DETECTION, CLASSIFICATION AND LOCATION IDENTIFICATION OF SHORT CIRCUIT FAULTS IN POWER SYSTEM NETWORK

A THESIS

Submitted to the University of Calicut

By

BINITHA JOSEPH MAMPILLY

(No:4340/2015/CU)

Under the supervision of

DR.SHEEBA V S

For the fulfilment of the award of the degree

DOCTOR OF PHILOSOPHY

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

GOVERNMENT ENGINEERING COLLEGE,THRISSUR

UNIVERSITY OF CALICUT

KERALA-INDIA

NOVEMBER 2024

DECLARATION

I hereby declare that this thesis entitled **Detection, Classification and Location identification of short circuit faults in power system network** submitted to the University of Calicut, for the award of Degree of Doctor of Philosophy under the Faculty of Engineering is an independent work done by me under the supervision and guidance of Dr. SHEEBA V. S, Professor, Department of Electrical and Electronics Engineering Research Centre, Government Engineering College Thrissur, University of Calicut. I also declare that this thesis contains no material which has been accepted for the award of any other degree or diploma of any University or Institution and to the best of my knowledge and belief, it contains no material previously published by any other person, except where due references are made in the text of the thesis.

Binitha Joseph Mampilly

4340/2015/CU,

Research Scholar

Department of Electrical and Electronics Engineering

Government Engineering College,Thrissur

ACKNOWLEDGEMENT

First and foremost I thank God Almighty for enabling me to submit the thesis. This thesis would not have been possible without the support and guidance of several people and I would like to take this opportunity to express my sincere gratitude towards them.

My deepest gratitude goes first to my supervisor Dr.(Prof).Sheeba V. S.,Retd. Principal, GEC, Thrissur for her sincere and timely support and guidance throughout the research. Amid her busy routine responsibilities she found time to evaluate ,correct and lead my research on the right path with continuous and consistent inputs. I remain indebted to her encouragements, continuous support, timely suggestions and discussion throughout my research work. I take this opportunity to express my heartfelt thanks to her for all the technical and moral help that she has offered.

I am grateful the Director and all the staff members of the Directorate of Research, Calicut University for their timely support to complete the work and in the final submission of the thesis.

I use this opportunity to thank my Doctoral committee members Dr. M. Nandakumar Christ Engineering College, and Dr. Jayan A.R. Government Enginering College, Thrissur for providing me timely directions in carrying out my research work.

I am also obliged to Dr. Jayanand B., Prof. Preetha K.P., Dr. Jasmine E.A., Dr. Meenakshi K. and Dr. Manju B. who in their capacity as Heads of the Department of Electrical and Electronics Engineering have helped me by providing the facilities in the department for carrying out my research work. The support extended to me by Dr. Neethu Varghese, Dr. Blessy ,Dr. Joseph K.D. and Dr. Premanand B. is also worth mentioning.

I am thankful to all the faculty members and staff members of the department of Electrical and Electronics Engineering, Govt. Engineering College, Thrissur for their help and motivation throughout the research period.

Finally I would like to acknowledge the unconditional love and support of my family. Without them this thesis could not have been accomplished.

Thrissur-9 **BINITHA JOSEPH MAMPILLY**

BONAFIDE CERTIFICATE

This is to certify that the work reported in this thesis entitled "**Detection, Classification and Location identification of short circuit faults in power system network "** that is being submitted by Mrs.Binitha Joseph Mampilly for the award of degree of Doctor of Philosophy, to the University of Calicut, is based on the bonafide research work carried out by her under my supervision and guidance in the Department of Electrical Engineering, Government Engineering College, Thrissur, University of Calicut. The results embodied in this thesis have not been included in any other thesis submitted previously for the award of any degree or diploma of any other University or institution.

Dr.Sheeba V.S.
(Supervising
Guide)

Department of Electrical
and Electronics Engineering,
Government Engineering
College,Thrissur.

Head of the Department
Electrical and Electronics
Engineering
Government Engineering College
Thrissur

Abstract

A microgrid is a network consisting of one or several loads and distributed generation (DG) sources that operate as a single aggregate load or source. Microgrids help to manage the DG sources more efficiently. The penetration of distributed renewable energy sources degrades the protection of microgrids, which leads to incorrect data flow in the energy systems. It is critical to detect faults , types of defects and location of faults in order to improve the protection and security of microgrids. To cater this issue in hybrid renewable energy system, a novel fault detection scheme is adopted using artificial intelligence. The deep learning techniques are applied for identification, classification and location identification of short circuit faults. Advanced feature extraction methods like empirical mode decomposition are carried out for fault detection in transmission lines and found to be more efficient compared to DWT. Fault detection and classification are carried out in an IEEE standard 30 bus network using Wavelet Transform (WT) and Bees Optimization Algorithm (BOA) based Improved Convolution Neural Network (ICNN). Matlab/Simulink is used to model a simple microgrid which is divided into four zones. Faults are simulated to generate training data for the neural network model. To improve the accuracy of fault detection, the features are extracted from the time series data using empirical wavelet transform (EWT). First, EWT evaluates the frequency components in the signal, then calculates the bounds and gets the basis of the oscillating components. The obtained samples are classified using a Hybrid Convolutional Recurrent Neural Network (HCRNN) and optimized by the Pelican Optimization Algorithm (POA). Eleven types of faults are identified along with the location of faults using the proposed system. The results are compared with the existing methods and found that the proposed method has improved the fault sample detection accuracy by 1.56%. The proposed approach

significantly reduce the response time to faults, thereby improving the reliability and efficiency of power systems.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

MG	Microgrid
DG	Distributed Generation Sources
ANN	Artificial Neural Network
BA-BO	Bees Algorithm Bayesian Optimisation.
CNN	Convolutional neural network.
EMD	Empirical node decomposition
SVM	Support Vector machine.
SCC	Short circuit current
TCSC	Thyristor controlled Series Capacitor.
PSD	Power Spectral Density
DWT	Discrete Wavelet Transform
FIS	Fuzzy Interference System
CNF	Concurrent Neuro Fuzzy
SCTL	Series Compensated Transmission Lines.
SGC	Smart Grid Controller.
SMG	Smart Microgrid
UFM	Unified Fault Matrix
MPPT	Maximum Power Point Tracking.
VMD	Variational Mode Decomposition.
SSO	Salp Swarm Optimisation.
KEMD	Krezing Empirical Mode Decomposition.
IMF	Intrinsic Mode Functions.
NDZ	Non Detection Zone

PAVMD	Parameter Adaptable Variational Mode Decomposition.
HIF	High Impedance Fault.
ELM	Extreme Learning Machine.
KELM	Kernelized Extreme Learning Machine
BP	Back Propogation.
GDA	Generalized Discriminant Analysis.
ANN	Artificial Neural Network.
VMD	Variational Mode Decomposition.
CWT	Continous Wavelet Transform.
EEMD	Ensemble Empirical Mode Decomposition.
RMSE	Root Mean Square Error.
PCA	Principal Component Analysis.
PMU	Phasor Measurement Units.
STPT	Short Time Fourier Transform.
HHT	Hilbert-Huang Transform.
EWT	Empirical Wavelet Transform.
KNN	K-Nearest Neighbours.
PSO	Particle Swarm Optimization.

CHAPTER1

INTRODUCTION

Nonavailability of fossil fuels, power system restructuring, deregulation and environmental pollution have increased the importance of renewable energy. Microgrid (MG) consists of one or several loads and Distributed Generation (DG) sources. DG sources at distribution level are effectively managed by the microgrid. Various types of DGs such as micro-turbine, diesel generator, battery storage, fuel cells, renewable energy resources, communication systems, control system and protection devices are integral parts of MGs. They operate in islanded mode or grid connected mode. Various types of DGs connected to microgrids pose challenges in protection, operation and controlling the MG. Further the MGs must be equipped to supply critical loads independently.

The fault flow magnitude, fault direction and fault duration may change the behaviour of protection mechanism used in MGs. So practically the kind of interfacing, the current levels of the fault etc need to be recomputed and power ratings of different protection equipments should be reorganized accordingly. The location of a fault point in the MG also results in protection coordination problems. Incipient faults are minor faults that may occur but may lead to big issues if not checked. Depending on duration of the fault there is sub cycle incipient fault and multicycle incipient fault. These faults may originate in different parts of the power system like underground cables or power transformers.

1.1 Motivation

With the concepts associated with microgrid involving growing concern among researchers, the importance of building an intelligent fault monitoring and diagnosis system capable of classifying and locating different types of faults is very crucial in today's power scenario.MG consists of low inertia DGs which lead to stability problems. Fault detection becomes challenging as the DG connected to MG have different types of control schemes depending on different modes of operation of MG. Power flow in MG is bidirectional. The conventional overcurrent protection mechanism is thus less reliable. Further these methods cannot resolve the prominent issues namely short-circuit power, nuisance tripping, bi-directional power flow, fault current level, reach of overcurrent relays, device discrimination etc. The features extracted from current and voltage signals dig out useful information and give better understanding of the nature of fault classification and location problems

Fault classification should be given equal importance in MG as is fault detection and localization methods. Majority of the faults occurring are unbalanced faults, so the identification of phase in which fault has occurred is of utmost importance as this can provide selective phase tripping and thereby provide a smart microgrid operation.

By applying mathematical calculations to big data the algorithms for fault classification acquire the potential to identify patterns in the data which would otherwise be an impossible task for humans. In big data classification vast and diverse datasets are grouped to get relevant information for operations, maintenance and decision making. Big data classification is applied to fault detection, load forecasting, asset management, real time monitoring and market optimization. The challenges here include data volume, velocity, data veracity and security. Intelligent electronic devices in the smart grid have helped to extract big volume data using which more accurate machine learning methods can be used for fault detection and localization.

Deep learning methods which use layered structure of algorithms called artificial neural network (ANN) are inspired by biological neural network of human brain, leading to a process of learning which is more efficient than standard machine learning methods. So the focus is on enhancing the analysis ability with minimum computational complexity. The determination of faulted bus and type of fault is very crucial in deciding the repair mechanisms with minimum time.

1.2 Objectives

Developing a reliable, accurate, fast fault detection and classification technique for microgrid protection in both grid connected and isolated conditions is the aim of the thesis The following tasks are carried out during the research.

1. Extracting features from the voltage and current signals and use it to detect the occurrence of short circuit fault.
2. To classify the faults to different categories of short circuit faults and find an accurate method to determine exact location of the fault
3. To propose a fault identification scheme and location particulars based on data mining methods
4. Find out hybrid methods to detect and classify faults in isolated as well as grid connected conditions of a typical microgrid within minimum time.

1.3 Contributions

The output of Distributed Energy Resources (DER) is intermittent and the features of inverter fed DGs present several problems to microgrid protection. The feature extraction is done from the huge volume of data available in the system pertaining to fault and no fault conditions. After feature extraction different classification methods are analysed. An efficient method is applied for detection and classification of faults. Without extracting the features in the testing phase, human brain is mimicked by applying deep learning methods.

The following are the contributions of this thesis

1. Simulated faults in transmission lines and used wavelet transform and empirical mode decomposition (EMD) to extract the features for detecting the short circuit faults effectively. Compared the two feature

extraction methods and found that Empirical mode decomposition provided the better results.

2. Simulated different faults in a microgrid connected to an IEEE13 bus system using Matlab/Simulink. Signal processing techniques are used for feature extraction and classification of 11 types of short circuit faults is done using Bees Algorithm-Bayesian Optimization (BA-BO) with an overall accuracy of 99.67%.
3. Designed a sample microgrid system with PV system and wind turbines. The microgrid is partitioned into four zones.11 types of faults are simulated in these zones. Hybrid CNN-RBN system is used along with Pelican Optimization which optimizes the training parameters. An increased accuracy of 1.56% is observed compared to the existing methods in the literature which use similar microgrid with different fault extraction and classification techniques. Empirical Wavelet Transform is used as the feature extraction technique utilizing the advantages of wavelet transform and EMD in dealing with nonlinear nonstationary signals.

1.4 Thesis Organization

The remaining chapters of the thesis are organized as below.

Chapter 2 gives a detailed review of the literature on short circuit fault detection and classification in bus system,microgrid *etc*. It also provides artificial intelligence and machine learning approaches which give accurate fault detection and classification.

Chapter 3 gives the elaborate theory of different types of faults, their importance, advantages of microgrid system etc. This chapter also gives an account of the feature extraction methods used in literature. The prominent classification methods are also reviewed elaborately.

Chapter 4 depicts the application of wavelet transform and empirical mode decomposition in fault detection in a typical transmission line. Comparison of both methods are also dealt with.

Chapter 5 presents fault simulations in IEEE 30 bus system with feature extraction and classification of faults using improved CNN along with Bees Algorithm.

Chapter 6 is devoted to a typical microgrid simulation.11 types of faults are analyzed .After feature extraction, classification is done using hybrid methods (CNN-RBN) with Pelican Optimization.

Chapter 7 gives conclusion and future scope for the research work carried out.

1.5 Summary

This chapter summarizes the motivation behind the research and advantages of fault detection with minimum time .The classification of faults also need to be done for efficient operation and protection of a microgrid system which is an integral part of the distribution system. The research contribution is outlined. The organization of the remaining chapters is also provided. The next chapter deals with literature review of different faults in power system with importance given to short circuit faults. The high accuracy obtained while using methods based on artificial intelligence is also discussed.

CHAPTER 2

LITERATURE SURVEY

2.1 Overview

The intricate web of interconnected electrical lines, known as the power grid, demands advanced and robust protection mechanisms. This is crucial, as various electricity- related issues can physically damage lines, necessitating swift repair and restoration. These repairs are vital for maintaining society's critical infrastructure and ensuring uninterrupted electricity supply. Faults are abnormal conditions that cause damage or disruption to the power system, such as short circuits, open circuits, or voltage fluctuations. Fault detection involves identifying the presence of a fault, while fault classification involves knowing the type of fault and locating it along with determining its severity and impact.

Accurately identifying and locating faults is key to efficient restoration. Unfortunately, pinpointing the exact location of a fault can be challenging. This has spurred the development of numerous approaches over time, each with its strengths and weaknesses. Various methods have been proposed for fault detection and classification, using different techniques such as signal processing, machine learning, artificial neural networks, wavelet transform, and synchrophasor measurements. Impedance-based methods measure the electrical impedance of the line to estimate the distance to the fault. Traveling wave-based methods analyze high-frequency waves generated by the fault to identify its location. Each method has its advantages and disadvantages, depending on the characteristics and conditions of the power system and the fault. The key challenges in accurately identifying the faults are presented below:

- **Complex Grid:** The vast and intricately interconnected nature of the grid makes pinpointing the source of a fault a complex task.

- **Diverse Fault Types:** Different types of faults, from short circuits to ground faults, exhibit unique signatures, requiring versatile detection methods.
- **Real-time Accuracy:** Precise and timely fault location is crucial for minimizing downtime and ensuring grid stability.

The above challenges can be overcome by combining different techniques which leverage the strengths of each method to improve accuracy and reliability. Incorporating real-time data from sensors and smart meters will enable dynamic fault detection and location. As the grid becomes increasingly interconnected, adequate cybersecurity measures are employed to protect against cyberattacks targeting fault detection and location systems. Forecasting in modern power systems is essential for maintaining grid stability, optimizing energy management, and improving economic efficiency. As renewable energy source integration increases, so does the complexity of forecasting challenges due to the inherent variability of wind and solar generation.

By continuously researching and developing advanced fault detection and location techniques, we can ensure a resilient and efficient power grid that supports societal needs. This chapter summarizes the importance of fault detection and location in power grids, highlighting the challenges, existing approaches, and future directions.

2.2 Review of faults on the Transmission Line

This section gives a detailed account of the research on transmission line fault detection, using different techniques as machine learning, transform-based models, deep learning techniques, principal component analysis, correlation methods, and time-synchronized methods. These approaches can accurately determine the location of problems by synchronizing readings from many places on the transmission line. This is especially useful for lengthy lines, when standard approaches may struggle to locate the problem correctly. Each category is briefly defined, including the basic idea and essential aspects. Conventional methods rely on data analysis and statistical methodologies, whereas contemporary methods use machine learning models and deep learning models. The difference between methods allows researchers to get a better grasp on the various

methodologies utilized in transmission line fault detection. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are good methods for detecting complicated patterns in massive datasets. These models may be trained using past fault data to detect and categorize defects in real-time.

2.2.1 Faults on the Transmission Line

Godse et al. [1] proposed a fault detection and classification technique for power transmission lines, relying on the morphology of mathematical features. The method involves extracting unique fault features using a morphology median filter, and the type of fault is determined by analysing with a decision tree classifier. The numerical and graphical outcomes of the extracted features demonstrate the effectiveness of the proposed strategy. The model was validated across various failure scenarios simulated on a high-voltage transmission line using EMTP/ATP and variable system parameters. The performance of the technique was further confirmed through real-world transmission line fault classification, highlighting its precision in fault identification and organizational capabilities. Additionally, the computational complexity of the approach was minimized. The fault detection model takes high computational time with less precision.

Lazzaretti et al. [2] introduced an online fault identification and categorization monitoring system, involving approximately 143 hours and 16 days of faults with a 5 kW power plant to assess fault detection accuracy. The study encompassed degradation, partial shadowing, open-circuit, and short-circuit scenarios for each type of fault. The experimental investigation revealed a classification phase accuracy of 95.44%, achieving an overall fault classification accuracy of 92.64%. The study included the analysis of concurrent faults, expanding beyond typical faults that may occur in the system, such as faults in Maximum Power Point Tracking

(MPPT) and additional types of short circuits. As a final validation step, the system is planned for integration into various photovoltaic facilities, some with higher-rated electrical capacity and located in diverse places with varying climate conditions. This broader implementation aims to enhance the model's generalization capacity. The details about identifying the MPPT faults and short circuit faults in the power system are not provided.

Davari et al. [3] proposed a system for detecting corona in UV-visible videos related to power distribution lines. The approach involves determining the incipient fault severity level and type for each video. Frames are extracted for processing each video pertaining to the nominal voltage of the power lines. Median filtering is applied to remove UV channel noises from the video, and corona discharges are identified in the frames using color thresholding. The incipient fault severity level is determined based on the observed discharge part ratio towards the equipment area. In comparison to state-of-the-art methods, this work demonstrated superior results and enhanced fault detection capabilities. It enables the automatic identification of incipient faults in distribution lines, considering environmental conditions. The authors focused on incipient faults in their work and did not mention the detection of any other types of faults. Usama et al. [4] proposed a defect detection and classification mechanism for power lines based on wavelet analysis. The wavelet regression approach focuses on analyzing high- frequency fluctuations (5-10 kHz) in amplified electrical signals to identify various types of faults. Wavelet regression extracts detailed information from the high-frequency region of the signal, allowing precise fault detection. Based on system dynamics, different thresholds are set to distinguish between different types of faults (ground faults, line-to-line faults, etc.). The wavelet analysis method demonstrated high accuracy in detecting electrical breakdowns in the tested system. While the wavelet analysis method excels at identifying the presence of a fault, pinpointing its exact location on the power line may be challenging due to the limitations of neural networks in handling real-time data.

Swetapadma et al. [5] proposed a fault location estimation scheme for various types of faults, such as morphing imperfections, multi-location defects, and frequent surge failures. They used the distributed parameter line model to calculate the line impedance. They also tested the effectiveness of their method under different conditions, such as fault type, location, resistance, and inception angle. The range of fault resistance is from 0.001 to 1%. However, these methods fail for parallel-connected circuits.

Huang et al. [6] gave a thorough analysis of Short-Circuit Current (SCC) in DC transmission lines, concentrating on artificial grounding faults in particular. They examine the current distribution and voltage behaviour around switches as they examine the early phases of fault events. They also investigate the effects of various fault scenarios and assess energy conversion stations' capacity to preserve network stability in the event of an SCC. Along with examining cutoff current distribution and peak/trough switch voltage values, they also explore the first few minutes of a DC synthetic foundation event.

Hofmann et al. [7] proposed a Unified Fault Matrix (UFM) approach for calculating shunt and series faults in power systems, considering the complete duality of these matrices. The UFM approach handles line-to-line short circuits and equipment disruptions with isolated neutral, allowing for customization. This duality simplifies calculations and analysis, making the method more efficient and adaptable. The authors improved efficiency by modifying only the terminal admittance matrix coefficients and not the grid topology. This model applies to diverse fault types, including line-to-line short circuits and isolated neutral cases.

2.2.2 Fault detection technologies in microgrid

In the realm of fault detection and classification in microgrid, Baloch et al. [8] utilized intelligent data mining strategies. The extracted features are then given to a logistic regression model. The subsequent fault classification is carried out through training an AdaBoost classifier. The evaluation of feature extractions, along with simulation results, is conducted within the SIMULINK/MATLAB software environment. The implementation and testing of the data mining model are performed using Python. To validate the efficacy of their approach, the researchers simulated both fault and fault-free scenarios, comparing the results with established methods such as random forest, Support Vector Machine (SVM), and decision tree techniques. This comprehensive methodology encompasses feature extraction, classifier training, simulation, and validation, highlighting the systematic and thorough approach taken by Baloch et al.[8] in their investigation of fault analysis in microgrids. The reliability of the system is very low and therefore the practical application is very rarer.

Wan et al. [9] have enhanced a rapid diagnosis technology for identifying short-circuit failures in a direct current microgrid. The study focuses on addressing multiple issues that may occur in both the conduit and the conversion device. Specifically, the regulation of the current shift at the beginning and end of the path is investigated. The authors introduce a grouping standard to classify the type of fault based on the rate of variation of fluctuating energy at the connection's top and termination. Additionally, an amplifier position standard is established to pinpoint the precise location of the error in the converter. It is important to identify that latency and connection issues are not addressed in this approach.

Khushi et al. [10] presented a smart microgrid approach for detecting fault locations in power lines within a distributed network. They emphasize the importance of an adaptive fault identification and elimination mechanism in a smart microgrid to mitigate undesired loads and enhance security. The study explores the trade-offs between efficiency and accuracy in a smart grid technology designed to handle ambiguous situations. In this research, a Smart Microgrid (SMG) is meticulously modeled. The SMG operates within a small, isolated region and employs a Smart Grid Controller (SGC) process. Notably, this system collaborates with a malfunction recognition mechanism to deal with any issues that may arise. During a brief timeframe, an equivalent voltage and current generate a wavelet activator signal. The study's findings are validated through simulation using the MATLAB Simulink platform integrated with the Smart Microgrid system.

Roy et al. [11] conducted an evaluation of a wavelet-based Power Spectral Density (PSD) method, utilized for fault detection in small grids. This study identifies faults and determines problematic stages, allowing for a focus on the entire defective bandwidth rather than just a single fundamental frequency. By analyzing signals from the transformer, the proposed method efficiently locates problematic sectors and reveals faults, eliminating the need for coordinated communications.

In the context of a low-voltage DC microgrid, Yadav et al. [12] introduced a filter capacitor current signature to detect and isolate short-circuit faults. Given the prevalence of short circuits in DC circuits and their associated risks, their approach leverages the composition of capacitors in DC microgrids. The study involves the development of a program to implement their fault identification method. Active sources such as photovoltaic panels and batteries are connected to passive loads through solid-state relays, DC cables, and DC-to-DC converters. The detection parameter is the average capacitor current, and the distributed network follows a zonal-type isolation configuration based on the iteration. The authors did not discuss the DC discharging in the power system.

2.2.3 Fuzzy Inference System

Swetapadma et al. [13] proposed a novel fault detection and location scheme for transmission lines leveraging fuzzy logic in the time domain. This method effectively identifies and locates various types of faults, including Port defects (Faults at the physical connection points of the line), Sequence imperfections (Faults affecting the sequence of phase voltages or currents), and Concurrent sequence and port abnormalities (Combined faults involving both sequence issues and port defects). The current and voltage waveforms are fed to the fuzzy logic system. Evaluations demonstrated high accuracy, with error margins of around 5% for pinpointing the conductor fault location and 1% for overall fault identification. Notably, the method successfully predicts the fault location and type for previously undocumented scenarios like concurrent faults involving sequence and parallel-shunt errors. However, it cannot currently differentiate between

specific types of port defects. Overall, the fuzzy-based scheme serves as a promising approach for accurate and versatile fault analysis in transmission lines, with advancements possible in further distinguishing port defect types.

Bhatnagar et al. [14] implemented a Fuzzy Interference System (FIS) for the identification and categorization of synchronous and unsymmetrical faults, as well as exceptional scenarios like developing flaws and high impedance. The outcomes of this study validate the FIS-based technique's ability to detect and classify errors within a single frame. Numerous researchers have proposed inspection and categorization algorithms employing computational intelligence. The system can be regarded as a reliable, rapid, and accurate defect determination and categorization strategy. However, it's worth noting that the fault identification duration is relatively lengthy.

Fault detection in series-compensated transmission lines (SCTLs) presents a unique challenge. Tabari et al. [15] proposed a method using a single circuit terminal's electrical and magnetic signals. Extracted features like power and current time variations, DC component decline, and fundamental frequency variations are directed to a fuzzy neural network for fault identification. The method proved successful across various configurations, demonstrating its robustness. However, practical implementation faces hurdles due to cost and sustainability concerns.

Naresh Kumar et al. [16] addressed the fault identification issue by refining a fuzzy inference system (FIS) using estimated resistances from each phase. This computationally efficient approach also demonstrated accurate fault location with evidence for its classification. The approach offer promising solutions for SCTL fault detection, each with its advantages and challenges. Monitoring consecutive lines for diverse faults remains a complex task, suggesting further research and development in this area.

Yadav et al. [17] proposed a fuzzy inference system (FIS) for fault detection and classification in multimodal communication cables. This system effectively identifies fault locations, types, and severities. Additionally, a practical implementation of the method using a single-end microcontroller at the transmission point protects the cable. Evaluations and simulations demonstrated that the proposed method can identify and categorize faults within 50% of the fault's onset time. However, utilizing a high sampling frequency in a traveling wave-based algorithm makes it incompatible.

Eboule et al. [18] presented the concurrent neuro-fuzzy technique (CNF) for identifying and tracking diverse faults in power cable networks. This method combines neural networks and fuzzy logic to model external imperfections. The authors explored its potential for fault detection and identification in long-distance communication cables. However, due to its early stage of development in fiber optics, advanced research will establish its generalizability and robustness. Existing methods for fault location in communication lines were also found to be inadequate.

Bhatnagar et al. [19] developed a fault detection and classification system for communication lines that combines a fuzzy inference system (FIS) with discrete wavelet transform (DWT). This approach uses DWT to extract relevant features from single-point signal measurements and then employs FIS to identify and categorize faults in both normal and noisy conditions. It can even detect evolving faults and maintain accuracy amidst changing operating environments. The resilience and diagnosis of cyber-attack control are not mentioned in the works.

Abbas et al. [20] introduced an adaptive neuro-fuzzy inference system (ANFIS)-based fault detection framework for hybrid dynamic systems. This method utilizes grid splitting and small segmentation techniques to effectively monitor empirical data. While demonstrating promising results in various settings, its primary focus remains on investigating technical malfunctions. Bhatnagar et al. [19] focus on communication lines, while Abbas et al.[20] target hybrid dynamic systems. Comparison of the performance of these methods with existing ones is not done effectively. Both methods boast high accuracy and adaptability, with Bhatnagar et al. [19] emphasizing robustness to noise and evolving faults.

2.2.4 Transforms-based models

Hubana et al. [21] used Discrete Wavelet Transform (DWT) for both detection and classification of faults in microgrids. Microgrids pose a challenge due to their dynamic nature and unique characteristics. By analyzing electrical signals using DWT, this approach identifies and categorizes faults based on their distinct signatures. The effectiveness of the method was validated using MATLAB Simulink simulations, providing promising results for future implementation in microgrid protection devices. The authors' focus was primarily on low-load conditions and constant states in their work. The conditions involving high loads or switching states are not addressed effectively.

Veerasamy et al. [22] introduced a graphical language classifier combined with DWT for detecting high-impedance faults in distribution power systems. Through Simulink network modeling, they extracted energy values from fault signals. DWT analysis then classified the fault types with 100% accuracy, outperforming a conventional fuzzy model that misclassified certain faults. This approach offers superior flexibility and accuracy while maintaining lower complexity. Even though all faults are discussed in this work by the authors they failed to address the faults for large loads.

Akhil Vinayak et al. [23] proposed a method using wavelet transform (WT) to analyze the stator current of the motor. They extract features using a specific WT configuration and calculate the standard deviation of these features at different decomposition levels. This feature set is then used by a Support Vector Machine (SVM) to classify various fault types. The method is claimed to be robust to variations in operating conditions and load.

Grcić et al. [24] propose a short-time Fourier transform (STFT) for fault detection in DC microgrids. They simulate various fault scenarios and analyze the resulting time signals using STFT to obtain the frequency spectrum. This spectrum is then fed into different machine-learning classifiers to identify the type of fault. The study demonstrates high accuracy with several classifiers achieving F1 scores above 91%. These two studies showcase different approaches for fault detection in electrical systems using signal analysis and machine learning. Akhil Vinayak et al.[23] 's method offers robustness to operating conditions, while Grcić et al.[24]'s method exhibits high accuracy with various classifiers. Both studies represent valuable contributions to the field of fault detection and prevention. Both studies failed to achieve protection over the system while performing the fault detection operation.

Azuara Grande et al. [25] proposed an effective method for ground fault detection in power systems using wavelet transform (WT). The ground fault voltages and currents were analyzed and tested using an arc ground fault model on the IEEE nine-bus standard test system in MATLAB/Simulink. The model successfully detected and cleared various ground faults at different locations, validating its effectiveness. The protection relay efficiency was evaluated based on fault location, demonstrating the method's robustness. This model is validated on the IEEE nine-bus standard test system with different fault scenarios and it successfully detected and cleared faults at various locations, demonstrating system efficiency. The generalized configuration is not applicable for all types of faults and does not discuss phase- to-phase faults throughout the work. The real-time implementation is also not mentioned in the work.

Lucas et al. [26] presented a Wavelet Transform model for diagnosing transient short-circuit faults. A new statistical index based on the cross-correlation function was developed to detect and characterize transient inter-turn short circuits (ITSCs). Principal component analysis and wavelet transform were used to identify the phase affected by the short circuit. After testing the algorithm on a three-phase induction motor the method could accurately detect, identify, and classify the transient short-circuit faults. By analyzing the acoustic emission (AE) signal in more detail, the system can potentially differentiate between various types of ITSCs and other issues, leading to more accurate diagnoses and targeted maintenance actions. Indeed, when considering the computational complexity of a system, higher complexity often translates to increased costs.

Harish et al. [27] developed a Wavelet Transform method to extract features for detecting transmission line faults. They developed a data-driven model to extract features from power system signals. They used the ensemble feature extraction model to detect and classify the transmission line faults. They compared their method with state-of-the-art methods and showed that it achieved a fault classification accuracy of 99.78% with minimal testing and training time. While this work focuses on other aspects, such as incipient faults and specific fault types, the security-related components were not explicitly covered.

Mohamed et al. [28] utilized a hybrid wavelet transform method for identifying faults. They used a redundant operation to extract features of small defects and make them more visible. They calculated the redundancy ratio of the numerical values on the original signal, which was about 36%. By applying a continuous wavelet transform, they extracted the fault characteristic more efficiently in the time-frequency domain from the redundant signal. They evaluated the early fault detection using advanced signal processing techniques.

2.2.5 Machine Learning based models

Banerjee et al. [29] presented a decision tree (DT) technique that uses predictive modeling to categorize and recognize several likely intermittent hybrid scenarios. The suggested approach begins with monitoring the transient amplitudes of electrical signals at various locations. The methodology is followed by the selection of attributes for the DT grouping strategy, which uses the gross weight parameter's result metrics. The extensive study findings confirm that the suggested technique detects and classifies each intermittent action with 100% accuracy. Verification was carried out using an uncertainty matrix. They are building a decision tree using the selected features to categorize and recognize different types of transient events, such as faults, islanding, and intentional switching. However, the decision tree may overfit the training data, resulting in worse accuracy on new data. Techniques like cross-validation and regularization can help to mitigate this risk .The quality of the power is low using this technique.

Achlerkar et al. [30] have developed a technique utilizing decision trees to detect and classify disturbances in grid-linked dispersed generating systems, considering both mixed and single power quality (PQ) issues. The study evaluates the suitability of the Variational Mode Decomposition (VMD) approach for distinguishing sound, irregular events (such as transients), and stationary PQ disturbances (such as harmonics, inter-harmonics, and flicker). Results indicate that VMD is effective in accurately estimating phasor qualities, including frequency, phase angle, and amplitude, along with other defining characteristics. Employing decision tree method ,features such as instantaneous amplitude (IA), mode central frequencies, zero crossings, and comparative mode energy ratios are extracted for the classification of single and mixed PQ disturbances. The proposed method's efficacy is tested across various noise levels and system operating conditions using artificial signal analysis, real occurrence-derived trouble signals, and signals generated through a real-time digital simulator platform. Over-discharging and internal short circuit issues are not overcome using this technique.

Gao et al. [31] introduced a detection methodology using the Enhanced Empirical Wavelet Transform (EWT), twin Support Vector Machine (SVM), and the Hankel Singular Value Decomposition (Hankel-SVD) denoising technique to target Subsynchronous Resonance-Induced Frequency (SAF) disturbances under varying operating conditions. The DC-bus current is denoised using the Hankel-SVD technique to effectively reduce unnecessary background noise and switching frequency impact. The denoised current is then decomposed by the empirical wavelet transform, and the composite multiscale iteration entropy for each frequency band is input into the Salp Swarm Optimization (SSO)-based Twin SVM classifier for the fault detection process. The proposed detection methodology achieved a remarkable detection accuracy of 98.10% on the collected data, outperforming other established approaches like wavelet decomposition, empirical mode decomposition, and statistical techniques such as mean, standard deviation, and entropy. The cross-validation is easily done with the proposed system.

Shao et al. [32] proposed a distinctive method for identifying Combined Heat and Power (CHP) unit islanding using a Support Vector Machine (SVM) and Kriging Empirical Mode Decomposition (KEMD). This approach utilizes the two-dimensional local signal fluctuation of the intrinsic mode functions (IMF) as the relay's data source. The relay undergoes a detection reduction and enters the Non-Detection Zone (NDZ) through an ideal signal selection model. The threshold selection challenge is addressed by employing the shark smell optimization methodology to optimize the suggested relay's SVM algorithm as a pattern recognition tool. Implemented in a microgrid with various distributed generation types, the method demonstrates advantages such as negligible NDZ, high detection time, 0% fail detection, and low relay cost. The interactions and coordination among multiple agents introduce additional computational overhead. Balancing the benefits of fault detection with the associated computational costs becomes crucial in such scenarios.

For Photovoltaic (PV) based microgrid scenario, Chakravorti et al. [33] discuss the analysis of disturbances in non-islanding and islanding modes. The microgrid is trained to operate in both islanding mode and grid-synchronized mode (i.e., IEEE 1547) to establish an effective pattern recognition system. The study introduces the Robust Regularized Random Vector

Functional Link Network and Parameter Adaptable Variational Mode Decomposition (PAVMD) to address the need for dynamic detection thresholds. The innovative PAVMD method, optimizing parameters using the firefly algorithm, is applied to the retrieved waveforms. Features are extracted from the output of the PAVMD approach, and the adaptability of PAVMD is investigated for various disturbances in both grid-connected and islanding modes, a unique contribution to the existing literature. The proposed approach is also evaluated in noisy conditions, achieving a reasonable and suitable level of classification accuracy. However, additional techniques should be included to limit the noise sensitivity level. Sarangi et al. [34] devised a methodology considering the variation in differential energy (DE) of bridges by employing an ensemble empirical mode decomposition approach on current waveforms for feature extraction. The High Impedance Fault (HIF) location is then provided with the extracted characteristics utilizing an adaptive multi-kernel extreme learning machine. To improve predictability, a diversion function is employed using a straightforward and adaptable approach based on forensic investigation (FBI) optimization. The research includes a comprehensive convergence analysis to assess the effectiveness of this updated optimization strategy. The proposed technique demonstrates efficacy and reliability, yielding favorable outcomes in terms of HIF identification and placement. Indeed, employing this method may lead to increased computational complexity and potentially compromise fault diagnosis accuracy. Striking a balance between computational efficiency and diagnostic precision becomes crucial in practical applications.

Samanta et al. [35] introduced a methodology involving Extreme Learning Machine (ELM) and Power Quality Event (PQE) detection with categorization using Empirical Mode

Decomposition (EMD). Essential features characterizing PQE signals are computed through the EMD approach, and a down-sampled Kriging Interpolation (KI) based EMD is recommended to enhance the speed and accuracy of the process. Power Quality Disturbances (PQDs) are classified using ELM, considering attributes obtained through the KI-EMD technique. The optimization of system variables using the Symbiotic Organism Search (SOS) optimization approach improves the reliability and efficiency of ELM. Comparative findings demonstrate improvements of 2-5% in terms of durability, speed, and accuracy compared to traditional approaches. Indeed, to achieve heterogeneous data, it is often necessary to gather information from multiple sources. However, this process can be challenging due to inefficient preprocessing algorithms.

Nsaif et al. [36] proposed a fast and accurate islanding detection technique with a near-zero non-detection zone for distributed solar systems. They developed a new islanding detection method by combining machine learning and signal processing techniques. They used variational mode decomposition to analyze the signals and extract the intrinsic-mode functions. They applied this decomposition to the positive and negative sequence component voltages and the power signals at the point of common coupling. They also used the ensemble bagged-trees method as the machine learning technique. They reported a detection time of 4.8 ms and a minimal non-detection zone of less than 4%. They claimed that their method was reliable and suitable for the distribution grid.

Li et al. [37] presented a novel technique for detecting DC series arc faults, which are dangerous and hard to detect. They observed and recorded the changes in the supply output voltage and the line current caused by arc faults. They proposed a detection technique that used both the supply output voltage and the line current signals. They applied the local mean decomposition (LMD) to obtain the unique frequency band of the line current with a better decomposition effect. They calculated the fuzzy entropy and the harmonic power of the corresponding frequency-band signals to reflect the variation in the line current complexity. They also selected the supply output voltage deviation standard as another feature for arc fault detection. They classified the extracted features using support vector machines (SVM).

Sarangi et al. [38] developed a system for safeguarding distributed generation (DG) integrated microgrid systems utilizing the Hilbert-Huang Transform (HHT) implemented with a Kernelized Extreme Learning Machine (KELM). The process involves obtaining Intrinsic Mode Functions (IMFs) by subjecting current signals from buses to Empirical Mode Decomposition (EMD). Subsequently, the differential and spectral energy of both buses are calculated using the largest IMF. Essential characteristics for protection features, such as differential standard deviation, energy levels, entropy, median, and mean, are then noted for each type of failure in a grid-connected system with looping and radial architecture, based on an IEC microgrid model examination. The proposed system significantly enhances accuracy and security. However, this method achieved minimum reliability, robustness, and interpretability.

Long et al. [39] introduced a novel fault diagnostic technique for addressing IGBT open- circuit problems in solar power production systems. The methodology involves adaptive filtering of noise in three-phase current using Empirical Mode Decomposition (EMD), followed by feature extraction and dimensionality reduction through statistical analysis and Generalized Discriminant Analysis (GDA). Fault pattern identification is then achieved using a Backpropagation (BP) neural network. Simulation trials confirm the accuracy and speed of the proposed method, which is also compared with conventional feature extraction techniques. The authors highlight that their approach improves fault recognition rates and the simplicity of the neural network topology.

Roy et al. [40] proposed and applied a fast and accurate fault detection algorithm to a smart microgrid model. The methodology integrates machine learning techniques and empirical mode decomposition (EMD) in the microgrid detection system. Artificial Neural Network (ANN) is employed to streamline the microgrid fault identification process, and the efficacy of the automated EMD and diagnostic method is compared with alternative methods. The suggested automated EMD for fault detection and evaluation technology demonstrates a significant improvement in classification accuracy compared to earlier methods, achieving an impressive total accuracy of 95.63% in the microgrid test-bed model. Addressing the challenges of increased energy consumption and improving energy storage systems is crucial for sustainable solutions.

In any interconnected system of distributed generation (DG) to the electrical grid, precise identification of power quality disturbances, both in non-islanding and islanding scenarios, is crucial for maintaining power quality, machinery functionality, and worker safety. Choudhury et al. [41] proposed intelligent methods and signal processing techniques to identify islanding occurrences with a very small non-detection region and classify power quality (PQ) problems with improved accuracy. A Multilayer Perceptron Neural Network is introduced to categorize islanding and non-islanding PQ occurrences. The islanding and PQ disturbance signature is extracted from acquired voltage signals using noise-resilient down- sampling EMD. Numerous numerical experiments, considering scenarios with and without noise, confirm the effectiveness of this study.

2.2.6 Deep Learning based models

Koley et al. [42] proposed an artificial neural network (ANN) to detect and classify all types of line faults in a six-phase distribution system. They developed eleven flexible ANN models that only used voltage and current measurements at the sending end of the line. They conducted experimental tests on a six-phase power line to validate their proposed design.

Their preliminary results showed that their ANN-based fault detector and classifier could successfully detect, classify, and locate the line faults. However, they noted that their method did not estimate the fault distance.

Devi et al. [43] applied deep learning for fault analysis and used it to locate the fault site in microgrids (MG). They introduced different types of system faults into the network and used their proposed method to analyze the results in each case. They tested their method in a realistic simulation environment. The method was effective in detecting and classifying different kinds of faults in the MG. They also located the faulty area of the MG with accuracy. The signal may fluctuate before attaining a steady value as the deep learning model converges during computation.

Assadi et al. [44] tested an artificial neural network (ANN) to detect and classify different types of faults, such as double-line-to-ground, three-phase, three-phase-to-ground, and open- circuit faults. They evaluated the performance of the ANN by varying the fault resistance, fault type, and fault inception time. They also analyzed the accuracy of the detection and classification process at each stage. They chose the best ANN architecture based on the number of hidden neurons in each layer. They conducted a comprehensive study to validate their choice. However, morphing faults were not considered in this study.

Zhang et al. [45] propose a novel model for accurate photovoltaic (PV) power forecasting. Their method utilizes Variational Mode Decomposition (VMD) and PV time series is decomposed into different frequency components. Convolutional Neural Networks (CNNs) is employed to learn the relationship between these components and future power output.Bi-directional Gated Recurrent Units (BiGRUs) are used to forecast future values of each component. The combined forecasts of all sub-modes provide the final PV power prediction. According to the authors, this method outperforms existing forecasting techniques. However, this method encountered computational burden and yielded inaccurate fault classification results.

Chen et al. [46] introduced a new model for series arc fault (SAF) detection in PV arrays. Their model, named "Excitation and Squeeze Inception Multi-input CNN," employs several key steps. First, it denoises current signals using normalization and Henkel singular value decomposition, particularly focusing on removing switching frequency noise. Then, the model utilizes a Convolutional Neural Network (CNN) trained on both frequency-domain and time-domain features to classify signals as either faulty or normal. This model achieves a 97.8% detection accuracy, surpassing traditional methods, and is claimed to be robust to factors like MPPT operation, shading variations, wind, long lines, and aging arrays.

Anjaiah et al. [47] tackle the challenge of accurately identifying and classifying photovoltaic (PV) faults in DC microgrids with distributed generation. Their clever approach combines two powerful techniques: Adaptive Variational Mode Decomposition (AVMD) to dissect fault current signals into informative components and an Improved Broad Learning System (IBLS) to efficiently categorize the fault type based on extracted features. This approach combines adaptive Variational Mode Decomposition (VMD) optimization with L-kurtosis- based feature selection to achieve maximum accuracy, all the while ensuring manageable computational resources. Additionally, Anjaiah et al. demonstrate the real-world applicability of their system by successfully implementing it on a dSPACE 1104 embedded processor.

Meanwhile, Han et al. [48] focus on optimizing power quality disturbances (PQDs) in power systems. They introduce a novel technique that leverages the power of Convolutional Neural Networks (CNNs) for efficient sub-dictionary prediction. This approach significantly reduces resource requirements by allowing CNNs to intelligently select and optimize the sub-dictionaries used for representing PQDs. Compared to conventional atomic decomposition methods, Han et al.[51] 's method demonstrates superior accuracy in sub-dictionary selection, as validated on the IEEE 1159.2 standard and synthetic datasets.

Eristi et al. [49] proposed a deep learning-based system where the power quality disturbances (PQDs) are identified using deep learning based systems in solar photovoltaic plants connected to power system networks. They used GoogleNet and AlexNet to receive the image files as input in this hybrid deep learning method. They performed neighborhood component analysis (NCA) on the features obtained from the last dropout layer of the architecture. They used a support vector machine (SVM) to classify the distinctive features obtained from the NCA process. They used the data PQD from an adapted IEEE 13-bus test model that included the solar photovoltaic system to evaluate their proposed method. They found that their hybrid deep learning method could accurately identify the PQDs even when the solar photovoltaic plant adversely affected the power quality of the integrated power system.

Wang et al. [50] used discrete wavelet transform and convolutional neural networks (CNN) for fault analysis. They used MATLAB/Simulink to model the traveling wave signals and the output fault signals. They used the Db4 wavelet to decompose the traveling wave signals into specific signals. They used two terminal traveling wave based method to locate the fault. They fed the wavelet detail coefficients to the CNN as input. They evaluated their algorithm on a power system and showed that it could effectively detect faults under different conditions, such as transition resistance, fault inception angle, fault location, and fault type. They noted that their method improved the power system stability and safety.

Xiong et al. [51] suggest a fault diagnosis technique that addresses various challenges, including diverse fault types, subtle fault features, ambiguity regarding fault type and mode, signal variation, instability, wide gaps among fault data classes, narrow gaps between classes, and nonlinearity. The authors recommend using a combination of the quantum genetic algorithm (QGA) with Support Vector Machine (SVM), mutual dimensionless indicator, and variational mode decomposition for electrical system fault diagnostics. The approach involves decomposing the initial signal into Intrinsic Mode Functions (IMF) using variational modal decomposition, deriving mutual undefined indicators for each IMF, and using QGA to optimize the SVM parameters. The proposed method demonstrates higher effectiveness and accuracy in fault identification and classification for building electrical systems, achieving a median test accuracy of 91.67%. However, this method is limited to diagnosing only six specific types of electrical faults because the extracted features from fault signals are minimal. Therefore, a composite fault diagnosis model that combines different feature extraction techniques or leverages additional data sources is necessary for more comprehensive and accurate fault identification.

Wang et al. [52] recommended a hybrid approach involving deep learning (DL) and frequency-domain decomposition for accurate photovoltaic (PV) power forecast intervals. The method adopts ensemble empirical mode decomposition (EEMD) to divide the original PV energy time-series data into high- and low-frequency sub-series, followed by statistical feature extraction. A modified Long Short-Term Memory (LSTM) scheme is employed to forecast sub-series with different intervals (minute-hour-day), using hyperparameters generated through Bayesian optimization (BO). The first-time node is analyzed using support vector regression (SVR) to minimize the prediction value's fluctuating error. This work exhibits low average absolute deviation (AbsDEV) and root mean square error (RMSE) values, especially in the seven-day forward prediction scenario, enhancing forecast accuracy and stability by an average of 15% compared to other prediction models.

2.2.7 Time-Synchronized Methods

Pan et al. [53] developed a method for classifying cyber-attacks and disturbances in power systems using heterogeneous time-synchronized data. They defined the term common path as a sequence of critical system states in temporal order that represent different types of cyber-attacks and disturbances. From labeled data logs common paths were automatically discovered using heterogeneous synchrophasor data fusion. They learned the common paths using a common path-mining model. The method could identify unique paths for each event type and compare them with state-of-the-art methods.

Pandey et al. [54] designed a method for detecting, localizing, and classifying events in power systems using synchrophasor data. They used the component location information and topology along with synchrophasor data for event analysis. They addressed the data quality issue of Phasor Measurement Units (PMUs) before using the data for event analysis. They used physics-based decision tree rules and density-based spatial clustering and statistics for event classification. They used graph search and statistical algorithms with topology information for event localization. They validated their algorithms with satisfactory results for IEEE 39 Bus and IEEE 14 Bus systems. However, an effective machine learning detector is needed for developing a real-time implementation tool with faster results.

Shrivastava et al. [55] presented a new synchronized data-driven model for improving the real-time situational awareness of power systems. They detected the events in the network using 18-cycle bus frequency data with a robust index. They developed novel indices based on statistical measures using frequency synchronized measurements and bus voltage magnitude data length to detect the event types. They validated the event location identification and classification using the event's signature based on rule-based inference. They captured the system's topological changes using real-time synchronized data. They applied their model to the standard IEEE 118 Bus and IEEE 39 Bus test systems.

Swain et al. [56] proposed a method for detecting faults in transmission line using Synchrophasor measurements and machine learning models. They used Phasor Measurement Units (PMUs) to monitor the power flow at different locations within the grid, which helped to optimize the grid efficiency and maintain the system stability. These were the key objectives of the smart grid 3.0 paradigm. Many machine learning models, such as K-Nearest Neighbour, Support Vector Machine, and Logistic Regression, are suggested to detect, classify, and clear the faults in transmission lines. They implemented their models in real- time on a physical laboratory 200 km transmission line and compared their performance.

Izadi et al. [57] proposed a synchronized Lissajous-based method for classifying events in power distribution networks using synchro-waveform measurements. They analyzed the shape of the synchronized Lissajous curves during events and disturbances and used them to classify the events. They considered the impact of the event type, location, and angle on the shape of the curves. They demonstrated the effectiveness of their event classification method using real-world field data and hardware-in-the-loop simulations. They showed that their method could accurately detect the start and end time of each event and classify the power quality events with high accuracy. A prior knowledge about the network is not needed and the data used is from only two waveform measurement units. It is unsuitable for several real- life applications despite high energy availability and it lacks reliability.

Kummerow et al. [58] proposed a synchrophasor-based online recognition method for power systems. They used synchrophasor applications to monitor and control transient system events. They increased the number of active grid components and ensured secure system operation with sufficient reserves. They provided additional information and improved the system operation with concise and interpretable results from synchrophasor applications. They developed a web-based online visualization tool and detected and classified disturbances using time series analysis. They enabled automated decision-making processes to mitigate the critical system states and ensure secure system operations. They evaluated their synchrophasor application modules at the transmission and distribution level and presented simulation and measurement-based results.

Shi et al. [59] proposed a matrix profile-based method for discovering and labeling power system events using synchrophasor data. They introduced a novel event discovery and labeling framework based on matrix profiles. Their framework was model-free, fast, scalable, and only required one user-defined parameter. They built matrix profiles by measuring the similarities between the subsequences of a time series. They automatically labeled the system events using synchrophasor data and evaluated their efficiency using PMU data.

2.2.8 Correlation-Based Analysis

Mukherjee et al. [60] presented a method for fault detection in long transmission lines, employing correlation-based analysis with post-fault transient oscillations of both current and voltage signals. The authors observed a decrease in RMS voltage value and an increase in phase current when a fault is detected. To address the tradeoff between current and voltage, a correlation analysis was conducted. They introduced noise to the signals and varied the fault location along the line to create a real-time environment. The approach achieved a prediction accuracy of 99.3%.

Roy et al. [61] introduced an innovative approach for detecting faulty phases based on correlation factor computation. The authors tested their method on compensated transmission lines and the IEEE-57 and IEEE-14 test beds. The analysis involved examining the positive and negative voltage relationships among the current transmission lines, particularly focusing on pole-to-ground faults.

An et al. [62] designed a system using Pearson correlation for fault detection in transmission lines, specifically single pole-to-ground faults. The authors considered positive correlation coefficients equal to 1 for single pole-to-ground faults and negative values (-1) for all other faults, emphasizing effectiveness under high-resistance grounding faults.

Gonzalez-Sanchez et al. [63] designed a security scheme for AC transmission lines based on traveling wave propagation. Utilizing distributed parameter theory, the authors analyzed correlations between two traveling waves for fault identification, allowing for precise fault distance evaluation with two wavefronts. The study concluded that this method is valid for improved identification of fault locations in transmission lines. Due to the correlation model and unnecessary complexity, the accuracy was compromised.

Jia et al. [64] addressed issues with conventional ratio braking type differential protection by designing a pilot protection technique based on Spearman's rank correlation coefficient. In the presence of an external fault in the transmission line, the traversing current flows through the line, causing both sides' current waveforms to flow in opposite directions. Internal faults, on the other hand, result in significant differences in transient current waveforms, which can be estimated using Spearman's rank correlation coefficient. The technique performs better in scenarios with weak power output and permanent failures.

Chatterjee et al. [65] developed a fault location approach using the novel cross-correlation technique for identifying single-phase faults in transmission lines. This method aims to quickly restore power by utilizing only voltage signals from end-to-end transmission lines. Features are extracted using cross-correlation and then forwarded to an ANN for accurate fault location, ensuring better accuracy in fault detection.

Reis et al. [66] presented an improved single-ended traveling wave technique for fault identification. The time delay between fault-induced incidents and reflected signals is evaluated using the correlation function. Unlike other approaches, this method has no impact on low-frequency signals. It uses the first incident surge for fault detection and monitoring buses. The authors claimed that the designed technique can effectively identify faults with location reliably.

Ahmed et al. [67] presented a cross-correlation-based technique for analyzing electromagnetic interferences (EMI). This method extracts signals of open circuit switch faults in a three-level NPC inverter, providing fast outcomes through cross-correlation among conducted EMI. Analyzing the internal structure, the study offers higher accuracy in detecting fault location compared to other methods.

Ma et al. [68] introduced a grey correlation analysis approach to analyze fault location in DC distribution. This technique analyzes aerial mode traveling differential current waveforms from the initial and end points of the DC line. Fault location identification is performed in association with the optimal time shift, enabling fault detection even at low sampling frequencies.

Yoo et al. [69] presented a correlation-based clustering algorithm for fault detection in transmission lines. Using a dimension mitigation clustering algorithm, fault index values are evaluated, and detection is identified if values exceed probabilistic limitations. While the physical meaning of data is challenging with clustering-based dimension mitigation, the algorithm gives efficient error free analysis. The authors conducted hydraulic test equipment analysis, achieving highly accurate fault detection. When transforming data, it can indeed become challenging to retain the original data's physical meaning.

Yi et al. [70] introduced a failure probability analysis mechanism using the Goal-Oriented (GO) technique, along with common cause failure and maintenance correlation. The repairable system considered in this work is a k-out-m configuration with the stated technique. The failure analysis is conducted using Markov Theory. The dynamic unavailability of the Hydraulic Oil Supply System (HOSS) is analyzed with the GO technique, ensuring higher efficacy compared to other techniques.

Sinha et al. [71] designed a method to analyze cross-country failures in distribution networks by extracting required features using cross-correlation. This employs a threshold-based fault detection technique. The cross-correlation technique restores the non-linear features of signals from the HIF and CCF syndrome. After filtering out low-frequency signals, negative and positive peaks are derived using the Correlogram. Normal and abnormal signals are identified using the QRS level. The Jellyfish optimization technique is used to choose accurate sensors along with the bus-housed CCHIF.

2.2.9 Principle Component Analysis

According to NdjakomoEssiane et al. [72], a principle component analysis (PCA) that relies on the examination of the system's major components and variations is used to identify and uncover faults in solar power systems. The variations in the voltage-power and electrical characteristics data are analyzed. After that, defects are found by using the rating and the component computation. The midway point idea was effectively applied to identify six unique operational periods. Using outputs from both a simulator environment and a real structure with 18 photovoltaic cells, the core analyzer demonstrated more accurate error identification. As a result, additional algorithm generators are required for several tests to interpret signals and determine the worth of the examination device.

Arabaci et al. [73] introduced a machine-learning algorithm for identifying and categorizing broken rotor bar (BRB) defects on varying degree of intensity. The data collection source was electrical energy, and features were gathered by modifying the temporal phase potential waveforms. The technique needs to consistently differentiate between functioning and malfunctioning machines for use in a work environment. Therefore, it is important to avoid both erroneous alerts and unnoticed malfunctions. Interestingly, fewer characteristics proved to be superior in terms of identification and categorization, as well as enabling faster evaluation. However, imbalanced tangential impulses are generated, which could potentially harm the shaft and rotation.

Wang et al. [74] proposed a cascaded H-bridge multilevel inverter systems for fault detection, combining Principal Component Analysis (PCA) for data dimensionality reduction and multi-class Relevance Vector Machine (mRVM) for classification. Voltage waveform characteristics of the transformer were chosen as malfunction diagnostic indicators for the error diagnostic technique based on an understanding of transformer characteristics. Reduction in size through PCA increases the rate of defect identification, and precise diagnosis is enhanced by mRVM, which produces numerical outcomes from its assessment. This method is used in experiments which provide deterministic responses for every failure while reducing the duration of the operation. Therefore, it proves challenging to quickly identify a mistake using traditional methods.

Elsamanty et al. [75] utilized Principal Component Analysis (PCA) to retain almost the entire information variance and reduce the complexity of environmental evaluation. The study demonstrates that independent Principal Components (PCs) can be extracted from the combined information, allowing for precise identification of both good and defective situations. This proves to be a reliable method for identifying structural issues in rotating equipment, potentially saving on maintenance costs and enhancing reliability in manufacturing environments. However, it may pose challenges in recognizing and differentiating certain technical issues.

Huang et al. [76] evaluated a machine learning algorithm addressing the issue of quick proximity finding in complex degree areas. The study introduces an automated setup technique for determining the appropriate nearest neighbor system for querying a specific set of information. It examines whether the method's settings depend on the features of the content source and aims to accommodate extremely massive data files that cannot be handled on individual devices. However, challenges arise when scaling to extremely massive dimension records on computational clusters, and the speed of the implemented methods becomes a crucial concern for handling large volumes of data.

Xiao et al. [77] introduced a weighted Principal Component Analysis (PCA) method to alleviate the impact of chaotic information in evidence samples while maintaining the relationship between attributes and forecasting reliability. This method is highly adaptable and can be applied to various solar energy sources to obtain characteristic information. The simulation allows for the anticipation of renewable generators in different scenarios. However, it is noted that its forecasting capability is weaker compared to long-term projections.

Kouadri et al. [78] proposed a Fault Detection and Diagnosis (FDD) method aimed at enhancing the necessary protection, availability, and reliability of transformers in various scenarios. The technique involves appropriately acquiring elements and selecting the optimal number of attributes. Various faults in generators are classified using an effective statistical framework. It is emphasized that a more sophisticated framework needs to be developed to account for the unpredictability of the operational environment, as it significantly impacts the quality of categorization.

Adar et al. [79] emphasized the use of the Principal Component Analysis (PCA) method, relying on the collection of operational, physical, and power generation data. This involves evaluating economic aspects using conventional metrics and analyzing the relationship between atmospheric conditions and performance variables. Examination of the correlation between weather variables and achievement metrics revealed that the quality proportion has an association with warmth but lacks a correlation with electromagnetic illumination. It demonstrates a significant relationship between absorption inefficiencies and a weak correlation between warmth and loss rates. However, it is noted that the computational complexity is higher.

In the context of high-voltage circuit breakers, Yang et al. [80] recommended the use of PCA with an optimized Support Vector Machine (SVM) for fault diagnosis. LabVIEW software is used to obtain signals and experimental simulation is conducted for circuit breaker machine fault states. The appropriate envelope spectrum is derived from the vibration signal collected using Hilbert Huang conversion. The rate of cumulative contribution, feature values, and each characteristic value's contribution rate are calculated through PCA for the final feature vector. The proposed model demonstrates efficient circuit breaker fault diagnosis with optimized accuracy and time, achieving a rate of over 90%.

Table 2.1 shows the comparative study of existing methods in fault detection.

Table 2.1: Comparative study of existing methods

Author	Renewable sources	Feature extraction	Classifier	Accuracy	Disadvantage
Veerasamy et al. [18]	PV	Discrete wavelet transform	LSTM	91.21%	Training can be difficult and longer
Mahela et al. [19]	Wind turbine	Stockwell transform	Fuzzy clustering technique	98.96%	Redundant data increases
Liang et al. [20]	PV	Self feature extraction	Adaptive convolutional neural network	95.8%	Computationally expensive
Fahim et al. [21]	Power source	Time series imaging based feature extraction model	Self-attention convolutional neural network	99.58%	Increased weight parameters lead to high training time
Roy et al. [22]	Wind turbine and PV	Wavelet transform	Power spectral density based analysis	96.78%	Poor reliability
Baloch et al. [26]	PV	Hilbert transform	Adaboost classifier	99.29%	Requires high resources
Kabeel et al. [24]	PV	Manual symmetrical component extraction	Artificial neural network	99%	Increased parameter with respect to layer size
Cao et al. [25]	PV, wind turbine, micro turbine and fuel cell	Bat optimization algorithm	Decision tree	97.36%	Poor accuracy

Prasad et al. [26]	PV, wind turbine and diesel generator	Particle swarm optimization	Optimal transient extracting transform	98.9%	Computational burden is high
Ahmadipour et al. [27]	PV and diesel generator	Maximal overlap discrete wavelet packet transform	Lagrangian particle swarm optimized support vector machine	98.41%	Fall in local optimal solution
Xiong et al[51]	Building electrical systems	Variational mode decomposition	Quantum genetic algorithm optimized SVM	91.67%	Accuracy very low

2.3 Research Gap

This review gives an account of the myriad strategies explored by researchers for detecting, classifying, and localizing defects specifically of transmission faults. The analysis provides a detailed study of the key benefits and drawbacks of these strategies, shedding light on the localization and classification accuracy achieved through diverse approaches. The research gaps analyzed are pointed out as follows:

- Traditional fault detection schemes depend on significant fault currents for efficient operation. Traveling wave or injection-based algorithms which were originally used suffer from reflected wave detection and discrimination issues. Detection of fault location is also not in the scope of traditional methods. Catering to the different network topologies (radial and loop) is also a challenge. So intelligent fault detection schemes are suited for microgrids which provide fault identification and location accuracy.

- However, most methods use a transformation to decompose the signal. The feature extracted by these methods has the problem of inappropriate feature selection, resulting in inaccurate detection. Self-adaptive algorithms like Empirical mode decomposition (EMD) are used to handle non-stationary and nonlinear phenomena. This method has the disadvantage of mode mixing which affects the security of microgrids, resulting in a protection problem. Variational mode decomposition (VMD) of fault signals was done in electrical system of a bulding[51] and classified using SVM but accuracy obtained after classification was found to be very low. Mode mixing problem of EMD is avoided with VMD , but being model driven rather than data driven it has less applications in the detection of short circuit faults of power system.
- Therefore, to deal with this empirical wavelet transform (EWT) is used, which can handle noisy and non-stationary signals [31], such as current signals. Due to this property, the EWT method could handle many non-linear systems [32], especially in energy signal processing.
- Concerns about the potential collapse of the entire grid leading to outages and impacting system reliability are highlighted. The use of Artificial Neural Networks (ANN) demands intensive training, especially with diversely distributed data, resulting in prolonged time consumption and increased complexity.
- Wavelet transforms, while providing increased decomposition levels, introduce computational complexities that contribute to accuracy issues. Moreover, the increased computational burden of this method adds to the overall cost.

- In high-noise environments, certain machine learning algorithms exhibit reduced accuracy and struggle to analyze specific probability classes, ultimately failing to mitigate higher feature dimensionality.
- Models based on correlation and time synchronization encounter challenges related to reliability and stability, resulting in lower precision. These observations underscore the complexities and trade-offs involved in the various fault detection and classification strategies employed in the realm of transmission faults.
- Furthermore, machine learning-based classifiers enable accurate defect detection with more resources and higher costs. This is due to the requirement of manual or semiautomatic feature extraction. Datasets need to be labelled and features are to be clearly defined.
- Deep learning, despite offering higher accuracy, operates within a black box framework, posing challenges in explaining its results. However, its prolonged training periods can complicate the task. Additionally, the deep learning approaches rely on the availability of substantial training data to be more effective. Deep learning methods like CNN [24] and RNN [21] provide tremendous advantages in classification. To mitigate overfitting problems increased number of parameters are required. Hybrid techniques with suitable optimization procedures can increase the accuracy. By tuning and optimizing the hyperparameters classification can be done effectively with unpredictable data.

2.4 Summary

The efficient operation of vital utilities and their impact on society hinges on the swift resolution of faults. Restoration and repair processes become imperative when faults occur, aiming to bring the affected lines back into operation promptly. However, the effectiveness of the restoration process is contingent on accurately and confidently predicting the position of the fault. Over time, many approaches have been proposed to address this challenge, each has its own set of advantages and drawbacks. The continuous evolution of techniques promotes the importance of refining and enhancing fault detection and location prediction methodologies in the dynamic landscape of electrical power systems. This chapter explains previous existing works in various categories of transmission line faults. Machine Learning utilizes advanced algorithms to analyze and interpret data and offers the ability to learn patterns and make predictions based on historical data. Time-synchronized methods involve synchronizing data readings from multiple locations on the transmission line and it is particularly effective for lengthy transmission lines.

Fault detection technologies focuses on microgrid systems and incorporates intelligent data mining strategies for effective fault identification. Deep Learning Techniques involve complex neural network architectures for fault identification and accommodate

intricate patterns and relationships in fault data. Principal Component Analysis focuses on reducing the dimensionality of data while retaining essential information. Correlation Methods explore relationships and dependencies between variables and utilize correlation coefficients to identify fault signatures. Transform-based models employ mathematical transformations such as wavelet transforms and enhance fault detection by decomposing signals into frequency components. Fuzzy logic based structures has enabled decision- making based on rule-based relationships within fuzzy logic. Despite the relatively lower computing cost, constructing membership functions and rules for fuzzy logic can be challenging. The fault distance is determined by calculating pre- and post-fault line impedances during fault detection. However, due to the feed received in each terminal circuit, the recorded impedance values are significantly higher than the actual line impedance, leading to inaccurate findings. It appears that recent state-of-the-art approaches, as discussed in the preceding sections, evaluated algorithms using simulated data with identical patterns and training data distribution. Each subsection presents a unique approach to fault detection, catering to specific challenges and scenarios within transmission line systems. These methodologies contribute to the advancement of fault detection technologies, offering a spectrum of tools for improving the reliability and efficiency of power transmission systems. Most of the recent works suggested wavelet transforms for feature extraction and a CNN model for fault classification. To tackle the challenges, new novel techniques are proposed in the following chapters.

The next chapter gives an account of different faults in a microgrid power system. Fault detection from voltage and current signal analysis using different feature extraction methods is detailed. Advantages and disadvantages of different feature extraction methods and different fault classification techniques are also summarized.

CHAPTER 3

MICROGRID AND FAULT ANALYSIS

3.1 Introduction

Fault detection in micro-grids is a crucial aspect of maintaining stability and reliability in power systems. Unlike traditional power systems, micro-grids incorporate multiple Distributed Generators (DGs) and can operate in both grid-connected and islanded modes, which complicates fault detection. Effective fault detection in micro-grids requires advanced methods to accurately identify and isolate faults quickly, ensuring minimal disruption to the power supply. These methods often include real-time monitoring, intelligent algorithms, and adaptive protection schemes. Traditional overcurrent relays, which rely on high fault currents from the main grid, may not function effectively due to the lower fault currents in islanded mode. In grid connected mode fault current is higher due to contribution from main grid. Inverter based resources like solar PV systems contribute to less fault current compared to synchronous generators. Fault location and control strategy of DG inverters affect the magnitude of fault current. If synchronous DG is connected fault current increases to (4-6) times rated current and if inverter based DG is connected current increases to (1.1-1.5) times rated current and only for few cycles(2-3). Microgrid impedance (through PCC transformer and lines) adds more restriction to the fault current. The fault current magnitude is too low in some cases to trip traditional overcurrent relays. Therefore, micro-grid fault detection systems need to be capable of handling variable fault current levels and distinguishing different fault conditions. Advanced technologies, such as digital relays, phasor measurement units (PMUs), and machine learning algorithms, are increasingly employed to enhance fault detection and response, ensuring that micro-grid remains resilient and operational under various conditions [81].

3.2 Microgrid Systems

Micro-grids are small-scale power supply networks designed to meet the growing demand for reliable, secure, sustainable, and green energy. They consist of several distributed energy resources (DERs), energy storage devices, communication facilities, and regulated loads. Micro-grids can operate in two distinct modes: grid-tied and autonomous (islanded). In the Grid-Tied Operation, the micro-grid is connected to the main AC grid. Primary AC grid supplies some part of the load, which provides additional stability and resource sharing. This connection allows energy exchange between the micro- grid and the main grid, enhancing overall efficiency and reliability. In contrast, while considering the Islanded Operation, the micro-grid disconnects from the main AC grid and operates independently. This mode is crucial during main grid outages or when intentional isolation is required to ensure local reliability. The micro-grid must independently balance supply and demand, relying solely on its own DERs and storage systems. The structure of A typical micro-grid is portrayed in Figure 3.1

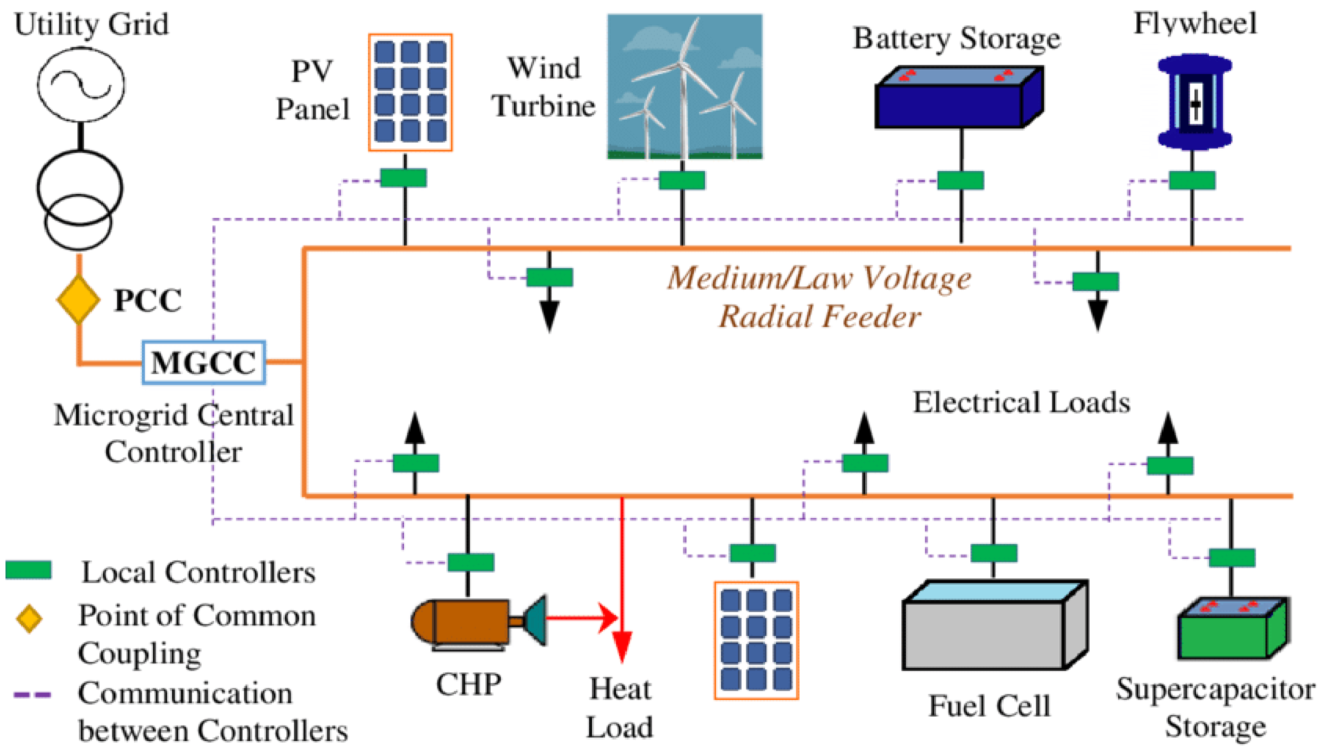


Fig 3.1: MG Structure

System Description of a general microgrid shown above is explained here. The sources are solar PV panels, wind turbines, diesel generators and combined power plants. Heat or Electrical loads are connected to the system. Storage options available are battery, flywheel, fuel cell and supercapacitor storage. Local Controllers control the energy sources and loads. Microgrid Central Controller gives command signal to each of the local controllers. Radial feeders are connected to various loads, storage devices and sources. The microgrid is connected to utility grid by a point of common coupling.

Due to the dynamic nature including switching between these modes, and the non- linear characteristics of system components, micro-grids pose unique challenges for system protection. The micro-grid can switch between grid-tied and autonomous modes, each requiring different protection strategies. Micro-grids can be arranged in looped or radial configurations, impacting fault detection and isolation mechanisms. Various DERs, such as solar panels, wind turbines, and batteries, each with unique electrical characteristics, add complexity to protection schemes. Thus, effective fault detection and classification are crucial for ensuring the safe operation of micro-grids. By developing specialized protection techniques tailored to the unique characteristics of micro-grids, we can enhance their reliability, stability, and overall performance, ensuring a seamless supply of high-quality electrical power [82].

3.3 Power System Fault

A key equipment in a power system is a transformer that is essential to the transfer of power. It has the ability to increase voltage, which will reduce power loss during transmission to the user. Conversely, the transformer may split electricity into several voltage levels to meet a range of user demands. Transformers often result in faults due to their complex construction and operation. However, it is remarkably hard to anticipate transformer failure. Furthermore, the entire system must halt in order to inspect and maintain the machinery in the event that a transformer disaster occurs. It follows that maintaining the transformer in optimal operating condition is seen to be crucial for power system diagnostics. Circuit breakers with a high voltage (more than 3 kV) are an additional crucial component of the power system. Controlling and safeguarding are its two primary purposes. The high voltage circuit breaker is designed to promptly cut off malfunctioning parts of the power system from the rest of the structure, allowing other parts to function without interference. First, it determines which and when the components of the power system need to be started or stopped based on requirements. However, a high voltage circuit breaker can manage the typical power line current while also responding quickly to aberrant currents such as overload and short circuit. High voltage circuit breakers are prone to mistakes that eventually spread to other areas of the power system and result in more serious incidents [83].

3.4 Types of Faults

The faults in the micro-grid power systems are categorized into two various types like [85]:

- Open Circuit
- Short Circuit

3.4.1 Open Circuit Faults

When there is a break in the electrical path that stops current from passing through the circuit, it is known as an open circuit fault. Fused out, loose connections, damaged wires, and faulty parts are some of the causes for the open circuit. An open circuit fault results in total power loss for the micro-grid component that is impacted. For example, if a conductor breaks, no electrical current may flow through and the circuit is rendered incomplete. It causes power outages, equipment shutdowns, and perhaps catastrophic system failures, particularly in areas that depend on constant electricity. Monitoring voltage and current levels is necessary for open circuit fault detection since an abrupt drop in either might be a sign of an open circuit. Some of the consequences of open circuit fault are:

- Open circuit faults result in a loss of current flow, leading to a power outage in the affected part of the micro-grid. While this can cause disruptions, the impact is usually localized to the specific area or equipment directly connected to the open circuit.
- Open circuit faults do not typically cause immediate physical damage to the system components, as there is no surge of current or excessive heat generated. This makes them less hazardous in terms of immediate safety concerns.
- Detecting and repairing open circuit faults is important for restoring normal operations and ensuring reliability. However, the urgency is lower compared to short circuit faults, as there is no immediate risk of further damage or danger.

3.4.2 Short Circuit Faults

A short circuit defect arises when a route of very low resistance is created between two locations in an electrical circuit that shouldn't be directly linked. It produces a lot of current flow, which can raise the temperature quickly and harm equipment. Failures in components, conductive debris, or insulation are common causes of short circuits. Overheating, fires, and catastrophic equipment failures can result from the increased current. Circuit breakers and fuses, among other protection devices, are made to recognise elevated current levels and cut off the impacted circuit to stop more harm. The difficulty with micro-grids, is coordinating these safety measures to isolate the failures and the disturbance caused to the system is very less. Some of the consequences of the short circuit fault are:

- Due to sudden surge of high current through the circuit enormous amount of heat is generated, causing insulation to melt, components to burn, and potentially starting fires. The high energy involved poses serious risks to equipment and human safety.
  - The excessive current can cause voltage drops and fluctuations, leading to instability in the entire micro-grid.
  - Short circuit faults must be detected and isolated immediately. Circuit breakers and fuses act as protective devices to act quickly to cut off the high current flow, preventing extensive damage and maintaining system integrity.
  - The damage caused by short circuits can be extensive and costly, affecting not just the faulty component but also other parts of the micro-grid due to the propagation of electrical and thermal stress.

  The magnitude of faults in different types of microgrid is given in table 3.1 below

Table 3.1 Fault currents in different Microgrid Systems.

Fault type/Microgrid Type	Fault Current characteristics
Grid-connected Microgrid	High fault currents due to grid's contribution
Islanded Microgrid	Lower fault currents due to DG sources
Inverter based resources (eg: solar PV)	Low fault currents compared to synchronous generators.
Synchronous generators(microgrids)	Contributes higher fault currents
Three phase fault(LLL)	Highest fault current magnitude.
Line to Line fault	Lower fault currents than LLL.
Line to ground fault(LG)	Vary depending on grounding type, R
High resistance Faults	Lower fault currents compared to bolted faults
DC Microgrids	Different fault characteristics.

3.5 Fault detection in Power Systems

Whenever a fault occurs the voltage and current signals exhibit certain variations in the features extracted which will help to detect and classify faults. These features are amplitude, phase, frequency, energy distribution of these signals, standard deviations etc. Considerable changes occur in the amplitude of voltage and current signals under fault. The impedance seen by relay may also change due to type of fault and the location where they occur. Traditional fault detection methods in power systems typically rely on established principles such as overcurrent protection, differential relaying, and impedance-based techniques. These methods use predefined thresholds and logic to detect anomalies in current, voltage, or impedance levels, triggering protective devices to isolate faults and prevent damage to equipment and ensure system reliability. However, traditional approaches may struggle with the complexities of modern power systems, such as distributed generation, varying fault conditions, and bidirectional power flow in micro- grids. Machine learning (ML) offers a promising alternative by leveraging computational algorithms that can learn from data patterns and adaptively improve fault detection accuracy. ML algorithms analyze large volumes of real-time data from sensors, PMUs, and other sources to identify subtle patterns indicative of faults. By learning from historical data and continuously updating models, ML-based fault detection systems can adapt to changing system dynamics and improve their ability to distinguish between normal and abnormal operating conditions. This capability makes ML particularly effective in enhancing fault detection accuracy, reducing false alarms, and enabling proactive maintenance in modern power systems.

3.6 Challenges in Microgrid Protection System

The various faults experienced by microgrids with diverse distributed generators are shunt faults and series faults. Due to inverter based nature of solar PV and wind turbines, unique fault characteristics are experienced resulting in high fault currents or harmonic distortion.

Apart from shunt and series faults, DG outage occurs by sudden failure or disconnection of a DG ,inverter faults such as overcurrent, overvoltage or control system failures. Loss of excitation of synchronous generators leading to voltage instability, unbalanced loading, overloading and harmonic distortion which may affect connected equipments are other failures that may occur in microgrid. Whatever be the DGs used the nature of the signal is analyzed. Features are extracted from the signals to find the nature of the fault.

Some of the challenges faced by the micro grid protection system are:

3.6.1 ***Modes of operation***: A micro-grid can operate in two modes: connected to the main grid and isolated (islanded). During a fault in grid-connected mode, the main grid provides a significant short-circuit current due to its vast capacity and robust infrastructure. In islanded mode, however, the micro-grid relies on local DGs such as solar panels, wind turbines, and small-scale generators, which offer much lower fault current due to their limited capacity. Here, the drastic change in fault current levels between the two modes complicates the functionality of conventional overcurrent relays, which are designed to operate based on the magnitude of the current. In grid connected mode, the high fault current readily triggers these relays to isolate the fault, but in islanded mode, the lower fault current may not be sufficient to activate the relays, potentially leaving faults undetected and compromising system protection. This necessitates the development of alternative protection strategies to ensure reliable operation in both modes.

3.6.2 ***Selectivity***: Selectivity ensures that a fault is isolated by the closest protective device,
minimizing disruption to the rest of the micro-grid. However, achieving selectivity in micro- grids is more complex due to challenges such as changing fault current levels and bi-directional power flow. When the micro-grid operates in grid-connected mode, the fault current levels are high, but they drop significantly in islanded mode due to the limited contribution of local DGs. Additionally, the presence of bi-directional power flow, where power can flow from both the main grid and the local DGs, complicates the coordination of protective devices. These factors make it difficult for conventional protection mechanisms to accurately detect and isolate faults, necessitating advanced protection strategies to maintain selectivity and ensure reliable operation of the micro-grid.

3.6.3 ***Islanding***: Unintentional islanding occurs when a fault or other event unexpectedly isolates the micro-grid from the main grid. In such situations, it is crucial for the micro-grid to quickly detect this separation and transition smoothly to islanded mode. It involves in ensuring stable operation using its limited resources, such as local DGs. Rapid detection and response are essential to maintain power quality, prevent equipment damage, and ensure the continuity of service to critical loads within the micro-grid.

Advanced control systems and protective mechanisms must be in place to manage the sudden change in operational dynamics and maintain the reliability and stability of the micro-grid.

3.6.4 ***Reverse Power Flow***: Unidirectional power flow, where electricity flows from the main grid to the consumers is the characteristic of traditional power systems. However, in micro- grids, power is injected back to the grid, creating bi-directional power flow. The bi-directional flow can confuse conventional relays, which may not be equipped to handle power coming from multiple directions. As a result, these relays might misinterpret the flow of electricity, potentially leading to misoperation, such as failing to isolate faults correctly or unnecessarily disconnecting parts of the micro- grid. This complexity necessitates the development of advanced protection strategies that can accurately detect and respond to faults in a system with bi-directional power flow, ensuring the reliable operation of the micro-grid.

3.6.5 ***Discrimination of the device***: Conventional protection schemes rely on coordination between relays to ensure that the closest device to the fault isolates it while others remain operational. However, in micro-grids, the bi-directional power flow introduced by DGs disrupts this coordination. The presence of power flowing in multiple directions can confuse the relays, leading them to misinterpret the fault location. As a result, relays might trip unnecessarily, causing unintended outages in healthy parts of the micro-grid. The disruption of relay coordination not only affects the reliability of the power supply but also complicates fault management and system stability. Advanced protection strategies are needed to address these challenges and ensure proper coordination in micro-grids with bi-directional power flow.

3.7 Signal Processing Tools for Fault Transient Analysis

Fault detection and isolation in micro-grid systems are critical for maintaining stability and reliability. The collected signals must be of good quality for accurate fault detection. To effectively detect faulty signals, it is essential to understand how each type of fault influences the signal. Signal processing techniques are employed to enhance the signal-to-noise ratio and conduct thorough spectral analysis [85]. Common approaches include:

- Fourier Transform
- Short Time Fourier Transform
- Wavelet Transform
- EMD-HHT
- EWT

3.7.1 Fourier Transform

The Fourier Transform is a mathematical technique used to analyze and decompose signals into their constituent frequencies. When a fault occurs in a power system, it generates transient signals that contain a wide range of frequency components. These transients can provide valuable information about the nature and location of the fault. Initially the Fourier Transform breaks down complex transient signals into simpler sinusoidal components. Here, the decomposition helps in isolating the frequencies that are most affected by the fault, providing insights into the characteristics of the fault.

Here, by transforming the time-domain signal into the frequency domain, we obtain a frequency spectrum. This spectrum shows the amplitude of various frequency components present in the signal. Faults typically introduce high-frequency components that stand out in the spectrum, and are used for identifying faults. The fixed width windowing function limits the applicability of the Fourier Transform based analysis of fault signal analysis.

3.7.2 Short Time Fourier Transform

STFT is a fundamental tool for analyzing signals in both the time and frequency domains.

It decomposes a signal into its constituent frequencies over time, providing a valuable view of non-stationary signals like fault transients. However, the specific implementation of STFT can vary, leading to a family of STFTs with different characteristics. A crucial aspect for fault transient analysis is obtaining a representation that avoids cross-terms. These artefacts arise when the chosen STFT window function (kernel) interacts with the signal components, leading to misleading information in the time-frequency domain.

3.7.3 Wavelet Transform

The wavelet transform is particularly well-suited for transient analysis because it provides a multi-resolution analysis of signals. This means that it can effectively capture both the high- frequency components, which are indicative of faults or transients, and the low-frequency components, which represent the steady-state operation of the system. Unlike the Fourier transform, which only analyzes the frequency content of a signal and assumes it is stationary, the wavelet transform can analyze non-stationary signals, making it ideal for the dynamic and often unpredictable nature of microgrid operations. Faults produce transient signals with time varying frequencies. The wavelet transform's variable window length adapts to these changes and provides better resolution. The analysis of high frequency components can immediately detect the occurrence of a fault and its location. Other phenomena like power swings have fewer high frequency components. The two various types of wavelet transform are:

I. ***Continuous***: CWT is the original form of wavelet analysis, introduced as an alternative to the Fourier Transform. CWT uses filtering techniques to analyse signals, which functions like an analog filter bank. CWT operates on the input signal in parallel using a combination of high-pass and low- pass filters at various scales. These scales act like neighbouring bands in the frequency domain, with increasing bandwidth as the center frequency goes up. This makes CWT a constant-Q filter bank, meaning the ratio of center frequency to bandwidth remains constant across scales. CWT performs filtering directly in the frequency domain. It essentially passes the signal through a series of band-pass filters with a constant Q response. CWT has a more intuitive physical interpretation compared to DWT. It is similar to a physical filter with a transfer function operating in both time and frequency domains. CWT filters cannot achieve ideal compactness, meaning they cannot be perfectly localized in both time and frequency domains. However, like some filter design techniques, CWT functions are created to be as compact as possible according to specific criteria.

(i) ***Discrete***: Unlike CWT's parallel filtering, DWT performs filtering sequentially on blocks of discrete data. It iteratively applies high-pass and low-pass filters to the signal, separating it into different frequency bands. DWT uses a scaling function to divide the frequency spectrum of the signal into half at each scale. This effectively doubles the time resolution while halving the frequency resolution, resulting in a constant time-frequency product. DWT uses a discrete set of scales, wherein scales define the level of stretching or compressing applied to the wavelet function. DWT filters are formulated mathematically, and their transfer functions are recursive. The decomposition of signal using the DWT is illustrated in Figure 3.2.

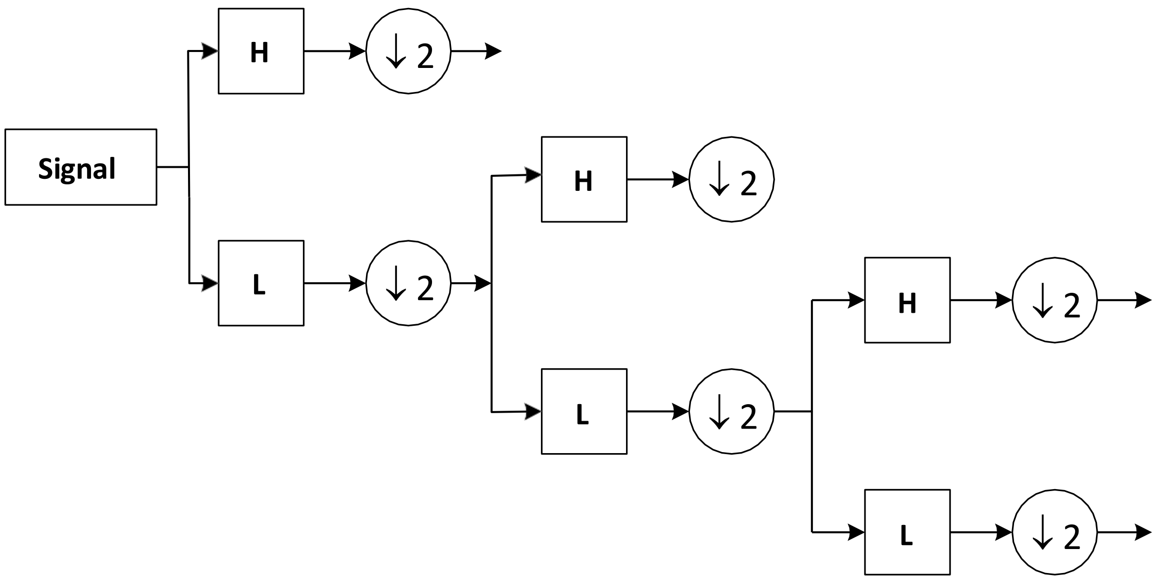


Fig 3.2: DWT based signal decomposition

The decomposition of the signal into high and low frequency components is employed with the down-sampling process. DWT performs down sampling by discarding half the coefficients. It reduces data redundancy and computational complexity. The characteristics of CWT and DWT are presented in Table 3.2.

Table 3.2: Characteristics of CWT and DWT

Feature	**CWT**	**DWT**
Filtering Approach	Parallel filter bank	Sequential filtering
Scale Discretization	Continuous	Discrete
Filter Type	Analog filtering Function	Mathematical filters with compact support
Frequency Resolution	Varies based on scale	Decreases with increasing scale
Time Resolution	Constant	Increases with increasing scale
Physical Realizability	Achievable	Not directly achievable

The high frequency domain contain critical information that conventional fault detection methods overlook. The sources of this high frequency signals are pulse width modulated (PWD) switching, parasitic capacitances, resonance effects, faults in converter etc. The nature and characteristics of high frequency signals is found from the waveform morphology(1-100kHz), spectral attributes(10kHz-1MHz), time frequency behaviour of signals(1-50kHz)) and statistical indices of the signals. Unlike current magnitudes, voltage magnitudes or phase angles, high frequency components respond instantaneously to fault events making fault detection and localization easy. The machine learning based classifiers utilize these high frequency features for fault indications.

The high frequency intensity during fault is high in PV due to high frequency PWM switching and fast current controllers that react within microseconds. HF signature is very high with battery energy storage system due to fast current control loops but is the most predictable one. The fuel cell inverters produce cleaner but consistent high frequency patterns. Wind turbines have medium high frequency intensity and more complex spectra. The diesel generators do not have appreciable high frequency components as they lack high frequency switching due to the domination of electrical response by mechanical inertia.

3.7.4 EMD-HHT

The Empirical Mode Decomposition (EMD) combined with Hilbert-Huang Transform (HHT) is new and effective method for analyzing fault signal transients in power systems.

- ***EMD based transformation***: EMD decomposes a signal into a set of intrinsic mode functions (IMFs). Each IMF represents a simple oscillatory mode embedded in the signal. The process involves sifting through the signal to identify local extrema,
  constructing envelopes using these extrema, and then averaging the envelopes to extract the IMFs. This is repeated iteratively until the signal is decomposed into a finite number of IMFs and a residual component. Unlike traditional Fourier or wavelet transforms, EMD does not require apriori selection of a basis function. It is highly adaptive as it derives the basis functions directly from the signal itself.
- ***HHT based Transformation***: After obtaining the IMFs from EMD, each IMF is subjected to the Hilbert Transform. This transform provides the instantaneous frequency and amplitude of the IMFs, yielding a time-frequency

representation of

the signal. The result is a Hilbert Spectrum that shows how the energy of the signal is distributed across different frequencies over time. The identification of transient events helps fault identification in power systems.

EMD-HHT excels in analyzing non-stationary signals, making it ideal for transient fault signals that exhibit sudden changes in frequency and amplitude. The method's adaptive nature ensures that the decomposition is tailored to the specific characteristics of the signal, providing a more accurate analysis of transient events. The Hilbert Transform provides detailed insights into the instantaneous frequency and amplitude variations.

3.7.5 EWT

The Empirical Wavelet Transform (EWT) is an advanced signal processing technique used for fault signal transient analysis in power systems. It combines the strengths of empirical methods with wavelet transform principles, providing a highly adaptive and detailed analysis of non-stationary and transient signals typically associated with faults. Unlike traditional wavelet transforms that use predefined wavelet functions, EWT designs wavelet filters based on the empirical properties of the signal itself. This means the wavelets are tailored to capture the specific features of the signal being analyzed. EWT partitions the frequency spectrum of the signal into different bands adaptively. Each band corresponds to a different mode of the signal, similar to the concept of IMFs in EMD. EWT provides a multi-resolution analysis of the signal. It means EWT can simultaneously capture both high-frequency transients and low- frequency trends, making it suitable for analyzing complex fault signals. Thus, EWT offers a sophisticated and highly adaptive approach for fault signal transient analysis in power systems. Wavelet filters are selected according to the specific characteristics of the signal . EWT has robustness against noise and effective in analyzing non-stationary signals. This makes it a valuable tool for maintaining the reliability and stability of modern power systems.

3.7.6 Comparison of Wavelet and EMD

The wavelet and EMD based fault transient analysis is presented in Table 3.3

Table 3.3: Comparison of Wavelet and EMD Transform

Feature	Wavelet Transform	EMD
Basis Functions	Mathematical wavelets with adjustable scale and shift	Intrinsic Mode Functions (IMFs) derived from the signal itself
Time-Frequency Resolution	Offers good control over both time and frequency resolution through scale and shift	Offers adaptive time-frequency resolution, better suited for non-stationary signals
Cross-Term Mitigation	Requires careful selection of mother wavelet to minimize cross-terms	Generally less prone to cross- terms due to data-driven approach
Computational Cost	High computational cost for long signals.	Lower computational cost compared to wavelets
Mathematical Foundation	Well-defined mathematical framework, easier to analyze theoretically	Operates on sifting process, less mathematically rigorous
Transient Signal Characterization	Effective for capturing transient components with specific frequency content	Can effectively capture transient components with varying frequencies
Suitability for Complex Signals	Well-suited for analyzing signals with multiple frequency components	More suitable for analyzing non-stationary and complex signals with transient components of varying frequencies

Here, the comparison portrays that EMD is more suitable for fault transient analysis of microgrids.

3.8 Comparison of EWT and DWT

The characteristics of the EWT and DWT based fault transient analysis is in Table 3.4.

Table 3.4: Comparison of EWT and DWT Techniques

Characteristic	EWT	DWT
Methodology	Decomposes signals based on adaptively designed wavelet filters tailored to the specific signal.	Decomposes signals using predefined wavelet functions like Haar, Daubechies, etc.
Adaptability	Highly adaptive to the signal characteristics, providing better resolution for varying signal features.	Less adaptive, relies on fixed wavelet functions which may not capture all signal characteristics accurately.
Frequency Resolution	Offers fine-tuned frequency resolution, especially useful for non-stationary signals.	Provides multi-resolution analysis, but the resolution is determined by the chosen wavelet function.
Signal Decomposition	Decomposes signals into empirical modes which are specifically adapted to the data.	Decomposes signals into approximation and detail coefficients using a hierarchical process.
Noise Sensitivity	Potentially more robust against noise due to adaptive nature of decomposition	Susceptible to noise, especially if the noise frequency overlaps with the signal frequency band.
Fault Detection Accuracy	Can provide high accuracy in detecting and isolating faults due to its adaptive nature.	Good accuracy, but dependent on the chosen wavelet and may require tuning for optimal performance.

The comparison based on the features of EWT and DWT indicates that EWT is more appropriate for the fault transient signal analysis.

3.9 Fault Classification Methods

Fault classification in micro-grids ensure reliability, stability, and efficient operation. Machine learning and deep learning approaches used for fault classification are detailed in this section.

3.9.1 CNN

CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to input data to extract features, pooling layers reduce the dimensionality of these features, and fully connected layers perform the final classification [86]. The structure of the CNN based fault classification is portrayed in Figure 3.3.

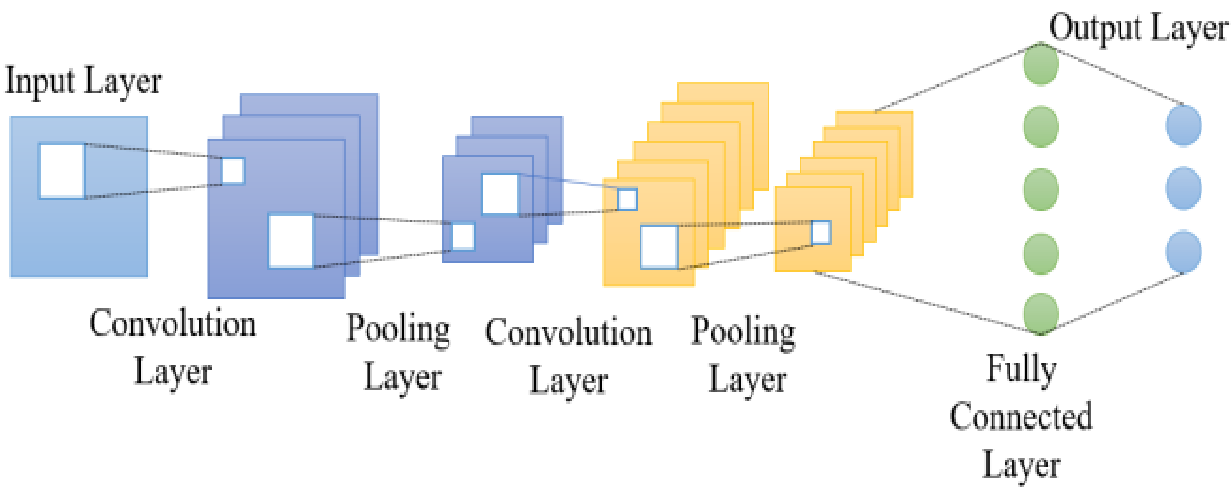


Fig3.3: CNN based fault classification

The detailed explanation concerning the key components of the CNN based fault classification are:

Input Layer: The input layer serves as the entry point for the data into the CNN. While considering fault classification, the input data is typically a time-series representation of electrical signals.

Convolution+ReLU: To detect local patterns, such as edges, spikes, or oscillations in the signal, the convolutional layer is used through the application of filters. Here, the number of filters determines the number of feature maps produced. Each filter captures a different aspect of the input data. Then, ReLU is used to introduce non- linearity into the model and allowing it to learn more complex patterns.

Pooling Layer: This layer reduces the dimensionality of the feature maps, making the network computationally efficient and less prone to over-fitting

Flatten: Flatten layer is used to convert the 2D feature maps into a 1D vector that can be fed into the fully connected layers.

Fully Connected: The flattened vector is fed into a fully connected (dense) layer where each neuron is connected to every neuron in the previous layer. This layer learns to map the extracted features to the fault classes.

Softmax: The output from the fully connected layer is fed into the softmax layer, which converts the raw scores into probabilities that sum to 1.

Thus, the CNN architecture effectively learns to classify faults in micro-grids by progressively extracting and refining features from the raw input data through convolutional and pooling layers. The fully connected and softmax layers then map these features to the fault classes, providing a probabilistic output that can be used for fault diagnosis and management.

3.9.2 KNN

K-Nearest Neighbours (KNN) is a simple, non-parametric, and lazy learning algorithm used for classification and regression tasks. In fault classification for microgrids, KNN can be used to identify the type of fault based on historical data of electrical measurements. KNN classifies a new data point by comparing it with a set of labelled data points in the training dataset. The new data point is assigned to the class most common among its K nearest neighbours, where K is a user-defined parameter [90]. The model of KNN based fault classification is shown in Figure 3.4.

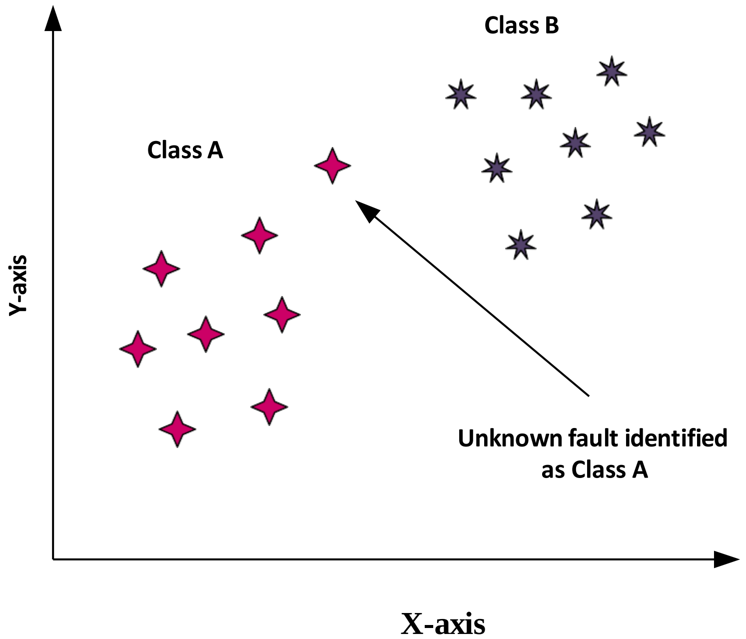


Fig 3.4: KNN based fault classification

The key steps utilized in the KNN based fault classification are:

- Calculate the distance between the new data point (query) and all points in the training dataset. Common distance metrics include Euclidean, Manhattan, and Minkowski distances.Identify the K data points in the training set that are closest to the query point based on the chosen distance metric.
- The query point is classified based on the majority class among its K nearest neighbors. If K=2, the two nearest neighbors' classes are considered, and the most common class is assigned to the query point.

3.9.3 PSO-SVM

Particle Swarm Optimization (PSO) [88] combined with Support Vector Machine (SVM) [89] is an advanced method for fault classification in microgrids. The hybrid approach leverages the strengths of both algorithms: PSO optimizes the parameters of the SVM, leading to improved classification accuracy and efficiency. SVM is a supervised learning model used for classification and regression tasks. It aims to find the optimal hyperplane that separates data points of different classes with the maximum margin. Its structure is portrayed in Figure 3.5.

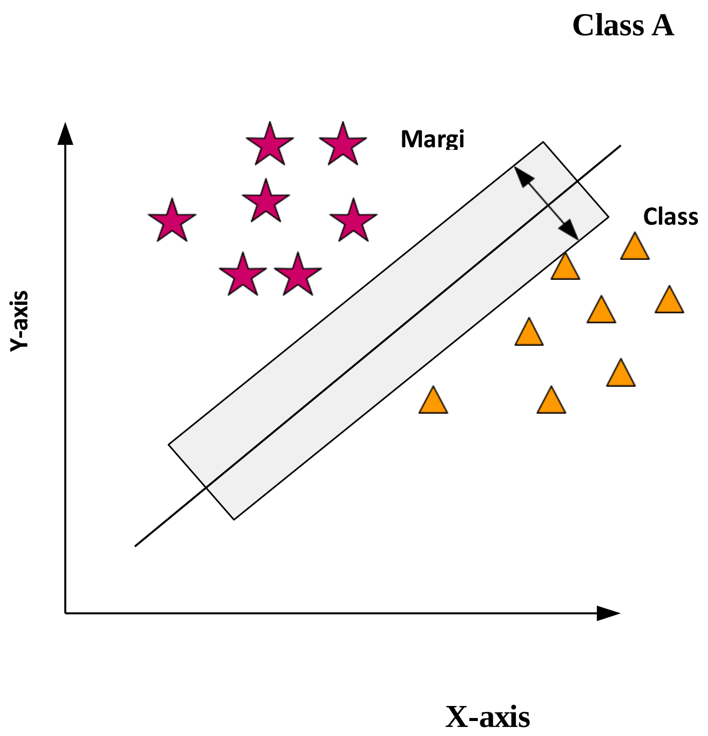


Fig 3.5: SVM based fault classification

SVM can handle non-linear relationships by using kernel functions like linear, polynomial, radial basis function (RBF) to transform the input space into a higher- dimensional space where a linear separator can be found. The hyper-plane acts as the decision boundary for classification. Here, SVM classifies the data into different fault types or normal operation based on the learned hyper-plane.

Hyper-parameters in SVM: The two various hyper-parameters of the SVM are:

- Regularization Parameter (C): Controls the trade-off between maximizing the margin and minimizing classification errors. A large value of C emphasizes correct classification of training examples, while the smaller value allows more misclassifications to achieve a larger margin.
- Kernel Parameters: Parameters specific to the chosen kernel function, such as the

gamma parameter in the RBF kernel, which defines the influence of a single training example.

The hyper-parameters of the SVM are fine-tuned using the PSO for enhancing the fault classification accuracy. PSO is a population-based optimization algorithm inspired by the social behaviour of birds flocking or fish schooling. The fitness function is used to improve candidate solutions to attain optimal solution. Thus the PSO+SVM-based fault classification method combines the optimization capabilities of PSO with the robust classification performance of SVM. By optimizing the SVM hyper-parameters using PSO, high classification accuracy and robustness are achieved.

3.10 Summary

This chapter details the power system fault along with the types of faults that affects the micro-grid power system. Then, the challenges associated with the power system fault detection and methods employed to overcome those challenges were discussed. Finally, the fault analysis and classification methods utilized for fault identification in micro-grid power system are discussed.

The next chapter presents an integrated system implemented in SIMULINK for transmission lines (TL) fault detection. Signals obtained from each phase are decomposed using EMD and also using DWT. Normalized values are compared to a threshold, with abnormal cases exceeding the threshold.

CHAPTER 4

Fault Detection In Transmission Line Using Empirical Mode Decomposition In A Grid Connected Power System

4.1 Introduction

Transmission lines are the most important components in the power system engineering for transmitting the electricity that is generated to different distribution units. Meanwhile, it also provides a bridge between the powerhouse and the consumers. There is a chance of occurrence of fault in the transmission line due to exposure to outside conditions. Hence to facilitate normal power system operation, early fault detection and fault restoration are very important. This chapter presents the techniques namely Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) for fault detection and classification. Comparison is done by calculating mean and standard deviation. The former is adopted to decompose the fault transients, by extracting the time and frequency domain data simultaneously. For the decomposition of transmission line voltages into the Intrinsic Mode Functions(IMFs), the latter is adopted. Apparently, four type of faults are generated in a grid linked power system and simulation is carried out using MATLAB/Simulink.

4.2 Model for the transmission line fault detection

For fault detection in the transmission lines, the EMD is proposed in this chapter. For the separation of intrinsic modes of the signal (IMFs) EMD is used[84]. Hilbert transform is used to obtain instantaneous frequency data from the IMFs. DWT is also used to extract the wavelet coefficients which is used to identify the occurrence of fault. For the comparative analysis between the EMD and DWT, various statistical parameters such as standard deviation and mean are utilized. The block diagram for the detection of fault using the EMD is depicted in Figure 4.1.

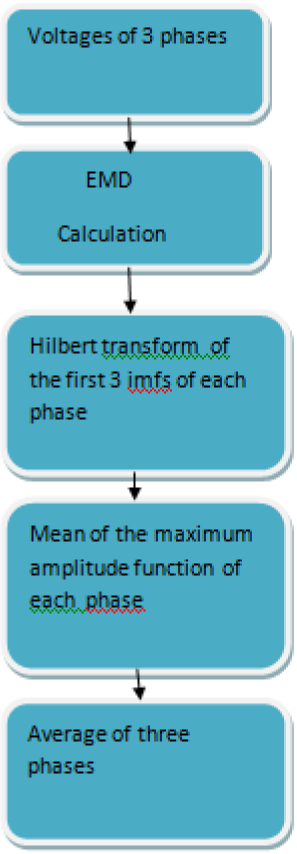


Fig 4 .1: Block diagram of fault detection using EMD

4 .2.1 Empirical Mode Decomposition

The signal decomposition into underlying oscillatory components of signal processing model is called EMD. This is a data-driven method and it never requires any previous knowledge of underlying oscillation characteristics and signal's frequency contents. This is the technique used for the adaptive analysis of the time-space for the interpretation of signals that are non-stationary and nonlinear. Modulated elements or the IMFs are obtained with the expression of zero mean amplitude and frequency. Basic and intrinsic oscillating modes are there in the time series. The main objective of this technique is to classify the intrinsic oscillations empirically based on the standard time scales followed by the decomposition of data. This process is known as sifting. This will remove the oscillations that have no zero crossings between the extremes [85]. Hence, the separation of information takes place on an overlapping timeline with the consideration of signal oscillations in each level using the EMD algorithm. The local characteristic time scale of the data is given importance in this decomposition. Steps involved in the EMD is given below.

- **Data decomposition**: The decomposition of time series signals into intrinsic mode functions (IMFs). The intrinsic mode function is a well defined function with the instantaneous frequency for the determination of original signal oscillatory modes.
- **Sifting process**: This process is used for the decomposition of signals via iterations. The maxima and minima are detected for all iterations with the association of mean envelope. This mean envelope is generated by interlinking the midpoints of local extreme. After subtracting the original signal from the mean envelope the IMF is created. This step continues till the convergence attained.
- **Residue**: The subtraction of signal resulted in two components namely IMF and the residue. The latter is the input to the next iteration of the sifting step and derives the IMF from it. This process is halted when it attains the stopping criteria.
- **Final decomposition**: At the end the residue attains the monotonic function and reaches the final stages of decomposition. The original signal can be obtained as the summation of all the extracted IMFs and the final residue.

The numerical values of Empirical mode decomposition is found as below

Consider the signal to be analyzed and decomposed as $f(t)$ and the average value of envelopes that produced up and down as n_1. Let the first element imf_1 is estimated as,

$$imf_1 = f(t) - n_1 \qquad (4.1)$$

The signal considered in the next step is $f_1(t) = f(t) - imf_1$ and its mean value is n_2 , in the next sifting process,

$$imf_2 = f_1(t) - n_2 \qquad (4.2)$$

This process of sifting is repeated until all *imfs* are separated or until the residue becomes negligible. Finally, the first signal $f(t)$ is expressed as the sum of *imf* elements along with the rest of the residue value.

$$f(t) = \sum_{i=1}^{M_e} imf_i(t) + h_{M_e}(t) \qquad (4.3)$$

The i^{th} *imf* is represented as imf_i and the last residue value is $h_{Me}(t)$. Following the process, the initial element that represents the original signal of $f(t)$ is imf_1 with the highest frequency component. The lowest frequency component is denoted as the last residue of the $f(t)$.

4 .2.2 Fault detection using EMD

The EMD algorithm is illustrated below.

- Connect the local maxima of the signal with a spline. Let U denote the spline that forms the upper envelope of the signal.
- Connect the local minima of the signal with a spline. Let L denote the spline that forms the lower envelope of the signal.
- Subtract the mean envelope $m = (U + L)/2$ from the signal to obtain an *imf*.
- Repeat Steps 1, 2 and 3 above until the resulting signal is a proper *imf* .The *imf* requirements are checked indirectly by evaluating a stoppage criterion.

- After finding an *imf*, this same IMF is subtracted from the signal. The residual is regarded as new data and fed back to Step 1 of the algorithm.
- The algorithm is completed when the residual of Step 5 is a monotonic function. The last residual is considered negligible.
- The signal is expressed as the sum of *imf* elements along with the rest of the residue value as given in equation 4.3.
- The i^{th} *imf* is represented as imf_i and the last residue value is $hM_e(t)$.

Once the first 3 *imfs*(*imf1*,*imf2*,*imf3*) are determined, Hilbert transform is applied on each to get instantaneous amplitude characteristics. Maximum of this values is selected and mean is found out. The same procedure is applied on 3 phases and finally the average of these is calculated as the final mean value. The standard deviation is also found in the similar manner.

The fault in any phase will affect the voltages in the three phases. The first 3 *imfs* are used for feature extraction since most of the frequency content is present in these *imfs* and this is sufficient for fault detection. In this work normal condition as well as different faulty conditions are simulated and the above procedure is followed. If the fault is in any phase the final mean value is found to be above a threshold value. The same has been found to be above 350 for the system simulated. The threshold is found out by a trial and error method. In this analysis only detection of a short circuit fault is done and different types of faults are not distinguished.

In this algorithm first empirical mode decomposition is done and the Hilbert transform is taken. The range of instantaneous amplitude and phase of the voltage signal of a particular phase varies on occurrence of the fault. There is variation in energy distribution also under short circuit faults. So the features like mean, standard deviation and energy distribution of instantaneous amplitudes can be selected as most significant features. In this study mean is taken to find out the occurrence of a fault. Average of the values from 3 phases can be taken to get an indication of fault occurring in any phase even though magnitude and nature of the signals may be different in different phases under different fault conditions.

Normalization of features can be made to make them comparable but since classification of fault is not attempted here, normalization is not done.

4.2.3 Discrete Wavelet Transform

DWT is the short wavelike function which is scaled and translated. In DWT, signals are represented on various scales. The time and frequency information is kept intact during transient analysis [86]. The wavelet associated with decomposing the signals in both time and frequency are termed as mother wavelet. The features like suppressing and strengthening of wavelet at different scales is carried out independently and evaluated by means of DWT. The given signal is decomposed into different sets and each set is a time series of coefficients describing the time evolution of the signal in the corresponding frequency band. Wavelet transform is capable of decomposing signal to different frequency components and transient phenomena can be studied by analyzing the high frequency components. As short circuit faults give rise to high frequency components, detection of such faults is made possible by wavelet transform analysis. Figure 4 .2 depicts the block diagram for fault detection using DWT. In DWT there is no fixed or explicit window size. It uses wavelets of different lengths to analyze signals. The selection depends on application. Narrow window size is used for high frequency components and wide window for low frequency components. Window size of 64 is used here. The number of decomposition levels specifies windowing effect. As the fault signals are non linear, non stationary signals, Haar wavelet is selected as the mother wavelet.

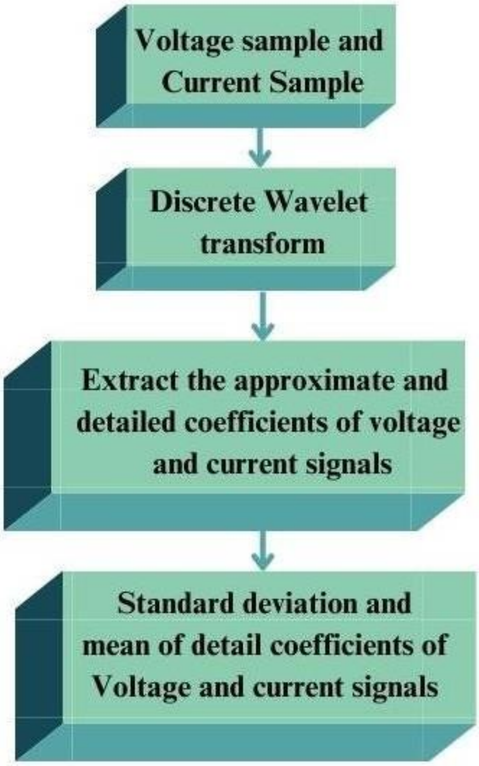


Fig 4.2: Block diagram for fault detection and calculation of parameters using DWT.

The wavelet transform is expressed as follows.

$$W\left[f(x,y)\right] = \left(f, \theta_{x,y}\right) = \int_{+\infty}^{-\infty} f(t)\frac{1}{\sqrt{x}}\theta^{*}\left(\frac{t-y}{x}\right)dt \qquad (4.4)$$

$w\left[f(x,y)\right]$ is the wavelet coefficient with the scale x and time y. The time-series signal of the waveform is $\left(f, \theta_{x,y}\right)$. The Normalization function here is $\frac{1}{\sqrt{x}}\theta^{*}$ with the shifting time of $\left(\frac{t-y}{x}\right)dt$. The main purpose of DWT is the implementation of discrete values of the scale and converting the parameter of Continous wavelet transform(CWT).The process of DWT can be determined as,

$$DWT_{a}(h,d) = \frac{1}{\sqrt{2^{h}}}\sum f(t)\theta\left(\frac{t-d^{2h}}{2^{h}}\right) \qquad (4.5)$$

Here, the scaling parameter is 2^h with the shifting parameter $d\,2^h$. The DWT evaluation is done by transmitting the signal through the high pass filters (HPF) and low pass filters(LPF). The signal decomposition using DWT is performed with specific resolution and varying scales at every step. The WT decomposes the signal into various frequency components using various scales and these components are wavelet coefficients. This is utilized to capture the signal details for varying resolutions and thus multi-resolution analysis is obtained. Detailed coefficients are the high frequency components. At each level the correlation between signal and wavelet is done and wavelet coefficients are obtained. The detail coefficients $(DC1, DC2,...)$ are the outputs of HPF and the approximation coefficients$(AC1, AC2,...)$ are obtained from the LPF. The decomposed signal components can reconstruct the original signal at each level.

4.2.4 Fault detection using DWT

The transient conditions developed in the transmission lines(TL) following the faults are analyzed using DWT. DWT is utilized efficiently for the fault detection process since it provides a fast, smooth, and exact fault analysis. It also mitigates the computational complexity, and the resources needed are also very less. The input signals are chosen from the three-phase TL signals and the required features are acquired after the decomposition of DWT [87]. Using 5 levels of maximum and minimum values of detail–coefficients the

features are extracted. Subsequently, the decomposition of horizontal, vertical, and diagonal levels is performed at each step. The maximum detail coefficient is obtained at level 4 and the minimum value from level 5.The coefficient values are found under normal and faulty conditions which enables fault detection.

4.3 Simulation Model

Figure 4.3 shows the fault detection with the proposed Simulink model using DWT and EMD. The transmission line of 30 km is used to connect voltage source and 21 km feeder . The operating voltage is 25 kV. The transmission line is operating with 25KV, 100MVA system. The receiving end load is 800W,0.8pf lagging at 25kV. The proposed system generates the voltage and current waveforms for fault diagnosis under various fault conditions. The simulation is carried out in the platform of MATLAB/Simulink and it provides the signal outputs. System specification table is also given below.

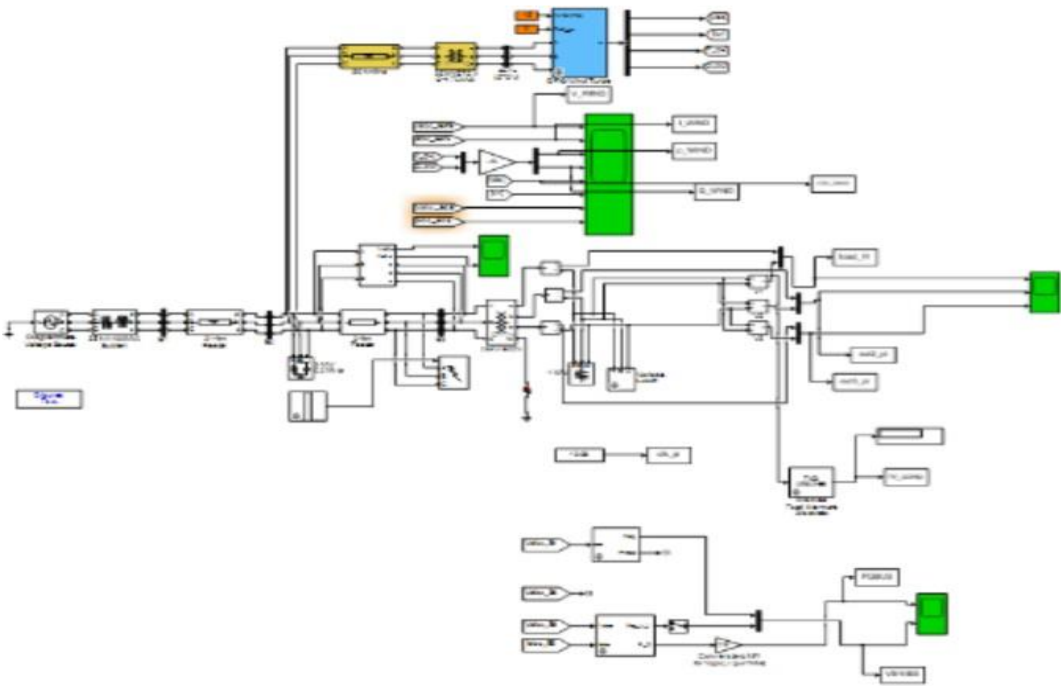


Fig 4 .3: The Simulink model .

Parameter	unit	Symbol	value
Voltage level	V_L	kV	25
Line length	L	km	30
Frequency	f	Hz	50
Conductor type	-	-	ACSR
Resistance/phase	R	ohm	2
Inductance/phase	L	H	0.010
Load			800W,0.8pf lag

During fault diagnosis, comparison of the signal values with normal voltage signals is done. By performing empirical mode decomposition, intrinsic mode functions are suitably obtained. By following the algorithm and procedure given in section 4.2.2, the mean value of amplitude function is found out. Later after comparison with threshold value, fault is detected. The same is done at different locations on the transmission line under different fault conditions. DWT is also used to identify the fault in the model.

4 .4 Results And Discussion

Waveforms obtained using EMD and DWT are illustrated in this section. Figure 4 .4 shows normal voltage and current signals along with grid voltage. This shows no fault condition in voltage and current waveforms.

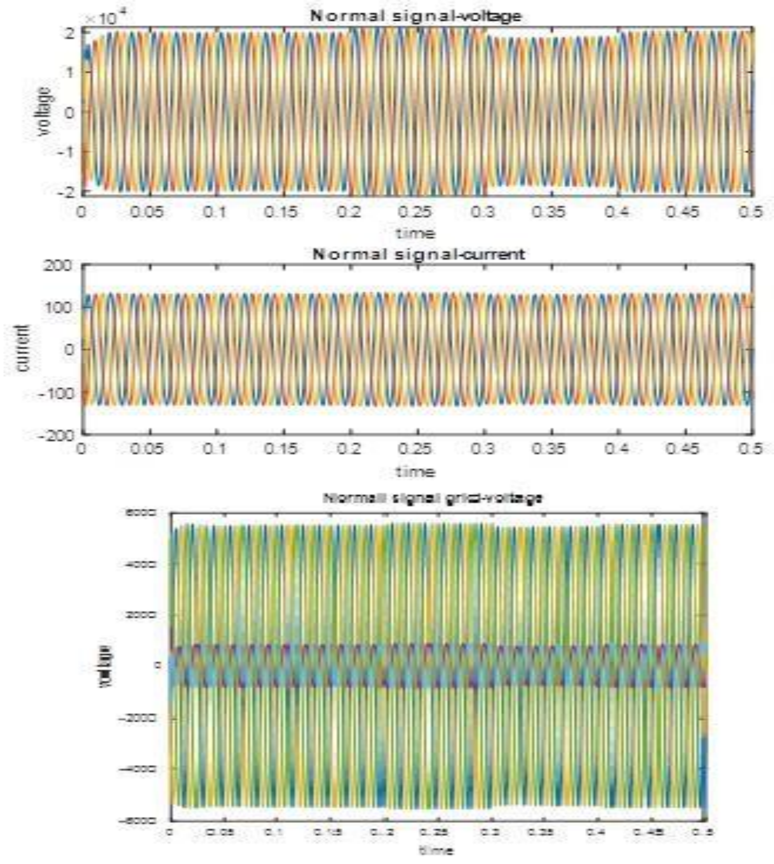


Fig 4 .4: Normal signal without fault (voltage ,current and grid voltage)

The voltage and current signals of phase-phase fault is given in Figure 4 .5. Figure 4 .6 plots the waveforms for phase-ground fault. The three-phase fault voltage and current signals are illustrated in Figure 4 .7. Figure 4 .8 illustrates the three-phase ground fault signals. For 0.2 to 0.3 seconds, the fault occurs and it is cleared after 0.3 seconds.

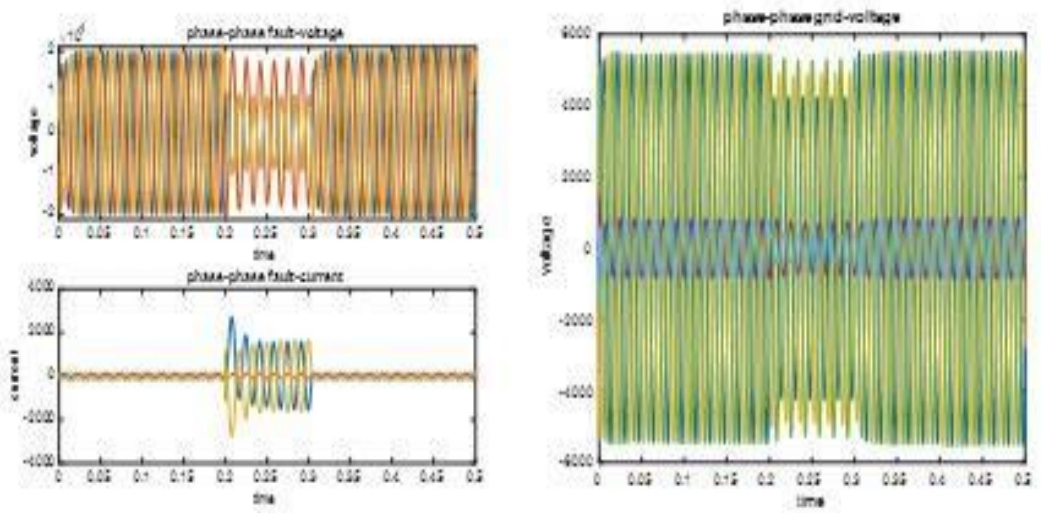


Fig 4 .5: The voltage and current signals of phase-phase fault

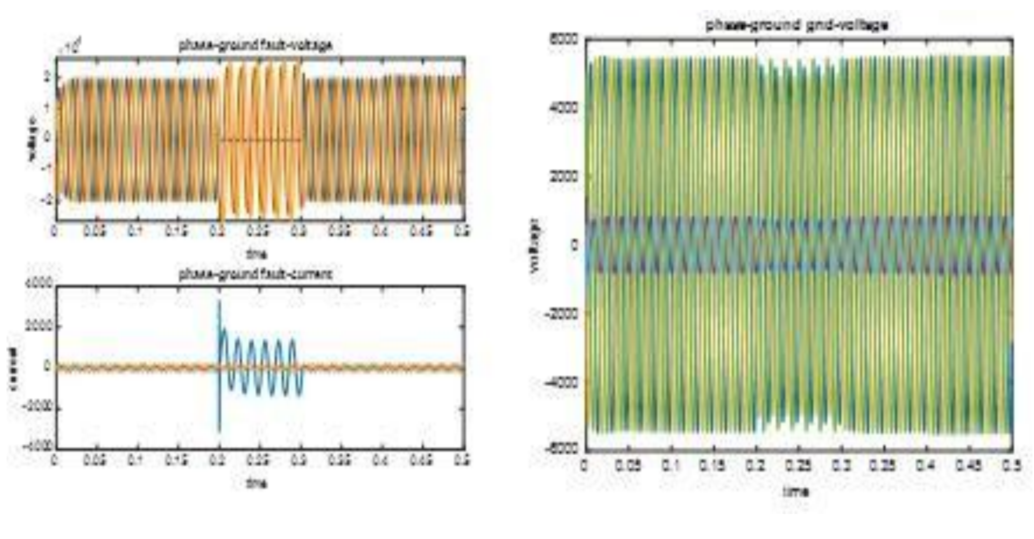


Fig 4 .6: The voltage and current signals of phase-ground fault

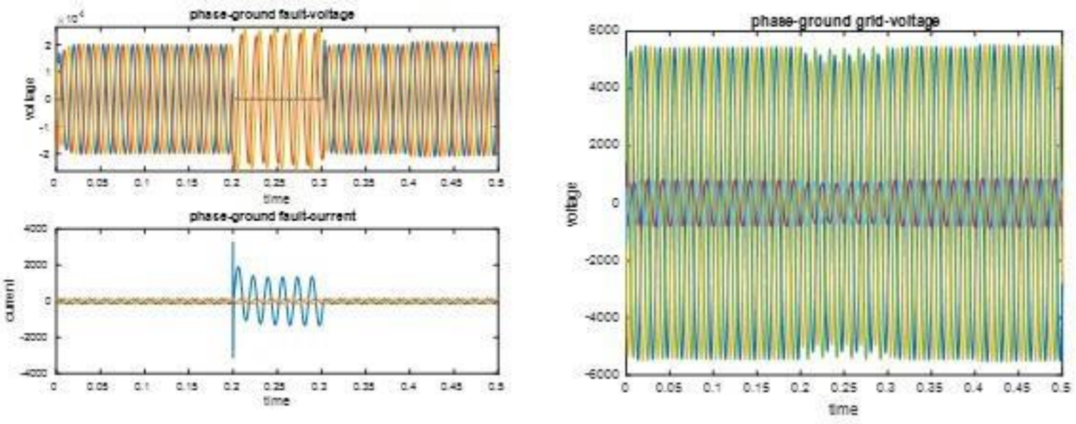


Fig 4 .7: Voltage and current signals of three phase fault

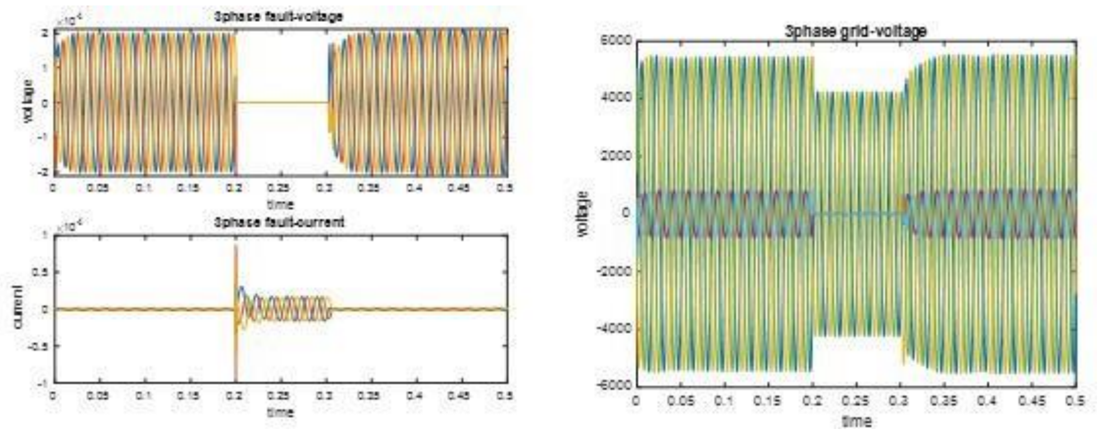


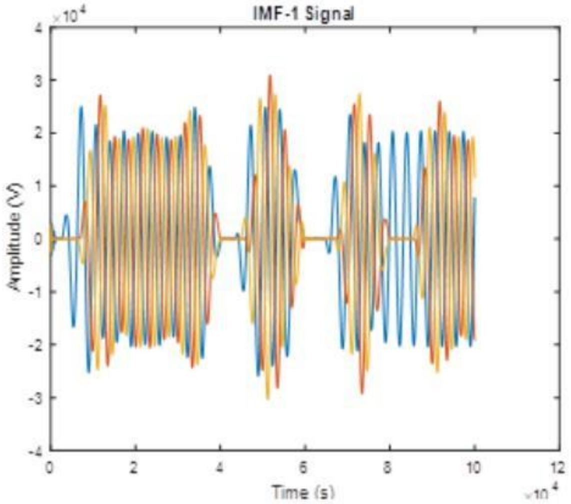
Fig 4 .8: The voltage and current signals of three-phase- ground fault

4 .4.1 <u>Signal Evaluation</u>

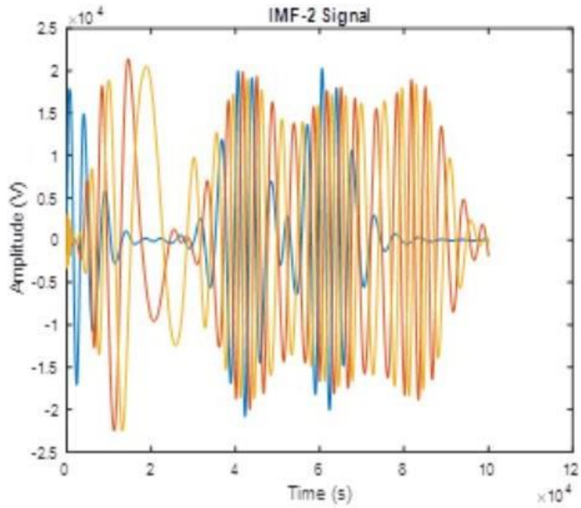
As evident from the waveforms obtained the current in the case of fault occurrence is of high magnitude and the features like magnitude, phase variations etc can be used to detect and identify the fault. The maximum and minimum value of oscillations due to line to line fault is found to be 3kA and 1.8kA respectively. The voltage at the fault point is also found to be reduced significantly. Using various feature extraction techniques it is possible to capture the transient nature of the fault. Fault detection can be done by analyzing signal characteristics at various time and frequency scales.

4 .4.1.1 EMD-normal signal

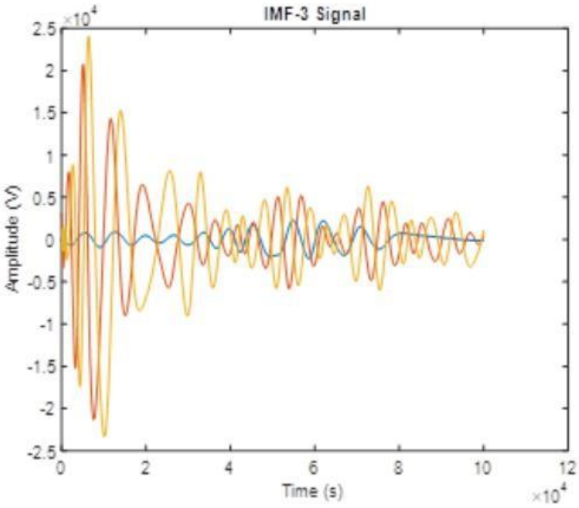
The transient components of voltage signals obtained from the sensors are analyzed. This section depicts the waveforms obtained after EMD-HT of the normal signal. After EMD *imf1*,*imf2* and *imf3* are obtained. Then Hilbert transform is determined for the IMFs. Mean of the resulting amplitude function is found out for the IMFs. Maximum of this value is found and the process is repeated for all the three phases. HHT has unique advantages in processing nonlinear and nonstationary signals. *Imf1*, *imf2*, and *imf3* of the normal signal is given in Figure 4.9. The wavelet transform of the normal signal is also found out and shown in Figure 4.10.



(i)



(ii)



(iii)

Fig 4.9: The normal signal waveform, (i) *imf1* (ii) *imf2* and (iii) *imf3*

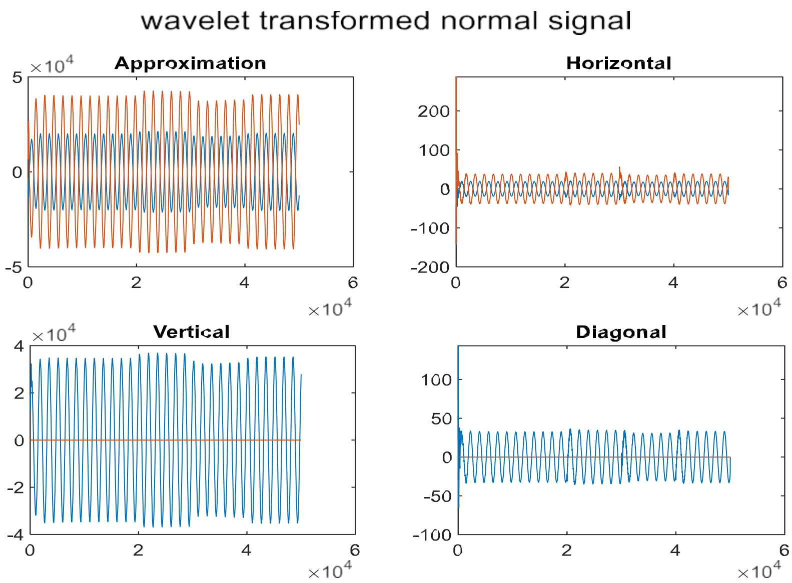
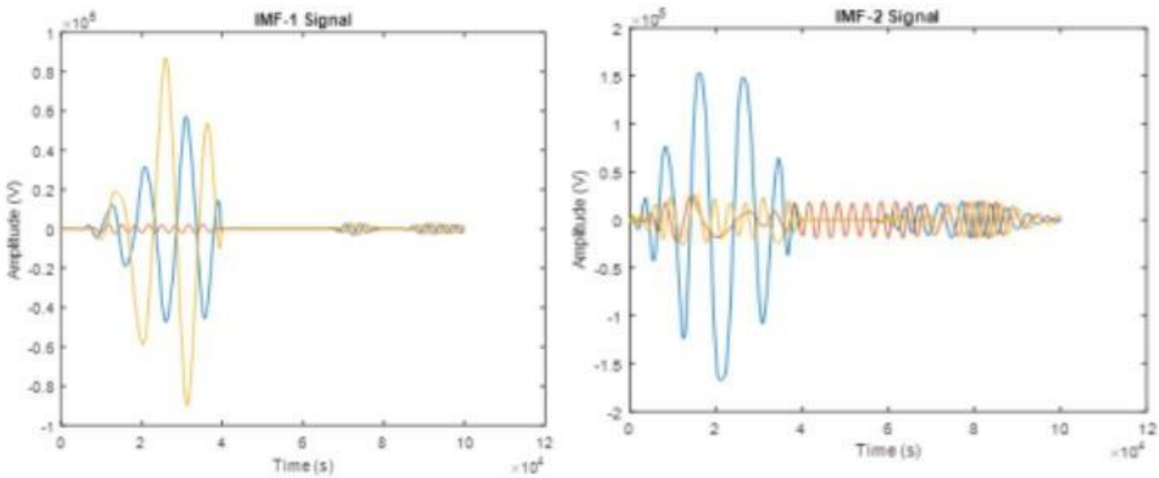


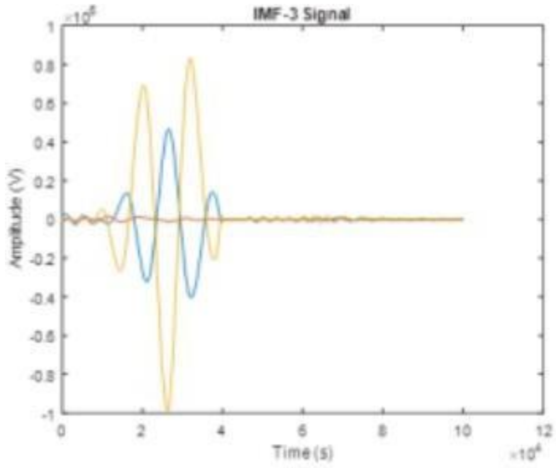
Fig 4.10: The wavelet transform of the normal signal

4.4.1.2 Fault Signal Evaluation of phase-phase fault

This section presents the results of EMD-HT of phase-phase fault signals. The waveforms of *imf1*, *imf2* and *imf3* of phase-phase fault signal are shown in Figure 4.11.



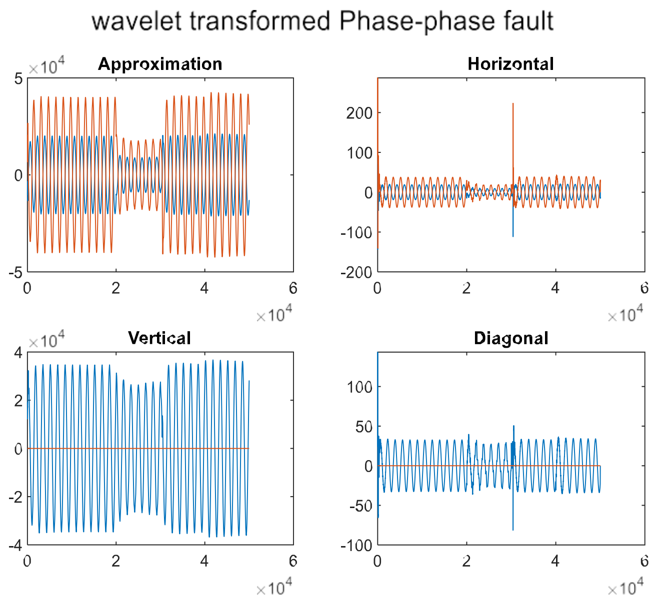
(i) (ii)



(iii)

Fig 4.11: The phase-phase fault waveforms, (i) *imf1*, (ii) *imf2* and (iii) *imf3*

This section discusses the outputs of discrete wavelet transform of phase-phase fault signals. Figure 4.12 shows the wavelet transform simulation outputs for the phase- phase fault

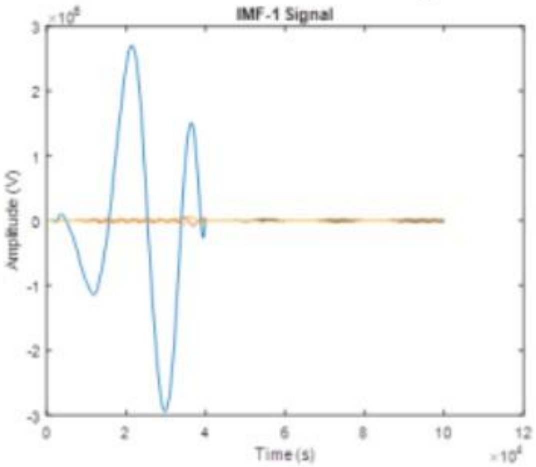


.

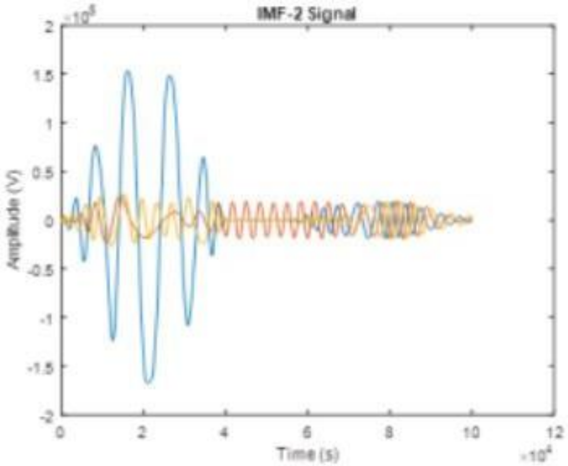
Fig 4.12: The wavelet transform simulation of phase–phase fault .

4.4.1.3 Phase-ground fault signal analysis

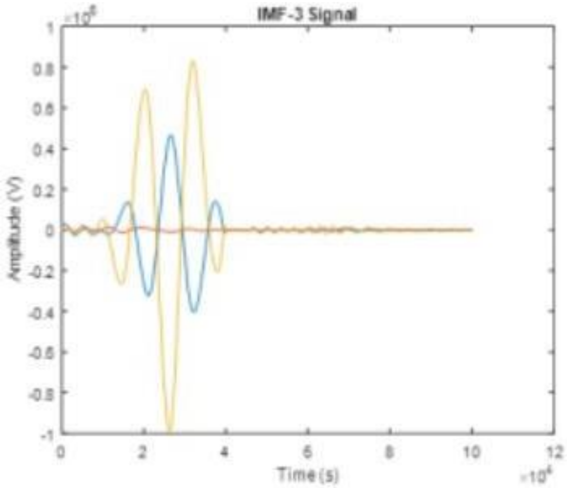
The phase-ground fault signal results are presented in the following section. Figure 4.13 displays the waveforms of *imf1*, *imf2* and *imf3* extracted from phase–ground fault signal by applying EMD. The wavelet transformed outputs of phase-ground fault signal is displayed in Figure 4.14.



(i)



(ii)



(iii)

Fig 4.13: The phase–ground fault waveforms (i) *imf1*, (ii) *imf2*, and (iii) *imf3*

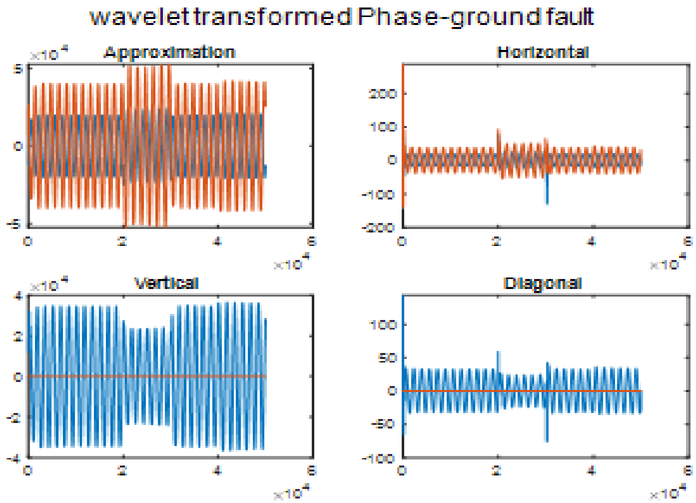
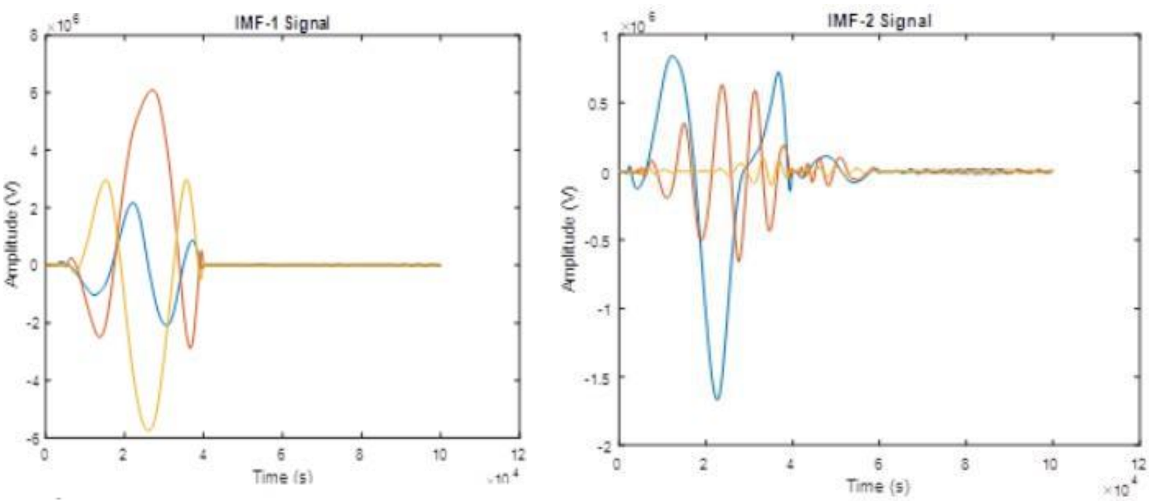


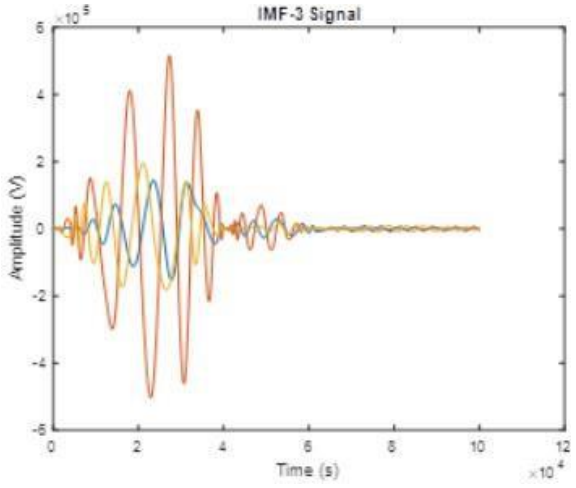
Fig 4.14: Wavelet transformed outputs of the phase ground fault

4.4.1.4 <u>Three-phase fault signal analysis</u>

This section explains the results corresponding to the EMD of the three-phase fault signal. Figure 4.15 depicts the waveforms of intrinsic mode functions (imfs) obtained on applying EMD to three-phase fault signal. The three-phase fault wavelet transform outputs are illustrated in Figure 4.16.



(i) (ii)



(iii)

Fig 4.15: The three-phase fault signal waveform (i) IMF1, (ii) IMF2, and (iii) IMF3

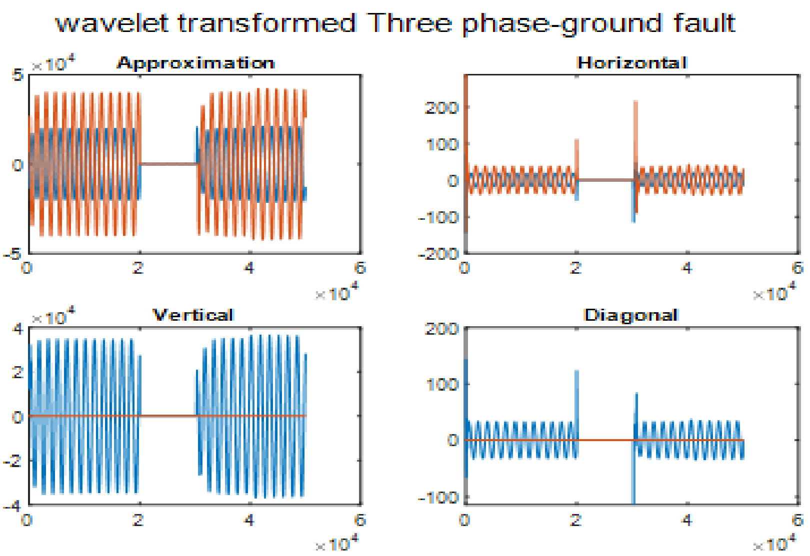
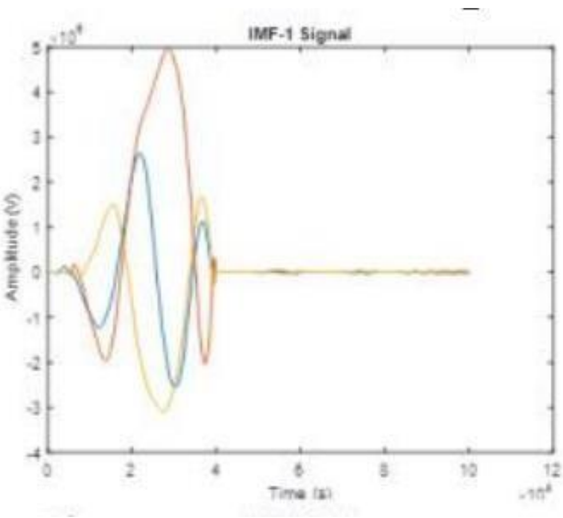


Fig 4.16: The three-phase fault wavelet transform outputs

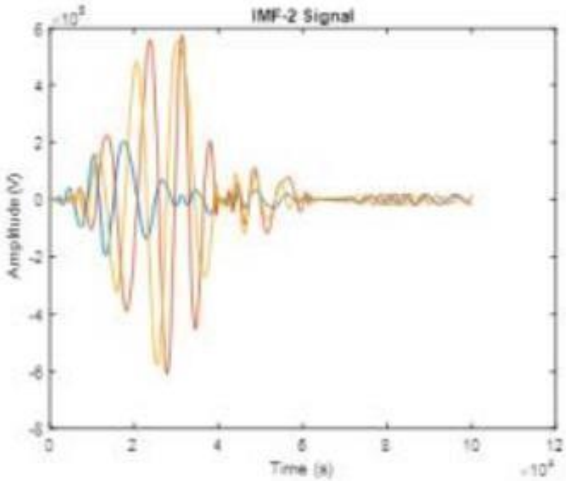
4.4.1.5 Three phase-ground fault signal analysis

The results of three-phase ground fault signal analysis using EMD-HT and Discrete wavelet transform are given in the figures below. Figure 4.17 plots intrinsic mode functions (*imf*s) extracted by performing EMD to the three-phase ground fault signal. The three-phase-ground fault wavelet transform outputs are-illustrated in Figure 4.18.

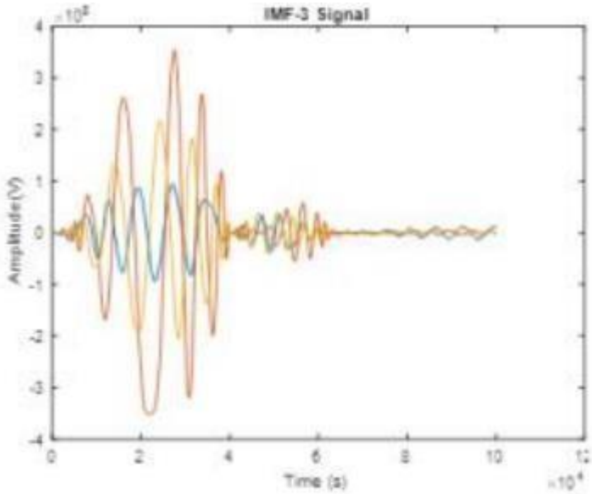
The mean value of amplitude function after application of EMD and Hilbert transform is compared with threshold value. This is found to be < 350 for normal signals, and for faults, it is found more than 350.Thus the threshold is selected based on this. Any random signal from the system also can be found to be normal or faulty based on this.



(i)



(ii)



(iii)

Fig 4.17: The three-phase ground signal waveform (i) *imf1*, (ii) *imf2*, and (iii) *imf3*

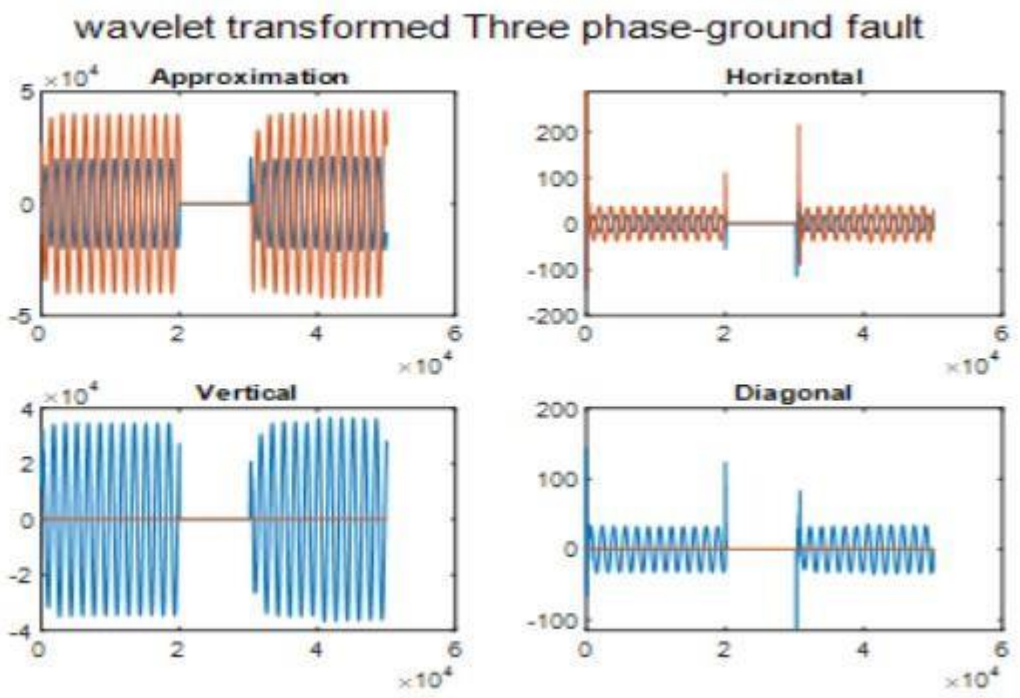


Fig 4.18: The three-phase ground signal waveform

The mean and standard deviation (SD) of both DWT and EMD-HT outputs of the voltage signals are calculated. The minimum SD values and maximum mean values are present in the EMD outputs when compared with that of DWT. This confirms that the coefficient extraction using EMD is superior to that using wavelet transform. Table 4.1 shows the standard deviation and mean of EMD of the fault signal as well as that of wavelet coefficients.

‘

Table 4.1: Comparison of standard deviation and mean values using EMD and DWT method

Signals	EMD method		Wavelet method	
	Mean	Standard deviation	Mean	Standard deviation
Normal	4.5480	35.3011	282.4088	5.2882e+04
P-P Fault	3.4313e+03	7.6175e+03	238.4229	5.0036e+04
P-G Fault	2.2745e+04	2.5481e+04	1.7338	5.3590e+04
3P Fault	1.7508e+04	2.2362e+04	216.8012	4.7159e+04
3P-G Fault	2.1829e+03	2.1168e+04	237.5379	4.7163e+04

4 .5 Summary

This section summarizes the fault diagnosis and detection in TL using DWT and EMD. The SIMULINK is used to implement and develop an integrated system for the proposed work. The voltage signals are obtained from every phase. The signals are decomposed by EMD to obtain IMF which are fed to HT and by DWT to obtain approximation and detail coefficients up to 5 levels. A threshold is found for faulty signal by trial and error. It is seen that when the system is running on normal conditions these values are less than the threshold value. The mean and standard deviation (SD) of both DWT and EMD-HT of normal signal and faulty signal are calculated. The accuracy of this work is 98.9%. Various types of faults are determined at different locations on TLs and the method is tested. In the next chapter various short-circuit fault types will be detected and classified efficiently using the data collected from the simulation model of IEEE 30 bus system by applying hybrid techniques along with feature extraction.

CHAPTER-5

Fault Detection Using Wavelet Transform And Improved Convolutional Neural Network

5.1 Introduction

For the fault detection and classification in the IEEE standard 30 bus network, this chapter suggests an innovative method based on the optimized deep learning technique. This employs Bees optimization algorithm based Improved Convolutional Neural Network (ICNN) incorporated with the wavelet transform (WT). The statistical features from each cycle of the current signals and post-fault voltage signals are extracted using the WT from the Bus. With the association of a series of low-pass and high-pass filters the power signals are converted into various frequency ranges by the WT. The normalization process is performed on the extracted features and forwarded to the ICNN block for the classification of fault. In the ICNN, operations like convolution and max pooling for feature analysis are effectuated and forwarded to the fully connected layer. Further, hyper-parameter tuning of ICNN is made with the novel Bees Bayesian optimization algorithm (BA-BO). Fault simulations are created on IEEE 30 bus system using MATLAB / Simulink and analyzed the outcomes. The testing accuracy obtained using the proposed technique is 99.67% which is higher than the existing techniques.

5.2 IEEE 30 Bus Network

The American electric Power system of December 1961 is approximated as the IEEE 30-bus network. The architecture of the standard IEEE 30 bus network is depicted in Figure 5.1 consisting of 30 buses, 6 generators, 24 loads, 4 transformers and 41 transmission lines. Generator 1 is the swing bus and other generators are in voltage control mode. The generators are rated 135kV with speed 1800rpm and with 4 poles. All loads in service are 3 phase and rated voltage of 135kV.The transformers are connected in 3 phase with rated voltage of 135kV – 33kV.Using suitable transformer taps voltage is reduced to distribution level. Thus 5kV is the voltage obtained in the buses selected

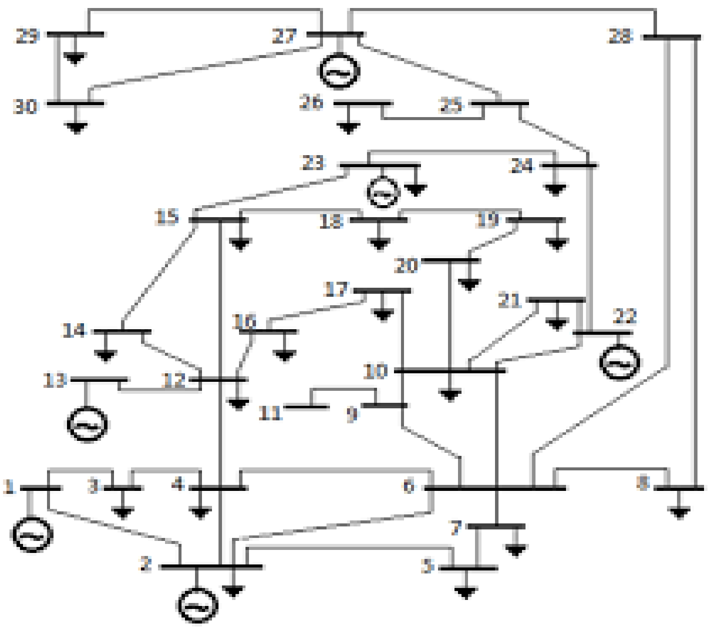


Fig. 5.1: Architecture of IEEE 30-bus network

5.3 Fault Detection Of IEEE Bus System Using the WT

Recent times have seen the increased usage of WT in the real-time applications of power systems and it was developed in the 1980s by researchers in the fields of signal and image processing. Moreover, it replaces the fixed-width windowing functions of short-time Fourier transform (STFT). For each spectral element, the width of the window is altered in the WT [88]. Abnormal operating conditions are detected by converting power signals into various frequency ranges by using low pass and high pass filters. The low frequency and high-scale components are referred to as WT approximation coefficients. The components of high frequency and low scale are referred to as detailed coefficients. Thus the coefficient matrix of the WT is the combination of detail and approximation coefficients [89]. Hence the WT replaces the FT for solving the issues in power system and is expressed as in equation 4.4.

The equation for discrete wavelet transform is given in equation 4.5.With the multi-resolution capacity, the WT is used for the pre-processing of data in various applications [90]. The WT is of two types, Discrete WT and Continuous WT, the former is easy to implement, since the latter requires altering the scale of the analysis window and shifting the window in time. The features are localized temporally or spatially based on the information gained.

5.4 Classification Of Faults

There are 11 types of faults in the power system and are either symmetrical or non-symmetrical faults [91]. These faults are again split into different types and are given below.

5.4.1 Symmetrical Faults

The symmetrical faults are the faults that include all three phases and it is also termed as balanced fault. When there is a short circuit in all three phases, it is called a symmetrical fault. It is further divided into three-phase fault and three-phase to-ground fault.

5.4.1.1 Three-phase fault

The most severe fault which involves the highest current is three phase fault and it occurs rarely.

5.4.1.2 Three phase line to ground fault

This fault occurs between the system's ground and the three phases. The three phases are shorted together and connected to ground. This is the most severe type of fault and so utilized for finding the circuit breaker rating.

5.4.2 Unsymmetrical Faults

With varying phase and amplitude of the current in the three-phase power system, this fault occurs. It might occur either with the open circuit or short circuit of the transmission or distribution line. This is mainly because of manual blunders or characteristic aggravations. This is basically of three kinds (i) Line to line fault, (ii) line to ground fault, and (iii) Double line to ground fault.

5.4.2.1 Line-to-Line Fault

When there is short-circuit between two conductors this fault occurs and is caused mainly due to the extremely high winds. With the wind swings the conductors touch each other and create a short circuit. 10 to 20% of faults are of this type.

5.4.2.2 Line to Ground Fault

This types of fault occurs when a conductor touches the ground or connects with the neutral or unbiased conductor. This contributes to 70 to 80% of faults in the power system.

5.4.2.3 Double line to ground Fault

From the name, it says that the connection of two lines and the ground produces this type of fault. This type of fault contributes to 10% of total power system faults. Such a phenomenon is not very frequent but it can occur if the insulation of two phases fails due to insulators getting damaged or due to a natural calamity, branches of a tree short two phases to the ground, or a part of an equipment breaks and shorts two phases by falling on them etc.

5.5 Fault Classification Model

This section describes the proposed ICNN optimized with hybrid BA-BO to detect and classify the short circuit faults in the system.

5.5.1 Improved Convolutional Neural Network (ICNN)

An interesting approach to fault identification is the CNN application for the classification of faults. The CNN is trained by using a few extracted features [92]. The fault diagnosis within the power systems like motors and transformers are performed using CNN. One of the widely utilized deep learning models is CNN, which is a feed-forward neural network (FFNN). The input and other data are allocated for further operations. The spatial subsampling, weight sharing, and local receptive fields are the three significant characteristics of CNN. The fully connected layer (FC), pooling layer, and convolutional layer (CL) make the CNN. The convolution operation initiates the process of CNN, the features are analysed via max pooling, and the last classification decision is obtained via FC layer. Figure 5.2 gives the structural diagram for CNN.

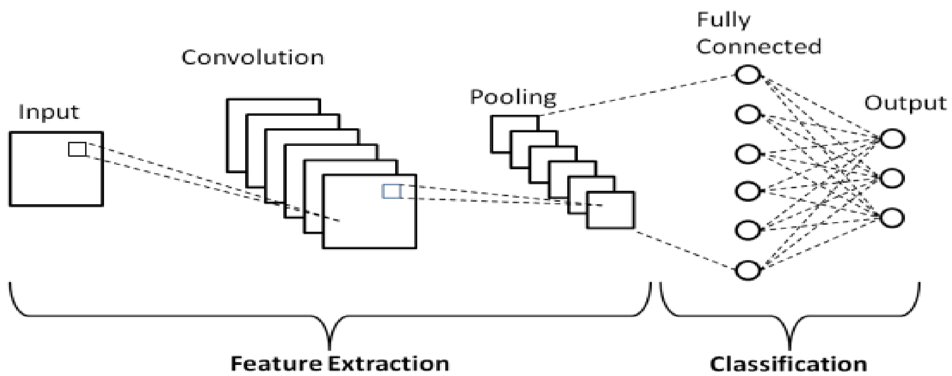


Fig. 5.2: The CNN structural diagram

The testing (30% of the dataset) and training (70% of the dataset) stages are the two stages in the model of classification [93]. The CNN model is trained using the training dataset and corresponding labels. From the raw data, the feature extraction is performed automatically via the proposed ICNN(improved CNN) . The raw data is processed as input in the testing phase and feature extraction is not carried out in the testing phase.

Two one-dimensional convolutional layers are stacked and can be utilized in the proposed ICNN approach. The convolutional layer extracts the features from the raw input data which is the first step. Tan-h function is used as the activation function of each convolutional layer. This lies in between [-1, 1]

5.5.1.1 Convolutional Layer

The feature extraction is done by the CL from the input data .The input of a convolutional layer is the output of the previous layer. The kernel size is same for all kernels and utilizes the weighting procedure for the extraction of local features. The mathematical expression of the CL is expressed as,

$$y_i^k = g\left(\sum_{j \in M_p} y_j^{k-1} * n_{ji}^k + d_i^k\right) \tag{5.1}$$

The k^{th} network layer is $y_i{}^k$, the nonlinear aviation function is g, and the selection of input maps denoted by M_p and n is the kernel matrix. The convolution operation is denoted by $(*)$ and d is the index variable of the kernel.

5.5.1.2 Pooling Layer

The input data size is minimized by adding a pooling layer in between every convolutional layer and also the over fitting is reduced by minimizing the input parameters to the next layer.

This is the sub-sampling layer which makes the representation invariant. The mathematical expression of the pooling layer is given as;

$$y_i^k = g(\beta_i^k down(y_i^{k-1} + d_i^k)) \tag{5.2}$$

The sampling function is represented by *down (.)* and β is the parameter producing translational invariance. In this layer the pooling operation called Max pooling occurs. It is responsible for downsampling and highlighting the most relevant feature in the receptive field. This is done without loosing the important attributes of the feature maps. For each receptive area, the largest or maximum value is calculated. Within the selected filter size, the maximum value is picked by the network and sent to the subsequent layer.

5.5.1.3 <u>Fully-connected Layer</u>

It is a traditional feed-forward neural network with softmax as the activation function in the output. The output layer which determines decision is made up of this fully connected layer. The output of the FC layer is in a single vector format unlike the convolution layers where it is in a matrix form. FC layer connects each input neuron to each output neuron within the layer. From each previous layer, aggregated and composite information in a simple vector format is present in the FC layer. The probability score for each class is in between 0 and 1 and is provided by the softmax function in the output layer. The formula below expresses the softmax function.

$$\sigma(y)_l = \frac{e^{z_l}}{\sum_{N=1}^{N} e^{z_N}}, for\ l = 1, \ldots\ldots N \tag{5.3}$$

where y is the vector of raw outputs from the neural network. The value of e=2.718.The i^{th} entry in the softmax output vector softmax(y) can be thought of as the predicted probability of the test input belonging to class i. The softmax activation function takes in a vector of raw outputs of the neural network and returns a vector of probability scores.

5.5.2 Novel Hybrid Bees Bayesian Algorithm

Genetic Algorithm (GA) is an optimization technique inspired by the gene's natural selection process in nature. For search problems and global optimization, accurate solutions are generated with the well-suited technique of GA and it involves the operations of mutation, crossover, selection, and evaluation. The network structure learning and updating the weights of neural network is done using GA. The Feed Forward Neural Network (FFNN) is trained with GA in the earlier works. During the process of neural network learning, the weights are optimized and accuracy is improved by GA compared to Back Propogation Neural Network (BPNN).

Proposed ICNN parameters are optimized with the help of a hybrid Bees and Bayesian optimization(BA-BO) approach. The objective function of the prediction model is constructed with the help of Bayesian Optimization (BO). The hyper-parameters of the network are identified and evaluated in the true objective function. The BO algorithm provides a global learning rate by employing Bees algorithm that optimizes the weight learning rate factor of fully connected layer and three connected layers.

According to the validation set, the classification accuracy is improved in the FC layer, and convolutional filter weights are updated via optimal learning rate.

One of the commonly used swarm-based optimizations is Bees Algorithm(BA) and the parameters are optimized with an intense search over local search. While optimizing the parameters of ICNN, classification error of the validation set is minimized by using Bayesian Optimisation(BO) technique. The foraging behavior of honeybees inspires the working principle. At random positions, scout bees (m) with its global search, and the fitness value is computed. Select the local search of best sites (n). To elite sites, launch an intensive search. The local searches are conducted to recruit more bees and the neighborhood search space size is decided. Randomly perform a global search and the best solutions are explored with recruited bees.

The global learning rate is adjusted to optimize the FC and three convolutional layers by employing BA-BO-ICNN. The BO optimization approach is employed to optimize the parameters like regularization in ICNN, momentum, initial learning rate, and section depth. After this BA algorithm is employed to optimize weight learning rate factor in each convolutional layers and fully connected layer. Optimum amount of weight update is achieved in the fully connected layer that performs classification. This improves the classification accuracy of validation set. Figure 5.3 illustrates the BA-BO algorithm flowchart.

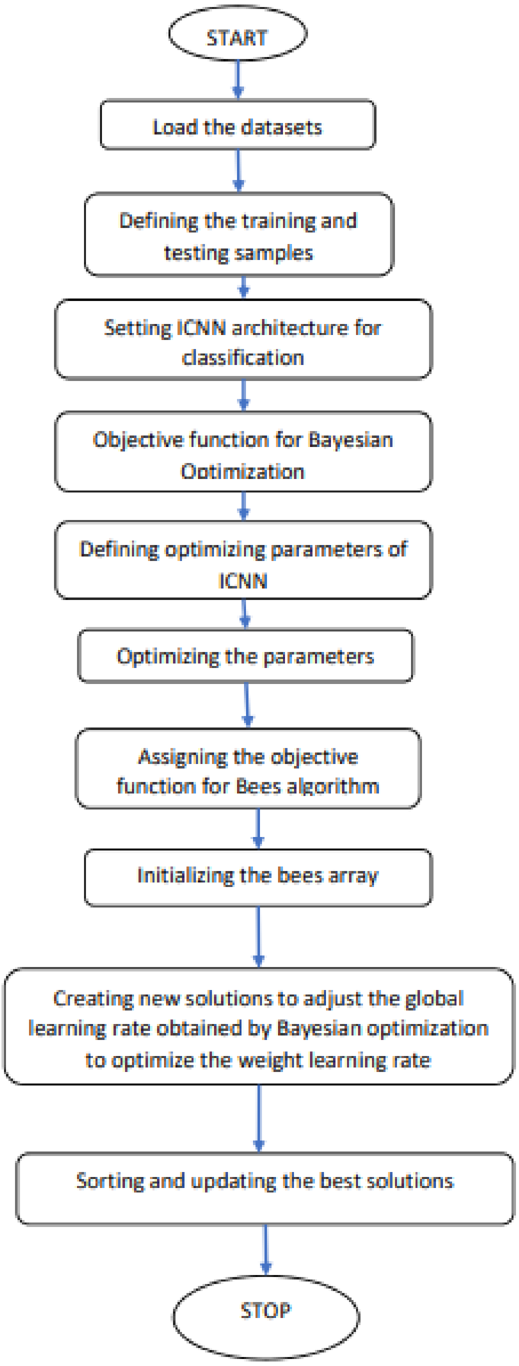


Fig. 5.3: The BA-BO-ICNN flowchart

5.6 Results And Discussion

The faults are simulated in the IEEE 30 bus system. Matlab/Simulink is utilized for the simulation and analysis of fault signals. The various voltage and current signals of buses 2, 14, 22, and 25 are depicted in figures 5.4, 5.5, 5.6, and 5.7 respectively. The voltage and current signals are taken as sample signals to understand faulty and normal conditions. The fault is applied in bus22 as an example to study the faulty signals. Transformer taps are suitably selected to get a distribution voltage of 5kV.The base voltage selected here is 135kV and fault analysis is done by changing the reactance(X) per unit value. Thus fault analysis is completed at different equivalent lengths (electrical) of transmission line 33(between bus 24 and bus 25).

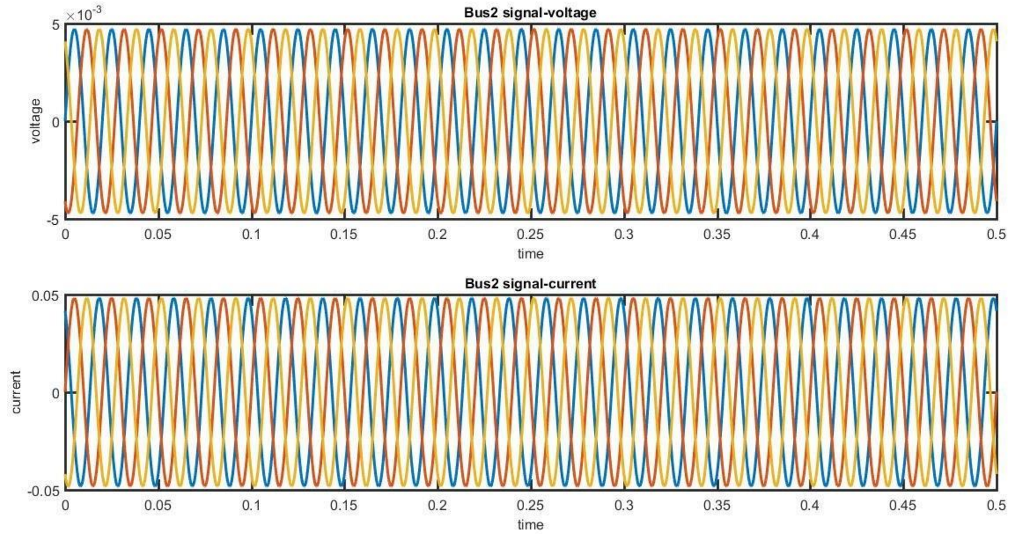


Fig. 5.4: Voltage and current signal of bus 2

As an example for detection purpose fault is created in buses 2,14,25,and 22 .Fault is created in bus 22 which is evident from the output signal. The voltage signal of bus 2 is approximately 5 kV and the current signal is 0.05A this represents the threshold values for normal situations and is depicted in Figure 5.4.

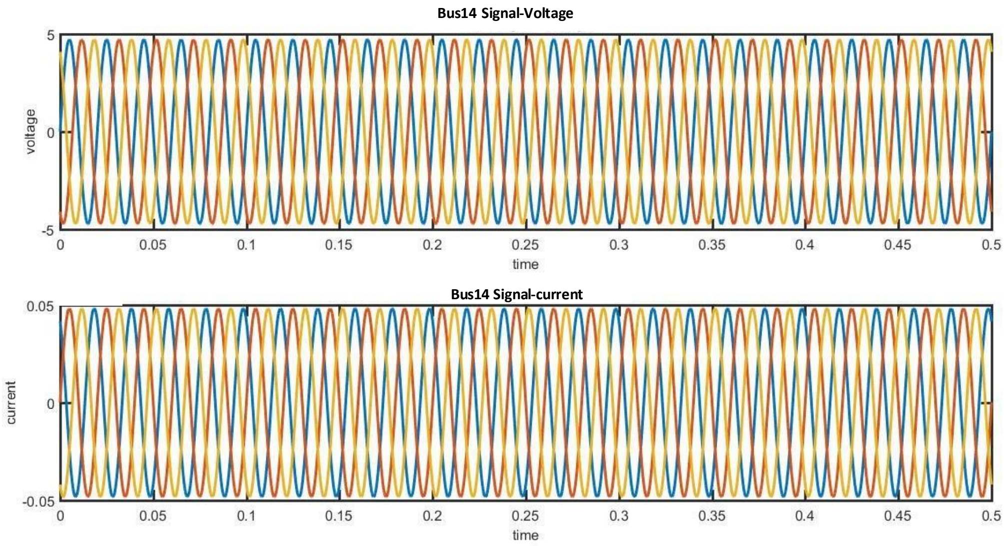


Fig. 5.5: Voltage and current signal of bus 14

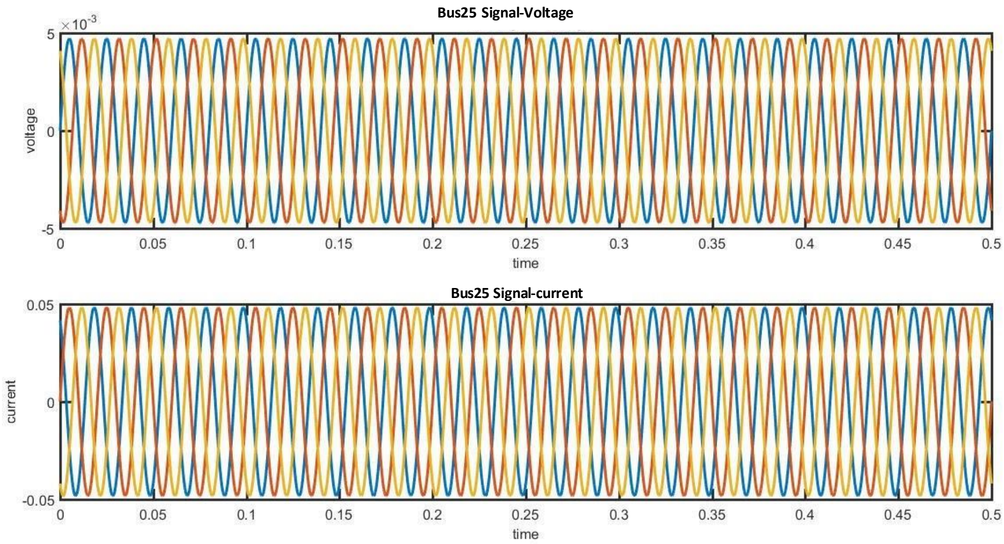


Fig. 5.6: Voltage and current signal of bus 25

At normal operating conditions, the threshold values of buses 14 and 25 are depicted in Figures 5.5 and 5.6 with a voltage equal to 5kV and 0.05A current.

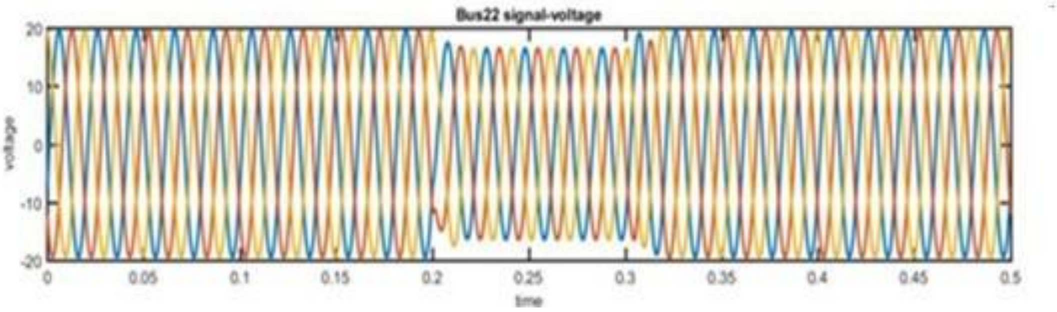


Fig. 5.7: Voltage of bus 22

The magnitude of voltage obtained for bus 22 is 20V and is depicted in figure 5.7 The voltage drops to 14V at about 0.2 seconds compared to other buses indicating the presence of fault.

5.6.1 Fault Detection using Wavelet Transform

The DWT of the signals are obtained for identification of faults using a set of low and high pass filters. In this process, the four coefficients such as horizontal, diagonal, approximate, and vertical are obtained. Thus high and low frequency information is obtained from the resulting voltage waveforms.

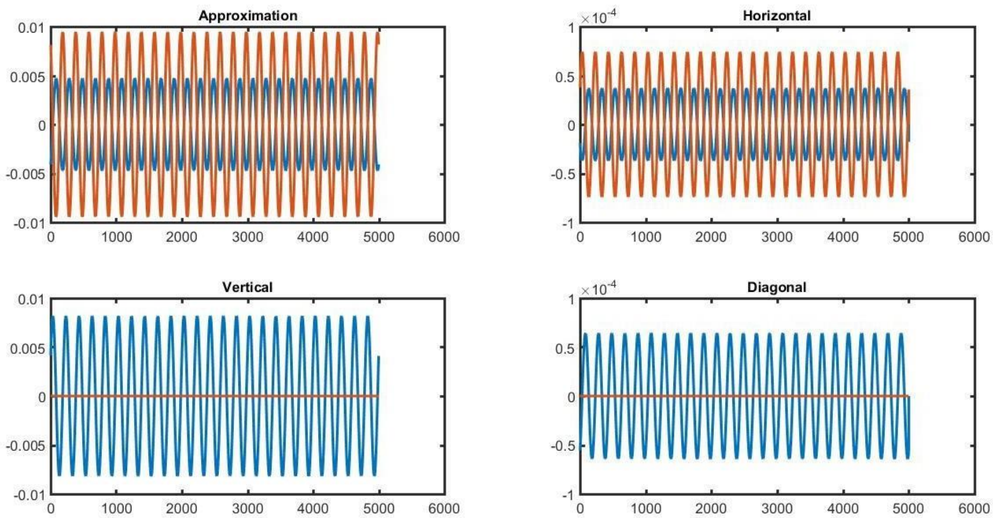


Fig.5.8: Coefficients of Wavelet transform

Using parameters such as mean, skewness, interquartile range, Kurtosis, standard, and entropy of each fault cases the coefficients are obtained as shown in Figure 5.8. The fault is detected by observing the appreciable increase in the mean values when compared to normal conditions. From the figures, it is observed that faults has occurred in the bus no.22.

5. 6.2 Classification using proposed improved CNN

Considered various scenarios of fault for the evaluation of the performance of fault classification. The scenarios are single line-to-ground faults (ag, bg, and cg), line-to-line faults (ab, bc, and ac), double line-to-ground faults (abg, bcg, and acg), three-phase faults, and three-phase ground faults. Simulations are done under different fault conditions. Data augmentation is done to obtain large number of samples in the dataset by time and spatial inversion technique. This will help to dig deeper into the internal features of the data. Approximately 1000 samples of each specific fault is used for classification. Finally normalization of the dataset is done before giving to classification model. This is done to get equal priority for all the features and to prevent any biasing of particular larger magnitude features thereby increasing accuracy . Normalization is done by min-max scaling. This is a commonly used normalization technique which rescales numerical features to a fixed range [0,1].

Extraction of relevant features from different fault cases is done and named (ag, bg, cg, ab, bc, ac, abg, bcg, acg, abc and abcg) with a number ranging from 1 to 10. To evaluate the classification accuracy the dataset is proportioned as 70% for training and 30% for testing. The confusion matrix of the proposed work is depicted in Table 5.1 and the various fault signals acquired for various cases are illustrated in Figures 5.9, 5.10, 5.11, and 5.12.

For multiclass classification confusion matrix is used to evaluate the performance of classifier on test data. The correct and false predictions for each class is summarized here. Terms of evaluation are

True positive(TP):when positive observation is predicted positive.

False negative(FN):when positive observation is predicted falsely as negative.

True negative(TN):when negative observation is predicted negative.

False positive(FP):when negative observation is classified falsely as positive.

Table 5.1: Overall Confusion Matrix

	ag	**bg**	**cg**	**ab**	**bc**	**ac**	**abg**	**bcg**	**acg**	**abc**	**abcg**
ag	955	0	0	1	3	0	0	1	0	1	0
bg	0	974	4	0	0	1	0	0	0	0	0
cg	3	0	952	1	0	0	0	0	0	1	3
ab	1	0	1	939	0	0	3	0	4	0	0
bc	0	1	0	0	971	5	0	1	4	0	0
ac	1	1	3	0	0	946	0	0	1	0	0
abg	1	0	1	0	3	0	950	0	1	3	0
bcg	1	2	0	1	0	0	0	939	0	0	2
acg	0	1	1	1	0	4	0	0	923	1	0
abc	1	3	0	0	1	0	0	0	0	985	0
abcg	0	1	0	1	1	0	1	2	0	0	998

The various parameters that are used to quantify the performance of the classifier are as follows

Recall: It is the ratio of the number of correctly classified positive observations to the total number of positive observations. High recall indicates the class is correctly recognized.

$$\text{Recall} = \frac{TP}{TP+FN} \ldots\ldots\ldots\ldots\ldots\ldots(5.4)$$

Precision:It is the ratio of the number of correctly classified positive observations to the total number of predicted positive observations. High precision indicates an input labelled as positive is indeed positive.

$$\text{Precision} = \frac{TP}{TP+FP} \ldots\ldots\ldots\ldots\ldots\ldots(5.5)$$

F1-score: It helps to have a measurement that represents the overall performance of the model. F1-score is computed using the harmonic mean in the place of arithmetic mean.It gives equal weight to both precision and recall

$$\text{F1-score} = 2 * \frac{(precision*recall)}{(precision+recall)} ..(5.6)$$

Accuracy:It measures the overall correctness of the model.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \ldots\ldots\ldots(5.7)$$

Overall Accuracy: 99.67%.

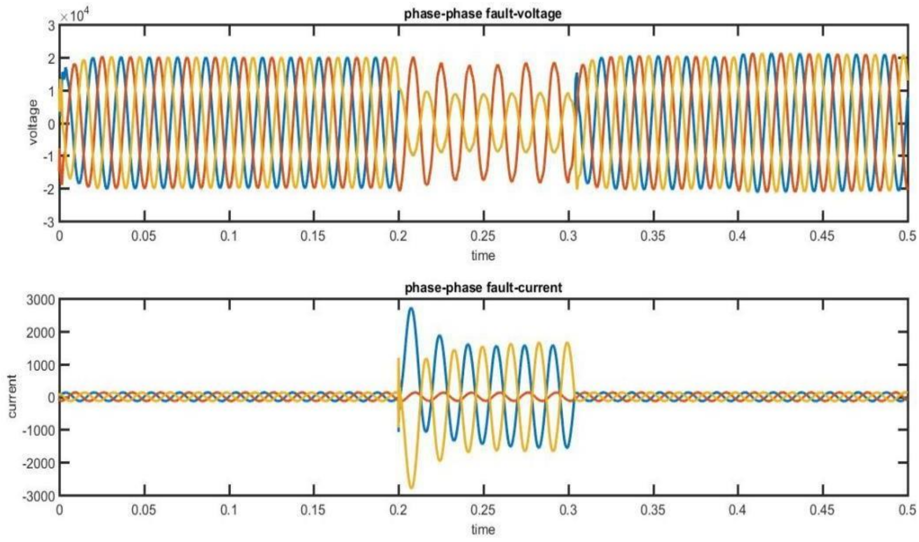


Fig. 5.9: Phase to phase fault signals

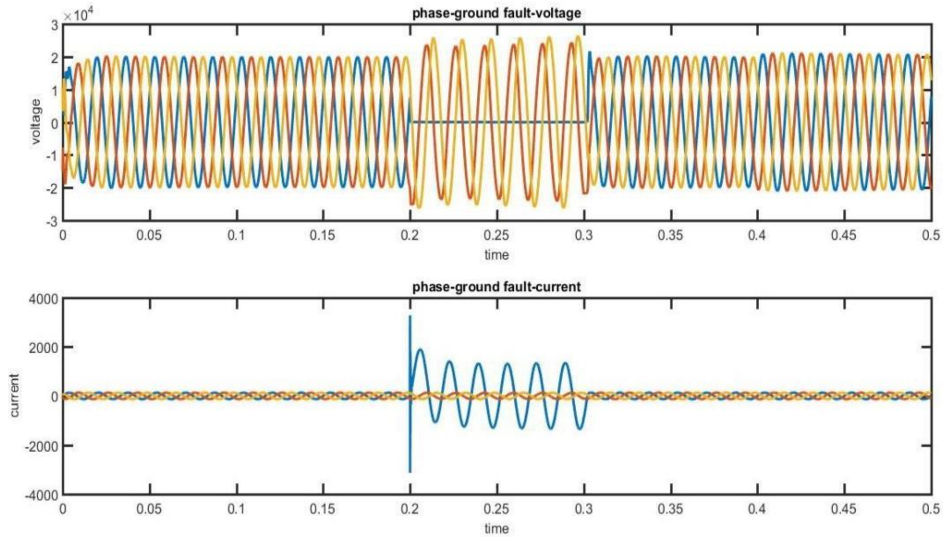


Fig. 5.10: Phase to ground fault signals

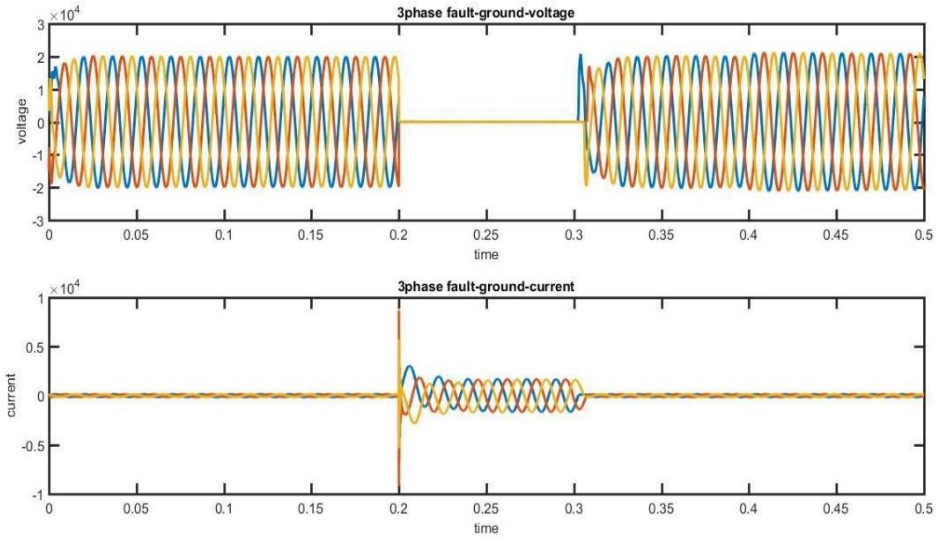


Fig. 5.11: 3-phase to ground fault signals

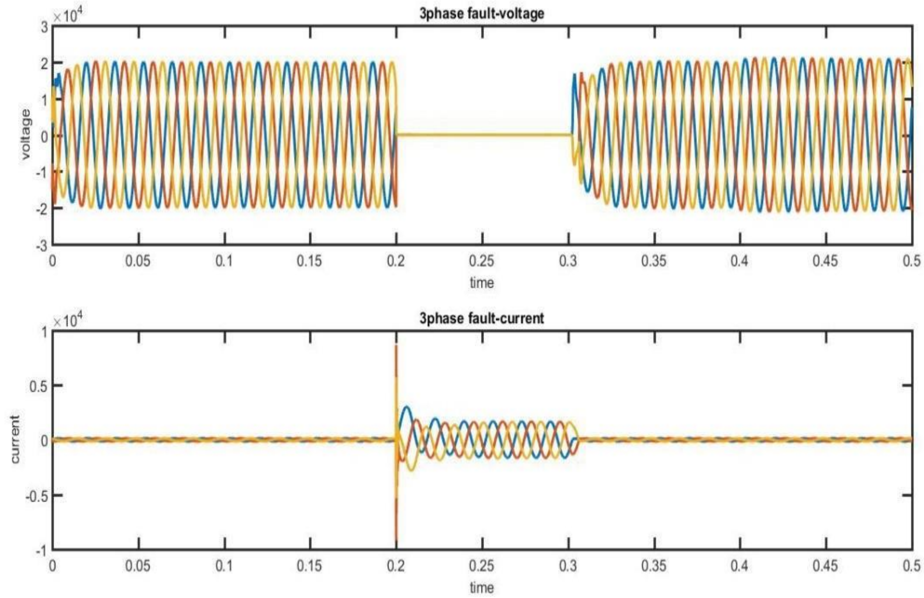


Fig. 5.12: Three-phase fault signal

To enhance reliability and accuracy, the proposed ICNN model is used. In this classification approach transfer learning method with fine tuning(utilizing BA BO optimization) and without fine tuning is proposed. The simulation is done at six different lengths of a transmission line. The different lengths are found by varying the per unit value of reactance in the lines. The accuracy is calculated with the true label results as shown in the Table 5.2.The number of iterations required for convergence is found as 15 to 23. Both training and testing hold 70% and 30% of the data respectively. The parameters accuracy ,precision ,F-measure ,recall etc are directly calculated from the confusion matrix using specific equations.

Table 5.2: The proposed WT with ICNN classification (With fine tuning)

Name of the measures	Length (km)					
	12.5	25	50	200	400	800
Precision (%)	97.58	97.53	96.43	95.32	93.07	89.58
Accuracy (%)	99.63	99.15	99.62	99.86	99.62	99.67
F-measure (%)	97.52	97.59	96.99	96.86	97.50	97.36
Recall (%)	97.26	97.86	98.45	95.32	92.68	82.64
Training time (s)	3428.14	2864.25	2794.18	3286.17	3294.75	3145.92

Fine tuning on 64 epochs are used to pretrain the layers with weights. The effect of tuning process in classification is clear from the improvement in the accuracy value.

Table 5.3: The proposed WT with ICNN classification (without fine-tuning)

Name of the measures	Length (km)					
	12.5	25	50	200	400	800
Precision (%)	74.03	74.94	71.97	72.46	72.91	62.38
Accuracy (%)	90.84	90.82	90.71	91.90	90.89	90.41
F-measure (%)	60.82	62.34	63.94	63.85	66.91	67.13
Recall (%)	60.42	61.93	63.48	66.13	63.09	59.37
Training time (s)	1103.56	1118.64	1108.15	1108.62	1182.03	1193.45

Though the tuning process takes more time, the overall error is greatly reduced. The two methods with the comparison of accuracy are depicted in Figure 5.13.

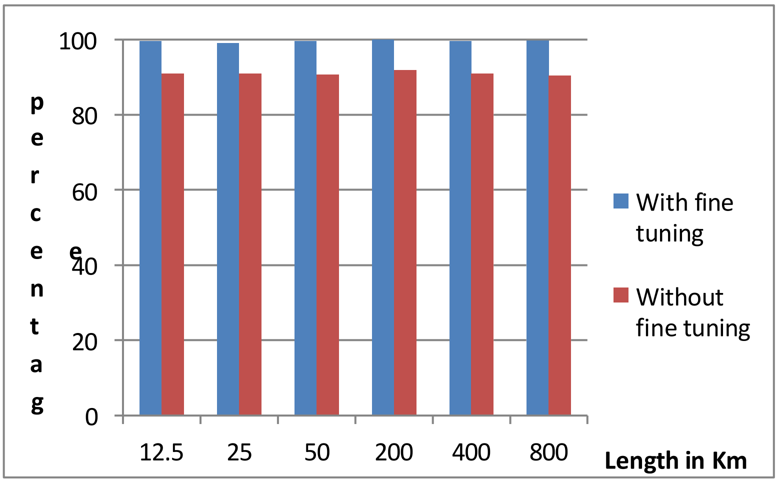


Fig. 5.13: The comparison of accuracy using the proposed ICNN (with and without tuning)

The MSE(mean square error) and the training time required using the proposed method are obtained for fault classification at different length of the bus. The value is found from the confusion matrix by assigning a penalty value to each errors in the cells. The values are indicated in Table 5.4.MSE is (sum of (actual-predicted)^2) / number of observations.

Table 5.4: The proposed WT with ICNN classification at 32-epochs

Name of the measures	Length (km)					
	12.5	25	50	200	400	800
MSE (m^2)	0.03×10^{-1}	0.72×10^{-1}	0.81×10^{-1}	8.72×10^{-2}	5.16×10^{-2}	5.94×10^{-2}
Training time (s)	2693.56	2863.48	2946.75	2831.64	2667.31	2557.82

MSE using the proposed method and that using a simple dedicated CNN is compared. The comparison is depicted in Figure 5.14.

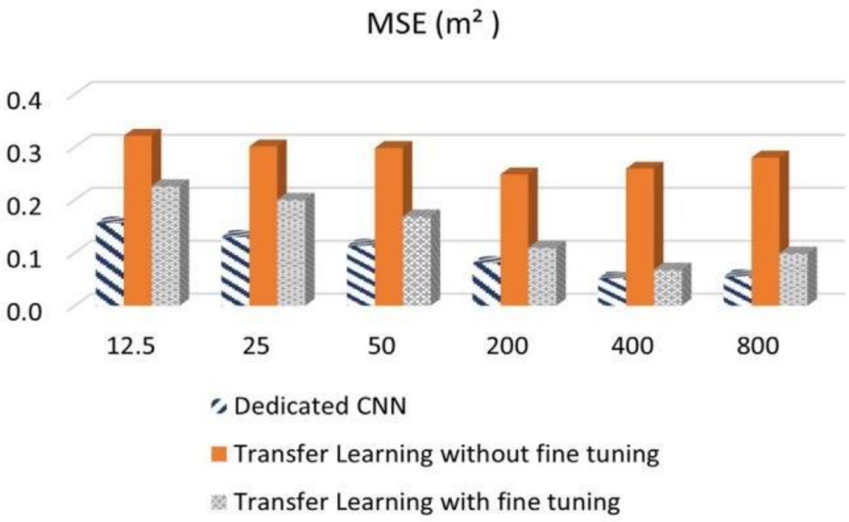
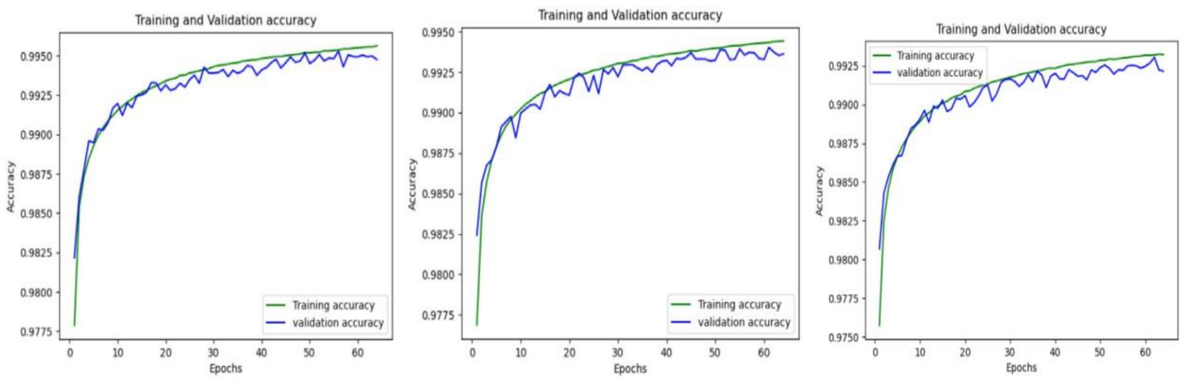
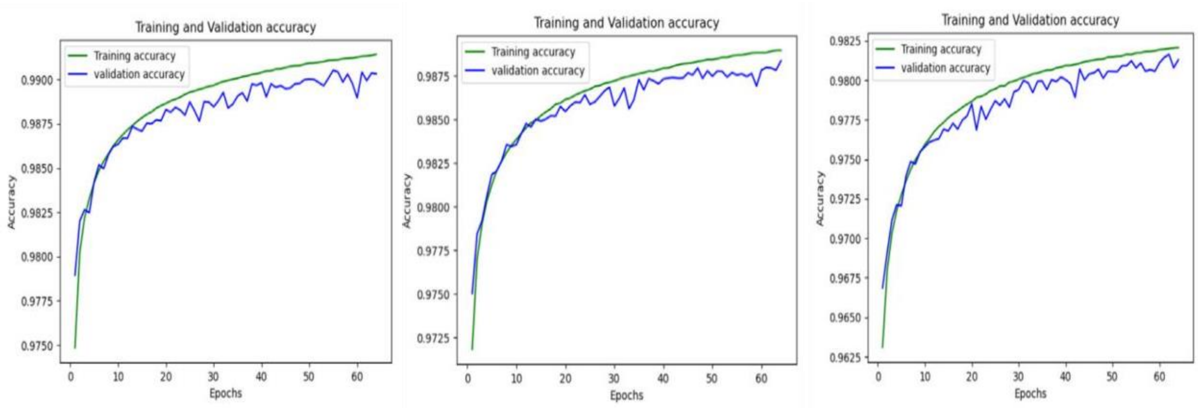


Fig. 5.14: The comparison of MSE results

The comparison shows the decrease in MSE when fine tuning is done. The training and validation accuracy variations for the two methodologies (with and without tuning) as applied to different transmission lengths are given in Figure 5.15. and Figure 5.16

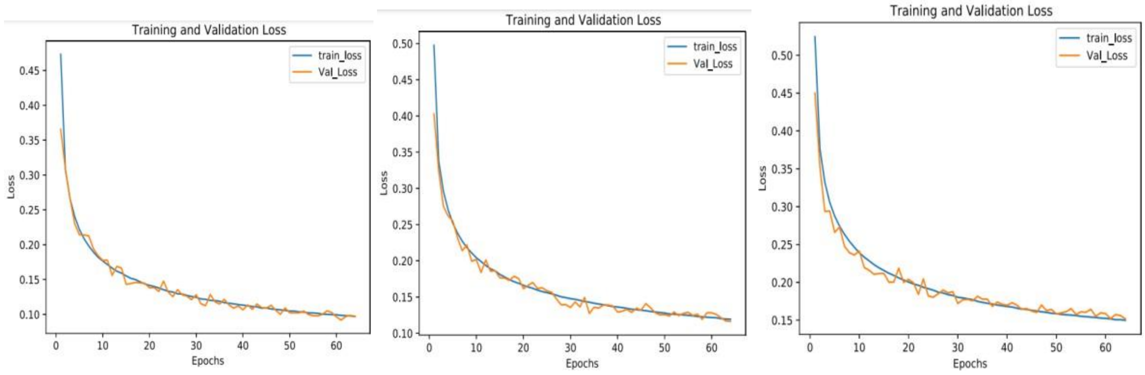


(i) (ii) (iii)

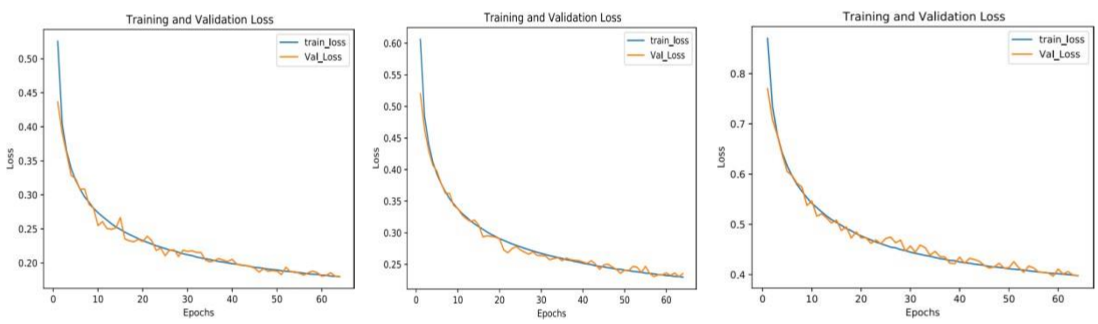


(iv) (v) (vi)

Fig. 5.15: The training and validation accuracies for fault classification at different transmission lengths(with fine-tuning) results (i) 12.5 km (ii) 25 km (iii) 50 km, (iv) 200 km, (v) 400 km and (vi) 800 km



(i) (ii) (iii)



(iv) (v) (vi)

Figure 5.16: The training and validation loss for fault classification at different transmission lengths(with fine-tuning) (i) 12.5 km (ii) 25 km (iii) 50 km, (iv) 200 km, (v) 400 km and (vi) 800 km

Table 5.6 shows the overall accuracy using the proposed method and other existing techniques. Higher and better overall accuracy is obtained using the proposed WT and ICNN models. From the proposed fault classification process the location of the fault can also be found out.

Table 5.5: Comparison of overall testing accuracy

Techniques	**Accuracy in percentage**
KELM [92]	98.61
SVM [91]	98.75
MKELM [90]	99.04
Proposed	**99.67**

The proposed method gave a higher accuracy of 0.63% when compared with MKELM. Also the accuracy was 1.06% higher than the KELM method and 0.92% higher than SVM method. This confirms the superiority of the proposed method over other existing techniques in terms of accuracy.

5.7 Summary

The method proposed in this chapter employs ICNN and WT models for fault detection and classification in an IEEE standard 30 bus network. In the bus the current signals and post- fault voltage cycles are retrieved and the significant features are extracted in the proposed model using WT. After normalization the extracted features are supplied as input to ICNN for enabling the classification process. The overall testing accuracy obtained is 99.67%. The proposed method is superior to existing classification methods in terms of testing accuracy. In the next chapter, higher and more accurate performance is attained by employing empirical wavelet transform and hybrid convolutional recurrent neural networks for the detection and classification of faults in a microgrid system with DGs connected to it.

CHAPTER- 6

An Empirical Wavelet Transform Based Fault Detection And Classification In Distributed Network Integrated Power System

6.1 Introduction

Protection of microgrids is very crucial in today's world and the distributed renewable energy sources tend to degrade the process. The security of microgrid depends on the ability to detect faults, types of defects and location of faults. A novel protection system based on artificial intelligence is adopted in this work. Microgrid system based on renewable energy is implemented to obtain the normal and faulty voltage and current data. The system is simulated using MatLab/Simulink platform. From the time series data, the features are decomposed using empirical wavelet transform (EWT). First, EWT evaluates the frequency components in the signal, then calculates the bounds and gets the basis of the oscillating components. The obtained samples are classified using a Hybrid Convolutional Recurrent Neural Network (HCRNN) and optimized by the Pelican Optimization Algorithm. Eleven types of faults are identified along with the location of faults using the proposed system. The results are compared with the existing methods and found that the proposed method has improved the fault sample detection accuracy by 1.56%.

Originally travelling waves were used for fault detection which suffered several discrimination issues. To cater to different network topologies and detect the location of faults, intelligent fault detection schemes are suited for microgrids. Most of these methods used some transformations to decompose signals and detected the fault. Self adaptive algorithms like Empirical Mode Decomposition(EMD)is used to handle noisy and non-stationary signals. This method has the disadvantage of mode mixing which affects the efficient operation. To overcome this, Empirical Wavelet Transform is proposed to handle noisy and nonstationary signals, especially in energy signal processing. CNN and RNN proved to have tremendous advantages in classification over the years. Overfitting is an important problem in these methods. So a hybrid of CNN and RNN is proposed here to solve the problem.

6.2 Proposed Methodology

IEEE 13 bus is used for distribution fault analysis and as a benchmark for validating new model and simulation tools before applying them to large feeders. This helps for analyzing unbalanced fault behaviour and validating protection co-ordination. A microgrid connected to IEEE 13 bus feeder is a common study case. A microgrid system is simulated and validated on the Matlab/Simulink platform. Solar PV and wind turbines are used to generate the required electricity to meet the load demand. Empirical Wavelet Transform is used to analyze the faults in the system by extracting relevant features.

The EWT examines the characteristics of both voltage and current waveforms. The feature extraction is done and are fed into the HCRNN classifier to determine different faults. Here, the bi-directional LSTM, a type of RNN, is considered, which is connected with CNN. The weights of HCRNN are optimized by the POA. The type of error and the location of error is determined. The basic outline of the proposed model is shown in Figure 6.1.

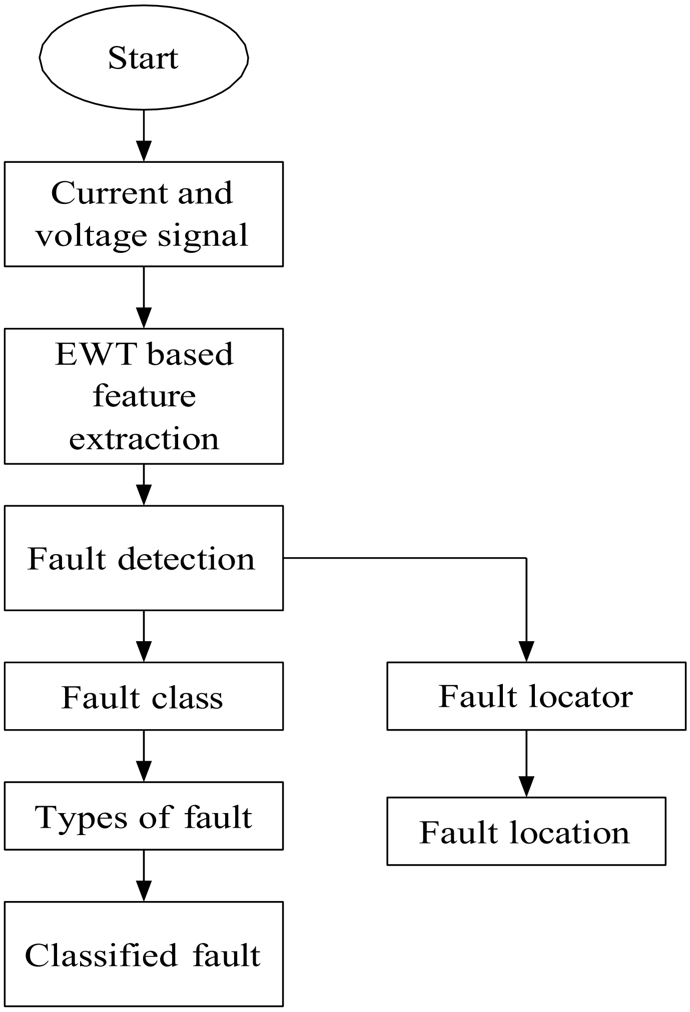


Fig. 6.1: Flowchart of the proposed methodology

6.2.1 EWT based feature extraction

In EWT, the measured electrical signals are split into different components by the Meyer wavelet-based EWT. Based on the decomposed signals, the proposed EWT extracts the features. The wavelet transform is often used to analyze the time and frequency of the signals [35]. A transition phase occurs between the adjacent filters in which the phase revolves around υ with a width of 2 τ_m. The empirical scaling function $\hat{\phi}_b(\upsilon)$ and empirical wavelets $\hat{\psi}_b(\upsilon)$ are given below.

A set of mutually orthogonal trigonometric functions and constants are designed in the transition stage.

$$\hat{\phi}_b(\upsilon)=\begin{cases}1; |\upsilon| \le (1-\alpha)\upsilon_m \\ \cos\left[\frac{\pi}{2}\chi\left(\frac{1}{2\alpha\upsilon_m}\left(|\upsilon|-(1-\alpha)\upsilon_m\right)\right)\right] \\ (1-\alpha)\upsilon_m \le |\upsilon| \le (1+\alpha)\upsilon_m \\ 0; others\end{cases} \quad 6.1$$

$$\hat{\psi}_b(\upsilon)=\begin{cases}1; (1+\alpha)\upsilon_m \le |\upsilon| \le (1-\alpha)\upsilon_{m+1} \\ \cos\left[\frac{\pi}{2}\chi\left(\left(|\upsilon|-(1-\alpha)\upsilon_{m+1}\right)/2\alpha\upsilon_{m+1}\right)\right]; \\ (1-\alpha)\upsilon_{m+1} \le |\upsilon| \le (1+\alpha)\upsilon_{m+1} \\ \sin\left[\frac{\pi}{2}\chi\left(\left(|\upsilon|-(1-\alpha)\upsilon_m\right)/2\alpha\upsilon_m\right)\right]; \\ (1-\alpha)\upsilon_m \le |\upsilon| \le (1+\alpha)\upsilon_m \\ 0; others\end{cases} \quad 6.2$$

Here, $\chi(x)$ denotes transition function, α is the coefficient, C is a transition, υ set as boundaries, m denotes useful mode number, $m = 1, 2, 3.....M$.

$$\alpha < \min\left(\frac{\upsilon_{m+1} - \upsilon_m}{\upsilon_{m+1} + \upsilon_m}\right) \quad 6.3$$

$$\tau_m = \alpha\upsilon_m, 0 < \alpha, 1 \quad 6.4$$

If Fourier transform is $F(.)$ and $F^{-1}(.)$ denote inverse Fourier transform. W_s^D is

given as

$$\int f(\tau)\overline{(\psi_b(\tau - l)d\tau)} = F^{-1}\left(\hat{f}(\upsilon)\hat{\psi}_b(\upsilon)\right) \quad 6.5$$

Approximation coefficients $W_s^D(0,l)$ can be calculated as,

$$\int f(\tau)\overline{(\eta_1(\tau - l)d\tau)} = F^{-1}\left(\hat{f}(\upsilon)\hat{\eta}_1(\upsilon)\right) \quad 6.6$$

$\hat{f}(\upsilon), \hat{\eta}_1(\upsilon), \hat{\psi}_b(\upsilon)$ are Fourier transforms of $f(l), \eta_1(l)$ and $\psi_b(l)$. The signal can be reconstructed as

$$f(l) = W_s^D(0,l) * \eta_1(l) + \sum_{m=1}^{M} W_s^D(m,l) * \psi_b(l) \quad 6.7$$

$$f(l) = F^{-1}\left(\hat{W}_s^D(0,\upsilon)\hat{\eta}_1(\upsilon) + \sum_{m=1}^{M} \hat{W}_s^D(m,\upsilon)\hat{\psi}_m(\upsilon)\right) \quad 6.8$$

where, $\hat{W}_s^D(0,\upsilon)$ and $\hat{W}_s^D(m,\upsilon)$ are the Fourier transforms of $W_s^D(0,l)$ and $W_s^D(m,l)$ [36]. Empirical mode results are

$$f_C(l) = W_s^D(C,l) * \psi_C(l) \quad 6.9$$

Once the empirical modes of a signal are obtained, the EWT extracts features from the measured signal.

6.2.2 HCRNN based fault classification

The extracted features obtained from EWT are further classified with the proposed HCRNN. The features are fed into the training and testing phases to identify the type of fault. The proposed HCRNN, which is comprised of the bidirectional LSTM (bi-LSTM) and CNN architectures, brings out benefits of both LSTM and CNN. Combining the bi-LSTM and CNN will improve the training and testing accuracy.

The RNN is a deep learning approach to process time series or sequential data. The Bi-LSTM performs better and processes the input in both forward and reverse directions. It contains an LSTM layer, input, a fully connected and a softmax layer. Bi-LSTM considers both past and future information to accurately predict the result. The additional weights should be distributed to get the new input vector, which is given to a layer of Bi-LSTM for result prediction, which is again fed into the softmax and transformation layer to get the result. The mathematical characteristics of the LSTM are given below:

$$\mathbf{Y} = \begin{bmatrix} y_x \\ h_{x-1} \end{bmatrix} \qquad 6.10$$

where, y_x denotes input at time x and h_x signifies hidden state. The mathematical characteristics of the input gate are given as

$$i_x = \Sigma\left(\mathbf{W}_f . \mathbf{Y} + s_f\right) \qquad 6.11$$

Here, Σ represents the activation function. $\mathbf{W_f}, \mathbf{W_i}, \mathbf{W_p}, \mathbf{W_q}$ denote the LSTM weight matrix and s_f, s_i, s_p, s_q indicate bias offset values. The forget gate representation is given below.

$$f_x = \Sigma\left(\mathbf{W}_i . \mathbf{Y} + s_i\right) \qquad 6.12$$

The output gate representation is given as,

$$z_x = \Sigma\left(\mathbf{W}_p . \mathbf{Y} + s_p\right) \qquad 6.13$$

The cell state representation is given as

$$c_x = f_x \otimes c_{x-1} + i_x \otimes \tanh(\mathbf{W}_q . \mathbf{Y} + s_q) \qquad 6.14$$

where, $\otimes$ denotes multiplication operation, and tanh is another activation function. The hidden state representation is given as

$$h_x = z_x \otimes \tanh\left(c_x\right) \qquad 6.15$$

The forward LSTM gets the past details, and the backward LSTM gets future details [37]. The architecture of bi-LSTM is shown in Figure 6.2. The Bi-LSTM hidden state also performs in the forward and backward direction, which is expressed as follows

$$h_x = \xrightarrow[LSTM]{}\left(h_{x-1}, y_x, c_{x-1}\right), x \in \left[1, X\right] \qquad 6.16$$

$$h_x = \overleftarrow{LSTM}(h_{x+1}, y_x, c_{x+1}), x \in [X, 1] \quad 6.17$$

$$H_x = [h_x, h_x] \quad 6.18$$

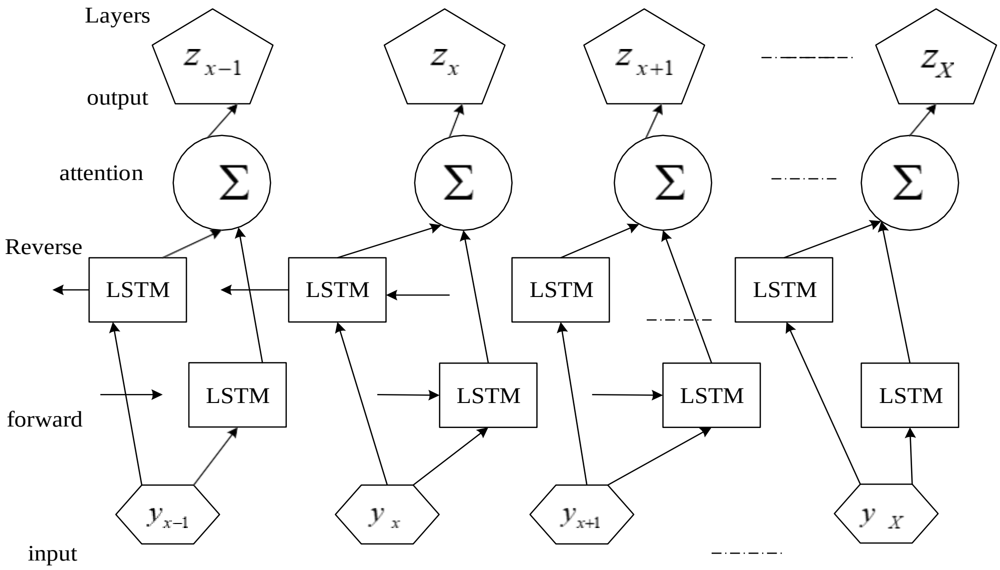


Fig. 6.2: Architecture of Bi-LSTM

The data from current and voltage signals are given to the CNN without pre-processing [38]. It can reduce the excessive dimensionality of images without affecting information using its built-in convolutional layer. HCRNN is used to capture the characteristics of both local and sequenced data. The input gets into the convolutional layers, followed by pooling layers performing spatial pooling. The output is then fed into a flattened layer, which converts those results into a single-dimensional feature array. The mathematical representation of the HCRNN is given as follows

$$Z(C_{out}) = \sum_{i=0}^{C_{in}-1} \mathbf{W}(C_{out}, i) * \mathbf{Y}(i) \quad 6.19$$

where, **Y** represents input, **Z** represents output, **W** indicates parameter matrix and C represents some features [39]. The architecture of CNN-LSTM is shown in Figure 6.3.

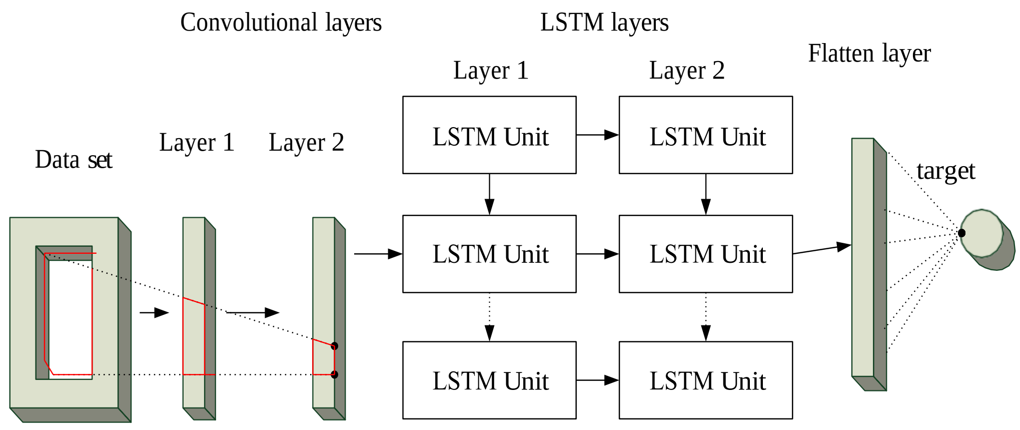


Fig. 6.3 Architecture of CNN-LSTM

6.2.3 POA optimised HCRNN for classification

In the POA optimised HCRNN classification, POA is used for optimizing the weights of HCRNN. In POA, pelicans are the search agents who always love to live and work together [40]. In the proposed method, the pelicans are considered as weight and bias of the HCRNN, whereas the pelican's best position is considered as optimum weight. The POA works on the principle of population based algorithm. Each member in POA provides an optimization result based on its position. At first, population members are randomized based on an upper and lower bound, which is given below.

$$y_{u,v} = k_v + rand\left(r_v - k_v\right), u = 1,2,..., N, v = 1,2,...,m, \qquad 6.20$$

where, $y_{u,v}$ represents v_{th} variable value, N denotes population members, m represents problem variables, *rand* signifies a random number, k_v is v_{th} lower bound and r_v is v_{th} upper bound. The members in the optimization algorithm are considered as the weights of the layers, which is shown as

$$\mathbf{Y} = \begin{bmatrix} Y_1 \\ : \\ Y_u \\ : \\ Y_N \end{bmatrix}_{N\times m} = \begin{bmatrix} y_{1,1} & .. & y_{1,v} & .. & y_{1,m} \\ : & & : & & : \\ y_{u,1} & .. & y_{u,v} & .. & y_{u,m} \\ : & & : & & : \\ y_{N,1} & .. & y_{N,v} & .. & y_{N,m} \end{bmatrix}_{N\times m} \quad 6.21$$

Here, **Y** represents the pelican population matrix, y_u indicates u_{th} pelican. Based on the candidate solution, the objective function can be calculated as given in the following equation,

$$\mathbf{G} = \begin{bmatrix} G_1 \\ : \\ G_u \\ : \\ G_N \end{bmatrix} = \begin{bmatrix} G(Y_{1)}) \\ : \\ G(Y_u) \\ : \\ G(Y_N) \end{bmatrix}_{N\times 1} \quad 6.22$$

where, **G** denotes the objective function vector G_u indicates the value of the objective function. The hunting strategy is simulated in two phases: exploration and exploitation. The pelicans identify where the prey is moving and then move to that identified area in the exploration stage. Optimum weight and bias values are obtained

by this algorithm.

$$y_{u,v}^{q_1} = \begin{cases} y_{u,v} + rand.(q_v - S.y_{u,v}), G_q < G_u; \\ y_{u,v} + rand.(y_{u,v} - q_v), else, \end{cases} \quad 6.23$$

Here, $y_{u,v}^{q_1}$ indicates the new position of the i_{th} pelican, S indicates a random

number, q_v represents the location of prey and G_q denotes objective function value. $\mathbf{Y_u}$ is given by

$$\mathbf{Y}_u = \begin{cases} Y_u^{q_1}, G_u^{q_1} < G_u; \\ Y_{u,} else, \end{cases} \quad 6.24$$

where, $Y_u^{q_1}$ represents i_{th} Pelican's new position and $G_u^{q_1}$ its objective function. The exploitation behaviour of the pelican algorithm is shown in the following equation,

$$y_{u,v}^{q_2} = y_{u,v} + J.\left(1 - \frac{x}{X}\right).(2.rand - 1).y_{u,v}, \quad 6.25$$

Here, based on the phase of exploitation, the new position is $y_{u,v}^{q_2}$, J denotes constant, neighbourhood radius is mentioned as $J.\left(1 - \frac{x}{X}\right)$, X indicates maximum iterations, and x means iteration count. Efficient updates have been used in this phase to approve or disapprove the new pelican status given as follows.

$$Y_u = \begin{cases} Y_u^{q_2}, G_u^{q_2} < G_u; \\ Y_{u,} else, \end{cases} \quad 6.26$$

where, $Y_u^{q_2}$ denotes new position and $G_u^{q_2}$ its objective function. The new position for a pelican is accepted if the value of the objective function is improved in that position. The tendency to move to non-optimal areas is avoided by such effective updation. The pseudo- code of POA is given in Table 6.1. The Flow chart of POA is given in Figure 6.4.

Table 6.1: POA Pseudo-code

Start POA.
1. Input information of the optimization problem.
2. Find the population members (N) and iterations (*X*).
3. Generate the initial position, and the objective function is calculated.
4. For x=1:*X*
6. Generate weight at random
6. For k=1:N
7. Phase of exploration.
8. For v=1:*m*
9. Examine weights using equation 6.23.
10. End.

Renew the member of i^{th} population by equation 6.24.
Phase of exploitation.
For v=1:*m*
Calculate the new position by equation 6.25
End.
Renew the member of i^{th} population by equation 6.26
End.
Update the best weight
End.
Output the optimal solution provided by POA

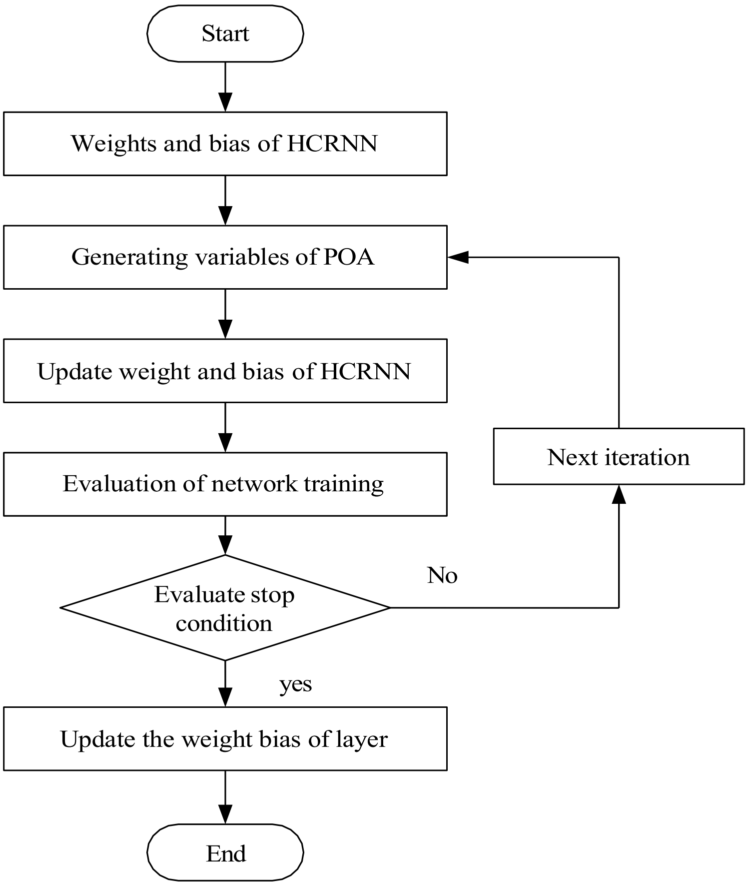


Fig. 6.4: HCRNN with POA approach for fault classification

The objective function is to maximize accuracy and minimize errors. Optimal parameters are found for the machine learning model to achieve the highest accuracy. The weights and bias for the modified CNN is optimized. Here POA aims to find out the parameters that yield the best objective function value namely highest accuracy.

Root mean square error(RMSE) is employed as a performance metric to evaluate the prediction error in fault estimation. The difference between the predicted values and actual values are measured providing insight into the accuracy of the model's predictions.

$$\Re M \delta E = \sqrt{\frac{\sum_{j=1}^{N} \left(P_j - A_j\right)^2}{N}}$$

N represents the total number of available training data. For the jth cycle, Pj denotes the target output. Aj refers to the actual value.

The MAE(Mean Absolute Error) is computed and expressed as

$$MAE = \frac{1}{m} \sum_{j=1}^{m} \left| P_j - A_j \right|$$

6.3 RESULTS AND DISCUSSION

The proposed method is validated using Matlab/Simulink platform by utilizing a sample microgrid system. The selection of PV and wind turbines as DG units in a microgrid is justified by their prevalence in contemporary hybrid renewable energy systems. This represents a realistic and challenging environment to be analyzed. The protection of microgrid can be improved when the intermittency and variability of the DGs often compromise the traditional fault detection methods. The system schematic is shown in Figure 6.5 and the system specification is given in Table 6.2

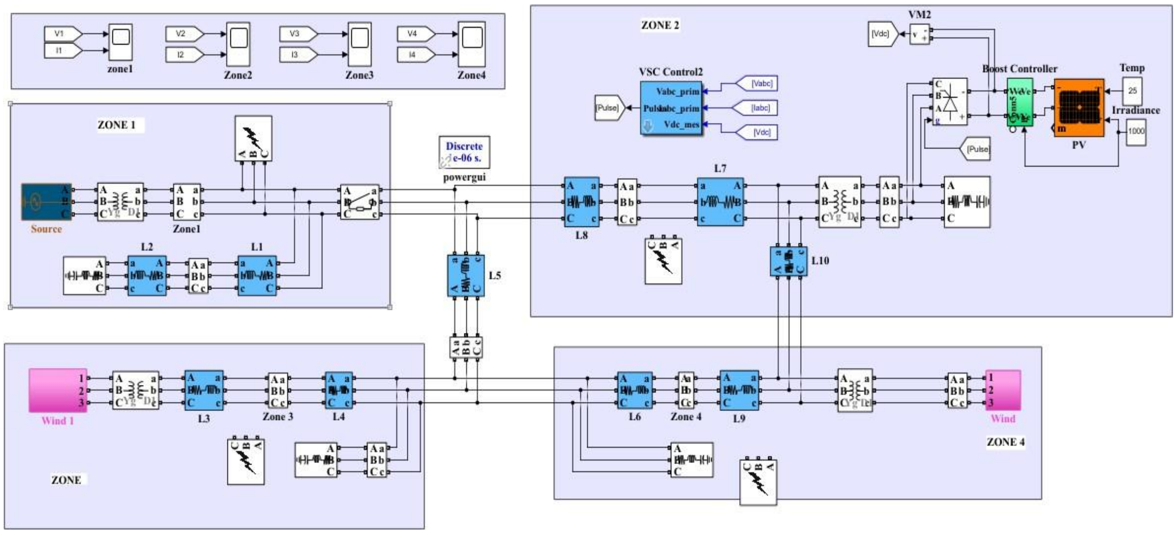


Fig 6.5: Schematic representation of the system.

Here, the microgrid system is divided into four zones. For validation 44000 data samples are created. The grid is connected in zone-1, and solar is added under zone-2. Moreover, the separate wind turbines are connected in zone-3 and zone-4.The system configuration for simulation is given in Table 6.3.

Table 6.2: System Specifications

Parameters	**Values**
Power output from PV	100KW
Cells per module	60
Open circuit voltage	36.6V
Short circuit current	7.97A
Nominal mechanical power of wind turbine	30KW
Speed of PMSG	3000rpm

Table 6.3: System configuration for simulation

PARAMETER	CONFIGURATION	COUNTS
MODES	Grid connected mode, islanded mode	2
ZONES	Grid, Solar-1, wind-1, wind-2	4
TYPES OF FAULTS	ABCG, ABC, AB, BC, AC, ABG, BCG, ACG, AG, BG, CG	11
FAULT RESISTANCE	0.001 to 1	-
TOTAL NUMBER OF SAMPLES	-	44000

The numerical indication of different faults is shown in Table 6.4.

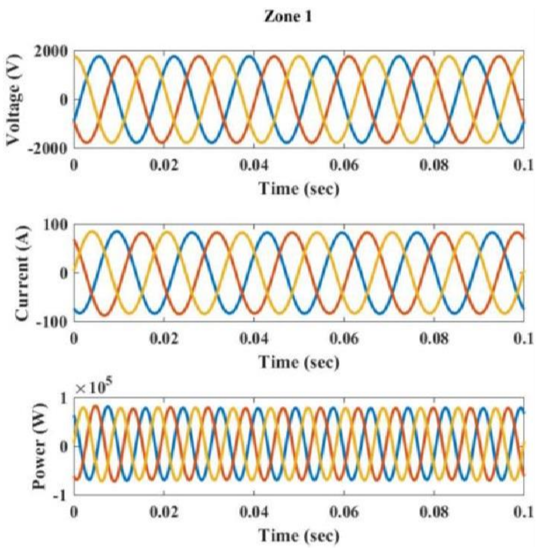
Table 6.4: Types of faults

Types of faults	Fault numbers
ABCG	1
ABC	2
ABG	3
AB	4
ACG	5
AC	6
AG	7
BCG	8
BC	9
BG	10
CG	11

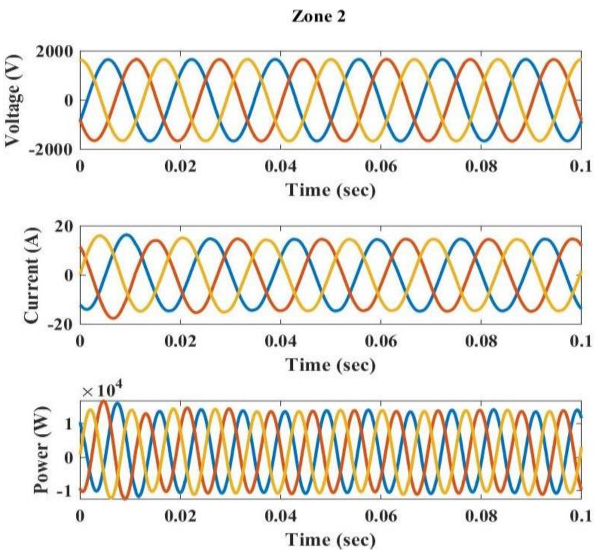
The separation of zones in the power system improves the detection accuracy of faults. The analysis of voltage and current signals is done in all zones, and the features are extracted using EWT. The different types of faults are initiated separately in the lines interconnecting the zones. Here, 1000 data samples are generated for 4 zones with 11 error types. The total sample count is derived by systematically simulating the system under various fault conditions: 11 different fault types (e.g., AG, ABCG) are applied across four distinct zones (Grid, Solar-1, Wind-1, Wind-2). Measurements of voltage and current waveforms are recorded for a 1-second duration during these normal and faulty conditions, and features are then extracted from this data using Empirical Wavelet Transform (EWT). Once the complete dataset of 44,000 samples is established, it is split for model development. Specifically, 70% of the total dataset, amounting to 35,200 samples, is allocated for training the Pelican Optimized Hybrid Convolutional Recurrent Neural Network (POA-HCRNN). This large training set ensures that the deep learning model can robustly learn the complex, non-symmetrical patterns associated with all fault types across all operational zones, minimizing error and enhancing the model's overall generalization capability. While training, the output values are not assigned, and the validation errors are monitored throughout the process. Data validation errors are increased when overfitting occurs in the given data. In this state, the training process stops to avoid overfitting the data, which could minimize the errors during training. After the data training, the data test is performed; this step can examine the classifier. The proposed method examines the zones where the error occurs and the types of error.

The voltage and current waveforms measured from four zones in the power system are shown in Figure 6.6. The figure shows three phase voltage, current and power waveforms for all zones. The power generated from zone-1, zone-2, zone-3 and zone-4 are 100kW, 10kW, 20kW and 10kW respectively. The measurement of all waveforms is for 1 second.

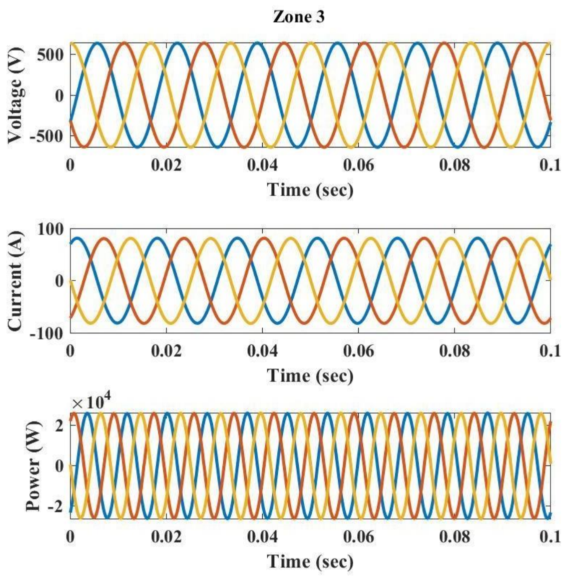
.



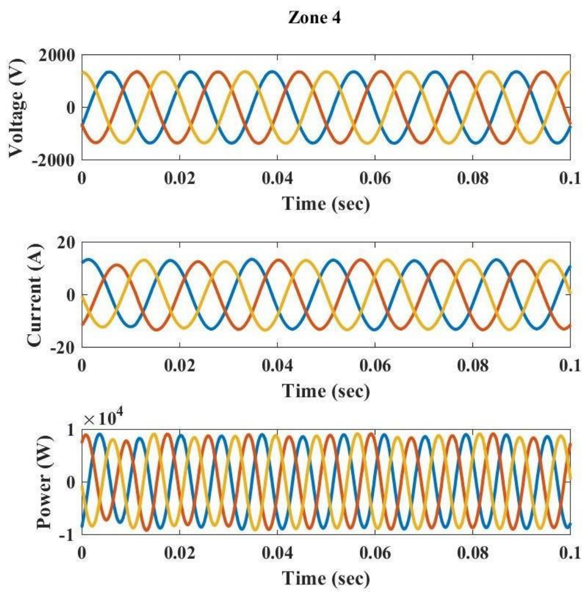
(a)



(b)



(c)

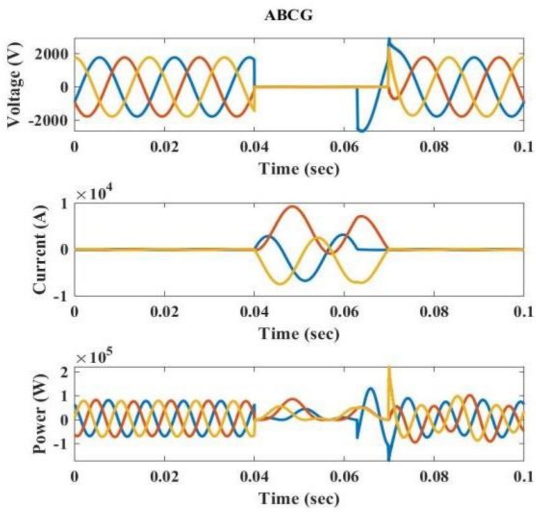


(d)

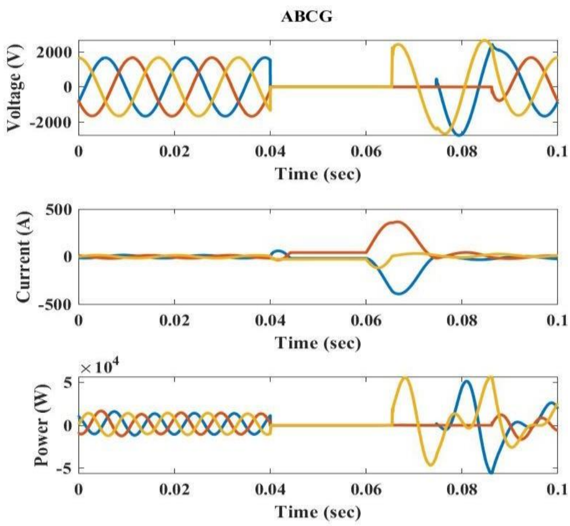
Fig. 6.6: System validated when no fault has occurred (a) zone-1, (b) zone-2, (c) zone-3, and (d) zone-4

The fault signal measured from all zones using the proposed method under ABCG fault is shown in Figure 6.7. Here, the voltage, current and power waveforms are given for all zones. The fault is applied between 0.04s to 0.06s, so the voltage becomes zero in all the zones. The voltage and current waveforms are distorted due to the impact of the fault in all phases. Consequently, all zones' power values are reduced during the fault condition

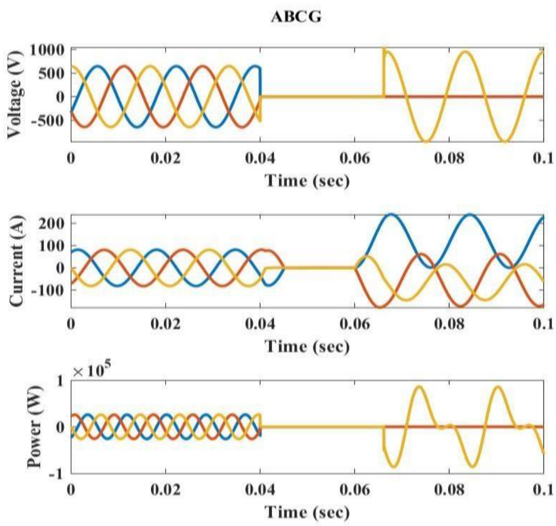
.



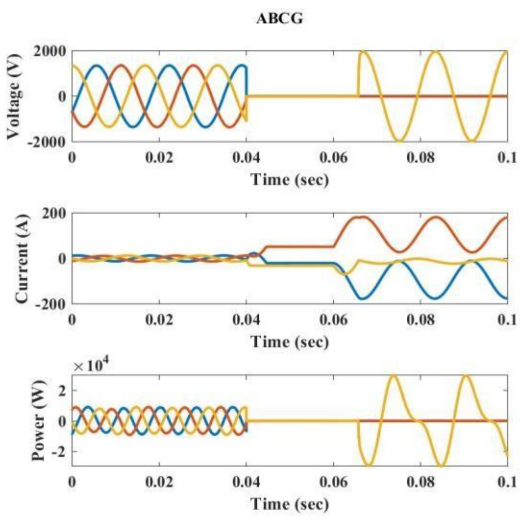
(a)



(b)



(c)



(d)

Fig. 6.7: Performance analysis under ABCG fault (a) zone-1, (b) zone-2, (c) zone-3 and (d) zone-4

The numerical values of the measured voltage, current and power at phase-1 under normal operating conditions and ABCG fault are shown in Tables 6.5 and 6.6, respectively.

Table 6.5: Analysis under normal operating conditions

Without fault						
Zone-1				**Zone-2**		
Time (s)	**Voltage (V)**	**Current (A)**	**Power (W)**	**Voltage (V)**	**Current (A)**	**Power (W)**
0.00	-886.77	68.73	-60874.64	-831.72	11.52	-9582.59
0.01	1618.05	-30.45	-49267.32	1500.13	-6.52	-8277.49
0.02	-1734.09	-23.66	41034.69	-1626.81	-6.32	8656.95
0.03	1187.53	66.22	78633.05	1126.17	12.55	14119.52
0.04	-187.07	-82.89	15506.86	-191.96	-14.52	2787.83
0.05	-884.89	69.11	-61153.27	-817.36	11.80	-9642.66
0.06	1619.36	-27.99	-45332.71	1520.96	-3.88	-5899.65
0.07	-1734.04	-22.42	38877.47	-1626.13	-4.59	7459.31
0.08	1187.45	66.71	78028.30	1123.99	12.24	13758.30
0.09	-186.90	-83.27	15563.24	-189.91	-14.76	2803.95
0.10	-884.81	69.31	-61323.72	-816.25	11.93	-9736.18
Zone-3				**Zone-4**		
0	-312.3272	-71.14146	22219.41	-667.8105	-11.53789	7706.1213
0.01	580.20138	34.152215	19816.16	1216.944	4.786563	5820.1921
0.02	-630.789	16.40956	-9720.18	-1326.441	1.8818299	-2496.136
0.03	440.201	-59.31318	-26109.7	929.8719	-8.99606	-8366.184
0.04	-79.24955	80.890303	-6410.52	-167.294	13.118139	-2194.586
0.05	-310.9654	-71.13979	22122.01	-653.7808	-11.44678	7483.6849
0.06	584.87418	34.564822	20216.07	1237.154	6.9851261	7404.5223
0.07	-630.4687	16.651997	-9868.09	-1324.664	2.6312142	-3486.474
0.08	439.85309	-59.44429	-26146.8	928.0404	-9.321382	-8650.619
0.09	-78.42343	80.782094	-6336.21	-163.5888	12.865983	-2104.73
0.1	-310.5431	-71.12023	22086.89	-651.7586	-11.36008	7404.0329

Table 6.6: Performance analysis under ABCG fault

ABCG fault						
Zone-1				**Zone-2**		
Time (s)	**Voltage (V)**	**Current (A)**	**Power (W)**	**Voltage (V)**	**Current (A)**	**Power (W)**
0	-886.768	68.7243463	-60873.8	-831.7111	11.52072	-9581.91
0.01	1618.0467	-30.447045	-49264.7	1500.1255	-6.51664	-8276.65
0.02	-1734.088	-23.665261	41037.64	-1626.816	-6.325398	8658.117
0.03	1187.5345	66.2165726	78634.47	1126.1797	12.54968	14120.65
0.04	-187.0681	-82.889292	15506.95	-191.9677	-14.52334	2788.012
0.05	8.562703	8483.08983	72638.18	0.0644557	43.06829	2.775995
0.06	2.1022001	2022.95462	4252.655	0.0646239	43.04014	2.781423
0.07	0.0065961	-36.968045	-0.24384	0.0400205	222.7979	8.916477
0.08	1189.8747	48.4792199	57684.2	0.5657055	42.71908	24.16642
0.09	-187.258	-101.02078	18916.95	-53.50219	-19.2232	1028.483
0.1	-884.7344	51.784719	-45816.7	-816.1773	7.255119	-5921.46
Zone-3				**Zone-4**		
0	-312.3243	-71.141351	22219.17	-667.7997	-11.53836	7706.313
0.01	580.2	34.1520055	19814.99	1216.9388	4.787413	5821.201
0.02	-630.7896	16.4097852	-9720.33	-1326.443	1.880896	-2494.9
0.03	440.20336	-59.313338	-26109.9	929.8806	-8.995404	-8364.65
0.04	-79.25278	80.8903301	-6410.78	-167.3061	13.11802	-2194.72
0.05	0.0803793	-0.0280619	-0.00226	0.0615752	51.49816	3.171011
0.06	0.0799134	-0.064434	-0.00515	0.0617755	51.39312	3.174837
0.07	0.0999916	-49.776645	-4.97725	-0.002004	132.8539	-0.2663
0.08	0.2132654	-128.46142	-27.3964	0.2552546	124.1744	31.69609
0.09	0.0357838	58.0102513	2.075826	-0.011972	44.50195	-0.53278
0.1	0.2092613	-163.66463	-34.2487	0.1704089	180.3796	30.73828

The mathematical equations for the performance parameters are listed below.

$$Accuracy = \frac{PT}{PT + NT} \tag{6.27}$$

$$Precision = \frac{PT}{PT + PF} \tag{6.28}$$

$$F1-score = \frac{2PT}{2PT + PF + NF} \tag{6.29}$$

$$Sensitivity = \frac{PT}{NT + PF} \tag{6.30}$$

where, PT is positive true, PF is positive false, NT is negative true, NF is negative false. The POA is used along with the HCRNN to enhance network accuracy. The optimum selection of these parameters greatly affects the classification accuracy. The detection accuracy of the proposed HCRNN before and after applying the POA is shown in Figure 6.8. The performance measures before and after applying the POA are depicted in Table 6.7.

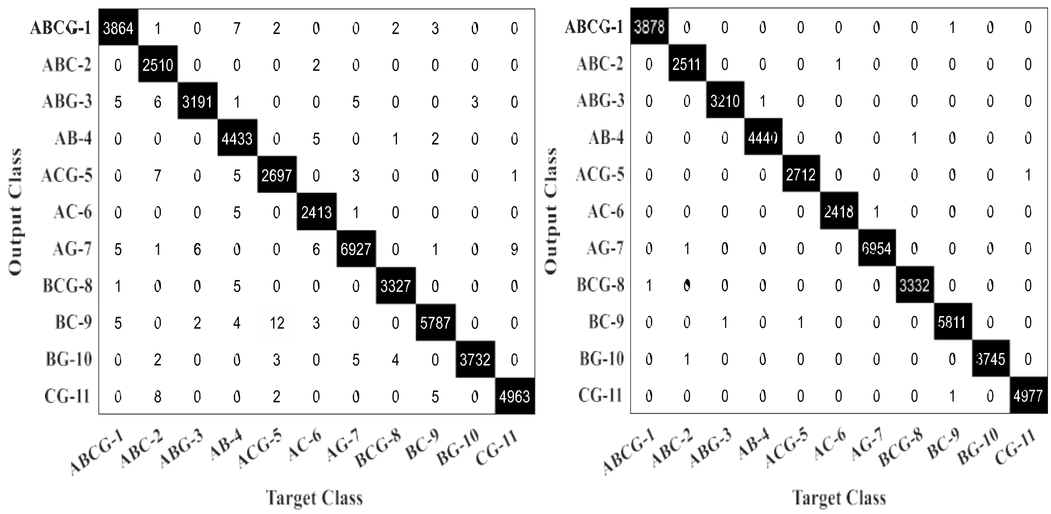


Fig. 6.8: Confusion matrix (a) Before optimization and (b) After optimization

Table 6.7: Performance analysis in terms of parameters under different conditions

Performance measures	Before optimization	After optimization
Overall accuracy	0.9965	0.9997
Mean precision	0.9909	0.9947
Mean Recall	0.9965	0.9997
Mean F1 Score	0.9937	0.9997
Mean Specificity	0.9916	0.992

The performance measures of the proposed method and a comparison with existing method based on CNN are shown in Table 6.8

Table 6.8: Performance measures of the proposed method

Performance measures	CNN [93]	HCRNN before optimization	Proposed method (POA-HCRNN)
Accuracy	0.9988	0.9965	0.9997
Precision	0.9988	0.9909	0.9947
Sensitivity	0.9988	0.9965	0.9997
F1-score	0.9988	0.9937	0.9997
Specificity	0.9995	0.9916	0.9920

The proposed method is compared with existing methods in terms of accuracy and shown in Table 6.9.From the comparative analysis, it is evident that the proposed method has improved the accuracy by 8.76% in comparison with LSTM method [94], 0.97% with ANN [100], 1.56% with SVM[103], 2.61% with decision tree [101], and 0.4% with self-attention based CNN [97]. The detection time of the method used is 10.34ms which is less than that of lagrangian particle swarm optimized support vector machine. This is shown in Figure 6.9. Harmonic noise and other errors are a common phenomenon in microgrids but is not accounted for the simulations done in this work.

. **Table 6.9:** Evaluation with state-of-art-techniques

Author	**Accuracy**
Rai et al. [93]	99.88%
Veerasamy et al. [94]	91.21%
Mahela et al. [95]	98.96%
Liang et al. [96]	96.8%
Fahim et al. [97]	99.58%
Roy et al. [98]	96.78%
Baloch et al. [99	99.29%
Kabeel et al. [100]	99%
Cao et al. [101]	97.36%
Prasad et al. [102]	98.9%
Ahmadipour et al. [103]	98.41%
Hong et al. [104]	96.8%
Tong et al. [l05]	98.28%
Rajesh et al. [106]	98.31%
Proposed	**99.97%**

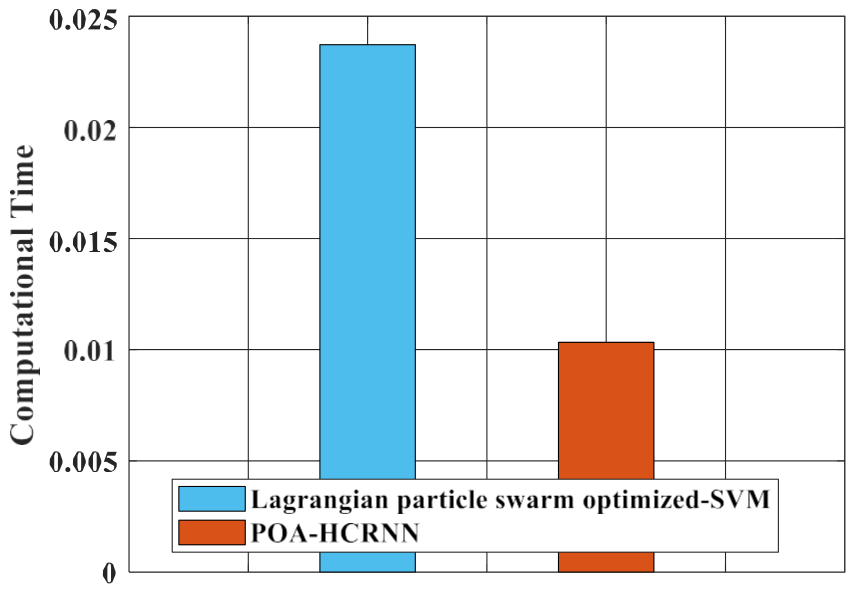


Fig. 6.9: Comparison of detection time with PSO

6.4 Summary

In this paper a technique is presented for fault detection and error classification in hybrid MG including photovoltaic cells, and wind turbines. EWT is used for feature extraction and HCRNN for error classification. To improve classification accuracy, POA is used together with HCRNN. The validation of the proposed model on the solar-wind hybrid power plant is done in MatLab/Simulink. In addition, the entire power supply system is divided into four zones to facilitate the detection process. In the proposed method 11 different types of faults are simulated separately on all zones, and the results are analyzed. In addition, the results of the proposed POA-HCRNN are compared with the existing approaches in terms of accuracy. The comparative analysis shows that the proposed POA-HCRNN improves the detection accuracy by 1.56%.The ability of POA to effectively solve design problems in real world applications further justifies the reduced computational complexity of the system. Using the proposed method not only the type of fault but also the location of fault can be identified. From the verification, it is confirmed that the proposed POA-HCRNN improves the classification accuracy in zone fault detection.

By applying efficient feature extraction methods and classification methods the problem of fault detection, classification and location identification has been done with high precision and efficiency.

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

This thesis aims to propose a reliable and accurate protection system for renewable energy based microgrid system. The presence of renewable energy sources, islanding of microgrids, bidirectional flow of active and reactive power have made the fault detection problem very complex. In this thesis different feature extraction methods(DWT,EMD and EWT)are considered. Eleven types of short circuit faults are simulated on IEEE 30 bus system and classification is done using CNN and hybrid BEES Bayesian optimization. The same was carried out on different lengths of the bus and the overall accuracy was found to be 99.67%. The accuracy of EMD over DWT in feature extraction is also analysed. EWT which has the advantages of both DWT and EMD in extracting the features of different fault scenarios is investigated.

Further analysis is done on renewable energy based microgrid system implemented in IEEE bus power network to obtain normal and faulty voltage and current data. EWT is used to extract features from the nonstationary nonlinear fault signals

The decomposed signals are fed to Pelican optimized Hybrid Convolutional Recurrent Neural Network(HCRNN) to classify various faults in the islanding mode of operation. The location of fault is also identified in this process. For proper validation the entire power system is divided into four zones and fault detection and classification are done. The ability of POA to solve problems in real world applications justifies the reduced computational complexity of the system which was found to be appreciably less compared to widely used PSO. Overall detection accuracy is increased by 1.56%.

As faults are often accompanied by arcing, the impact of the non-linear fault resistance on the performance of the model can be studied as future work. Furthermore, the method can be extended to detect and classify 'evolving faults' i.e. faults that begin in one phase and spread to other phases subsequently. In this thesis, we assumed only a single fault on the system at any given time, however, further research can be done to study the impact of multiple faults in different parts of the microgrid using the proposed methods. Noisy systems and microgrid working in different network topologies can be examined to improve the method further.

REFERENCES

[1] Godse, R. and Bhat, S., “Mathematical morphology-based feature-extraction technique for detection and classification of faults on power transmission line”. *IEEE Access*, 8, pp.38459-38471,2020.

[2] Lazzaretti, A.E., Costa, C.H.D., Rodrigues, M.P., Yamada, G.D., Lexinoski, G., Moritz, G.L., Oroski, E., Goes, R.E.D., Linhares, R.R., Stadzisz, P.C. and Omori, J.S., “A monitoring system for online fault detection and classification in photovoltaic plants”. *Sensors*, 20(17), p.4688,2020.

[3] Davari, N., Akbarizadeh, G. and Mashhour, E. “Intelligent diagnosis of incipient fault in power distribution lines based on corona detection in UV-visible videos”. *IEEE Transactions on Power Delivery*, 36(6), pp.3640-3648,2020

[4] Usama, Y., Lu, X., Imam, H., Sen, C. and Kar, N.C. “Design and implementation of a wavelet analysis-based shunt fault detection and identification module for transmission lines application”. *IET Generation, Transmission & Distribution* 8(3), pp.431-441., 2014

[5] Swetapadma, A. and Yadav, A. “Improved fault location algorithm for multi-location faults, transforming faults and shunt faults in thyristor controlled series capacitor compensated transmission line”. *IET Generation, Transmission & Distribution*, 9(13), pp.1597-1607, 2015.

[6] Huang, C., Zhang, B., Ma, Y., Zhou, F. and He, J. “Analysis of short-circuit current characteristics and its distribution of artificial grounding faults on DC transmission lines”. *IEEE Transactions on Power Delivery*, 33(1), pp.520-528,2017.

[7] Hofmann, L. “Unified fault matrix method for the calculation of shunt and series faults in power systems with complete duality of shunt and series fault matrices”. *Electric Power Systems Research*, 189, p.106556. , 2020

[8] Baloch, S. and Muhammad, M.S “An intelligent data mining-based fault detection and classification strategy for microgrid”. *IEEE Access*, 9, pp.22470-22479, 2021.

[9] Wan, Q., Zheng, S. and Shi, C.”A rapid diagnosis technology of short circuit fault in DC microgrid”. *International Journal of Electrical Power & Energy Systems*, 147, p.108878, 2023.

[10] Khushi, F., Motakabber, S.M.A., Bhattacharjee, A., Alam, A.Z., Azman, A.W. and Hussain, F.”A smart microgrid approach for distributed network combined with power line fault location detection”. *IEEE International Conference on Automatic Control & Intelligent Systems (I2CACIS)* (pp. 7-12). IEEE,June 2021.

[11] Roy, S. and Debnath, S. “A wavelet based PSD approach for fault detection and classification in grid connected inverter interfaced microgrid”. *Measurement*, p.114079, 2023

[12] Yadav, N. and Tummuru, N.R,”Filter Capacitor Current Dynamics-Based Frequency Domain Fault Detection Approach for Grid-Connected Low-Voltage DC Microgrid”. IEEE Transactions on Industrial Electronics, 2023.

[13] Swetapadma, A. and Yadav, A,” Fuzzy inference system approach for locating series, shunt, and simultaneous series-shunt faults in double circuit transmission lines”. *Computational intelligence and neuroscience*, pp.79-79, 2023.

[14] Bhatnagar, M. and Yadav, “A Fault detection and classification in transmission line using fuzzy inference system. In 2020 5th IEEE International Conference on Recent Advances and Innovations in Engineering” *(ICRAIE)* (pp. 1-6). IEEE, December 2020.

[15] Tabari, M. and Sadeh, J “Fault location in series-compensated transmission lines using adaptive network-based fuzzy inference system”. *Electric Power Systems Research*, 208, p.107800, 2022.

[16] Naresh Kumar, A., Sanjay, C. and Chakravarthy, M,”Fuzzy inference system- based solution to locate the cross-country faults in parallel transmission line”. *The International Journal of Electrical Engineering & Education*, 58(1), pp.83-96, 2021.

[17] Yadav, A., Ashok, V. and Pazoki, M,”Protection scheme for hybrid transmission system using fuzzy inference system and microcontroller”. *Evolutionary Intelligence*, pp.1-15, 2022.

[18] Eboule, P.S.P. and Hasan, A.N,”Accurate fault detection and location in power transmission line using concurrent neuro fuzzy technique”. *PrzeglądElektrotechniczny*, 97(1), pp.37-45, 2021.

[19] Bhatnagar, M., Yadav, A. and Swetapadma, A,” Fuzzy based relaying scheme for high impedance faults in DG integrated distribution system”. *Electric Power Systems Research*, 202, p.107602, 2021.

[20] Abbas, M. and Zhang, D,”A smart fault detection approach for PV modules using Adaptive Neuro-Fuzzy Inference framework”. *Energy Reports*, 7, pp.2962-2975, 2021.

[21] Hubana, T., Šarić, M. and Avdaković, S,”New approach for fault identification and classification in microgrids”. *In Advanced Technologies, Systems, and Applications IV-Proceedings of the International Symposium on Innovative and Interdisciplinary Applications of Advanced Technologies (IAT 2019)* (pp. 27-39). Springer International Publishing, 2020.

[22] Veerasamy, V., Abdul Wahab, N.I., Vinayagam, A., Othman, M.L., Ramachandran, R., Inbamani, A. and Hizam, H,”A novel discrete wavelet transform-based graphical

language classifier for identification of high-impedance fault in distribution power system". *International Transactions on Electrical Energy Systems*, 30(6), p.e12378. ., 2020.

[23] Akhil Vinayak, B., Anjali Anand, K. and Jagadanand, G,"Wavelet-based real-time stator fault detection of inverter-fed induction motor". *IET Electric Power Applications*, 14(1), pp.82-90, 2020.

[24] Grcić, I., Pandžić, H. and Novosel, D,"Fault detection in dc microgrids using short-time fourier transform". *Energies*, 14(2), p.277, 2021.

[25] Azuara Grande, L.S., Granizo, R. and Arnaltes, S,"Wavelet Analysis to Detect Ground Faults in Electrical Power Systems with Full Penetration of Converter Interface Generation". *Electronics*, 12(5), p.1085, 2023.

[26] Lucas, G.B., De Castro, B.A., Ardila-Rey, J.A., Glowacz, A., Leão, J.V.F. and Andreoli, A.L."A Novel Approach Applied to Transient Short-Circuit Diagnosis in TIMs by Piezoelectric Sensors, PCA,and Wavelet Transform". *IEEE Sensors Journal*. 2023

[27] Harish, A., Asok, P. and Vasudevan, J.M. "Evaluation of Wavelet Transform Based Feature Extraction Techniques for Detection and Classification of Faults on Transmission Lines Using WAMS Data". *Advances in Electrical and Electronic Engineering*, 20(4), pp.405-417, 2023

[28] Mohamed, Y.N., Seker, S. and Akinci, T.C. "Signal Processing Application Based on a Hybrid Wavelet Transform to Fault Detection and Identification in Power System". *Information*, 14(10), p.540, 2023

[29] Banerjee, S. and Bhowmik, P.S. "A machine learning approach based on decision tree algorithm for classification of transient events in microgrid". *Electrical Engineering*, pp.1-11,2023

[30] Achlerkar, P.D., Samantaray, S.R. and Manikandan, M.S. “Variational mode decomposition and decision tree based detection and classification of power quality disturbances in grid-connected distributed generation system”. *IEEE Transactions on Smart Grid*, 9(4), pp.3122-3132, 2016

[31] Gao, Wei, and Rong-Jong Wai. "Series arc fault detection of grid-connected PV system via SVD denoising and IEWT-TWSVM." *IEEE Journal of Photovoltaics* 11, no. 6 (2021): 1493-1510.

[32] Shao, Z., Wakil, K., Usak, M., Heidari, M.A., Wang, B. and Simoes, R. Kriging “Empirical Mode Decomposition via support vector machine learning technique for autonomous operation diagnosing of CHP in microgrid”. *Applied Thermal Engineering*, 145, pp.58-70, 2018

[33] Chakravorti, T., Priyadarshini, L., Dash, P.K. and Sahu, B.N, “Islanding and non-islanding disturbance detection in microgrid using optimized modes decomposition based robust random vector functional link network”. *Engineering Applications of Artificial Intelligence*, 85, pp.122-136, 2019.

[34] Sarangi, S., Sahu, B.K. and Rout, P.K,”High-impedance fault identification and location by using mode decomposition integrated adaptive multi-kernel extreme learning machine technique for distributed generator-based microgrid”. *Electrical Engineering*, 105(1), pp.383-406,2023.

[35] Samanta, I.S., Rout, P.K., Swain, K., Cherukuri, M. and Mishra, S.” Power quality events recognition using enhanced empirical mode decomposition and optimized extreme learning machine”. *Computers and Electrical Engineering*, 100, p.107926, 2022

[36] Nsaif, Y.M., Lipu, M.H., Hussain, A., Ayob, A. and Yusof, Y. “Island detection for grid connected photovoltaic distributed generations via integrated signal processing and

machine learning approach”. *International Journal of Electrical Power & Energy Systems*, 154, p.109468. ., 2023

[37] Li, Y., Lu, Q., Pang, M., Chen, Y., Guo, J., Wang, Z. and Su, M,.” DC Series Arc Fault Detection Method Based on Local Mean Decomposition and Support Vector Machine”. *In 2021 IEEE 1st International Power Electronics and Application Symposium (PEAS)* (pp. 1-7). IEEE, November 2021

[38] Sarangi, S., Sahu, B.K. and Rout, P. “KAn optimized machine learning-based time-frequency transform for protection of distribution generation integrated microgrid system”. *In Green technology for smart City and society: proceedings of GTSCS* 2020 (pp. 385-399). Springer Singapore, 2021.

[39] Long, H., Ma, M., Guo, W., Li, F. and Zhang, X. “Fault diagnosis for IGBTs open-circuit faults in photovoltaic grid-connected inverters based on statistical analysis and machine learning”. *In 2020 IEEE 1st China International Youth Conference on Electrical Engineering* (CIYCEE) (pp. 1-6). IEEE, November2020,

[40] Roy, G., Ghosh, S. and Roy, A. “A Novel Approach to Microgrid Fault Detection Using Empirical Mode Decomposition”. *In Applications of Networks, Sensors and Autonomous Systems Analytics: Proceedings of ICANSAA* 2020 (pp. 103-111). Springer Singapore, 2022

[41] Choudhury, A.R., Nayak, P., Mallick, R.K., Agrawal, R., Mishra, S. and Panda, G. “Islanding detection and power quality disturbance classification in multi DG based microgrid using down sampling empirical mode decomposition and multilayer neural network”. *International Journal of Emerging Electric Power Systems*, 2023

[42] Koley, E., Yadav, A. and Thoke, A.S.”A new single-ended artificial neural network-based protection scheme for shunt faults in six-phase transmission line”. *International Transactions on Electrical Energy Systems, 25*(7), pp.1257-1280, 2015.

[43] DEVI, A.D., ALSAIF, F. and ALSULAMY, S., “Deep Learning Based Relay for Online Fault Detection, Classification, and Fault Location in a Grid-Connected Microgrid”, 2023.

[44] Assadi, K., Slimane, J.B., Chalandi, H. and Salhi, S.”Shunt faults detection and classification in electrical power transmission line systems based on artificial neural networks”. *COMPEL-The international journal for computation and mathematics in electrical and electronic engineering*,2023.

[45] Zhang, C., Peng, T. and Nazir, M.S. “A novel integrated photovoltaic power forecasting model based on variational mode decomposition and CNN-BiGRU considering meteorological variables”. *Electric Power Systems Research*, 213, p.108796. ., 2022

[46] Chen, X., Gao, W., Hong, C. and Tu, Y.”A novel series arc fault detection method for photovoltaic system based on multi-input neural network”. *International Journal of Electrical Power & Energy Systems*, 140, p.108018, 2022.

[47] Anjaiah, K., Dash, P.K. and Sahani, M.”Detection of faults and DG islanding in PV-Wind DC ring bus microgrid by using optimized VMD based improved broad learning system”. *ISA transactions*, 131, pp.533-551, 2022.

[48] Han, Y., Feng, Y., Yang, P., Xu, L. and Zalhaf, A.S.”An efficient algorithm for atomic decomposition of power quality disturbance signals using convolutional neural network”. *Electric Power Systems Research*, 206, p.107790, 2022.

[49] Eristi, B. and Eristi, H, “Classification of Power Quality Disturbances in Solar PV Integrated Power System Based on a Hybrid Deep Learning Approach”. *International Transactions on Electrical Energy Systems*, 2022.

[50] Wang, Z. and Xu, L.”Fault detection of the power system based on the chaotic neural network and wavelet transform”. *Complexity,* 2020, pp.1-15, 2020.

[51] Xiong, J., Qian, W., Cen, J., Li, J., Liu, J. and Tang, L”A fault diagnosis method for building electrical systems based on the combination of variational modal decomposition and new mutual dimensionless”. *Scientific Reports,* 13(1), p.4567, 2023.

[52] Wang, L., Mao, M., Xie, J., Liao, Z., Zhang, H. and Li, H .”Accurate solar PV power prediction interval method based on frequency-domain decomposition and LSTM model”. *Energy,* 262, p.125592. ., 2023.

[53] Pan, S., Morris, T. and Adhikari, U.”Classification of disturbances and cyber- attacks in power systems using heterogeneous time-synchronized data”. *IEEE Transactions on Industrial Informatics*, 11(3), pp.650-662, 2015.

[54] Pandey, S., Srivastava, A.K. and Amidan, B.G.”A real time event detection, classification and localization using synchrophasor data”. *IEEE Transactions on Power Systems*, 35(6), pp.4421-4431, 2020.

[55] Shrivastava, D.R., Siddiqui, S.A. and Verma, K.”A new synchronized data-driven-based comprehensive approach to enhance real-time situational awareness of power system”. *International Transactions on Electrical Energy Systems,* 31(5), p.e12887, 2021.

[56] Swain, K., Anand, A., Samanta, I.S. and Cherukuri, M .”Machine Learning-Based Approaches for Transmission Line Fault Detection Using Synchrophasor Measurements in a Smart Grid*”. In Smart Grid 3.0: Computational and Communication Technologies* (pp. 77-92). Cham: Springer International Publishing, 2023.

[57] Izadi, M. and Mohsenian-Rad, H.”A synchronized lissajous-based method to detect and classify events in synchro-waveform measurements in power distribution networks”. *IEEE Transactions on Smart Grid*, 13(3), pp.2170-2184, 2022.

[58] Kummerow, A., Monsalve, C., Brosinsky, C., Nicolai, S. and Westermann, D.” A novel framework for synchrophasor based online recognition and efficient post-mortem analysis of disturbances in power systems”. *Applied Sciences*, 10(15), p.5209. ., 2020

[59] Shi, J., Yu, N., Keogh, E., Chen, H.K. and Yamashita, K.” Discovering and labeling power system events in synchrophasor data with matrix profile”. *In 2019 IEEE Sustainable Power and Energy Conference (iSPEC)* (pp. 1827-1832). IEEE, November 2019.

[60] Mukherjee, A., Kundu, P.K. and Das, A. “A Correlation-Based Classification of Power System Faults in a Long Transmission Line. In Emerging Technologies in Data Mining and Information Security”. *Proceedings of IEMIS 2020, Volume 2* (pp. 113-121). Springer Singapore, 2021.

[61] Roy, S., Babu, N.P., Babu, P.S. and Reddy, N.N. “Correlation Factor- based Fault-Phase Detection for Series Compensated Transmission Line”. *In 2020 IEEE Applied Signal Processing Conference (ASPCON)* (pp. 344-348). IEEE, October 2020.

[62] An, N., Shu, H., Yang, B., Cao, P., Song, J. and Guo, Y.”Voltage Correlation Based Single Pole-to-Ground Fault Detection of MMC-HVDC Transmission Line”. *IEEE Access*, 9, pp.118124-118133. ., 2020.

[63] Gonzalez-Sanchez, V. H., V. Torres-García, and D. Guillen. "Fault location on transmission lines based on travelling waves using correlation and MODWT." *Electric Power Systems Research* 197 (2021): 107308.

[64] Jia, K., Yang, Z., Zheng, L., Zhu, Z. and Bi, T. “Spearman correlation-based pilot protection for transmission line connected to PMSGs and DFIGs”. *IEEE Transactions on Industrial Informatics,* 17(7), pp.4532-4544, 2020.

[65] Chatterjee, B. and Debnath, S. “Cross-correlation based single-phase fault location scheme for transmission lines using one-end voltage”, 2021.

[66] Reis, R.L.A., Lopes, F.V., Neves, W.L.A., Fernandes Jr, D., Ribeiro, C.M.S. and Cunha, G.A. “An improved single-ended correlation-based fault location technique using traveling waves”. *International Journal of Electrical Power & Energy Systems*, 132, p.107167, 2021.

[67] Ahmed Taleb, C.M., Ben Hadj Slama, J., Nasri, O. and Ndongo, M. “Cross- correlation based fault electromagnetic signature extraction for open-circuit fault diagnosis in NPC inverters”. *Electrical Engineering*, 105(3), pp.1911-1921, 2023.

[68] Ma, T., Hu, Z., Xu, Y. and Dong, H.”Fault location based on comprehensive grey correlation degree analysis for flexible DC distribution network”. *Energies*, 15(20), p.7820, 2022.

[69] Yoo, Y.”Data-driven fault detection process using correlation based clustering”. *Computers in Industry*, 122, p.103279, 2020.

[70] Yi, X.J., Xu, C.H., Liu, S.L., Xing, M.X. and Mu, H.N.”Failure analysis of repairable systems with k-out-of-m configuration considering with common cause failure and maintenance correlation based on goal oriented method”. *Engineering Failure Analysis*, 140, p.106615, 2022.

[71] Sinha, P., Paul, K., Chatterjee, S., García Márquez, F.P., Ogale, J., Ali, A. and Khan, B “Cross-country high impedance fault diagnosis scheme for unbalanced distribution network employing detrended cross-correlation”. *IET Generation, Transmission & Distribution*, 2023.

[72] NdjakomoEssiane, S., Gnetchejo, P.J., Ele, P. and Chen, Z.”Faults detection and identification in PV array using kernel principal components analysis”. *International Journal of Energy and Environmental Engineering*, 13(1), pp.153-178. ., 2022.

[73] Arabaci, H. and Mohamed, M.A.”A knowledge-based diagnosis algorithm for broken rotor bar fault classification using FFT, principal component analysis and support vector machines”. *International Journal of Intelligent Engineering Informatics*, 8(1), pp.19-37, 2020.

[74] Wang, T., Xu, H., Han, J., Elbouchikhi, E. and Benbouzid, M.E.H. "Cascaded H- bridge multilevel inverter system fault diagnosis using a PCA and multiclass relevance vector machine approach". *IEEE Transactions on Power Electronics*, 30(12), pp.7006-7018, 2015.

[75] Elsamanty, M., Ibrahim, A. and Salman, W.S."Principal component analysis approach for detecting faults in rotary machines based on vibrational and electrical fused data". *Mechanical Systems and Signal Processing*, 200, p.110559, 2023.

[76] Huang, J. and Gao, Y. "Converter fault diagnosis method based on principal component analysis combined with improved similarity classifier". *In 2019 Chinese Automation Congress (CAC)* (pp. 5051-5054). *IEEE*, November,2019.

[77] Xiao, Y., Zou, C., Chi, H. and Fang, R. "Boosted GRU model for short-term forecasting of wind power with feature-weighted principal component analysis". *Energy*, 267, p.126503, 2023.

[78] Kouadri, A., Hajji, M., Harkat, M.F., Abodayeh, K., Mansouri, M., Nounou, H. and Nounou, M."Hidden Markov model based principal component analysis for intelligent fault diagnosis of wind energy converter systems". *Renewable Energy*, 150, pp.598-606. ., 2020.

[79] Adar, M., Najih, Y., Gouskir, M., Chebak, A., Mabrouki, M. and Bennouna, A. "Three PV plants performance analysis using the principal component analysis method". *Energy*, 207, p.118315, 2020.

[80] Yang, L., Zhang, K., Chen, Z. and Liang, Y.": Fault diagnosis of WOA-SVM high voltage circuit breaker based on PCA Principal Component Analysis". *Energy Reports*, 9, pp.628-634, 2023.

[81] Zaben, M., Worku, M. Y., Hassan, M. A., & Abido, M. A. "Machine Learning Methods for Fault Diagnosis in AC Microgrids". *A Systematic Review. IEEE Access*.(2024).

[82] Rahman Fahim, S., K. Sarker, S., Muyeen, S. M., Sheikh, M. R. I., & Das, S. K. “Microgrid fault detection and classification: Machine learning based approach, comparison, and reviews”. *Energies*, 13(13), 3460,2020.

[83] Ma, D., Liang, Y., Zhao, X., Guan, R., & Shi, X.” Multi-BP expert system for fault diagnosis of power system”. *Engineering Applications of Artificial Intelligence*, 26(3), 937-944,2013.

[84] Caprioglio, P., Smith, J. A., Oliver, R. D., Dasgupta, A., Choudhary, S., Farrar, M. D., & Snaith, H. J. “Open-circuit and short-circuit loss management in wide- gap perovskite pin solar cells”. *Nature communications*, 14(1), 932,2023.

[85] Rajabi, S., Azari, M. S., Santini, S., & Flammini, F. “:Fault diagnosis in industrial rotating equipment based on permutation entropy, signal processing and multi-output neuro- fuzzy classifier”. *Expert systems with applications*, 206, 117754,2022.

[86] Pan, P., Mandal, R. K., & Rahman Redoy Akanda, M. M.”Fault classification with convolutional neural networks for microgrid systems”. *International Transactions on Electrical Energy Systems*, 2022(1), 8431450,2022.

[87] Bao, C., Zhang, T., Hu, Z., Feng, W., & Liu, R. “Wind turbine condition monitoring based on improved active learning strategy and KNN algorithm”. *IEEE Access*, 11, 13545-13553,2023.

[88] Zhang, H., Guo, X., & Zhang, P. “Improved PSO-SVM-Based Fault Diagnosis Algorithm for Wind Power Converter”. *IEEE Transactions on Industry Applications*,2023.

[89] Eldeghady, G. S., Kamal, H. A., & Hassan, M. A. M.” Fault diagnosis for PV system using a deep learning optimized via PSO heuristic combination technique”. *Electrical Engineering*, 105(4), 2287-2301,2023.

[90]Teke Gush, Syed Basit Ali Bukhari, Khalid Khawaja, Samuel Admasie, Ji Soo Kim & Chul-Hwan Kim, "Intelligent Fault Classification and Location Identification Method for Micro grids Using Discrete Orthonormal Stockwell Transform-Based Optimized Multi-Kernel Extreme Learning Machine," *Energies*, 2019.

[91]Malathi Veluchamy & N.S. Marimuthu, "Support vector machine for fault detection in transmission line," *International Journal of Engineering Intelligent Systems for Electrical Engineering and Communications*, PP 13-18, 2007.

[92]Omer Ertugrul, Mehmet Tagluk, & Yilmaz Kaya, "Fault detection at power transmission lines by extreme learning machine," *21st Signal Processing and Communications Applications Conference*, PP 1-4, 2013.

[93]Rai P, Londhe ND, Raj R (2021) "Fault classification in power system distribution network integrated with distributed generators using CNN". *Electric Power Systems Research* 192: 106914.

[94]Veerasamy V, Wahab NI, Othman ML, Padmanaban S, Sekar K, Ramachandran R, Hizam H, Vinayagam A, Islam MZ (2021) LSTM recurrent neural network classifier for high impedance fault detection in solar PV integrated power system. IEEE Access 9: 32672-32687.

[95] Mahela OP, Khan B, Alhelou HH, Siano P (2020) "Power quality assessment and event detection in distribution network with wind energy penetration using stockwell transform and fuzzy clustering". *IEEE Transactions on Industrial Informatics* 16(11): 6922-6932.

[96] Liang J, Jing T, Niu H, Wang J (2020) "Two-terminal fault location method of distribution network based on adaptive convolution neural network". *IEEE Access* 8: 54035-54043.

[97] Fahim SR, Sarker Y, Sarker SK, Sheikh MR, Das SK (2020) "Self attention convolutional neural network with time series imaging based feature extraction for transmission line fault detection and classification". *Electric Power Systems Research* 187: 106437.

[98] Roy S, Debnath S (2021) "PSD based high impedance fault detection and classification in

distribution system.” *Measurement 169*: 108366.

[99] Baloch, Shazia, and Mannan Saeed Muhammad. “An intelligent data mining-based fault detection and classification strategy for microgrid.” *IEEE Access* 9 (2021): 22470-22479.

[100] Kabeel, Mohamed A., Mai M. Eladany, and Azza A. ElDesouky. “A Centralized Protection Scheme for Microgrids with Artificial Neural Network-Based on Fault Detection and Location.” *In 2022 23rd International Middle East Power Systems Conference (MEPCON)*, pp. 1-5. IEEE, 2022.

[101] Cao, Hanhua, Dongming Zhang, and Shujuan Yi. “Real-Time Machine Learning-based fault Detection, Classification, and locating in large scale solar Energy-Based Systems: Digital twin simulation.” *Solar Energy* 251 (2023): 77-85.

[102] Prasad, Ch Durga, Monalisa Biswal, Manohar Mishra, Josep M. Guerrero, and Om P. Malik. “Optimal threshold-based high impedance arc fault detection approach for renewable penetrated distribution system.” *IEEE Systems Journal* (2022).

[103] Ahmadipour, Masoud, Muhammad Murtadha Othman, Rui Bo, Zainal Salam, Hussein Mohammed Ridha, and Kamrul Hasan. “A novel microgrid fault detection and classification method using maximal overlap discrete wavelet packet transform and an augmented Lagrangian particle swarm optimization-support vector machine.” *Energy Reports* 8 (2022): 4854-4870.

[104] Hong C, Zeng ZY, Fu YZ, Guo MF (2020) “Deep-Belief-Networks Based Fault Classification in Power Distribution Networks.” *IEEJ Transactions on Electrical and Electronic Engineering* 15(10): 1428-1435.

[105] Tong H, Qiu RC, Zhang D, Yang H, Ding Q, Shi X (2021) “Detection and classification of transmission line transient faults based on graph convolutional neural network.” *CSEE Journal of Power and Energy Systems* 7(3): 456-471.

[106] Rajesh P, Shajin FH, Rajani B, Sharma D (2022) “An optimal hybrid control scheme to achieve power quality enhancement in micro grid connected system.” *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields e3019*