ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

CONDITION MONITORING AND FAULT DETECTION FOR ELECTRICAL POWER SYSTEMS USING SIGNAL PROCESSING AND MACHINE LEARNING TECHNIQUES

Ph.D. THESIS

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Department of Electrical Engineering

Electrical Engineering Programme

AUGUST 2024

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

SİNYAL İŞLEME VE MAKİNE ÖĞRENME TEKNİKLERİ KULLANILARAK ELEKTRİK GÜÇ SİSTEMLERİ İÇİN DURUM İZLEME VE ARIZA BELİRLEME

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AĞUSTOS 2024

Yasmin NASSER MOHAMED, a Ph.D. student of İTU Graduate School student ID 504202033, successfully defended the thesis/dissertation entitled "CONDITION MONITORING AND FAULT DETECTION FOR ELECTRICAL POWER SYSTEM USING SIGNAL PROCESSING AND MACHINE LEARNING TECHNIQUES", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : 7 August 2024
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To my father,

FOREWORD

As the world moves towards a more sustainable future, developing and optimising electrical power systems using innovative technologies is crucial. My research, which focuses on enhancing condition monitoring and fault detection for electrical power systems using a combination of signal processing and advanced machine learning techniques, has the potential to inspire significant change. This thesis not only reflects a fulfilment of rigorous academic pursuits but also symbolises a personal journey enriched by invaluable contributions from many.

First and foremost, I praise ALLAH the Almighty, the Most Gracious, and the Most Merciful for His blessings bestowed upon me during my studies and in completing this thesis. May Allah's blessings also reach His final Prophet Muhammad (peace be upon him), his family, and his companions.

I owe a profound debt of gratitude to my advisor, Prof. Dr. Şahin Serhat ŞEKER, whose extensive expertise and steadfast support have been fundamental in shaping the direction and the execution of my research. His encouragement to challenge conventional methodologies has been invaluable, and his mentoring, drawn from rich professional experience, has significantly enriched my academic journey. Similarly, I extend my deepest thanks to Prof. Dr Ramazan ÇAĞLAR, whose guidance and unwavering motivation have been crucial in advancing my research. Their insights and encouragement have been vital to my achievements in this challenging and rewarding journey. I also extend my sincere thanks to Prof. Dr. Tahir Çetin AKINCI for his support, and to the esteemed members of Istanbul Technical University for their contributions to my academic growth. My gratitude goes to the University of Djibouti for the opportunity to pursue my PhD studies, which has been an integral part of my professional and academic development.

I must also express my heartfelt thanks to my family, whose love and encouragement have been my steadfast anchor. Their unwavering faith in my abilities has sustained me through challenges and milestones, and their role as a stable support system has been integral to my journey. Additionally, I am deeply grateful to my father, who inspired me to pursue my PhD studies. His motivation and belief in my potential were foundational to my journey. Though he is no longer with us (May ALLAH have mercy on you), his spirit and encouragement guide me daily. I thank my best friends (Ayan Pierre Abdi and Oubah Isman Okieh) for their continual support and encouragement.

Special thanks are extended to a dear friend who provided unyielding support when my motivation waned throughout my PhD journey. His presence and encouragement were invaluable, and he was always there to help lift me up and push me forward.

August 2024

Yasmin NASSER MOHAMED
(Electrical Engineer)

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ABBREVIATIONS

3P : Three-phase
ANN : Artificial Neural Networks
ASO : Algebraic Summation Operation
CBM : Reliability-Centered Maintenance
CNN : Convolutional Neural Network
CM : Corrective Maintenance
CWT : Continuous Wavelet Transform
DGA : Dissolved Gas Analysis
DGs : Distributed Generators
DL : Deep Learning
DLG : Line to Line to Ground
DT : Decision Tree
DWT : Discrete Wavelet Transform
EDD : Electricity of Djibouti
END : Energy Not Distributed
FDA : Fisher Discriminant Analysis
FC : Fault Classification
FD : Fault Detection
FFT : Fast Fourier Transform
HPLC : High-performance Liquid Chromatography
KNN : K-Nearest Neighbor
LL : Line to Line
LSTM : Long Short-Term Memory
MDL : Minimum Description Length
MRWA : Multi-Resolution Wavelet Analysis
OLTC : On Load Tap Changer
PCA : Principal Component Analysis
PD : Partial Discharge
PV : Photovoltaic
RBM : Risk-Based Maintenance

RF **:** Random Forest

RM **:** Reactive Maintenance

RP **:** Redundancy Property

RBF **:** Radial basis function

SIC **:** Shannon’s Information Criterion

SLG **:** Single Line to Ground

STFT **:** Short-Time Fourier Transform

SWT **:** Stationary Wavelet Transform

SVM **:** Support Vector Machine

TLs **:** Transmission lines

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CONDITION MONITORING AND FAULT DETECTION FOR ELECTRICAL POWER SYSTEMS USING SIGNAL PROCESSING AND MACHINE LEARNING TECHNIQUES

SUMMARY

Electrical power systems are essential for sustaining daily activities, economic growth, and societal advancement. However, as the demand for electricity increases, these systems become more complex and prone to faults and disturbances. Faults are unexpected deviations from standard operating conditions that can disrupt operations, incur significant maintenance costs, and lead to system failures if not addressed promptly. Transmission lines, responsible for over 85% of faults in power systems, are particularly vulnerable. Common faults in transmission lines include open circuit and short circuit faults. Open circuit faults disrupt power flow and cause voltage fluctuations due to mechanical stress, environmental factors, ageing infrastructure, or operational errors. Short circuit faults create low-impedance pathways that result in current surges, causing severe consequences such as equipment damage, system instability, power outages, and safety hazards like fires and explosions.

The evolution of maintenance strategies in electrical power systems has shifted from reactive to more proactive methodologies, with condition monitoring systems playing a crucial role. These systems continuously monitor the performance and status of electrical equipment to detect early signs of deterioration, faults, or failures. Effective condition monitoring involves collecting real-time data through various sensors and devices, which is then processed using advanced fault detection and classification algorithms.

Ensuring effective fault detection and classification is essential for minimising downtime and ensuring the reliability and safety of power systems. Advanced technologies and continuous monitoring play a vital role in mitigating the impact of faults and maintaining the overall health of electrical power infrastructure. These are particularly important for developing countries like Djibouti, which relies heavily on Ethiopia for electricity due to its lack of self-energy production despite having high energy potential. With a population of one million and an electrification rate of 55%, Djibouti aims to achieve 100% electrification by 2035. However, due to an outdated maintenance framework, Djibouti's power system, managed by the Electricity of Djibouti (EDD), faces significant reliability and efficiency challenges. The system suffers from frequent operational disruptions and unscheduled downtimes, with approximately 85% of the total Energy not Distributed (END) due to unplanned outages. Current reactive maintenance practices result in high costs, extended outages, and substantial economic losses.

Implementing advanced condition monitoring strategies using modern technologies like wavelet transforms and machine learning can significantly enhance the reliability and efficiency of Djibouti's electrical power systems. These strategies enable proactive identification and resolution of potential faults, reducing downtimes and improving system resilience. This thesis explores and validates the application of these advanced

technologies in Djibouti's context, establishing robust fault detection and classification models.

This study developed three models to address these challenges: two for fault detection and one for fault classification. The models use the data collected by the simulation conducted on the Djibouti power grid to evaluate various fault scenarios using MATLAB/SIMULINK. The simulation involved modelling short-circuit conditions, specifically three-phase faults, under different settings to observe their effects on the power system. Fault types, including single line-to-ground, double-line-to-ground, and line-to-line, were classified and simulated to assess their impact on the system's voltage and current stability.

The first fault detection model employed in the Djibouti power grid utilises the Short-Time Fourier Transform (STFT) for non-stationary signal analysis. This method is instrumental in providing a sensitive and real-time assessment of fault characteristics. By focusing on various types of faults, such as single-line-to-ground (SLG), double-line-to-ground (DLG), and three-phase faults, STFT helps distinguish the specific impacts of each fault type on the power system's reliability and efficiency. The simulation results from the STFT analysis reveal that three-phase and DLG faults display specific high-frequency components upon fault clearance, highlighting their significant transient nature. Conversely, SLG faults exhibit a broad frequency band with lower amplitude, indicating a less distinct transient behaviour. However, the fixed-size window of the STFT poses limitations in capturing the full spectrum of SLG fault characteristics, suggesting that more refined techniques, such as wavelet transforms, may be necessary to improve fault detection accuracy and enhance the system's diagnostic capabilities.

The second fault detection model addresses the challenge of detecting minor, unseen defects in transmission lines. It employs a novel fault detection methodology utilising a hybrid wavelet transform approach. This methodology, intended for the Djibouti power grid, combines Stationary Wavelet Transform (SWT) and Continuous Wavelet Transform (CWT) to enhance the detection of abnormal voltage signals caused by short-circuit faults and transient phenomena. The process begins with the decomposition of signals into detail and approximation coefficients using SWT. Shannon's Information Criterion (SIC) determines the optimal decomposition level to represent signal features and prevent overfitting effectively. The signals are then reconstructed using an Algebraic Summation Operation (ASO), which amplifies minor defects, making them more visible for the subsequent application of CWT. The Continuous Wavelet Transform (CWT) revealed previously undetectable frequency components, specifically the 12th, 13th, 14th, and 16th components. The effectiveness of this approach is validated through simulations that use artificial signals designed to mimic specific harmonic disturbances known to occur in power systems. The simulation evaluates various fault scenarios, revealing that the hybrid method can detect and analyse fault types successfully. This comprehensive approach allows for precise fault detection and characterisation, which is crucial for maintaining the stability and reliability of the power system.

The fault classification in electrical power systems highlights the advantages of machine learning techniques over traditional methods, particularly for the Djibouti power system. It introduces three machine learning classifiers: Decision Trees (DT), Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM). The methodology involves data pre-processing using oversampling, feature extraction

via Discrete Wavelet Transform (DWT), and evaluation through k-fold cross-validation. The findings show that SVM, particularly with a polynomial kernel, achieves the highest accuracy and precision among the classifiers. Though less accurate, DT provides high interpretability and can improve with parameter tuning. LSTM performs well with sequential data, showing excellent specificity, though its overall effectiveness is slightly less than that of SVM. Each classifier's performance is analysed using confusion matrices, revealing their strengths and weaknesses in handling different fault types. The chapter concludes that integrating advanced machine learning techniques significantly enhances fault diagnosis and system reliability, advocating for a tailored choice of classifier based on the specific needs of the fault classification task.

The importance of condition monitoring, fault detection, and classification in maintaining the stability and efficiency of power systems is underscored. Continuous monitoring allows for early fault detection and timely maintenance, preventing unplanned outages and extending equipment lifespan. Integrating advanced technologies such as unmanned aerial vehicles (UAVs), IoT devices, and machine learning algorithms enhances the effectiveness of fault management strategies.

In conclusion, implementing advanced condition monitoring, fault detection techniques, and sophisticated fault classification models can significantly improve the reliability and efficiency of power systems in Djibouti. Future work should explore integrating these classifiers into a hybrid model to enhance fault classification accuracy and reliability further. Practical applications, such as intelligent data collection and decision-making robots, can be developed to ensure a more stable, efficient, and robust power infrastructure.

SİNYAL İŞLEME VE MAKİNE ÖĞRENME TEKNİKLERİ KULLANILARAK ELEKTRİK GÜÇ SİSTEMLERİ İÇİN DURUM İZLEME VE ARIZA BELİRLEME

ÖZET

Elektrik güç sistemleri günlük faaliyetlerin, ekonomik büyümenin ve toplumsal ilerlemenin sürdürülmesi için gereklidir. Ancak elektriğe olan talep arttıkça bu sistemler daha karmaşık hale gelmekte ve arızalara ve bozulmalara yatkın olmaktadır. Arızalar, standart çalışma koşullarından beklenmedik sapmalar olup, operasyonları kesintiye uğratabilir, önemli bakım maliyetlerine neden olabilir ve derhal ele alınmazsa sistem arızalarına yol açabilir. Bu anlamda güç sistemlerindeki arızaların %85'inden fazlasından sorumlu olan iletim hatları özellikle kritik durumdadır. İletim hatlarındaki yaygın arızalar açık devre ve kısa devre arızalarını içerir. Açık devre arızaları güç akışını bozar ve mekanik stres, çevresel faktörler, eskiyen altyapı veya operasyonel hatalar nedeniyle voltaj dalgalanmalarına neden olur. Kısa devre arızaları düşük empedanslı yollar oluşturarak akım dalgalanmalarına neden olur ve ekipman hasarı, sistem kararsızlığı, elektrik kesintileri, yangın ve patlama gibi güvenlik tehlikelerine yol açar.

Gürümüzde elektrik güç sistemlerinde bakım stratejilerinin gelişimi, reaktif yöntemlerden daha çok proaktif yöntemlere doğru kaymış ve durum izleme sistemleri çok önemli bir rol kazanmıştır. Bu sistemler, bozulma, hata veya arızaların erken belirtilerini tespit etmek için elektrikli ekipmanın performansını ve durumunu sürekli olarak izler. Etkili durum izleme, çeşitli sensörler ve cihazlar aracılığıyla gerçek zamanlı verilerin toplanmasını içerir ve bu veriler daha sonra gelişmiş arıza tespit ve sınıflandırma algoritmaları kullanılarak işlenir.

Arıza tespitinin ve sınıflandırmasının etkili bir şekilde yapılması, arıza süresinin en aza indirilmesi ve güç sistemlerinin güvenilirliğinin ve güvenliğinin sağlanması için çok önemlidir. Gelişmiş teknolojiler ve sürekli izleme, arızaların etkisini azaltmada ve elektrik enerjisi altyapısının genel sağlığını korumada hayati bir rol oynamaktadır. Bunlar, yüksek enerji potansiyeline sahip olmasına rağmen kendi enerji üretiminin olmaması nedeniyle elektrik enerji ihtiyacı için büyük ölçüde Etiyopya'ya bağımlı olan Cibuti gibi gelişmekte olan ülkeler için özellikle önemlidir. Bir milyonluk nüfusu ve %55'lik elektrifikasyon oranıyla Cibuti, 2035 yılına kadar %100 elektrifikasyona ulaşmayı hedeflemektedir. Ancak Cibuti Elektrik Kurumu (EDD) tarafından yönetilen elektrik sistemi, eski teknolojisi nedeniyle önemli güvenilirlik ve verimlilik sorunlarıyla karşı karşıyadır. Sistem, plansız kesintiler nedeniyle dağıtılamayan toplam enerjinin (END) yaklaşık %85'i ile sık sık operasyonel kesintiler ve plansız kesinti sürelerinden muzdariptir. Mevcut reaktif bakım uygulamaları ise yüksek maliyetlere, uzun süreli kesintilere ve önemli ekonomik kayıplara neden olmaktadır.

Dalgacık dönüşümleri ve makine öğrenimi gibi modern yöntemleri kullanarak gelişmiş durum izleme stratejilerinin uygulanması, Cibuti elektrik güç sisteminin güvenilirliğini ve verimliliğini önemli ölçüde artırabilir. Bu stratejiler, potansiyel arızaların proaktif olarak tespit edilmesini ve çözülmesini sağlayarak kesinti sürelerini

azaltır ve sistem işlevselliğini artırır. Bu tez, sağlam arıza tespit ve sınıflandırma modelleri oluşturarak bu gelişmiş teknolojilerin Cibuti bağlamında uygulanmasını araştırmakta ve doğrulamaktadır.

Bu çalışma, bu zorlukları ele almak için üç model geliştirmiştir bu modellerin: ikisi arıza tespiti ve biri arıza sınıflandırması içindir. Modeller, MATLAB/SIMULINK kullanılarak çeşitli arıza senaryolarını değerlendirmek için Cibuti elektrik şebekesinde gerçekleştirilen simülasyonla toplanan verileri kullanmaktadır. Simülasyon, kısa devre koşullarının, özellikle de üç fazlı arızaların, güç sistemi üzerindeki etkilerini gözlemlemek için farklı ayarlar altında modellenmesini içermektedir. Tek hattan toprağa, çift hattan toprağa ve hattan hatta dahil olmak üzere arıza türleri sınıflandırılmış ve sistemin gerilim ve akım kararlılığı üzerindeki etkilerini değerlendirmek için simüle edilmiştir.

Cibuti elektrik şebekesinde kullanılan ilk arıza tespit modelinde, durağan olmayan sinyal analizi için Kısa Zamanlı Fourier Dönüşümü (STFT) kullanılmaktadır. Bu yöntem, arıza özelliklerinin hassas ve gerçek zamanlı bir şekilde değerlendirilmesini sağlamaktadır. STFT, tek faz toprak (SLG), iki faz toprak (DLG) ve üç fazlı arızalar gibi çeşitli arıza türlerine odaklanarak, her bir arıza türünün güç sisteminin güvenilirliği ve verimliliği üzerindeki belirli etkilerini ayırt etmeye yardımcı olur. STFT analizinden elde edilen simülasyon sonuçları, üç fazlı ve DLG arızalarının, arıza giderildikten sonra belirli yüksek frekanslı bileşenler sergilediğini ve önemli geçici cevap biçimlerini ortaya koymaktadır. Buna karşılık, SLG arızaları daha düşük genlikli geniş bir frekans bandı sergileyerek daha az belirgin bir geçici davranışa işaret etmektedir. Bununla birlikte, STFT'nin sabit boyutlu penceresi, SLG arıza özelliklerinin tüm spektrumunu yakalamada sınırlamalar getirmekte, arıza tespit doğruluğunu artırmak ve sistemin teşhis yeteneklerini geliştirmek için dalgacık dönüşümleri gibi daha duyarlı tekniklerin gerekli olabileceğini düşündürmektedir.

İkinci arıza tespit modeli, iletim hatlarındaki küçük, görünmeyen kusurları tespit etme zorluğunu ele almaktadır. Hibrit dalgacık dönüşümü yaklaşımını kullanan yeni bir arıza tespit metodolojisi kullanmaktadır. Cibuti elektrik şebekesi için tasarlanan bu metodoloji, kısa devre arızaları ve geçici olayların neden olduğu anormal voltaj sinyallerinin tespitini geliştirmek için Durağan Dalgacık Dönüşümü (SWT) ve Sürekli Dalgacık Dönüşümünü (CWT) birleştirir. Süreç, SWT kullanılarak sinyallerin detay ve yaklaşım katsayılarına ayrıştırılmasıyla başlar. Shannon'un Bilgi Kriteri (SIC) sinyal özelliklerini temsil etmek ve aşırı uyumu etkili bir şekilde önlemek için en uygun ayrıştırma seviyesini belirler. Sinyaller daha sonra Cebirsel Toplama İşlemi (ASO) kullanılarak yeniden yapılandırılır, bu da küçük kusurları güçlendirerek sonraki CWT uygulaması için daha görünür hale getirir. Sürekli Dalgacık Dönüşümü (CWT) daha önce tespit edilemeyen frekans bileşenlerini, özellikle de 12., 13., 14. ve 16. bileşenleri ortaya çıkarmıştır. Bu yaklaşımın etkinliği, güç sistemlerinde meydana geldiği bilinen belirli harmonik bozuklukları taklit etmek için tasarlanmış yapay sinyalleri kullanan simülasyonlar aracılığıyla doğrulanmıştır. Simülasyon çeşitli arıza senaryolarını değerlendirerek hibrit yöntemin arıza türlerini başarılı bir şekilde tespit ve analiz edebildiğini ortaya koymaktadır. Bu kapsamlı yaklaşım, güç sisteminin istikrarını ve güvenilirliğini korumak için çok önemli olan hassas arıza tespiti ve karakterizasyonuna olanak tanır.

Elektrik güç sistemlerinde arıza sınıflandırması, özellikle Cibuti güç sistemi için makine öğrenimi tekniklerinin geleneksel yöntemlere göre avantajlarını da vurgulamaktadır. Bu çalışmada üç makine öğrenimi sınıflandırıcısı tanıtılmaktadır:

Karar Ağaçları (DT), Uzun Kısa Vadeli Bellek (LSTM) ağları ve Destek Vektör Makineleri (SVM). Metodoloji, aşırı örnekleme kullanarak veri ön işleme, Ayrık Dalgacık Dönüşümü (DWT) yoluyla özellik çıkarma ve k-kat çapraz doğrulama yoluyla değerlendirmeyi içerir. Bulgular, özellikle polinom çekirdeği ile SVM'nin sınıflandırıcılar arasında en yüksek doğruluk ve kesinliğe ulaştığını göstermektedir. Daha az doğru olmasına rağmen, DT yüksek yorumlanabilirlik sağlar ve parametre ayarlaması ile gelişebilir. LSTM, genel etkinliği SVM'den biraz daha az olsa da mükemmel başarım göstererek sıralı verilerle iyi bir performans gösterir. Her sınıflandırıcının performansı karışıklık matris hesabı kullanılarak analiz edilmiş ve farklı hata türlerini ele almadaki güçlü ve zayıf yönleri ortaya çıkarılmıştır. Bu bölüm, gelişmiş makine öğrenimi tekniklerinin entegre edilmesinin arıza teşhisini ve sistem güvenilirliğini önemli ölçüde artırdığı sonucuna varmakta ve arıza sınıflandırma görevinin özel ihtiyaçlarına göre özel bir sınıflandırıcı seçimini sağlamaktadır.

Böylece bu çalışma ile güç sistemlerinin istikrarını ve verimliliğini korumada durum izleme, arıza tespiti ve sınıflandırmanın önemi vurgulanmaktadır. Sürekli izleme, erken arıza tespiti ve zamanında bakım yapılmasını sağlayarak plansız kesintileri önler ve ekipman ömrünü uzatır. İnsansız hava araçları (İHA'lar), IoT cihazları ve makine öğrenimi algoritmaları gibi gelişmiş teknolojilerin entegre edilmesi, arıza yönetimi stratejilerinin etkinliğini artırmaktadır.

Sonuç olarak, gelişmiş durum izleme, arıza tespit teknikleri ve sofistike arıza sınıflandırma modellerinin uygulanması, Cibuti'deki güç sistemlerinin güvenilirliğini ve verimliliğini önemli ölçüde arttırabilir. Gelecekteki çalışmalar, arıza sınıflandırma doğruluğunu ve güvenilirliğini daha da arttırmak için bu sınıflandırıcıları hibrit bir modele entegre etmeyi keşfetmelidir. Daha istikrarlı, verimli ve sağlam bir enerji altyapısı sağlamak için akıllı veri toplama ve karar verme robotları gibi pratik uygulamalar da geliştirilebilir.

1. INTRODUCTION

In our modern world, electrical systems are indispensable, powering everything from small electronic devices to large industrial machinery. Among these systems, power systems play a pivotal role in managing the generation, transmission, and distribution of electrical power on a large scale. A reliable and continuous electricity supply is essential for sustaining daily activities, economic growth, and societal advancement. It supports critical healthcare services and financial stability, enhances quality of life, and maintains necessary public services(Heffron et al., 2020).

However, as the electricity demand grows, power systems have become increasingly complex and susceptible to faults and disturbances. A fault is an unexpected deviation from a system's standard operating conditions, affecting one or more essential characteristics(Gautam & Jhala, 2015). Faults disrupt normal operations but do not necessarily lead to complete system failure. In contrast, a failure indicates a permanent cessation of the system's ability to perform a required function under specified conditions, often making the system inoperable until repairs are made. Even minor faults, if not promptly rectified, can evolve into significant issues, leading to substantial maintenance costs and power system failures(Elmasry & Wadi, 2022).

Power systems face vulnerabilities from ageing infrastructure, natural disturbances like storms and earthquakes, human errors, and environmental factors like corrosion and mechanical wear. These challenges can lead to frequent failures, particularly within the transmission and distribution networks (Ahmed et al., 2023). Transmission lines, responsible for over 85% of faults in power systems, are especially prone to disturbances due to their exposure to harsh environmental conditions (Aleem et al., 2015; Singh et al., 2011).

The most commonly observed faults in electrical transmission systems are open circuit faults and short circuit faults. Open circuit faults, or series faults, occur through a discontinuity in the electrical circuit, disrupting power continuity, unbalancing loads, and causing voltage fluctuations. Causes include mechanical stress, environmental

factors, ageing infrastructure, and operational errors such as improper manipulation of switches or circuit breakers. Conversely, short circuit faults occur when an unintended connection forms between two points in the circuit, creating a low-impedance pathway that leads to an abrupt surge in current flow. These can result from mechanical damage, human errors during installation, and insulation failures, permitting direct contact between conductors.

The effects of short circuit faults are diverse and severe, including(Nasser Mohamed et al., 2024; Santoso et al., 2012):

Current surge: A substantial reduction in impedance causes an overwhelming current flow, overheating conductors, transformers, and other components, possibly leading to insulation breakdown and infrastructure damage.

Voltage drop: The increased current flow through the fault impedance causes a voltage drop at the fault location, which can propagate across the network, destabilizing voltage levels. Asymmetrical faults can unbalance voltages across phases, disrupting the performance of three-phase equipment.

System instability: Current and voltage fluctuations can cause transient oscillations and short-lived disturbances, disrupting the stability of generators and other system components. Substantial defects could initiate power swings, impacting the balance of interconnected networks.

Equipment stress: Increased fault current produces significant electromagnetic forces, placing mechanical strain on conductors and structures and potentially causing thermal damage, such as the melting of conductors or insulation breakdown.

Arc formation: Phase-to-phase or phase-to-ground faults can create electric arcs, posing risks of severe burns, fires, explosions and damaging insulation and adjacent components.

Power interruptions: Faults often lead to power outages, varying in duration and intensity based on the fault's severity and location, ranging from temporary disruption to prolonged outages.

Quality of power supply: Faults cause significant disturbances in voltage levels, resulting in sags or dips that affect sensitive equipment, with sudden variations in

current and voltage causing harmonic distortions and leading to voltage fluctuations, flickering, and intermittent power outages.

The prevalence of different fault types, as shown in Figure 1.1, includes (Gururajapathy et al., 2017; Tokel et al., 2018):

- Single line-to-ground faults, occurring with a probability of approximately 70-80%, are the most frequent but are considered less severe.
- Line-to-line faults occur less frequently, with an occurrence rate of about 8-10%, and are deemed to be medium in severity.
- Line-to-line-to-ground faults involving two lines, and the ground occur in approximately 10-17% of cases and are considered severe due to their impact on the system.
- The least common are three-phase faults, occurring only about 3% of the time, but they are highly severe due to their extensive damage and disruption potential.

Short-circuit faults cause significant disturbances in power systems, leading to extensive equipment damage, service loss, and potential cascading failures. Such faults can destabilize the entire power grid, resulting in widespread outages and substantial economic losses. Moreover, conductor temperatures can spike dramatically during short-circuit conditions, with short-circuit currents sometimes exceeding 10,000 A (Mohd Zainuddin et al., 2020). The most severe consequence of these faults is the potential for fatalities among electrical workers, with overhead power lines and electrical equipment being primary hazards. These represent 32% and 44% of the average causes of such incidents in the U.S. in 2005 (Khawaja et al., 2017). These risks underscore the critical need for effective fault management strategies.

The increasing complexity of power systems has necessitated the development of sophisticated management and protection technologies. Advances in smart grid technologies enable better prediction and response to system disturbances through real-time monitoring and automated control systems. Regulatory frameworks also play a crucial role in ensuring that power systems are stable, efficient, and adaptable to evolving technological landscapes and environmental challenges(Molęda et al., 2023).

Given the high rate of faults and the critical nature of power systems, ensuring their reliability and stability is a monumental task. While complete prevention of faults is nearly impossible, implementing continuous condition monitoring can significantly mitigate failure rates. This proactive strategy involves early fault detection and classification, allowing maintenance teams to address faults before they escalate into significant failures, thereby enhancing the overall lifespan of equipment and ensuring operational efficiency and system reliability (da Silva et al., 2012; Johal & Mousavi, 2008; Motaghare et al., 2018).

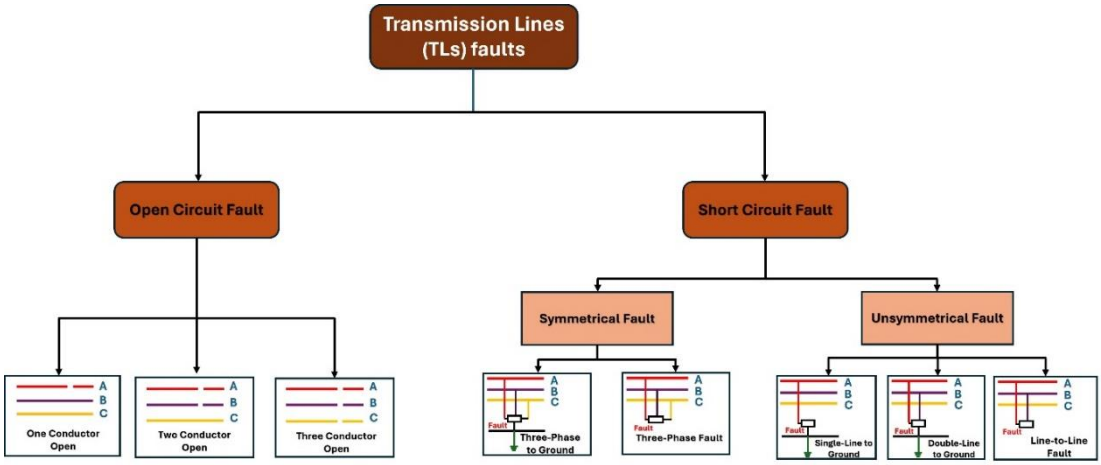


Figure 1.1 : Transmission lines faults classification.

1.1 Literature Review

Since most faults occur in transmission lines, this literature review will primarily focus on these structures. This study will comprehensively investigate the condition monitoring systems, fault detection, and classification methodology.

1.1.1 Maintenance strategies evolution

The evolution of maintenance strategies in electrical power systems has transitioned from reactive approaches to more proactive methodologies to enhance reliability and efficiency and minimise maintenance costs(Alvarez-Alvarado et al., 2022). Figure 1.2 illustrates the evolution of maintenance over time (Poór et al., 2019).

Initially, power systems predominantly relied on breakdown maintenance, also known as corrective maintenance (CM) or reactive maintenance (RM), where repairs were made post-failure, leading to significant downtime and costs (Motaghare et al., 2018). This reactive approach focused on addressing breakdowns as they occurred and was

marked by economic inefficiencies. As a result, during the second industrial revolution, there was a strategic shift towards preventive maintenance, which involves scheduled maintenance based on equipment life cycles to prevent failures before they occur (Alvarez-Alvarado et al., 2022; Molęda et al., 2023; Motaghare et al., 2018). This shift represented a fundamental change in maintaining operational integrity and reducing unplanned downtimes.

Advancements during the third industrial revolution introduced sophisticated strategies such as Condition-Based Maintenance (CBM), Reliability-Centered Maintenance (RCM), and Risk-Based Maintenance (RBM) (Alvarez-Alvarado et al., 2022). CBM uses real-time data from sensors to guide maintenance decisions, optimise maintenance schedules, improve operational efficiency, extend equipment lifespan, and reduce costs(Teixeira et al., 2020). RCM, introduced by Nowlan in 1978, aims to ensure equipment reliability by focusing on critical failure modes and tailoring maintenance accordingly (Bertling, 2002; Yssaad et al., 2014). This method is particularly beneficial for organisations where breakdowns constitute over 20-25% of total maintenance activities, leading to the most cost-efficient maintenance solutions(Yssaad et al., 2014).

Further developing RCM, Risk-Based Maintenance (RBM) was initially introduced into power systems as "operation risk assessment" by Vittal in 1997(M.-X. Zhao et al., 2012). RBM integrates risk assessment with maintenance planning, prioritising maintenance tasks based on the likelihood and impact of failures and optimising resource allocation(Gordon & Martinez, 2018; Mehairjan, 2017; M.-X. Zhao et al., 2012). According to Maninen *et al.*, RBM is widely used in various industries, including power transmission, to assess the timeframe and urgency of replacements for overhead lines (Manninen et al., 2022).

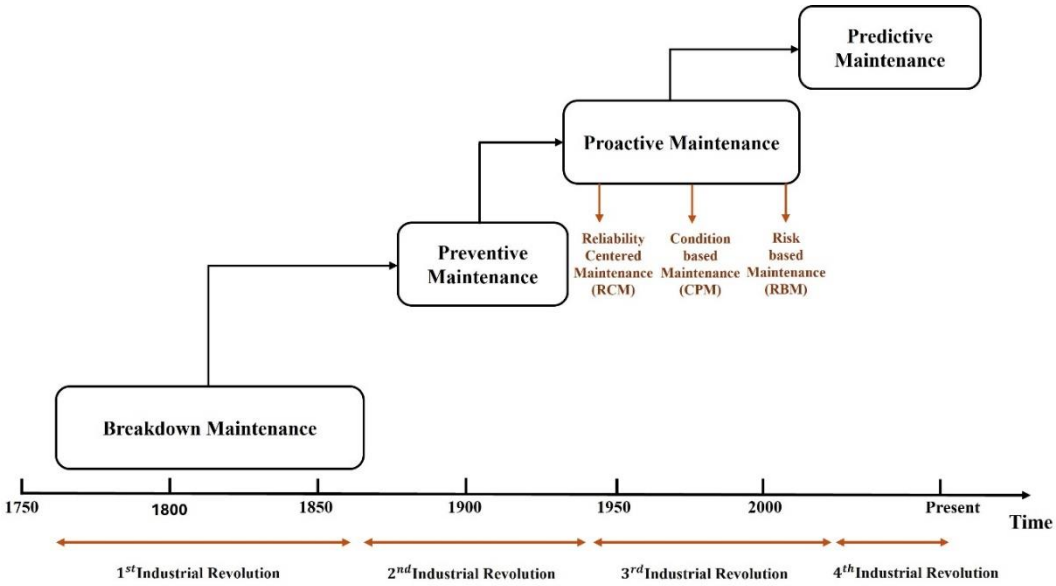


Figure 1.2 : Evolution of maintenance over the last decades (Alvarez-Alvarado et al., 2022; Poór et al., 2019).

The latest stages in the evolution of maintenance strategies involve predictive maintenance, leveraging big data, advanced analytics, and machine learning to predict and optimise maintenance schedules, thereby minimising downtime and extending equipment life (da Silva et al., 2012; Gidiagba et al., 2024; Goswami & Roy, 2019, 2019; Molęda et al., 2023; Righetto, Cardoso, et al., 2021; Righetto, Martins, et al., 2021). This strategy is supported by robust condition monitoring systems that continuously collect and analyse data to detect potential faults early, ensuring the stability and resilience of the power grid(Righetto, Cardoso, et al., 2021).

Condition monitoring systems are at the core of these advanced maintenance strategies. Continuous monitoring using various technologies collects real-time data crucial for accurately assessing a system's operational health. The subsequent sections will delve into the specifics of condition monitoring system and fault detection and classification techniques.

1.1.2 Condition monitoring systems

Transmission lines are vital for maintaining power systems' stability and efficiency, accounting for over 85% of faults. These lines comprise several vital components, including conductors, insulators, towers, ground wires, and various elements within substations. Each component is prone to different faults, which can disrupt power delivery and pose significant safety risks. Common faults in transmission lines include

line faults and substation faults, constituting 58% and 32% of all faults, respectively (Babu et al., 2016).

Substation faults mainly involve critical components such as power transformer and circuit breaker failures. Other faults include conductor corrosion, insulator failure, and structural damage to towers and ground wires. Short-circuit faults, for example, are the primary cause of line faults. These occur when electrical current bypasses the average load via a low-resistance path due to physical damage, insulation failure, or external interference from wildlife or fallen branches. Such faults can cause severe equipment damage, fires, and extensive power outages.

Continuous condition monitoring systems are essential to address these issues. These systems continuously or periodically monitor the performance and status of electrical equipment and infrastructure to detect early signs of deterioration, faults, or failures. They are fundamental in predictive maintenance strategies, which prevent unplanned outages and enhance system reliability by addressing potential issues before they escalate into significant problems. Additionally, condition monitoring extends the lifespan of equipment by preventing premature failure and reducing maintenance costs by focusing on predictive rather than reactive maintenance, which often involves more costly and extensive repairs(Molęda et al., 2023).

To effectively implement these condition-monitoring techniques, it is essential to understand the central architecture of condition-monitoring systems. This architecture typically consists of several layers, as shown in Figure 1.3, and each layer plays a critical role in the overall monitoring process(Patil et al., 2019).

The first layer is the data acquisition layer, which involves various sensors and devices to collect real-time data from the transmission line components. The literature describes the use of various devices for critical elements of transmission lines, including power transformers, circuit breakers, conductors, and insulators (Alshorman & Alshorman, 2021; Bayram, 2015; Dehghanian et al., 2019; Govindaraju et al., 2016; Han & Song, 2003).

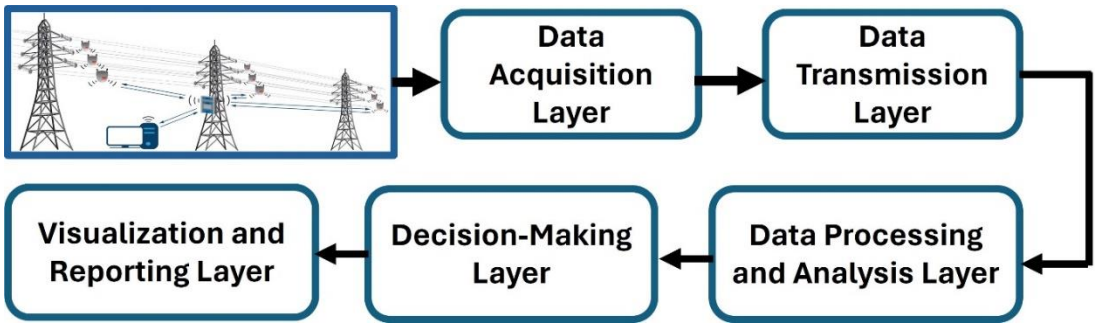


Figure 1.3 : Condition monitoring flowchart.

This foundational condition-monitoring approach has evolved significantly since its inception in the late 19th century. Initially, condition monitoring focused on direct measurements of electrical parameters such as voltage, current, and temperature, complemented by manual visual inspection of equipment, which could be more practical, time-consuming, and costly (Alshorman & Alshorman, 2021; Han & Song, 2003; Manninen et al., 2018). Early practices utilised primary devices like voltmeters, ohmmeters, and ammeters. Building on these foundational practices, the field of condition monitoring began to evolve rapidly with technological advancements.

One of the significant advancements in monitoring techniques involves using unmanned aerial vehicles (UAVs). Rezinkina et al. suggested the usage of unmanned aerial vehicles (UAVs) equipped with sensors to monitor various electrical and physical processes, including corona discharges and their acoustic characteristics (Rezinkina et al., 2020; Yeesparan et al., 2018). The 2000s brought about significant changes with the introduction of networking capabilities and the early stages of the Internet of Things (IoT) (Guo et al., 2019; J. Wang et al., 2021). Aerial images in deep learning models and online condition monitoring are advanced methods, and they have also been explored for electrical power systems, including insulator monitoring. These advancements enabled remote monitoring and data collection, leading to centralised monitoring systems overseeing multiple machines in different locations. This era saw the beginning of the integration of condition monitoring systems with enterprise resource planning (ERP) systems, enhancing maintenance scheduling and resource management (Molęda et al., 2023).

In addition to technological advancements, monitoring weather conditions such as temperature, wind direction, humidity, and wind speed is crucial. Weather stations installed near transmission towers provide data that affects the entire transmission line

systems, including insulators, towers and conductors. Consequently, a significant amount of research has been conducted in this area. Thermal stress monitoring, sag monitoring, dynamic line rating (DLR), and tension monitoring are techniques used to prevent thermal overload and stress and ensure system reliability and safety. Some of these techniques are used to monitor other components, such as transmission towers and support, as well as insulators and connectors(Mohd Zainuddin et al., 2020).

Despite these advancements, there are still challenges in implementing effective monitoring techniques. Li and Li (2017) thoroughly examined different monitoring techniques used in various power equipment systems and the corresponding challenges encountered. According to them, transmission line systems frequently utilise Online monitoring techniques such as distributed temperature sensors (DTS), sheath current monitoring, vibration, and motion sensing to detect physical movement and corona discharge detection employing ultraviolet (UV) cameras and sensors. The main challenges in these methods involve effectively handling extensive datasets and appropriately understanding intricate signals (S. Li & Li, 2017). Several authors have conducted deep research into various faults that can occur in transmission lines, such as overheating, excessive sag due to load, capacity limits, pole damage, deterioration of tower, underground cables issues, short circuits, insulation breakdown, flashover, etc (de Nazaré & Werneck, 2010; J. Lin et al., 2015; Mawle et al., 2020; Moldoveanu et al., 2016; Patil et al., 2019; Polyakov et al., 2018; Yang et al., 2007). They provided monitoring techniques such as distributed sensor networks (SNs), dynamic thermal imaging systems, sensor nodes, wireless sensor networks, real-time data monitoring, acoustic emission analysis, and current and voltage sensors.

Innovative solution continues to emerge, such as the method proposed by Wang et al., which is based on vibration analysis of transmission towers using wireless sensors (L. Wang et al., 2021). Remote monitoring is essential for current and voltage measurements. PMU devices are used for real-time detection, providing insights into the type of faults in case short circuit faults occur [43]. Some studies utilise real-time data to predict and monitor physical attributes of the system, such as line sag, which are crucial for maintaining system integrity and preventing failures (Hsu et al., 2019; Lijia et al., 2012). Hua et al. effectively employ this technique, using the communication channel to assess and predict cable health, thus minimising the need for additional sensors or devices (Huo et al., 2018). Accelerometers are placed at

various tower positions using the existing infrastructure to measure vibration acceleration. An innovative approach to condition monitoring systems involves utilising existing infrastructure, such as power line communications and vibration, to monitor transmission tower health (L. Zhao et al., 2019).

Power transformers are another critical power grid component, requiring diverse diagnostic methods to identify and prevent failures. Various studies on condition monitoring and diagnostic methods for power transformers synthesise a comprehensive range of techniques crucial for identifying and analysing transformer faults, particularly emphasising the vulnerabilities of transformer components and underlining the evolution of these methodologies. According to a study conducted in 1999, windings are the components most susceptible to failures (Cardoso & Oliveira, 1999). Another study showed that On Load Tap Changer (OLTC) and winding are the top failures. These underscore the importance of closely monitoring these aspects.

Moreover, another study indicates that 75% of transformer malfunctions may be traced back to insulation breakdown, highlighting the crucial requirement for thorough diagnostic methods (S. Li & Li, 2017). The most critical fault detection methods identified include Dissolved Gas Analysis (DGA) and chemical detection (High-performance Liquid Chromatography), which are instrumental in identifying decomposition products in transformer oil. Although highly sensitive, these methods face challenges in accurately localising faults. Other methods include Partial Discharge (PD) detection, leakage flux calculations, frequency response analysis, and temperature monitoring using fibre optic sensors. Although less commonly used for transformers, vibration monitoring can detect mechanical faults in On Load Tap Changers (OLTC) (Cardoso & Oliveira, 1999; Gockenbach & Borsi, 2008; Han & Song, 2003). These methods provided an accurate and complete diagnosis of power transformers(Cardoso & Oliveira, 1999; Gockenbach & Borsi, 2008). The convergence of these methodologies augments the accuracy and completeness of transformer diagnostics. It suggests the integration of cutting-edge technologies like big data, the Internet of Things (IoT), and cloud computing in future diagnostic strategies and machine learning (Dr. S. G. Paul et al., 2022; Pawar & Deosarkar, 2017; Tran et al., 2020; Zhuang et al., 2019). This comprehensive survey underscores the critical evaluation and synthesis of established and emerging techniques, reflecting a profound understanding necessary for the continued innovation and application in

transformer condition monitoring and diagnosis, with particular attention to the high-risk areas of windings and insulation.

Unlike transformers, switchgear components such as circuit breakers are also subject to rigorous condition monitoring to ensure system safety and reliability. Switchgear encompasses various electrical distribution devices, including circuit breakers, switches, fuses, and additional components. It serves the essential functions of controlling, protecting, and isolating electrical equipment, promoting the electrical system's stability and safety. On the other hand, a circuit breaker is a safeguarding device designed to automatically disconnect the electrical current to a circuit in cases of overload or short circuit. It functions primarily to cease current flow once protective relays identify a fault. As a crucial element of switchgear, circuit breakers (CBs) require stringent maintenance to ensure their reliability since they play a pivotal role in protection. Additionally, it has been stated in some studies that CBs significantly impact system reliability, and because of that, they are the most critical equipment for frequent maintenance. A standard method employed in conventional condition monitoring to detect issues in circuit breaker performance involves analysing the signatures of trip and close coils (Dehghanian et al., 2019; Johal & Mousavi, 2008; Nurubeyli et al., 2015).

Similarly, insulators are crucial in power transmission lines and distribution systems that maintain electrical separation between conductive parts and their environments. Several adverse effects may arise when these components are compromised, impacting the transmission system's operation and efficiency. These effects include leakage currents, corona discharge, weakened insulation, system instability, increased maintenance costs, and heightened safety hazards. Such issues can degrade equipment and pose significant risks to workers. Therefore, it is essential to employ condition-monitoring techniques. The literature highlights several experimental approaches to monitor insulator conditions, including electro-optic e-field sensors and current sensors for insulator leakage current, infrared thermal imaging, ultrasonic waves, acoustic fault diagnosis, and array signal processing techniques (Kim & You, 2011; Palangar et al., 2022; Park et al., 2017; Volat et al., 2013). However, a common limitation is their reliance on a single indicator to assess insulator conditions, which can compromise reliability due to susceptibility to environmental and industrial factors.

Additionally, while many studies focus on the physical properties of insulators, leakage current characteristics are noted for revealing essential, inherent qualities of insulators using current sensors (Rocha et al., 2019). Leakage current analysis is highlighted as more straightforward and accurate for determining an insulator's state than other techniques. Today's systems are applying the YOLO object detection model in conjunction with UAVs for transmission line insulators, demonstrating a leap towards autonomous monitoring solutions that can detect and classify defects in transmission line insulators with high accuracy and minimal human intervention (Liu et al., 2021; Panigrahy & Karmakar, 2024).

In summary**,** the data acquisition layer for transmission line elements uses various devices to collect data based on potential faults. These devices include sensors or devices for power transformers, circuit breakers, conductors, and insulators, which gather essential real-time data. Table 1.1 below illustrates the types of devices used and the specific components they monitor.

Table 1.1: The type of devices used for condition monitoring.

Condition Monitoring Technique	Systems Used In	Description and Application
Thermal Imaging (Infrared Thermography)(Volat et al., 2013)	Electrical panels, connectors, bearings, transmission lines	Detects heat anomalies indicative of excessive resistance, overloads, or faulty components, preventing potential failures.
Vibration Analysis(Khadersab & Shivakumar, 2018)	Rotating machinery such as turbines, fans	Monitors changes in vibration patterns to identify wear, misalignment, or imbalance, crucial for maintenance in mechanical systems.
Partial Discharge Monitoring(Han & Song, 2003)	High-voltage equipment like transformers, switchgears, transmission lines	Measures discharge patterns to monitor the integrity of electrical insulation, preventing catastrophic failures due to insulation breakdown.
Oil Analysis(Cardoso & Oliveira, 1999)	Transformers, hydraulic systems	Tests insulating oil for properties like dielectric strength and presence of gases to detect issues like arcing or overheating, essential for maintaining transformer health.
Ultrasonic Detection(Park et al., 2017)	Steam and gas pipelines, electrical systems	Identifies high-frequency noises from leaks or electrical discharges, useful for pinpointing leaks and preventing efficiency losses.
Online Monitoring(X. Zhang et al., 2021)	Power generation, distribution systems, and transmission lines	Uses sensors and data acquisition systems to continuously monitor parameters like current and voltage, facilitating real-time diagnostics and predictive maintenance strategies.
Dissolved Gas Analysis (DGA)(Tran et al., 2020)	Transformers	Identifies decomposition products in transformer oil to detect faults.
High-performance Liquid Chromatography (HPLC)(Cardoso & Oliveira, 1999)	Transformers	Analyses the chemical composition of transformer oil to identify faults.
Leakage Flux Calculations(Cardoso & Oliveira, 1999)	Transformers	Measures leakage flux to detect transformer faults.

Table 1.1 (continued) : The type of devices used for condition monitoring.

Condition Monitoring Technique	Systems Used In	Description and Application
Frequency Response Analysis(Han & Song, 2003)	Transformers	Analyses the frequency response of transformers to detect faults.
Fiber Optic Temperature Sensors(Cardoso & Oliveira, 1999)	Transformers	Monitors the temperature of transformers to prevent overheating.
LIDAR (Light Detection and Ranging)(Azevedo et al., 2019)	Transmission lines	Employs laser light to measure distances to the transmission lines and detect sagging, swaying, and other structural changes that could indicate risks or failures.
Drone Surveillance(Panigrahy & Karmakar, 2024)	Transmission lines	Utilizes drones equipped with cameras and sensors to visually inspect transmission lines and surrounding vegetation for potential hazards or damage.
Trip and Close Coil Signature Analysis(Johal & Mousavi, 2008)	Circuit breakers	Analyses the performance of circuit breakers to detect issues.
Thermal Imaging Systems(Ha et al., 2012)	Conductors, electrical panels, connectors	Detects heat anomalies to prevent potential failures.
Acoustic Emission Sensors(Park et al., 2017)	Conductors, steam and gas pipelines	Identifies high-frequency noises from leaks or electrical discharges.
Voltage and Current Sensors(Gopakumar et al., 2018)	Conductors, general transmission lines	Monitors electrical parameters to detect faults and ensure system reliability.
Electro-optic E-field Sensors(Volat et al., 2013)	Insulators	Assesses insulator conditions to detect faults.
Corona Discharge Detection using UV Cameras and Sensors(S. Li & Li, 2017)	General transmission lines	Detects corona discharges to identify faults.
PMU Devices(Gopakumar et al., 2018)	General transmission lines	Provides real-time data for current and voltage measurements to detect faults.

Table 1.1 (continued) : The type of devices used for condition monitoring.

Condition Monitoring Technique	Systems Used In	Description and Application
Weather Stations(Mohd Zainuddin et al., 2020)	General transmission lines	Collects environmental data such as temperature, wind direction, humidity, and wind speed to monitor conditions affecting the transmission lines.
Current Sensors for Leakage Current(Moldoveanu et al., 2016)	Insulators	Monitors leakage currents to assess insulator conditions.
Ultrasonic Waves(Palangar et al., 2022)	Insulators, steam and gas pipelines	Identifies leaks or electrical discharges in insulators and pipelines.
YOLO Object Detection Model with UAVs(Panigrahy & Karmakar, 2024)	Insulators	Detects and classifies defects in insulators autonomously.
Accelerometers(L. Zhao et al., 2019)	Transmission towers	Measures vibration acceleration to monitor structural health.
Wireless Sensors(J. Lin et al., 2015)	Transmission towers	Analyses vibration to monitor the health of transmission towers.
Distributed Temperature Sensors (DTS)(S. Li & Li, 2017)	General transmission lines	Monitors thermal stress and temperature variations along transmission lines.
Sheath Current Sensors(S. Li & Li, 2017)	General transmission lines	Detects physical movement and corona discharges.

Following data collection, the data is transmitted to central processing units through the data transmission layer. Advanced networking capabilities and IoT devices facilitate real-time data transmission and enhance the monitoring system's reliability.

The next critical step is data processing and analysis. This layer involves advanced algorithms, including fault detection and classification techniques. This study employs signal processing and machine learning techniques to detect and classify faults from the collected data.

1.1.3 Fault detection and classification techniques

After gathering data from monitored systems using various technological sensors, the next step is the data processing and analysis layer. This layer interprets the recorded data by employing fault detection and classification methodologies. This layer transforms raw data into actionable insights through advanced algorithms and analytical techniques, identifying potential faults and facilitating timely maintenance interventions. Fault detection in power systems is crucial due to electrical power networks' complexity and critical nature. Practical techniques are essential to ensure power delivery's reliability, safety, and efficiency. Once faults are detected, they must be classified to address them appropriately. These techniques can be broadly classified into three primary categories: data-driven approaches, model-based methods, and signal-based techniques.

Data-driven techniques use historical data and tools from machine learning, statistical analysis, and artificial intelligence to predict and identify faults efficiently. This method's effectiveness stems from its ability to learn from past data and improve over time, making it particularly suited for complex and dynamic environments like power systems. Several studies highlight the application of data-driven methods for fault detection in power transmission lines(Abdullah et al., 2024; K. Chen et al., 2016; Firos et al., 2023; Rai et al., 2021; Tîrnovan & Cristea, 2019; Tokel et al., 2018).

For instance, Abdullah et al. developed a methodology using artificial neural networks (ANN) to detect and identify faults in power transmission lines. This approach utilises the pattern recognition capabilities of ANNs to analyse electrical signal data and identify inconsistencies that may indicate faults(Abdullah et al., 2024).

Additionally, Firos et al. explored the use of three different machine learning models: Support Vector Machine (SVM), Naïve Bayes (NB), and Random Forest (RF) to detect

faults. Their research concluded that the Naïve Bayes model was the most effective, achieving an accuracy rate of 97.78%. This high level of accuracy demonstrates the potential of Naïve Bayes, a probabilistic classifier, in handling complex datasets and making accurate predictions based on the probabilistic relationships between features in the data(Firos et al., 2023).

The literature also reveals a significant reliance on Artificial Neural Networks (ANNs), as demonstrated by Zaidan et al., who employed ANNs for effective fault classification and clearance. Their work highlights the adaptability of ANNs to the dynamic conditions of power systems in real-time scenarios(Zaidan, 2019).

Jamil et al. and Manojna et al. further expanded the application of machine learning in fault detection, employing feed-forward neural networks with back-propagation and various machine learning models such as SVM and K-Nearest Neighbors (KNN), respectively. These methods handled complex fault scenarios with high accuracy and optimised fault classification through various input combinations(Jamil et al., 2015; Manojna et al., 2021).

Tokel et al. introduced a novel approach by integrating machine learning with delays in phasor measurement streams, significantly enhancing fault detection systems' responsiveness. This method, focusing on the synchronisation issues in modern power grids, showcases an innovative use of technology to improve system reliability(Tokel et al., 2018).

The application of deep learning is also prominent, as demonstrated by Rai et al., who developed a Convolutional Neural Network (CNN) tailored for fault classification in power distribution networks integrated with distributed generators (DGs). This approach, which directly classifies faults without requiring manual feature extraction, highlights the growing trend of deep learning in power systems.

Sarwar et al. addressed the challenges of high-impedance fault detection using a combination of principal component analysis (PCA_, FDA, and SVM). Their work enhances the detection capabilities under varying load conditions, showcasing the robustness of machine-learning techniques in traditionally challenging fault scenarios(Sarwar et al., 2020).

The integration of traditional and advanced methodologies is further elaborated in the comprehensive reviews by Chen et al. and Praveen Rai et al., which discuss the

effectiveness of combining wavelet transforms with neural networks and SVM and employing CNNs in fault classification, respectively. These methods are highly adaptable and continually improve as they process more data, though they require a substantial initial dataset to be effective(K. Chen et al., 2016; Y. Q. Chen et al., 2018; Rai et al., 2021).

On the other hand, model-based techniques use mathematical or physical models of the system to detect deviations between predicted and actual system behaviours. This approach is compelling in scenarios where accurate system models exist, but the precision of the models constrains its efficacy. Various research papers have been conducted in the literature.

Rodriguez-Cortes et al. proposed a model-based approach for detecting faults in power systems, explicitly identifying lost lines and bus load changes. The methodology employed a dynamic model of the system's generators using swing equations and utilised a nonlinear observer to monitor state-dependent signals for faults. This approach allows for generating a residual signal that can detect and distinguish between the two types of faults effectively. Numerical simulations demonstrated the method's efficacy in accurately identifying and differentiating between lost lines and bus load changes, highlighting the potential of model-based methods to enhance the reliability and safety of power system operations (Rodriguez-Cortes et al., 2006).

Salah et al., on the other hand, presented a unique method to identify automotive electric power generation systems using parameter estimation. This approach involved creating a dynamic model of a three-phase synchronous generator and employing a trust-region optimisation method to detect deviations in system parameters that indicate faults. The technique proved effective in identifying mechanical faults in alternator bearings by comparing changes in system dynamics through parameter values with those of a regular system. Founded results demonstrated that this method could offer a more straightforward and insightful way to detect faults than traditional signal-based techniques, enhancing reliability and safety in automotive operations (Salah et al., 2021).

Isermann focused on advanced model-based techniques for improving fault detection and diagnosis in essential systems across industries. It explores methodologies like parameter estimation, observers, parity equations, and signal models. Case studies

demonstrated these methods' effectiveness, including fault detection in aircraft valve actuators, passenger car stability systems, and diesel engine subsystems. These applications highlighted the significant enhancements in system reliability, safety, and efficiency offered by model-based fault detection and diagnosis(Isermann, 2005).

De Angelo et al. introduced a model-based strategy for detecting stator faults in induction motors using a state observer. This method effectively isolates stator inter-turn short circuit faults by generating a vector of specific residuals from the decomposition of current estimation errors. The approach is independent of the fault's phase and robust against load variations and supply voltage unbalances. Extensive experimental validation showed that the method can reliably detect faults early and accurately, with low sensitivity to non-fault disturbances, thereby enhancing preventive maintenance capabilities and system reliability. This makes it particularly valuable for industrial applications where induction motors are critical components(De Angelo et al., 2009).

Lastly, signal-based techniques prioritise the analysis of signals using diverse methodologies. A signal is data that originates from a system, reflecting its operational state or dynamic behaviour. Consequently, the analysis of such signals employs time-domain analysis, frequency-domain analysis, and time-frequency domain analysis to extract relevant features effectively (Molęda et al., 2023).

Time domain or temporal analysis is an initial approach often used in fault detection within power systems, analysing signals as they vary over time. While it provides a straightforward visualisation of data, allowing for the direct observation of peaks, impulses, and other irregularities associated with faults, its limitations become evident when dealing with complex systems(Molęda et al., 2023). Specifically, time domain analysis struggles to accurately identify underlying periodic or harmonic components of signals, which are crucial for diagnosing specific types of mechanical or electrical faults. This limitation stems from its inability to decompose a signal into its constituent frequencies. It makes it less practical for systems where fault signatures are closely tied to specific frequency bands or where the signal includes noise that obscures time-based features(He et al., 2017).

Frequency-domain analysis was introduced to overcome these limitations, using tools like the Fourier Transform (FT), developed by Joseph Fourier in 1807. This method is

a commonly used mathematical transform method involving transforming time-domain signals into the frequency domain, a process significantly enhanced by Cooley and Turkey's development of the Fast Fourier Transform (FFT) in 1965. This technique is pivotal for conducting harmonic analysis, assessing system stability, and evaluating power quality, which is essential for identifying and mitigating issues such as harmonics, voltage disturbances, and resonance problems. By transforming time-domain signals into the frequency domain, FFT enables the identification of characteristic frequencies and harmonics that signify specific faults, thereby providing a deeper insight into the system's dynamic behaviour (Bayram, 2015; Gao & Yan, 2011; Jurado & Saenz, 2002; Peng & Chu, 2004a; Polikar, 1999; Şengüler & Seker, 2017).

Yoo introduced a method to enhance fault detection in induction motors by integrating FFT with Principal Component Analysis (PCA). Initially, FFT is applied to convert motor current signals into the frequency domain, emphasising the characteristic frequencies vital for fault identification. This transformation facilitates a more detailed understanding of the motor's operational state, allowing for early fault detection, which is crucial for the maintenance and prevention of failures (Yoo, 2019). Furthermore, several studies have utilised the Fourier transform to shift signal information to the frequency domain, as faults may remain undetected in the time domain (S. Agarwal et al., 2017; Kar & Mohanty, 2008; Ogboh & Ezechukwu, 2019).

However, frequency domain analysis is excellent at finding steady-state or periodic faults but is not as good at dealing with non-stationary signals. In such cases, where frequency components vary over time due to changes in system load or operational conditions, the true nature of faults can be obscured, making them more challenging to detect and analyse using solely frequency-based methods. This limitation underscores the need for additional analytical techniques to accommodate the variability inherent in non-stationary signals(Gao & Yan, 2011).

Researchers have developed methods for time-frequency analysis to overcome the limitations of analysing time and frequency data separately. One of these methods is the Short-Time Fourier Transform (STFT), introduced by Dennis Gabor in 1946(Gabor, 1946; Ji et al., 2021). The STFT is a crucial tool for analysing power systems, providing insights into electrical signals' time and frequency characteristics. It is beneficial for detecting transient faults (Satpathi et al., 2018a), assessing power

quality (Mishra, 2019), monitoring voltage stability by detecting short-duration voltage variations (Anggriawan et al., 2020), analysing load behaviour, and machine fault extraction by converting vibration signals into 2D time-frequency images (Du et al., 2020). In addition, STFT was applied in several studies to detect faults in bearings, gears, and pumps in combination with machine learning (Ji et al., 2021; Jingyi et al., 2019; L.-H. Wang et al., 2017; Q. Zhang & Deng, 2023; W. Zhao et al., 2016), and these studies have been achieved using it. STFT's ability to identify disturbances and oscillations aids in the proactive management of system issues, ensuring operational reliability. Its adaptability comes from the ability to adjust window sizes to suit specific analytical needs(Nasser Mohamed et al., 2024; Satpathi et al., 2018a), though this also introduces a dependency that can affect resolution and computational efficiency.

The Short-Time Fourier Transform (STFT) provides valuable insights into power system analysis. However, it faces significant challenges, particularly the trade-off between time and frequency resolution due to its fixed window size. With a wide window, frequency resolution is enhanced at the expense of time resolution, making it challenging to track rapid signal changes. Conversely, a narrow window improves time resolution but reduces frequency resolution, potentially overlooking critical spectral nuances. These limitations prompted the search for an alternative mathematical tool, leading to the development of Wavelet Transform (Gao & Yan, 2011; Polikar, 1999).

Initially hinted at by Alfred Haar in 1909, Wavelet Transform offers a more adaptable approach than STFT by allowing variable window sizes that adjust to the frequency being analysed. This capability enables more precise time and frequency localisation, making it especially effective for non-stationary signal analysis where signal characteristics evolve over time. The development of Wavelet Transform was significantly advanced by Jean Morlet and Alex Grossman in the 1980s, who refined the technique by using different window functions for analysing various frequency bands. Yves Meyer further enhanced this in 1985 when he developed orthogonal wavelet basis functions with better time-frequency localisation properties (Polat & Özerdem, 2018).

The evolution of wavelet theory continued with Ingrid Daubechies in the 1990s, who utilised multiresolution wavelet analysis to construct a widely used family of wavelet applications (Gao & Yan, 2011; Polikar, 1999). This progression addressed the limitations faced by STFT and highlighted the resilience and collaborative nature

essential for significant advancements in mathematical theories and applications. Wavelet Transform thus represents a critical development in signal analysis, providing a robust tool for handling the complexities of modern power systems. Wavelet transforms have been used in machine condition monitoring and fault diagnostics over the last decade, and they have proven effective in time-frequency signal analysis, fault feature extraction, singularity detection, denoising, signal compression, and system identification (Peng & Chu, 2004a).

Wavelet transforms are versatile mathematical tools used for signal analysis, characterised by different types tailored to specific applications. The Continuous Wavelet Transform (CWT) offers a satisfactory resolution in time-frequency space, which is ideal for detailed signal analysis. In the literature, the specific method has been widely used in various studies for its effectiveness in extracting time-frequency information from signal data, aiding in diagnosing system faults and power quality disturbances. Li et al., Al Tobi et al., and Xi et al. demonstrated the integration of CWT with convolutional neural networks (CNN) for enhancing fault feature extraction, showing high classification accuracies in transformer and machinery fault diagnosis (Al Tobi et al., 2022; C. Li et al., 2023; Xi et al., 2023). Similarly, Lala et al. and Perez-Anaya et al. employed CWT to detect power disturbances in electrical systems, including renewable energy setups, confirming the transform's capacity to identify subtle signal anomalies efficiently (Lala et al., 2018; Perez-Anaya et al., 2024). These studies underline CWT's utility in improving diagnostic accuracies across various applications, highlighting its adaptability and precision in handling non-stationary signals in complex operational environments.

In literature, most of the studies use the discrete wavelet transform (DWT) rather than the continuous wavelet transforms (CWT) due to its efficiency in processing and analysing real-world signals and data (Ahmed et al., 2023; Aleem et al., 2015; Asman et al., 2022; D. Paul & Mohanty, 2019; Yumurtaci et al., 2020). DWT systematically decomposes a signal through successive high-pass and low-pass filters, achieving a multi-hierarchical representation. This method is particularly advantageous for signal and image compression applications, where preserving high-frequency components while data size is crucial. Malla et al. discuss the effectiveness of wavelet transform (WT) techniques, specifically discrete wavelet transforms (DWT), for fault detection in overhead power transmission lines. The proposed technique enabled the precise

decomposition of the signal into different frequency components, which can effectively capture the transient change and disturbances caused by faults (Malla et al., 2019). Chen et al. introduced DWT as an effective method, and he highlighted various applications of WT, mentioning that different mother wavelets, such as bior3.9, Meyer, coif5, Db10, and Sym8, are recommended for fault detection based on their properties and the specific requirements of the fault detection system (K. Chen et al., 2016).

The Discrete Wavelet Transform (DWT) is highly valued for efficient multiresolution analysis in signal processing. However, it lacks translation invariance, making it sensitive to shifts in the input signal. This shift-variance can significantly impact applications requiring precise feature alignment, such as signal classification and feature extraction. The Stationary Wavelet Transform (SWT), or undecimated wavelet transform, was developed to overcome these limitations. Unlike DWT, SWT omits the down-sampling step at each decomposition level, maintaining the original signal length and ensuring full translation invariance. This design results in a redundant output, which, although increasing computational and storage demands, actually benefits the detection of minor defects. According to Nasser Mohamed et al., the concept of redundancy in wavelet transform is explored by applying the stationary wavelet transform (SWT) for fault detection in power systems. The SWT's redundancy enhances the visibility and detection of minor defects, aiding predictive maintenance by allowing early fault identification. The paper quantifies this redundancy, highlighting its significant contribution to improving the reliability and effectiveness of fault detection methods in power systems (Nasser Mohamed et al., 2023). Another study used the redundancy concept, where the authors used stationary wavelet transform (SWT) for predictive fault detection in electric motors (Bayram & Şeker, 2017). They highlighted the redundancy of the transformation as a beneficial feature. SWT is known for its redundant nature due to the need for decimation in its calculation process. This redundancy, often seen as undesirable in other contexts, is advantageous here as it aids in amplifying and more precise identification of hidden fault signatures that are not detectable by conventional methods. The paper elaborates on using the algebraic summation operation (ASO) to enhance this redundancy, making the SWT a powerful tool for early and predictive fault detection by emphasising otherwise obscure fault indicators in the motor's vibration spectra (Bayram & Şeker, 2017).

In the realm of fault detection and classification, hybrid methodologies combine various techniques to use the strength of each approach, leading to improved accuracy and robustness. These methodologies integrate data-driven, model-based, and signal-based techniques to develop a comprehensive system for detecting and classifying faults. This system can address the limitations of individual methods. The first hybrid approach involves combining data-driven and model-based techniques. Data-driven methods, such as machine learning algorithms, effectively identify patterns and faults in historical data. The resulting hybrid system can more accurately detect and diagnose faults when integrated with model-based methods, which use mathematical models to predict system behaviour. Another hybrid methodology integrates signal-based methods, such as wavelet transform transforms or Fourier analysis, which are adept at extracting features from signals. These features can then be used as inputs for machine learning models, enhancing their ability to classify faults. For instance, a hybrid system might apply wavelet transforms to decompose a signal into its constituent frequencies and then use a machine learning model like a neural network to classify the fault based on these frequency components. Table 1.2 summarises the various hybrid methodologies in the literature, describing how different techniques are integrated and their performances.

Table 1.2: Overview of various fault detection and classification methods in power systems.

Author(s)	Proposed methods	Application used	Accuracy/Performance	Dataset Size/Type
Ray et. al(Ray et al., 2017)	DWT and ANN	Tested on a 300 km, 735-kV, 50 Hz transmission line model using MATLAB.	DWT-based method Detection: 100%, Classification: 97.43%. ANN-based method Detection: 87.27%, Classification: 65.43%.	Simulated and real data (720 faults, real records from CHESF)
Rai et. Al(Rai et al., 2021)	CNN	Mixed TLs and distribution network with PV as DG.	99.92%	Simulated and real data (10-fold cross-validation)
Sami Ekici(Ekici, 2012)	SVM and WT	High-voltage power TLs.	Fault classification error $< 1\%$, average error in fault location $< 0.26\%$.	Simulated data
Goni et al.(Goni et al., 2023)	Extreme Learning Machine (ELM)	Transmission lines TLs	Fault Classification (FC) 99.18% for TL_1 99.09% for TL_2 Fault Detection (FD) 99.53% for TL_1, 99.60% for TL_2.	Simulated data
Sharma et al.(Sharma et al., 2016)	Wavelet Transform and ANN	Transmission network	MSE: 1.81×10^{-9}, MAE: 9.27×10^{-6}, RMSE:4.25×10^{-5}, SSE: 8.86×10^{-9}.	Simulated and real data (MATLAB)
Jamil et al.(Jamil et al., 2015)	ANN	Electrical power TLs	Satisfactory performance under varying conditions.	Simulated and real data (MATLAB)
Fahim et al.(Fahim et al., 2021)	CNN with Sparse Filtering	Power transmission systems	Accuracy: 99.47% - 99.72%, Robustness: 99% against noise, >97% for high impedance faults.	Simulated and real data
Magagula et al.(Magagula et al., 2017)	DWT and SVM	power distribution network	Fault detection and classification 98.5%.	Simulated data

Table 1.2 (continued) : Overview of various fault detection and classification methods in power systems.

Author(s)	Proposed methods	Application used	Accuracy/Performance	Dataset Size/Type
Moradzadeh et al.(Moradzadeh et al., 2022)	CNN-LSTM	TLs	98.4%	463 samples
Belagoune et al.(Fahim et al., 2021)	LSTM	LTs	87.09-100%	334 test cases
Asman et al.(Asman et al., 2021)	RMS-DWT and Decision Tree	TLs network	97.4%	840 samples

1.2 Motivation and Contribution

Despite the advancements observed in the literature, there are gaps in how effectively these technologies are integrated into existing power systems, particularly in developing countries such as Djibouti. Djibouti, officially the Republic of Djibouti, is located on the horn of Africa with a 23,000 km2 area. The country has a high potential for Renewable Energy, but unfortunately, Djibouti does not produce self-energy and is highly dependent on Ethiopia's electricity. Djibouti has one million inhabitants, and the electrification rate of this country is 55%. The plan is to have an electrification rate of 100% in 2035.

Djibouti's electrical power system faces significant reliability and efficiency challenges, exacerbated by an outdated maintenance framework. As the sole electricity provider, Electricity of Djibouti (EDD) heavily relies on a combination of ageing fossil-fuel power plants, generators, and imported electricity. This setup is afflicted by frequent operational disruptions, with unscheduled downtimes constituting a significant portion of total operational time. Approximately 85% of the total Energy not Distributed (END) results from unplanned outages, as shown in Figure 1.4. Current maintenance practices primarily focus on reactive strategies, addressing faults and failures only after they have caused system disruptions. Additionally, the fault correction process takes a long due to the extensive time required to identify the fault location and classification.

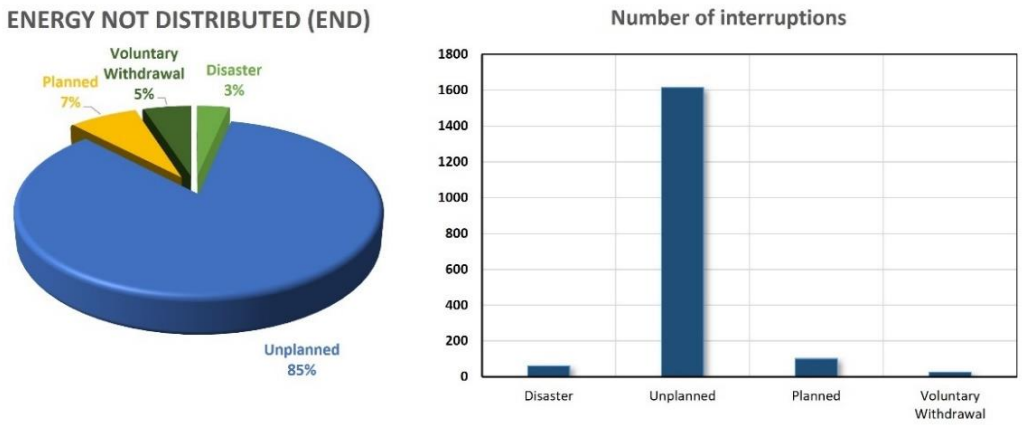


Figure 1.4 : Distribution of energy (END) and interruption numbers occurring in Electricity of Djibouti (EDD).

This reactive approach results in high maintenance costs, extended outages, and substantial economic losses, challenging the stability of the power supply essential for economic growth and societal stability. The lack of advanced, real-time maintenance strategies limits the ability to predict and mitigate faults effectively, further compromising the resilience and efficiency of the power infrastructure.

Given these circumstances, there is a critical need to implement condition monitoring strategies that can use modern technologies such as wavelet transforms and machine learning for fault detection and classification. Such strategies would enable proactive identification and resolution of potential faults, significantly reducing downtimes and enhancing the reliability and efficiency of Djibouti's electrical power systems. This thesis proposes to explore and validate the application of these advanced technologies in Djibouti's context, aiming to establish a robust fault detection and classification model.

This thesis contributes to electrical engineering through significant methodological advancements and practical applications. Firstly, the study uses a sensitive detection within a brief timeframe using STFT with a frequency resolution of 2 Hz. Additionally, it provides a risk assessment framework to evaluate the severity of different faults, aiding in predictive system management. The second contribution introduces the innovative use of the redundancy property (RP) of the stationary wavelet transform (SWT) to detect minor defects observed in short circuit faults, as well as the minimum phase shifting found by Daubechies wavelet of order 1 (db1), also known as the Haar wavelet. Effective detection is enhanced by the signal reconstruction model, with algebraic summation to amplify signals, resulting in more accessible and more accurate interpretation.

Lastly, the study utilises an innovative combination of discrete wavelet transform (DWT) and machine learning techniques for fault classification. DWT is widely used due to its computational efficiency, making it suitable for real-time applications. Machine learning (ML) techniques, such as Support Vector Machine (SVM), Decision Tree (DT), and Long Short-Term Memory (LSTM), offer several advantages over traditional methods, including the ability to learn from data, adapt to new fault patterns, and provide faster and more accurate fault diagnosis. A detailed performance evaluation highlights the strengths and weaknesses of each hybrid classifier method. The main contribution of this study is a comprehensive performance evaluation that

highlights the strengths and weaknesses of each hybrid classifier method, offering a detailed analysis that will guide the selection and application of these techniques in practical settings.

The practical application for addressing the high demand for reliable electrical energy infrastructure in Eastern Africa contributes to energy policy and international trade objectives. This initiative is crucial for improving power reliability and supporting the economy in the region.

This combined approach is set to establish a new standard in fault detection and classification methods, especially in settings where existing technologies are either outdated or lacking entirely. By integrating these powerful signal processing and machine learning techniques, the research aims to significantly reduce the downtime caused by electrical faults and improve the maintenance strategies of EDD. This will improve the reliability and efficiency of the electrical supply in Djibouti and add to the global knowledge base in fault diagnosis and system monitoring. The innovative, adaptable model can be applied in similar contexts worldwide.

1.3 Objective and Structure of the Thesis

The primary purpose of this thesis is to develop and simulate robust fault detection and classification models in electrical power systems using advanced wavelet transform and machine learning techniques. This research addresses the challenges faced by the Electricity of Djibouti (EDD) in monitoring and diagnosing system faults efficiently to reduce downtime and enhance overall reliability. The specific objective of the thesis can be clearly described as follows.

- The aim is to analyse and detect electrical faults in the Djibouti power system using the Short-Time Fourier Transform (STFT). This involves modelling the power grid with accurate parameters in MATLAB-SIMULINK, simulating various fault scenarios, and analysing the impact of these faults on the system's performance and reliability.
- To develop and validate a hybrid wavelet transform method for early detection and identification of faults in power systems. This method combines stationary and continuous wavelet transforms to enhance the detection of minor defects, aiming to provide more reliable operation conditions through predictive

maintenance by applying this advanced signal processing technique on the Djibouti power grid model.

- To categorise types of faults using machine learning techniques, including Support Vector Machine (SVM), Decision Tree, and Long Short-Term Memory (LSTM), and subsequently compare the performance of these three methods.

The structure of the thesis can be outlined as follows:

Chapter 1: The first chapter provides a comprehensive overview of the topic, outlining the significance of reliable power systems in modern society and the challenges posed by increasing complexity and susceptibility to faults. It defines the objectives of the thesis, which focus on enhancing fault detection and classification in power systems through advanced methodologies. The chapter also presents the organisation of the thesis, detailing how each subsequent chapter will build on the concepts introduced. Furthermore, it thoroughly reviews the literature on condition monitoring systems and fault detection methodologies. It sets the foundation for the detailed investigations and proposed solutions discussed in later chapters.

Chapter 2 outlines the mathematical techniques employed for fault detection and classification in electrical systems, focusing on transmission lines. It covers the Short-Time Fourier Transform (STFT) for analysing non-stationary signals' frequency content and balancing time and frequency resolutions using various window functions. Wavelet Transforms (WT) are explored, including Continuous Wavelet Transform (CWT) for detailed time-frequency analysis, Discrete Wavelet Transform (DWT) for efficient signal decomposition, and Stationary Wavelet Transform (SWT) for preserving time-invariant structures. The chapter also discusses Machine Learning techniques such as Support Vector Machines (SVM) for high-dimensional data classification, Decision Trees (DT) for recursive partitioning based on feature values, and Long Short-Term Memory networks (LSTM) for managing long-term dependencies in sequential data tasks. These methods form the basis for advanced fault detection and classification in power systems.

Chapter 3: This chapter overviews Djibouti's power system, highlighting its strategic location and energy potential. Managed by Electricité de Djibouti (EDD), the country has grown in electricity production due to interconnection with Ethiopia but faces

challenges with local generation and frequent outages. It describes the current grid infrastructure and recent renewable energy projects to improve electrification. Using MATLAB/SIMULINK, the power system is modelled to analyse faults and enhance reliability and efficiency.

Chapter 4 presents the application of mathematical methods for fault detection in the Djibouti power grid model using MATLAB/SIMULINK. It simulates various fault scenarios, such as single-line-to-ground, double-line-to-ground, and three-phase faults. Two primary case studies are highlighted: Short-Time Fourier Transform (STFT) implementation and a hybrid wavelet transform method. The STFT is used for feature extraction and fault detection, focusing on the riskiest fault types identified through risk evaluation. The hybrid wavelet transform method, combining Stationary Wavelet Transform (SWT) and Continuous Wavelet Transform (CWT), is proposed for enhanced fault detection. Simulation results demonstrate the effectiveness of these methods in identifying fault characteristics and improving the reliability of the power system.

Chapter 5: Chapter 5 focuses on classifying faults in Djibouti's power systems using machine learning techniques. The process starts with pre-processing the dataset through oversampling to prevent overfitting, followed by feature extraction using Discrete Wavelet Transform (DWT) to obtain features like energy content, entropy, variance, and maximum coefficient. The chapter then details the implementation and evaluation of three classifiers: Decision Trees (DT), Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM). Each classifier's performance is assessed using metrics such as accuracy, precision, recall, and F1 score, with SVM demonstrating superior performance overall.

Chapter 6: This chapter concludes the thesis with a comprehensive discussion of the findings and offers recommendations for improving Djibouti's power system. The chapter summarises the key outcomes from the fault detection and classification studies, highlighting the effectiveness of machine learning techniques, particularly SVM, in accurately classifying faults. It emphasises the need for advanced monitoring and diagnostic tools to enhance system reliability and prevent outages.

2. MATHEMATICAL METHODS

In this study, various mathematical techniques have been applied to detect and classify faults in electrical systems, specifically focusing on transmission lines. The methods used are as follows:

2.1 Short-Time Fourier Transform (STFT)

The Short-Time Fourier Transform (STFT) is a powerful mathematical tool used to analyse the frequency content of non-stationary signals, which vary over time(Kehtarnavaz, 2008). It extends the traditional Fourier Transform, by dividing a signal into shorter segments or 'frames,' assuming each segment remains approximately stationary, and applying the Fourier Transform individually to each segment. This approach allows us to accurately observe how the spectrum of a signal changes over time. Mathematically, the STFT is defined as (Gundewar & Kane, 2022; D. Li et al., 2023):

$$STFT_{\{x(t)\}}(t,\omega) = \int_{-\infty}^{+\infty} x(\tau) w^*(\tau - t) e^{-j\omega\tau} d\tau \qquad (2.1)$$

Where $x(t)$ is the signal being analysed, $w^*(\tau - t)$ is the complex conjugate of the window function centered around time t, t represents time, ω represents angular frequency, and τ is the integration variable.

The choice of window function $w(t)$ in the Short-Time Fourier Transform (STFT) is ca versatile aspect, as it can be adapted to balance both the time and frequency resolutions of the analysis. Different window functions are used to meet the specific analysis requirements, as shown in table 2.1:

The fundamental challenge with the STFT is the trade-off between time and frequency resolution, which is a direct consequence of the Heisenberg Uncertainty Principle. This principle suggests that it is impossible to precisely determine both the time at which something happens and the frequency content of what happens at that time. In signal

processing terms, the uncertainty can be quantified by the (Oppenheim & Magnasco, 2013):

Table 2.1 : Comparison of different window function for signal processing.

Window Function	Description	Advantages	Disadvantages
Rectangular(Boukharouba, 2017; K. Wang et al., 2021)	Treats each point equally within the window.	Simple; good temporal resolution.	Poor frequency resolution; significant spectral leakage.
Hamming(Podder et al., 2014; Tan & Jiang, 2013)	Tapered window reducing side lobes of the frequency response.	Better frequency resolution than rectangular; reduced spectral leakage.	Moderate Side Lobe Attenuation.
Hanning (Hann)(Braun, 2001)	Smooth tapering at the boundaries.	Further reduction in spectral leakage; smooth transitions.	Trades time resolution for frequency resolution.
Gaussian(Brynolfsson & Hansson-Sandsten, 2015)	Gaussian curve for tapering, minimizing the time-bandwidth product.	Excellent frequency resolution; minimal spectral leakage.	Poor time resolution; computationally complex.
Blackman(Podder et al., 2014)	Wider tapering curve than hamming or Hann, with additional cosine terms.	Very good frequency resolution; extremely low spectral leakage.	Poorer time resolution.
Kaiser(Podder et al., 2014)	Variable parameters to adjust trade-offs between main lobe width and side lobe level.	Flexible adjustment; can optimize for specific applications.	Requires parameter optimization; computationally demanding.

$$\sigma_t \sigma_f \geq \frac{1}{4\pi} \tag{2.2}$$

Where σ_t and σ_f re the standard deviation of the window function in time and frequency domains, these standard deviations quantify the extent to which the window

function spreads across each domain—a smaller σ_t results in better time localization, indicating a window that is narrow in time. Conversely, a smaller σ_f means better frequency localization, signifying a window is narrow in frequency. However, this sharp localization in one domain broadens the spread in the other, illustrating the fundamental trade-off described by the uncertainty principle.

Several critical parameters must be defined to effectively apply the STFT. When carefully selected, these parameters play a crucial role in tailoring the STFT to meet the specific needs of signal processing tasks.

- **Sampling Frequency f_s**: Determines the data acquisition rate per second, influencing the STFT's time and frequency resolution(Satpathi et al., 2018b).
- **Number of Input Sample** (n) affects the length of the window and, thereby, the spectral resolution; increasing nn enhances the frequency resolution(Satpathi et al., 2018b).
- **The Total Number of FFT Points** (N): Adjusting N improves the frequency resolution (Satpathi et al., 2018b).
- **Window Function $w(n)$** should be chosen based on its frequency domain characteristics, and there are several window functions to choose from, including rectangular, B-Spline, polynomial, cosine-sum, adjustable, and hybrid windows (Ukil et al., 2020). The Gaussian window is a type of adjustable window that is used for transient signal analysis. For narrow band random signals, Hanning and Hamming from the cosine-sum window are suitable(Arikan et al., 2020).
- **Hop Size** (H) Smaller hop sizes yield better time resolution(Satpathi et al., 2018b)**.**

By carefully selecting these parameters and understanding the inherent limitations due to the Heisenberg Uncertainty Principle, engineers and analysts can tailor the STFT to meet the specific needs of their signal processing tasks. This understanding, coupled with the right parameter choices, ensures the potential for optimal analysis of complex, time-varying signals.

2.2 Wavelet Transforms

The wavelet transforms (WT), which were developed to overcome the constraints of the Fourier transform, are mathematical techniques for studying data such as signals or pictures with properties that fluctuate across multiple scales(Molęda et al., 2023). WT processes excellent feature extraction is among the best analysis methods. It works by breaking signals into shifted and scaled wavelets. Wavelet families can be observed as orthonormal, orthogonal, or biorthogonal (Gawali et al., 2015; Schneider & Farge, 2006; Ukil et al., 2020). The orthogonal and biorthogonal wavelet families have a linear phase feature beneficial data reconstruction (Akinci et al., 2013; *Orthogonal and Biorthogonal Filter Banks - MATLAB & Simulink*, n.d.). One of the fundamental advantages of wavelets is that they enable localization in both time and frequency domains at once. The second key advantage of wavelets is that they are speedy to compute when using the wavelet transform. In addition, the capacity of wavelets, which separates minor characteristics in a signal, is a crucial advantage.

2.2.1 Continuous wavelet transform

The Continuous Wavelet Transform (CWT) is a powerful mathematical technique used to analyse and decompose signals or data into their frequency components within both time and frequency domains. It is particularly effective for capturing non-stationary or time-varying signals. The CWT operates with continuous scaling and shifting parameters, introducing redundancy but providing a detailed and comprehensive signal analysis. The CWT for a signal $f(t)$ is defined by the following formula (Martinez-Ríos et al., 2022; Seker & Ayaz, 2003):

$$CWT_f(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-b}{a} \right) dt \qquad (2.3)$$

Where:

- $f(t)$ is the input signal being analysed.
- ψ^* is the complex conjugate of the mother wavelet.
- a is the scale parameter, controlling the width (frequency) of the wavelet.
- b is the translation (time shift) parameter.

The mother wavelet must satisfy the admissibility condition to represent and reconstruct signals while preserving their essential properties accurately, and it is defined as (Seker & Ayaz, 2003):

$$\int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty \tag{2.4}$$

Where:

- $\psi(\omega)$ is the Fourier transform of the mother wavelet $\psi(t)$.
- ω is the angular frequency.

This admissibility condition guarantees that the wavelet function can accurately represent the signal's information content (Martinez-Ríos et al., 2022).

Choosing the appropriate mother wavelet is crucial for practical signal analysis. Different families of mother wavelets are suitable for capturing various signal features. Some widely used wavelet families in CWT include:

- Generalized Morse Wavelet (“morse”)

This flexible and adaptable wavelet family encompasses a wide range of oscillatory behaviours. It is beneficial for analysing non-stationary and complex signals as it can capture both narrowband and broadband properties (Martinez-Ríos et al., 2022; Olhede & Walden, 2002; Whitney, 2019).

- Analytic Morlet Wavelet (“amor”)

The Analytic Morlet Wavelet is designed to capture and analyse signals' localised oscillations and transient phenomena. Its shape resembles a Gaussian curve modified by a sinusoidal oscillation, making it suitable for analysing signals with both frequency and time fluctuations. Neuroscience often uses this wavelet to analyse brain oscillations (Cohen, 2019).

- Bump wavelet (“bump”)

The Bump Wavelet is localised in both the time and frequency domains, making it effective for identifying signal transitions and rapid changes. Despite its simplicity, it is highly effective for detecting sharp signal features (Silik et al., 2021).

In summary, the choice of wavelet family depends on the characteristics of the signal being analysed and the specific features that need to be extracted. Each wavelet family has distinct properties that make it suitable for different applications. The Generalized Morse Wavelet is versatile for complex signal analysis, the Analytic Morlet Wavelet excels in capturing localised oscillations, and the Bump Wavelet is ideal for detecting rapid changes. Selecting the appropriate wavelet ensures that the signal's essential features are accurately represented and analysed, making CWT a valuable tool in various research and application fields.

2.2.2 Discrete wavelet transform

The Discrete Wavelet Transform (DWT) enhances computational efficiency by discretising the scale and translation parameters, sampled at base 2. This discretisation eliminates the redundancy present in the Continuous Wavelet Transform (CWT), making DWT particularly useful for practical applications such as fault detection, denoising, and feature extraction(Ray et al., 2017).

DWT decomposes a signal into a set of coefficients that represent the signal at different scales and positions. This process involves passing the signal through high-pass and low-pass filters to obtain detail and approximation coefficients. The mathematical formulation of the DWT is as follows(Edwards, 1991):

- Approximation Coefficients $A_{j,k}$

$$A_{j,k} = \sum_n x[n]\phi_{j,k}[n] \tag{2.5}$$

  Where:

  $x[n]$ is the discrete input signal

  $\phi_{j,k}[n]$ is the scaling function (low-pass filter) at scale j and position k.

- Detail Coefficient $D_{j.k}$

$$D_{j.k} = \sum_n x[n]\psi_{j,k}[n] \tag{2.6}$$

  Where:

  $\psi_{j,k}[n]$ is the wavelet function (high-pass filter) at scale j and position k.

The wavelet function $\psi_{j,k}[n]$ and the scaling function $\phi_{j,k}[n]$ are derived from the mother wavelet, which is the basis for all wavelets generated in the analysis. The mother wavelet determines the characteristics and efficiency of the DWT in capturing information about the signal. Choosing an appropriate mother wavelet is crucial as it affects both the ability to analyse different signal features and the transform's computational efficiency. Some commonly used mother wavelets include:

- Haar wavelet

The Haar wavelet is fundamental and early form of wavelet. It is distinguished by a discontinuous function that evaluates local means and variances within a signal. The Haar wavelet is highly efficient in analysing abrupt changes in a signal, such as edges in image processing and signal processing(Nasser Mohamed et al., 2023; Stanković & Falkowski, 2003).

- Daubechies wavelets

Developed by Ingrid Daubechies, these wavelets are famous for their compactly supported orthogonal wavelets with maximum number of vanishing moments for a given support width. Daubechies wavelets are very useful in various applications, including signal and image compression, because they can efficiently represent data with smooth and sharp variations. In various studies, db1, db2, db4, bd5, db6, and db8, and db10 have been recommended mother wavelets for fault detection(K. Chen et al., 2016; Pothisarn et al., 2020; Saravanababu et al., 2013).

- Coiflet wavelets

They are a type of wavelet created by Ingrid Daubechies, designed to have scaling functions and wavelet functions with vanishing moments, both for the wavelet and its dual. This approach makes them particularly effective in applications where symmetry is important, such as signal processing(Wai Keng et al., 2013). According to (Gawali et al., 2015) coif5 is suitable for fault detection.

- Symlet wavelets

Symlet wavelets, developed as a variant of Daubechies wavelets, are mainly designed to provide a more symmetric wavelet function. This symmetry offers advantages in various feature extraction tasks, especially signal and image processing. A study

proved that symlet5 and symlet7 effectively extracted power band features from EEG signals (Mahmoodin et al., 2015).

- Biorthogonal wavelets

Biorthogonal wavelets use two related wavelet functions, one for decomposition and one for reconstruction. This biorthogonality provides greater design flexibility and offers advantages in symmetry and smoothness, making them highly effective for feature extraction applications, such as image compression. Commonly used biorthogonal wavelets include Bior 2.2, and Bior 3.9(K. Chen et al., 2016; K et al., 2021).

- Meyer wavelets

Meyer wavelet is an orthogonal wavelet introduced by Yve Meyer. It mainly has excellent frequency localisation and time properties. Additionally, it is known for its smooth and infinitely differentiable nature. The wavelet is well-suited for applications requiring detailed frequency analysis and signal reconstruction due to its ability to handle Fourier transform properties efficiently. From (Kankar et al., 2011) the Meyer wavelet was selected as a mother wavelet for feature extraction in fault diagnosis because this wavelet had the highest ratio of energy to Shannon entropy.

By sampling the scaling and shifting parameters, the DWT provides high time resolution at higher frequencies and high-frequency resolution at lower frequencies. The DWT functions as a filtering operation with a dyadic strategy, utilising down-sampling through the iterative Mallat algorithm.

A vital feature of the DWT is its ability to perform multi-level decomposition, known as Multi-Resolution Wavelet Analysis (MRWA). MRWA creates a decomposition tree using low-pass and high-pass wavelet filters, successively separating the signal into low-frequency (approximation) and high-frequency (detail) components. This hierarchical approach maintains good time and frequency resolution across various scales, making it highly effective for analysing signals at multiple resolutions. Figure 2.1 below illustrates the MRWA decomposition tree, demonstrating the multi-level filtering of low-frequency and high-frequency components.

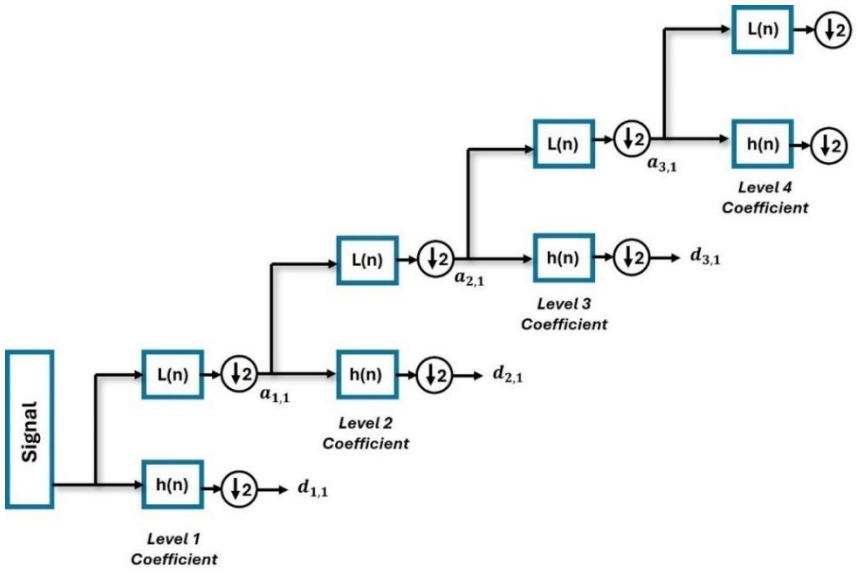


Figure 2.1 : Multi-level decomposition tree in Discrete Wavelet Transform.

The DWT's discretisation of scaling and translation parameters and efficient filtering operations make it a powerful tool for various signal-processing applications. Its multi-level decomposition capability through MRWA further enhances its utility, providing a comprehensive framework for detailed signal analysis.

2.2.3 Stationary Wavelet Transform

Wavelet transforms are potent tools for signal analysis that can be categorised into decimated and undecimated operations, depending on the type of wavelet transform (WT). Both types of WTs can simultaneously extract local spectral and temporal information, making them highly effective for various applications (Masood et al., 2017). Based on their operational types, WTs can be considered redundant. While redundancy may seem undesirable due to increased computational requirements, it is beneficial for detecting minor defects that might otherwise go unnoticed (Bayram & Şeker, 2017). Minor defects, or invisible faults, can cause significant damage if undetected.

The Stationary Wavelet Transform (SWT) is a popular method redundancy. Redundancy in signal processing and wavelet transform refers to preserving all original data points throughout the transformation process without any reduction or decimation. This approach has advantages and disadvantages, which are summarised in Table 2.2.

Table 2.2 : Advantages and disadvantages of redundancy in SWT (Bayram & Şeker, 2017; Nasser Mohamed et al., 2023; Şengüler, 2017).

Advantages	Disadvantages
Time-Invariant Analysis Preserves time-invariant properties, crucial for detecting and analysing transient changes and small defects.	*Increased Computational Load* Higher computational complexity compared to DWT due to processing all data points at each level.
Enhanced Fault Detection Provides detailed and accurate detection of subtle signal features by preserving all data points.	*Memory Usage* Increases memory usage due to the preservation of all data points at each level of decomposition.
Improved Signal Reconstruction Enhances the ability to reconstruct the original signal without any loss of information.	*Slower Processing Speed* Results in slower processing times, which can be a drawback in real-time applications or scenarios requiring quick analysis.
Effective for Transitory Signals Magnifies errors to characterize the properties of defective signals, making it useful for analysing small defects.	*Complexity* The additional computational steps can introduce complexity in implementation and analysis.

Unlike the Discrete Wavelet Transform (DWT), which is a decimated operation, the SWT is undecimated. In other words, SWT does not downsample the signal at each level of transformation, preserving the time-invariant structure and making it particularly useful for identifying transient changes and minor defects in signals (Nason & Silverman, 1995). Although SWT is computationally slower due to its redundancy, this property enhances its ability to detect instantaneous changes and transients, which are critical in many engineering applications (Yusuff et al., 2014). Additionally, it helps magnify errors and characterise the properties of defective signals.

SWT is recommended over DWT because of its capacity to maintain the time-invariant structure, which DWT loses due to downsampling (Bayram & Şeker, 2017). In contrast to the DWT, which involves a convolution process followed by decimation, the SWT skips the decimation step and up-samples filter coefficients at each transformation level. This process makes the SWT a translation-invariant modification of the DWT, producing a redundant representation not present in traditional Multi-Resolution Analysis (MRA) (Nason & Silverman, 1995). As a result, the SWT is also known as the undecimated wavelet transform, or "Algorithm à Trous" in French. Figure 2.1 illustrates the decomposition process of SWT, showing how the signal is divided into

low-frequency (approximation coefficients) and high-frequency (detail coefficients) components (Bayram & Şeker, 2017).

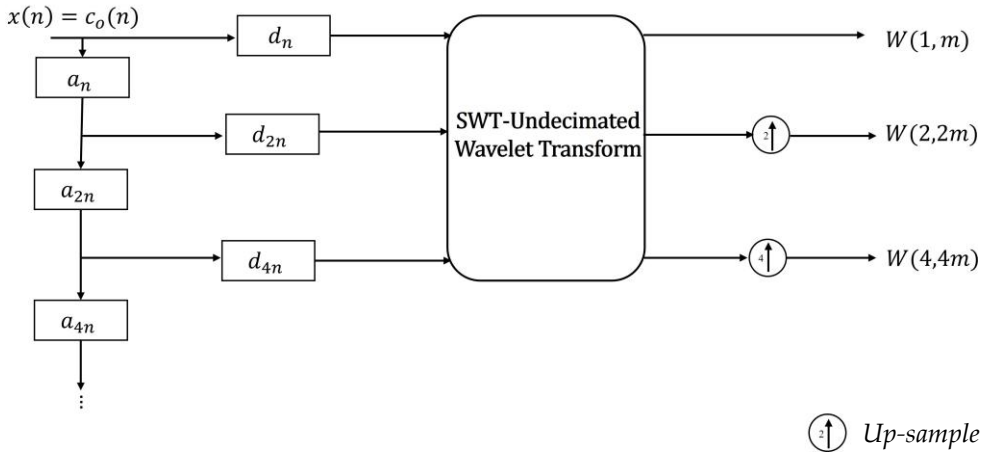


Figure 2.2 : Stationary wavelet transform block diagram.

Selecting the appropriate mother wavelet for effective use of WT is crucial and challenging, especially for characterising transient signals. The different types of mother wavelets in the literature are Haar, Coiflet, Daubechies, Symmlet, etc (Aleem et al., 2015; Gautam & Jhala, 2015; Martinez-Ríos et al., 2022; Masood et al., 2017). The most commonly used ones are Haar and Daubechies; however, when it comes to power system fault signals, therefore, Daubechies wavelet is the most suitable one(Aleem et al., 2015; Martinez-Ríos et al., 2022; Polat & Özerdem, 2018). Following that, the Daubechies mother wavelet makes the calculation short and fast for transient analysis(Bhowmik et al., 2009).

2.3 Machine Learning Techniques

Machine Learning (ML), a branch of Artificial Intelligence, is rapidly gaining ground in power engineering, particularly in fault classification(Gutierrez-Rojas et al., 2022). Integrating ML techniques can significantly enhance power systems' efficiency, reliability, and stability, especially in transmission lines. These techniques empower advanced data analysis and decision-making processes crucial for modern power systems' evolution. ML encompasses supervised learning (SL), unsupervised, semi-supervised, reinforcement, and deep learning (DL), as illustrated in Figure 2.3. Among these, SL and DL are extensively utilised in engineering applications.

Supervised learning (SL) and deep learning (DL) techniques offer powerful tools for various engineering applications, including fault detection, load forecasting, anomaly

detection, and fault classification (Fahim et al., 2021; Goswami & Roy, 2019; Shakiba et al., 2023). SL techniques like SVM, decision trees, and random forests are widely used for their interpretability and effectiveness in classification and regression tasks. On the other hand, DL techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long term-short memory (LSTMs) stand out with their advanced capabilities for handling complex data structures, making them indispensable in modern engineering solutions.

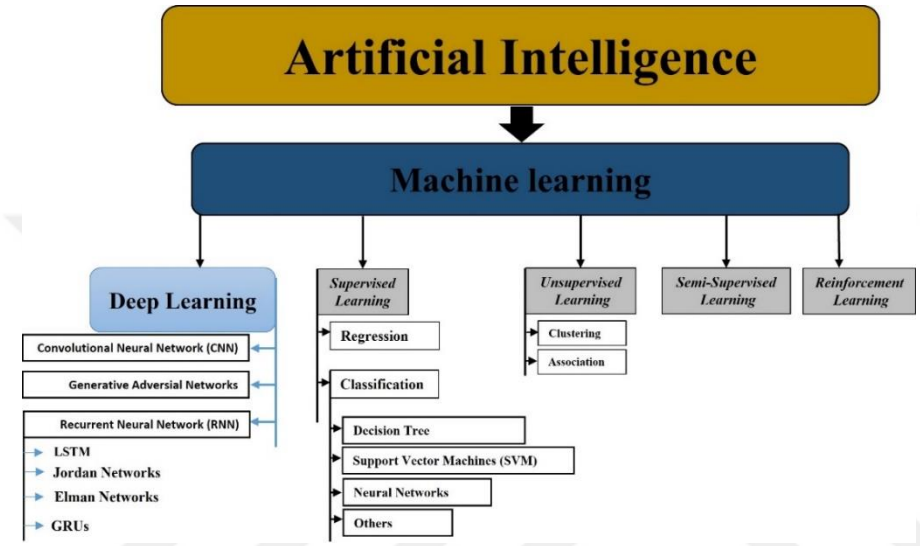


Figure 2.3 : Overview of Artificial Intelligence and Machine learning techniques.

In this study, Support Vector Machines (SVM), Decision Trees (DT), and Long Short-Term Memory networks (LSTM) will be utilised for fault classification due to their complementary strengths and capabilities, as detailed below.

2.3.1 Support vector machine (SVM)

Support Vector Machine (SVM), invented by Cortes and Vapnik in 1995, is a robust supervised learning algorithm widely used for classification and regression tasks(K. Chen et al., 2016). It is particularly effective in handling high-dimensional datasets, making it a popular choice for fault classification in transmission line faults(Shakiba et al., 2023). SVM has several advantages over other machine learning algorithms, including its speed and simplicity of implementation(Shakiba et al., 2023). Additionally, SVM is memory-efficient because it uses a subset of training points during validation.

SVM classifiers can be employed in various ways, including binary and multi-class classifications (Jodaei et al., 2024). These capabilities make SVM a versatile and efficient tool for numerous applications in transmission lines and beyond.

Classification using SVM involves training and testing data composed of numerous instances. Given a training dataset of n points (x_i, y_i), where $x_i \in R^d$ is the feature vector and $y_i \in \{-1,1\}$ is the class label, the SVM aims to find the optimal hyperplane that separates the two classes. The principle of SVM is illustrated in Figure 2.4 The hyperplane $g(x)$ is defined as follows (Awad & Khanna, 2015; Jodaei et al., 2024; Ramesh Babu & Jagan Mohan, 2017; Suthaharan, 2016b):

$$g(x) = w^T.x + b = 0 \tag{2.7}$$

Where w is the weight vector and b is the bias term. This hyperplane maximises the margin between the two classes, ensuring optimal separation and improving classification performance.

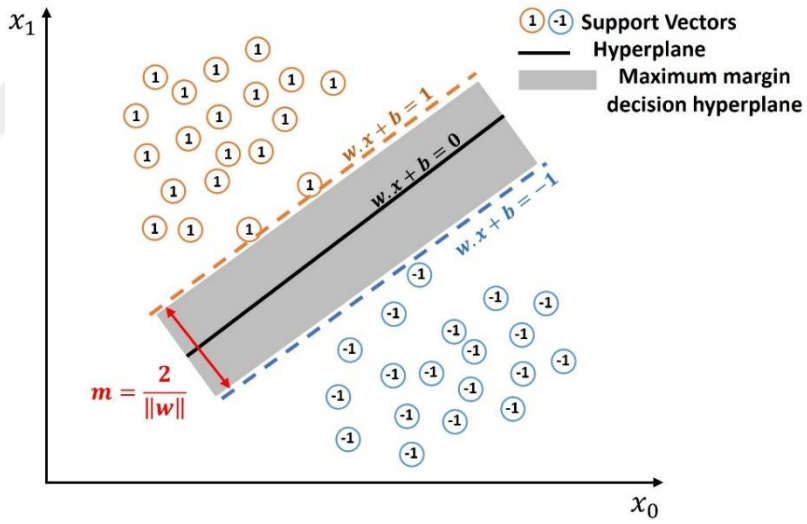


Figure 2.4 : Illustration of SVM classification (Shakiba et al., 2023; Q. Wang et al., 2021).

To classify the data points accurately, the SVM algorithm need to find the value of the parameters such as the weight vector and the bias term that result in the best separation of the classes in the training data. The best separation is achieved by maximising the margin m, which is the distance between the hyperplane and the nearest data point of each class. Maximising this distance leads to higher classification accuracies for the data points. The margin is defined as shown in the following (Ramesh Babu & Jagan Mohan, 2017):

$$m = \frac{2}{\|w\|} \tag{2.8}$$

To maximise m, the weight vector w should be minimised. For a given set of linearly separable data, this leads to the following optimization problem (Awad & Khanna, 2015; Ramesh Babu & Jagan Mohan, 2017; Suthaharan, 2016b):

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i \tag{2.9}$$

Subject to:

$$y_i(w.x_i + b) \geq 1 - \xi_i \qquad \xi_i \geq 0 \tag{2.10}$$

Where C is the cost parameter that controls the trade-off between maximising the margin and minimising the classification error, ξ_i is the slack variables, w is the weight vector, b is the bias term, x_i is the feature vectors of the training data points.

For nonlinear classification, SVM uses kernel functions to map the input features into a higher-dimensional space. Various kernel functions, such as linear kernel, polynomial kernel, Radial basis function (RBF), gaussian RBF kernel, and sigmoid kernel, are commonly used. The common kernel functions formulas as follows (Awad & Khanna, 2015; Hong et al., 2017; Jing & Zhang, 2010):

- Linear Kernel

$$K(x_i, x_j) = x_i.x_j \tag{2.11}$$

- Polynomial Kernel

$$K(x_i, x_j) = ({x_i}^T.x_j + c)^d \tag{2.12}$$

- Radial basis function (RBF) Kernel

$$K(x_i, x_j) = \exp\left(\gamma\left\|x_i - x_j\right\|^2\right) \tag{2.13}$$

- Gaussian RBF Kernel

$$\gamma = \frac{1}{2\sigma^2} \tag{2.14}$$

$$K(x_i, x_j) = \exp\left(\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{2.15}$$

- Sigmoid kernel

$$K(x_i, x_j) = \tanh\left(\gamma\left(x_i{}^T . x_j + c\right)\right) \tag{2.16}$$

Where x_i and x_j are the feature vectors of two data points, $\|x_i - x_j\|^2$ is the squatted Euclidean distance between the two feature vectors, c is the bias term, d is the degree of the polynomial, γ is a parameter that determines the width of the Gaussian function, and σ is the standard deviation of the Gaussian function.

A flowchart can visualise the steps involved in the classification process to provide a clearer understanding of how the SVM algorithm operates. This flowchart, shown in Figure 2.5, outlines the sequence of operations, from data preprocessing to model training, validation, and evaluation, by calculating the performance metrics, ensuring a comprehensive overview of the SVM classifier algorithm.

The performance metrics are used to evaluate any ML classifiers, including SVM. These performance metrics include (Al Kharusi et al., 2022; Kharusi et al., 2023):

- **Accuracy**

Accuracy is the most widely used performance metric. It is measured by the proportion of correctly classified instances out of the total instances, indicating the overall correctness of the model. The following formula defines it:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2.17}$$

Where:

TP (*True Positives*): Correctly classified positive instances.

TN (*True Negatives*): Correctly classified negative instances.

FP (*False Positives*): Incorrectly classified negative instances as positive.

FN (*False Negatives*): Incorrectly classified positive instances as negative.

- **Precision**

Precision is the proportion of true positive instances out of the predicted ones. It measures the accuracy of the positive predictions made by the model. It is formally defined as follows:

$$Precision = \frac{TP}{TP + FP} \tag{2.18}$$

- **Recall**

Recall measures the proportion of correctly classified positive instances out of all actual positive instances. It is also known as the true positive rate (TPR) or sensitivity. It is formally defined as follows:

$$Recall = \frac{TP}{TP + FN} \tag{2.19}$$

- **F1 Score**

The F1 Score is the harmonic mean of precision and recall, balancing the two metrics. It is formally defined as follows:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{2.20}$$

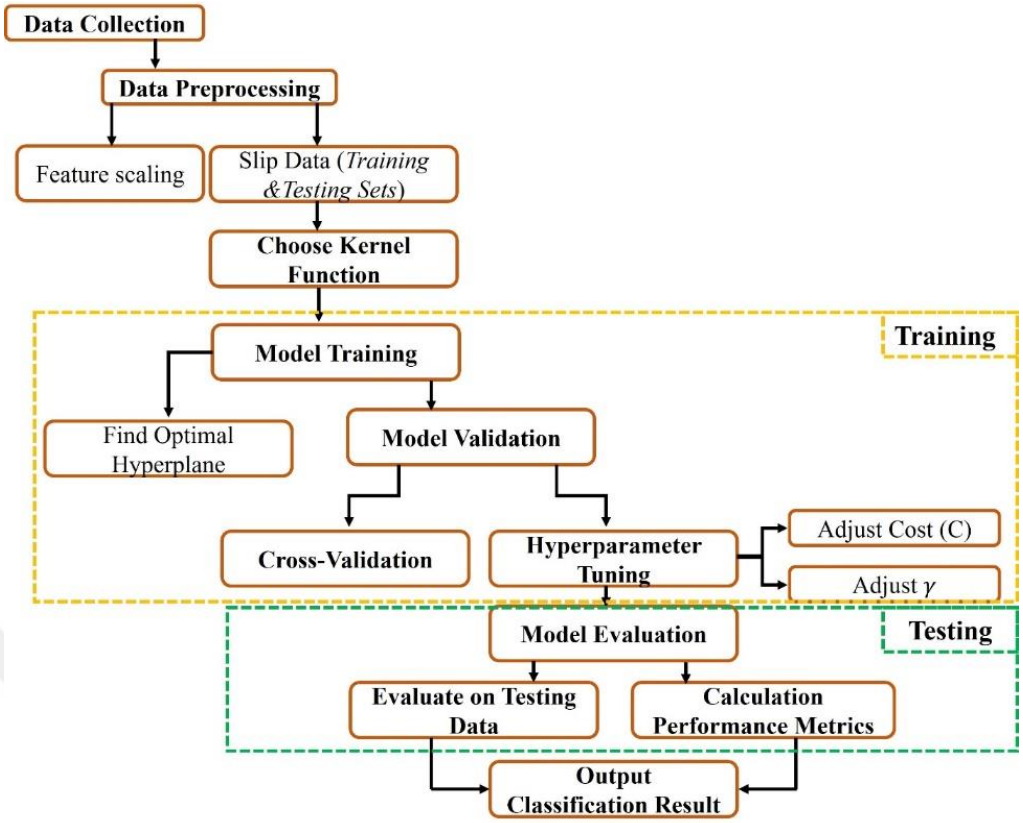


Figure 2.5 : Flowchart of the SVM classifier algorithm.

To achieve optimal model performance, the hyperparameters, especially C and γ, must be carefully tuned. This tuning is often done using techniques such as cross-validation to find the best combination of C and γ that minimises the validation error (Jodaei et al., 2024).

The Radial Basis Function (RBF) kernel and the Gaussian RBF kernel are essentially the same, with different parametrisations. Both are widely used in SVMs for their ability to handle nonlinear data and create smooth decision boundaries by mapping the data into an infinite-dimensional space (Ramesh Babu & Jagan Mohan, 2017). The Gaussian RBF kernel has performed best in most experiments (Jing & Zhang, 2010).

2.3.2 Decision Tree (DT)

Decision Tree (DT) is one of the commonly used algorithms for classification and regression tasks. It offers several advantages, including flexibility, a nonparametric nature, and the capability to handle nonlinear relationships between features and classes. Its ease of interpretation, understanding, and visualisation makes it particularly useful for decision-making (Navada et al., 2011). The DT algorithm uses a top-down approach called recursive splitting. This process involves breaking down the dataset

into smaller subsets while building the decision tree incrementally. The critical components of a Decision Tree (DT) are illustrated in the following sections, where Figure 2.6 depicts the structure of a Decision Tree (Asman et al., 2021; SONG & LU, 2015; Tîrnovan & Cristea, 2019):

- **Root Node**

The starting point of the decision tree that represents the entire dataset. The first split occurs in the root node based on the most significant feature.

- **Branches**

These connectors between nodes represent the decision pathways based on feature values. A decision tree model is formed using a hierarchy of branches. Branches lead from the root node to decision nodes and from decision nodes to leaf nodes.

- **Decision nodes**

There are internal nodes where decisions are made based on the values of features. Each decision node splits the dataset into subsets based on a specific feature and threshold.

- **Leaf nodes**

Terminal nodes that provide the final classification or regression outcome. Each leaf node represents a class label in classification tasks or a value in regression tasks.

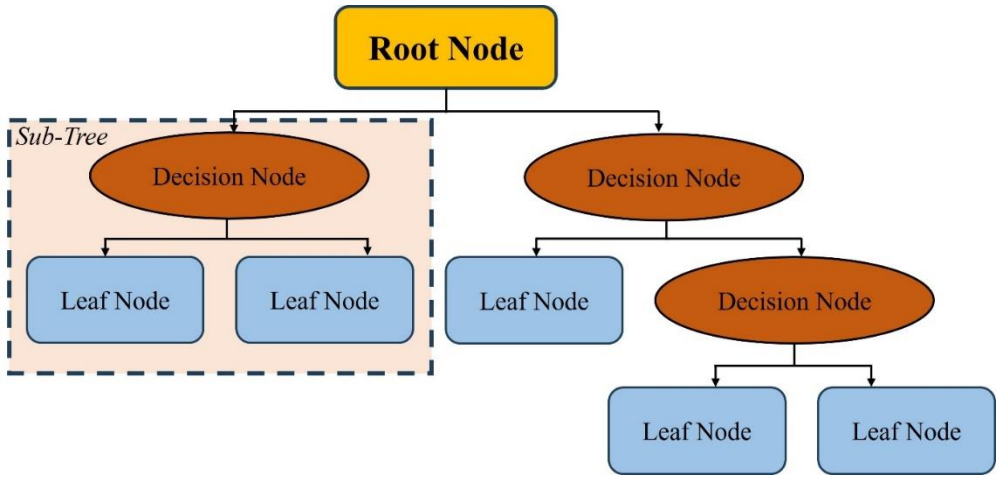


Figure 2.6 : The structure of a Decision Tree (DT) (Asman et al., 2021; Charbuty & Abdulazeez, 2021).

Various DT algorithms exist, each with unique characteristics and applications. Some of the most well-known DT algorithms include Iterative Dichotomizer 3 (ID3), the

successor of ID3 (C4.5), and Classification and Regression Trees (CART) (Charbuty & Abdulazeez, 2021).

As mentioned above, decision trees are constructed by recursively partitioning the dataset into subsets based on feature values. The choice of splitting at each node is driven by specific criteria designed to maximise the purity of the resulting subsets. Common splitting criteria, depending on the type of DT algorithm used, include Gini Impurity, entropy, and information gain parameters.

The Gini Impurity, also known as the Gini Index, is a measure used to evaluate splits in the dataset. It represents the likelihood of incorrect classification of a randomly chosen element if it was randomly classified according to the distribution of the class labels in the dataset. In the context of machine learning, particularly with the CART (Classification and Regression Tree) algorithm, the Gini index is used to measure the impurity of a node (Lu et al., 2022). CART is one of the most commonly used decision tree algorithms and can be employed for classification and regression tasks.

In the context of a classification tree, the Gini impurity is used to select the optimal feature and determine the best binary split point. The algorithm constructs a binary tree, where each node has at most two child nodes. This recursive structure can either be empty or consist of a single node with left and right pointers to two sub-trees.

For a given dataset D, if there are N classes and p_k represents the probability that a sample belongs to the k_{th} class, the Gini Impurity is calculated as follows (Lu et al., 2022; Suthaharan, 2016a):

$$FG(D) = 1 - \sum_{k=1}^{N} p_k(1 - p_k) = 1 - \sum_{k=1}^{N} {p_k}^2 \tag{2.21}$$

Where is the probability of the k_{th} class.

Information gain is another common splitting criterion and an important criterion for the ID3 algorithm. ID3 (Iterative Dichotomiser 3), developed by Ross Quinlan in 1986, is a classical algorithm used to generate a decision tree from a dataset. ID3 is a foundational algorithm in the field of machine learning and serves as the basis for more advanced algorithms like C4.5 and C5.0. It is primarily used for classification tasks, where the aim is to assign categorical labels to input data based on feature values.

The operation principle of ID3 involves starting with the root node and selecting the best attribute that best classifies the training data by measuring Information Gain (IG). IG measures the reduction of entropy (disorder) achieved by partitioning the data based on the attribute. Entropy measures the uncertainty in the dataset E, and it is defined as follows (Charbuty & Abdulazeez, 2021; Suthaharan, 2016a):

$$Entropy(E) = \sum_{i=1}^{c} p_i log_2(p_i) \quad (2.22)$$

Where p_i is the proportion of instances belonging to class i in set E.

Information Gain IG is the difference between in entropy before and after splitting the dataset on an attribute A.

$$Information\ Gain\ (E, A) = Entropy(E) - \sum_{v \in A} \frac{|E_v|}{|E|} Entropy(E_v) \quad (2.23)$$

Where E_v is the subset of E where attribute A has value v.

Pruning is a crucial technique used to enhance the performance and generalisation of decision trees by reducing their complexity. It helps prevent overfitting, which occurs when a decision tree becomes too complex and starts to capture noise in the training data rather than the underlying patterns. There are two main types of pruning: pre-pruning and post-pruning (Lu et al., 2022).

Pre-pruning, also known as early stopping, involves halting the growth of the decision tree at an early stage based on predefined criteria. These criteria may include reaching a maximum depth, having a minimum number of samples required to split a node, or ensuring a minimum gain in purity to justify a split. The advantages of pre-pruning include preventing the tree from becoming overly complex and overfitting the training data, leading to more straightforward and more interpretable trees. Additionally, pre-pruning saves computation time by avoiding unnecessary splits. However, the disadvantages are that stopping the tree's growth too early might result in a model that is too simple to capture the underlying patterns in the data, leading to underfitting. Moreover, the effectiveness of pre-pruning heavily depends on the choice of stopping criteria, which might be challenging to set optimally for all datasets.

On the other hand, post-pruning involves allowing the decision tree to grow to its full extent and then pruning back nodes that provide little to no additional predictive

power. Common methods of post-pruning include cost-complexity pruning, which evaluates the performance of subtrees and selects the optimal balance between complexity and accuracy. The advantages of post-pruning are that it helps improve the model's ability to generalise to new data by removing nodes that do not contribute significantly to predictive performance. This allows the tree to be as complex as needed initially and then prunes it back to the optimal size, ensuring that essential patterns are noticed. As a result, post-pruning often leads to a more accurate and reliable model than unpruned trees. However, the disadvantages include the fact that growing the entire tree and then pruning it back can be computationally more expensive than pre-pruning. Additionally, the process requires a validation set or cross-validation, which can be resource-intensive and may not always be available.

In conclusion, choosing the appropriate pruning type significantly impacts decision tree models' performance and interpretability. Pre-pruning can prevent overfitting and save computation time but risks underfitting. Although more computationally intensive, post-pruning often results in better generalisation and model performance. Understanding and applying the proper pruning technique can make decision tree models more effective and reliable for various machine-learning tasks.

2.3.3 Long Short-Term Short Memory network (LSTM)

An LSTM (Long Short-Term Memory) is a specialised type of recurrent neural network (RNN), which itself is a subset of deep neural networks (DNNs). RNNs extend the capabilities of traditional artificial neural networks (ANNs) by introducing loops in the network, allowing them to maintain and utilise information across different time steps. RNNs are particularly powerful for sequential data tasks, such as time series analysis and natural language processing. LSTM networks enhance RNNs by incorporating memory cells and gates that manage the flow of information, addressing issues like the vanishing and exploding gradient problems commonly encountered in standard RNNs (Belagoune et al., 2021; Moradzadeh et al., 2022).

A single LSTM unit consists of four primary components: the forget gate f_t, the input gate i_t, the output gate o_t, and a memory cell, where $c_t \in R^{d_t \times 1}$. These gates work together to regulate the flow of information within the unit, allowing the network to maintain and utilise long-term dependencies effectively. Figure 2.7 illustrates the

structure and the flow of information in an LSTM cell, highlighting the interactions between these components.

The LSTM cell receives the previous hidden state h_{t-1} and the current input x_t. These inputs are concatenated and passed through the various gates. Each gate has an activation function and uses the input weight W and the recurrent weight , which correspond to the current input and the previous hidden state, respectively. This structure allows each gate to effectively regulate the information flow based on the current input and the previous hidden state (Gonzalez, 2018).

The forget gate f_t first decides which parts of the previous cell state c_{t-1} should be retained or forgotten, using the sigmoid activation function σ. The forget gate is calculated as follows (P. Agarwal et al., 2022; Rafique et al., 2021):

$$f_t = \sigma\left(W_f \cdot x_t + U_f \cdot h_{t-1} + b_f\right) \tag{2.24}$$

Where the sigmoid function is defined as(Gonzalez, 2018):

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{2.25}$$

Next, the input gate i_t and the cell candidate $\tilde{c}_t$ determine which new information should be added to the memory unit. The input gate uses the sigmoid activation function and is calculated as follows (P. Agarwal et al., 2022; Rafique et al., 2021):

$$i_t = \sigma(W_i \cdot x_t + U_i \cdot h_{t-1} + b_i) \tag{2.26}$$

The cell candidate $\tilde{c}_t$ generates new candidate value using the hyperbolic tangent function, calculated as follows(P. Agarwal et al., 2022; Belagoune et al., 2021):

$$\tilde{c}_t = tanh(W_c \cdot x_t + U_c \cdot h_{t-1} + b_c) \tag{2.27}$$

Where the hyperbolic tangent function is defined as(Gonzalez, 2018):

$$tanh = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{2.28}$$

The memory unit c_t is the updated by combining the previous memory unit (modulated by the forget gate) and the new candidate value (modulated by the input gate), which is given by (P. Agarwal et al., 2022; Rafique et al., 2021):

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \tag{2.29}$$

This step integrates the retained past information with the new information, updating the cell state to hold relevant data for future time steps.

Finally, the output gate o_t determines what part of the updated memory unit should be output as the hidden state. This is calculated as (Moradzadeh et al., 2022; Rafique et al., 2021):

$$o_t = \sigma(W_o \cdot x_t + U_o \cdot h_{t-1} + b_o) \tag{2.30}$$

The hidden state h_t is then computed by applying the output gate to the updated memory unit, given by (P. Agarwal et al., 2022; Moradzadeh et al., 2022):

$$h_t = o_t \circ \tanh(c_t) \tag{2.31}$$

Where $\{W_f, W_i, W_c, W_o\}$ are the weight matrices for the current input x_t, $\{U_f, U_i, U_c, U_o\}$ are the weight matrices for the previous hidden state h_{t-1}, $\{b_f, b_i, b_c, b_o\}$ are the bias terms, and the symbol $\circ$ denotes the Hadamard product, indicating that the operations are performed element-wise.

The hidden state h_t serves as the output of the LSTM unit for the current time step and as input to the LSTM unit at the next time step. Following this process, the LSTM cell effectively manages and utilises long-term dependencies, making them highly effective for a wide range of sequential data tasks, including time series prediction, natural language processing, classification, speech recognition, and anomaly detection (P. Agarwal et al., 2022; Gonzalez, 2018).

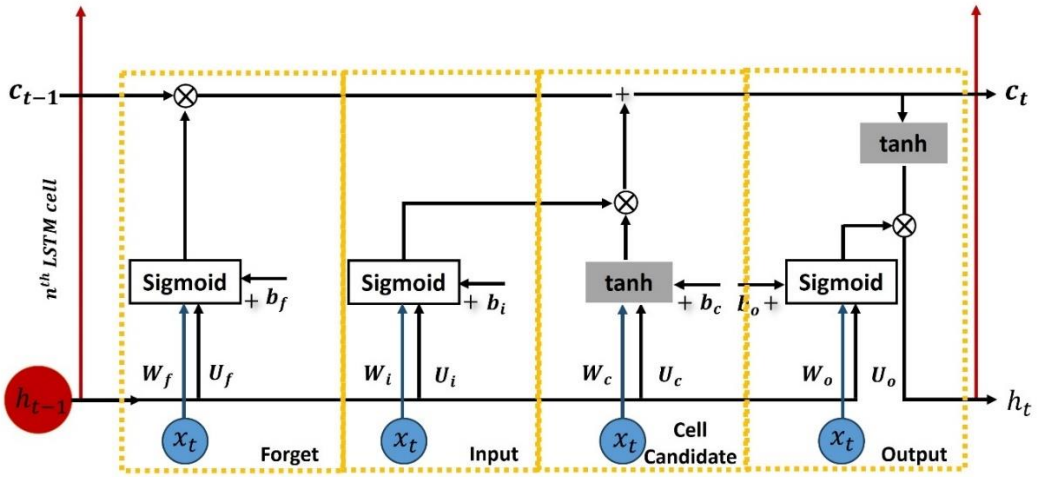


Figure 2.7 : Detailed architecture of a LSTM cell(Belagoune et al., 2021; Moradzadeh et al., 2022; Rafique et al., 2021).

3. DJIBOUTI POWER SYSTEM MODELLING

Djibouti, also known as the Republic of Djibouti, is a small country covering 23,000 km² located on the Horn of Africa, specifically at a latitude of 11.7913° North and a longitude of 42.8796° East, with an elevation of 4 meters above sea level. Its strategic location makes it a vital hub and positions it among the top African countries with high energy potential. Since 1960, Electricité de Djibouti (EDD) has been the primary provider managing the generation, transmission, and distribution of electricity not only within the city but also across regions including Ali-Sabieh, Arta, Dikhil, Obock, and Tadjourah. In 2021, EDD served approximately 73,200 customers, playing a crucial role in distributing electricity and supporting the nation's development. The frequent power cuts a few years ago was particularly problematic during the hot summers when temperatures could reach 45°C, highlighted the challenges in the energy sector and underscored the importance of addressing energy reliability.

Turning to more recent developments, from 2003 to 2022, Djibouti experienced significant electricity production growth, increasing from 270 GWh to 628.45 GWh, as shown in Figure 3.1. This growth is primarily attributed to the Djibouti-Ethiopia interconnection, which enables Djibouti to import substantial electricity from Ethiopia. This strategic partnership has greatly enhanced Djibouti's energy capacity, effectively meeting the rising demand and significantly contributing to the nation's energy security. Despite this growth, Djibouti needs more local power generation capacity. Previously, the country's fuel power plants operated at a capacity of 130 MW, but due to the unreliability of ageing generators, this has been reduced to 60 MW(Aye, 2009; Guelleh et al., 2023). This reduction has created significant dependence on Ethiopian energy, making Djibouti heavily reliant on imports to meet its electricity needs. This dependency underscores the strategic importance of the interconnection but also highlights the vulnerability of relying too heavily on external energy sources.

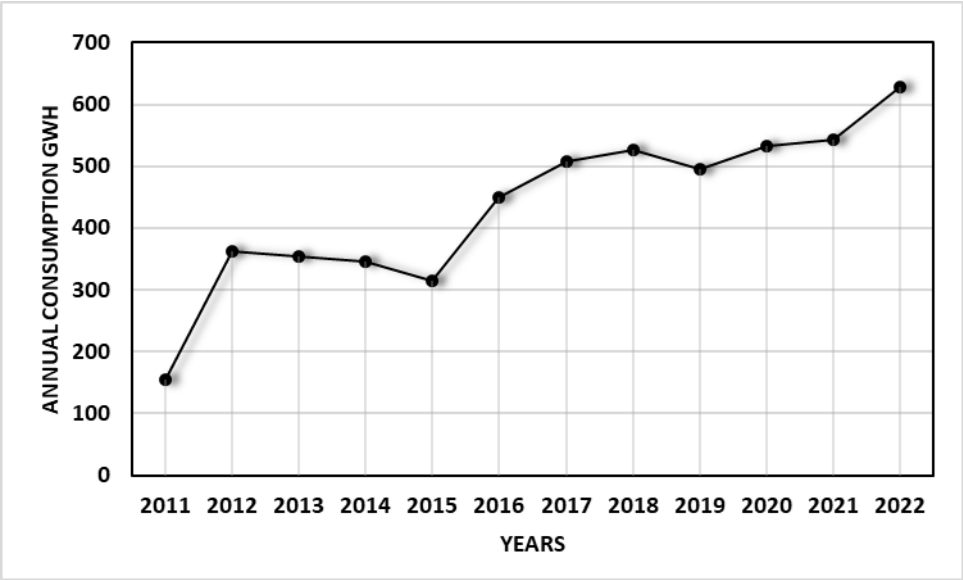


Figure 3.1 : The Djibouti annual electrical consumption in GWh.

Djibouti's population of approximately one million people experiences an electrification rate of 55%. However, ambitious plans are to increase this rate to 100% by 2035 as part of Djibouti's commitment to sustainable development. These plans include the construction of a 30 MWp solar photovoltaic power plant in Grand Bara and a 60 MW wind farm in Ghoubet (Isman Okieh et al., 2023; Wone, 2023). These initiatives mark a pivotal shift from Djibouti's reliance on imported fossil fuels and interconnected power from Ethiopia to embracing renewable energy sources like solar and wind power. These projects aim to dramatically improve national electrification and foster socio-economic development, potentially increasing the country's overall power generation capacity by approximately 75% because the energy consumed in summer is around 115 MW and in winter 67.5 MW in 2022. In a recent development, the wind farm project was inaugurated in September 2023, marking a significant milestone in Djibouti's energy sector.

A significant portion of energy loss in Djibouti is attributed to non-distributed energy resulting from unplanned outages, predominantly caused by instabilities and failures in the power system. Notably, about 80% of these failures originate from transmission and distribution network faults. Although the system in Djibouti can effectively retain its integrity when faced with a single-phase short circuit, it encounters difficulties in handling three-phase short circuits, frequently resulting in voltage collapses. Therefore, it is essential to model and simulate the power system to comprehend its response in different scenarios and improve its ability to withstand such failures.

3.1 Power Grid Description

Djibouti relies on a single state-owned utility, Electricity of Djibouti (EDD), established on January 21, 1960. EDD holds a legal monopoly on the transportation and distribution of electricity throughout the country. The Djibouti power grid combines the fuel and hydropower plants, which Ethiopia supplies through the interconnection agreement, as shown in Figure 3.2. Figure 3.2 illustrates two main lines connecting Ethiopian cities Hurso and Adagala to Djibouti. The distances between the lines are approximately 296,4 km and 165.4 km (Table 3.1). The lines from Hurso and Adagala to Jaban'as station are 230 kV, and several voltage transformations occur. The lines are routed to other stations using two 230/63 kV transformers and 50/63 MVA with two types of cooling (ONAN/ONAF). Over the line, each station has the following equipment: a manual line disconnector, earthing switch, a shunt reactor, circuit breaker, busbar disconnector, current transformer, and voltage transformer. Substations include the Ali-Sabieh interconnection, AL-Bawadi, Doraleh, and railway stations (Nagad, Hol-Hol, and Ali-Sabieh).

Additionally, it depicts the grid in Djibouti city, where two fuel power plants in Boulaos and Marabout station are the primary facilities. Boulaos station was the first to be constructed in 1976 and includes about 12 Diesel generators with capacities ranging from 5 to 14 MW. In the past, Boulaos and Marabout power plant stations generated a combined total of 113 MW of electricity, with smaller-scale production occurring in districts such as Tadjourah, Dikhil and Obock, which contribute around 10 MW together. Additionally, the utility's infrastructure consists of five primary independent fuel power plants collectively used to enhance the nation's energy capacity and stability.

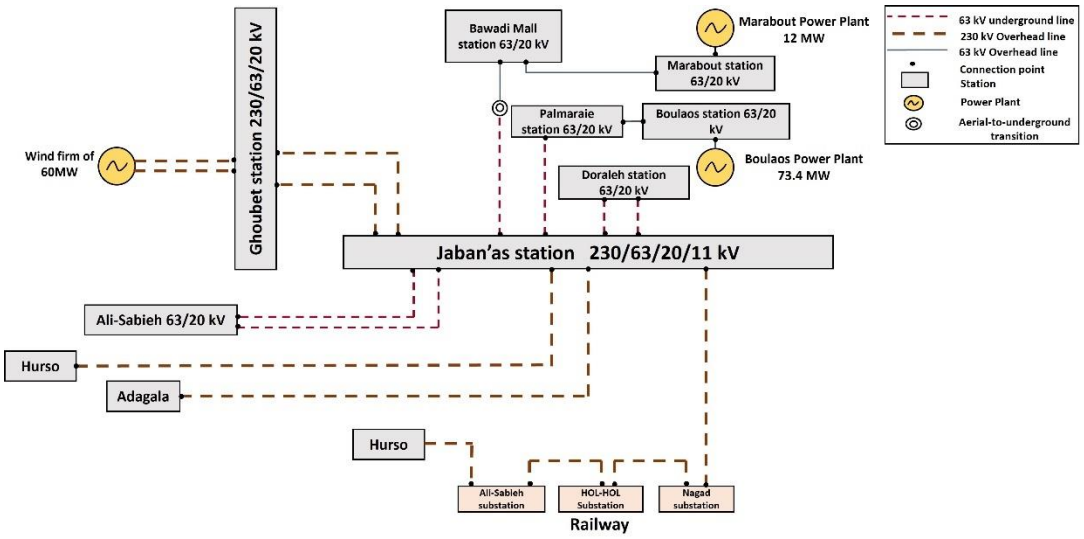


Figure 3.2 : Simplified block diagram of the Djibouti Power Grid.

With the increase in consumption that Djibouti populations experienced, EDD could not anymore handle the increase in energy demand. A significant boost to the power supply comes from the Ethiopian interconnection project, officially inaugurated in October 2011, which allowed for the importation of 315 MW. This interconnection runs through a double line of 230 kV reaching Jaban'as station, where it is managed by two step-down transformers that convert 230 kV to 63 kV, alongside other transformers for 63/20 kV and 63/11 kV conversions. Initially, power in Djibouti was primarily generated by diesel generators at Boulaos and Marabout stations, where the initial voltages of 5.5 kV and 15 kV are stepped up to 20 kV and 63 kV respectively. This substantial evolution from the early limitations to a more robust and interconnected energy network marks significant progress in ensuring better energy security and efficiency for Djibouti.

The transmission and distribution network includes six stations: Jaban'as, Boulaos, Palmaraie, Doraleh, Marabout, and Ali-Sabieh, located in the city and districts, as shown in Figure 3.3. Notably, the Boulaos and Marabout stations serve dual roles in generation and distribution. Most distribution networks operate at 20 kV, with 90% of the lines underground, while most transmission lines are overhead. The MATLAB/SIMULINK model of the Djibouti power grid is constructed using technical data that includes parameters transformers (from table 3.1), transmission lines and voltage levels at stations (from table 3.2).

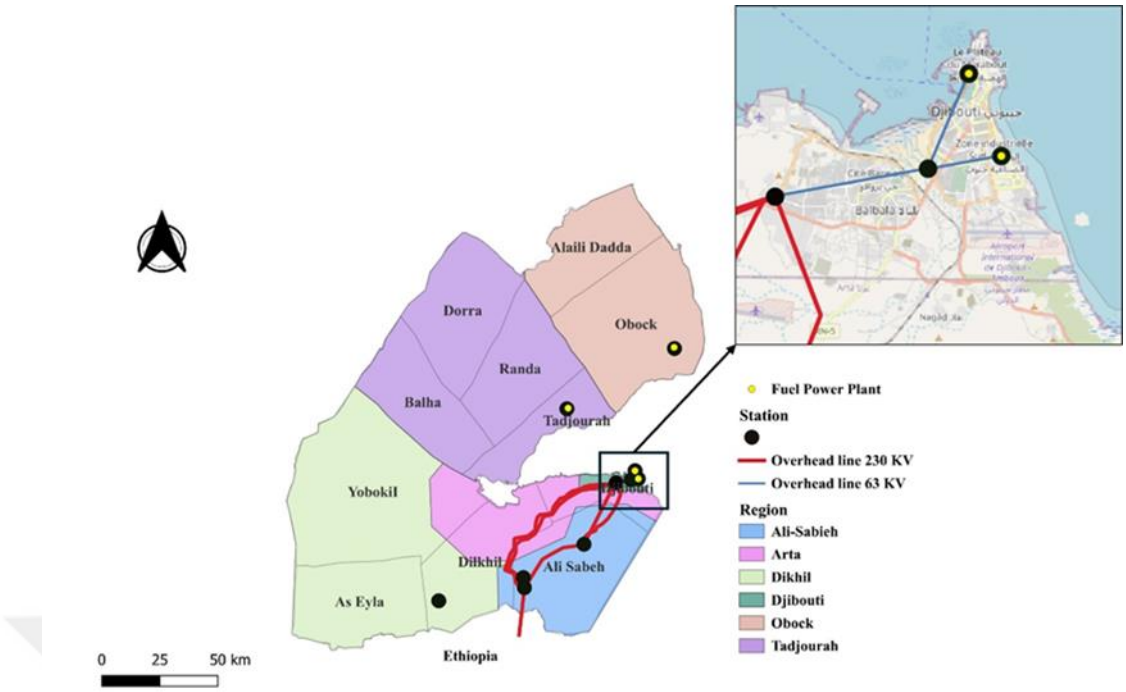


Figure 3.3 : The Djibouti electrical grid configuration map

Table 3.1 : Transformers parameters used in the different stations of Djibouti Power system.

Name	Sending-node	Receiving-node	Voltage ratio kV	Rated Power MVA	% Cu losses	Leakage Impedance [%]
Al-Bawadi	ALBAW_63	ALBAW_20	63/20	12	0.23616	7.56
Ali-Sabieh	ALISAB_63	ALISAB_20	63/20	12	0.23616	7.56
Boulaos	BOULA_63	BOULA_20	63/20	36	0.74952	17
Doraleh	DORA_63	DORA_20	63/20	40	0.74952	17
Jaban'as	JABA_230	JABA_63	230/63	63	0.38997	12.5
Jaban'as	JABA_230	JABA_63	230/63	63	0.38997	12.5
Jaban'as	JABA_230	JABA_63	230/63	63	0.38997	12.5
Marabout	MARAB_63	MARAB_20	63/20	40	0.74952	17
Palmaraie	PALME_63	PALME_20	63/20	40	0.74952	17
TS-Nagad	NAGAD_230	NAGAD_27.5	230/27.5	25	0.39007	8.21
TS-Holhol	HOL_230	HOL_27.5	230/27.5	25	0.39007	8.21
TS-Alisabieh	TSALISAB_230	TSALISAB_27.5	230/27.5	25	0.39007	8.21

Table 3.2 : Transmission line parameters used in Djibouti grid.

Line	Sending-node	Receiving-node	Nominal Voltage kV	Rated Power	Length	Type of line (OHL/UGC
21PK12 6-690PALME-1	JABA_63	690PALME-1	63	72	9	OHL
690PALME-1 ALBAW_63-1	690PALME-1	ALBAW_63-1	63	72	1.8	UGC
HURSO-JABAN_230-1	HURSO-	JABAN_230-1	230	200	296.4	OHL
ADAGALA-JABAN_230-1	ADAGALA-	JABAN_230-1	230	200	165.4	OHL
JABA_DORA_63-1	JABA_63	DORA_63-1	63	72	3.5	OHL
TS_NAG_230-1 TS_HOL_230-1	TS_NAG_230-1	TS_HOL_230-1	230	200	30	OHL

Table 3.2 (continued) : Transmission lines parameters used in Djibouti grid.

Line	Sending-node	Receiving-node	Nominal Voltage kV	Rated Power	Length	Type of line (OHL/UGC
JABA_DORA_63-1	JABA_63	DORA_63-1	63	72	3.5	OHL
TS_NAG_230-1 TS_HOL_230-1	TS_NAG_230-1	TS_HOL_230-1	230	200	30	OHL
TS_HOL_230-1 TS_ALIS_230-1	TS_HOL_230-1	TS_ALIS_230-1	230	200	32.5	OHL
BOUL-PALM_63_UGC-1	BOUL-	PALM_63_UGC-1	63	72	5	UGC
BOUL-MARAB_63_UGC-1	BOUL-	MARAB_63_UGC-1	63	72	4.5	OHL
JABAN_230-1 ALIS_230-1	JABAN_230-1	ALIS_230-1	230	200	78	OHL
JABAN_230-1 TS_NAG_230-1	JABAN_230-1	TS_NAG_230-1	230	200	7	OHL

3.2 Power Grid Modelling

MATLAB SIMULINK provides a graphical programming environment ideal for modelling, simulating, and analysing multi-domain dynamical systems such as power grids. It features a user-friendly visual drag-and-drop interface, a comprehensive library of pre-built blocks specifically for electrical systems, and seamless integration with MATLAB for advanced data analysis and visualisation. SIMULINK's capabilities extend to multi-domain simulation, real-time simulation, and model-based design, making it highly effective for thorough simulations of power grid systems. Its automated code generation and hardware-in-the-loop simulations are precious for efficiently developing and testing complex control strategies, which helps shorten development cycles and enhance system reliability and performance.

Using the simplified diagram (Figure 3.2) and the Djibouti power grid data (Table 3.1 and 3.2), the system modelling can be presented using MATLAB/SIMULINK in Figure 3.4. This study chose a discrete time domain with a 50 μs sampling period over a continuous simulation model due to the excessive computational time required by the latter. Using a finer sampling interval allows the discrete model to approximate the behaviour of the continuous system more closely, which is crucial for accurately capturing fast transients and high-frequency dynamics that are essential for a reliable model.

The Djibouti power system model incorporates several key SIMULINK blocks:

- Three-phase voltage source connected in series with an RL branch block: Represents the generation sources.
- Three-phase V-I measurement block: Used for busbar monitoring.
- Transmission lines modeled with three-phase PI section line blocks: Represent the transmission infrastructure.
- Three-phase breaker block: Facilitates system isolation and protection.
- Transformers represented by three-phase, two-winding blocks: Reflect the transformation of voltage levels.
- Loads modeled using three-phase Series RLC blocks: Simulate the power consumption.

These components are interconnected to accurately simulate the interconnected power network of Djibouti. The simulation's stopping time was 0.2 sec, and the 3-phase fault occurred at $1/60$s with a fault resistance $R_{on} = 0.01\Omega$, ground resistance $R_g = 0.01\Omega$, and snubber resistance $R_s = 1e6\ \Omega$.

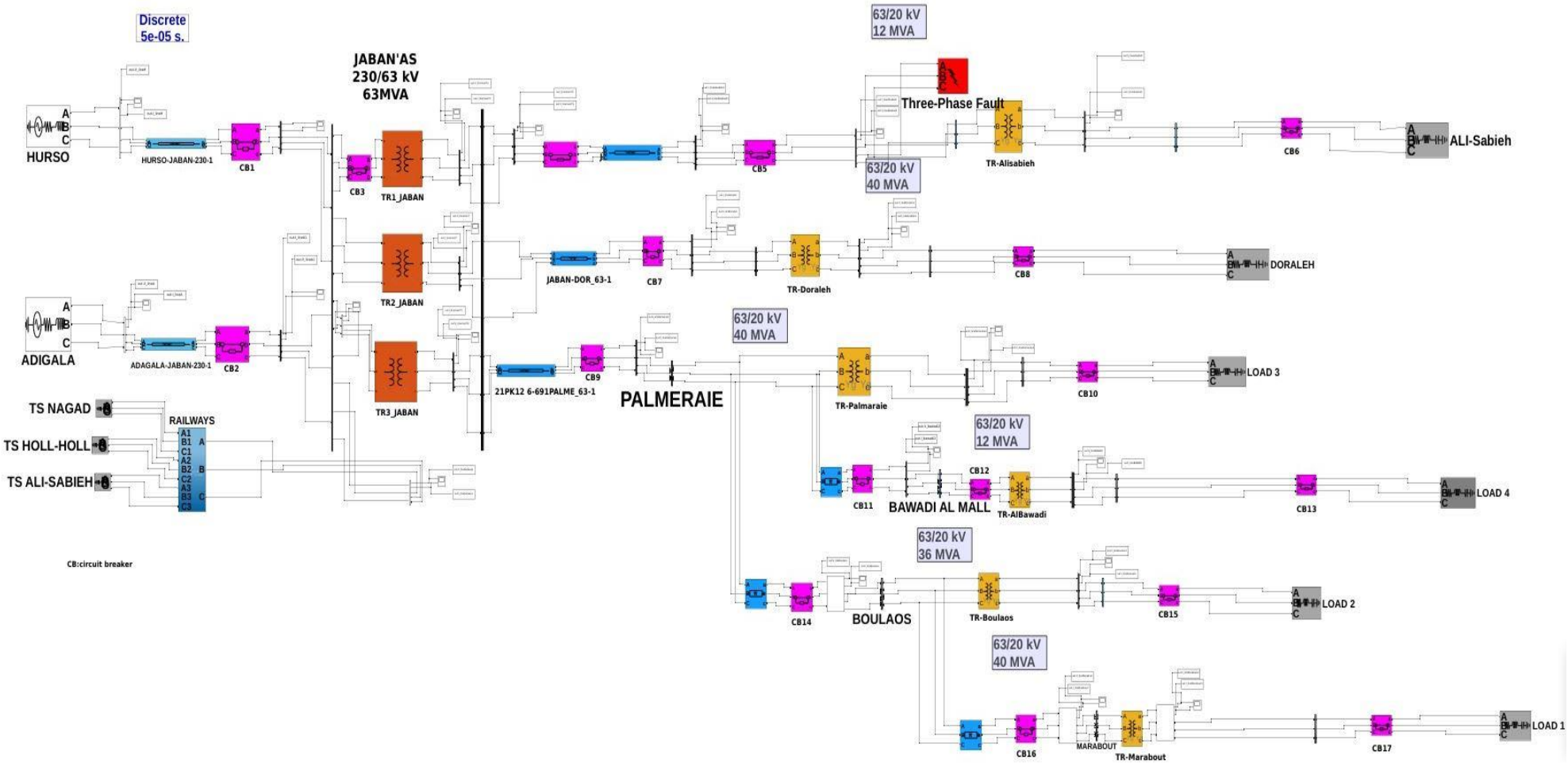


Figure 3.4 : A MATLAB/SIMULINK model of the Djibouti power system.

4. APPLICATIONS OF MATHEMATICAL METHODS FOR FAULT DETECTION AND THEIR RESULTS

The Djibouti power grid model, detailed in Figure 3.4, is used as a case study in this research. The modelling and simulation were performed using MATLAB/SIMULINK, employing a discrete-time approach with a 50 μs sampling period for efficiency. The study's stopping time was at 0.2 sec, and the 3-phase fault occurred at $1/60$s with specific fault resistances such as fault resistance $R_{on} = 0.01\Omega$, ground resistance $R_g = 0.01\Omega$, and snubber resistance $R_s = 1e6\ \Omega$.

The Djibouti power system model simulates a short circuit under various scenarios. To simulate short circuit conditions, three-phase faults were implemented in the line between Jaban 'as and Ali-Sabieh (JABAN 63-1 and ALIS 20-1). Table 4.1 below depicts the eleven fault categories: single-line-to-ground, double-line-to-ground, three-phase, three-phase-to-ground, and line-to-line faults.

Table 4.1 : Fault type classification in power system.

Fault type	Phase A	Phase B	Phase C	Ground G
A-G	**1**	0	0	**1**
B-G	0	**1**	0	**1**
C-G	0	0	**1**	**1**
A-B	**1**	**1**	0	0
B-C	0	**1**	**1**	0
A-C	**1**	0	**1**	0
AB-G	**1**	**1**	0	**1**
BC-G	0	**1**	**1**	**1**
AC-G	**1**	0	**1**	**1**
ABC	**1**	**1**	**1**	0
ABC-G	**1**	**1**	**1**	**1**

The simulation results are obtained for all fault conditions, but those shown in Figure 4.1 are Phase A to ground (A-G), Phase AB to ground, Phase A-B, three-phase fault ABC, three-phase fault ABC to ground, and normal condition (pre-fault).

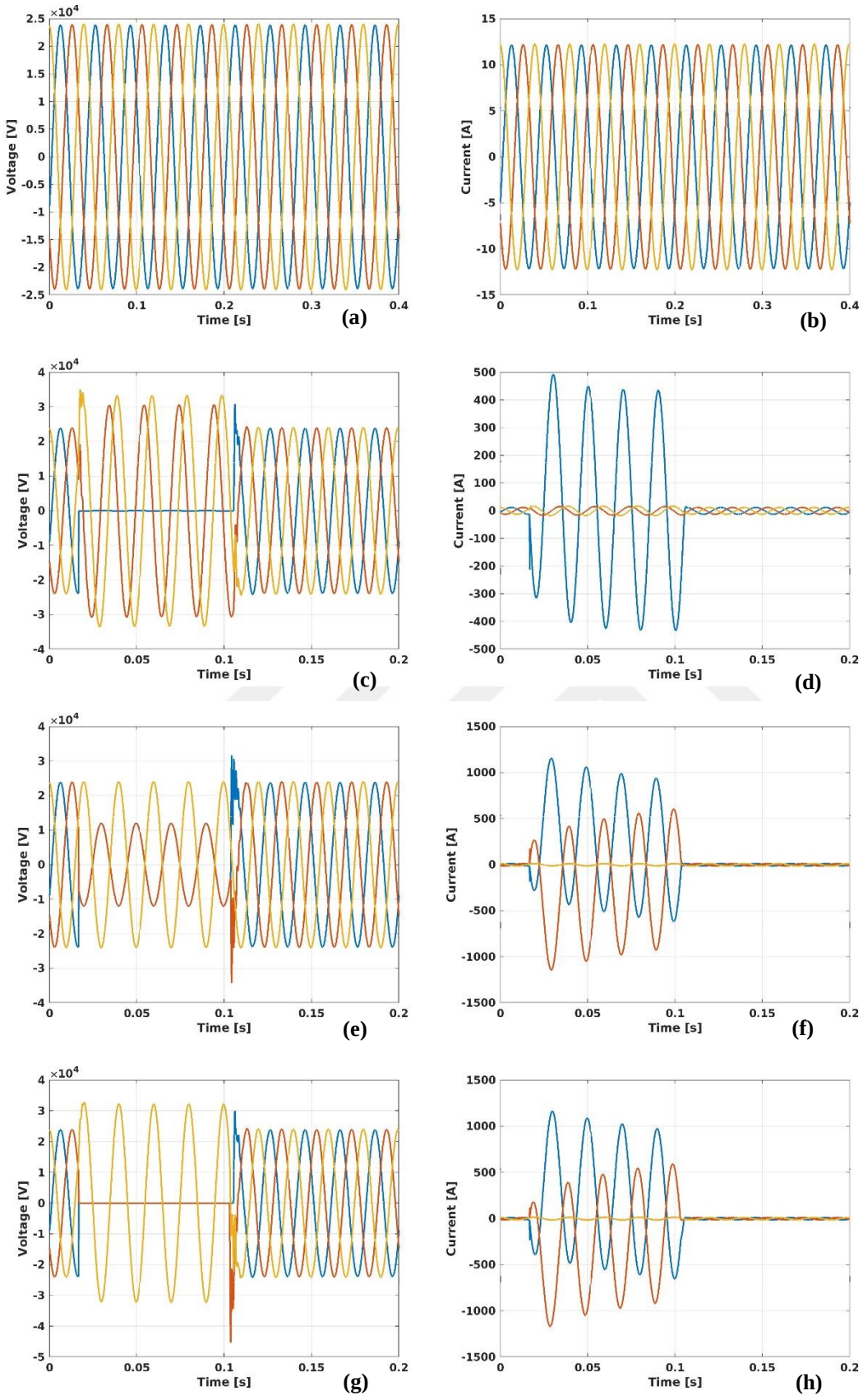


Figure 4.1 : Simulated results for voltage and current signals: Normal condition {(a), (b)}, A-G fault {(c), (d)}, A-B fault {(e), (f)}, AB-G fault {(g), (h)}, ABC fault {(i), (j)}, and ABC-G fault {(k), (l)}.

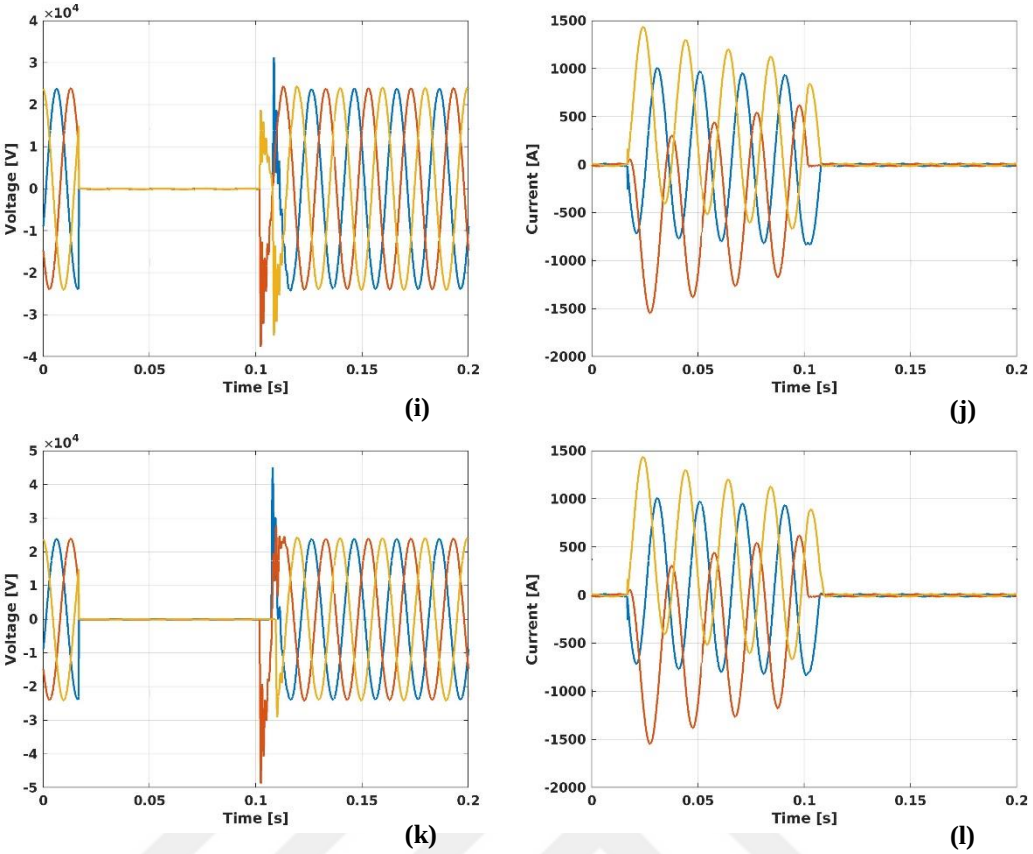


Figure 4.1 (continued): Simulated results for voltage and current signals: Normal condition {(a), (b)}, A-G fault {(c), (d)}, A-B fault {(e), (f)}, AB-G fault {(g), (h)}, ABC fault {(i), (j)}, and ABC-G fault {(k), (l)}.

The simulated findings in Figure 4.1, comprising voltage and current signals under different conditions, offer valuable insights into the impact of various faults on the system. Under normal conditions, both voltage and current signals exhibit stable and balanced values. In contrast, the fault conditions show significant deviations from these standard values. For example, during an ABC fault, the current surges to about 15% higher than the values observed under normal operating conditions.

Each sub-figure in Figure 4.1 shows transient states, distinguishing actual faults from transients based on disturbance duration, magnitude, and frequency analysis. Actual faults tend to induce sustained disturbances, resulting in substantial voltage and current magnitude deviations. In contrast, transients are characterized by their brief, short-lived nature and often exhibit higher frequency components than faults. This distinction is crucial for accurately diagnosing and responding to faults, as it allows for the differentiation between temporary disturbances and more severe, persistent issues within the power grid.

In this study, fault detection was performed using feature extraction through two mathematical methods: Short-Time Fourier Transform (STFT) and hybrid wavelet transform. Following detection, fault classification was performed using several machine learning algorithms to ensure precise identification and effective response to various fault types.

4.1 Case Study I: Implementation and Results of STFT

This study aims to present the Djibouti power grid model and then develop a technique for fault characteristic detection using the short-time Fourier Transform, a commonly used method for non-stationary signals (Peng & Chu, 2004b). Figure 4.2 shows a flowchart of the proposed approach to determining the fault feature. The fault detection process involves several steps: extracting voltage and current signals, applying STFT to the riskiest faults (determined by calculating risk values for all fault types), and identifying the faulty signal features.

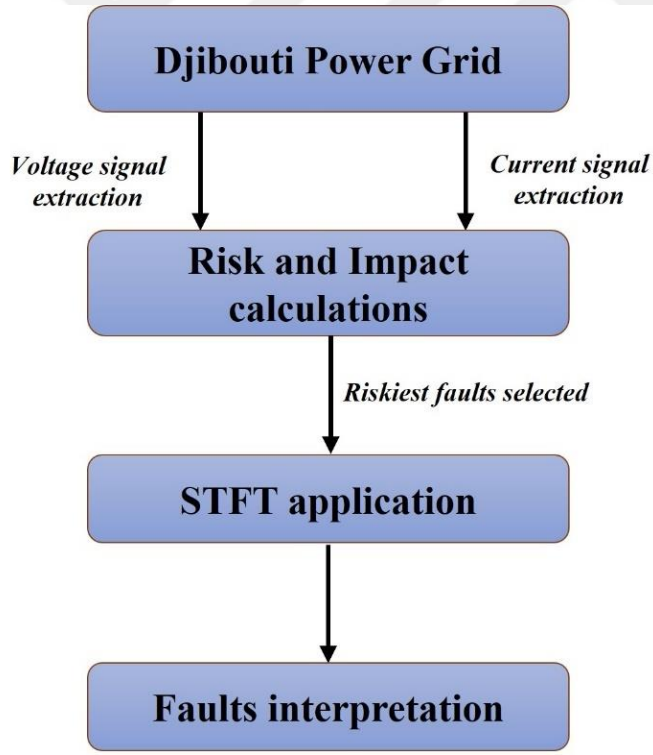


Figure 4.2 : Flowchart of the proposed fault detection approach.

4.1.1 STFT implementation on simulated data

Once the simulated signals have been collected, the next step is the application of the Short-Time Fourier Transform (STFT) for feature extraction. STFT is used to analyse

non-stationary signals, providing both time and frequency information, which is crucial for identifying fault characteristics. The signals shown in Figure 4.1 are analysed using STFT to determine the fault properties. The STFT parameters used in this study are as follows:

- The sampling frequency $f_s = 20kHz$,
- a window size of 1024,
- $nfft = 4096$,
- Window function type: Hamming is widely used in signal processing, particularly Fourier analysis and STFT. The Hamming window is an extension of the Hann window, and it is defined by the formula (Gundewar & Kane, 2022; Rakshit & Ullah, 2019):

$$w(n) = 0.54 + 0{,}46cos\left(\frac{2\pi n}{N}\right) \tag{4.1}$$

Where n is the sample number, and N is the total number of samples in the window.

- Hop Size H=256,
- Frequency resolution: $\Delta f = \frac{f_s/_2}{nfft} = 2\ Hz$
- Time resolution: $\Delta t = {}^{1}/_{\Delta f}$

The frequency resolution indicates the ability to distinguish between closely spaced frequencies in the signal, whereas the time resolution represents the duration of the window function. The product of time and frequency resolutions is known as the uncertainty principle UP, and it is expressed as (Millette, 2013; Nicola, 2023; Özhan, 2022):

$$UP = \Delta f . \Delta t \geq \frac{1}{4\pi} \tag{4.2}$$

This inequality arises from the mathematical propriety of the Fourier transform and the nature of the window function used in STFT. The window function used in this study, the Hamming function, is designed to have a narrower main lobe than a

rectangular window. This characteristic means that it provides better frequency resolution.

The Short-Time Fourier Transform (STFT) will be used to analyse specific faults identified through risk and impact analysis rather than applied to all types of faults. Risk assessment can be performed using the data presented in Table 4.2.

Table 4.2 : Probability of occurrence and severity of faults (Gautam & Jhala, 2015).

	Probability of occurrence	Severity
Single line to ground (SLG)	70-80%	Less
Line to line fault (LL)	8-10%	Medium
Line to line to ground (DLG)	10-17%	Severe
Three phase faults (3P)	3%	Highly severe

According to Table 4.2, the most common fault is a single line to ground, but it is less severe than other faults. In terms of severity, the line-to-line fault is more severe than the single line-to-ground fault but less severe than the LL-G fault. These criteria cannot provide a definitive selection of the type of faults. As a result, the risk evaluation is computed in the following manner. The risk description is defined mathematically by the following formula:

$$Risk = probability \times Severity \tag{4.3}$$

Table 4.3 presents the mean values of the probability of fault occurrences and the coding severity between 1 and 4 for each case. The risk table is then generated using Eq. (4.3) and shown in Table 4.3.

Table 4.3 : The risk calculation.

Fault types	Mean values of failure probability	Severity	Risk value
SLG	0.75	Less (1)	0.75
LL	0.09	Medium (2)	0.18
DLG	0.13	Severe (3)	0.39
3P	0.03	Highly severe (4)	0.12

As shown in Table 4.3, the single line-to-ground type has the highest risk level with a value of 0.75, followed by the DLG type. In this case, the DLG has a lower risk value than the SLG, but its impact factor is exceptionally high, and its damage is massive. As a result, the STFT analysis is limited to the DLG and SLG cases.

Furthermore, 3 phase faults are analysed because, according to the literature, they are rare faults, but if they occur, the damage is severe. From the Djibouti power system network, the system may retain its integrity if an SLG fault occurs. The protection devices can quickly eliminate it, but the system cannot withstand three-phase short circuit faults because they cause voltage collapses(Dommisse et al., 2022).]. As a result, 3 phase faults, DLG faults, and SLG faults in the time domain are represented in Figure 4.3.

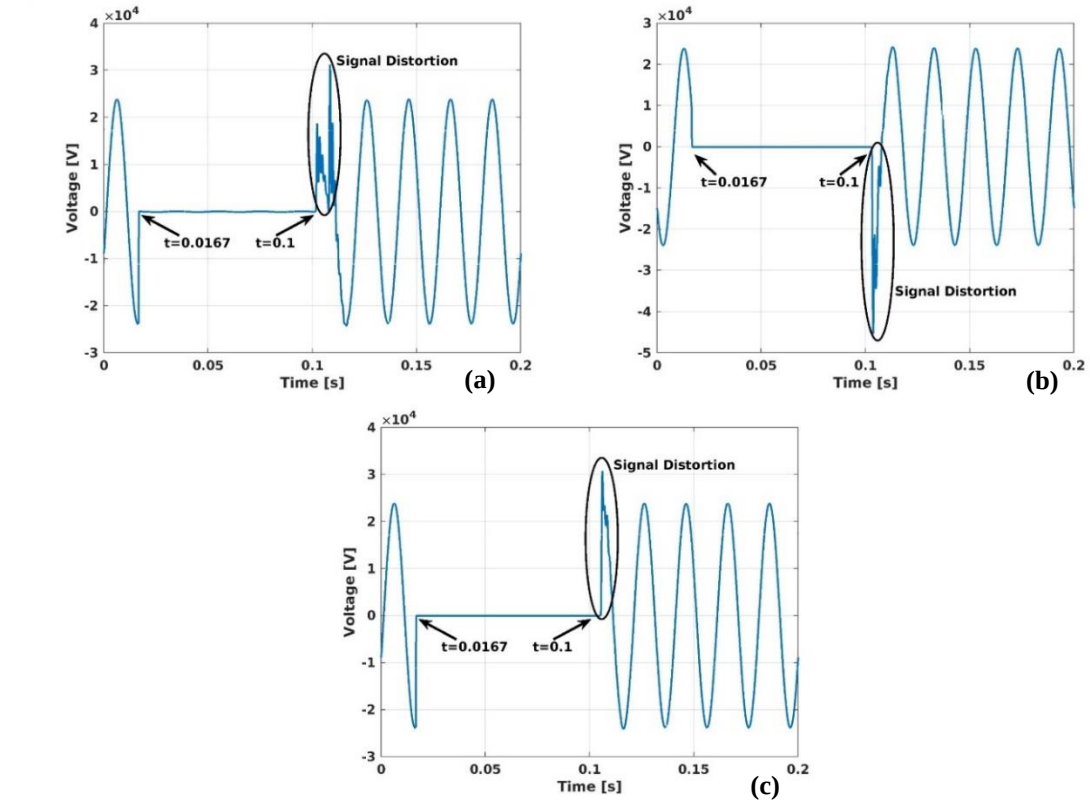


Figure 4.3 : Signal in time domain :(a) three-phase fault (3P): phase A; (b) double line to ground fault (AB-G): phase B; (c) single line to ground (A-G): phase A.

4.1.2 Simulation results

The short-time Fourier transform requires the signal to be a single vector; therefore, only one phase signal has been examined. The size of the distortion helps to identify which line phase has more distortion than the other. Phase A has more distortion in the fault region in the ABC fault; phase B has a disruption in the AB-G fault, and phase A

has a disturbance in the A-G fault because it is the only faulted phase. Furthermore, distortion in all three voltage signals is around 0.1 sec in Figure 4.3. STFT is used to analyse the characteristics of the faulty region, and the results are shown in Fig.4.4.

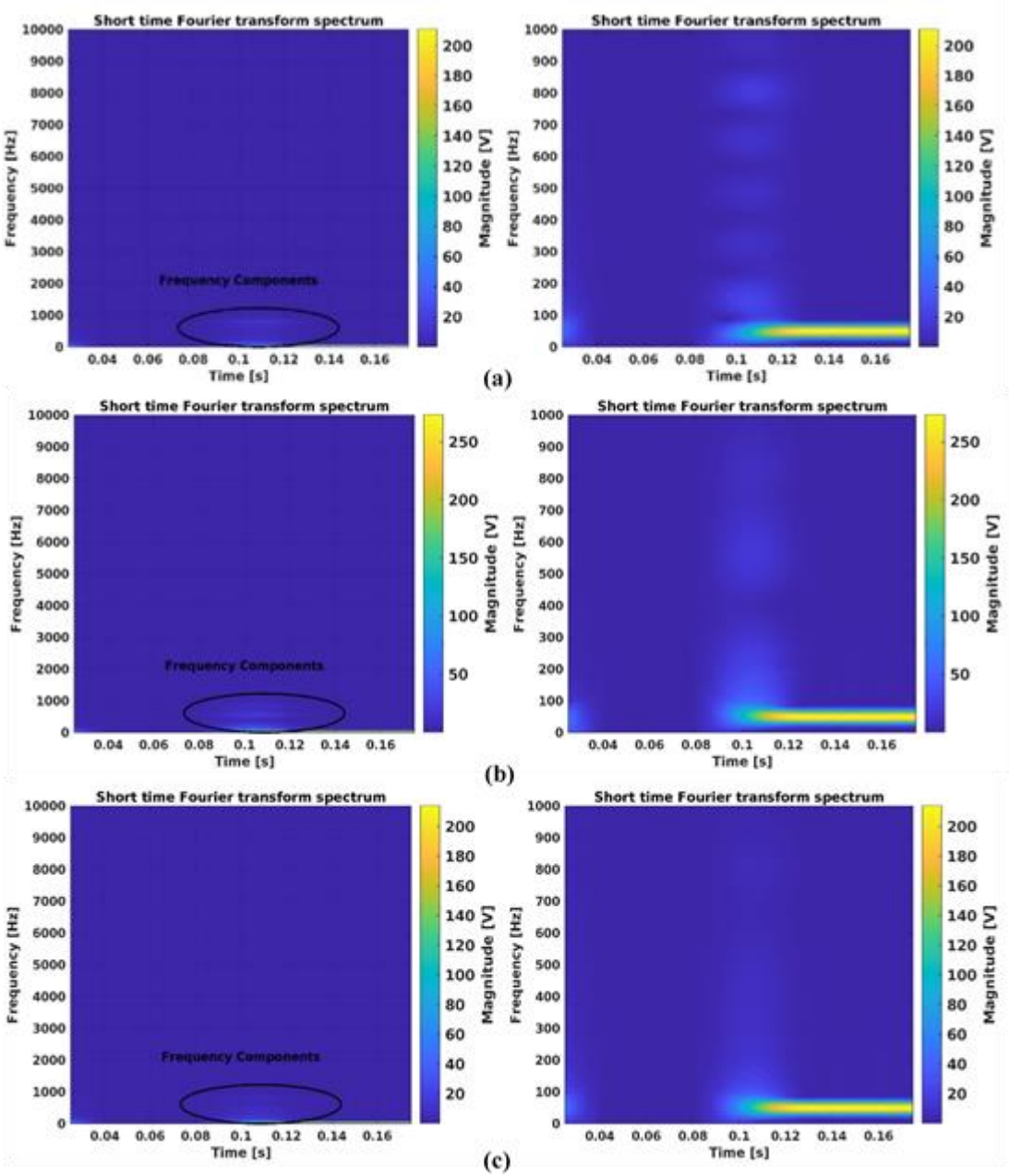


Figure 4.4 : STFT application on ABC fault signal; (b) STFT application on AB-G fault signal; (c) STFT application on A-G fault signal.

The STFT spectrum is presented in Figure 4.4. According to Fig. 4.4-(a) (b) (c), 0.1 sec is when the fault is cleared using a circuit breaker, and at this time, a band with high frequency components can be identified in all figures. The frequency values seen at 0.1024 sec in this region are shown in Table 4.4:

Table 4.4 : The frequency values seen from the spectrum.

Fault types	Frequency values (Hz)				
ABC	154.37	336,91	488.23	654.29	805.7
AB-G			546.9		
A-G			----		

Table 4.4 shows that the ABC and AB-G signal faults have specific frequency values, whereas the A-G fault reveals a band with no specific frequency value but a frequency component reaching 1kHz with a low amplitude.

When the acquired frequency values are divided by the fundamental frequency (50 Hz), harmonic components of low magnitude can be observed. These frequency components are not harmonics, but they are transients. Both harmonics and transients cause wave distortion, but transients are more temporary than harmonics (Sarwito et al., 2018). The harmonic and inter-harmonic measurements are then taken in the steady state rather than the transient state. Harmonics are typically generated by non-linear loads used for power factor correction to reduce power system losses (Ghorbani & Atashpar, 2011; Macii & Petri, 2018).

Transients are abrupt changes in voltage, current, or both. By IEEE 1159-2019, transients are categorised as impulsive or oscillatory. Oscillatory transients are further divided into three types based on frequency values: low frequency (less than 5kHz), medium frequency (5-500kHz), and high frequency (0.5-5 MHz). This phenomenon is caused by both external (lightning strikes, energised line opening and closing, breaker opening and closing, and so on) and internal sources (switching operation, high resistance fault, switch-mode power supply, etc.) (Sivaraman & Sharmeela, 2021). The oscillatory transient caused by the opening and closing of the breaker is observed in this study (Bollen et al., 2005). Furthermore, the detected frequency components are classified as low frequency. Although the transient state is short, its impact on power system devices is critical. Low frequency in general has a significant impact on power quality, which can reduce system performance and reliability (Santoso et al., 2012). Even though it is only temporary, it has the potential to damage power system protection devices and heat circuit components, potentially damaging insulation. This

potential damage underscores the importance of our research in understanding and mitigating these risks.

Generally, a key drawback of the Short-Time Fourier Transform (STFT) is its limited time-frequency resolution. This limitation stems from STFT's use of a fixed-size window for the Fourier transform, which might need to be more adept at capturing the complexities of specific signals (Bach et al., 2023). Although the method employing STFT for sensitive detection is effective in the context of the mentioned study, it has its limitations. It successfully and accurately identifies the frequency characteristics of three-phase and double line-to-ground faults. However, detecting the characteristics of single line-to-ground (SLG) faults needs to be improved. SLG faults exhibit minor distortions, but the method underlines a limitation in detecting all types of faults, indicating a potential area for further refinement in fault detection techniques.

After a detailed analysis of the voltage signals, the current signals are subjected to the same application process for consistency. The results of this comprehensive analysis are presented in Figure 4.5, providing the fault characteristics under the selected fault conditions. This thorough examination ensures that all aspects of the electrical disturbances are accurately captured and evaluated, providing a solid foundation for this research.

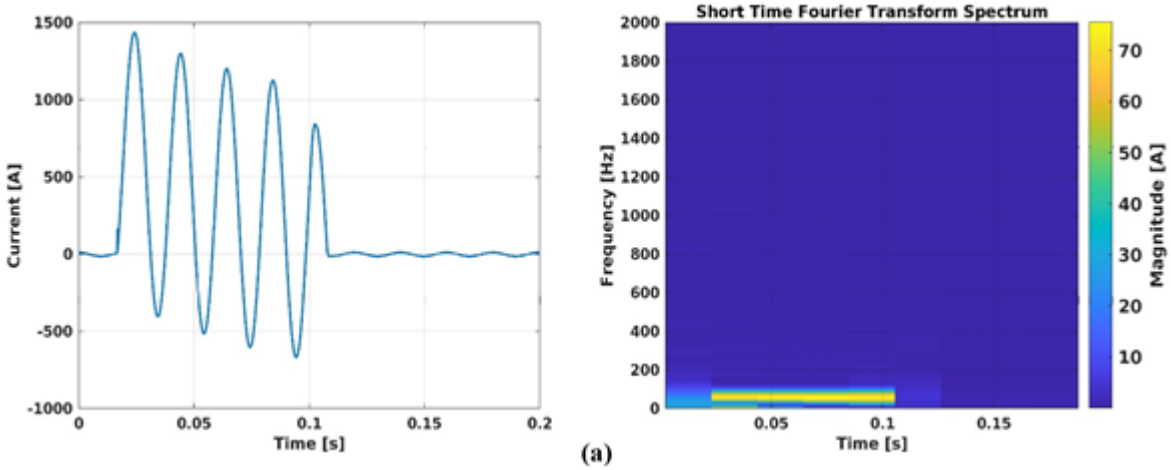
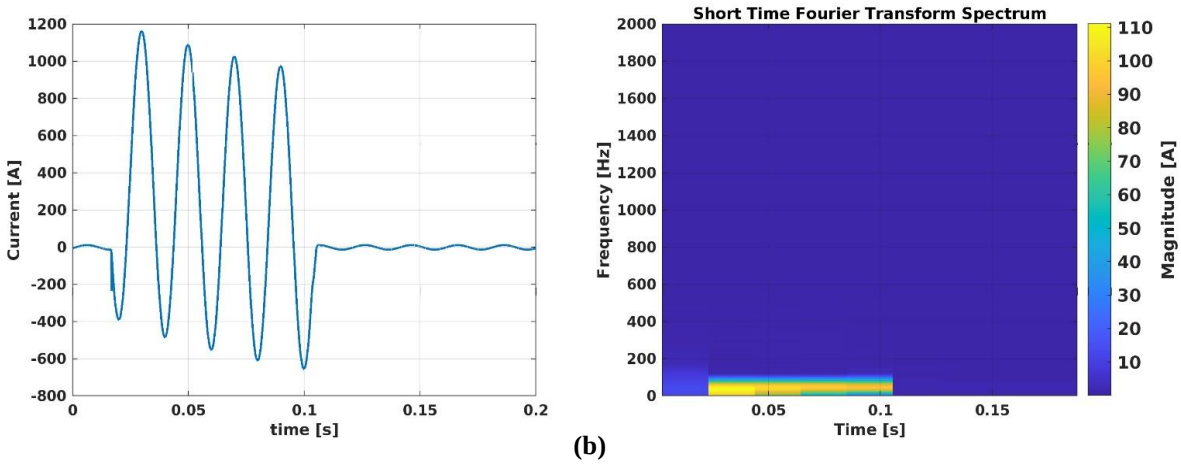
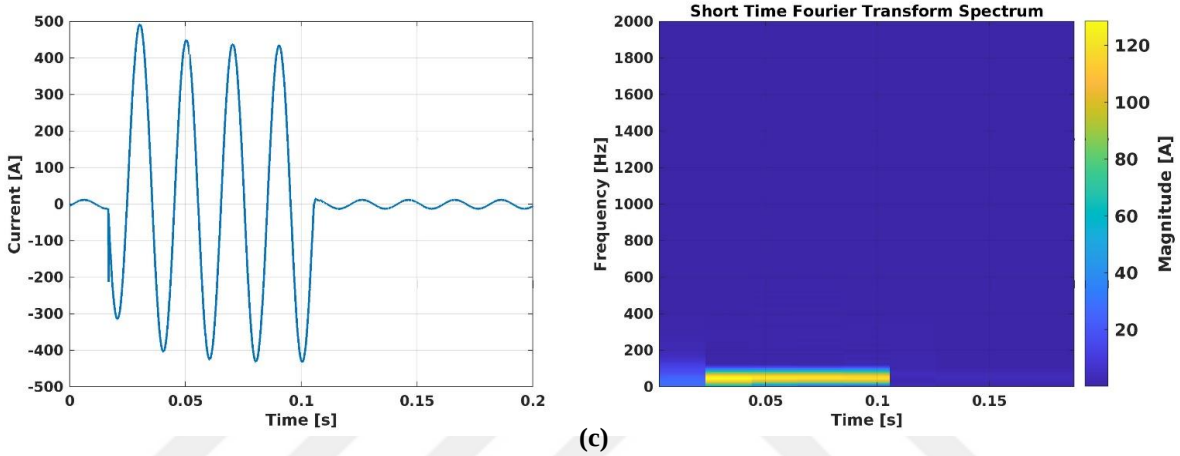


Figure 4.5 : STFT results current signals: (a): ABC fault, (b): AB-G fault and (c): A-G fault.



(b)



(c)

Figure 4.5 (continued): STFT results current signals: (a): ABC fault, (b): AB-G fault and (c): A-G fault.

Figure 4.5 depicts the current signals and spectrums from the STFT application. The figure shows an increase in current but no distortion. The ABC fault has a high fault current value, followed by the AB-G fault and, finally, the A-G fault. As a result, the spectrum for the three types of faults shows a high amplitude of 50Hz, which is the fundamental frequency.

4.2 Case Study II: Implementation and Results of Hybrid Wavelet Transform

In this case study, a novel approach for fault detection is proposed based on the future work recommended from the previous study. The study's primary purpose is to determine the characteristics of abnormal voltage signals induced by short-circuit faults and transient phenomena. The data used are the same collected from a Simulink model of the Djibouti power grid, as shown in Figure 3.4. Figure 4.6 depicts a flowchart illustrating the proposed approach for identifying fault features.

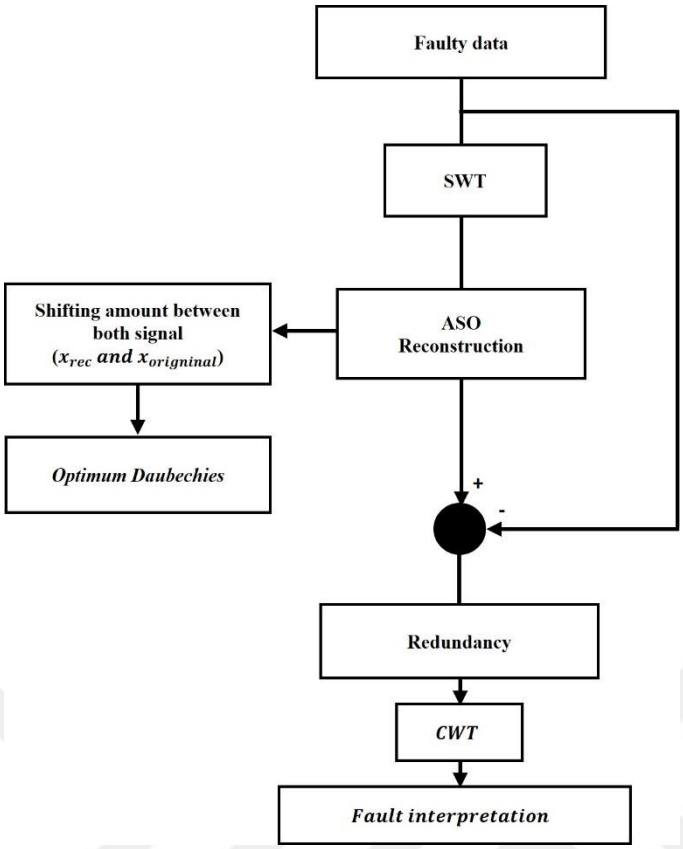


Figure 4.6 : Summary of workflow steps.

4.2.1 Research methodology

The hybrid wavelet transform combines SWT and CWT for fault detection. The procedure begins with decomposing the collected signal into details and approximation coefficients using SWT. Shannon's information criterion (SIC), also known as the Minimum Description Length (MDL), determines the decomposition level using the formula(Seker, 1993):

$$L = log_2\left(\frac{f_s}{2 \times f_{min}}\right) \tag{4.4}$$

SIC guides the selection of decomposition levels in wavelet-based signal analysis to avoid overfitting and accurately represent signal features (Vashishtha & Kumar, 2022). When the specified decomposition level L is unsatisfactory, a level between 1 and the detected SIC'number is recommended:

$$1 \leq L < SHI \tag{4.5}$$

$$L_{optimum} = \frac{SHI - 1}{2} \tag{4.6}$$

This optimum level, a key factor in our method, ensures not only effective feature extraction but also the preservation of signal information, providing a robust approach to fault detection.

The algebraic summation operation (ASO) is applied to reconstruct the signal (Bayram & Şeker, 2017). This undecimated reconstruction operation is employed to benefit from the redundancy of SWT for fault detection. The block diagram in Figure 4.7 illustrates the ASO operation.

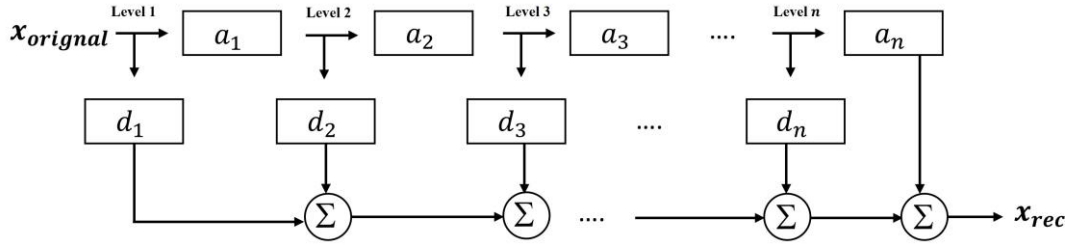


Figure 4.7 : Block diagram for reconstruction using ASO.

The ASO process involves summing all detail coefficients and the most recent approximation to reconstruct the signal [19]:

$$x_{rec} = d_1 + d_2 + d_3 + \cdots + d_n + a_n \tag{4.7}$$

Where d is the detail and a is the approximation. The reconstruction signal is amplified due to the up-sampling operation of SWT, making minor defects easily detectable. The undecimated reconstruction amplifies small defects, facilitating instantaneous changes. Subsequently, CWT is applied to the reconstruction signal because the redundant transform makes minor defects more visible. Before applying CWT, signal shifting for different Daubechies wavelet numbers is calculated to find the optimum one.

An artificial signal with known characteristics is generated to validate the effectiveness of this approach. The signal combines third and fifth harmonics with noise and a healthy signal. Harmonics have long existed in power systems, and researchers have explored various solutions to mitigate their effects (Arrillaga et al., 1997; Ghorbani & Atashpar, 2011; Martinez-Velasco, 2014). The causes of harmonics are often attributed to power electronic equipment, arcing equipment, and saturable

devices such as ageing transformers (Macii & Petri, 2018; Santoso et al., 2012). Additionally, harmonics can be generated by short-circuit faults. The third and fifth harmonic components illustrate non-linear load availability, while the noise reflects weak communication within the equipment. The formula for the artificial signal is shown below:

$$x' = x_h + 0.5\,sin(2pif_3t) + 0.6\,sin(2pif_5t) + error \tag{4.8}$$

$$error = 0.2randn(1, N) \tag{4.9}$$

Where $randn(1, N)$ is a MATLAB command to generate N random numbers with standard normal distribution, x_h is the healthy signal, N is the number of samples, f_3 is the third harmonic, and f_5 is the fifth harmonic. Harmonics pose a significant challenge due to their substantial impact on power systems, starting with heating the insulation and causing damage (Sivaraman & Sharmeela, 2021). The third and fifth harmonics are particularly common, with the third harmonic causing a rapid increase in current, which is very dangerous for the system (Arrillaga et al., 1997; H. C. Lin, 2007; Macii & Petri, 2018). Therefore, detecting faults before any damage occurs is essential for maintaining the stability of the power system.

4.2.2 Simulation outcomes for fault detection

The proposed methodology was applied to signals from the simulation of short circuits under various scenarios. Table 4.5 below outlines the five fault categories used in this case study: single-line-to-ground, double-line-to-ground, three-phase, three-phase-to-ground, and line-to-line faults. Figure 4.8 illustrates the representation of these fault categories in the time domain.

Table 4.5 : Classification of the fault type in transmission lines.

Fault type	Phase A	Phase B	Phase C	Phase G
A-G	1	0	0	1
A-B	1	1	0	0
AB-G	1	1	0	1
ABC	1	1	1	0
ABC-G	1	1	1	1

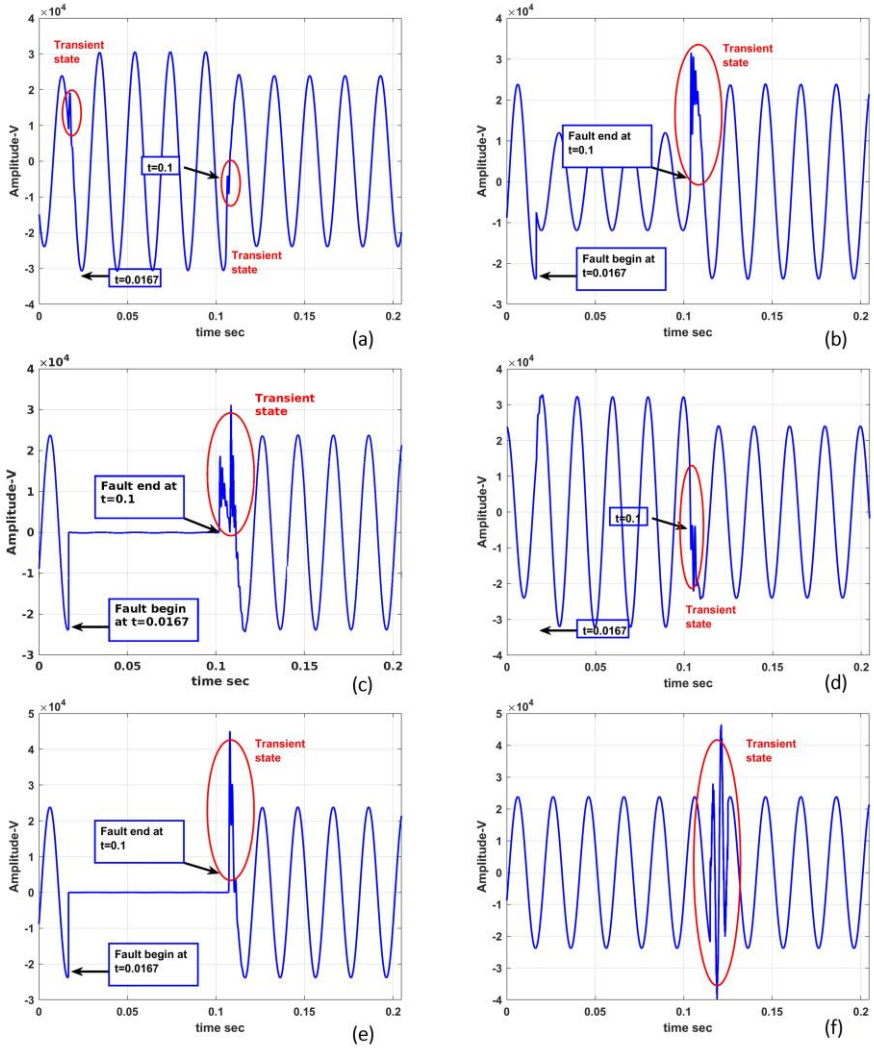


Figure 4.8 : The signal representation for (a) A G fault phase B, (b) A B fault, (c) A B C fault, (d) ABC G fault, (e) AB G fault, and (f) Artificial signal fault.

Figure 4.8 illustrates that a short circuit fault generates a transient signal at its initiation and clearance. In the event of a three-phase fault, the voltage drops to zero, leading to signal distortion and a significant rise in current. This case study focuses exclusively on the voltage parameter, as minor defects caused by temporary phenomena are more observable. The signal selected is based on the distortion size; hence, for A-B and AB-G faults, other phases were examined instead of the faulty phases, as the distortion size in the faulty phases was insignificant.

Deriving fault characteristics using straightforward mathematical procedures is challenging. Therefore, the redundancy technique of SWT is employed, making it the optimal method for easily extracting small defects. The process is thorough, beginning by calculating the Shannon Information Criterion to determine the appropriate level of signal decomposition. With a sampling rate of 20 kHz, the level of decomposition is

7, and the optimum level, according to the formula, is 3. Additionally, the Daubechies wavelet number is chosen to prevent any curve shifting. For each fault type, the mother wavelet number is selected by calculating the signal shifting amount, as illustrated in Figure 4.9, ensuring accurate fault detection and analysis.

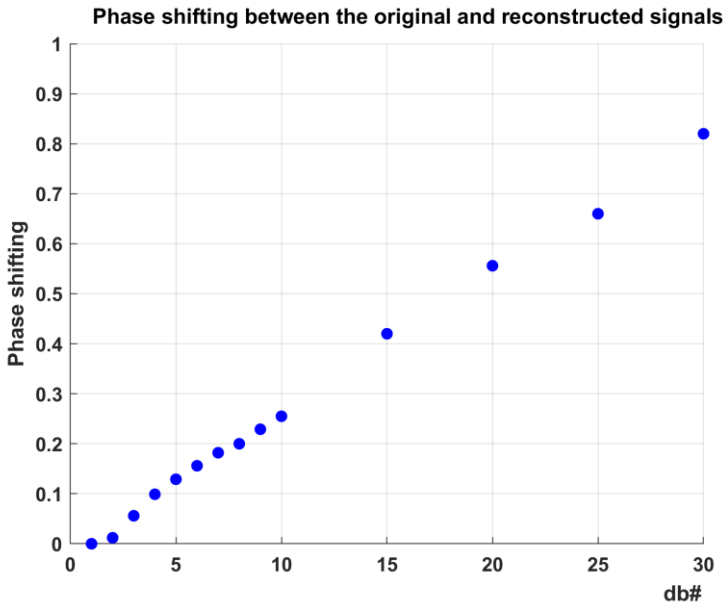


Figure 4.9 : Shifting amount for the reconstructed signal and the original signal.

According to Figure 4.9, the shift illustrates the phase difference between the original and reconstructed signals' waveforms. This figure indicates the phase shifting corresponding to the Daubechies wavelet number (db#) used in this application. It is noted that the Daubechies number is directly related to the phase shifting distance. In other words, a higher Daubechies number indicates a more significant phase shifting between the reconstructed and the original signals. Therefore, the least number of Daubechies is recommended to avoid any shifting. The Daubechies wavelet with the filter coefficient [1, 1], known as db1, shares the exact approximation of the Haar wavelet. Consequently, db1 is suggested in this case study because it ensures zero shifting between the reconstructed and original signals. The decomposition results for the chosen mother wavelet are shown in Figure 4.10.

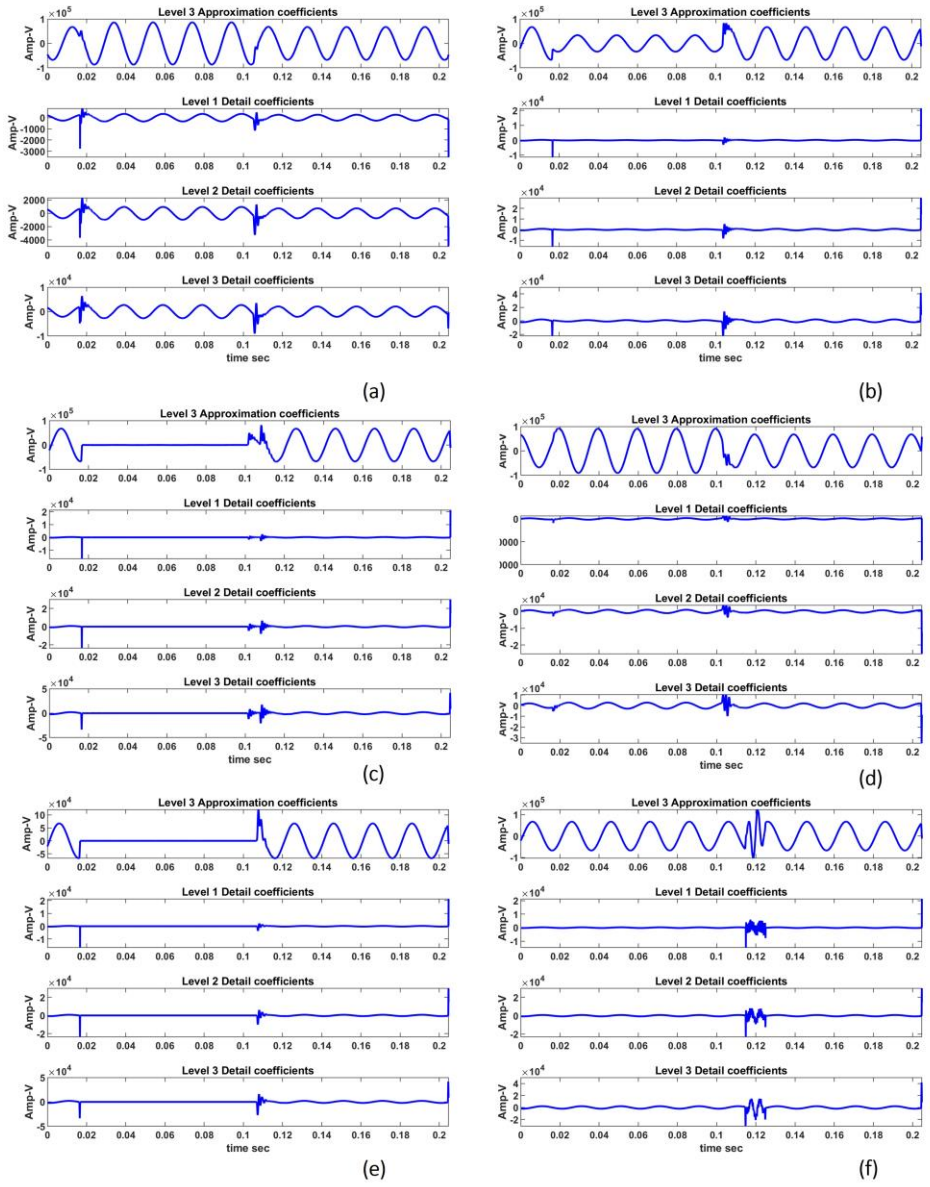


Figure 4.10 : The signal decomposition using SWT for (a) A G fault phase B, (b) A B fault, (c) ABC fault, (d) ABC G fault, (e) AB G fault, and (f) Artificial signal fault.

Figure 4.10 illustrates the signal decomposition using SWT, displaying both approximation and detail coefficients for various faults. At the selected optimum decomposition level, three details and one approximation are identified, representing high- and low-frequency components, respectively. Figure 4.10 shows that each sub-figure shows a high frequency at approximately 0.1 seconds, coinciding with the time of the short-circuit block simulation's disconnection. This high-frequency results from transient phenomena, which are rapid changes within the power system.

Following the decomposition, the complex process of signal reconstruction is performed using the ASO operation. This involves the summation of the three details

and one approximation shown in Figure 4.10. The reconstructed signal mirrors the original signal's shape but is amplified. This method effectively facilitates signal extraction, leveraging the SWT property known as 'redundancy.' The complexity of the ASO operation and its role in enhancing small defect detection is depicted in Figure 4.11.

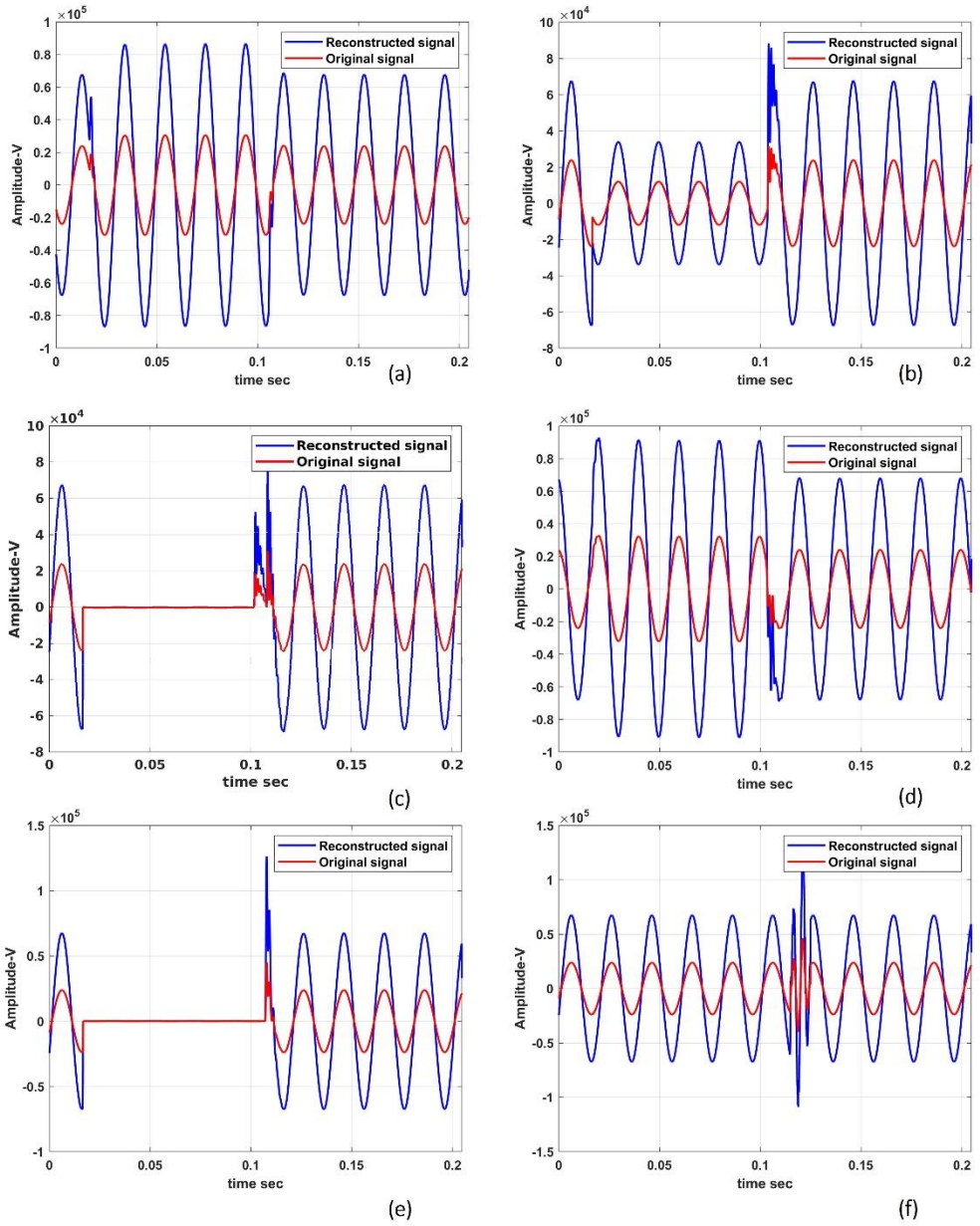


Figure 4.11 : Double plot for reconstruction and original signals for (a) A-G fault phase B, (b) A-B fault, (c) ABC fault, (d) AB-G fault phase C, (e) ABC-G fault, and (f) Artificial signal fault.

Due to the up-sampling approach of SWT, redundancy is observed with high precision, allowing for rapid and easy extraction of minor defects that were previously challenging to detect. By using db1, which is similar to a Haar wavelet, the

reconstructed signal and the original signal exhibit zero shifting. Although the order of Daubechies was determined by calculating the signal's shifting amount, some researchers in the literature have suggested that other Daubechies wavelet types, such as db8 and db4, are also effective for signal de-noising and fault detection (Asman et al., 2022; Gautam & Jhala, 2015; Polat & Özerdem, 2018).

The Haar wavelet, calculated without a temporary array and based on discontinuity, plays a crucial role in the reconstruction process due to its step function appearance. After performing the reconstruction using ASO, which generates redundancy, the wavelet transform is employed to extract features from the transient signal. Specifically, the continuous wavelet transform (CWT) is applied, utilizing different mother wavelet families depending on the signal's characteristics. Analytic wavelets are used in CWT to determine time-frequency parameters accurately [14].

Consequently, a unique mother wavelet is used for each fault type, as described in Table 4.6 (Ghorbani & Atashpar, 2011).

Table 4.6 : The Mother wavelet family selected for the different fault types.

Fault type	Mother wavelet selected
A-G	‘bump’
A-B	‘amor’
AB-G	‘amor’
ABC	‘morse’
ABC-G	‘bump’
Artificial signal	‘morse’

The appropriate mother wavelet family is selected depending on the type of fault and the form of distortion. For example, an A-G fault typically presents a relatively minor flaw that is not easily visible in the time domain; thus, a bump wavelet is suitable for detecting and characterizing such faults. The amor wavelet is commonly used for fault types with sinusoidal oscillations, such as AB and AB-G. Conversely, the Morse wavelet is well-suited for a wide range of oscillatory phenomena, including ABC and artificial signals. Once the suitable mother wavelet is chosen, the results from the continuous wavelet transform are shown in Figure 4.12.

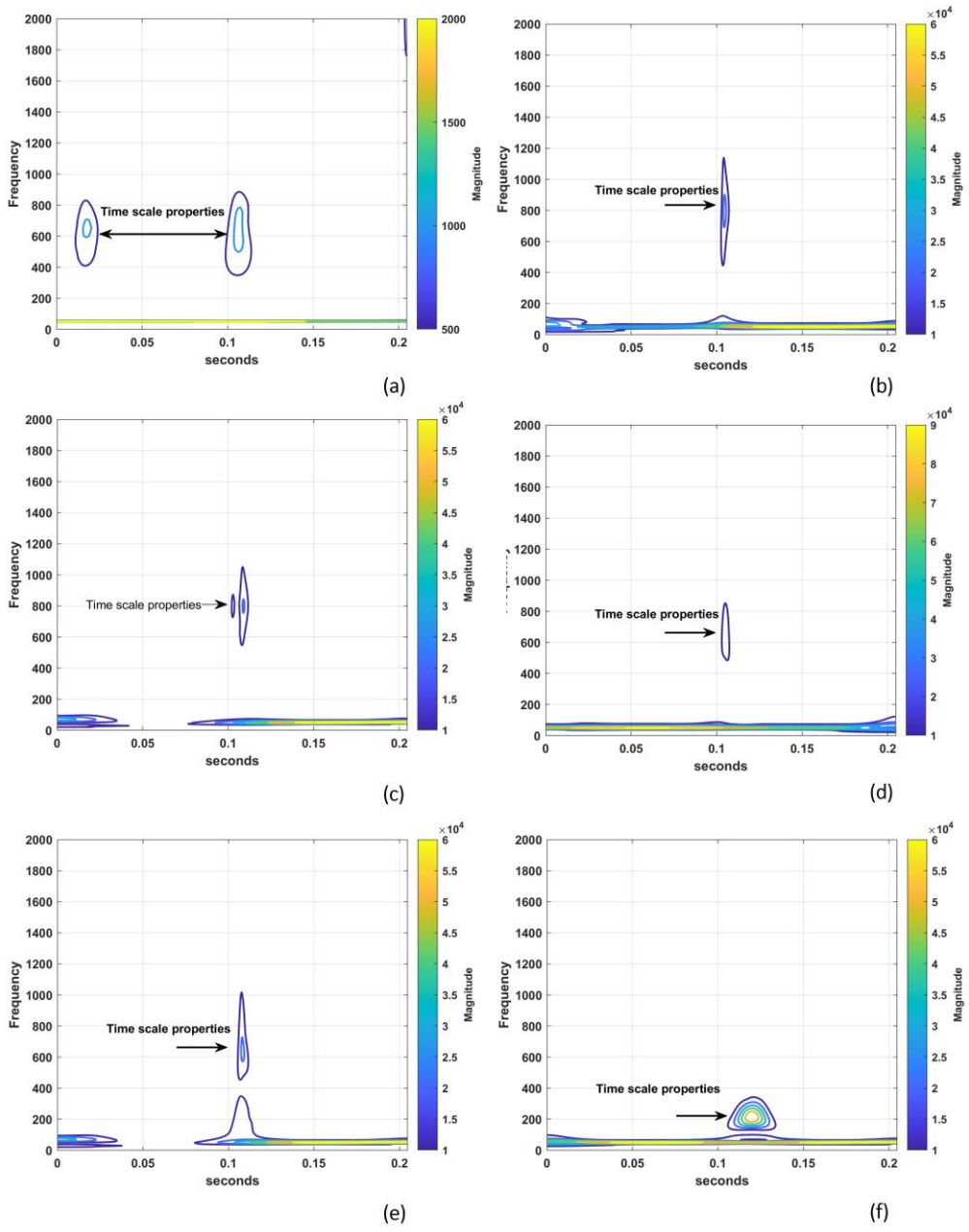


Figure 4.12 : Wavelet transform application on signals (a) A-G fault phase B, (b) A-B fault, (c) ABC fault, (d) AB-G fault phase C, (e) ABC-G fault, and (f) Artificial signal.

Detecting a minor defect is challenging due to its subtle nature; however, using the up-sampling approach makes this hidden characteristic easier to extract. The original signal is amplified by applying the undecimated reconstruction approach using the ASO operation, facilitating the extraction process using the continuous wavelet transform. Figure 4.12 displays the spectrum where fault characteristics are identified. It includes six sub-figures: the first five depict the spectrum for the recorded signal

from MATLAB Simulink, and the last pertains to the artificial data. Table 4.7 below presents the fault characteristics detected from the spectrum shown in Figure 4.12.

Table 4.7 : The fault characteristics detected from the spectrum.

Fault type	Fault time detected	Frequency detected
A-G	0.01667-0.1167 sec	600-650 Hz
A-B	0.1167 sec	800 Hz
AB-G	0.1167 sec	800 Hz
ABC	0.1167 sec	700 Hz
ABC-G	0.1167 sec	700 Hz

As previously discussed, the fault characteristics presented in the table were found using the spectrum from the continuous wavelet transform (CWT) applied to the recorded signals. Table 4.7 shows the frequency components observed from the simulation, specifically the 12th, 13th, 14th, and 16th components, which were detected due to faults in the power system. The undecimated reconstruction method aids in clearly extracting minor defects, as demonstrated by its application to the artificial signal with a known characteristic, confirming the method's effectiveness. While physical faults are always visible, minor system disturbances often go unnoticed. Therefore, the redundancy achieved through the undecimated reconstruction approach is highly effective for identifying minor disturbances in power system faults.

Figure 4.12-f confirms the effectiveness of the proposed methodology for characteristic extraction. Even when only a part of the artificial signal was inserted, the methodology was able to identify the added frequency components, the 3rd and 5th harmonics, with the detected frequency of 250 Hz corresponding to the 5th harmonic. This adaptability underscores the potential of the proposed methodology for detecting small defects in the power system in various scenarios.

Overall, the accuracy of the developed technique relies on the stationary wavelet transform (SWT). The effectiveness of this method is inherent in the SWT itself. During the decomposition of signals using the stationary wavelet transform, signal reconstruction is achieved with minimal phase shifting, facilitated by the db1 or Haar wavelet function. This minimal phase shift is a crucial indicator of the data accuracy

used in the study. Additionally, the stationary wavelet transform is inherently redundant, effectively amplifying fault signatures under minimal phase conditions.

5. FAULT CLASSIFICATION USING MACHINE LEARNING TECHNIQUES AND ITS RESULTS

After identifying a failure in the system, it is critical to classify the fault appropriately. This classification specifies the unique type of fault, enabling precise and effective repair procedures. These targeted actions ensure that resources like time, labour, and materials are used efficiently, improving the system's overall performance and reliability. Moreover, accurate fault classification supports immediate corrective measures and contributes to developing predictive maintenance strategies. By understanding the fault features and causes of different types of faults, system operators can implement proactive measures to prevent future occurrences. This proactive approach minimises unexpected downtimes and extends the lifespan of the system's components.

Additionally, the data gathered from fault classification can be used to refine and improve the fault detection algorithms, creating a continuous cycle of improvement that enhances the system's resilience and efficiency over time. Finally, including fault detection and classification in the maintenance framework results in a more robust and reliable electricity infrastructure, promoting operational stability and economic growth. This approach is highly beneficial for Djibouti's power systems, which frequently encounter outages and experience prolonged correction times due to delays in classifying fault types and locating faults.

Historically, fault classification in transmission lines has relied on traditional methods such as impedance-based techniques, travelling wave methods, and signal processing applications. While these methods have been effective, they often require sophisticated calculations and substantial historical data and may need help to adapt to changing system conditions. In contrast, implementing advanced machine learning algorithms for fault classification can significantly enhance the efficiency and accuracy of the classification process, particularly for Djibouti's power systems. Various machine learning algorithms have been applied in fault classification, including supervised learning algorithms such as Support Vector Machines (SVM)(Magagula et al., 2017),

Decision Trees (DT)(Asman et al., 2021), Random Forest (RF), and Neural Networks(Y. Q. Chen et al., 2018) ,all of which have demonstrated effective accuracy. Additionally, deep learning (DL) techniques, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks (Fahim et al., 2021), have also proven to be highly effective in fault classification. These advanced techniques offer superior adaptability and accuracy, making them well-suited to the dynamic conditions of modern power systems. The proposed methodology in this study is that three techniques will be selected based on their unique abilities to analyse complex datasets efficiently: decision trees, long short-term memory (LSTM) networks, and support vector machines (SVM). Before this, the signal feature will be extracted using DWT by the signal decomposition. The proposed methodology is illustrated in the following workflow shown in Figure 5.1. The flowchart illustrates a fault classification based on a Djibouti SIMULINK model in various steps.

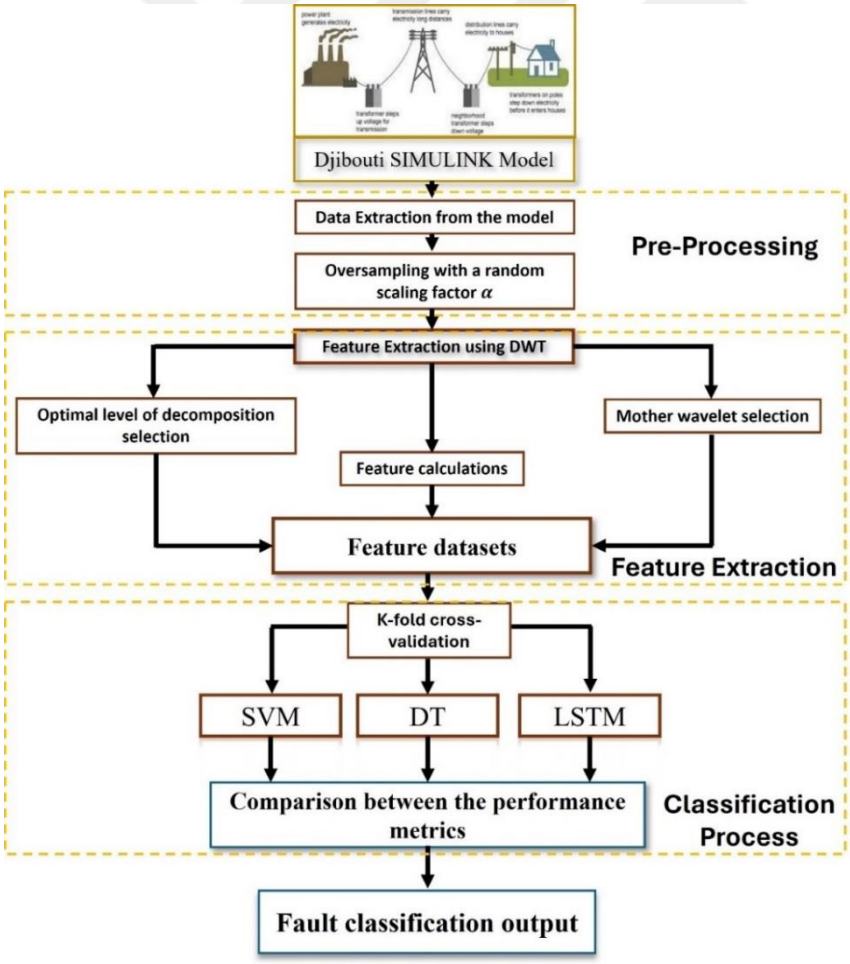


Figure 5.1 : Workflow for fault classification in the Djibouti electrical systems using machine learning.

5.1 Pre-Processing Stage

This study utilised a comprehensive array of datasets representing regular operation and fault conditions. As described in previous studies, the original set consisted of 11 different types of faults taken from the Djibouti grid SIMULINK model. Because the original dataset was small, using machine learning algorithms directly for fault classification was considered suboptimal due to the risk of overfitting (Shang et al., 2021).

To mitigate this issue, the oversampling technique was employed to increase the dataset size in the MATLAB programming Language. Oversampling, in this context, refers to the process of artificially increasing each dataset. However, more than replicating existing data points is required, as it could lead to model overfitting due to repeated instances.

Consequently, a more sophisticated approach was adopted where each dataset underwent 1000 iterations of simulation to introduce variability into the signal data. The approach is defined using the following formula:

$$dataset_{new} = \alpha \times dataset \tag{5.1}$$

$$\alpha = rand(1) \tag{5.2}$$

For each dataset corresponding to a unique signal condition, a new dataset $dataset_{new}$ is loaded and modified by a random scaling factor α each iteration to introduce controlled variability, simulating real-world fluctuations in signal amplitude. Where $rand(1)$ generates only one random number with uniform distribution in MATLAB. This method simulates slight variations in fault characteristics, effectively generating a more diverse and extensive dataset. Such an approach enhances the robustness of the machine learning model against variations in real-world operational conditions and helps better capture the complex dynamics of fault scenarios. The fault classification is detailed in the Table 5.1.

Table 5.1 : Fault classification in the Djibouti power system.

	No-Fault	Single-phase to ground			Two phases to ground			Phase to phase			Three-phase	Three-phase to ground
Phase A	0	1	0	0	1	0	1	1	0	1	1	1
Phase B	0	0	1	0	1	1	0	1	1	0	1	1
Phase C	0	0	0	1	0	1	1	0	1	1	1	1
Ground	0	1	1	1	1	1	1	0	0	0	0	1
Fault Names	normal	AG	BG	CG	ABG	BCG	ACG	AB	BC	AC	ABC	ABCG
Number of Faults	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Class label	1	2	3	4	5	6	7	8	9	10	11	12

Table 5.1 categorises various types of electrical faults and their representation across three phases (A, B, C) and ground. It includes single-phase to-ground faults (AG, BG, CG), two-phase to-ground faults (ABG, BCG, ACG), phase-to-phase faults (AB, BC, AC), and three-phase faults with and without ground involvement (ABC, ABCG). Each fault type is represented with a binary indicator (1 for involved, 0 for not involved) across the phases and ground. A dataset consisting of 1000 instances is generated for each type of fault. Upon completion of the data pre-processing phase, the following step initiates the feature extraction process, utilising Discrete Wavelet Transform (DWT) to analyse and quantify the characteristics of the generated datasets.

5.2 Feature Extraction Process

Feature extraction and selection are crucial steps before classification. They enhance model accuracy, reduce overfitting, improve computational efficiency, and increase interpretability and decision-making (Khalid et al., 2014; Lee et al., 2024; Medjahed, 2015; Moslhi et al., 2024; Warke et al., 2024; Yusuff et al., 2011). Feature extraction is commonly performed using the Discrete Wavelet Transform (DWT), a signal processing method that is preferred over the Continuous Wavelet Transform (CWT) due to its efficiency and effectiveness (K. Chen et al., 2016). The discrete wavelet transform (DWT) is a signal decomposition technique representing signals as wavelets.

It provides a multi-resolution analysis by breaking down the signal into approximation and details coefficients at various scales. This decomposition captures both frequency and location information. Finding the optimal decomposition level and the mother wavelet that suits the feature extraction is crucial during feature extraction.

This study chose the db1 mother wavelet due to its unique property of zero shifting between the original and the reconstructed signals, ensuring precise signal alignment and accuracy in the analysis (Nasser Mohamed et al., 2023).

After selecting the mother wavelet, the next step involves determining the decomposition level. The decomposition level refers to the number of times the original signal is iteratively decomposed into approximation and detail coefficients. This choice is made based on several factors, including the length of the signal, its frequency content, and the purpose of the decomposition. This study's signal analysing

length is 4096, and the frequency content is 20kHz. The maximum decomposition level L_{max} depends on the length of the signal N and the length of the chosen wavelet filter N_w. For the db1 wavelet, the filter length is 2. The maximum level can be calculated with the following formula (Das & Bagci Das, 2023; Németh, 2019):

$$L_{max} = log_2\left(\frac{N}{N_w} - 1\right) \tag{5.3}$$

However, in practical applications, determining the optimal decomposition level is crucial for practical signal analysis. The optimal level is determined by equation 4.6, around five levels. This level is chosen to balance over-simplification and excessive detail, ensuring that significant features of the signal are neither lost nor obscured by noise. For a signal $x[n]$, a wavelet decomposition at the chosen optimal decomposition $j = 5$ produces:

- Approximation coefficient at level $= 5$, cA_5 represents the low-frequency components of the signal, capturing the main trend parts of the signal.
- Detail coefficients at the level from 1 to $j = 5$, cD_1, cD_2 ,…, cD_5, capturing the high-frequency components, often corresponding to the signal's abrupt change or transient components.

Once the signal is decomposed, the next step involves calculating features from the concatenated coefficients (approximation and detail coefficients). Feature calculation transforms these coefficients into a set of values that are effective for further analysis. In this study, the features selected are the following:

- Energy content

Signal energy content calculation is a commonly used measurement in engineering (Boashash, B., 2016). In signal processing, it represents the total magnitude of the signal squared over a given time. For a discrete signal $x[n]$ where n denotes the discrete time index, the energy E of the signal is defined as(Asuhaimi Mohd Zin et al., 2015):

$$E = \sum_n |x(n)|^2 \tag{5.4}$$

In case that the signal is the wavelet coefficients obtained from the wavelet decomposition of the signal, the energy is calculated in a similar manner where c represents the set of wavelet coefficients (concatenated coefficients):

$$E = \sum |c(i)|^2 \tag{5.5}$$

Equation 5.5 calculates the energy by summing up the squares of each coefficient. The energy of the wavelet coefficients is a critical feature in many applications, including pattern recognition, fault detection and classification.

- Entropy

Entropy is a concept that originates from thermodynamics and information theory, where it is used to quantify the uncertainty or disorder within a system. In signal processing, entropy is used to measure the randomness of the wavelet coefficients c, it is calculated as(Rangari & Yadav, 2017; Zheng-you et al., 2006):

$$Entropy = -\sum \left(c^2 log(c^2 + \epsilon)\right) \tag{5.6}$$

Where ϵ is a small positive number added to prevent taking the logarithm of zero, entropy is often used as a feature in condition monitoring and pattern recognition where a change in entropy can indicate the presence of fault in the system.

- Variance

Variance is a statistical measure that quantifies the dispersion of a set of data points around their mean. For analysing wavelet coefficients, the variance is similarly calculated as the statistics approach, and it is defined as(Musa et al., 2017):

$$variance = \frac{1}{N}\sum_{i=1}^{N}(c_i - \bar{c})^2 \tag{5.7}$$

Where c_i are the wavelet coefficients, $\bar{c}$ is the mean of these coefficients, and N is the number of coefficients. Variance is significant in signal processing because it characterises the energy spread across different frequencies represented by the wavelet coefficients. It helps to understand the deviation in current or voltage signals.

- Maximum coefficient

Maximum coefficient refers to the most considerable absolute value among the coefficients(Guillen et al., 2015). For a set of wavelet coefficients c, the maximum coefficient is calculated as:

$$MaxCoeff = \max(|c|) \tag{5.8}$$

The maximum coefficient is a critical parameter that helps assess fault severity, locate faults, and classify different types of faults. Different types of faults generally generate distinct patterns in the wavelet coefficient(Guillen et al., 2015). Therefore, the maximum coefficient, especially when observing the corresponding frequency band and time, can help classify the type of fault.

- Cross-correlation

Cross-correlation is a statistical parameter that compares the similarity between two signals. This parameter is widely used in signal processing to show how datasets are related to each other across different times(Yadav et al., 2011). For two discrete signals $x[n]$ and $y[n]$, the cross-correlation $R_{xy}[m]$ at lag m is mathematically defined as(Dasgupta et al., 2015):

$$R_{xy}[m] = \sum_{n} x[n] \cdot y[n+m] \tag{5.9}$$

The most critical aspect of feature extraction is selecting the most informative and relevant features for the classifier. The aim is not just to use all calculated features but to select those that significantly enhance the performance of the classification model since effective feature selection helps reduce the problem's dimensionality, improve model accuracy, and ensure that the classifier is robust to variations in signal input. In this study, several features have been calculated, as shown previously, because these features have been utilised in various studies (Asuhaimi Mohd Zin et al., 2015; Guillen et al., 2015; Musa et al., 2017; Rangari & Yadav, 2017; Yadav et al., 2011). Based on this initial selection, a further analysis should be conducted to determine which features specifically enhance the performance of the classifiers.

Following the initial feature selection, a refined selection process is essential to identify specific features that prevent overfitting and enhance classifier performance.

Given that the original datasets were relatively small, and an oversampling approach was employed to augment their size, conducting a thorough analysis of these datasets is crucial. The approach involved multiplying the dataset by a scaling factor to generate multiple instances of each fault type. This iterative simulation and feature extraction methodology significantly improve the dataset's utility for training robust machine learning models, ensuring that the models developed are accurate and capable of generalising well across different operational conditions and fault types.

Subsequently, feature calculation was performed, and the results are presented in Figure 5.2 to Figure 5.6:

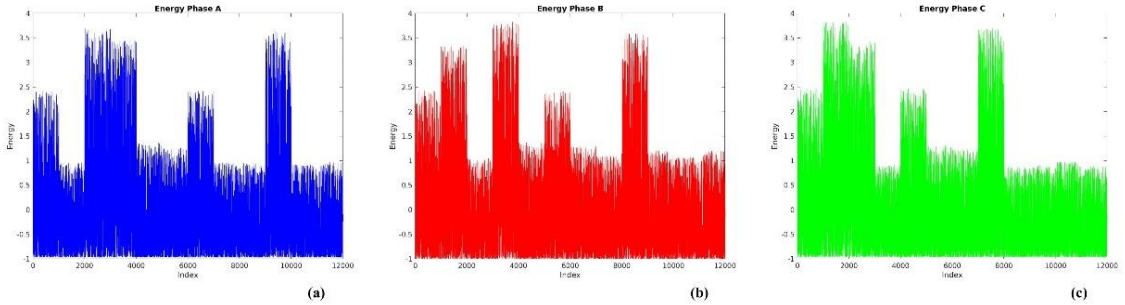


Figure 5.2 : Representation of energy in different phases-(a) energy_phaseA, (b) energy_phaseB, (c) energy_phaseC.

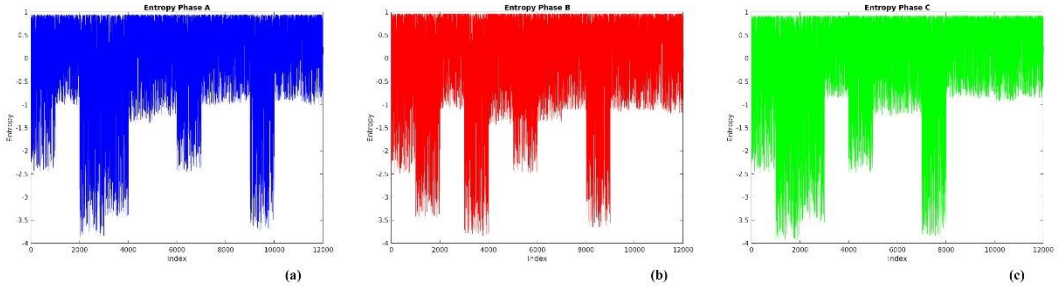


Figure 5.3 : Representation of entropy in different phases-(a) entropy_phaseA, (b) entropy_phaseB, (c) entropy_phaseC.

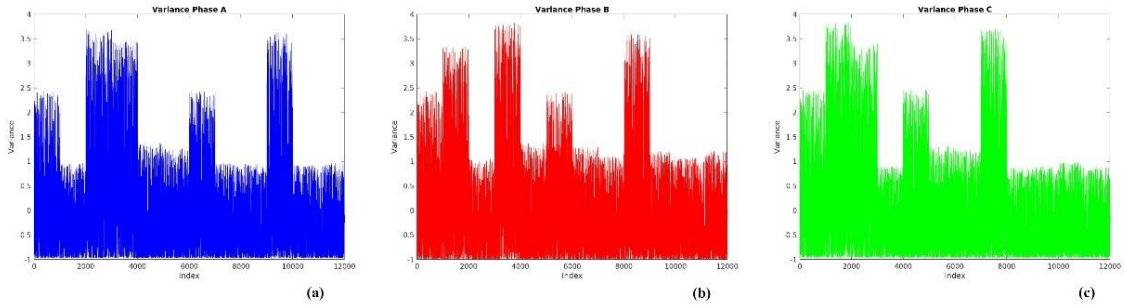


Figure 5.4 : Representation of variance in different phases-(a) variance_phaseA, (b) variance_phaseB, (c) variance_phaseC.

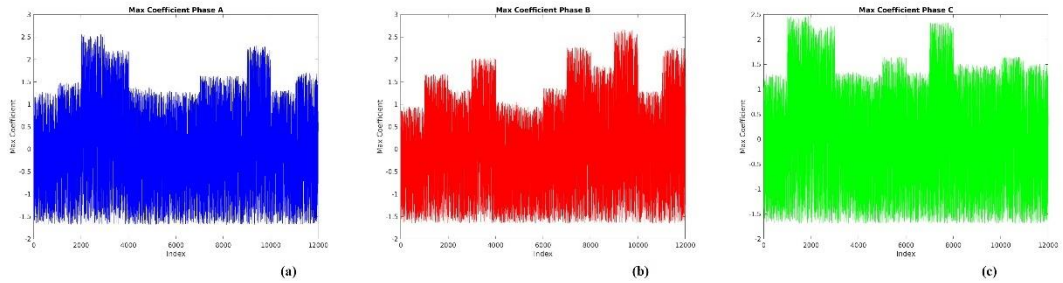


Figure 5.5 : Representation of maximum coefficient in different phases-(a) max coefficient_phaseA, (b) max coefficient_phaseB, (c) max coefficient_phaseC.

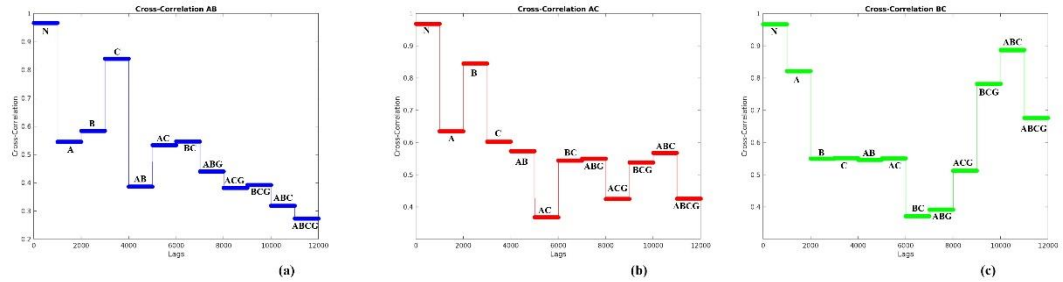


Figure 5.6 : Illustration of cross-correlation between phases - (a) cross-correlation between phases A and B, (b) cross-correlation between phases A and C, (c) cross-correlation between phases B and C.

The figures above display representations of feature distributions, from which it is observed that the energy content and variance appear similar. However, a detailed analysis of the differences between the two signals reveals key distinctions, as depicted in Figure 5.7. Figure 5.7 clearly illustrates the differences between two features: energy and variance. These two features vary slightly in terms of their values.

Figure 5.6 illustrates the cross-correlation between phases, demonstrating the impact of various faults on the phases. A consistent correlation is observed for each fault type, indicating that the generated signals primarily differ in amplitude yet share similar phase characteristics. This high level of precision in the correlation may lead to overfitting in classifiers. Consequently, this feature should be excluded from the classifier inputs to prevent potential model overfitting. The inputs for the classifiers include energy, entropy, variance, and maximum coefficient.

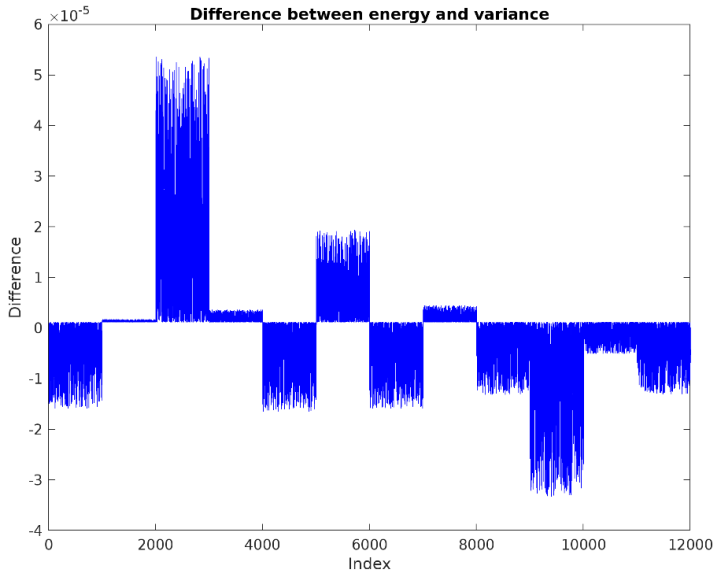


Figure 5.7 : Difference between the energy and variance features.

5.3 Classification Procedures

Following the feature extraction, calculation, and selection process, the refined data is employed to classify various types of faults. Implementing a k-fold cross-validation technique involves dividing the data set into k-equal subsets to enhance the performance and robustness of the selected classification models. This technique allows each subset to serve once as a testing set while the remaining subsets are used for training. This cycle is repeated k times, with each k folds as the test data once. This method ensures comprehensive evaluation by using every data point for training and validation, which enhances model reliability by preventing overfitting and ensuring that the models are not biased to a specific subset of data.

In this study, three distinct classifiers are utilised: Support Vector Machine (SVM), Decision Trees (DT), and Long Short-Term Memory (LSTM) networks, each fine-tuned for optimal fault classification accuracy. For validation, a k-fold cross-validation method is implemented with the following configuration:

- Partition Type: $kfold$
- Number of Test Sets: 10
- Training Set Size per Fold: 10800
- Testing Set Size per Fold: 1200

This structured validation approach improves the generalizability of the models and enhances their robustness across diverse fault conditions, ensuring that our classifiers deliver reliable and accurate results.

5.3.1 Support vector machine (SVM)

The SVM classifier, known for its effectiveness in multiclass classification, employs the ***fitcecoc*** function from MATLAB to train the SVM model for multiclass classification using Error-Correcting Output Codes (ECOC). This function is particularly well-suited for scenarios where classification involves more than two classes, making it ideal for addressing the complex nature of fault classification in transmission lines. Additionally, this function employs a *one-vs-one* coding design, wherein a binary classifier is trained for every pair of classes. It ensures precise differentiation and high accuracy across multiple class scenarios.

To effectively capture the nonlinear relationships, present in the dataset, a variety of kernel functions are rigorously tested to determine which best captures the relationship within the dataset. These include linear, polynomial, Gaussian, radial basis function (RBF), and sigmoid kernels. Following that, for each kernel function, the model's hyperparameters, such as *BoxConstraint* and *KernelScale* use the values in Table 5.2. These hyperparameters refer to the cost (C) and gamma γ parameter.

Table 5.2 : Default hyperparameters for SVM kernels in MATLAB.

Kernel Function	BoxConstraint	KernelScale	Polynomial Order
Linear	1	Not applicable	Not applicable
Gaussian	1	Auto (Heuristic)	Not applicable
RBF	1	Auto (Heuristic)	Not applicable
Polynomial	1	Auto (Heuristic)	3
Sigmoid	1	Auto (Heuristic)	Not applicable

Table 5.2 outlines the default hyperparameter values for SVM kernel functions within MATLAB. The BoxConstraint parameter is crucial in managing the trade-off between maximising the margin between classes and minimising classification errors. A high BoxConstraint value tends to reduce classification errors on training data, enforcing strict adherence to accurately classifying all training data. Conversely, a lower value increases the model's generalizability by permitting more margin violations, thus reducing the risk of overfitting, although it may lead to underfitting.

As shown in Table 5.2, the BoxConstraint is set to 1, striking a balanced approach that performs well across various scenarios. This balanced setting prevents the model from becoming overly strict or permissive, making it an ideal choice for initial model training and exploration. The KernelScale is set to 'auto', allowing MATLAB to adaptively adjust the scale based on the input data's statistical properties. This adaptive scaling significantly reduces the need for manual calibration and effectively accommodates diverse data distributions.

When it comes to the polynomial order, this parameter is specific to the polynomial kernel. It is set to a default of 3, providing a cubic transformation that effectively captures complex patterns in the data. This polynomial order makes the kernel particularly suitable for datasets that are not linearly separable, enabling it to model intricate relationships within the data.

For each fold and each kernel type, the SVM model is trained on the training data subset and then used to predict labels on the corresponding test subset. After prediction, key performance metrics are calculated, including accuracy, recall, specificity, precision, and the F1 score. These metrics comprehensively evaluate the model's performance across different aspects, such as its overall accuracy and balance between precision and recall. Additionally, a confusion matrix for each kernel is compiled from the results of each fold, providing detailed insight into the classification performance across different fault types.

5.3.2 Decision Tree (DT)

The Decision Tree (DT) classifier was employed in this study due to its high interpretability and proven effectiveness in fault classification tasks. The ***fitctree*** function in MATLAB was utilized to implement the DT classifier, allowing for robust model training on labelled data. This function facilitates the building of the decision tree and supports complex classification tasks efficiently.

The dataset was partitioned using the cross-validation method into distinct training and testing sets. This approach ensures that the model is both trained and validated on separate data segments, enhancing its reliability and validity by preventing data leakage and ensuring that the findings are robust across independent data samples.

For the training phase, the configuration of the DT model was carefully selected to optimize performance and prevent overfitting. The parameters set for the model were as follows:

- **Split criterion:** The model uses a split criterion of GDI (Gini diversity Index). GDI was chosen due to its efficacy in minimising node impurity. This metric evaluates the impurity of nodes and selects the binary split that maximally reduces impurity in the resulting child nodes, which is ideal for achieving accurate and meaningful classifications.
- **MinParent**: This parameter determines the minimum number of samples required in a node to be split, set at 10 in this DT model. It helps prevent overfitting by ensuring that decisions are based on adequate data, reduces variance for more excellent model stability, and enhances computational efficiency by limiting unnecessary splits.
- **MinLeaf**: The minimum number of samples required in a leaf node was set to 1, enabling highly detailed classification. However, this setting is carefully balanced with other parameters to prevent the model from fitting into the data's noise.
- **MaxSplits**: This parameter restricts the maximum number of splits in the tree, directly influencing the model's complexity and size. It is crucial in optimizing computational efficiency and ensuring the model remains interpretable. For this study, the value of MaxSplits is set to 10799. This calculation ensures that the tree's growth is appropriately scaled to the size of the training dataset.
- **NVarToSample**: This parameter is used in DT to specify the number of features to be considered for splitting at each node. In this study, it is configured to 'All', which means that all available features in the dataset are evaluated for making the best split decision at each node. This setting ensures that the model utilizes the complete features, facilitating a comprehensive data analysis.
- **MergeLeaves**: This feature allows the merging of similar leaves during the post-training phase, which helps simplify the model and enhance prediction efficiency. The primary benefits include preventing overfitting by simplifying the model, improving the tree's interpretability due to fewer and broader rules,

and enhancing generalization to new data by focusing on more significant patterns.

- **Prune**: This parameter is turned on to enable the pruning of non-informative branches after the tree is fully grown. This step is vital for removing redundancies and minimizing overfitting, thereby improving the model's generalization capability.

The model was trained on the training dataset following the initial setup and configuration. Subsequently, it was used to predict the labels for the training dataset and an independent testing set to evaluate its performance. The performance metrics were calculated to assess the model's effectiveness in each cross-validation process fold. These metrics included accuracy, recall, specificity, precision, and F1-score, comprehensively evaluating the classifier model.

5.3.3 Long Short-Term Memory (LSTM)

The dataset used for fault classification was initially pre-processed to obtain the relevant features required for the LSTM model. Given the potential class imbalance observed in the initial dataset, an oversampling strategy was employed. After several trials, an oversampling factor of 100 was found to be optimal, effectively enhancing the representation of minority classes. This approach ensured a more balanced dataset, which is crucial for training a robust classification model.

The fault classification model was implemented using MATLAB's ***trainNetwork*** function, configured with a five layers network architecture specifically designed for sequence data processing:

- Input Layer: It configures the network to accept the input feature set's size, aligning with the dimensions of the calculated features.
- LSTM Layer: This layer contains 100 hidden units. It is critical for learning dependencies within the sequence data, utilizing internal mechanisms such as forget, input, and output gates to manage information effectively over time. It employs the tanh activation function for the cell state and a sigmoid activation for the gates, which are standard choices for managing the flow of information through the network.

- Fully Connected Layer: This layer plays a pivotal role in the model, as it maps the output of the LSTM layer to the number of classes in the dataset. In this study, the dataset comprises 12 classes, and this layer is instrumental in translating the learned features into class scores.
- Softmax Layer: It converts the scores from the fully connected layer into probabilities by applying the softmax function over the 12 classes. This normalization allows for the interpretation of the output as class probabilities.
- Classification Layer: This layer uses the probabilities to calculate a cross-entropy loss during training and to classify inputs during inference.

The LSTM network was trained using a 10-fold cross-validation method that ensures the model's generalizability and robustness. In this setup, the dataset was divided into ten subsets. In each fold, one subset was used as the test set of 12000 samples, and the remaining nine subsets were used as the training set of 108000 samples. The model was optimized using the Adam optimizer, chosen for its effectiveness in handling sparse gradients and adapting the learning rate during training. Training settings, which included a defined number of epochs, batch size, and a learning rate schedule to optimize the network's performance gradually, are detailed in Table 5.3. The model's performance was evaluated in each fold based on standard classification metrics such as accuracy, precision, recall, specificity, and F1-score.

Throughout the training process, the network's learning dynamics were closely monitored. A series of plots provided insights into changes in loss and accuracy over epochs, offering a comprehensive view of the model's training progress (see Figure A.1).

Table 5.3 : Training parameters for the LSTM network.

Property	Value
Gradient Decay Factor	0.9
Squared Gradient Decay	0.999
Epsilon	$1e^{-8}$
Initial Learn Rate	0.0010
Max Epochs	15
Learn Rate Schedule	piecewise
Learn Rate Drop Factor	0.2000
Learn Rate Drop Period	10
Mini Batch Size	128

Table 5.3 (continued) : Training parameters for the LSTM network.

Property	Value
Shuffle	every-epoch
L2 Regularization	$1e^{-4}$
Gradient Threshold	1 (as '12norm')
Gradient Threshold Method	Inf
Verbose	0
Plots	training-progress

5.4 Simulation Results

This section presents the comprehensive results from the simulation studies aimed at classifying transmission line faults. The following sections show that each classifier model, rigorously applied according to the proposed methodologies, has generated a distinct set of outcomes.

5.4.1 Results from SVM

The SVM classifier was evaluated by testing various kernel functions to identify which one offers the best performance for fault classification. This process is critical as the choice of kernel function can significantly impact the effectiveness of the SVM in handling the data's nonlinearities. The performance results of the SVM classifier with different kernel functions are shown in the following tables (from Table 5.4 to Table 5.7).

Table 5.4 : SVM model performance metrics using linear kernel.

kfold	Accuracy	Recall	Specificity	Precision	F1Score
1	0.90167	0.90167	0.99106	0.92845	0.91486
2	0.8925	0.8925	0.99023	0.91896	0.90554
3	0.90417	0.90417	0.99129	0.92953	0.91667
4	0.8975	0.8975	0.99068	0.92413	0.91062
5	0.90917	0.90917	0.99174	0.93116	0.92003
6	0.915	0.915	0.99227	0.93499	0.92489
7	0.89083	0.89083	0.99008	0.93571	0.91272
8	0.89333	0.89333	0.9903	0.92057	0.90675
9	0.92083	0.92083	0.9928	0.93609	0.9284
10	0.89167	0.89167	0.99015	0.93495	0.9128
Average	**0.901667**	**0.901667**	**0.99106**	**0.929454**	**0.915328**

Table 5.5 : SVM model performance metrics using Gaussian kernel.

kfold	Accuracy	Recall	Specificity	Precision	F1Score
1	0,91667	0,91667	0,99242	0,94722	0,9317
2	0,90583	0,90583	0,99144	0,94002	0,92261
3	0,91	0,91	0,99182	0,94123	0,92535
4	0,90917	0,90917	0,99174	0,94245	0,92551
5	0,91333	0,91333	0,99212	0,94547	0,92913
6	0,91583	0,91583	0,99235	0,94722	0,93126
7	0,9075	0,9075	0,99159	0,94311	0,92496
8	0,89167	0,89167	0,99015	0,93469	0,91267
9	0,92583	0,92583	0,99326	0,95274	0,93909
10	0,90917	0,90917	0,99174	0,94419	0,92635
Average	**0,9105**	**0,9105**	**0,991863**	**0,943834**	**0,926863**

Table 5.4 illustrates the performance of the SVM classifier with linear kernel function, showing consistent results across all the evaluation metrics. The average accuracy and recall values are approximately 0.90167, indicating that the classifier correctly identifies about 90% to 92% of positive and negative instances. The specificity is high, around 0.99, indicating excellent identification of true negatives. The average precision and F1 scores are also robust, at 0.92945 and 0.91533, respectively.

According to Table 5.5, the Gaussian kernel presents slightly higher performance metrics than the linear kernel, with the average accuracy and recall mostly above 0.91. Specificity remains high at about 0.99, similar to the linear kernel. Precision and F1 scores are higher, peaking at around 0.94 and 0.927, respectively, suggesting a better balance between precision and recall than the linear kernel. The RBF kernel has the same performance as the Gaussian kernel, as shown in Table 5.6, which is expected as the RBF is a type of Gaussian kernel. It shows a strong balance of precision and recall, with high specificity, making it very effective in classifying true negatives.

Table 5.6 : SVM model performance metrics using RBF kernel.

kfold	Accuracy	Recall	Specificity	Precision	F1Score
1	0,91667	0,91667	0,99242	0,94722	0,9317
2	0,90583	0,90583	0,99144	0,94002	0,92261
3	0,91	0,91	0,99182	0,94123	0,92535
4	0,90917	0,90917	0,99174	0,94245	0,92551
5	0,91333	0,91333	0,99212	0,94547	0,92913
6	0,91583	0,91583	0,99235	0,94722	0,93126
7	0,9075	0,9075	0,99159	0,94311	0,92496
8	0,89167	0,89167	0,99015	0,93469	0,91267

Table 5.6 (continued) : SVM model performance metrics using RBF kernel.

kfold	Accuracy	Recall	Specificity	Precision	F1Score
9	0,92583	0,92583	0,99326	0,95274	0,93909
10	0,90917	0,90917	0,99174	0,94419	0,92635
Average	**0,9105**	**0,9105**	**0,991863**	**0,943834**	**0,926863**

The polynomial kernel shown in Table 5,7 significantly outperforms the other kernels in almost all metrics, with an average accuracy and recall of 0.9846 and a specificity close to 0.99. The precision and F1 scores are the highest among all kernels, exceeding 0.98, which indicates a superior ability to predict positive classes accurately and a high overall efficiency of the model. Also, the classification using the sigmoid kernel does not yield satisfactory results despite being generally adequate.

Table 5.7 : SVM model performance metrics using polynomial kernel.

kfold	Accuracy	Recall	Specificity	Precision	F1Score
1	0,98583	0,98583	0,99871	0,98711	0,98647
2	0,98667	0,98667	0,99879	0,98851	0,98759
3	0,98417	0,98417	0,99856	0,98522	0,98469
4	0,98833	0,98833	0,99894	0,98901	0,98867
5	0,99	0,99	0,99909	0,99064	0,99032
6	0,98333	0,98333	0,99848	0,98489	0,98411
7	0,98333	0,98333	0,99848	0,98476	0,98404
8	0,985	0,985	0,99864	0,98622	0,98561
9	0,98083	0,98083	0,99826	0,98265	0,98174
10	0,97917	0,97917	0,99811	0,98181	0,98048
Average	**0,984666**	**0,984666**	**0,998606**	**0,986082**	**0,985372**

While all kernels demonstrate high specificity, indicative of solid performance in identifying true negatives, the polynomial kernel particularly excels, showcasing superior performance across all metrics. This superior performance suggests that the polynomial kernel is exceptionally well-suited for the dataset that classifies transmission line faults. However, given its near-perfect performance metrics, it is crucial to conduct further checks for overfitting to ensure the model's robustness and generalizability. Overfitting and underfitting evaluations are essential to validate that the observed high performance reflects the model's efficacy. These considerations are detailed in the analysis result in Table 5.8.

Table 5.8 : Evaluation of overfitting in the SVM model using polynomial kernel.

kfold	Accuracy	Recall	Specificity	Precision	F1Score	Training Accuracy
1	0,98667	0,98667	0,99879	0,98746	0,98706	0,98565
2	0,98667	0,98667	0,99879	0,98752	0,98709	0,98602
3	0,98333	0,98333	0,99848	0,98524	0,98428	0,98667
4	0,98583	0,98583	0,99871	0,9873	0,98657	0,98676
5	0,98167	0,98167	0,99833	0,9836	0,98263	0,98537
6	0,98833	0,98833	0,99894	0,98958	0,98896	0,98574
7	0,98417	0,98417	0,99856	0,98534	0,98475	0,98519
8	0,98417	0,98417	0,99856	0,98605	0,98511	0,98602
9	0,99	0,99	0,99909	0,99057	0,99029	0,98648
10	0,985	0,985	0,99864	0,98605	0,98553	0,9862

Table 5.8 provides comprehensive performance metrics for evaluating the SVM model with a polynomial kernel, particularly in the context of overfitting. The table reveals that training accuracy aligns closely with test accuracy across all evaluations, indicating robust generalisation to new data, which is crucial for practical applications. The consistently high specificity underscores the model's reliability in minimising false positives. Furthermore, the precision and F1 scores are notably high, demonstrating that the model not only accurately identifies positive cases but does so with a significant degree of reliability. This balance between detecting true positives and avoiding false positives is vital for the effectiveness of the classifier.

The results in Table 5.8 highlight the robustness of the SVM model with a polynomial kernel, and there are no apparent signs of overfitting or underfitting. The model's performance is stable across various folds, suggesting it is well-tuned and effectively captures the underlying patterns in the data without being overly fitted to the training set. Additionally, analysing the confusion matrix (Fig.28) would provide a further understanding of the classifier's accuracy in distinguishing between true positives, true negatives, false positives, and false negatives. This matrix is critical as it visually represents the classifier's decisions.

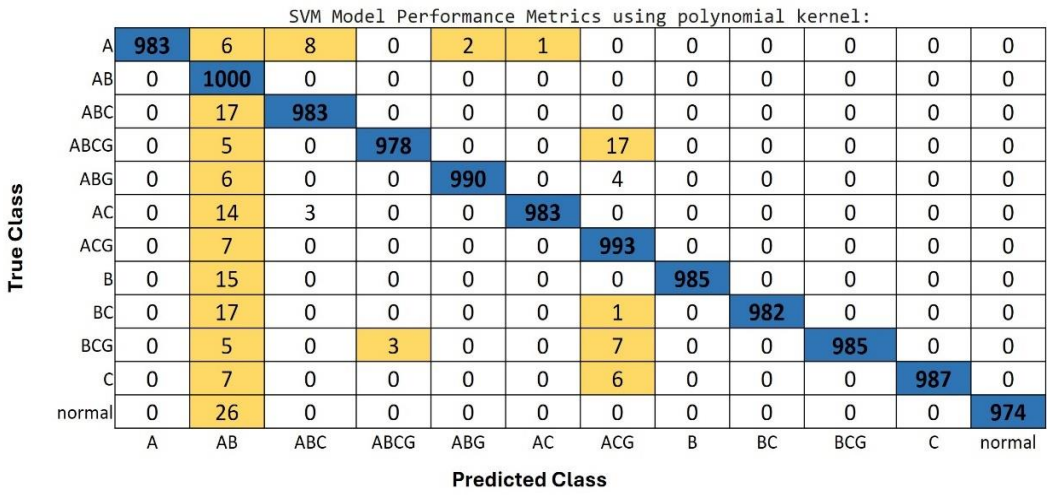


Figure 5.8 : The confusion matrix of SVM model.

Figure 5.8 illustrates the confusion matrix for the SVM model using a polynomial kernel. The rows represent the actual classes, and the columns represent the predicted classes. The SVM model has shown high performance in AB, ABG, and ACG, with a very high classification of 1000, 990, and 993, respectively. However, there are misclassifications in several classes, such as class A being misclassified into ABC and AB a few times, and class AC notably being misclassified into B and BC. To ensure a comprehensive understanding of the classification model's robustness and effectiveness for transmission line faults, further evaluating the DT classifier in the next step is crucial.

5.4.2 Results from DT

The second phase of the analysis involves evaluating the Decision Tree (DT) classifier on the same dataset. The results obtained are shown in Table 5.9, following the proposed methodology, which involves model configuration and the training process.

Table 5.9 : Decision Tree model performance metrics.

kfold	Accuracy	Recall	Specificity	Precision	F1Score
1	0,9625	0,9625	0,99659	0,96289	0,96269
2	0,9725	0,9725	0,9975	0,97267	0,97259
3	0,9625	0,9625	0,99659	0,96384	0,96317
4	0,96833	0,96833	0,99712	0,96925	0,96879
5	0,98417	0,98417	0,99856	0,98425	0,98421
6	0,965	0,965	0,99682	0,96538	0,96519
7	0,96417	0,96417	0,99674	0,96454	0,96435
8	0,95833	0,95833	0,99621	0,95895	0,95864

Table 5.9 (continued) : Decision Tree model performance metrics.

kfold	Accuracy	Recall	Specificity	Precision	F1Score
9	0,97083	0,97083	0,99735	0,9711	0,97097
10	0,96917	0,96917	0,9972	0,96955	0,96936
Average	**0,96775**	**0,96775**	**0,997068**	**0,968242**	**0,967996**

Table 5.9 presents the performance metrics for a Decision Tree (DT) classifier evaluated on the same dataset previously used for the SVM analysis. Both accuracy and recall are closely aligned, with an average value of 0.96775. These metrics indicate that the DT classifier 96% consistently and correctly identifies positive and negative cases across different folds. The specificity values are incredibly high, averaging around 0.997, which demonstrates the model's effectiveness at correctly identifying true negatives and minimizing false positives. The average precision value is around 0.97, which suggests that when the model predicts an instance as positive, there is a high likelihood that it is indeed positive. The F1 score indicates that the DT classifier has a balanced performance between precision and recall. Using 10-fold cross-validation helps mitigate the risk of overfitting by training and testing the model across all available datasets, ensuring a comprehensive evaluation. However, confirming whether the model remains stable when subjected to small perturbations in the data is still crucial. Therefore, the overfitting verification is shown in Table 5.10. This verification can help ascertain the robustness of the model and its ability to generalize well.

Table 5.10 : Evaluation of overfitting in the DT model.

kfold	Accuracy	Recall	Specificity	Precision	F1Score	Training Accuracy
1	0,98083	0,98083	0,99826	0,98118	0,98101	0,98972
2	0,96333	0,96333	0,99667	0,96412	0,96373	0,98935
3	0,96917	0,96917	0,9972	0,96964	0,9694	0,98935
4	0,97333	0,97333	0,99758	0,97334	0,97333	0,98972
5	0,965	0,965	0,99682	0,96581	0,9654	0,98796
6	0,96917	0,96917	0,9972	0,96948	0,96932	0,98898
7	0,9675	0,9675	0,99705	0,96852	0,96801	0,9912
8	0,96417	0,96417	0,99674	0,96519	0,96468	0,98972
9	0,97167	0,97167	0,99742	0,97195	0,97181	0,98861
10	0,96917	0,96917	0,9972	0,96958	0,96937	0,99019

Table 5.10 presents the performance metrics for the DT model, highlighting a consistent training accuracy trend ranging from approximately 0.987 to 0.9912. The training accuracy is higher than the validation accuracy across all corresponding folds.

This gap suggests a degree of overfitting despite employing 10-fold cross-validation, a method generally used to mitigate overfitting. Thus, there is a clear need for further parameter tuning of the DT classifier. After extensive testing with various configurations of MinLeaf, MinParent, and MaxSplits, the optimal settings were identified as MinLeaf of 1, MinParent of 4, and MaxSplits of 10799. These parameters generate cross-validated loss values ranging from 0.0255 to 0.0290, as shown in Table 5.11. This low loss indicates that, on average, the model incorrectly predicts approximately 3% of the cases across different subsets of the data during cross-validation, where a significant improvement indicating robust model performance is observed. The performance metrics for these tuned parameters are displayed in Table 5.12, offering a refined view of how well the model performs with the adjusted settings.

Table 5.11 : The cross-validated loss across the various fold.

kfold	cross-validated loss
1	0.0278
2	0.0283
3	0.0281
4	0.0255
5	0.0268
6	0.0265
7	0.0290
8	0.0262
9	0.0264
10	0.0264

Table 5.12 : The performance metrics after the parameters tuning.

kfold	Accuracy	Recall	Specificity	Precision	F1Score	Training Accuracy
1	0,98333	0,98333	0,99848	0,98352	0,98343	0,99667
2	0,98083	0,98083	0,99826	0,98102	0,98093	0,99722
3	0,975	0,975	0,99773	0,97525	0,97513	0,99704
4	0,97667	0,97667	0,99788	0,97696	0,97681	0,99713
5	0,97	0,97	0,99727	0,97039	0,9702	0,99657
6	0,97333	0,97333	0,99758	0,97356	0,97344	0,99704
7	0,97333	0,97333	0,99758	0,97361	0,97347	0,99676
8	0,975	0,975	0,99773	0,97529	0,97514	0,99722
9	0,97333	0,97333	0,99758	0,97362	0,97348	0,99648
10	0,98	0,98	0,99818	0,98041	0,98021	0,99759

According to Table 5.12, the tuning of the parameters not only enhanced the training accuracy but also improved the validation accuracy. Additionally, the narrow gap

between the training and validation accuracies suggests that the model exhibits minimal overfitting. This gap indicates practical parameter tuning, which has led to a well-generalizing model. To further assess the model's performance and confirm these findings, an analysis based on the confusion matrix was conducted, illustrated in Figure 5.9. This additional analysis helps to visualize the model's predictive accuracy in classifying between classes, providing deeper insights into its performance across various categories.

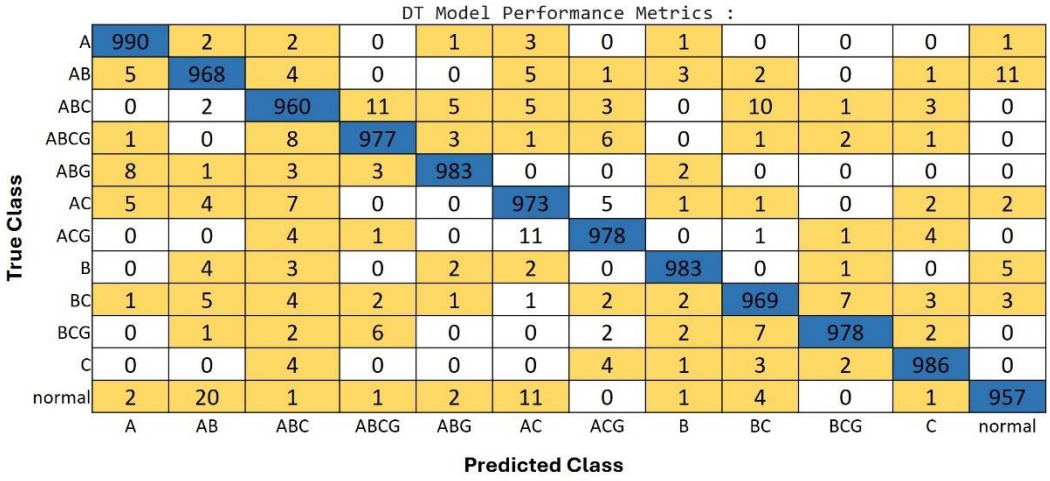


Figure 5.9 : Model The confusion matrix of DT model.

Figure 5.9 presents the confusion matrix for the Decision Tree (DT) model, highlighting correct predictions along the diagonal cells and misclassifications in the off-diagonal cells. Notably, the "normal" class, representing no-fault data, is frequently misclassified, indicating specific challenges in distinguishing this category from others. Moreover, misclassifications are observed across all classes, highlighting broader challenges in the DT model's classification accuracy.

Overall, while the Decision Tree (DT) classifier achieves a good level of accuracy, it does not perform as well as the SVM classifier, which utilizes a polynomial kernel. The SVM achieves a higher average accuracy of 0.9846 compared to the DT's average accuracy of 0.96775. This comparison underscores the SVM's superior ability to manage complex patterns and deliver higher precision across multiple metrics, making it more suited for scenarios requiring detailed pattern recognition and robust predictive performance. However, there is hope for further enhancement in classification performance for transmission lines faults, as the potential of the Long Short-Term Memory (LSTM) network will be tested to classify the same dataset.

5.4.3 Results from LSTM

In the final phase of the classification process, the Long Short-Term Memory (LSTM) network is selected for its proficiency in managing sequence data. The proposed methodology's results, which included calculating the performance metrics and analysing the confusion matrix, are detailed in Table 5.13 and Figure 5.10.

Table 5.13 : The performance metrics for LSTM model.

kfold	Accuracy	Recall	Specificity	Precision	F1Score
1	0,9883	0,99	1	0,99	0,99
2	0,985	0,99	1	0,99	0,99
3	0,9817	0,98	1	0,98	0,98
4	0,975	0,97	1	0,98	0,98
5	0,9867	0,99	1	0,99	0,99
6	0,9633	0,96	1	0,97	0,97
7	0,9725	0,97	1	0,98	0,97
8	0,9783	0,98	1	0,98	0,98
9	0,9725	0,97	1	0,98	0,97
10	0,9817	0,98	1	0,98	0,98
Average	**0,9785**	**0,978**	**1**	**0,982**	**0,98**

Table 5.13 showcases the exceptional performance of the LSTM model, with accuracy values ranging from 0.9633 to 0.9883 and an average accuracy of 0.9785. The model consistently maintains high average values for recall at 0.978, precision at 0.982, and an F1 score of 0.98. Notably, the model consistently achieves perfect specificity in all folds, demonstrating its exceptional ability to avoid false positives entirely. To fully understand the model's ability to accurately classify each class, it's crucial to examine the confusion matrix (Figure 5.10). This additional analysis provides insights into the model's performance across different classes, identifying any potential areas for improvement in class-specific classification.

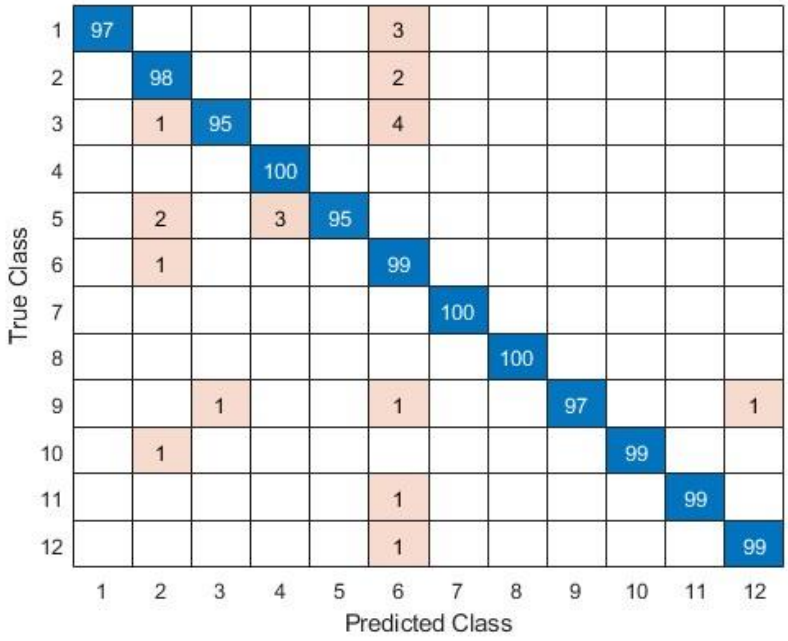


Figure 5.10 : The confusion matrix for LSTM model.

Figure 5.10 displays the confusion matrix for the LSTM model, detailing its classification performance across 12 diverse classes, such as A, AB, ABC, ABCG, ABG, AC, and others. Typically, each class has a size of 1000, but to a 10-fold cross-validation, the dataset for each class in the LSTM model is reduced proportionally. Therefore, the matrix reveals exceptionally high diagonal values for many classes, indicating vital accuracy in predictions. For instance, specific classes like ABCG, AC, B, and BCG (corresponding to 4, 6, 8, and 10) achieved perfect scores 100, showcasing that each instance within these categories was accurately identified. However, there are notable instances of misclassification, such as class A (1) being incorrectly predicted as ABC (3) on three occasions and class AB (2) being misclassified as ABC (3) twice. Moreover, Class ABC (3) experienced misclassifications with Class AB (2) and ABCG (4). Other misclassifications were also observed in Classes 5 and 9. Despite these issues, the LSTM model demonstrates robust classification capabilities across a broad range of classes, although minor misclassifications are observed in a few cases.

In comparison, as shown in Figure 5.11, both the LSTM and SVM classifiers exhibit high-performance levels. However, the SVM consistently outperforms the LSTM regarding accuracy, precision, recall, and F1 scores. The LSTM model has slightly lower overall performance metrics, but it excels in specificity, achieving a perfect score. This indicates its exceptional ability to avoid false positives, which is

particularly advantageous when handling time-series data as it effectively captures temporal dynamics, ensuring that actual negative events are rarely misclassified as positives.

While useful in scenarios requiring model interpretability, the DT classifier model displays lower performance metrics compared to both SVM and LSTM. Consequently, the SVM demonstrates superior performance over both LSTM and DT classifiers.

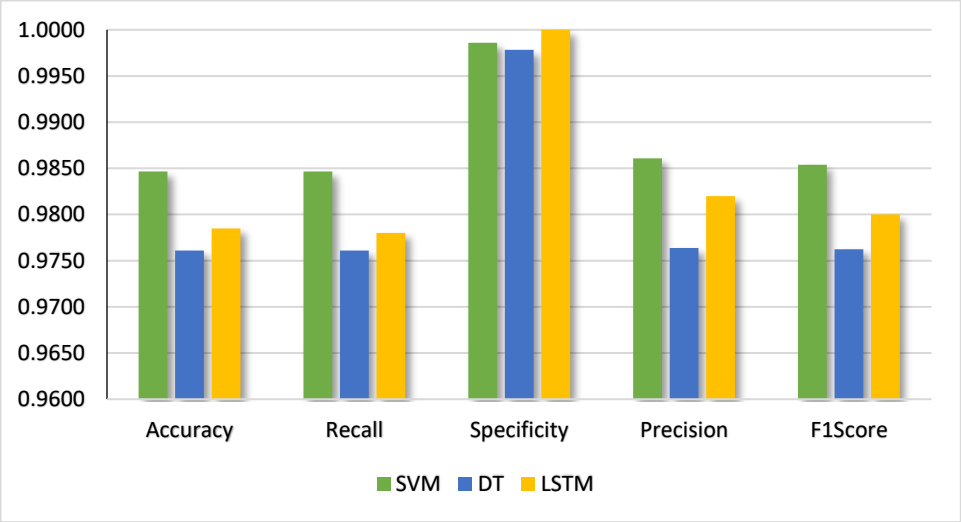


Figure 5.11 : Comparison of classification performance metrics for the classifiers.

Overall, selecting the appropriate classifier is a critical decision that depends on the specific requirements and complexities of the fault classification task. Each classifier has its strengths and limitations.

The Support Vector Machine (SVM) with a polynomial kernel is highly recommended for tasks requiring high precision and the ability to distinguish complex patterns. The polynomial kernel allows SVM to fit non-linear decision boundaries, making it adept at handling datasets where relationships between features are not straightforward. This capability makes it particularly useful in environments where accuracy in distinguishing between different types of faults is paramount.

In scenarios involving temporal data, such as sequences of events or time series, where it is crucial to minimize false positives, the Long-Short-Term Memory (LSTM) network is a robust choice. LSTMs are recurrent neural networks capable of learning order dependence in sequence prediction problems. This makes them ideal for applications where the timing and order of events are critical, such as the sequential detection of anomalies or faults in transmission lines.

Decision Trees (DT) are beneficial in contexts that require high model interpretability. They provide precise and straightforward visualizations of decisions, which is invaluable for communicating the model's logic to stakeholders needing a technical background. However, Decision Trees are prone to overfitting, especially with complex datasets. Measures such as pruning (removing parts of the tree that do not provide additional power) or setting minimum sample size limits for each node can be implemented to overcome overfitting.

6. CONCLUDING REMARKS AND FUTURE WORKS

In conclusion, transmission lines, which account for 85% of system faults, pose significant challenges as they can damage protective systems and substantially deteriorate electrical equipment. This issue is particularly critical in developing countries such as Djibouti, where frequent power outages are responsible for approximately 85% of the total END (Energy Not Distributed). Given these challenges, enhancing the monitoring and maintenance of transmission systems is crucial. Developing robust fault detection and classification models is essential for improving power systems' operational reliability and safety.

This study introduces two models for fault detection and one for fault classification, utilizing signals obtained from short circuit simulations in MATLAB/SIMULINK. The flowchart in Figure 5.12 provides a comprehensive summary of all methodologies and results. The fault detection models effectively identify and analyse various fault characteristics, including one based on Short-Time Fourier Transform (STFT) and another using hybrid wavelet transforms. The classification model employs advanced machine learning techniques, such as Support Vector Machine (SVM), Decision Tree (DT), and Long Short-Term Memory (LSTM), to accurately classify different fault types. These models collectively enhance the fault management capabilities of power systems, particularly in regions with significant energy distribution challenges.

The first fault detection model uses the Short-Time Fourier Transform (STFT) to analyse non-stationary signals for identifying fault characteristics in the Djibouti power system, focusing on single line-to-ground (SLG), double line-to-ground (DLG) and three-phase faults. The findings indicate that three-phase and DLG faults show specific high-frequency components upon fault clearance at 0.1 sec, while SLG faults display a broad frequency band with lower amplitude. Current signal analysis reveals increased current during faults, with the highest values for three-phase faults. Risk evaluation highlights SLG faults as the most frequent and risky, followed by severe DLG faults. However, the model's fixed-size window limits its ability to capture SLG

faults fully, suggesting the need for more refined detection techniques like wavelet transforms to enhance accuracy and resolution.

The second fault detection model addresses the challenge of detecting minor, unseen defects in transmission lines that significantly impact electrical equipment. Using the undecimated reconstruction approach with Stationary Wavelet Transform (SWT), the model amplifies minor defects to facilitate feature extraction. The methodology involves decomposing the signal using SWT, with the decomposition level determined by Shannon's information criterion. The undecimated reconstruction using the ASO operation further enhances feature extraction. Applying the Continuous Wavelet Transform (CWT) revealed previously undetectable harmonic components, specifically the 12th, 13th, 14th, and 16th harmonics. The method was validated by applying it to a known feature added to an artificial signal, and the results confirmed its efficiency in detecting minor disturbances in the power system. This approach underscores the importance of advanced signal processing techniques in improving fault detection accuracy and ensuring the reliability of power systems, highlighting its effectiveness in capturing critical fault characteristics that traditional methods might overlook.

The fault classification model employed three distinct machine learning classifiers, such as support vector machine (SVM), decision tree (DT), and Long Short-Term Memory (LSTM), to evaluate their effectiveness in fault classification for transmission lines. Each classifier was rigorously tested across various metrics, including accuracy, recall, specificity, precision, and F1 score.

The SVM, particularly with a polynomial kernel, demonstrated exceptional performance. It delivered high metrics across all categories and effectively handled nonlinear relationships. This makes SVM particularly valuable for complex fault classification tasks where precision is crucial, minimising false positives and negatives.

On the other hand, while offering high interpretability, the DT classifier showed limitations in terms of overfitting, with discrepancies between training and validation accuracy. Despite tuning efforts, DT did not match SVM's overall performance but remains viable where model transparency is prioritised.

In contrast, the LSTM classifier excelled in handling sequence data, showing high specificity, which is invaluable in fault classification involving time-series analysis. Although it slightly lagged behind SVM in overall performance metrics, and it outperformed DT in handling temporal dynamics.

Thus, the choice of classifier is a crucial decision that should be made based on the specific requirements of the fault classification task. SVM with a polynomial kernel is recommended for high precision and complex patterns. LSTM is a robust choice for scenarios involving temporal data where avoiding false positives is crucial. DT is useful in contexts requiring model interpretability, though careful handling is necessary to avoid overfitting. The decision on which classifier to use should be collaborative, involving all stakeholders in the fault classification task.

These findings contribute to the academic understanding of fault detection and classification techniques and provide practical insights for enhancing the reliability and efficiency of power systems in Djibouti, as the Djibouti power system experienced numerous unscheduled outages due to the faults. Since Djibouti's power is imported from Ethiopia, most faults originate on the Ethiopian side and involve either voltage or frequency instability. To address these challenges, it is recommended that a deep condition monitoring system be installed and that faults be archived in a database to aid in future system reliability improvements.

Implementing the undecimated reconstruction approach with Stationary Wavelet Transform (SWT) to detect any minor defects in power systems and the advanced machine learning techniques can lead to a more stable, efficient, and robust power infrastructure, which is critical for supporting economic growth and technological advancement in the region.

Future works include simulating other types of signals to confirm the effectiveness of this detection approach using the undecimated reconstruction. A practical application could also involve using intelligent robots to collect data from cracks in insulators and slack cable connections. This data could then be transferred to computers for final decision-making using the proposed mathematical methods in Djibouti.

Moreover, it is important to explore integrating various classifiers into a hybrid model that combines their strengths to further enhance fault classification accuracy and

reliability. This integration could provide a comprehensive solution showing each classifier's unique advantages, thereby optimising fault management in power systems.

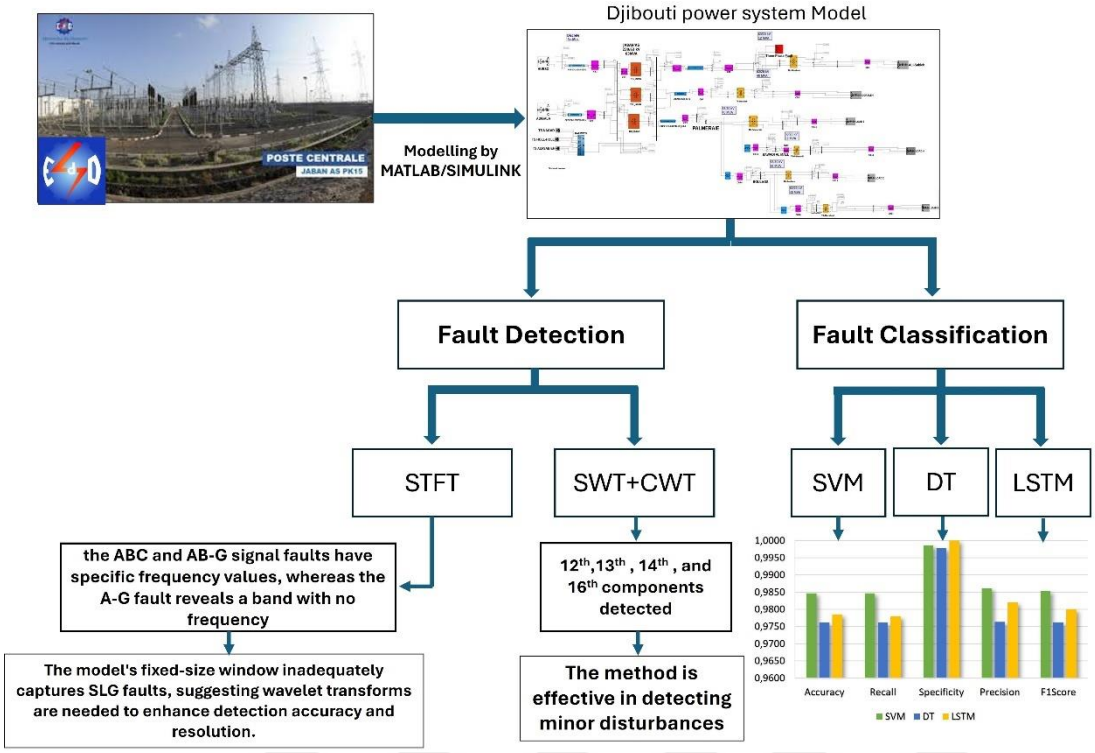


Figure 6.1 : Overview of fault detection and classification in the Djibouti power system.

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APPENDICES

APPENDIX A: Training accuracy and loss metrics across epochs for different folds and data sources for the classification algorithms.

APPENDIX A : Training accuracy and loss metrics across epochs for different folds and data sources for the classification algorithms.

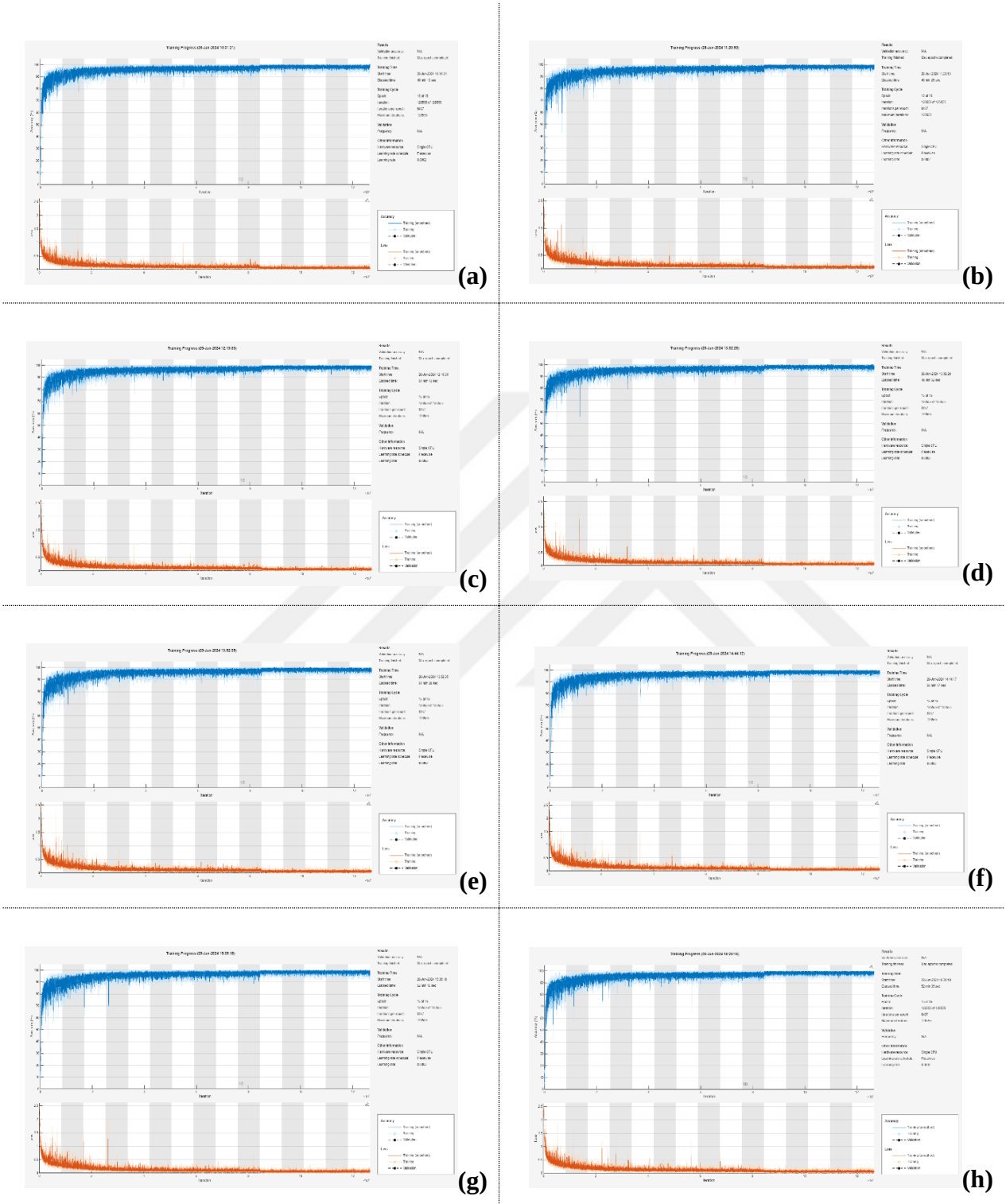
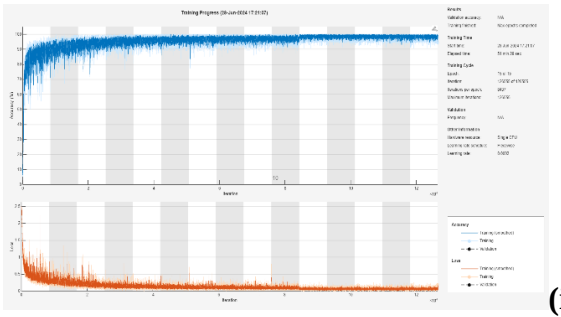
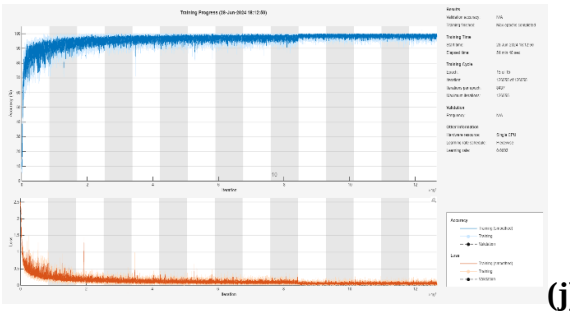


Figure A.1 : Training accuracy and loss metric plots for different kfold: (a)-fold 1, (b)-fold 2, (c)-fold 3, (d)-fold 4, (e)-fold 5, (f)-fold 6, (g)-fold 7, (h)-fold 8, (i)-fold 9, (j)-fold 10.



(i)



(j)

Figure A.1 (continued) : Training accuracy and loss metric plots for different kfold: (a)-fold 1, (b)-fold 2, (c)-fold 3, (d)-fold 4, (e)-fold 5, (f)-fold 6, (g)-fold 7, (h)-fold 8, (i)-fold 9, (j)-fold 10.

Table A.1 : Features and labels for various faults scenarios.

Energy_phaseA	Entropy_phaseA	Variance_phaseA	MaxCoeff_PhaseA	CrossCorrelation_AB	Labels
1,29	-1,27	1,29	0,73	0,97	normal
1,82	-1,82	1,82	1,00	0,97	normal
-0,91	0,90	-0,91	-1,30	0,97	normal
-0,20	0,20	-0,20	0,32	0,55	A
-0,73	0,72	-0,73	-0,55	0,55	A
1,62	-1,65	1,62	1,48	0,58	B
2,75	-2,84	2,75	2,10	0,58	B
-0,33	0,36	-0,33	-0,20	0,84	C
-0,52	0,54	-0,52	-0,44	0,84	C
-0,54	0,55	-0,54	-0,37	0,39	AB
1,18	-1,20	1,18	1,25	0,39	AB
-0,91	0,89	-0,91	-1,17	0,53	AC
0,27	-0,24	0,27	0,54	0,53	AC
-0,79	0,78	-0,79	-0,99	0,55	BC
0,89	-0,86	0,89	0,51	0,55	BC
0,18	-0,19	0,18	0,88	0,44	ABG
-0,06	0,05	-0,06	0,60	0,44	ABG
-0,07	0,08	-0,07	0,58	0,38	ACG
-0,51	0,51	-0,51	-0,06	0,38	ACG
2,63	-2,66	2,63	1,84	0,39	BCG
0,24	-0,21	0,24	0,36	0,39	BCG
-0,92	0,91	-0,92	-1,22	0,32	ABC
0,78	-0,77	0,78	1,20	0,32	ABC
-0,64	0,64	-0,64	-0,28	0,27	ABCG
-0,97	0,94	-0,97	-1,63	0,27	ABCG

Table A.1 (continued) : Features and labels for various faults scenarios.

Energy_phaseB	Entropy_phaseB	Variance_phaseB	MaxCoeff_PhaseB	CrossCorrelation_AC	Labels
1,28	-1,29	1,28	0,47	0,97	normal
1,82	-1,85	1,82	0,70	0,97	normal
-0,94	0,92	-0,94	-1,32	0,97	normal
0,74	-0,72	0,74	0,45	0,64	A
-0,45	0,46	-0,45	-0,46	0,64	A
0,14	-0,15	0,14	0,58	0,85	B
0,64	-0,67	0,64	1,02	0,85	B
-0,30	0,33	-0,30	-0,25	0,60	C
-0,50	0,53	-0,50	-0,47	0,60	C
-0,56	0,56	-0,56	-0,49	0,57	AB
1,17	-1,22	1,17	0,94	0,57	AB
-0,90	0,89	-0,90	-1,21	0,37	AC
0,91	-0,90	0,91	0,29	0,37	AC
-0,87	0,86	-0,87	-0,95	0,54	BC
0,26	-0,28	0,26	0,58	0,54	BC
0,25	-0,24	0,25	1,37	0,55	ABG
-0,01	0,02	-0,01	1,04	0,55	ABG
1,15	-1,11	1,15	0,75	0,43	ACG
0,10	-0,06	0,10	0,07	0,43	ACG
0,73	-0,67	0,73	2,17	0,54	BCG
-0,41	0,45	-0,41	0,57	0,54	BCG
-0,94	0,93	-0,94	-1,19	0,57	ABC
0,92	-0,96	0,92	1,18	0,57	ABC
-0,62	0,63	-0,62	-0,03	0,43	ABCG
-0,99	0,97	-0,99	-1,59	0,43	ABCG

Table A.1 (continued) : Features and labels for various faults scenarios

Energy_phaseC	Entropy_phaseC	Variance_phaseC	MaxCoeff_PhaseC	CrossCorrelation_BC	Labels
1,32	-1,29	1,32	0,75	0,97	normal
1,86	-1,83	1,86	1,02	0,97	normal
-0,91	0,88	-0,91	-1,30	0,97	normal
0,95	-0,94	0,95	0,94	0,82	A
-0,36	0,36	-0,36	-0,21	0,82	A
1,47	-1,50	1,47	1,27	0,55	B
2,53	-2,62	2,53	1,85	0,55	B
-0,69	0,69	-0,69	-0,54	0,55	C
-0,77	0,76	-0,77	-0,72	0,55	C
-0,33	0,35	-0,33	-0,41	0,55	AB
2,18	-2,16	2,18	1,17	0,55	AB
-0,90	0,87	-0,90	-1,12	0,55	AC
0,31	-0,25	0,31	0,81	0,55	AC
-0,84	0,82	-0,84	-0,98	0,37	BC
0,24	-0,21	0,24	0,56	0,37	BC
1,81	-1,84	1,81	1,42	0,39	ABG
1,23	-1,24	1,23	1,08	0,39	ABG
-0,11	0,13	-0,11	0,50	0,51	ACG
-0,52	0,53	-0,52	-0,13	0,51	ACG
0,50	-0,46	0,50	1,11	0,78	BCG
-0,47	0,48	-0,47	-0,07	0,78	BCG
-0,92	0,88	-0,92	-1,17	0,89	ABC
0,83	-0,78	0,83	1,52	0,89	ABC
-0,65	0,64	-0,65	-0,37	0,68	ABCG
-0,96	0,92	-0,96	-1,63	0,68	ABCG

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PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

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