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

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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, 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.

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CERTIFICATE by BTP Guide

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

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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 decision 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.

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I would like to thank my BTP supervisor, Dr. Trapti Jain, for her constant support in structuring the project and for her valuable feedback which helped me in the course of the project. She gave me an opportunity to discover and work in this domain. She guided me thoroughly and pulled me out of the craters of failures I faced all through the period.

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I am also thankful to all my family members, friends and colleagues who have been a constant source of motivation. Finally, I offer sincere thanks to everyone else who knowingly or unknowingly helped me complete this project.

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Abstract

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.

In this project, a novel method is proposed to detect and classify the different short circuit faults in a transmission line. Effects of fault on the frequency components present in the current signal have been studied broadly, which creates the logic for accurate detection and classification of faults. The current and voltage data for different faults were generated by simulating a sample power system network using Simulink in MATLAB. Data was collected by varying different parameters, like fault resistance, fault duration and fault location. 300 km long transmission line was used.

I used **Tunable Q-Wavelet Transform (TQWT)** to achieve the goal of accurate detection and classification of faults. This method is suitable for online fault detection which will help in quick and reliable operation of protection schemes. The classifier was trained for 36 datasets and an accuracy of 100% was obtained when tested for 261 datasets.

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Chapter 1

Introduction

This chapter highlights the background and motivation for the project. The problem statement of the project has been described and the importance of the results is also clearly portrayed. Towards the end, the objectives and expectations to solve the problem statement as far as possible.

1.1 Background

Generally, when a fault occurs in transmission line, unless it is severe it is unseen. But gradually these minor faults can lead to damage of transformer and can turn havoc to human life. It may also initiate fire. Present day in India, we do not have a system in hand that would let us know in real time once a fault occurs. Matter of concern is that since we do not have a real-time system, this leads to damage of the underlying equipment connected and turns out to be a threat to human around. In order to avoid such incidents to the maximum extent, maintenance or checking of the transmission lines are generally carried out on a frequent basis. This leads to increased manpower requirement. The fact remains that the real intention of this is not met as many a times line failure may be due to rain, toppling of trees which cannot be predicted. Like in Western Ghats where the transmission lines are usually drawn amidst the forest and places like Chirapunjee where massive rainfall almost sets everything standstill.

Also, all the pre-proposed methods either have high accuracy or have fast computation time, but not both, making them unsuitable for online analysis. To overcome these problems, a real-time solution is proposed. This method has lesser computation time as well as is accurate. The real intention of detecting fault in real time and protecting the transformer at the earliest is realized. It is important to note that transformers are very costly. An 11KV transformer on an average costs 3000 US$. So here we are proposing a cost effective, fast and accurate method to detect and classify faults aiding in improving safety.

1.2 Motivation

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.

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

Table 1 Occurrence of faults

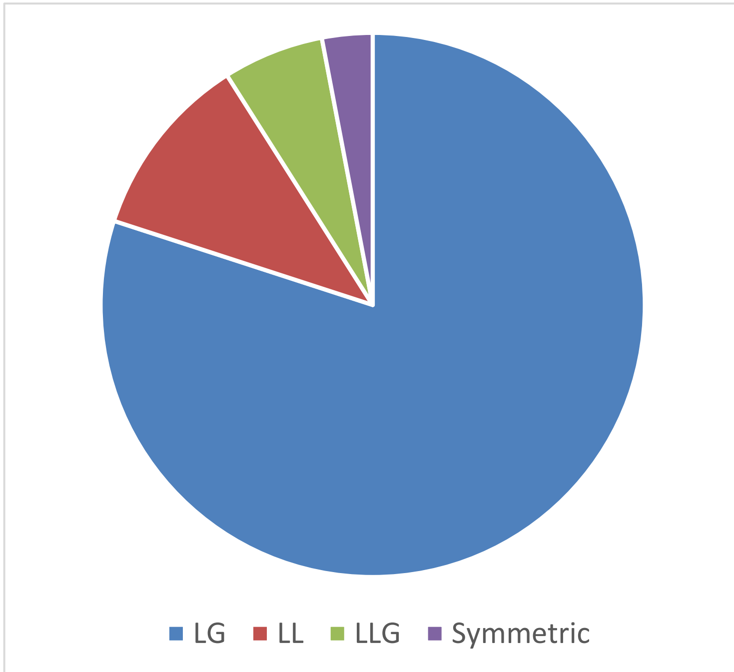

Figure 1. 1 Frequency of occurrence of faults

1.3 Objectives

The main objectives of this project are:

- To increase the accuracy in detection and classification results, so as to design a reliable algorithm.
- To achieve the goal of lesser computation time. It is necessary because the data need to be monitored continuously so that while new data get buffered, the previous data is already processed and passed through the classifier and its corresponding results are obtained. So, as soon as the new data arrives to the classifier, it is ready to process it. This makes the algorithm suitable for online purposes, which is very important for making this method practical.

1.4 Project Outline

1 Current and voltage signal generation for different faults in Transmission line.

2 Normalization of signals with amplitude of 1st cycle.

3 Frequency spectrum of signals using Tunable Q-Wavelet Transform.

4 Energy computation for different frequency components.

5 Training of a rule-based classifier tree.

6 Testing of the algorithm.

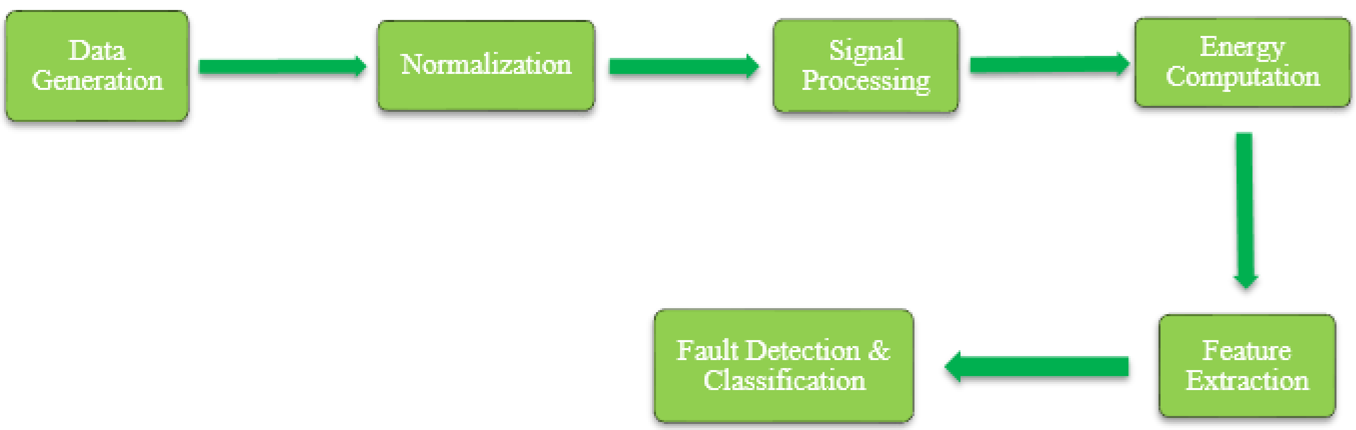

Figure 1. 2 Project Outline

Chapter 2

Literature Review

The problem statement and the objectives mentioned in chapter 1 are real life problems pertaining to classification. Accuracy and fast computation is very important in many domains such as in power systems. A novel algorithm based on Tunable Q-Wavelet Transform is used for fast and accurate fault detection and classification. This chapter focuses on the basics of fault analysis, importance of wavelet transform and TQWT concepts and its importance.

2.1 Faults

An electrical fault is defined as the deviation of voltage and current from their respective 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 a fault occurs, it causes excessively high currents to flow which causes the damage to equipment and devices. Fault detection and analysis is necessary to select or design suitable switchgear equipment, electromechanical relays, circuit breakers and other protection devices. There are mainly two types of faults in the electrical power systems. 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. LLL (Triple line fault) and LLL-G (Triple line to ground fault) faults lie in this category.

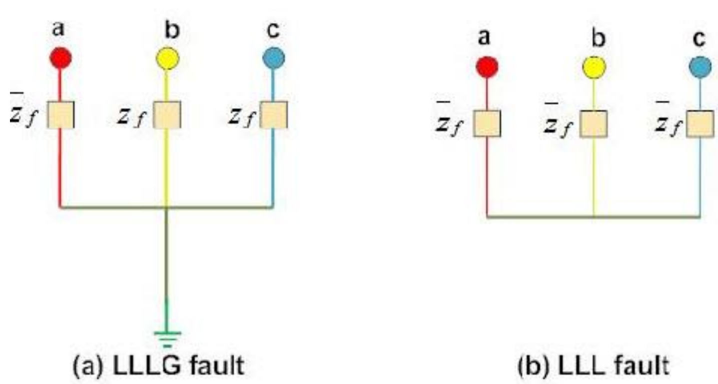

Figure 2. 1 Symmetrical faults

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 equipment. Fig 2.1.1 shows two types of three phase symmetrical faults. Analysis of these faults 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 faults are very common and less severe than symmetrical faults. There are mainly three types of unsymmetrical faults, namely, single line to ground fault (L-G), double line fault (L-L) and double line to ground (LL-G) fault.

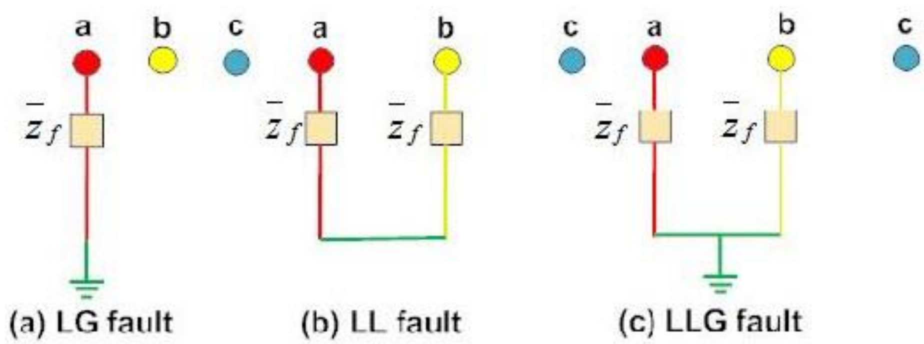

Figure 2. 2 Unsymmetrical faults

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. 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.

Causes of electrical faults

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

Table 2: Causes of electrical faults

Effects of electrical faults

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

Table 3: Effects of electrical faults

2.2 Signal Processing Techniques

To analyze these faults, data is often available as a form of sampled time function that is represented by a time series of amplitudes. In many cases, the most distinguished information is hidden in the frequency content of the signal. The frequency spectrum of a signal is basically the frequency components (spectral components) of that signal. The most conventional and reliable method to obtain frequency spectrum of a signal is Fourier transform.

Signals are mainly classified as stationary and non-stationary signals, based on the times at which different frequency and amplitude components are present in the signals. Signals whose frequency and amplitude content do not change in time are called stationary signals. In other words, all the frequencies occur at all the times, and amplitude is same throughout. But most of the real-life signals are non-stationary signals. Fourier transform gives the spectral content of the signal, but it gives no information regarding where in time those spectral components appear. Therefore, Fourier transform is not a suitable technique for non-stationary signals, with one exception: Fourier transform can be used for non-stationary signals, if we are only interested in what spectral components exist in the signal, but not interested where these occur. However, if this information is needed, i.e., if we want to know, what spectral component occur at what time (interval), then Fourier transform is not the right transform to use.

Time-frequency information related to disturbance waveforms can be obtained by using 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 Wavelet Transform 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 oscillatory behavior 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 Tunable Q-Wavelet Transform, Empirical Mode Decomposition, S-transform and recursive Newton-type algorithm, to analyze stationary and non-stationary signals.

Tunable Q-wavelet transform belongs to a family of adaptive wavelets capable of extracting different components of a signal. This method has an advantage of adaptability according to the oscillatory behavior of the analyzed signal and can isolate the different frequency components of the signal. TQWT has been employed in this work.

2.3 Soft Computing Techniques

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.

Chapter 3

Data Generation

The simulation is developed in MATLAB to generate the transient voltages and currents for a basic power system network. Simulink in MATLAB software is used to simulate different operating and fault conditions on a high voltage transmission line, namely single phase to ground fault, line to line fault, double line to ground and three phase short circuit. Data was collected by varying the fault resistance, fault location and fault duration. For the simulation purpose, following power system network was used.

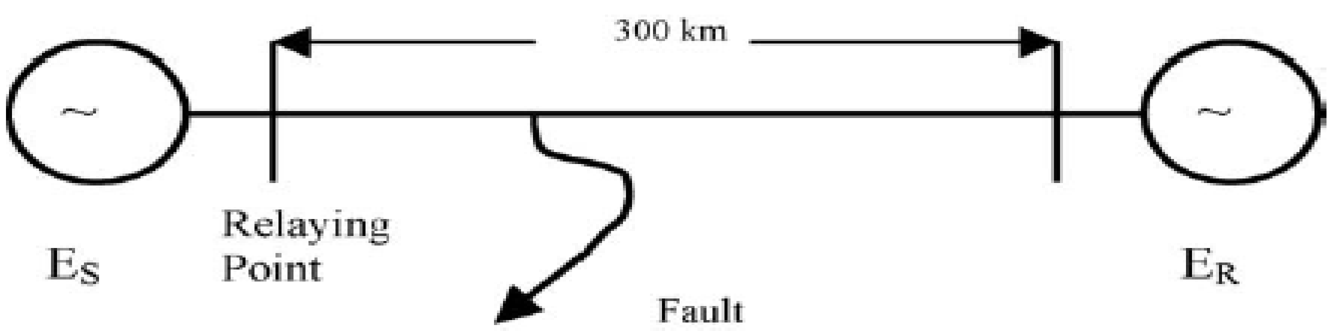

Figure 3. 1 Sample Power System Network

Data was collected from sites at an interval of approximately every 10 km (in a line of total length of 300 km); 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. Fault resistance was also varied. In totality, 260 samples of data were collected. Simulation time was 1 second and sampling frequency was taken to be 20kHz. In addition, a zero sequence analyser was used to detect the presence of ground in a fault. 11 kV was generated using a 3-phase power source. This voltage was then stepped up to 400 kV using a transformer. The circuit was intentionally kept symmetric from both sides.

The current waveforms for different faults are shown below:

1. **No fault**

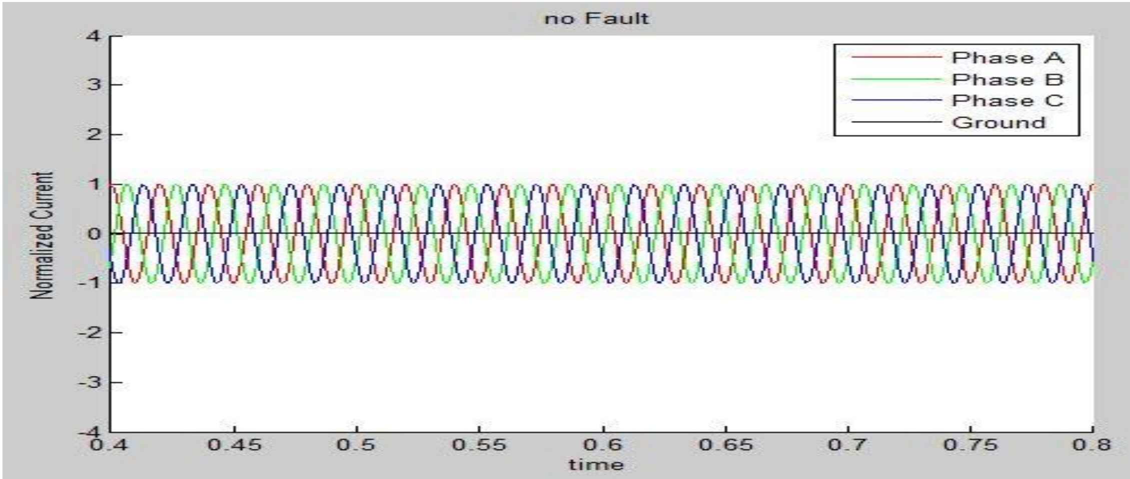

Figure 3. 2 Current waveform (no fault)

2. **AG fault**

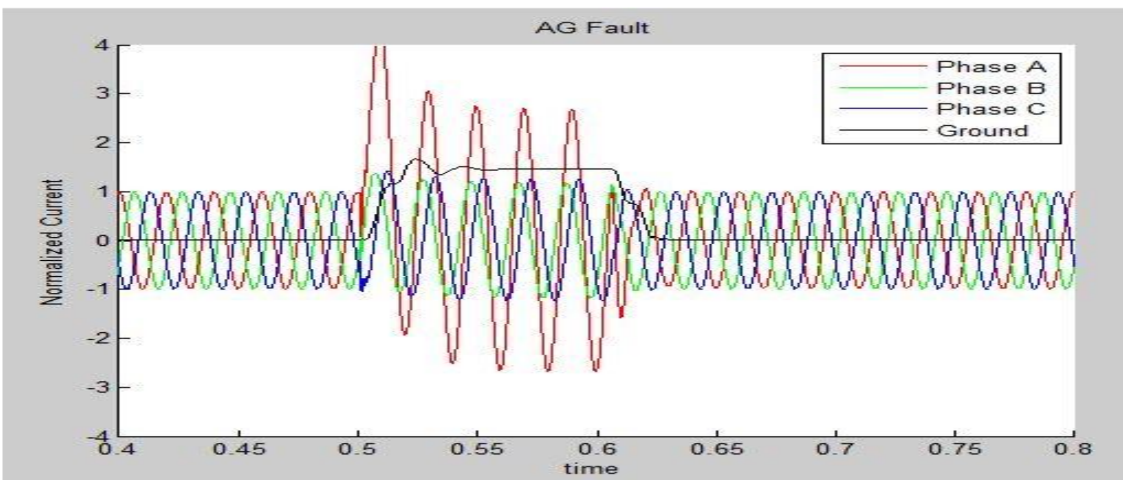

Figure 3. 3 Current waveform (AG fault)

3. **BG fault**

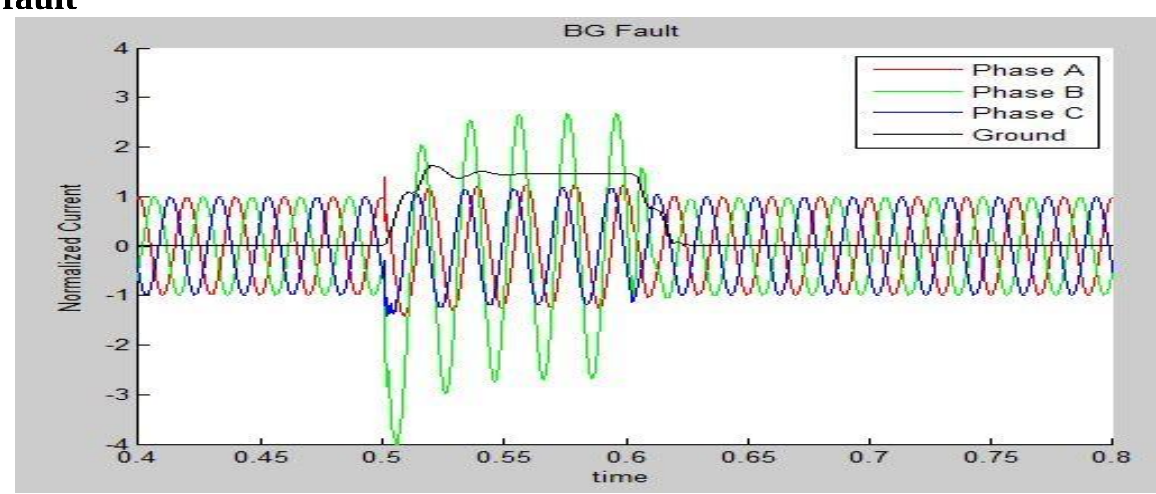

Figure 3. 4 Current waveform (BG fault)

4. CG fault

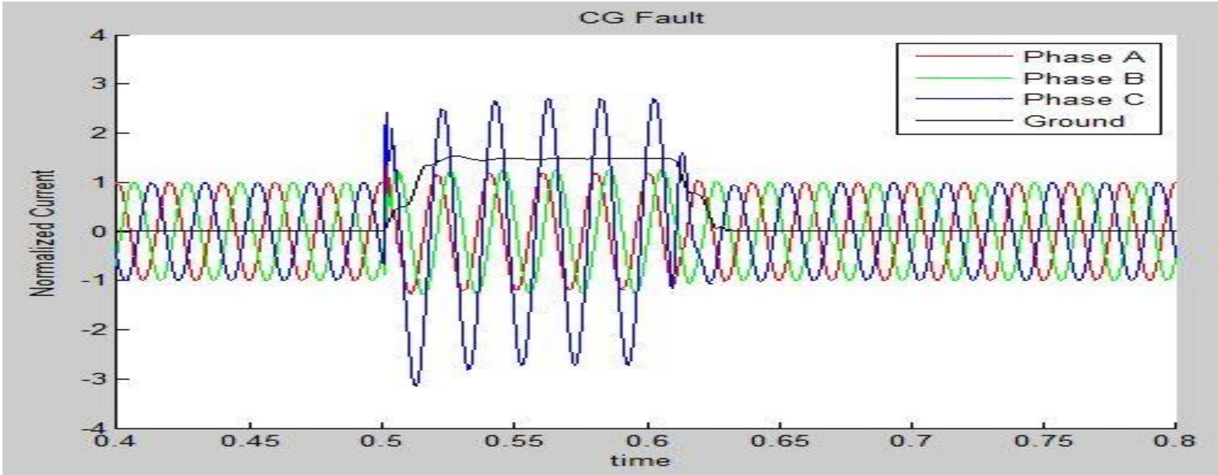

Figure 3. 5 Current waveform (CG fault)

5. AB fault

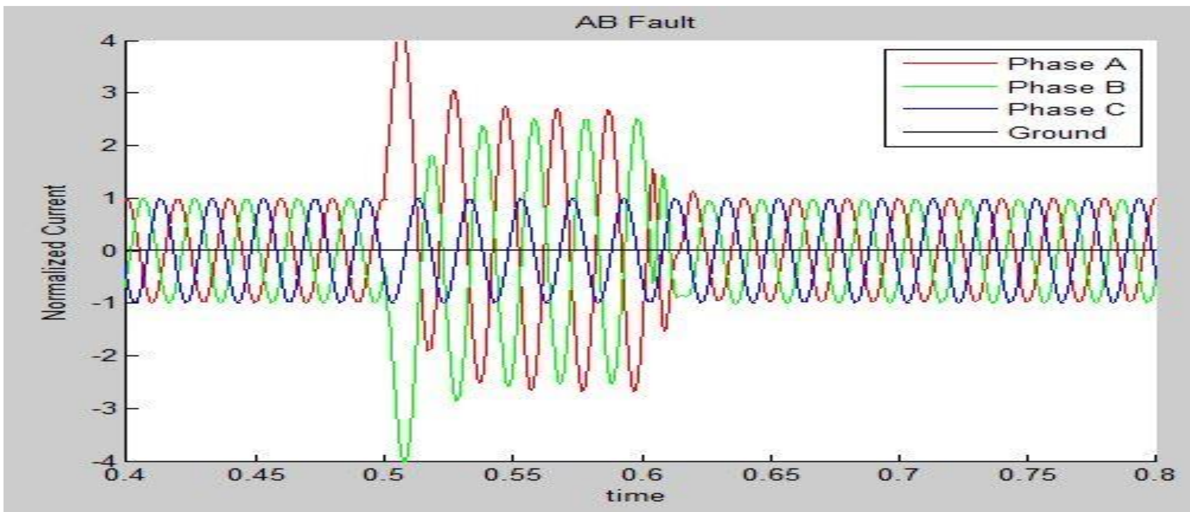

Figure 3. 6 Current waveform (AB fault)

6. BC fault

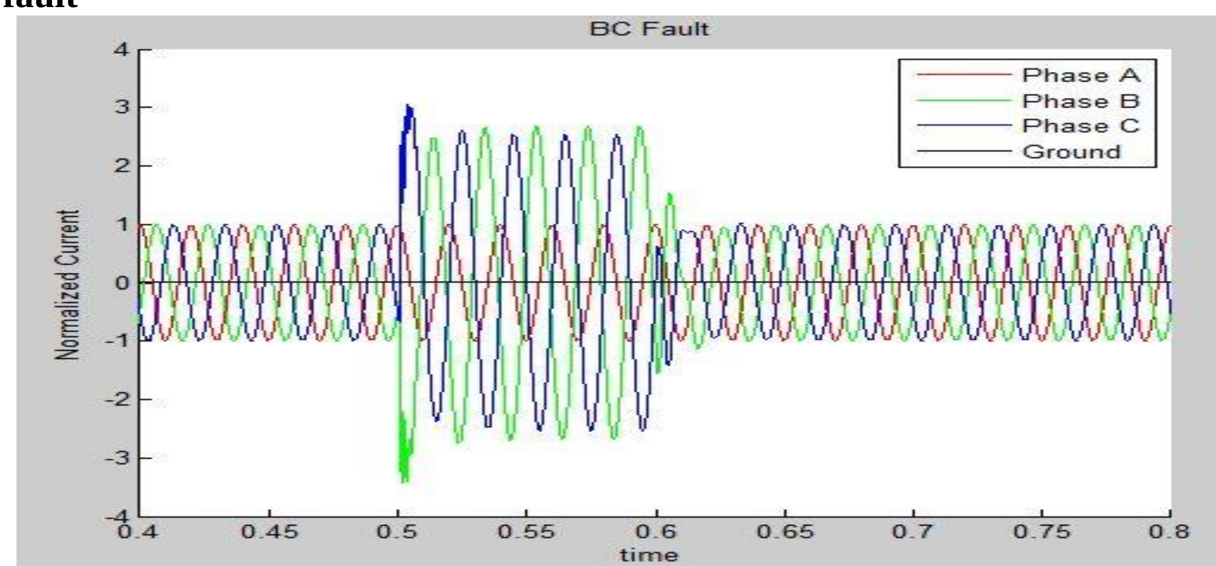

Figure 3. 7 Current waveform (BC fault)

7. AC fault

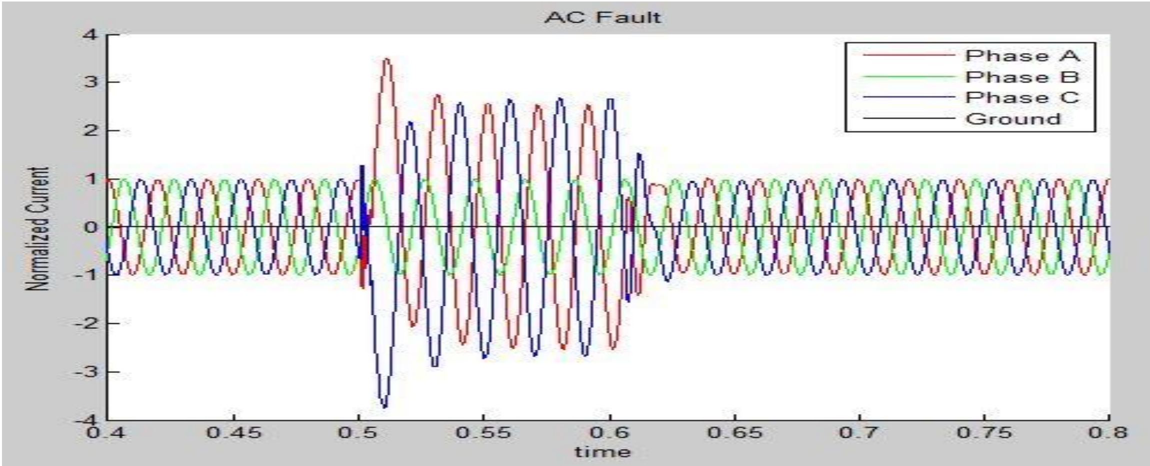

Figure 3. 8 Current waveform (AC fault)

8. ABG fault

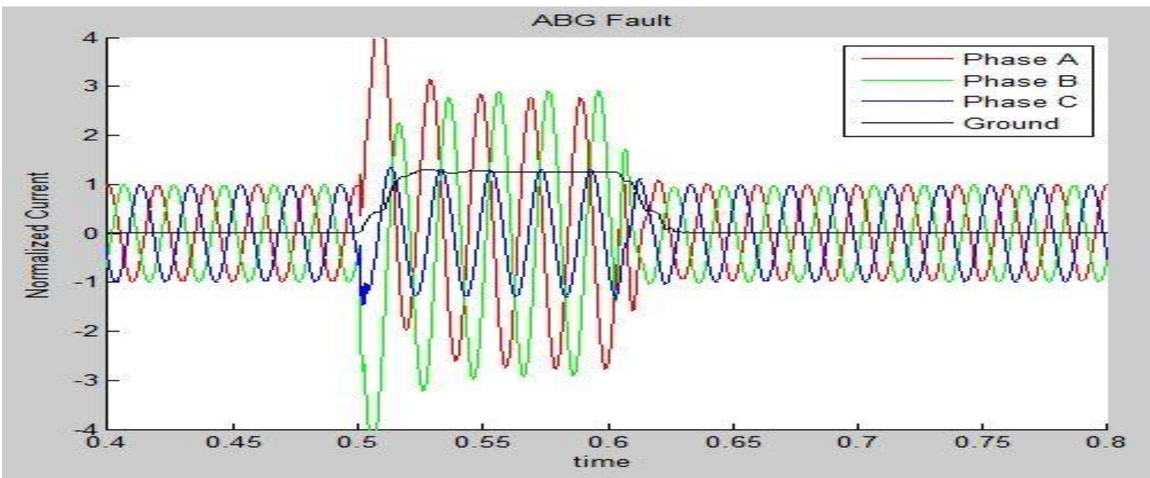

Figure 3. 9 Current waveform (ABG fault)

9. BCG fault

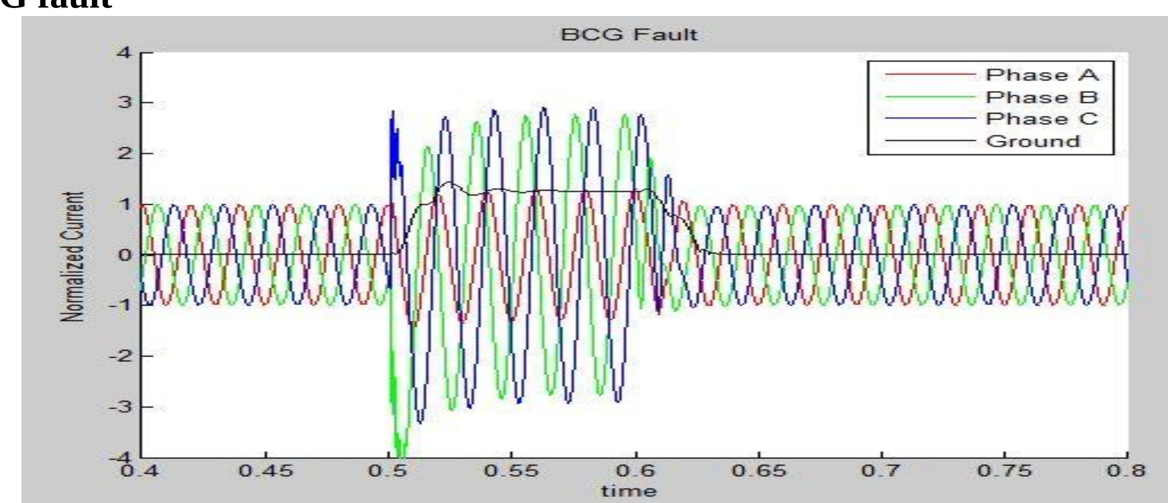

Figure 3. 10 Current waveform (BCG fault)

10.ACG fault

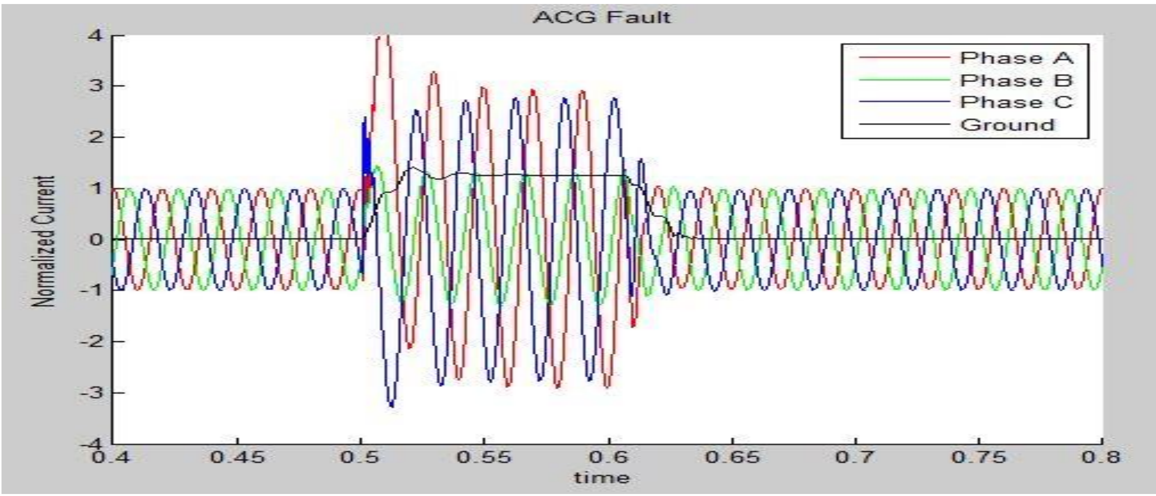

Figure 3. 11 Current waveform (ACG fault)

11.ABC fault

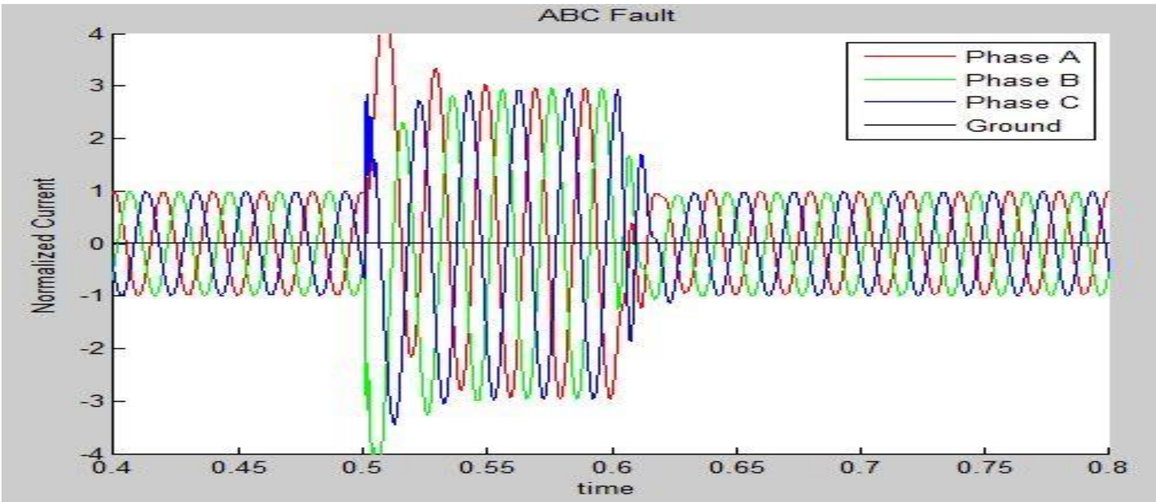

Figure 3. 12 Current waveform (ABC fault)

12.ABCG fault

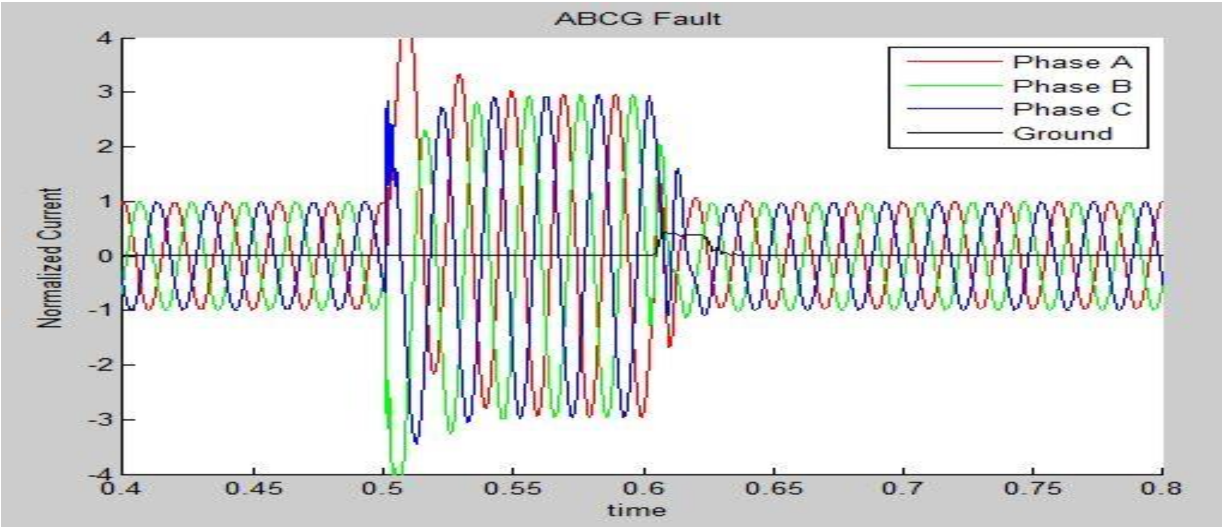

Figure 3. 13 Current waveform (ABCG fault)

Chapter 4

Tunable Q-Wavelet Transform

4.1 Description

Ideally, the Q-factor of a wavelet transform should be chosen in part according to the oscillatory behavior of the signal to which it is applied. For example, when using wavelets for the analysis and processing of oscillatory signals (speech, EEG, etc.), the wavelet transform should have a relatively high Q-factor. On the other hand, when processing signals with little or no oscillatory behavior (such as a scan-line from a photographic image), the wavelet transform should have a low Q-factor. However, other than the continuous wavelet transform, most wavelet transforms provide little ability to tune the Q-factor of the wavelet. The dyadic wavelet transform has a low Q-factor and is therefore suitable for non-oscillatory (i.e. piecewise-smooth) signals.

TQWT is a flexible discrete-time wavelet transform suitable for analysis of oscillatory signals. This transform facilitates tuning of its Q-factor denoted as Q and specifying its over-sampling rate or redundancy denoted as r along with number of levels of decomposition (j). The Parameter Q Controls the oscillatory behaviour of wavelet and the parameter r controls the excessive ringing in order to localize the wavelet in time without affecting its shape. The filters employed in TQWT have rational transfer functions that are more computationally efficient and are easily specified directly in frequency domain. In addition, the TQWT inherits the perfect reconstruction property of wavelet transform.

One-level decomposition using TQWT for signal s[n] is illustrated in the following Figure.

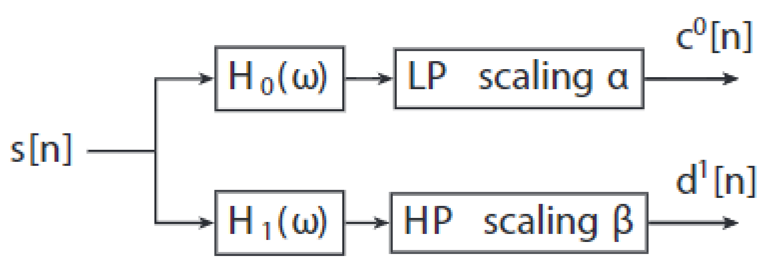

Figure 4. 1 The single level TQWT based decomposition filter bank

The low pass scaling parameter α and high pass scaling parameter β are obtained using Q and r as follows:

$$\beta = \frac{2}{Q+1} \quad \text{and} \quad \alpha = 1 - \frac{\beta}{r}$$

The implementation of j^{th} level TQWT based decomposition is achieved by iteratively applying two channel filters banks to the low-pass sub-band signal. At each stage of TQWT based decomposition, the input signal s[n] with sampling rate fs is decomposed into low-pass sub-band signal $c^0[n]$ and high-pass sub-band signal $d^1[n]$ having sampling frequencies αfs and βfs respectively as illustrated in Fig. 4.1. The generation of low-pass sub-band $c^0[n]$ uses low-pass filter $H_o(\omega)$ followed by low-pass scaling which is denoted as LP Scaling α, and similarly the generation of high-pass sub-band $d^1[n]$ uses $H_1(\Omega)$ And HP Scaling β. The low-pass scaling preserves the low-frequency components of the signal and it depends on scaling parameter. Similarly, the high-pass scaling preserves the high-frequency components of the signal and it depends on scaling parameter β. It has been shown that for perfect reconstruction $\alpha + \beta > 1$.

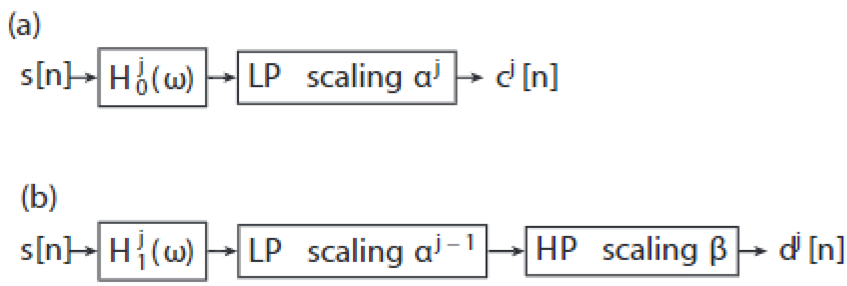

Figure 4. 2 The equivalent system for jth level TQWT based decomposition of input signal s[n] to generate (a). Low-pass sub-band signal cj[n] and (b). High-pass sub-band signal dj[n]

4.2 Tuning of Parameters

The performance of the TQWT is fully determined by the input parameters Q, r and the number of levels J. Perfect tuning of Q, r and J will make the methodology suitable for online detection.

The first step is to extract fundamental and harmonic components using TQWT. For this purpose, TQWT parameters need to be tuned on the basis of the frequencies present in the signal. The tuning of parameters was done by keeping in mind that fundamental frequency component (50 Hz) must lie in the range of first bandpass filter.

TQWT parameters were tuned using the following equations:

$$r = \frac{2}{(Q+1) - \frac{(Q+1)^J}{(Q\times 200)^{\frac{1}{J-1}}}} \quad (1)$$

$$floor(\frac{\log\left(\beta * \frac{N}{8}\right)}{\log\left(\frac{1}{\alpha}\right)}) \geq J \quad (2)$$

The tuned parameters were Q = 2.01, r=1.325625, J=8.

Figure 4.3 shows the frequency responses of band-pass filters (blue) and the frequency spectrum of the current signal (red). The highest peak corresponds to the fundamental frequency and lies in the range of first bandpass filter.

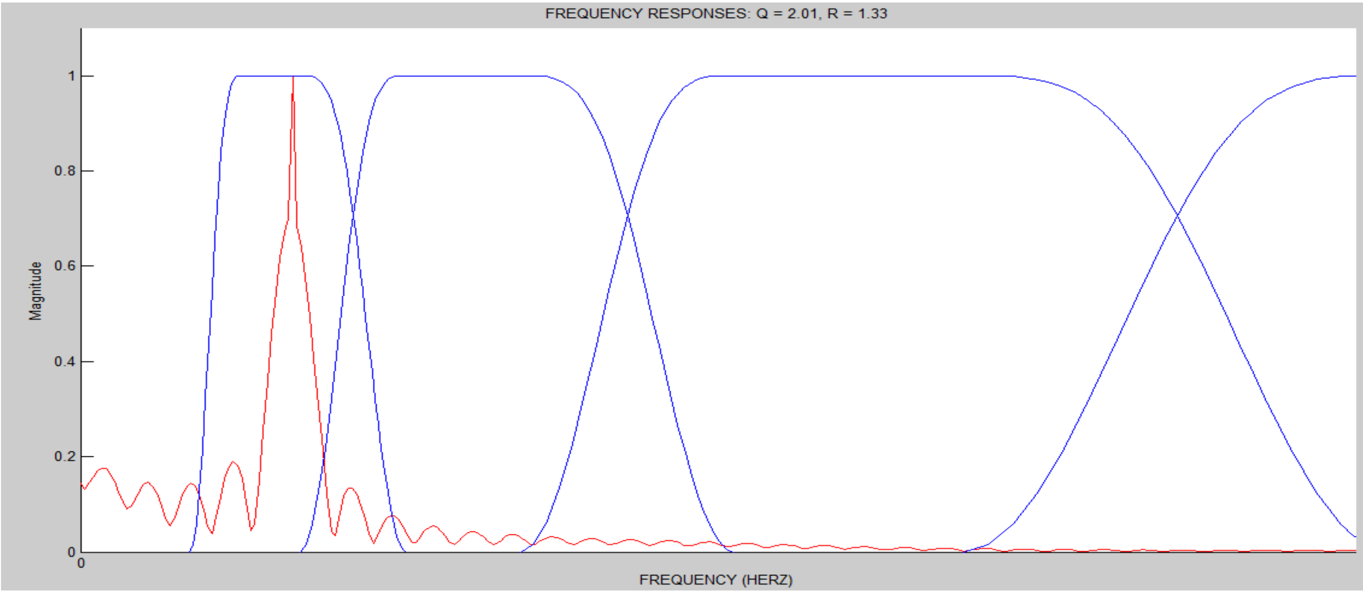

Figure 4. 3 Frequency responses of band-pass filters (blue), Frequency spectrum of current signal (red)

Chapter 5

Feature Extraction

In this project, classification has been carried out for short circuit faults of overhead transmission lines. Total 11 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.

5.1 Energy Computation

Energy computation follows the Parseval's Energy Theorem. Energy of all the 9 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:

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

Since, fundamental component lies in the first bandpass filter, therefore, E_8 = Energy of fundamental component of the signal, and E_1 + ……. + E_7 + E_9 corresponds to the energy corresponding to all the other frequencies.

5.2 Features

Four features (reducible to three) are used to detect and classify the fault present in a system. All features are based on Energy Ratio. These features are:

a. F_1 = ratio of fundamental energies of phases a and b = E_{fa}/E_{fb}
b. F_2 = ratio of fundamental energies of phases b and c = E_{fb}/E_{fc}
c. F_3 = ratio of fundamental energies of phases c and a = E_{fc}/E_{fa} (can be computed from F_1 and F_2, wherever needed).
d. F_4 = ratio of fundamental energies of zero sequence component in faulted signal and no fault signal = $\log_{10} (E_{fo}/(E_{fo})_{no})$

* E_f refers to the energy of fundamental component. The faulted phase will have more fundamental energy as compared to the non-faulted phase. Based on this rule, some threshold values were set. The detection step was achieved by means of a set of rules obtained from the comparison of these 4 features and the threshold values. The plots of all the feature for various faults are covered in Section 5.2.3 along with the threshold values for features.

Chapter 6

Fault Detection & Classification

6.1 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 - commonly represented by squares
2. Chance nodes - represented by circles
3. End nodes - represented by triangles

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.

6.2 Classification of faults

For classification purpose a rule based decision tree classifier is used. Rules are based on the following information.

As it is known that the faulted phase has higher fundamental component's energy than non-faulted phase's fundamental component's energy. This information can be used for fault detection. As F1 corresponds to ratio of fundamental energy in phase A and phase B, so ideally if F1 is greater than 1, it signifies that phase A is faulted and phase B is not. If F1 is approximately equal to 1, it signifies that phase A and phase B either both have fault, or both don't have fault. The same thing applies for F2 and F3.

The presence of ground is detected by F4. If it is very high, it indicates the presence of ground. If it is approximately equal to 1, then it is no fault condition. Based on this information and closely observing the variation of feature values for 36 samples, some threshold values were set, based on which a fault will be detected and classified further.

1. **Threshold values**
   - **a.** The threshold values corresponding to F1, F2 and F3 are as follows:
     - **i.** T1_low = 0.8
     - **ii.** T1_high = 1.2
     - **iii.** T2 = 1.4
   - **b.** The threshold values corresponding to F4 are as follows:
     - **i.** T0 1_low = 9
     - **ii.** T0 1_high = 12
     - **iii.** T0 2 = 17
2. **Rules of classification**

Fault detection and classification rules are as follows:

- If, F1 ∈ (T1_low, T1_high)
  - Both phase A & phase B are involved in fault
  - Or, both phase A & phase B are not involved in fault.
- If, F1 > T2
  - Phase A is involved in fault and phase B is not involved in fault.
- If, F2 ∈ (T1_low, T1_high)

- Both phase B & phase C are involved in fault
- Or, both phase B & phase C are not involved in fault.

- If, F2 > T2
  - Phase B is involved in fault and phase C is not involved in fault.
- If, F3 ∈ (T1_low, T1_high)
  - Both phase C & phase A are involved in fault
  - Or, both phase C & phase A are not involved in fault.
- If, F3 > T2
  - Phase C is involved in fault and phase A is not involved in fault.
- If, F4 > T0 2
  - Ground is involved in the fault.
- If, F4 ∈ (T0 1_low, T0 1_high)
  - Ground is not involved in the fault.
- If, F4 > T0 2
  - Ground is involved in the fault.

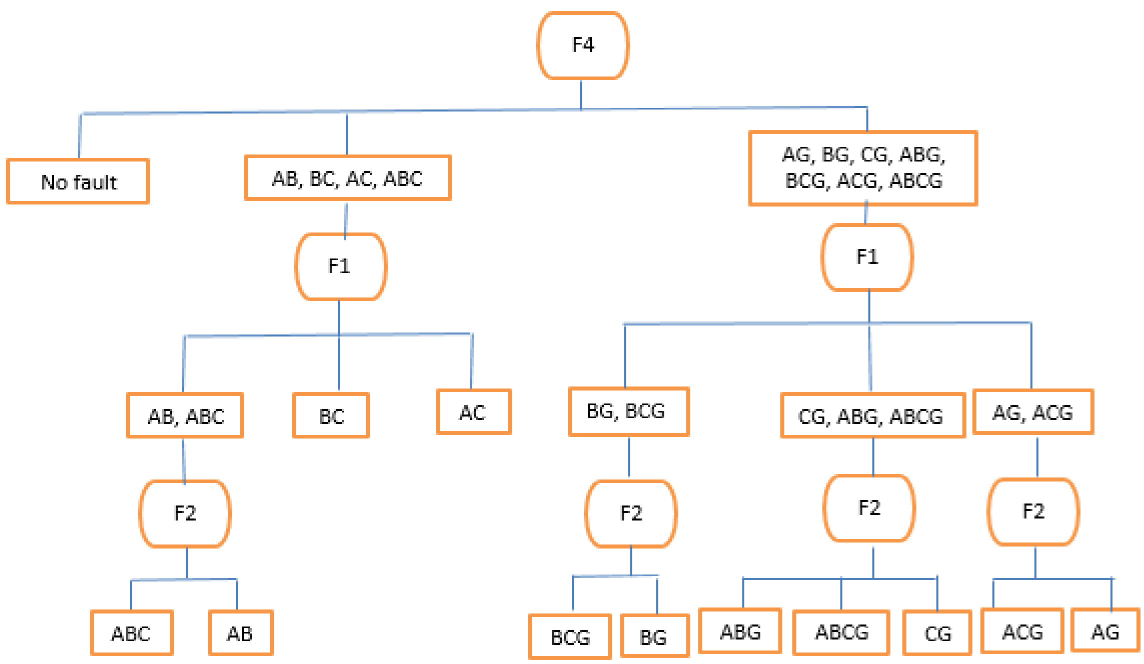

Figure 6. 1 Rule based Decision Tree

3. Plots of features

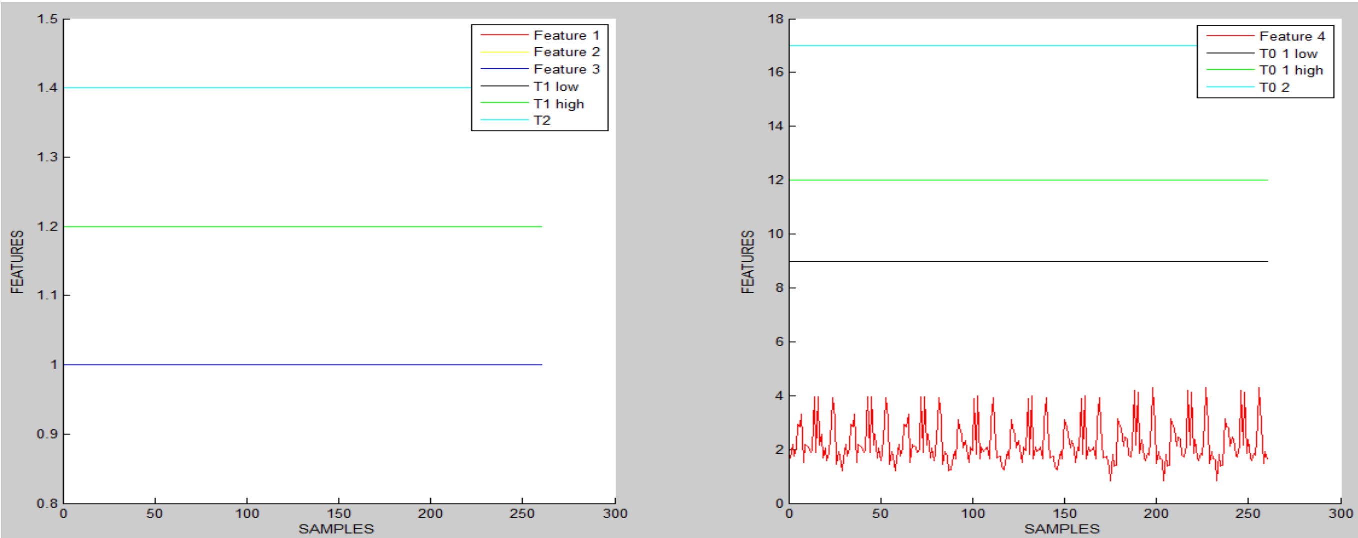

Figure 6. 2 Features: No fault

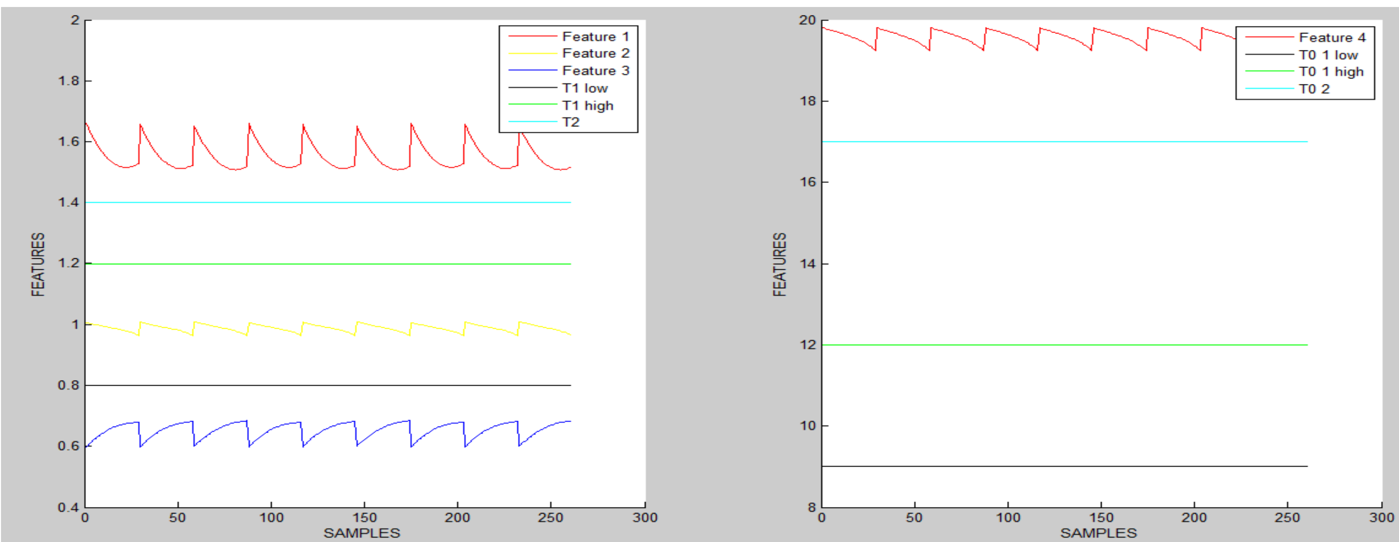

Figure 6. 3 Features: AG fault

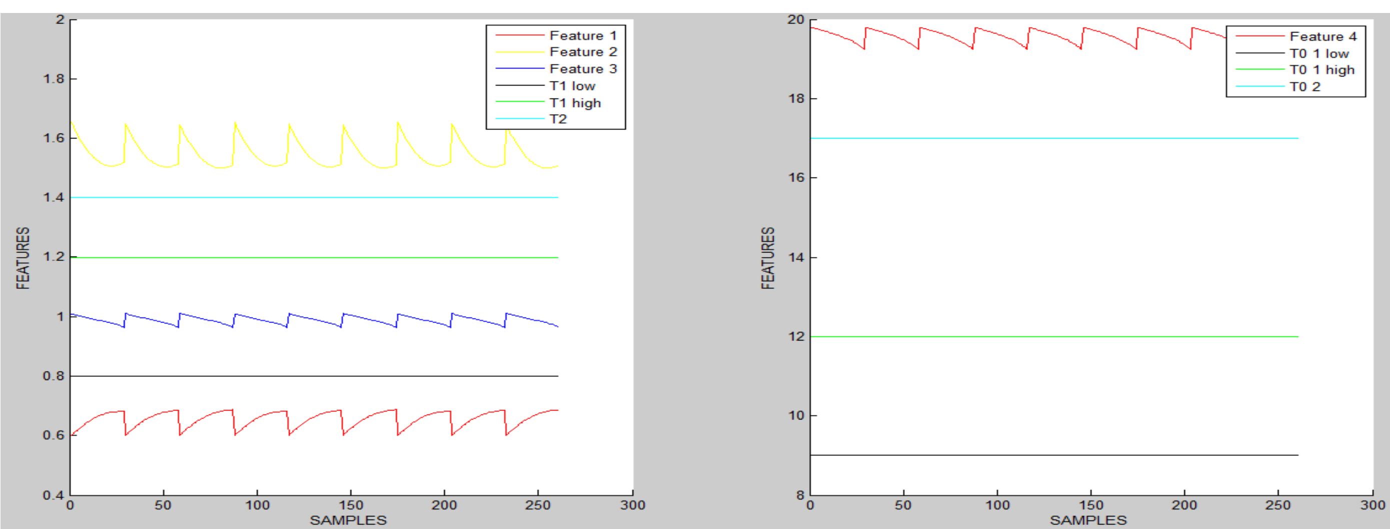

Figure 6. 4 Features: BG fault

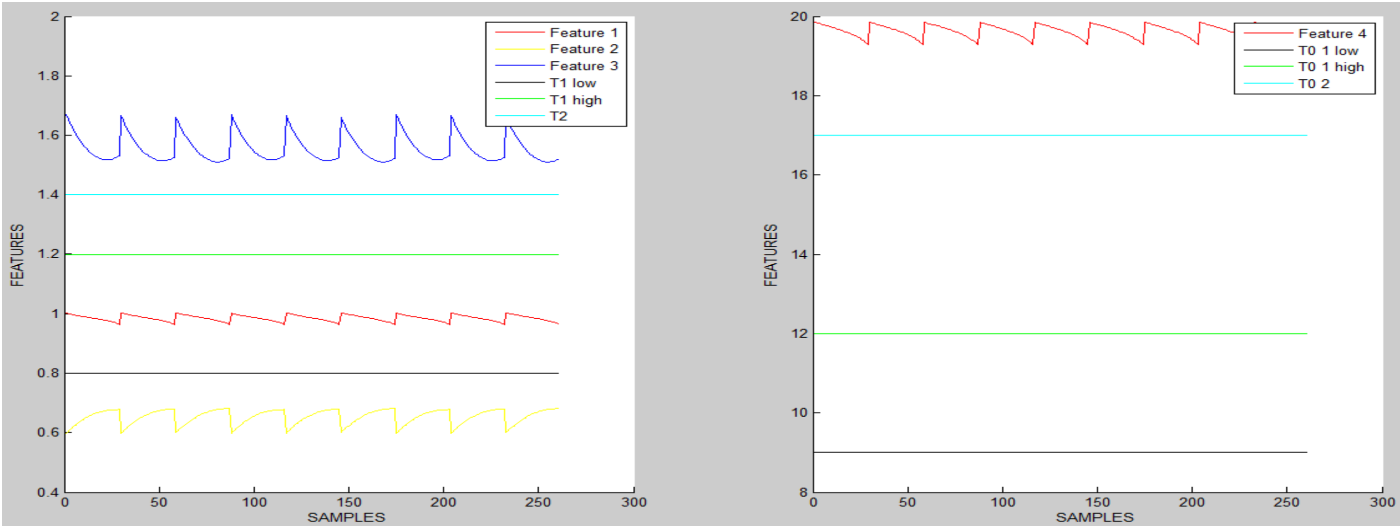

Figure 6. 5 Features: CG fault

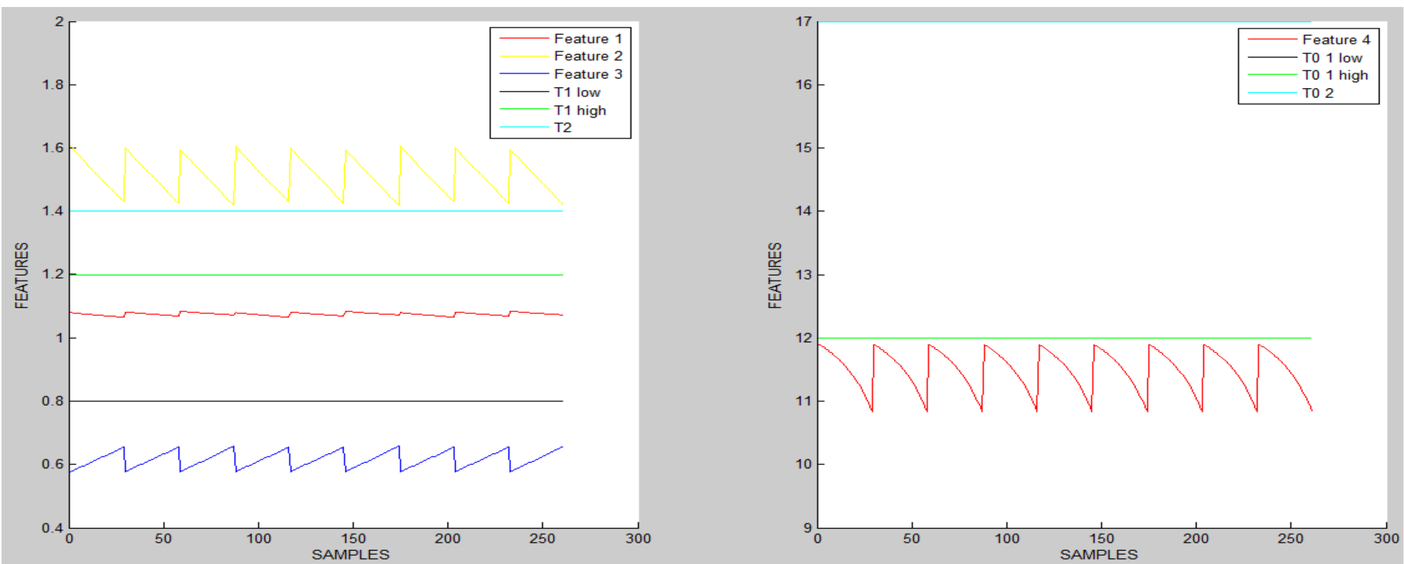

Figure 6. 6 Features: AB fault

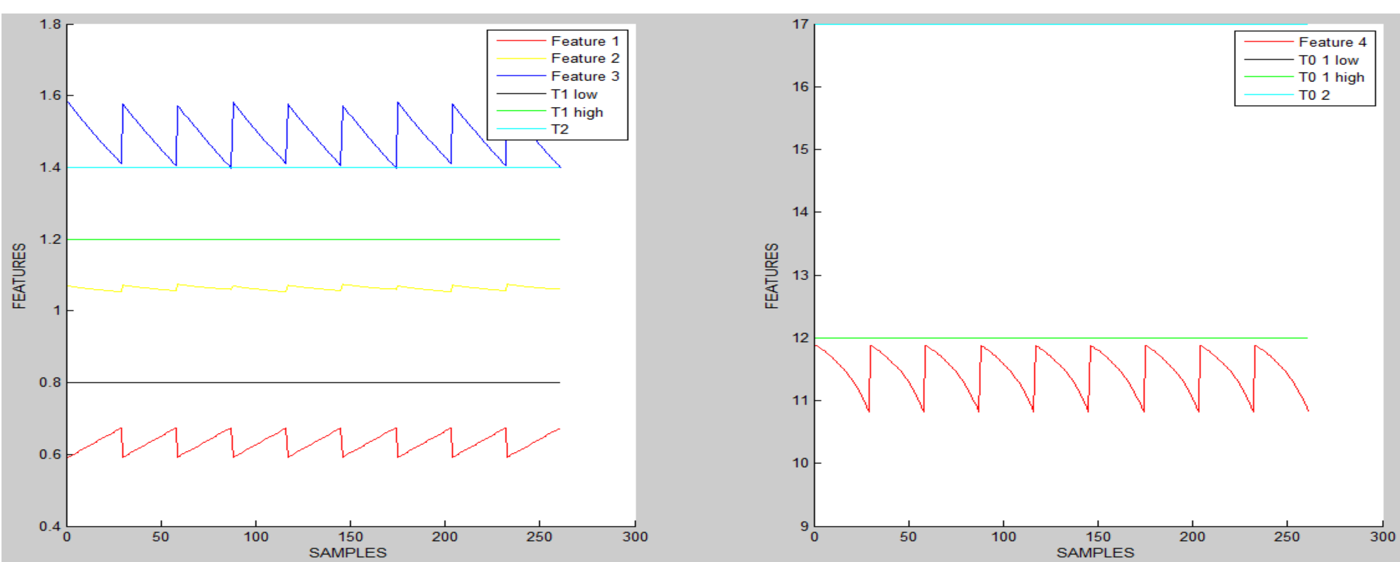

Figure 6. 7 Features: BC fault

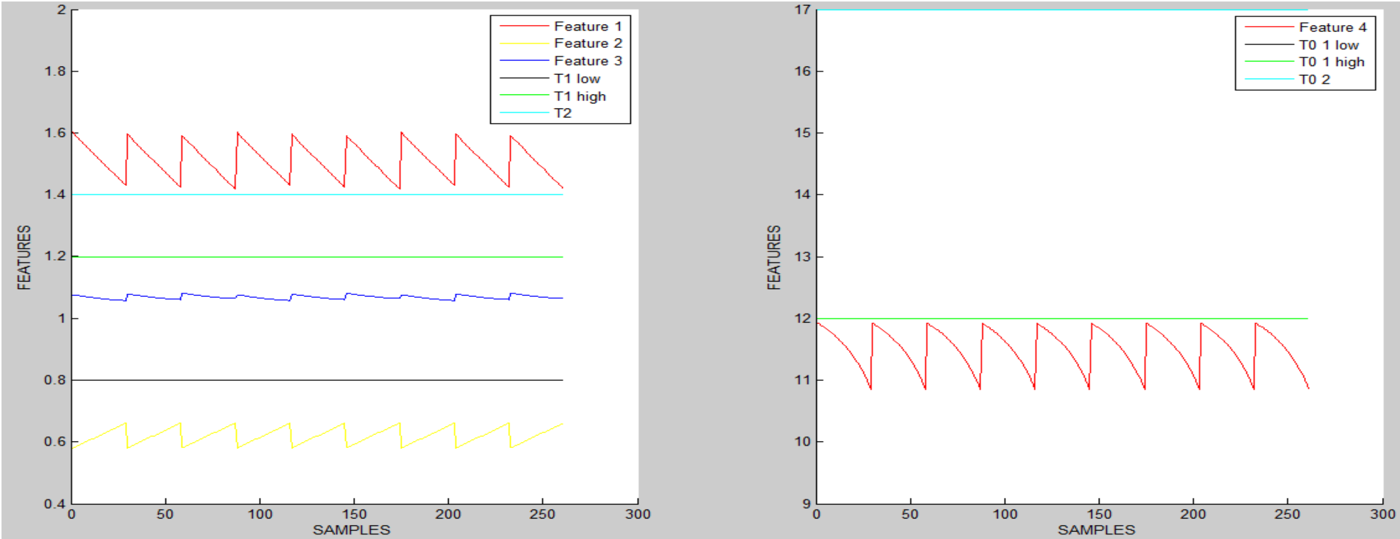

Figure 6. 8 Features: AC fault

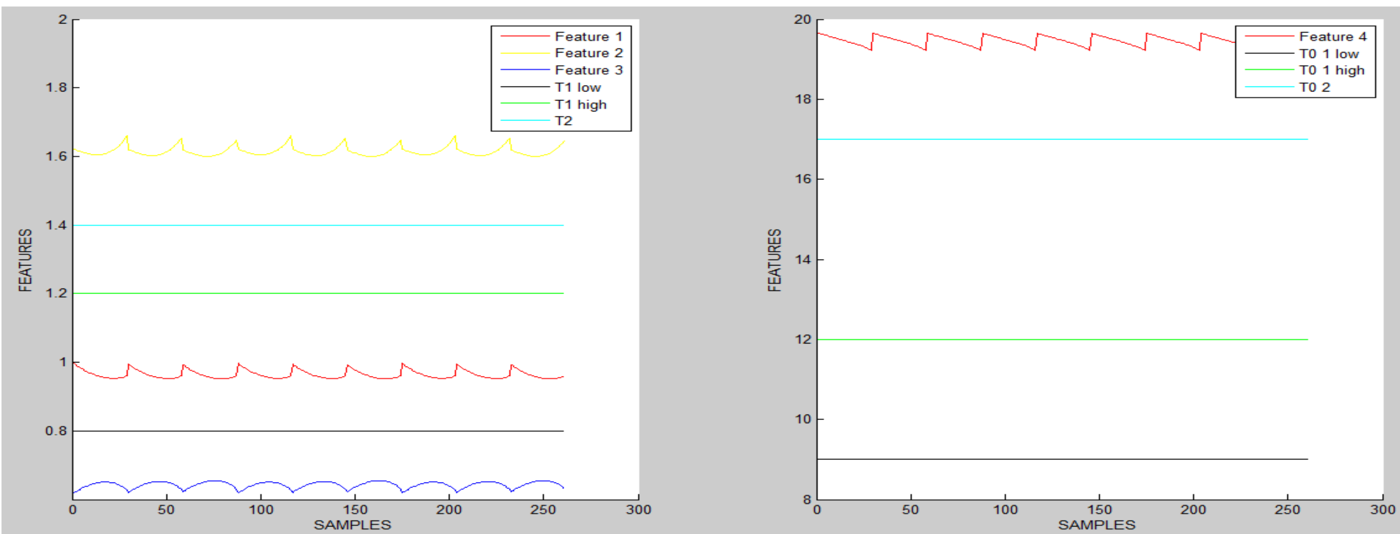

Figure 6. 9 Features: ABG fault

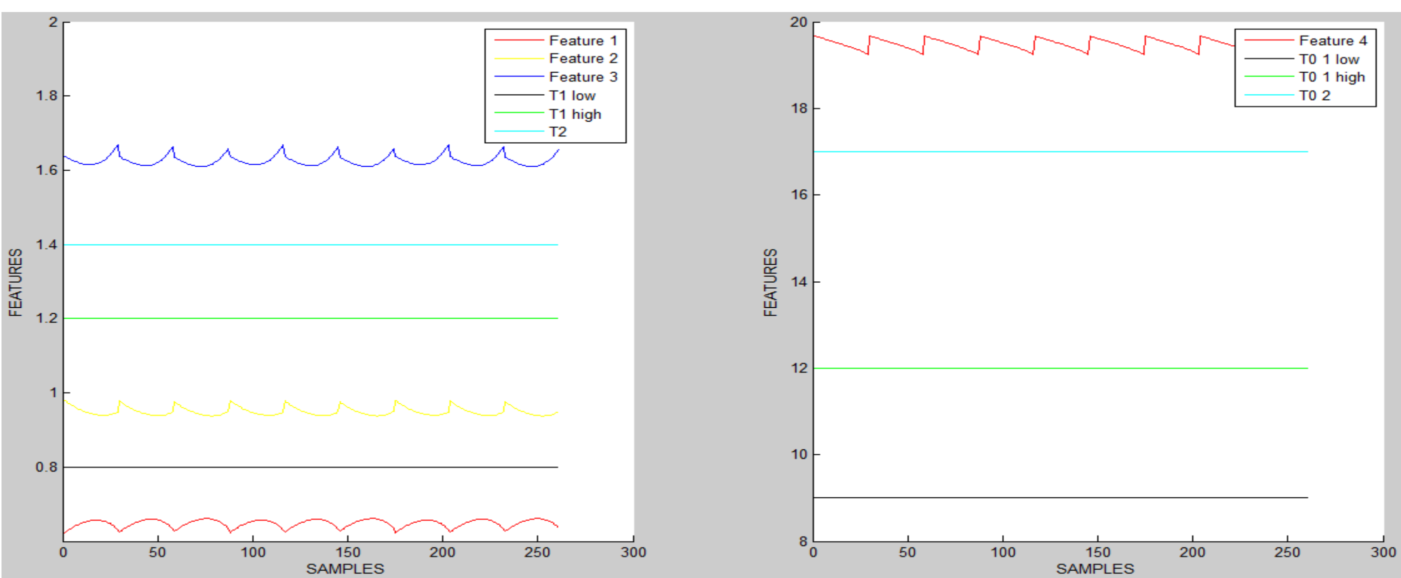

Figure 6. 10 Features: BCG fault

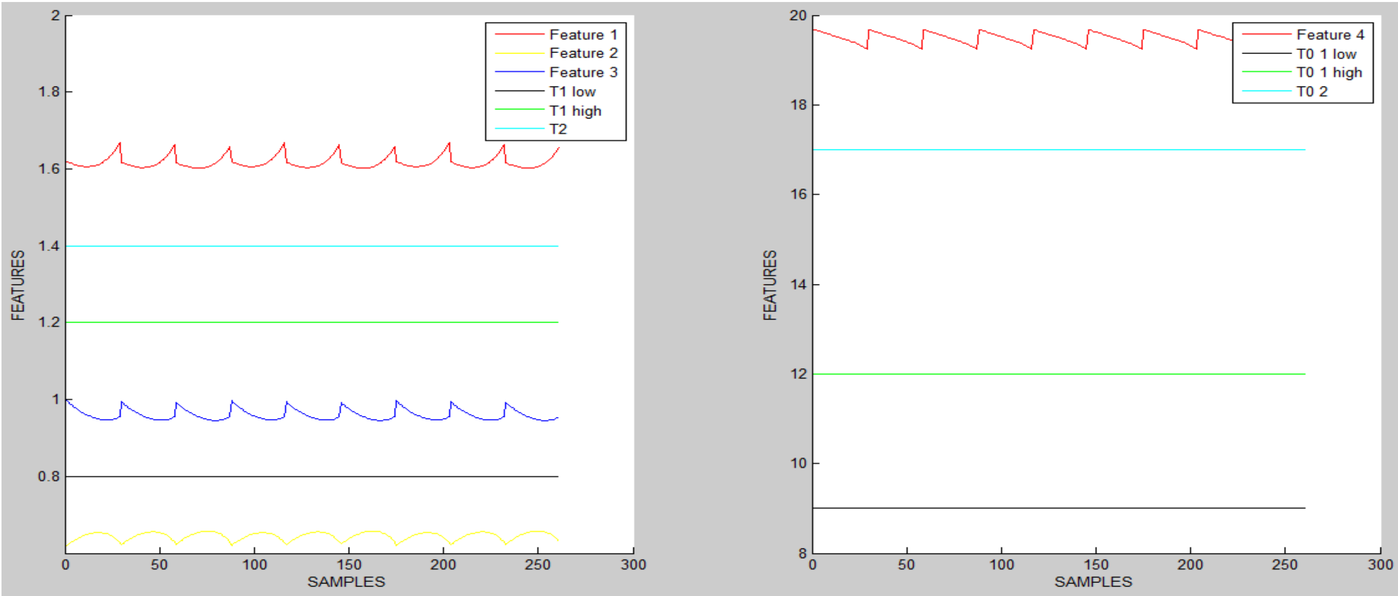

Figure 6. 11 Features: ACG fault

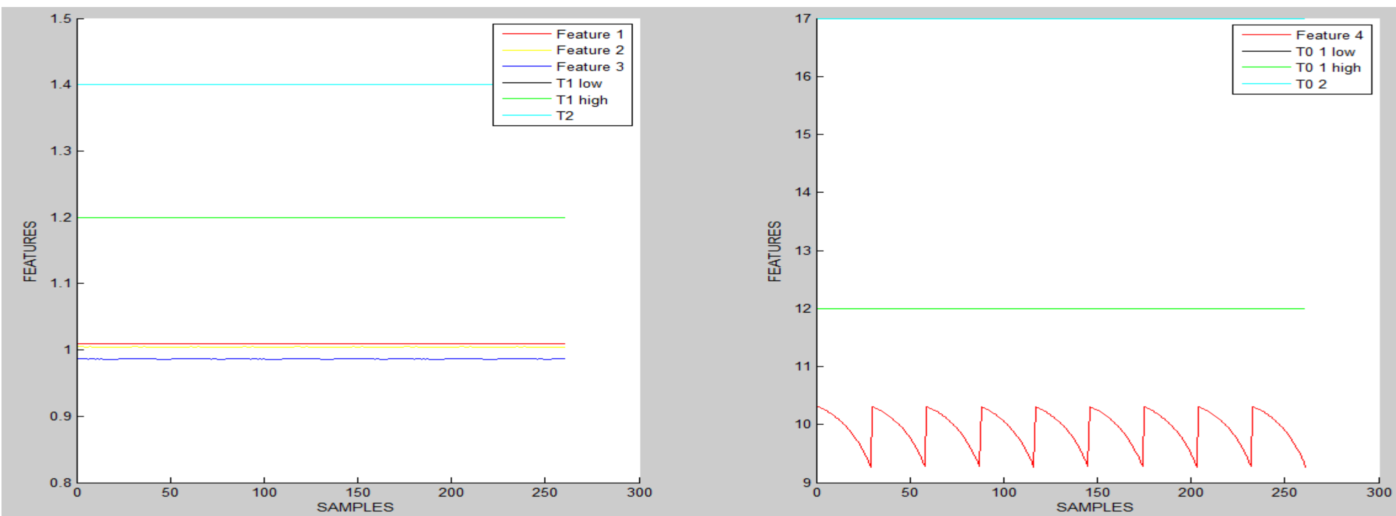

Figure 6. 12 Features: ABC fault

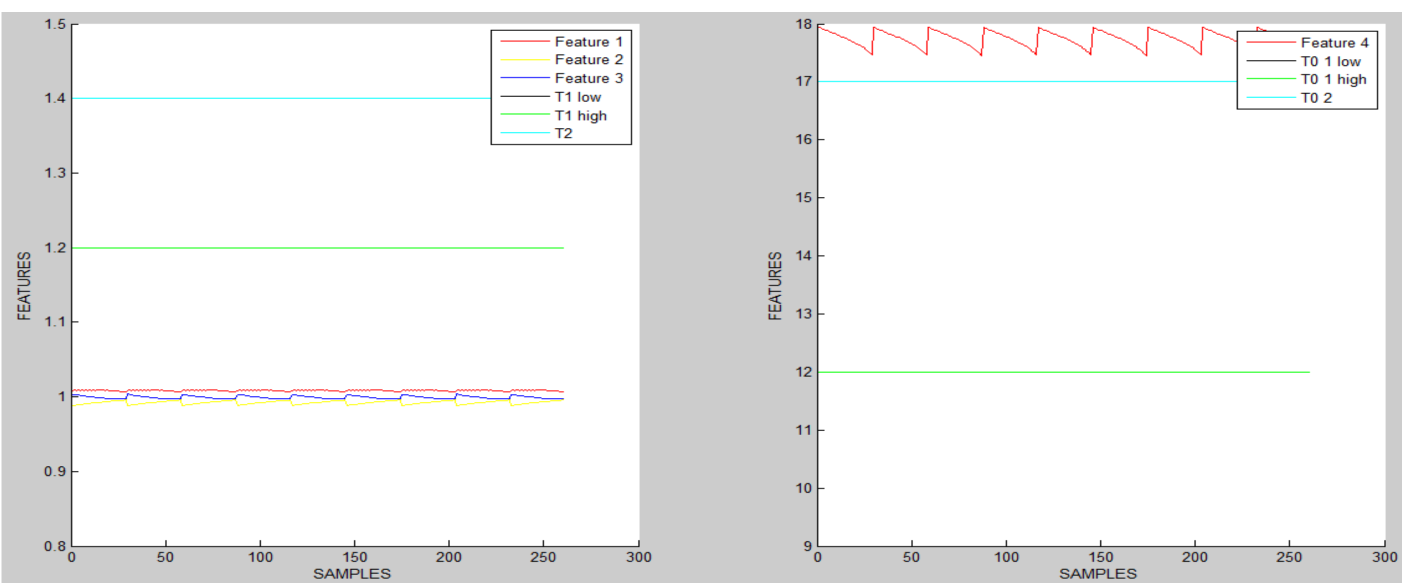

Figure 6. 13 Features: ABCG fault

Chapter 7

Results and Discussions

The current and voltage data for different faults were generated by simulating the shown network using Simulink in MATLAB. Data was collected by varying the fault location, at approximately every 10 km (in a line of total length of 300 km); 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. In totality, 260 samples of data were collected. 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.

The classifier was trained for 36 datasets and then tested for 260 datasets. An accuracy of 100% was observed. The computation time for a single dataset was 0.057215 seconds (when performed on an 8 GB Quadcore PC).

This is an adaptive and simple algorithm as for any system, it tunes the TQWT parameters based on the oscillatory behavior of the signals. Also, the features implemented do not require any no fault information other than F4, which makes it highly scalable.

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

Table 4 Faults and class labels

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 5 Results: % accuracy for various faults

Chapter 8

Conclusions

In this work, a new fault detection and classification approach using TQWT and a rule based decision tree has been proposed. The TQWT 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%. Also, this method has a very less computation time as compared to the pre-existing methods with highly reliable results. This is so because TQWT is a basic DFT based algorithm, unlike pattern recognition. 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 and faster computation in comparison to recent techniques. Proposed algorithm can be used in power faults monitoring software.

The key benefits of the proposed methodology above the pre-existing methods are:

- Adaptive
- Scalable
- Accurate
- Faster computation

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 further lesser computation time and memory space. This method can be implemented in a real power system network to achieve highly reliable results as well as fast computation, making it highly suitable for online detection. This method will be able to process the already buffered data well before the new data buffers.

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