DEVELOPMENT OF A FAULT LOCATION AND IDENTIFICATION SYSTEM FOR UNDERGROUND POWER CABLES BASED ON WAVELET-ANFIS METHOD

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EE300-0015/15

A Thesis submitted to Pan African University Institute for Basic Sciences, Technology and Innovation in partial fulfillment of the requirements for the degree of Master of Science in Electrical Engineering (Power Systems Option)

2017

DECLARATION

I hereby declare that this thesis is my original work and has not been presented for award of MSc degree in this or any other University.

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DEDICATION

This research work is dedicated to my wife Patience Zawaira, my Father and my Mother, and my siblings Elaine Chenesai Zawaira, Reginald Tafadzwa Zawaira, Michael Takudzwa Zawaira and Edlight Chiratidzo Zawaira.

ACKNOWLEDGMENT

I would like to express my deepest gratitude and appreciation to the Almighty God, for the Grace and never ending love and favours upon my life. Deepest gratitude and appreciation also to Prof. G. N. Nyakoe and Dr. C. M. Muriithi who were my supervisors for their support, advice and suggestions throughout the course of this research. I also want to appreciate the efforts of fellow engineering students who played a major role and contributed equally towards the success of this research, not forgetting Patience Zawaira, my family and my brother Edwell Tafara Mharakurwa for their undeniable support. May the Almight God continue to bless you all. Special thanks goes to PAUISTI Administration for their support. This research would not have been possible without the scholarship award from African Union Commission, to which i am greatly indebted.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

AC	Alternating Current
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
BA	Bees Algorithm
BPNN	Back-Propagation Neural Network
DWT	Discrete Wavelet Transform
FIS	Fuzzy Inference System
FS	Fuzzy System
GA	Genetic Algorithm
H	High
HIF	High Impedance Fault
HP	High Pass
L	Low
LH	Lower High
L-G	Line to Ground
L-L	Line to Line
L-L-G	Line to Line to Ground
L-L-L	Line to Line to Line
L-L-L-G	Line to Line to Line to Ground
LL	Lower Low
LP	Low Pass
M	Medium
MH	Medium High
ML	Medium Low

MRA	Multi Resolution Analysis
RMS	Root Mean Square
TDR	Time Domain Reflectometer
UH	Upper High
UL	Upper Low
WT	Wavelet Transform
XLPE	Cross-Linked Polyethylene
Z	Zero

NOMENCLATURE

∞ infinity symbol

$\int$ integration of functions

$\sum$ summation - sum of all values in range of series

α Alpha representing a real value

β Beta representing a imaginary value

γ Gamma representing the wave propagation constant

ω Angular Frequency

Ψ Psi representing mother wavelet

C Capacitance

dI change in current

dt change in time

dV change in voltage

dz change in distance

e exponential

G Conductance

g Low pass filter

h High pass filter

I current

j imarginary quantity

L Inductance

R Resistance

s Signal s

t time

V voltage

Z Impedance

ABSTRACT

Transmission lines are the backbone of electrical power systems and other power utilities as they are used for transmission and distribution of power. Power is distributed to the end user through either overhead cables or underground cables. In the case of underground cables, their propensity to fail in service increases as they age with time. The increase in failure rates and system breakdowns on older underground power cables are now adversely impacting system reliability and many losses involved. Therefore it is readily apparent that necessary action has to be taken to manage the consequences of this trend. At any given length of a cable, its deterioration or indication of failure manifests itself through discrete defects. Identification of the type of defects and their locations along the length of the cables is vital in order to minimize the operating costs by reducing lengthy and expensive patrols to locate the faults, and to speed up repairs and restoration of power in the lines. In this study, a method that combines wavelets and neuro-fuzzy technique for fault location and identification is proposed. A 10km, 34.5KV, 50Hz power transmission line model was developed and different faults and locations simulated in MATLAB/SIMULINK, and then certain selected features of the wavelet transformed signals were used as inputs for training and development of the Adaptive Network Fuzzy Inference System (ANFIS). The results obtained from ANFIS output were compared with the actual values. Comparison of the ANFIS output values and the actual values show that the percentage error was less than 1%. Thus, it can be concluded that the wavelet-ANFIS technique is accurate enough to be used in identifying and locating underground power line faults.

Keywords: ANFIS, Discrete wavelet transform (DWT), Fault location, Fault types, and Underground cables

CHAPTER 1

INTRODUCTION

1.1 Background

In electrical power systems, transmission and distribution lines are pivotal links that accomplish the continuity of service from the generating plants to the end users. Electrical power can be distributed to the end user through either overhead cables or underground cables. The main goal of the connections is to provide power in a safe, reliable and affordable way to the end user. This is achieved by maintaining a reliable voltage level, correcting the power factor through use of reactive compensation and offering as close to continuous service as possible in order to meet demand.

In the past decade, electricity demand has increased rapidly in metropolitan areas. All over the world, large scale underground power cable installations networks are replacing overhead transmission lines due to environmental concerns in densely populated areas. Underground cables are mostly used in distribution systems because they are more secure than overhead lines and cannot be damaged by lightning or storms. Underground cable systems are manufactured to have long life with reliability. However, the useful life span of these cables is not infinite [1]. Mashikian and Szatkowski, [2] highlighted that as these underground cables age, their propensity to fail in service increases, thus at any given length of a cable, its deterioration or indications of failure manifests itself through discrete defects.

Most cable manufacturers have estimated the life of underground cable systems installed in the range of 30 to 40 years. Today, a large portion of underground cables are towards the end of their design life, and the infrastructures reaching the end of their reliable service life. Due to the old age of the cables, the increasing failure rates and system breakdowns on these older systems are now adversely impacting system reliability. Therefore, it is readily apparent that necessary action has to be taken to manage the consequences of this trend [3]. Complete replacement of old or failing cable system is not an option since cable systems do not age uniformly.

Underground cable faults may be in form of series faults in which the cable is cut without the electrical insulation being broken, or shunt faults in which a break in the electrical insulation occurs without the conductor itself being cut. Studies have shown that one of the most common fault that leads to failure in underground power cables is the high impedance fault (HIF). In this type of fault, there is no substantial increase in current since the high impedance restricts the flow of fault current rendering it more difficult to detect [4]. For an underground cable, the HIF is normally caused by insulation defects that expose the conductor to non-conducting elements. HIF is an example of an incipient fault. Incipient faults occur as a result of the gradual aging process and would normally degenerate into permanent faults. Altamirano et al, [3] further articulated that incipient faults develop into permanent faults due to electrical over stress together with mechanical deficiency, unfavorable environmental conditions and chemical pollution, which causes permanent and irreversible damage on the insulation.

To improve the reliability of a distribution system, accurate identification of a faulted segment is required in order to reduce the interruption time during fault. Therefore, a rapid and accurate fault detection method is required to accelerate system restoration, reduce outage time, minimize financial losses and significantly improve the system reliability and ensure customer power quality. Conventionally, methods that have been used for identifying and locating the cable defects, were time consuming and inefficient. This led to the introduction of better techniques of fault identification such as Time Domain Reflectometer (TDR), Discrete Wavelet Transformation (DWT) and artificial intelligence based methods. However, in order to further improve the power reliability and reduction in power outages, more research needs to be done to accurately detect the fault location. The quick restoration of power is necessary for reliable operation of power system equipment and customer satisfaction. This study aimed at developing an underground cable fault identification and location system by use of artificial intelligence and wavelet analysis.

1.2 Problem Statement

Underground cable faults lead to serious disruptions of power supply and many losses to both the consumer and the power utility. Most of the underground cable faults affecting the network are as a result of aging and continuous deterioration of cable qualities and properties along the length of the cable. In order to improve on the quality, availability and reliability of power, there is need of innovations to increase the accuracy of fault identification and location on systems which are currently being used. In general, the ever increasing failure rates and system breakdowns on older underground power cables are now adversely impacting system reliability and the losses involved; therefore it is readily apparent that necessary action be taken to manage the consequences of this trend.

1.3 Justification

Being able to accurately locate the fault location will not only help the power utility to save money and time in concentrating the search in wrong locations but it will also help reduce power outage time to the consumers and save money to the utility. The power utility is able to know the exact location of the faults enabling them to prepare the consumers for possible power outage. The safety aspect is improved due to the introduction of proper location estimation mechanisms. This research proposes an innovative technique in fault identification and location in an underground power cables based on wavelet-ANFIS method.

1.4 Objectives

1.4.1 Main Objective

The main objective of this research is to develop a fault location and identification system for underground power cables based on wavelet-ANFIS technique.

1.4.2 Specific Objectives

The specific objectives of the research are stated as follows:

1. To model an underground power cable for fault simulation.
2. To formulate a wavelet-ANFIS technique for fault location and identification.
3. To determine the accuracy of the fault identification system.

1.5 Scope

The scope of this research was limited to the development of a general fault identification and location technique for underground cables. An underground power cable model was developed based on the line parameters and simulated to test the performance of the system. Wavelet-ANFIS technique was applied to identify the faults, the results were used to identify the fault locations. The general idea was to develop a highly accurate fault location system that was used to identify faults.

1.6 Thesis Outline

This thesis is organized as follows:

Chapter 1 provides an introductory background on the fault location, how the faults affect the system and gives a brief introduction about the methods currently being used to address similar problems. The research problem statement, objectives and significance of the study are also presented.

Chapter 2 highlights the different approaches used in fault location and identification. It also introduces different types of faults affecting the system, different types of techniques that have been used to solve the problem and technological advancement in areas of wavelet transformation and artificial intelligent techniques and how these techniques have been implemented in different applications.

Chapter 3 presents the parameters which were used to develop the transmission line model. Methodology for fault identification, wavelet transformation for fault location and ANFIS training and development was also presented.

Chapter 4 gives the results obtained through simulation of the proposed transmission line and their discussion. Results from different line faults on transmission line obtained using wavelet analysis and ANFIS are presented and discussed to evaluate the performance of the system.

Chapter 5 outlines the main conclusions, thesis contributions and suggestions for future work.

CHAPTER 2

LITERATURE REVIEW

This chapter seeks to establish and highlight the essential theory and critical assessment of the related work done by other researchers needed for the development of the proposed research. The reviewed literature concerning transmission line faults, wavelet analysis and artificial intelligent techniques for fault location is presented.

2.1 Background of Fault Location

In electrical power systems, transmission and distribution lines are pivotal links that accomplish the continuity of service from the generating plants to the end users. For the past 5 decades, electric power systems have rapidly grown [4]. Transmission lines are improving in length and capacity in terms of voltage levels and power being transmitted. These lines however are susceptible to faults which emanate from factors including insulation breakdown, short circuits and defects within the insulation of the cables. In most cases, electrical faults manifest themselves as mechanical damage which must be repaired urgently before returning the line to service [1]. The longer the power outages, the greater the damage is caused. Therefore, quick identification of fault location and restoration of power is essential for all utilities.

The speedy and precise fault location plays a pivotal role in accelerating system restoration, reducing outage time and improving system reliability [4]. Accurate location of transmission line faults has been a subject of interest to electric engineers and utilities. The major reason for this interest is mainly because accurate location of fault can reduce time required for bringing back service to customers [5]. In the past, utilities had to rely on sending staff to inspect the transmission line, which required several hours to find the actual location. A very high degree of accuracy is thus required which of cause is difficult to achieve using conventional techniques. In order to fix the fault quickly, finding the accurate location of fault point is the key [6]. In transmission and distribution systems, underground cables have been used because they are more secure than overhead lines and cannot be damaged by lightning or storms. These underground cable systems are manufactured to have a long life with reliability.

However, as the cables age, they start to develop internal faults, which in the long run will result into a full blown fault [2]. Internal failures in underground cables result from gradual weakening or deterioration of the insulation materials between core and sheath. Voids and impurities in the insulation material or between boundaries of different material, can initiate a process called treeing which leads to insulation breakdown [7]. When the insulation breaks, an electric arc forms a low impedance path between the cable's core and sheath allowing a large fault current to start flowing and hence resulting in protection system disconnection. When the protection system disconnects, the fault either develops into a series fault or remain as a shunt fault [3]. Cross-linked polyethylene (XLPE) as a solid dielectric has often been used as the main insulation material in high voltage AC-cables [8].

Electrical trees are formed by locally increased electrical stress and propagate comparatively fast in the insulation material for the cables until it breaks down. Water trees on the other hand are another cause of insulation breakdown. They are formed by local defect on the insulation material and in the presence of moisture. Water trees normally propagate very slowly over many years and are hard to detect since no partial discharge appears. When this insulation breaks down, an electric arc forms a low impedance path between the cable's core and sheath [9].

2.2 Types of underground cable faults and location

In electrical networks, equipment is at times subjected to several types of faults while they are in operation. In general, a fault in an electric power system can be defined as any abnormal condition within the system that involves the electrical failure of the power system equipment. Under normal operating conditions, electrical equipment in power system network operates at normal voltage and current ratings. Once the fault occurs, voltage and current values deviates from their nominal ranges. Faults in power system can cause over-current, under voltage, or in other cases unbalance of the phases, reversed power and high voltage surges [8]. When a fault occurs, normally the impedance of the machines or transmission cables may change from existing values to new values till the fault is cleared. If the fault is allowed to persist, it can lead to a voltage breakdown [10]. There are different types of cable faults, which must be classified first before they can be located. Underground cable fault location is that process of locating faults which affect underground cables. Electrical faults in three-phase power systems are mainly classified into two categories namely open and short circuit faults. These two types of faults, are further divided into symmetrical or unsymmetrical faults [11].

2.2.1 Open Circuit Faults.

Open circuit faults or series faults occur as a result of failure of one or more conductors. These types of faults are referred to as unsymmetrical or unbalanced type of faults except when it is a three phase open fault. In a transmission line, if one of the phases gets melted or broken, the actual loading of the alternator is reduced and this raises the acceleration of the alternator, thereby it runs at a speed slightly greater than synchronous speed [12]. The increase in speed causes over voltages in other transmission lines resulting in an unbalance of the power system voltages and currents that causes great damage to the equipment.

2.2.2 Short Circuit Faults

A short circuit or shunt faults can be defined as an abnormal connection of very low impedance between two points of different potential, either intentionally or accidentally. Shunt faults are the most common and severe kind of faults that result in the flow of abnormal high currents through the equipment or transmission lines. If these faults are allowed to continue even for a short period, they can result in the extensive damage to the equipment. Shunt faults are caused by insulation failure between phase conductors or between earth and phase conductors or both. A number of short circuit fault conditions fall under this category which include three phase to earth, three phase clear of earth, phase to phase, single phase to earth, two phase to earth [11].

2.2.3 Symmetrical and Unsymmetrical faults

As discussed above, faults are mainly classified into open and short circuit faults and further divided into either symmetrical or unsymmetrical faults depending on how they affect the system.

2.2.3.1 Symmetrical faults

A symmetrical fault or balanced fault is a fault which gives rise to symmetrical fault currents that are displaced 120^0 from each other. This type of fault occurs when all the three phases are simultaneously short circuited. When these faults occur, they cause very severe damage to the equipment regardless of the system remains in balanced condition. They only occur as either line to line to line (L-L-L) or line to line to line to ground (L-L-L-G). In reality, these types of fault rarely occur as compared to unsymmetrical faults. A rough estimate of the occurrence of symmetrical faults is in the range of 2 to 5% of the total system faults [11].

2.2.3.2 Unsymmetrical faults

The most common types of faults that occur in the power system network are unsymmetrical faults. This kind of fault gives rise to unbalanced currents in the system, having different magnitudes with unequal phase displacement. Unsymmetrical faults include both open circuit faults and short circuit faults excluding L-L-L-G and L-L-L. A single line-to-ground (LG) fault is one of the most common types of faults that affect power systems and experiences show that 70%-80 % of the faults that occur in power system are of this nature. Regardless of being the most common type of faults, they are less severe compared to other faults. A line to line fault occur when a live conductor get in contact with another live conductor. These are also less severe faults and their occurrence range is between 15%-20%. In double line to ground faults, two live conductors come in contact with each other as well as with the ground. This type of fault is severe and the occurrence of these faults is about 10% when compared with total system faults[11].

2.3 Theoretical model of underground cable

The solution for a uniform transmission line which has losses can be obtained with the equivalent circuit for the elementary cell shown in Figure 2.1.

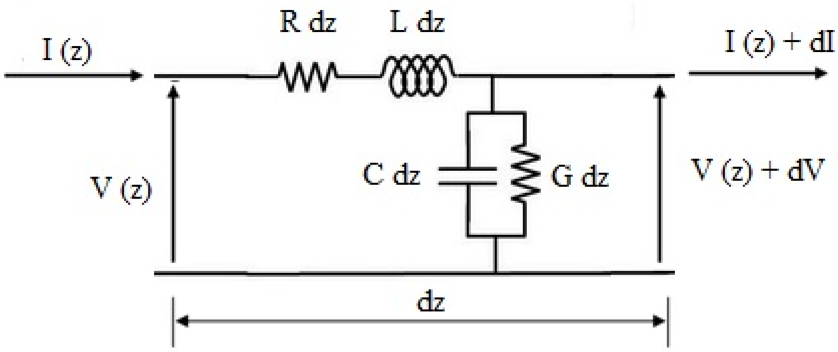

Figure 2.1: Section of a transmission line

The series impedance of the circuit in Figure 2.1 determines the variation of the voltage from the sending end, input to the receiving end, and the output of the cell. The corresponding equation for the series impedance of the circuit is:

$$(V + dV) - V = -\left(j\omega L dz + R dz\right) I \tag{2.1}$$

From the above equation, we can obtain a first order differential equation for the voltage as follows:

$$\frac{dV}{dz} = -\left(j\omega L + R\right) I \tag{2.2}$$

The current flowing through the shunt admittance determines the input-output variation of the current and the corresponding circuit equation is:

$$dI = -\left(j\omega C dz + G dz\right)\left(V + dV\right) \tag{2.3}$$

$$dI = -\left(j\omega C + G\right) V dz - \left(j\omega C + G\right) dV dz \tag{2.4}$$

From Equation (2.2) and using analogous system for current, a first order differential equation for the current will be:

$$\frac{dI}{dz} = -\left(j\omega C + G\right) V \tag{2.5}$$

Equations (2.2) and (2.5) describe the behavior of voltage and current on the lossy transmission line. These two equations are referred to as the "telegraphers' equations" for the lossy transmission line. To obtain a set of uncoupled equations, Equations (2.2) and (2.5) are differentiated with respect to the coordinate z, to produce the "telephonists' equations" for the lossy line. These telephonists' equations for the transmission line are uncoupled second order differential equations and they are also wave equations. The wave propagation constant γ which is a complex quantity is:

$$\gamma = \sqrt{\left(j\omega L + R\right)\left(j\omega C + G\right)} = \alpha + j\beta \tag{2.6}$$

$$\frac{d^2 I}{dz^2} = -\left(j\omega C + G\right)\frac{dV}{dz} = \left(j\omega C + G\right)\left(j\omega L + R\right) I \tag{2.7}$$

The telephonists' equations, Equation (2.6) and (2.7) for the transmission line are uncoupled second order differential equations and they are also wave equations. The general solution for the voltage equation is:

$$V\left(z\right) = V^{+}e^{-\gamma z} + V^{-}e^{\gamma z} = V^{+}e^{-\alpha z}e^{-j\beta z} + V^{-}e^{\alpha z}e^{j\beta z} \tag{2.8}$$

From Equation (2.6), the real part α of the propagation constantγ describes the attenuation of the signal due to resistive losses and the imaginary part β describes the propagation properties of the signal waves. The exponential terms including α are the real parts, therefore, they only affect the magnitude of the voltage phasor. The exponential terms including β have unitary magnitude and are purely imaginary argument, so they affect only the phase of the waves in space. The current distribution for the transmission line can be obtained by differentiating the result of the voltage:

$$\frac{dV}{dz} = -\left(j\omega L + R\right) I = -\gamma V^{+} e^{-\gamma z} + \gamma V^{-} e^{\gamma z} \tag{2.9}$$

Which gives

$$I\left(Z\right) = \sqrt{\frac{\left(j\omega C + G\right)}{\left(j\omega L + R\right)}} \left(V^{+} e^{-\gamma z} - V^{-e^{\gamma z}}\right) \tag{2.10}$$

$$= Z_0 \left(V^{+} e^{-\gamma z} - V^{-} e^{\gamma z}\right) \tag{2.11}$$

The characteristic impedance of the transmission line is given by Equation (2.12):

$$\frac{1}{z_0} = \sqrt{\frac{\left(j\omega C + G\right)}{j\omega L + R}} \tag{2.12}$$

$$Z_0 = \sqrt{\frac{j\omega L + R}{j\omega C + G}} \tag{2.13}$$

This characteristic impedance of the line is applicable for both loss-less and lossy transmission lines. This characteristic impedance does not depend on the line length, but only on the material of the conductors, the dielectric material surrounding the conductors and the geometry of the line cross section, which determine L, R, C, and G.

2.4 Fault Location Methods

Currently, fault location techniques are developed in many different ways. The most important characteristics of fault location methods are accuracy and reliability. Methods developed for locating faults on transmission lines can be classified into two fundamental categories, techniques based on power-frequency components and techniques based on utilizing the higher-frequency components of the transient fault signals [5]. The first one is based on using voltage and current values and necessary system parameters to calculate fault location. The fault location methods based on voltage and current measurements are proposed in [13], [14]. Methods based on impedance matrix to establish equations governing the relationship of the measurements and fault location was also proposed in [15], [16], [17]. The second technique is based on using traveling wave. Techniques based on representing transmission lines by either first or second order differential equations and traveling-wave techniques have resulted in a number of commercial developments [18]. Results obtained from the two techniques proved to be difficult in taking system variation into account as the rules are fixed. The techniques did not have the ability to adapt dynamically to system operating conditions, and to make correct decisions if signals are uncertain. To address the problem, both techniques have been combined with artificial intelligent techniques to address the problem of uncertain values.

2.5 Main Problems of Fault Location Method

Use of impedance calculation method in locating faults is much easier and cheaper to implement than traveling wave method because hardware investment is low. Nevertheless, the accuracy of impedance calculation method can easily be affected by many factors which include transition resistance, nonlinear voltage transformers and asymmetrical transmission lines. The traveling wave based method involves transient signal, which are less affected by the above mentioned factors [14]. Thus, the error of traveling wave method is significantly lower compared to the impedance calculation method. Since traveling wave based method is unaffected by fault resistance and transmission line types, a two-end systems is more reliable and accurate than impedance calculation method [4].

The main factors contributing to the accuracy of traveling wave based fault location method are the propagation time and velocity of the traveling wave. Inspite of the traveling wave method being better than the impedance calculation method, there however some problems experienced [13]. Firstly, to distinguish between the traveling wave reflection and the remote end of the line is still a problem. Secondly, the uncertainty of the traveling wave such as the randomness of fault types and fault transition time can affect the accuracy. Another factor to consider is that the velocity of traveling wave is affected by different climates and environments. Lastly, the sample rate of recording signals is a significant factor which affects the accuracy of traveling wave based method [13].

2.6 Wavelet based method

Wavelet transform is an effective mathematical method for analyzing transient traveling wave. It has been widely used in many applications with the inclusion of faulted phase identification, traveling wave fault location, and transformer protection [19]. Basically discrete wavelet transform, is the breaking up of a signal into shifted and scaled versions of the original mother wavelet. By using Fourier transform, a sinusoidal wave can be broken down into sine waves of various frequencies. Analogously, wavelet transform has the ability to break a signal into shifted and scaled versions of the mother wavelet. A wavelet is a waveform of effectively limited duration and an average value of zero. Wavelet transform allows time localization of different frequency components of a signal [20]. Taking a comparison between a wavelets and sine waves, it can be observed that signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoidal wave.

Wavelets tend to be irregular and asymmetric and are capable of revealing aspects of data that other signal analysis techniques miss. These aspects include breakdown points, trends, discontinuities in higher derivatives, and self-similarity [21]. Because of its ability to offer a different view of data as compared to traditional techniques, wavelet analysis can compress or de-noise a signal without appreciable degradation. A time-scale representation of a digital signal is obtained using digital filtering techniques. By this, filters of different cut-off frequencies are used to analyze the signal at different scales [22]. This therefore means the signal is passed through high pass filters to analyze the high frequencies and through low pass filters to analyze the low frequencies. Hence the initial signal (S) is decomposed into two main components namely approximation (A) and detail (D). The approximation is the high scale, low-frequency component of the signal. The detail part is the low-scale, high-frequency component. One signal can be broken down into many lower resolution components by decomposition process which is iterative with successive approximations being decomposed in turn. This is called the wavelet decomposition, represented by Figure 2.2.

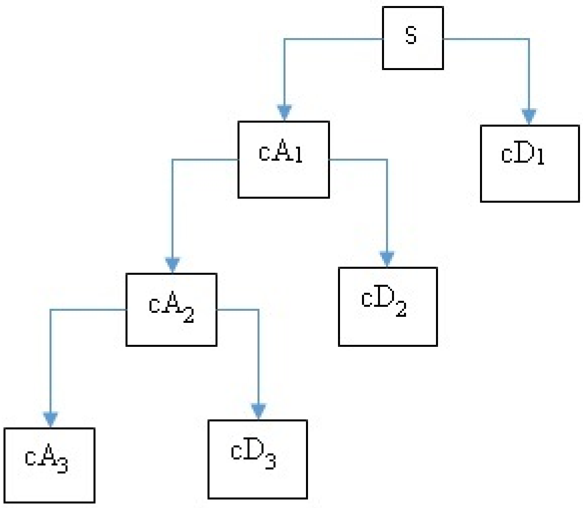

Figure 2.2: Wavelet signal decomposition

Wavelet Transform (WT) has been found to be very useful in analyzing transient signals. Due to its ability to examine the signal in both time and frequency in a distinctly different way, it has become useful in a number of sophisticated wavelet-based methods for signal manipulation and interrogation. Therefore, wavelet analysis is appropriate for quick alterations in transient signal analysis [2]. One of the strengths for wavelet analysis is the capacity to show the local features of a specific area of a large signal [11, 12]. In wavelet analysis, a wavelet transform decomposes transients into a series of wavelet components. Each specific component corresponds to a time-domain signal that covers a specific frequency band that contains more detailed information. The way these wavelets localize the information in the time–frequency plane, is by exchanging one type of resolution by another. Because of this, it makes wavelet transform techniques to be more suited for analyzing non-stationary signals [8]. Wavelet behaves more like a mathematical function that satisfies some mathematical requirement to represent the signal in the time domain [23].

The general ideal about wavelet is that, it is utilized to extract distinctive information from different kinds of data such as signal and image. The type of approach for fault identification and classification is implemented using multi resolution analysis (MRA) of current and voltage signals [24]. MRA is a process of disintegrating a signal into different levels of resolutions [25]. At first the signal will be passed through two discrete wavelet transform (DWT) filters, which is the high pass (HP) filter and low pass (LP) filter. The output sample signals from the HP filter are referred to as the detail coefficients, whereas those from the LP filter are referred to as the approximated coefficients. After the first level has been done, the next level will be to obtain samples from LP filter. They are then further processed through HP and LP filters forming the second level. In this way, the original signal can be processed through many different levels, if there is need of resolution of the signal. A wavelet based technique was proposed in [24]to detect, classify and discriminate the transients and the reflected signal from noise, the algorithm is based on multiple scale correlation of wavelet transform, introduced using current signal from one ends. Using this algorithm, the faulty phase can be detected and then classified by the approximation components of the three phases.

In some applications of the discrete wavelet transform (DWT) for identifying the phase with fault appearance, the coefficients of positive sequence current signals are calculated and employed in fault detection decision algorithm. The results obtained show that the proposed algorithm can indicate fault types with accuracies higher than 90%. A technique of using discrete wavelet transform, combined with back-propagation neural network (BPNN) for classifying fault types in underground distribution system was proposed in [26]. In [27], studying the respective characteristics of wavelet analysis and curve fitting, a flat coefficient was defined so as to distinguish the mutation of the signal. Then combining the wavelet analysis with curve fitting method to detect the pulse starting point of traveling wave, then finally calculating the fault distance. Reference[28] proposed a fault detection and classification scheme which is based on discrete wavelet analysis for power cables. The numerical test results of the scheme were very encouraging.

2.7 Artificial intelligence based methods

Artificial Intelligence is a broad name used for a number of technologies, which include Fuzzy Systems, Neural Networks, Genetic Algorithms and Bees Algorithm amoung others. These technologies have been used differently on power system and some of their uses were to identify faults. Most theories developed for fault location and power system protection were based on deterministic evaluation schemes [29]. They had some challenges, mainly because of the complex system models, uncertain determined parameters, the large amount of data that must be processed and changing system configurations [2]. Recently, intelligent soft computational techniques mentioned above have been used to emulate human perception and learn from training examples in the database to predict future events [30]. Artificial intelligent techniques have the ability to re-establish any process without plenty of analysis. Thus these techniques are now attracting great attention in addressing problems that lack simple and well-defined mathematical model [6].

In most power system problems, fault data can be uncertain to make a decision regarding its location [31]. When this happens, this type of data is classified as fuzzy data. But considering the fact that Fuzzy Inference Systems (FISs) have the capability of non-linear mapping, Fuzzy can be used to find a very close relationship between data samples so as to locate the fault on transmission lines. This therefore makes FIS ideally suited for providing high degree of accuracy in different fault types and locations. An Adaptive Neuro-Fuzzy Inference System (ANFIS) based fault classification scheme in neutral non-effectively grounded distribution system was proposed in [32]. In this method, the transient currents will be obtained by wavelet transform after faults occur. According to the statistic characteristic of transient currents in diverse fault types, the fault identifiers are defined.

An adaptive network based approach presented in [18] chose the parameters of fuzzy system used for the training process. In this technique, an adaptive technique is used to find the best parameter for the fuzzy so that it can be used for fault location. As was discussed by [33], a method that employs neural network for fault classification and location in underground cables was designed. The ability for the ANNs for pattern recognition and classification were used to design the model. The use of neural networks in many applications is very sparse due to some limitations. When a power system is in transient period, the operation cannot be easily described by artificial explicit knowledge because it is affected by many unknown parameters. But the integration of neural network and fuzzy logic system makes it possible to learn from the prior obtained data sets.

In [34], a single ended fault location algorithm for a transmission line was proposed based on neural networks. The input to the ANN are the pre- and post-voltages and currents phasors. The output of the system is the fault resistance and fault distance. A fault location algorithm using Adaptive Network-Based Fuzzy Inference System (ANFIS) for a network with both transmission lines and under-ground cables was proposed in [20]. The method uses fundamental frequency of three-phase current and neutral current as inputs to estimate the fault location in terms of distance in kilometer. The neural networks was also used in [35] to improve the operation of fuzzy inference system. The method was based on neural network (NN) algorithm combined with Fuzzy for fault detection and classification on transmission lines. Another algorithm for fault detection and classification of low impedance faults and high impedance faults using ANFIS was presented in [36].

The proposed method, managed to detect and classify fault type in a transmission line based on RMS value of phase currents and zero sequence current. In [25], application of wavelet fuzzy neural network in locating single line to ground fault in distribution lines are discussed. Fuzzy logic and ANN were used to locate the fault. In artificial Intelligence techniques, the fault detection unit is built based on various training data at fault and no fault conditions. The fault classification unit will be built at different situations and different types of fault. After this has been done, the unit is tested using testing data. The fault identifiers can show the fault traits for different fault types and show different disciplinarian in these different faults also.

2.8 Summary

From the for-going literature review, it is noted that a number of techniques for fault identification and location have been proposed. Much of the work which has been done utilizes the wavelet concept to identify the changes in the line parameters. Many researchers worked on this area combining that concept with other technologies such as Fuzzy System, Neural Networks and Bees Algorithm. The aim was to either increase on the accuracy of fault location or speed. In this study, the same concept of Discrete Wavelet Transformation (DWT) combined with ANFIS, was used for the identification of faults in underground cables in a simpler and much faster way but at the same time increasing accuracy of the system. The proposed method made use of how the transmission lines are related to one another so that the differences can be used to identify any fault type. Speed and accuracy was greatly considered and the system designed was able to identify the fault accurately and fast.

CHAPTER 3

METHODOLOGY

This chapter highlights the steps followed in addressing the research objectives. The transmission system is developed, and then used to identify the fault type. Fault signals were generated which were analyzed under wavelet analysis then later used in development of an ANFIS for fault location.

3.1 Development of the transmission line model

The basic structure of the transmission line consists of the generator, the transmission system and a constant load. From the model, actual system parameters were used to come up with a MATLAB model that was simulated to generate fault signals. The development of the transmission line was done under MATLAB/SIMULINK environment. The line considered is a 10km, 34.5KV, 50Hz underground power cable. The system analysed post fault conditions and all the simulations done were to generate fault signals which were used to identify and locate the faults and generate a database. The fault was created after every 0.1km, with a simulation time of 0.0001s, resistance per unit length = 0.022Ω, inductance per unit length = 0.079 mH and capacitance per unit length = 0.038 μF. A 0.1km distance was chosen so as to create a bigger database that was used in the development and designing of an ANFIS which is reliable and accurate in distance estimation. The system was considering a constant load. An assumption was made that the underground cables are not affected by external interference of other cables on the underground and the system was only to identify actual faults not disturbances in the systems which can correct themselves. Figure 3.2 shows the line model which was developed.

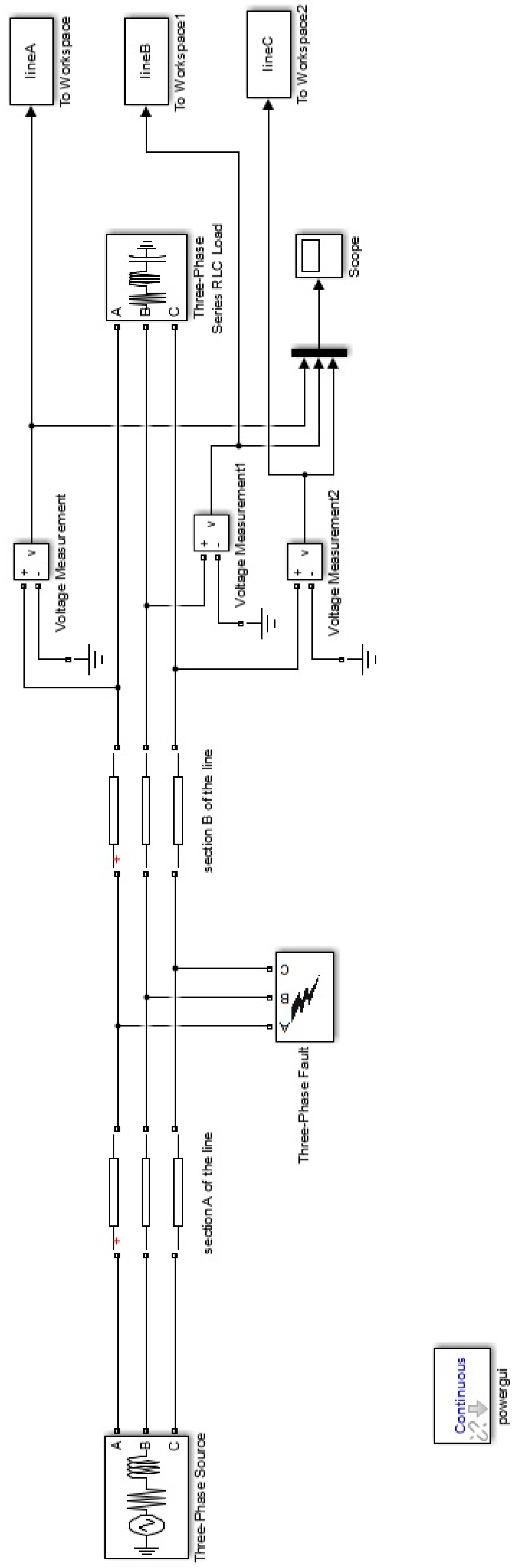

Figure 3.1: Transmission Line model

3.2 Fault introduction

Fault identification was done in post fault conditions. For the system to identify the fault in post fault conditions, the fault was assumed to have occurred already when the simulation was initiated. The nature of the fault and the specification of the fault were changed in the three phase fault tool box. This enables the system to have different types of fault and at different locations to cover wide scenarios which might affect the transmission system. Because transmission lines can experience single line or double phase or three phase faults, the faults were also introduced at these different locations with different behaviors.

3.3 Fault identification

After the transmission line had been designed, the system was simulated to identify the type of fault that has affected the system and on which phase. Figure 3.3 highlights the basic flow process which was followed to identify the type of the fault affecting the system. In achieving the set objective, the initial stage was to analyse the wave signals of the transmission line so as to identify which phase(s) have been affected. Simulated cable data from the phase which has a fault is transferred to Discreet Wavelet Analysis in MATLAB/SIMULINK environment for data processing and analysis.

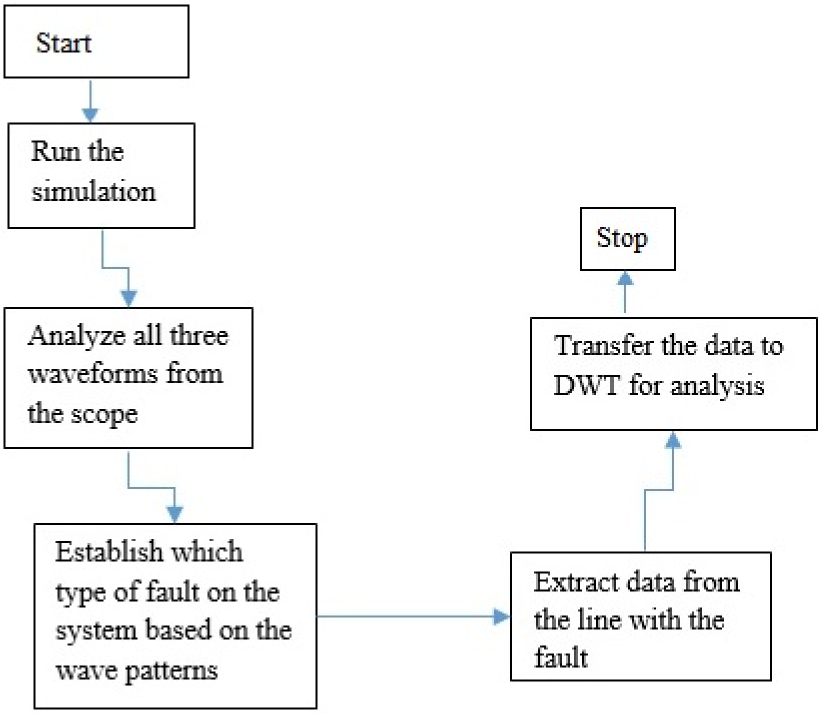

Figure 3.2: Fault identification flow chart

The transmission line model system was simulated to identify the type of fault on the affected phase. The system was designed with a means of observing all the phases on the transmission line on one platform. The fault data from the toolbox on the line was used to locate the fault. To distinguish the faults, different wave forms were observed. For a single line fault, only one phase had a lower magnitude of voltage as compared to the other two. In a double phase fault, two of the signals with faults indicated some deviations from the expected wave form. When the type of the fault had been established, fault data, which can be referred to as signal **s** from the line was analyzed under wavelet transform to extract useful information pertaining to the fault.

3.4 Fault location using Discrete Wavelet Transformation

To enable fault location along the transmission line, the initial stage is to analyze the fault signals so as to identify the affected phase(s). Simulated line data from the affected phase is transferred to Discrete Wavelet Transformation environment for data processing and analysis. To accomplish the task, features of the line voltage signals are extracted based on discrete wavelet transform with daubechies4 (db4) as the mother wavelet. Daubechies wavelets, are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function which generates an orthogonal multiresolution analysis. The mother wavelet db4 was chosen because it works best for fast transients.

The feature extracted from the line is an index representing the location of the fault, represented by spikes on the DWT. Analysing signal **s** under discrete wavelet analysis, involves passing the signal through a number of filters. Firstly the sample signal **s** is passed through a low pass filter which has an impulse response **g** resulting in a convolution of the two. Passing the signal under low pass filter enables the extraction of approximation coefficients of the signal to identify changes in signal properties. This can be illustrated by Equation (3.1).

$$s\left[n\right] = \left(x * g\right)\left[n\right] = \sum_{k=-\infty}^{\infty} x\left[k\right] g\left[n-k\right] \tag{3.1}$$

The signal was further decomposed simultaneously using a high pass filter **h**. Passing the signal under high pass filter enables the extraction of detailed coefficients of the signal to identify changes in signal properties. Both outputs from the high pass filter and low pass filter, produces detail coefficients and approximation coefficients respectively. Extraction of the features will help in giving a clear view on the signal and helps to magnify the changes so that it can be easily identified. The two filters are related to one another and they are referred to as the quadrature mirror filters shown by Figure 3.4.

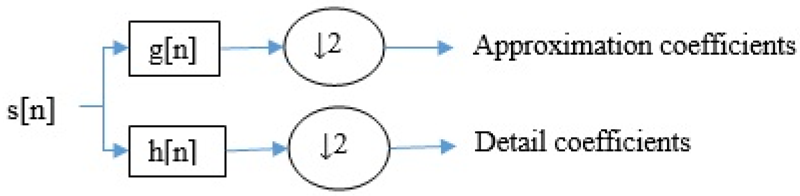

Figure 3.3: Signal coefficients

At this stage half the frequencies of the signal have been removed, according to Nyquist's rule, half the samples can be discarded. Equation (3.2) and (3.3) represents the two new coefficients of the initial signal.

$$y_{low}\left[n\right] = \sum_{k=-\infty}^{\infty} x\left[k\right] h\left[2n-k\right] \tag{3.2}$$

$$y_{high}\left[n\right] = \sum_{k=-\infty}^{\infty} x\left[k\right] g\left[2n-k\right] \tag{3.3}$$

After the first decomposition, the signal had halved the time resolution since only half of each filter output characterises the signal. The two outputs each have half the frequency band of the input so the frequency resolution has been doubled. Depending with the level to which the signal has to be analysed, the process of passing the new signal over the low pass and high pass filter will continue until the level of analysis has been achieved. The levels depends on the user. At every level, the signal will be passed through high and low pass filter and the signal resolution will at each stage also double from the the previous resolution. This will help the signal to be clearly viewed and to remove any noise which might be in the signal or any disturbance which might occur. At every level, a certain amount of noise and small disturbances will be eliminated making the signal clearer to analyse and to expose the changes in the signal parameters. The summation of the two equations can be written more concisely as:

$$y_{low} = (x * g) \tag{3.4}$$

$$y_{high} = (x * h) \tag{3.5}$$

To further increase the frequency resolution of the signal and the approximation coefficients decomposed with the high pass and low pass filters, the decomposition process was repeated a number of times and then down-sampled. This can be represented as a binary tree, Figure 3.5, known as a filter bank with nodes representing a sub-space of different time-frequency localisation.

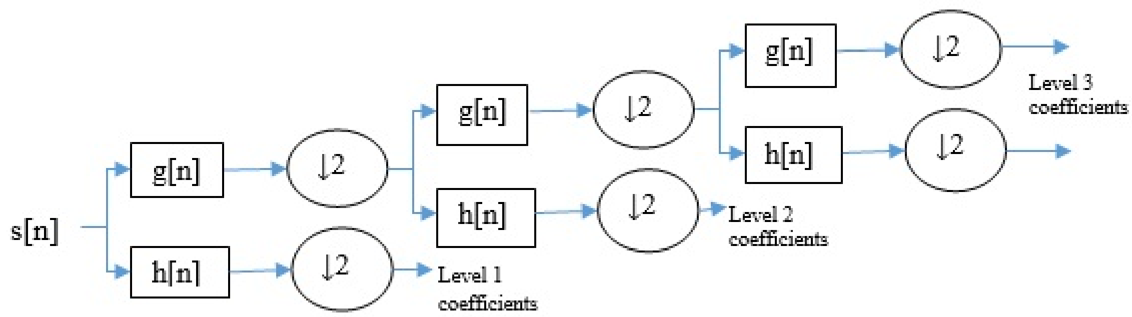

Figure 3.4: Signal decomposition

At each level in Figure (3.5), the signal is decomposed into low and high frequencies. Because of the decomposition process, the input signal was of a multiple of 2^n where n represents the number of levels. If a signal has to be analysed to level three, it means the signal s when viewed from level 3, has been magnified to 8 times the resolution of the initial signal. This is shown by table 3.1 below, where signal s is the initial signal.

Table 3.1: Signal Resolutions

level	resolution	name of signal	factor
0	initial resolution of signal s	s	s
1	2 times resolution of signal s	d1	2*s
2	2 times resolution of signal d1	d2	4*s
3	2 times resolution of signal d2	d3	8*s
4	2 times resolution of signal d3	d4	16*s
5	2 times resolution of signal d4	d5	32*s

The filter bank implementation of wavelets in general can be interpreted as computing the wavelet coefficients of a discrete child wavelets from a given mother wavelet ψ(t). In this case, the mother wavelet is shifted and scaled by powers of two as shown be equation (3.6).

$$\Psi_{j,k}(t) = \frac{1}{\sqrt{2^j}}\Psi\left(\frac{t-k2^j}{2^j}\right) \tag{3.6}$$

Where j is the scale parameter and k is the shift parameter.

In the case of a child wavelet in the discrete mother wavelet, Equation (3.7), the wavelet coefficient γ of a signal x(t) is the projection of signal x(t) onto a wavelet analysis of length 2^N.

$$\gamma_{jk} = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{2^j}}\Psi\left(\frac{t-k2^j}{2^j}\right)dt \tag{3.7}$$

Signal S was analysed up to level 5 and useful fault information from the wavelet analysis was used to develop an ANFIS. Appendix 1 shows the database which was used as inputs to the development of the ANFIS. In MATLAB/SIMULINK, wavelet analysis was simplified to click and execute function using the graphic user interface provided, the above mentioned process is what happens inside the tool box. In analysing any signal, the signal is imported from a file, then identify the wavelet type to use and analysing the signal to what level and the system produces the results. Figure 3.6 below represents the graphical user interface for wavelet analysis.

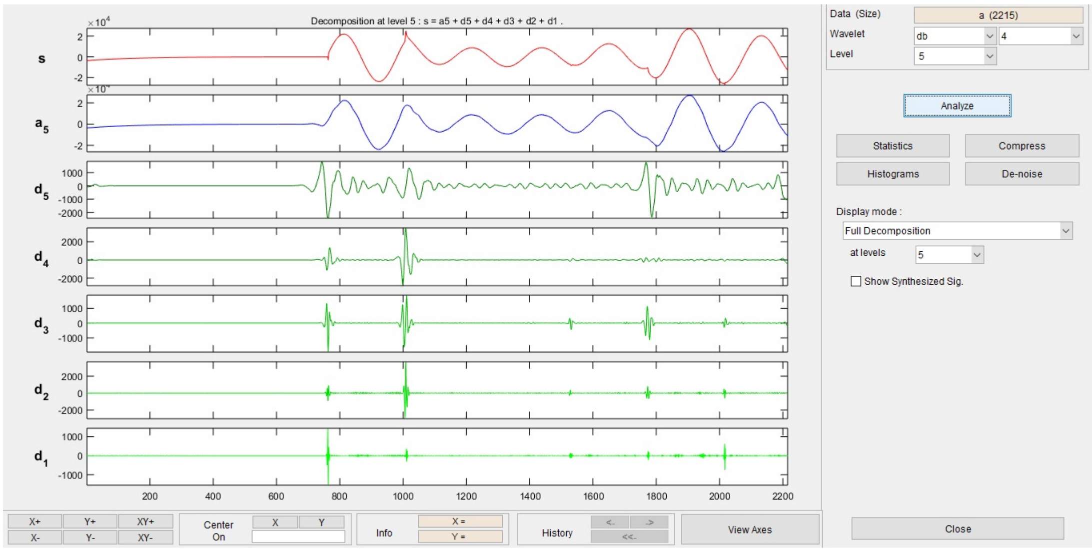

Figure 3.5: Wavelet Analysis Graphic user interface

3.5 ANFIS model for fault location

The basic structure of the proposed design of ANFIS consists of the fault index from the wavelet transformation, the hidden layer and the fault distance. The system has one input, the fault index and one output which is for identifying the fault distance. Figure 3.7 is the basic structure of the ANFIS which was considered for fault location.

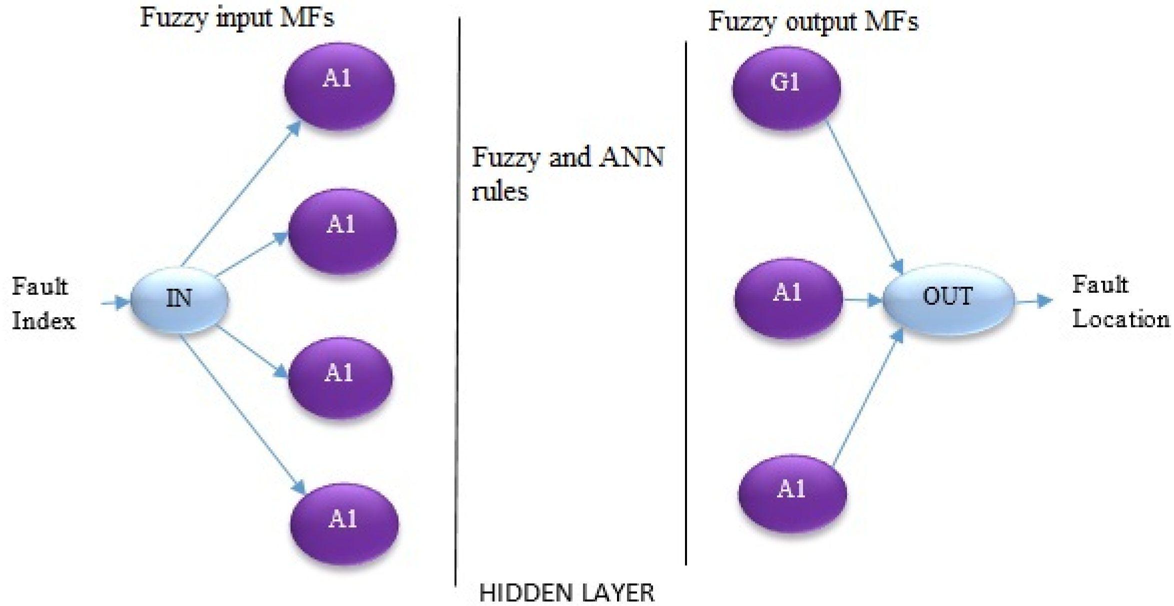

Figure 3.6: ANFIS Structure

The database created after wavelet analysis (Appendix 1) for different faults and locations was used as the input in the development of an ANFIS. Depending on the knowledge of the system, there are basically three types of estimation models that can be used to solve such a problem. One of them, black box, is very useful when the primary concentration is in fitting the data irrespective of the particular mathematical structure of the model. Since black-box modeling is usually a trial-and-error process, the database which was created in wavelet analysis, (Appendix 1) was used to train, design and test the ANFIS. Figure (3.8) is displays the initial stage of loading data into the black box for the development of the ANFIS, and Figure (3.9) represents the training process of the system. Basically the end result was to develop a model which can accurately estimate the fault location given the fault signals from the transmission line.

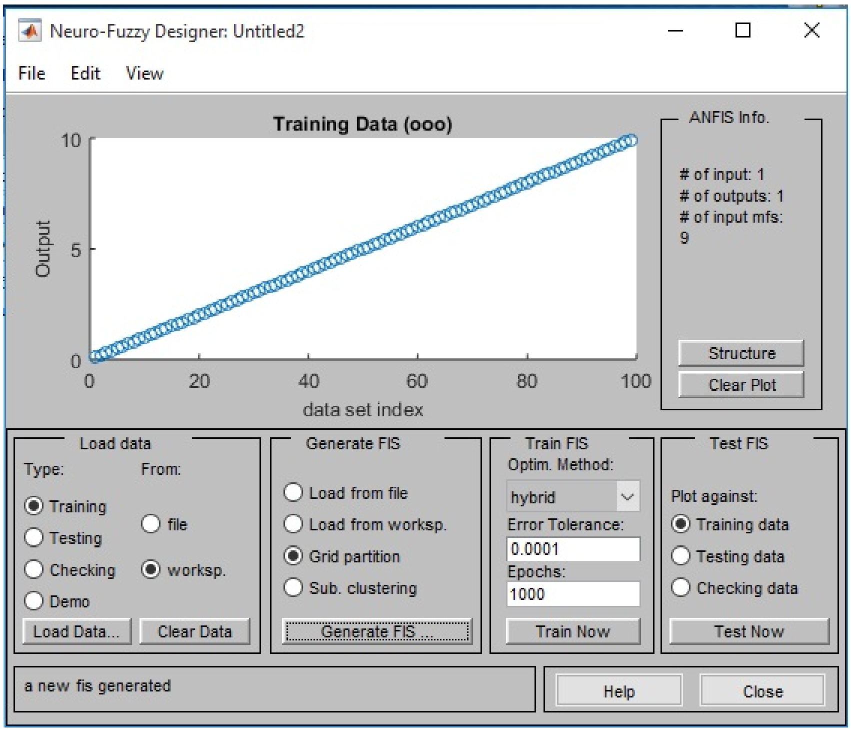

Figure 3.7: Loading data for ANFIS training

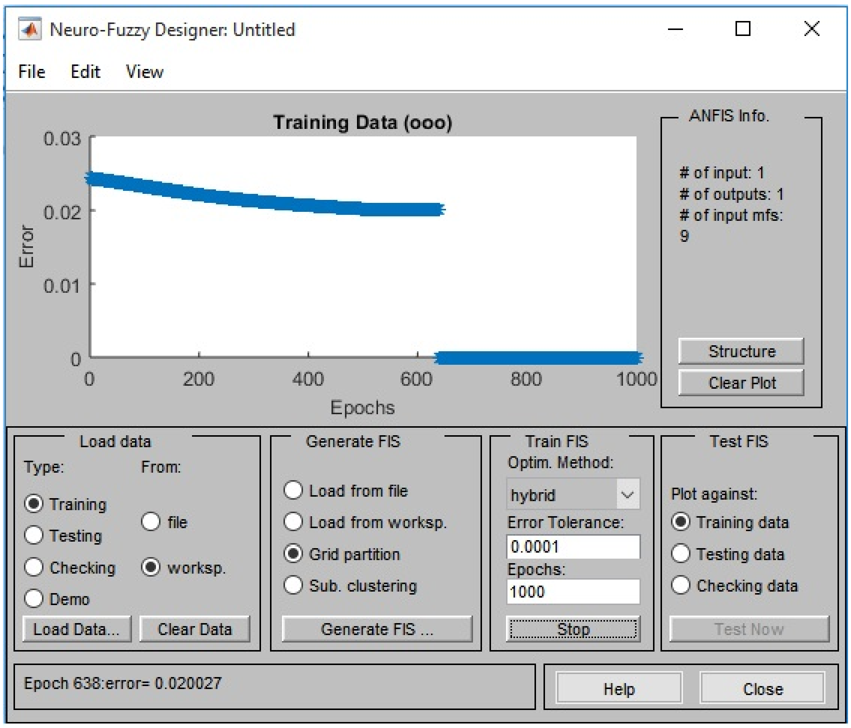

Figure 3.8: Training the ANFIS

The ANFIS was trained from the fault data which was developed under wavelet analysis after 99 simulations had been done. Testing of the system was done with the training data to see if the system has been properly trained. Figure 3.10 shows the verification process for testing the system and to identify any outliers so as to see the effectiveness of the training

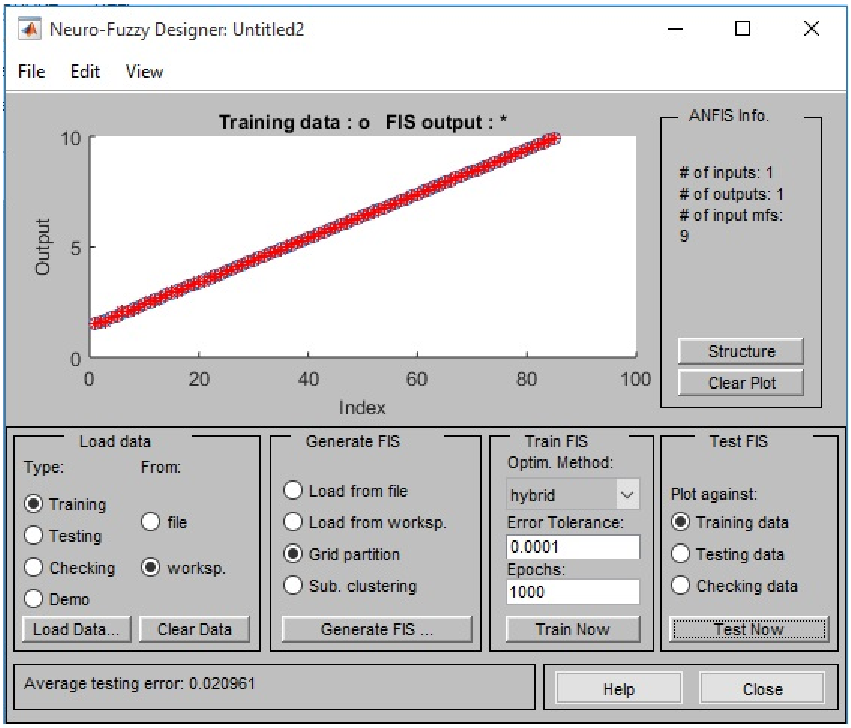

Figure 3.9: Testing the ANFIS structure

After the development and testing of the model, the ANFIS structure is presented in Figure (3.11). Since the development of the structure used the black box, most of the processes and components of the ANFIS will have to be extracted after the processes. Presented below are the processes which were happening in the background as the ANFIS was being trained.

ANFIS info:

Number of nodes: 40

Number of linear parameters: 18

Number of nonlinear parameters: 27

Total number of parameters: 45

Number of training data pairs: 99

Number of checking data pairs: 0

Number of fuzzy rules: 9

Start training ANFIS ...

1 0.0511743

2 0.0511677

Designated epoch number reached –> ANFIS training completed at epoch 2.

ANFIS info:

Number of nodes: 40

Number of linear parameters: 18

Number of nonlinear parameters: 27

Total number of parameters: 45

Number of training data pairs: 99

Number of checking data pairs: 0

Number of fuzzy rules: 9

Start training ANFIS ...

1 0.0511677

2 0.051161

Designated epoch number reached –> ANFIS training completed at epoch 2.

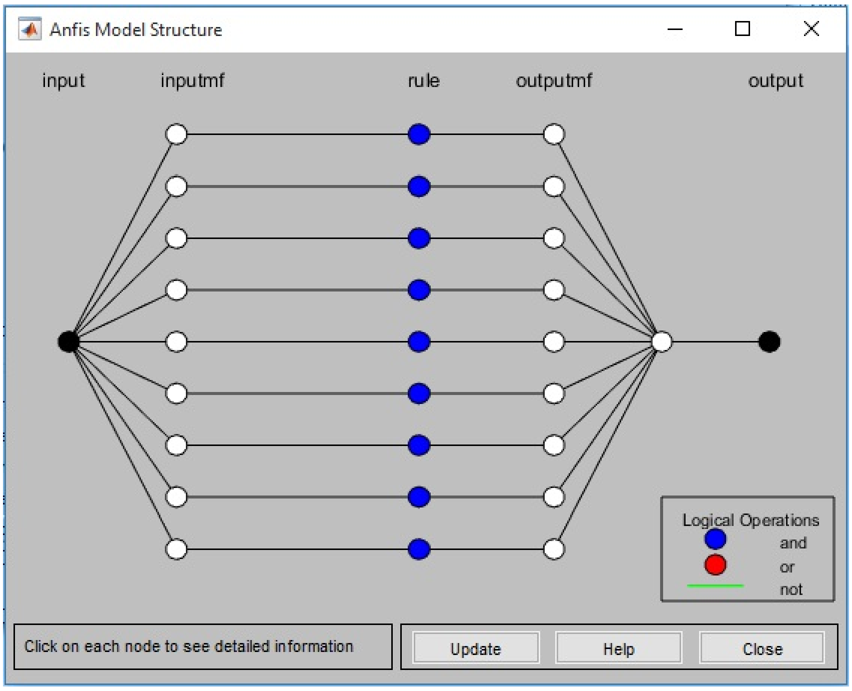

Figure 3.10: ANFIS Model Structure

3.5.1 Fuzzification

Fault index was the input variable used in the fuzzy input block function. Within the input block functions, after testing different membership functions it was observed that triangular membership functions were giving satisfactory results.

3.5.1.1 Fault index input variable:

The fault index is basically the variable which indicates when the fault is occurring. The index is basically a function of time considering the speed of the signal and when it is indicating the fault. The membership function was divided into nine levels, Upper High (UH), Medium High (MH), Lower High (LH), High (H), Medium (M), Low (L), Lower Low (LL), Medium Low (ML), and Upper Low (UL). The membership functions for index are represented in Figure 3.12.

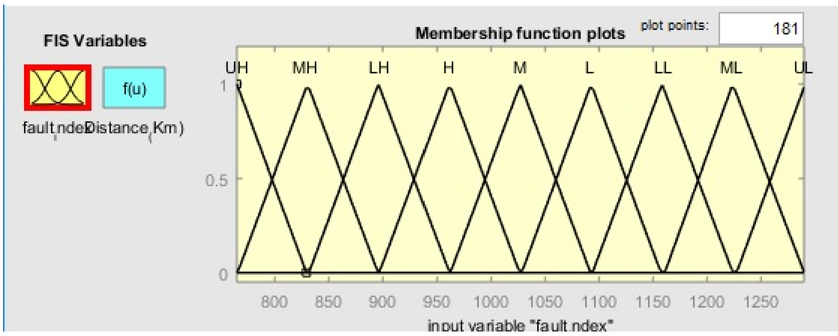

Figure 3.11: Membership Functions for fault index

3.5.2 Formulation of the Rules

Lists of intuitive rules that govern the operation of the ANFIS were made. The system was using hybrid training mechanism under black box to generate the rules. The system managed to generate the rules on its own so as to solve the problem and locate the fault. Contrasting to the conventional control method which uses a mathematical model, the rules are developed in linguistic form of IF–THEN statements. The ANFIS has a single input and single output. The input for the ANFIS is fault index. The universe of discourse for the fault index cover a range of [760, 1300]. A choice of nine membership functions for the input fuzzy variables was chosen. Because it has one input, it means 9 rules in the rule base. These rules were generated automatically by the ANFIS since it used the black box to train the system. The resulting rule are shown below.

The rules can be read as shown below:

1. *If (fault_index is UH) then (Distance_(Km) is MF1)*
2. *If (fault_index is MH) then (Distance_(Km) is MF2)*
3. *If (fault_index is LH) then (Distance_(Km) is MF3)*
4. *If (fault_index is H) then (Distance_(Km) is MF4)*
5. *If (fault_index is M) then (Distance_(Km) is MF5)*
6. *If (fault_index is L) then (Distance_(Km) is MF6)*
7. *If (fault_index is LL) then (Distance_(Km) is MF7)*

8. *If (fault_index is ML) then (Distance_(Km) is MF8)*
9. *If (fault_index is UL) then (Distance_(Km) is MF9)*

The Sugeno-type inference engine was used for defuzzification. Figure 3.13 is showing the rule viewer which was used to identify the fault given the line fault details.

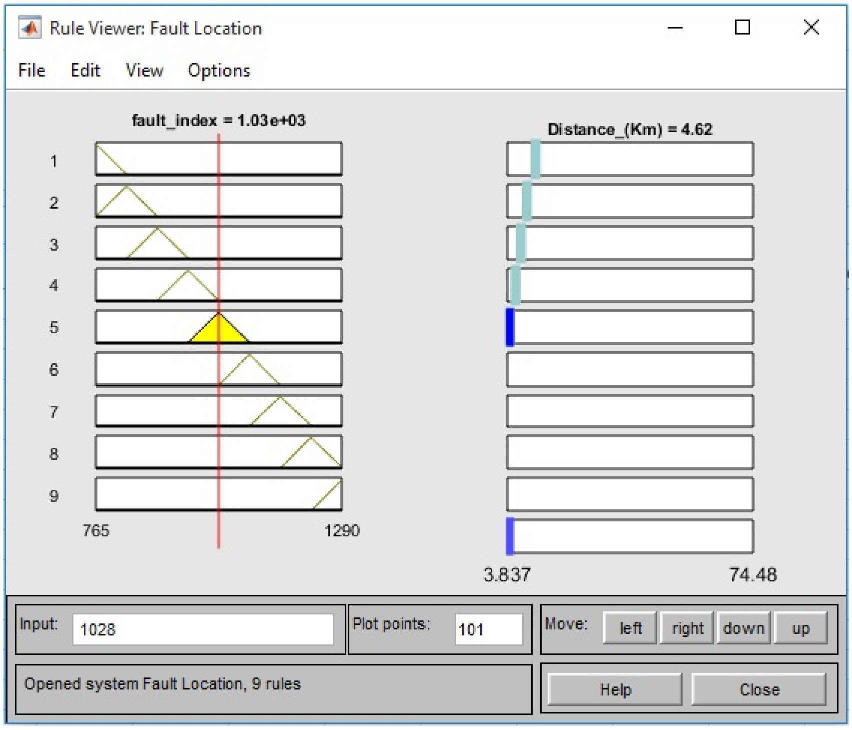

Figure 3.12: Fuzzy Model Rules

3.5.3 Defuzzification

A Sugeno-type fuzzy inference system (FIS) was used in this study. The output of a zero-order model is a smooth function of its input variables as long as the neighboring MFs in the antecedent have enough overlap, and for a first-order fuzzy model, the overall output was obtained via weighted average. Input fuzzy sets and rules are converted into an output fuzzy set, and then into a crisp output for identifying the fault location. Through the firing of ANFIS rules, an output value was decoded by the defuzzifier component to give a crisp value.

3.5.3.1 Fault distance output variable:

The output of the system contained 9 membership functions which were generated by the ANFIS when it was being trained for the fault identification and location. Figure 3.14 shows the structure of the output as seen in MATLAB.

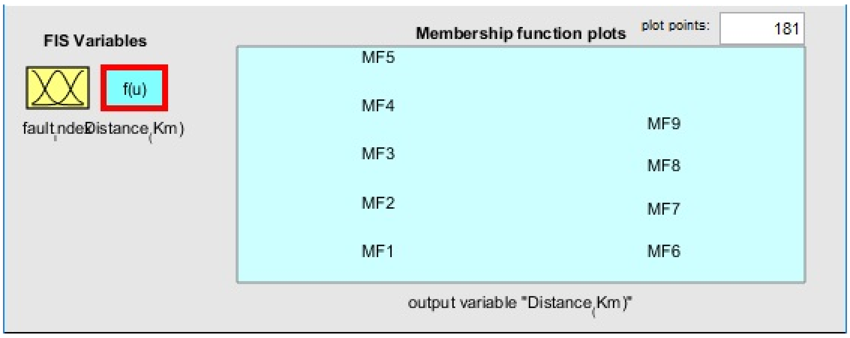

Figure 3.13: Output Membership Functions for distance

CHAPTER 4

RESULTS AND DISCUSSION

This chapter describes the results obtained through transmission line simulation, wavelet transform and ANFIS for fault location. Analysis and evaluation of the results to obtain the accuracy of the system is also presented.

4.1 Fault identification

The results presented in this section, are to identify the type of fault based on the signals obtained from the transmission line.

4.1.1 Normal Condition

Figure 4.1 shows three-phase voltage signals for Line A, Line B and Line C and their detail coefficients at no fault condition. It is observed from Figure 4.1 that at no fault, the amplitude of all the signals is the same and the nature of the wave is smooth. The spike appearing at the beginning of the signal indicates the current initiation stage in the transmission line. The straight line displayed by all the signals shows the time the simulation is initiated until other parameters of the line can identify the initiation stage. If there are no faults on the system, the signals are expected to appear as shown in Figure 4.1.

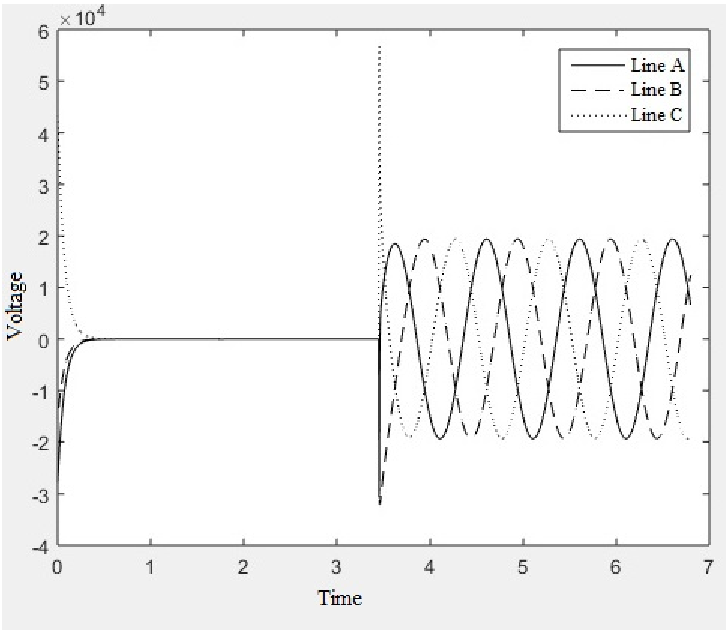

Figure 4.1: Line signals at no fault

4.1.2 Single phase fault

Figure 4.2 shows three-phase voltage signals for Line A, Line B and Line C and their detail coefficients at single phase fault condition. From Figure 4.2, it is observed that Line A has been affected because of the change in the amplitude on the signal and the introduction of the second spike. From the observation, it is deduced that the system has suffered a single phase fault because of the one line which has shown a deviation from the expected. The fault in line A affects the behavior of other lines. This is indicated by the small deviations observed on line B and Line C. Because the system initially started as a balanced three phase system, when one of the lines has been affected, it interferes with the other lines.

Comparing Figure (4.1) and (4.2), apart from the changes in the amplitude, it is observed that there is another spike appearing on Figure (4.2). The straight line displayed by the entire signal represents the initiation time for the simulation. The spike appearing at the beginning of the signal represents the current initiation stage in the transmission line. The second spike indicates the fault location. The fault appears on the system at a specific time which after wavelet analysis shows the location of the fault. Once the fault has been identified the phase to which it had affected, fault data was transferred to wavelet analysis for fault location.

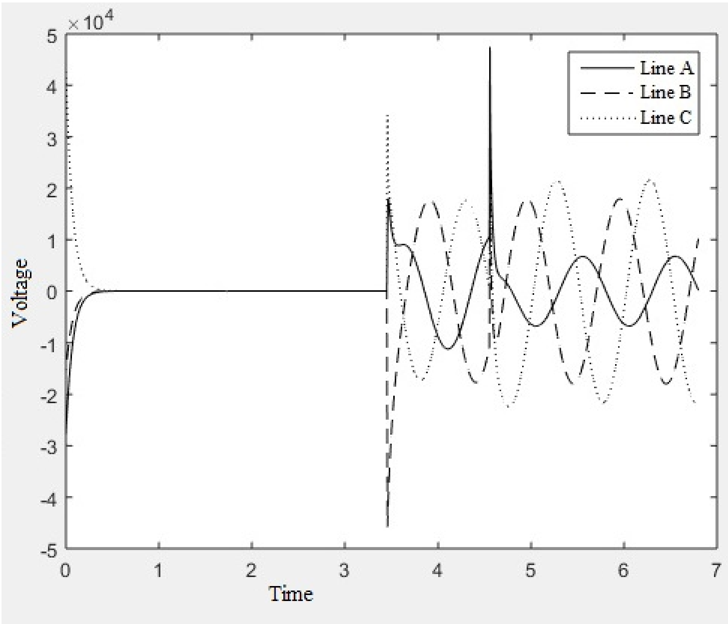

Figure 4.2: Fault identification for single phase fault

4.1.3 Double phase fault

Figure 4.3 shows three-phase voltage signals for Line A, Line B and Line C and their detail coefficients at double phase fault condition. It is observed from Figure 4.3 that Line A and Line B have both been affected because of the change in the amplitude of the two signals for line A and B and the introduction of the second spike. From Figure 4.3, both the amplitudes of Line A and Line B have been affected, indicating a double phase fault and the signals have been merged into one. This indicates that the system has lost its symmetry and the two affected lines are starting to behave the same way, because of the faults in them. Magnitude of signal from line C has been affected because of the faults in the other two lines. This can be observed by small changes observed on line C.

Comparing Figure (4.1) and (4.3) it is observed that there is another longer spike appearing in Figure 4.3. The straight line displayed by all signals represents the initiation time for the simulation. The spike appearing at the beginning of the signal represents the current initiation stage in the transmission line. The second spike indicates the fault initiation stage. The fault appears on the system at a specific time which after wavelet analysis shows the location of the fault. The signal for line C is showing a small increase in the magnitude after every cycle as a result of the effects of the faults on the other two phases. Data from any of the two affected lines was transferred to wavelet analysis for fault location. Line data from the other line, can be used for verification on the fault location.

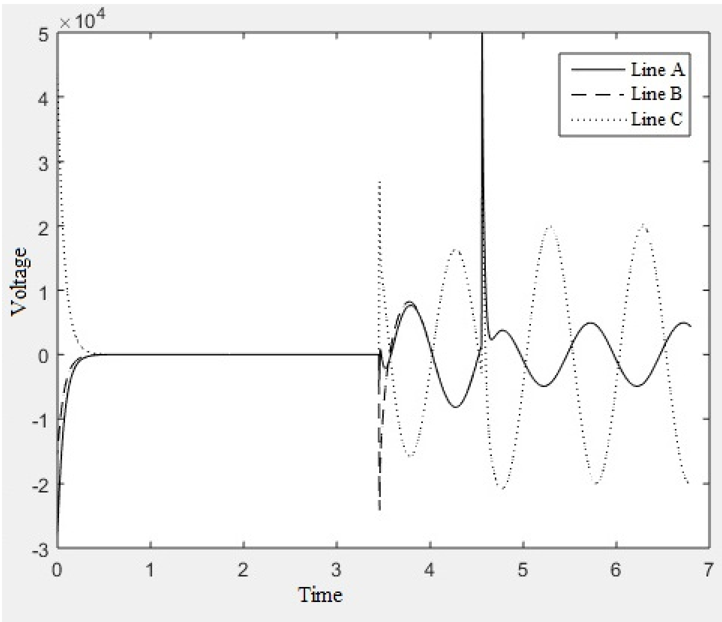

Figure 4.3: Fault identification for double phase fault

4.1.4 Three-phase fault

A three-phase voltage signal for Line A, Line B and Line C and their detail coefficients at three phase fault condition is represented by Figure 4.4. From the figure, it is observed that all the phases have been affected and all signals have been combined together into one straight line, the zero line. No power is being transmitted to the other end because of the nature of the signal. Based on the behavior of the system, it can be concluded that this type of fault is a symmetrical fault because all the lines are behaving the same. The spikes appearing on the figure, indicates the location of the fault. Analyzing the signal under wavelet analysis, the fault can be located using any one of the fault data from the transmission lines.

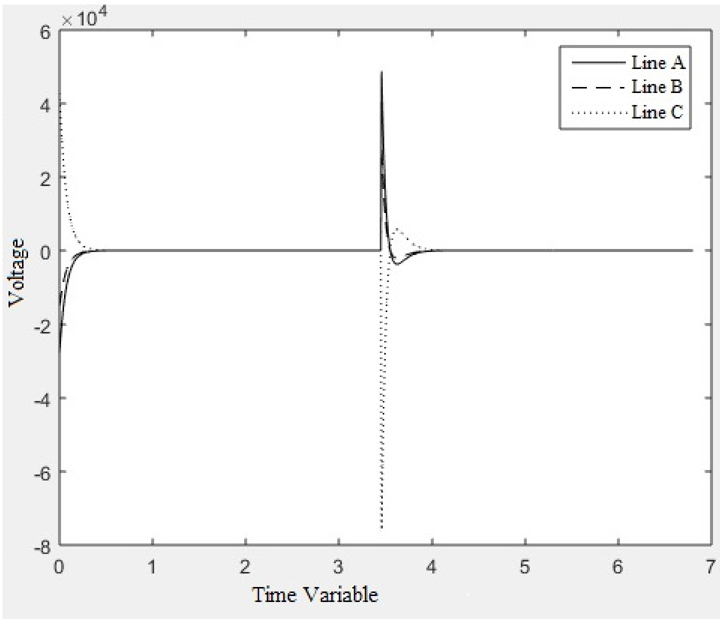

Figure 4.4: Fault identification for three phase fault

4.2 Wavelet transformation

Figure 4.5 shows wavelet transformation for any fault signal obtained from the lines. The signal is analyzed under wavelet analysis to identify where the spikes are occurring and consistent and identify the fault index used in ANFIS for fault location.

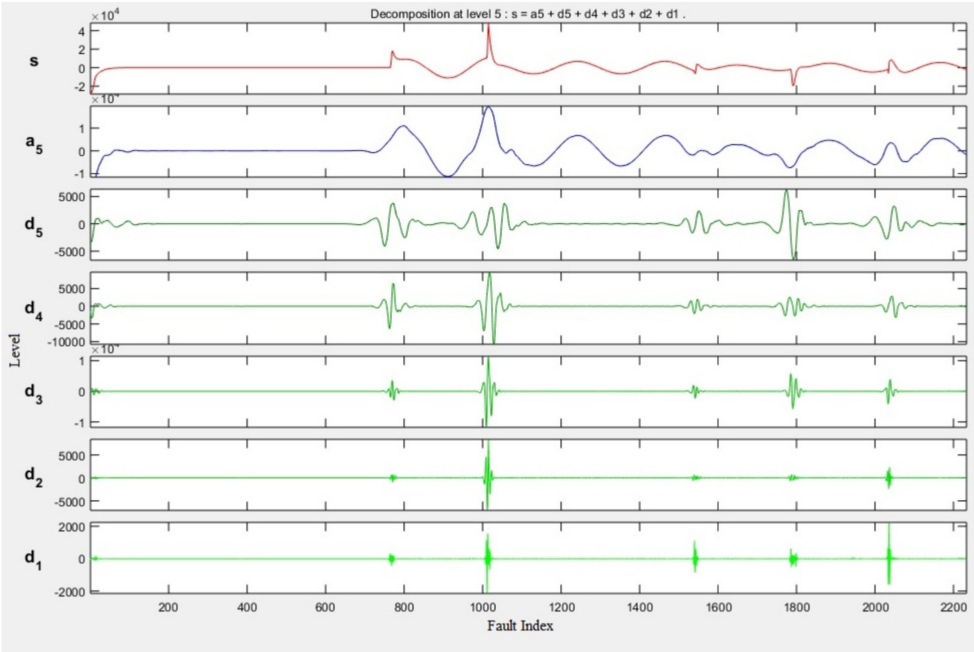

Figure 4.5: Wavelet analysis under DWT

On Figure 4.5, the signal has been analyzed up to level 5 of analysis, indicated by d1 – d5 on the vertical axis of Figure 4.5. The levels indicated by d1 - d5 represents the decomposition levels. On the first decomposition d1, the signal had halved the time resolution since only half of each filter output characterises the signal. At every level, the resolution is twice that of the previous scale. The s in the figure represents the original signal obtained from the underground cable data. The a5 represents the approximate details of the signal at level 5. The numbers at the left side of the figure, represent the magnitude of the fault signal. This is as a result of either the fault current, or the fault resistances or changes in current at the fault location. Since that section was not part of the research scope, not much concentration was given on that area to identify what really contribute to changes in amplitude of the fault signal.

The nature of the plot of detailed coefficients at level 1 reveals a sharp spike which corresponds to the fault initiation process. According to DWT theory, the spikes represent the highest frequency within the fault signal, but it is also however, not practical to identify a fault based on these spike only since such spikes will occur every time there is a sudden change in the cable current signal. So for precise and accurate fault location, all the levels were observed to identify consistency of spike location on all the levels. Under wavelet analysis, the location appeared as an index or number as a result of the partitions within wavelet, instead of the time variable. The index was used in ANFIS to identify the location of the fault. The ANFIS was developed in a way that it makes use of the wavelet index to locate the fault in terms of distance.

4.3 ANFIS for fault location

The ANFIS graphic user interface was obtained for fault location. On the system, the data obtained from wavelet transform was used to identify the location of the fault. To test the efficiency and establish the accuracy of the system, a number of simulations had to be done and identify how the system will perform. Using equation 4.1 to identify the accuracy of the system, Table 4.1 is showing the results of the simulations done at random fault locations selected on the line to establish the accuracy of the ANFIS.

$$\%Error = \frac{(Actual\ distance - calculated\ distance)}{Actual\ distance} * 100 \tag{4.1}$$

Basing on the simulations done, the percentage error of the system is in the range of -5.52 to 3.77%, and the average being = -0.4%

Table 4.1: Test values and error estimation

actual distance (km)	calculated distance (km)	difference (km)	% error
1.45	1.53	-0.08	-5.52
1.96	1.99	-0.03	-1.53
2.03	2.09	-0.06	-2.96
2.65	2.55	0.10	3.77
3.14	3.14	0.00	0.00
3.90	3.90	0.00	0.00
4.21	4.26	-0.05	-1.19
4.73	4.73	0.00	0.00
5.30	5.29	0.01	0.19
5.91	5.91	0.00	0.00
6.43	6.44	-0.01	-0.16
6.68	6.69	-0.01	-0.15
7.32	7.33	-0.01	-0.14
7.56	7.56	0.00	0.00
8.45	8.43	0.02	0.24
8.84	8.83	0.01	0.11
9.30	9.29	0.01	0.11
9.68	9.68	0.00	0.00
Average			**-0.40**

From Table 4.1, it is observed that the general difference between the simulated values and the actual fault locations are around 0.1 or -0.08. If expressed as a percentage error from a specific line segment as shown in Figure 4.6, in other sections, the percentage error is big. The system was generally accurate across different segments of the line as shown in Figure 4.6 with the bottom 3km from the sending end constituting most of the greatest errors as compared to the upper region. On distances less than 3km, the percentage error is large because the overall distance being considered is small. Regardless of the actual error being small, it affects the overall percentage error of the system. Generally the system was showing errors along the whole section of the cable. This is mainly caused by the training data used.

On the training data, after wavelet analysis the index had a very small margin between the two consecutive test values. So when simulating faults which are in between test values, it resulted in a lot of errors because the system was trying to estimate the values, based on the given data. When this happens, it overally affects the accuracy of the system. Since these ranges are as a result of the partitions within the wavelet tool box, it can not be changed. Based on the test values, the system is accurate enough with an accuracy of 99.6% as compared to other techniques ranging from 97.5% to 99%, to be used for fault location and identification.

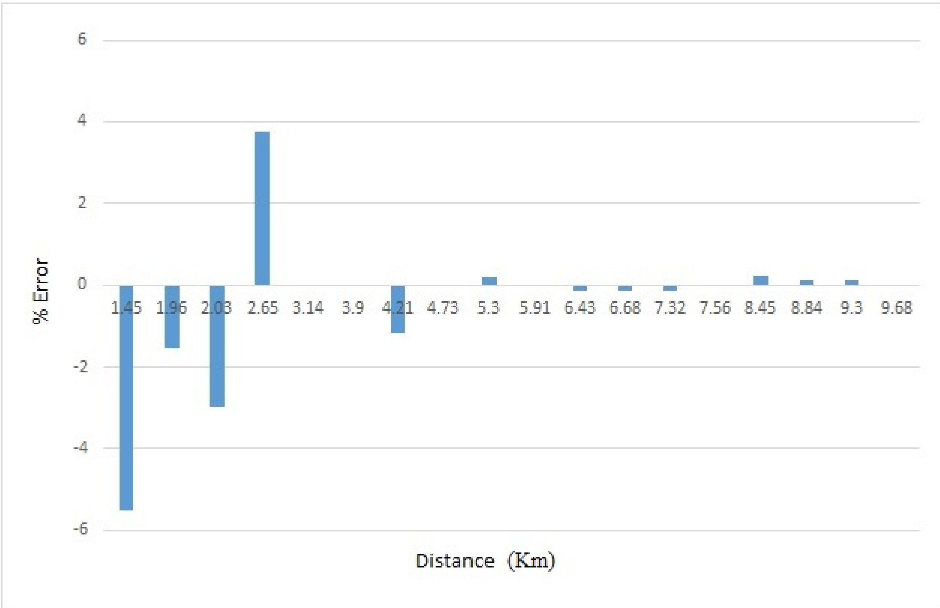

Figure 4.6: Distance and percentage error graph

4.3.1 Fault location at Adjacent fault locations

To evaluate the performance of the system on faults close to one another, simulations were done at different locations, maintaining the same distance between adjacent locations. Table 4.2 shows the simulations carried out from 4.5 – 5.5Km. The location was chosen because it is at the center of the line and leaning same distance from either sides. This was done to see how the system behaves in locations which are close to one another and on either side of the line if divided by half. From the table, it is observed that the range of the faults was between -0.03 to 0.04%, while the average percentage error at that specific line section was 0.036%. It is also noted that the system was showing errors along the whole studied section of the cable. This was as a result of the training data after wavelet analysis, the index had a very small margin between the two consecutive test values. So when simulating faults which are in between the test values, the system resulted in errors because the system was trying to estimate the values, based on the given data. Given any input values, the system has to estimate the fault location based on the data used to create and train the ANFIS. This is clearly shown by Figure 4.7.

Table 4.2: Test values at adjacent fault locations

actual distance (km)	calculated distance (km)	difference (km)	% error
4.50	4.53	-0.03	-0.67
4.60	4.60	0.00	0.00
4.70	4.66	0.04	0.85
4.80	4.78	0.02	0.42
4.90	4.90	0.00	0.00
5.00	5.00	0.00	0.00
5.10	5.11	-0.01	-0.20
5.20	5.21	-0.01	-0.19
5.30	5.29	0.01	0.19
5.40	5.42	-0.02	-0.37
5.50	5.48	0.02	0.36
Average			**0.036**

As shown in Figure 4.7, the accuracy of the system was between -0.67 to 0.85%, while the average percentage error on the analyzed segment was 0.036%. Generally from the test values, the system is accurate enough with an accuracy of around 99.96%.

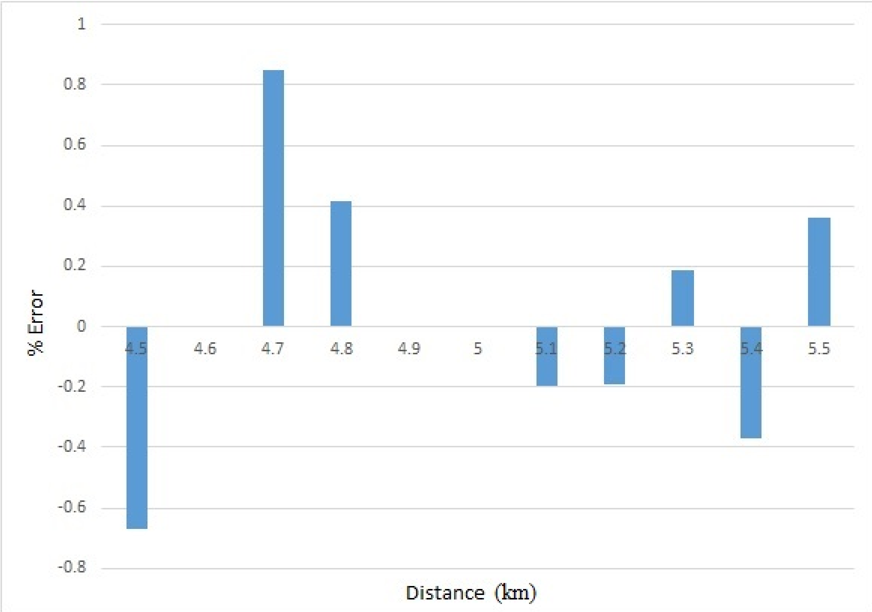

Figure 4.7: Distance and % error graph at adjacent locations

4.4 Evaluation of results

To evaluate the accuracy of the system designed, the results obtained were validated with results obtained by other researchers. However, it is crusial to note that the methods used where different, parameters used were also different and distances used were different.

4.4.1 Evaluation of the proposed methods using percentage errors

To be able to compare the results, overall percentage error of proposed methods by other researchers was used, based on the results achieved. Figure 4.8 shows the results of the comparisons.

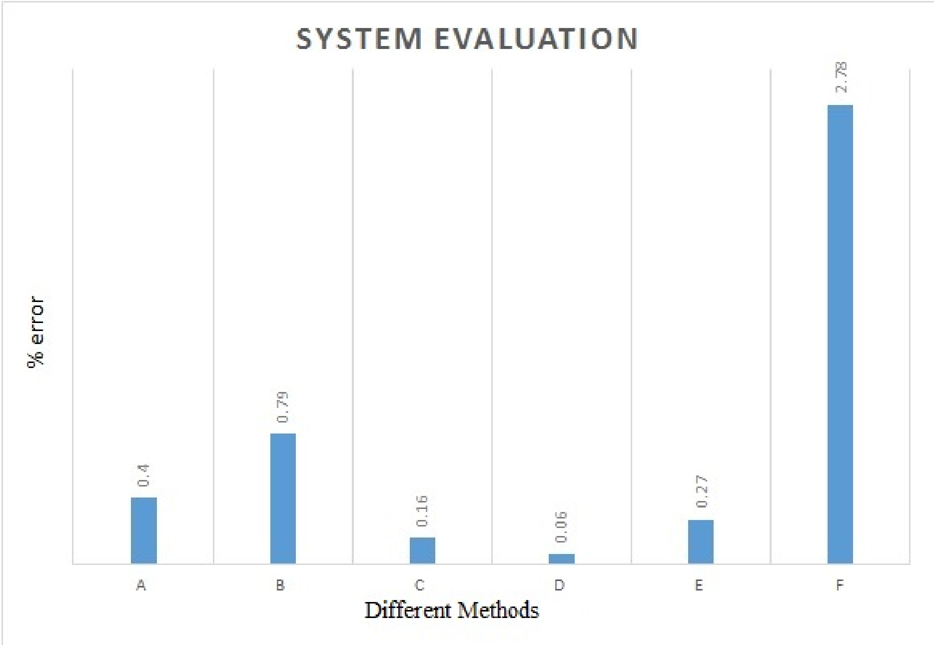

Figure 4.8: Evaluating system accuracy basing on % errors

From Figure 4.8, method A with a percentage error of 0.4%, is the proposed Wavelet-ANFIS technique and the results are considered for a distance of 10km with db4 as the mother wavelet. Whilst 0.79% (B) error was obtained by Barakat [37] after using a distance of 5.375km, fault resistance of 200Ω and an inception angle of 0^0. Basing on traveling wave technique using wavelet analysis and GPS timing, Tabatabaei, et al[21] proposed a pre-measurement method for lg faults, and a percentage error of 0.16% (C) was obtained. They further considered a post-measurement method for lg faults for a distance of 100km and fault resistance of 50Ω, and results obtained was a percentage error of 0.06% (D). Malathi and Marimuthu in[38], suggested a method which made use of vector machine approach for fault location in power transmission line and achieved a percentage error of 0.27% (E) for a distance of 100km, fault resistance of 100Ω and db5 as the mother wavelet. Lastly Adamu and Iliya [39] achieved a percentage error of 2.78% (F) when they considered a distance of 100km and db5 as the mother wavelet in estimating the fault location on power transmission lines using discrete wavelet transform.

It can be concluded that from Figure 4.8, the proposed method (A) is not the most accurate of all the proposed method, but it is competitive and accurate enough to be used for fault location. By addressing the weaknesses shown by the proposed method (A), it is believed that its accuracy can be improved and satisfactorily used in fault location.

4.4.2 Evaluation of the proposed methods using actual distances

To further identify how accurate each method is, a comparison of the actual fault distances was considered so as to identify which distance is terms of error does each system accommodate. this can be shown clearly by Figure 4.9 below.

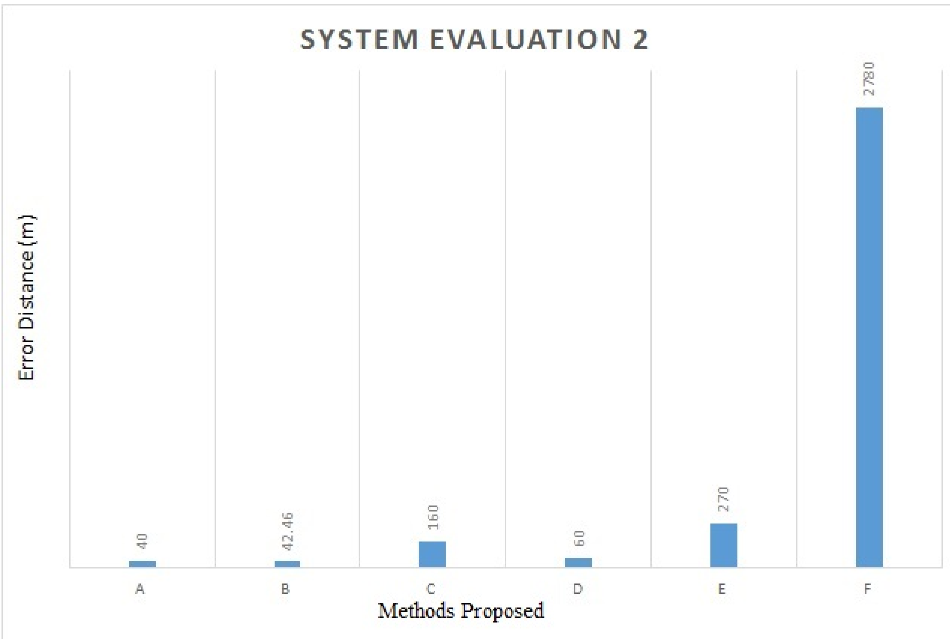

Figure 4.9: Evaluating system accuracy basing on actual distances

The symbols used (A, B, C, D, E, F) in Figure (4.9) represents the same methods discussed in the previous subsection. From figure 4.9, it is observed that the method proposed in this work is more accurate in terms of the error distance.

Therefore in conclusion, the method proposed in this work is competitive enough and accurate enough to be used for fault location.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Simulations for the transmission line for 34.5kV, 10km underground power cable was performed using MATLAB/SIMULINK. In this work, the proposed method used wavelet decomposition which provided more features about the signal. The most suitable wavelet family was made to identify fault type and estimate the fault location on the transmission line. It was found that better results were achieved using Daubechies 'db4' wavelet. The extracted information about the signal was used to develop an Adaptive Neuro-Fuzzy Inference System (ANFIS) which was later used to identify the fault location. The ANFIS was able to locate the fault with an accuracy of 99.6%. The main aim of this study was to develop a method for fault location and identification for underground power cables based on wavelet-ANFIS technique. Performance of Adaptive-Neuro Fuzzy Inference System in fault location was assessed and results were obtained. Finally it was shown that the proposed method is accurate enough to be used in detection of transmission line faults.

5.2 Recommendations

It was noted from simulation results that the system was experiencing a number of errors along the whole length of the cable. This was as a result of the training data used. As can be seen from the appendix, the training data had a small margin between consecutive fault lengths. This will automatically lead to many errors when we want to investigate faults in between test values. This however can not be fixed using the proposed design, but if it can be changed or modified, to address the problem more accurately.

The system however failed to identify the differences between Line to line faults and Line to Line to Ground faults. when carrying out simulations, the system was producing the same waveform, which made it difficult to differentiate between the two types of faults. There is need for further investigation to address the fault error, so that the system can work better.

We also recommend further research to focus more on how the faults develop and how they affect the system so that a predictive fault location system can be improved to help the power utility and the consumers manage the use of their equipment and reduce losses to both parties.

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APPENDIX A

ANFIS TRAINING DATA

fault index	distance (Km)
1290	0.1
1256	0.2
1256	0.3
1255	0.4
1238	0.5
1238	0.6
1238	0.7
1238	0.8
1238	0.9
1238	1.0
1219	1.1
1219	1.2
1203	1.3
1202	1.4
1192	1.5
1186	1.6
1186	1.7
1176	1.8
1172	1.9
1164	2.0
1163	2.1

1157	2.2
1151	2.3
1143	2.4
1134	2.5
1134	2.6
1126	2.7
1120	2.8
1114	2.9
1113	3.0
1107	3.1
1098	3.2
1094	3.3
1088	3.4
1086	3.5
1079	3.6
1078	3.7
1074	3.8
1067	3.9
1064	4.0
1059	4.1
1055	4.2
1047	4.3
1043	4.4
1037	4.5
1033	4.6
1030	4.7

1023	4.8
1016	4.9
1010	5.0
1003	5.1
997	5.2
993	5.3
987	5.4
984	5.5
978	5.6
973	5.7
968	5.8
964	5.9
959	6.0
954	6.1
959	6.2
954	6.3
949	6.4
934	6.5
930	6.6
924	6.7
920	6.8
914	6.9
910	7.0
905	7.1
901	7.2
896	7.3

890	7.4
885	7.5
881	7.6
876	7.7
870	7.8
865	7.9
861	8.0
856	8.1
851	8.2
846	8.3
841	8.4
837	8.5
832	8.6
827	8.7
821	8.8
817	8.9
812	9.0
808	9.1
802	9.2
798	9.3
790	9.4
788	9.5
783	9.6
779	9.7
773	9.8
765	9.9