Modelling of a Protective Scheme for AC 330 kV Transmission Line in Nigeria

Vincent Nsed Ogar

Submitted in fulfilment of the requirements for the
Degree of Doctor of Philosophy

James Watt School of Engineering
College of Science and Engineering
University of Glasgow

October 2023

Abstract

Transmission lines play a vital role in the reliable and efficient delivery of electrical power over long distances, and these lines are affected by faults that occur due to lightning strikes, equipment failures, human, animal or vegetation interference, environmental factors, ageing equipment, voltage sag or grid faults adverse effects on the line. Therefore, protecting these transmission lines becomes crucial with the increasing demand for electricity and the need to ensure grid stability. The modelling process involves the development of a comprehensive protection scheme utilising modern technologies and advanced algorithms. The protection scheme encompasses various elements, including fault detection, fault classification, fault location, and fault clearance. It incorporates intelligent devices, such as protective relays and communication systems, to enable rapid and accurate fault identification and isolation.

First, a 330 kV, 500 km three-phase Delta transmission line is modelled using MATLAB/SIMULINK. A section of the Delta network in Delta State Nigeria was used since the entire Nigeria 330 kV network is large. Faulty current and voltage data were generated for training using the CatBoost, 93340 data sizes comprising fault data from three-phase current and voltage extracted from the Delta transmission line model in Nigeria were designed, and twelve fault conditions were used. The CatBoost classifier was employed to classify the faults after different machine language algorithm was used to train the same data with other parameters. The trainer achieved the best accuracy of 99.54%, with an error of 0.46%, at 748 iterations out of 1000 compared to GBoost, XBoost and other classification techniques.

Second, the Artificial Neural Network technique was used to train this data, and an accuracy of 100% was attained for fault detection and about 99.5% for fault localisation at different distances with 0.0017 microseconds of detection and an average error of 0% to 0.5%. This model performs better than Support Vector Machine and Principal Component Analysis with a higher fault detection time. The effect of noise signal on the ANN model was studied, and the discrete wavelet technique was used to de-noise the signal for better performance and to enhance the model's accuracy during transient.

Third, the wavelet transforms as a data extraction model to detect the threshold value of current and voltage and the coordination time for the backup relay to trip if the primary relay does not operate or clear the fault on time. The difference between the proposed model and the model without the threshold value was analysed. The simulated result shows that the trip time of the two relays demonstrates a fast and precise trip time of 60% to 99.87% compared to other techniques used without the threshold values. The proposed model can eliminate the trial-and-error in programming the instantaneous overcurrent relay setting for optimal performance.

Fourth, the PSO-PID controller algorithm was used to moderate the load frequency of the transmission network. Due to the instability between the generation and distribution, there is always a switch in the stability of the transmission or load frequency; therefore, the PSO-PID algorithm was used to stabilise the Delta power station as a pilot survey from the Nigerian transmission network. Also, a hybrid system with five types of generation and two load centres was used in this model. It has been shown that the proposed control algorithm is effective and improves system performance significantly. As a result, the suggested PSO-PID controller is recommended for producing high-quality, dependable electricity. Moreover, the PSO-PID algorithm produces 0.00 seconds settling time and 0.0005757 ITAE. It's essential to carefully consider potential drawbacks like complexity and computational overhead, sensitivity to algorithm parameters, potential parameter convergence and limited interpretability and assess their impact on the specific LFC application before implementing a PSO-PID controller in a power system.

When implemented with the model in this research, the Delta transmission line network will reduce the excessive fault that occurs in the transmission line and improve the energy efficiency of the entire network when replicated with the Nigerian network.

Generally, for the effective design and implementation of the protection scheme of the 330 kV transmission line, the fault must be detected and classified, and the exact location of the fault must be ascertained before the relay protection and load frequency control will be applied for effective fault management and control system.

University of Glasgow

College of Science & Engineering

Statement of Originality

Name: Vincent Nsed Ogar
Registration Number: XXXXXX

I certify that the thesis presented here for examination for a PhD degree of the University of Glasgow is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it) and that the thesis has not been edited by a third party beyond what is permitted by the University's PGR Code of Practice.

The copyright of this thesis rests with the author. No quotation from it is permitted without full acknowledgement.

I declare that the thesis does not include work forming part of a thesis presented successfully for another degree.

I declare that this thesis has been produced in accordance with the University of Glasgow's Code of Good Practice in Research.

I acknowledge that if any issues are raised regarding good research practice based on a review of the thesis, the examination may be postponed pending the outcome of any investigation of the issues.

Signature: ....
Date: 20th october 2023

List of Publications

Journals

1. **Ogar, V.N**, K. A. A. Gamage, and S. Hussain, "Protection for 330 kV transmission line and recommendation for Nigerian transmission system: a review," International Journal of Electrical and Computer Engineering (IJECE), vol. 12, no. 3, p. 3320, 2022, doi: 10.11591/ijece.v12i3.pp3320-3334.

2. **Ogar, V.N.**; Hussain, S.; Gamage, K.A.A. Transmission Line Fault Classification of Multi-Dataset Using CatBoost Classifier. Signals 2022, 3, 468-482. https://doi.org/10.3390/signals3030027.

3. **Ogar, V.N.**; Hussain, S.; Gamage, K.A.A. The Use of Instantaneous Overcurrent Relay in Determining the Threshold Current and Voltage for Optimal Fault Protection and Control in Transmission Line. Signals 2023, 4, 137-149. https://doi.org/10.3390/signals4010007.

4. **Ogar, V.N**, S. Hussain, and K. A. A. Gamage, 'The use of artificial neural network for low latency of fault detection and localisation in transmission line', Heliyon, vol. 9, no. 2, p. e13376, Feb. 2023,
doi: 10.1016/J.HELIYON.2023.E13376.

5. **Ogar,V.N**, S. Hussain, and K. A. A. Gamage, "Load Frequency Control Using the Particle Swarm Optimisation Algorithm and PID Controller for Effective Monitoring of Transmission Line," Energies, vol. 16, no. 15, p. 5748, Aug. 2023, doi: 10.3390/en16155748.

Conference Proceedings

1. **Ogar, V. N**., Gamage, K. A.A. , Hussain, S. and Akpama, E. J. (2021) Transmission Line Fault Detection and Classification of Multi-Dataset Using Artificial Neural. International Conference on Information Technology and Economic Development (ICITED2021), Calabar, Nigeria, 18-20 Nov 2021.

Contents

List of Tables

List of Figures

List of Acronyms

AAC	All Aluminium Conductors
AAAC	All Aluminium-Alloy Conductors
ACAR	Aluminium Conductor Alloy-Reinforced
ACSS	Aluminium Conductor Steel Supported
AC	Alternating Current
ACFR	Aluminium Conductor Carbon Reinforced
ACCR	Aluminium Conductor Composite Reinforced
AIICNN	Adaptive Intraclass and Interclass Convolutional Neural Network
AGC	Automatic Generation Control
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
CNN-LSTM	Convolutional Neural Network and Long Short Term Memory
CWT	Continuous Wavelet Transform
DBN	Deep Belief Network
DC	Direct Current
DL	Deep Learning
DKPCA	Dynamic Kernel Principal Component Analysis
DFT	Discrete Fourier Transform
DMT	Definite Minimum Time
DNN	Deep Neural Network
DT	Decision Tree
DWT	Discrete Wavelet Transform
DQN	Deep Q-Network
ELM	Extreme Learning Machine
EMTP	Electromagnetic Transients Program
EMI	Electromagnetic Interference
MSE	Mean Square Error
EPFA	Equivalent Power Factor Angle
FL	Fuzzy Logic

FA	Firefly Algorithm
FACTS	Flexible Alternating Current Transmission System
FIA	Fault Inception Angle
FIS	Fuzzy Interference System
FRA	Frequency Response Analysis
GBDT	Gradient Boosting Decision Tree
GA	Genetic Algorithm
GCN	Graph Convolutional Networks
GPS	Global Positioning System
GSA	Gravity Search Algorithm
GPR	Gaussian Process Regression
GRC	Generation Rate Constraint
GTZACSR	Gap-Type ZT-Aluminium Conductor
HLCL	Human-Level Concept Learning
HHT	Hilbert-Huang Transform
HVDC	High Voltage Direct Current
IEA	International Energy Agency
1DCNN	1-D Convolutional Neural Network
IDMT	Inverse Definite Minimum Time
IEC	International Electro-technical Commission
IEEE	Institute of Electrical and Electronics Engineers
idCNN	inflated Convolutional Neural Network
ITAE	Integral Time Absolute Error
KNN	K-Nearest Neighbour
KPCA	Kernel Principal Components Analysis
L-L	Line to Line Fault
L-G	Line to Ground Fault
L-L-G	Double Line to Ground Fault
L-L-L-G	Three Phase to Line Fault
LFC	Load Frequency Control
MLP	Multi-Layer Perception
MPC	Model Predictive Control
MSE	Mean Square Error
MRA	Multi-Resolution Analysis
MW	Mother Wavelet
NCVAE-AFL	Normalised Conditional Variational Auto-Encoder with Adaptive Focal Loss
OCR	Overcurrent Relay
PCA	Principal Component Analysis

PDPI	Proportional Derivative Proportional Integral
PID	Proportional Integral Derivative
PMU	Phesor Measurement Unit
PNN	Probabilistic Neural Network
PNN	Probabilistic Neural Network
RNN	Recurrent Neural Network
PSCAD	Power Systems Computer Aided Design
PQD	Power Quality Disturbance
PSO	Particle Swarm Optimisation
RBF	Radial-Basis Function
RBFNN	Radial Basis Function Neural Networks
RDRP	Random Dimensionality Reduction Projection
RL	Reinforced Learning
RLS	Recursive Least-square
RF	Random Forest
RNN	Recursive Neural Network
RMSE	Root Mean Square Error
SRC	Sparse Representation Classification
SSU	Supply and Switching Unit
SSSC	Static Synchronous Series Compensator
SVM	Support Vector Machine
TCSC	Thyristor-Controlled Series Capacitor
TL	Transmission Line
TEC	Thevenin Equivalent Circuit
TMS	Time Multiplier Setting
TCN	Transmission Company of Nigeria
UL	Unsupervised Learning
WSCC	Western System Coordinating Council
WT	Wavelet Transform

List of Symbols

H_z	Hertz
C_j	J level scaling coefficient
d_j	The j level wavelet function
J	Highest wavelet level
$\Phi(t)$	The scaling function
$\psi(t)$	wavelet function
$x(t)$	wavelet signal
X_1, X_2, X_n	represent the input voltage and current
W_1, W_2, W_n	Represent input variable's synaptic weights
m	Training set
λ	The weight decay
θ	The Activation threshold, fault incipient angle
R_j	Predetermined value of neuron
ΔW_{kj}	Weight change
∂E	Error of output layer
α	Learning rate
F	The cost function
R_1, R_2, R_n	Positive and negative sequence resistance
R_o	Zero sequence resistance
L_1, L_2, L_3	Positive and negative sequence inductance
L_o	Zero sequence inductance
$C-1, C_2, C_3$	Positive and negative sequence capacitance
C_o	Zero sequence capacitance
R_s	Source resistance
R_{on}	Fault resistance
R_g	Ground resistance
R_s	Snubber resistance
C_s	Fault capacitance
$L(H)$	Smooth loss function

D	training data
TP	true Positive
TN	True Negative
FP	False Positive
FN	False Negative
V_a	Voltage in phase A
V_b	Voltage in phase B
V_c	Voltage in phase C
I_a	Current in phase A
I_b	Current in phase B
I_c	Current in phase C
I_{min}	Minimum short-circuit current
I_{pr}	Threshold value of the current protection
I_{st}	Steady state component of the highest load current
$\frac{X}{R}$	System ratio at the fault point
F_c	Equivalent frequency response
P_i	Percentage increment of the tripping time of relay
T_A	Tripping time without the threshold value
T_B	Tripping time using the proposed model
X_i^k	The position of individual i until iteration k
$Pbest_i^k$	The best position of individual iteration
$Gbest_i^k$	The position of the group iteration
w_{max}, w_{min}	The initial and final weights
$Iter_{max}$	The maximum iteration number
$iter$	Current iteration number
H	The generator inertia constant
ΔP_m	Change in mechanical power
ΔP_{gs}	Power from the generating station
ΔP_e	Net change in the electrical load demand
$\Delta P_L(freq)$	Frequency independent load change
$\Delta\omega$	The sensitive load frequency change
τ_t	Turbine time constant
ΔP_v	Change in steam value
ΔP_g	Power output of the governor
τ_g	Governor time constant
K_p	The Proportional gain
K_i	The integral gain
K_d	The derivative gain

Acknowledgements

My most profound gratitude goes to the Almighty God for showering me with His mercies, love, good health and sustenance throughout my PhD. I am eternally grateful to Him for the wisdom, inspiration, strength, and favour that enabled me to secure this Tertiary Education Trust Fund (TETfund) scholarship.

My special appreciation goes to my first supervisor, Prof.Kalum Gamage, for his constant guidance, support, encouragement, and motivation that enabled me to complete this research. He was always available and responsive whenever I encountered difficulties and challenges during my research. Thank you for creating the enabling environment that enabled me to excel in my research and collaborate with fellow researchers. I am deeply grateful to my second supervisor, Dr. Sajjad Hussain, for believing in me, giving me the needed push to perform better and improve myself, and dedicating time weekly to discuss and guide me in every step of this research. To Dr Attai Abubakar, Dr. Daniel Abara and Dr Kenechi Omenka, you guys have been of immense help in discussing my ideas, reviewing and proofreading my manuscripts, and providing the motivation to continue my research work.

I appreciate the Tertiary Education Trust Fund (TETFund) of the Federal Republic of Nigeria for sponsoring this PhD research and the Cross River University of Technology, Calabar, for granting me the training leave I needed to pursue my PhD.

I sincerely appreciate my lovely wife, Evelyn Ogar, for her patience, love, support and care during my PhD journey. Also, my beautiful daughter, Praise Ebuobasi Nsed Ogar, for always sitting by me or struggling with my computer. To my parents, Elder Thomas Ogar Nkom and Mrs Florence Ogar Nkom, for their support, prayers, love and encouragement. My siblings, Victor, Eunice, Mary, Sylvester, Amba, Manyo and Nsan, for standing by me. My special appreciation goes to my Uncle, Dr Sylvester E.N Ebaye and his lovely Wife, Dr Asenath E.N Ebaye and his children, Associate Prof. Akpama E. James, the Dean of Faculty of Engineering CRUTECH Calabar, and Prof. Owan Enoh, former Vice Chancellor CRUTECH for approving my scholarship.

I would not be able to mention the names of everyone who assisted me during my research, but for those who contributed in one way or the other towards completing my PhD, I appreciate you all.

Chapter 1

Introduction

1.1 Research Overview

The electrical power system consists of different segments interacting with each other, including generation, transmission and distribution. The transmission line is an essential power system component since it transfers electricity from the generating station to the distribution and the end-users. These components, such as circuit breakers, transformers, and fuses, are interconnected through the transmission lines and are subjected to inevitable faults, which cannot be controlled manually to the required standards except by advanced techniques [1, 2].

A transmission line fault refers to any abnormal condition on a transmission line, a power transmission system that carries electricity from a power generation facility to a substation. Transmission line faults include short circuits, open circuits, and ground faults. These faults can cause damage to the transmission line equipment, disrupt the power supply, and even lead to power outages [3].

Various factors, including equipment failure, natural disasters, and human error, can cause transmission line faults. Several methods are used to detect and locate faults on transmission lines, such as distance protection, current differential protection, and overcurrent protection. The protection method choice depends on the transmission line's specific characteristics and the equipment connected to it.

Several things can happen on a transmission line when a fault occurs, depending on the type of fault and the protection system in place.

- Voltage sag: A fault on a transmission line can cause a temporary voltage drop, known as voltage sag. The extent of the voltage drop depends on the location and severity of the fault.

- Protective relays trip: When a fault occurs, protective relays detect the fault at each end of the transmission line and send a signal to the circuit breaker to trip. This isolates the faulted section of the transmission line from the rest of the power system.

- Power outage: If the fault is severe enough and not cleared quickly, it can cause a power outage for customers served by the affected transmission line.
- Damage to equipment: The fault current that flows through the transmission line during a fault can cause damage to the equipment, including the conductors, insulators, and other components.
- Arcing and fires: In some cases, a fault on a transmission line can cause arcing, leading to fires and damage to nearby buildings or structures.
- Restoration of service: The transmission line can be restored once the fault is cleared or restored immediately after the fault occurs. This may involve replacing damaged equipment or repairing the conductors or insulators.

It is important to note that transmission lines are designed with redundancy to minimize the impact of faults. This includes having multiple transmission lines serving the same area and backup power sources and protection systems to isolate and clear faults quickly [4].

Transmission line protection models are intended to identify transmission line faults and isolate the affected segment from the remainder of the system. The protection system comprises relays attached to the transmission line. It is intended to detect faults and send a trip signal to the circuit breakers, causing the defective segment of the line to be disconnected and isolated from the main transmission line to prevent system collapse. Transmission line protection system modelling entails simulating the protection scheme's behaviour under different fault scenarios to verify that it performs appropriately and dependably. The simulation models may adjust the protection settings and assess the protection scheme's performance under various operating systems.

It is crucial to quickly detect and locate transmission line faults to minimise damage and restore the power supply as soon as possible. This is typically done using protection devices such as relays and monitoring the transmission line for abnormal conditions using sensors and other monitoring equipment.

According to the International Energy Agency (IEA), the global transmission and distribution network increased from around 2.2 million km in 1990 to approximately 6.9 million km in 2018, representing an increase of around 214% over this period. It should be noted that this data only covers the period from 1990 to 2018 [5]. This is due to the fast expansion of electric power networks over the last several decades. Free markets and deregulation have been implemented all over the globe, and they have resulted in ever-stricter standards for supplying a consistent and high-quality supply of electricity without appreciable increases in the cost of the energy being provided. Supply continuity, dependability, and reliability are crucial in modern power systems. A higher need for high-quality power-system protection and control devices, together with their auxiliary equipment, has emerged as being of utmost significance due to the enforced stringent criteria [6, 7].

1.1.1 The Transmission Line Model

The transmission line model is a mathematical representation of an electrical transmission line used in power systems. It provides a simplified representation of the behaviour of signals or electrical power as they propagate along the line.

The basic transmission line model consists of a series of lumped electrical components that approximate the distributed parameters of the actual transmission line. These lumped elements include resistance (R), inductance (L), conductance (G), and capacitance (C). The model assumes that the transmission line is infinitely long and has uniform parameters along its length.

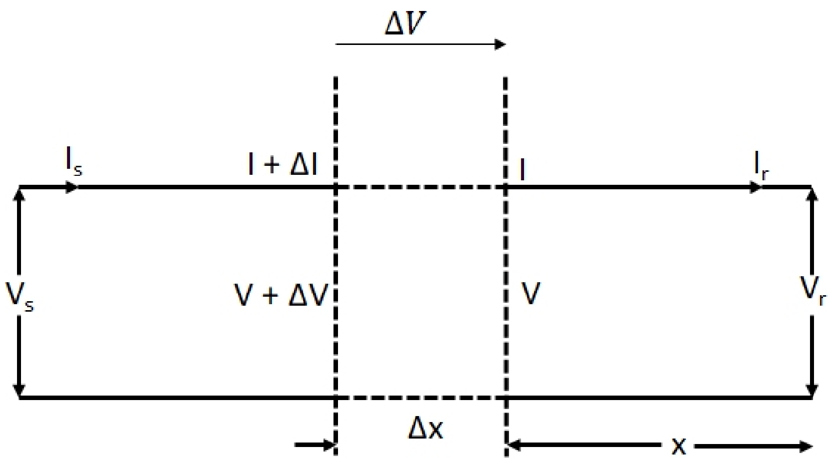


Figure 1.1: Long Transmission line model [8]

The primary parameters used in the transmission line model are the characteristic impedance Z_o and the propagation constant Y. The characteristic impedance represents the impedance that the line would present to a signal if it were terminated in a purely resistive load. The propagation constant describes the propagation characteristics of the signals along the line, including the phase velocity and attenuation.

A long transmission line consists of 160 km and above and is represented in Figure 1.1 and 1.2 representing the long transmission line and the equivalent

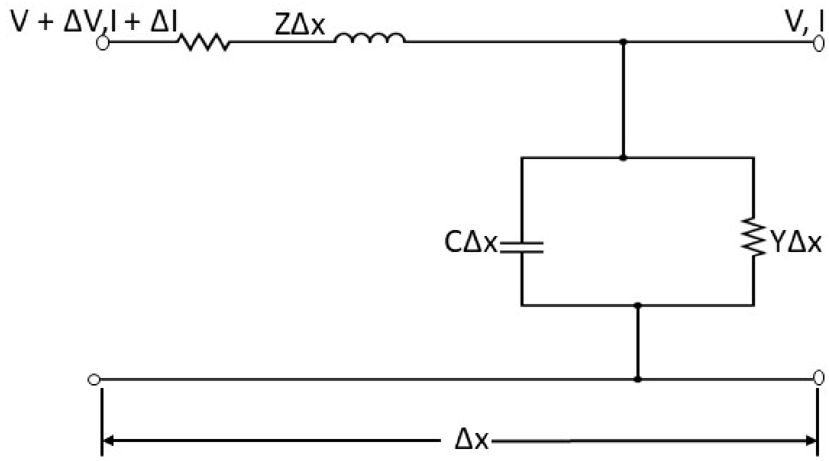


Figure 1.2: Equivalent circuit of a long transmission line [8]

circuit, respectively. The derivation of the transmission line model is shown in Appendix A

1.2 Problem Statement

Over the next few decades, the use of transmission lines expanded rapidly as electric utilities began to build power plants and transmission networks to meet the growing electricity demand. In the early 20th century, the development of alternating current (AC) power transmission technology allowed for longer transmission distances and higher voltage levels, increasing the transmission system's efficiency [9]. These increase in transmission line capacity and the high demand for electricity with corresponding growth in the population worldwide has put a demand on electricity transmission, thereby leading to faults.

Nigeria's transmission line faces the same challenges and is prone to faults due to its peculiarities. The Transmission Company of Nigeria (TCN) evacuates electricity from generation to distribution nationwide. The 330 kV transmission network is the primary line that connects all the generating stations and load centres into a single grid. The network covers about 5,523.8 km and about 15,000 km [10, 11]. This vast transmission network has been exposed to different types of faults, such as symmetrical and unsymmetrical faults, which affect the network not to perform to its maximum capacity. The installed capacity is about 12522 MW, while the output is about 7689.04 MW as of December 2019 [12]. With this, only 3733.01 MW was transmitted to distribution substations or load centres, which is inadequate for a country with a population of about 200 million. About 3583.23 MW of electricity was wasted or unused due to faulty transmission lines and losses. This has been a significant problem in the Nigerian power sector, coupled with other factors like faulty and ageing equipment, bad weather conditions and poor government policies. Nigeria uses the distance relay protection and overcurrent protection scheme for its network [12]. The sulphur Hexafluoride (SF_6) circuit breaker is also used for overcurrent protection. The weak protective nature of the line has cost the government and investors in the power sector losses in revenue and power loss along the line. Hence, the adverse effect on the economy is devastating [13].

The transmission line is generally the most affected by faults in the power system components; therefore, protecting it from faults to avert system collapse is necessary. This system collapse will cause power shortages and blackouts, energy loss, and damage to power system equipment like transformers and circuit breakers. These can affect the country's economy and cause the loss of jobs. Furthermore, when faults occur in transmission lines or power systems, the relays are expected to send signals to the circuit breaker to trip on time. This may not sometimes happen because of faulty types of equipment and wrong relay settings, and sometimes the relay is configured based on trial and error.

Transmission lines are susceptible to various types of faults, including short-circuits, ground faults, and open-circuits, which can result in power outages, equipment damage, and safety hazards. Therefore, it is essential to have an effective fault protection system that can quickly detect and isolate faults while minimising the impact on the power system. The main challenges in transmission line fault protection include:

Detection of faults: Faults in transmission lines can be intermittent and occur in different forms. Therefore, it is essential to have a fault detection system that can quickly identify the presence of a fault and distinguish between different types of faults. Fault detection systems must operate in real-time to quickly identify and respond to faults. The algorithms and techniques used for fault detection should be efficient and capable of processing large volumes of data within tight time constraints. This has affected the Nigerian transmission network to perform optimally.

Localisation of faults: Once a fault is detected, it is necessary to determine its location accurately. This can be challenging, especially for long transmission lines with multiple branches. The transmission line includes limited information about the exact location of faults, and measurement of the accuracy of voltage, current and other parameters is limited due to errors in measurement, sensor limitation and noise signal. Also, fault transients are challenging to analyse and extracting relevant information to localise fault accurately can be complex. Communication and data synchronisation can be challenging due to the vast land mass, and the long transmission line length of the Nigerian TL is difficult to impedance because of non-uniform line parameters, which affects fault signals.

Discrimination of faults: Different types of faults require different protection schemes. Discriminating between faults is critical in selecting the appropriate protection scheme to minimise the impact on the power system.

Speed of operation: Fault protection systems must operate quickly to isolate faults before they can cause significant damage to the transmission line and the connected equipment.

Sensitivity and selectivity: Fault protection systems must be sensitive enough to detect minor faults and selective enough to avoid nuisance tripping caused by transient disturbances or non-fault conditions. The Nigeria TL network relays and circuit breakers are obsolete, making detecting faults in real-time difficult.

Overall, the problem statement of transmission line fault protection is to develop an effective protection system that can detect, locate, and isolate faults quickly and accurately while minimising the impact on the power system. This requires a combination of advanced sensing, computing, and control technologies and appropriate protection schemes and strategies.

1.3 Research Motivation

Transmission lines are the power grid's backbone, and their dependable performance is critical to the overall operation of the power system. Faults in transmission lines may create interruptions in power delivery, affecting industry, commerce, equipment breakdown and everyday life. To limit downtime and avoid future damage, it is vital to identify, categorise, and localise problems in transmission lines as fast and correctly as possible [14].

One of the motivations of this research is to provide more accurate and efficient ways of identifying and diagnosing defects in real-time. Manual inspections are time-consuming, costly, and prone to human mistakes in traditional fault detection, categorisation, and localisation approaches, on the other hand, automated systems may swiftly detect faults and offer early notice of possible issues, allowing operators to take proactive actions to avoid outages or reduce their effect.

Secondly, this study enhances power system performance by lowering the time it takes to detect and diagnose defects. This may assist in lessening the length and severity of power outages, equipment damage and overall system dependability. Moreover, correct fault classification may give helpful information for transmission system maintenance and improvements.

Thirdly, technical advancements have created new and more complex fault detection, classification, and localisation procedures. The machine learning algorithm, artificial intelligence, and data analytics are examples of developing technologies that may be used to analyse multi-data and detect patterns that may suggest the existence of faults. These approaches can potentially increase the accuracy and efficiency of fault detection, classification, and localisation, allowing for the discovery of transient faults that would otherwise be difficult to detect.

Finally, improving fault detection and localisation in transmission lines can have significant economic and environmental benefits, by minimising downtime and reducing the need for maintenance and repairs, the reliability of the power system can be improved, leading to increased productivity and reduced costs, additionally, identifying faults early may prevent more severe damage to the transmission line and reduce the risk of environmental contamination from surges or other hazardous materials.

1.4 Research Objectives

This research aims to model the transmission line protection scheme using Nigeria's 330 kV a transmission line as a case study. The research has the following objectives:

1. To model a 330 kV, 500 km transmission line with simulated fault conditions at different distances along the transmission line. This involves using MATLAB/SIMULINK to model a 330 kV, 500 km transmission line using different sim power tools and configuring them with all the transmission line parameters.

2. To identify different types of faults in the transmission line and generate a faults dataset from the simulated model using MATLAB/SIMULINK.

3. To classify the fault using the data generated from the transmission line model. This can be achieved by using artificial intelligence and different machine learning techniques to train the data generated from the designed model for fault detection, classification and localisation.

4. To classify the fault using the data generated from the transmission line model and integrate the result acquired from the machine learning model into the power system for effective fault management in the transmission line.

5. To design an instantaneous overcurrent and voltage relay for optimum protection of the 330 kV transmission line and using the particle swarm optimisation method to control the load frequency of the transmission line for optimal fault protection.

1.5 Research Contributions

The major contribution of this thesis is summarised as follows:

1. One of the research contributions is the implementation of the existing Catboost algorithm for fault classification. The Catboost classifier can classify faults accurately with speed. It is an efficient technique in machine learning because of its quick response to a fault and can handle multi-dataset. Additionally, the model's ability to train with noisy data without affecting system accuracy and performance. This algorithm has an accuracy of 99.54%, compared to ELM and PCA, with an accuracy of 98% and 99.12%, respectively.

2. A fault detection and localisation algorithm was modelled, which has the accuracy and speed of sending the signal to the exact location of the fault and the type of fault initiated. The artificial neural network is proposed. This approach provides rapid, reliable, and accurate fault identification and localisation in transmission lines. Also, detecting many fault circumstances, such as defective voltage and current, minimises fault detection time delay. The proposed algorithm's performance was assessed by simulating several errors and training them with the ANN model, and the results were compared with existing models, which showed better performance. In addition, the model will be used to develop transmission line fault management and protection in power systems. Also, introducing the DWT to de-noise the signal for effective fault detection and localisation and to prevent noise during transient improves accuracy and model performance.

3. The use of threshold values of faulty current and voltage to configure the instantaneous overcurrent and overvoltage relay to achieve timely and accurate trip time and reduce the delay time of relays for speedy, prompt sending fault signal to the circuit breaker to isolate faulty lines. This research has led to the developing of more robust protection schemes that can handle complex fault scenarios and ensure power systems' safe and reliable operation.

4. The load frequency plays a significant role in power system stability; therefore, the use of particle swarm optimisation for the control and stability of the transmission frequency for effective and efficient voltage stability. In general, modelling transmission line protective schemes has significantly improved protection schemes' efficiency, accuracy, and reliability. These advances have played a critical role in ensuring the safe and reliable operation of the power system.

1.6 Thesis organisation

The remaining part of this thesis is organised as follows:

Chapter Two explains the history of transmission lines and the different types of faults. It also enumerates and explains the types of faults that occur in the transmission lines, the causes and the Nigeria transmission network. It also analysed the relevant research on the protection of the transmission line and the various techniques used in detecting, classifying and localising faults in the transmission line. Also, the conventional, hybrid and machine learning techniques were discussed. The different techniques were compared and analysed based on fault type, application area, the accuracy of analysed results, fault detection time, and trip time was also analysed. Also, the advantages and disadvantages of the different techniques were enumerated, and the research gap was discussed.

Chapter three explains using the Catboost classifier to classify faults in transmission lines using a multi-dataset. This chapter discussed fault classification and using the CatBoost classifier to classify faults into different categories. A 330 kV, 500 km three-phase transmission line was modelled using SIMULINK to extract faulty data from twelve fault scenarios. The multi-dataset was used to train the Catboost classifier, and the results were analysed, showing the classifier's efficiency concerning the speed of execution and accuracy of the result. The results were compared with other classifiers for fault classification performance, accuracy and speed.

The contribution of the CatBoost algorithm to transmission line fault classification is as follows:-

- Transmission line faults are accompanied by the noise signal; therefore, only the de-noised signal was used to train the data using the CatBoost algorithm. These assist in improving the accuracy of the results

- The introduction of ground resistance of 0.001Ω to detect residual voltage and transient current on the transmission line helps to improve the sensitivity of the algorithm and the entire model.

Chapter four focuses on fault detection and localisation, and the ANN technique is used to detect and locate faults on the modelled transmission line. The technique is used due to its low fault detection and localisation latency. The chapter focuses on using extracted data from Chapter three to detect faults in transmission lines. Four primary fault conditions were considered: single-phase to ground fault, double-phase to ground fault, three-phase to ground fault and no-fault conditions. Also, a SIMULINK model was designed to locate faults accurately and timely, emphasising the four major fault scenarios selected as a case study. The achievement of chapter four include:-

- Using the Simulink model to design an ANN algorithm for transmission line location was achieved. This method locates and detects the fault location with precision and an accuracy of 100 % and 99.5% for fault detection and localisation, respectively.
- The model can operate multi-data sets with different fault conditions simultaneously due to its pattern recognition and parallel processing capabilities, making it unique in terms of non-linearity.

The main theme of Chapter five is the use of instantaneous overcurrent relays in determining the threshold Current and voltage for optimal fault protection and control in the transmission line. The wavelet transform technique determined the modelled transmission line's faulty threshold current and voltage. The threshold values were used to determine the trip time and setting of the relays to ascertain the operating time, time delay and accuracy of the trip time of the circuit breaker. Comparing the results with deep learning and machine learning techniques shows that the threshold values obtained from wavelet transform assisted in the fast setting of the relay, which leads to a prompt response time to trip the circuit breaker. The achievement of chapter five include:-

- The proposed algorithm uses the threshold values for setting the overcurrent and overvoltage relay. Additionally, fault signals are accompanied by noise. Therefore, using the wavelet transform to determine the threshold current and voltage helps de-noise the signal to attain stability in the system.
- It also serves as a fast gateway for instantaneous relay settings for optimal protection of transmission and distribution line fault detection and isolation using a circuit breaker.

Finally, Chapter Six focuses on load frequency control in the transmission line. This is one of the significant parameters to check during the generation and transmission of electricity to maintain the generating frequency and load frequency for a steady and reliable power system. A SIMULINK model was generated, and the Principal swarm optimisation algorithm was used to determine and maintain the load frequency at 50 Hz. The main achievement of chapter six include:-

- The PSO-PID algorithm controls the LFC of the power system. The model was designed using the PSO-PID controller to optimise the load frequency using the ITAE cost function to determine the improved controller and the cost function of the PSO-PID algorithm. Comparing with the conventional approach, the algorithm provided precision and speed due to the hybrid method used and the introduction of the PID controller.

In summary, the transmission line protection scheme has been explained in detail, the various fault types were different literature was compared with the proposed methodology, and the research gap was highlighted. Fault detection, classification and localisation were also explained using different literature. The CatBoost classifier was used to classify faults, while the artificial neural network was used to detect and locate faults in the transmission line. The instantaneous overcurrent and overvoltage relay was used as a tripping device after the threshold values generated from the wavelet transform were used to set the relay for fast circuit breaker tripping. Finally, the load frequency control was applied to maintain the load frequency of the transmission line for stability and reliability of the entire power system. The particle swarm optimisation algorithm is used to control the frequency of the transmission line.

Chapter 2

Literature Review

This chapter briefly discusses faults and their various types on the transmission line. Also, a brief introduction to the Nigeria 330 kV transmission line and its networks. Then, an overview of fault detection, classification and localisation and the necessary protection techniques. Also, various machine learning (ML) algorithms are applied in transmission line fault analysis. Finally, recent literature on the main topic is reviewed. The research gap identified in each algorithm and the techniques used in fault classification, detection, and localisation were also analysed.

2.1 The Transmission Line

History as it that power transmission started far back in 1882 [15,16]. The French physicist Deprez was the first to complete a long-distance direct current transmission test, which has evolved in annals of the power industry. He transmitted a voltage of about 1500-2000 V through a 75 km telegraph wire of about 4.5 mm in diameter. It was generated by a direct current generator installed in the Miebach coal mine. It was transmitted to the first electrically lit international electrochemical exhibition at a Glass Palace in Munich and used to provide electricity for some construction work. In 1891, the Frankfurt power line was the world's first three-phase alternating current high voltage transmission line with a length of 175 km and 15.2 kV [17, 18]. In 1908, the first 110 kV transmission line was built in the United States; later, a 230 kV line was built in 1923. From the 1950s, the electric power sector developed rapidly as the amount of voltage transmitted increased to 380 kV in 1952, 500 kV in 1964, 735 kV, 750 kV and 767 kV transmission lines were built in Canada, the Soviet Union and the United States from 1965 to 1969 [17]. In 2009, about a 1000 kV transmission line was used in China, making it the highest alternative voltage transmission built and operational [18, 19].

2.1.1 Main Components of The Transmission Line

The primary function of the transmission line structure is to support the conductor, which is achieved by maintaining the mechanical structure of the system without deformation under maximum load conditions. Other reasons are to provide an electrical path to earth for fault current and provide a whole-of-line cost, effective service, including lattice tower/masts, steel tubular poles, and concrete poles [20]. The main component of the transmission line includes Resistance, inductance, capacitance, and conductance.

The Conductor

These are the main components of the transmission line, comprising aluminium conductors and reinforced steel. Others include all aluminium conductors (AAC), all Aluminium-alloy conductors (AAAC), and aluminium conductor alloy-reinforced (ACAR). Some conductors operating in high temperatures up to $150^o c$ include aluminium conductor steel supported (ACSS), the gap-type ZT-aluminum conductor (GTZACSR), which uses heat-resistant aluminium over the steel core with a small annular gap between the steel and the first layer of aluminium strands. In recent times, composite materials are being used, such as aluminium conductor carbon reinforced (ACFR) and aluminium conductor composite reinforced (ACCR) [21].

The Insulator

They are usually low-conductivity materials in which the passage of electric current is minimal. Strings of porcelain, toughened glass, or polymer discs are used to keep conductors together without harming the tower. Insulators of various varieties include pin insulators, suspension insulators, strain insulators, stay insulators, and shackle insulators. All of them are shield wires, high steel strength conductors situated above the phase conductor against lightning and function as an overcurrent protection mechanism. Resistance, inductance, capacitance, and conductance are other electrical components of transmission lines. The four parameters exist between the conductor and the ground; conductance accounts for leakage current at overhead line insulators and via cable insulation. Second, since it is changeable, it cannot be considered.

2.2 Transmission Line Faults

A power system fault is an unexpected circumstance where equipment connected to one of the system's primary voltages has an electrical breakdown. Two different sorts of faults mainly occur. The first is an insulation failure that leads to short-circuit faults; it can be brought on by excessive stress, which causes the insulation to deteriorate over time, or by an unexpected overvoltage condition. The second fault is an open-circuit fault or a failure that interrupts the flow of electricity.

2.2.1 Basic Types of Faults in Transmission Line

Four different types of faults occur in the transmission line, which includes

1. Open circuit faults
2. Short circuit faults
3. Symmetrical faults
4. Unsymmetrical faults

Open circuit faults result from one or more conductors failing, also called series faults. A short circuit is described as an anomalous connection of very low impedance between two locations of different potential in a transmission line, whether purposeful or unintentional. These are the most frequent and dangerous failures, causing abnormally large currents to flow through the machinery or transmission lines. The equipment suffers significant harm when these faults are ignored, even briefly. Shunt faults are another name for short circuit faults. A breakdown in the insulation between the phase conductors, the ground, or both brings these problems.

Symmetrical faults, also known as balanced faults, are a type of electrical fault in a power system that involves symmetrical or balanced conditions. These faults occur when the fault impedance and conditions are the same for all three phases of the electrical system. The term "symmetrical" refers to the fact that the fault conditions are balanced and identical for each phase of the system. All phases are short-circuited to the ground or occasionally to one another in these faults. Despite being uncommon, this requires a high current of more than 10kA. In this type of fault, the system's three phases are either earthed together or short-circuited to one another. At the same time, unsymmetrical faults cause a three-phase system to have an uneven current and phase shift. The distribution or transmission lines' open or short circuits generate asymmetrical faults. A natural disruption or human error causes them [1], and these do not involve three-phase [22]. Asymmetrical faults, also known as unbalanced faults, occur when the three phases of an electrical power system are not in balance. This means that the voltage and current levels in each phase are unequal, resulting in an uneven flow of electricity throughout the system.

Line to Line Fault (L-L)

When two-phase lines come into touch with each other, whether by wind or other forces or when they are overhead or beneath, these types of faults can develop, as shown in Figures 2.1 (a), (b) and (c) representing LL in phases AB, BC and CA respectively. 15% of power system failures are of this type, where it is difficult to estimate the bounds of the fault impedance [23].

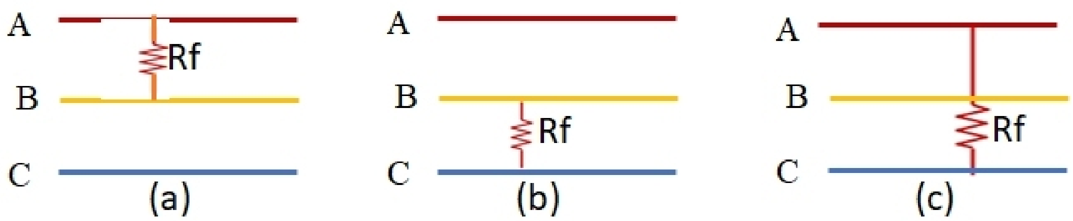


Figure 2.1: Line-to-Line Fault

Single Line To Ground Faults (L-G)

The L-G fault contributes to about 80% of the total faults in transmission and distribution lines and is also called a short circuit fault [24]. When a single line-to-ground fault occurs, the voltage of all phases except the faulted phase increases; sporadic arc grounding may cause arc voltage spikes and feeder inaccessibility, which can easily lead to a short circuit between phases [25]. The L-G fault is represented in Figures 2.2 (a),(b) and (c), enumerated as L- G faults in phases A, B and C, respectively. Since the neutral point is not directly grounded during L-G, the steady-state current flows solely through the grounded capacitance.

Double Line To Ground Fault (L-L-G)

The LLG faults contribute about 10% of the power system faults and turn into three-phase or three phases to ground faults if not cleared on time. The occurrence occurs when two phases collide with the ground due to a falling tree or another event. This can be seen in Figure 2.3 (a) L-L-G at phase ABG, (b) L-L-G at phase BCG, and (c) L-L-G at phase ACG, respectively.

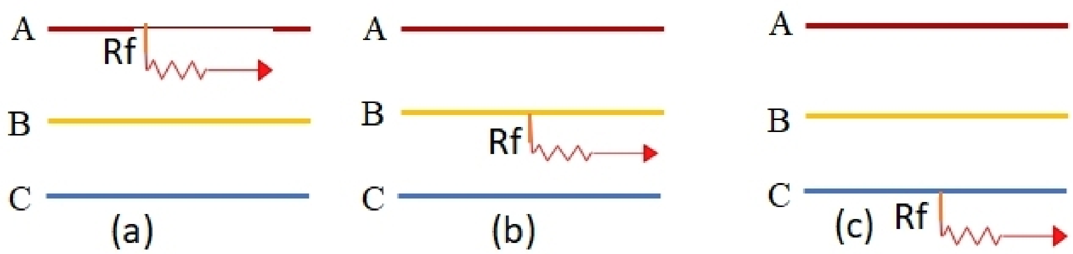


Figure 2.2: Single Line to Ground Fault

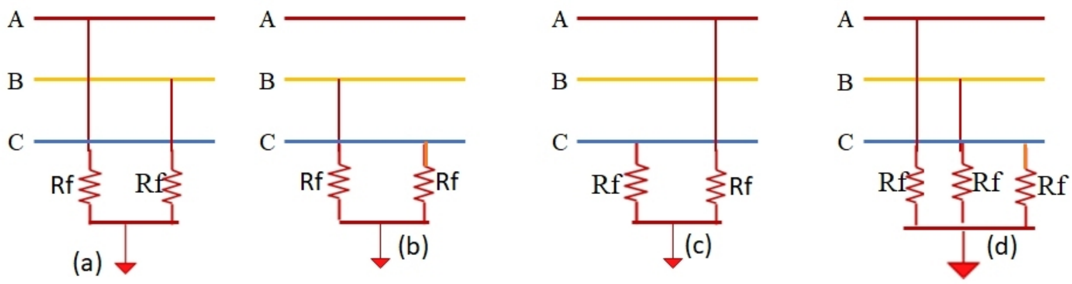


Figure 2.3: Double Phase to Ground Faults

Three Phase to Ground Faults

Three phase-to-ground faults (L-L-L or L-L-L-G) account for 5% of total faults in the power system network, are uncommon and are of greater severity. These are symmetrical faults caused by the tower collapsing, equipment failure, and a line connecting the remaining phases. When the voltage level drops to zero, the fault current magnitude increases, which can result in significant damage [23]. This can be seen in the diagram in Figure 2.3 (d).

2.2.2 Causes of Faults

Open-circuit faults can occur when joints on cables or overhead lines fail or all three phases of a circuit breaker or disconnector fail to open or close. Weather causes the vast majority of short-circuit faults, which after that by equipment failure, lightning strikes, snow or ice accumulation, heavy rain, strong winds or gales, salt pollution depositing on insulators on overhead lines and in substations, floods and fires near electrical equipment are typical weather factors that cause short-circuit faults.

Lightning strikes can produce currents ranging from a few kilo-amps to 100 or 200 kA for several microseconds. If the strike strikes an overhead line or its earth wire, the voltage generated across the insulator may be so high that it causes a back-flashover and short circuit. As a result, a transient power frequency short-circuits current flows through one or all three phases of a three-phase electrical circuit.

Equipment failure can result in faults, which can be caused by internal insulation failure due to ageing and degradation, breakdown due to high switching or lightning overvoltages, mechanical incidents, or improper installation. Most short-circuit faults on primarily overhead line systems, typically 80-90%, tend to occur on overhead lines, with the remainder occurring on substation equipment and busbars combined. Long-term average short-circuit fault statistics on a high-voltage transmission system with overhead line steel tower construction, such as the England and Wales transmission system, show that around 300 short-circuit faults occur annually. 60-70% are one-phase to earth, 25% are phase to phase, 5% are three-phase to earth, three-phase clear of the earth, and 3% are two-phase to earth. Lightning strikes cause approximately 77% of single-phase-to-earth faults, followed by wind, gales, and salt pollution on insulators. Although lightning can cause some phase-to-phase faults, snow/ice, followed by wind/gales that cause two line conductors to collide, are the most common causes of these faults. Most three-phase and two-phase earth faults in England and Wales are caused by lightning, followed by wind and gales [3].

2.3 The Nigerian Transmission Network

The Transmission Company of Nigeria (TCN) manages the electricity transmission network in the country. The 330 kV transmission network is the first network that connects all generating plants and load centres in all parts of the country to a single synchronised network. Hence its economic importance cannot be overemphasised [26]. This vast network is open to both symmetrical and unsymmetrical faults. Nigeria's transmission grid comprises a full-scale (theoretical) transmission capacity of 7,500 MW and above 20,000 km of transmission lines. Currently, the transmitting size of 5,300 MW is larger than the average working generating capacity of 3,880 MW, which is below the overall generating capacity of 12,523 MW. The entire installation is typically spiral, without redundancies, thus creating internal accuracy issues. At a mean of about 7.4%, the losses throughout the system are high when compared to other Nations' models of about 2% to 6%. Nigeria transmits 330 kV to 132 kV, which will be stepped down to 33 kV and 11 kV, known as the distribution network. The most common causes of transmission line fault in Nigeria include weak grounding systems, the type of conductors used or ageing conductors, and the geographical terrain; these consist of swamps and forests, weather/climate due to high rainfall and thunderstorm. Other factors include line losses, corona effect, lack of spare parts and technical human resources.

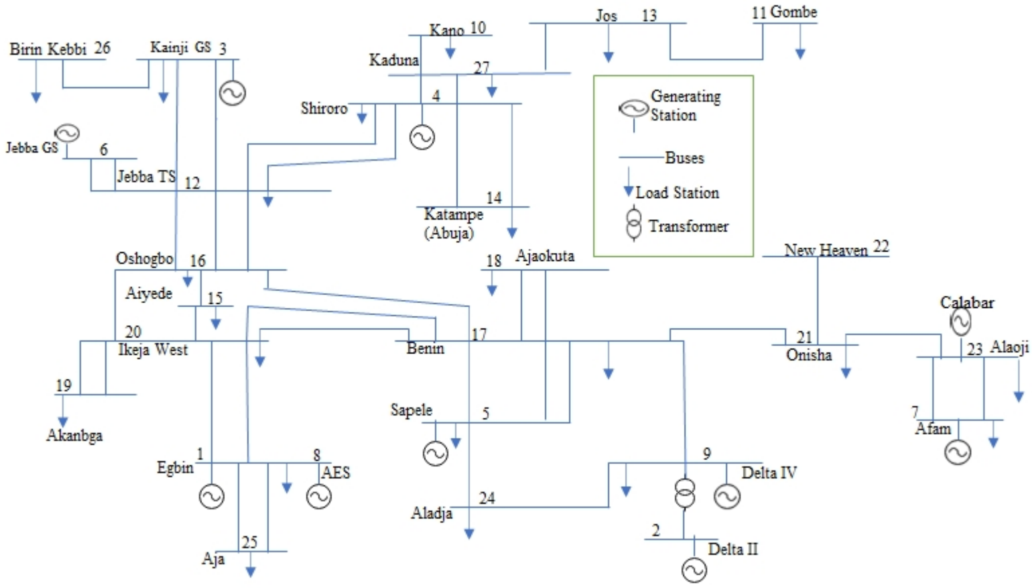


Figure 2.4: Single line diagram of Nigeria 330 kV line [27]

Non-technical issues like vandalism and poor government policies are some of Nigeria's causes of transmission line failure. Protecting the transmission line is very important, considering the associated faults, and this cannot be overemphasised. Firstly, it helps to identify and isolate the damaged section of the system to avoid system collapse. Secondly, it helps to protect against overload and fault current to feedback to the transformer or generators, which will help to provide steady electricity to end-users.

Nigeria uses an overcurrent distance protection relay system for its network. This scheme has some drawback which includes limited fault resistance measurement capacity. Table 2.1 describes the diagram in Figure 2.4, showing the bus number, bus rating, transformers, generating stations and load centres. In Nigeria, the network, as shown in Figure 2.4, consists of a 330 kV high voltage line with about 27 buses and ten generating stations scattered across the country. This transmission line is synchronised to a single network with a single control Centre only at Oshogbo [27].

2.4 Protection of Transmission line

The fault must be detected and classified for a transmission line to be fully protected. The location of the fault must be accurate for quick isolation of the line to protect it from system collapse. Figure 2.5 represent a simplified explanation of a network's fault correction flow. The input signal consists of high voltage

Table 2.1: Bus description of Nigeria 330 kV transmission system network [27]

Bus Number	Bus Name/Rating (MVA/MV)	Bus Number	Bus Name/Rating (MVA/MV)
1	Egbin (+800 MW)	15	Ayede (-77-j91) MVA
2	Delta (+300 MW)	16	Oshogbo (–120-j76) MVA
3	Kainji (+400 MW)	17	Benin (-161-j82) MVA
4	Shiroro (+600 MW)	18	Ajaokuta (–63-j32) MVA
5	Sapele (90 MW)	19	Akangba (-233-j119) MVA
6	Jeba GS (+300 MW)	20	IK West (-334-j171) MVA
7	Afam (+470 MW)	21	Onitsha(-131-j67) MVA
8	AES (+300 MW)	22	New Heaven (-113-j57) MVA
9	Okapi (+490 MW)	23	Alaoji(-164-j83) MVA
10	Kano (-253-j129) MVA	24	Aladja (-48-j24) MVA
11	Gombe (-74-j38) MVA	25	Aja (120-j62) MVA
12	Jeba TS (-8-j4) MVA	26	Birnin Kebi (-70-j36) MVA
13	Jos (-82-j42) MVA	27	Kaduna(-150-j77) MVA
14	Katampe (-200-j103) MVA		

sent to the current and voltage signal acquisition, which helps convert it to either analogue to digital or vice versa. The next stage is the data processing unit, which helps extract the data or signal the useful information needed in the module.

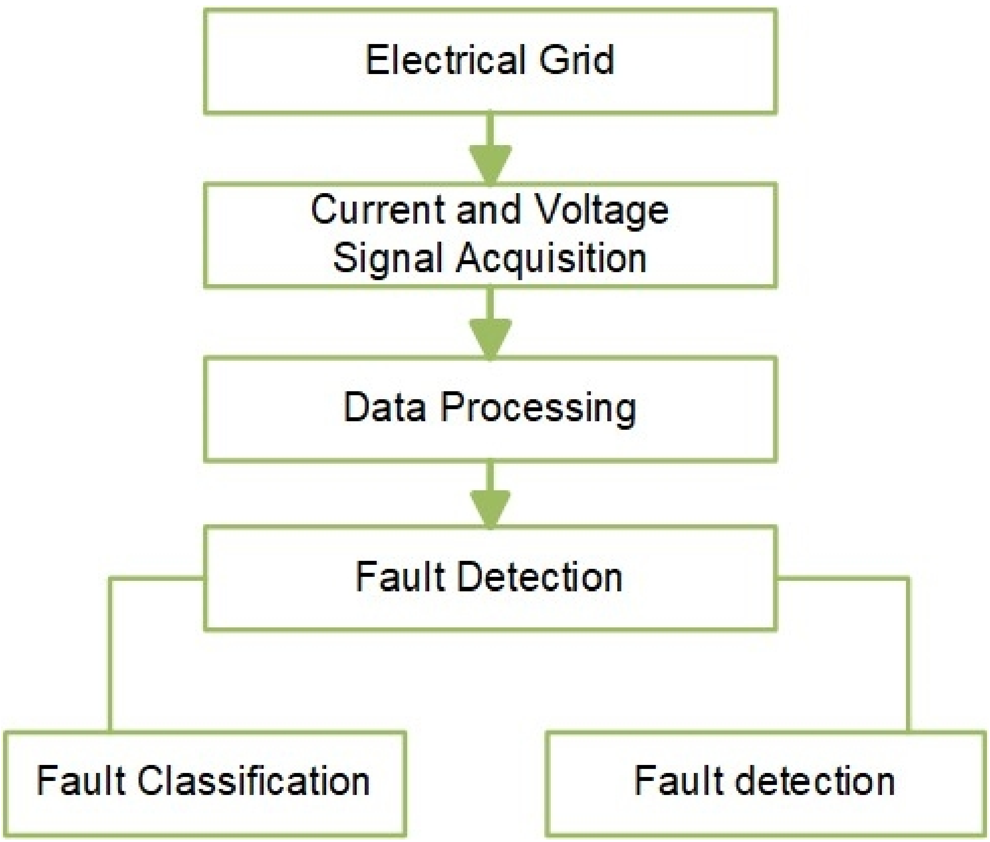


Figure 2.5: Fault location, detection and classification diagram [28]

The fault detection unit provides a reliable and fast relaying operation. The dominant protective relays for the transmission line are the overcurrent protection relay, directional overcurrent relay, distance relay, and pilot relay. This Relay helps to shield the line against symmetrical and unsymmetrical faults. However, it does not guarantee full protection due to frequent short circuit faults at the distribution network [29]. The fault locator and classifier section are used to locate the exact distance of the fault and determine the fault type and phase.

2.5 Relevant Research on Protection of Transmission Line

This section will discuss some approaches used to protect transmission lines and will be divided into fault detection, classification and localisation. Recent literature on fault in transmission line detection, classification, and location shows that many studies have been conducted on the subject. However, this research has identified some disadvantages and will be enumerated. Two major techniques have been used to analyse this concept: conventional and machine learningtechniques. The conventional methods include:-

1. Mobile robot approach
2. Distance relay approach
3. Wavelet transform approach
4. Fuzzy logic approach

Other hybrid techniques which involve the combination of two or three techniques include

1. Neuro-fuzzy technique
2. Wavelet and ANN technique
3. Wavelet and fuzzy-logic technique
4. Wavelet and neuro-fuzzy technique

The rising development of power systems calls for innovative fault diagnosis techniques to prevent unforeseen interruptions and expenses incurred due to power outages. Transmission lines are a critical component of such systems. Therefore, the machine learning techniques have been used for fault detection, classification

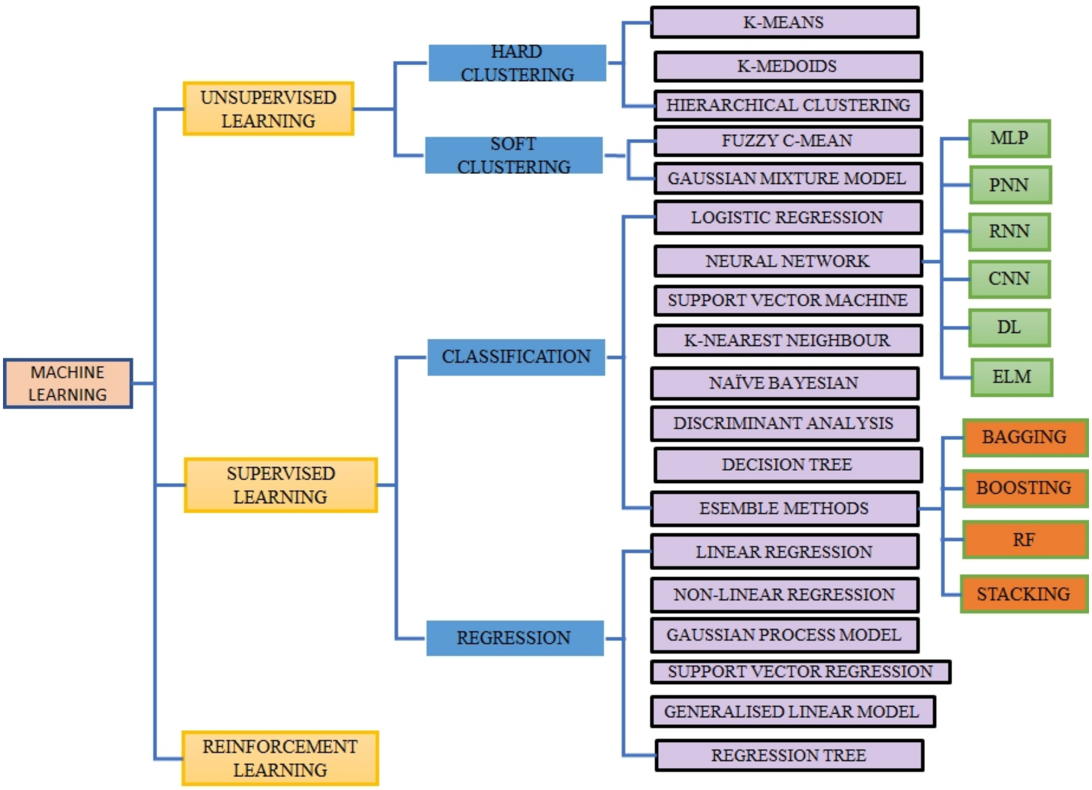


Figure 2.6: Summary of fault diagnostic techniques using machine learning [28]

and localisation of transmission lines and are discussed in this section as shown in Figure 2.6. Four main steps are performed in machine learning techniques employed for optimal performance. The first step is to collect data from TL current and voltage signals generated by power system simulators like Matlab/Simulink. Following that, data sampling approaches are employed. The third step is to apply data preprocessing and feature extraction methods such as Discrete Fourier Transform (DFT) and Discrete Wavelet Transform (DWT) to extract significant features. Finally, a method for fault identification (detection and classification of TL faults) and fault location estimation is identified [28].

2.5.1 Inspection Robot Approach

Using an inspection robot in a transmission line to check for mechanical damage has helped to reduce costs in terms of outages and man-hour wastage due to fault [24, 30, 31]. The three main robots used for inspection are climbing, flying and hybrid robots. The research proposed hybridising two robots into a single robot as a better power transmission line monitoring model. Some of the drawbacks of the paper include poor battery capacity, electromagnetic shielding, and advanced control for uncertainties such as wind disturbance [24]. Another research based on a mobile robot was designed with the help of a controller, a programmable device, an integrated circuit card, a monitor for the development network, and a mobile robot. The robot is placed on the transmission line, which assists in detecting mechanical faults on the transmission line [32]. This robot will send the information to the controller and appear on the screen. Also, another article on the multi-unit serial inspection robot the transmission network focused on designing a four tri-arm inspection robot mechanism that has an obstacle-crossing ability, uses fewer motors and is lightweight for motor and cable [31]. The article did not discuss lightning fault (overcurrent fault) and other symmetrical faults, so complete protection is not provided. Other advanced monitoring robots consist of advanced sensing and imaging system that can detect and jump over an obstacle, and the information will be monitored on a screen. The device consists of three main parts: the robot motion control unit, the communication control unit, and the remote monitoring control unit [32, 33]

2.5.2 Distance Relay Approach

In the distance relay approach, the overcurrent relays (OCR) are commonly utilised for transmission and distribution network protection. Because of the variable short-circuit levels and load profile, the growing use of dispersed generators in distribution networks poses a problem for traditional relays. The analysis may be performed in defective and standard settings using an adaptive Thevenin circuit equivalent [34–36]. The circuit equivalent variation influences the time-overcurrent relay characteristics: tripping time and pick-up parameters. This determines the time it takes for the relay to trip and the current to trigger to identify the fault location [29,37]. In [29], the method uses relay tripping time and current pick-up characteristics tuned to the Thevenin equivalents. The pick-up current is converted to impedance. Only the stepwise evolving Thevenin equivalent is considered for transformation and adaptation based on the least square estimate. Examples include power networks operating in an island mode or setups incorporating wind farms linked to the power grid. The Thevenin-equivalent-based technique reduced tripping time and adjusted the pick-up current to the equivalent impedance.

In [38] on 'the use of adaptive current protection scheme' highlights the challenges encountered in current differential protection concerning speed, accuracy, and sensitivity. This helps to detect the fault and the unreliability if such a protection scheme arises if the shunt capacitance current is neglected in the line. Also, errors may occur due to the core saturation with decaying DC.

A new approach for controlling restrictive areas for fast fault detection was introduced using the phasor approach for current differential protection with a series compensated transmission line as a reference. The electromagnetic transient program simulation was used to analyse the results [39, 40]. In [41], the Thyristor-controlled Series Capacitor (TCSC) was introduced as a high-frequency, extra-high voltage transmission line protection device. The result shows that introducing TCSC can affect the line if it fails to operate. The wavelet transform uses transient protection to solve the problems caused by TCSC. The analysis results demonstrated that the appearance of TCSC in extra-high voltage lines is accurate. Another paper used an extreme learning machine combined with the wavelet transform technique to test about 28,800 faults at different locations by changing the inception angle, fault resistance, distance, load angle, and percentage compensation level. MATLAB Simulink was used to simulate the result, indicating that the approach suits various systems and operating conditions [42].

2.5.3 Wavelet Transform Approach

The wavelet transform (WT) is a mathematical tool to analyse the power system transient signals. It dilates a single prototype function to decompose a signal into different scales with varying levels of resolution. It provides a local signal representation in both the time and frequency domains. This wavelet transform capability is used to locate, classify, and detect fault conditions. The basic idea behind wavelet analysis is to choose an appropriate wavelet function known as the "mother wavelet" and then analyse it using shifted and dilated versions of this wavelet [43]. In this method, the fault signals are transformed into various frequency bands using the discrete wavelet transform and the Daubechies wavelet transform, which may then be utilised to identify the faults [44,45]. These signals can be represented in terms of both the scaling and wavelet function, as shown in the equation 2.1 below;

$$f(t) = \Sigma_n CJ^n \Phi^{t-n} + \Sigma_n \Sigma_{j=0}^{J} d_j(n) 2^{\frac{j}{2}} \Psi(2^j t - n) \tag{2.1}$$

Where C_J is the J level scaling coefficient, d_j is the j level wavelet function. $\Phi(t)$ is the scaling function, $\Psi(t)$ is the wavelet function, J is the highest wavelet level, and t is the time. Each wavelet is created by the scaling and translation operations of the mother wavelet [43]. The continuous WT for a given signal $x(t)$ to the parent wavelet $\Psi(t)$ is shown in equation 2.2.

$$CWT_{\Psi} x(a,b) = W_x(a,b) = \int_{-\infty}^{\infty} x(t) \Psi a, b(t) dt \tag{2.2}$$

where $\Psi a, b(t) = \mid a \mid^{\frac{1}{2}} \Psi(\frac{t-b}{a})$, a (scale) and b (translation) are real numbers [46]. For discrete-time systems, the discretion process leads to the time-discrete wavelet series given in equation 2.3.

$$DWT_{\Psi}x(m,n) = \int_{-\infty}^{\infty} x(t)\Psi m, n(t)dt \tag{2.3}$$

Where $\Psi.m, n(t) = a_0{}^{\frac{-m}{2}}\Psi\left(\frac{t-nb_o a_0^m}{a}\right)$, $a = a_0{}^m$ and $b = nb_0 a_0{}^m$ [46]. The wavelet transform is a practical technique for classifying faults in a transmission line. This is explained in [46]. It recommends a system utilising the wavelet technique and current measurement to classify faults in the line. Analysis was carried out using MATLAB under diverse fault conditions. The stability of the line was tested using various fault criteria, and the results obtained were reliable. A pilot wavelet was chosen using multi-resolution analysis (MRA) to check the signal at multiple resolutions and frequencies, which is helpful for low-frequency signals. In [47], an in-depth discussion of the wavelet transforms (WT). WT is a popular feature extraction method in various fault diagnostic systems. In practice, discrete wavelet transform (DWT) is employed rather than continuous WT to extract the properties of voltage and current data over several frequency bands (CWT). Thus, choosing which mother wavelet (MW) and decomposition level to utilise before producing features using DWT is critical. In [48], a comprehensive analysis of several mother wavelets for fault detection and classification and suggested mother wavelets for fault identification. Although multiple sample rates were used, the frequency boundaries were more essential than the decomposition level. Coefficients are chosen as a feature as seen in [49–51] at various detail levels. In [52], the wavelet transform is used to decompose measured signals and extract the most relevant features, which aids in Support Vector Machine (SVM) training, notably in terms of achieving superior classification performance with high accuracy. After collecting functional characteristics from the measured signals, three SVM classifiers are used to make a fault or no-fault judgement on any phase or many phases of a transmission line. WT can also be used as a hybrid method for fault classification and location, as seen in wavelet and Artificial Neural Networks (ANN) [53–55], wavelet and fuzzy-logic technique [56–60]. Also, Wavelet and Neuro-fuzzy technique [61,62]. In [63], WT was used for data extraction and processing for a deep learning-based intelligent approach for fault detection and classification in transmission lines.

2.5.4 Fuzzy Logic Technique

Zadeh [64] invented fuzzy theory in the 1960s, but it has only recently become popular for fault detection and transmission line protection. Fuzzy logic systems are similar to humans' long-standing thinking abilities. It provides a trade-off between accuracy and importance, a skill to human data interpretation abilities. Fuzzy Logic (FL) is a soft computing method that depends on set theory perceptions relating to fuzzy systems, IF-THEN rules, which are a collection of linguistic and reasoning-based assertions. The method of generating a non-linear mapping between an input and an output envisioned using fuzzy logic is known as fuzzy inference. Any FIS comprises four main units: fuzzification, rule base, inference engine, and defuzzification. The fuzzification unit's goal is to execute a mapping from the scalar-valued input vector to the fuzzy matching set. The rule base is linguistic and user-specified. If the rules have several antecedents, various fuzzy operations produce a single firing point in the inference engine. The defuzzification component converts the fuzzy set output into crisp values comprising the FIS resulting output.

Various fault scenarios were thoroughly examined in [65]. Aside from examining symmetrical and unsymmetrical fault instances, a detailed examination of severe fault scenarios such as evolving faults, high impedance faults, and faults near the boundaries was conducted. The Mamdani-type FIS was designed using the Fuzzy logic toolbox in MATLAB. The following are the stages for designing the FIS system:

1. Define input and output: In this case, inputs are the essential components of voltage and current signals, and output is the circuit breaker's trigger signal.

2. Create a triangle membership function corresponding to the high, middle, and low input and output signal ranges.

3. Develop rules: For example, if the voltage and current signals are low, the trigger signal will also be low.

4. Simulation of the final system.

The block diagram in Figure 2.7 shows how voltage and current across each circuit component are measured for possible overcurrent and short circuit faults in major components. A fuzzy controller is created for each component. The number of monitored signals N is lowered as required, with voltages having precedence over currents since they are less costly and easier to measure. P values, such as mean

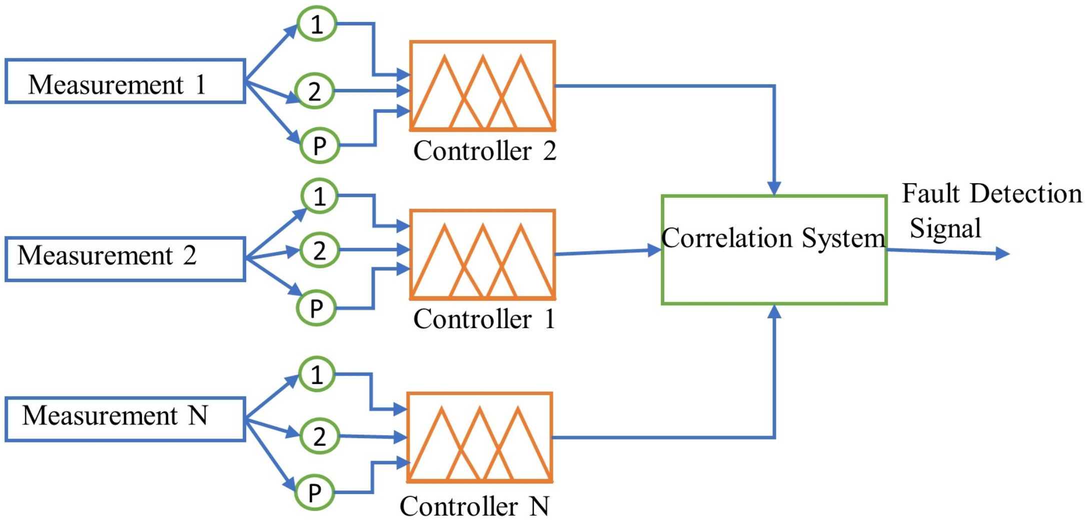


Figure 2.7: Block diagram of a fuzzy logic fault detection pathway

or RMS value, would then be determined for each N signal. These values are then supplied into fuzzy controllers, each devoted to a distinct failure mode. Fuzzy controllers use the P amounts per fault mode to provide an output value that is compared across all controllers. The correlation block in Figure 2.7 picks the highest value from all fuzzy controller outputs and declares a defect identified. When a failure is detected, redundant components are activated to replace the faulty component as required [66].

2.5.5 Real-Time Protection With Phasor Measurement Unit Technique

Monitoring the transmission line and its parameters (resistance, inductance, capacitance and shunt conductance) is necessary for transmission line protection [67]. The synchrophasor-based real-time transmission line parameter monitors the system by tracking the parameter using an estimation algorithm model to get accurate data from the Network. Real-time data were gathered from the utility network and simulated with the new algorithm proposed. It was observed that it performed better under unfavourable conditions. However, some of the traditional methods, such as the supervisory control and data accusation systems [68], digital fault recorders [69], and travelling wave fault locators [70], were also used. Other monitoring systems are based on informing the operator of the problem and fault in the Network, so the introduction of multi-agent systems has an intelligent response and self-troubleshooting of the system using MATLAB/Simulink to simulate the model. When an outage is detected, the system can disconnect the transmission line, clear the fault and provide flexible protection alternatives and fast response to a fault.

Another essential technique in the monitoring transmission line is the phasor measurement unit (PMU) technique. This device produces the harmonised measurement of real-time phasor of voltage and current. Harmonisation is accomplished by sampling voltage and current waveform using global positioning system (GPS) timing signals. PMU provides the magnitude and phase angle of the system in real-time [71]. In [72], it proposed a fault-monitoring methodology for alternative power grid monitoring. This module can classify and detect faults in a transmission line. This is achieved using PMU while studying the equivalent power factor angle (EPFA) variation to help detect a fault in the Network. A fault location method for two-terminal multi-section composite transmission lines that combine overhead lines and underground power cables that employ synchronised phasor measurements acquired by global positioning system (GPS)-based phasor measurement units (PMUs) or digital relays with embedded PMUs or fault-on relay data synchronisation algorithms. A unique fault section selector is expected to pre-select the fault line section [73]. The expected approach can find a problem on an overhead line or an underground power wire. The selected approach has a strong theoretical foundation regarding computational convolution and is undeviating and uncomplicated [54].

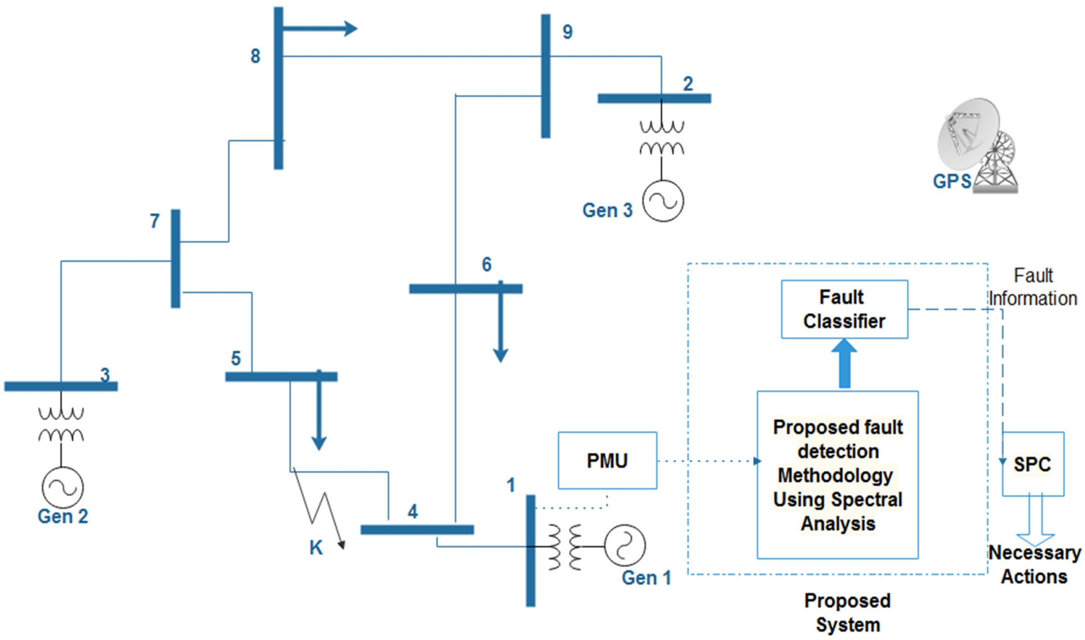


Figure 2.8: A Block Diagram of Fault Classification Technique Using The PMU

Figure 2.8 below represents a block diagram of a western system coordinating council (WSCC), which was modelled as a case study in [74]. The system line parameter was represented in [72]. The transmission line connected to buses 4 and

5 is taken as a case study. The fault was introduced at separate intervals of 20 km from bus 4. The equivalent power factor angle of generator one was selected for fault monitoring at a reasonable condition and had a constant value. In contrast, a line-to-ground fault occurs in loops 4-5 (20 km at bus 4) at 0.04 s with R of Zero ohms and fault inception angle (FIA) of 0^0. Also, [75] analyses the deviation of transient power and the relationship between the network specification during the fault. This is accomplished by aligning voltage and current at both ends of the line to discover an internal and external fault and a DC fault.

Comparing the different protective schemes in transmission line

The various conventional protective schemes have advantages and disadvantages, as seen in Table 2.2 based on techniques and configuration of their fault types and methodology used in fault classification, detection and localisation. Also, table 2.3 compares the input and output data needed for simulations or training of the various techniques.

2.6 Machine Learning and Artificial Intelligence Technique

Several machine learning and AI techniques have been used in fault detection, classification and localisation. These techniques are shown in Figure 2.6 and will be explained in detail.

ML is a family of algorithms that, unlike traditional or heuristic algorithms, can learn from datasets without being explicitly coded [85]. They have been used in various domains, including natural language processing and computer vision. They are presently gaining popularity in wireless communications for the following reasons [28, 86, 87]: For starters, they may discover hidden user behaviours or network features from past data that cannot be analysed analytically. Second, unlike heuristic algorithms, they can adapt to changing network circumstances to optimise network performance. Finally, they need little human intervention in the deployment process, making them a catalyst for network automation or self-organizing networks. They are generally classed according to the quantity and kind of supervision they get throughout their training time. ML algorithms are classified into six categories: supervised learning (ML), unsupervised learning (UL), semi-supervised learning, deep learning (DL), reinforcement learning (RL), and federated learning (FL). However, only supervised techniques are presented in this thesis since these methods are used for defect detection, classification, and

Table 2.2: Comparing the different protection schemes

Protection Type	Method Used	Advantages	Disadvantages
Series compensated transmission line.	The use of KR9 1 and EM9 1 Relay	Initiation of the trip after fault.	No-fault identification
Current differential protection	Dynamic phasor and series compensated TL	Speed and accuracy in detecting faults	No-fault correction and isolation
Thyristor-controlled series capacitor	Thyristor-controlled series capacitor (TCSC)	Fault location and identification fault isolation	No fault isolation
Wavelet Approach	WT and DWT	Fault classification and detection	No-fault isolation and Relay reclose
ANN Approach	Uses ANN, Distributed and hierarchal Neural Network, Backpropagation	Fault classification, detection and identification	No-fault isolation
Fuzzy Logic Approach	Fuzzy logic	Fault identification	No fault isolation
Fuzzy and ANN	ANN, Fuzzy logic and Fuzzy set approach	Fault classification and identification	No-Fault correction
Wavelet and ANN	DWT, ANN and Continuous Wavelet Transform (CWT)	Fault identification, classification and location	No-Fault correction
Monitoring robot	Uses a sensor robot	Fault location and mechanical fault or cable damage	Cannot detect symmetrical and unsymmetrical fault
PMU Technique	uses EPFA, GPS and PMU	Detect the exact location and fault classification	No-fault classification and fault correction
Transcient power Measurement technique	PMU	Fault isolation and identification	No fault correction
Distance relay technique	Distance relay, microprocessor based distance relay	Fast and accurate detection of fault and isolation	No accurate monitoring of fault location
Extreme learning machine	WT-ELM, DWT	Fault identification and selection	Lack of fault isolation

Table 2.3: Comparing input and output data on the various technique

Technique used	**Line length (Km)**	**Fault resistance (Ω)**	**Input data**	**% error**	**Accuracy**	**Output**	**Ref.**
ANN	100	1 – 100	Fault current and voltage	Min. 1.472, max. 7	78% - 99.9%	Detection, classification	[75]
SVM	200	0 – 50	LLL fault current	0.015 – 0.7	99.833%	Detection, location	[52]
WT and SVM	330	0.01-50	Fault current	-	100% for Gaussian and Polynomial kernel function	Classification, detection	[52]
Extreme learning machine (ELM)	100	0-100	Fault current signal	1.3%-4.8%	98%	Classification	[76]
PCA	150	0.0585	Single line fault	0.011% -2.413%	99.129%	Localisation	[77]
T-transform and PNN	300	0-100	Fault current signal	-	90%-100%	Classification and detection	[78]
SRC and RDRP	300	0.1148-44.92	Three phase fault voltage	-	99.3%-99.6%	Classification	[79]
Fuzzy logic	300	0.001	current signal	-	97%	Classification and Detection	[80]
Fuzzy logic and WT	300	0-50	current signal	-	99%	Classification	[56]
WT	60	50	current signal	0.1%	89%	Localisation	[81]
Least Square Error	100	-	current and voltage magnitudes	0.0099%	-	Localisation	[82]
ANN and WPT	360	-	current signal	2.05%	98%	Localisation	[83]
Fuzzy-neuro method	177.4	-	current and voltage signal	0.1%	-	Detection	[84]

localisation.

2.6.1 Artificial Neural Network Technique

Artificial Neural Networks have traditionally been used with great success in various sectors of fault analysis. This is one of the most extensively utilised artificial intelligence technologies, critical in constructing a robust power system failure management model. An ANN model typically has three primary layers: input, hidden, and output. The input layer receives data or signals from the model, which can be fault current or voltage sent into the model. The hidden layer extracts patterns associated with the analysed process or system. The output is in charge of creating and displaying the final network output. These layers handle most internal network processing, which involves the results processed from other layers. ANN has several advantages that allow it to be widely used in developing fault management models that are exceptionally effective [88].

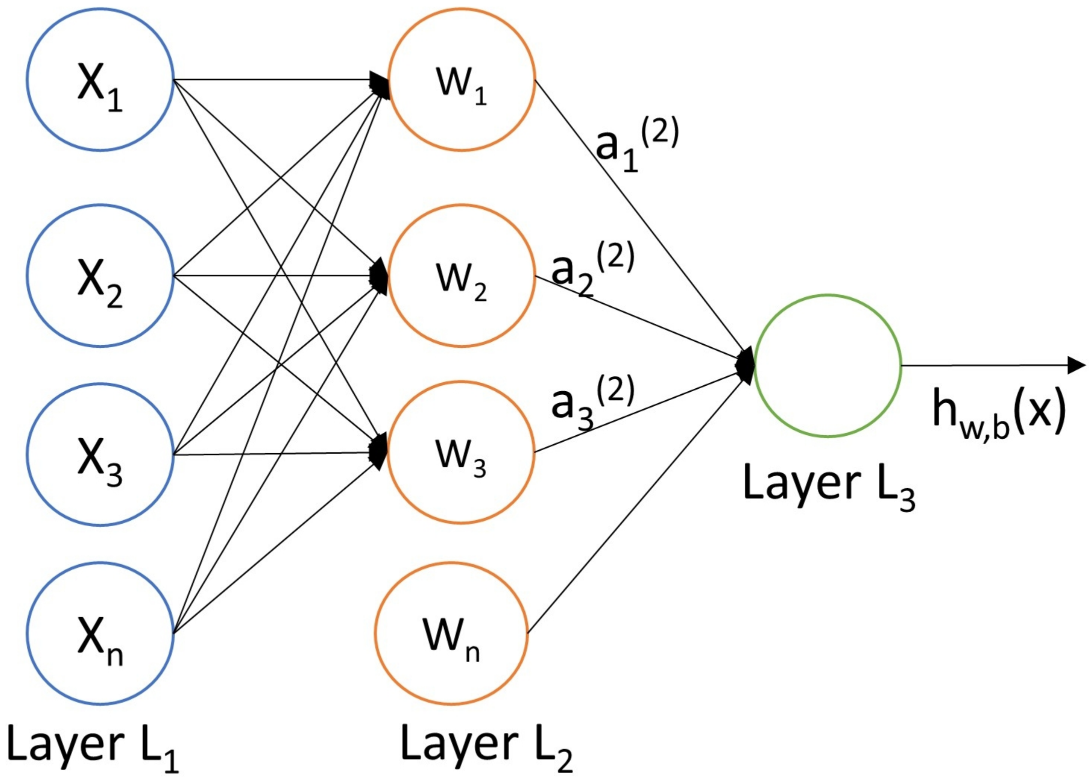


Figure 2.9: A multi-layer Artificial Neural Network model

Figure 2.9 is a multi-layer neural network, and $X_1, X_2, ..., X_n$ represents the external source input signal which represents the faulty current and voltage signals. $W_1, W_2, ..., W_n$ represent every input variable's synaptic weights and enable the evaluation of their importance to the model's functionality. for a fixed training dataset of $(x^{(1)}, y^{(1)}), ..., (^{m}, y^{(m)})$ of m training sample, and using the batch gradient decent, the cost function for a single dataset is given by equation 2.4

$$J(W, b; x, y) = \frac{1}{2} \parallel b(x) - y \parallel \tag{2.4}$$

while for a training set of m sample is defined as shown in equation 2.5 and 2.6

$$J(W, b) = \left[\frac{1}{m} \sum_{i=1}^{m} J(W, b; x^{(i)}, y^{(i)}) \right] + \frac{\lambda}{2} \sum_{l=1}^{nl-1} \sum_{i=1}^{s} l \sum_{j=1}^{sl+1} (W_{ji}^{(l)})^2 \tag{2.5}$$

$$= \left[\frac{1}{m} \sum_{i=1}^{m} \left(\frac{1}{2} \parallel hw, b(x^{(i)} \right) - y^{(i)} \parallel^2) \right] + \frac{\lambda}{2} \sum_{l=1}^{nl-1} \sum_{i=1}^{s} l \sum_{j=1}^{sl+1} (W_{ji}^{(l)})^2 \tag{2.6}$$

where $J(W, b)$ is an average sum of the square error term and equation 2.6 is the weight decay or regularisation term that decreases the weight's magnitude and helps prevent overfitting. Also, λ is the weight decay parameter.

Σ is the linear aggregator that combines all input signals weighted by synaptic weights to generate an activation function. θ Is the activation threshold or bias used to identify the suitable point that the linear aggregator makes. U denotes the activation potential. If this value is positive, then $U \geq \theta$, the model has an excitatory potential; otherwise, it will be inhibitory. g is the activation function, while y is the output signal. The result produced by ANN, as proposed by McCulloch and Pitts [88], is represented by equation 2.7

$$U = \sum_{i=1}^{n} w_1.x_i - \theta \tag{2.7}$$

And $y = g(u)$. Therefore, the ANN gives the model a set of values that reflect the input variable by multiplying each neuron input from its associated synaptic weight, calculating the activation potential from the weighted sum of the input signal, and removing the activation threshold. It also employs an appropriate activation function in the activation potential to restrict neuron output and assemble it by applying the neural activation function. The error of a neuron j in the output layer Y is given as shown in equation 2.8

$$E_j = \frac{1}{2}(R_j - Y_j)^2 \tag{2.8}$$

Where R_j is the predetermined value, and the total error E of the output layer is shown in equation 2.9

$$E = \Sigma_j E_j = \frac{1}{2}\Sigma_j (R_j - Y_j)^2 \tag{2.9}$$

To reduce the error E in terms of the weight change ΔW_kj and using the delta rule to integrate the learning rate α in addition to the gradient descent method strategies for defining weight change, as shown in equation 2.10

$$\Delta W_kj = -\alpha.\frac{\partial E}{\partial W_kj}; 0 < \alpha \leq 1 \tag{2.10}$$

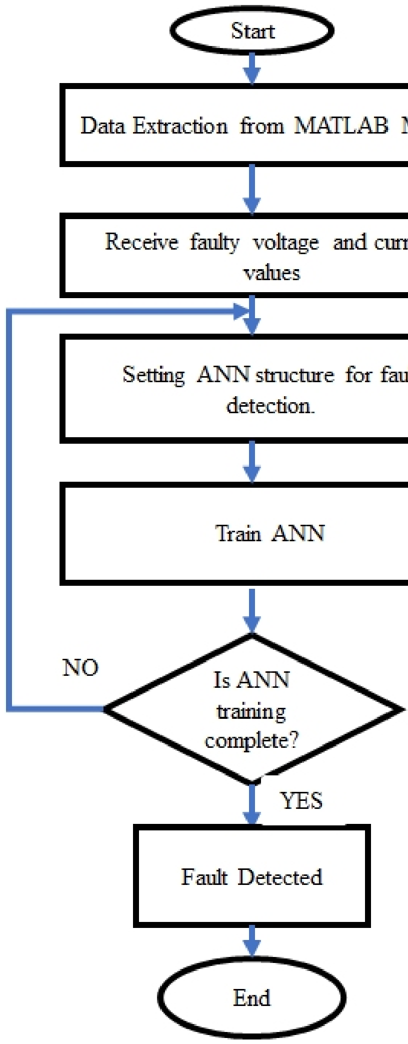


Figure 2.10: A flow chart for ANN algorithm for fault detection [89, 90]

The weight change will be negative if the gradient is positive and vice versa if the gradient is negative. As a result, a negative symbol has been placed on the right side. It has been demonstrated that backpropagation learning with enough hidden layers may estimate any nonlinear function to arbitrary precision. As a result, the backpropagation learning neural networks are excellent for signal prediction and system modelling [91]. The flow chart in Figure 2.10 describes how the algorithm is executed from the data extraction to fault detection. This is achieved by:

1. presenting a set of values to the neuron, representing the input variables.
2. Each neuron's input should be multiplied by the corresponding synaptic weight.
3. The activation potential created by the weighted sum of the input signals is obtained, and the activation threshold is subtracted.
4. using a suitable activation function to reduce the output of the neurons.
5. Utilize the neural activation function in the activation potential to compile the output.

The multiple layers comprise one or more hidden neural layers and solve various issues, such as function approximation, pattern classification, system identification, process control, optimization, and robotics [92]. The multi-layer typically has three classes of layers: an input layer, which is used to transfer the input vector to the network, hidden layers of computation neurons; and an output layer, which is made up of at least one computation neuron and produces the output vector [93].

The ANN has been used in different literature for fault detection, classification and localisation. In [94], the ANN was used in power systems for pattern recognition and classification to detect quantities like noise absorption and fault tolerance. These will not affect the variation in system parameters, which include system voltage and line current. This technique was applied in the power system, and positive feedback was attained [95]. Also, in [96], A 230 kV, three-phase, the two-machine power system was used to analyse the measurement of the transmission line problem. The training pattern was developed by simulating the various faults on the Network. Parameters like fault location, fault type, resistance and initiation time were varied to achieve the practice template to cover many fault conditions. A total of 3600 models and a transmission line distance of 100 km were initiated in the training ANN distance relay. Some of the significant areas of ANN that can be implemented include fault detection and classification, and in this method, a three-phase voltage and current are fed at one end. The feed-forward ANN propagation design was introduced to identify and classify faults in the three phases. These faults are simulated with diverse parameters to test the efficiency of the process using MATLAB [97].

In another article titled application of ANN in protective relaying of the transmission line, the writer used the ADALINE model to explain the use of ANN in transmission line protection, considering the distance relay. The model could locate the operating point correctly in the decision space. The ANN is used as a conversational relay with two inputs: current and voltage, and the suggested quantity can be used to model the microprocessor framework [98]. Also, in [99,100], an Investigation of Faults in the Nigerian Power System Transmission Line Using ANN focuses on performing three functions: detection, classification, and isolation of faults. It detects two signals and chooses the best signal with the least error as output; it also classifies signals based on preference and isolates the signal with the most severe fault.

ANN technique has been used to model the Nigerian Network. The article evaluated the performance of ANN-based relays linked to both ends of the line using the feedforward non-linear managed backpropagation method. PSCAD/EMTP software was used to model the Network. The fault was generated from both sides of the transmission line, and two different power sources were fed into the system with different fault inception angles, locations, and resistance. The fault current will be analysed and used for the testing and training of data using MATLAB. The result was simulated and confirmed using data from a microprocessor-based Relay connected to the Network. This shows that ANN accurately identifies, classifies, and localises the genuine fault on the transmission line more precisely [99]. The analysis was also done using regression analysis and the mean square error (MSE). Regression analysis is used to test and analyse the system and the output of the system. If regression is 1, there is a closed relationship between the output and target, but if regression is zero, it means that the system has not yet converged, and their difference is still huge, which shows that the Network needs to be checked for faults. On the other hand, the MSE tests the average square difference between normalised output and the target. When MSE is zero, it shows no error in the process, but the error is higher if it is more significant than 0.4. Therefore, for a sound system, MSE should be within the range of 0.0000 to 0.4000 [100]. Also, in [101] backpropagation technique was used to detect and identify the fault on the Network. It was trained with conjugate gradient backpropagation with high accuracy and low percentage error.

2.6.2 Support Vector Machine Classifier Technique (SVM)

SVM, a supervised ML approach capable of solving regression and classification issues, is one of the most extensively used classification algorithms [102]. Its benefits over other ML methods include being quick and easy to build, having minimal processing burden, and providing excellent accuracy even with little data. SVM locates a hyperplane in an N-dimensional space, where N is the number of attributes used to classify the data. SVMs can classify faults in TLs and use an alternate loss function to determine fault locations. Depending on the dataset, SVM employs linear or non-linear kernels such as polynomial, Gaussian, and radial basis function (RBF) [103]. It can also solve multi-class classification problems, and it helps to minimise cost function (F) as shown in equation 2.11 [104–106].

$$F = \left[\frac{1}{n} \sum_{i=1}^{n} max(0, 1 - y_i(w^T x_i - b)) \right] + \lambda \parallel w \parallel^2 \tag{2.11}$$

Where y_i is the ith target, w is the weights matrix and $w^T x_i - b$ is the ith output, and λ is the weight decay enhances the margin size and keeps the data point x_i on the correct group.

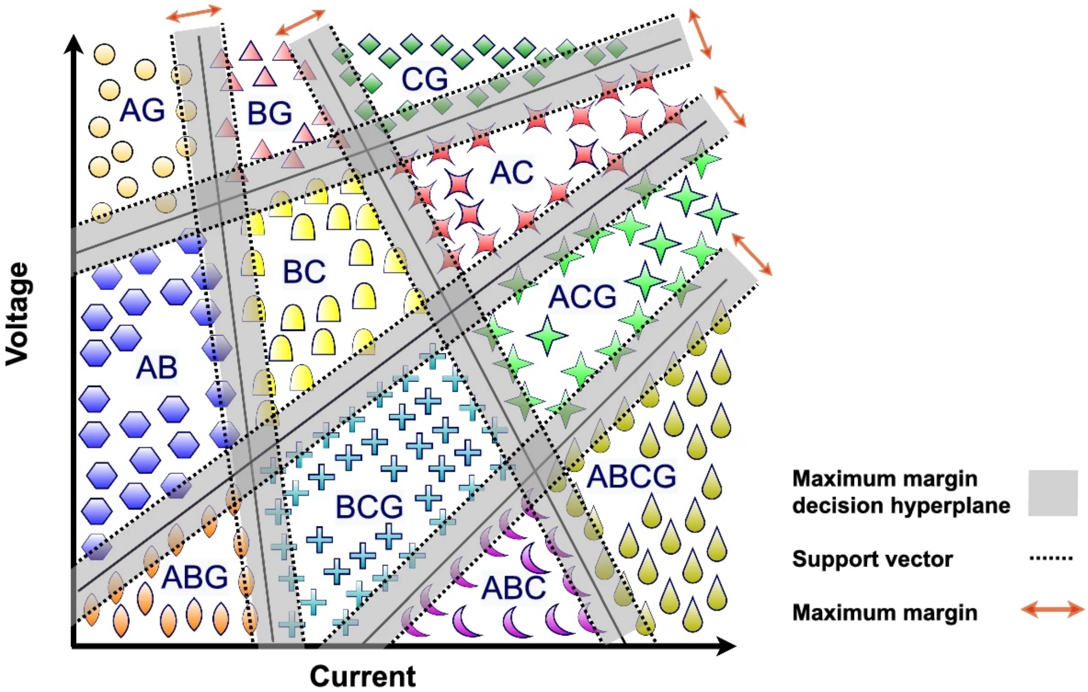


Figure 2.11: Schematic of 11 transmission line fault classification using SVM

Figure 2.11 shows a hint of the SVM approach of fault classification. The black dotted lines in this figure represent the hyperplanes that divide the fault types, shown in different forms. The broad grey lines represent class margins, whereas the solid black lines represent the maximum margin decision hyperplane.

2.6.3 Supervised Learning Techniques

Supervised learning is the process of learning a mapping between a collection of input variables X and an output variable Y and then using that mapping to predict the outcomes of unseen data. The most significant approach in machine learning is supervised learning, which is especially crucial in processing multi-media data. Supervised learning techniques generate models from this training data, which may be used to categorise additional unlabeled data [107, 108]. This research will be limited to a supervised learning algorithm to classify, detect and locate faults on the transmission lines.

Classification Technique

The classification methods are used to categorise the input data. The classifiers generate a discrete answer since they only estimate the class of unseen data based on the class labels in the previous dataset. Input data is classified using classification models, fault classification, voice recognition, and credit scoring are examples of typical uses [109]. A summary of supervised learning-based techniques used in fault detection and classification is shown in Table 2.4 below, showing the fault type, an application used for the simulation and the type of fault analysed.

Fault Localisation Techniques

Accurate and exact fault location is critical for expediting transmission line restoration, reducing outage duration, and significantly enhancing system dependability. Fault location is defined as physically identifying the location of a fault in a power system. Fault location in transmission lines is becoming more critical in power system research [120, 121]. Different approaches have been used to solve transmission line fault localisation, and the supervised learning-based methods are summarised in Table 2.5 below.

Fault Detection Technique

Normally, fault detection comes before classification and location estimate. The extracted characteristics are used to identify faults. When using a self-governing approach for fault detection, the classifier and locator are triggered only when a defect has been definitively discovered. Furthermore, there is no need to develop fault detection algorithms when classifiers and locators can differentiate between normal and abnormal circumstances [45]. The various supervised learning-based fault detection techniques are shown in Tables 2.4 and 2.5, enumerating the fault type, software used for fault data extraction, and the application area covered.

2.6.4 Research Gap on Transmission Line Protection Techniques

Recent literature on fault detection, classification, and location in transmission lines shows that much research has been done on the topic. However, this research

Table 2.4: Machine Learning-based Fault Detection and Classification Techniques

ML Technique Used	Fault Type	Application Area	Software used	Fault Analysed	Reference
CNN	Three phase fault	220 kV, 100 km Line	MATLAB	Detection and Classification	[110]
SVM	Three Phase Fault	213.15 W PV panel connected to grid at 400 V	MATLAB	Detection and Classification	[111]
DT	Three Phase fault	400 kV, 100 km Line	ATP-EMTP	Detection and Classification	[112]
HLCL	Incipient fault	IEEE-13 Bus system	PSCAD	Detection and Classification	[113]
KNN	Three Phase fault	90 km Line prototype	MATLAB	Classification	[114]
DNN	Three phase fault	IEEE-34 bus system	DigSILENT Power Factory	Calssification and Detection	[115]
RF	Three Phase Fault	9216 fault case	PSCAD	Classification	[116]
ANN	Three Phase Fault	IEEE-13 Bus System	OpenDSS	Detection and Classification	[117]
DBN	Three Phase Fault	IEEE-34 bus system	MATLAB	Detection and Classification	[118]
AdaBoost+Cart	L-G Fault	10 kV Distrubution System	PSVAD	Detection and Classification	[119]

Table 2.5: Machine Learning-based Fault Localisation Techniques

ML Technique Used	**Fault Type**	**Application Area**	**Software Used**	**Output**	**Ref.**
PCA	Three Phase Fault	220 kV Line	PSCAD	Localisation, Detection	[122]
GPR, SVM	Three Phase Fault	132 kV	DigSILENT Power Fctory	Localisation detection Classification	[123]
PNN	Three phase Fault	400 kV, 300 km	MATLAB	Localisation Detection Classification	[124]
CNN, DQN	L-G Fault	230 kV, 72 km	-	Localisation Detection	[125]
ACNN	Three Phase Fault	IEEE-33 Bus System	MATLAB	Localisation Detection Classification	[126]
ANN, GPR	High Impedance Fault	22 kV	Power World	Localisation Detection Classification	[127]
SVM	Three Phase Fault	400 kV	ATP	Detection Localisation Classification	[68]
ELM	L-G Fault	500 kV, 300 km	MATLAB	Localisation	[128]
GCN, PCA + SVM	L-G,L-L LLG Fault	EEE-123 Bus System	Open DSS	Localisation	[129]
Bagging, Boosting, RBFNN	Three Phase Fault	750 kV, 600 km	MATLAB	Localisation Classification Detection	[130]

has identified some drawbacks and will be enumerated. Two major techniques have been used to analyse this concept: conventional and machine learning techniques. The conventional technique include distance relay approach [131], the use of mobile robot [32, 132–135]. Fuzzy logic approach [56, 57, 84], wavelet approach [46], Neuro-fuzzy technique, wavelet and fuzzy approach [62, 136]. While the machine learning approach includes the Artificial Neural Network (ANN) [99, 137], Support Vector Machine (SVM) [1,138], Decision Tree (DT) [139], Principal Component Analysis (PCA) [77]. All these methods have been successful based on their accuracy and precision of classification and localisation of faults. However, there is some hindrance which will be discussed in the literature. Some techniques, like the Wavelet Technique WT, are useful when time and frequency data are needed and are sensitive to noise and harmonics. It also requires a high sampling rate and is time-consuming because getting a referred wavelet and the number of decomposition is done by trials. WT and ANN are predominantly used for fault detection and classification [55].

Many hybrid methods, such as S-transform and ANN, have been combined to analyse faults in different scenarios. This method was used to detect and classify faults on the transmission line. Though the ANN and SVM have produced good results in identifying faults, they need a large volume of data for their training, making it complex to handle [140].WT detects faults accurately and instantly, though it is difficult to differentiate between the various fault conditions [141]. Although most of these methods have been used recently, some challenges exist, such as not being applicable for high-frequency signals and high computational complexity for Hilbert-Huang transform HHT [142]. Using Principal Component Analysis in machine learning is a fast and straightforward method that minimises re-projection error and is immune to noise. However, the convergence matrix is always large if the number of dimensions exceeds the number of data points, making it challenging to obtain the convergence matrix [143]. The DT is another technique used in fault classification, though it uses RMS current and DWT to generate data for the fault classification. The classifier performance of different parameters is used to obtain the best decision tree classification. [139].

Also, in [141], three ANN approaches were compared to each other for fault classification. They include PNN, Back Propagation Neural Networks (BPNN) and Radial Basis Function Neural Networks (RBFNN). These methods had their drawbacks because they were used on faulty voltage and current signals and focused more on the time and speed of execution of the training. Although most of these methods have been used recently, some challenges exist, such as not being applicable for high-frequency signals and having high computational complexity, as found in Hilbert-Huang Transform (HHT) [144]. The Convolutional Neural Network (CNN) is another technique used in fault classification with positive output in accuracy and speed. Still, the computational cost for offline analysis is relatively high [143]. Principal Component Analysis (PCA) in machine learning is a fast and straightforward method that reduces re-projection error and is immune to noise. It is also used to map data from multidimensional space to low dimensional subspace to mitigate dimensionality, where the variance of the data can be perceived in the best way possible. Also, the Kernel Principal Component Analysis (KPCA) and the SVM are used for real-time fault diagnosis of high-voltage circuit breakers, where a sample reduction algorithm based on similarity degree function is used to analyse the similarity between samples to detect faults [145]. Dynamic Kernel Principal Component Analysis (DKPCA) [146]. However, suppose the number of dimensions exceeds the number of data points. In that case, the convergence matrix is always significant, making it challenging to obtain the convergence matrix for data with varying properties and capabilities [143] and [79].

Deep learning intelligent diagnosis techniques have also been used in fault classification, such as the Wavelet Packet Distortion and Convolutional Neural Network [147]. It applies the wavelet packet distortion to generate a faulty data sample, while the convolutional neural network is used to classify the fault into different categories. However, the wavelet packet function uses Daubechies wavelet (DB4) for extraction, which does not have a theoretical justification. The Adaptive Intraclass and Interclass Convolutional Neural Network (AIICNN) [148] is applied in the algorithm to enhance sample distribution differences by applying designed intraclass and interclass constraints. While the 1-D Convolutional Neural Network (1dCNN) has an activation function added to it to enlarge the heterogeneous distance and reduce the homogeneous distance between samples for proper classification. Normalized Conditional Variational Auto-Encoder with Adaptive Focal Loss (NCVAE-AFL) are also used to classify faults into different categories [149]. In [14], the convolutional Neural Network and Long Short Term Memory (CNN-LSTM) were used to identify and locate fault using the frequency response analysis (FRA) to extract the fault. This method is used to detect faults timely and accurate.

Each of the methods mentioned above has disadvantages and limitations. Some of the main noticeable observations are the inability of most articles to extensively explain fault classification in terms of fault clearing time, thereby making it difficult to isolate or take on significant fault repairs within the shortest possible time. Also, discrete wavelet transform (DWT) and Decision Tree [150] have limited time resolution capability and low performance for high-performance faults. Wavelet and Data mining [150], K- Nearest Neighbours (KNN) and Decision Tree [151], are limited to the fault classification technique only without considering the speed and precision of the result. In [152], fault classification was not determined in the S-transform technique, and the effect of noise in the transmission line was not considered in the model [153]. Differential and Hibert-Huang transmission methods are expensive and have no-fault directions. In addition, for fault classification, the mathematical morphology and Recursive Least-square (RLS) methods [154] involves using a mathematical morphology-based fault feature extraction scheme. This method has high calculation and technical standards that require a professional to implement. Furthermore, they use either single phase-to-ground or double phase-to-line fault data for their training [77, 144, 155]. Another shortfall of most methods is the inability to consider noise and disturbance in the transmission line networks since they are inevitable. This method will also address the effect of noise signals and disturbances and how they can be reduced or eliminated for optimal system performance and the accuracy of results.

Table 2.6: Comparing the different protection schemes

Protection Type	**Method Used**	**Advantages**	**Disadvantages**	**Ref.**
Series compensated TL	The use of KR9 1 and EM9 1 Relay	Initiation of the trip after fault.	No-fault identification	[156]
Current differential protection	dynamic phasor and series compensated TL	Speed and accuracy in detecting faults	No-fault correction and isolation	[40]
Thyristor-controlled series capacitor	TCSC)	Fault location and identification fault isolation	No-fault isolation	[41]
Wavelet Approach	WT and DWT	Fault classification and detection	No-fault isolation and Relay reclose	[157]
ANN Approach	Uses ANN, Distributed and hierarchal Neural Network, Backpropagation	Fault classification, detection and identification	No-fault isolation	[75]
Fuzzy Logic Approach	Fuzzy logic	Fault Identification	No-fault isolation and reclose	[62]
Fuzzy Neural Network Approach	ANN, Fuzzy logic and Fuzzy set approach	Fault classification and Identification	No-fault correction	[84]
Wavelet and ANN Approach	DWT, ANN and CWT	Fault Identification, classification and localisation	No-fault correction	[158]

Protection Type	**Method Used**	**Advantages**	**Disadvantages**	**Ref.**
Monitoring Robot Technique	Sensor Robot	Fault Location and mechanical or cable danage	cannot detect symmetrical and unsymmetrical fault	[84]
PMU Technique	EPFA and GPS	Detects exact location and Fault Classification	No fault classification and fault correction	[67, 72]
Transcient power measurement technique	PMU	fault identification and isolation	No fault correction	[159]
Distance Relay Technique	Distance relay Microprocessor-Based distance relay	fast and accurate detection of fault and isolation	No accurate monitoring of fault location	[39]

2.6.5 Comparing the Tripping and Settling Time of ANN and Fourier Technique

Comparing the tripping time of the protective Relay at different kilometres using ANN and the Fourier Algorithm in Tables 2.8 highlights the time it takes the Relay to trip and settle back to normal. About 32 cases were analysed for all the voltage levels and line lengths. At the end of every voltage level, it shows the percentage of faults where the Fourier algorithm is slower than the ANN [160].

Table 2.8: Comparing the Medium time of tripping in milliseconds for ANN and Fourier algorithm technique

Voltage level	Algorithm	50 km	74 km	150 km
138 kV	ANN	6.88	8.16	6.90
	Fourier Algorithm	14.20	15.63	13.70
	No. of Cases	97	100	100
345 kV	ANN	11.40	10.55	9.75
	Fourier Algorithm	16.70	16.20	15.40
	No. of Cases	100	100	100
500 kV	ANN	7.60	6.77	6.17
	Fourier Algorithm	13.06	12.43	12.56
	No. of Cases	97	97	97

Table 2.9: Comparing the Medium time for settling in milliseconds for ANN and Fourier algorithm technique

Voltage level	Algorithm	50 km	74 km	150 km
138 kV	ANN	12.28	13.65	12.17
	Fourier Algorithm	17.97	18.75	18.12
	No. of Cases	94	97	100
345 kV	ANN	17.15	17.57	18.46
	Fourier Algorithm	19.50	18.30	18.53
	No. of Cases	75	69	100
500 kV	ANN	36.85	35.03	44.42
	Fourier Algorithm	16.85	17.00	16.93
	No. of Cases	41	47	35

From Table 2.9, the ANN-based algorithm performs better than the Fourier algorithm for transmission lines with a range of 345 kV. Also, this is more reliable than the ANN-based algorithm for cases where the voltage level of transmission lines is higher than 345 kV. Also, the impact of fault resistance on the accuracy of the evaluated impedance was analysed. It was discovered that the reactance and the fault resistance of the measured Relay depend on the line to the fault load [160]. The fuzzy logic-based protection system is easy to implement, and the results are accurate under the assumption of fault distance, fault resistance, line length and pre-fault power flow. Although accuracy cannot be guaranteed in large networks, the fuzzy-neuro approach is introduced because of its reliable relaying algorithm during the execution and classification of the fault. This sensitive change requires a massive dataset for training and many neurons, which affects their accuracy and speed in protecting an extensive network [136].

2.7 Summary of Literature Review

Considering the benefits and drawbacks of the aforementioned classifiers, it is possible to conclude that machine learning-based approaches offer preferable solutions to Transmission line faults detection, classification, and localisation estimation issues. The ELM Supports noisy datasets, simple implementation, very quick training time, high prediction accuracy, and faster performance speed than Feedforward neural network(FNN) [161] and other conventional and hybrid methods.

The hybrid method does not have a robust system and inefficient noisy dataset handling, slow training and testing process, a heavy computational load and sensitivity to feature selection methods.

A detailed evaluation of Machine Learning approaches for faults detection, classification, and localisation in transmission lines has been provided. These approaches have been classified into three categories: conventional, hybrid, and machine learning. The core concept, essential equations, and significant papers are presented and summarised for each approach. In this chapter, the significance of this survey is addressed in comparison to the current review studies. Moreover, the benefits and drawbacks of machine learning methodologies have been thoroughly examined and summarised to give a clear road map for future study. Overall, research contributions in modelling transmission line protection schemes have significantly improved protection schemes' efficiency, accuracy, and reliability. These advances have played a critical role in ensuring power systems' safe and reliable operation.

Chapter 3

TL Fault Classification using CatBoost

3.1 Introduction

The electrical power system consists of different segments interacting with each other, including generation, transmission, and distribution. The transmission line is an integral part of the power system since it transfers electricity from the generating station to the distribution and the end-users. These components are interconnected through the transmission lines, which are subject to faults and cannot be controlled manually except through advanced techniques [1]. A fault in a transmission line causes significant damage to the entire power system's reliability, affecting the power output, loss of installations, power outage, and system collapse. It is imperative to design a model that will classify and locate this fault with great speed, accuracy, and precision to isolate the fault immediately identified for proper fault protection and management.

In a transmission line, fault classification is essential for protecting the network. Therefore, adequate measures must be implemented to achieve maximum protection to avert system collapse and energy output. Faults can be categorised in a power system based on incipient, unpredictable faults [162]. Incipient faults are transient, while unforeseen faults occur due to human interference, lightning, and extreme weather conditions directly affecting the entire network.

Researchers have been brainstorming the best way to protect transmission lines from fault in recent years. To protect the transmission line, the faults must be accurately classified according to their types to quickly isolate the line and prevent system collapse [163]. However, feedback generated from fault classification can significantly assist in detecting fault location for fast clearing time to restore power [164]. In recent literature, fault classification using machine learning has been discussed, such as; Artificial Neural Network (ANN) [99,137,160,165,166], Support Vector Machine (SVM) [1,138,162], Decision Tree (DT) [167] and the Probabilistic Neural Network (PNN) [141].

All these methods have been used for the classification of faults. However, some techniques, like the wavelet technique (WT), are helpful when time and frequency data are needed, although this technique is sensitive to noise and harmonics and requires a high sampling rate. It is time-consuming because getting a referred wavelet and the number of decomposition is done by trials. Also, although WT detects faults accurately and instantly, it is difficult to differentiate between the various fault conditions [141]. WT and ANN are predominantly used for fault detection, and classification [55]. Many hybrid methods have been combined to produce good results; s-transform and ANN methods were used to classify faults on the transmission line. Though the ANN and SVM have produced good results in identifying faults, they need a large volume of data for their training, making them complex to handle [124]. Also, in [141], three ANN approaches were compared to each other for fault classification. They include PNN, Back Propagation Neural Networks (BPNN) and Radial Basis Function Neural Networks (RBFNN). These methods produced good and accurate results. However, they were used on faulty voltage and current signals and focused more on the time and speed of execution of the training. Although most of these methods have been used recently, some challenges exist, such as not being applicable for high-frequency signals and high computational complexity, as found in Hilbert-Huang Transform (HHT) [144]. The Convolutional Neural Network (CNN) is another technique used in fault classification with positive output in accuracy and speed. Still, the computational cost for offline analysis is relatively high [143]. Principal Component Analysis (PCA) in machine learning is a fast and straightforward method that reduces re-projection error and is immune to noise. It is also used to map data from multidimensional space to low dimensional subspace to mitigate dimensionality, where the variance of the data can be perceived in the best way possible. Also, the Kernel Principal Component Analysis (KPCA) and the SVM are used for real-time fault diagnosis of high voltage circuit breaker, where a sample reduction algorithm based on similarity degree function is used to analyse the similarity between samples to detect faults [145] and Dynamic Kernel Principal Component Analysis (DKPCA) [146]. However, suppose the number of dimensions is greater than the number of data points. In that case, the convergence matrix is always significant, making it challenging to obtain the convergence matrix for data with varying properties and capabilities [143] and [79].

Deep learning intelligent diagnosis techniques have also been used in fault classification, such as the Wavelet Packet Distortion and Convolutional Neural Network [147]. It applies the wavelet packet distortion to generate a faulty data sample, while the convolutional neural network is used to classify the fault into different categories. However, the wavelet packet function uses Daubechies wavelet (DB4) for extraction, which does not have a theoretical justification. The Adaptive Intraclass and Interclass Convolutional Neural Network (AIICNN) [148] is applied in the algorithm to enhance sample distribution differences by applying designed intraclass and interclass constraints. While the 1-D Convolutional Neural Network (1dCNN) has an activation function added to it to enlarge the heterogeneous distance and reduce the homogeneous distance between samples for proper classification. Normalized Conditional Variational Auto-Encoder with Adaptive Focal Loss (NCVAE-AFL) are also used to classify faults into different categories [149]. In [14], the convolutional Neural Network and Long Short Term Memory (CNN-LSTM) were used to identify and locate fault using the frequency response analysis (FRA) to extract the fault. This method is used to detect faults timely and accurate.

Each of the methods mentioned above has disadvantages and limitations. Some of the main noticeable observations on this subject did not focus more on fault classification in terms of fault clearing time, thereby making it difficult to isolate or take on significant fault repairs within the shortest possible time. Also, discrete wavelet transform (DWT) and decision Tree [150] have limited time resolution capability and low performance for high-performance faults. Wavelet and Data mining [150], K- Nearest Neighbours (KNN) and Decision Tree [151], are limited to the fault classification technique only without considering the speed and precision of the result. In [152], fault classification was not determined in the S-transform technique, and the effect of noise in the transmission line was not considered in the model [153]. Differential and Hibert-Huang transmission methods are expensive and have no-fault direction. In addition, for fault classification, the mathematical morphology and Recursive Least-square (RLS) methods [154] involves using a mathematical morphology-based fault feature extraction scheme. This method has high calculation and technical standards that require a professional to implement.

Researchers have widely used the machine learning method due to the increased involvement of communication and computation in transmission systems [154]. Research shows that most techniques use a smaller data set to train their algorithm, giving high-accuracy results [90]. Also, they use either single phase-to-ground fault, or double phase-to-line fault data for their training [77, 144, 155]. Another shortfall of most methods is the inability to consider noise and disturbance in the transmission line networks since they are inevitable. This method will also address the effect of noise signals and disturbance and how they can be reduced or eliminated for optimal system performance and accuracy of results [158].

Due to the shortcomings of the different algorithms and models discussed in the literature on fault classification, the CatBoost classifier algorithm is proposed for training fault data from single-phase, double-phase, and three-phase-to-ground faults. Twelve data-sets types will be used for fault classification, and the CatBoost classifier will train the data. This classifier is proposed for its accuracy, speed and ability to train a multi-data-set of a transmission line fault within the shortest possible time. The model is used because it can handle heterogeneous data with categorical features, is sensitive to hyper-parameters, and can handle noisy data [168]. Also, the uniqueness of the proposed model is the ability to train noise data without affecting the accuracy and performance of the system. The fault data will comprise four fault conditions in different scenarios, and the analysis is divided into two major parts. First is the network modelling to extract fault cases from the transmission line using Matlab/Simulink. The next is to detect and classify the faults using the data generated from the simulations to detect and classify faults with the help of a trained classifier [112].

3.2 Modelling of 330 kV, 500 km Transmission Line

Machine learning needs many data-sets for practical training, and those data-sets are obtained from the model of a 330 kV, 500 km transmission line network shown in Figure 3.1 below. The parameters from Tables 3.1 and 3.2 are used to create the model in Simulink as in Figure 3.2. This model generates fault data of single line to ground, double line to ground and three-phase to ground fault. This data is used to train machine learning for fault classification. It will also be applied to validate the data for accuracy, Root Mean Square Error (RMSE) and precision of the result.

Figure 3.1 represents a three-phase, 330 kV transmission line model developed and implemented in this article. It consists of a Nigerian 330 kV transmission line which cut across a 500 km distance and was modelled using Matlab/Simulink. The ground resistance used is 0.01 Ω based on the IEEE recommendation for ground resistance, which is 0 Ω to 50 Ω range for the ideal situation [169]. Also, a

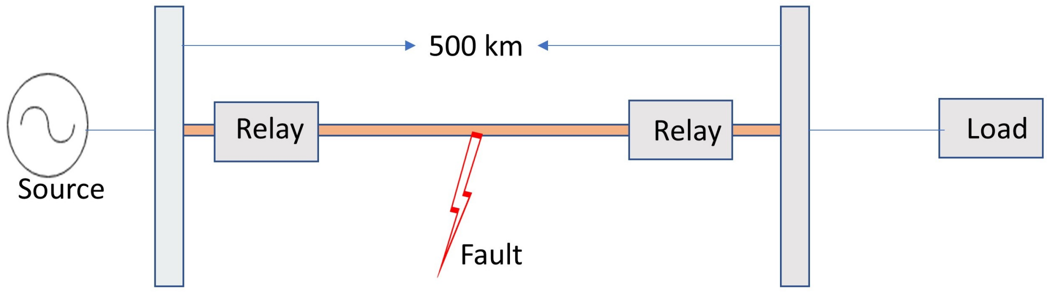


Figure 3.1: A 330 kV three-phase, 500 km transmission line model

minimum fault line voltage of 0.001 V (minimum standard value) and the incipient fault angle (0 to -30°) were used to get the maximum arc resistance value. The small ground fault resistance is chosen to detect transient faults because a higher resistance value will lead to over-voltage and current, so the system may not classify minor faults. Therefore, the higher the fault resistance, the lower the fault detection. A three-phase fault simulator simulates the fault at a different location on the transmission line for proper classification.

Table 3.1: Parameters of 330 kV, 500 km transmission line

Sequence	**parameter**	**Value**	**Unit**
Positive and negative sequence resistance	R_1, R_2	0.01273	Ω/km
Zero sequence resistance	R_0	0.3864	Ω/km
Positive and negative sequence inductance	L_1, L_2, L_3	$0.9337\text{x}10^{-3}$	H/km
Zero sequence inductance	L_0	$4.1264\text{x}10^{-3}$	H/km
Positive and negative sequence capacitance	C_1, C_2, C_3	$12.74\text{x}10^{-9}$	F/km
Zero sequence capacitance	C_0	$7.751\text{x}10^{-9}$	F/km

Table 3.1 shows the model parameters where R_1 and R_2 are positive and negative sequence resistances of phases 1 and 2, respectively. L_1, L_2 and L_3 represent the positive and negative sequence inductance of phases 1, 2 and 3, respectively, whereas C_1, C_2 and C_3 represent the positive and negative sequence voltages of phases 1,2 and 3, respectively. Finally, R_0, C_0 and L_0 represent the zero resistance, capacitance, and inductance sequence respectively.

Table 3.1 and 3.2 are generic data used for modelling the scheme. These data are collected from the Nigeria transmission network, like the phase voltage, source resistance, and the positive and negative sequence impedance. These data are used to design the model.

Tables 3.1 and 3.2 represent input data for modelling a 330 kV 500 km transmission line that was designed. Simulations were carried out by inducing the fault into the line at a 300 km distance. The parameters were carefully selected

Table 3.2: Fault parameters of the proposed model

System components	**Parameters /units**	**Value**
Phase to phase voltage	voltage(kV)	330
Source resistance Rs	Ohms (Ω)	0.8929
Source inductance	H	16.58x10^{-3}
Fault incipient angle	θ in degree	0° and -30°
Fault resistance R_{on}	Ohms (Ω)	0.001
Ground resistance R_g	Ohms (Ω)	0.01
Snubber resistance R_s	Ohms (Ω)	1.0x10^{-6}
Fault capacitance C_s	F	infinite
Switching time	seconds	0.2

Table 3.3: Fault types in binary representation

Class	**Fault type**	L_1 **(a)**	L_2 **(b)**	L_3 **(c)**	**G (g)**
1	a-g	1	0	0	1
2	b-g	0	1	0	1
3	c-g	0	0	1	1
4	a-b	1	1	0	0
5	a-c	1	0	1	0
6	b-c	0	1	1	0
7	a-b-g	1	1	0	1
8	b-c-g	0	1	1	1
9	a-c-g	1	0	1	1
10	a-b-c	1	1	1	0
11	a-b-c-g	1	1	1	1
12	No fault	0	0	0	0

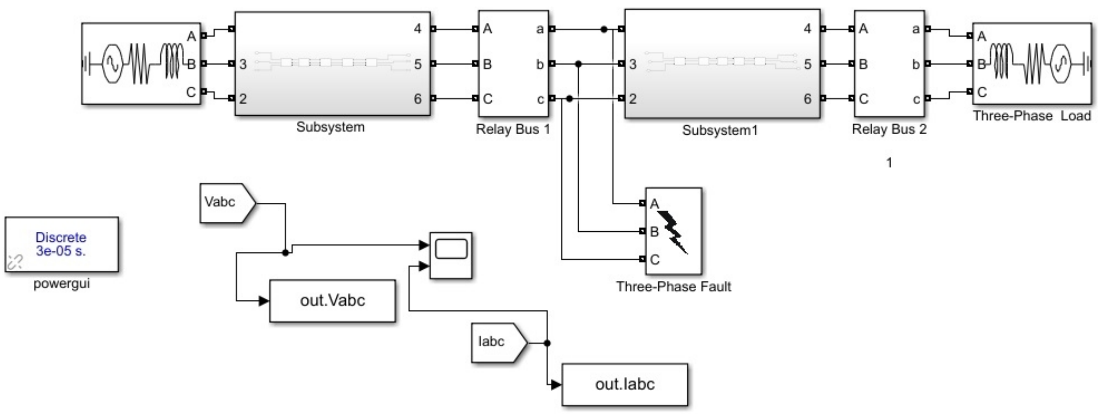


Figure 3.2: Simulink Model of 330 kV. 500 km transmission line

based on the standard of the International Electro-technical Commission (IEC 60909) [170].

Fault voltage and current data were generated from the model in a different scenario, and twelve fault conditions were considered. These are a-g, b-g, c-g, a-b, b-c, a-c, a-b-g, b-c-g, a-c-g, a-b-c, a-b-c-g and no-fault as seen in Table 3.3, where a = fault at phase A, b = fault at phase B, c = fault at phase C and g is the ground fault G. The binary representation shows the fault and no-fault conditions representing 1 and 0, respectively. It indicates the fault number assigned to each fault condition.

3.3 Methodology

Classifying faults using phase and zero-sequence current fault data obtained from simulated models is possible. The diagram in Figure 3.3 shows the data processing model for machine learning used for this research. It involves accessing and loading the data collected from the simulated model into the trainer. Next, the data collected is processed by looking for the data points located outside the fitted end of the rest of the data to check if they can be ignored or considered. [170].

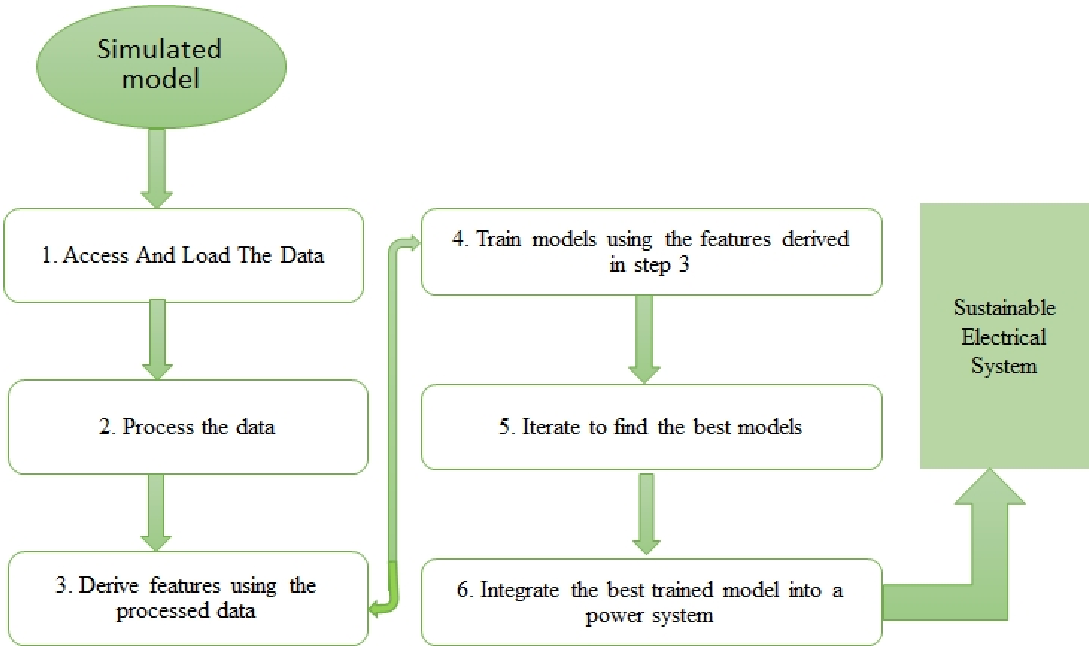


Figure 3.3: The data processing model for machine learning

The next step is deriving features by turning the information into a machine-learning algorithm to improve the accuracy, boost model performance, improve model interpretability and prevent over-fitting. This is preceded by building and training the model, where a confusion matrix will be plotted that compares the classification made by design with the actual data collected. Next, we improve the model by checking the correlation matrix to remove the variables that are not correlated. The fault data type was introduced in the 500 km, 500 kV transmission line, and the data-set is divided into training, testing, and validation data.

Each data-set will be trained and analysed for final validation, accuracy, error and performance.

3.3.1 Data Preparation and Extraction

The faulty data were extracted using a Simulink model from Figure 2.10, and the waveform was generated from the model to show the frequency of fault occurrence. The graphs in Figures 3.4 to 3.7 show the waveform to validate the presence of a fault in the network. The faulty current and voltage are generated and used for machine learning training to classify and locate faults in the transmission line. The waveform displayed in Figure 3.4 shows a standard voltage and current sinusoidal waveform.

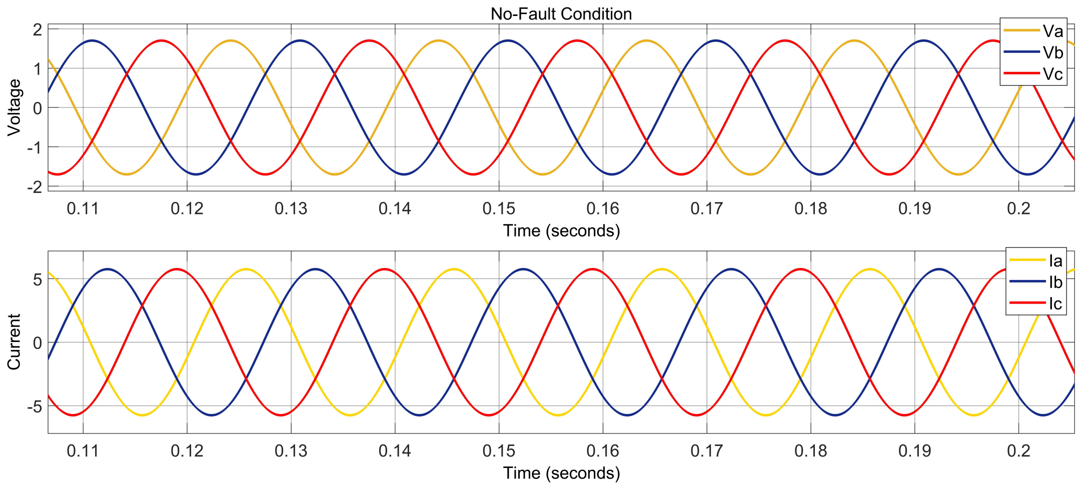


Figure 3.4: Three-phase at no fault condition

Under the no-fault state, the waveform is sinusoidal and has no distortion due to noise or fault, so the resultant waveform is standard, as seen in Figure 3.4. When the fault occurs, the fault current of the power transmission line becomes abnormally high, while the fault voltage decreases to a low value.

Figure 3.5 shows a three-phase to a ground fault where the current and voltage waveform of phase V_a, V_b, V_c and I_a, I_b, I_c are distorted, and there is a sudden decrease in their magnitude. Also, in Figures 3.6 and 3.7, the voltage and current of phases B, C and A were also distorted due to faults in the line, respectively. All these waveforms show distortion due to faults. The switching time of the fault model was set at 0.2 s, and the fault location was at the 250 km distance of the transmission line. Figures 3.4 to 3.7 illustrate fault detection in four different fault scenarios: no-fault, single phase to ground-fault, double-line-to-ground fault, and three-phase to ground fault. The fault current and voltage data were generated, and machine learning was used in training the data to detect, classify

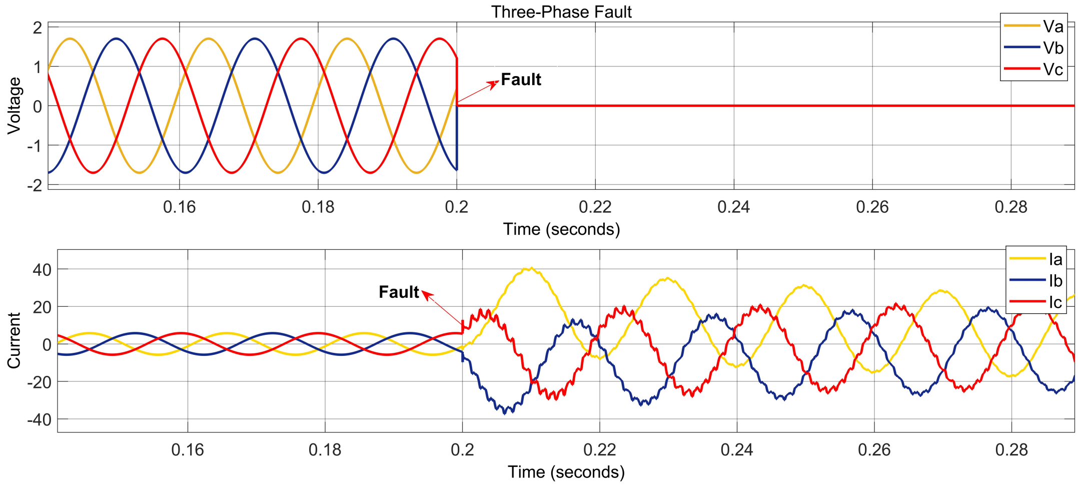


Figure 3.5: Three-phase to ground fault (a-b-c-g)

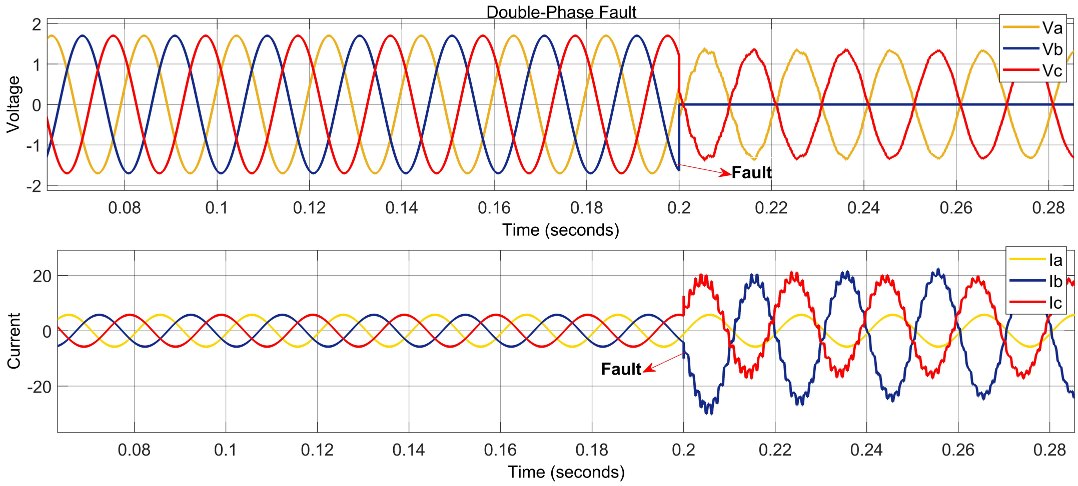


Figure 3.6: Double phase to ground Fault (a-b-g)

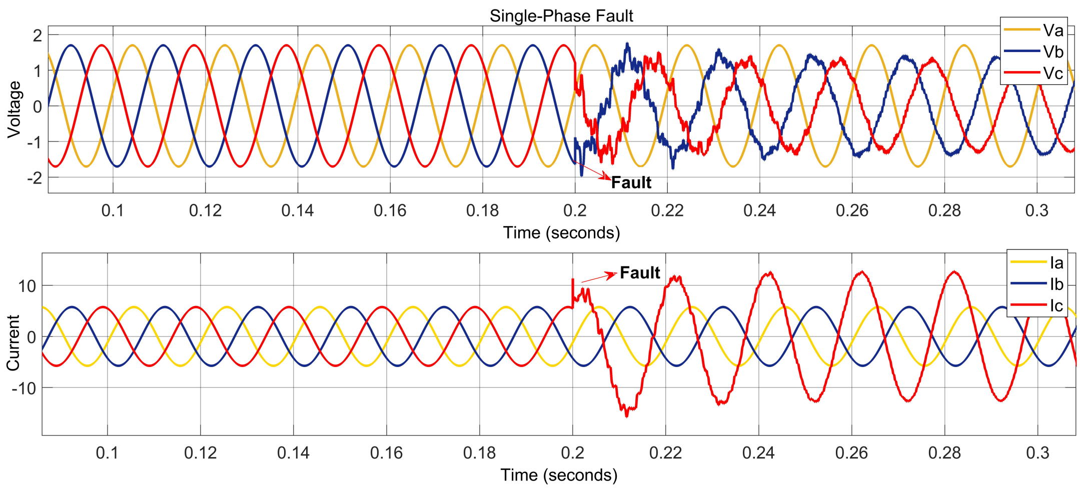


Figure 3.7: Single-phase to ground fault (a-g)

and locate the fault on the transmission line. The current in Figures 3.5, 3.6 and 3.7 increased drastically, and the voltage was reduced to zero, as shown in Figure 3.6, confirming the transmission line fault.

3.3.2 The Use of CatBoost in Fault Classification

The CatBoost classifier algorithm is used as a machine learning tool for training data-sets for fault classification due to its performance, ease of use, and handling of categorical features automatically as compared to other machine learnings techniques like the PCA, SVM and ANN without any explicit pre-processing of data to convert all categories of fault data into numbers. A team of engineers from Yandex proposed the model in 2017 [171]. Gradient boosting is a good machine learning tool for solving heterogeneous, noisy data and complex variables. It uses binary decision trees as base predictors. It has robust characteristics of reducing hyper-parameter tuning and lowering the data's chances of overfitting. It combines Gradient Boosting Decision Tree (GBDT) and categorical features, focuses on categorical variables, and deals with gradient bias, and prediction shift problems [172]. It helps to improve the robustness of the algorithms by putting all sample data sets into the algorithm for training. When transforming the characteristics of each sample, the target value of the model will be calculated first before the sample, and subsequent weight and priority are added. Assuming a data sample size in (3.1) is given as

$$D = \{(X_j, Y_i)\}; j = 1, ...m, \tag{3.1}$$

Where $X_j = (x_j^1, x_j^2, ...x_j^n)$ is a vector of n features and response feature $Y_i \in R$, which can be binary (that is 1 or 0), and sample (X_j, Y_i) identically and independently distributed by an unknown distribution $P(.,.)$. The aim is to train a function $H : R^n \to R$ which minimises the expected loss given in the equation below in (3.2)

$$L(H) = EL(y, H(x)), \tag{3.2}$$

Where $L(.,.)$ is a smooth loss function and (X, y) is a sample of test data drawn from the training data D [172].

Special Features of the CatBoost Algorithm

- **Handling Categorical Variables:** CatBoost is specifically designed to handle categorical variables often present in real-world data-sets. It uses an algorithm called "ordered boosting", which can effectively handle categorical variables and convert them into numerical values before training the model.

- **Handling Missing Values:** CatBoost can handle missing values in the data set without imputation. This is particularly useful when working with data-sets with a high percentage of missing values.

- **Built-in Feature Selection:** CatBoost has built-in feature selection capabilities, which can identify the most important features in the data-set. This can help improve the performance of the model and reduce overfitting.

- **Parallel Processing:** CatBoost has built-in parallel processing support, making it faster than other gradient-boosting libraries. This is particularly useful when working with large data-sets.

- **Handling Overfitting:** CatBoost has a built-in mechanism to handle overfitting, which is a common problem when working with decision trees. This mechanism is based on randomising the input data before each iteration and is known as "permutation importance."

- **Handling Different Types of Data:** CatBoost can deal with different kinds of data, like numerical, categorical, and text data.

- **Model interpretability:** CatBoost provides feature importance and partial dependence plots, which help understand how the model makes predictions.

- **High performance:** CatBoost is known for its high performance on classification and regression problems. It is often used in competitions and real-world applications.

The CatBoost also helps improve the algorithm's robustness by putting all sample data sets into the algorithm for training. When transforming the characteristics of each sample, the target value of the model will be calculated first before the sample, and subsequent weight and priority are added. The CatBoost classifier requires minimal data preparation and handles missing values for numerical and non-encoded categorical variables. The classification accuracy is used as a criterion to assess the result of fault classification.

However, the CatBoost algorithm has some limitations, including **Limited Support for Time Series Data:** CatBoost is not specifically designed for time series data, making it less suitable for problems that involve time series data.

Limited Support for Handling Imbalanced Data: CatBoost does not currently have built-in support for handling imbalanced data, making it less suitable for problems where the classes are highly imbalanced.

Limited Support for Handling High-dimensional Data: CatBoost is not explicitly designed for high-dimensional data, making it less suitable for problems involving many features. It is worth noting that some of these limitations can be overcome by using appropriate pre-processing, feature engineering, and ensemble techniques. However, it's essential to evaluate if the model best fits the problem before using it and the necessary precautions were taken before selecting the algorithm.

3.3.3 Training of Data-sets Using CatBoost Algorithm

About 93340 data-sets of four types of faults comprising 23340 data-set for each fault case of a single line, double line to ground, three-phase to ground fault, and no-fault condition, were generated from the fault detection model from Matlab/Simulink. The data were divided into training and test data-sets of 70% and 30%, respectively. The CatBoost classifier was used as a machine learning tool to train the data-set. The choice of the classifier was due to its performance and ease of usage. Also, the classifier can handle categorical features automatically without explicit pre-processing to convert all the categories of fault data into numbers. It also has a robust characteristic of reducing hyper-parameter tuning and lowering the chances of over-fitting the data. The machine learning trainer was simulated with the following parameters:

Table 3.4: CatBoost Classifier training parameter

CatBoost model is fitted	**True**
Iterations	1000
Depth	10
Loss function	Multiclass
Leaf estimation method	Newton
Class weight	0.001, 0.01, 0.9, 0.001
Random strength	0.1

The input data for the classifier are fault current and voltage of the transmission line model in Figure 3.2. Also, the parameters from Table 3.4 are used to train the data, and the CatBoost classifier was employed as a machine learning tool for the dataset. The CatBoost classifier is preferred because it is easy to use, efficient and works well with categorical variables. It doesn't require data pre-processing to train. Also, it uses limited time to complete the training. For an effective fault management system, fast detection and classification of faults are essential in power system protection. This technique is perfect in resolving this compared to other methods with higher training time. The parameters were carefully selected through parameter tuning and training to obtain better results and ensure the data was fitted.

3.4 Results and Discussion

The parameter from Table 3.4 above is used to train the classifier, and the best test accuracy was achieved at 748 iterations out of 1000, which is 99.54% with an error of 0.46%. This result confirms that the classifier model works perfectly, and the different types of faults were trained and classified with high accuracy. The no-fault condition was trained separately, and an accuracy of 100% was obtained. This was trained separately to attain a near-perfect classification due to the complexity of the data-set. Table 3.5 represents the classifier's confusion matrix, which describes the precision, recall, F1-score, and support. An $N \times N$ matrix is often used to evaluate the performance of the classifier model, where N is the number of target classes. The matrix compares the target value with the predicted machine-learning model and the error involved. The table shows that the no-fault condition represents 0, the single line to ground fault is 1, the double line to ground is 2, and the three-phase to ground fault represents 3. Class 0 was kept at zero because it was at no fault condition while others were trained. The result shows that the model was well-fitted, and the four fault types were well-classified.

Table 3.5: Confusion matrix for the fault classification

	0	0	0	6955	0
	1	0	4862	2051	0
True Class	2	0	0	7048	0
	3	0	0	2013	5073
		0	1	2	3
		Predicted Class			

The accuracy of the model is given as

$$\textbf{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{3.3}$$

where TP = True positive, TN = True Negative, FP = False Positive and

FN = False Negative. Also,

$$\textbf{Precision} = \frac{TP}{TP + FP}. \tag{3.4}$$

It tells how many predicted cases were positive and determines whether the model is reliable. In Table 3.5, the precision in single-phase to ground and three-phase fault is 1, which shows the model works perfectly well. 'Recall' shows how many of the actual positive cases were predicted correctly and is given by

$$\textbf{Recall} = \frac{TP}{TP + FN}. \tag{3.5}$$

The double line to ground fault was predicted correctly compared to other faults, as shown in Table 3.5. Also, the F1-Score is the harmonic mean of Precision and Recall and is given by:

$$\textbf{F1 - Score} = \frac{2}{\frac{1}{Recall} + \frac{1}{Precision}} \tag{3.6}$$

Table 3.6: Fault classification report

Fault type	Classes	Precision	Recall	F1-Score	Support
A-G	1	1.00	0.70	0.83	6913
B-C-G	2	0.39	1.00	0.56	7048
A-B-C-G	3	1.00	0.72	0.83	7086
No fault	0	0	0	0	0
	Micro Avg	0.61	0.81	0.69	21047
	Macro Avg	0.80	0.81	0.74	21047
	Weighted Avg	0.80	0.81	0.74	21047

True-positive indicates that the classifier predicted a true event, and the event is true. In contrast, true-negative indicates that the classifier predicted a false event, and the event is false. The classifier predicted that an event would occur, but it was incorrect. Still, the event is not true, whereas a false-negative indicates that the event was predicted incorrectly and was, therefore, false. The results from the fault classification report in Table 3.6 also affirm that the classifier produced perfect results. Therefore, it is a better classifier for training multi-data sets than other results from the reviewed literature in this research.

3.5 Discussion

The CatBoost classifier produced exceptionally perfect results due to its accuracy and precision compared to other methods used in many works of literature. In another research, sparse representation classification with random dimensionality reduction projection technique was used to classify faults [173]. This method generated results ranging from 93.9%, 96.8% and 98.8% for 10 dB, 20 dB and 30 dB, respectively, which vary according to fault type [79]. In [124], S-transform and neural networks were used in fault classification, and the average classification accuracy was 99.6%. Still, the research of [124] was based on three-phase fault compared to four different fault types used in this paper. The Recursive Neural Network (RNN) was used in [79], and about 500 fault data was used, and the classifier failed to classify L-L and L-L-G fault types at 140 km.

Tables 3.7 and 3.8 compare the different machine learning techniques used in fault classification based on the various methods and justify the algorithm's use, focusing on accuracy, speed, and strength. The CatBoost classifier produces a better result than other classifiers, as seen in Table 3.7,

with an accuracy of 99.54%. The CatBoost technique was chosen for its speed, accuracy and low training time to classify faults according to their categories. Also, it can handle multi-data-set of different fault currents and voltage simultaneously.

However, it could classify the fault at some distance with an accuracy of 98.67%, so the classifier's inability to classify all the different types of faults at different locations made it unsuitable for proper fault classification techniques. The CatBoost algorithm has proven to be a better machine learning tool in fault classification and detection for data training and is highly recommended for optimum, accurate output results.

Figure 3.8 shows a separate analysis of the performance of the CatBoost model where the single-phase and three-phase fault performs optimally with an accuracy of 100% while the recall value was higher for the double phase-to-ground fault.

The novelty of this paper is based on the use of the CatBoost classifier in transmission line faults classification. Tables 3.7 and 3.8 enumerate some distinctive features of the CatBoost classifier over other machine learning algorithms, including overall accuracy of results of 99.54% and individual line faults accuracy of 100% in three face fault classification and speed of execution at 58.5 s compared with the SVM. The model can also handle multi-data-set, combines multiple categorical features, and overcome gradient bias. Also, it prevents data overfitting and pre-processing during training compared to other techniques that use trial and error for parameter tuning, unlike different machine learning algorithms like SVM, K-NN, CNN and RNN.

Table 3.7: Comparing different machine learning techniques for accuracy in fault classification

Technique Used	Input parameter	Fault types	Data size	% Accuracy	Strength	Weakness
WT,CNN [147]	vibration signal	400 different fault condition	2400	97.78%	speed of 8 s to execute and easy to use	The WT Packet is not theoretically proven.
ANN [174]	Three-phase voltage and current waveform	10 different fault condition	7920	78.1%	Easy to use and implement, Repro-gramming is not needed	Requires a system with a high processor, Longer training time.
Proposed CatBoost Classifier	Voltage and current signal	Single-phase fault,double phase fault, three-phase fault and no-fault	93340 X 6	99.54%	Higher accuracy, speed and low training time.multiple feature classification	It needs a high-performance operating system to train the data.

Table 3.8: Comparing different machine learning techniques for accuracy in fault classification

Technique Used	Input parameter	Fault types	Data size	% Accuracy	Strength	Weakness
BPNN [167]	Voltage and current	AG, BG, CG, ABG, ACG, BCG, AB, AC, BC, ABC, ABCG	1188	97.3%	easy to execute, it requires less number of neurons for training.	Slow to use, computationally expensive, can't be used to solve complex andlarge problems. Slow convergence.
RBFNN [167]	Voltage and current	AG, BG, CG, ABG, ACG, BCG, AB, AC, BC, ABC, ABCG	1188	99.3%	Faster than BPNN, easy to use.	Not suitable for non-linear systems and large dataset
PNN [167]	Voltage and current	AG, BG, CG, ABG, ACG, BCG, AB, AC, BC, ABC, ABCG	1188	99.4%	It can handle multi-dataset to classify faults. Also, no learning process is required.	Expensive to implement, and learning can be slow, high processing time if the network is extensive.
RDRP [79]	Voltage signal of 10 dB, 20 dB and 30 dB	Single, double and three-phase fault	480	93.9, 96.8% and 96.8%	It can work well with small datasets	Not suitable for multiple datasets and low prediction accuracy.
CNN [143]	Three phase Voltage and current	10 different fault condition	92077	99%	Used to solve multi-channel sequence recognition problem	The computational cost of offline mode is expensive

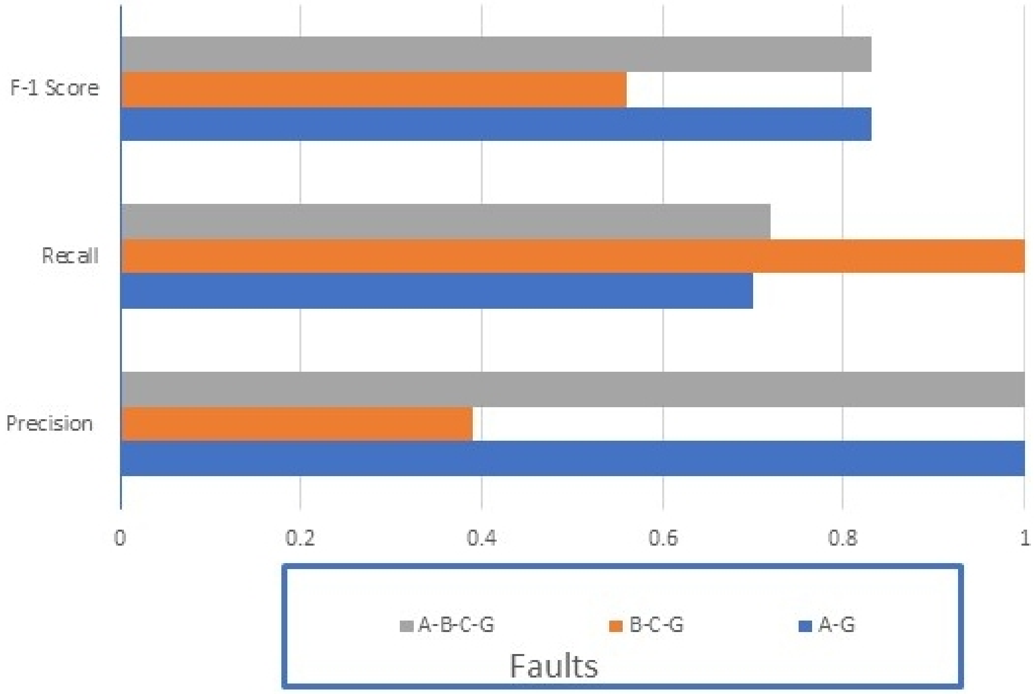


Figure 3.8: Performance of the different faults types

3.5.1 The Effect of Noise and Disturbance in the Proposed Algorithm

Power Quality Disturbance (PQDs) and noise signals would cause adverse effects on the classification of faults in transmission line accuracy. During feature selection and extraction, it is necessary to consider noise and signal disturbance considering the voltage swell, voltage sag, voltage interruption, voltage flicker, transient oscillation, harmonics and transient impulse. The proposed model compared noise signals and PQDs with other articles. It was observed that the CatBoost classifier performs better, with accuracy remaining at 99.54% both in noise and noiseless signals. This shows that the method can effectively reduce the effects of noise and disturbance on classification accuracy. In [175], the ANN technique was used for classification with noiseless signal accuracy of 87.55% and 82.44% at 20 dB noise. Also, in [176], the DWT was used for feature extraction, and the SVM was used for fault classification with an accuracy of 100% without disturbance while 98% and 95.6% accuracy at 30 dB and 20 dB noise, respectively.

The proposed method's novelty is the model's ability to de-noise the signal for optimal performance as seen in Figures 3.9 and 3.10. The current signal in the three phase-to-ground faults is de-noised for optimal model performance before

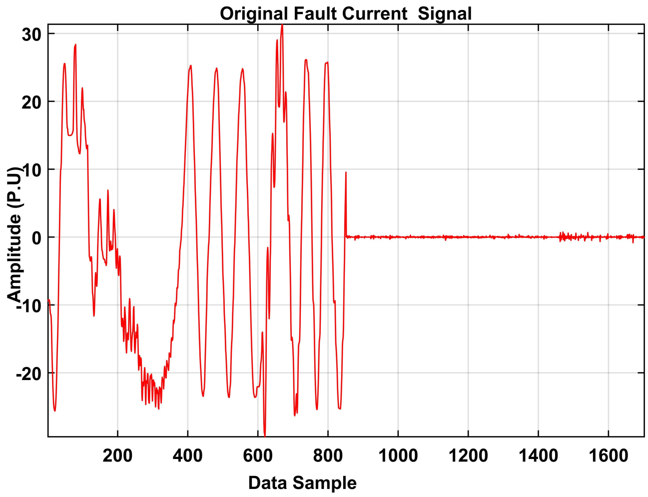


Figure 3.9: Fault Current with Noise Signal

it is integrated into the CatBoost classifier. In Figure 3.9, the base current rose to 30 P.U, which causes a disturbance in the system but was reduced to 28 P.U as seen in Figure 3.10. the4 process can continue to achieve a zero signal-to-noise ratio in the system.

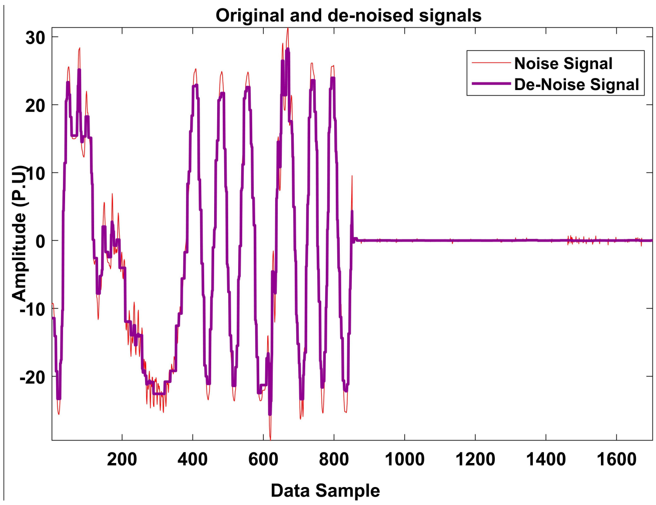


Figure 3.10: Fault Current With De-Noise Signal

Also, the power quality can be improved by this method for quality control and online and offline fault classification with noise and noiseless data. This can be applied in fault management and protection in high voltage transmission lines and the distribution network, and the technique can help in fault management and protection when noise and disturbances are inevitably present.

3.6 Conclusion

Faults always affect the transmission line and cause significant damage to equipment and disruption in power supply to the customers or end-users. These faults occur due to bad weather conditions, faulty equipment and transient faults due to human interference. Hence there is a need to model a system that will classify, detect and isolate faults accurately with speed within the shortest detection time.

This paper proposed using CatBoost classifier as the preferred algorithm for fault classification due to its high accuracy and ease of training. This technique is achieved by designing a 330 kV, 500 km transmission line using Matlab/Simulink to extract fault current and voltage to identify the fault phase for each faulty voltage and current waveform. A 93340 fault data-set was used to train the algorithm, which provides better accuracy of 99.54%. The classifier algorithms can train categorical data with multi-data-set like SVM, ANN and XBoost classifier. This paper has addressed the classification of a multi-dataset of faulty voltage and current in transmission lines focusing on speed, accuracy and precision in classifying faults for fast detection and isolation of faults. Also, the results will serve as a guide on transmission line fault protection management systems and design. After being compared to other methods used in other literature, the CatBoost classifier was justified for the transmission line fault classification model. This paper can be improved by varying the fault resistance to different values from 0.01Ω to 50Ω and above. Also, the model can be optimised for real-time data mining and training automatically for effective fault protection mechanisms.

Chapter 4

Fault Detection and Localisation

4.1 Introduction

Electric generation, transmission, and distribution are interrelated elements of the electrical power system. The transmission line is a crucial power system that transfers electricity from the generating station to the final users. These components are connected via transmission lines, are prone to failure, and can only be controlled remotely by complicated procedures [1]. Ageing machinery, lightning, human interaction, and severe weather conditions contribute to problems on the transmission line. However, power quality is the most critical factor in an electrical network. When a transmission line malfunctions, the power quality diminishes, directly affecting power production [177]. Fault detection and localisation are essential for protecting the network in a transmission line. Therefore, adequate steps must be taken for maximum protection to avert system collapse. In protecting the transmission line from destruction, the fault must be detected, and the fault location must quickly be accurate for proper line isolation [163]. However, feedback from fault detection can significantly assist in fault localisation for fast clearing time and restoring power [164]. Identifying the fault location of a transmission line in a power system is critical to facilitate quick response and maintaining power supply reliability [178].

The detection and localisation of transmission lines have mainly been accomplished using traditional machine learning and deep learning techniques. The traditional method uses a distance protection relay over current, and voltage relays as a switching mechanism for fault protection [131, 179]. The use of mobile robot [32, 133–135, 180] for transmission line monitoring and line defect detection. Also, the fuzzy logic approach [56, 57, 84], Wavelet Transform approach (WT) [46, 57], Neuro-fuzzy technique [84, 136], wavelet and fuzzy approach [56, 57, 62]. While the machine learning approach includes the Artificial Neural Network (ANN) [99, 137, 160, 165, 166, 181], Support Vector Machine (SVM) [1, 138, 162], Decision Tree (DT) [182]. These techniques have some drawbacks like the WT is useful when time and frequency data are needed though sensitive to noise and harmonics. It also requires a high sampling rate and is time-consuming to get a referred wavelet. Also, the number of decomposition is achieved by trials and is predominantly used for fault detection [55]. In [91], the back-propagation neural network was used as an alternative fault detection and localisation method. This can be used to design an effective distance relay protection scheme for a long transmission line. However, the model has poor accuracy in fault classification.

Many hybrid methods have been used to improve its fault detection and localisation performance, such as the S-transform and ANN [124]. This method was used to identify transmission line defects, though it did not consider a multi-class data set of fault data [124]. Also, the ANN and SVM were used in identifying faults, and it needs a large volume of data for their training, making it complex to handle and time-consuming. WT is also used in fault detection, though it is difficult to differentiate between the various fault conditions [141]. Though most of these methods have been used recently, there are some challenges. For example, the Hilbert-Huang Transform (HHT) is inapplicable for high-frequency signals and has high computational complexity [142].

Using Principal Component Analysis (PCA) in machine learning is a fast and straightforward method that minimises re-projection error and is immune to noise. However, If the number of dimensions exceeds the number of data points, the convergence matrix will always be big, making it challenging to obtain the convergence matrix [143]. The PCA is also used to map data from high dimensional space to low dimensional subspace to decrease the dimensionality of the data for a better understanding of the variance of the data. Research shows that most of these techniques use a smaller dataset to train their algorithm, giving high-accuracy results. Also, they use either single phase to ground fault, or double phase to line fault data for their training [77, 144, 155]. With the focus on machine learning and deep learning techniques, single Phase, double Phase, and three phases to ground fault datasets will be used simultaneously to detect and locate the fault in the transmission line.

DWT and DT [183] have poor performance for high-performance faults and limited temporal resolution capabilities when considering fault location. Using data mining and wavelets [150], Decision Tree (DT) and K-Nearest Neighbors (KNN) are used, although they do not quantify fault location [151]. The S-transform approach was only investigated in [152]. For fault identification and detection, morphology in mathematics and the Recursive Least-square (RLS) method [112] are employed to identify fault characteristics based on mathematical morphology. This approach is difficult to maintain since it is employed in incredibly intricate situations that are not home in nature. Another disadvantage of the previously discussed approaches was their inability to focus more on fault localisation. Localisation of faults facilitates rapid diagnosis and power restoration during an outage by pinpointing the exact location of the problem.

Transmission line fault analysis normally requires three main activities for a successful fault management system: fault sensing or detection, categorising the problem into various categories, and identifying the spot to disclose the zone where the fault occurred [163]. The extraction of fault features is being considered. First, this may be accomplished by modelling the network in MATLAB/SIMULINK to extract fault instances from the transmission line. The next step is to identify and localise the flaws using the data provided by the simulated model and an ANN-trained classifier [112].

Because of the delay in fault detection and the increased role of communication and computers in transmission systems [154], this study aims to offer a novel ANN-based approach for rapid, reliable, and accurate fault identification and localisation in transmission lines. Also, Detecting various types of faults, such as voltage and current abnormalities, minimises the time delay in fault detection. The suggested algorithm's performance was assessed by simulating several errors and training them with the ANN model, and the results were encouraging. In addition, the suggested model will be used to develop transmission line fault management and protection in power systems.

One of the technique's significant disadvantages is the model's inability to train on non-numerical data. Therefore, interpreting the findings is always challenging as matching results with real-life circumstances and issue statements.

4.2 The Artificial Neural Network Technique

This section has been explained in section 2.6.1. Artificial Neural Networks (ANN) in fault detection and localisation involve using a computational model inspired by the human brain to analyse electrical power systems for faults. ANNs offer a data-driven approach to these tasks, and their application can be summarised as follows:

- Data Collection: The first step in using ANNs for fault detection and localisation is to gather relevant data from the power system. This data typically includes voltage and current measurements, which are acquired from various locations in the system.

- Data Preprocessing: Raw data collected from the power system may be noisy and require preprocessing. This step involves cleaning, filtering, and transforming the data to make it suitable for ANN analysis.

- Training the Neural Network: ANNs are trained using historical data, including normal and fault conditions. The network learns to recognise patterns in the data associated with different fault scenarios. During training, the network adjusts its internal parameters to minimise fault detection and localisation errors.

- Feature Extraction: ANNs often employ feature extraction techniques to identify relevant characteristics in the data. These features can help the network differentiate between normal and fault conditions.

- Fault Detection: Once the ANN is trained, it can be applied to real-time or recorded data to detect the presence of a fault. The network compares the incoming data to the patterns it learned during training and identifies deviations that indicate a fault.

- Fault Localisation: ANNs can also be used to estimate the location of a fault in the power system. The network can triangulate the fault's position based on the differences in arrival times or magnitudes of fault-related signals by analysing the data from multiple measurement points.

- Accuracy Assessment: The performance of the ANN model is assessed in terms of accuracy, precision, and recall in fault detection and localisation tasks. This helps evaluate the reliability and effectiveness of the network.

- Optimisation: Fine-tuning the ANN model may be necessary to improve its accuracy and adapt it to specific system conditions. This may involve adjusting network architecture, hyperparameters, or training data.

- Real-Time Application: In practice, ANNs can be deployed for real-time monitoring of power systems, where they continuously analyse incoming data to detect faults and estimate their locations. Rapid response is crucial for minimising the impact of faults on the system.

- Integration with Protection Systems: ANN-based fault detection and localisation systems are often integrated with protective relays and control systems. When a fault is detected and located, the protection system can take appropriate actions, such as opening circuit breakers to isolate the faulted section of the system.

The multiple layers comprising one or more hidden neural layers can solve various issues involving function approximation, pattern classification, system identification, process control, optimisation, and robotics [92]. The multi-layer typically has three classes of layers: an input layer, which is used to transfer the input vector to the network; hidden layers of computation neurons; and an output layer, which is made up of at least one computation neuron and produces the output vector [93].

4.3 Methodology

The Artificial Neural Network technique needs many datasets for practical training obtained from the model in Figure 3.1. The parameters from Tables 3.1 and 3.2 are used to model the simulink in Figure 3.3. This model generates fault data of single line to ground, double line to ground and three-phase to ground fault. This data is used to train the machine learning using the ANN algorithm to check for fault detection, classification and localisation. It will also be used to validate the data for accuracy, Root Mean Square Error (RMSE) and precision of result location.

Figure 3.1 depicts the three-phase, 330 kV transmission line model created and installed. It comprises a 500 km long Nigerian 330 kV transmission line simulated in Matlab/Simulink, as illustrated in Figure 3.2. The ground resistance chosen is 0.01 Ω based on the IEEE ground resistance standard of 0–50 Ω for the ideal circumstance [169]. Tables 3.1 and 3.2 illustrate the input data for modelling a 500 km, 330 kV, 50 Hz transmission line. Simulations were done by placing the fault into the line 300 km distant. The parameters were carefully selected per the IEC 60909 standard [170].

In addition, the fault line minimum value of 0.001 Ω and the incipient fault angle (0° to 30°) were utilised to compute the maximum arc resistance value. Because a larger resistance value might create overvoltage and current, the system may be unable to detect small problems. This is why a low-ground fault resistance is used to identify transient faults. As a result, the greater the fault resistance, the lower the defect detection. A three-phase fault simulator mimics the failure at a different position on the transmission line.

Table 3.1 shows the model's parameters, where R_1 and R_2 are positive and negative sequence resistance of phases 1 and 2. L_1, L_2 and L_3 are positive and negative sequence inductance of phases 1, 2 and 3, while C_1, C_2 and C_3 are positive and negative sequence voltage of phases 1,2 and 3, respectively. R_0, C_0 and L_0 are the zero resistance sequence, capacitance and inductance, respectively.

Twelve fault conditions were considered, and fault voltage and current data were acquired separately. As shown in Table 3.3, they are a-g, b-g, c-g, a-b, b-c, a-c, a-b-g, b-c-g, a-c-g, a-b-c, a-b-c-g, and no-fault. Where a = fault at phase A, b = fault at phase B, c = fault at phase C, and g = the ground fault G.

To train for accuracy, precision, and speed, phase and zero-sequence current fault and voltage data from simulated models may be utilised for fault classification, identification, and detection. The machine learning data processing model used for this paper is shown in Figure 3.3. The simulated model's data must be obtained and put into the trainer. The data is then analysed by searching for data points outside the fitting end of the remainder of the data to determine whether they may be ignored or considered [154]. The next step is to create features from the data by putting it into a machine-learning algorithm to improve model performance, model accuracy, and model interpretability and prevent over-drafting. A confusion matrix will be shown to compare the design classification with the data obtained. This is done before constructing and training the model. The next step is to improve the model by deleting variables that are not associated, as shown by the correlation matrix. The fault data type was created by a 500 km, 500 kV, and 50 Hz transmission line, and the dataset is divided into three categories: training data, testing data, and validation data. Each dataset will be trained before evaluation for ultimate performance, accuracy, and error validation.

4.3.1 Data Preparation and Extraction

The faulty data were extracted using a Simulink model from Figure 3.2, and the waveform was generated from the model to show the frequency of fault occurrence. The data was normalised to boost the speed of training on the feature on a future basis. The rows and columns were normalised according to the formula in equation 4.1

$$x_i = \frac{(x_i - {m_x}^{(1)})}{\sigma_X} \tag{4.1}$$

Where ${m_x}^{(1)}$ represents the mean value of the row vector X and σ_X is the standard deviation of the row vector X. The dataset consists of a 6 x 33336 matrix. The dataset is divided into three sections, with 23336 fault data used for training, 5000 for testing and 5000 for data validation.

The graphs in Figures 4.1, 4.2, and 4.3 show the waveform to validate the presence of a fault in the network. The faulty current and voltage are generated and used for machine learning training to classify and locate faults in the transmission line.

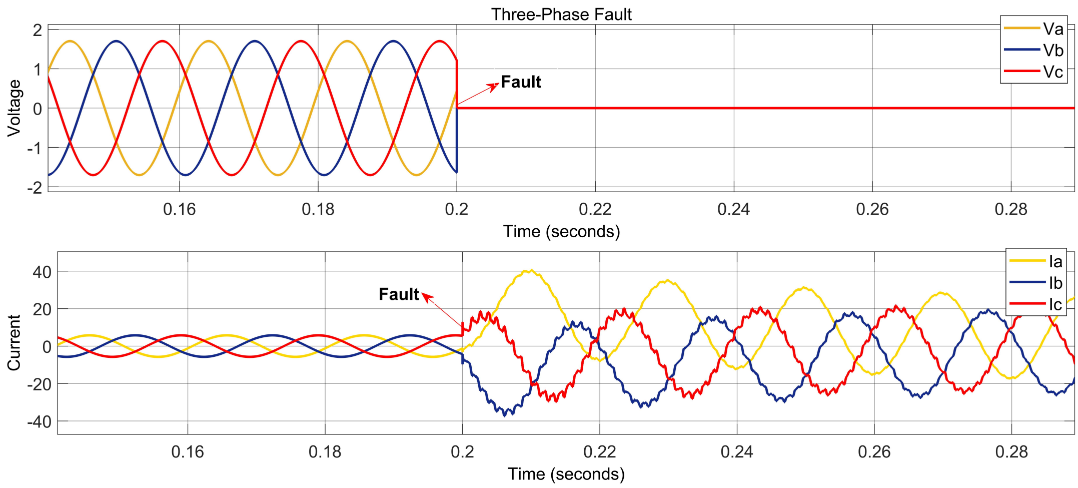


Figure 4.1: Three-phase to ground fault (a-b-c-g)

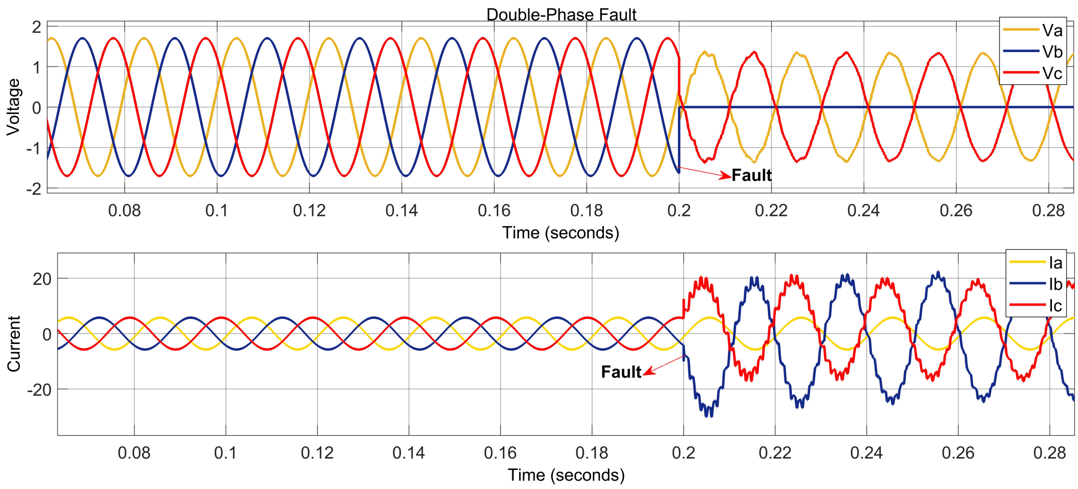


Figure 4.2: Double phase to ground Fault (a-b-g)

When a fault occurs, the power transmission line's fault current becomes abnormally high while the fault voltage falls low [184]. Figure 4.1 shows the current and voltage waveforms of phases V_a, V_b, V_c and I_a, I_b, I_c twisted owing to a three-phase to ground fault, with their magnitudes quickly falling. Figures 4.1 and 4.2 also show distorted voltage and current for phases B, C, and A owing to line failures. As a consequence of the issue, all of these waveforms show distortion; the fault model's switching time was set to 0.2 s, and the fault was placed 250 km from the transmission line.

Figures 4.1, 4.2, and 4.3 depict fault detection in four distinct fault types: no

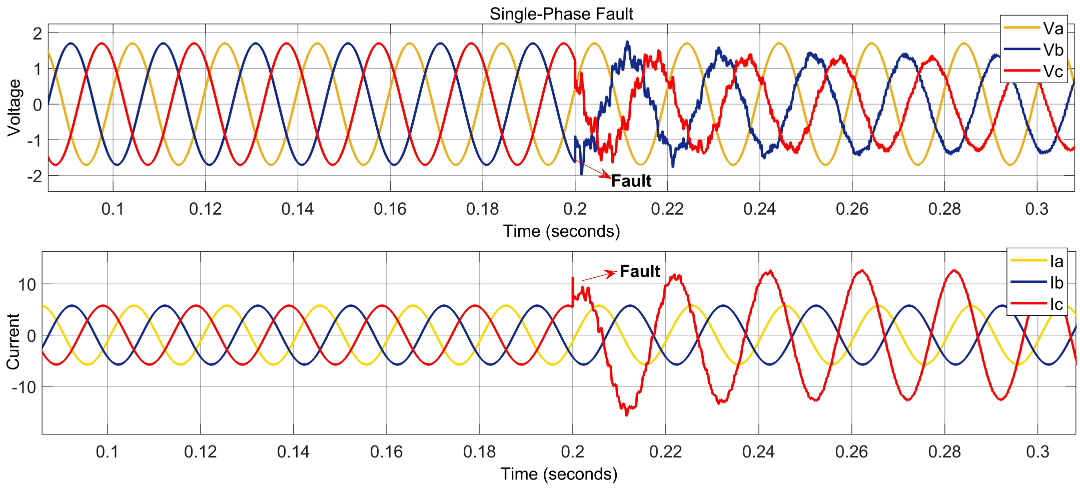


Figure 4.3: Single-phase to ground fault (a-g)

fault, single phase to ground fault, double line to ground fault, and three-phase to ground fault. Using the fault current and voltage data obtained, machine learning was used to train the data to identify, categorise, and pinpoint the transmission line issue. Figures 4.1, 4.2, and 4.3 indicate a significant rise in current, while Figures 4.1 show a voltage drop to zero, confirming the transmission line failure.

Figures 4.1, 4.2, and 4.3 confirm the occurrence of a transmission line fault. At the same time, selecting 0.001 Ω as the minimal fault resistance allows the model to identify transient faults. Raising the fault resistance reduces fault detection and may result in incorrect data that affect electrical installations, leading to system collapse, as seen in Figure 4.4 where the voltage signal stays constant but the current signal increases.

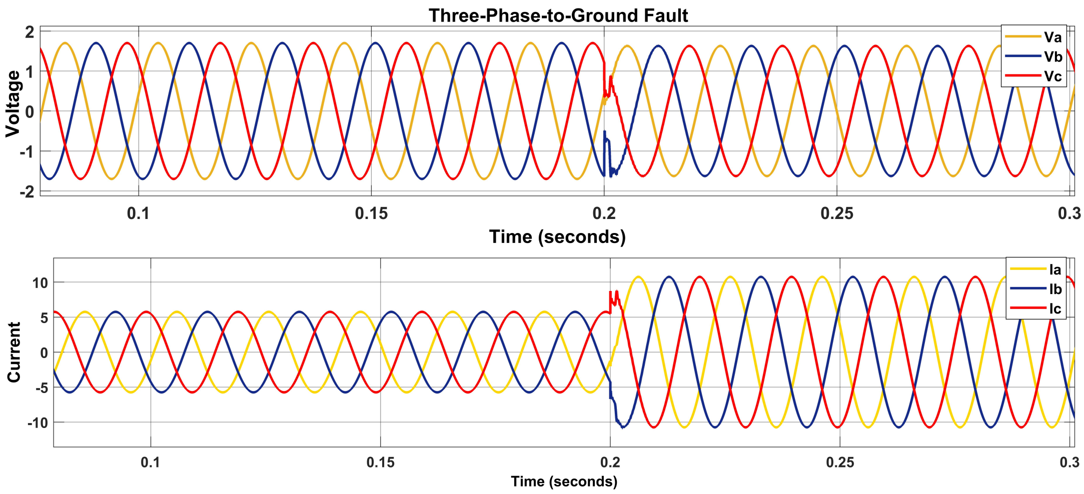


Figure 4.4: Three-phase-to-ground fault at 100 Ω fault resistance.

When the fault resistance increases to 100 Ω, there is a corresponding increase in the fault current, as seen in Figure 4.4. When it reduces to 50 Ω, there is

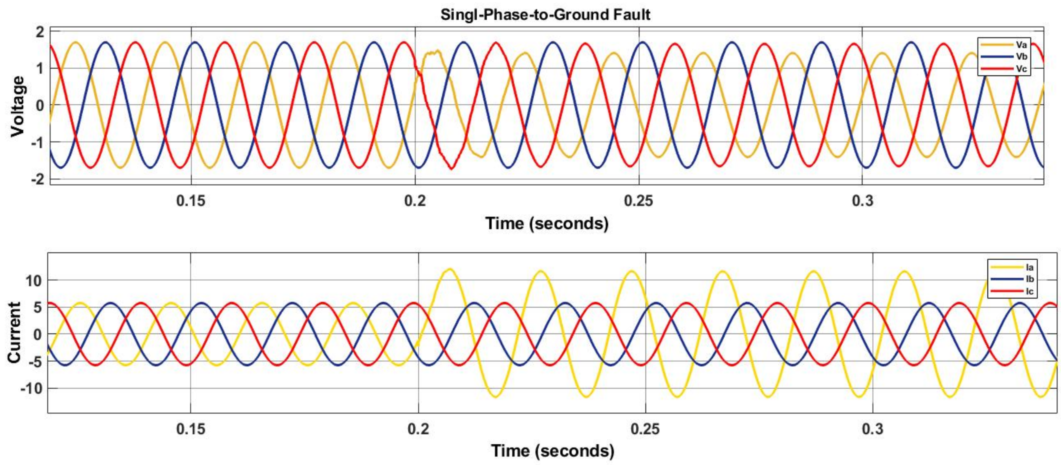


Figure 4.5: Single-Phase-to-Ground Fault 50 Ω fault resistance.

a corresponding current increase in the faulty phase, but the voltage remains constant, as seen in Figure 4.5. Therefore, the fault resistance must be very small to extract accurate faulty current data for effective fault detection. Also, when the fault resistance is too high, the model's sensitivity to detect transient faults will be very low, and the dataset extracted will not be reliable.

The training algorithm used for the dataset is implemented using the ANN algorithm in the MATLAB application, and a sigmoid activation function was selected based on the dataset for easy training. The faulty dataset for six diffident fault conditions was used as the input data to train the algorithm.

4.4 Results and Discussion

The ANN technique is used to classify and detect the fault in the network, and a data size of 33336 was generated from Figure 3.2 and used for the algorithm's training. The data size was chosen based on the simulated faults result of the voltage and current waveform. The data is divided into training, testing and validation in 80%, 15% and 5%, respectively, to avoid over-fitting. The faulty current and voltage phase values were used as input data, while the three-phase value and ground phase were used as input layers. The sigmoid function is the activation function, given in equation 4.2 below.

$$f(x) = \frac{1}{1 + e^{-}x} \tag{4.2}$$

Where x is the net input chosen through the trial and error method till the training is fitted, the selection of the sigmoid activation function was based on the target input value of 0 and 1 and due to the normalisation of the dataset in

Table 3.3. However, the tanH activation function was also used, but the accuracy was the same with a time of execution was 0.006 s. The activation function helps to maintain the output or predicted value in a particular range with high accuracy and efficiency of the model [185]. In backpropagation neural networks, the Sigmoid is a non-linear AF that is frequently utilised. It is a bounded differentiable real function defined for real input values and has smoothness to some extent and positive derivatives everywhere. The sigmoid function introduces a hybrid sigmoidal network with varied parameter configurations in different layers and influences the pace of backpropagation learning. The error signal, oscillation, and asymmetrical input problems can be diminished by controlling and adjusting the sigmoid function parameter configuration at various levels [186].

A total of six input parameters, 15 input layers, 2 output layers and 4 output result (L-G, L-L, L-L-G, and L-L-L-G) is used for the training. The algorithm performance was analyzed, and the Mean Square Error (MSE), epoch and training time were also considered.

A confusion matrix was used to evaluate the model's performance, comparing the actual target values with those predicted by the ANN model. It also gives a holistic view of the model's performance and the type of error involved in the system. The result also explains the practical use of ANN in transmission line faults management system plans.

Figure 4.6 shows the configuration used for the training, which consists of a 6-15-2-4 structure. This configuration was selected after a training series, and the best data fitting was achieved, and the hidden layer was set at 15 to achieve the best configuration. This consists of 6 input data (three-phase current and voltage I_a, I_b, I_c and V_a, V_b, V_c) and four output data (L-G, L-L, L-L-G, L-L-L/L-L-L-G) are the same as a-g, b-c-g and a-b-c-g, which is used for the training.

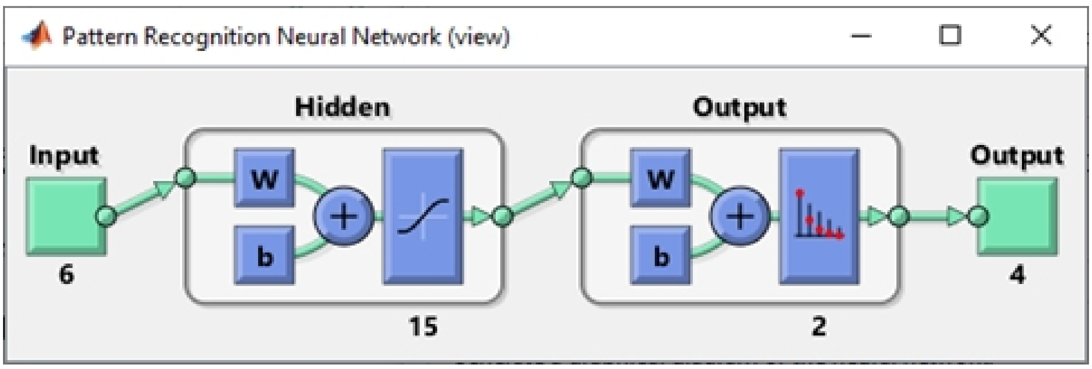


Figure 4.6: ANN Training configuration for fault Detection.

The confusion matrix in Figure 4.7 summarises the model's fault detection prediction. It tests the dataset or validates data with expected values and makes predictions in each row. It also makes correct predictions of each class and the number of incorrect predictions. The no-fault condition represents 1, the single line to ground fault represents 2, the double line to the ground represents 3, and the three phases to ground fault represent 4. About 33,336 fault data was used for training with 100% accuracy and 0% confusion state. Meanwhile, 23,336 datasets were used to validate and train the fault data with 100% accuracy, as seen in Figure 4.7

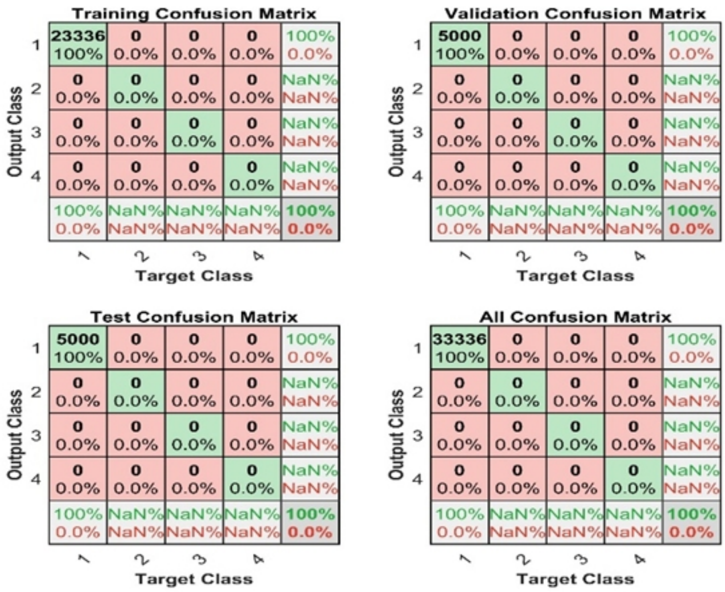


Figure 4.7: ANN Confusion Matrix for fault detection

The histogram in Figure 4.8 shows the error between the target and predicted values after training the ANN network. The difference between the target and the output has a zero error value of -0.00739, showing minimal error.

The network's best validation performance was 0.17329 at 332 epochs, as shown in Figure 4.8. This is a good performance because the network is fitted, and the best-fit line is close to the train line, validation and test line because they have related features that do effective training, as shown in Figure 4.9 below.

From Figure 4.10, the model has a maximum level of allowable failure of 6 at 338 epochs and a gradient of 2.1803×10^{-6}. This graph shows that the model is good because the network gradient performance is in perfect condition and minimal due to its performance.

The ANN algorithm uses the confusion matrix to predict the true positive, true negative, false positive and false negative for the model. At the same time, the error histogram predicts the error in the trained data. Also, the network performance shows the value of the train data, test data, validation data and the

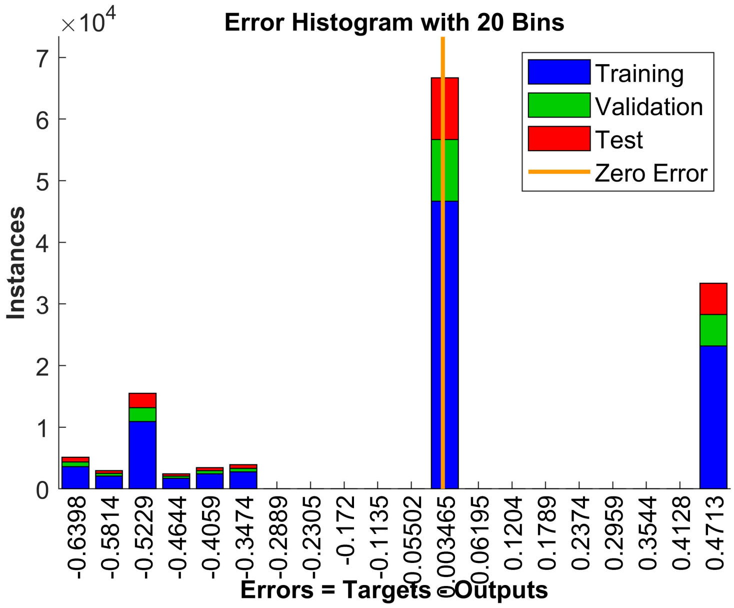


Figure 4.8: Error Histogram for the ANN Network

line of best fit. It also shows the validation failure of fault on the train data.

4.4.1 Fault Localisation Results

The model is also designed for fault localisation in the transmission line using Simulink to generate a neural network classifier to predict the fault location. The input parameters are the fault current and voltage of a three-phase line. The input is then fed into the classifier to detect the fault location. These fault types and locations are displayed on a screen for easy accessibility. Possible action is taken for a fast and effective fault management plan, as seen in Figures 4.11, 4.12 and 4.13

In Figure 4.11, the line-to-line fault and the three-phase-to-ground fault were detected at the 200 km distance of the transmission line.

Also, Figure 4.12 shows that fault was in zone 2,3 and 4 while zone 1 had no fault. This method clearly shows the type of fault detected and the zone where the fault is found. The network is segmented into zones and circuits for easy identification. Figure 4.11 shows that the fault was situated in the circuit or line 2. This can be replicated in other fault conditions to detect and locate the exact spot of the fault for easy isolation and power restoration.

This model outperforms others since it specifies the kind of fault and its location at any given moment. This will enable the maintenance crew to clear the faulty line faster and is useful in the transmission line fault management

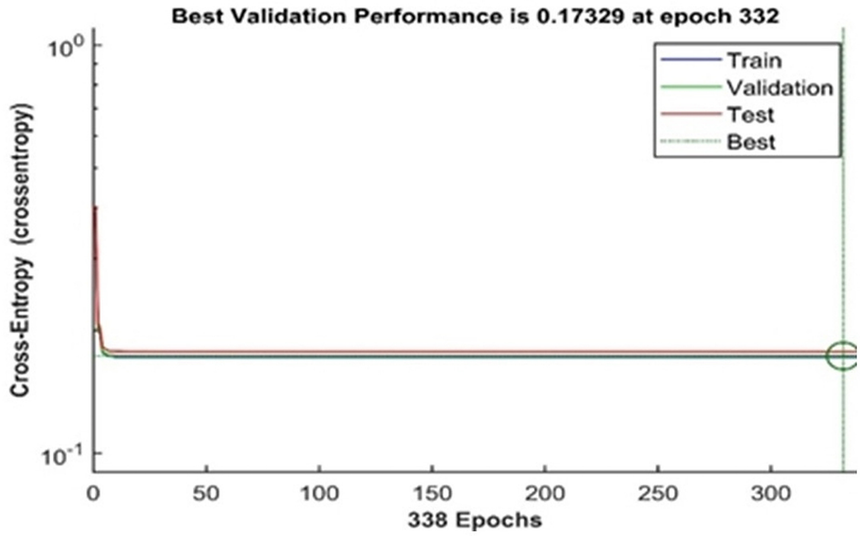


Figure 4.9: ANN network performance.

system.

Table 4.1: Fault Location at Different Distances.

Fault Type	**Actual Fault Distance (km)**	**Estimated Fault Location (km)**	**% Error**
	100	103.78	3.78
Single Line to Ground	250	252.65	1.06
	450	448.67	-0.30
	100	101.67	1.67
Double line to Ground	250	253.98	1.59
	450	452.10	0.47
	100	100.98	0.98
Line To Line	250	252.77	1.11
	450	450.98	0.22
	100	100.87	0.87
Three Phase To Ground	250	252.10	0.84
	450	451.98	0.44

The Fault location at different distances was considered as seen in Table 4.1, which shows the actual distance and the estimated distance of fault location at different points in the transmission line. The actual fault distance and the estimated fault location were measured. The percentage error was determined for each distance using line-to-ground, double-line-to-ground, line-to-line, and three-phase-to-ground faults. The percentage error between the estimated and actual distance is very low, confirming the model's viability.

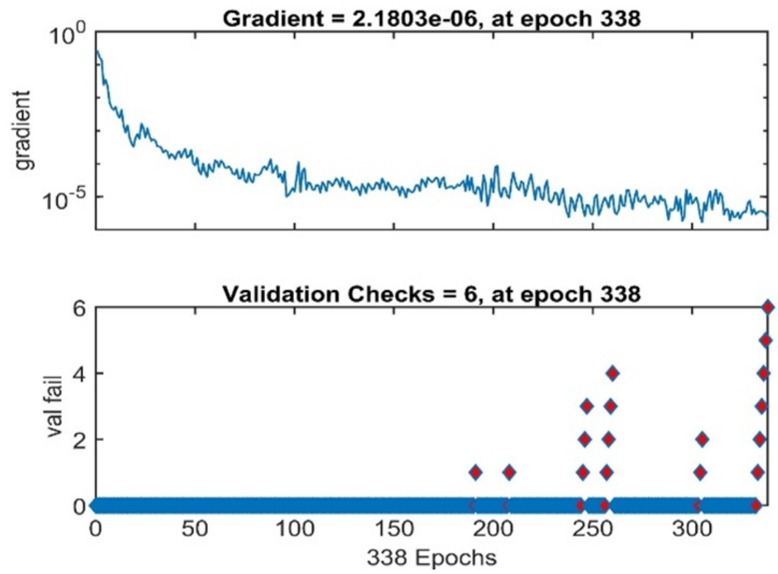


Figure 4.10: Validation Failures

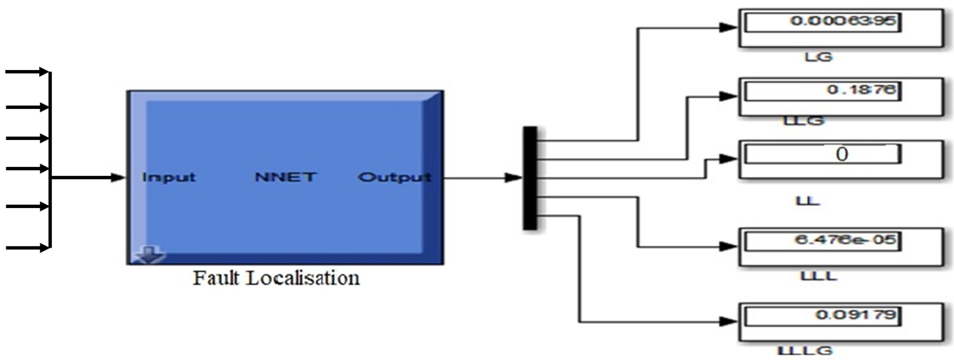


Figure 4.11: L–L and three-phase fault detected at 200 km distance.

4.4.2 Comparative analysis of the ANN technique for latency and other machine learning techniques

Rapid and timely identification of faults aids in separating the damaged line, protecting the system from the dangerous repercussions of the faults. The adverse effect may lead to power outages, damage to installation, and cost implications, thereby affecting the economy. Furthermore, information from fault categorisation can enhance the prompt discovery of a faulty point, minimising the time necessary to remove faults and swiftly restore electricity service. As a result, many scientific investigations are being conducted to develop a robust, accurate, rapid and timely strategy for detecting and localising the faults on transmission lines [14].

Table 4.2 compares the execution timings of multiple fault localisation and detection methods in the transmission line. In comparison, WPT and ANN take

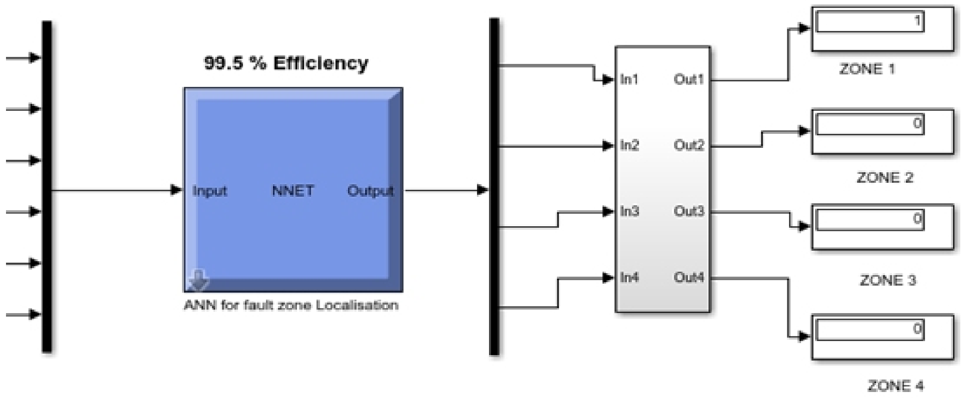


Figure 4.12: Fault location at three zones.

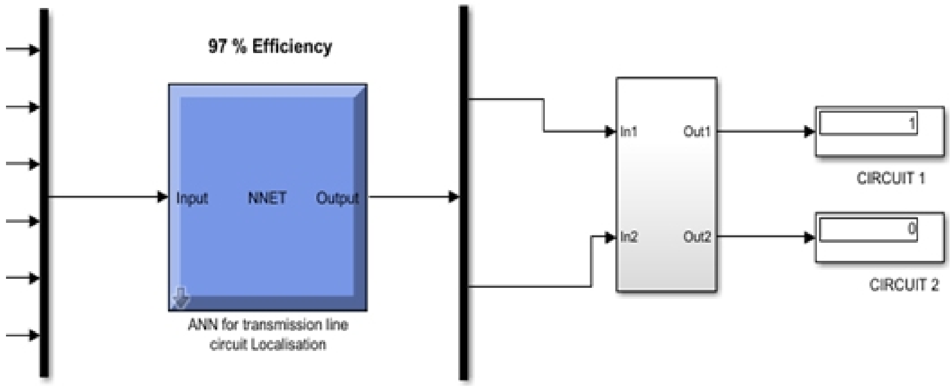


Figure 4.13: Fault location at line 1.

110 s, WT takes 4.000 s, PMU takes 0.800 s, while the ANN technique takes 0.0017 s to execute. Because it exceeds the competition in terms of speed with a percentage error of 0.007%, the ANN is preferred for fault localisation and detection.

4.4.3 Effect of Noise Signal on the Proposed Model

Noise signals reduce the accuracy of identifying and detecting transmission line defects. Noise signals such as voltage sags, transients, harmonics, electromagnetic interference (EMI), lightning strikes, power equipment, and voltage interruptions must be considered while selecting and extracting fault characteristics.

The kind and strength of the noise signal determine the impact of noise on fault detection and localisation. High noise may hide fault signals, making it harder for fault detection algorithms to identify and localise defects effectively. Moreover, noise may cause false alarms and mislead fault detection systems into identifying non-existent defects or improperly localising them. This might lead

Table 4.2: Comparison of percentage error and speed of execution of different algorithms used for fault localisation.

Algorithm used	**Input used**	**% Error**	**Time of execution**
WPT and ANN [83]	Current signal	2.05%	110 s
Adaptive Network-Based Fuzzy Inference System(ANFIS) [187]	Three-phase current	0.07%	2.600 s
Radial Bias Function (RBF) [188]	Positive sequence voltage and current waveform	2.8%	0.530 s
Discrete WT [189]	Single-phase voltage signal	1.67%	4.000 s
Linear discrimination principle [190]	Three phases current and voltage signal	2.66%	0.032 s
PMU [178]	Voltage signal	4%	0.800 s
DWT & ANN [158]	Current signal	12.78% for ANN and 0% for DWT	0.15 s
Proposed ANN Solution	Voltage and current signal	0.007%	0.0017 s

to unneeded maintenance or repair work, which can be expensive and time-consuming.

Several strategies are utilised to reduce the influence of noise on fault identification and localisation. Filtering methods are used to eliminate noise from signals, signal processing techniques are used to increase the signal-to-noise ratio, and improved fault detection algorithms are used to differentiate between fault signals and noise.

The DWT was employed for feature extraction, and the SVM was used for fault classification in [176], with an accuracy of 100% when there is no disturbance and 98% and 95.6% accuracy at 30 dB and 20 dB noise, respectively.

Figure 4.14 depicts the fault signal with noise, whereas Figure 4.15 depicts the de-noised signal. To get a de-noise signal, it is recommended that noise be removed using the DWT approach during fault extraction. The data gathered from this approach will be employed in an ANN classifier for extremely accurate results.

To get a de-noise signal, it is recommended that noise be removed using the DWT approach during fault extraction. The data gathered from this approach will be employed in an ANN classifier for extremely accurate results.

Figures 4.14 and 4.15 show a faulty signal with noise and a de-noise signal,

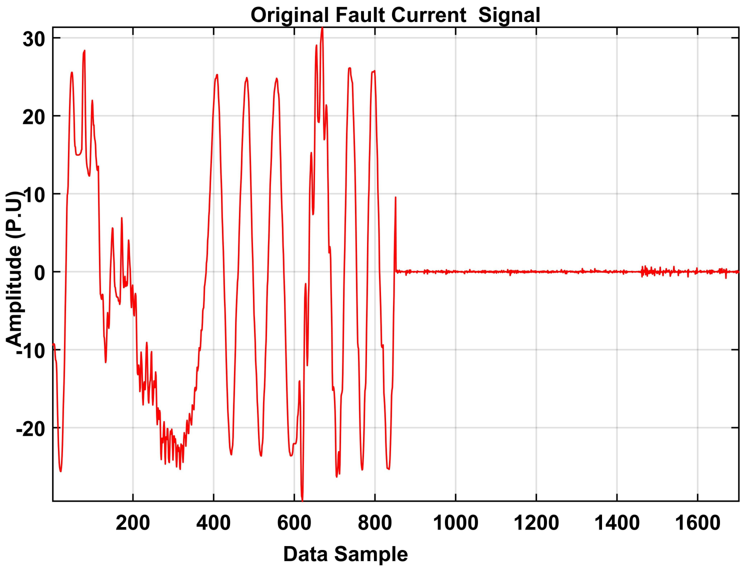


Figure 4.14: . Fault signal with noise.

respectively. The model was examined for noise regularisation by adding noise to the input vector during training and using the tanH activation function to train the noise vector. The accuracy decreased substantially to 78%, as shown in Figure 4.16, confirming that without de-noising the noise signal from the system, it will drastically affect the output result, and the accuracy will drop.

4.5 Conclusion

This paper has investigated using artificial neural networks for fault detection and localisation in the transmission line. A 330 kV, 500 km, 50 Hz three-phase transmission line was modelled using Matlab/Simulink to generate the RMS value of faulty voltage and current signals from the defective line. About 12 different fault scenarios were considered, and 33,336 data samples of faulty current and voltage were taken from various locations in the transmission line to detect faults using ANN and to use the module for fault localisation. The different faults were discussed, especially single, double, and three-phase. The data were trained for accuracy, speed, and precision, achieving a 100% accuracy rate for fault detection and a 99% accuracy rate for fault localisation at separate locations. The time for fault detection is vital in fault protection, and this paper has focused on the speed of execution for prompt fault detection. This technique produces excellent results compared to conventional methods like SVM and DWT.

However, the ANN technique has some disadvantages, including a large volume of data required for optimal performance and difficulty in determining the

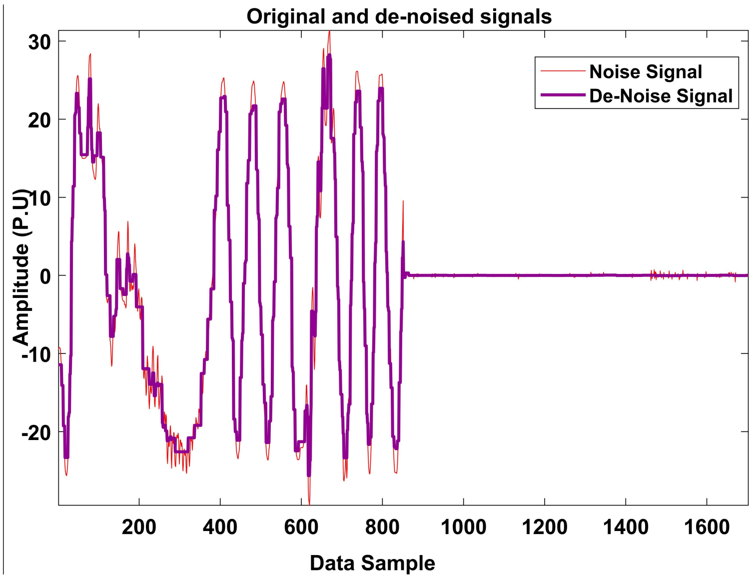


Figure 4.15: Fault with De-noise signal.

proper network structure for the best performance of the model. This paper has limitations: The fault data generated were only based on the minimum fault resistance of 0.001 Ω. The fault angle can be varied by increasing or decreasing it for optimal fault detection. Also, Noise was not considered during the simulation though it was mentioned.

The results generated from this can also be recommended for designing effective fault management and protecting power systems.

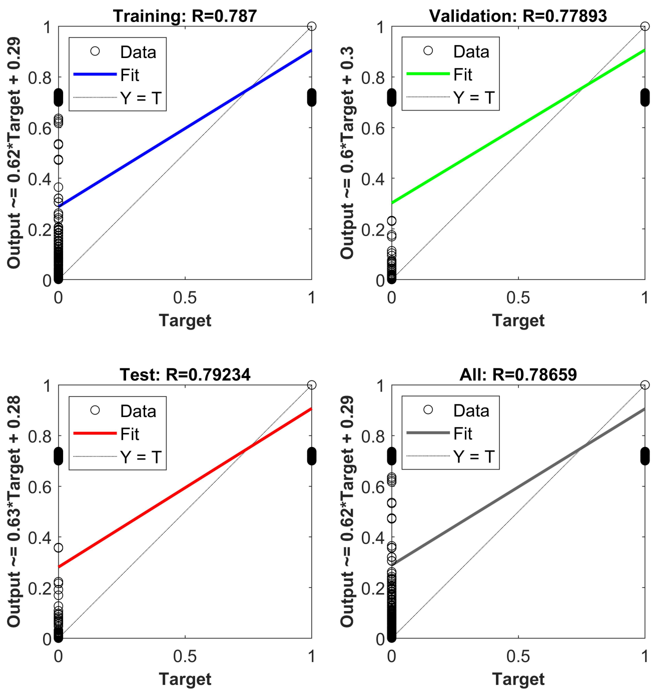


Figure 4.16: Regression Fit for the noise signal data.

Chapter 5

Optimal Relay Protection of TL

5.1 Introduction

The power system's major and minor components are critical in transmitting electricity from where it is made to the customer. However, the fault protective relay is the most crucial and sensitive of all these components. These comprise the overcurrent and overvoltage relay protection. When there are problems with transmission lines, consumers lose power, which is inconvenient and could cost them money. Damage to the power system or a power outage at the consumer's end could result in financial losses. When a failure occurs on the transmission lines, it is critical to protect them [191].

Overcurrent protection is capable of operating under any fault condition. The current pickup value of the relay must be higher than the maximum value of the expected output or normal load flow. The overcurrent relay is commonly utilised in radial transmission and distribution systems [192]. In the event of an abnormal condition or fault, such as a short circuit, the protective relay de-energises the defective component of the distribution power system, preventing the rest of the system from being impacted [193]. The relays are introduced to prevent the incidents mentioned earlier and their impact on customers. Properly coordinated relays are critical for the power system network because improper coordination can have significant implications for the electrical network, such as power outages, equipment damage, and utility station faults. The current magnitude increases when the power system malfunctions, causing network damage [194]. The fault current is measured by the overcurrent relays and compared to predetermined threshold values. When the current level exceeds the threshold, a trip order is delivered, and the appropriate circuit breaker opens its contacts and isolates the faulted area after a predetermined time delay. However, if the relay is faulty, it will damage the installation or the system will collapse.

Some literature has recently proposed tools to aid transmission and distribution system protection based on overcurrent relay settings. In [195], an approach for fault calculation in imbalanced distribution systems was disclosed where the primary protective devices and functions employed in distribution systems have mathematical models. This method makes complete three-phase representations possible, and the solution is achieved directly in phase coordinates. In [196], an integrated optimising model for current relay coordination with challenging, practical limitations based on a gradient-based optimiser was analysed, and the model was used to enhance the protection coordination of the transmission and distribution network with some constraints such as false tripping actions. In [197,198], this study describes a computational tool that was created to automatically calculate the adjustments of all distribution network protection devices to acquire the best technological application, optimise its performance, and make protection studies easier. In [199], it presents a straightforward method in which two-phase faults were diagnosed based on the negative sequence current value, and the operating conditions of the suggested criteria arising from negative and zero sequence currents were automatically selected based on the three-phase short-circuit criterion. However, the paper fails to introduce the controller operation of the circuit breaker for adequate tripping of the transmission line. The methodology determines the protection settings and in another paper, [200], based on real-time estimation of the Thevenin Equivalent Circuit (TEC). The estimation process used the voltage and current values in the positive sequence, and a system of nonlinear equations was solved repeatedly using the Gauss-Newton method. Additionally, in [201], a new adaptive protection method to set online overcurrent relays in distribution networks was implemented for the mis-coordination of the overcurrent relay.

The connecting and disconnecting of transmission lines and their components are critical to changing fault currents' magnitude and flow direction. Change in the network configuration also leads to a disturbance in the overcurrent relay functionality. The fault current signal affects the power transformer and other components when a fault occurs in the transmission line. Therefore, the circuit breaker needs to open immediately to prevent damage to the installation. The fault current magnitude is greater than the standard load current, so the relay should be signed to operate and trip the circuit breaker for all currents above the relay settings. The overcurrent relay needs a backup relay for proper coordination such that if one fails to trip, the backup relay will trip automatically.

To protect the transmission lines against multi-phase faults, the overcurrent protection criterion with a fixed current threshold and time-independent operation on fault current value is frequently utilised. Usually, two of these protection relays are currently deployed. The situation right now acting as the time-delay short-circuit, and the initial line of defence overload prevention identified by the $I >$ symbol must adhere to the subsequent conditions as shown in equation 5.1,

$$I_{min} > I_{pr} > I_{st}, \tag{5.1}$$

where I_{min} is the minimum short-circuit phase current of the transmission line with $I >$ protection, I_{pr} is the threshold value of the current protection, and I_{st} is the steady state component of the highest load current of the line [199]. Such protection relays respond only to phase current values and are typically definite minimum time (DMT) overcurrent relays configured to meet selectivity requirements.

According to the literature reviewed above, this paper proposed the following approaches:

1. The use of wavelet transforms to determine the threshold voltage and current of faulty transmission lines;

2. A designed model to determine the tripping time and the operating time of instantaneous over current relay at different fault-resistant values;

3. A protection scheme was designed to evaluate and determine the response time of relays in different zones.

Contribution of the Proposed Algorithm

The proposed algorithm performs better than those mentioned in the literature due to its speed in obtaining the threshold values for setting the overcurrent and overvoltage relay. Additionally, fault signals are accompanied by noise. Therefore, using the wavelet transform to determine the threshold current and voltage helps denoise the signal to attain stability in the system. It also serves as a fast gateway for instantaneous relay settings for optimal protection of transmission and distribution line fault detection and isolation with the use of a circuit breaker.

5.2 Proposed Algorithm

The proposed model uses the discrete wavelet transform to generate the threshold current and voltage for the overcurrent relay setting. This method is a fast and reliable process to determine the pickup current, minimum and maximum threshold current and voltage for the fast and accurate detection of transient or overcurrent faults in the transmission line. The proposed model improves the relay protection level, reduces the operating time of the relay and better coordinates between the primary and backup relay.

5.2.1 Wavelet Transform

Wavelet transform is a powerful signal processing technique that can determine the threshold voltage and current values in power systems fault detection and protection. Here's how wavelet transform can be applied to this task:

- Signal Decomposition: Wavelet transform decomposes a signal into multiple scales or levels. In the context of power systems, the voltage and current waveforms are typically complex and contain information related to various system events, including fault conditions.

- Feature Extraction: Wavelet transform helps extract relevant features from the voltage and current waveforms at different scales or levels. These features can include details about the transient behaviour of the signals during fault events.

- Thresholding: After decomposing the signals and extracting features, a thresholding technique can be applied to identify the significant components of the signals. Thresholding involves setting certain coefficients or components to zero based on their magnitude. The choice of thresholding technique and threshold value is crucial and often depends on the specific application.

- Denoising: By removing or setting to zero the insignificant components of the signals through thresholding, wavelet transform can effectively denoise the signals. This helps isolate the relevant fault-related information from noise and disturbances in the signal.

- Fault Detection and Localization:** The processed signals with the thresholding applied can be analysed to detect faults and estimate their locations. The transformed signals are often more informative for these tasks, as they emphasise transient features characteristic of fault conditions.

- Threshold Optimisation:** The choice of threshold values is essential in the wavelet transform process. Optimising the threshold values may involve experimentation and using signal-to-noise ratio (SNR) or other metrics to ensure that fault-related information is retained while noise is minimised.

- Performance Evaluation:** The effectiveness of using wavelet transform in determining threshold voltage and current values for fault detection and protection can be evaluated based on criteria such as detection accuracy, fault location accuracy, and system stability under fault conditions.

Wavelet transform is particularly useful in scenarios where voltage and current waveforms exhibit complex behaviour during fault events, and traditional methods may not be as effective in separating the relevant fault information from noise and other disturbances. By decomposing the signals into different scales and applying thresholding, wavelet transform can enhance the accuracy and sensitivity of fault detection and protection systems in power systems.

5.2.2 Data Acquisition

A 330 kV, 50 Hz, 500 km transmission line was modelled using MATLAB/SIMULINK, and 11 different types of faults were induced in the model, and the fault current data were collected and recorded, as shown in the table below. A wavelet transform syntax was applied to obtain the maximum coefficient current for phases A, B and C. $[C, 1]$ = wavedec(x,n, wname), where wavedec is the function which decomposes the signal. X is the signal generated, n is the wavelet layer, wname is the name of wavelet type and C is the output wavelet decomposition vector, while l is the number of coefficients by layer.

The voltage and current of the grid experience transients when faults occur. Using a discrete wavelet transform to analyse these transients, the defect can be categorised [44]. The zero sequence and phase transient currents are analysed to determine the fault that occurred. Wavelet transform identifies the phase-related fault by calculating the energy of transients linked to each phase and ground.

MATLAB/Simulink was used to simulate the model using the RLC load at the receiving end, while the three-phase source block was used at the sending end; 330 kV, 500 km, 50 Hz and a three-phase transmission line were used for the model. The coefficient of each fault type was calculated and compared with the threshold value by checking the maximum and minimum threshold values.

Table 5.1 shows the maximum coefficient value of the different fault types. In contrast, Table 5.2 represents the maximum and minimum threshold values for each current fault phase.

Table 5.1: Faulty current and voltage data in kA and kV.

Fault Types	**Coef of I_a**	**Coef of I_b**	**Coef of I_c**	**Coef of V_a**	**Coef of V_b**	**Coef of V_c**
ABC-G	533.0974	495.1115	575.3335	0.0000	0.0000	0.0000
ABC	395.1943	587.4911	474.7873	-0.0001	0.0000	0.0001
AB-G	338.5069	531.6202	32.9732	0.6655	-1.6882	1.0227
AC-G	306.5768	22.3418	620.4303	1.5501	-0.1691	-1.3810
BC-G	26.1066	608.8079	294.0561	-1.2685	1.6153	-0.3468
A-B	855.3816	385.9281	17.8156	-1.2792	1.6102	-0.3311
A-C	299.0803	19.8595	574.5684	-1.2897	1.6050	-0.3154
B-C	15.3783	420.5652	355.8047	-1.3001	1.5996	-0.2996
A-G	307.6007	39.5083	20.8305	-1.3103	1.5941	-0.2838
B-G	32.6032	199.6292	28.3545	-1.3205	1.5885	-0.2680
C-G	15.1679	28.6647	364.3873	0.4383	-1.6423	1.2040
No-Fault	10.6870	15.1958	23.0105	1.4530	0.0390	-1.4920

Table 5.2: Threshold value of current at different fault locations

Fault Types	**Threshold of I_a**		**Threshold of I_b**		**Threshold of I_c**		**Threshold of I_g**
	Max	**Min**	**Max**	**Min**	**Max**	**Min**	
ABC-G							18.6876
ABC							56.9488
AB-G					531.6202	32.9732	25.7012
AC-G			620.4303	22.3418			15.5710
BC-G	608.8079	26.1066					20.9355
A-B					855.3816	17.8156	28.2445
A-C			574.5684	19.8595			34.5217
B-C	420.5652	15.3783					16.8326
A-G			307.6007	39.5083	307.6007	20.8305	18.3399
B-G	199.6292	32.6032			199.6292	28.3545	24.7174
C-G	364.3873	15.1679	364.3873	28.6647			15.5710
No-Fault	23.0105	10.6870	23.0105	15.1958	23.0105	23.0105	13.0455

5.3 Modelling of the High Sensitive Overcurrent Relay

This protection switchgear block contains a current transformer, a circuit breaker (52) and an IDMT overcurrent relay (51P) that operate when the current exceeds the relay's predetermined value. This relay operates based on the IEC 60255 standard for normal inverse the Inverse Definite Minimum Time (IDMT) trip characteristics, as seen in Figure 5.1. It also contains a phasor measurement unit (PMU) and two Supply and Switching Units (SSU) connected to a separate bus with 10 kA, 6 kA and 4 kA faults. These fault values are obtained from Tables 5.1 and 5.2. The input voltage was a 330 kV high-voltage transmission line, and an output display of the relay status showed the tripping time and fault current.

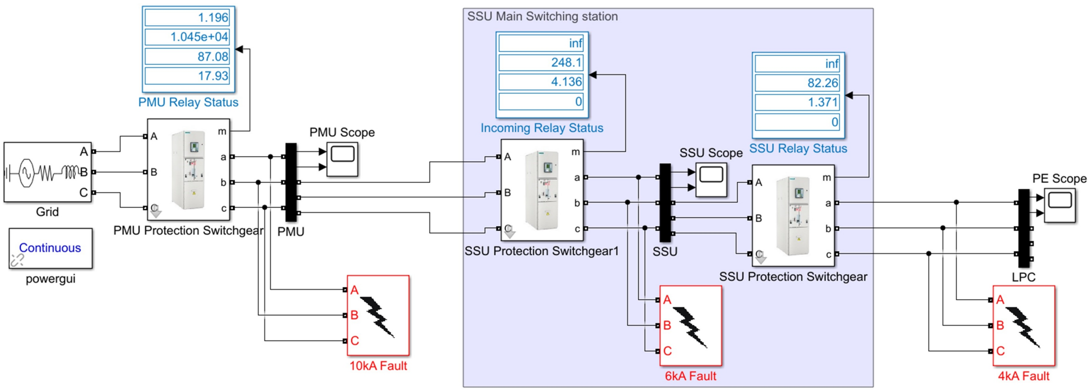


Figure 5.1: Instantaneous overcurrent relay block model

The overcurrent relay activates when the fault current exceeds the relay pickup current. The pickup current is calculated in operating time. The inverse definite minimum time (IDMT) is the time taken before the circuit breaker trips when an overcurrent is initiated in a circuit or the transmission line is also calculated. The operating time is defined as a fixed parameter such that an instantaneous overcurrent relay is produced when the operating time is set to zero [202]. This can be illustrated in Figure 5.2 below and, to calculate the trip time, the IEEE C37.112-1996 equation for the trip time used is given In equation 5.2 as:

$$t(I) = TD\left(\frac{A}{(\frac{1}{I_s})^p - 1} + B\right), \tag{5.2}$$

Where A is the time factor for the overcurrent trip, I is the actual current, Is is the relay pickup setting, p is the exponent for inverse time, and B is the time coefficient for the overcurrent trip. While the IEC 60255 IDMT trip curve equation is given by equation 5.3

$$t(I) = TMS\left(\frac{k}{(\frac{1}{I_s})^{\alpha} - 1}\right), \tag{5.3}$$

where α and k are the curve constants and seen in Table 5.3 below.

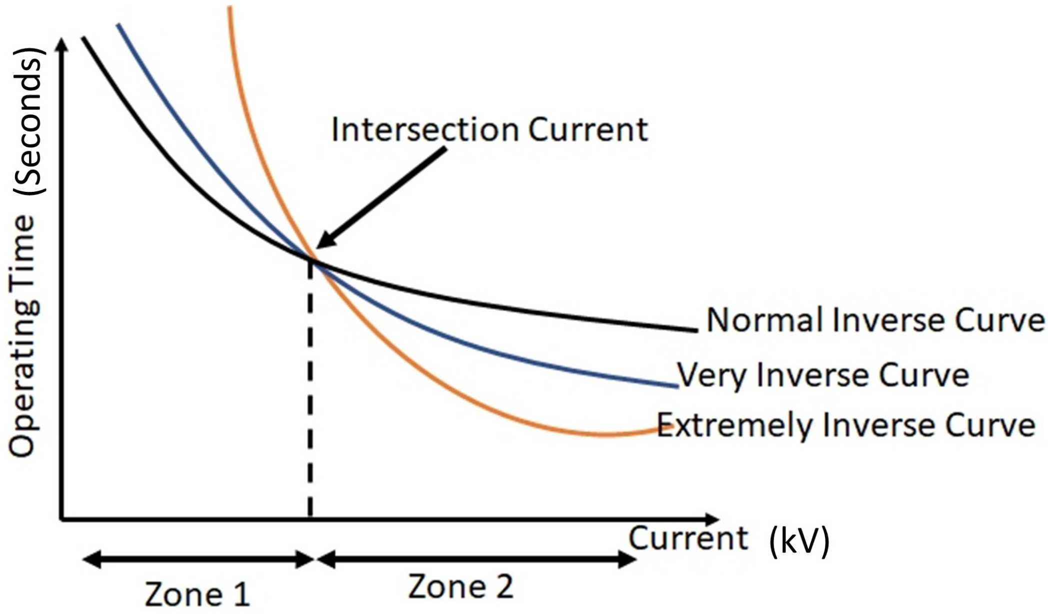


Figure 5.2: The IDMT Overcurrent Relay Curve

Table 5.3: IDMT curve constant.

Curve Type	**K**	α
Normal Inverse Curve	0.140	0.020
Very Inverse Curve	13.5	1
Extremely Inverse Curve	80	2
Long-Time Standard Curve	120	1

5.4 Results and Discussion

The threshold current or peak make current and the short circuit breaking current can be calculated by finding the RMS symmetrical current $i"k$; the peak make current for a single radial current is calculated using the peak factor k as shown in equation 5.4 and 5.5.

$$i_p = k\sqrt{2i"k}, \tag{5.4}$$

where $k = 1.02 + 0.98x10^{-3}\left(\frac{X}{R}\right)$.

$$Peakfactor = \sqrt{2}\left[1 + sin\left\{tan^{-1}(\frac{X}{R})\right\} exp\left\{\frac{-[\frac{\pi}{2} + tan^{-1}(\frac{X}{R})]}{\frac{X}{R}}\right\}\right], \quad (5.5)$$

where the $\frac{X}{R}$ is the system ratio at the fault point. The RMS current is given by I_rms total at $\frac{1}{2}$ cycle (KA),

$$I_rms = \sqrt{I + 2exp\left[-\frac{\frac{\pi}{2}}{\frac{X}{R}}\right]} XI_rms, \quad (5.6)$$

at $\frac{1}{2}$ cycle(KA) and $\frac{X}{R} = \left(\frac{X_c^P}{R_c^P}\right) \times \frac{f}{f_c}$ for single phase to Earth faults . f is the normal frequency and f_c is the equivalent frequency represented in equation 5.6.

The model generated the threshold current when the fault resistance was set at 0.01 Ω, 50 Ω and 100 Ω, respectively. The response times of the three different relays were also analysed, as seen in Tables 5.4 to 5.6.

Table 5.4: Threshold current at fault resistance of 0.01 Ω.

Fault Type	**Fault Resistance = 0.01 Ω**		
Three-phase to ground fault	**Relay 1**	**Relay 2**	**Relay 3**
Threshold Current (kA)	259	8.524	2.826
TMS (Seconds)	2.991	0.1421	0.04709
Trip Time (Seconds)	0.01	0.01	0.01
Double phase to ground fault	**Relay 1**	**Relay 2**	**Relay 3**
Threshold Current (kA)	358.9	13.25	4.424
TMS (Seconds)	2.991	0.2208	0.07373
Trip Time (Seconds)	0.01	0.01	0.01
Single line to ground fault	**Relay 1**	**Relay 2**	**Relay 3**
Threshold Current (kA)	358.8	16.43	5.478
TMS (Seconds)	2.99	0.2739	0.0913
Trip Time (Seconds)	0.01	0.01	0.01

The tripping time varied as the fault resistance changed from 0.01 Ω to 100 Ω at different fault conditions. In Table 5.4, when the fault resistance was at 0.01 Ω, the trip time was 0.01 s at the three relays and all the fault conditions. At the same time, it was quite different when the fault resistance changed to 50 Ω. The trip time was reduced to zero seconds at a double line to ground and a single line to ground fault at relays 1 and 3 with a variation in relay 2 of about 0.91 s as seen in Table 5.5. The time multiplier setting (TMS) for each of the relays was set at 1 s, 2 s and 5 s, and the error after tripping was about 0.9 s, which is minimal, as seen in Table 5.6 (0.98 s, 0.89 s and 0.96 s) for the three phases to ground fault. This can be seen in Figure 5.3 A–C, where the TMS was set to 5

Table 5.5: Threshold current at fault resistance of 50 Ω.

Fault Type	**Fault Resistance = 50 Ω**		
Three-phase to ground fault	**Relay 1**	**Relay 2**	**Relay 3**
Threshold Current (kA)	358.7	355.8	117.9
TMS (Seconds)	2.989	5.93	1.966
Trip Time (Seconds)	0.01	0.9198	0.01
Double phase to ground fault	**Relay 1**	**Relay 2**	**Relay 3**
Threshold Current (kA)	358.7	355.7	118.3
TMS (Seconds)	2.989	5.929	1.971
Trip Time (Seconds)	0.000	0.9193	0.000
Single line to ground fault	**Relay 1**	**Relay 2**	**Relay 3**
Threshold Current (kA)	358.5	355.5	118.5
TMS (Seconds)	2.987	5.925	1.975
Trip Time (Seconds)	0.000	0.9185	0.000

Table 5.6: Threshold current at fault resistance of 100 Ω.

Fault Type	**Fault Resistance = 100 Ω**		
Three-phase to ground fault	**Relay 1**	**Relay 2**	**Relay 3**
Threshold Current (kA)	358.2	353.9	117.9
TMS (Seconds)	2.985	5.899	1.966
Trip Time (Seconds)	0.000	0.9149	0.9039
Double phase to ground fault	**Relay 1**	**Relay 2**	**Relay 3**
Threshold Current (kA)	358.1	353.8	118.3
TMS (Seconds)	2.984	5.897	1.971
Trip Time (Seconds)	0.000	0.9145	0.9035
Single line to ground fault	**Relay 1**	**Relay 2**	**Relay 3**
Threshold Current (kA)	358	353.7	349.5
TMS (Seconds)	2.984	5.895	5.824
Trip Time (Seconds)	0.000	0.9136	0.9026

s, 2 s and 1 s, respectively.

A backup relay was added to the network for optimal system performance to prevent feedback faults. In instances where relay 1 failed to operate, it sent the signal to relays 2 and 3 for better coordination and protection.

The threshold current also varied as the fault resistance increased and was slightly different in the different fault types, as seen in Table 5.6, where the threshold current was an average of 358 kV in relay 1 and was slightly different in relay 3 of the single phase-to-ground fault.

Transmission line faults can be identified with less accuracy when noise signals occur. When choosing and extracting fault characteristics, noise signals such as voltage sag, transients, harmonics, and voltage interruption must be considered. In [176], the DWT was utilised for feature extraction, and the SVM was used for fault classification, with 100% accuracy when there was no disturbance and

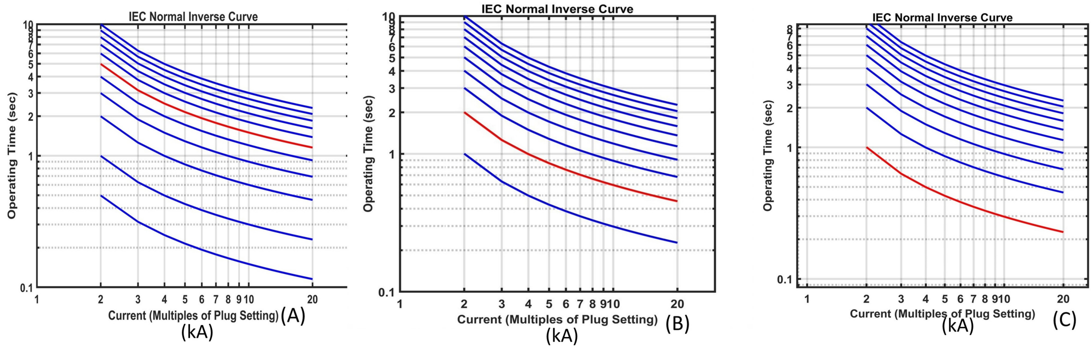


Figure 5.3: Time multiplier settings at 1 second.

98% and 95.6% accuracy when there was 30 dB and 20 dB noise, respectively. It is recommended that noise be removed using the DWT approach during fault extraction to obtain a denoised signal.

5.4.1 Validation of the Result Using the Threshold Current and Voltage with Other Models for the Sensitivity of TMS

Two scenarios were created in Figures 5.4 and 5.5 to show when three phase-to-ground faults were initiated to bus A and B, and the relay was applied in bus B while bus A was without a relay. In the implementation of the proposed model in Figure 5.4, the circuit breaker tripped at 0.05 s and was restored at the maximum threshold current. When the relay was initiated, the line tripped at 0.04 s, and the operating time delay was 0.035 s, as seen in Figure 5.5.

The application of the instantaneous overcurrent relay has reduced the operating time drastically, thereby protecting the entire system from collapsing. The threshold value is an easy way to detect faults and prevent transmission line fault protection tripping delays. The overshoot at Bus B/l_1 in Figure 5.5 shows that the maximum threshold coefficient was at the highest with 620.4303 kA as seen in Table 5.2 (AC-G). Additionally, the minimum threshold was the lowest at the no-fault condition with 10.6870 kA.

The instantaneous overcurrent and voltage relay function model is shown in Figure 2.6 of relay 1. The trip time for the current is shorter (Figure 2.6a) compared to the voltage, while the time delay was at zero seconds in each case. This shows a better tripping time than the model without the relay setting, as seen in Figure 2.4. In addition, the fault current trip time was 0.05 s, while the voltage trip time was 0.35 s, as opposed to 0.04 s in Figures 2.4 and 2.5. The reduction of the tripping time was due to the introduction of instantaneous

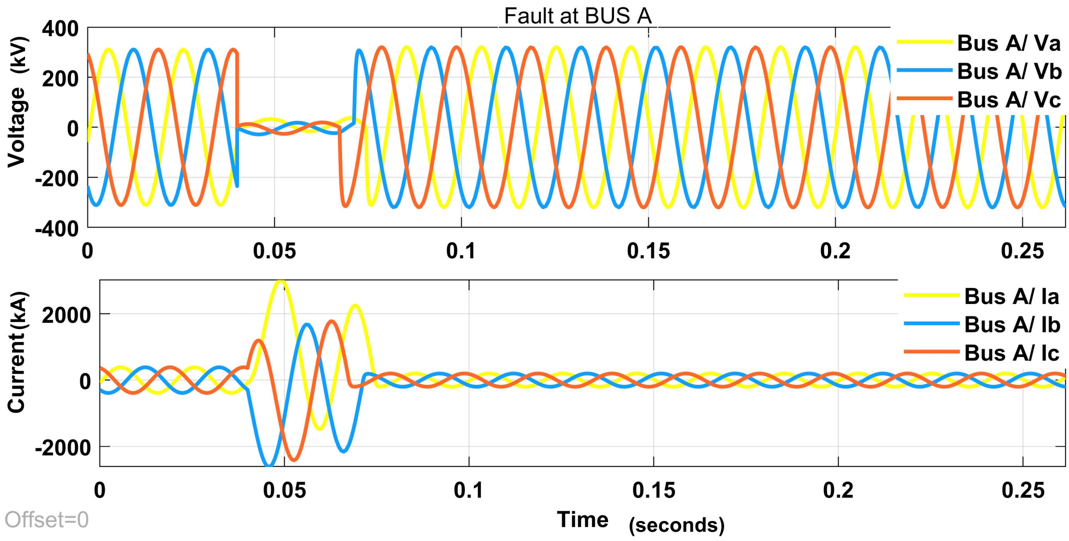


Figure 5.4: Fault at bus A without the relay.

Table 5.7: Percentage accuracy of the proposed model at bus A.

Fault Type	**Trip time Without proposed Model (Sec)**	**Trip Time With Proposed Model (Sec)**	**% Increase in Accuracy**
L-G	0.25	0.03	85.00
L-L-G	0.38	0.05	99.87
L-L-L-G	0.10	0.04	60.00

overcurrent and voltage relay settings with the help of the threshold voltage and current of the model.

Figure 5.6 represented the initial condition when the trip time was 0.35 s without setting the instantaneous overvoltage relay at bus B. However, it reduced to 0.05 s when the model was implemented, as shown in Figure 5.5 above.

In Figure 5.8, the reference tripping time of the three-phase-to-ground fault at relay 2 shows that the line tripped at 0.2 s without applying the proposed model.

The performance of the proposed model is shown in Table 5.7 with a percentage increase in the tripping time without the application of the model compared to the proposed model, and it shows that at bus A, the double line to ground fault shows 99.87% with a difference of 0.33 s. The same also applies to three phase-to-ground faults and single phase-to-ground faults.

The differences in the various fault condition tripping times were computed to find the percentage increment of the tripping time of the normal system without

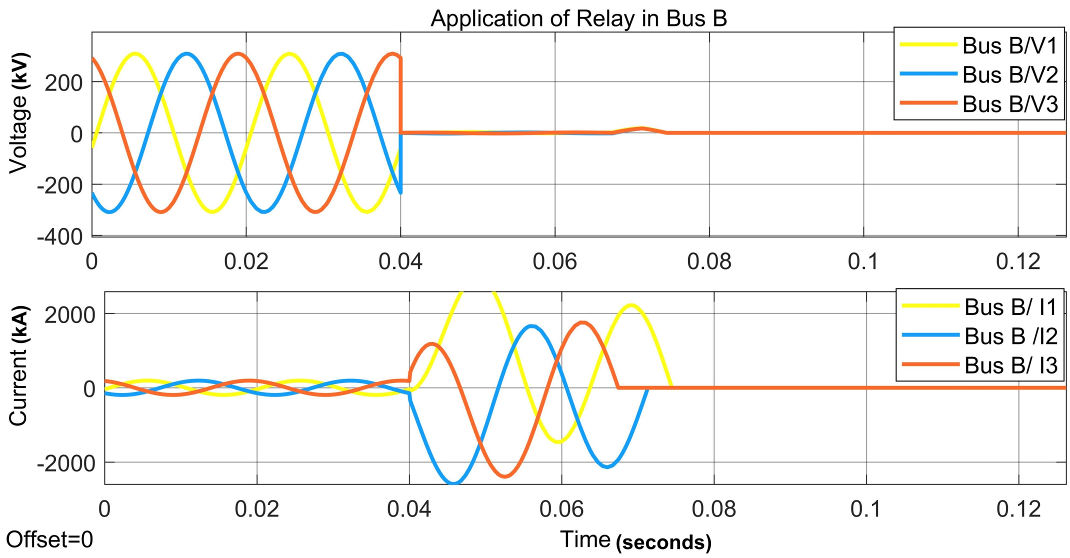
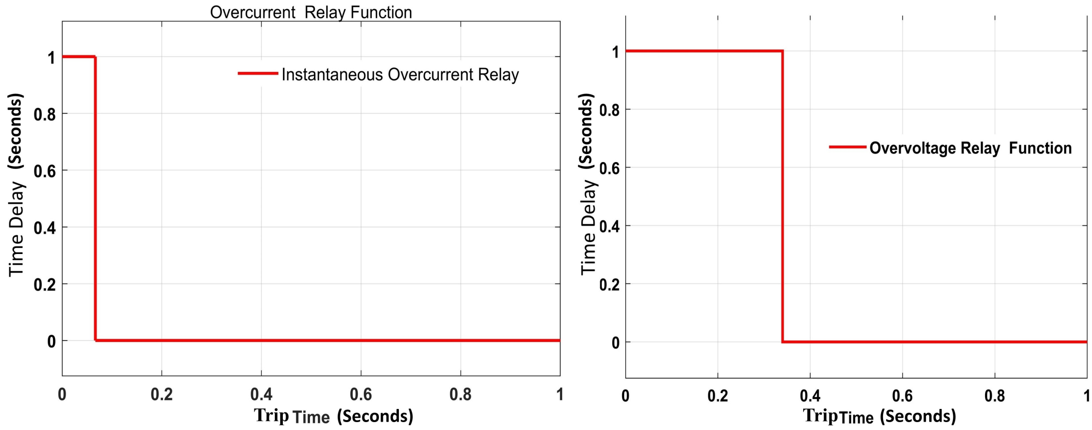


Figure 5.5: Application of relay at bus B.



(a) Overcurrent relay function (b) Overvoltage relay function

Figure 5.6: The overcurrent and voltage relay function at relay 1 before setting.

the threshold value. The proposed model is shown in Equation 5.7 below.

$$P_i = \frac{T_A - T_B}{T_A} \times 100, \tag{5.7}$$

where P_i is the percentage increment of the tripping time of the relay, T_A is the tripping time without the threshold value, and T_B is the tripping time using the proposed model.

At bus B relay 1, there were significant changes in the tripping time with the double-line-to-ground fault of 84.38% and a difference of 0.27 s, as seen in Table 5.8. The proposed model improved the tripping time and reduced the time delay of the relay to sense a fault signal and trip, compared to [203], which focused on

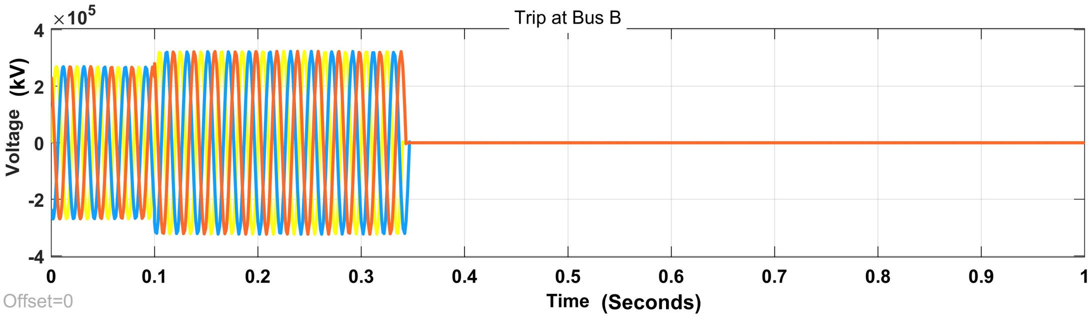


Figure 5.7: Overvoltage Trip at Bus B.

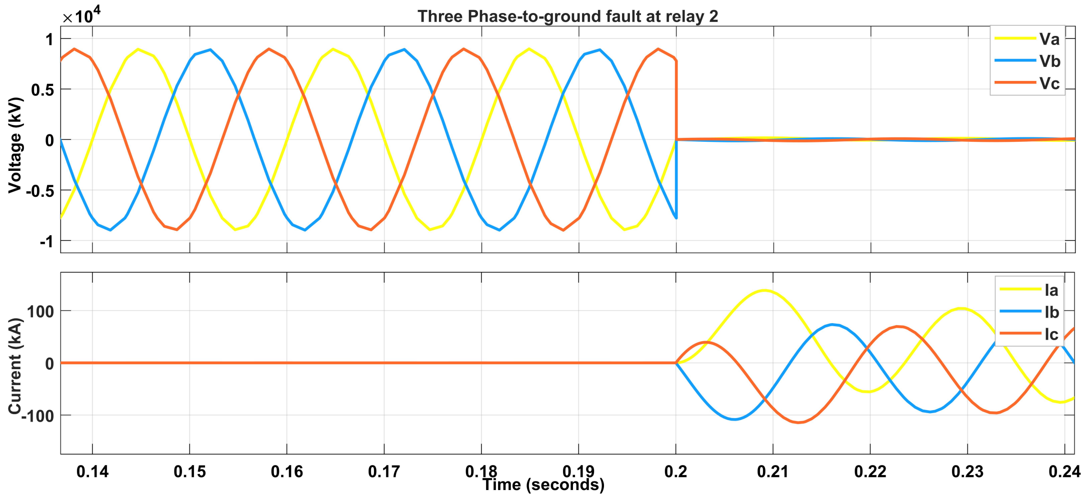


Figure 5.8: Three phases to ground fault at relay 2.

the selection and reliance of backup relays to trip in a fault condition.

5.4.2 Comparison of the Proposed Algorithm with the Deep Learning-Based Results

The deep learning-based method was compared with the proposed algorithm for accuracy and tripping time. In [204], an artificial intelligence search algorithm and a genetic algorithm were employed to find the optimal relay setting coordination time. The result shows that the tripping time varied from 0.10 s to 0.69 s at different fault levels. The operating time varied from 0.28 s to 6.3 s at different

Table 5.8: Percentage accuracy of the proposed model at bus B.

Fault Type	**Trip time Without proposed Model (Sec)**	**Trip Time With Proposed Model (Sec)**	**% Increase in Accuracy**
L-G	0.10	0.03	70.00
L-L-G	0.32	0.05	84.38
L-L-L-G	0.20	0.04	80.00

fault locations. In [205], the Radial Bias Function Neural Network (RBFNN) to learn and detect short-circuit fault current was implemented in the microprocessor of a digital relay on a distribution feeder to detect short-circuit faults using inverter-based distributed energy resources. The offline training time was 0.414 s, the detection time was 0.0136 s, and the trip time was 0.5 s. In [206], a directional overcurrent relay was used at different setting groups to detect faults at various locations. The optimal coordination of directional overcurrent relays in clusters was obtained using a machine learning algorithm and a genetic algorithm with heuristic adjustment. The operating time was 497.4069 s. The tripping times were set at 0.282 s and 0.593 s for different clusters. In [207], a dual-path mixed-domain residual threshold network was used for fault diagnosis in bearings, the soft threshold function was employed as the nonlinear transformation layer, and dilated convolution was used to create a dual-path neural network to identify the critical features in the signal without using any signal denoising algorithms. The algorithm's accuracy was about 99.97% on Gaussian noise and 99.98% on real noise. On the other hand, this paper focused on feature extraction at various noise levels and thresholds for machine learning training. Still, the difference lies in the direct application of the proposed model without the combination with other algorithms, as seen in [207], where the channel attention mechanism, spatial attention mechanism, and residual structure were all combined in the dual-path mixed-domain residual threshold network. The soft threshold function was used as the nonlinear transformation layer, and dilated convolution was used to make a dual-path neural network. This was done so that the signal's most essential parts could be found without using algorithms to remove noise.

Compared to the literature, the data extraction stage is simpler with the help of the threshold current and voltage. It does not require another medium to extract the threshold value; thus, it produces fast and accurate results for the relay setting without needing relay coordination. Additionally, the wavelet transform can de-noise fault signals so that it can be applied to every kind of noise signal.

5.5 Conclusions

This paper has proposed using the threshold voltage and current value as a standard for coordinating and setting the instantaneous overcurrent relay protection. The simulated result was analysed to confirm the model's viability in calculating the high-voltage transmission line relay's tripping, delay, and operating times. It also analyses or detects the maximum and minimum threshold voltage and current suitable for optimising the relay and circuit breaker for optimal performance. This technique helps reduce the delay and improve the relay's tripping time. One of the constraints of this technique is the inability to optimise the threshold current for different current and voltage types. However, this technique discriminates poorly in distinguishing between fault currents at different points when the fault impedance between two points is small.

Additionally, coordinating is challenging and necessitates changes as the load increases and the optimisation of the model to accommodate different voltage inputs synchronously. This process can be used for all fault types. Therefore, it has a superior and effective tripping time compared to other techniques in the literature.

Chapter 6

Load Frequency Control in TL using PID-PSO

6.1 Introduction

Load Frequency Control (LFC) is used in electric power systems to maintain a comparatively consistent frequency, distribute the load among the generators, and manage tie-line exchange schedules. The power system desperately needs load frequency control because the transmitting frequency must correspond to the generating and load frequency, which must synchronise to prevent faults on the transmission line. If the typical frequency is 50 Hz or 60 Hz and the system frequency drops below 47.5 Hz or rises over 52.5 Hz on a 50 Hz frequency band, the turbine blades will likely be harmed, and the generator may stall [208]. The two main variables that vary when there is a transient power demand are area frequency and tie-line power exchange. [209]

The primary objective of LFC is to keep the power system's frequency constant by adjusting the power generation to match the power consumption. The LCF system consists of the primary and the secondary control. The Primary Control is responsible for quick response to sudden changes in power consumption by adjusting the power generation to match it. It operates on a time scale of seconds. It is typically implemented using governors on power generators. At the same time, the secondary control is responsible for maintaining the balance between power generation and consumption over a longer time scale of minutes to hours. It is typically implemented using Automatic Generation Control (AGC), which adjusts the power output of generators to meet the load demand. The LFC system works by continuously monitoring the power system frequency. When the frequency deviates from the nominal value, the primary control system quickly responds by adjusting the power output of the generators to bring the frequency back to the little value. The secondary control system then takes over and adjusts the power output to keep the frequency at the nominal value over a longer time scale. Load Frequency Control is essential for maintaining the stability of the power system and ensuring that the power supply is reliable. It helps to prevent power outages and blackouts by quickly responding to changes in power consumption and adjusting the power generation to match it. In power systems with multiple power generators, the LFC system is typically implemented using a central control system that coordinates the actions of the individual generators. The LFC system can also be implemented using advanced control methods such as Model Predictive Control (MPC) and artificial intelligence-based methods.

A modest variation in load power in a single-area power system that runs at a fixed frequency results in an imbalance of power between supply and demand. The first solution to this mismatch issue is removing kinetic energy from the system, which leads to a decline in system frequency. The old load's power consumption reduces as the frequency steadily drops. When the newly added load is diverted by lowering the power required by the old load and power linked to kinetic energy is eliminated, substantial power systems may achieve equilibrium at a single point. Without a doubt,a balance is reached at the expense of frequency decrease. To maintain this balance, the system takes some control action; governor activity is unnecessary. In such a situation, the frequency is significantly reduced.

The critical component of a power system that ensures continuous power delivery to the customer is load frequency control. Automatic Generation Control (AGC) technically accomplished power system frequency control. To maintain sensible load and generation balance, frequency control splits the load across generators and adjusts the tie-line power to predetermined levels [208].

Different literature has discussed the LFC in transmission lines using conventional methods to stabilise the load frequency of the power system. In [210], it suggests a novel PSO-based multi-stage fuzzy controller for solving the LFC issue in a restructured power system. This control technique was adopted because of power systems' rising complexity and changing structure. This newly developed control strategy combines the fuzzy PD and integral controllers with a fuzzy switch to achieve the desired level of robust performance, such as frequency regulation, load demand tracking, and disturbance attenuation. These occur under load fluctuation for various plant parameter changes and system nonlinearities.

A PSO-based method automatically modifies membership functions to save design effort and improve fuzzy system control. The PSO method suggested in this study is simple to implement and requires no extra processing complexity. Experimenting with this approach yields reasonably promising results. The capacity to leap out the local optima, convergence accuracy and speed is significantly improved, resulting in high precision and efficiency. However, the settling time and the overshoot were high, reducing the controller's performance.

In [211], a hybrid generation system consisting of solar photovoltaic, wind turbine generators, geothermal power plant, and electric vehicle aggregators to improve the stability of the system by implying the Genetic Algorithm (GA) and the PID controller to reduce the settling time and overshoot.

Large frequency oscillations occur when the Load Frequency Controller (LFC) system does not correct the imbalanced power [212]. To that purpose, an artificial neural network (ANN) based on particle swarm optimisation (PSO) is being proposed to modify the settings of the PID controller in the MG structure. The simulation results show that using PSO-based ANN makes the system stable in the minimum amount of time. Also, the amplitude of frequency oscillations, overshoot, and settling time is minimised. These error values determine the area control error input signal to the PID controller unit, the primary purpose of which is to minimise the error at the output. As a consequence of the preceding explanation, the PSO methodology produces much better results than the fuzzy and trial techniques since the fuzzy approach takes a long execution time to execute many linguistic rules in a multi-area system simultaneously. Second, obtaining the suitable language rule matrix to achieve the required outcomes is time-consuming. A high number of iterations is necessary to get ideal values of PID gains via a trial technique [213].

In [214], it advocated improving load frequency management using a PID controller and a Static Synchronous Series Compensator (SSSC). Particle Swarm Optimisation (PSO) determines the optimal parameters for the PID controller. Though it was only used for one area of LFC, it is limited to specific algorithms. Also, [215] suggested an optimisation approach that combines the best aspects of three optimisation techniques: the Firefly Algorithm (FA), Particle Swarm Optimisation (PSO), and Gravity Search Algorithm (GSA) to accomplish automated load frequency management of the multi-source power system, the suggested technique was employed to set the parameters of a Proportional Integral Derivative (PID) controller. The integral time absolute error was employed as the goal function. Moreover, the controller was calibrated to guarantee that the multi-source power system's tie-line power and frequency remained within acceptable parameters. Recently, the Multi-Verse Optimisation approach produced improved tuning of the fractional order Proportional Derivative Proportional Integral (PDPI) controller for LFC, both with and without the HVDC connection [216].

In [217], a nature-inspired stochastic evolutionary algorithm was presented to attain the best LFC. An inter-phase power controller [218] or a Flexible Alternating Current Transmission System (FACTS) controller can enhance the power quality of a two-area power system.

In [219], it evaluates the viability of integrating wind turbines into conventional power production, and a PSO and Model Predictive Control (MPC) technique is presented for LFC with wind turbines. The particle swarm optimisation algorithm is integrated to lessen the computational cost of executing the MPC strategy. The control quality is repeatedly optimised using the cost function of MPC as the objective function of PSO. Moreover, simulations confirmed the effects of physical restrictions like the Generation Rate Constraint (GRC) and the governor's dead zone [220]. The results show that this approach performs quickly and dynamically. However, the Control strategy may result in slow iterative operation or local optimal solution problems.

In [221], a PSO for a single-area power system based on load frequency control (LFC) is described. The goal was to develop a PSO-optimised self-tuning PID controller for controlling a specific region of linked power systems. According to the comparative study, the suggested controller may provide the optimum dynamic response for a step load change compared to a standard Proportional-Integral (PI) controller.

in [222], the type 2 Fuzzy PID controller was used for frequency control of the power system with distributed sources, and the accuracy of the system was 94.71%. Due to the low inertia of the microgrid, the virtual inertia control was not considered in the paper.

Deep reinforcement learning has also been used for load control in micro-grids where a partially observable Markov decision process was used in privacy protection of load control as seen in [223].

6.1.1 The Main Contribution of the proposed model

The PSO-PID controller's key contribution to Load Frequency Control (LFC) enables efficient real-time tweaking of PID parameters to keep system frequency and tie-line power flow within acceptable bounds.

PID controllers have traditionally been employed in LFC systems, but determining proper PID settings may be difficult, particularly for large-scale power systems. Large-scale power systems involve complex dynamics, multiple interconnected components, and diverse operating conditions, making it challenging to find optimal PID settings that provide stable and reliable control. System uncertainties like generator characteristics, line parameters and load variations can affect the output. Also, system complexity and interconnection and oscillation can affect the system. The PSO method optimises the PID parameters effectively by leveraging on a group of potential solutions and repeatedly refining them towards an optimum solution. However, modelling, simulation, optimisation, advanced control techniques, expert knowledge, and iterative refinement can help achieve suitable PID settings that provide stable and reliable control in such systems as applied in the proposed model.

The PSO-PID controller in LFC can also manage power system non-linearities and uncertainties, which may impact system frequency and tie-line power flow. The PSO algorithm enables real-time tuning of PID parameters, ensuring that the LFC system can swiftly respond to changes in the power supply.

Compared to typical PID controllers, the PSO-PID controller in LFC provides a more efficient and resilient solution for regulating system frequency and tie-line power flow within acceptable limits in power systems.

The conventional controller is required to construct the automated load frequency control system. The PID controller has several flaws. These flaws include requiring a long time to restore the frequency and power deviation to their nominal values and experiencing excessive frequency variation error.

The proposed model uses an isolated power system generation with the conventional energy source. The model was designed using the PSO-PID controller to optimise the load frequency using the ITAE cost function to determine the improved controller and the cost function of the PSO-PID algorithm compared with the conventional approach.

6.2 The Particle Swarm Optimisation

Particle swarm optimisation (PSO) is an intelligent evolutionary algorithm inspired by the social behaviour of flocking birds or schooling fish. Kennedy and Eberhart presented the PSO approach for the first time in 1997 [224, 225]. PSO algorithm can provide high-quality solutions in less time and with more steady convergence characteristics than other stochastic approaches such as genetic algorithm [221, 226].

In an $n-$dimensional space, let the position and individual i be represented as vectors $X_i = (x_i, ..., x_{in})$ and $V_i = (v_i, ...v_{in})$ in a PSO algorithm. Let

$$Pbest_i = ({x_i}^{pbest}, ...{x_{in}}^{pbest}) \tag{6.1}$$

and

$$Gbest_i = ({x_i}^{gbest}, ...{x_n}^{gbest}) \tag{6.2}$$

equation 6.1 and 6.2 be individual i^{gbest} positions so far and their neighbours' best position so far, respectively. Utilising this information, the PSO algorithm modifies the updated velocity of individual i using equation 6.3

$$V - i^k + 1 = \omega V_i^k + c_1 r_1 \times (Pbest_i{}^k - X_i{}^k) + c_2 r_2 \times (Gbest_i{}^k - X_i{}^k) \qquad (6.3)$$

Where,
V_i^k is the velocity of individual i at an iteration k. ω is the inertia weight parameter,
c_1, c_2 is the acceleration coefficients,
r_1, r_2 represents the random numbers between 0 and 1,
$X_i{}^k$ is the position of individual i until iteration k.
$Pbest_i{}^k$ is the best position of individual iteration and
$Gbest_i{}^k$ is the position of the group iteration.
The value of c_1, c_2 and ω are predetermined and generally, the weight ω is shown in equation 6.4

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min}) \times \frac{iter}{Iter_{max}} \qquad (6.4)$$

Where,
$\omega_{max}, \omega_{min}$ is the initial and final weights,
$Iter_{max}$ is the maximum iteration number,
$iter$ current iteration number

The moves from the individual position of the current to the next velocity modified in equation 6.3 is shown in equation 6.5

$$X_i{}^{k+1} = X_i{}^k + V_i^{k+1} \qquad (6.5)$$

PSO's improved PID controller is intended for LFC and tie-power control. The objectives are to manage the frequency and inter-area tie-power with adequate oscillation damping while achieving good performance. The optimal values of the K_P, K_I and K_d parameters for a PID controller are quickly and precisely determined in this work utilising a PSO. In a typical PSO run, an initial population is produced at random. The original population is known as the 0th generation. Each member of the initial population has a unique performance index value. The PSO then generates a new population based on the performance index information. The system must be simulated to acquire the performance index value for each person in the present population. The PSO then uses the reproduction crossover and mutation operators to create the next generation of humans. These methods are continued until the population has converged and the optimal parameter value has been identified [227].

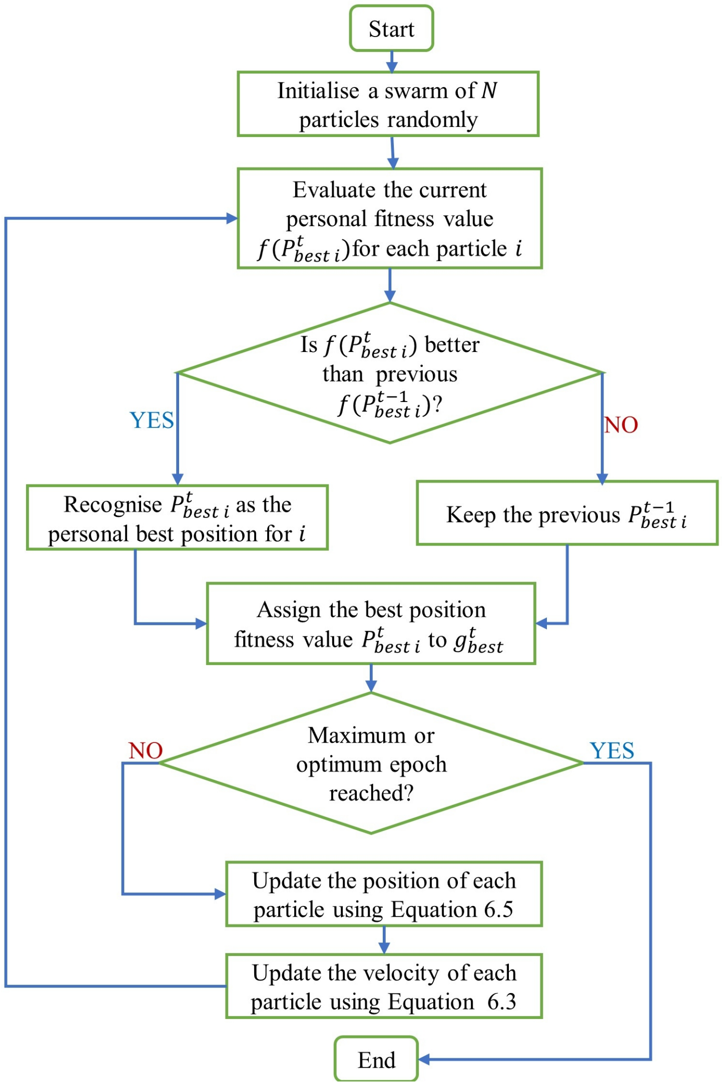


Figure 6.1: The model flowchart for PSO

Figure 6.1 represents a flowchart model of the PSO step-by-step algorithm implementation. Set the parameters for the PSO algorithm, such as the number of particles, maximum iterations, and inertia weight. Then , set the particle positions and speeds at random inside the search space. Estimate the fitness function for each particle using the LFC problem, and the fitness function should represent the system's performance, such as frequency deviation and tie-line power deviation. Then, update each particle's own best position and fitness. Update the swarm's overall best position and fitness, and the PSO method is used to update the velocity and location of each particle. The new velocity and location should fall inside the scope of the search. This system is repeated until the maximum number of iterations is achieved, or a good solution is discovered by using the best control action for the power system to keep frequency and tie-line power variations within acceptable limits.

6.3 System Model

The load frequency control strategy's primary goal is to offer consumers high-quality, dependable electricity within an integrated system. Variations in active power cause the system's frequency to fluctuate. As a result, a control technique is developed to regulate load frequency regulation using control loops. Two typical techniques, transfer function and state variable, are used to convert the power system model into a mathematical model by making sure appropriate assumptions [228–230].

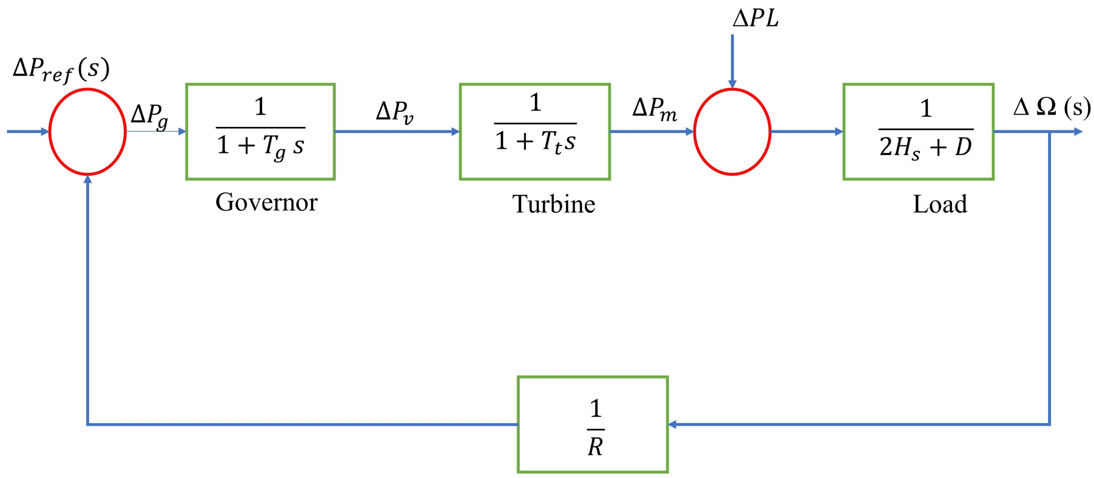


Figure 6.2: Transfer Function Model of a Power Station [231]

A section of the transfer function model of the Delta Power Station Nigeria is designed as shown in Figure 6.2, and the primary sections are explained below.

Generator Model

The generator equation has been derived from the swing equation in [232] as shown in equation 6.6

$$\Delta\omega(s) = \frac{1}{2Hs}[\Delta P_m(s) + \Delta P_{gs}(s) - \Delta P_e(s)] \tag{6.6}$$

Where,
ΔP_m is the change in mechanical power
ΔP_{gs} is the power from the generating station
ΔP_e net change in the electrical load demand and
H is the generator inertia constant.

Load Model

The power system includes assistive and inductive loads that are frequency-independent and dependent. As a result, the net change in load power may be defined as the sum of frequency-sensitive and frequency-insensitive load changes [233]. Some of the factors that affect the electric load include:

Meteorological factors: Weather, climate, temperature, humidity, and solar radiation.

Temporal or calendar factors: the hours of the day, the days of the week, the seasons, and so forth.

Economic factors such as industrial development, GDP, and so on.

Unexpected Factors: Sporting Activities, Festivals, etc.

Client Factors: Consumption type, building size, electric appliances, workforce count, etc. This is represented in equation 6.7 below

$$\Delta P_e(s) = \Delta P_L + D\Delta\omega \tag{6.7}$$

Where ΔP_L is the frequency-independent load change while $D\Delta\omega$ is the sensitive load frequency change and D is the ratio of percentage change in load to the frequency. The interaction between load variation and frequency fluctuation may be represented in equation 6.8 as expressed below

$$\Delta P_L(freq) = D\Delta\omega = \frac{\Delta P_L(freq)}{\Delta\omega} \tag{6.8}$$

Turbine or Prime Mover Model

It is the source of mechanical power, which derives its energy from the combustion of coal or gas or nuclear fission. The turbine's transfer function may be expressed as the ratio of the change in mechanical output power $\Delta P_m(s)$ to the change in steam valve position $\Delta P_v(s)$ given in equation 6.9

$$G_T(s) = \frac{\Delta P_m(s)}{\Delta P_v(s)} = \frac{1}{1 + S\tau_t} \tag{6.9}$$

Where τ_t is the turbine time constant.

Governor Model

The speed governor operates as a comparator [234] as expressed in equation 6.10 below

$$\Delta P_g(s) = \Delta P_{ref} - \frac{1}{R}\Delta\omega(s) \tag{6.10}$$

Where ΔP_g is the power output of the governor, ΔP_{ref} is the reference set power, and $R$is the speed regulation. Equation 6.11 expresses the relationship between governor input and valve opening, as shown below.

$$\Delta P_v(s) = \frac{1}{1 + s\tau_g}\Delta P_g(s) \tag{6.11}$$

Where τ_g is the governor time constant in seconds.

6.3.1 The Proportional Integral Derivative (PID) Controller

PID controllers are commonly used in industrial control systems as a control loop fed back. It computes the difference between the measured process variable and the intended set point. PID settings are fine-tuned to guarantee good closed-loop performance. It is used to increase dynamic performance and lower steady-state error [231]. The gains are automatically achieved by turning the model in MATLAB Simulations to obtain (K_p, K_i, K_d). Where K_p decreases the rise time, K_d reduces the overshoot and the setting time, and K_i eliminate the steady-state error. In [235], the area control error theory associated with the PID control system is as follows in equations 6.12, 6.13, and 6.14 below

$$P_{out} = K_p e(t) \tag{6.12}$$

$$I_{out} = K_i \int_0^t e(t)dt \tag{6.13}$$

$$D_{out} = K_d \frac{d}{dt} e(t) \tag{6.14}$$

Where K_p is the Proportional gain
K_i is the integral gain, and
K_d is the derivative gain.

The transfer function of the controller is shown in equation 6.15 below

$$G_{PID}(s) = K_p + \frac{K_i}{s} + K_d s \tag{6.15}$$

and the control signal for maintaining the system frequency is shown in equation 6.16.

$$U(s) = -G_{PID}(s) \times ACE(s) \tag{6.16}$$

ACE is the area control error of the system, and U is the governor's input signal for managing the valve output based on the power system's load demand. The $ACE = B \times \Delta\omega$ and B are the bias factors, as $B = \frac{1}{R} + D$ and $D\omega$ is the frequency deviations.

6.4 Modelling of the Proposed power system

The proposed model is the Delta thermal generating station, a part of the Nigeria transmission line model, as seen in Figure 2.4. The network was modelled with the following specifications, as shown in Table 6.1 below:

Table 6.1: System parameters

Parameters	Specification
Normal Frequency (Hz)	50 Hz
Turbine-rated Power (PL)	300 MW
The turbine time constant (T_t)	0.5 seconds
Governor time constant (T_g)	0.2 seconds
Governor speed regulation (R)	0.05 PU
Generator inertia constant (H)	5 seconds
Load variation (D)	0.8

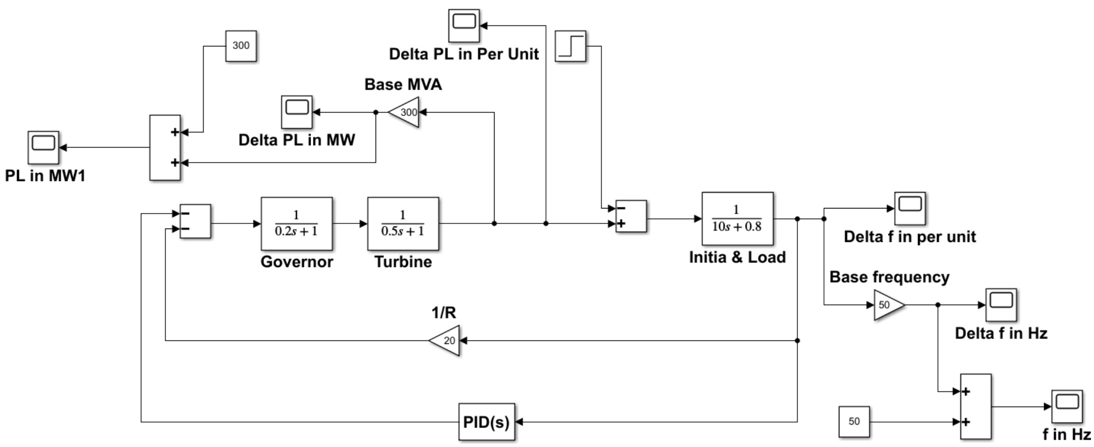


Figure 6.3: System Model with PID controller

The Simulink model for frequency control was generated using the transfer functions of the modelled power network using the MATLAB/Simulink environment. The PID controller gain value was optimised and implemented using a distinct PSO technique-coding mfile in MATLAB. The nominal system parameter values were taken from Table 6.1 to normalise the frequency and modelled as shown in Figure 6.3 with the introduction of the PID controller. The governor speed regulation R is 0.05 PU, so $\frac{1}{R}$ is 20.

The controller gain value is determined by selecting the objective function in which ITAE was used as a desired output. Then, initialise a population of particles where each particle represents a potential set of controller gain values of 0.9994, 0.7741 and 0.1858 for K_p, K_i and K_d, respectively, with the velocity vector. Then, evaluate the fitness performance of each particle by calculating the objective function value based on the controller gain values. Update the particle velocity and position to determine its best position and global best. These processes are repeated in multiple iterations to decide the termination condition, extract the best solution, and implement the controller. It is important to note that the success of the PSO algorithm in determining optimal controller gain values depends on factors such as the complexity of the control problem, the choice of the objective function, and the proper tuning of PSO parameters like swarm size, inertia weight, acceleration coefficients, termination criteria.

6.5 Methodology

The proposed algorithm uses the PSO algorithm to determine the controller gain value of K_i, K_p and K_d, which are achieved by turning in MATLAB simulation to eliminate the steady state error, to decrease the rise time and to reduce the overshoot and settling time respectively.

The proposed system is modelled and simulated as shown in Figure 6.4. First, it was modelled without the PID controller, and the PID controller was included to normalise the load frequency. A two-area thermal energy network was added to the design to maintain stability and control with good oscillation damping.

The PSO algorithm was introduced by initialising an array of particles with random positions to normalise the inequality constraints of the different particles. Verify the fulfilment of the equality criteria and, if necessary, revise the output and evaluate the fitness function of each particle. Compare the current value of the fitness function to the particle's prior best value. If the current fitness value is smaller, assign the current fitness value and the current positions. Determine the current global minimum fitness value among the current position to compare the present value with the previous to ascertain the best-fit value.

The effect of the gain values (proportional gain, integral gain, and derivative gain) in a PID controller can significantly impact the behaviour and stability of

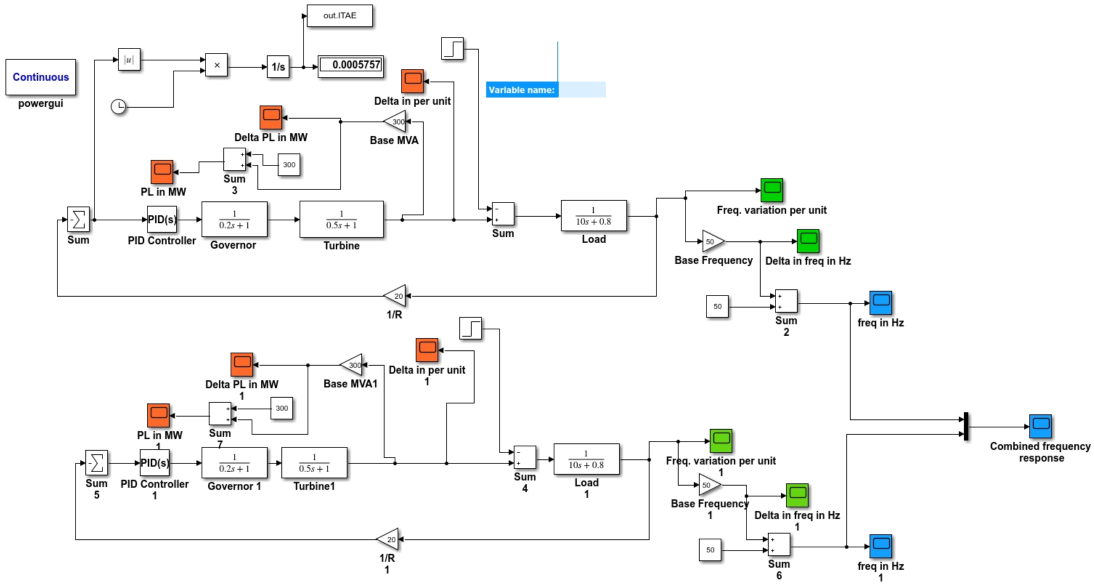


Figure 6.4: Complete Simulated Model with PID controller

the power system. Here are the effects of PID gain on a power system are as follows:

- Stability: The proportional gain (P) influences the system's stability. Higher proportional gain can lead to faster responses to control errors but may also increase the risk of oscillations or instability. Lower proportional gain results in a more stable system but can lead to slower responses.

- Load Variations: PID controllers in power systems must adapt to load variations and disturbances. The gain values should be set to ensure the system can respond to such changes effectively without excessive overshoot, oscillations, or instability.

- Accuracy: Proper tuning of PID gain values is critical for achieving the desired accuracy in regulating parameters like voltage and frequency. Well-tuned PID controllers can maintain these parameters within acceptable limits under various operating conditions.

- Transient Response: The integral and derivative gains (I and D) influence the system's transient response. A higher integral gain can reduce settling time but may lead to overshoot and oscillations. The derivative gain can dampen oscillations and improve the transient response, but if set too high, it can also introduce noise and instability.

This has influenced the performance of the model by increasing the accuracy and stability of the load frequency, as seen in Figure 6.14 for stabilisation of frequency variation.

6.6 Results and Discussion

The system was modelled using the designed parameters in Table 6.1 to design the model in Figure 6.4, the system was implemented using MATLAB, and the mfile code was executed for the PSO algorithm. The system was modelled using the designed parameters in Table 6.1 to design the model in Figure 6.4, the system was implemented using MATLAB, and the mfile code was implemented for the PSO algorithm. The PID controller was tuned by minimising the ITAE for optimal performance. The optimised parameters were used to determine the effectiveness of the proposed technique.

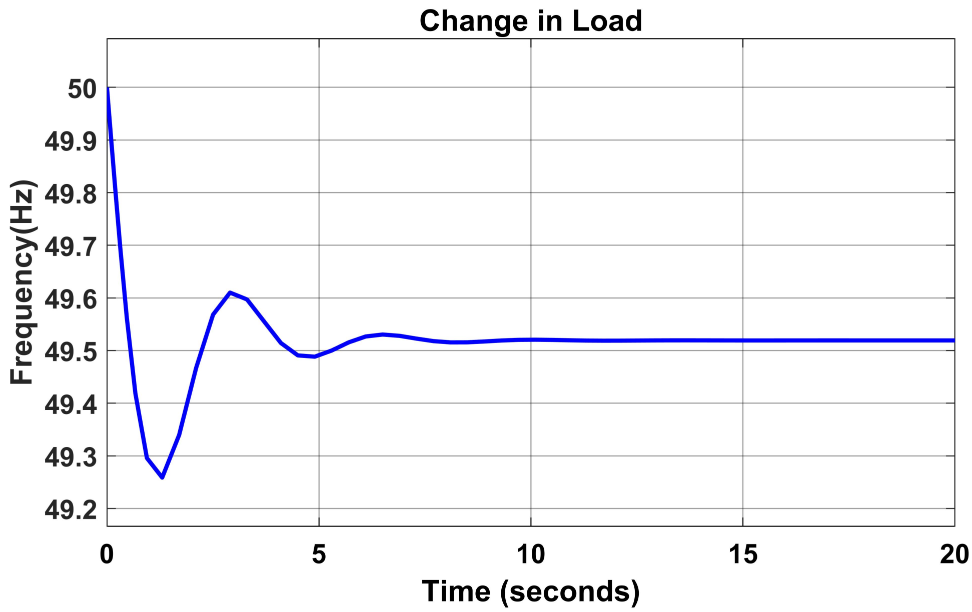


Figure 6.5: Load Frequency Without PID Controller

Figure 6.5 represents the base frequency of the base load without the PID controller and when the PSO parameters have not been fine-tuned. There was an overshoot of 49.6 Hz, which later changed to 49.55 Hz, causing a variation in the load frequency. Also, in Figure 6.6, the PID controller was applied to the model without the PSO algorithm. The frequency reluctantly moved to 50 Hz, and the settling time was 5 to 10 seconds before normalising. The time delay affects the power system and can lead to power loss; therefore, there is a need for a fast and accurate settling time of the load frequency.

In Figure 6.7, the base load was also affected by dropping from 300 MW to 299 MW, and about 1 MW of electricity was lost due to a fault in the load frequency.

Also, when the total load frequency was increased to 350 MW, there was an overshoot due to overcurrent, as seen in Figure 6.8.

The frequency variation deviated rapidly, as seen in Figure 6.9 without the

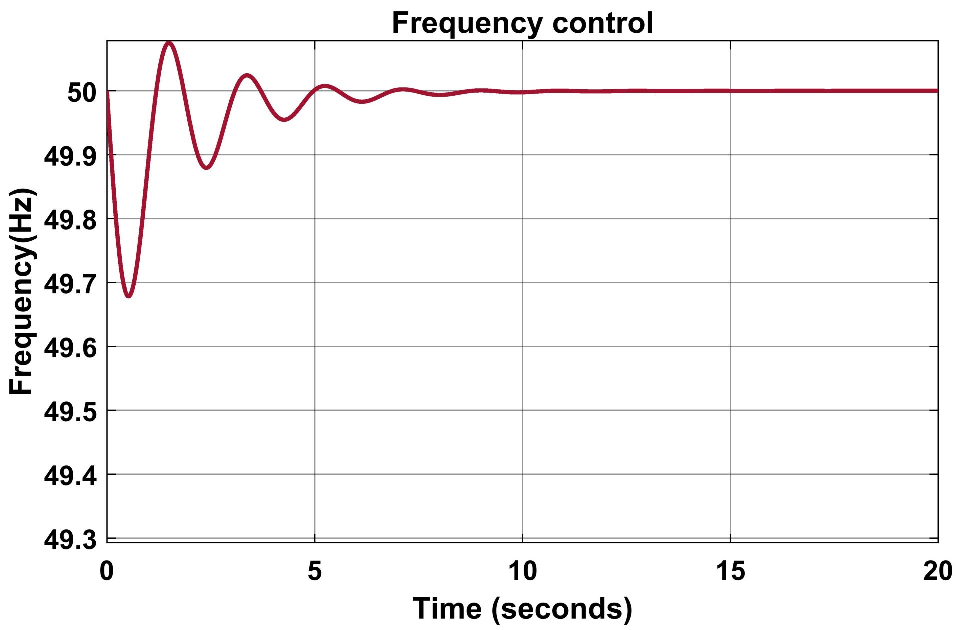


Figure 6.6: Load Frequency With PID Controller

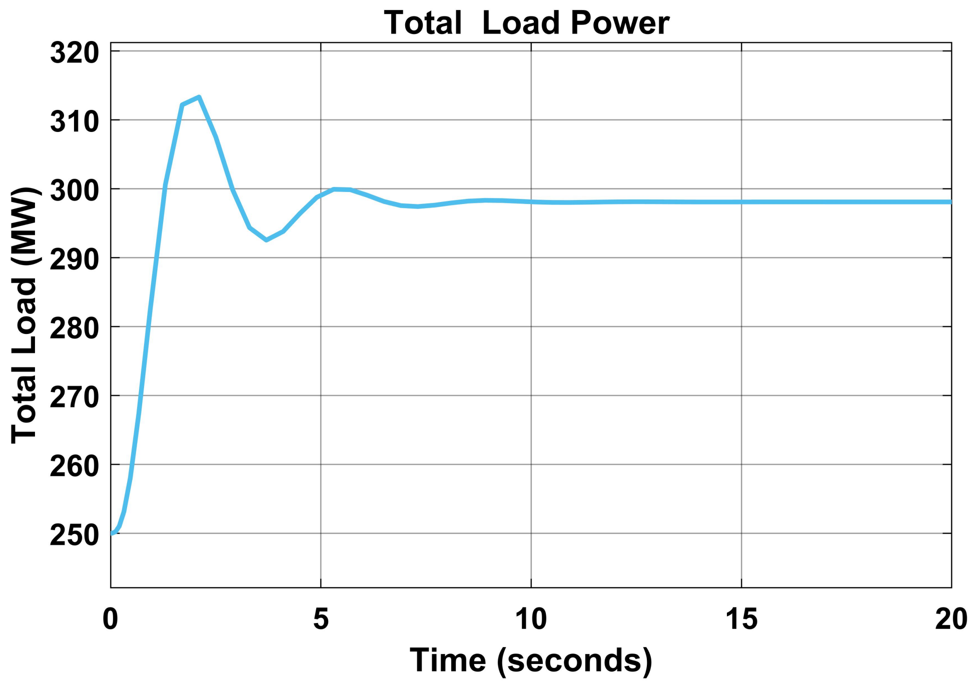


Figure 6.7: Base Load without PID Controller

PID controller and normalised with the introduction of the PID controller, as seen in Figure 6.10. To maintain the load frequency with minimum time delay and overshot, the PSO algorithm is introduced to the model.

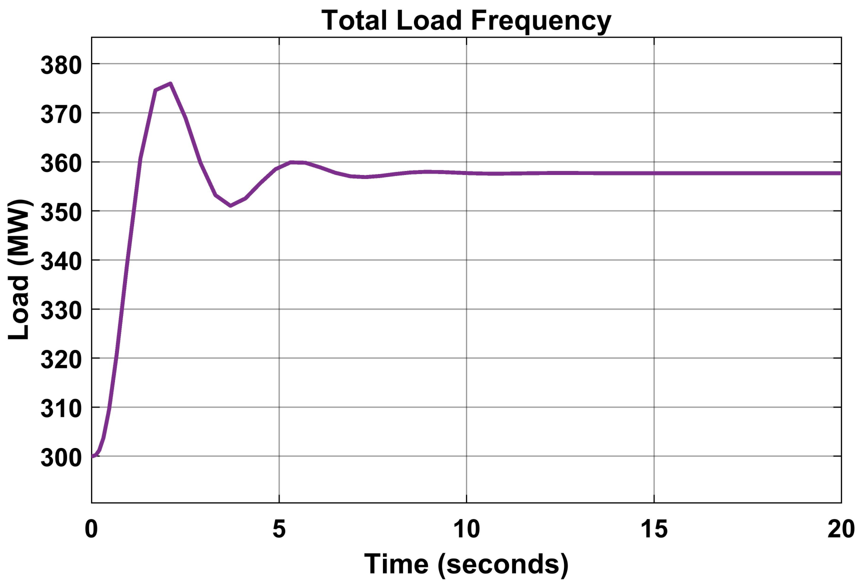


Figure 6.8: Load frequency with PID controller

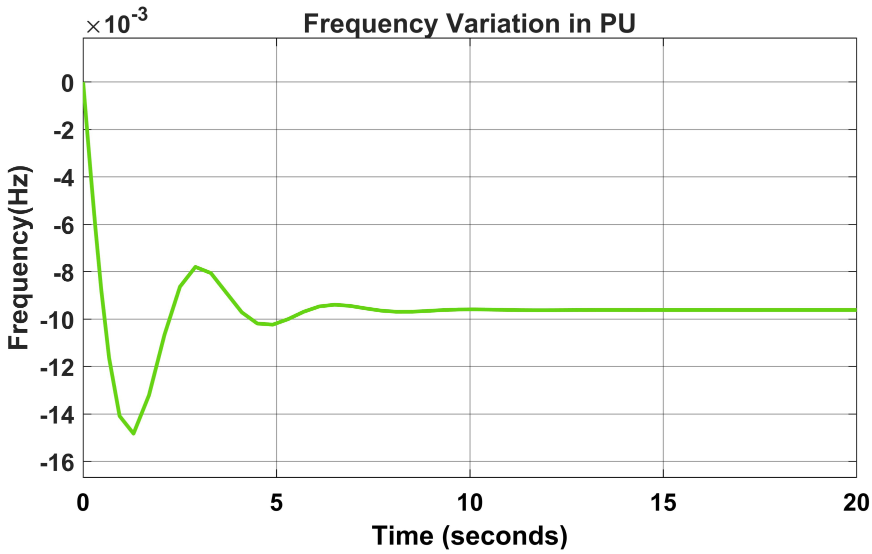


Figure 6.9: Frequency Variation without PID Controller

6.6.1 Frequency Control Using The PSO Algorithm

The PSO algorithm was applied using MATLAB Code to Figure 6.4, increasing the load to 360 MW for the changes. Also, the combined frequency changes, as explained in the results.

In figure 6.11, the change in base load was changed due to load frequency variation, but this was normalised using the proposed algorithm from 0.19 PU to 0.2 PU, as seen in Figure 6.12.

Also, the variation in load changes from 0.5 seconds in Figure 6.11 to 0.2 seconds in Figure 6.12. The change in the settling time made the proposed model

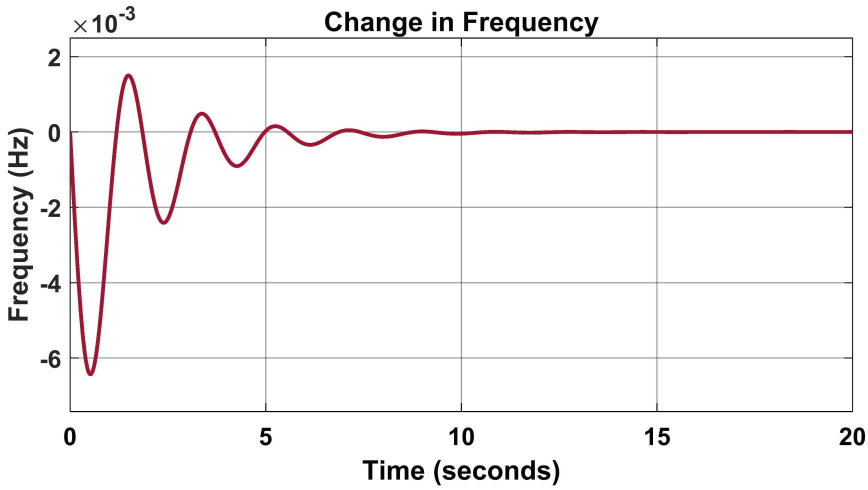


Figure 6.10: Frequency Variation Using PID Controller

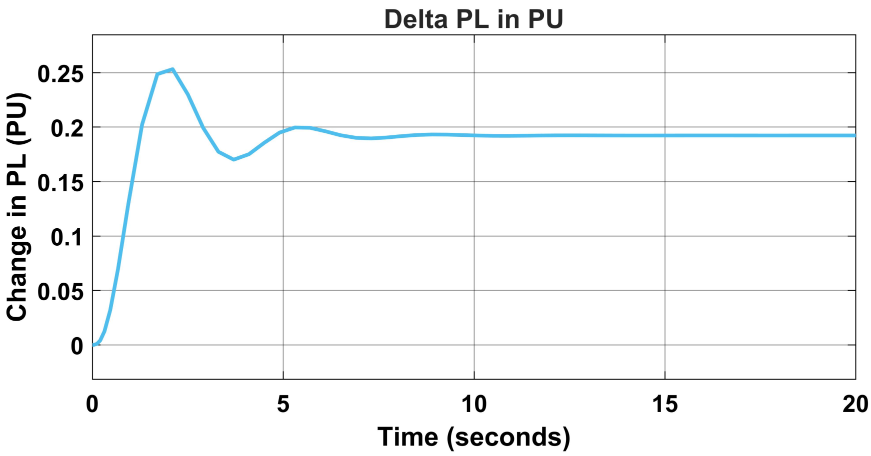


Figure 6.11: Change in Load(PU) without PID Controller

more reliable than the PID controller and, hence, faster in fault clearing time.

In figure 6.13, the combined frequency response of the PID controller and the PSO algorithm shows that the proposed algorithm performance is better based on the settling time and fault clearing time of zero seconds using the PSO algorithm.

Also, the frequency variation in PU was reduced from o.8 seconds in Figure 6.10 to zero seconds using the PSO and the PID controller in Figure 6.14.

The performance indices of the proposed model are measured by the ITAE, which is 0.0005757. This is minimal as compared to [236] with 0.7741 for K_p, 0.9994 for K_i and 0.1850 for K_d. Also, the model's system dynamic response is tested by varying the load from 300 MW to 350 MW at a load variation of 0.2 PU.

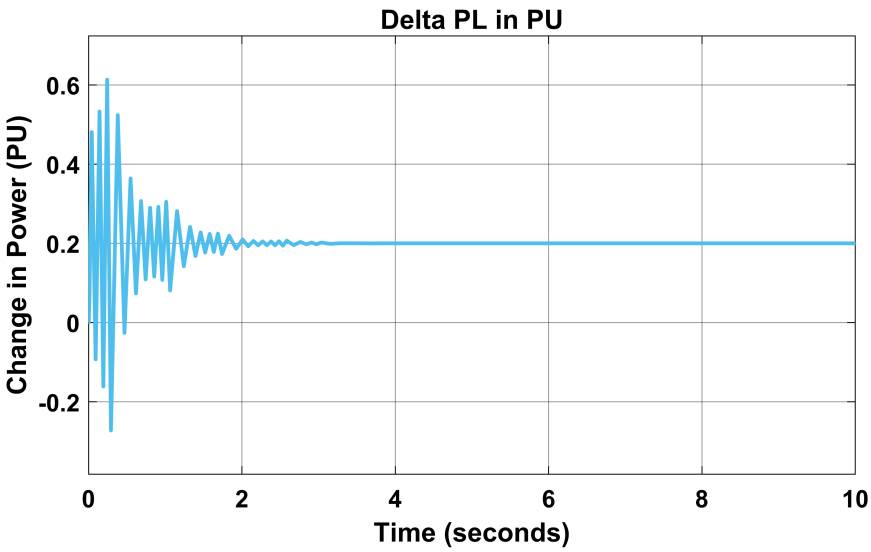


Figure 6.12: Change in Load(PU) with PSO-PID Controller

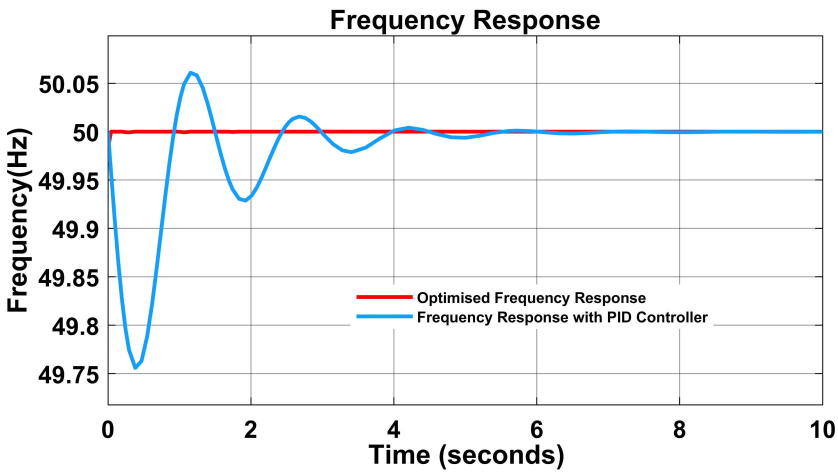


Figure 6.13: Combined Frequency Response using PSO-PID Controller

6.6.2 Comparing the PSO-PID controller algorithm with other LFC Techniques

The PSO-PID controller algorithm was compared to other techniques, as shown in Table 6.2. The algorithm was compared with the fuzzy controller with a settling time of 15.4 s [237] as compared with the proposed algorithm of 0.00 s settling time and a performance index of 0.0005757 ITAE. Also, the settling time of the ANN SVM, ANFI, and ANN-PID controller is higher than the proposed algorithm, as shown in Table 6.2. Compared to PI and PID controllers, the PSO-PID controller has shown superior quick settling time, reduced overshoot and undershoot, and fewer oscillations.

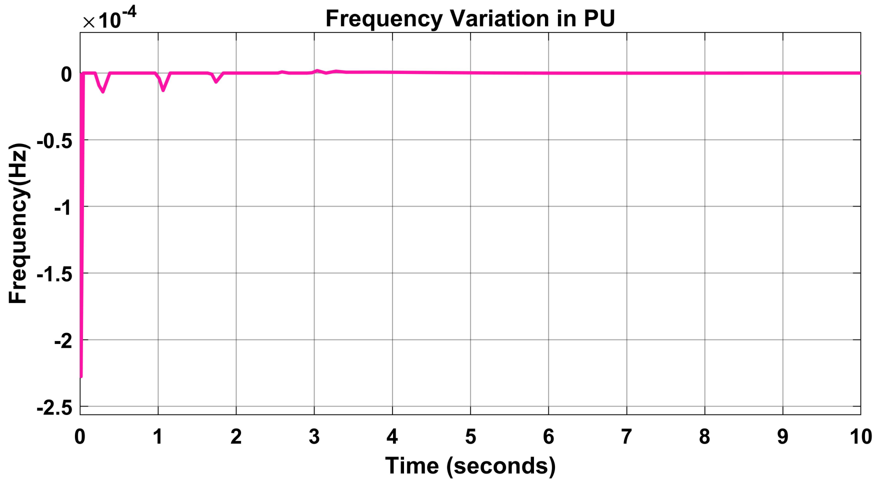


Figure 6.14: Frequency Variation in PU using PSO-PID Controller

Table 6.2: Comparing the proposed model and the other algorithm used

Controller Used	**Settling time (s)**	**Controller Error**	**Overshoot**	**Reference**
FUZZY Controller	7.20	0.2%	0.027	[237]
Fuzzy Controller	15.4	2.5%	2.33	[238]
PID controller	16.58	0.732	0.0206	[239]
ANN-PID Controller	6.5	0.04%	0.1090	[234]
Optimal ANN	50.0	0.06%	3.4	[240]
ANFIS controller	8.5	-	-0.45	[241, 242]
BESSO-PID Controller	10.4767	-	0.0001	[243]
DE-PID Controller	11.1892	-	0.001	[244]
PID-PSO Controller	2.93	0.055%	0.052	[245]
SVM Controller	10.5	7.09%	0.25	[246]
GA-PID Controller	21.8	0.0075	0.04	[211]
GA-PID Controller	5.0	0.50025	0.0	[247]
Proposed Algorithm with PID	5.0	0.0005757	0.45	
Proposed Algorithm with PSO-PID	0.0	0.0005757	0.0	

The PSO algorithm has a potential for premature coverage because the algorithm has several parameters, such as the population size, inertia weight, and acceleration coefficients, which must be appropriately selected to achieve optimal performance. The performance of the PSO-PID controller in LFC may be sensitive to the values chosen for these parameters, and sub-optimal parameter settings could result in reduced controller performance or convergence to local optima. Therefore, the proposed algorithm increases the iteration value to reduce premature convergence for optimal results, as seen in Figure 6.15.

Other methods can be used to reduce frequency variation or control power

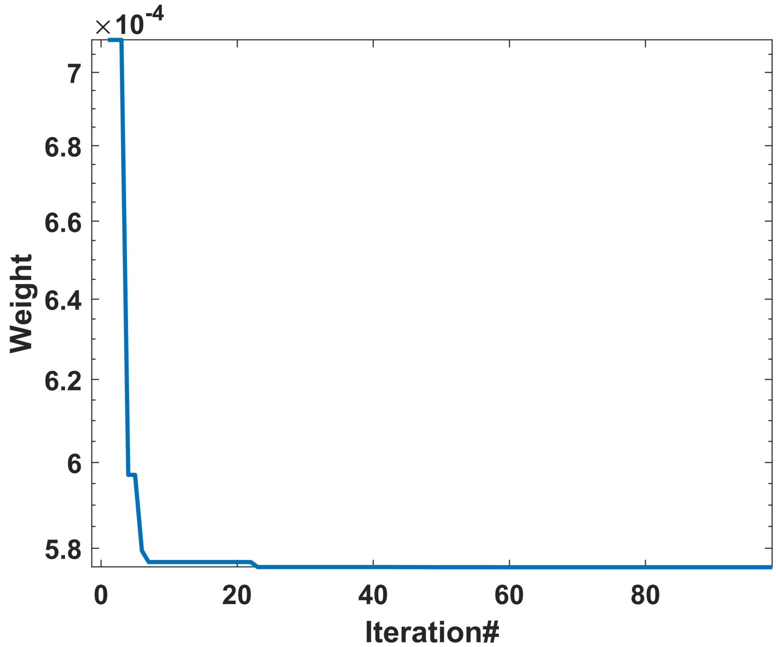


Figure 6.15: Iteration of the PSO Algorithm

system and frequency stability, and these include

- Automatic Generation Control (AGC): AGC is a control system that adjusts the output of generators in response to variations in frequency to maintain the balance between generation and load. When the frequency falls, AGC may automatically boost the output of other generators to compensate for the lost generation, restoring the frequency to its usual range.

- Load shedding: Load shedding is a control method used to minimise power system demand during times of low generation or high demand. Load shedding may be used to lower the load on the system and assist in restoring the frequency to its normal range in the case of a frequency deviation. This may include disconnecting individual loads or lowering the electricity usage of specific consumers or areas.

- Reserve capacity: The generating capacity available to the system beyond the predicted demand is called reserve capacity. Reserve capacity is crucial because it acts as a buffer to absorb unforeseen occurrences like the abrupt loss of a generator. By ensuring that the system has appropriate reserve capacity, the frequency variation may be corrected rapidly without jeopardising system stability.

- Interconnection with surrounding systems: Interconnection with neighbouring power systems may offer new generation sources while also assisting in balancing energy supply and demand across a larger region. Interconnection with surrounding systems may give extra assistance to help restore the frequency to its normal range in the case of a frequency deviation.

- Energy storage: Energy storage technologies, such as batteries or pumped hydro storage, may be utilised to store surplus generating capacity and release it as required. Therefore, it assists in maintaining system stability by deploying energy storage to offer extra assistance to the system during times of low generation.

  Power system operators may use these steps to guarantee that the frequency stays within a small range, reducing the danger of power outages or equipment damage.

The novelty of this technique is the interconnection of hybrid generation plants synchronised to a single grid and using the PID-PSO algorithm to control the load frequency for optimal performance and to stabilise the generation and the load frequency.

6.7 Conclusion

A novel particle swarm optimised LFC was examined in this work for autonomous load frequency regulation of the Delta thermal generating station, a part of the Nigeria transmission line model. The network was modelled without the PID controller using the system parameters generated through a mathematical model, and then the PID Controller was introduced for parameter turning. The mfile of the PSO algorithm code was generated using MATLAB to generate the K_p, K_i and K_d parameters. First, more adaptive tuning mechanisms for the PID controller settings are obtained, and the system's sensitivity is raised. It has been shown that the suggested control algorithm is effective and improves system performance significantly. As a result, the suggested PSO-PID controller is recommended for producing high-quality, dependable electricity. Moreover, the PSO-PID algorithm produces 0.00 s settling time and 0.0005757 ITAE. It's essential to consider potential drawbacks like complexity and computational overhead carefully. Also, the sensitivity to algorithm parameters, potential parameter convergence and limited interpretability and assessment of their impact on the specific LFC application before implementing a PSO-PID controller in a power system. Proper parameter tuning, robustness analysis, and performance evaluation are crucial to ensure the effective and reliable operation of the controller. The suggested controller algorithm is relatively reliable and accurate in power system management and load frequency control compared to conventional methods. This work can be improved by including more generating stations synchronised into a single network.

The PSO-PID (Particle Swarm Optimisation - Proportional Integral Derivative) controller algorithm has several advantages over other conventional methods in Load Frequency Control (LFC), including:

- Better performance: PSO-PID controller algorithm has been found to provide better control performance than conventional PID controllers in LFC systems. This is due to the ability of PSO to optimise the PID parameters to achieve the desired control objective.

- Robustness: PSO-PID controller algorithm is robust, and can handle variations in load and system parameters, which are common in power systems.

- Flexibility: PSO-PID controller algorithm can be easily adapted to different power system models and can be used to control different types of generators.

- Fast convergence: The PSO algorithm has fast convergence compared to other optimisation techniques, which makes it suitable for real-time control applications.

- Easy to implement: The PSO-PID controller algorithm is easy to implement and does not require complex mathematical models or sophisticated programming skills.

Overall, the PSO-PID controller algorithm has proven to be an effective and efficient approach for Load Frequency Control (LFC) in power systems, offering better control performance, robustness, flexibility, fast convergence, and ease of implementation.

Chapter 7

Conclusions and Future Work

The contributions of this thesis are summarised in this chapter. In addition, the opportunities for future research of this work are also identified and enumerated.

7.1 Conclusion

This section presents a chapter-by-chapter summary with other significant contributions and implications of the research work carried out in this thesis.

Chapter 1 presents an overview of the research work carried out in the thesis. The transmission line fault was discussed, and the types of faults that occur in the transmission line were enumerated and explained in detail. The problem statement outlines the main issues of the thesis, like the present state of the Nigerian 330 kV transmission line and the development of an effective protection system that can detect, locate, and isolate faults quickly and accurately while minimising the impact on the power system. This requires a combination of advanced sensing, computing, and control technologies and appropriate protection schemes and strategies.

The research motivation and the core objectives, which involve modelling the Nigeria 330 k transmission line, identify the different types of faults on the network by classifying, detecting and localising the faults. Also, machine learning analyses the data generated from the modelled system to detect and locate faults for the optimum fault management system. were also discussed

Chapter 2 explains in detail the literature review of the thesis, focusing on a brief introduction to the transmission line, types of faults and a brief introduction to the Nigeria 330 kV transmission line. Also, an overview of fault detection, classification and localisation and the necessary protection techniques. Also, various machine learning (ML) algorithms are applied in transmission line fault analysis. They are compared with conventional techniques like the inspection robot, PMU, Fuzzy logic technique, distance relay protection technique, wave transform technique and other hybrid techniques analysed. The ML techniques were also compared with the conventional and hybrid methods. The core concept, essential equations, and significant papers are presented and summarised for each approach.

The Significance of the thesis is addressed in comparison to the current review studies. Moreover, the benefits and limitations of machine learning methodologies have been thoroughly examined and summarised to give a clear road map for future study.

Overall, research contributions in modelling transmission line protection schemes have significantly improved protection schemes' efficiency, accuracy, and reliability. These advances have played a critical role in ensuring power systems' safety and reliable operation.

Chapter 3 proposed the use of the CatBoost classifier as the preferred algorithm for fault classification due to its high accuracy and ease of training. This approach is accomplished by building a 330 kV, 500 km transmission line in Matlab/Simulink and extracting fault current and voltage waveforms to determine the fault phase for each defective voltage and current waveform. The system was trained using a 93340 defect data set, with an accuracy of 99.54%. Classifier algorithms such as SVM, ANN, and XBoost may train categorical data using many data sets. This work addressed the classification of a multi-dataset of defective voltage and current in transmission lines, emphasising speed, accuracy, and precision in fault classification for quick fault identification and isolation. The findings will also serve as a reference for transmission line fault prevention management systems and architecture. The CatBoost classifier was justified for the transmission line fault classification model after being compared to other approaches utilised in previous papers. The chapter also emphasises the effect of noise signals on fault classification and how it can be reduced to optimal results.

Chapter Four analysed and investigated the use of artificial neural networks for fault detection and localisation in the transmission line. A 330 kV, 500 km, 50 Hz three-phase the transmission line was modelled using Matlab/Simulink to generate the RMS value of faulty voltage and current signals from the malfunctioning line. Around 12 distinct fault situations were explored, and 33,336 data samples of defective current and voltage were collected from various places along the transmission line to identify faults using ANN and to utilise the module for fault localisation. The various faults were explored, mainly single, double, and three-phase. The data was trained for accuracy, speed, and precision, with a defect detection accuracy of 100% and a fault localisation accuracy of 99% at independent sites. The time required for fault detection is critical in fault protection, and this study has concentrated on the execution speed required for rapid fault detection. This methodology gives better results than traditional fuzzy logic and DWT approaches.

Chapter Five explains the application of the threshold voltage and current values presented as a standard for coordinating and establishing the instantaneous overcurrent relay protection in the transmission line. The simulated results were analysed to establish the model's validity in computing the high-voltage transmission line relay's tripping, delay, and operational times. It also analyses or detects the maximum and least threshold voltage and current that may be used to optimise the relay and circuit breaker for best performance. This strategy reduces latency and improves relay tripping time. One of the technique's limitations is the difficulty in optimising the threshold current for varied current and voltage types. Nevertheless, when the fault impedance between two sites is modest, this approach discriminates poorly in differentiating between fault currents at various places.

Finally, chapter six discussed a novel particle swarm-optimised LFC that was examined in this work for autonomous load frequency regulation of the Delta thermal generating station, a part of the Nigeria transmission line model. The network was modelled without the PID controller using the system parameters generated through a mathematical model, and then the PID Controller was introduced for parameter turning. The mfile of the PSO algorithm code was generated using MATLAB to generate the K_p, K_i and K_d parameters. First, more adaptive tuning mechanisms for the PID controller settings are obtained, and the system's sensitivity is raised. It has been shown that the suggested control algorithm is effective and improves system performance significantly. As a result, the suggested PSO-PID controller is recommended for producing high-quality, dependable electricity. Moreover, the PSO-PID algorithm produces 0.00 s settling time and 0.0005757 ITAE. It's essential to carefully consider potential drawbacks like complexity and computational overhead, sensitivity to algorithm parameters, potential parameter convergence and limited interpretability and assess their impact on the specific LFC application before implementing a PSO-PID controller in a power system. Proper parameter tuning, robustness analysis, and performance evaluation are crucial to ensure the effective and reliable operation of the controller. Compared to the conventional method, the suggested controller algorithm is relatively reliable and accurate in power system management and protection load frequency control.

7.2 Recommendation and Further Work

The section highlights recommendations and further research that will improve performance on the techniques proposed in this thesis.

1. Transmission Line Fault Classification of Multi-dataset using CatBoost Classifier.

   - The CatBoost algorithm can be optimised for real-time data mining and training automatically for an effective fault protection mechanism. Considering optimising the method and techniques for real-time inference, ensuring low latency and high accuracy for fault classification applications that require a timely response.
   - In fault classification, imbalanced datasets are common, where some fault classes may have fewer samples than others. Investigate techniques to handle class imbalance, such as oversampling, under-sampling, or utilising different sampling strategies like SMOTE (Synthetic Minority Over-sampling Technique) to improve the performance of CatBoost.
   - In the feature extraction or data accusation, The ground resistance can be increased to see the impact on fault classification on the transmission line and the system's behaviour concerning the current, voltage and temperature of the surrounding environment.

2. The Use of Artificial Neural Network for Low Latency of Fault Detection and Localisation in Transmission

   - Real-time fault detection and location should be applied using the ANN techniques such as online learning and adaptive neural networks can be explored to enable continuous monitoring and quick response to faults as they occur in real-world systems.
   - Time-frequency analysis technique can be employed for quick and accurate feature extraction, and selection should be focused on effectively representing fault data for training using machine learning.
   - Failure Mode and Effects Analysis (FMEA) method should be researched further for identifying and prioritising systems, processes, or faults. It entails assessing the consequences of each prospective failure, calculating its chance of occurrence, and giving severity and detection ratings. Fault localisation and detection efforts may be efficiently prioritised by concentrating on high-risk failure scenarios.

- Other power systems software like Power Factory, ETAP and PSCAD can be used for data extraction rather than focusing only on MATLAB/SIMULINK.

3. The use of Instantaneous Overcurrent Relay in Determining the Threshold Current and Voltage For Optimal Fault Protection and Control In Transmission Line.

    - The reliability of an instantaneous overcurrent relay in transmission line protection is paramount; therefore, it is necessary to conduct a reliability analysis of the relay coordination scheme to assess its effectiveness in detecting and clearing faults. Utilise techniques such as fault tree analysis, reliability block diagrams, or Monte Carlo simulations to quantify the reliability and availability of the protective system.
    - Perform sensitivity analysis to assess the impact of changes in system parameters, relay settings, or fault characteristics on the coordination scheme. Identify potential vulnerabilities or areas for improvement and evaluate the robustness of the coordination scheme under different operating conditions.
    - It is also advised to Investigate the use of communication systems for enhanced relay coordination in transmission lines. Communication-assisted coordination techniques utilise real-time data exchange between relays and central control systems to improve fault detection, localisation, and coordination accuracy.

4. Load Frequency Control in TL using PSO

    - The proposed algorithm faces premature convergence; therefore, a convergence speed controller should be applied to reduce the convergence speed if it is too fast and increase it if it is too slow for optimal performance. Also, particle stability analysis, redistribution mechanisms, and random sampling control parameters can be employed for optimum performance.
    - The grid system is becoming hybrid and sophisticated; therefore, there is a need to consider multi-grid connection systems in the design of the LFC of the power system. Also, multi-machine dynamic equivalent models could be examined instead of single machines for studies concerning simplified dynamic equivalent models. This way, the frequency variations through the system after a disturbance can be captured.

- A historical database may be generated by applying one or more specified procedures to numerous simulated situations. This would enable the development of an estimating tool capable of operating at a steady state, similar to the one shown in [248].

Appendix A

7.3 Mathematical Modelling of a Long Transmission Line

From Figures 1.1 and 1.2 let z be the series impedance per unit length
y be the shunt admittance per unit length
$Z = zl =$ total series impedance
and $Y = yl$ is the total shunt admittance.// The length dx of the line at a distance x from the receiving end of the voltage and current at a distance x is V and I at a distance $X + dx, V + \Delta V$ and $I + \Delta I$ respectively.

$$\Delta V = Iz\Delta x; \Delta I = Vy\Delta x \tag{7.1}$$

from equation 7.1

$$\frac{\Delta V}{\Delta x} = Iz; \frac{\Delta I}{\Delta x} = Vy \tag{7.2}$$

limit as $\Delta x \to 0$ reduces to

$$\frac{\delta V}{\delta x} = Iz \tag{7.3}$$

and

$$\frac{\delta I}{\delta x} = Vy \tag{7.4}$$

differentiating equation 7.3

$$\frac{\delta^2}{\delta x^2} - zyV = 0 \tag{7.5}$$

The solution of equation 7.5 is given as

$$V = A\ \exp(\sqrt{yx}.x) + B\ \exp(-\sqrt{yz}.x) \tag{7.6}$$

from equation 7.4 and 7.6 let

$$Z_c = \sqrt{\frac{z}{y}} \text{ and } \gamma = \sqrt{yz} = \alpha + j\beta \tag{7.7}$$

Where Z_c is known as the characteristic impedance and γ is the propagation constant. Equation 7.6 and 7.7 are rewritten as

$$V = Ae^{\gamma x} + Be^{\gamma x} \tag{7.8}$$

$$I = \frac{I}{Z_c}(Ae^{\gamma x} - Be^{\gamma x}) \tag{7.9}$$

the receiving end voltage and current are determined at $x = 0$, $V = V_r$ and $I = I_r$. Substituting these values in equation 7.8 and 7.9
$V_r = A + B$
$I_r = \frac{1}{Z_c}(A - B)$
$A = \frac{V_r + I_r Z_c}{2}$ and $B = \frac{V_r + I_r Z_c}{2}$ Substituting the values of A and B in equations 7.8 and 7.9, we obtain

$$V = \frac{V_r + I_r Z_c}{2} e^{\gamma x} + \frac{V_r + I_r Z_c}{2} e^{-\gamma x} \tag{7.10}$$

and

$$I = \frac{1}{Z_c}\left[\frac{V_r + I_r Z_c}{2} e^{\gamma x} - \frac{V_r + I_r Z_c}{2} e^{-\gamma x}\right] \tag{7.11}$$

The following formula clearly shows that V, and I (magnitude and phase) are functions of distance x, receiving end voltage V_r and current I_r, and line parameters, which means they change as we go from the receiving end to the transmitting end. Furthermore, the quantities Z_c and γ from equation 7.10 and 7.11 are complex so,
$Z_c = \sqrt{\frac{z}{y}} = \sqrt{\frac{r + j\omega L}{g + j\omega C}}$ and for a lossless line, $r = 0, g = 0$
$Z_c = \sqrt{\frac{L}{C}}$. The propagation constant $\gamma = \alpha + j\beta$ has the real part known as the attenuation constant, and the quadrature component β is called the phase constant and is measured in radians per unit length. So equation 7.10 becomes

$$V = \frac{V_r + I_r Z_c}{2} e^{\alpha x}.e^{j\beta x} + \frac{V_r - I_r Z_c}{2} e^{-\alpha x}.e^{-j\beta x} \tag{7.12}$$

Since the current expression is identical to the voltage, the current may be considered the total of the incident and reflected current waves. The voltage and current equations may be rearranged as follows:

$$V = V_r.\frac{e^{\gamma x} + e^{-\gamma x}}{2} + I_r Z_c \frac{e^{\gamma x} - e^{-\gamma x}}{2} = V_r cosh\gamma x + I_r Z_c sinh\gamma x \tag{7.13}$$

$$I = \frac{1}{Z_c}\left[V_r \frac{e^{\gamma x} - e^{-\gamma x}}{2} + I_r Z_c \frac{e^{\gamma x} + e^{-\gamma x}}{2}\right] \tag{7.14}$$

so,

$$I = \frac{V_r}{Z_c}\text{sinh}\gamma x + I_r \text{cosh } \gamma x \tag{7.15}$$

Rewriting these equations for $x = l$, where $V = V_s$ and $I = I_s$

$$V_s = V_r \text{cosh } \gamma l + I_r Z_c \text{sinh } \gamma l \tag{7.16}$$

$$I_s = V_r \frac{\text{sinh } \gamma l}{Z_c} + I_r \text{cosh } \gamma l \tag{7.17}$$

Equation 7.16 and 7.17 relate the sending end voltage and current with the receiving end quantities. These quantities are related by the general equation

$$V_s = AV_r + BI_r \tag{7.18}$$

$$V_s = CV_r + DI_r \tag{7.19}$$

where A, B, C and D are such that
$A = D$ and $AD - BC = 1$
Comparing the coefficient of the equation 7.14 and 7.15 with the 7.16 and 7.17 respectively,
$A = \text{cosh } \gamma l$
$B = Z_c \text{sinh } \gamma l$
$C = \frac{\text{sinh } \gamma l}{Z_c}$
and $D = \text{cosh } \gamma l$
Therefore, $A = D = \text{cosh}\gamma l$ and
$AD - BC = \text{cosh}^2 \gamma l - Z_c \text{ sinh } \gamma l . \frac{\text{sinh } \gamma l}{Z_c} = 1$

Bibliography

[1] M. R. Singh, T. Chopra, R. Singh, and T. Chopra, "Fault classification in electric power transmission lines using support vector machine," *Int. J. Innov. Res. Sci. Technol*, vol. 1, no. 12, pp. 388–400, 2015.

[2] M. Shafiullah, M. Abido, and A. Al-Mohammed, *Power system fault diagnosis: a wide area measurement based intelligent approach*. Elsevier, 2022.

[3] N. Tleis, *Power systems modelling and fault analysis: theory and practice*. Elsevier, 2007.

[4] Y. Srinivasarao, S. Pavani, and G. Sudharmi, "Detection of fault location in transmission lines," *Int. J. Appl. Eng. Res*, vol. 12, no. 1, 2017.

[5] S. Kufeoglu, M. Pollitt, and K. Anaya, "Electric power distribution in the world: Today and tomorrow," 2018.

[6] R. Das and D. Novosel, "Review of fault location techniques for transmission and sub–transmission lines," in *Proceedings of 54th annual Georgia tech protective relaying conference*, 2000.

[7] K. Zimmerman and D. Costello, "Impedance-based fault location experience," in *2006 IEEE Rural Electric Power Conference*. IEEE, 2006, pp. 1–16.

[8] X. Jiao and Y. Liao, "A linear estimator for transmission line parameters based on distributed parameter line model," in *2017 IEEE Power and Energy Conference at Illinois (PECI)*. IEEE, 2017, pp. 1–8.

[9] A. Alassi, S. Bañales, O. Ellabban, G. Adam, and C. MacIver, "Hvdc transmission: Technology review, market trends and future outlook," *Renewable and Sustainable Energy Reviews*, vol. 112, pp. 530–554, 2019.

[10] U. Onochie, H. Egware, and T. Eyakwanor, "The nigeria electric power sector (opportunities and challenges)," *Journal of Multidisciplinary Engineering Science and Technology*, vol. 2, no. 4, pp. 494–502, 2015.

[11] O. J. Ayamolowo, E. Buraimoh, A. O. Salau, and J. O. Dada, "Nigeria electricity power supply system: The past, present and the future," in *2019 IEEE PES/IAS PowerAfrica*. IEEE, 2019, pp. 64–69.

[12] Y. N. Chanchangi, F. Adu, A. Ghosh, S. Sundaram, and T. K. Mallick, "Nigeria's energy review: Focusing on solar energy potential and penetration," *Environment, Development and Sustainability*, vol. 25, no. 7, pp. 5755–5796, 2023.

[13] E. N. Vincent and S. D. Yusuf, "Integrating renewable energy and smart grid technology into the nigerian electricity grid system," *Smart Grid and Renewable Energy*, vol. 2014, 2014.

[14] A. Moradzadeh, H. Teimourzadeh, B. Mohammadi-Ivatloo, and K. Pourhossein, "Hybrid cnn-lstm approaches for identification of type and locations of transmission line faults," *International Journal of Electrical Power & Energy Systems*, vol. 135, p. 107563, 2022.

[15] S. Annestrand, "Power transmission, high-voltage," in *Encyclopedia of Physical Science and Technology (Third Edition)*, third edition ed., R. A. Meyers, Ed. New York: Academic Press, 2003, pp. 35–55. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B0122274105006086

[16] H. Zhou, W. Qiu, K. Sun, J. Chen, X. Deng, F. Qian, D. Wang, B. Zhao, J. Li, S. Li *et al.*, *Ultra-high voltage AC/DC power transmission.* Springer, 2018.

[17] Y. Hu and K. Liu, *Inspection and monitoring technologies of transmission lines with remote sensing.* Academic Press, 2017.

[18] D. Huang, Y. Shu, J. Ruan, and Y. Hu, "Ultra high voltage transmission in china: developments, current status and future prospects," *Proceedings of the IEEE*, vol. 97, no. 3, pp. 555–583, 2009.

[19] "Chapter 1 - general," in *UHV Transmission Technology.* Oxford: Academic Press, 2018, pp. 3–20. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B978012805193100001X

[20] A. EPRI, "Transmission line reference book–200 kv and above," *Electric Power Research Institute*, 2005.

[21] A. Peterson Jr and S. Hommann, "Transmission line conductor design comes of age," *Transmission and Distribution World*, vol. 7, pp. 62–68, 2003.

[22] V. Ogar, D. Abara, and E. Akpama, "Symmetrical and unsymmetrical faults analysis: Using nigeria 330-kv grid as case study," in *2017 IEEE 3rd International Conference on Electro-Technology for National Development (NIGERCON).* IEEE, 2017, pp. 1–7.

[23] P. R. Varghese, M. Subathra, C. Mathew, and S. T. George, "Analysis and simulation of faults in a radial distribution network," in *AIP Conference Proceedings*, vol. 2670, no. 1. AIP Publishing LLC, 2022, p. 060004.

[24] X. Wang, J. Gao, X. Wei, Z. Zeng, Y. Wei, and M. Kheshti, "Single line to ground fault detection in a non-effectively grounded distribution network," *IEEE Transactions on Power Delivery*, vol. 33, no. 6, pp. 3173–3186, 2018.

[25] R. Rajesh Kanna, R. Raja Singh, and D. Arun Dominic, "Impact analysis of single line to ground fault on industrial loads using typhoon hil," in *Innovations in Electrical and Electronic Engineering.* Springer, 2021, pp. 63–79.

[26] A. A. Elbaset and T. Hiyama, "Fault detection and classification in transmission lines using anfis," *IEEJ Transactions on Industry Applications*, vol. 129, no. 7, pp. 705–713, 2009.

[27] C. J. Nnonyelu, T. C. Madueme, and B. Anyaka, "Power system contingency analysis: a study of nigeria's 330kv transmission grid," in *Proceedings of the Energy Source for Power Generation Conference, Nsukka, Nigeria*, 2013, pp. 21–23.

[28] F. M. Shakiba, S. M. Azizi, M. Zhou, and A. Abusorrah, "Application of machine learning methods in fault detection and classification of power transmission lines: a survey," *Artificial Intelligence Review*, pp. 1–38, 2022.

[29] A. Rahmati, M. A. Dimassi, R. Adhami, and D. Bumblauskas, "An overcurrent protection relay based on local measurements," *IEEE Transactions on Industry Applications*, vol. 51, no. 3, pp. 2081–2085, 2014.

[30] M. A. Jalal, K. M. Sahari, A. Anuar, A. M. Arshad, and M. Idris, "Conceptual design for transmission line inspection robot," in *IOP conference series: Earth and environmental science*, vol. 16, no. 1. IOP Publishing, 2013, p. 012094.

[31] G. Tao and L. Fang, "A multi-unit serial inspection robot for power transmission lines," *Industrial Robot: the international journal of robotics research and application*, 2019.

[32] S. Montambault and N. Pouliot, "About the future of power line robotics," in *2010 1st International Conference on Applied Robotics for the Power Industry*. IEEE, 2010, pp. 1–6.

[33] T. Disyadej, J. Promjan, P. Muneesawang, K. Poochinapan, and S. Grzybowski, "Application in o&m practices of overhead power line robotics," in *2019 IEEE PES GTD Grand International Conference and Exposition Asia (GTD Asia)*. IEEE, 2019, pp. 347–351.

[34] H. B. Funmilayo, J. A. Silva, and K. L. Butler-Purry, "Overcurrent protection for the ieee 34-node radial test feeder," *IEEE Transactions on Power Delivery*, vol. 27, no. 2, pp. 459–468, 2012.

[35] P. Mahat, Z. Chen, B. Bak-Jensen, and C. L. Bak, "A simple adaptive overcurrent protection of distribution systems with distributed generation," *IEEE Transactions on Smart Grid*, vol. 2, no. 3, pp. 428–437, 2011.

[36] T. Keli and J. Jáger, "Advanced coordination method protection relays using non-standard," *IEEE Transactions on Power Delivery*, vol. 23, no. 1, pp. 52–57, 2008.

[37] M. S. Almas, R. Leelaruji, and L. Vanfretti, "Over-current relay model implementation for real time simulation & hardware-in-the-loop (hil) validation," in *IECON 2012-38th Annual Conference on IEEE Industrial Electronics Society*. IEEE, 2012, pp. 4789–4796.

[38] P. Gangadharan, T. Sidhu, and A. Klimek, "Influence of current transformer saturation on line current differential protection algorithms," *IET generation, transmission & distribution*, vol. 1, no. 2, p. 270, 2007.

[39] M. Biswal, "Adaptive distance relay algorithm for double circuit line with series compensation," *Measurement*, vol. 53, pp. 206–214, 2014.

[40] S. Dambhare, S. Soman, and M. Chandorkar, "Adaptive current differential protection schemes for transmission-line protection," *IEEE Transactions on Power Delivery*, vol. 24, no. 4, pp. 1832–1841, 2009.

[41] Q. Liu, Z. Wang, and Y. Xu, "Research on the influence of tcsc to ehv transmission line protection," in *2008 Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies.* IEEE, 2008, pp. 2258–2261.

[42] V. Malathi, N. Marimuthu, S. Baskar, and K. Ramar, "Application of extreme learning machine for series compensated transmission line protection," *Engineering Applications of Artificial Intelligence*, vol. 24, no. 5, pp. 880–887, 2011.

[43] D. Guillen, M. R. A. Paternina, J. Ortiz-Bejar, R. K. Tripathy, A. Zamora-Mendez, R. Tapia-Olvera, and E. S. Tellez, "Fault detection and classification in transmission lines based on a psd index," *IET Generation, Transmission & Distribution*, vol. 12, no. 18, pp. 4070–4078, 2018.

[44] G. S. Navyasri, K. Deepa, V. Sailaja *et al.*, "Fault analysis in three phase transmission lines using wavelet method," in *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI).* IEEE, 2022, pp. 248–254.

[45] A. Mukherjee, P. K. Kundu, and A. Das, "Transmission line faults in power system and the different algorithms for identification, classification and localization: a brief review of methods," *Journal of The Institution of Engineers (India): Series B*, vol. 102, no. 4, pp. 855–877, 2021.

[46] A. Prasad and J. B. Edward, "Application of wavelet technique for fault classification in transmission systems," *Procedia Computer Science*, vol. 92, pp. 78–83, 2016.

[47] S. Mallat, *A wavelet tour of signal processing.* Elsevier, 1999.

[48] N. U. Gawali, R. Hasabe, and A. Vaidya, "A comparison of different mother wavelet for fault detection & classification of series compensated transmission line," *Int. J. Innov. Res. Sci. Technol*, vol. 1, no. 9, pp. 57–63, 2015.

[49] K. H. Kashyap and U. J. Shenoy, "Classification of power system faults using wavelet transforms and probabilistic neural networks," in *Proceedings of the 2003 International Symposium on Circuits and Systems, 2003. ISCAS'03.*, vol. 3. IEEE, 2003, pp. III–III.

[50] U. B. Parikh, B. Das, and R. P. Maheshwari, "Combined wavelet-svm technique for fault zone detection in a series compensated transmission line," *IEEE Transactions on Power Delivery*, vol. 23, no. 4, pp. 1789–1794, 2008.

[51] V. Malathi, N. Marimuthu, and S. Baskar, "Intelligent approaches using support vector machine and extreme learning machine for transmission line protection," *Neurocomputing*, vol. 73, no. 10-12, pp. 2160–2167, 2010.

[52] B. Bhalja and R. Maheshwari, "Wavelet-based fault classification scheme for a transmission line using a support vector machine," *Electric Power Components and Systems*, vol. 36, no. 10, pp. 1017–1030, 2008.

[53] S. K. Shukla, E. Koley, and S. Ghosh, "A hybrid wavelet–apso–ann-based protection scheme for six-phase transmission line with real-time validation," *Neural Computing and Applications*, vol. 31, no. 10, pp. 5751–5765, 2019.

[54] K. C. Wakhare and N. Wagh, "Review of various algorithms for protection of transmission line," *International Journal of Engineering Research & TechnologyVol*, vol. 4, pp. 346–351, 2015.

[55] F. B. Costa, K. M. Silva, B. A. Souza, K. M. C. Dantas, and N. S. D. Brito, "A method for fault classification in transmission lines based on ann and wavelet coefficients energy," in *The 2006 IEEE International Joint Conference on Neural Network Proceedings.* IEEE, 2006, pp. 3700–3705.

[56] O. A. Youssef, "Combined fuzzy-logic wavelet-based fault classification technique for power system relaying," *IEEE transactions on power delivery*, vol. 19, no. 2, pp. 582–589, 2004.

[57] M. J. Reddy and D. K. Mohanta, "A wavelet-fuzzy combined approach for classification and location of transmission line faults," *International Journal of Electrical Power & Energy Systems*, vol. 29, no. 9, pp. 669–678, 2007.

[58] L. Saikia, S. Borah, and S. Pait, "Detection and classification of power quality disturbances using wavelet transform, fuzzy logic and neural network," in *2010 Annual IEEE India Conference (INDICON).* IEEE, 2010, pp. 1–5.

[59] H. Talhaoui, T. Ameid, O. Aissa, and A. Kessal, "Wavelet packet and fuzzy logic theory for automatic fault detection in induction motor," *Soft Computing*, pp. 1–15, 2022.

[60] P. Jayaswal and A. Wadhwani, "Application of artificial neural networks, fuzzy logic and wavelet transform in fault diagnosis via vibration signal analysis: A review," *Australian Journal of Mechanical Engineering*, vol. 7, no. 2, pp. 157–171, 2009.

[61] C. Jung, K. Kim, J. Lee, and B. Klöckl, "Wavelet and neuro-fuzzy based fault location for combined transmission systems," *International Journal of Electrical Power & Energy Systems*, vol. 29, no. 6, pp. 445–454, 2007.

[62] A. Hossam-Eldin, A. Lotfy, M. Elgamal, and M. Ebeed, "Combined traveling wave and fuzzy logic based fault location in multi-terminal hvdc systems," in *2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC)*. IEEE, 2016, pp. 1–6.

[63] S. R. Fahim, S. K. Sarker, S. Muyeen, S. K. Das, and I. Kamwa, "A deep learning based intelligent approach in detection and classification of transmission line faults," *International Journal of Electrical Power & Energy Systems*, vol. 133, p. 107102, 2021.

[64] L. Zadeh, "Some thoughts about appealing directions for the future of fuzzy theory and technologies along the path traced," in *Fuzzy Logic and Applications: 12th International Workshop, WILF 2018, Genoa, Italy, September 6–7, 2018, Revised Selected Papers*, vol. 11291. Springer, 2019, p. 240.

[65] M. Bhatnagar and A. Yadav, "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)*. IEEE, 2020, pp. 1–6.

[66] W. Chen, L. Wang, A. Ulatowski, and A. M. Bazzi, "A fuzzy logic approach for fault diagnosis and recovery in phev and ev chargers," in *2014 IEEE Transportation Electrification Conference and Expo (ITEC)*. IEEE, 2014, pp. 1–5.

[67] D. R. Gurusinghe and A. D. Rajapakse, "Efficient algorithms for real-time monitoring of transmission line parameters and their performance with practical synchrophasors," *IET Generation, Transmission & Distribution*, vol. 11, no. 5, pp. 1134–1143, 2017.

[68] S. C. Patel and P. Sanyal, "Securing scada systems," *Information Management & Computer Security*, 2008.

[69] M. Chantler, P. Pogliano, A. Aldea, G. Tornielli, T. Wyatt, and A. Jolley, "The use of fault-recorder data for diagnosing timing and other related faults in electricity transmission networks," *IEEE Transactions on Power Systems*, vol. 15, no. 4, pp. 1388–1393, 2000.

[70] M. A. Baseer, "Travelling waves for finding the fault location in transmission lines," *Journal Electrical and Electronic Engineering*, vol. 1, no. 1, pp. 1–19, 2013.

[71] J. Li, Y. Zhang, C. Ma, and C. Cheng, "Research on multifunctional automatic transmission line automatic robot system," in *Journal of Physics: Conference Series*, vol. 1074, no. 1. IOP Publishing, 2018, p. 012010.

[72] P. Gopakumar, B. Mallikajuna, M. Jaya Bharata Reddy, and D. K. Mohanta, "Remote monitoring system for real time detection and classification of transmission line faults in a power grid using pmu measurements," *Protection and Control of Modern Power Systems*, vol. 3, no. 1, pp. 1–10, 2018.

[73] A. Rahideh, M. Gitizadeh, and S. Mohammadi, "A fault location technique for transmission lines using phasor measurements," *International Journal of Engineering and Advanced Technology (IJEAT)*, vol. 3, no. 1, 2013.

[74] Z. Zheng, T. Tai, J. S. Thorp, and Y. Yang, "A transient harmonic current protection scheme for hvdc transmission line," *IEEE Transactions on Power Delivery*, vol. 27, no. 4, pp. 2278–2285, 2012.

[75] A. Jain, A. Thoke, and R. N. Patel, "Double circuit transmission line fault distance location using artificial neural network," in *2009 World Congress on Nature & Biologically Inspired Computing (NaBIC)*. IEEE, 2009, pp. 13–18.

[76] H. Wu, J. Yang, L. Chen, and Q. Wang, "A new method for identifying a fault in t-connected lines based on multiscale s-transform energy entropy and an extreme learning machine," *PloS one*, vol. 14, no. 8, p. e0220870, 2019.

[77] A. Mukherjee, P. K. Kundu, and A. Das, "A supervised principal component analysis-based approach of fault localization in transmission lines for single line to ground faults," *Electrical Engineering*, vol. 103, no. 4, pp. 2113–2126, 2021.

[78] S. Samantaray and P. Dash, "Transmission line distance relaying using machine intelligence technique," *IET generation, transmission & distribution*, vol. 2, no. 1, pp. 53–61, 2008.

[79] L. Cheng, L. Wang, and F. Gao, "Power system fault classification method based on sparse representation and random dimensionality reduction projection," in *2015 IEEE Power & Energy Society General Meeting*. IEEE, 2015, pp. 1–5.

[80] B. Das and J. V. Reddy, "Fuzzy-logic-based fault classification scheme for digital distance protection," *IEEE transactions on power delivery*, vol. 20, no. 2, pp. 609–616, 2005.

[81] H. Jung, Y. Park, M. Han, C. Lee, H. Park, and M. Shin, "Novel technique for fault location estimation on parallel transmission lines using wavelet," *International Journal of Electrical Power & Energy Systems*, vol. 29, no. 1, pp. 76–82, 2007.

[82] Z. M. Radojevic, V. V. Terzija, and N. Djuric, "Numerical algorithm for overhead lines arcing faults detection and distance and directional protection," *IEEE transactions on power delivery*, vol. 15, no. 1, pp. 31–37, 2000.

[83] S. Ekici, S. Yildirim, and M. Poyraz, "Energy and entropy-based feature extraction for locating fault on transmission lines by using neural network and wavelet packet decomposition," *Expert Systems with Applications*, vol. 34, no. 4, pp. 2937–2944, 2008.

[84] H. Wang and W. Keerthipala, "Fuzzy-neuro approach to fault classification for transmission line protection," *IEEE Transactions on Power Delivery*, vol. 13, no. 4, pp. 1093–1104, 1998.

[85] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Communications surveys & tutorials*, vol. 21, no. 3, pp. 2224–2287, 2019.

[86] H. Yang, X. Liu, D. Zhang, T. Chen, C. Li, and W. Huang, "Machine learning for power system protection and control," *The Electricity Journal*, vol. 34, no. 1, p. 106881, 2021.

[87] R. Vaish, U. Dwivedi, S. Tewari, and S. M. Tripathi, "Machine learning applications in power system fault diagnosis: Research advancements and perspectives," *Engineering Applications of Artificial Intelligence*, vol. 106, p. 104504, 2021.

[88] I. Silva, D. Spatti, R. Flauzino, and L. Liboni, "Alves, sfdr artificial neural networks," 2017.

[89] V. N. Ogar, S. Hussain, and K. A. Gamage, "The use of artificial neural network for low latency of fault detection and localisation in transmission line," *Heliyon*, vol. 9, no. 2, 2023.

[90] N. A. M. Leh, F. M. Zain, Z. Muhammad, S. Abd Hamid, and A. D. Rosli, "Fault detection method using ann for power transmission line," in *2020 10th IEEE international conference on control system, computing and engineering (ICCSCE)*. IEEE, 2020, pp. 79–84.

[91] E. B. M. Tayeb and O. A. A. A. Rhim, "Transmission line faults detection, classification and location using artificial neural network," in *2011 International Conference & Utility Exhibition on Power and Energy Systems: Issues and Prospects for Asia (ICUE)*. IEEE, 2011, pp. 1–5.

[92] I. N. Da Silva, D. H. Spatti, R. A. Flauzino, L. H. B. Liboni, and S. F. dos Reis Alves, "Artificial neural networks," *Cham: Springer International Publishing*, vol. 39, 2017.

[93] W. Xiang, H.-D. Tran, and T. T. Johnson, "Output reachable set estimation and verification for multilayer neural networks," *IEEE transactions on neural networks and learning systems*, vol. 29, no. 11, pp. 5777–5783, 2018.

[94] T. Dalstein and B. Kulicke, "Neural network approach to fault classification for high speed protective relaying," *IEEE Transactions on Power Delivery*, vol. 10, no. 2, pp. 1002–1011, 1995.

[95] G. Chawla, M. S. Sachdev, and G. Ramakrishna, "Design, implementation and testing of an artificial neural network based admittance relay," *IFAC Proceedings Volumes*, vol. 39, no. 7, pp. 125–130, 2006.

[96] M. Sanaye-Pasand and H. Khorashadi-Zadeh, "An extended ann-based high speed accurate distance protection algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 28, no. 6, pp. 387–395, 2006.

[97] M. Dehghani, M. H. Khooban, and T. Niknam, "Fast fault detection and classification based on a combination of wavelet singular entropy theory and fuzzy logic in distribution lines in the presence of distributed generations," *International Journal of Electrical Power & Energy Systems*, vol. 78, pp. 455–462, 2016.

[98] L. Lai, "Application of neural networks to fault classification and protection," 1997.

[99] U. Uzubi, A. Ekwue, and E. Ejiogu, "Artificial neural network technique for transmission line protection on nigerian power system," in *2017 IEEE PES PowerAfrica*. IEEE, 2017, pp. 52–58.

[100] V. Ogboh and T. Madueme, "Investigation of faults on the nigerian power system transmission line using artificial neural network," *Journal of Renewable and Sustainable Energy Reviews*, vol. 23, no. 2, pp. 342–351, 2015.

[101] K. A. K. Ali, A. A. Sahito, A. M. Soomro, and S. M. Jiskani, "The transmission line fault detection and identification using artificial neural network," *International Journal of Electrical Engineering & Emerging Technology*, vol. 4, no. SI 1, pp. 1–7, 2021.

[102] H. Zhang, Y. Li, Z. Lv, A. K. Sangaiah, and T. Huang, "A real-time and ubiquitous network attack detection based on deep belief network and support vector machine," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 3, pp. 790–799, 2020.

[103] H. Wu, Q. Wang, K. Yu, X. Hu, and M. Ran, "A novel intelligent fault identification method based on random forests for hvdc transmission lines," *Plos one*, vol. 15, no. 3, p. e0230717, 2020.

[104] W. S. Noble, "What is a support vector machine?" *Nature biotechnology*, vol. 24, no. 12, pp. 1565–1567, 2006.

[105] D. Krupenev, D. Boyarkin, and D. Iakubovskii, "Improvement in the computational efficiency of a technique for assessing the reliability of electric power systems based on the monte carlo method," *Reliability Engineering & System Safety*, vol. 204, p. 107171, 2020.

[106] M. Wang, W. Chai, C. Xu, L. Dong, Y. Li, P. Wang, and X. Qin, "An edge computing method using a novel mode component for power transmission line fault diagnosis in distribution network," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–14, 2020.

[107] P. Cunningham, M. Cord, and S. J. Delany, "Supervised learning, in 'machine learning techniques for multimedia'," 2008.

[108] S. Shalev-Shwartz and S. Ben-David, *Understanding Machine Learning: From Theory to Algorithms*. Cambridge University Press, 2014.

[109] M. Paluszek and S. Thomas, *MATLAB machine learning.* Apress, 2016.

[110] S. R. Fahim, Y. Sarker, S. K. Sarker, M. R. I. Sheikh, and S. K. Das, "Self attention convolutional neural network with time series imaging based feature extraction for transmission line fault detection and classification," *Electric Power Systems Research*, vol. 187, p. 106437, 2020.

[111] H. R. Baghaee, D. Mlakić, S. Nikolovski, and T. Dragicević, "Support vector machine-based islanding and grid fault detection in active distribution networks," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 8, no. 3, pp. 2385–2403, 2019.

[112] R. Godse and S. Bhat, "Mathematical morphology-based feature-extraction technique for detection and classification of faults on power transmission line," *IEEE Access*, vol. 8, pp. 38 459–38 471, 2020.

[113] S. Xiong, Y. Liu, J. Fang, J. Dai, L. Luo, and X. Jiang, "Incipient fault identification in power distribution systems via human-level concept learning," *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 5239–5248, 2020.

[114] T. Goswami and U. B. Roy, "Predictive model for classification of power system faults using machine learning," in *TENCON 2019-2019 IEEE Region 10 Conference (TENCON).* IEEE, 2019, pp. 1881–1885.

[115] J. James, Y. Hou, A. Y. Lam, and V. O. Li, "Intelligent fault detection scheme for microgrids with wavelet-based deep neural networks," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 1694–1703, 2017.

[116] D. Patil, O. Naidu, P. Yalla, and S. Hida, "An ensemble machine learning based fault classification method for faults during power swing," in *2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia).* IEEE, 2019, pp. 4225–4230.

[117] H. A. Tokel, R. Al Halaseh, G. Alirezaei, and R. Mathar, "A new approach for machine learning-based fault detection and classification in power systems," in *2018 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT).* IEEE, 2018, pp. 1–5.

[118] P. Xi, P. Feilai, L. Yongchao, L. Zhiping, and L. Long, "Fault detection algorithm for power distribution network based on sparse self-encoding neural network," in *2017 International Conference on Smart Grid and Electrical Automation (ICSGEA).* IEEE, 2017, pp. 9–12.

[119] X.-D. Zeng, M.-F. Guo, and D.-Y. Chen, "Machine-learning-based single-phase-to-ground fault detection in distribution systems," in *2017 IEEE Conference on Energy Internet and Energy System Integration (EI2)*. IEEE, 2017, pp. 1–6.

[120] J. Abubakar and A. Abdulkareem, "Critical review of fault detection, fault classification and fault location techniques for transmission network." *Journal of Engineering Science & Technology Review*, vol. 15, no. 2, 2022.

[121] Z. Bukvišová, J. Orságová, and D. Topolánek, "Unsymmetrical fault location on 110 kv lines," in *2018 19th International Scientific Conference on Electric Power Engineering (EPE)*. IEEE, 2018, pp. 1–5.

[122] Q. H. Alsafasfeh, I. Abdel-Qader, and A. M. Harb, "Fault classification and localization in power systems using fault signatures and principal components analysis," 2012.

[123] K. Moloi and A. Yusuff, "A support vector machine based fault diagnostic technique in power distribution networks," in *2019 Southern African Universities Power Engineering Conference/Robotics and Mechatronics/Pattern Recognition Association of South Africa (SAUPEC/RobMech/PRASA)*. IEEE, 2019, pp. 229–234.

[124] N. Roy and K. Bhattacharya, "Detection, classification, and estimation of fault location on an overhead transmission line using s-transform and neural network," *Electric Power Components and Systems*, vol. 43, no. 4, pp. 461–472, 2015.

[125] H. Teimourzadeh, A. Moradzadeh, M. Shoaran, B. Mohammadi-Ivatloo, and R. Razzaghi, "High impedance single-phase faults diagnosis in transmission lines via deep reinforcement learning of transfer functions," *IEEE Access*, vol. 9, pp. 15 796–15 809, 2021.

[126] J. Liang, T. Jing, H. Niu, and J. Wang, "Two-terminal fault location method of distribution network based on adaptive convolution neural network," *IEEE Access*, vol. 8, pp. 54 035–54 043, 2020.

[127] K. Moloi, J. Jordaan, and Y. Hamam, "High impedance fault classification and localization method for power distribution network," in *2018 IEEE PES/IAS PowerAfrica*. IEEE, 2018, pp. 84–89.

[128] F. Ünal and S. Ekici, "A fault location technique for hvdc transmission lines using extreme learning machines," in *2017 5th International Istanbul Smart Grid and Cities Congress and Fair (ICSG)*. IEEE, 2017, pp. 125–129.

[129] K. Chen, J. Hu, Y. Zhang, Z. Yu, and J. He, "Fault location in power distribution systems via deep graph convolutional networks," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 1, pp. 119–131, 2019.

[130] A. N. Hasan, P. P. Eboule, and B. Twala, "The use of machine learning techniques to classify power transmission line fault types and locations," in *2017 International Conference on Optimization of Electrical and Electronic Equipment (OPTIM) & 2017 Intl Aegean Conference on Electrical Machines and Power Electronics (ACEMP)*. IEEE, 2017, pp. 221–226.

[131] A. Swetapadma and A. Yadav, "Directional relaying using support vector machine for double circuit transmission lines including cross-country and inter-circuit faults," *International Journal of Electrical Power & Energy Systems*, vol. 81, pp. 254–264, 2016.

[132] J. Sawada, K. Kusumoto, Y. Maikawa, T. Munakata, and Y. Ishikawa, "A mobile robot for inspection of power transmission lines," *IEEE Transactions on Power Delivery*, vol. 6, no. 1, pp. 309–315, 1991.

[133] J. Katrasnik, F. Pernus, and B. Likar, "A survey of mobile robots for distribution power line inspection," *IEEE Transactions on power delivery*, vol. 25, no. 1, pp. 485–493, 2009.

[134] G. Rui, Z. Feng, C. Lei, and Y. Jun, "A mobile robot for inspection of overhead transmission lines," in *Proceedings of the 2014 3rd International Conference on Applied Robotics for the Power Industry*. IEEE, 2014, pp. 1–3.

[135] S. Fu, W. Li, Y. Zhang, Z. Liang, Z. Hou, M. Tan, W. Ye, B. Lian, and Q. Zuo, "Structure-constrained obstacles recognition for power transmission line inspection robot," in *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2006, pp. 3363–3368.

[136] K. V. Babu, M. Tripathy, and A. K. Singh, "Recent techniques used in transmission line protection: a review," *International Journal of Engineering, Science and Technology*, vol. 3, no. 3, 2011.

[137] A. Swetapadma and A. Yadav, "An artificial neural network-based solution to locate the multilocation faults in double circuit series capacitor compensated transmission lines," *International Transactions on Electrical Energy Systems*, vol. 28, no. 4, p. e2517, 2018.

[138] M. J. B. Reddy, P. Gopakumar, and D. Mohanta, "A novel transmission line protection using dost and svm," *Engineering Science and Technology, an International Journal*, vol. 19, no. 2, pp. 1027–1039, 2016.

[139] S. H. Asman, N. F. Ab Aziz, U. A. Ungku Amirulddin, and M. Z. A. Ab Kadir, "Decision tree method for fault causes classification based on rms-dwt analysis in 275 kv transmission lines network," *Applied Sciences*, vol. 11, no. 9, p. 4031, 2021.

[140] N. P. Theodorakatos, N. M. Manousakis, and G. N. Korres, "Optimal placement of phasor measurement units with linear and non-linear models," *Electric Power Components and Systems*, vol. 43, no. 4, pp. 357–373, 2015.

[141] A. H. Abdulwahid, "A new concept of an intelligent protection system based on a discrete wavelet transform and neural network method for smart grids," in *2019 2nd International Conference of the IEEE Nigeria Computer Chapter (NigeriaComputConf)*. IEEE, 2019, pp. 1–6.

[142] M. Mishra and P. K. Rout, "Detection and classification of micro-grid faults based on hht and machine learning techniques," *IET Generation, Transmission & Distribution*, vol. 12, no. 2, pp. 388–397, 2018.

[143] P. Chopra and S. K. Yadav, "Pca and feature correlation for fault detection and classification," in *2015 IEEE Recent Advances in Intelligent Computational Systems (RAICS)*. IEEE, 2015, pp. 195–200.

[144] P. Rai, N. D. Londhe, and R. Raj, "Fault classification in power system distribution network integrated with distributed generators using cnn," *Electric Power Systems Research*, vol. 192, p. 106914, 2021.

[145] J. Ni, C. Zhang, and S. X. Yang, "An adaptive approach based on kpca and svm for real-time fault diagnosis of hvcbs," *IEEE Transactions on Power Delivery*, vol. 26, no. 3, pp. 1960–1971, 2011.

[146] Q. Wang, B. Wei, J. Liu, and W. Ma, "Data-driven incipient fault prediction for non-stationary and non-linear rotating systems: methodology, model construction and application," *IEEE Access*, vol. 8, pp. 197 134–197 146, 2020.

[147] M. Zhao, X. Fu, Y. Zhang, L. Meng, and B. Tang, "Highly imbalanced fault diagnosis of mechanical systems based on wavelet packet distortion and convolutional neural networks," *Advanced Engineering Informatics*, vol. 51, p. 101535, 2022.

[148] X. Zhao, J. Yao, W. Deng, P. Ding, Y. Ding, M. Jia, and Z. Liu, "Intelligent fault diagnosis of gearbox under variable working conditions with adaptive intraclass and interclass convolutional neural network," *IEEE Transactions on Neural Networks and Learning Systems*, 2022.

[149] X. Zhao, J. Yao, W. Deng, M. Jia, and Z. Liu, "Normalized conditional variational auto-encoder with adaptive focal loss for imbalanced fault diagnosis of bearing-rotor system," *Mechanical Systems and Signal Processing*, vol. 170, p. 108826, 2022.

[150] D. P. Mishra, S. R. Samantaray, and G. Joos, "A combined wavelet and data-mining based intelligent protection scheme for microgrid," *IEEE Transactions on Smart Grid*, vol. 7, no. 5, pp. 2295–2304, 2015.

[151] V. N. Ogar, K. A. Gamage, and S. Hussain, "Protection for 330 kv transmission line and recommendation for nigerian transmission system: a review." *International Journal of Electrical & Computer Engineering (2088-8708)*, vol. 12, no. 3, 2022.

[152] S. Kar and S. R. Samantaray, "Time-frequency transform-based differential scheme for microgrid protection," *IET Generation, Transmission & Distribution*, vol. 8, no. 2, pp. 310–320, 2014.

[153] N. Roy and K. Bhattacharya, "Identification and classification of fault using s-transform in an unbalanced network," in *2013 IEEE 1st International Conference on Condition Assessment Techniques in Electrical Systems (CATCON)*. IEEE, 2013, pp. 111–115.

[154] A. Raza, A. Benrabah, T. Alquthami, and M. Akmal, "A review of fault diagnosing methods in power transmission systems," *Applied Sciences*, vol. 10, no. 4, p. 1312, 2020.

[155] A. Elnozahy, K. Sayed, and M. Bahyeldin, "Artificial neural network based fault classification and location for transmission lines," in *2019 IEEE Conference on Power Electronics and Renewable Energy (CPERE)*. IEEE, 2019, pp. 140–144.

[156] B. Vyas, R. P. Maheshwari, and B. Das, "Protection of series compensated transmission line: Issues and state of art," *Electric power systems research*, vol. 107, pp. 93–108, 2014.

[157] P. V. Rao, S. A. Gafoor, and C. Venkatesh, "Detection of transmission line faults by wavelet based transient extraction," *International Journal on Electrical & Power Engineering*, vol. 2, pp. 42–46, 2011.

[158] P. Ray, D. P. Mishra, K. Dey, and P. Mishra, "Fault detection and classification of a transmission line using discrete wavelet transform & artificial neural network," in *2017 International Conference on Information Technology (ICIT)*. IEEE, 2017, pp. 178–183.

[159] S. Tom and J. Thomas, "Hvdc transmission line protection based on transient power," *Procedia Technology*, vol. 25, pp. 660–668, 2016.

[160] R. C. Dos Santos and E. C. Senger, "Transmission lines distance protection using artificial neural networks," *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 3, pp. 721–730, 2011.

[161] P. Balakrishnan and S. Gopinath, "A new intelligent scheme for power system faults detection and classification: A hybrid technique," *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, vol. 33, no. 5, p. e2728, 2020.

[162] G. W. Chang, Y.-H. Hong, and G.-Y. Li, "A hybrid intelligent approach for classification of incipient faults in transmission network," *IEEE Transactions on Power Delivery*, vol. 34, no. 4, pp. 1785–1794, 2019.

[163] A. Rahmati and R. Adhami, "A fault detection and classification technique based on sequential components," *IEEE Transactions on Industry Applications*, vol. 50, no. 6, pp. 4202–4209, 2014.

[164] K. Chen, C. Huang, and J. He, "Fault detection, classification and location for transmission lines and distribution systems: a review on the methods. high volt 1: 25–33," 2016.

[165] A. Prasad and J. B. Edward, "Importance of artificial neural networks for location of faults in transmission systems: A survey," in *2017 11th International Conference on Intelligent Systems and Control (ISCO)*. IEEE, 2017, pp. 357–362.

[166] P. R. Manke and S. Tembhurne, “Artificial neural network classification of power quality disturbances using time-frequency plane in industries,” in *2008 First International Conference on Emerging Trends in Engineering and Technology*. IEEE, 2008, pp. 564–568.

[167] S. R. Alsubhi, K. Laabidi, and L. Hsairi, “Comparison of several artificial neural network approaches for fault classification in power transmission lines,” in *The 7th International Conference on Engineering & MIS 2021*, 2021, pp. 1–6.

[168] S. A. Al-Shaibani and P. Bhalchandra, “A framework for implementing prediction algorithm over cloud data as a procedure for cloud data mining,” 2021.

[169] V. De Andrade and E. Sorrentino, “Typical expected values of the fault resistance in power systems,” in *2010 IEEE/PES Transmission and Distribution Conference and Exposition: Latin America (T&D-LA)*. IEEE, 2010, pp. 602–609.

[170] D. Sweeting, “Applying iec 60909, fault current calculations,” *IEEE Transactions on Industry Applications*, vol. 48, no. 2, pp. 575–580, 2011.

[171] L. Prokhorenkova, G. Gusev, A. Vorobev, A. V. Dorogush, and A. Gulin, “Catboost: unbiased boosting with categorical features,” *Advances in neural information processing systems*, vol. 31, 2018.

[172] Y. Zhang, Z. Zhao, and J. Zheng, “Catboost: A new approach for estimating daily reference crop evapotranspiration in arid and semi-arid regions of northern china,” *Journal of Hydrology*, vol. 588, p. 125087, 2020.

[173] A. A. Ibrahim, R. L. Ridwan, M. Muhamme *et al.*, “Comparison of the catboost classifier with other machine learning methods,” *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 11, pp. 738–748, 2020.

[174] M. Jamil, S. K. Sharma, and R. Singh, “Fault detection and classification in electrical power transmission system using artificial neural network,” *SpringerPlus*, vol. 4, no. 1, pp. 1–13, 2015.

[175] M. Mishra, “Power quality disturbance detection and classification using signal processing and soft computing techniques: A comprehensive review,” *International transactions on electrical energy systems*, vol. 29, no. 8, p. e12008, 2019.

[176] H. Erişti, A. Uçar, and Y. Demir, “Wavelet-based feature extraction and selection for classification of power system disturbances using support vector machines,” *Electric power systems research*, vol. 80, no. 7, pp. 743–752, 2010.

[177] E. U. Haq, H. Jianjun, K. Li, F. Ahmad, D. Banjerdpongchai, and T. Zhang, “Improved performance of detection and classification of 3-phase transmission line faults based on discrete wavelet transform and double-channel extreme learning machine,” *Electrical Engineering*, vol. 103, no. 2, pp. 953–963, 2021.

[178] P. Gopakumar, M. J. B. Reddy, and D. K. Mohanta, “Transmission line fault detection and localisation methodology using pmu measurements,” *IET Generation, Transmission & Distribution*, vol. 9, no. 11, pp. 1033–1042, 2015.

[179] C. Xu and S. A. Boggs, “High frequency loss from neutral wire-shield interaction of shielded power cable,” *IEEE transactions on power delivery*, vol. 23, no. 2, pp. 531–536, 2008.

[180] J. Sawade, K. Kusumoto, T. Munakata, Y. Maikawa, and Y. Ishikawa, “A mobile robot for inspection of power transmission lines [j],” *IEEE Trans Power Delivery*, vol. 1, pp. 309–315, 1991.

[181] P. Osofisan and C. Nwaeke, “Application of artificial neural network (ann) for short-term load forecasting: Case study on national control centre (phcn),” *Oshogbo, Osun State, Nigeria, Journal of Engineering and Applied Sciences*, vol. 5, no. 2, pp. 78–83, 2010.

[182] V. Santi, “Predicting faults in power grids using machine learning methods,” Master’s thesis, NTNU, 2019.

[183] S. Netsanet, J. Zhang, and D. Zheng, “Bagged decision trees based scheme of microgrid protection using windowed fast fourier and wavelet transforms,” *Electronics*, vol. 7, no. 5, p. 61, 2018.

[184] C. Fei and J. Qin, “Fault location after fault classification in transmission line using voltage amplitudes and support vector machine,” *Russian Electrical Engineering*, vol. 92, no. 2, pp. 112–121, 2021.

[185] C. Nwankpa, W. Ijomah, A. Gachagan, and S. Marshall, “Activation functions: Comparison of trends in practice and research for deep learning,” *arXiv preprint arXiv:1811.03378*, 2018.

[186] J. Han and C. Moraga, "The influence of the sigmoid function parameters on the speed of backpropagation learning," in *International workshop on artificial neural networks*. Springer, 1995, pp. 195–201.

[187] J. Sadeh and H. Afradi, "A new and accurate fault location algorithm for combined transmission lines using adaptive network-based fuzzy inference system," *Electric Power Systems Research*, vol. 79, no. 11, pp. 1538–1545, 2009.

[188] K. Gayathri and N. Kumarappan, "Accurate fault location on ehv lines using both rbf based support vector machine and scalcg based neural network," *Expert systems with applications*, vol. 37, no. 12, pp. 8822–8830, 2010.

[189] G. Carpinelli, D. Lauria, and P. Varilone, "Voltage stability analysis in unbalanced power systems by optimal power flow," *IEE Proceedings-Generation, Transmission and Distribution*, vol. 153, no. 3, pp. 261–268, 2006.

[190] Y.-G. Zhang, Z.-P. Wang, J.-F. Zhang, and J. Ma, "Fault localization in electrical power systems: A pattern recognition approach," *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 3, pp. 791–798, 2011.

[191] S. Matthewman, H. Byrd *et al.*, "Blackouts: a sociology of electrical power failure," *Social Space (Przestrzeń Społeczna)*, pp. 31–55, 2013.

[192] M. Y. Suliman and M. Ghazal, "Design and implementation of overcurrent protection relay," *Journal of Electrical Engineering & Technology*, vol. 15, no. 4, pp. 1595–1605, 2020.

[193] M. Rojnić, R. Prenc, H. Bulat, and D. Franković, "A comprehensive assessment of fundamental overcurrent relay operation optimization function and its constraints," *Energies*, vol. 15, no. 4, p. 1271, 2022.

[194] Z. Xu, I. Voloh, and M. Khanbeigi, "Evaluating the impact of increasing system fault currents on protection," in *2017 70th Annual Conference for Protective Relay Engineers (CPRE)*. IEEE, 2017, pp. 1–20.

[195] J. J. G. Ledesma, L. R. de Araujo, and D. R. R. Penido, "A method for evaluation of overcurrent protection in unbalanced distribution systems," *International Transactions on Electrical Energy Systems*, vol. 26, no. 2, pp. 412–428, 2016.

[196] A. Draz, M. M. Elkholy, and A. El-Fergany, "Over-current relays coordination including practical constraints and dgs: Damage curves, inrush, and starting currents," *Sustainability*, vol. 14, no. 5, p. 2761, 2022.

[197] L. Comassetto, D. Bernardon, L. Canha, and A. Abaide, "Software for automatic coordination of protection devices in distribution system," *IEEE Transactions on Power Delivery*, vol. 23, no. 4, pp. 2241–2246, 2008.

[198] C.-R. Chen, C.-H. Lee, and C.-J. Chang, "Optimal overcurrent relay coordination in power distribution system using a new approach," *International Journal of Electrical Power & Energy Systems*, vol. 45, no. 1, pp. 217–222, 2013.

[199] J. Andruszkiewicz, J. Lorenc, B. Staszak, A. Weychan, and B. Zieba, "Overcurrent protection against multi-phase faults in mv networks based on negative and zero sequence criteria," *International Journal of Electrical Power & Energy Systems*, vol. 134, p. 107449, 2022.

[200] S. Jimenez, E. Vázquez, and F. Gonzalez-Longatt, "Methodology of adaptive instantaneous overcurrent protection setting," *Electronics*, vol. 10, no. 22, p. 2754, 2021.

[201] P. Esmaili, A. A. B. M. Zin, and O. Shariati, "On-line overcurrent relays setting approach in distribution networks by implementing new adaptive protection algorithm," in *2015 IEEE Tenth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP)*. IEEE, 2015, pp. 1–6.

[202] R. Hemmati and H. Mehrjerdi, "Non-standard characteristic of overcurrent relay for minimum operating time and maximum protection level," *Simulation Modelling Practice and Theory*, vol. 97, p. 101953, 2019.

[203] A. Ahmarinejad, S. M. Hasanpour, M. Babaei, and M. Tabrizian, "Optimal overcurrent relays coordination in microgrid using cuckoo algorithm," *Energy Procedia*, vol. 100, pp. 280–286, 2016.

[204] C. SO, K. LI, K. LAI, and K. FUNG, "Application of genetic algorithm to overcurrent relay grading coordination," in *IEE conference publication*, 1998, pp. 283–287.

[205] L. He, S. Rong, and C. Liu, "An intelligent overcurrent protection algorithm of distribution systems with inverter based distributed energy resources," in

2020 IEEE Energy Conversion Congress and Exposition (ECCE). IEEE, 2020, pp. 2746–2751.

[206] S. D. Saldarriaga-Zuluaga, J. M. López-Lezama, and N. Muñoz-Galeano, "Optimal coordination of over-current relays in microgrids using unsupervised learning techniques," *Applied Sciences*, vol. 11, no. 3, p. 1241, 2021.

[207] Y. Chen, D. Zhang, H. Zhang, and Q.-G. Wang, "Dual-path mixed-domain residual threshold networks for bearing fault diagnosis," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 12, pp. 13 462–13 472, 2022.

[208] K. S. Parmar, S. Majhi, and D. Kothari, "Load frequency control of a realistic power system with multi-source power generation," *International Journal of Electrical Power & Energy Systems*, vol. 42, no. 1, pp. 426–433, 2012.

[209] M. A.-A. Sarker and A. K. Hasan, "Load frequency control in power system," *SEU Journal of Science and Engineering*, vol. 10, no. 2, pp. 24–30, 2016.

[210] H. Shayeghi, A. Jalili, and H. Shayanfar, "Multi-stage fuzzy load frequency control using pso," *Energy conversion and management*, vol. 49, no. 10, pp. 2570–2580, 2008.

[211] K. Anuradhika and P. Dash, "Genetic algorithm-based load frequency control of a grid-connected microgrid in presence of electric vehicles," in *Sustainable Energy and Technological Advancements: Proceedings of ISSETA 2021.* Springer, 2022, pp. 435–447.

[212] A. Safari, F. Babaei, and M. Farrokhifar, "A load frequency control using a pso-based ann for micro-grids in the presence of electric vehicles," *International Journal of Ambient Energy*, vol. 42, no. 6, pp. 688–700, 2021.

[213] S. S. Dhillon, J. S. Lather, and S. Marwaha, "Multi area load frequency control using particle swarm optimization and fuzzy rules," *Procedia Computer Science*, vol. 57, pp. 460–472, 2015.

[214] D. Lastomo, H. Setiadi, M. R. Djalal *et al.*, "Enabling pid and sssc for load frequency control using particle swarm optimization," in *2017 3rd International Conference on Science in Information Technology (ICSITech).* IEEE, 2017, pp. 182–187.

[215] D. K. Gupta, A. V. Jha, B. Appasani, A. Srinivasulu, N. Bizon, and P. Thounthong, “Load frequency control using hybrid intelligent optimization technique for multi-source power systems,” *Energies*, vol. 14, no. 6, p. 1581, 2021.

[216] P. K. Sahoo, S. Mohapatra, D. K. Gupta, and S. Panda, “Multi verse optimized fractional order pdpi controller for load frequency control,” *IETE Journal of Research*, vol. 68, no. 5, pp. 3302–3315, 2022.

[217] N. Sakellariou, “Current and potential decommissioning scenarios for end-of-life composite wind blades,” *Energy Systems*, vol. 9, pp. 981–1023, 2018.

[218] C. H. KOM, “Understanding interphase power controller: a description,” *Journal of Electrical Engineering, Electronics, Control and Computer Science*, vol. 6, no. 3, pp. 19–24, 2020.

[219] W. Fan, Z. Hu, and V. Veerasamy, “Pso-based model predictive control for load frequency regulation with wind turbines,” *Energies*, vol. 15, no. 21, p. 8219, 2022.

[220] A. Kunya, M. Argin, and S. Kucuksari, “Optimal load frequency control of multi-area power system considering incremental control action,” in *2019 IEEE texas power and energy conference (TPEC)*. IEEE, 2019, pp. 1–6.

[221] H. Gözde, M. Taplamacıoğlu, I. Kocaarslan, and E. Çam, “Particle swarm optimization based load frequency control in a single area power system,” *University Of Pitesti–Electronics And Computers Science, Scientific Bulletin*, vol. 2, no. 8, 2008.

[222] S. Kullapadayachi Govindaraju, R. Sivalingam, S. Panda, P. R. Sahu, and S. Padmanaban, “Frequency control of power system with distributed sources by adaptive type 2 fuzzy pid controller,” *Electric Power Components and Systems*, pp. 1–22, 2023.

[223] Z. Qin, D. Liu, H. Hua, and J. Cao, “Privacy preserving load control of residential microgrid via deep reinforcement learning,” *IEEE Transactions on Smart Grid*, vol. 12, no. 5, pp. 4079–4089, 2021.

[224] J. Kennedy and R. C. Eberhart, “A discrete binary version of the particle swarm algorithm,” in *1997 IEEE International conference on systems, man, and cybernetics. Computational cybernetics and simulation*, vol. 5. IEEE, 1997, pp. 4104–4108.

[225] M. Shariati, M. S. Mafipour, P. Mehrabi, A. Bahadori, Y. Zandi, M. N. Salih, H. Nguyen, J. Dou, X. Song, and S. Poi-Ngian, "Application of a hybrid artificial neural network-particle swarm optimization (ann-pso) model in behavior prediction of channel shear connectors embedded in normal and high-strength concrete," *Applied sciences*, vol. 9, no. 24, p. 5534, 2019.

[226] P. J. Angeline, "Using selection to improve particle swarm optimization," in *1998 IEEE International Conference on Evolutionary Computation Proceedings. IEEE World Congress on Computational Intelligence (Cat. No. 98TH8360).* IEEE, 1998, pp. 84–89.

[227] R. N. Rao and P. R. K. Reddy, "Pso based tuning of pid controller for a load frequency control in two area power system," *International Journal of Engineering Research and Applications (IJERA)*, vol. 1, no. 3, pp. 1499–1505, 2015.

[228] S. Mahboob Ul Hassan, M. A. Ramli, and A. H. Milyani, "Robust load frequency control of hybrid solar power systems using optimization techniques," *Frontiers in Energy Research*, p. 730, 2022.

[229] S. Yang-Wu, M. Xun, P. Ao, W. Yang-Guang, C. Ting, W. Ding, and Z. Jian, "Load frequency control strategy for wind power grid-connected power systems considering wind power forecast," in *2019 IEEE 3rd Conference on Energy Internet and Energy System Integration (EI2).* IEEE, 2019, pp. 1124–1128.

[230] M. R. Tur, M. Wadi, A. Shobole, and S. Ay, "Load frequency control of two area interconnected power system using fuzzy logic control and pid controller," in *2018 7th International Conference on Renewable Energy Research and Applications (ICRERA).* IEEE, 2018, pp. 1253–1258.

[231] S. S. Aung and Z. M. Htike, "Modeling and simulation of load frequency control for three area power system using proportional integral derivative (pid) controller," *American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)*, vol. 26, no. 2, pp. 301–315, 2016.

[232] Q. Qiu, R. Ma, J. Kurths, and M. Zhan, "Swing equation in power systems: Approximate analytical solution and bifurcation curve estimate," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 30, no. 1, p. 013110, 2020.

[233] J. D. Glover, M. S. Sarma, and T. Overbye, *Power system analysis & design, SI version*. Cengage Learning, 2012.

[234] K. Kumari, G. Shankar, S. Kumari, and S. Gupta, "Load frequency control using ann-pid controller," in *2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*. IEEE, 2016, pp. 1–6.

[235] W. Tan, "Unified tuning of pid load frequency controller for power systems via imc," *IEEE Transactions on power systems*, vol. 25, no. 1, pp. 341–350, 2009.

[236] B. Dhanasekaran, J. Kaliannan, A. Baskaran, N. Dey, and J. M. R. Tavares, "Load frequency control assessment of a pso-pid controller for a standalone multi-source power system," *Technologies*, vol. 11, no. 1, p. 22, 2023.

[237] E. Çam and I. Kocaarslan, "Load frequency control in two area power systems using fuzzy logic controller," *Energy conversion and Management*, vol. 46, no. 2, pp. 233–243, 2005.

[238] E. Çam, "Application of fuzzy logic for load frequency control of hydroelectrical power plants," *Energy conversion and management*, vol. 48, no. 4, pp. 1281–1288, 2007.

[239] Y. Arya, "Improvement in automatic generation control of two-area electric power systems via a new fuzzy aided optimal pidn-foi controller," *ISA transactions*, vol. 80, pp. 475–490, 2018.

[240] A. J. Mohammed, S. D. Al-Majidi, M. K. Al-Nussairi, M. F. Abbod, and H. S. Al-Raweshidy, "Design of a load frequency controller based on artificial neural network for single-area power system," in *2022 57th International Universities Power Engineering Conference (UPEC)*. IEEE, 2022, pp. 1–5.

[241] A. M. Osman, M. A. Magzoub, and A. Salem, "Load frequency control in two area power system using ga, sa and pso algorithms: A comparative study," in *2021 31st Australasian Universities Power Engineering Conference (AUPEC)*. IEEE, 2021, pp. 1–8.

[242] Q. M. BABAKHANI, "Load frequency control in two area power system using sliding mode control," 2014.

[243] T. D. Raj, C. Kumar, P. Kotsampopoulos, and H. H. Fayek, "Load frequency control in two-area multi-source power system using bald eagle-sparrow search optimization tuned pid controller," *Energies*, vol. 16, no. 4, p. 2014, 2023.

[244] S. Feleke, R. Satish, S. R. Salkuti, and A. Y. Abdelaziz, "Load frequency control in two-area interconnected systems using de-pid and pso-pid," in *Power Quality in Microgrids: Issues, Challenges and Mitigation Techniques.* Springer, 2023, pp. 391–407.

[245] N. Nireekshana, R. Ramachandran, and G. Narayana, "A novel swarm approach for regulating load frequency in two-area energy systems."

[246] P. Appikonda and R. S. Kasibhatla, "Design of support vector machine controller for hybrid power system automatic generation control," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 44, no. 2, pp. 3883–3907, 2022.

[247] A. Hemeida, S. Mohamed, and M. Mahmoud, "Load frequency control using optimized control techniques," *JES. Journal of Engineering Sciences*, vol. 48, no. 6, pp. 1119–11 136, 2020.

[248] S. Sharma, S.-H. Huang, and N. Sarma, "System inertial frequency response estimation and impact of renewable resources in ercot interconnection," in *2011 IEEE power and energy society general meeting.* IEEE, 2011, pp. 1–6.