B. TECH. PROJECT REPORT

On

Detection and Classification of Faults in Power Systems

BY

Arpit Nama
130002004

DISCIPLINE OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY INDORE

December 2016

Detection and Classification of Faults in Power Systems

A PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degrees

of

BACHELOR OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

Submitted by:

Arpit Nama (130002004)

Guided by:

Dr. Trapti Jain,

Assistant Professor,

Electrical Engineering

INDIAN INSTITUTE OF TECHNOLOGY INDORE

December 2016

CANDIDATE'S DECLARATION

I hereby declare that the project entitled "**Detection and Classification of Faults in Power Systems"** submitted in partial fulfilment for the award of the degree of Bachelor of Technology in Electrical Engineering completed under the supervision of **Dr. Trapti Jain, Assistant Professor, Department of Electrical Engineering,** IIT Indore is an authentic work.

Further, I declare that I have not submitted this work for the award of any other degree elsewhere.

Arpit Nama
B.Tech. IV Year
Discipline of Electrical Engineering
Date- 5th December 2016

CERTIFICATE by BTP Guide

It is certified that the above statement made by the student is correct to the best of my knowledge.

Dr. Trapti Jain
Assistant Professor
Discipline of Electrical Engineering
Indian Institute of Technology, Indore
Date- 5th December 2016

Preface

This report on “Detection and Classification of Faults in Power Systems" is prepared under the guidance of Dr. Trapti Jain, Assistant Professor, Electrical Engineering, IIT Indore.

Through this report, I have tried to provide a brief description of the technologies that have been already used to detect and classify the faults in a power system. I have also tried to produce an efficient novel algorithm for classification which will be suitable to use for online detection. I have tried and tested the same on variable datasets. Further, I have designed the algorithm using a rule based classification tree corresponding to the same. I have also tried to implement this proposed algorithm to the best of my abilities.

I have tried to the best of my abilities and knowledge to explain the proposed algorithms in detail. The comparison of proposed algorithm with already existing models is also discussed. I have also added plots and figures to make it more illustrative.

Arpit Nama
B.Tech. IV Year
Discipline of Electrical Engineering
IIT Indore

Acknowledgements

I would like to express my sincere gratitude to my guide, Dr. Trapti Jain for giving me the opportunity to work on this project. Her timely guidance and invaluable suggestions were extremely helpful throughout the course of the project.

I would like to extend my gratitude to Mr. Karthik Thirumala and Mr. E.S.N. Raju for giving us their valuable time in the useful academic discussions I have had with them.

I am also extremely thankful to Ms. Surbhi Goyal, my family and other friends of mine for helping with their constant support and motivation during the entire period of this project work.

Arpit Nama

B.Tech. IV Year

Discipline of Electrical Engineering

IIT Indore

Abstract

Power transmission is a major issue in Electrical Engineering after Power generation. Fault in transmission lines is common and major problem to deal with in this stream. Here, a technique is presented to detect and classify the different faults on a transmission lines for quick and reliable operation of protection schemes. MATLAB software is used to simulate different operating and fault conditions on high voltage transmission line, namely single phase to ground fault, line to line fault, double line to ground fault and three phase short circuit fault. Effects of variations in the fault resistance, distance to fault have been studied broadly on the current of the system which creates the logic for detection and classification of faults. Thus, accurate and advanced tools and techniques are required to identify and classify these faults. This work proposes a detection and classification technique for several faults.

In this work decision tree has been proposed for accurate detection and classification of various faults. Firstly, the signal is analyzed using Empirical Wavelet Transform to obtain its mono-frequency components. The decomposed fundamental signals are utilized to extract features based on energies ratio. Based on features, decision tree is designed for classification of most significant types of faults of Transmission lines accurately. All the computations are performed using the highly efficient computation tool MATLAB.

Table of Contents

List of Figures

List of Table

Chapter 1

Introduction

1.1 Electrical Faults

Modern power systems involve large amount of investment. An electric power system comprises of generation, transmission, and distribution of electric energy. Growth of power systems has led to very complex networks extended across large areas. In such situations, the proper functioning of a modern power system is heavily dependent upon the healthy operation of the transmission lines within it. Transmission lines are used to transmit a huge amount of power over a long distance. But as these lines are located in the open atmosphere, they are highly affected by different types of abnormal conditions or faults. Therefore, they are very likely to be subjected to different types of electrical faults. If the faults are not detected and removed quickly then, in the worst case, they may create instability of the power system, resulting in the shutdown of either the large parts of the network or the complete network. The causes and the consequences of faults can be minimized by operating the power system in a proper way and using sophisticated protective relays. It is desirable that this protection system must be able to identify different types of faulty conditions within a minimum possible time delay.

Power transmission is a major concern in Electrical Engineering after power generation. Faults in transmission lines are common and are major problem to deal with in this field. Transmission line protection is an important issue in power system engineering because 85-87% of power system faults are occurring in transmission lines. Transmission line relaying involves three major parts: detection, classification and localization of the fault. It must be done as fast and accurate as possible to de-energize the faulted line, protecting the system from the harmful effects of the fault.

Short circuit faults are most probable and severe faults in a 3-phase transmission line. Possible short circuit faults are L-G faults, LL faults, LL-G faults, LLL fault and LLL-G fault. LLL and LLL-G faults are symmetric faults.

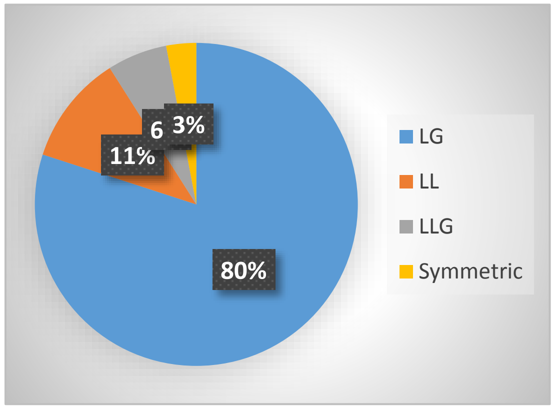

Figure 1.1 Frequency of occurrence of faults (Practically)

Causes of electrical faults

- Weather conditions
- Human errors
- Equipment failures
- Smoke of fires

Effects of electrical faults

- Over current flow
- Loss of equipment
- Electrical fires
- Danger to operating personnel
- Disturbs interconnected active circuits

1.2 Signal Processing Techniques

To analyze these faults, data are often available as a form of sampled time function that is represented by a time series of amplitudes. When dealing with such data, the Fourier transform (FT)-based approach is most often used. FT provides the frequency information; however, it is not capable of providing time information about signal disturbances. For instance, time-frequency information related to disturbance waveforms can be obtained by using the STFT, but transient signals cannot be adequately described with this transform due to a fixed window size and it suffers severely from the Heisenberg uncertainty principle, causing it to undergo a "trade-off" between time resolution and frequency resolution. To overcome the drawback of STFT, the WT provides the time-scale analysis of the non-stationary signal since it decomposes the signal into time-scale representation rather than time-frequency representation.

This is one of the reasons for the creation of the wavelet transform (or multiresolution analysis in general), which can give good time resolution for high-frequency events, and good frequency resolution for low frequency events, which is the type of analysis best suited for many real signals. Wavelet transform, which is a popular signal analysis method, offers continuous and discrete wavelet transforms (CWT and DWT) and wavelet packet transform (WPT) for the feature extraction of signals. The analysis of a signal with the discrete wavelet transform (DWT) or the wavelet packet transform (WPT) requires a proper selection of mother wavelet, decomposition levels, and sampling frequency. The selection of these parameters, along with a suitable choice of a mother wavelet, differs for the signals containing different frequency components and this limits the application of WT and WPT to analyze real-time non-stationary signals. To overcome these drawbacks, various adaptive techniques have been proposed, such as the Empirical Mode Decomposition, S-transform and recursive Newton-type algorithm, to analyze stationary and nonstationary signals. Recent contributions have extended the concepts to hybrid methods using DFT and parametric methods. Parametric methods such as Prony, Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT), Multiple Signal Classification (MUSIC), etc., have been used to estimate the harmonics.

In August 2013, a new approach, empirical wavelet transform (EWT), has been proposed by Gilles to build a family of adaptive wavelets capable of extracting different components of a signal. This method has an advantage of adaptability according to the analyzed signal and can isolate the different modes of the signal. EWT has been employed in this work.

1.3 Soft Computing Tools

The proper diagnosis of power faults problems requires a high level of engineering expertise. New and powerful tools for the analysis and diagnosis of power faults are currently available. They can be categorized as supervised or unsupervised. Many of the available tools of interest are those based on rule-based classification, decision-tree based, Bayes Classifier, Artificial Neural Network, fuzzy logic and support vector machine etc.

1.4 Outline of Projects Tasks

- To generate different power faults of Transmission lines
- To decompose the signal using Empirical Wavelet Transform
- To model a faults detection system using Decision Tree
- Classification of various faults

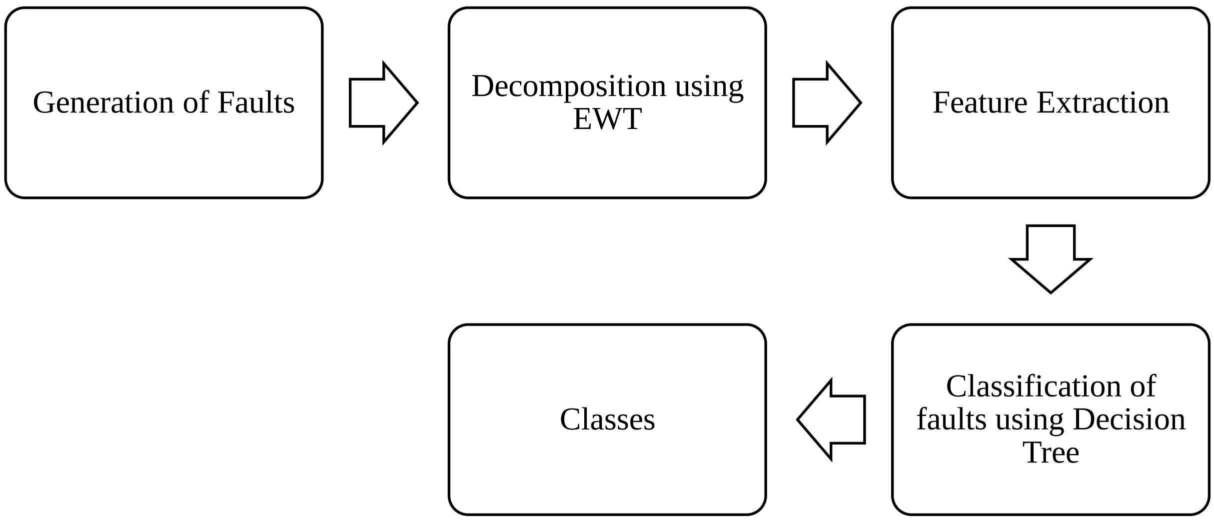

Figure 1.2

1.5 Organization of Project Report

Chapter 2 describes the mechanism of Empirical Wavelet Transform in detail, followed by step-wise explanation of the stages involved in a EWT which has been employed in this work.

Chapter 3 mentions the various short circuit faults in transmission lines of power systems that are considered in this work, with their introduction.

Chapter 4 . Feature extraction comprises of EWT analysis to decompose the fault signal into the mono-components. Parameters extraction is presented using the decomposed signals. This is followed by the proposed features, along with the motivation behind using them.. The extracted features are used for preparing the database of different power Systems faults to be used for training of the classifier for modelling a faults detection system.

Chapter 5 gives a literature review of the classifier employed in this work. This is followed by the description of the proposed methodology for modelling a faults detection system.

Chapter 6 presents the classification results.

Chapter 7 concludes the work.

Chapter 2

Empirical Wavelet Transform

2.1 Description

EWT is a newly proposed technique to adaptively detect the different modes of the signal and accordingly build the empirical wavelets to represent the signal by different modes detected. Empirical wavelets means building a set of wavelets adapted to the processed signal, i.e. in Fourier domain means building a set of band-pass filters. Adaptation here lies in detecting filter's supports according to the information located in the processed signal. Modes can be thought of as the principal components (referred to as amplitude modulated-frequency modulated (AM-FM) components) of the signal which represent the signal completely. Following are the steps involved in EWT – Fourier transform and segmentation, filter construction, and empirical transform.

The adaptability in this transform is provided by the segmentation of Fourier axis. Segmentation of Fourier axis is done in a way so as to separate different portions of spectrum which correspond to modes that are centered around a specific frequency and of compact support. To find such boundaries we find (N-1) local maximas in the Fourier Spectrum. For this set of maximas along with 0 and π, we define boundaries ω_n of each segment as the center between two consecutive maximas, where $\omega_0 = 0$ and $\omega_n = \pi$. Each segment is denoted as $A_n = [\ \omega_{n-1} : \omega_n\ ]$. Centred around each ω_n, we define a transition phase T_n of width $2\gamma\omega_n$ where γ is chosen according to the properties of intrinsic mode function (IMF) to get a tight frame, from γ is given in Eq. (2.1).

$$\gamma = \min_n \left(\frac{\omega_{n+1} + \omega_n}{\omega_{n+1} - \omega_n}\right) \tag{2.1}$$

By utilizing the idea used in the construction of Littlewood–Paley and Meyer's wavelets, a set of band-pass filters or empirical wavelets is constructed. Empirical scaling function $\hat{\Phi}_n(\omega)$ and empirical wavelet function $\hat{\psi}_n(\omega)$ used for the EWT are as given in literature.

The detailed coefficients $\omega^{\varepsilon}_{f}(n, t)$ obtained by EWT, as given in Eq. (2.2), are defined by the inner products with the empirical wavelets.

$$w^{\in}_{f}(n, t) = f, \psi_n = \int f(\tau)\overline{\psi_n(\tau - t)}\, d\tau \tag{2.2}$$

And the approximation coefficients $w^{\in}_{f}(0, t)$, given in Eq. (2.3), are defined by inner product with the scaling function.

$$w^{\in}_{f}(n, t) = f, \phi_n = \int f(\tau)\overline{\phi_n(\tau - t)}\, d\tau \tag{2.3}$$

And the reconstructed signal $\overline{f(t)}$ is obtained by the following equation:

$$\overline{f(t)} = w^{\in}_{f}(0,t) * \phi_1(t) + \sum w^{\in}_{f}(n, t) \times \psi_n(t) \tag{2.4}$$

2.2 Working of EWT

The empirical wavelet transform, proposed by Gilles detects the boundaries of the frequency components in Fourier spectrum and build the wavelet filter accordingly to extract the different modes of the signal.

The segmentation of Fourier spectrum need not be pre-defined, but chosen according to the analysed signal information, providing adaptiveness to the EWT.

A flowchart is shown on the next page that describes the working of EWT.

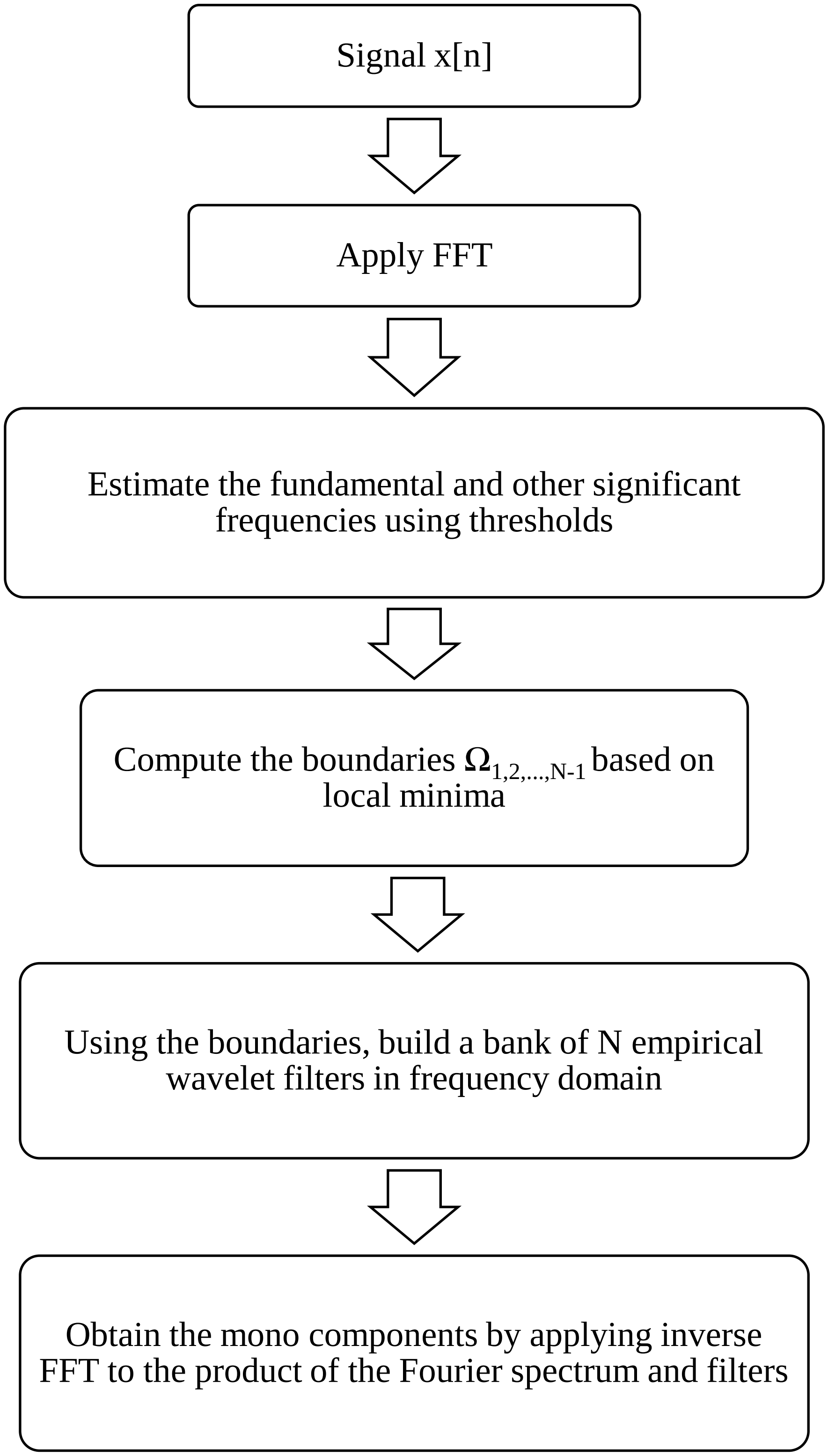

Figure 2.1 Flow chart

Example for finding mono frequency components using EWT :

Step 1 :
The frequencies of the signal $x\ [k]$ have been estimated by computing the Fast Fourier Transform (FFT) of the original signal. Figure 2.2 shows the FFT Spectrum.

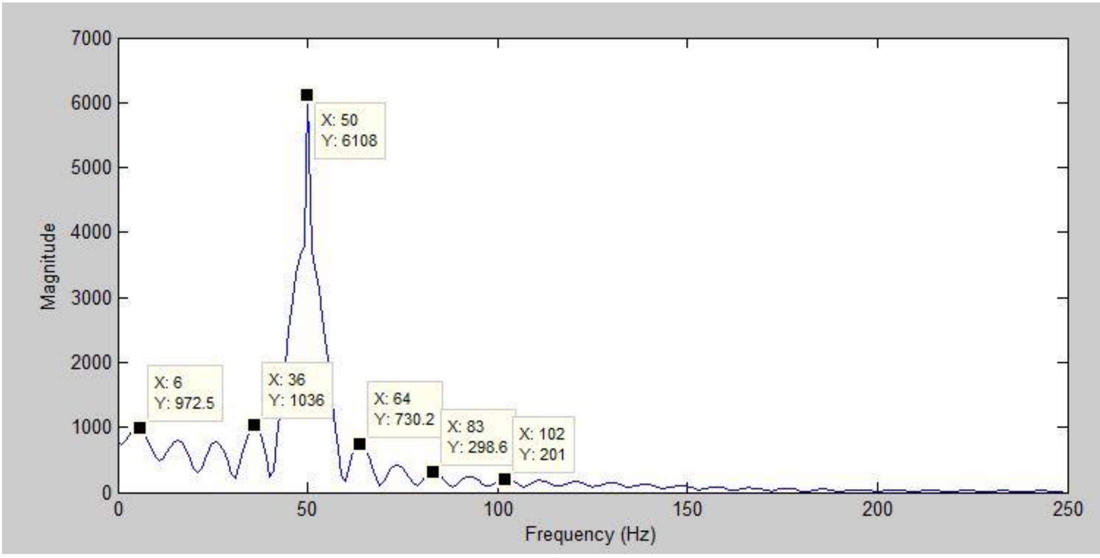

Figure 2.2 Estimated Frequency Spectrum

Step 2:
Frequencies fundamental as well as others are estimated. This has been achieved from the original Fourier spectrum X(ω) by defining magnitude and frequency separation thresholds. The magnitude threshold is set to 2% of the fundamental frequency magnitude and the threshold for minimum frequency separation is specified as 10 Hz.

f = {6 36 50 64 83 102 121 138} Hz

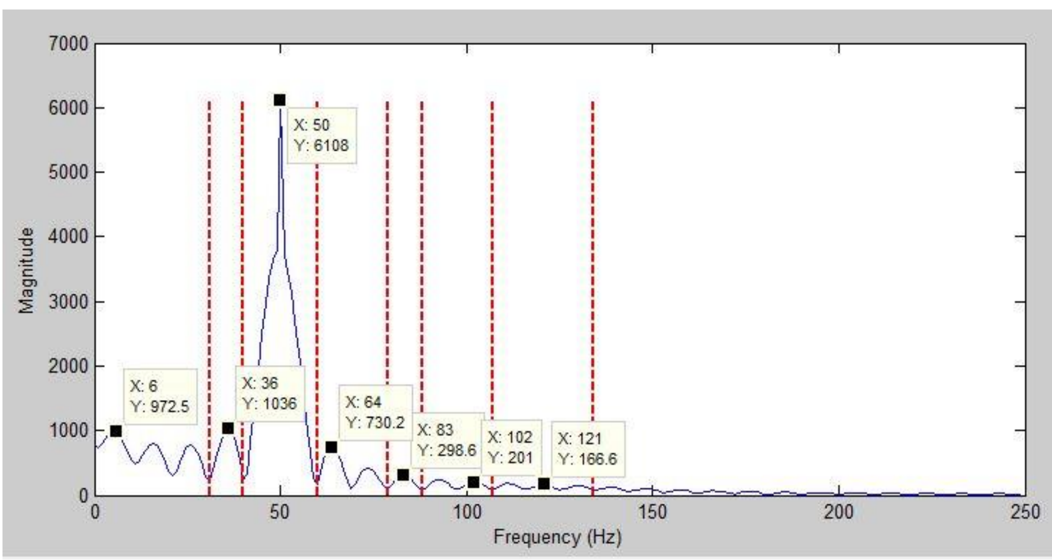

Figure 2.3 Segmented Fourier Spectrum

Step 3:
Then, the segmentation of the Fourier spectrum $[0, f_s/2]$ is done by defining boundaries for each estimated frequency, f_i. The boundaries Ωi are the local minima between two consecutive frequencies f_i, f_{i+1} as shown in figure 2.3.

Step 4:
Assuming $\Omega_o = 0$ and $\Omega_N = f_s/2$, the Fourier segments will be $[0, \Omega_1]$, $[\Omega_1, \Omega_2]$,…, $[\Omega_N, fs/2]$. Based on the boundaries computed, one low-pass filter and N-1 band-pass filters, corresponding to scaling function $\Phi(\omega)$ and wavelet function $\psi_i(\omega)$, respectively, are defined in the frequency domain as shown in (2.5) and (2.6).

$$\Phi(\omega) = \begin{Bmatrix} 1 & if|\omega| \leq (1-\gamma)\Omega_1 \\ \cos\left(\frac{\pi}{2}\beta(\Upsilon, \omega, \Omega_1)\right) & if(1-\Upsilon)\Omega_1 \leq |\omega| \leq (1+\gamma)\Omega_1 \\ 0 & otherwise \end{Bmatrix} \tag{2.5}$$

$$\psi_i(\omega) = \begin{Bmatrix} 1 & if(1+\gamma)\Omega_i \leq |\omega| \leq (1-\gamma)\Omega_{i+1} \\ \cos\left(\left(\frac{\pi}{2}\right)\beta(\gamma, \omega, \Omega_{i+1})\right) & if\ (1-\gamma)\Omega_{i+1} \leq |\omega| \leq (1+\gamma)\Omega_{i+1} \\ \sin\left(\left(\frac{\pi}{2}\right)\beta(\gamma, \omega, \Omega_i)\right) & if\ (1-\gamma)\Omega_i \leq |\omega| \leq (1+\gamma)\Omega_i \\ 0 & otherwise \end{Bmatrix} \tag{2.6}$$

where, $\beta(\gamma, \Omega_i) = \beta(1/2\gamma\Omega_i(|\omega| - (1-\gamma)\,\Omega_i))$ is an arbitrary function fulfilling the following properties

$$\beta(\gamma, \omega, \Omega) = \begin{Bmatrix} 0 & if\ \left(\frac{1}{2\gamma}(|\omega| - (1-\gamma)\Omega)\right) \leq 0 \\ 1 & if\ \left(\frac{1}{2\gamma}(|\omega| - (1-\gamma)\Omega)\right) \geq 1 \\ \beta(\gamma, \omega, \Omega) + \beta\big(1 - (\gamma, \omega, \Omega)\big) = 1 & if\ \left(\frac{1}{2\gamma}(|\omega| - (1-\gamma)\Omega)\right) \in [0,1] \end{Bmatrix} \tag{2.7}$$

The parameter γ ensures no overlap between the two consecutive transition areas.

Since the scaling and empirical wavelet functions are adaptive and the modes extracted contain only one frequency component, this technique can be used for decomposing the fault signal.

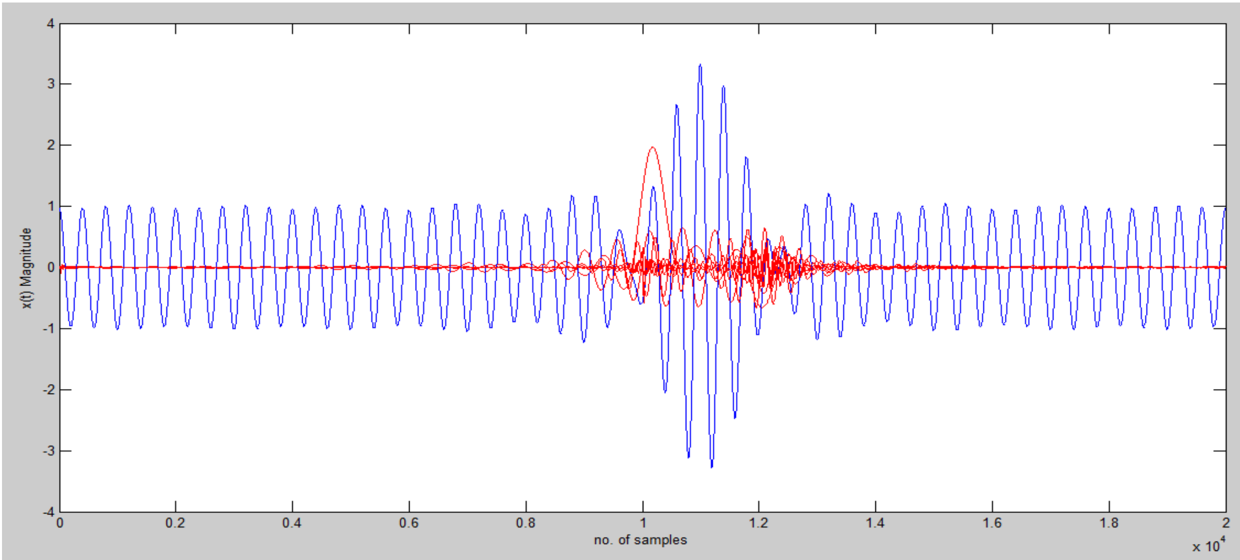

Figure 2.4 Extracted mono frequency signals

.

After taking the inverse FFT of decomposed mono frequencies components, we get different mono frequency signals, as shown in figure 2.4. Here, Blue waveform represents the fundamental frequency waveform of the faulted phase of that signal which is used for example purpose. In fundamental frequency waveform, amplitude variation is observed in a particular interval. This shows, there is fault in that phase and that interval is fault duration. And disturbance (other frequencies components) is also observed in the fault duration. By these characteristics, we can use this technique in detection and classification of faults in power systems.

Chapter 3

Electrical Faults

Electrical fault is the deviation of voltages and currents from nominal values or states. Under normal operating conditions, power system equipment or lines carry normal voltages and currents which results in a safer operation of the system.

But when fault occurs, it causes excessively high currents to flow which causes the damage to equipments and devices. Fault detection and classification is necessary to select or design suitable switchgear equipments, electromechanical relays, circuit breakers and other protection devices.

There are mainly two types of faults in the electrical power system. Those are symmetrical and unsymmetrical faults.

1.Symmetrical faults

These are very severe faults and occur infrequently in the power systems. These are also called as balanced faults and are of two types namely line to line to line to ground (L-L-L-G) and line to line to line (L-L-L).

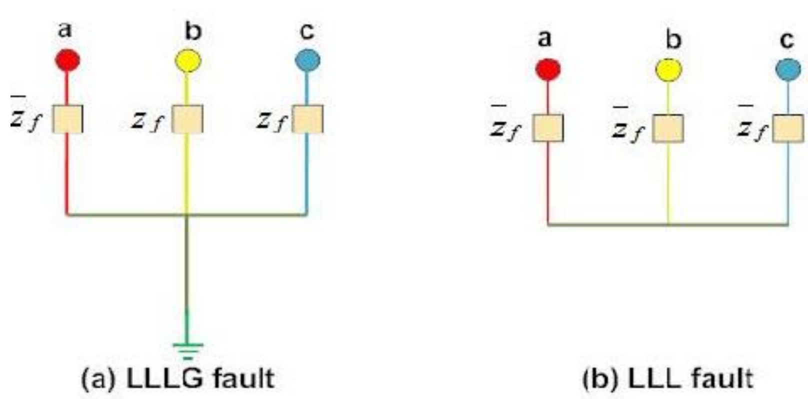

Figure 3.1 Symmetrical faults

Only 2-5 percent of system faults are symmetrical faults. If these faults occur, system remains balanced but results in severe damage to the electrical power system equipments.

Above figure shows two types of three phase symmetrical faults. Analysis of these fault is easy and usually carried by per phase basis. Three phase fault analysis or information is required for selecting set-phase relays, rupturing capacity of the circuit breakers and rating of the protective switchgear.

2.Unsymmetrical faults

These are very common and less severe than symmetrical faults. There are mainly three types namely line to ground (L-G), line to line (L-L) and double line to ground (LL-G) faults.

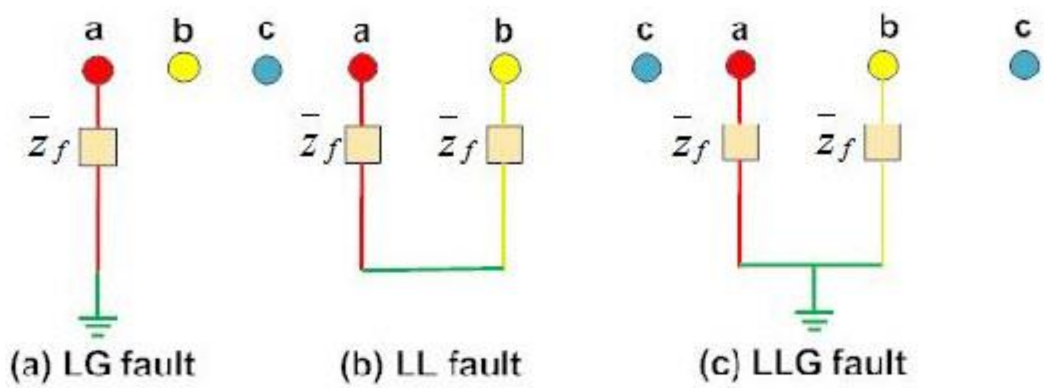

Figure 3.2 Unsymmetrical faults

Line to ground fault (L-G) is most common fault and 65-70 percent of faults are of this type. It causes the conductor to make contact with earth or ground. 15 to 20 percent of faults are double line to ground and causes the two conductors to make contact with ground. Line to line faults occur when two conductors make contact with each other mainly while swinging of lines due to winds and 5- 10 percent of the faults are of this type. Table 3.1 presents the occurrence of faults.

These are also called unbalanced faults since their occurrence causes unbalance in the system. Unbalance of the system means that that impedance values are different in each phase causing unbalance current to flow in the phases. These are more difficult to analyze and are carried by per phase basis similar to three phase balanced faults.

Table 3.1 Occurrence of faults

Faults	Occurrence
LG faults	65%-70%
LLG faults	15%-20%
LL faults	5%-10%
3-Ø faults	5%

Current waveforms for different faults is shown below :

1. No fault

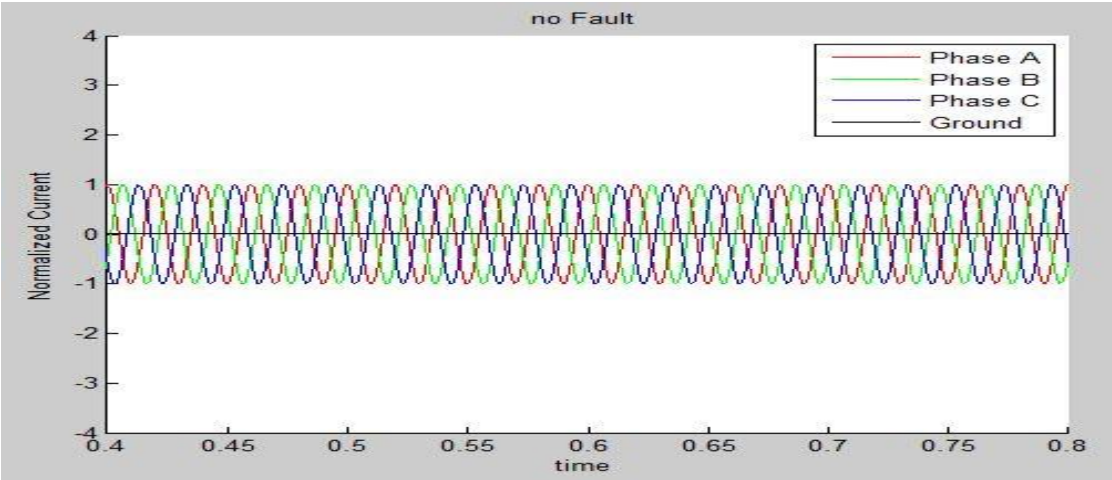

Figure 3.3

2. AG fault

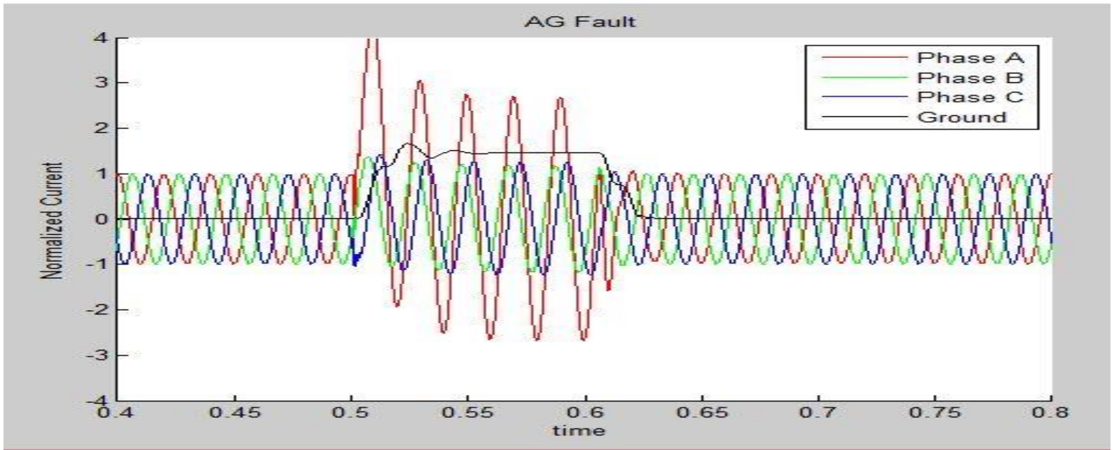

Figure 3.4

3. BG fault

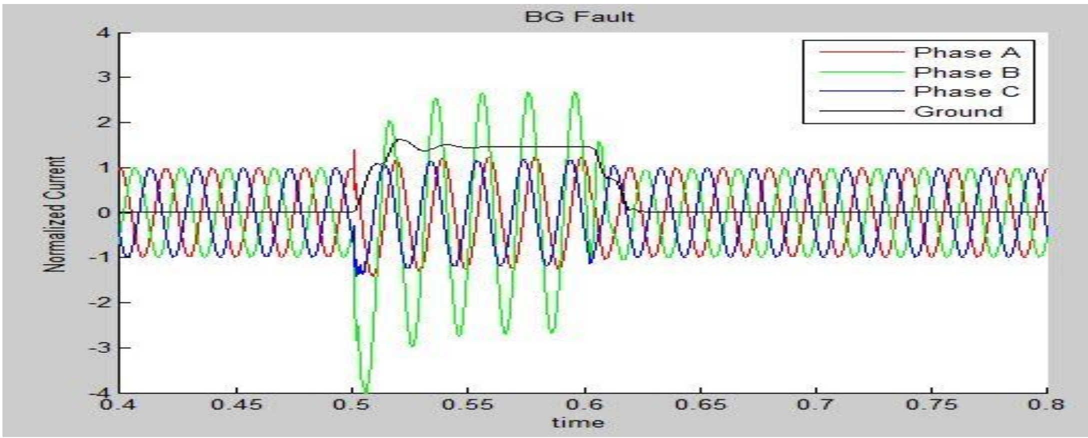

Figure 3.5

4. CG fault

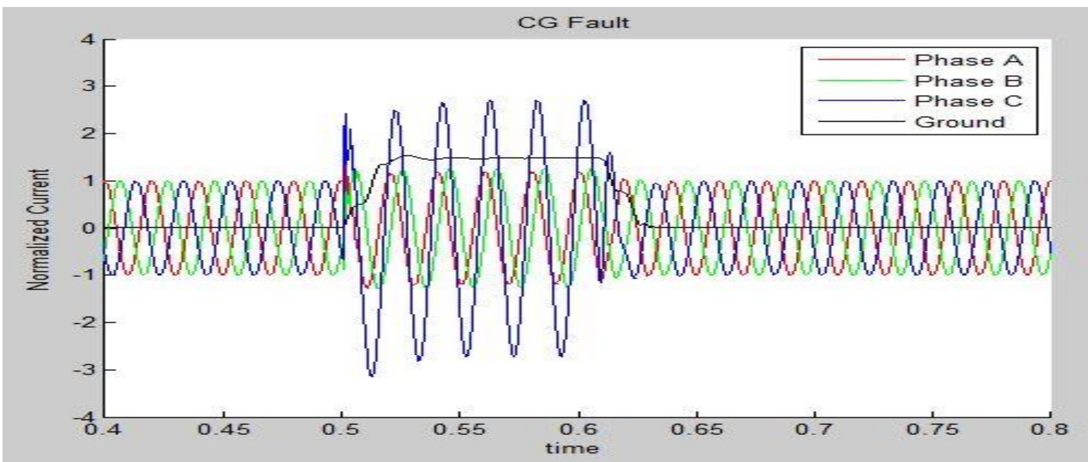

Figure 3.6

5. AB fault

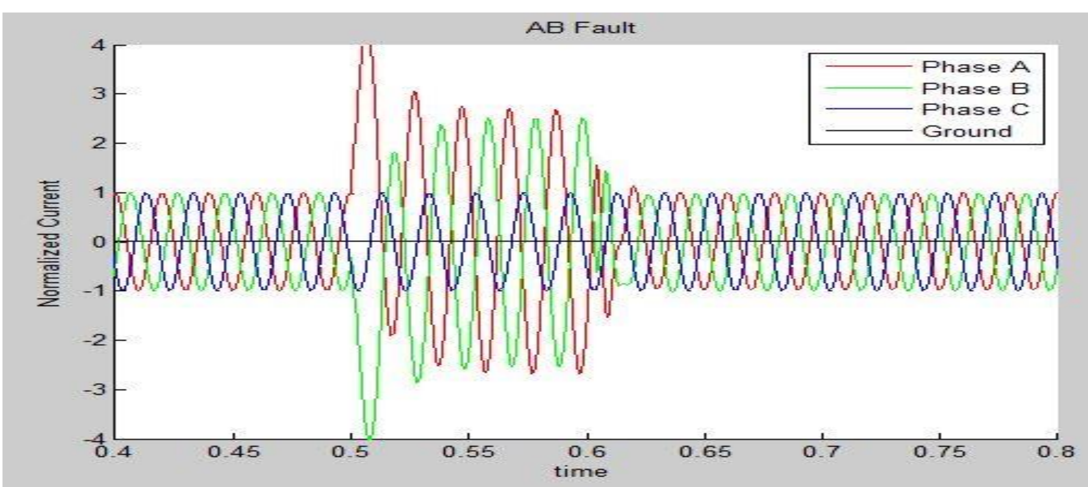

Figure 3.7

6. BC fault

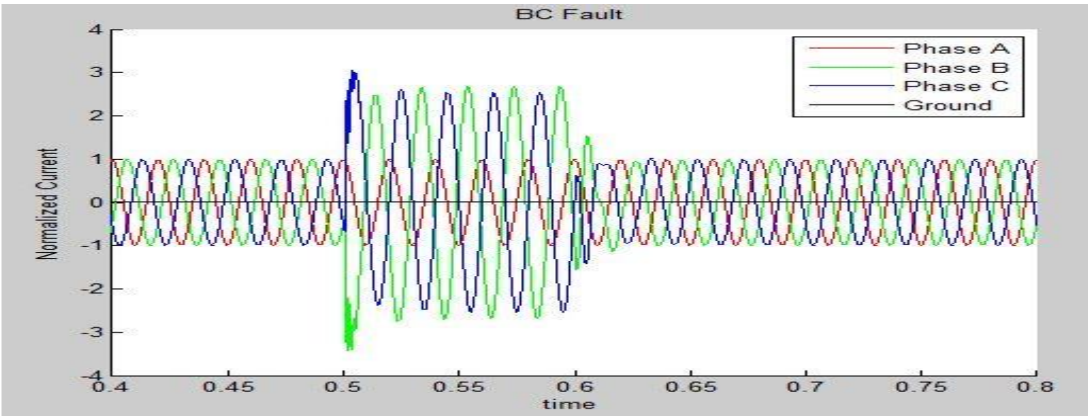

Figure 3.8

7. AC fault

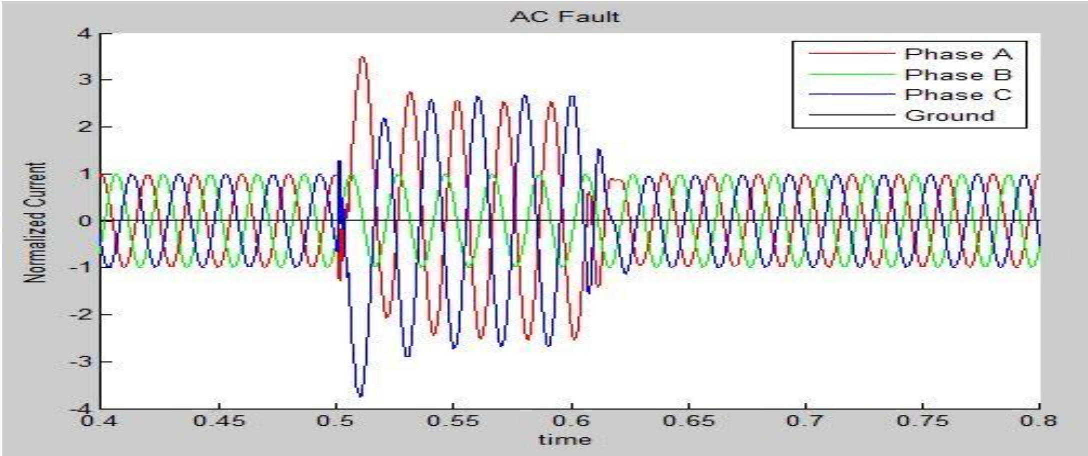

Figure 3.9

8. ABG fault

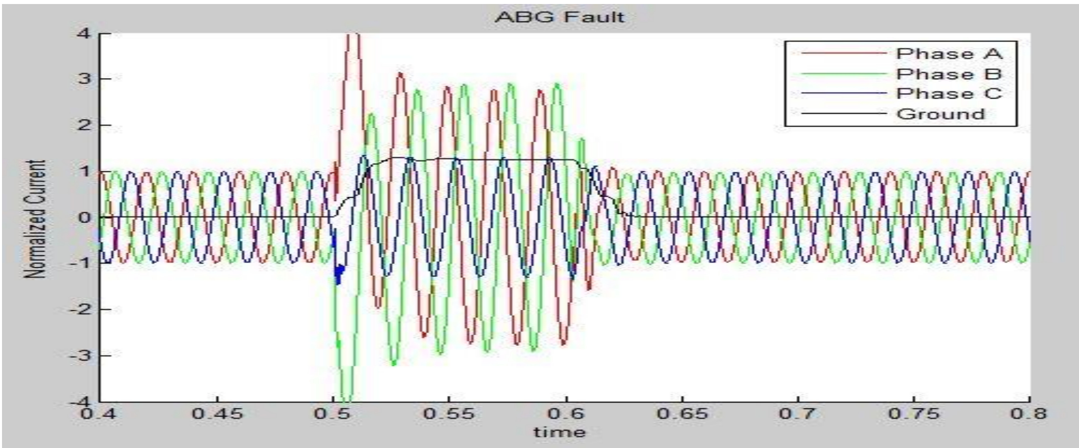

Figure 3.10

9. BCG fault

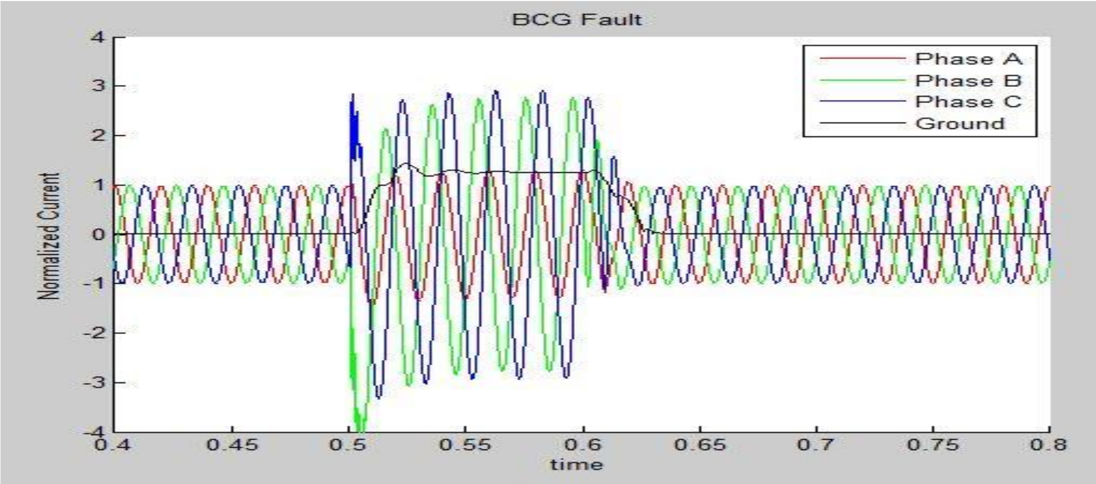

Figure 3.11

10.ACG fault

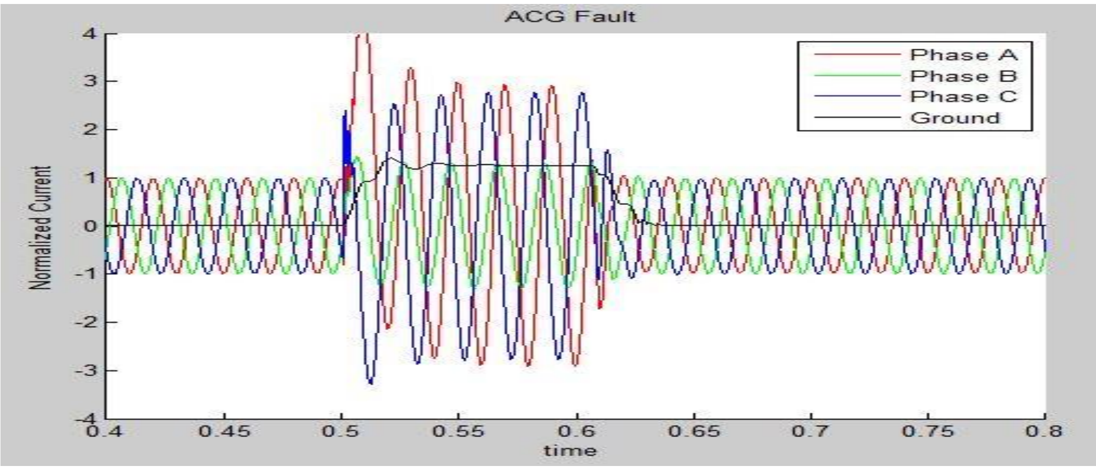

Figure 3.12

11.ABC fault

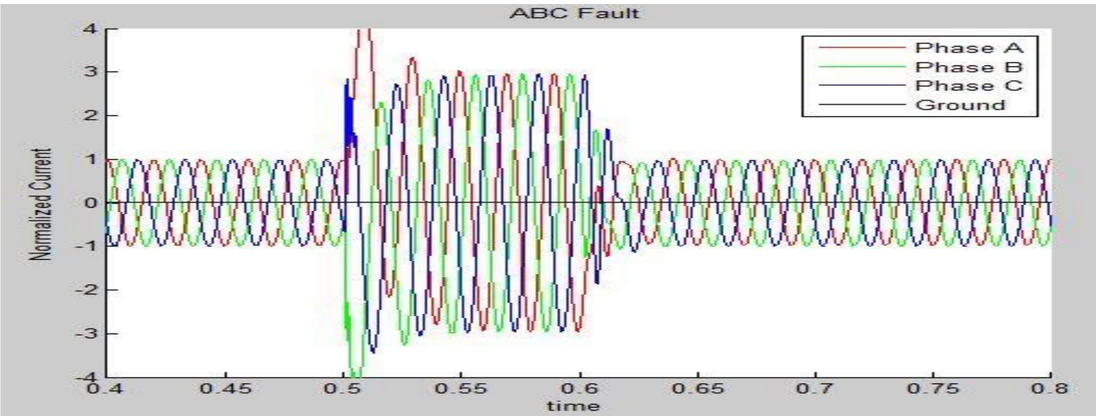

Figure 3.13

12.ABCG fault

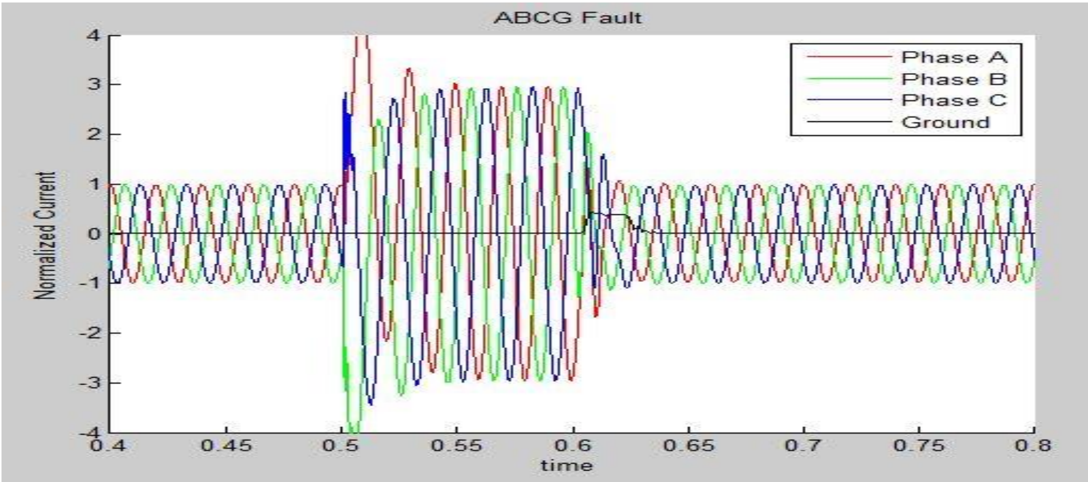

Figure 3.14

Table 3.2 Faults with class labels

Faults	Class labels
No fault	C0
AG fault	C1
BG fault	C2
CG fault	C3
AB fault	C4
BC fault	C5
AC fault	C6
ABG fault	C7
BCG fault	C8
ACG fault	C9
ABC fault	C10
ABCG fault	C11

Chapter 4

Feature Extraction

In this project, classification has been carried out for short circuit faults of overhead transmission lines. Total 11 types of faults and no fault case have been considered. Zero sequence analyzer is used for ground detection in faults. It is observed that during fault, current increases by 2-5 times w.r.t. no fault values in the faulted phase.

4.1 Energy Computation

Energy computation follows the Parseval's Energy Theorem. Energy of all wavelet coefficients for all the 3 phases and zero sequence component were calculated and finally classified in two groups, one containing the fundamental frequency components (50 Hz) and the other containing all the rest of the frequency components. Energy of a set of wavelet coefficients is computed as:

$$E_i = \sum_{n=1}^{length(Wi)} (Wi(n)^2)$$

E_f refers to Energy of fundamental components and sum of rest energies refers to Energy of remaining frequency components.

4.2 Features

Four features are used to detect and classify the fault present in a system. All phase features are based on Energies Ratio. These features are

- $Fa = E_{f}\_a / E_f$ (no_fault)

  = ratio of fundamental energies of phase A in faulted signal and no fault signal
- $Fb = E_{f}\_b / E_f$ (no_fault)

  = ratio of fundamental energies of phase B in faulted signal and no fault signal
- $Fc = E_{f}\_c / E_f$ (no_fault)

  = ratio of fundamental energies of phase C in faulted signal and no fault signal
- $Fo = \log_{10} (E\_o)$

  = total energy of zero sequence component in faulted signal

It was observed that the faulted phase has more fundamental energy as compared to the no fault condition. Based on this rule, threshold values were set. The detection and classification step was achieved by means of a set of rules obtained from the comparison of these four features and the threshold values. Value of Fo will help us determine if the ground is involved in fault or not. The plots of all the feature for various faults with the threshold values for features are below :

Features Plot :

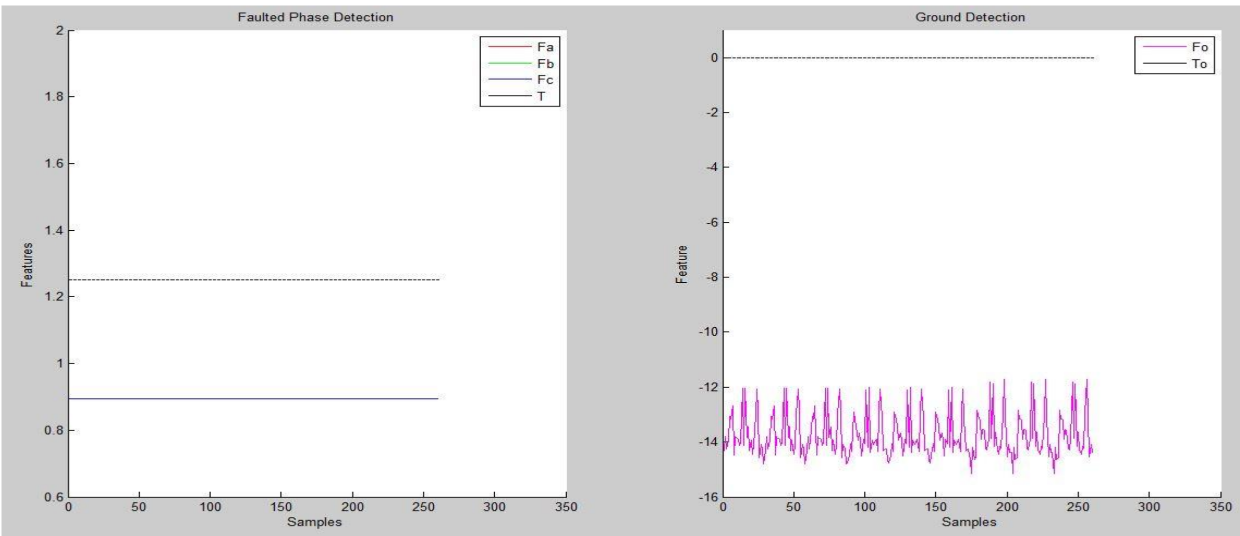

Figure 4.1 No Fault

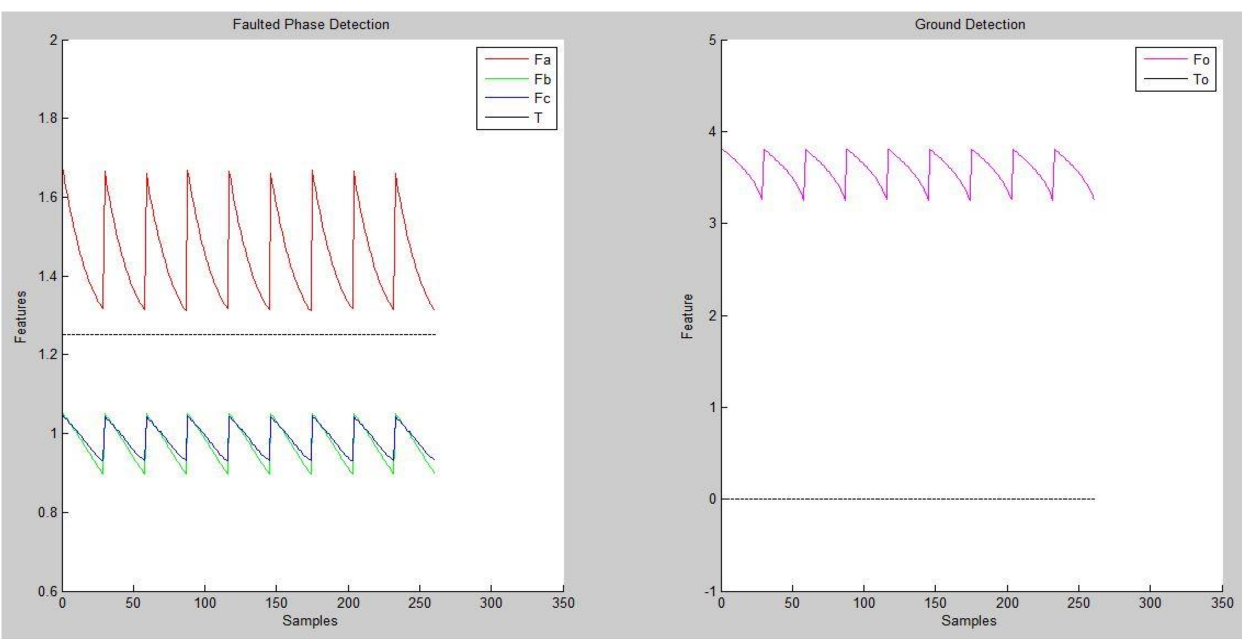

Figure 4.2 AG Fault

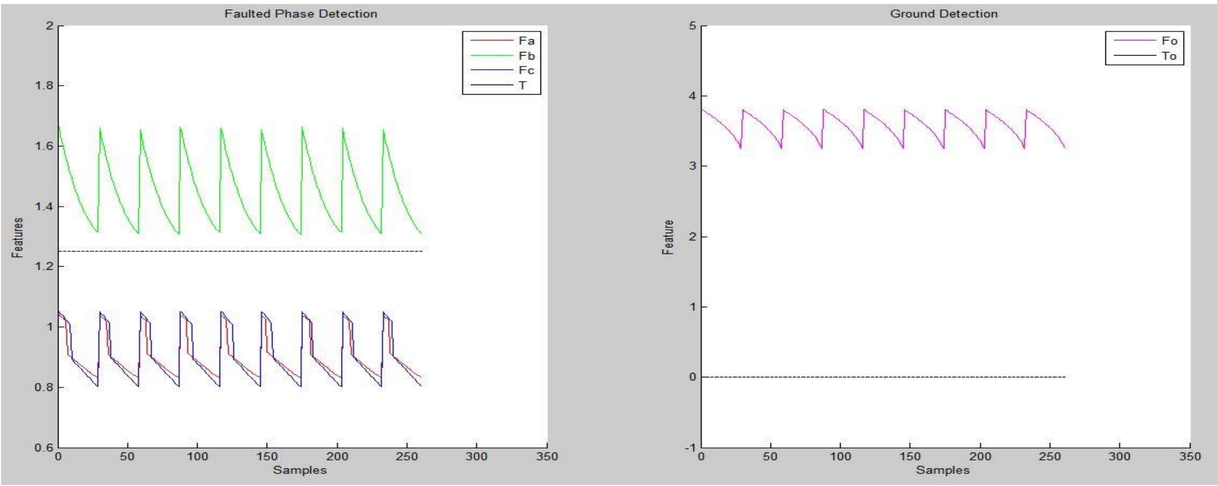

Figure 4.3 BG Fault

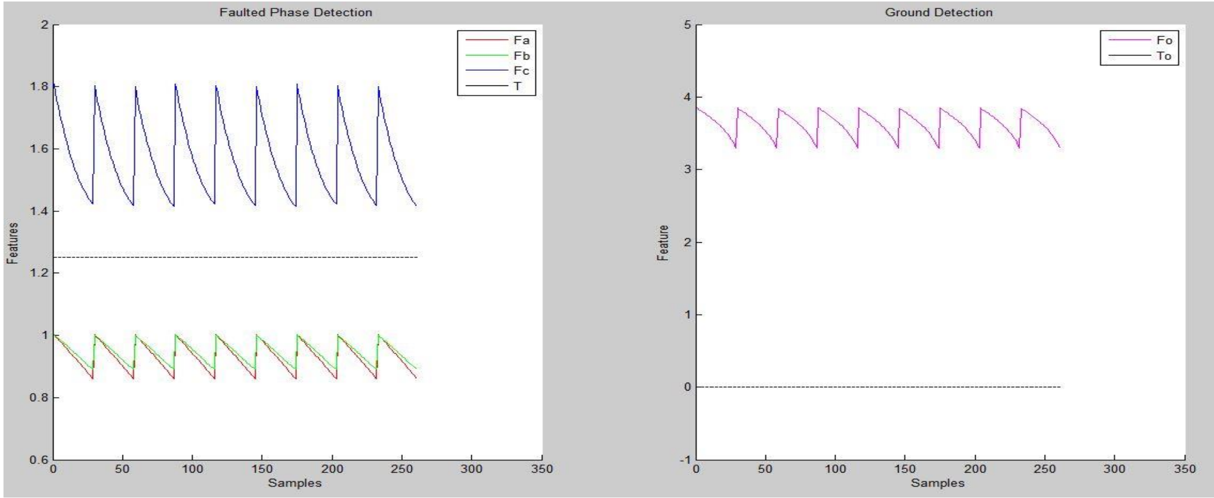

Figure 4.4 CG Fault

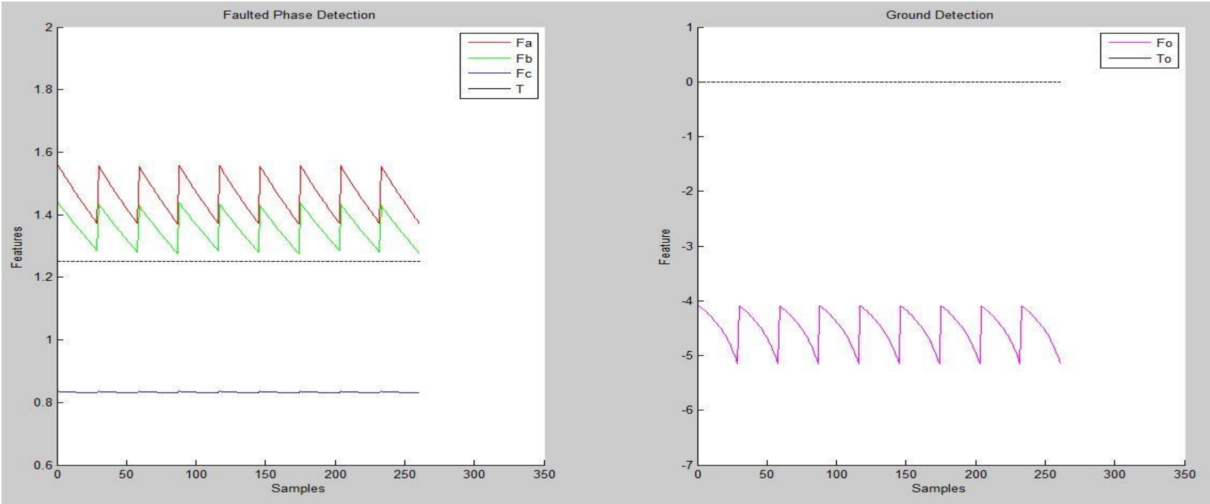

Figure 4.5 AB Fault

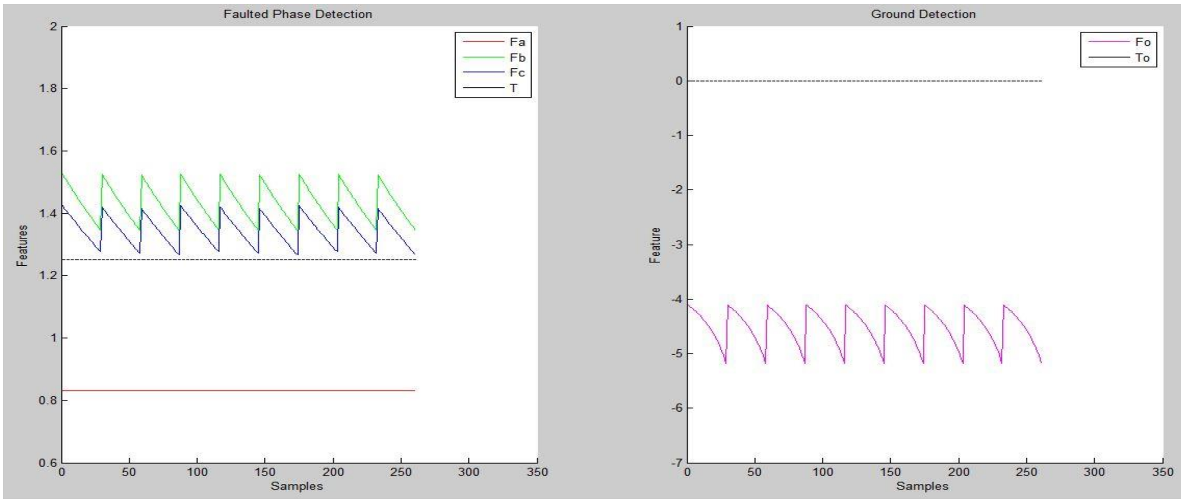

Figure 4.6 BC Fault

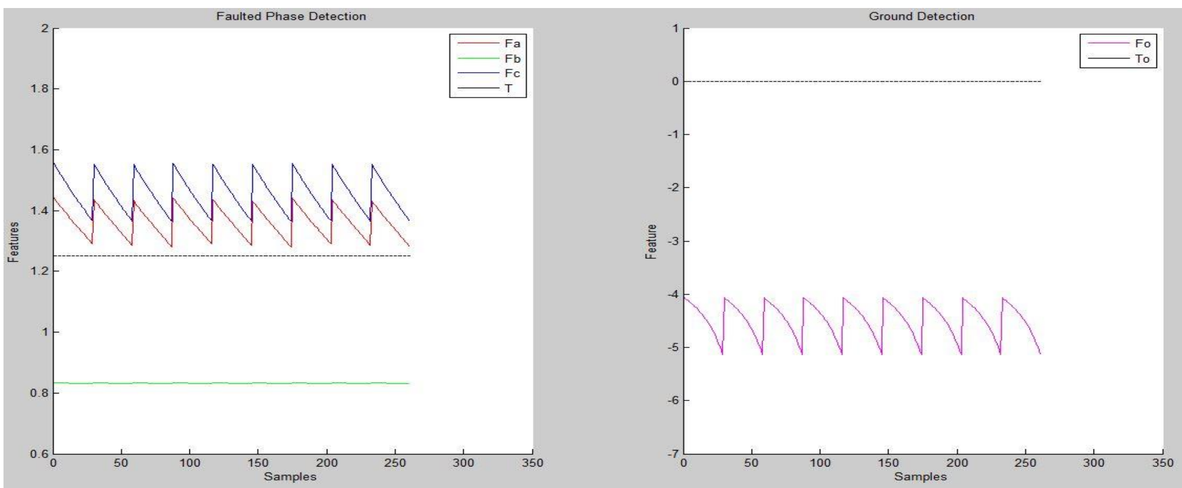

Figure 4.7 AC Fault

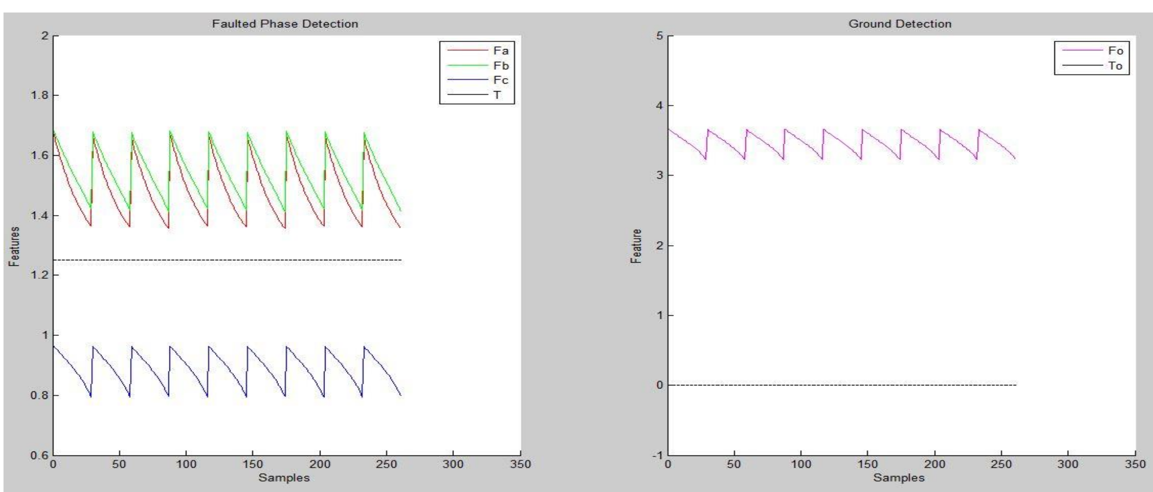

Figure 4.8 ABG Fault

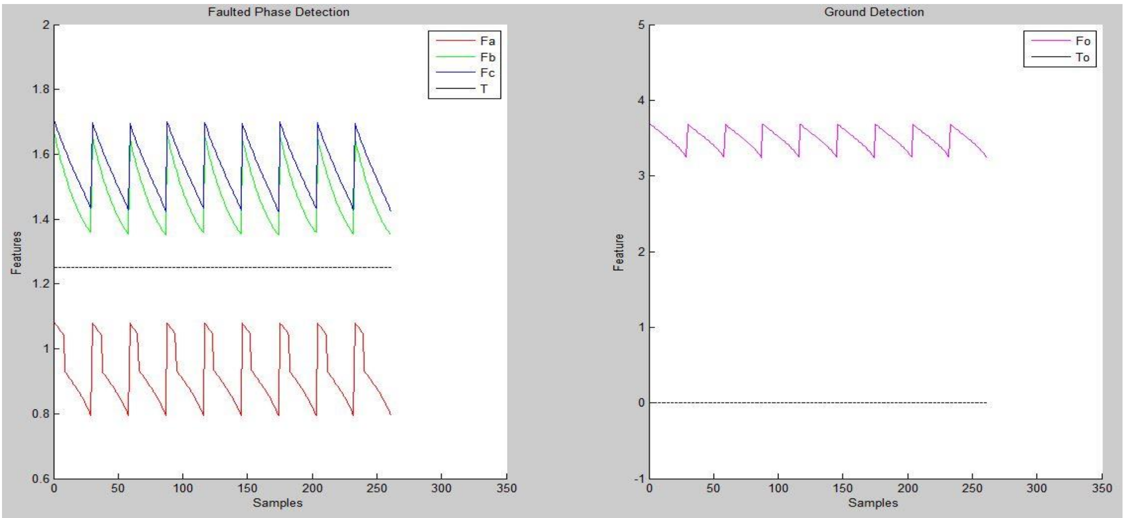

Figure 4.9 BCG Fault

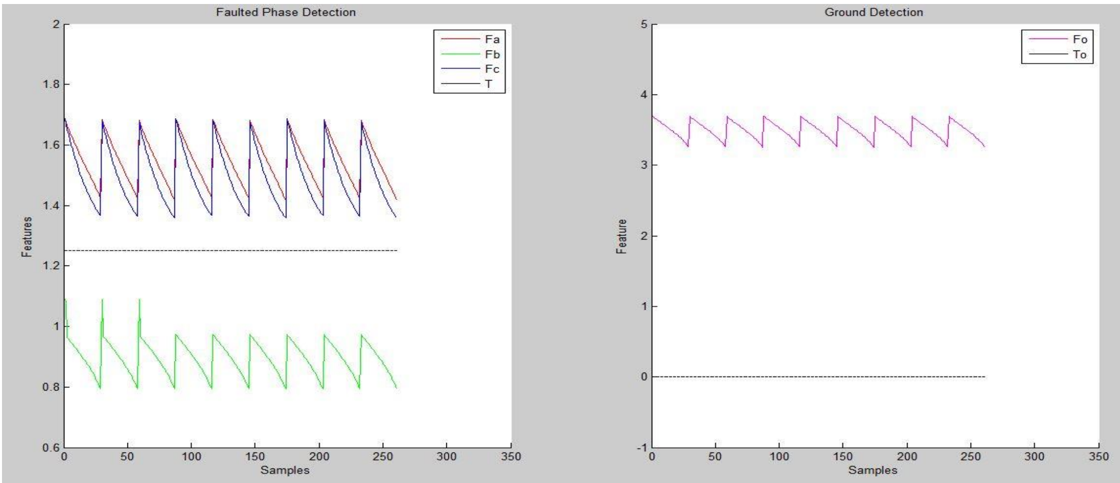

Figure 4.10 ACG Fault

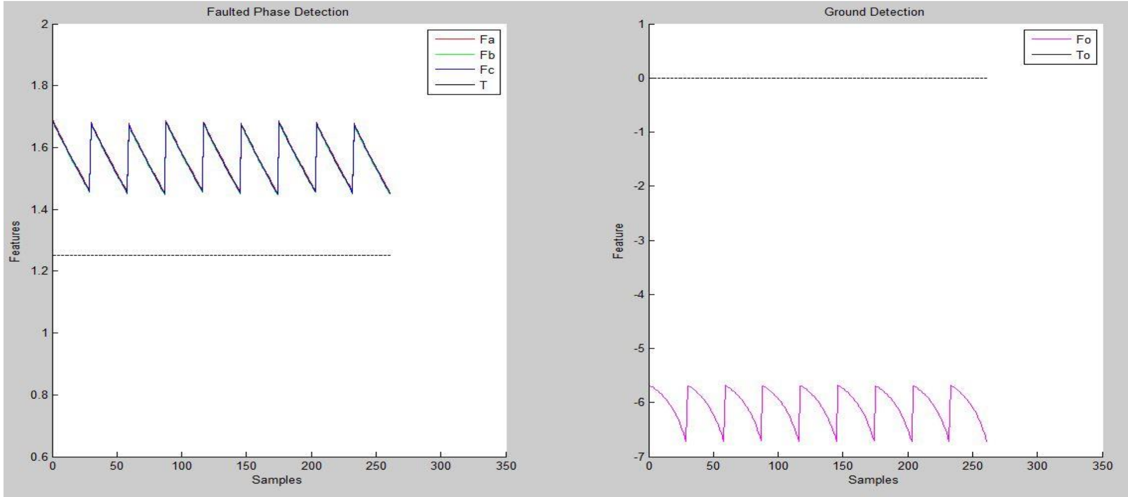

Figure 4.11 ABC Fault

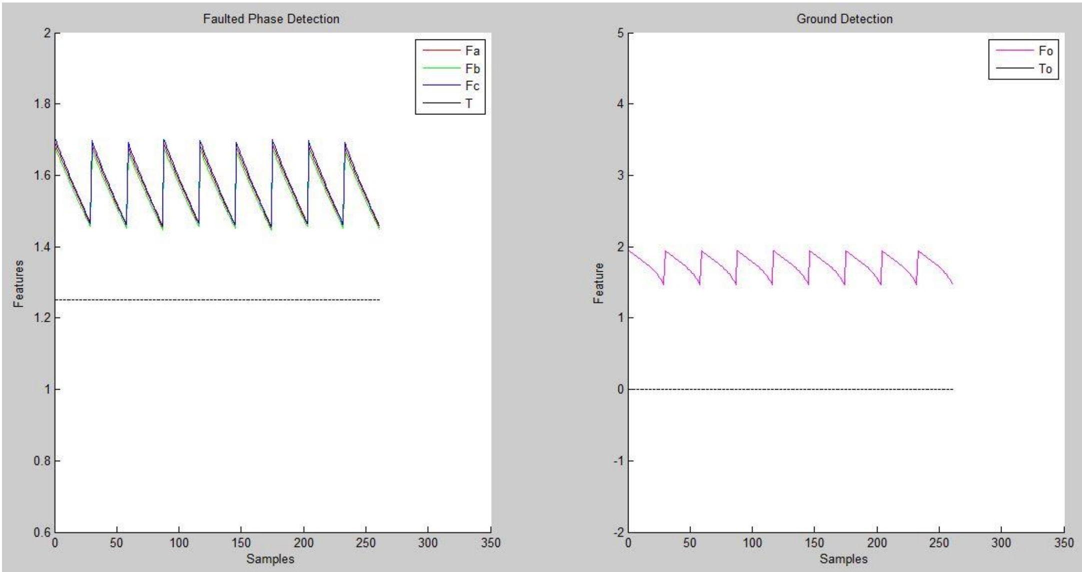

Figure 4.12 ABCG Fault

Threshold Value : It is based on observation that faulted Phase features values are varying in range of 1.3 to 1.75 so Threshold value (T) is chosen is 1.25. And To is to be taken as 0 because Fo is ideally zero when there is no ground involved in fault.

Table 4.1 Rules table for fault detection

Class label	Faults	Conditions			
C0	No fault	Fo < To	Fa < T	Fb < T	Fc < T
C1	AG fault	Fo > To	Fa > T	Fb < T	Fc < T
C2	BG fault	Fo > To	Fa < T	Fb > T	Fc < T
C3	CG fault	Fo > To	Fa < T	Fb < T	Fc > T
C4	AB fault	Fo < To	Fa > T	Fb > T	Fc < T
C5	BC fault	Fo < To	Fa < T	Fb > T	Fc > T
C6	AC fault	Fo < To	Fa > T	Fb < T	Fc > T
C7	ABG fault	Fo > To	Fa > T	Fb > T	Fc < T
C8	BCG fault	Fo > To	Fa < T	Fb > T	Fc > T
C9	ACG fault	Fo > To	Fa > T	Fb < T	Fc > T
C10	ABC fault	Fo < To	Fa > T	Fb > T	Fc > T
C11	ABCG fault	Fo > To	Fa > T	Fb > T	Fc > T

Chapter 5

Decision Tree

5.1 Introduction to Decision Tree

A decision tree provides a highly effective structure within which we can lay out options and investigate the possible outcomes of choosing those options. A decision tree also helps us to form a balanced picture of the risks and rewards associated with each possible course of action. It is a flowchart -like structure in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represents classification rules. In decision analysis, a decision tree and the closely related influence diagram are used as a visual and analytical decision support tool, where the expected values (or expected utility) of competing alternatives are calculated.

A decision tree consists of 3 types of nodes:

1. Decision nodes

2. Chance nodes

3. End nodes

Decision trees are commonly used in operations research and operations management. If in practice decisions have to be taken online with no recall under incomplete knowledge, a decision tree should be paralleled by a probability model as a best choice model or online selection model algorithm. Another use of decision trees is as a descriptive means for calculating conditional probabilities.

Among decision support tools, decision trees (and influence diagrams) have several advantages. Decision trees:

- Are simple to understand and interpret. People are able to understand decision tree models after a brief explanation.
- Have value even with little hard data. Important insights can be generated based on experts describing a situation (its alternatives, probabilities, and costs) and their preferences for outcomes.
- Allow the addition of new possible scenarios.
- Help determine worst, best and expected values for different scenarios.
- Use a white box model. If a given result is provided by a model.
- Can be combined with other decision techniques.

5.2 Classification of faults

For classification purpose Decision Tree is used. In this work, four features are used to detect and classify the faults type.

At each level only one feature is used to classify the faulted signals and no fault signals. At first level, feature Fo is checked, it divides the signals into two parts based on threshold value. After the first level, we have two groups of signals, one groups has ground involved faulted signals and other group has remaining faulted signals and no fault signals. At second level, feature Fa is checked and based on threshold value we further divide groups into two parts which either have faulted phase A or not. Similarly at next level we check for feature Fb and at the last level, feature Fc is checked and this is how we got classified signals as follow :

[ABCG ABG ACG AG BCG BG CG ABC AB AC BC no_fault]

Table 5.1 Relation between features and Phase

Features	**Phase Involvement in fault**
Fa	Phase A
Fb	Phase B
Fc	Phase C
Fo	Ground

Decision tree is modelled in figure 5.1 based on above mentioned features.

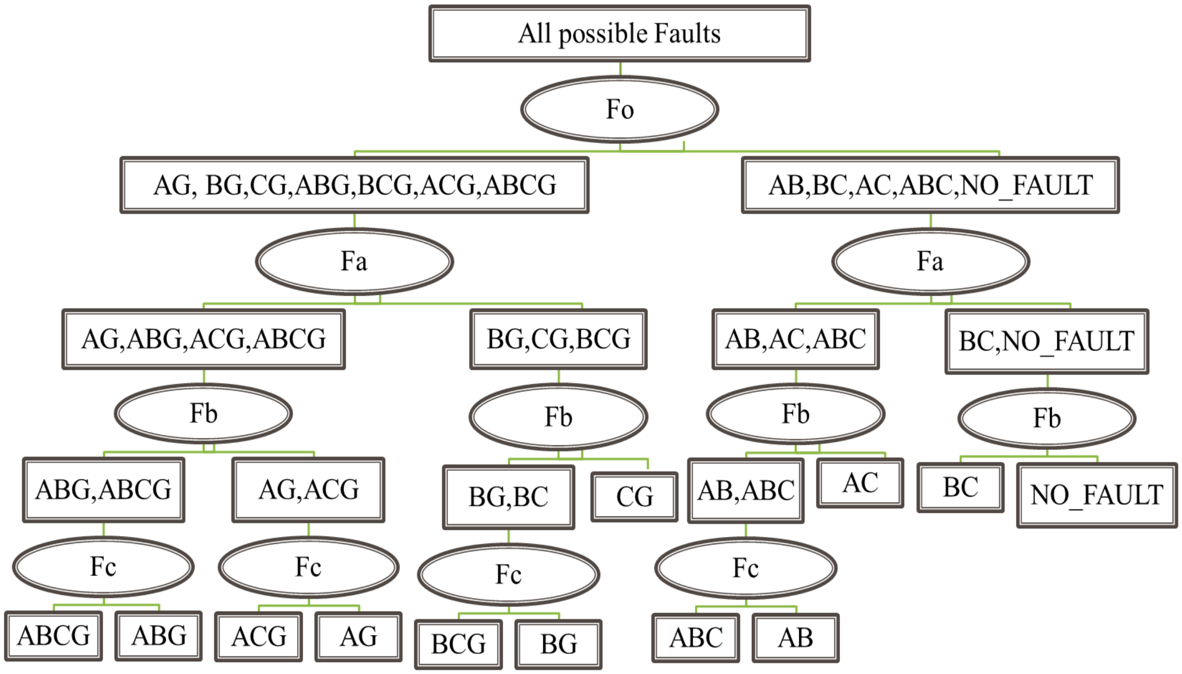

Figure 5.1 Decision Tree

Chapter 6

Results and Discussions

A database with 260 signals for each of the 11 faults, plus 260 for a no fault signal is generated. These signals are based on the mathematical models reported in [1] and shown in Table 3.2. For each class, the 260 signals are divided in 60 for training and 200 for testing the proposed methodology, respectively. While signal generation, different kinds of possible variations are taken into consideration. Three separate fault durations were considered while generating the data – 0.5-0.6 sec, 0.6-0.7 sec and 0.7-0.8 sec. and fault location variation of about 10 km is taken. The model was simulated for 1 second and sampling frequency was taken to be 20 kHz. In addition, a zero sequence analyser was used to detect the presence of ground in a fault. The fundamental frequency of the signals was 50 Hz, corresponding to a real power system of 50 Hz frequency.

Table 6.1 shows the results that all faults signals (each has 260 samples) are classified with 100% accuracy. Table 6.2 lists the average accuracy for all types of short circuit faults.

Table 6.1 Classification Results

Classes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
C1	100										
C2		100									
C3			100								
C4				100							
C5					100						
C6						100					
C7							100				
C8								100			
C9									100		
C10										100	
C11											100
% Accuracy	100	100	100	100	100	100	100	100	100	100	100

Table 6.2 Recognition Accuracy

	LG fault	LL fault	LLG fault	3-phase fault
% Accuracy	100	100	100	100

Chapter 7

Conclusions

In this work, a new fault detection and classification approach using EWT and decision tree has been proposed. The EWT has been utilized for signal processing, following that a series of statistical calculations were performed to form the feature vectors. The feature vectors were then fed as inputs to the decision tree. The proposed algorithm was verified using synthetic signals generated in MATLAB. The algorithm is found capable of classifying most significant faults with a high accuracy of 100%. The analysis and results presented in this work clearly show the potentiality of the proposed algorithm in classifying the faulted waveforms. The algorithm presented higher accuracy in comparison to recent techniques. Proposed algorithm can be used in power faults monitoring software.

Future Scope

This work can be extended to recognize more number of combined short circuit faults. Further work can be done for improving the efficiency by inclusion of additional features. In addition, better classifier can be used, that takes lesser computational time and memory space.

References

[1]. S.R. Samantaray, P.K. Dashb, and G. Panda, "Fault classification and location using HS-transform and radial basis function neural network"

[2]. K. M. Silva, B. A. Souza and N. S. D. Brito, "Fault Detection and Classification in Transmission Lines Based on Wavelet Transform and ANN," *IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 21, NO. 4, OCTOBER 2006.*

[3]. Manohar Singh, Dr. B.K Panigrahi and Dr. R. P. Maheshwari' "Transmission Line Fault Detection and Classification" *PROCEEDINGS OF ICETECT 2011*.

[4]. Mohammad Ali Adelian and Rahul S Desai, "Using Wavelet for Finding Fault Place and Neural Network for Types of Fault in Transmission Lines", *International Journal of Engineering Research and General Science Volume 2, Issue 4, June-July, 2014*.

[5]. Shilpi Sahu and Dr. A. K. Sharma, "Detection of Fault Location in Transmission Lines using Wavelet Transform", *Shilpi Sahu et al. Int. Journal of Engineering Research and Applications, Vol. 3, Issue 5, Sep-Oct 2013, pp.149-151*.

[6]. M. Prakash, S. Pradhan and S. Roy, "Soft Computing Techniques for Fault Detection in Power Distribution Systems: A Review"

[7]. The Wavelet Tutorial by Robi Polikar.

[8]. J. Gilles, "Empirical Wavelet Transform," *IEEE Trans. Signal Process.*, vol.61, no.16, pp.3999-4010, Aug. 2013

[9]. T. Karthik Thirumala, Dr. Amod C. Umarikar and Dr. Trapti Jain, "Empirical Wavelet Transform based Single Phase Power Quality Indices", *Power Delivery, IEEE Transactions on* 30.1 (2015): 445-454.