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DETECTING AND CLASSIFYING TRANSMISSION LINE FAULTS BY USING ARTIFICIAL NEURAL NETWORK

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IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE DEGREE OF MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONICS ENGINEERING

Supervisor: Prof. Dr. Doğan ÇALIKOĞLU

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I hereby declare that all the information in this study I presented as my Master's Thesis, called "Detecting and Classifying Transmission Line Faults by Using Artificial Neural Network" has been presented in accordance with the academic rules and ethical conduct. I also declare and certify on my honor that I have fully cited and referenced all the sources I made use of in this present study.

08. 02. 2018

Hussein Al-HUSSEINI

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LIST OF ABBREVIATIONS

ANN	**:**	Artificial Neural Network
BP	**:**	Back propagation
CT	**:**	Current Transformer
CSV	**:**	Comma Separated Values
DFT	**:**	Discrete Fourier Transform
EMTP	**:**	Electromagnetic Transient Program
F	**:**	Fault
FPGA	**:**	Field Programmable Gate Array
GRNN	**:**	Generalized Regression Neural Network
GSM	**:**	Global System of Mobile Communication
I	**:**	Current
KHz	**:**	Kilo Hartz
Km	**:**	Kilo Meter
KNN	**:**	K- nearest neighbors
Lf	**:**	Line Fault
L-G	**:**	Single phase to Ground
L-L	**:**	Phase to Phase
L-L-L	**:**	Triple phase
MLP	**:**	Multi-Layer Perception
MRA	**:**	Multi Resolution Analysis
MSPC	**:**	Multivariate Statistical Process Control
MSE	**:**	Mean Square Error
PCA	**:**	Principal Component analysis
RBF	**:**	Radial Basis Function
Rf	**:**	Resistance Fault
RMS	**:**	Root Mean Square
TL	**:**	Transmission Line
V	**:**	Voltage
VHDL	**:**	Very high-speed Hardware Description Language
VT	**:**	Voltage Transformer

ABSTRACT

DETECTING AND CLASSIFYING TRANSMISSION LINE FAULTS BY USING ARTIFICIAL NEURAL NETWORK

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Master, Department of Electrical and Electronic

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Power transmission is a major issue in Electrical Engineering. Fault in transmission lines is a common and major problem in power system. In this study, we present the method to detect and classify different faults in transmission line that has high reliability to protect the power system. If any fault or disturbance is generated in transmission line without quick detection, it will cause damage for equipment and economic losses for the power system.

This thesis presents Artificial Neural Network (ANN) to detect and classify faults in transmission lines. The method reduces outage times due to faults. We have proposed a digital detection system to detect and classify fault that happens in a 400 KV transmission line by employing ANN technology. The system consists of two functional sections: a fault detection unit and a fault classification unit. The two parts are implemented in MATLAB. Fault detection was proposed by creating simulation for current and voltage signals of different fault conditions that obtain through simulation. The waveforms obtained in the simulation were trained using the ANN method with the MATLAB program. Our method consists of eight variables as inputs and one as output. The results of simulation appeared good performance of ANN for the fault detection. The time of detection was very fast after fault happened. For the fault classification unit, our model improved that it has valid performance also. For this unit it can be classified eleven different types of faults.

Keywords: Transmission Line, Fault Detection and Classification, Artificial Neural Network.

ÖZET

YAPAY SİNİR AĞININ KULLANILMASI İLE İLETİM HATTI HATALARININ TESPİT EDİLMESİ VE SINIFLANDIRILMASI

Al-Husseini, Hussein

Elektrik ve Elektronik Bölümü Yüksek Lisansı

Tez Danışmanı: Prof. Dr. DOĞAN ÇALIKOĞLU

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Güç iletimi, Elektrik Mühendisliği alanında ana bir başlıktır. İletim hatlarındaki hatalar, elektrik sistemindeki yaygın ve esas problemlerdendir. Bu çalışmada, elektrik sistemini korumak amacıyla yüksek güvenilirliğe sahip iletim hatlarındaki farklı hataları tespit etme ve sınıflandırma amacıyla yöntemi ortaya koymaktayız. İletim hattında hızlı tespit olmadan herhangi bir arıza veya karışıklık meydana gelir ise, ekipman hasarına ve güç sistemi için ekonomik kayba neden olacaktır.

Bu tez, iletim hatlarındaki hataları tespit etmek ve sınıflandırmak amacıyla Yapay Sinir Ağ Kullanımını ortaya koymaktadır. Yöntem, bir hatanın devre dışı olma süresini kısaltır. Yapay Sinir Ağı teknolojisinin işletmeye alınmasıyla bir 400 KV'lik iletim hattında meydana gelen hataları tespit etmek ve sınıflandırmak amacıyla dijital bir tespit sistemini önermiş bulunmaktayız. Sistem, bir hata tespit ünitesi ve bir hata sınıflandırma ünitesi olmak üzere iki fonksiyonel üniteden meydana gelmektedir. İki parça MATLAB'da uygulanmıştır. Hata tespiti, simülasyon yoluyla elde edilen farklı hatalı şartların akım ve voltaj sinyalleri için simülasyon yaratılarak önerilmiştir. Simülasyonda elde edilen dalga şekilleri, MATLAB programı ile Yapay Sinir Ağı yöntemi kullanılarak çalışılmıştır. Yöntemimiz, sekiz muhtelif giriş ve bir çıkıştan meydana gelmektedir. Simülasyonun sonuçları, hata tespiti için Yapay Sinir Ağına dair iyi bir performans göstermiştir. Arızanın gerçekleşmesinin ardından tespit süresi çok hızlı gerçekleşmiştir. Hata sınıflandırma ünitesi için modelimiz, aynı zamanda geçerli performansa sahip olduğunu da göstermiştir. Bu ünite için, on bir farklı türde hata olarak sınıflandırılabilir.

Anahtar Sözcükler: İletim Hattı, Hata Tespiti ve Sınıflandırma, Yapay Sinir Ağı.

CHAPTER ONE

INTRODUCTION

1.1 Presentation of The Work

In this thesis, the use of Artificial Neural Network (ANN) in the detection and the classification of faults on the electrical power transmission lines is investigated. (TL is used for " Transmission Line " from this point on.)

The prime motivation behind this thesis was the significant impact the very accurate fault detection could make if employed in a power transmission and distribution system, in terms of the amount of money and time that can be saved. The main goal of fault detection is to detect faults in the power system with the highest practically achievable accuracy. When the physical dimensions and size of TL's are considered, the accuracy with which the designed fault detection finds faults in a power system becomes very important.

One of the significant aspects on which this thesis concentrates is the analysis of the phase voltages and currents in a TL during various fault conditions and how they can be utilized in the design of an efficient fault detector.

A fault locator with satisfactorily high accuracy can be achieved with the help of artificial neural networks by using a large data set for the training and learning processes. This eliminates the need for proficiency in power systems, which is a necessity when working with expert fuzzy systems. Hence, this thesis focuses on the design of a fault locator that can be used even by people who are non-experts in the field of power system.

1.2 Artificial Neural Network

ANN is equipped with distinct parallel processing, nonlinear mapping, associative memory, and offline and online learning abilities. The wide uses of ANNs with their exciting outcomes make them an effective diagnostic tool in electrical power systems. Their versatility with a multitude of applications can be seen in other areas of science and engineering research. ANN is a complex network of interconnected neurons where the firing of electrical pulses via the ANN's connections leads to information propagation. ANN is trained by using previously selected fault samples as inputs and a set of fault information as an output for fault diagnosis applications. Neural networks are comprised of primarily three basic learning algorithms, namely supervised learning, unsupervised learning, and reinforced learning. The most commonly used supervised learning algorithm is also referred to as learning with a teacher. This is applied when the target identifies values that are associated with each input in a training set. Figure 1.1 presents the architecture of ANN.

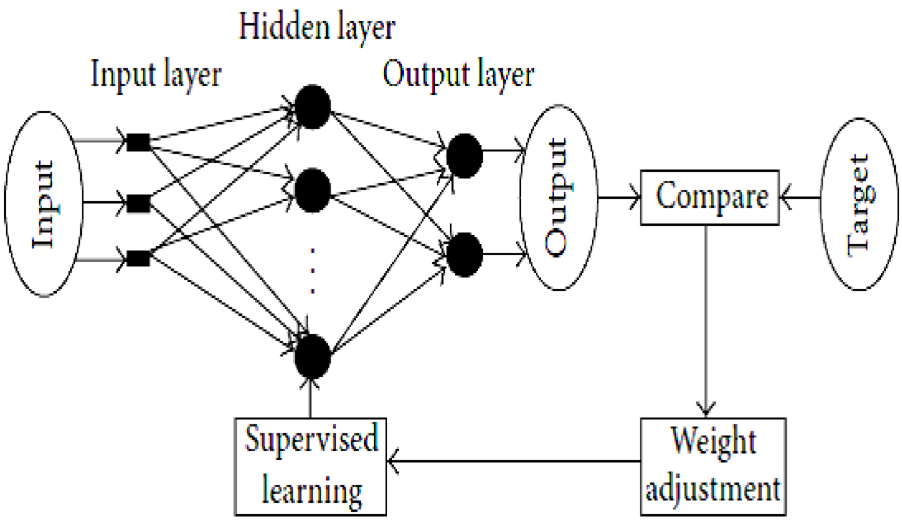

Figure 1.1: ANN architecture

An error Back Propagation (BP) neural network was applied for diagnosis of faults in a power system. However, slow speed training and the shortcomings of local optima lead to the introduction of an additional momentum factor for problem solving.

The Radial Basis Function (RBF) neural network has a quicker learning speed and ability of arbitrary function approximation. The simulation results of the 4-bus test system show that the capability of an RBF neural network in grid fault diagnosis was better than the conventional BP neural net. To solve improper problems, neural network topologies are altered and there is a need to retrain the network. The true capacity of multilayer perception and the Generalized Regression Neural Network (GRNN) used intended for fault estimation in electrical power systems. GRNN has the advantage of faster learning, a global optimum, and a lower requirement of a comprehensive sample.

They fed the failure information into multilayer perception and the outcome was given as an output to the GRNN. They also compared ANN fault diagnosis methods with expert system diagnostic methods and found that ANN based methods may avoid the need for expertise and expert knowledge hence keeping away from hard work.

1.3 Problem Formulation

We employed the technology of Artificial Neural Network in our work to detection and classification faults. The system is consisting of two functional sections fault detection unit and fault classification unit. The two parts implemented in MATLAB. We assumed eleven types of faults in our TL. All types of faults were treated individually at the simulation time.

We designed and train ANNs for solving specific troubles which are hard to solve by the human beings or ordinary computational algorithms. The computational importance of the training to the modify of certain weights which are the main elements of ANN. This one of main variations of the ANN approach to trouble solving than classic computational algorithms which work step-by-step. Also, classic method detects and classifies a fault based on the fundamental element of each signal might not complete the required analysis. Hence, various studies did not address series faults or not a universal ANN system, but splits the system into some of sections each one for alike fault kind different phase.

Consequently, in this study modern method has been adopted to detect of the faults and classification of the fault on TL with a very short time by using ANN.

An electrical power system consists of various parts, one of them is TL, where power is transmitted from producing stations and substations through TL to customers [22]. Both approaches might be meeting many kinds of failures, usually indicate to as a “fault,” which is simply defined as unwanted accident that could affect the stability of the power system. Furthermore, if an anything connected with a bare power conductor, a short circuit or fault is said to have happened. Reasons of faults are various, including lighting, wind damage, trees falling pass transmission line, vehicles or aircraft colliding with TL or poles, birds shorting phases or damage.

To maintain stability of a power system disturbances such as fault inception should be detected immediately. The protection relay in a TL should disconnect the faulty component from the system in the shortest possible time and prevent incidental problems such as the loss of stability and equipment damage. The faulty component is then detected and the relay is operated. The damaged component must be repaired to allow the faulty component to function again in the system. Because of the length of the TL, fault location algorithms must be used to determine the point of the fault [8].

The problem of classifying the faults in TL is a so hard issue. It is a first interest of the power to determine fault and classify it. Basically, protective relays, special control devices, protection software and recording devices are utilized to know faults. It is very significant to show all the data about the fault so as to detect it and then accurate it as soon as possible [12].

Currently, various studies are presented to learn about methods of fault detection in distribution and transmission networks that depended on smart methods like fuzzy-set theory, ANNs.

As demonstrated in Chapter Two (Literature survey), the main problem in power system TL is faults. From the definition, a fault can occur in many situations, including line to line and line to ground. This error can occur in power systems due to multiple reasons and the commonly observed risks are the multitude of electrical currents flow from lines with a high degradation in signal of voltage, which in turn leads to unfortunate fires and explosions. A TL or generally a power system needs to be reliable and protected against such errors.

Protection in power systems can be observed in the literature [Chapter 2] and hence, the need for robust power transmission is a critical issue due to highly increased loads. The design of a fault detection scheme is not an easy task. Our project is an attempt to implement a protection system based on artificial intelligence technology.

1.4 Fault Categories in a Power System

A fault is a number of unwanted events that can provisionally interrupt the steady condition of a power system. A short circuit is the most dangerous type of fault as the movement of currents can reason hotness which might problems to devices and other parts of a power system. Faults can be classified into three kinds: symmetrical faults, unsymmetrical faults, and open circuit faults.

1.4.1 Symmetrical faults

A fault that results in symmetrical fault currents (equal currents with 120 degree displacements) is known as a symmetrical fault. A three-phase fault is an example of a symmetrical fault where all three phases are short circuited with or without involving the ground.

1.4.2 Unsymmetrical faults

The different unsymmetrical faults include the following fault types that can occur in T.L are described:

1. Line to Ground (L-G) Fault: An L-G is a short circuit among any one of the phase conductors and the earth (prevalence is 70%-80%). It may be caused either by insulation failure among a phase conductor and a ground.
2. Two lines to Ground (L-L-G) Fault: The L-L-G is a short circuit among any two phases and an earth (prevalence is 10%-17%).

3. Line to Line (L-L) Fault: is a short circuit among any two lines of the system (prevalence is 8%-10%).
4. Three-lines (L-L-L) Fault: is a short circuit among any three phases of the system (prevalence is 2%-3%).

1.4.3 Open circuit fault

This kind of fault happens because of cutting in path. These faults happen when one or additional phases break. These cases may rise when circuit breakers or isolators open but failure to shut down any lines. When the circuit open, the current flows will be unbalanced in the system.

1.5 Thesis Organization

This first, “Introduction,” chapter looks at the definitions of faults and their categories with the research objectives and problem definition.

The second chapter, “Literature Survey,” covers the several problems that prevent the protection of a typical TL system and discusses the relevant studies that look at fault detection and location with the technologies found for that purpose.

The third chapter, “Artificial Intelligence,” introduces the concept behind artificial intelligence and neural networks. A few ANN architectures that are usually employed are discussed and the various learning strategies employed in training process of ANNs along with critical factors that affect the size and output of a trained network are discussed in this chapter.

The fourth chapter, “Methodology,” deals with the actual implementation and development of the neural networks and their architectures proposed for two different parts of the fault location process, fault detection and classification fault. An overview of training and testing processes employed with neural networks in this work is outlined in this chapter.

The fifth chapter, “Practical Models,” presents a series of simulation results that were obtained using MATLAB, SimPowerSystems and the Artificial Neural Networks Toolboxes in Simulink in detail to emphasize the efficiency and accuracy factors of the proposed fault locator.

The sixth chapter, “Conclusion and Recommendations,” concludes the entire research work and the thesis. It discusses the results obtained in the previous chapters. Moreover, the scope for future work and possible extensions to this work are outlined briefly in this chapter.

CHAPTER TWO

LITERATURE SURVEY

In the literature, there are many researches was conducted in the field of protection for TL. Those studies were taken place by using of many methods such as ANN, fuzzy logic, Genetic algorithm and extra.

2.1 Wavelet Transform Approach

In the approach, a novel wavelet transforms used for fault detection and classification method is studied [1]. The method involves analysis of fault induced transient that can provide extensive data about the fault detection and classification fault kind. These fault transients with system voltage and current can be effectively analyzed with the wavelet transform technique. Two bus systems with various fault condition and their combination are simulated. The simulation results indicate that the wavelet transform is an effective technique in field of fault detect and classify of various fault categories [1].

Different types of fault are simulated on two bus power system models. Ten kinds of short circuit fault such as single line to ground fault, dual line fault and triple line fault on all three phases with or without involvement of ground are artificially simulated on MATLAB two bus power system model. With various fault condition corresponding current and voltage waveform information generated and is recorded at one of the end of the system. Check of these results by well waveform show essential change among the normal and faulty condition. These changes are used in detecting the faulty condition [2].

Author said that correct detection of many faults happening on TL is much vital. In this study, detecting and classifying of several these faults is gotten depending on existing data through wavelet analysis of power systems transients. Maximum norm values, maximum detail factor and power of the current signals are considered from the Wavelet Toolbox in MATLAB/Simulink [3].

Writer mentioned that TL protection is a significant subject in power system since 85-87% of power system faults are happening on TL. This study gives method to classify the various faults on TL for fast and reliable process of protection schemes. It also a modern method for quick and precise detection as well as classification of power system faults utilizing neoteric signal operating methods. Method includes wavelet analysis of faulty voltage and current waveforms, which are registered at an appropriate oversight location in multi-bus power system to collect worthy data wanted in detection and classification of faults [4].

TL faults mainly consist of five kinds: L-G, L-L, L-L-G, L-L-L and L-L-L-G. But effect of L-L-L and L-L-L-G faults is same. So, the study has taken only L-L-L fault. In all four different faults are classified after faulty condition is detected in the system with the beginning of computers, it gets simpler to simulate a power system in different -software's available for simulation. Currently, many simulation software's similar PSCAD and MATLAB/SIMULINK are offered in the shop. The deliberating considered „Standard IEEE System‟ and simulated it in PSCAD/EMTP software. The information found from simulation is transferred to Wavelet Toolbox of MATLAB for obtaining the many parameters similar occurrence of harmonics and overvoltage [5].

The researcher has dealt with implementation of wavelet based isolation technique for detecting and classifying of faults in TL. The three phase current signals of the two ends are synchronized with the help of Global Positioning System clock. These signals are invalid with Haar wavelet to get estimated factors over moving window of half cycle. Approximate coefficients obtained over a half cycle are compared with the preceding half cycle of the same polarity to compute isolation factors at each finish. A Fault computed by addition isolation factors of local and the other end is compared by threshold to detect and classify faults. The suggested algorithm has been tested well for many kinds of faults at different fault locations and various fault happening angles [6].

A novel technique for fault detecting and classifying on TL has been used. This technique named Fuzzy-Wavelet Singular Values gathers benefits of wavelet transform and singular value decomposition, then utilizes fuzzy logic for detecting and classifying of fault. The suggested algorithm utilizes singular amounts of wavelet transform of three phases and zero sequence current for fault detecting and classifying. Input of fuzzy logic is singular amounts wavelet transform of zero sequence and three phases currents. Three phases in this article are used to detect the faulty phase from sound phase, and zero-sequence is utilized to detect phase to ground fault.

The used algorithm is capable to detect many kinds of fault and this protection scheme is strength to parameters like fault resistance, fault location and fault kind. The suggested structure is capable to detect the fault inside 10 ms from fault beginning to prohibit several troubles like stability and loss of devices. The MATLAB software is utilized to design the system [8].

The approach is presenting a discrete wavelet transform and neural network method to fault detecting and classifying on TL. The detection and classification are executed by using power of detail factors of phase signals utilize as input to neural network to classify faults on TL. Neural network performs well when treated with various fault cases and system parameters. Model of 220kv, 200 km transmission is chosen. Generator of 500 MW is connected at one end and 4 loads are connected at 13.8 KV and 220 KV. Different faults are simulated on that line by many parameters [13].

The study is describing the implementation of wavelet multi resolution analysis approach for location of TL faults. Simulation study has been executed by two power system models using Electromagnetic Transient Program and MATLAB. Three phase current samples at one end of TL are used as inputs. The various kinds of faults at various working cases have been treated for carrying out simulation studies. Problem of fault location by wavelet analysis proposed in this approach does not follow a set rule. However, by carrying out extensive simulation study it has been observed that a linear relationship exists between fault location and the normalized absolute value of wavelet multi resolution analysis details. The simulation results presented confirm the feasibility of proposed scheme [18].

2.2 Microprocessor Approach

The 8051 microprocessor is having numerous strong features such as integrated Universal Asynchronous Receiver-Transmitter, it is known as a serial port. The truth 8051 has an integrated serial port means that we can readily read and write values to the serial port. If it were not for the integrated serial port, writing a byte to the serial line will be a boring operation requesting turning on and off of the I/O lines in fast succession to correctly "clock out" each singular bit, involving start bits, stop bits and parity bits. The work has been done by configuring the serial ports process design and baud ratio. Once formed, all need to be done is write to a Serial port From Reading (SFR) data to write a value to the serial port or read the same SFR to read a value from the serial port. The 8051 will give information once it has completed sending the letter that was written. Thus, it can process when information is taken a byte. Temperature sensor Analog-to-Digital Converter, Microcontroller 8051 and Liquid Crystal Display were used for showing faults and parameters; Global System for Mobile communication board was used to send fault message to power board. Through using this method, various faults of three phase TL can be detected one can observe the Temperature, Voltage and Current by means of Global System for Mobile communication modem by sending message [15].

Author stated that; nowadays, technology developed and its integration is an important part of human life that demand of the electrical energy for the domestic, commercial and industrial loads is taking enhanced. Also, managing the electrical energy delivery system is receiving extra complicated. Thus, inspecting such type of faults is an essential and complex task in power system. For precise detection and study of these faults, there is a needed of design that detects this fault on TL.

The faults which happen on TL result to interruptions of the power source. A developed approach in this concern can be designed to have an in-built intelligence to sense the occurrence of fault on TL Thus, to make sure a secured process of delivery and decrease a happened by incidents, a far-off monitoring and controlling system is advanced. This study is proposing a fault detection and classification from the fault on TL based on MATLAB with Arduino 328 hardware which helps in highly reducing the human effort, minimizes times and works safely and accurately without human intervention [19].

TL protection is a highly necessary subject in power system. TL is linked between generation units with loads. the generation units are far away from the load. So, runs some kilometers and hence a possibility of a fault happening in the phase is great. More than 75 percent of power system faults are happening on TL. Between the other power system element, this TL damages more from sudden disaster. So, the accuracy of the working system degrades earlier to its worst state. So, in this study, the work is to produce a protecting system used adaptive method to stop expansion of these faults and protection system with irregular cases. The function of protecting system will detect and classify kind of fault and send a tripping signal to reorganize it back to a healthful case next restart the breaker. Investigation of various kinds of faults in TL is done through an implementation of evolutionary programming tools of MATLAB software and Arduino mega 2560 microcontroller [20].

2.3 Neural Network Approach

A precise fault classifying algorithm for Teed Transmission Circuit depend on implementation of ANN is offered in this method. Suggested algorithm utilizes voltage and current signals of each division measured at one end of teed circuit to detect and classify double phase to earth faults. ANN has the capability to classify the nonlinear relation among measured signals by recognizing various samples of the related signals. Adaptive protection structure depended on implementation of ANN is tested for double phase to earth faults, variable fault position, fault resistance and fault beginning angle.

The ANN work can be well via it is trained on various faults cases to get precise results. The overall test results obviously display that fault is detected and classified inside one cycle. Thus, suggested adaptive protection method is proper for teed transmission circuit fault detecting and classifying. Outcomes of working studies display that suggested neural network-based model can get better work of conventional fault chosen algorithms [4].

Protection of power system always been a great area of research for the new researcher and research communities in this context many work has been done for the classification and detection of the fault for the analysis of the system. A three-phase TL is an essential component of the power system.

In this research, different types of fault are classified in the three-phase TL. In the present scenario, the both end ratios are considered for the data acquisition of voltage and currents. These states are measured and fed to the control panel for the fault analysis and detection. These techniques are very much accurate for the short and medium transmission line. But for long TL classification needs the accuracy and actual detection of the fault and direction of the fault. For a 400kV, 100MVA, and 400 km TL is simulated and worked in MATLAB/SIMULINK environment [7].

The algorithm utilizes the fundamental components of voltage and current signals. The results show the appropriateness of suggested method and its confronted to variable system cases. The simulation outcomes of ANN based fault detecting and classifying. These outcomes show that algorithm properly to detect and classify faults [9].

2.4 Other Techniques

In this section, the other techniques are found in the literature search to detects the occurrence of a fault on power TL. Those technologies have also participated in the researches by paying a lot of efforts to classify and locate the fault. Some of them are employing telecommunication and electronic techniques such as Global System of Mobile Communication for detecting of fault. Others such as Principle Component Algorithm, fundamental Components of voltage and current and K-Nearest Neighbors algorithm are alternatives for fault detection and classification. The following are the most relevant articles in this regard.

Power transmission is a major issue in electrical engineering after power generation. Fault in TL is common and major problem in power system. In this study, presenting of method to detect the location of the various faults on TL for fast and dependable process of protection schemes. The simulation is advanced in MATLAB to generate the fundamental component of the transient voltage and current. MATLAB software is utilized to simulate various working and fault cases in high voltage TL.

Effects of variations in the fault resistance (Rf), distance to fault (Lf) have been studied widely on the voltage, current and its relation to impedance of the system which creates the logic for detection, classification and location of faults [10].

An essential feature of an electrical network is continuity of service with a high level of reliability. This motivated many researches to investigate power systems in an effort to improve reliability by focusing on fault detection and classification. In this method, a modern protective relaying framework to detect and classify faults in TL is existing. By using principal component analysis approaches, this system will recognize and classify any fault instantaneously. Also, by utilizing the curve fitting polynomial method with our data that got from the ideal fault signature, the location of the fault can be determined with an important precision [11].

This article is presented a review of the improvements in digital relays for preservation of TL. For a new power system, eclectic high-speed rescue of faults on high voltage TL is unstable and this review show the intelligent applications for fault detecting and classifying on power TL. The achieved method in this field for serving relays that work with computer, digital communication manufactures and other practical improvements, to prevent damages and simplify safe and dependable power systems. Different works have been performed to contain the methods of TL defense mentioned in the literature up to October 2010. The emphasis of this article is the greatest modern methods, such as ANN, fuzzy logic, fuzzy-neuro, fuzzy logic-wavelet based and phasor measurement unit-based ideas in addition other classic approaches used on TL protection [12].

Research is involving a very active and extremely preservative subject was worked for TL system. Here we used the K-Nearest Neighbors algorithm method on input current samples from Electromagnetic Transient Program (EMTP) information, to become the satisfactory and quick answer by the relays. The hardware explanation language named very high speed integrated circuit is utilized to achieve its hardware understanding on Field Programmable Gate Array. High frequency current signals are used from EMTP soft-ware information, which is utilized as an input signal to our system. Wavelet transformation is the highly active tool for receiving the information about its Transient current signals. By taking the knowledge about its input current samples and compared it with test information samples from Electromagnetic

Transient Program information, we get precise outcomes about its fault realization and classification by K-Nearest Neighbors classifier [14].

The technical development and its combination are played role important in human life. In these days, request on electric power for domestic, commercial and industrial loads is growing. Also, the management of electric power distribution system is becoming more complex. There are many systems designed to detect TL fault for an employer to simply identify current state of distribution line. the final aim is observed distribution line status constantly and protective a fault of distribution line due to restraints for example overvoltage, under voltage, SLG, DLG faults. If any of these does happen then an operator can simply detect the fault [16].

Major objective of this study to detects the alteration in working temperature range of the high voltage TLs and insulators. Thus, it should be observed frequently to avoid faults. In proposed system thermopile array is used to monitor the operating temperature. The thermopile array sensor is mounted on a parallax servo motor to monitor a wide area and gives us a thermal image. This project is made to send an emergency message to the electrical substation through Global System of Mobile Communication once TLs and insulator exceeds maximum working temperature range [17].

Multivariate Statistical Process Control methods are now extensively used for presentation monitoring, fault detection and diagnosis in industrial processes. Conventional MSPC methods are based on latent variable projection approaches such as Principal Component Analysis (PCA). These approaches are appropriate for steady-state procedures. For the systems where, transient values of the operation must be taken into account, the utilize of conventional PCA technique reasons false alarms and missing data that significantly decreases from the accuracy of the monitoring systems. In this study, a technique is suggested to overcome false alarms which happen in the transient statuses according to variable operation cases and missing information trouble. The suggested monitoring technique is applied and investigated experimentally on an electromechanical operation. The monitoring results prove that suggested methodology affords reliable fault detection for both the steady-state and transient operations [21].

CHAPTER THREE

ARTIFICIAL NEURAL NETWORKS

3.1 Introduction

Neural networks are a new method of programming computers. They are exceptionally good at performance pattern recognition and other tasks that are very difficult to program using conventional methods. Programs that employ neural nets are also capable of learning on their own and adapting to changing conditions [23].

An Artificial Neural Network (ANN) is an information processing paradigm that is taken of the biological nervous systems, such as human brain's information processing mechanism as shown in Figure 3.1.

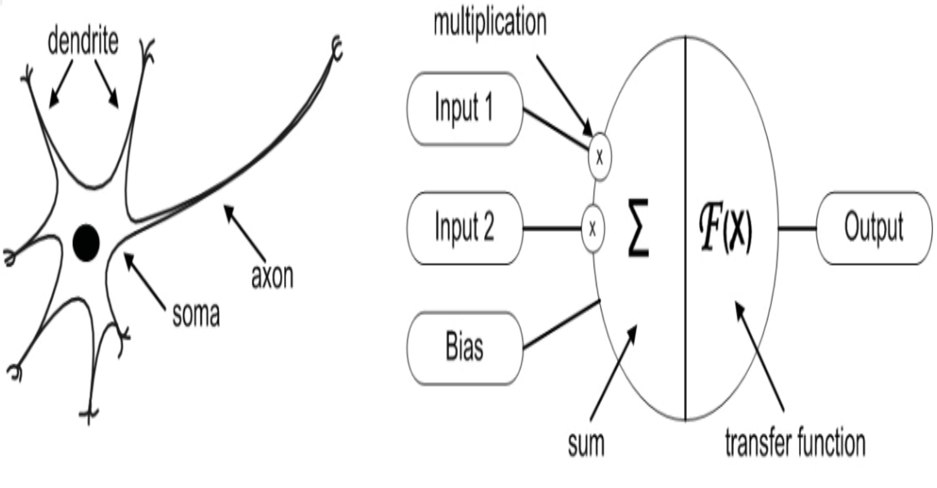

Fig.3.1: Biological and artificial neuron design

The brain of human, an ideal neuron gathers signals from others depending on a group of structures named dendrites. The neuron sends orders of electrical activity depending on a long and thin stand named as an axon, which divided into thousands of branches. At end of each branch, a structure named a synapse converts the activity from the axon into electrical effects that prevent activity in the linked neurons [25].

3.2 Artificial Neuron Model

The basic building block of ANN is the neural. A neural is a processing unit which has some inputs and only one output. As shown in Figure 3.2.

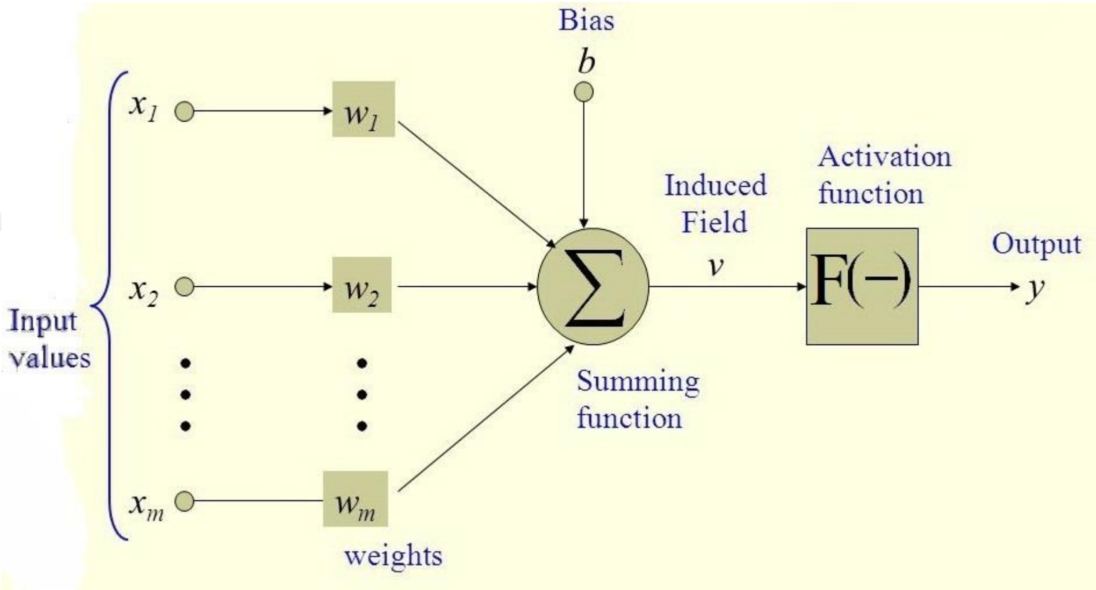

Fig 3.2: Components of the neuron

ANN is a mathematical model. The model has three rules: multiplication, summation and activation function [24].

Each input (x_i) is weighted by a factor (w_i) and the whole sum of inputs is calculated (I) all inputs as below equation:

$$\mathbf{I} = W_1 X_1 + W_2 X_2 + \dots + W_n X_n$$

$$\mathbf{I} = \sum_{j=1}^{n} W_j X_j$$

$$\mathbf{V}_k = \sum_{i=1}^{m} W_{kj} X_j + b_k$$

$$\mathbf{y}(\mathrm{k}) = \mathbf{F}\left(\sum_{i=0}^{m} w_i(k) \cdot x_i(k) + b_k\right) \quad \textbf{(3.1)}$$

Where:

- X_i (k): is input value in discrete time (k) where (i) goes from 0 to m,
- W_i (k): is weight value in discrete time (k) where (i) goes from 0 to m,
- b : is bias, an external parameter that can be modeled by adding an extra. (correction factor for the output magnitude depend on activation function).
- F : is a transfer function, (Activation function).
- y(k): :is output value in discrete time (k).

Activation function defines properties of ANN and performs a mathematical operation on the signal output. An activation function decides how powerful the output from the neuron should be based on the sum of its inputs. Depending upon the application's requirements, the most appropriate activation function is chosen. The following set of functions [26]:

(i) Step function

Step function is binary function that has only two probable output values zero and one. The situation can be described with equation 3.2 and as shown Figure 3.3.

$$F(V_k) = \begin{cases} 1 & \text{if} \quad V_k \geq 0 \\ 0 & \text{if} \quad V_k < 0 \end{cases} \quad \textbf{(3.2)}$$

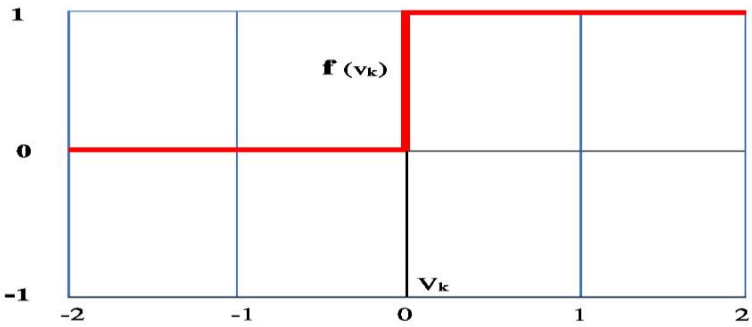

Figure. 3.3: Step activation function

(ii) Linear function

The situation can be described with equation 3.3 and as shown Figure 3.4.

$$F(V_k) = \begin{cases} 1 & \text{if} \quad V_k > 1 \\ -1 & \text{if} \quad V_k < -1 \\ V_k & \text{if} \quad |V| < 1 \end{cases} \tag{3.3}$$

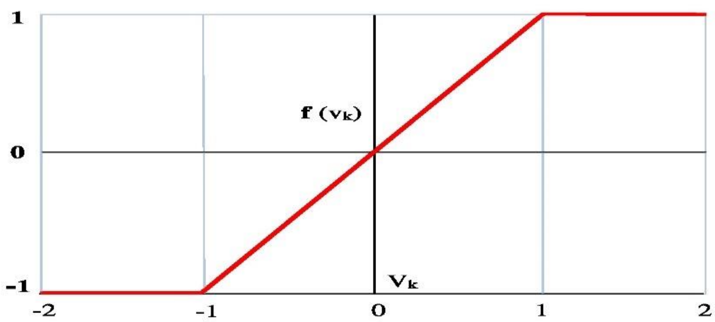

Figure 3.4: Piece wise linear activation function

(iii) Non-linear function (Sigmoid)

The sigmoid function is most utilized. Sigmoid function has readily calculated derivate. It can be significant when calculating weight updates in the ANN.

- Sigmoid unipolar function

The situation can be described with equation 3.4 and as shown Figure 3.5.

$$F(v) = \frac{1}{1 + e^{-Bv}} \tag{3.4}$$

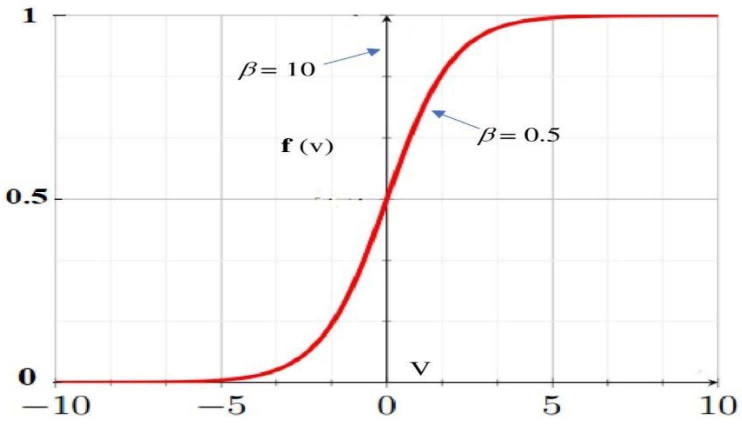

Figure 3.5: Sigmoid unipolar activation function

● Sigmoid bipolar function

The situation can be described with equation 3.5 and as shown Figure 3.6.

$$F(v) = tan\,h(BV) = \frac{1 - e^{-2B}}{1 + e^{-2B}} \tag{3.5}$$

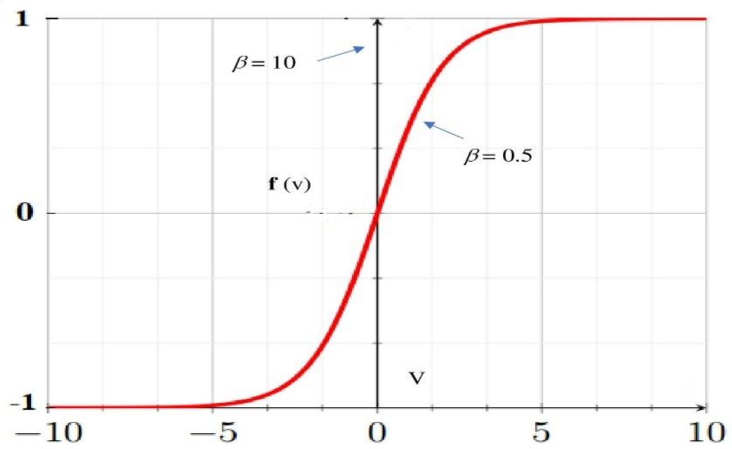

Figure 3.6: Bipolar activation function

The types of ANN are depended on the whole possibility and computational ability. We can simply understand the fact use of ANN that complexity can grow from a few basic and simple rules.

Generally, ANNs are building by putting the neurons in layers and connecting the outputs of neurons from one layer to the inputs of neurons from the next layer. As shown in Figure 3.7 [27].

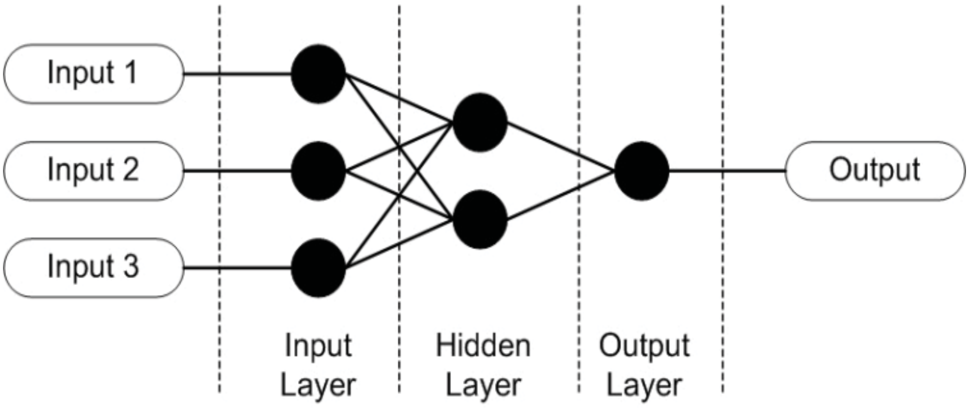

Figure 3.7: Example of simple artificial neural network

The ANN divided into three layers as following:

(a) Input layer.
The entrance of ANN. The inputs are weight what means that every input value is multiplied.

(b) Hidden layer.
Perform most of the internal processing is being in this layer.

(c) Output layer.
Responsible for presenting the final network outputs is being in this layer.

3.3 Architecture of ANN

The structure of an artificial neural community defines how it's many neurons are set in relation to every other. Connecting of the layers can be divided into the following [28]:

(i) Feed forward (Multilayer network)

As depicted in Figure 3.8 architecture of feedforward networks. they are consisting of one or more than one layers. They are used in the solution of various problem.

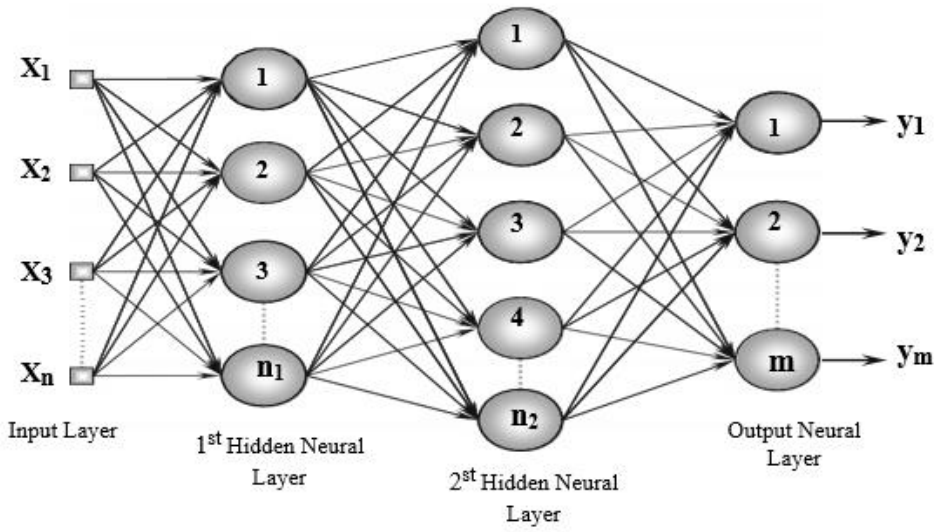

Figure 3.8: Example of a feedforward network with multiple layers

(ii) Feedback (Recurrent network)

Figure 3.9 illustrates the outputs of neurons are using as feedback inputs for different neurons. One of the output notifications be fed to the middle class.

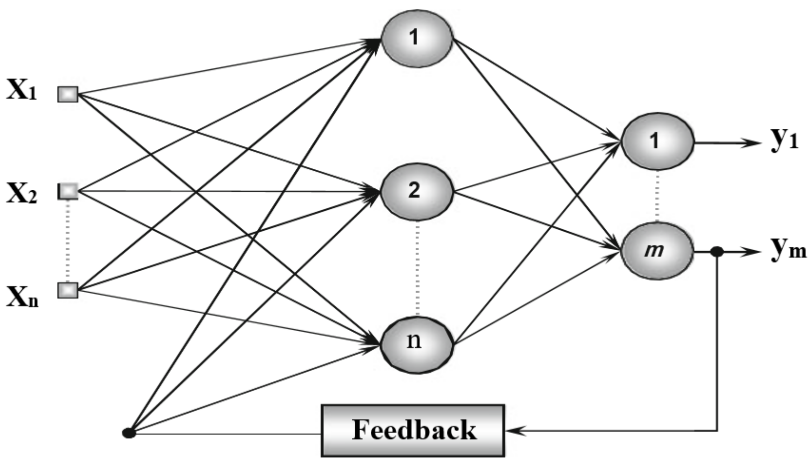

Figure. 3.9: Example of a recurrent network

3.4 Training Processes and Properties of Learning

Before we use the ANN, we need to teach it to solve the type of problem given. One of the characteristic features of ANN is their ability to learn from the presentation of samples that express the behavior of the system. Hence, after the network has learned the relationship between inputs and outputs, it can generalize solutions meaning that the network can produce an output which is close to the expected or desired output of any given input values.

The set of steps used to train the network is named the learning algorithm. During its implementation, the network will be able to extract system features that are specified from the samples obtained from the system. The process of using all the training data once and updating the weights is called an epoch. The whole training process consists of a number of epochs in an iterative manner. There are three main learning paradigms [27]:

(i) Supervised learning

In this approach, each training sample consists of input signals and their corresponding outputs. It is an ideal state of clear inference where the variables of network are regulated by the required outputs knowing a previously for inspected system.

(ii) **Unsupervised learning**

In this approach, it does not require any knowledge of the respective desired outputs. Thus, the network needs to organize itself when there are existing particularities between elements that compose the entire sample set. The application of an algorithm based on it. The learning algorithm adjusts the synaptic weights and thresholds of the network in order to reflect these sets within the network itself.

(iii) **Reinforcement learning**

Approaches based on reinforcement learning are considered a difference of supervised learning methods. The network learning process is usually done by trial and error because the only available response for a given input is whether it was satisfactory or unsatisfactory.

3.5 The Backpropagation Algorithm

The BackproPagation (BP) algorithm is used in layered feed-forward ANN. The BP is a multi-layer feed forward, supervised learning network based on gradient descent learning rule. We provide the algorithm with samples of inputs and outputs. The idea of BP algorithm is to reduce the error (the difference between actual and expected results) until ANN learns the training data.

The activation function of artificial neural in ANNs application the BP algorithm is a weighted sum. The sum of the inputs Xi multiplied by their respective weights Wji [30].

Usually, BP network has two steps, training and testing. During the training step, the network is "shown" sample inputs and the correct classifications.

The following Figure 3.10 shows Construction of BP neural network that includes an input layer, one hidden layer and an output layer.

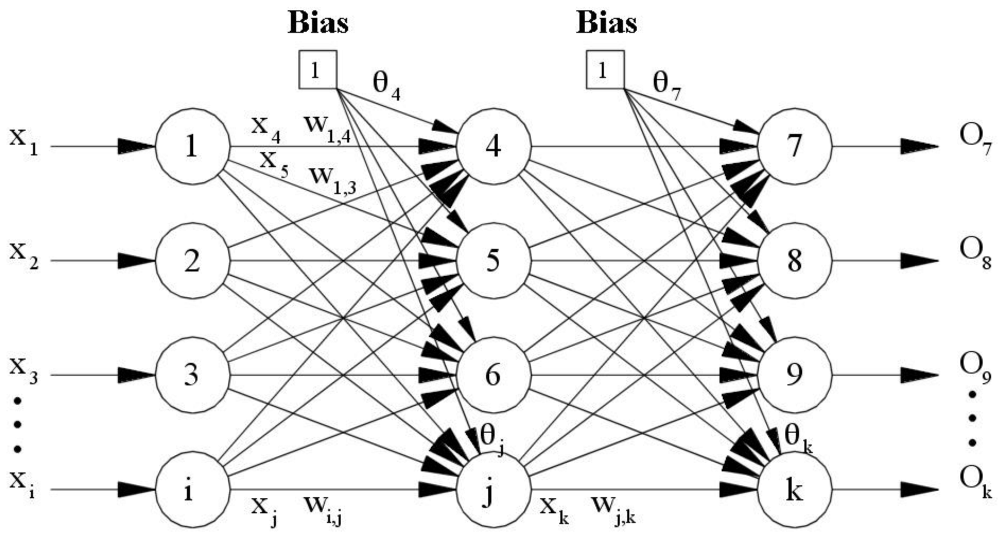

Figure 3.10 Backpropagation Neural Network with one hidden layer

The operations of the BP neural networks can be divided into two steps: feedforward and Backpropagation.

In feedforward step, an input pattern is applied to input layer and its effect propagates layer by layer through the network until an output is produced. The network's actual output value is compared to the expected output, and an error signal is computed for each of the output nodes.

The output error signals are transmitted backward from the output layer to each node in the hidden layer that immediately contributed to output layer. This process is then repeated layer by layer until each node in the network has received an error signal that describes its relative contribution to overall error.

Once the error signal for each node has been determined. The errors are then used by the nodes to update the values for each connection weights until the network converges to a state that allows all the training patterns to be encoded.

The BP algorithm looks for the minimum value of the error function in weight space using a technique called the delta rule or gradient descent. The weights that minimalize the error function is then considered to be a solution to the learning problem [31].

These are tested against the correct outputs to see how accurate the guesses of network. Radical changes in the latest theory are indicated by large changes in the weights, and small changes may be seen as minor adjustments to the theory.

When a specified training pattern is fed to the input layer, weighted sum of the input to the (j^{th}) node in the hidden layer is given by equation 3.6:

$$N_e t_j = \sum W_{ij} X_j + \theta_j \tag{3.6}$$

The θ_j term is weighted value from a bias node that always has an output value of 1.

The bias node is considered a "pseudo input" to each neuron in hidden layer and output layer. It is used to overcome the problems associated with situations where values of an input pattern are zero. If any input pattern has zero values, neural network could not be trained without a bias node [32].

The "Net "term is known as the action potential. It is passed onto a suitable activation function. The resulting value from the activation function specifies the neuron's output and becomes the input value for the neurons in next layer connected to it. Since one of requirements for the BP algorithm is that activation function is differentiable, a typical activation function used is the Sigmoid equation [32].

$$O_j = x_k = \frac{1}{1 + e^{-Net_j}} \quad \textbf{(3.7)}$$

3.6 Error Computations and Weight Modifications

A- **Output layer**

The difference between the actual output and the expected output is given by equation 3.8

$$\Delta_K = t_k - y_k \quad \textbf{(3.8)}$$

Where

t_k : target output

y_k : network output

The error signal for node k in the output layer can be calculated as equation 3.9.

$$\delta_k = \Delta_k \, y_k(1 - y_k)$$

Or

$$\delta_k = (t_k - y_k)y_k \,(1 - y_k) \quad \textbf{(3.9)}$$

where the [$O_k(1-O_k)$] term is the derivative of Sigmoid function.

With the delta rule, the change in the weight connecting input node j and output node k is proportional to error at node k multiplied by activation of node j [33].

The formulas used to modify the weight, $W_{j,k}$, between the output node k, and the node j is equation 3.10 and equation 3.11.

$$\Delta w_{jk} = I_r\, \delta_k\, X_k \qquad \textbf{(3.10)}$$

$$w_{jk} = w_{jk} + \Delta w_{jk} \qquad \textbf{(3.11)}$$

where

Δw_{jk}: is the change in weight among nodes(j) and(k),

Ir: is the learning rate.

The learning rate is a relatively small constant that indicates the relative change in weights. If the learning rate is too low, the network will learn very slowly. If learning rate is too high, the network may oscillate around minimum point (refer to Figure 3.10), overreaching the lowest point with each weight adjustment, but never actually reaching it. Usually learning rate is very small with 0.01 not an uncommon number Some modifications to the BP algorithm allows the learning rate to decreases from a large value during the learning process.

To improvement the process of updating the weights, a modification to equation 3.10 is made:

$$\Delta w_{ik}^{n} = I_r\, \delta_k\, X_k + \Delta w_{ik}^{(n-1)}\, \mu \qquad \textbf{(3.12)}$$

Here the weight update during the nth iteration is determined by including a momentum term (μ), which is multiplied to the (n-1) th iteration of the Δw_{ik}. The introduction of the momentum term is used to accelerate learning procedure by "encouraging" the weight changes to continue in the same direction with larger steps. Furthermore, the momentum term prevents the learning process from settling in a local minimum by "over stepping" the small "hill". Typically, the momentum term has a value between 0 and 1. As shown in Figure 3.11 [33].

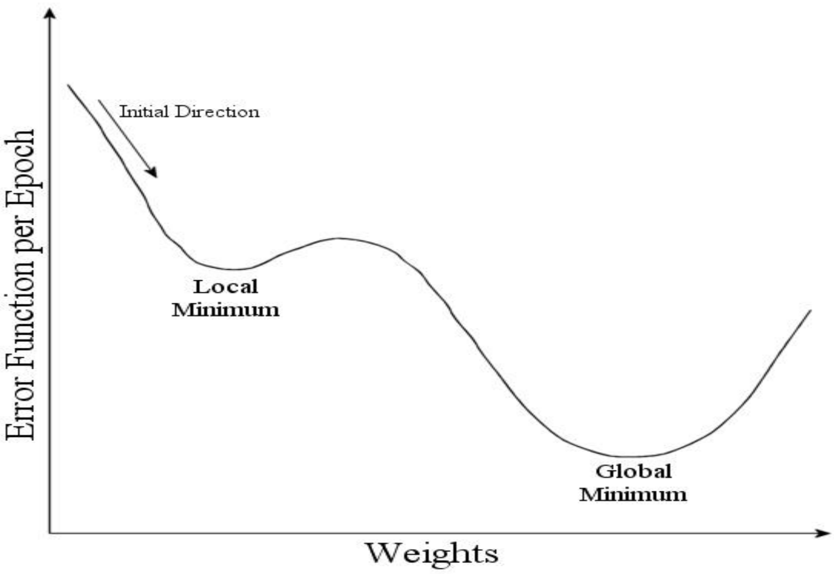

Figure 3.11 Global and Local Minima of Error Function

B- **Hidden layer**

The error signal for node j in the hidden layer can be calculated as equation 3.13.

$$\delta_k = (t_k - O_k)O_k \sum(W_{jk}\delta_k) \quad \textbf{(3.13)}$$

Where sum term adds the weighted error signal for all node k in the output layer. As before, the formula to adjust the weight $w_{i,j}$ between the input node i and the node j is equation 3.14 and equation 3.15 [33].

$$\Delta w_{ij}^{n} = I_r\, \delta_j\, X_j + \Delta w_{ij}^{(n-1)}\, \mu \quad \textbf{(3.14)}$$

$$W_{ij} = W_{ij} + \Delta W_{ij} \quad \textbf{(3.15)}$$

C- Universal error

Finally, BP is derived by assuming that it is desirable to minimalize the error on the output nodes over all the patterns presented to the ANN. The following equation is used to calculate the error function E (Main Square Error (MSE)) for all patterns as equation 3.16.

$$E = mse = \frac{1}{N}\sum_{i=1}^{N}(t_k - y_k)^2 \qquad \textbf{(3.16)}$$

Ideally, the error function should have a value of zero when ANN has been correctly trained. However, is numerically unrealistic [34].

CHAPTER FOUR

METHODOLOGY

4.1 Outline

TL protection is a significant subject in power engineering because 85-87% of power system faults are happening on TL. In this chapter, we used ANN to detect and classify faults in power TL. The benefit of ANN in this field is how it can get the outputs using same inputs. As we mentioned previous chapter, there are different types of ANN that use to detect and classify faults on TL. In our work, we chose special type of ANN that call Fitting Neural. As shown in Figure 4.1 it contains of three layers, input layer, hidden layer and output layer.

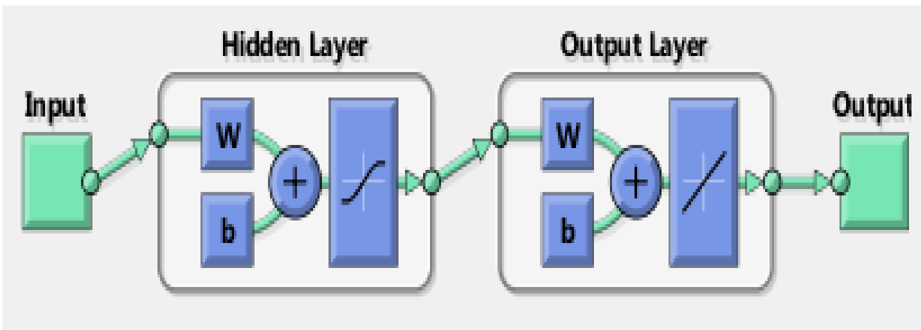

Figure 4.1: Fitting Artificial Neural Network

In this type, it has feed forward network with sigmoid function hidden neurons. Fitting ANN recognize by one hidden layer with low number of neurons as compared with other types. Also, it is less complex than the other types according to number of neurons inside the hidden layer one that means it have high speed and accurate in its work.

4.2 Modelling the Three-Phase Transmission Line System

The system consists of a typical 400 KV three phase transmission line connects between a generator at one ends and a sub-station on either side as shown in Figure 4.2.

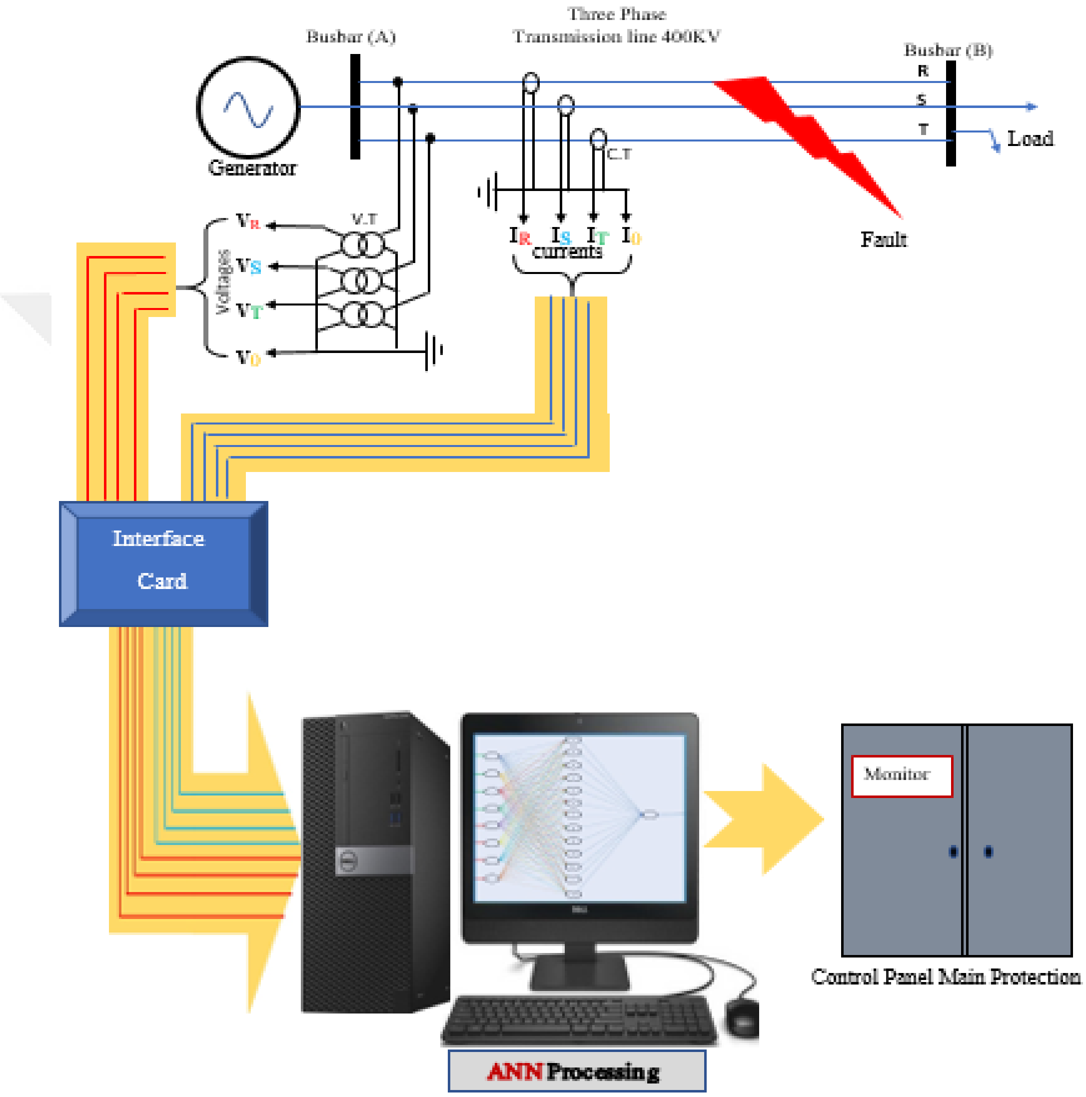

Figure 4.2: diagram of the transmission line under study

4.3 Algorithm Of Our Work

At bus A will be obtained voltage and current signals via the current transformer (CT) and voltage transformer (VT). After pretreatment, they will be introduced into the fault detector in order to announce the presence or not of a fault. When detection is complete, a phase of fault classification will be treated mentioning its kind on transmission line.

As illustrated in Figure 4.3 to be done, the phase currents {$I_R(k)$, $I_S(k)$ and $I_T(k)$} and the voltages {$V_R(k)$, $V_S(k)$ and $V_T(k)$} are treated using an antialiasing filter to remove frequencies not wanted starting from a wave form sampled at a frequency of 1 kHz. After that the signal will pass into normalizer to adjusted level of the ANN [-1, +1]. The ANN output is indexed either with a value of 1 (fault presence) or 0 (fault absence). However, one full cycle Discrete Fourier Transform (DFT) is used to analyze the fundamental component of three-phase voltages and currents which will be renowned as follows {I_R (k), I_S (k), I_T (k),V_R (k),V_S (k) and V_T (k) }. Therefore, the magnitudes of fundamental components of zero sequence current I_0 (k) and voltage V_0 (k) signals are presented into the suggested algorithms in order to announce faults connected to ground.

Normalization is need about the sigmoid function at output layer in neural networks. An input within the range of [-1, +1] approximates the linear character of the activation function very well.

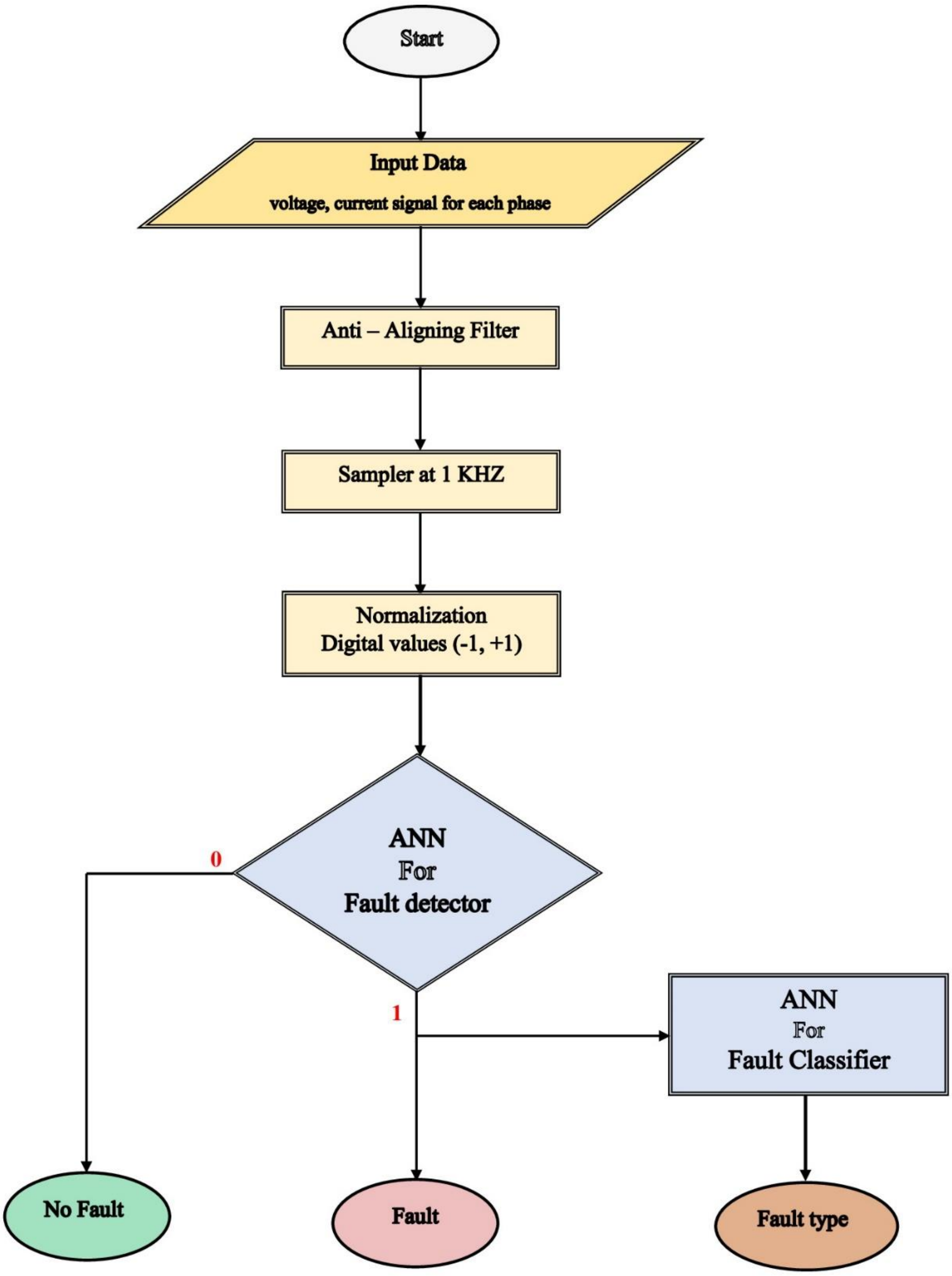

Figure 4.3: Algorithm of methodology

4.4 Structure ANN for Fault Detector

The proposed neural detector is designed to indicate a fault presence or absence. The appearance of such a fault is given via classifying directly the power system state starting from the instantaneous voltages and currents.

The execution computing time (time during which a program is running) is reduced before the voltage and the current signals enter into ANN by the division of the magnitudes of the fundamental voltages and the currents 50 Hz in fault time V_i (k) and I_i (k) to the pre-fault fundamental voltages V_{i-PF} (k) and current I_{i-PF} (k) in related phase.

$$\frac{I_i(k)}{I_{i-PF}} \quad \text{and} \quad \frac{V_i(k)}{V_{i-PF}} \qquad \text{with} \quad i=\{R, S, T\}$$

We used the magnitudes of fundamental of the zero sequence currents I0 (k) and voltages V0 (k) to ensure additive performance to the proposed neural detector and to optimize the size of ANN as shown in Figure 4.4 and equation 4.1 [35].

$\mathbf{X}_{F\text{-}set}$ Input vectors taken from neural fault detector.

$\mathbf{Y}_{F\text{-}det}$ output of the suggested detector.

$$\mathbf{X}_{F\text{-}det} = \left\{\frac{I_R(k)}{I_{R-PF}(k)}, \frac{I_S(k)}{I_{S-PF}(k)}, \frac{I_T(k)}{I_{T-PF}(k)}, \frac{V_R(k)}{V_{R-PF}(k)}, \frac{V_S(k)}{V_{S-PF}(k)}, \frac{V_T(k)}{V_{T-PF}(k)}, I_0(k), V_0(k)\right\} \tag{4.1}$$

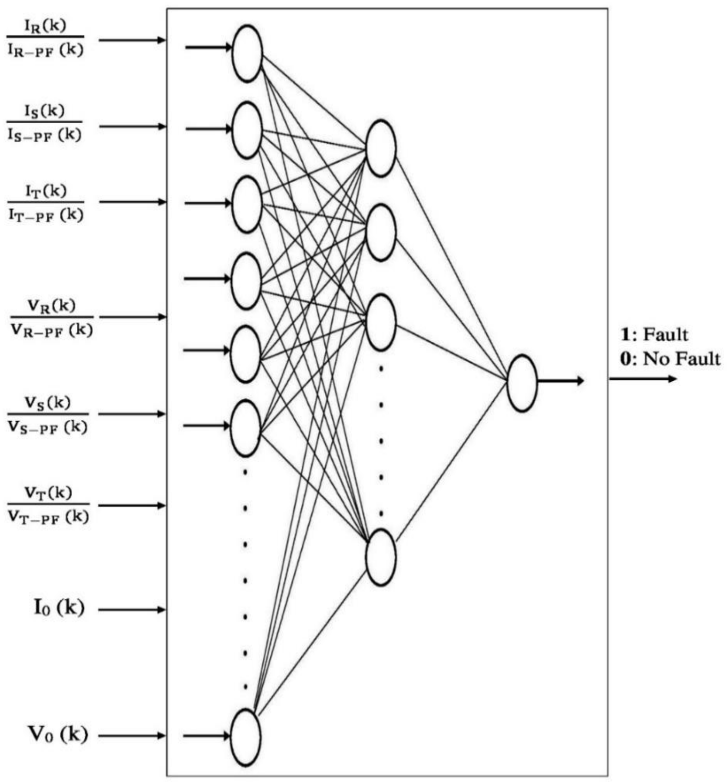

Figure 4.4: ANN Fault Detector Structure

We have eight inputs (V_R, V_S, V_T, I_R, I_S, I_T, V_0, I_0) to ANN and twelve signals, one without fault occurrence and eleven for the fault type occur.

In order to obtain a good training and effective performance, we work to simulate different types of faults in different conditions. These conditions included different fault resistances (Rf) in three cases (rf=0.1, rf=10, rf=100) **Ω**. Then, we have 36 cases, ten times. We repeat this structure and then get 360 signals.

The backpropagation algorithm is very significant to ANN a good training and test it correctly.

At the training time, various structures (neuron numbers in the hidden layer) with various parameters (training rate and transfer functions) are evaluated in order to determine the optimal network structure to produce a good training and to have the best results during the test.

Table 4.1 shows the values for all the different types of faults and the no fault case. The fault has been simulated on a 400km long transmission line at a distance of 200 km.

Table 4.1: Sample of input to ANN for different fault cases

Fault Type	**Input vector**							
	V_R	V_S	V_T	I_R	I_S	I_T	V_0	I_0
No fault	4120.465	4118.54	4121.371	5.564213	5.562359	5.566946	3.26e-07	6.36e-10
AG	1.468859	4419.836	4510.83	15.7399	5.323502	4.644963	2530.547	6.27377
BG	4518.036	25.74522	4425.594	4.635907	15.73804	5.323926	2537.897	6.291734
CG	4420.998	4508.726	1.469703	5.320838	4.641888	15.74905	2533.141	6.280134
ABG	1.547571	1.512107	4665.006	15.74182	15.73358	4.258255	2199.405	5.452721
ACG	1.478145	4661.299	1.51419	15.74409	4.254809	15.74902	2195.435	5.442908
BCG	4663.578	1.547261	1.513689	4.255634	15.73355	15.74782	2197.99	5.44941
ABCG	1.579654	1.206895	1.325619	15.73806	15.74343	15.74382	1.41e-06	3.88e-10
ABC	1.573937	1.573643	1.574202	15.7412	15.73845	15.74407	2.48e-07	5.71e-10
AB	2060.634	2060.737	4122.196	14.14776	13.65862	5.569758	0.390804	0.000969
AC	2058.063	4116.849	2057.961	13.67485	5.561928	14.16502	0.389852	0.000967
BC	4120.51	2059.789	2059.896	5.565702	14.14927	13.66998	0.390627	0.000968

4.5 Faults Classification

As been discussed in the previous sections, fault may exist due to a short circuit between one phase of the transmission lines and other phases which were well known as a line to line fault, this may involve more than one phase and such is called a multiple line fault. The same concept can be applied to line or lines to ground fault when any line or all of it is in contact with earth such may exist due to tall trees that in touch with the transmission lines.

For the above and if we assume the phases are denoted as A, B, and C where the earth is denoted as G, the fault can be classified into the following nominee [36]:

1- AG: phase A is short circuited with ground.

2- BG: phase B is short circuited with ground.

3- CG: phase C is short circuited with ground.

4- AB: phase A is short circuited with phase B

5- AC: phase A is short circuited with phase C

6- BC: phase C is short circuited with phase B

7- ABC: phases A, B and C are in contact.

8- ACG: phases A and C are in sort circuit with ground.

9- BCG: phases B and C are in sort circuit with ground.

10- ABG: phases A and B are in sort circuit with ground.

11- ABCG: all phases are in contact with ground.

4.6 Structure ANN for Fault Classification

When a fault detected on transmission line., the next step is to recognize a fault kind. This section presents a classification phase analysis of the faults by using ANN. The fault classifier proposed is composed of four independent ANNs for each phase (R, S, T) and the other for the ground (G) which is called ANN-R, ANN-S, ANN-T, and ANN-G, respectively. Each conceived network (ANN-R, ANN-S, ANN-T) takings into account two parameters (three-phase voltage and current value put on the scale compared to their corresponding pre-fault values), these parameters are sampled at a frequency of 1kHz in order to form a drop window of 4 samples of length 5ms for each signal. Thus, the input numbers of each network equal to eight is indicated by the vector ($X^{i}{}_{F\text{-class}}$) with $i = \{R, S, T\}$.

However, the ground fault detection is indicated by the ANN-G, this treats the zero-sequence voltage and zero-sequence current which will be sampled in the same way before described acceptable to form an input vector materialized by eight inputs indicated by the vector ($X^{G}{}_{F\text{-class}}$) as equation 4.2.

$$X^{i}{}_{F\text{-class}} = \left\{\frac{I_i(k)}{I_{i-PF}(k)}, \ldots\ldots\ldots \frac{I_i(k+3)}{I_{i-PF}(k-3)} \quad \frac{V_i(k)}{V_{i-PF}(k)}, \ldots\ldots\ldots \frac{V_i(k+3)}{V_{i-PF}(k-3)}\right\}$$

$$X^{G}{}_{F\text{-class}} = \{I_0\,(K), \ldots\ldots\ldots\, I_0\,(K+3), V_0\,(K), \ldots\ldots\ldots\, V_0(K+3)\} \qquad \mathbf{(4.2)}$$

Where

$i = \{R, S, T\}$

As shown in Figure 4.5 the structure of fault classification is based on neural network at 4 outputs. Each neural network agrees to the fault condition of each of the three phases (R, S, T), and one output for the ground line (G). Thus, the outputs are 0 or 1 indicating the absence or the presence of a fault on the corresponding line (R, S, T or G). The neuron numbers of the hidden layer are selected after a certain number of tests according to a fault kind which occurs in the system. The output neurons must be 0 or 1. Thus, can assign the fault type [36].

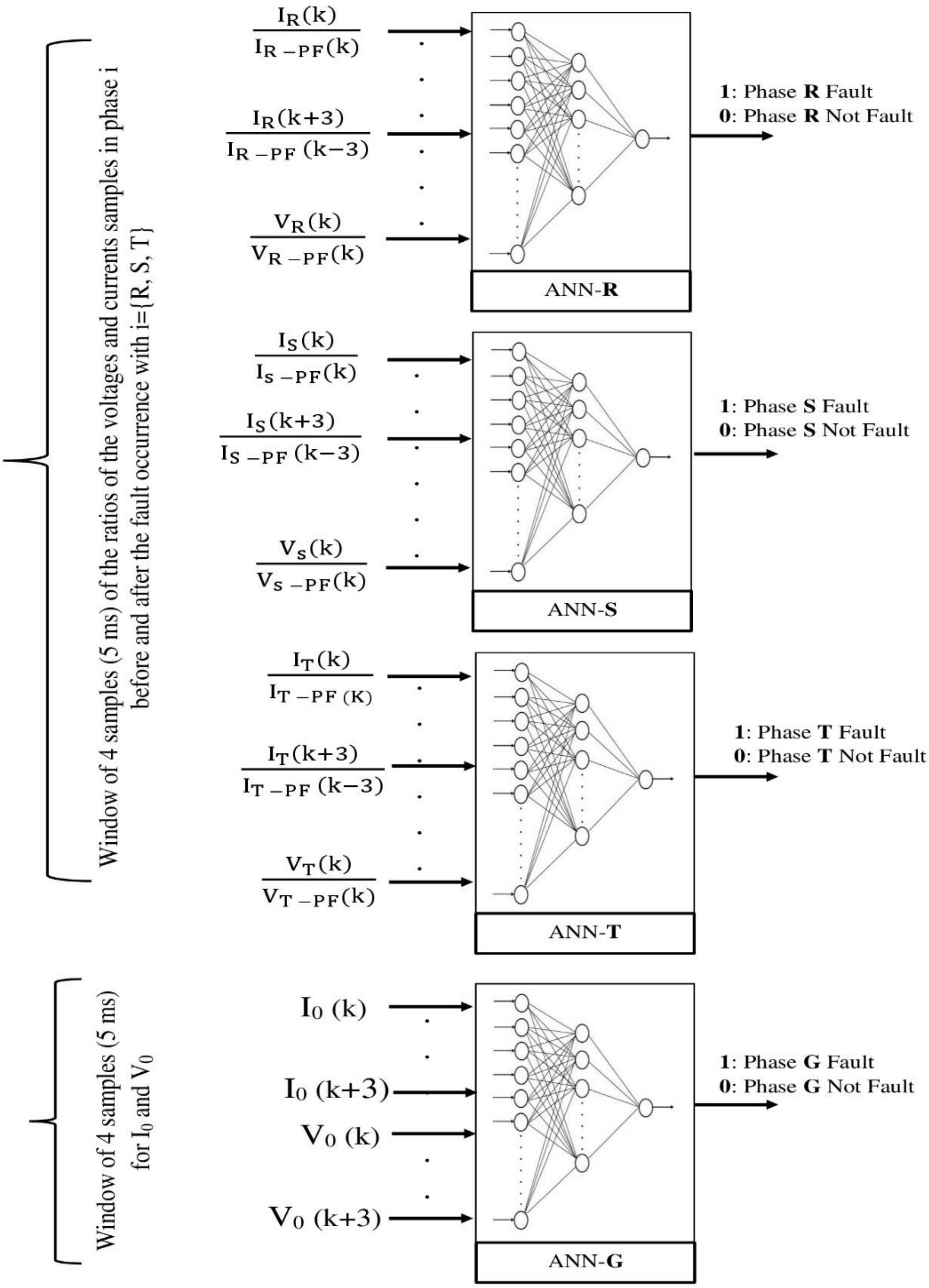

Figure 4.5: Fault Classification Structure

The ANN is used to classify the fault in this project where a data of the above cases is provided to the said ANN and the last is being trained to detect the fault type and pass the information to the controller.

The controller is designed in such way to break up the system/ separating the generator end from the load as in Simulink model as will be discussed in the preceding chapters.

Gathering the signals of current in all fault possibilities and providing the same in the format of digital samples with time to the classifier is forming the step of fault classification. Within the classifier, Artificial Neural Networks are established. The process in this step is to train the ANN to detect different kinds of fault and produce a control signal/message to the controller step hereafter.

The controller is about converting the information from the ANN step into the format that understandable by the analogue systems like circuit breakers. The digital/binary signaling between the ANN step and the circuit breaker involve a multiplexer to segregate the ANN output array and such process is called serial to parallel conversion, this is followed by a logical operator to unite the multiple digits signals into a single message.

Finally, the digital data converter is created where the binary format is being converted into a double type of digits in which understandable by the machinery units circuit breakers. The following figure is depicting the control steps as described beforehand.

4.7 Algorithm Interfacing

Using of a block called “from workspace” that provided in MATLAB’s Simulink library, the workspace can be connected with Simulink so that the controlling messages can be exchanged between them smoothly. Once the control message has arrived into the Simulink, serial to parallel process is started to convert the row of binary digits into a parallel format, a de multiplexer is used for fulfilling this corner. displays are placed after each output of this de multiplexer so that user can notify the faulty phase (fault status and information will have appeared in the Simulink), displays block are named as phase R, S, T, and ground whenever the reading is seen “one” it indicates that phase is suffering from fault; otherwise “zero” indicates no fault. This information is merged together by using of OR logic gate.

OR gate is necessary to take out one digit from multiple inputs in such way if a fault occurs at any phase OR gate will produce “one” otherwise if no any phase is experiencing fault then the OR gate will produce “zero”, the truth table or the said logic OR is provided in table 4.1. the final result or the logic gate is then transferred into a double format to trigger the circuit breaker. The last circuit breaker is connected to the three- phase to trip all the phases in case of a fault, according to this project, the circuit breaker may return automatically after clearing the fault by passing another/fresh control message from the classifier workspace into the Simulink.

Table 4.2: OR gate truth table

Input (X)	Input (Y)	Output (Z)
0	0	0
0	1	1
1	0	1
1	1	1

CHAPTER FIVE

SIMULATION MODEL AND RESULTS

5.1. Background

In this thesis in the first step we created the 11 type of faults which was mentioned in chapter four. A Power system of generator 400 Kilovolts is serving inductive three phase loads through 400 Km transmission line is being implemented in Simulink, a fault is created by using the functional blocks from the Simulink library to generate different types of fault in the mid of transmission line i.e. 200 Km distance from the load and generator ends. Traveling current and voltage waveforms are being observed in each case and provided to the classifier algorithm which is done in MATLAB using Fitting ANN. MATLAB program is hereafter generating the control signal that indicates the fault type and used for fault clearance.

5.2 System Description

Simulink library is referred to implement a complete standard power system so that the following components are selected: -

5.2.1 Power generator

The generator supplies power to the load through the transmission line of 400 Km, in this three-phase system is used to provide 11 KV to the load, the generator frequency is50 Hz. The generator supplies power to the load through the transmission line of 400 Km, in this three-phase system is used to provide 11 KV to the load, the generator frequency is 50 Hz. Figure 5.1 shows three-phase generator as in Simulink library.

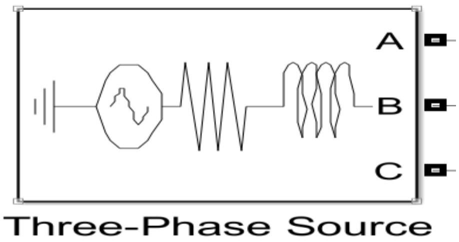

Figure 5.1: Three phase generator as in Simulink library.

5.2.2 Transmission lines

As depicted in Figure 5.2, using the Simulink distribution parameters to implement the transmission lines required to transfer the electric power from the generator to the load, three phase distribution parameters are used by varying the length of each unit to 200 Km.

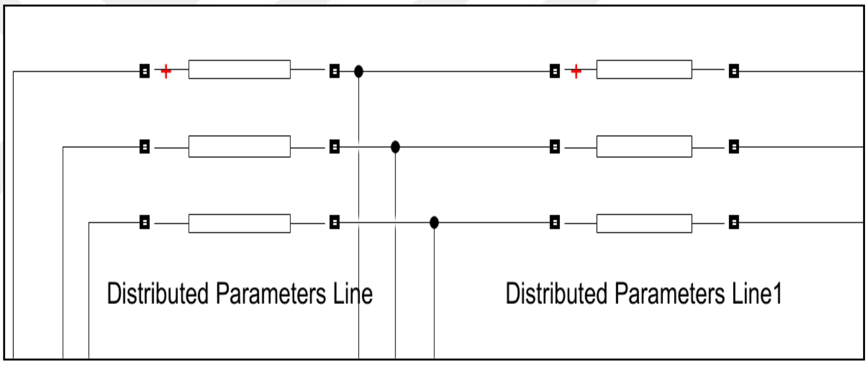

Figure 5.2: Distribution parameters

5.2.3 Power consumer

In here, the three-phase inductive load is used and rated of 80 MW and 30 MVA. Figure 5.2 shows using three-phase load as implemented in Simulink.

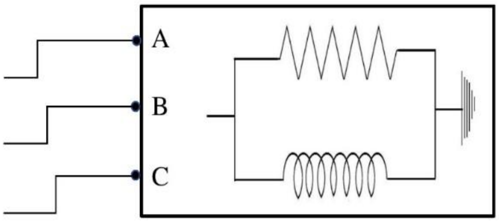

Figure 5.3: Three-phase load

5.2.4 Fault generator

In order to test the system under various fault circumstances, a three- phase fault block is being introduced, it is available at Simulink library. Hereafter the fault type can be set as ABC, AB, BCG etc. Fault impedance is required to be specified as well and in this case, it is kept equal to 0.05 ohm as depicted in Figure 5.4.

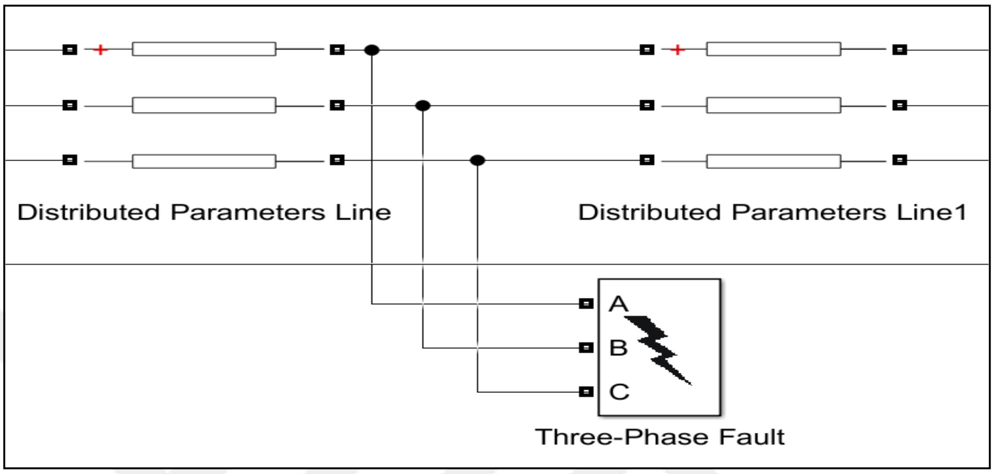

Figure 5.4: three -phase fault generator block.

5.2.5 Monitoring and measurements

As depicted in Figure 5.5, voltage and current measurements are used to calculate the voltages and currents traveling through transmission lines, this calculation is happening individually for every phase in the system. Furthermore, scope is used to plot the voltages and currents in each phase and for monitoring those signals by exporting the data from each phase to the workspace of MATLAB, this data is presented as CSV ("Comma Separated Values") file format as database which involving rows and columns, the columns are nothing but phase currents and the time slot of each current reading. Thus, each database is comprised as samples which are the currents of each phase respected to time. Sampling is having a great impact to analysis the readings and decomposing the signals into their principle characteristics. Database is set for every fault occurrence such as AB, ABG, ABC etc.

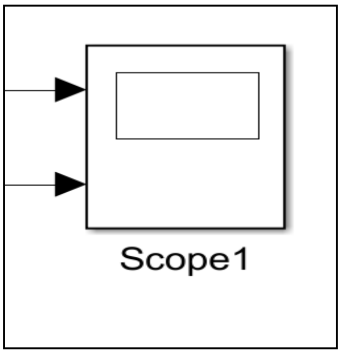

Figure 5.5: Measurement blocks.

5.3 Controllers

As been discussed in chapter four, the controller is receiving input from the classifier and this input is digitally formatted/binary form. For the other hand, the controller will make/view the indications of phase faults like where the fault is actually taking place/ phase number. A controller is combining the signals and making an output to trigger the circuit breaker. Figure 5.6 is depicting the controller process. The controller is hardware-based system that connected to the software part to establish a smart system underlying by Artificial Neural Network (ANN) classifier and digital signal processing schemes to implement fast and efficient controlling to prevent the losses and damages of fault.

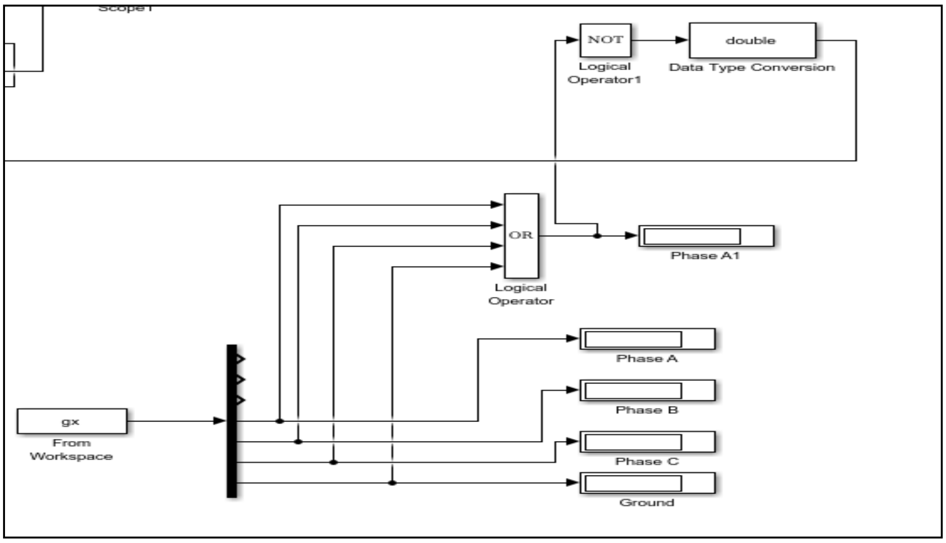

Figure 5.6: logical controller

5.4 System Functions

Generation of power is taking place at generator side as three- phase generator is producing 11 KV at each phase with 120 degree of phase angle. Power is transmitted to the load through the transmission line and in our case, distribution parameters are adopted so that Simulink model will consider that: load is locating on 400 Kilo meters away from the generator. A fault is introduced in the middle of the transmission line by applying a three-phase fault block for Simulink library, the fault resistance is selected to be same with a different type of faults as shown in Figure 5.7

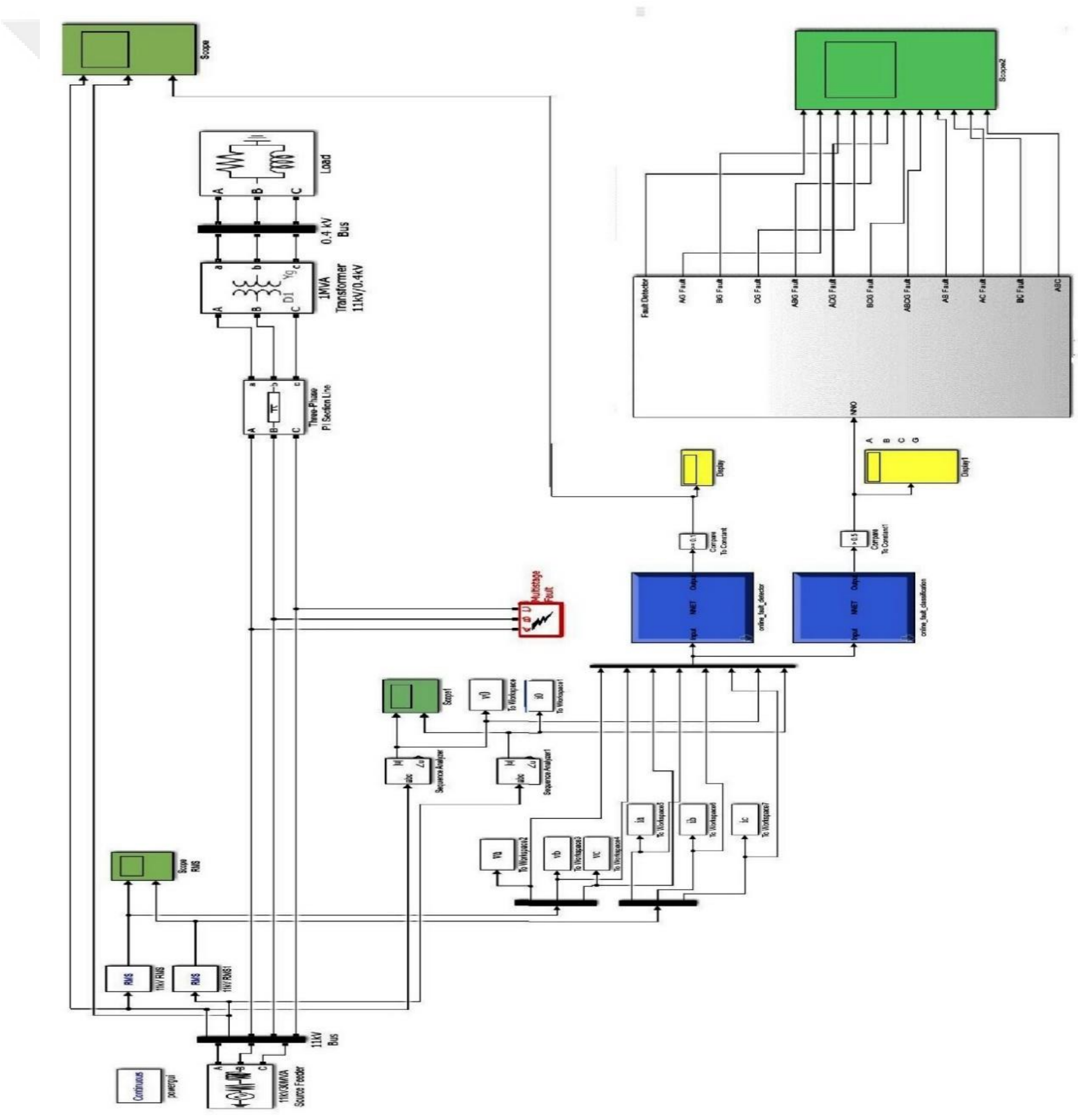

Figure 5.7: Fault detection and Classification Simulink Model

In this model the 11kV and 30MVA Source Feeder is used and the parameter is shown in table 5.1.

Table 5.1: Parameter of Source Feeder

Parameter	Value	Unit
Phase-to-phase voltage	11000	Vrms
Phase angle of phase A	0	degrees
Frequency	50	Hz
3-phase short-circuit level at base voltage	30	MVA
Base voltage	11000	Vrms ph-ph
X/R ratio	0.01	ratio
Base voltage	11000	Vrms ph-ph
X/R ratio	0.01	ratio

The 1MVA Transformer with 11kV/0.4kV is used and the parameter is illustrated in table 5.2.

Table 5.2: Parameter of Transformer

Parameter	Value	Unit
Nominal power and frequency	[1e6, 50]	[Pn(VA), fn(Hz)]
Winding 1 parameters	[11e3, 0.002, 0.08]	[V1 Ph-Ph(Vrms), R1(pu), L1(pu)]
Winding 2 parameters	[0.4e3, 0.002, 0.08]	[V2 Ph-Ph(Vrms), R2(pu), L2(pu)]
Magnetization Resistance Rm	500	pu
Magnetization Inductance Lm	500	pu

For Three-Phase PI Section Line the parameter is available in table 5.3.

Table 5.3: Parameter of Three-Phase PI Section Line

Parameter	Value	Unit
Frequency used for RLC Specification	50	Hz
Positive- and zero-sequence resistances	[0.0275 0.275]	[r1 r0] (Ohms/km)
Positive- and zero-sequence inductances	[0.422/(2x50xpi) 1.169/(2x50xpi)]	(H/km) [l1 l0]
Positive- and zero-sequence capacitances	[9.483×10^{-9} 6.711×10^{-9}]	(F/km) [c1 c0]
Line length	400	km

For Load the parameter is available in table 5.4.

Table 5.4: Parameter of Load

Parameter	Value	Unit
Nominal phase-to-phase voltage Vn	1000	Vrms
Nominal frequency fn	50	Hz
Active power P	10,000	W
Inductive reactive Power QL	100	positive var
Capacitive reactive power Qc	0	negative var

The fault parameter is available in Table 5.5.

Table 5.5: Parameter of Fault

Parameter	Value	Unit
Switching times	[0.1 0.5]	s
Fault resistance Ron	0.1, 10, 100	Ohm
Ground resistance Rg	0.01	Ohm
Snubber resistance Rs	1000	K Ohm
Snubber capacitance Cs	inf	F

Different types of fault are applied to test the system response are applied simultaneously. Voltage and current of each phase are tested before fault an after fault. The data are provided into the ANN classifier so the algorithm will make the decision of fault type and will give the order to the controller to shut down the generator till the time of fault clearance.

The controller is designed to receive the control message from the smart algorithm and then exclude the indicators that imply the fault location per phase. These indicators are then converted into a digital signal of binary format entering into the logic OR gate, a reason behind the OR gate is to unify multiple signals into one/single message that converted by further block into a double format and sent to the circuit breaker. The circuit breaker is triggering by this signal and hence it is separating the generator side from the load. The fault may clear as soon as possible and later the generator can be started again.

5.5 Training and Testing

In order to train the neural network, we need a set data called the training dataset which is a set of inputs (x) and target outputs (t) into the neural network.

The procedure of training ANN includes tuning the values of the weights and biases of the network presentation function. The default presentation function for feedforward networks is Mean Square Error (MSE).

MSE is the average squared error among the network outputs (y) and target output (t) [34]. The MSE for each output in each iteration is calculated by:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2 \qquad \textbf{(5.1)}$$

Where:

N : number of iterations.

t : target output.

y : network output.

5.5.1 Training Algorithm

As an illustration of how the training works, reflect the simplest optimization algorithm-gradient descent. It updates the network weights and biases in the direction in which the performance function decreases most rapidly, the negative of the gradient. One iteration of this algorithm can be written as [33]:

$$X_k + 1 = X_k - A_k\ G_k \quad \textbf{(5.2)}$$

Where:

X_k : is a vector of current weights and biases

G_k : is the current gradient

A_k : is the learning rate .

This equation is iterated until the network converges. In our work, we used algorithm Levenbeg-Marquardt (trainlm). It is recommended for most problems.

The input vectors and target vectors will be randomly divide up 360 samples into three sets as follows:

- **Training**
  Training 70% 252 samples. these are presented to the network during training, and the network is adjusted according to its error.

- **Validation**
  These are used to measure network generalization, and to halt training when generalization stops improving.

- **Testing**
  These have effect on training and so provide an independent measure of network performance during and after training.

Figure 5.8 shows the training algorithm.

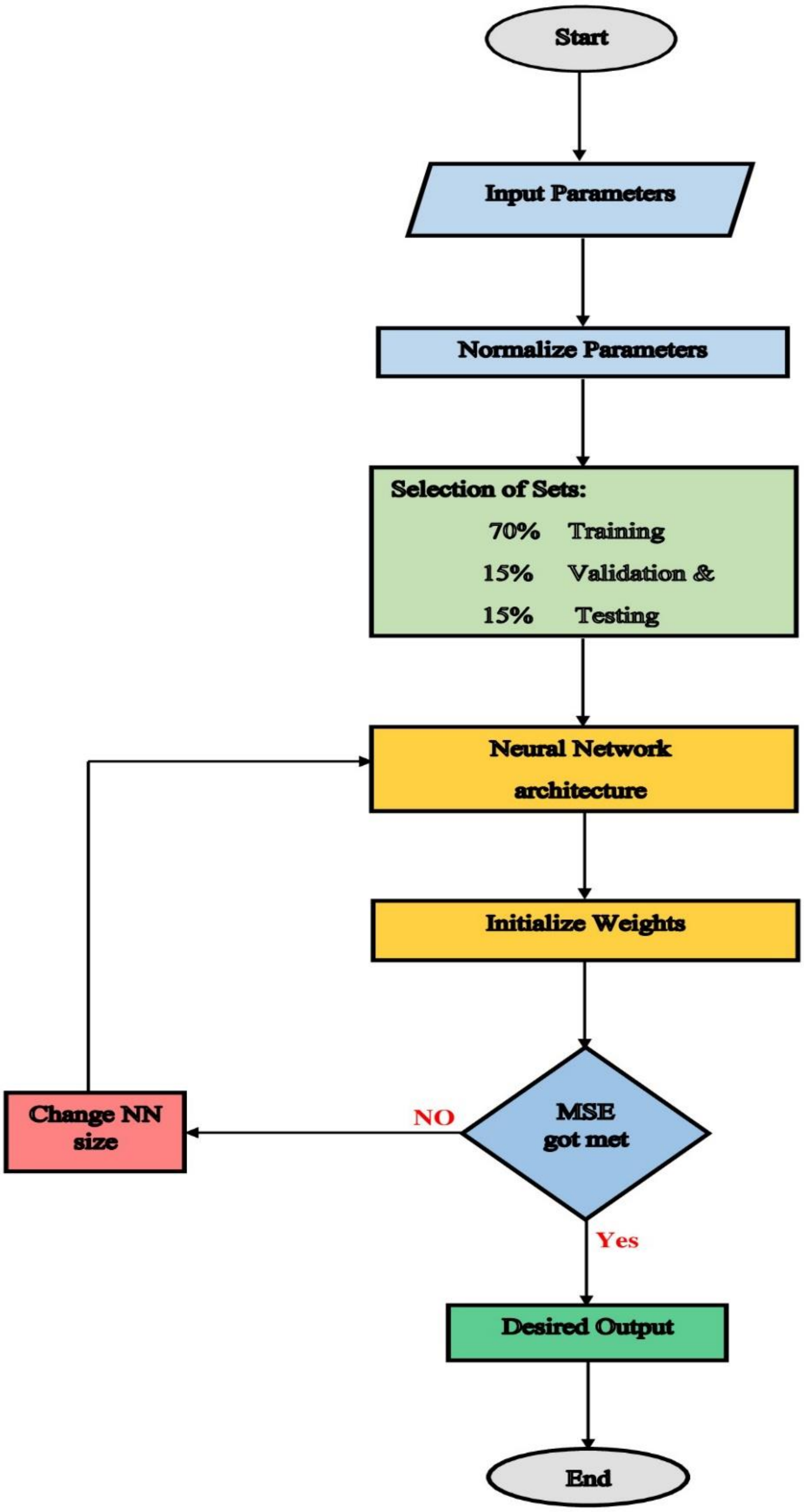

Figure 5.8: diagram of training

5.6 Fault Detection

In this work, the external signal is implemented upon fault detection using an ANN. There are eight entries for ANN through a fault detecting operation, voltage for each phase, current for each phase, zero sequence currents and zero sequence voltages. The values of input are normalized with deference to the pre-fault values of voltages and currents respectively. Choosing a suitable network size is very important because it reduces network training time and greatly enhances the ability of a neural network to represent the problem.

The developed architecture of ANN has two layers. The number of neural networks selected was 13 after a number of simulations were performed. It has one hidden layer with 13 neurons. For illustration purpose, several neural networks that achieved satisfactory performance are shown and the best neural network has been described further. Figure 5.9 shows the training performance plot of the neural network with 10 neurons. It can be seen that the network did not achieve the desired Mean Square Error (MSE) goal by the end of the training process. The value of the MSE is 1.1641 e^{-09} as shown Figure 5.9.

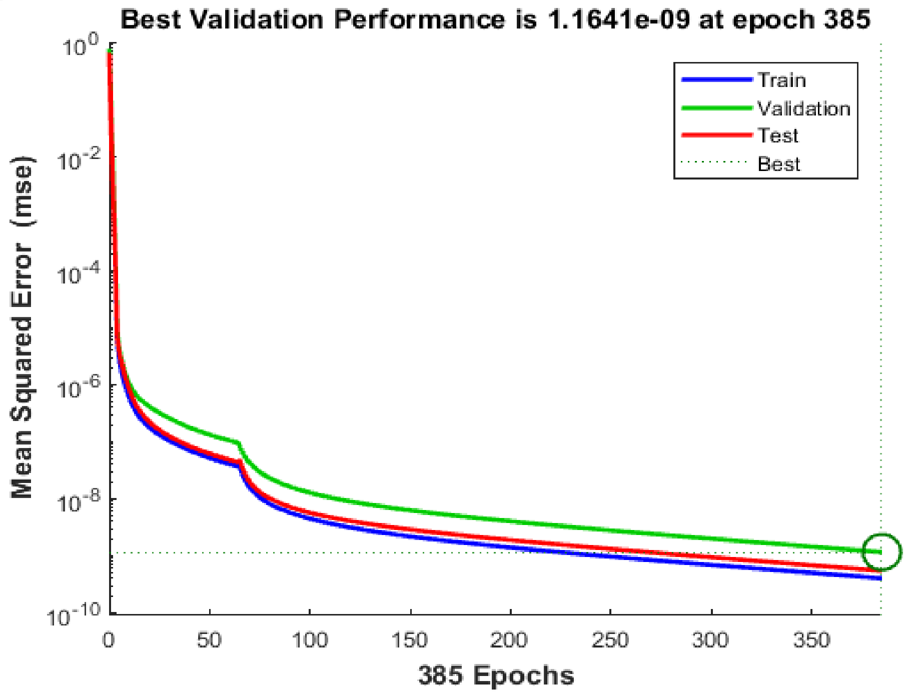

Figure 5.9: Mean-square error performance of the network with 10 neurons

Figure 5.10 shows the training performance plot of the neural network 15 number of neurons. It can be seen that the network did not achieve the desired MSE goal by the end of the training process. The value of the MSE is 1.6844 e^{-11} as shown Figure 5.10.

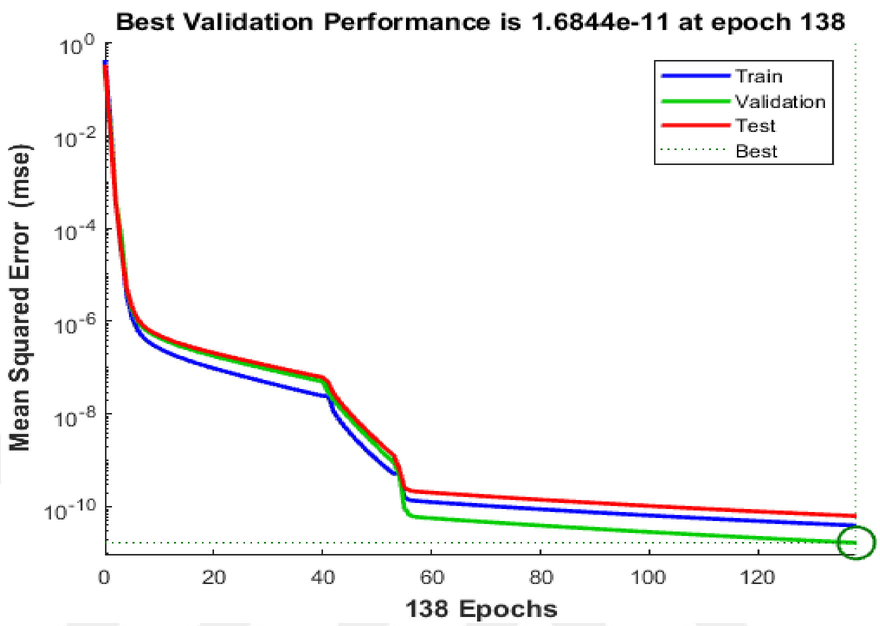

Figure 5.10: Mean-square error performance of the network with 15 neurons

Figure 5.11 shows the training performance plot of the neural network 20 number of neurons. It can be seen that the network did not achieve the desired MSE goal by the end of the training process. The value of the MSE is 7.0343 e^{-12} as shown Figure 5.11.

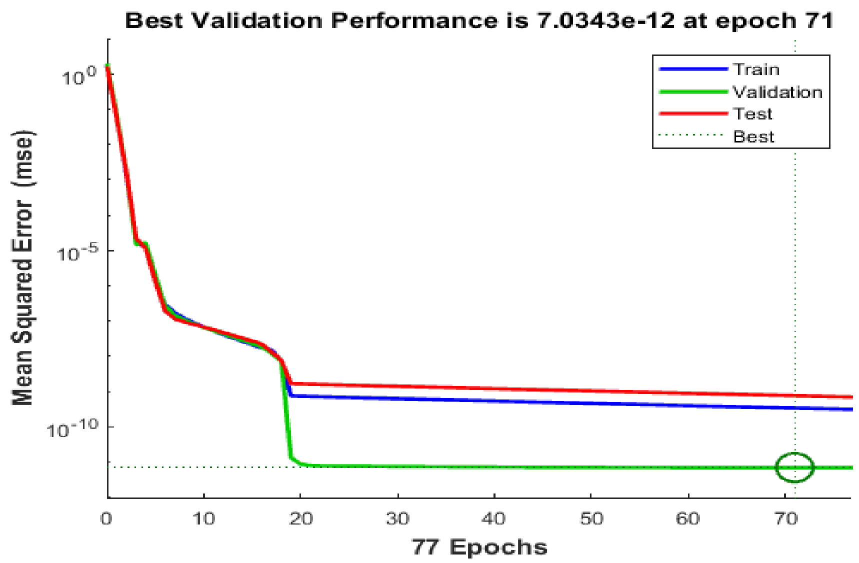

Figure 5.11: Mean-square error performance of the network with 20 neurons

Figure 5.12 shows the training performance plot of the neural network13 number of neurons. It is clear that training performance displayed through the neural network is fine. The overall MSE of the trained neural network is less than the pre-defined value of 0.0001. The value of the MSE is 1.4589 e^{-15} as shown Figure 5.12 delivered in the finish of the training of the network. Thus, this architecture was selected final for given input and output.

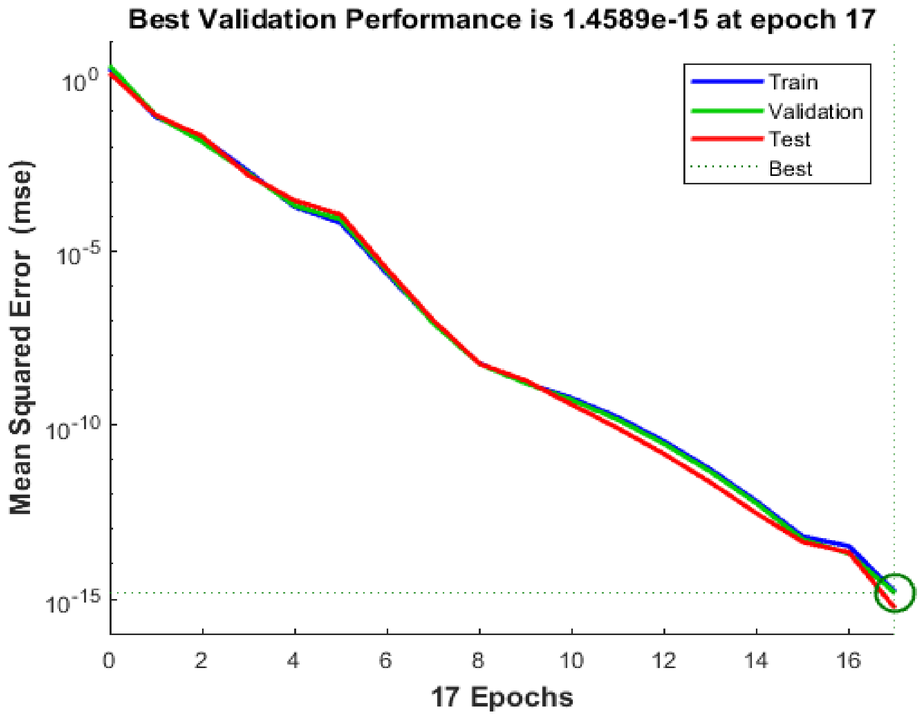

Figure 5.12: Mean-square error performance of the network with 13 neurons

5.6.1 Training the fault detection ANN

The training set consists of total 360x8 inputs and 360x1 output pattern (330 for each eleven faults and 30 for the no fault case). It basically shapes a set of eight inputs and one output in each input–output pattern. The output of the neural network is in simple yes or no form, i.e. 1 or 0, which indicates whether the fault has been occurred or not.

This information usually is used for training purpose the ANN. After the training of ANN, its presentation is checked through plotting linear regression plot that correlates targets to outputs as displayed in Figure 5.13.

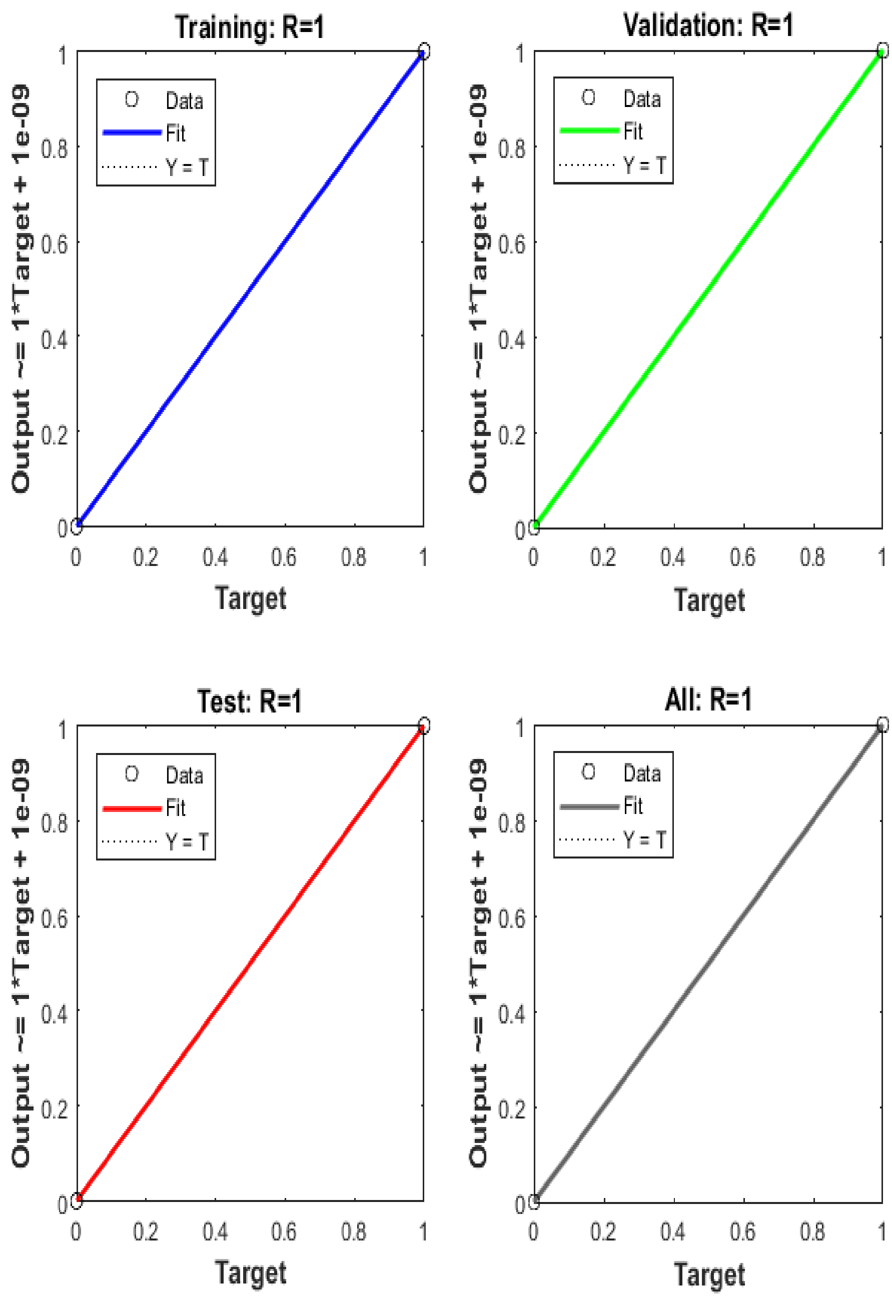

Figure 5.13: Regression Fit of the outputs vs targets for the network.

The correlation factor (r) measures of how healthy the ANNs targets can track variations in the outputs (0 being no correlation at all and 1 being a complete correlation). In this case, the correlation coefficient be (R=1) which indicates excellent correlation.

Another means of testing the performance of ANN is plot the confusion matrices for the different types of errors that happened for the trained ANN. Figure 5.14 plots the confusion matrix for the three phases of training, testing and validation.

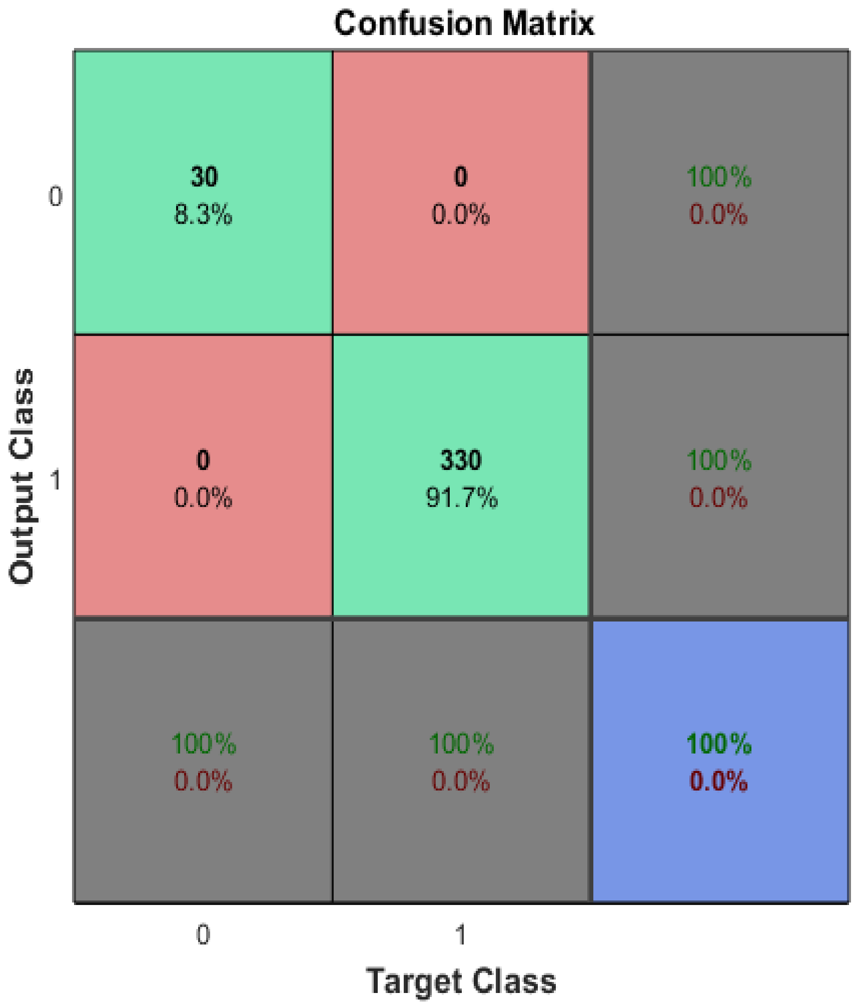

Figure 5.14: Confusion matrices for training, testing and validation phases

The green square shows quantity of suitcases that have been classified correctly via the ANN. The red square indicates the quantity of suitcases that have been incorrectly classified via the ANN. The blue square indicates the total percentage of suitcases that have been classified properly in green and bad in red. It can be seen that the chosen ANN has 100 percent precision in fault detection.

5.7 Fault Classification

The fault classification algorithm is discussed in this chapter with the ANN settings to get minimum error at the time of result/decision making. Current and voltage monitoring scheme that play the role of database that going as input into classifier, effects of faults on those signal is also studied, accordingly the target of detection/training at ANN classifier is implemented as a matrix of (n, m) dimensions. The classifier will be generated a message including the fault information to the controller and relay circuit which is in turn cutting of connection between the generator and load till the fault is cleared. The relay circuit that interfaced between the software are algorithm and hardware/Simulink model.

Table 5.6, illustrates the faults and the perfect output for each fault. Target of this algorithm is set to be (12x4) matrix.

Table 5.6: Fault classifier ANN outputs for various faults

Type of Fault	Phase 'A'	Phase 'B'	Phase 'C'	Ground
No Fault	0	0	0	0
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
AB	1	1	0	0
BC	0	1	1	0
CA	1	0	1	0
ABG	1	1	0	1
BCG	0	1	1	1
CAG	1	0	1	1
ABC	1	1	1	0
ABCG	1	1	1	1

5.7.1 Training the fault classifier ANN

After setting up the classifier input (local database) and classifier target, hence it becomes ready for training procedure as stated in this section. The training function is used for this process is "trainlm", the approximation type is "purelin" and "tansig"; the iteration numbers are set to fifty and LR is set to 5 x 10^{-3}, so that the standard deviation of error is minimized.

The neural network is 8-13-4, 8 neurons in the input layer, 1 hidden layer with 13 neurons in it and 4 neurons in the output layer. This structure of ANN has fulfilled satisfactory results.

As depicted in Figure 5.15 the curves of testing and validation have similar characteristics which are a sign of efficient training. Also, the MSE of trained ANN is 0.0094668.

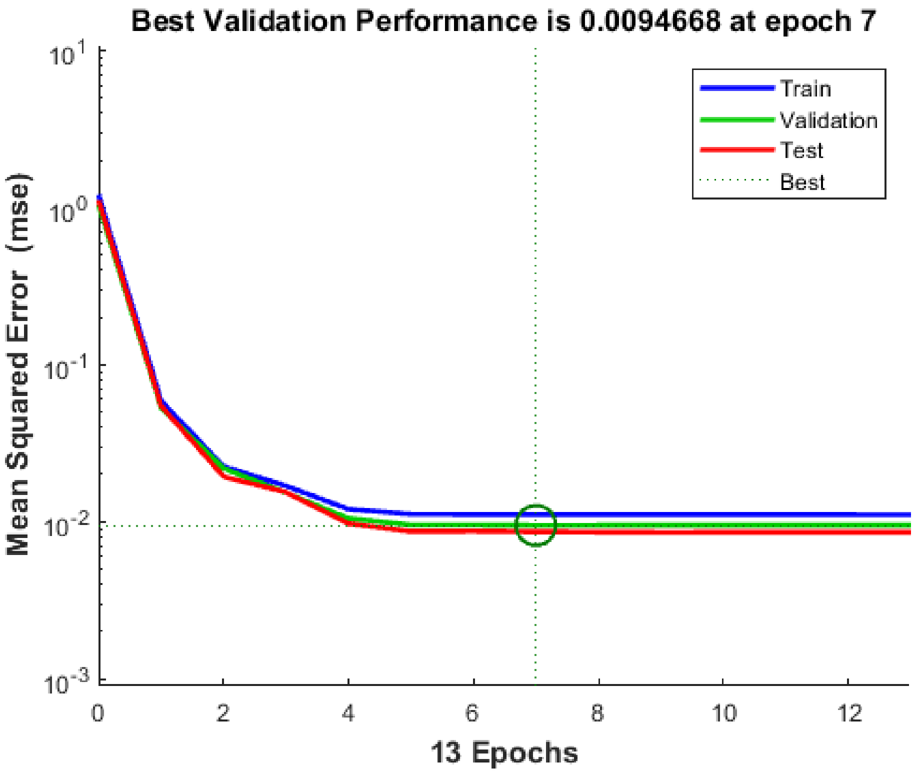

Figure 5.15: Mean-square error performance of the network.

5.8 Testing the Fault Classifier ANN

we can be tested the performance of the trained neural network by plot the linear regression that relates the targets to the outputs. As depicted in Figure 5.16 the correlation coefficient(R) is being 0.97819 which shows the satisfactory correlation among the targets and the outputs.

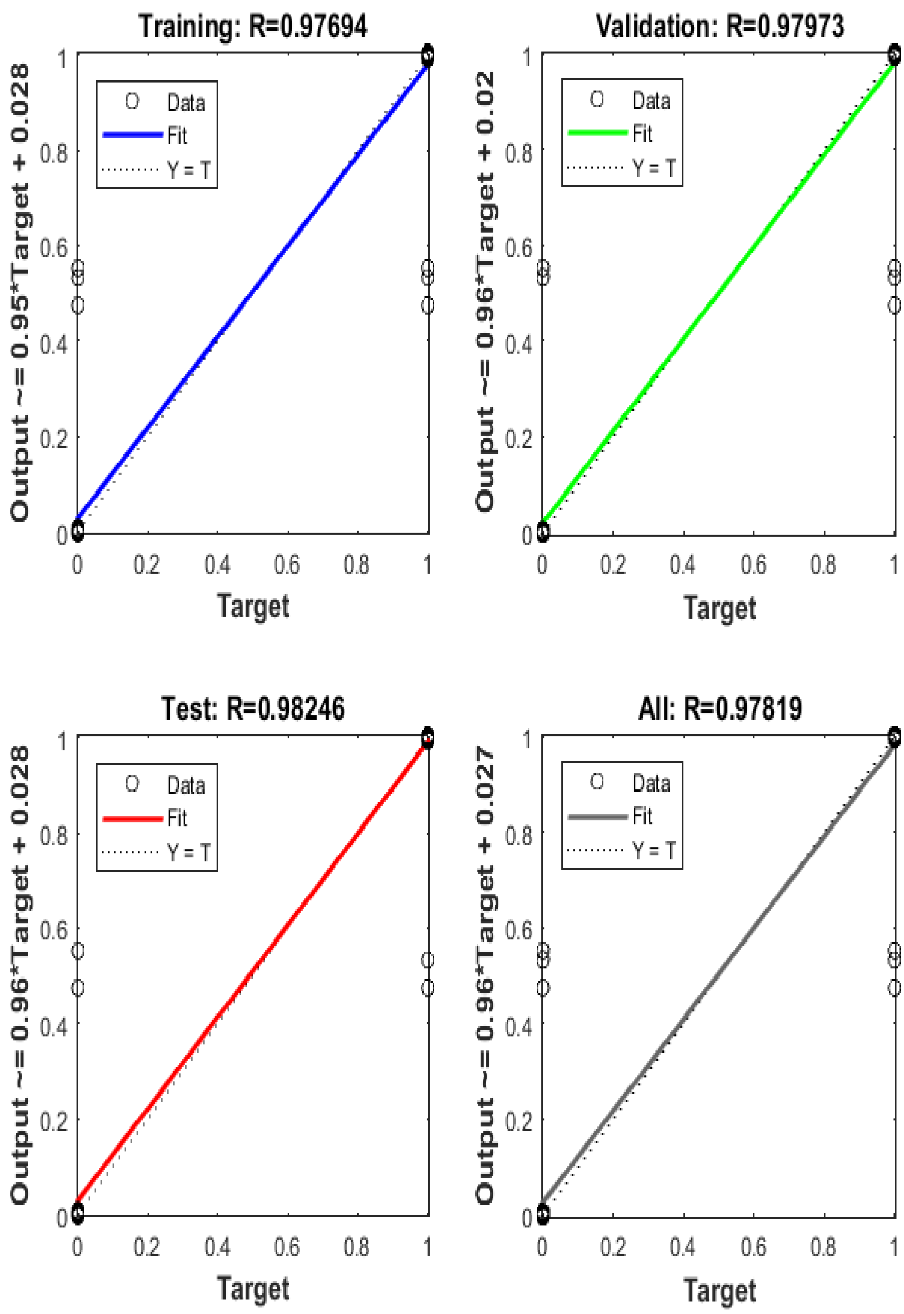

Figure 5.16: Curve of regression Fit for the outputs vs. targets of the proposed ANN

As depicted in Figure 5.17 the efficiency of the trained ANN is 61.1% to check the kind of a fault. The ANN can distinguish between the all eleven kinds of faults on TL.

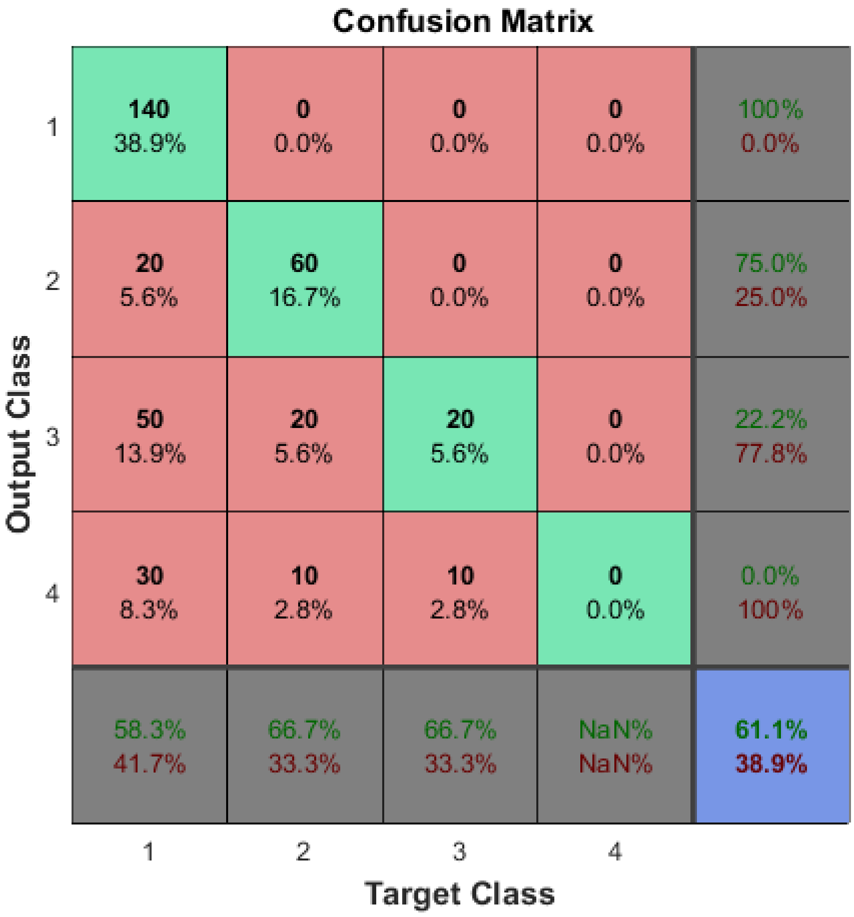

Figure 5.17: Confusion matrix for the training, validation and testing phases

Testing the system with different types of fault and after the proper detection of that fault by ANN classifier and controlling signal transmission to the controlling relay, the system will remain shut down till fault is removed and will not respond to any other process if the same is made in Simulink model.

We can be noted from displayed in Figure 5.18 the output of fault detector is 0 that means there is no fault on a TL. also, we can be noted Figure 5.19.

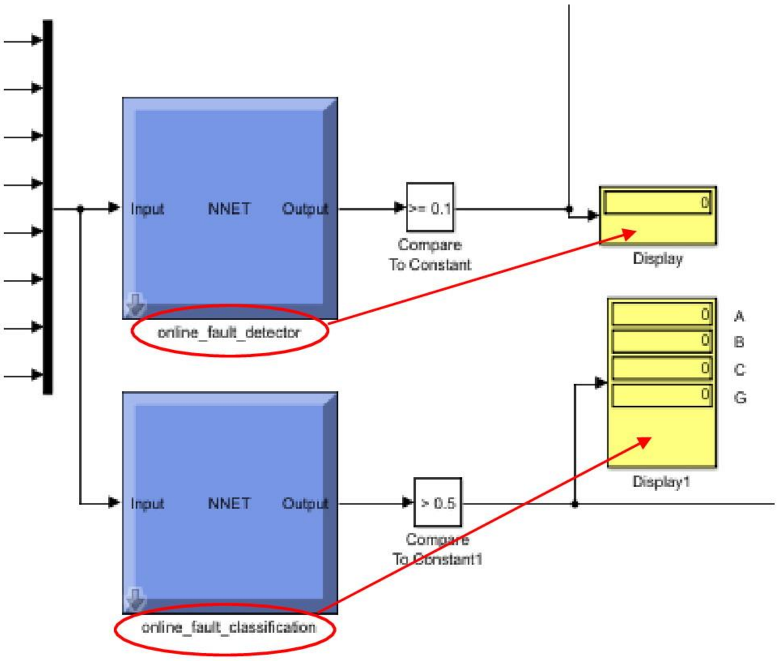

Figure 5.18: ANN result for non-fault

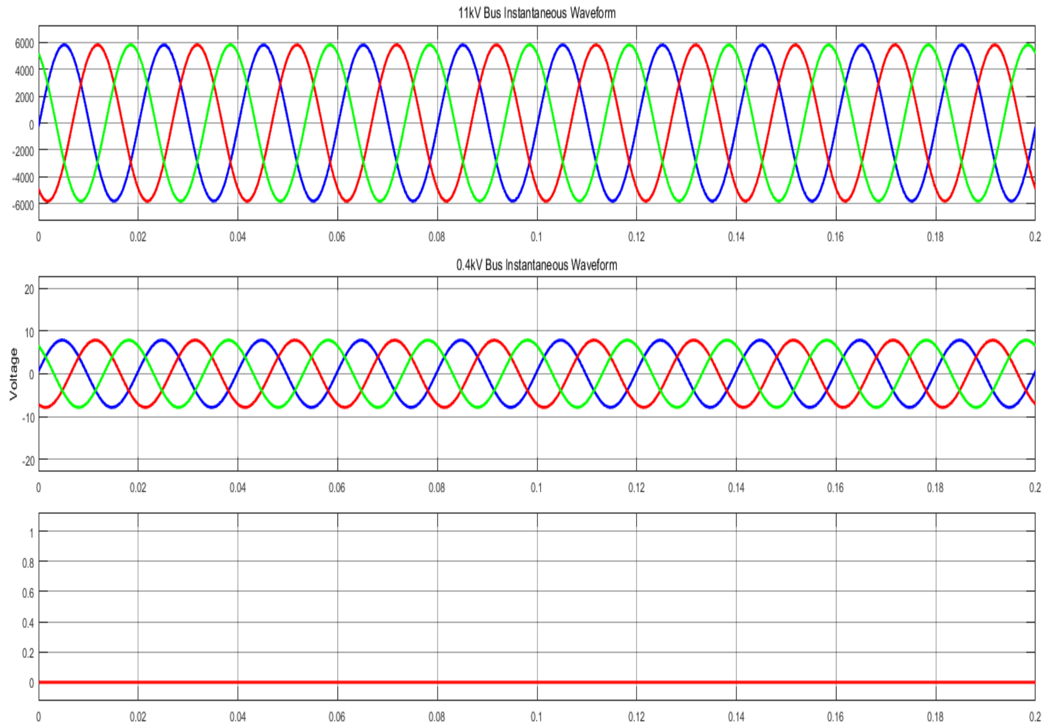

Figure 5.19: There is no fault

We can note from displayed in Figure 5.20 the output of fault detector is 1 that means there is a fault on a TL. also, we can know type of the fault from fault classification and can be noted Figure 5.21.

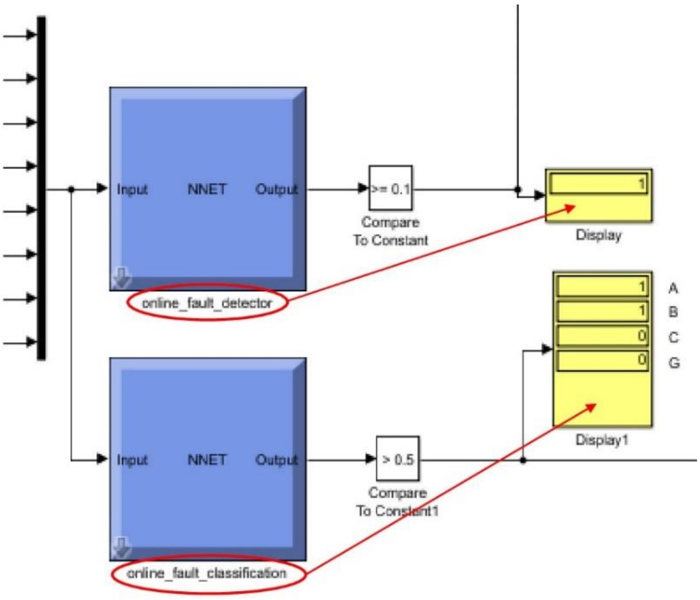

Figure 5.20: There is a fault

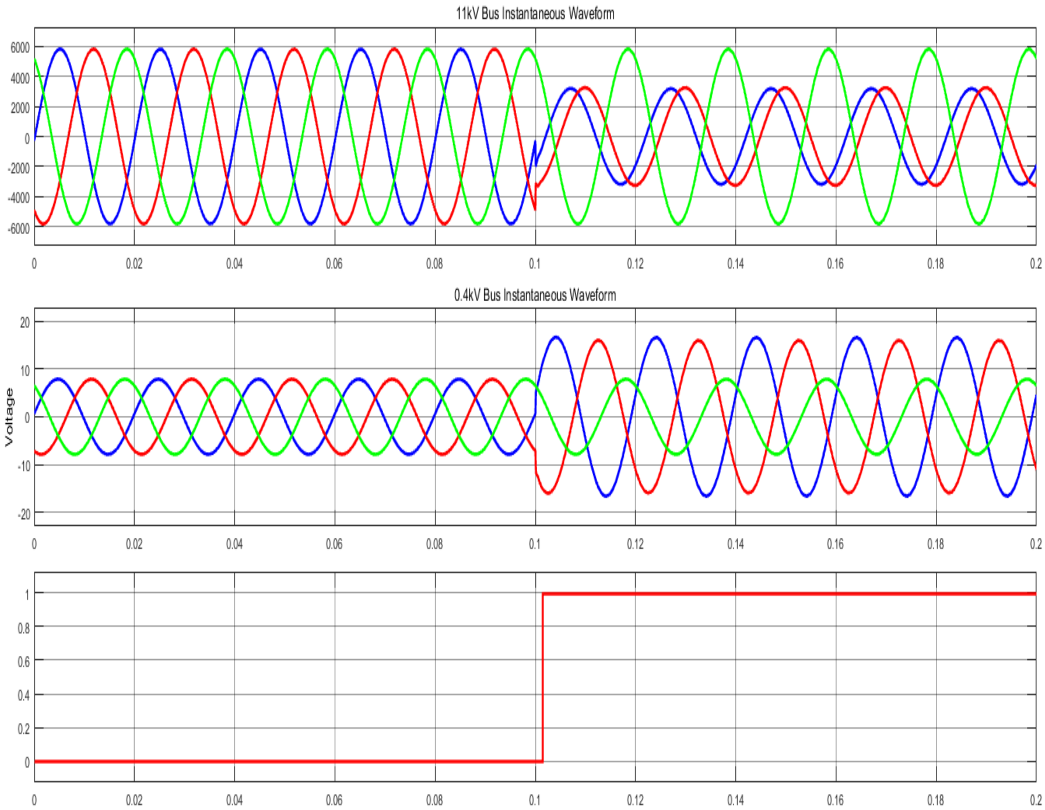

Figure 5.21: Fault between phase A and phase B

Figure 5.22 shows the speed of error detection by ANN where the fault is detected immediately when it is on the power TL. We can be noted Figure 5.23.

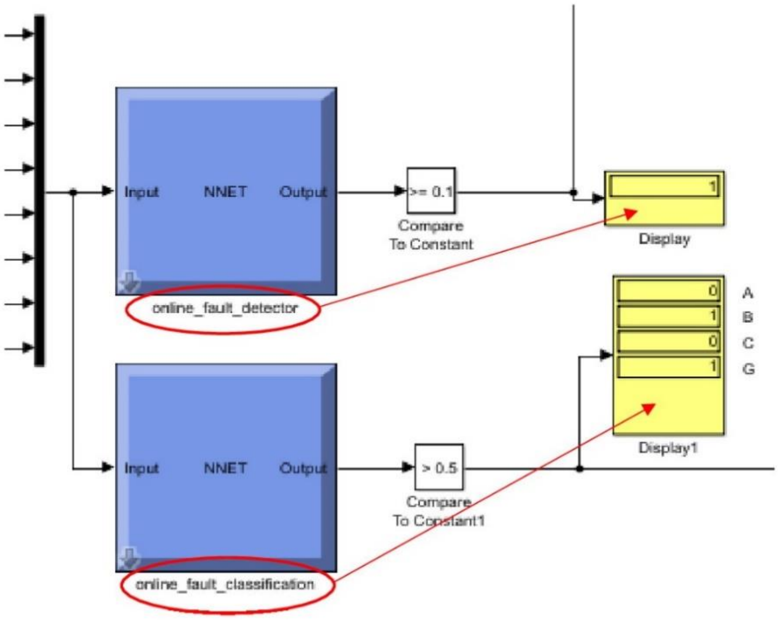

Figure 5.22: There is a fault between B and G

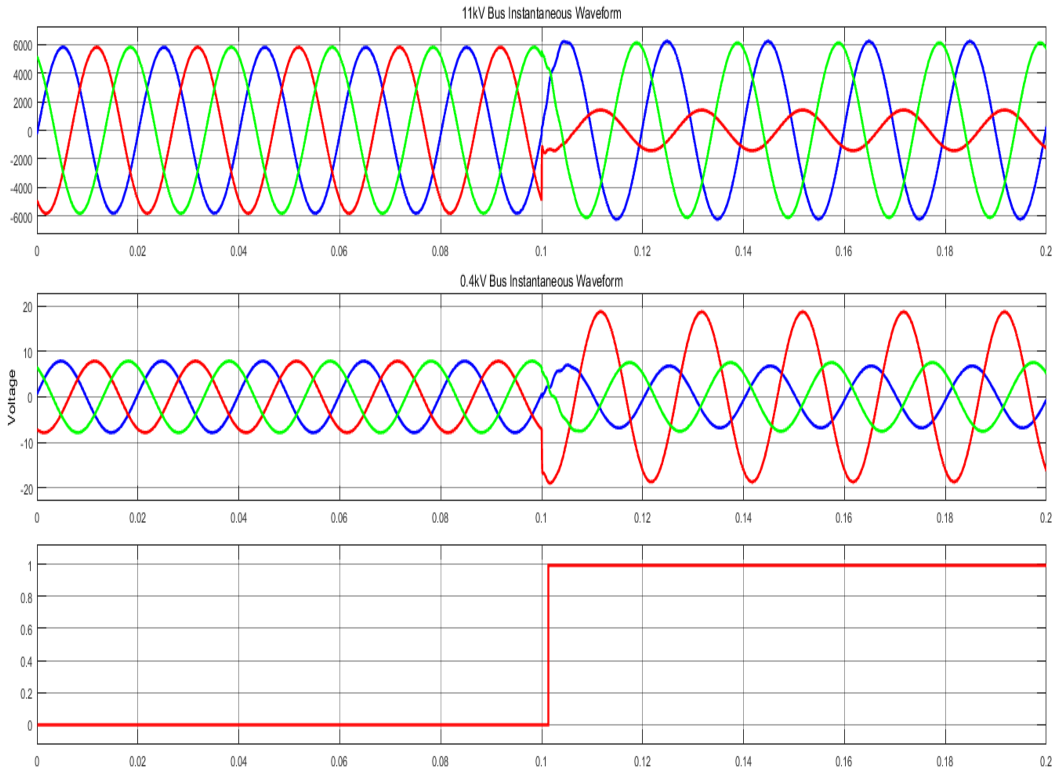

Figure 5.23: Fault between phase B and phase G

From the previous figures, we can observe how fast the Artificial neural network performs to detect and classification the fault which occurs on the power TL where the fault is detected instantaneously.

By enlarging the wave of fault as depicted in Figure 5.24, we observe that time of the fault occurred at 0.1sec and time of detection the fault by neural network at 0.101sec that means the time of detection the fault is 1msec after the fault occurs.

Also, we can understand how this method works in high speed and high reliability for protecting transmission line.

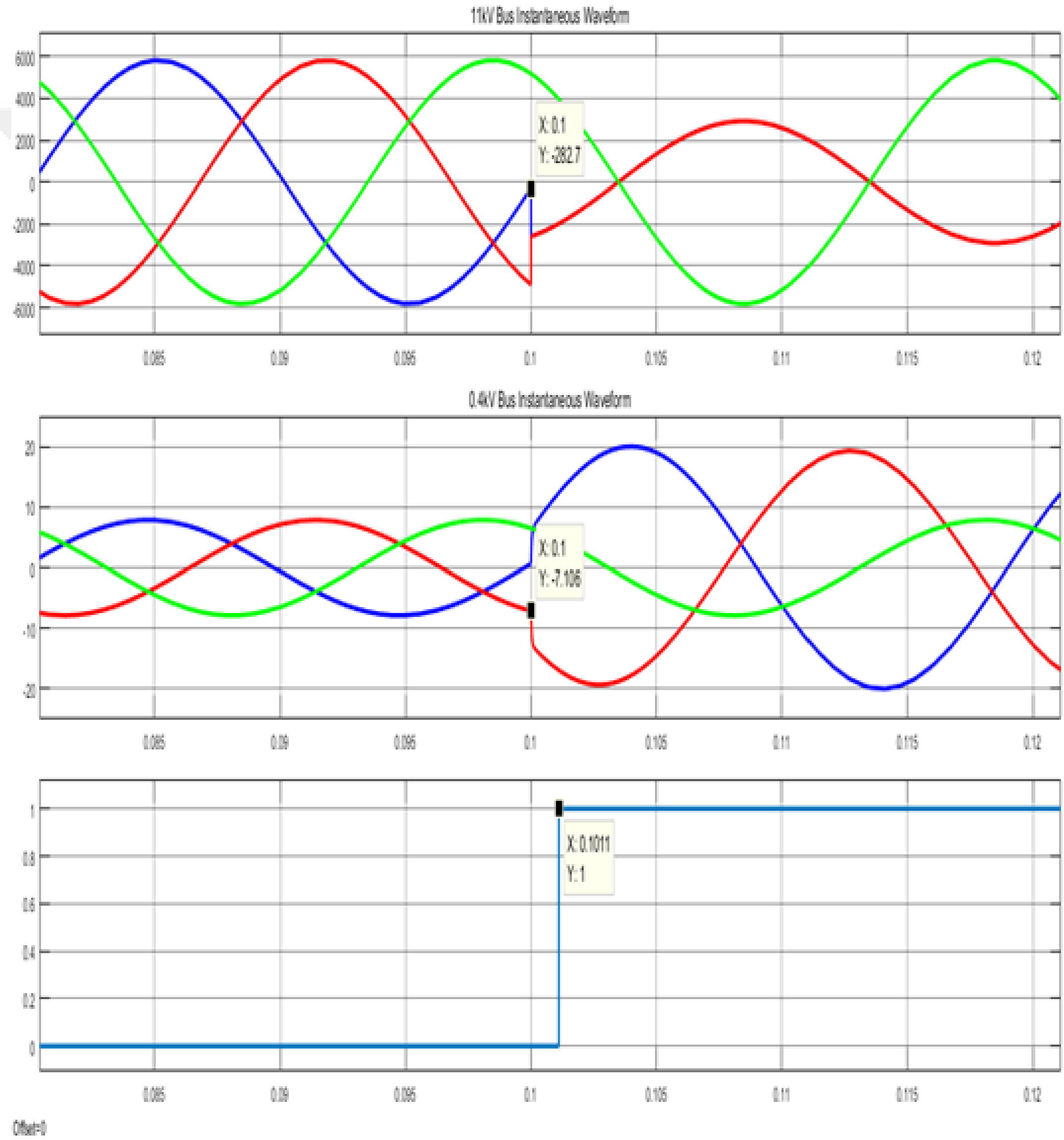

Figure 5.24: Fault time detection

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

This thesis has been investigated the protection of power transmission lines against faults which occurrence by adopting a smart method of protection and monitoring. This method based on the neural network to recognize all eleven type of faults that may happen in power transmission lines. We used the value of Root Mean Square (RMS) for currents and voltages as inputs to artificial neural network. The protection devices chosen depending on the system specifications and work, so that short circuit level of each component calculated with care and accordingly such component can enter to service, such precautions are important to prevent any unwanted effects of error.

Furthermore, if any error such as fault takes place within the system, it is mandatory to clear it immediately. The control and monitoring algorithms that adopted using software and hardware integration are having a great impact to recover the power system as compared to the traditional means of protection by using the mechanical switches. A smart fault detection system is designed to detect the fault and classify it and ultimately separating the faulty part of power system until it is getting corrected. Artificial neural network is proven means to perform fast and accurate solutions in this regard.

6.2 Model Implementation

Simulink library is used to implement a complete power system of three phase generator and 400 km transmission line/distribution parameters. The generated power is transported to an inductive load. A three- phase fault was integrated in mid of transmission line to produce different type of fault. The fault resistance was kept constant for all iterations. Similarly, using the logic gates and digital signal processing a relay circuit is designed to exude the commands of fault algorithm and remove the faults upon their occurrence. The Simulink model is connected with code/MATLAB workspace by using the functional blocks from the library and setting up the path of data.

6.3 Classifier Strength

The smart fault classification scheme is being designed using artificial neural network. It contains of two layers that are used for modelling. The first layer is including thirteen nodes and the second layer is remarked as output layer and involving single node. The fitness functions are used in both of layers. The artificial neural network is got the results with minimum error. The program is established in such way where all internal processes are displayed on the command window.

In our work, we got good result according to the high features of our model. Fitting artificial neural network characterizes for high speed and reliability. Also, it has low numbers of neurons inside of hidden layer. The complexity of fitting neural network is very simple.

As a possible extension to this work, it would be quite useful to analyze all the possible neural network architectures and to provide a comparative analysis on each of the architectures and their performance characteristics. As we suggest, the generalized regression neural network represents another neural network models that can support the fault detection in transmission lines. It is also very simple method and very new to use in this field.

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