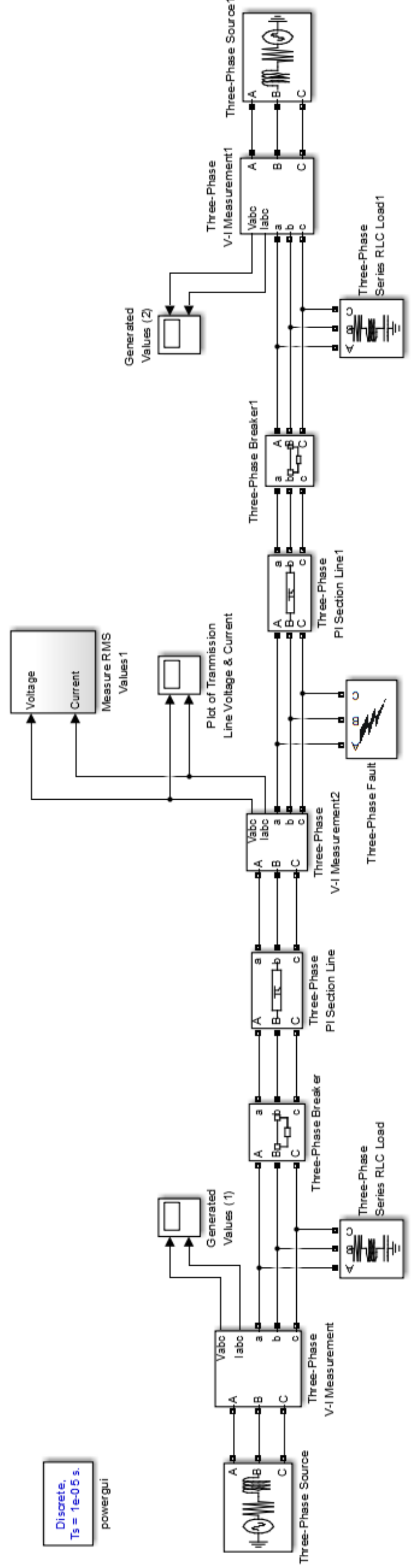

Figure 4.2: Three Phase transmission line model

DC value (i.e. it converts AC to DC). This DC voltage is proportional to the amplitude of the AC signal.

There are more advanced methods which can be used, however it was found that the RMS values are satisfactory. For more advanced fault detection systems, more advanced filtering methods and increase speed methods can be used.

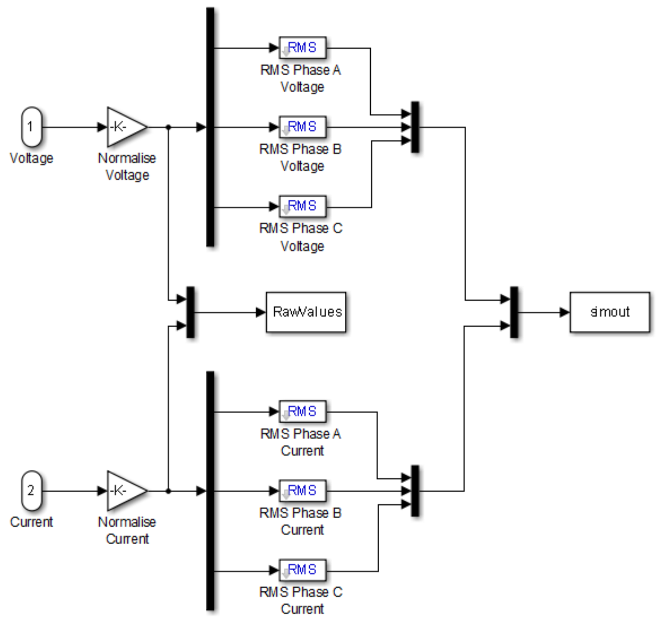

Figure 4.3: Pre-Processing of voltage and current values

4.2.2 The ANN Classifier

The ANN Classifier is shown in Figure 4.4. As can be seen, it has six (6) inputs, namely, Voltages (Va, Vb, Vc) and Currents (Ia, Ib, Ic), as processed by Figure 4.3. The ANN consists of 10 hidden layers and 1 output layer. Its objective (based upon its training) is to identify an Earth Fault on Phases A, B and C. The output is trained to give a response to any of the fault conditions presented, and thus represents a Common Fault Alarm (or Trip).

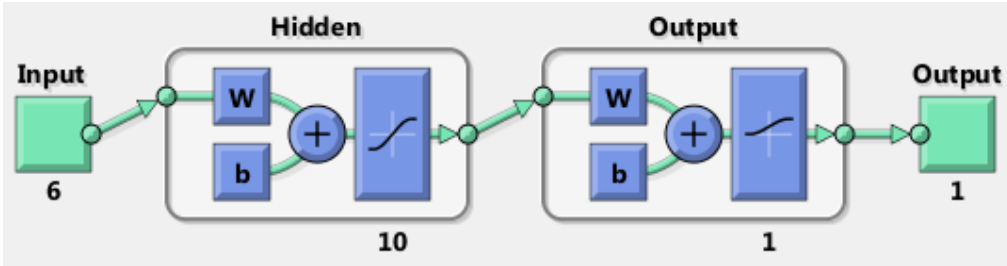

Figure 4.4: The ANN classifier for fault detection

Figure 4.5 gives a more detailed view of the designed ANN, and its input, hidden and output layers.

The inputs and outputs of the neural network should have a number of hidden layers according to the complexity of the problem being solved and a number of neurons of each layer of the ANN. As can been seen in the figures, a neural network of three layers, six neurons in the input layer and one neuron in the output layer is used (as indicated in Figure 4.4 and also in Figure 4.5). The logsig function evaluates the output and recommends the best results on the hidden layer and output layer according to the Bias Weights (b).

To achieve the right magnitude and correlations for the total number of the inputs and outputs of the neural network, training of the ANN is required. The selection of the inputs of the neural network is based on the size and complexity of the problem. The higher the number of inputs and the number of outputs are, the more detailed the complexity of the ANN is. This results in a large number of hidden layers. The size of the hidden layers allows for effective decision making. The input are based upon 50Hz and three phase voltages and currents, these are normalized to DC as described in section 4.2.1.

The three phase voltages and currents were measured on both ends of the transmission line. The type of fault was classified along the length of the transmission line, whereby the ANN output would confirm a fault for any of the three phases.

Table 4.2 show the Input Weights (IW) matrix values. It can be seen that the matrix is N=10, representing the 10 hidden layers, M=6, representing the 6 inputs. Table 4.3 shows the Bias Weights (BW). The matrices shown are the actual ANN designed using the Matlab ANN Toolbox, and is the weights and gains for the ANN.

Table 4.2: Input Weights of the designed ANN, also showing the Layer Weights.

Input Weights (IW{1,1}), 10x6 Matrix						Layer Weights (LW{2,1})
-0.6478	-1.0780	-0.5879	-0.4086	-0.4511	-0.3898	7.3045
0.7809	-0.3765	0.9040	1.1360	-0.2817	0.7930	-4.7174
0.4548	-5.2399	-1.0093	-2.8288	1.0471	-0.1295	-4.1398
15.9880	3.4181	0.9163	0.9583	2.4478	1.9218	14.0010
4.9901	1.3711	-1.8564	-2.1194	0.7854	-0.6745	-4.8849
9.7072	11.2895	6.7822	6.2822	0.3717	-0.7470	14.1694
-0.9817	-1.0902	-0.5546	0.9550	-2.2204	-1.5649	3.55790
1.1028	4.0494	3.7793	-0.1119	-1.8710	1.1822	-6.8985
-2.8505	-2.9793	3.4406	-0.1867	1.2249	0.3858	3.5667
5.9391	-2.1316	-1.3176	-0.4334	1.7804	-2.0251	-6.7917

Table 4.3: Bias Weights (b)

Bias Weights (b{1})
3.0729
-2.3121
-0.17041
0.3229
-1.5588
-1.4883
-0.6653
-0.9699
-0.5427
-0.4555
Bias Weight (b{2})
6.4490

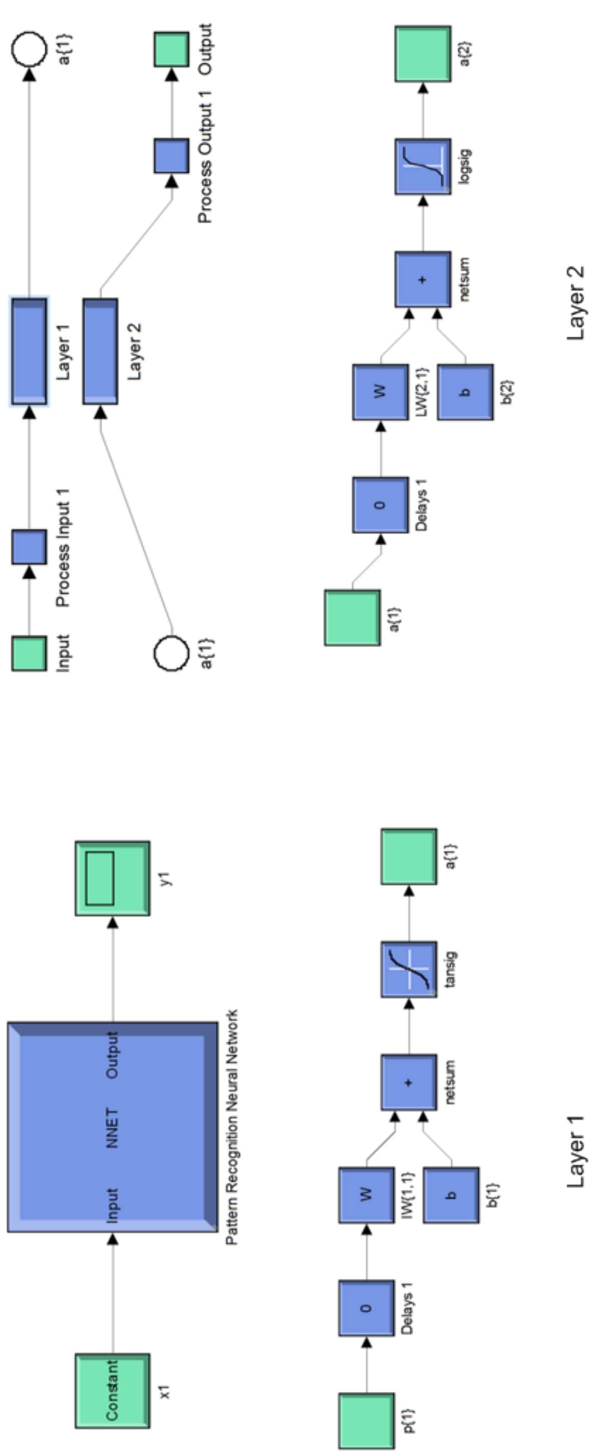

Figure 4.5: Overview of the ANN in Matlab Simulink

4.3 Performance of the ANN

Figure 4.6 show the correlation between the Training Data Set and the Validation Date Set. As can be seen, the correlation is good. This means that the performance of the ANN to identifying the faults correctly are good. This is also shown in Figure 4.7, which shows the Error Histogram, which acceptable performance.

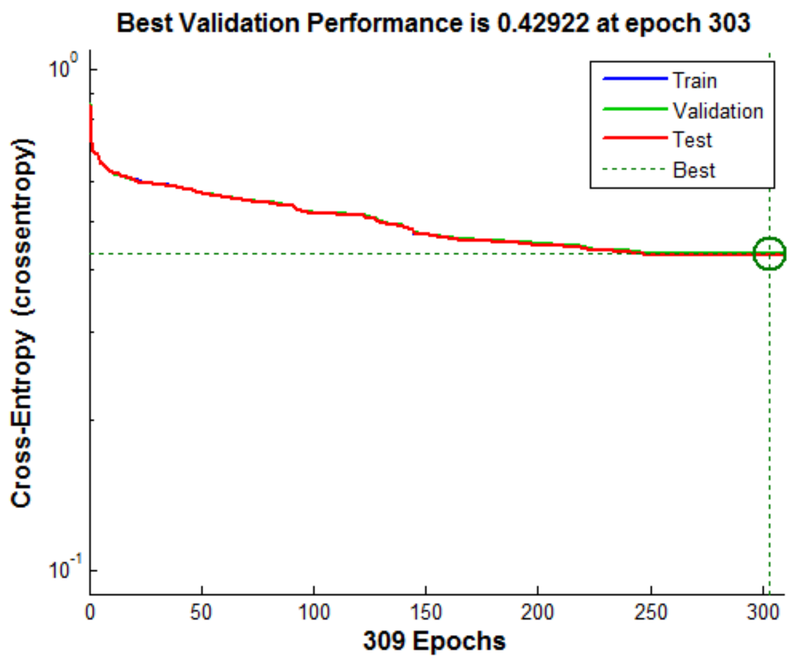

Figure 4.6: Performance of the training process

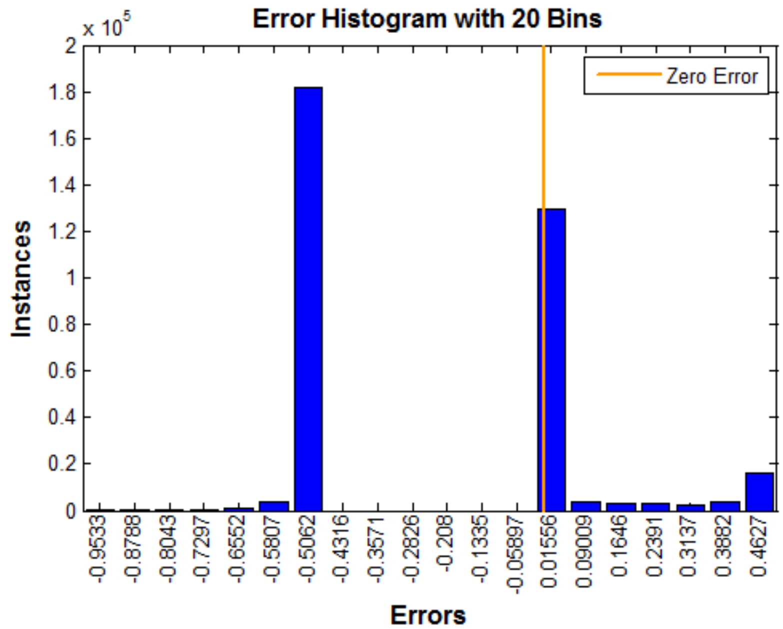

Figure 4.7: Performance of ANN, showing Error

The training data is composed of Fault Data, used as reference based upon a number of Matlab Simulink simulations. (Detailed graphs of the training data, and simulations performed to obtain the training data is shown in the appendix). It should be noted that the performance of the ANN greatly depends upon the accuracy of the training data and the correlation of the output requirements. Therefore, great care and preparation should be performed on the training data for best results.

4.4 Simulink Simulation of the Transmission Line Power System

The aim of this section is to show simulation results on the performance of the ANN Fault Detector.

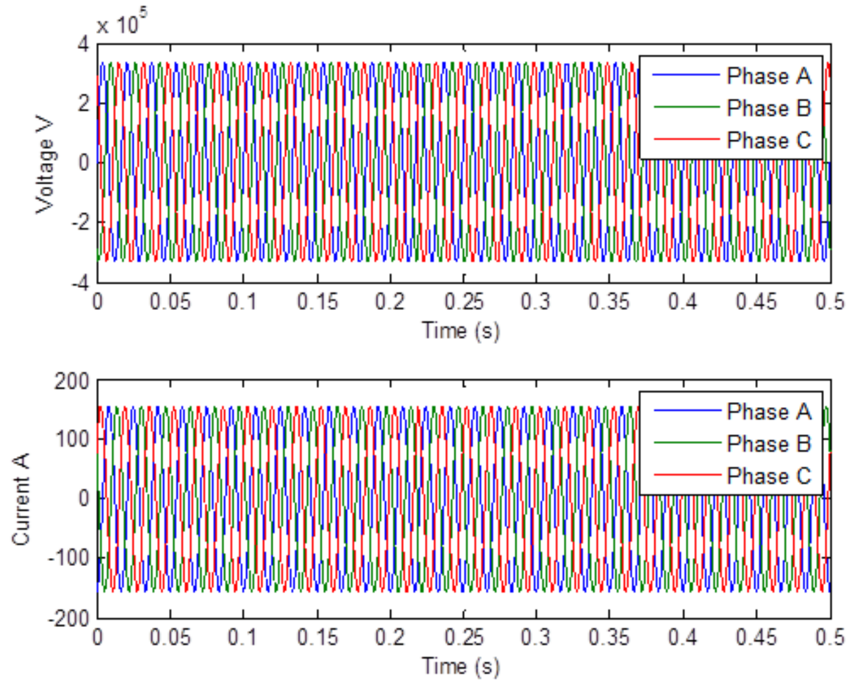

Figure 4.8: Typical voltage and current waveforms of a three phase system, with no fault.

Figure 4.8 show the Voltages and Currents of a three phase transmission line with no fault present. As can be seen, the frequency of oscillation is 50Hz, with voltage and current phases 120^oout of phase. The Simulink model was described in section 4.2 more fully.

Figure 4.9 shows the output of the RMS conversion, which scales and filters the AC values. This signals forms the inputs to the ANN for all voltages and phases.

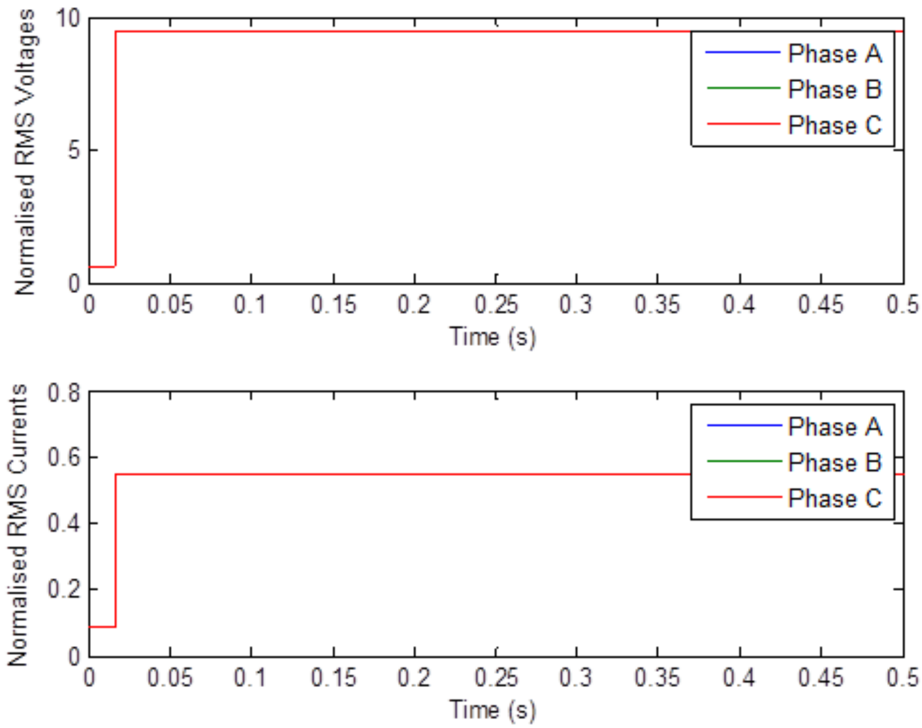

Figure 4.9: RMS Values of voltage and current, with no fault.

4.4.1 Three Phase System Results with a Fault

The simulation studies were done for different combinations of fault resistances on the Transmission Lines. Different fault types of short-circuit including line-ground (A-G), line-line-ground (A-B-G), and line-line-line-ground (A-B-C-G) are considered for each these combinations. Figure 4.10 show the Voltage and Current waveforms for a Phase A Ground Fault. As can be seen, the Phase A voltage drops, with increases in currents in all phases.

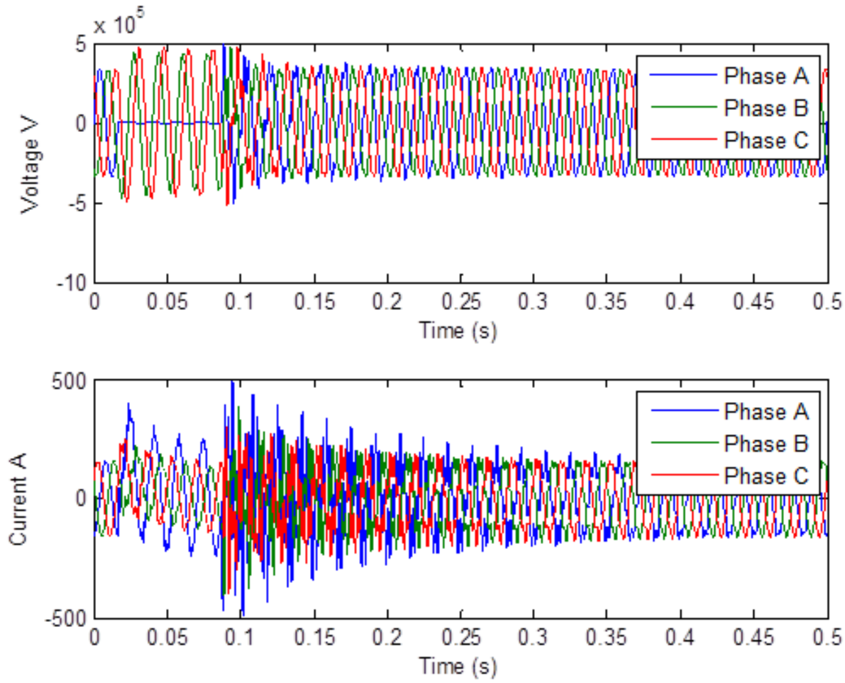

Figure 4.10: Voltage and current waveforms for a Phase A ground fault, Lf = 100km

Also notices the transient impact which the ground fault has on the performance of the AC Voltages and Currents. For each different type of fault the signature of the transient waveforms are different, and this difference forms the characteristic discriminator in classifying and interpreting the location of the fault by ANN (see Figure 4.11).

The appendix shows much of the different faults, each of these faults a earth faults on the phases. It is noticed that each faults is characteristically different from each other, and combined to form training data sets for the ANN training process.

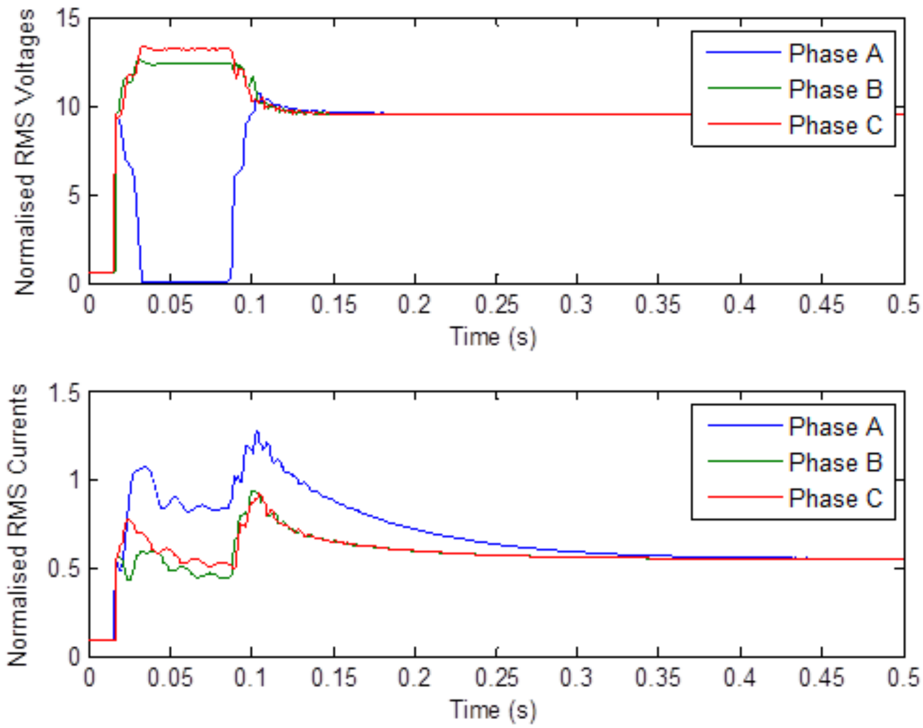

Figure 4.11: RMS voltage and current waveforms for a Phase A ground fault, Lf = 100km.

4.4.2 Performance of the ANN Fault Detector

Figure 4.16 show the ANN fault detector. As can be seen, Voltage and Current inputs are normalized, filtered and converted to RMS (or equivalent DC). These signals then forms inputs to the ANN fault detector (area highlighted). Simulation results show the accuracy of the ANN fault detector (Figure 4.13).

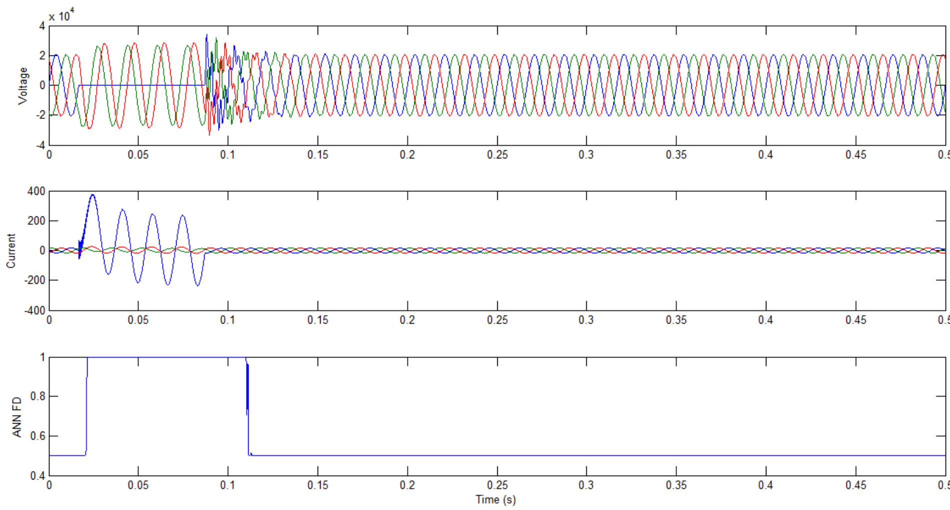

Figure 4.12: ANN response to Phase A fault

As can be seen in Figure 4.13 (bottom graph), the ANN Fault Detector (ANN FD) correctly identified the fault. Thus ANN forms a good method for pattern recognition, such as the determination of Faults. Much of the accuracy of the ANN FD depends upon the training data, and the accuracy of the target responses required of the ANN. Figure 4.13,Figure 4.14 and Figure 4.15 shows more results on the performance of the ANN for different faults. It is clearly seen that the ANN correctly identifies the fault. Improved training data could also improve the performance more.

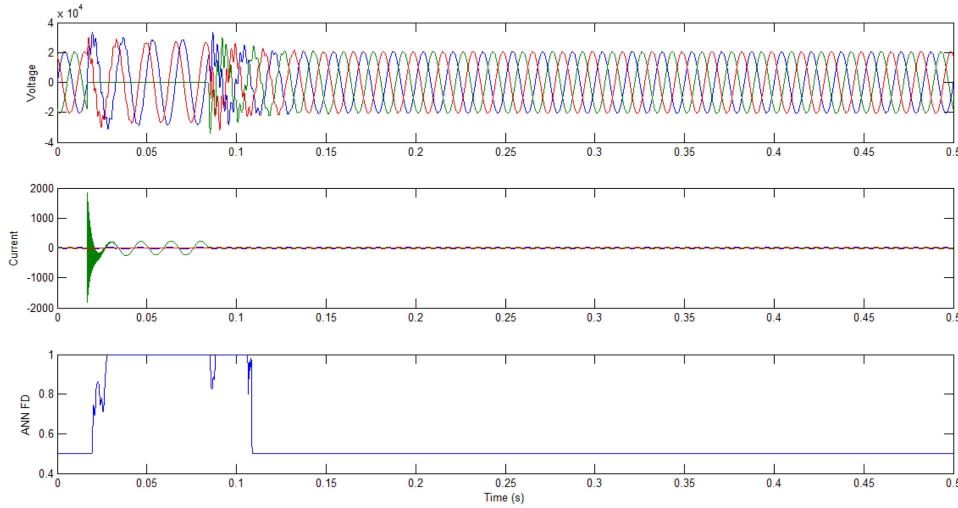

Figure 4.13: ANN Response to Phase B fault

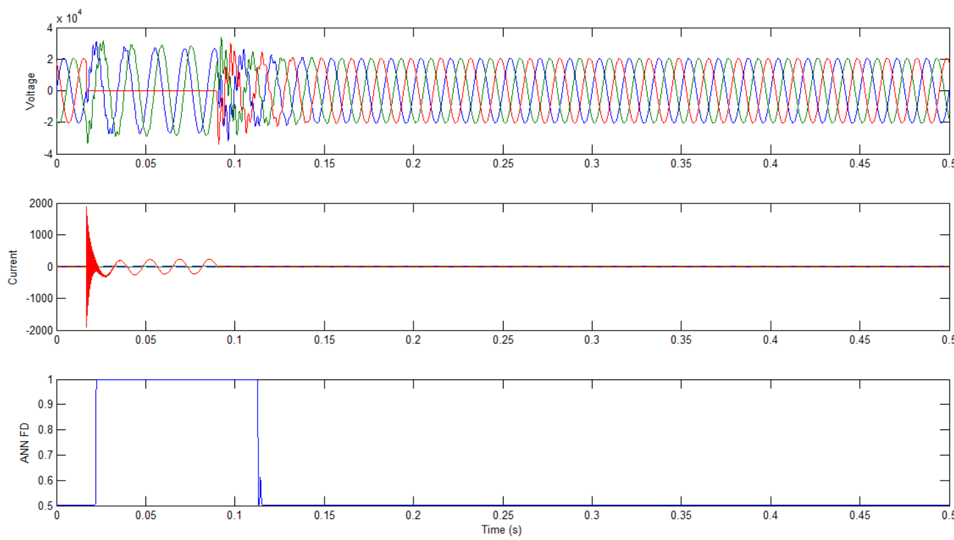

Figure 4.14: ANN response to Phase C fault

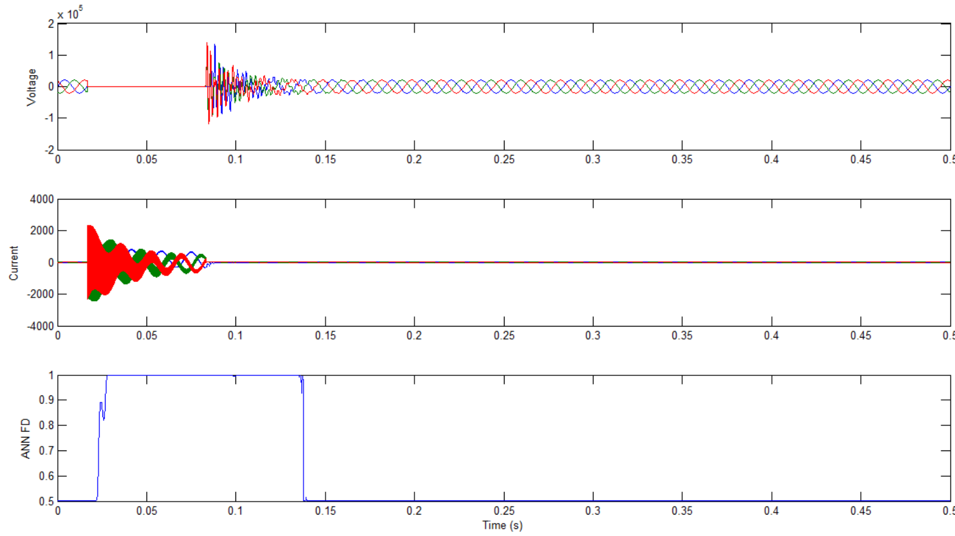

Figure 4.15: ANN response to ABC fault

4.5 Summary of Chapter

This Chapter illustrated the design of an ANN for the detection of transmission line Faults. It showed that ANN can successfully identify faults as illustrated by the outputs of the ANN. The faults simulated within the Matlab / Simulink environment were transmission line earth faults. Results showed that the ANN can be used for the identification and diagnosis of transmission line faults.

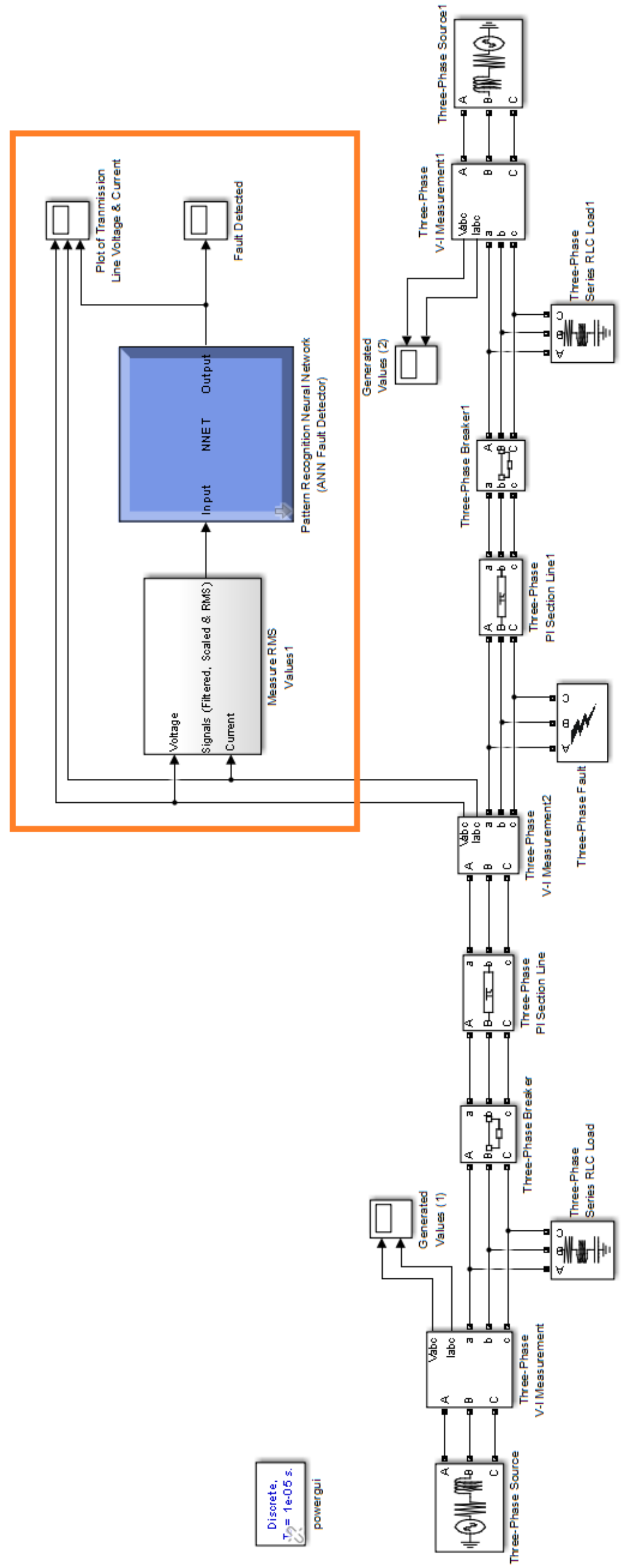

Figure 4.16: Simulink Model showing ANN fault detector

5 Conclusion and Recommendations

Transmission Lines forms part of power systems, however system operators experiences a high volume of faults. In response to this, there has been a number of attempts to mitigate transmission line faults. The aim of this dissertation was to investigate the feasibility of Artificial Neural Networks as a fault detection mechanism for transmission lines. There are three protection methods for transmission lines namely, fault detection, fault classification and fault location determination.

The application of Artificial Neural Networks (ANN) to fault detection have been the focus of this dissertation. The objective of this research was to detect electrical faults and to classify them in real time within a simulated environment. The tool used for this purpose was Matlab / Simulink, using tools from the Artificial Neural Network Toolbox and the SimPower Systems Toolbox.

It has been shown as contained within the literature and document content, that ANN forms a good method of transmission line fault detection and that it accurately identifies faults. This present study have also confirmed its application and that good performance results can be obtained by using ANN, appropriately trained using validated training data.

Of the objectives, much have been confirmed, re-examined and detailed within the Dissertation. Of one of the objectives not fully examined is that of fault location determination via ANN, primarily due to time constraints of this project. The determination of fault location via ANN is reserved as a future study with its manifold applications.

The research methodology followed was to perform a comprehensive literature review, followed by an analysis of ANN and its application to transmission line fault detection. The literature review focussed on understanding what fault detection is and its many methods of application. The analysis and simulation study (Chapters 3, and 4) have shown that much preparation of data is needed for the training of the ANN. This by far forms the most time consuming component of ANN design and application. It is noted that ANN has many application uses, and functions but diligent care is needed in data preparation and formulation.

The ANN fault detector measured faults effectively and faster, therefore the possibilities that the equipment on the transmission line will be protected is high. In addition the ANN fault detection method was tested and proved to be accurate for all types of faults. These results indicated that the ANN output values are accurate, less affected by phase voltages or phase currents and less affected by frequency changes.

Some of the challenges experienced was that we could not execute all of the objectives mentioned, in particular the determination of location. However, the basic principle of applying ANN to transmission line fault detection have been illustrated, and how it is applied to classify faults. Extending these results to the determination of fault location would consist of preparing appropriate data, based upon the distance of the fault in simulation, and this information would then be used to train the ANN accordingly.

Performance results show the feasible application of ANN to transmission line fault detection and diagnosis. This contribution of this work are as follows.

1. We have confirmed the application of ANN to the application of transmission

line fault detection.

2. We have showed that acceptable performance results can be obtained and that ANN Fault Detectors have practical application.

Future work will focus on better understanding the influence of training data, and also of minimizing the amount of training data necessary to perform good ANN design. In addition, we would also like to investigate the performance of ANN on real hardware such as embedded systems, to analyst the processing speed performance of ANN.

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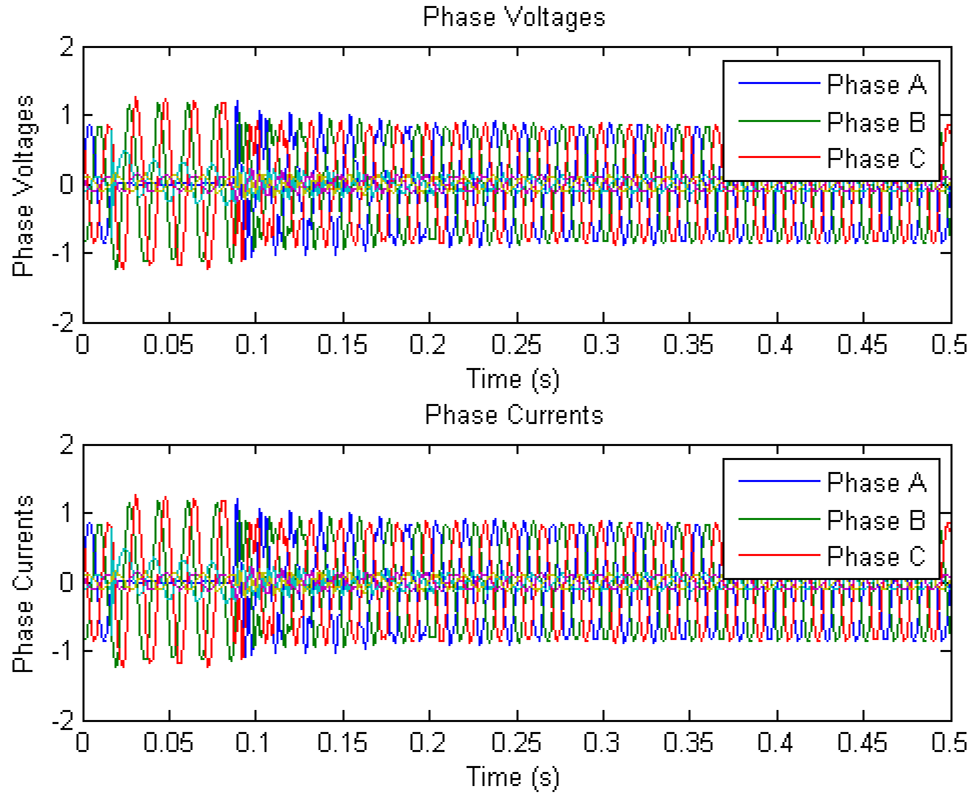
7 Appendix 1

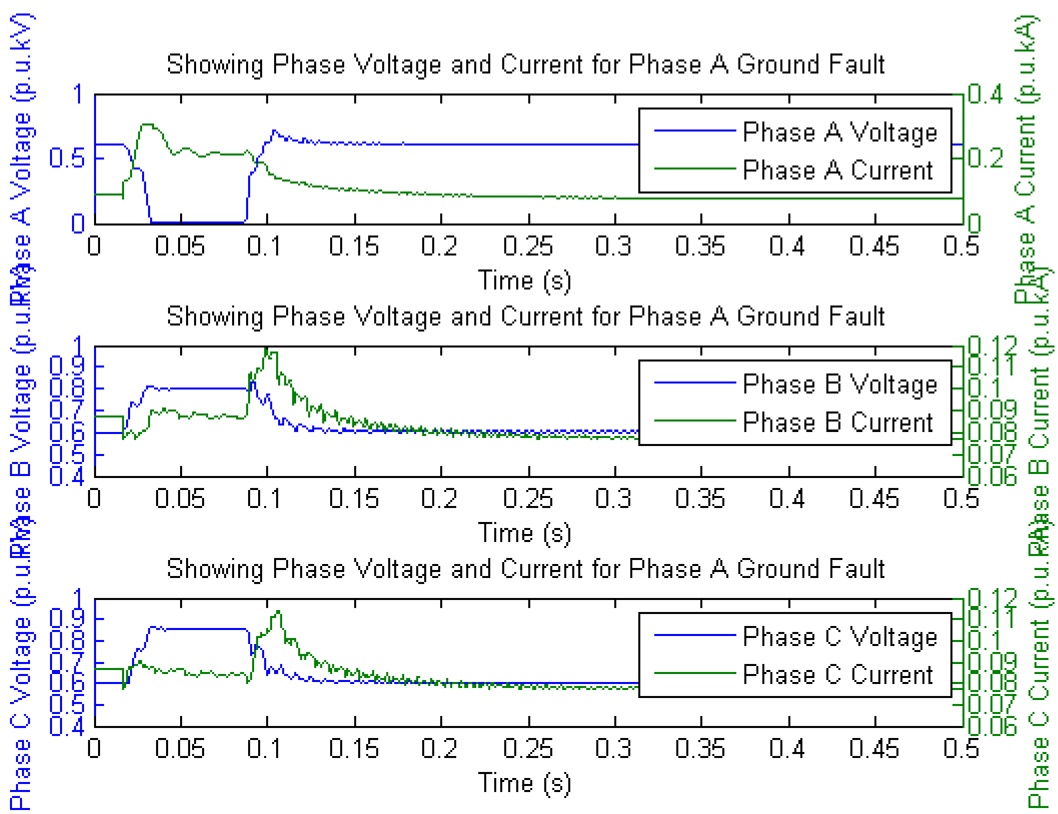
7.1 Matlab Code for Simulation of Model

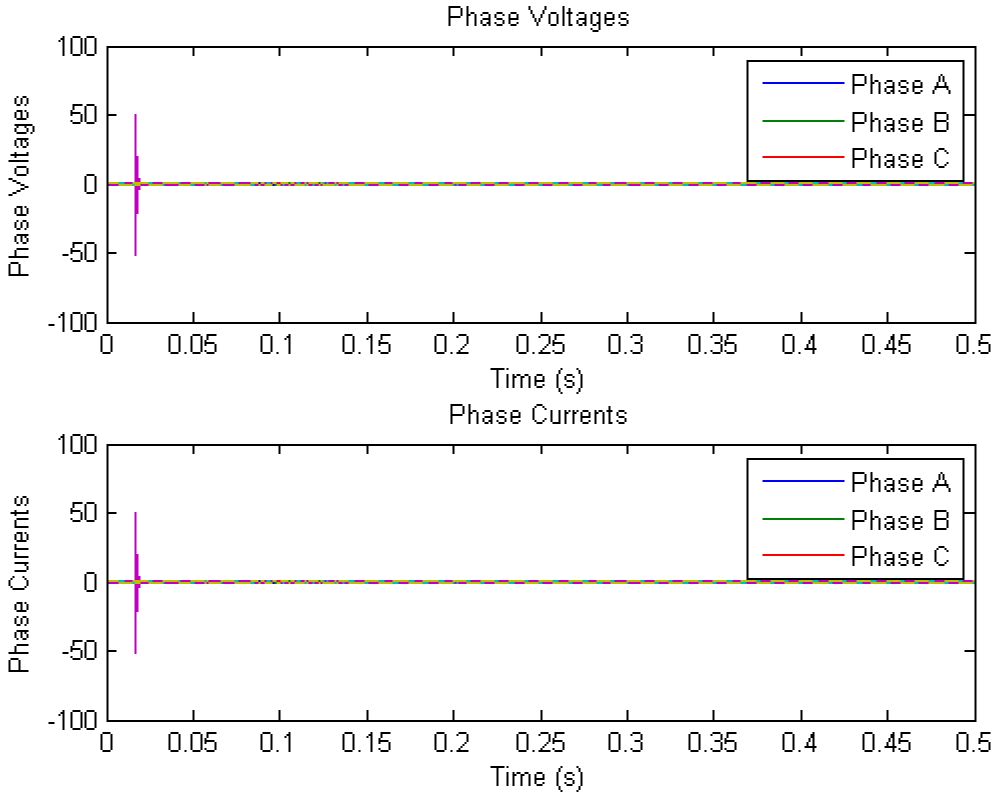
7.2 Code for Training ANN

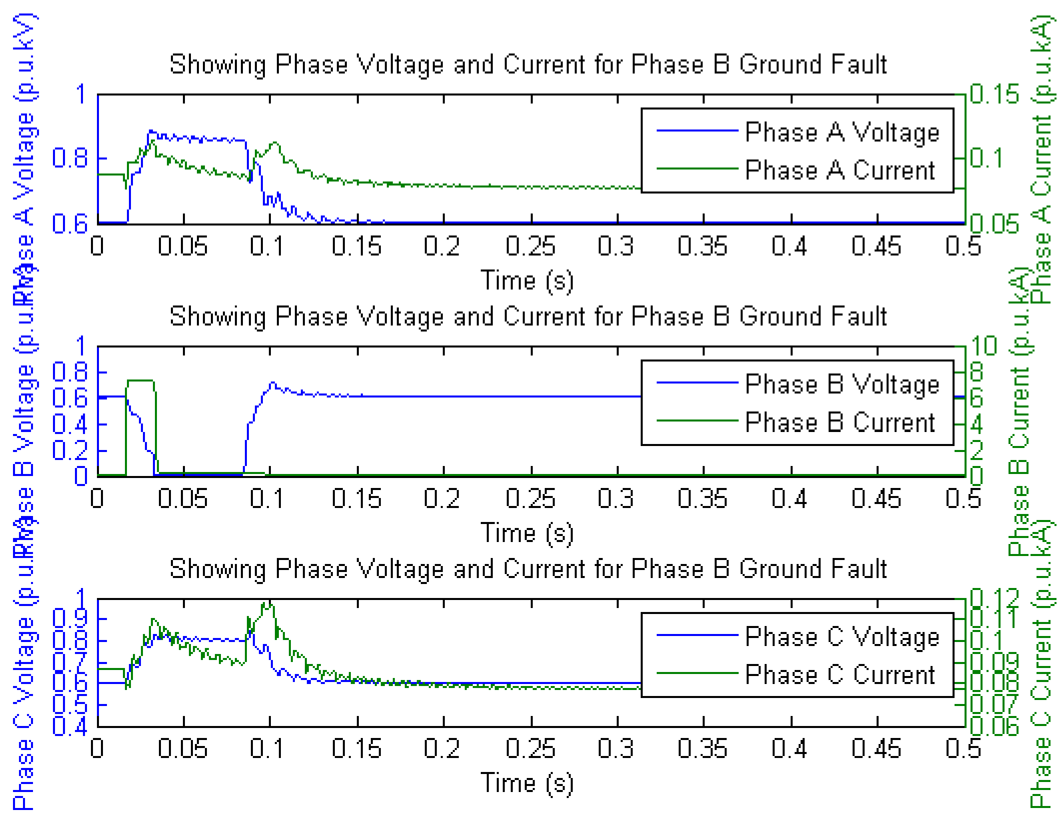
```
close all;
clear;

Tlen = 500; % Transmission Length...
Options = simset('SrcWorkspace','current');
DataV = [];
DataC = [];

for count = 1:7

    switch count

        case 1
            str = 'PhaseAFlt.slx';
            strT = 'Showing Phase Voltage and Current for Phase A Ground Fault';

        case 2
            str = 'PhaseBFlt.slx';
            strT = 'Showing Phase Voltage and Current for Phase B Ground Fault';

        case 3
            str = 'PhaseCFlt.slx';
            strT = 'Showing Phase Voltage and Current for Phase B Ground Fault';

        case 4
            str = 'PhaseABFlt.slx';
            strT = 'Showing Phase Voltage and Current for Phase A and Phase B Grou

        case 5
            str = 'PhaseACFlt.slx';
            strT = 'Showing Phase Voltage and Current for Phase A and Phase C Grou

        case 6
            str = 'PhaseBCFlt.slx';
            strT = 'Showing Phase Voltage and Current for Phase B and Phase C Grou

        case 7
            str = 'PhaseABCFlt.slx';
            strT = 'Showing Phase Voltage and Current for Phase ABC Ground Fault';

        otherwise

    end

    sim(str,[],Options);

    % RawValues....
    Tr = RawValues.time;
    Voltager = RawValues.signals.values(:,1:3);
    Currentr = RawValues.signals.values(:,4:6);

    % RMS Values...
```

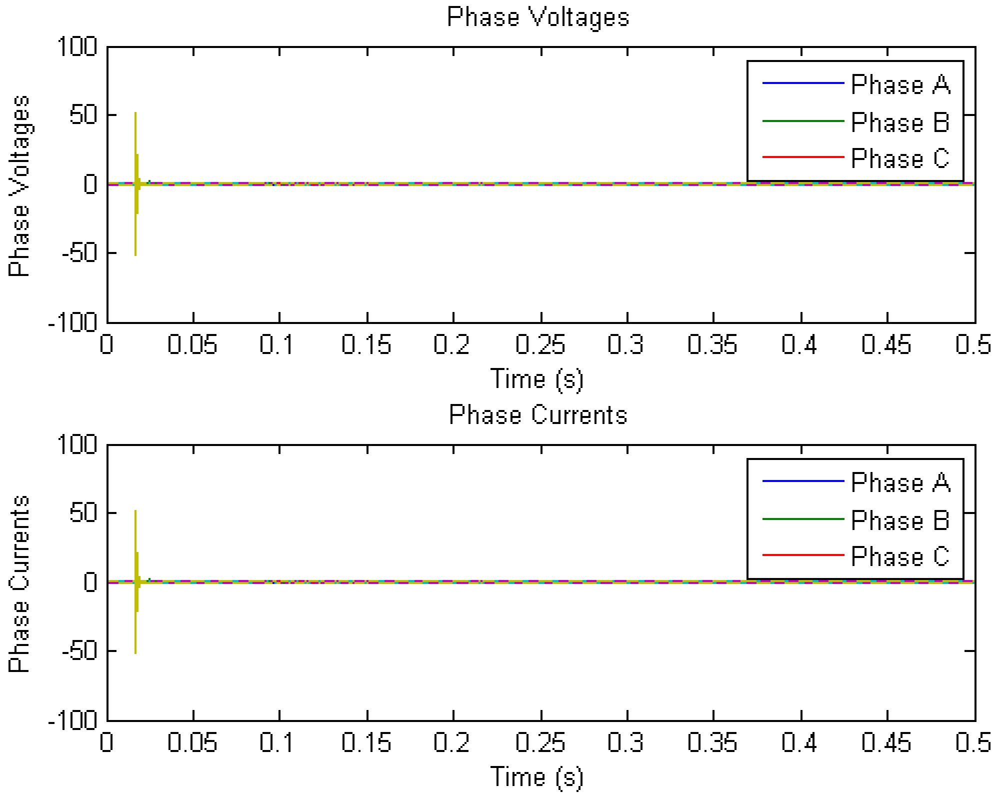
```
    T = simout.time;
    Voltage = simout.signals.values(:,1:3);
    Current = simout.signals.values(:,4:6);

    % Pack Values for ANN Training Data...
    DataV = [DataV;Voltage];
    DataC = [DataC;Current];

    % Plot the RawValues....
    figure;
    subplot(211);
    plot(Tr,Voltager,Tr,Currentr);
    title('Phase Voltages');
    legend('Phase A','Phase B','Phase C');
    xlabel('Time (s)');
    ylabel('Phase Voltages');

    subplot(212);
    plot(Tr,Voltager,Tr,Currentr);
    title('Phase Currents');
    legend('Phase A','Phase B','Phase C');
    xlabel('Time (s)');
    ylabel('Phase Currents');


    % Plot the RMS Values....
    figure;
    subplot(311);
    [hAx, hLine1, hLine2] = plotyy(T,Voltage(:,1),T,Current(:,1));
    title(strT);
    legend('Phase A Voltage','Phase A Current');
    xlabel('Time (s)');
    ylabel(hAx(1),'Phase A Voltage (p.u.kV)');
    ylabel(hAx(2),'Phase A Current (p.u.kA)');

    subplot(312);
    [hAx, hLine1, hLine2] = plotyy(T,Voltage(:,2),T,Current(:,2));
    title(strT);
    legend('Phase B Voltage','Phase B Current');
    xlabel('Time (s)');
    ylabel(hAx(1),'Phase B Voltage (p.u.kV)');
    ylabel(hAx(2),'Phase B Current (p.u.kA)');

    subplot(313);
    [hAx, hLine1, hLine2] = plotyy(T,Voltage(:,3),T,Current(:,3));
    title(strT);
    legend('Phase C Voltage','Phase C Current');
    xlabel('Time (s)');
    ylabel(hAx(1),'Phase C Voltage (p.u.kV)');
    ylabel(hAx(2),'Phase C Current (p.u.kA)');


end
```

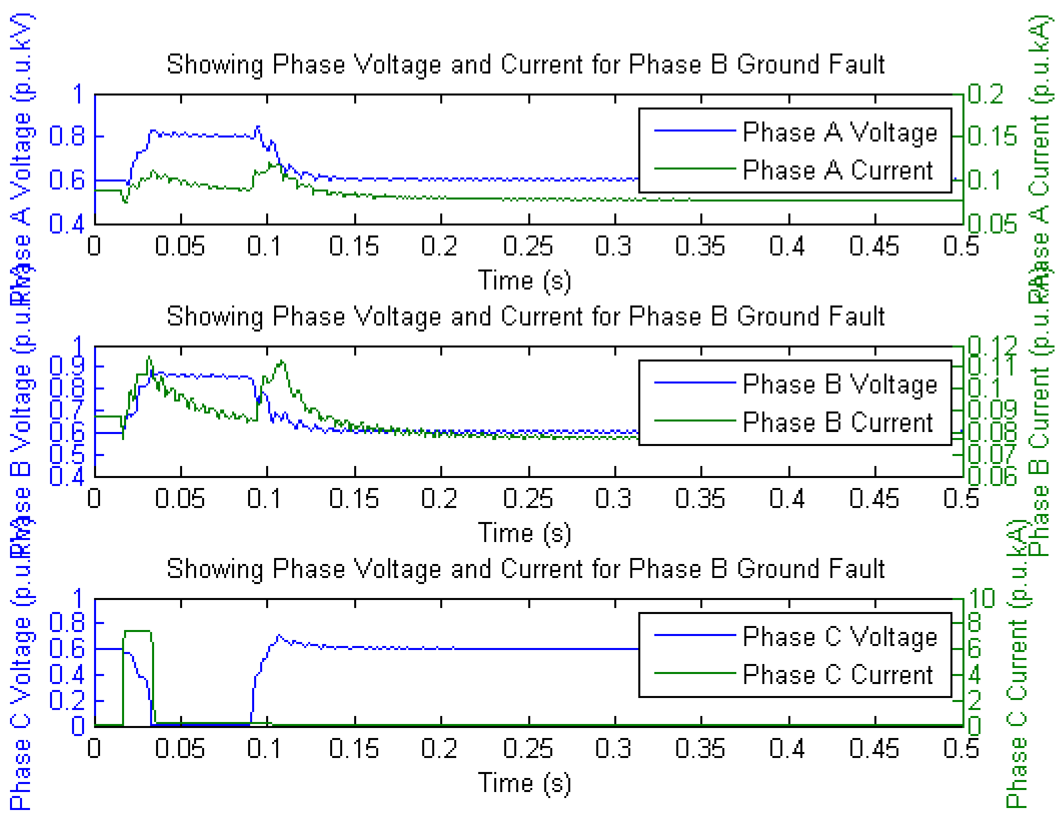

Phase Voltages
Phase Voltages
Time (s)
Phase A
Phase B
Phase C
Phase Currents
Phase Currents
Time (s)
Phase A
Phase B
Phase C

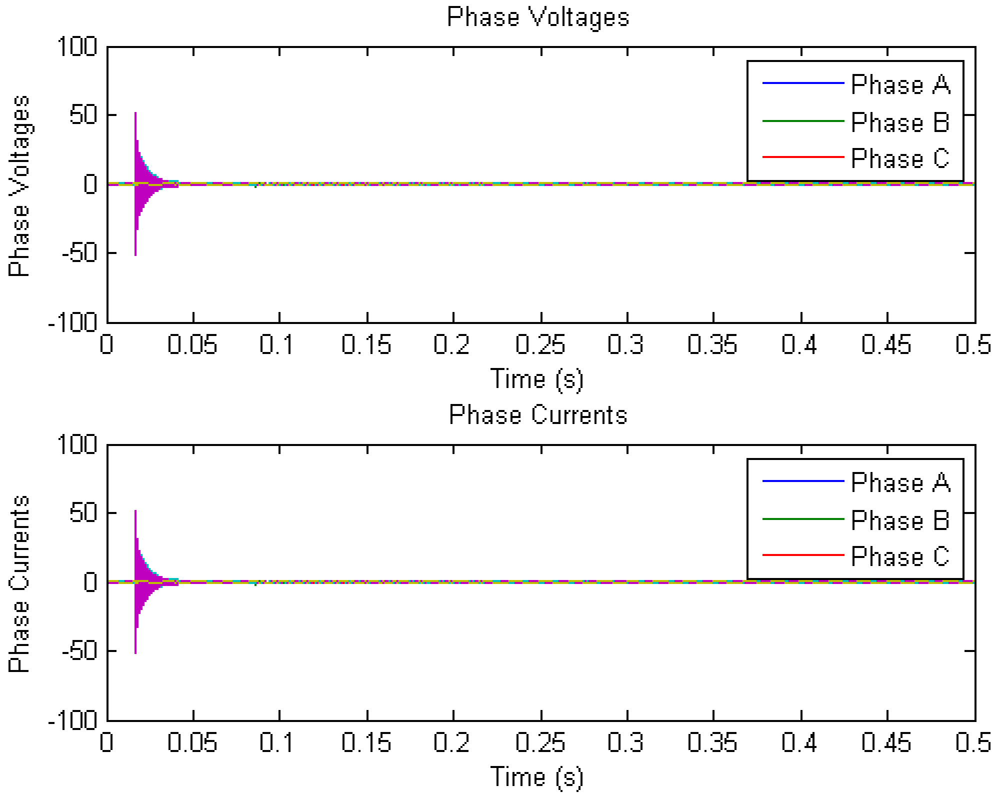

Showing Phase Voltage and Current for Phase A Ground Fault
Phase A Voltage (p.u.kV)
Phase A Current (p.u.kA)
Time (s)
Phase A Voltage
Phase A Current
Showing Phase Voltage and Current for Phase A Ground Fault
Phase B Voltage (p.u.kV)
Phase B Current (p.u.kA)
Time (s)
Phase B Voltage
Phase B Current
Showing Phase Voltage and Current for Phase A Ground Fault
Phase C Voltage (p.u.kV)
Phase C Current (p.u.kA)
Time (s)
Phase C Voltage
Phase C Current

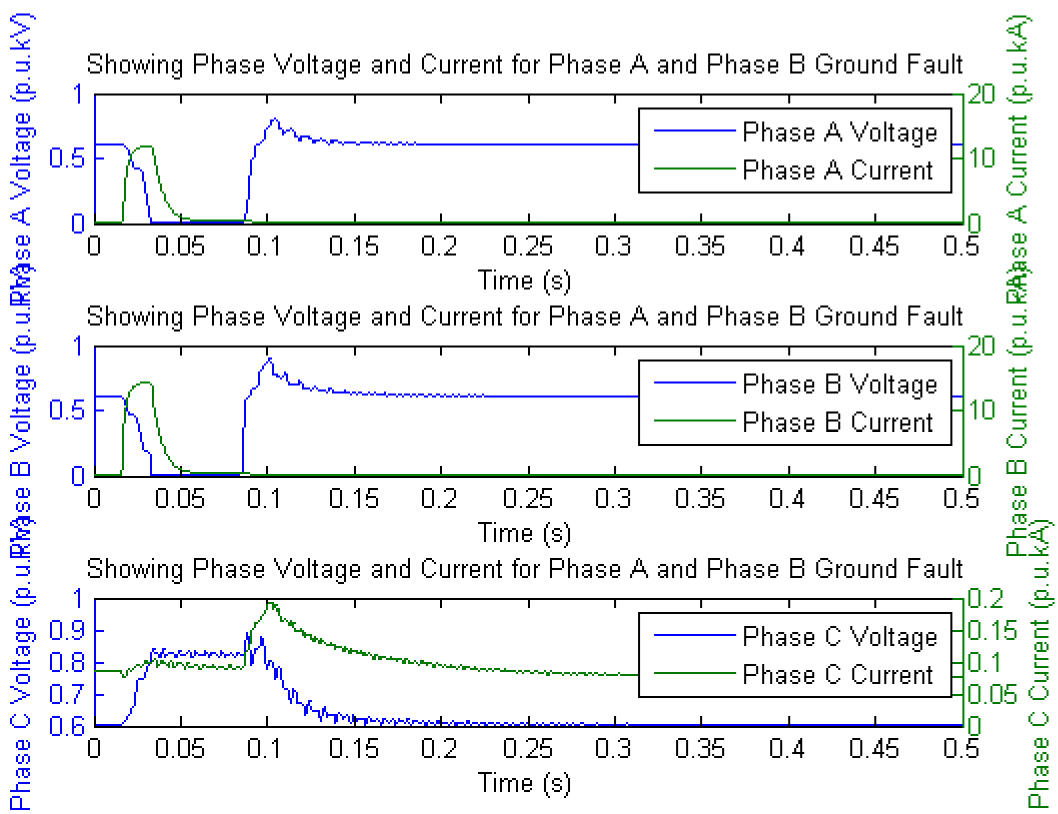

Phase Voltages
Phase Voltages
Phase A
Phase B
Phase C
Time (s)
Phase Currents
Phase Currents
Phase A
Phase B
Phase C
Time (s)

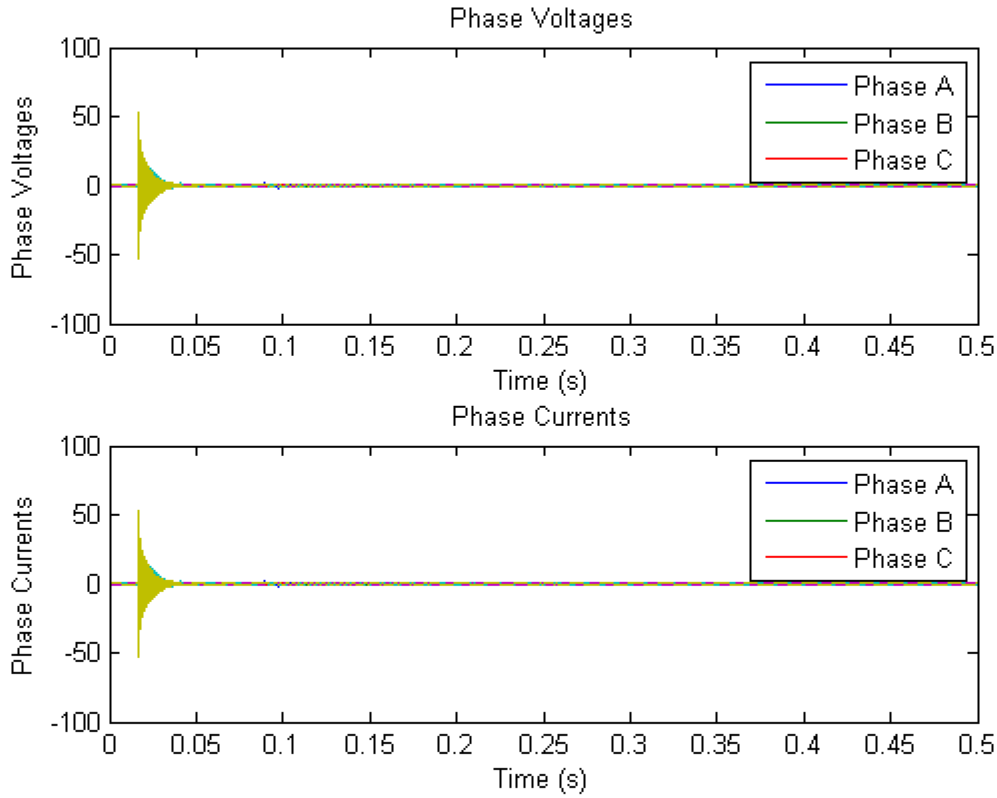

Showing Phase Voltage and Current for Phase B Ground Fault
Phase A Voltage (p.u.kV)
Phase A Current (p.u.kA)
Phase A Voltage
Phase A Current
Time (s)
Showing Phase Voltage and Current for Phase B Ground Fault
Phase B Voltage (p.u.kV)
Phase B Current (p.u.kA)
Phase B Voltage
Phase B Current
Time (s)
Showing Phase Voltage and Current for Phase B Ground Fault
Phase C Voltage (p.u.kV)
Phase C Current (p.u.kA)
Phase C Voltage
Phase C Current
Time (s)

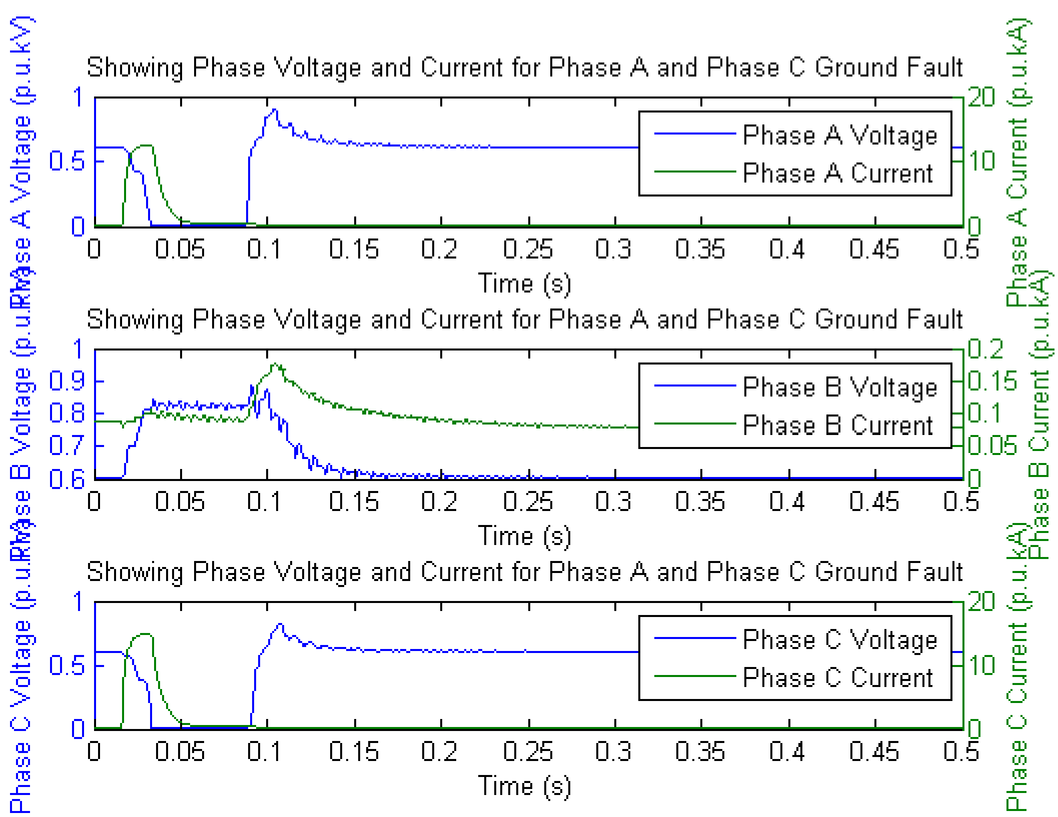

Phase Voltages
Phase Voltages
Time (s)
Phase A
Phase B
Phase C
Phase Currents
Phase Currents
Time (s)
Phase A
Phase B
Phase C

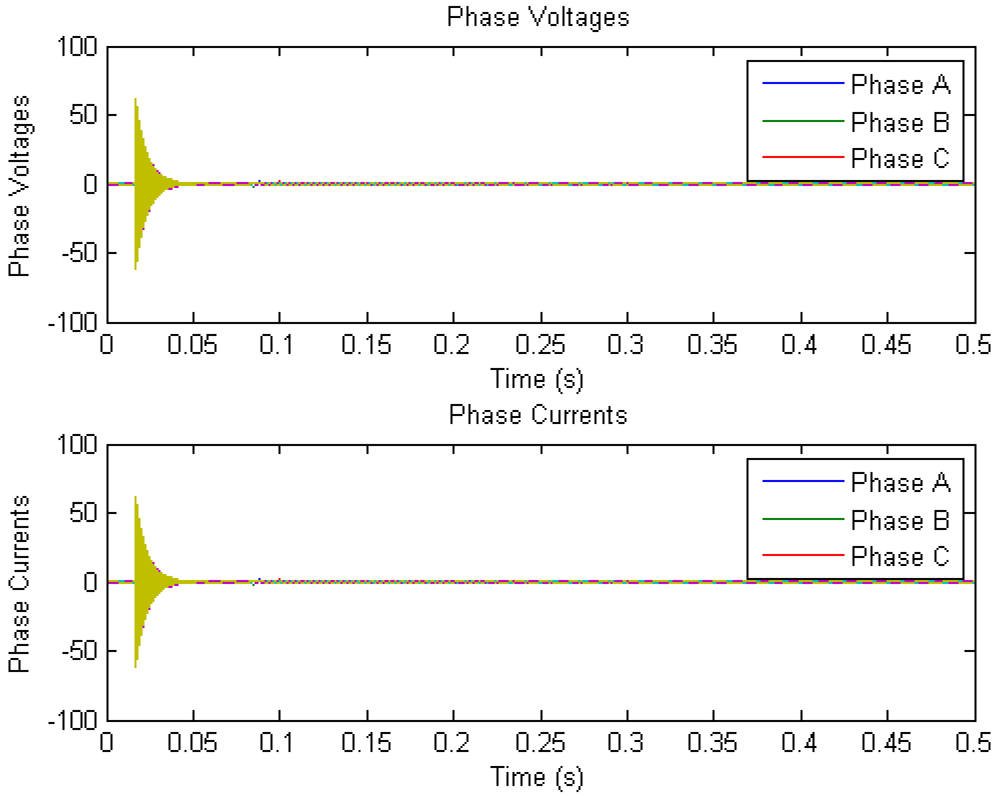

Showing Phase Voltage and Current for Phase B Ground Fault
Phase A Voltage (p.u.kV)
Phase A Current (p.u.kA)
Time (s)
Phase A Voltage
Phase A Current
Showing Phase Voltage and Current for Phase B Ground Fault
Phase B Voltage (p.u.kV)
Phase B Current (p.u.kA)
Time (s)
Phase B Voltage
Phase B Current
Showing Phase Voltage and Current for Phase B Ground Fault
Phase C Voltage (p.u.kV)
Phase C Current (p.u.kA)
Time (s)
Phase C Voltage
Phase C Current

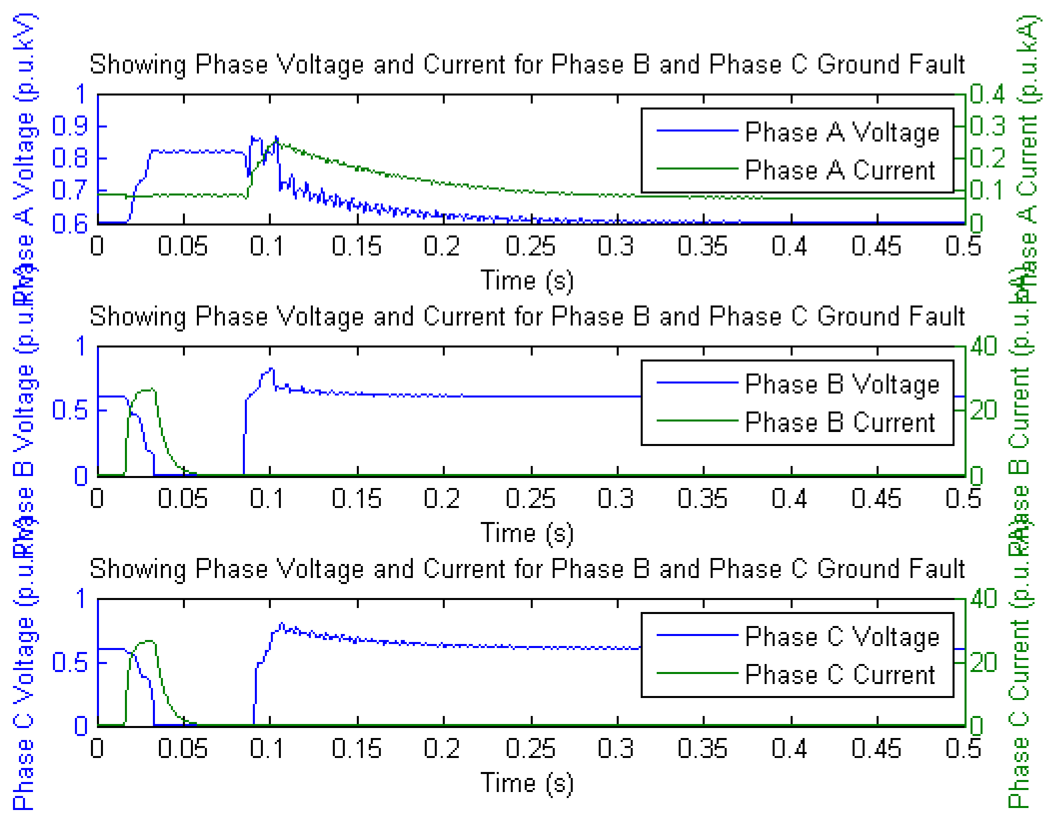

Phase Voltages
Phase Voltages
Phase A
Phase B
Phase C
Time (s)
Phase Currents
Phase Currents
Phase A
Phase B
Phase C
Time (s)

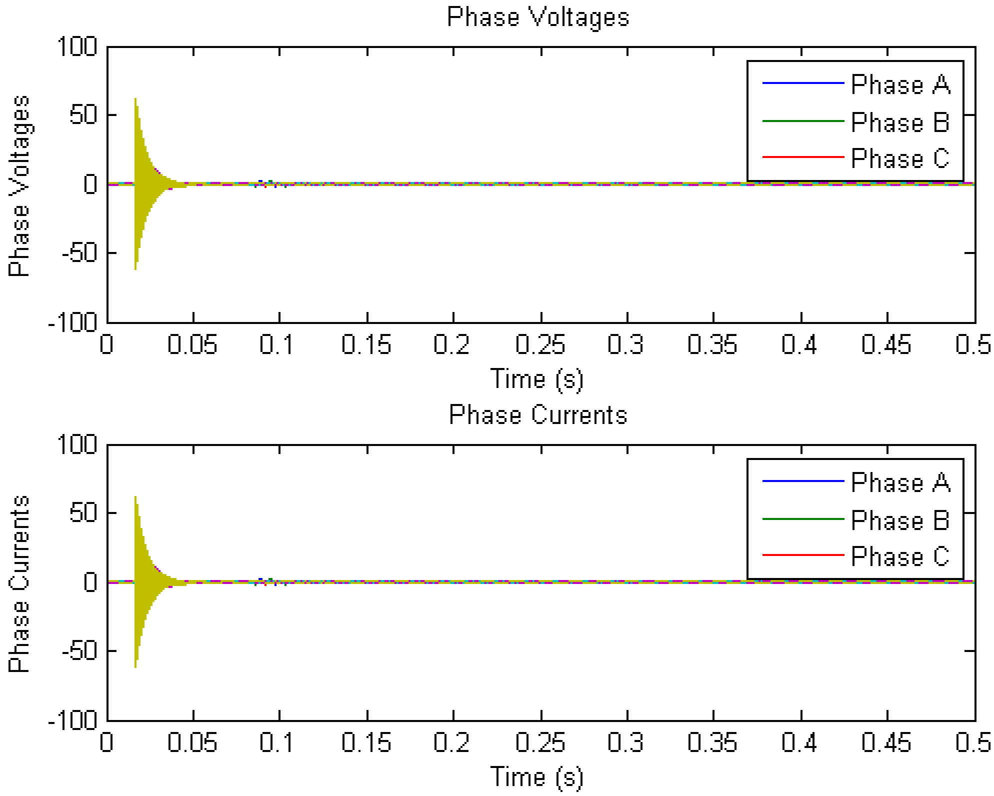

Showing Phase Voltage and Current for Phase A and Phase B Ground Fault
Phase A Voltage (p.u.kV)
Phase A Current (p.u.kA)
Phase A Voltage
Phase A Current
Time (s)
Showing Phase Voltage and Current for Phase A and Phase B Ground Fault
Phase B Voltage (p.u.kV)
Phase B Current (p.u.kA)
Phase B Voltage
Phase B Current
Time (s)
Showing Phase Voltage and Current for Phase A and Phase B Ground Fault
Phase C Voltage (p.u.kV)
Phase C Current (p.u.kA)
Phase C Voltage
Phase C Current
Time (s)

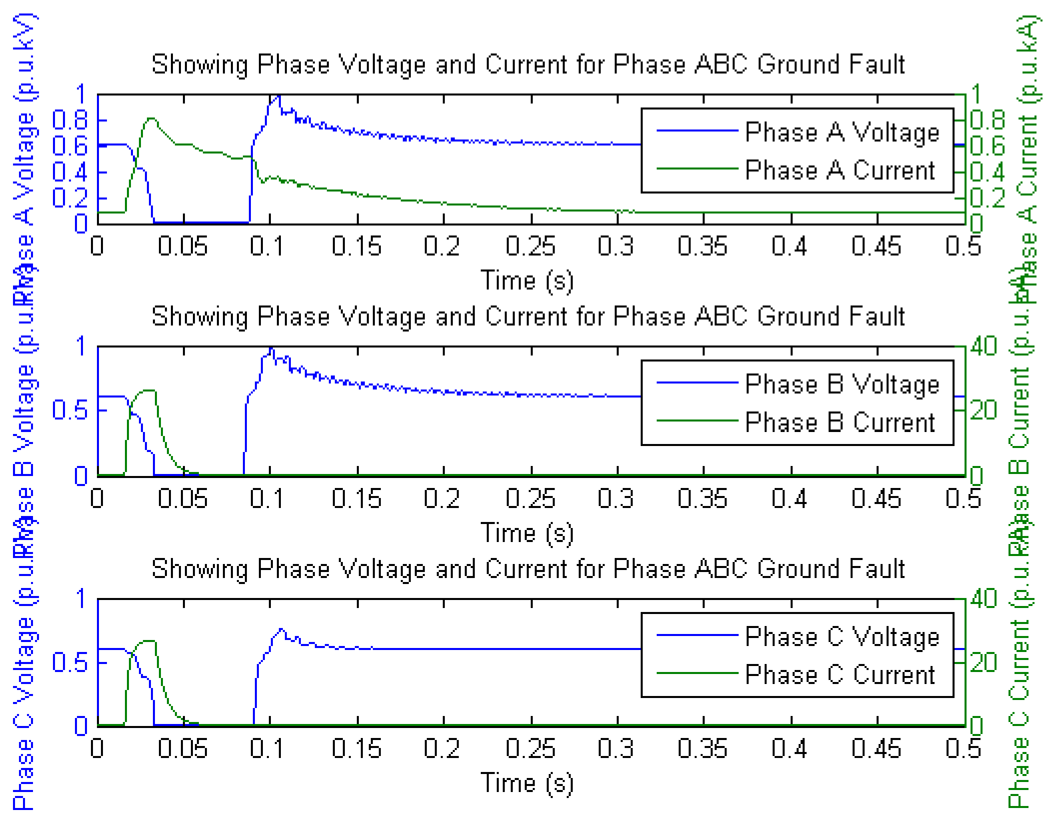

Phase Voltages
Phase Voltages
Time (s)
Phase A
Phase B
Phase C
100
50
0
-50
-100
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Phase Currents
Phase Currents
Time (s)
Phase A
Phase B
Phase C


Showing Phase Voltage and Current for Phase A and Phase C Ground Fault
Phase A Voltage (p.u.kV)
Phase A Current (p.u.kA)
Phase A Voltage
Phase A Current
Time (s)
Showing Phase Voltage and Current for Phase A and Phase C Ground Fault
Phase B Voltage (p.u.kV)
Phase B Current (p.u.kA)
Phase B Voltage
Phase B Current
Time (s)
Showing Phase Voltage and Current for Phase A and Phase C Ground Fault
Phase C Voltage (p.u.kV)
Phase C Current (p.u.kA)
Phase C Voltage
Phase C Current
Time (s)


Phase Voltages
Phase Voltages
Phase A
Phase B
Phase C
Time (s)
Phase Currents
Phase Currents
Phase A
Phase B
Phase C
Time (s)

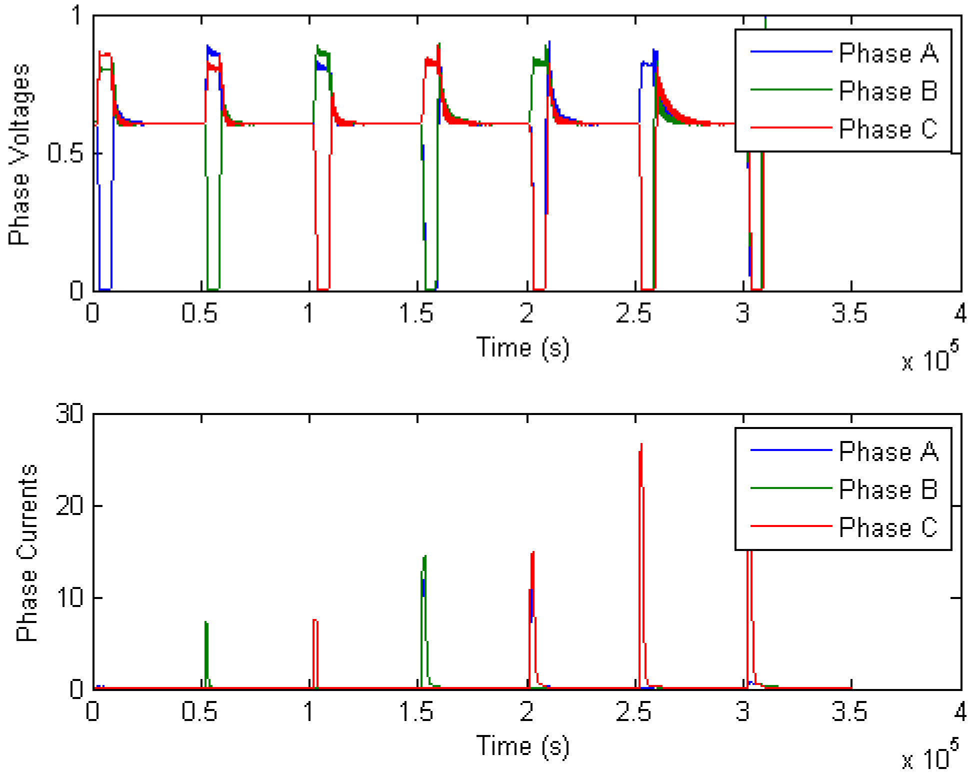

Showing Phase Voltage and Current for Phase B and Phase C Ground Fault
Phase A Voltage (p.u.kV)
Phase A Current (p.u.kA)
Phase A Voltage
Phase A Current
Time (s)
Showing Phase Voltage and Current for Phase B and Phase C Ground Fault
Phase B Voltage (p.u.kV)
Phase B Current (p.u.kA)
Phase B Voltage
Phase B Current
Time (s)
Showing Phase Voltage and Current for Phase B and Phase C Ground Fault
Phase C Voltage (p.u.kV)
Phase C Current (p.u.kA)
Phase C Voltage
Phase C Current
Time (s)


Phase Voltages
Phase Voltages
Time (s)
Phase A
Phase B
Phase C
Phase Currents
Phase Currents
Time (s)
Phase A
Phase B
Phase C


Showing Phase Voltage and Current for Phase ABC Ground Fault
Phase A Voltage (p.u.kV)
Phase A Current (p.u.kA)
Phase A Voltage
Phase A Current
Time (s)
Showing Phase Voltage and Current for Phase ABC Ground Fault
Phase B Voltage (p.u.kV)
Phase B Current (p.u.kA)
Phase B Voltage
Phase B Current
Time (s)
Showing Phase Voltage and Current for Phase ABC Ground Fault
Phase C Voltage (p.u.kV)
Phase C Current (p.u.kA)
Phase C Voltage
Phase C Current
Time (s)

Plot all Faults Together...

```
figure;
subplot(211);
plot(DataV,'DisplayName','DataV');
xlabel('Time (s)');
ylabel('Phase Voltages');
legend('Phase A','Phase B','Phase C');


subplot(212);
plot(DataC,'DisplayName','DataC');
xlabel('Time (s)');
ylabel('Phase Currents');
legend('Phase A','Phase B','Phase C');
```



Determinine the Faults Vectors for Training of Data Sets....

```
%... DataV, DataC is used as Training Data Sets...
```

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```
% Solve a Pattern Recognition Problem with a Neural Network
% Script generated by Neural Pattern Recognition app
% Created Mon Jul 20 23:54:40 PDT 2015
%
% This script assumes these variables are defined:
%
%   Data - input data.
%   Target - target data.

clear all;
close all;
clc;
load('TrainData.mat');

x = Data';
t = Target';

% Create a Pattern Recognition Network
hiddenLayerSize = 10;
net = patternnet(hiddenLayerSize);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};


% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% For help on training function 'trainscg' type: help trainscg
% For a list of all training functions type: help nntrain
net.trainFcn = 'trainscg';  % Scaled conjugate gradient

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'crossentropy';  % Cross-entropy

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
  'plotregression', 'plotfit'};


% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
```

```
y = net(x);
e = gsubtract(t,y);
tind = vec2ind(t);
yind = vec2ind(y);
percentErrors = sum(tind ~= yind)/numel(tind);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t  .* tr.valMask{1};
testTargets = t  .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotconfusion(t,y)
%figure, plotroc(t,y)
%figure, ploterrhist(e)

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
if (false)
  % Generate MATLAB function for neural network for application deployment
  % in MATLAB scripts or with MATLAB Compiler and Builder tools, or simply
  % to examine the calculations your trained neural network performs.
  genFunction(net,'myNeuralNetworkFunction');
  y = myNeuralNetworkFunction(x);
end
if (false)
  % Generate a matrix-only MATLAB function for neural network code
  % generation with MATLAB Coder tools.
  genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
  y = myNeuralNetworkFunction(x);
end
if (false)
  % Generate a Simulink diagram for simulation or deployment with.
  % Simulink Coder tools.
  gensim(net);
end
```

```
Error using '
Out of memory. Type HELP MEMORY for your options.

Error in TransmissionLineFDANN (line 17)
x = Data';
```

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