ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

HIGH IMPEDANCE FAULT DETECTION IN MEDIUM VOLTAGE DISTRIBUTION SYSTEMS USING WAVELET TRANSFORM

M.Sc. THESIS

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Department of Electrical Engineering

Electrical Engineering Programme

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

DALGACIK DÖNÜŞÜMÜ KULLANILARAK ORTA GERİLİM DAĞITIM SİSTEMLERİNDE YÜKSEK EMPEDANSLI ARIZA TESPİTİ

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To my beloved family,

FOREWORD

In the name of Allah, the most gracious the most merciful, first and foremost, I thank Him for all the blessings and strength that have been bestowed upon me throughout this Journey.

To those who believed when the path seemed uncertain, to the unsung heroes of countless hours who provided unwavering love and the foundation upon which I stand, to the ones who stood by me through every challenge, sharing both my struggles and joys—my family, friends, and mentors—your unwavering faith and steadfast support have been the bedrock upon which this journey was built. I am also grateful to my professors, who guided me through the academic labyrinth with wisdom and patience. A special acknowledgement to my advisor Prof. Dr. Ömer Usta for his continuous dedication and guidance throughout my thesis research. Each of you has been a beacon in this journey, and this thesis is not just a product of my effort, but a reflection of the community that shaped it. With heartfelt gratitude, I dedicate this work to all of you.

January 2024 Baraa MAKKAWI
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ABBREVIATIONS

HIF	: High impedance fault
PS	:Power Systems
DS	: Distribution system
WT	: Wavelet Transform
CWT	: Continuous Wavelet Transform
DWT	: Discrete Wavelet Transform
MRA	: Multi-Resolution Analysis
ED	: Energy of Detail
NN	: Neural Network
ANN	: Artificial Neural Network
CNN	: Convolutional Neural Network
RNN	: Recurrent Neural Network
RGR	: Ratio Grounded Relaying
RCGA	: Real Coded Genetic Algorithm
db	: Daubechies
bior	: Biorthogonal
coif	: Coiflet
sym	: Symlet

SYMBOLS

Ψ	: Wavelet
$\Psi(t)$	: Wavelet Function
R	: Resistance
V	: Voltage
I	: Current
a	: Scale parameter
b	: Translation parameter
$x[n]$	: Discrete signal
$a_j[n]$	: approximation coefficient
$d_j[n]$	: Detail coefficient
$h[n]$	: Low-pass filter
$g[n]$	: High-pass filter

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HIGH IMPEDANCE FAULT DETECTION IN MEDIUM VOLTAGE DISTRIBUTION SYSTEMS USING WAVELET TRANSFORM

SUMMARY

The increasing complexity of distribution systems demands innovative approaches to fault detection, particularly for high impedance faults which are characterized by low fault currents that often elude conventional detection methods. This thesis addresses this challenge by focusing on the development of a novel and reliable algorithm for high impedance fault detection in medium voltage distribution systems. The methodology employed is pivoted on wavelet transform analysis, a powerful tool for signal processing and analysis, to enhance fault detection capabilities. Wavelet transform provides the analysis of different frequency components of a signal with good time and frequency localization.

The main objective of this research is to address the limitations of existing high impedance fault detection methods by proposing a new algorithm that offers improved reliability and accuracy. The proposed algorithm leverages wavelet transform to carry out a multi resolution analysis using ‘sym5’ as a mother wavelet to extract level 5 detail coefficients from the electrical current signals of the distribution system. These coefficients capture subtle variations of high frequency components which are indicative of high impedance faults. By calculating the energies of the level 5 coefficients for each phase and the neutral, and subsequently integrating the results to determine the average slope at each phase and neutral, a robust metric for fault detection is established.

The algorithm's effectiveness is validated through extensive testing, with results consistently aligning with expectations. The testing phase involves simulated fault scenarios using MATLAB/Simulink software to assess the algorithm's performance under various conditions. The outcomes demonstrate the algorithm's ability to accurately detect high impedance faults and the faulty phase(s), showcasing its potential as a valuable tool for enhancing the reliability of medium voltage distribution systems.

In conclusion, the research presents a successful algorithm for high impedance fault detection, offering a promising solution to a critical challenge in power distribution systems. The proposed method exhibits a level of reliability that surpasses traditional approaches, laying the foundation for improved fault detection strategies. However, recognizing the complexity and variability of real-world distribution systems along with the difficulty in modeling high impedance faults perfectly, further testing on real world situations is recommended to validate the algorithm's performance under diverse operating conditions and in the presence of additional system complexities.

To ensure the algorithm's practical applicability, it is essential to conduct field tests in real-life distribution systems. These tests will provide insights into the algorithm's adaptability to varying environmental conditions and its ability to accommodate the nuances of different distribution network configurations. Additionally, the algorithm's performance in the presence of multiple simultaneous faults and its response to transient conditions warrant investigation to assess its robustness.

Recommendations for future research include expanding the algorithm's capabilities to address more complex fault scenarios and exploring opportunities for integration with emerging technologies such as machine learning for enhanced fault detection and classification. Continued collaboration with industry stakeholders and power system operators is crucial to fostering the adoption of this innovative algorithm and ensuring its seamless integration into practical applications.

In summary, this thesis contributes a significant advancement in high impedance fault detection, offering a reliable algorithm grounded in wavelet transform analysis. The potential impact of this research extends to the improvement of power system reliability and resilience, safeguarding against faults that pose challenges to traditional detection methods. Through ongoing research, testing, and collaboration, the proposed algorithm holds the promise of becoming an indispensable tool in the ongoing evolution of medium voltage distribution systems.

DALGACIK DÖNÜŞÜMÜ KULLANILARAK ORTA GERİLİM DAĞITIM SİSTEMLERİNDE YÜKSEK EMPEDANSLI ARIZA TESPİTİ

ÖZET

Elektrik, mobil telefonlar, mutfak eşyaları, elektrikli aletler, aydınlatma ve elektrikli araçlar da dahil olmak üzere yaşamımızın çeşitli yönlerinin işleyebilmesi için hayati bir öneme sahiptir. Elektrik müşterilere ulaştırabilmek için tam bir güç sistemi (GS) gereklidir ve bu sistem üç ana aşamadan oluşur: Güç Üretimi, İletim ve Dağıtım. Dağıtım sistemleri (DS), düşük empedanslı arızalar gibi hatalara karşı hassastır (DEA), bu arızalar koruyucu cihazlar tarafından kolayca tespit edilebilen yüksek hata akımları üretir. Yüksek empedanslı arızalar (YEA), görece düşük hata akımına sahip olmaları nedeniyle geleneksel koruma cihazları tarafından tespit edilmesi zor olan hatalardır.

Yüksek empedanslı arızalar (YEA'lar), kolayca tespit edilemeyen ve geleneksel koruma cihazları tarafından ortadan kaldırılamayan bir tür hatadır. YEA'lar, enerjili bir iletkenin yüksek empedans profiline sahip bir malzeme ile temas ettiğinde ortaya çıkar, bu malzemeler arasında ağaç dalları, beton, çakıl, asfalt, kum, çimento veya ince çakıl bulunabilir. Bu hatalar, yer yüzeyi malzemesi, yüzey nemliliği, hava koşulları, yük tipi, besleme konfigürasyonu ve gerilim seviyeleri gibi faktörlerden etkilenir.

YEA'lar, yangına neden olan ark oluşumu, özellikle hata kuru bitki örtüsü veya hasar görmüş kablo izolasyonu içinde meydana geldiğinde, önemli risklere neden olabilir. YEA'ları tespit etmek, bu hatalarla ilişkilendirilen ince ve aralıklı özellikleri tanıyabilen sinyal işleme ve makine öğrenimi gibi gelişmiş yöntemleri gerektirir ve elektrik şebekesinin güvenliği ve güvenilirliğini sağlamak için önemlidir. Ayrıca, YEA'lar, güç dağıtım sistemlerinde düşük akım seviyeleri, aralıklı doğa, yangın tehlikeleri, gerilim dalgalanmaları, sistem istikrarsızlığı ve ekipman hasarı gibi önemli etkiye neden olabilir. Bu sorunları ele almak için YEA'ları tespit etmeye odaklanmış yeni algoritmalar gereklidir. Yeni algoritmalar geliştirilerek, elektrik şebekesini daha iyi koruyabilir ve YEA riskini azaltabiliriz.

YEA'lar, diğer elektrik hatalarından farklı olan benzersiz özelliklere sahiptir. Bunlar, özelliklerde değişkenlik, düşük akım seviyeleri, ark ve yangın tehlikeleri, gerilim dalgalanmaları, doğrusallık dışı, gerilim ve akım dalga formlarında düşük frekanslı bileşenler, akım dalgalarında asimetrinin yanı sıra arkın aralıklı, akım dalga formlarında yüksek frekanslı bileşenler, durağan olmayan akım ve akım birikimi ve omuzdur. YEA tespit için yaklaşımları, bu tezde belirtilen klasik ve sezgisel yaklaşımlara ayrılmıştır.

Dalgacık Dönüşümü (DD), sinyalleri ve fonksiyonları hem zaman hem frekans alanlarında analiz etmek için kullanılan matematiksel bir araçtır. Bir sinyali küçük, iyi lokalize edilmiş dalgacıklara ayırarak sinyalin lokal özelliklerini veya ani değişikliklerini daha esnek bir şekilde temsil eder. DD'nin iki ana türü vardır: sürekli dalgacık dönüşümü (SDD) ve kesik dalgacık dönüşümü (KDD). SDD, bir sinyal üzerinde ölçeklendirilmiş ve çevrilen sürekli bir dalgacık fonksiyonudur, sinyalin frekans içeriğini farklı ölçeklerde sürekli olarak analiz eder. Öte yandan, KDD, pratik uygulamalarda genellikle daha hesaplamalı olarak etkilidir ve kesik ölçek ve çeviri

içerir. DD, sinyal işleme, görüntü sıkıştırma, veri sıkıştırma ve özellik çıkarma gibi çeşitli uygulamalarda kullanılır ve özellikle istasyoner olmayan veya zamanla değişen sinyallerin analizi için uygundur.

Yüksek Empedanslı arıza Modelleme etkili tespit teknikleri için kritiktir, çünkü gerçek hayattaki YEA'lar, simetri, rastlantılılık, doğrusallık ve ark oluşumunun dinamik özellikleri gibi hassas bir şekilde simüle etmeyi içerir. Birçok YEA modeli bulunmaktadır, bunlar arasında Emanuel modeli (1990), David Chan, S. R. Nam, T.M Lai, Yong Sheng ve Steven M. Rovnyak, ve A.R Sedighi modeli bulunmaktadır. YEA'ların modellenmesi, davranışlarını anlamak açısından önemlidir.
Bu çalışmadaki önerilen YEA modeli, T.M Lai'nin basitleştirilmiş YEA modeline dayanmaktadır. Bu model, hava ile toprak arasındaki veya ağaçlar arasındaki yayın hattındaki ark voltajını temsil eden Vp ve Vn voltajlarına sahip iki DC kaynağı (DC1 ve DC2) ve iki diyot (D1 ve D2) arasına yerleştirilmiş R1 ve R2 dirençlerini içerir. Model, değişken dirençler (R1 ve R2) ile kullanılan temel bir model olarak, ağaçların direncini ve/veya toprak direncini temsil etmek için kullanılır.
Bu çalışma için test sistemi, bir 33kV jeneratörün birbirine bağlı olduğu bir 33/20kV iki sargılı trafo, 20 km uzunluğundaki iletim hatları ve 800kW güce sahip bir statik yük içeren temel bir dağıtım sistemi kullanmaktadır.
Bilgisayar simulasyonları, test için MATLAB R2022b ve Simulink kullanılarak gerçekleştirilir. Önerilen YEA modeline bir 20kV kaynağı bağlanır ve V-I karakteristik eğrisini çıkarmak için simüle edilir, bu eğri voltaj ve akım arasında doğrusal olmayan bir ilişkiyi gösterir. MATLAB'de, bir 33kV üç fazlı kaynak, bir 33/20kV iki sargılı trafoya bağlıdır; bu trafo, üç fazlı voltaj ve akımı kaydetmek için bir V-I ölçüm bloğuna bağlıdır, üç fazlı bir pi kesiti hattına, başka bir V-I ölçüm bloğuna ve bir statik yüke bağlanmıştır. Sistem, düşük dirençli topraklama ile toprak hatasını kontrol etmekte ve toprak hatası akımını sınırlamakta, ekipman hasarını önlemekte ve aşırı gerilimi azaltmaktadır.
Önerilen YEA tespit yöntemi, özellikle YEA tespit etmek için kullanılan kesik dalgacık dönüşümleri üzerine dayanmaktadır. Bu yaklaşım, güç hatları ağında YEA'laı tespit etmek gibi yüksek hassasiyet gerektiren uygulamalar için uygundur.
Önerilen YEA tespit yöntemi, dalgacık dönüşüm analizi, özellikle de kesik dalgacık dönüşümü (KDD) üzerine dayanmaktadır. Bu teknik, zaman-frekans alanında sinyalleri analiz etmek için güçlü bir yöntemdir. Aynı anda zaman ve frekans bilgisi sağlayabilir, bu da düşük akım değerleri ve doğrusal olmayan özelliklere sahip YEA'ları tespit etmek için uygun hale getirir. KDD ayrıca frekans ve zaman açısından Çoklu Çözünürlük Analizi (ÇÇA) sunar, bu da geçici sinyalleri ve hataları analiz etmek için önemlidir. KDD, basitliği ve benzer hassasiyeti nedeniyle CDD yerine kullanılmaktadır, ancak daha hızlı zaman-frekans analizi sunmaktadır. Model, ana dalgacığı düşük geçiş filtresi olarak ve ikincilini yüksek geçiş filtresi olarak kullanan çok aşamalı bir filtre kullanmaktadır. Yüksek geçiş filtrelerinin sonuçları "yaklaşımlar" olarak adlandırılırken, detaylar YEA tespiti odak noktasıdır. Özellikle 'sym5' olan Symlet dalgacığı, enerjiyi koruma, sinyal analizi için yardımcı olma, önemli özellikleri çıkarma ve ani değişiklikler ve kesintiler de dahil olmak üzere farklı sinyal özelliklerine uyum sağlama yeteneği nedeniyle ana dalgacık olarak seçilmiştir. 5 seviyeli bir ÇÇA ayrıştırması, akım sinyallerini analiz etmek ve özelliklerini çıkarmak için uygulanır.
Önerilen YEA tespit algoritması, akım sinyallerinin trafonun ikincil sargısından çıkarılmasından sonra gerçekleştirilen KDD'nin 5. seviye detay analizine dayanmaktadır. Algoritma, tüm fazlar ve nötr için trafo ikincilindeki akım sinyallerini

çıkarma, akım sinyalleri üzerinde 'sym5' ana dalgacığını kullanarak KDD/ ÇÇA gerçekleştirme, detay d5 katsayılarını çıkarma ve çizme, detay d5'in enerjisini (ED5) hesaplama, alan değişim eğrilerini çizme ve enerjileri ve eğimleri karşılaştırma işlemlerini içerir, böylece YEA veya dengesiz yük değişimi olup olmadığını belirler.

Bu Yüksek Lisans araştırma tezi, dağıtım sistemlerinde YEA tespiti etrafındaki tartışmalara odaklanmaktadır. Sorun, YEA'lar tarafından üretilen rastlantılılık ve düşük hata akımı tarafından ortaya çıkarılmaktadır. Yeni bir YEA tespit algoritması, özellikle kesik dalgacık dönüşümü (KDD) kullanılarak önerilmektedir. KDD, sistem transformatör ikincilinde çıkarılan akım sinyallerinin çok çözünürlü analizi için kullanılmaktadır.

Beş farklı durumun test edildiği simülasyon sonuçları, önerilen algoritmanın potansiyel olarak hassas bir YEA tespit algoritması olduğunu göstermektedir. Algoritma, dengesiz yük değişim koşulları ile YEA durumları arasında ayrım yapmada başarılı oldu, farklı enerji değerlerinden tek fazlı YEA veya çift fazlı YEA tespit etmede başarılı oldu ve sistemde bulunan hatalı faz veya fazları tespit etmekte başarılı oldu. Ancak, bazı sınırlamalar, algoritmanın düşük akım seviyelerinde, özellikle 5A'nın altındaki akımlarda YEA'yı tespit edebilmesine rağmen hatalı fazı tespit etmekte başarısız olduğunu gösterdi.

Bu tezde özetlenen YEA tespit algoritması şu anda erken geliştirme ve uygulama aşamalarındadır. Bir YEA'nın doğru bir şekilde modellemesi zorlu bir görev olduğu için, MATLAB ve Simulink aracılığıyla gerçekleştirilen simülasyon sonuçlarının hassasiyetten yoksun olabileceği ve potansiyel olarak gerçek dünya senaryolarından farklılık gösterebileceği kabul edilmektedir. Algoritmanın doğruluğunu doğrulamak için gerçek dünya testleri ve analizleri önemlidir. Ayrıca, simülasyon basit bir dağıtım sistemi üzerinde gerçekleştirildiği için, algoritmanın daha karmaşık sistemler üzerinde test edilmesi ve özellikle sofistike durumları ele alması gereklidir. Bunun yanı sıra, gelecekteki çalışmalar, algoritmanın güvenilirliğini artırmak için hata konumu belirleme özelliklerini içermeyi içerebilir.

1. INTRODUCTION

Nowadays, almost everything in the world depends on electricity. Due to the rapid evolution in technology, people became more dependent on energy, the simplest thing to consider is mobile phones which almost everyone in this world use, without electricity they won't work; kitchenware, electrical tools, lighting, electric cars etc. almost everything needs and electrical source to function.

For electricity to reach customers, a complete power system (PS) is needed. A PS consists of three main stages which are: Power Generation, Transmission and Distribution. Most problems occurring in power systems occur in the distribution systems (DS). DS are vulnerable to a lot of faults that may occur such as two phases contacting each others (2-phase fault), three phases contacting each others (3-phase fault) or other faults such as single phase to ground, double phase to ground etc… such faults are considered low impedance faults (LIF) and they produce very high fault currents which can be detected easily with the protective devices found in the PS. While other faults which have a high impedance amplitude, that are called high impedance faults (HIF), are very hard to be detected due to their relatively low fault current which cannot be detected by conventional protection devices. HIFs are usually a result of contact between an energized conductor and tree branch, concrete, gravel, sand etc… which are material of high impedance profile (are usually considered insulators). The results of HIF are dangerous for both the PS and the life of individuals.

Fast and reliable detection of high impedance faults (HIF) in distribution systems (DS) has been a persistent challenge to electric engineers in this field. The reason is because conventional fault detection techniques such as overcurrent relays and fuses fail to detect HIFs due to their relatively small fault currents.

1.1 Purpose of Thesis

The aim of this thesis is to deploy a reliable HIF detection algorithm in distribution systems. To develop such an algorithm, MATLAB/Simulink software is used to model the system and simulate and test the results.

In this thesis a new strategy for detection of HIF based on the analysis of discrete wavelet transform (DWT) to detect the faulty phase(s). The algorithm is capable of detecting different types of HIFs and the faulty phase(s) as well. Current signals of all phases and the neutral at the transformer of substation are analyzed using DWT. Fault detection process is accomplished by decomposition of current signals, extracting fifth details components, calculating energy of details at the fifth level, inspection of the aria variation curves and extracting the average slopes at each phase and the neutral. Comparison of energy levels and slopes between normal operating conditions and other conditions are compared to derive a functional detection algorithm.

Simulation results showed up very good results yielding to the conclusion that the proposed algorithm may be considered precise and fully functional in detection of HIFs.

1.2 Outline of The Thesis

In chapter 1 a brief introduction about power systems and different types of faults along with the problem in detection of HIF is discussed, and the purpose of this thesis is clearly explained.

Chapter 2 is an introduction and explanation of HIFs, their characteristics, effect, and different detection approaches that are discussed in literature are presented.

Chapter 3 held wavelet transform (WT), explained what is WT and some history about it along with the two different types of it, Continuous wavelet transform (CWT) and discrete wavelet transform (DWT). Also types of mother wavelets are presented in this chapter.

HIF modeling is discussed in chapter 4, how different scientists at different times proposed different types of models for HIFs.

In chapter 5 the proposed test system is presented along with its implementation in MATLAB/Simulink, the proposed HIF model is given along with how it is presented in MATLAB and its parameters, the test system that is used for simulation is also given along with all its parameters. Also the proposed HIF detection algorithm is explained briefly in this chapter

Chapter 6 handles the simulation and results, 5 different test cases are represented and simulated, all the results of each test case are explained in this chapter

Chapter 7 is the final chapter in this thesis, it is the conclusion of the overall work done in this study and a recommendation for a future work that might be done.

2. HIGH IMPEDANCE FAULTS (LITERATURE REVIEW)

2.1 High Impedance Fault (HIF)

Faults in distribution systems fall under two main categories: 1- Low impedance faults and 2- High impedance faults. Low impedance faults are very common and can be easily detected with conventional protection devices such as an over current relay and a circuit breaker, on the other hand, despite being less common, high impedance faults are not easily detected and conventional protection devices cannot detect and eliminate them.

2.1.1 What is a HIF?

A high impedance fault is the type of fault that, as it name implies, has a high impedance value, by which the fault current is in the range of normal current in the system and under the maximum load current. So conventional protection devices are not able to detect it and it is considered a non-faulty condition for such devices, resulting in no-trip which means no isolation of fault. Unlike low impedance faults, where the faulted conductors create a direct and low-resistance path to ground, high impedance faults involve a partial or intermittent connection to ground.

High impedance faults occur as a result of a contact between an energized conductor and material of high impedance profile such as a tree branch, concrete, gravel, asphalt, sand, cement and thin gravel. HIFs are influenced by factors such as the ground surface material, surface humidity, weather conditions, load type, feeder configuration and voltage levels [1]. The factors that have the most influence on HIF are surface humidity and material; higher humidity results in higher fault current magnitude and different material result in different voltage-current characteristics [2, 3].

High impedance faults can cause significant risks, such as the potential for arcing that may lead to fires, especially when the fault occurs in dry vegetation, damaged cable insulation, or insulators. Detecting HIFs requires advanced methods, such as signal processing and machine learning, to recognize the subtle and intermittent characteristics associated with these faults and ensure the safety and reliability of the electrical grid.

Examples of HIFs are displayed in figures 2.1, 2.1 and 2.3.

Figure 2.1 : HIF due to the contact of tree limb with a primary conductor [16]

Figure 2.2 : Energized downed conductor implemented by Texas A&M University [17]

Figure 2.3 : HIF testing on a dry tire [18]

2.1.2 HIF Effect

Most power system faults affect and endanger electrical equipment, while HIFs have consequences on living beings. Hence, since these faults are not detected by overcurrent relays, it is a must to develop new algorithms which are specialized in detecting such faults. HIFs are usually accompanied with an arc. During an HIF flammable gas may be generated, or the evolution of an arc near flammable material may result in fire and explosion [4]. Moreover, due to the generation of current, an unintentional contact between the energized conductor and a line crewmen or a member of the public or any living being would occur resulting in fatal conditions [5].

A study reported that 5 to 10% of distribution faults are HIFs [6], another study reported that around 25% of down conductors which are considered HIFs are not detected using overcurrent relays [7].

HIFs can have several significant effects on power distribution systems, which directly impact the reliability, safety, and operational efficiency of the electrical network. Key effects that are associated with HIFs are:

- Intermittent Nature: The intermittent behavior if HIFs, causing the faulted connection to ground to come and go, adds complexity to their detection, as the fault may not be continuously present.

- Fire Hazard: When a HIF occurs in areas with dry vegetation or compromised insulation, arcing occurs, possessing a significant fire hazard, leading to potential damage to equipment and posing risks to personnel and nearby structures.
- System Instability: In some cases, HIFs can result in system instability, affecting the overall performance of the power grid. Intermittent and low-current nature of these faults may not appear immediately, potentially leading to prolonged system issues if not promptly identified and addressed.
- Equipment Damage: The arcing associated with HIFs can cause damage to equipment, including transformers, insulators, and other components in the affected portion of the power distribution system.

Given the potential fire hazards and operational challenges posed by high impedance faults, it's crucial to employ advanced detection and protection methods that go beyond traditional overcurrent devices.

2.1.3 HIF Characteristics

HIFs show some peculiar features that distinguish them from other types of electrical faults. Understanding these features is crucial to the development of effective detection and mitigation strategies.

Here are the key characteristics of high impedance faults:

- Variability in Characteristics: The characteristics of HIFs can vary depending on factors such as the type of insulation, environmental conditions, and the specific location within the power distribution system.
- Low Current Levels: Unlike low impedance faults, where a direct and low-resistance path to ground results in high current flows, HIFs involve partial or intermittent connections, leading to lower current levels.
- Arcing and Fire Hazard: The high resistance in the fault path can lead to arcing. In environments with combustible materials, such as dry vegetation, HIFs pose a significant fire hazard, as the arcing can ignite surrounding materials.

- Voltage Fluctuations: HIFs can cause fluctuations in voltage levels within the power distribution system. These fluctuations may be subtle but can affect the stability and reliability of the electrical network.
- Non-linearity: V-I characteristic curve is usually nonlinear in nature due to the existence of an arc [8, 9].
- Low and high frequency components in voltage and current waveforms: because of the non-linearity of HIF, waveforms contain harmonics up to 300 Hz for voltage and 600Hz for current [10, 11]
- Asymmetry of the current waveform: a difference in the peak value and the shape of positive and negative half cycles in HIF current is present due to the difference between the breakdown voltage and the positive and negative voltage values [12, 13].
- Intermittence of the arc: arc generates a non-steady pattern of current since it generates few conduction cycles followed by few non-conductions cycles [4].
- Non-stationary current: current frequency spectrum varies with time [14].
- Current buildup and shoulder: current gradually builds up to maintain a constant magnitude (shoulder) for several cycles [15].

2.2 HIF Detection Approaches

Various approaches where implemented and discussed in literature over the past years. Some of them are considered classical approaches which depend on classically extracting HIF features, and others are considered heuristic which are based on intelligently decisive tools. In the following part approaches will be discussed. Figure 2.4 shows a flowchart of HIF detection approaches [19].

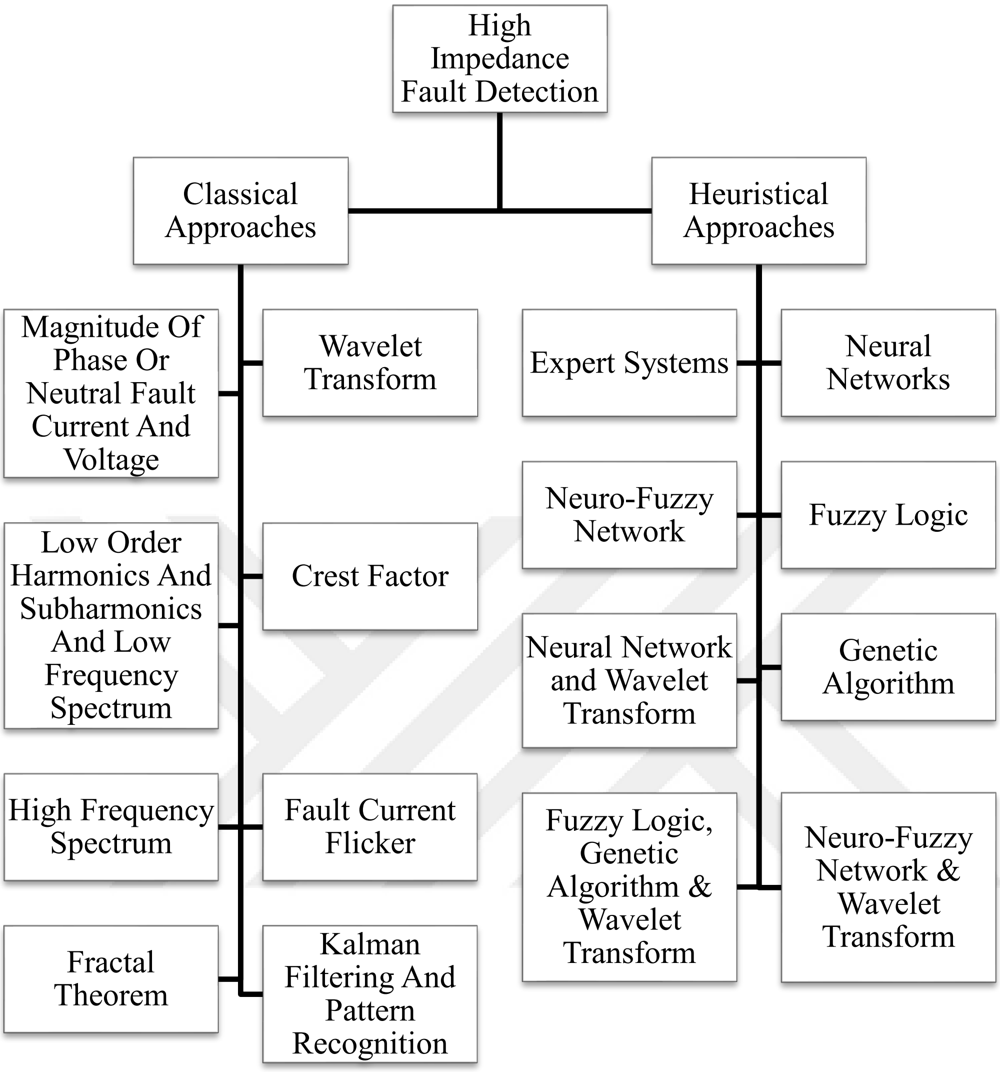

Figure 2.4 : HIF Detection Algorithms [19]

2.2.1 Classical Approaches

2.2.1.1 Magnitude of Phase or Neutral Fault Voltage and Current

One method for detecting HIFs is monitoring the magnitude of phase or neutral voltages and currents.

HIFs often produce small current flowing through the faulted phase, by monitoring the magnitude of both phase voltage and current abnormal conditions can be detected. In healthy systems voltage and current must be in phase and their magnitudes should be consistent with the systems operating conditions, while the presence of an HIF may result in the current waveform exhibiting high harmonic content and be out of phase with the voltage waveform.

On the other hand, HIFs sometimes involve connection between a conductor and ground by which the neutral might get involved, so by monitoring the magnitude of the neutral voltage and current indications of fault may be observed.

Many approaches where presented based on the idea of extracting the magnitude of fault voltage and current, but all these methods proved to be inaccurate and non-reliable, since most frequently these algorithms failed to detect HIFs. Some of these approaches are a proportional relaying algorithm by introducing a new electromechanical relay [20], ratio grounded relaying (RGR) algorithm [21], change in neutral voltage and zero sequence current [22], modified directional earth fault relay [23], and dissipation factor (DF) based criterion [24] etc.

2.2.1.2 Low Order Harmonics, Sub-harmonics and Low-Frequency Spectrum

HIFs can cause distinctive harmonic components and frequency variations in the current waveform. So a valuable method for detecting HIFs may be by monitoring low order harmonics, sub-harmonics, and the low-frequency spectrum.

High Impedance Faults often result in non-linear current waveforms, leading to the generation of low order harmonics (multiples of the fundamental frequency), so a method of indicating HIFs is monitoring the presence of significant low order harmonics (such as the 2nd and 3rd harmonics).

Moreover, High Impedance Faults can introduce sub-harmonics, which are frequencies that are fractions of the fundamental frequency, in the current waveform, resulting in non-linear behavior. A design of detection systems can be implemented to detect abnormal sub-harmonic content in the current signal as a potential indication of a HIF.

In addition, HIFs may lead to changes in the low frequency components of the current waveform, so monitoring the low frequency spectrum may be a good approach for detection of variations associated with HIFs.

This approach focuses on the variation of one or more characterizing or non-characterizing harmonics fault signal in order to detect HIFs. Some of the proposed methods using this approach are: a method based on negative sequence current [25], analyzing spectral behavior of low frequency in terms of magnitude and phase [26], obtaining features to distinguish arcing faults from switching events by analyzing the low order harmonic current [27], also an algorithm was proposed concerning the increase in energy level of harmonics and the degree of randomness associated with arcing HIFs[28], and others developed a scheme based on the concept of quasi-static ripple harmonics and sub/super harmonic frequencies [29].

2.2.1.3 High Frequency Spectrum

High-frequency spectrum analysis for HIF detection involves analyzing the frequency components of the current waveform at higher frequencies. High Impedance Faults often introduce high-frequency transients or oscillations in the current waveform that are not present during normal operating conditions.

High-frequency spectrum analysis can be applied for HIF detection using transient analysis, since HIFs may generate high-frequency spikes, transients or short duration oscillations in current waveform, by monitoring and analyzing the transient behavior in the high frequency spectrum, abnormal patterns associated with HIFs may be revealed. Also high frequency harmonics analysis is another way for HIF detection, since HIFs usually produce high-frequency harmonics or frequency components beyond the normal power system frequency (usually 50 or 60 Hz). So an indication of a fault condition may be by analyzing the high frequency spectrum for the presence of harmonics above a certain threshold. In addition frequency domain analysis may be implemented to detect HIFs since it examines the entire spectrum of the current waveform, including the high-frequency range, and HIFs introduce frequency components distinct from normal system operation in the high-frequency spectrum.

HIFs are characterized with the creation of high frequency components in current signals. In this regard, one approach in detecting HIF was to localize high frequency energy levels in current signals, unfortunately, some normal events such as capacitor switching also cause high frequency levels similar to HIF, but in a HIF case the increase if energy level has a random nature. In order to solve such issue a criteria called randomness criteria was defined. Some researchers used high frequency impedance monitoring while others presented an algorithm based on random behavior of HIF to detect HIFs [30, 31].

2.2.1.4 Feature Extractors (Kalman, Fractal, and Wavelet)

For state estimation in dynamic systems, recursive mathematical algorithms like Kalman filtering can be applied. Although Kalman filtering isn't usually utilized alone for detecting High Impedance Faults (HIFs), it can be combined with other signal processing methods to increase fault detection or state estimate accuracy in power systems.

The application of fractal theory for HIF detection involves analyzing the fractal properties of signals, such as voltage and current waveforms, to identify patterns or irregularities associated with high impedance faults. Fractal theory is particularly useful for characterizing the complexity and self-similarity of signals across different scales.

A powerful signal processing tool that can be employed for HIF detection in power systems is wavelet transform, it is particularly useful for analyzing signals in both the time and frequency domains simultaneously, making it well-suited for identifying transient events and irregularities associated with HIFs.

A general approach to using wavelet transform for HIF detection may be as follows:

- Signal Decomposition: by applying wavelet transform to decompose the voltage or current waveform into different frequency components across multiple scales, then decomposing the results in a set of wavelet coefficients that represent the signal's behavior at different levels of frequency detail.
- Thresholding: setting a threshold on the wavelet coefficients to differentiate between significant features and noise helps in denoising the signal and highlighting important features, making it easier to identify HIF-related patterns.
- Analysis of Approximation Coefficients: by focusing on the approximation coefficients obtained after wavelet decomposition. Significant changes in the approximation coefficients, especially during fault conditions, may indicate the presence of HIFs.
- Identification of Transients: Wavelet transform is effective in capturing transient events in the signal. Identifying and analyzing transient features in the

wavelet domain, HIFs may introduce sudden changes or transients in the current waveform.

- Time-Frequency Localization: One of the advantages of wavelet transform is its ability to provide time-frequency localization. Analyzing how the energy in different frequency bands changes over time helps in identifying patterns associated with HIFs.
- Pattern Recognition: by utilizing machine learning or pattern recognition techniques to analyze the wavelet coefficients and classifying normal and fault conditions. Training a classifier on a dataset that includes examples of normal operation and HIF conditions.
- Multiresolution Analysis: Taking advantage of the multiresolution analysis capability of wavelet transform to capture information at different levels of detail, by which information from multiple scales can be valuable for detecting faults with varying characteristics.

Wavelet transform provides a flexible framework for extracting relevant information from signals, and its adaptability to both transient and steady-state conditions makes it suitable for HIF detection. However, careful consideration of wavelet selection, thresholding, and interpretation of the results is essential for a successful implementation.

Usually HIFs are accompanied with variations in frequency spectrum along with harmonic components, these components are of a non-stationary and time varying nature because of the dynamics of arc faults. As a result, approaches such as Fractal theorem, Wavelet transform and Kalman filtering which deal with time varying nature of fundamental and harmonic components using feature extractors are very convenient to recognize the pattern and identify HIFs.

Kalman filtering theory was used as an approach by some researchers for obtaining the best estimation for time variation of fundamentals and harmonic components [32], while others analyzed HIFs using fractal techniques [33]. On the other hand, wavelet transform may be the most used technique for detection and analyzing HIFs in distribution systems, some researchers used wavelet analysis filter banks by which TACS switch controls the open/close loop of HIF in order to introduce asymmetry and nonlinearity [34], others used multi-resolution analysis based on Morlet wavelet transform [35], while some used a combination of discrete wavelet transform (DWT) along with RMS conversion and frequency range to apply a pattern recognition based algorithm to detect HIFs [36].

Other techniques such as Crest factor, fault current flicker and Cross-Winger-Ville distribution were also used as algorithms for detecting HIFs by some researchers.

2.2.2 Heuristic Approaches

2.2.2.1 Expert Systems

HIFs in power distribution systems may be difficult to detect using traditional methods due to low current levels. Expert systems can be used to improve the detection of HIFs by incorporating domain knowledge and rules based on the characteristics of such faults.

Expert systems may be of different forms that might be designed for HIF detection, some of them as follows:

- Knowledge Acquisition: Gathering domain knowledge from experts in power systems and high impedance fault detection and identifying key features and characteristics of high impedance faults, such as voltage fluctuations, waveforms, and patterns associated with these faults.
- Rule-Based System: Developing a set of rules based on the acquired knowledge to evaluate the system's behavior and defining rules that capture the unique signatures of high impedance faults, considering factors like voltage sags, transients, and spectral analysis.
- Data Acquisition and Preprocessing: Collecting data from the power distribution system, including voltage and current waveforms then preprocessing the data to extract relevant features that can be used in the rule-based system.
- Inference Engine: Implementing an inference engine that uses the rules to make decisions about the presence of high impedance faults, the engine should be able to interpret the preprocessed data and apply the rules to identify potential high impedance fault conditions.

- Decision Making: Defining a decision-making process that considers the results of the rule evaluation and incorporating a confidence level or certainty factor to account for uncertainties in the data and rules.
- Feedback Mechanism: Implementing a feedback mechanism that allows the expert system to learn and adapt over time, then using historical data to refine the rules and improve the accuracy of the high impedance fault detection.
- Integration with Monitoring System: Integrating the expert system with the overall power distribution monitoring system and ensuring that the expert system can receive real-time data and provide timely alerts or recommendations based on its analysis.
- Testing and Validation: Testing the expert system using simulated high impedance faults and real-world data to validate its performance, then Fine-tuning the rules and parameters based on the testing results.

Expert systems are programs that learn, adapt, invent and accumulate the combined wisdom of a profession. These systems are considered to be one of the effective tools used to detect HIFs, it was used by several researchers. For example, some researchers developed a knowledge-based expert system to detect faults by monitoring frequency changes [37], other researchers used the combination of several algorithms such as: expert arc detector, energy, randomness detector, load analysis, load event detector, load extraction, arc burst pattern analysis, spectral analysis, and arcing suspected identifier algorithm, as an expert system in order to detect HIFs [38].

2.2.2.2 Neural Networks

An approach to detect HIFs that leverages machine learning to identify patterns associated with such faults is using neural networks (NN). NN can be trained on data containing examples of normal and fault conditions, learning to recognize the features that indicate HIFs.

NN implementation can be divided to the following stages:

- Data Collection: Gathering data from power distribution systems, including both normal and fault conditions, including information like voltage and current waveforms, as well as any relevant features associated with HIFs.

- Data Preprocessing: Cleaning and preprocessing the data to extract relevant features, it may involve techniques like normalization, filtering, and feature extraction.
- Dataset Labeling: Labeling data to indicate whether each instance corresponds to a normal state or a high impedance fault.
- Neural Network Architecture: Choosing an appropriate neural network architecture, that could be a feed-forward neural network, a convolutional neural network (CNN), or a recurrent neural network (RNN), depending on the nature of the data.
- Training: Splitting the dataset into training and validation sets, then training the neural network using the labeled training data and adjusting the weights and biases to minimize the difference between predicted and actual fault states.
- Validation: Validating the trained neural network on a separate set of data that it has not seen before to ensure it works well with new instances.
- Testing: Testing the neural network on additional datasets, including simulated faults and real-world data, to evaluate its performance.
- Fine-Tuning: Fine-tuning the neural network based on testing results to improve its accuracy.
- Integration with Monitoring System: Integrating the neural network into the power distribution monitoring system to analyze real-time data.
- Alerts or Recommendations: Implementing a system for the neural network to provide timely alerts or recommendations based on its analysis.
- Adaptation and Learning: Implementing mechanisms for the neural network to adapt and learn over time based on feedback and new data.

An important notice is that the success of NN depend on the availability of sufficient data for training it. In addition, precise consideration should be given to the interpretability of NN's decisions, especially in critical systems like power distribution.

Artificial Neural Networks (ANN) are also used to detect HIFs by some researchers. ANN consists of several neurons to import input data called 'input layer' and a number of neurons to export the output called 'output layer', also there may be a number of neurons in between the input and output layers that are arranged in layers called 'Hidden layers'. For example, some researchers used ANN in HIF detection by collecting samples of substation current during normal and abnormal feeder operation which are used then to teach the neural network rules for fault detection [39-40], others proposed an approach using ANN that has an advantage of using a small number of necessary neurons, short measuring sliding data window and easy interpretation of obtained output signals [41].

2.2.2.3 Neuro-Fuzzy Networks

Neuro-Fuzzy networks are a combination of neural networks and fuzzy logic, its aim is to leverage the strengths of both fuzzy and neural networks in order to be able to solve complex problems involving uncertainty, imprecision, and nonlinear relations.

Implementation of neuro-fuzzy network can be as follows:

- Data Collection: Collecting a dataset including examples of normal and fault conditions in power distribution systems including relevant features such as voltage and current waveforms.
- Data Preprocessing: Cleaning and preprocessing the data, extracting features that are indicative of HIFs. This may involve normalization, filtering, and feature extraction.
- Dataset Labeling: Labeling data to indicate whether each instance is a normal state or a high impedance fault.
- Neuro-Fuzzy System Design: Designing the structure of the neuro-fuzzy system typically involves combining a neural network with fuzzy logic components.
- Fuzzy Rule Base: Developing a fuzzy rule base that captures expert knowledge about HIFs and should express the relationships between input features and the possibility of a fault.
- Membership Functions: Defining membership functions that characterize the fuzzy sets associated with input and output variables, it helps in modeling the uncertainty in the system.

- Training the Neuro-Fuzzy System: Training the neural network using the labeled dataset, fuzzy logic components help in dealing with uncertainty, allowing the system to handle imprecise information.
- Validation: Validating the trained neuro-fuzzy system on a separate set of data not used during training to ensure its generalization capabilities.
- Testing: Testing the neuro-fuzzy system on additional datasets, including simulated faults and real-world data, to evaluate its performance.
- Fine-Tuning: Fine-tuning the neuro-fuzzy system based on testing results to improve its accuracy.
- Integration with Monitoring System: Integrating the neuro-fuzzy system into the power distribution monitoring system to analyze real-time data.
- Adaptation and Learning: Considering mechanisms for the neuro-fuzzy system to adapt and learn over time based on feedback and new data.

Implementing neuro-fuzzy systems has an advantage that is their ability of modeling complex, non-linear relationships while accommodating imprecision and uncertainty present in real world.

Some researchers proposed a novel technique by which it makes comparative analysis of feeder responses to pulses injected at the beginning of the feeder for different normal and abnormal configurations, then an artificial neuron set composed of 'neo-fuzzy' neurons was trained to detect HIFs from normal events [42].

2.2.2.4 Fuzzy Logic

Using fuzzy logic to detect HIFs involves designing a system that can handle imprecise and uncertain information.

Fuzzy logic approach can be implemented as follows:

- Defining Input Variables: Identifying relevant input variables related to power distribution system characteristics, such as voltage fluctuations, waveforms, and patterns associated with HIFs.
- Membership Functions: Defining membership functions for each input variable, which describe how each input value contributes to different fuzzy sets.

- Fuzzy Rules: Developing a set of fuzzy rules based on expert knowledge or empirical observations that should express relationships between the input variables and the likelihood of a high impedance fault.
- Inference Mechanism: Implementing an inference mechanism that combines the fuzzy rules to make decisions. Common methods include the Mamdani or Sugeno models.
- Fuzzification: Applying fuzzification to the input variables, converting crisp values into fuzzy values based on the defined membership functions.
- Rule Evaluation: Evaluating the fuzzy rules based on the fuzzy input values, it also involves combining the fuzzy sets according to the defined rules.
- Aggregation: Aggregating the results from individual rules to obtain a fuzzy output.
- Defuzzification: Applying defuzzification to convert the fuzzy output into a crisp decision, which represents the probability or certainty of an HIF.
- Threshold Setting: Establishing thresholds to categorize the output into fault or non-fault conditions. The choice of thresholds depends on the specific requirements of the detection system.
- Testing and Validation: Testing the fuzzy logic system using simulated high impedance faults and real-world data to validate its performance.
- Fine-Tuning: Fine-tuning the membership functions, rules, and thresholds based on testing results to improve the accuracy of the HIF detection.
- Integration with Monitoring System: Integrating the fuzzy logic system with the overall power distribution monitoring system, ensuring it can process real-time data.

Fuzzy logic can model complex relationships and handle uncertainties in a rule-based framework. Thorough testing and validation are crucial to ensuring the system's effectiveness.

Some researchers developed a fuzzy logic decision making technique as an option to improve DSTRP high impedance fault detection algorithm [43].

2.2.2.5 Genetic Algorithm

Genetic algorithms can be used to detect HIFs, it involves optimizing a set of parameters or rules to enhance the accuracy of the detection system.

Genetic algorithm for HIF detection can be implemented according to the following:

- Defining the Detection Problem: Clearly defining the HIF detection problem and the parameters or rules that need optimization.
- Encoding Solutions: Representing potential solutions as individuals in a population.
- Initial Population: Generating an initial population of individuals randomly or based on some prior knowledge.
- Fitness Function: Defining a fitness function that evaluates how well an individual (set of parameters or rules) performs in detecting HIFs, it should be based on the accuracy of the detection system.
- Selection: Selecting individuals from the current population to form a mating pool based on their fitness. Individuals with higher fitness have a higher chance of being selected.
- Crossover (Recombination): Performing crossover (recombination) on pairs of individuals in the mating pool to create new individuals, which mimics the genetic process of combining information from two parents.
- Mutation: Introducing mutations to some individuals in the population to add diversity helps explore a broader search space.
- New Population: Forming a new population using the individuals from crossover and mutation.
- Evaluating Fitness of New Population: Evaluating the fitness of the new population using the fitness function.
- Termination Criteria: Determining termination criteria, such as a maximum number of generations or reaching a desired level of performance.

- Applying Results: Extracting the best-performing individual or set of parameters from the final population as the solution to the optimization problem.
- Integrating with HIF Detection System: Incorporating the optimized parameters or rules into the HIF detection system.
- Testing and Validation: Testing the HIF detection system using simulated faults and real-world data to validate its performance.

When the search space is large and complex genetic algorithms are particularly efficient and precise. They mimic the process of natural selection and evolution to find optimal solutions. In the situation of HIF detection, genetic algorithm can be applied to optimize parameters or rules influencing the accuracy of the detection system. The success of the approach depends on careful design of the encoding, fitness function, and genetic operators, as well as thorough testing and validation.

Genetic algorithm is a metaheuristic optimization technique driven from process of natural selection and evolution, it is well known to be used in places where complex optimization and search problems need to be solved. That's why some researchers proposed this approach to detect HIFs, such as the detection method by using real coded genetic algorithm (RCGA) in order to analyze harmonics and phase angles of the fault current signals [44].

2.2.2.6 Combinations (Neural-Wavelet, Fuzzy-Genetic-Wavelet, Neuro-fuzzy-Wavelet)

Combining different techniques, such as neural networks, fuzzy logic, genetic algorithms, and wavelet analysis, can enhance the robustness and accuracy of HIF detection systems. A variety of researchers went with the idea of combining several approaches in order to improve the detection of HIFs and invent more reliable techniques.

Some used a combination of wavelet and neural networks by which discrete wavelet transform (DWT) was used to process for feature extraction and preparing data for artificial neural networks for calculations and detection [45, 46].

Others combined fuzzy logic, genetic algorithm, and wavelet transform as a proposition to detect HIFs by which wavelet transform was used for feature extraction and selection of fault current signal, while fuzzy logic was used as fuzzy inference system for fault classification and the genetic algorithm was applied for input membership functions adjustment.

While other researchers combined neural networks, fuzzy logic and wavelet transform to detect HIFs, a wavelet multi-resolution signal decomposition method was used for feature extraction, then features were fed to an adaptive neural fuzzy inference system (ANFIS) for identification and classification [47].

2.3 Summary

In this chapter an introduction to power system faults was made, characterizing the faults in two categories: Low Impedance Faults and High Impedance Faults. Then the idea of HIF was discussed explaining what is a HIF and how it is a serious issue in power distribution systems, its effect on the power system and living beings, its characteristics and some pictures of real life events of HIF. After that, the different approaches that are discussed before in literature were presented, these approaches were divided into two types: Classical Approaches and Heuristical Approaches. All approaches were discussed in details of how they were applied by researchers before.

As a conclusion HIF is a very serious issue that not only effect the power distribution systems, but also have a severe effect on living being lives and result in destruction of equipment and most of the times ends up in fire due to the produced arc resulting from it. As for the detection approaches, from the classical approaches the wavelet transform proved its dominancy over other approaches and most researchers in these days depend on WT in their researches to develop and improve the detection methods. Even heuristical approaches proved to be a good idea to detect HIFs in distribution systems, but even in heuristical approaches wavelet transform is used and combined with other approaches to improve and have more precise detection of the fault.

3. WAVELET TRANSFORM

A wavelet transform (WT) is a mathematical tool used to analyze signals and functions in both time and frequency domains. The basic idea of a WT is to decompose a signal into small and well localized functions called wavelets. Unlike Fourier transform which was the only tool available in the nineteenth century, which represents a signal as the sum of sinusoidal functions with constant frequency, WT uses wavelets that are well localized in time and frequency. This allows a more flexible representation of signals with localized features or sudden changes.

WT has two main types: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). CWT is defined as a continuous wavelet function scaled and translated across the signal, it provides a continuous analysis of the signal's frequency content at different scales by representing the signal in terms of the scale and location parameters. On the other hand, DWT is often more computationally efficient in practical applications, it involves a discrete set of scales and translations, a signal is decomposed into approximation coefficients (representing the coarse details) and detail coefficients (representing the fine details) at different scales. This decomposition is performed iteratively to create a multiresolution analysis of the signal.

Various applications need the use of WT such as signal processing, image compression, data compression, and feature extraction. They are precisely suited for analyzing signals that are characterized as non-stationary or time-varying.

3.1 History of Wavelet Transform

Development of wavelet theory and wavelet transform roots deeply in both mathematics and signal processing.

The early concepts of wavelet turns back to the 1800s where the concept of analyzing functions at different scales was introduced by mathematicians such as Joseph Fourier the founder of the Fourier transform that analyses functions in the frequency domain. In 1909, the Hungarian mathematician Alfred Haar introduced the first wavelet, Haar wavelet was based on a simple, piecewise constant function. Haar's work laid the foundation for later developments in wavelet theory. In the 1980s, the French mathematician and signal processing researcher Stéphane Mallat played a pivotal role in the development of wavelet theory by introducing the concept of multiresolution analysis and constructing wavelet bases that allowed for efficient representation of signals at different scales. Mallat's work, particularly his book "A Wavelet Tour of Signal Processing," contributed significantly to the popularization of wavelet transforms.

Researchers like Yves Meyer, Ronald Coifman, and Ingrid Daubechies made significant contributions to the mathematical foundations and practical applications of wavelet transforms.

The 1980s and 1990s were crucial decades for the development and formalization of wavelet theory. Several mathematicians and researchers made significant contributions during this time where the formalization of the continuous wavelet transform CWT and discrete wavelet transform DWT took place. In 1980 a geophysicist called Jean Morlet introduced the Morlet wavelet, a complex-valued wavelet that is widely used in signal processing. The Morlet wavelet has good frequency localization and is particularly suitable for analyzing signals with oscillatory components. After that, in 1985 Yves Meyer, a French mathematician that contributed to the understanding of wavelet theory and its applications, introduced the concept of "wavelet bases" and provided a mathematical foundation for the construction of wavelets. In a 1987 paper, Christopher Brislawn formulated the concept of a discrete wavelet transform and introduced the term "wavelet transform". His work helped in overcoming the gap between continuous wavelet transforms and practical, discrete implementations. In 1989, the French mathematician Stéphane Mallat published a seminal paper titled "A Theory for Multiresolution Signal Decomposition: The Wavelet Representation", in which Mallat introduced the concept of multiresolution analysis and provided a framework for constructing wavelets with desirable properties. This work formed the basis for the development of both continuous and discrete wavelet transforms. A Belgian mathematician that made significant contributions to the theory of wavelets called Ingrid Daubechies developed a family of wavelets known as Daubechies wavelets between 1988 and 1992, which are orthogonal and have compact support. These wavelets played a crucial role in the development of the discrete wavelet transform (DWT) and its efficient implementation.

Wavelet transforms contributed numerous applications in various fields, including signal and image processing, compression, denoising, and feature extraction. The ability of wavelets to capture both time and frequency information with good localization made them attractive for analyzing non-stationary signals. DWT gained prominence due to its computational efficiency and was widely adopted in practical applications.

Wavelet transforms continue to be an active area of research, with ongoing efforts to refine techniques, develop new wavelet functions, and explore applications in diverse fields such as data analysis, image processing, and machine learning.

3.2 Wavelet Transform in Mathematics

The mathematical representation of a wavelet is ψ, it is a square integral function of Hilbert space $L^2(R)$.

Wavelet transform is of two types: the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT).

3.2.1 Continuous Wavelet Transform (CWT)

A continuous wavelet transform (CWT) is a mathematical technique used to analyze the frequency content of a continuous signal over both time and scale. CWT provides a distinctive feature compared to the traditional Fourier analysis by which it examines the local behavior of a signal simultaneously in both time and frequency domains.

CWT uses a wavelet function, denoted as $\psi(t)$, which is a small, oscillatory waveform, which is often chosen to be localized in both time and frequency. It acts like a "window" that can be adjusted to different scales and positions. The wavelet function is then dilated and translated to analyze the signal at different scales and positions. The scale parameter (a) controls the width of the wavelet, and the translation parameter (b) determines its position along the signal. A CWT equation is denoted by equation 3.1 below.

$$CWT(a,b) = \int_{-\infty}^{+\infty} f(t).\frac{1}{\sqrt{a}}\psi^{*}\left(\frac{t-b}{a}\right)dt \tag{3.1}$$

Where $f(t)$ is the continuous signal being analyzed, and $\psi^*(t)$ is the complex conjugate of the wavelet function. The integral is taken over all time, and the result is a two-dimensional function in the a-scale and b-translation space.

High values of $|CWT\ (a,b)|$ indicate regions in the signal where the wavelet closely matches a portion of the signal at a particular scale and position. Varying a and b can view how different scales and positions contribute to the signal.

CWT is particularly useful for analyzing signals with non-stationary or time-varying characteristics, so it is used in various applications, including signal processing, feature extraction, time-frequency analysis, and image processing.

The main drawback of CWT lies in the computational complexity and redundancy.

3.2.2 Discrete Wavelet Transform (DWT)

A continuous wavelet is used for analyzing and processing discrete signals in a way that captures both high and low-frequency components at different resolutions, it is generally obtained by sampling the continuous wavelet transform.

Signal Decomposition:

DWT decomposes a discrete signal $x[n]$ into approximation coefficients ($a_j[n]$) and detail coefficients ($d_j[n]$) at different scales (or levels j). At each level of decomposition, the signal is split into two components: the approximation, representing the low-frequency content, and the detail, capturing the high-frequency content. Decomposition is achieved using a pair of low-pass and high-pass filters ($h[n]$) and ($g[n]$) respectively. The signal is convolved with these filters to obtain the approximation ($a_{j+1}[n]$) and detail ($d_{j+1}[n]$) coefficients by equations 3.2 and 3.3.

$$a_{j+1}[n] = \sum_k h[k] \, . \, a_j[2n-k] \quad (3.2)$$

$$d_{j+1}[n] = \sum_k g[k] \, . \, a_j[2n-k] \quad (3.3)$$

After convolution, the signal is downsampled by a factor of 2 to reduce its length and prepare for the next level of decomposition, decomposition process is repeated iteratively until the desired level of resolution is reached or until the signal cannot be further decomposed. The original signal can be reconstructed from the approximation and detail coefficients using a synthesis process, which involves upsampling and convolution with the corresponding synthesis filters. Approximation coefficients ($a_j[n]$) capture the low-frequency content, while the detail coefficients ($d_j[n]$) capture the high-frequency content. DWT provides a multiresolution analysis of the signal, meaning that it represents the signal at different levels of detail and resolution.

DWT is particularly useful in the field of signal and image processing for tasks such as compression, denoising and feature extraction. The ability of DWT to represent signals in a hierarchical and localized manner makes it useful for analyzing signals with both smooth and rapidly changing components.

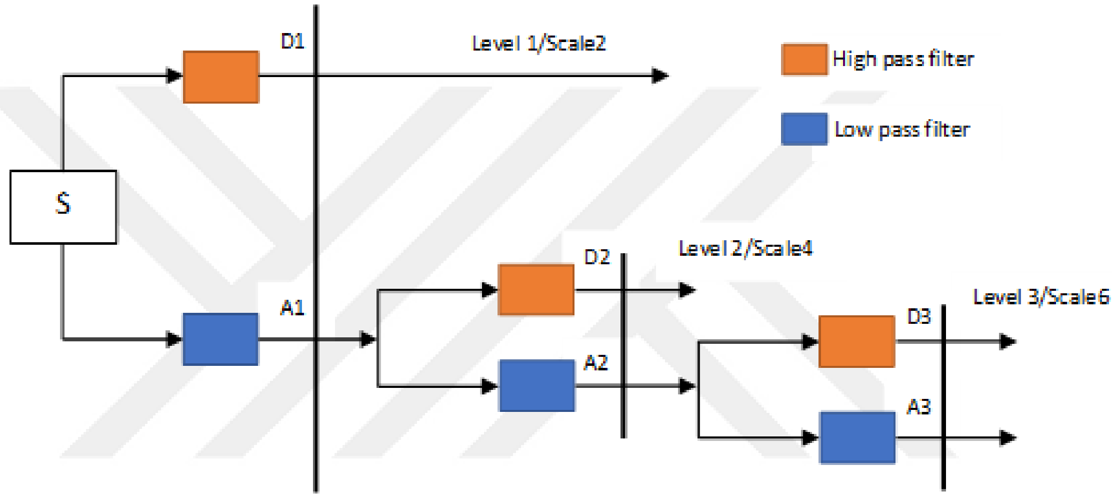

Figure 3.1 : Wavelet Transform Signal Decomposition

3.3 Mother Wavelet Types

Mother wavelets, which are also known as analyzing wavelets or basis functions, are used to decompose signals into different scales and frequencies. Mother wavelets come in various forms and types each with unique characteristics and applications, the most used mother wavelet types are the following:

3.3.1 Haar Wavelet

Introduced by Alfred Haar in the early 20th century, the Haar wavelet is considered the simplest and most basic wavelet used in wavelet analysis, it has a simple piecewise constant shape as shown in the figure 2 below. It is considered the building block of the more complex wavelets. As mentioned before a Haar wavelet function is a piecewise constant that takes the value of +1 in one half of its support interval and -1 in the other half.

So Haar wavelet is defined as follows:
$$\begin{cases} 1\ for\ 0 \le t < \frac{1}{2} \\ -1\ for\ \frac{1}{2} \le t < 1 \\ 0\ otherwise \end{cases}$$

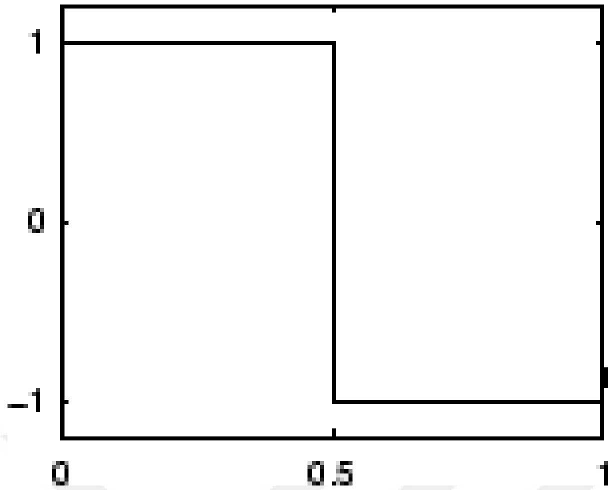

Figure 3.2 : Haar Wavelet

It has good localization properties in both time and frequency domains. Its support in the time domain is confined to a small interval, and it is capable of representing step-like discontinuities in signals.

Haar wavelet is not commonly used in practical applications, but it is often employed for educational purposes to illustrate the basic concepts of wavelet analysis, it provides a foundation for understanding the principles of wavelet transforms and serves as a launch or introduction to more complex wavelets.

3.3.2 Daubechies Wavelets

Daubechies wavelets which are named after the Belgian mathematician Ingrid Daubechies are a family of orthogonal wavelets. They are widely used in signal processing and image compression due to their desirable properties, such as orthogonality, compact support, and good time and frequency localization. The Daubechies wavelet types are denoted by a number N, determining the degree of the wavelet and the number of vanishing moments. Figure 3 represents the various types of Daubechies wavelets.

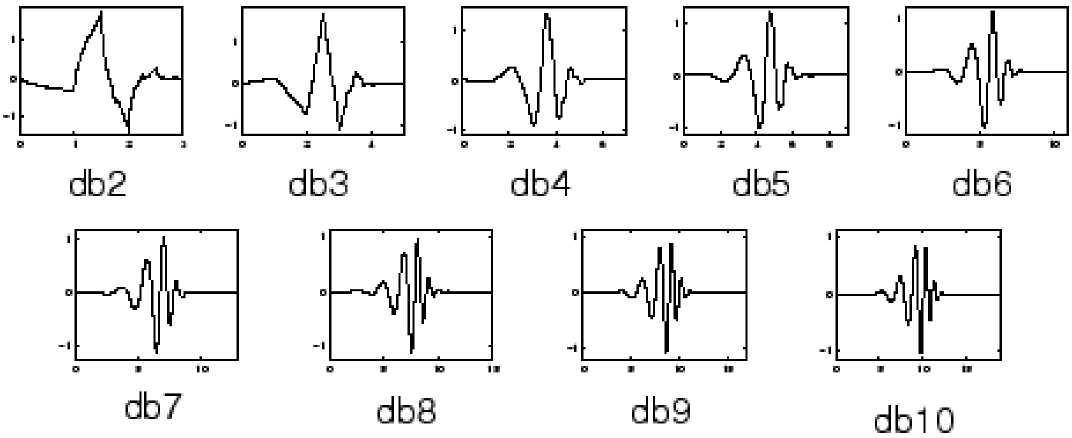

Figure 3.3 : Daubechies wavelet types

Daubechies wavelet family consists of two functions, a wavelet function ($\psi(t)$) and a corresponding scaling function ($\phi(t)$). The wavelet function is used for high-pass filtering (capturing details), while the scaling function is used for low-pass filtering (capturing trends). Daubechies wavelets are of various orders, denoted by db1, db2, db3…..db10, each corresponding to a different number of vanishing moments. For example, db1 is equivalent to the Haar wavelet, db2 has two vanishing moments, db3 has three vanishing moments, and so on. The vanishing moments essentially controls the smoothness of the wavelet function. The more vanishing moments a wavelet has, the smoother it is. Smoother wavelets are better suited for capturing smoother features in a signal, while wavelets with fewer vanishing moments are better at capturing sharp changes or discontinuities in the signal.

Applications using Daubechies wavelets are signal processing, image compression, denoising and solving partial differential equations, choosing a specific wavelet depends on several requirements such as smoothness, vanishing moments, and support length as per a particular application.

3.3.3 Biorthogonal Wavelets

Biorthogonal wavelets are a type of mother wavelets that works with two wavelet functions, one for decomposition (analysis) and another for reconstruction (synthesis). This helps in greater flexibility in adapting to specific signal characteristics and applications. These functions are considered filters where the analysis and synthesis filters are referred as low-pass and high-pass filters. Biorthogonal wavelets are designed to satisfy specific orthogonality conditions between the analysis and synthesis filters, in order to ensure that the energy of the signal can be accurately represented during both decomposition and reconstruction. They are considered flexible in design due to the use of different filters for analysis and synthesis. Different types or shapes of biorthogonal wavelets are shown in figure 4 below.

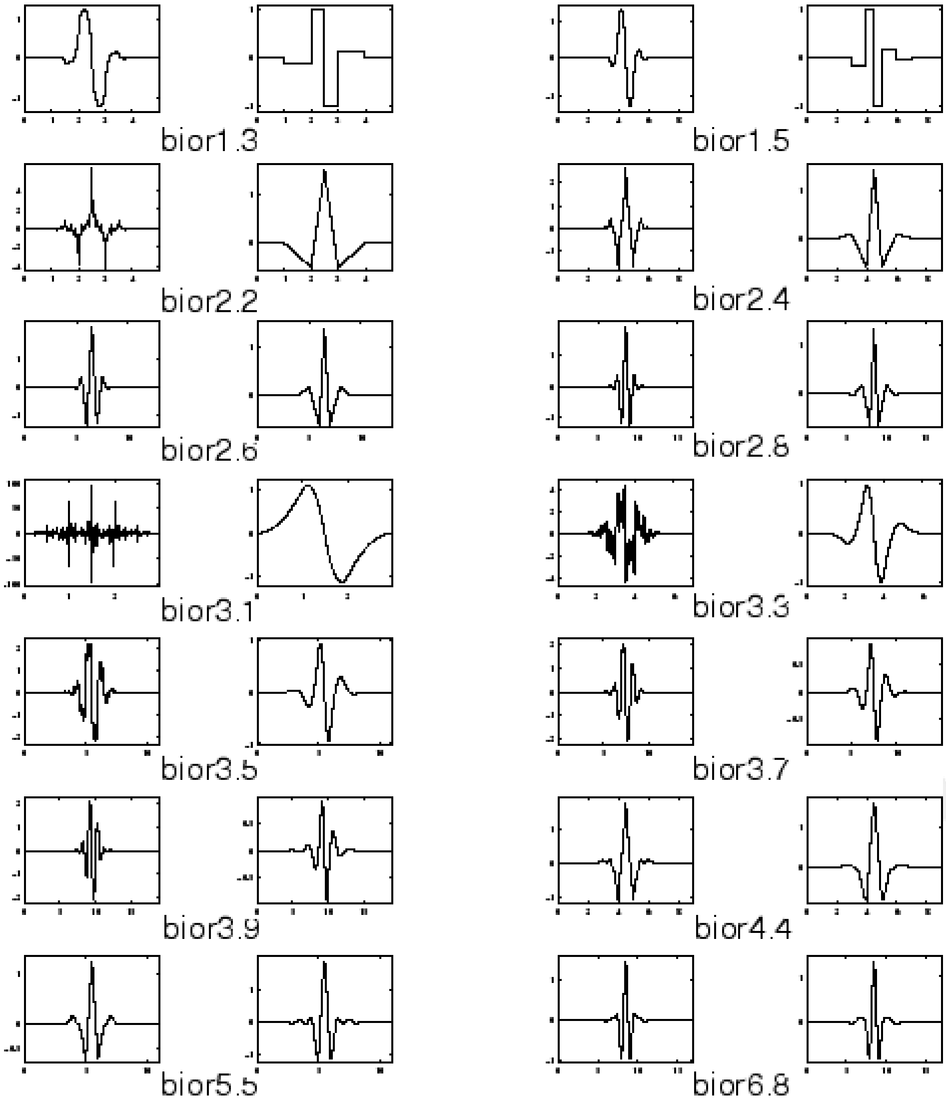

Figure 3.4 : Biorthogonal wavelet types

Biorthogonal wavelet transforms can be used in various fields, including signal processing, image compression, and data analysis. They are especially used in applications where the characteristics of the signal may be better captured by different functions for analysis and synthesis.

3.3.4 Coiflet Wavelets

"Coherent wavelets" or as known as Coiflet wavelets are another family of mother wavelets, they are very suitable for applications where preserving the smoothness of a signal or image is important since they are designed to have compact support and high level of smoothness. Coifflets wavelets are considered a sub-type of orthogonal wavelets, since they use separate wavelet functions for analysis and synthesis which allows greater flexibility and adaptability to different signals. Since their wavelet functions have finite non-zero values within a specific range and are zero elsewhere, Coiflet wavelets are considered to have compact support, giving them the advantage in applications where localized information is important, such as in image compression. Coiflet wavelets have different types, such as Coiflet1, Coiflet2, etc., each with variations in their properties, the number associated with the Coiflet name corresponds to the number of vanishing moments. Figure 5 presents different types of Coiflet wavelets.

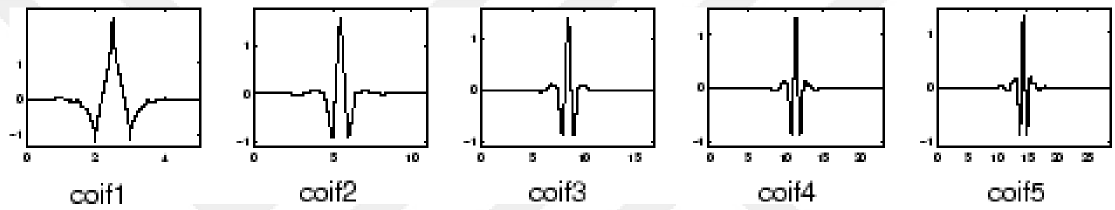

Figure 3.5 : Coiflet wavlets types

Smoothness of Coiflet wavelets leads to them having higher degree of regularity in their oscillations, which can be useful when processing signals or images with smooth variations. Coiflert wavelets are mainly used in applications for signal processing tasks such are signal denoising, compression and feature extraction, and they are also used in image compression algorithms , where the ability to represent images in a compact form is vital.

3.3.5 Symlet Wavelets

Symlet wavelets, short for "symmetric" wavelets, are another type of mother wavelets that are used in signal processing and image compression. They are designed to combine the properties of both orthogonality and symmetry. Similar to Coiflet wavelets, Symlet wavelets are considered a sub-type of biorthogonal wavelets, using different functions for analysis and synthesis.

Symlet wavelets have different types, such as Symlet2, Symlet4, etc. The number associated with the Symlet name indicates the number of vanishing moments and influences the smoothness of the wavelet. Figure 6 presents the different types of Symlet wavelets.

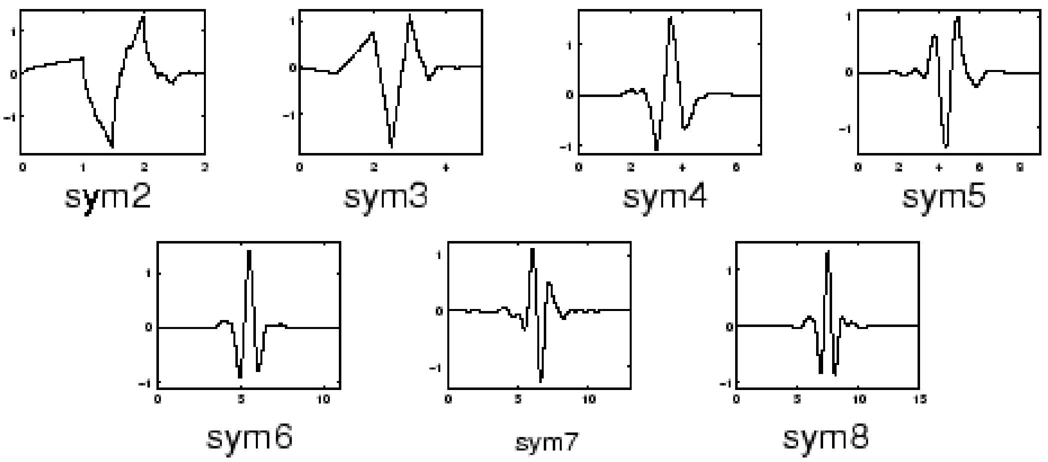

Figure 3.6 : Symlet wavelets types

Orthogonality of Symlet wavelets means that the wavelet functions are orthogonal to each other, which is beneficial for preserving energy and aiding in signal analysis. Symmetry is also an important characteristic of Symlet wavelets, they have mirror symmetry, which is an advantage in applications where signal features are symmetrically distributed.

3.3.6 Morlet Wavelet

Adrien Morlet, a French mathematician is the founder or Morlet wavelet. This type of wavelet is commonly used in signal processing and time-frequency analysis. Morlet wavelet is a complex-valued wavelet, it has both real and imaginary components, which is particularly useful in capturing both amplitude and phase information of a signal. It also has an oscillatory shape, resembling a sine wave with a Gaussian window. Combining frequency localization (sine wave) and time localization (Gaussian window) makes it suitable for analyzing signals with distinct frequency components. Morlet wavelet can be adjusted to different frequencies, allowing it to be tuned to specific frequency bands of interest, making it useful for analyzing signals with varying frequency content. Figure 7 shows the Morlet wavelet.

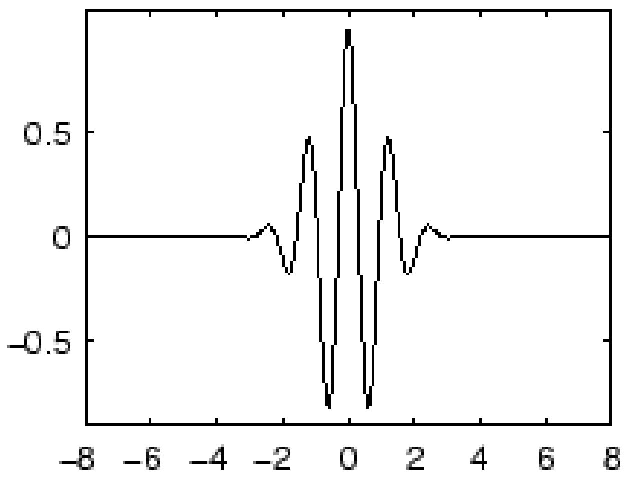

Figure 3.7 : Morlet Wavelet

Morlet wavelet's combination of time and frequency localization makes it a very useful tool for analyzing signals with non-stationary and time-varying frequency characteristics. It is used in several domains, including signal processing, neuroscience, and geophysics.

3.3.7 Meyer Wavelet

Meyer wavelet belongs to the family of compactly supported wavelets and is designed to have certain desirable properties, such as symmetry, regularity, and compact support, it is often used in signal denoising and compression.

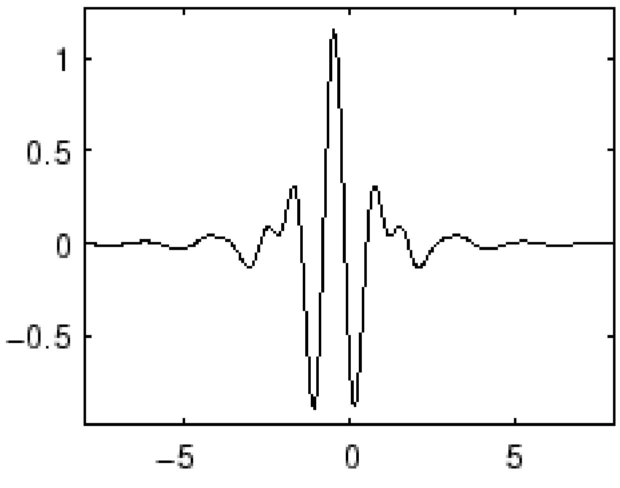

Figure 3.8 : Meyer Wavelet

Meyer wavelet is designed to be regular, ensuring smoothness in its oscillations, it is also it is considered symmetric, which means its wavelet function is mirror-symmetric around a central point.

3.3.8 Gaussian Wavelet

Typically, a Gaussian wavelet refers to a wavelet derived from a Gaussian function which is a bell-shaped curve that is characterized by its symmetry and smoothness.

A Gaussian wavelet is created by using a Gaussian function g(t) as the basis of the wavelet. The Gaussian function is defined as follows:

$$g(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{t^2}{2\sigma^2}} \tag{3.4}$$

Where t is the time variable, σ is the standard deviation (controlling the width of the bell curve), and π is the mathematical constant.

Gaussian wavelets provide good frequency localization in the time-frequency domain. They are of finite support by which they don't drop to exactly zero at some finite distance. However, a truncated version is often used for particular purposes, resulting in a wavelet with compact support.

Gaussian wavelets are particularly useful in tasks where a smooth and well-localized wavelet is desired. Applications include signal processing, image analysis, and feature extraction.

4. HIGH IMPEDANCE FAULT MODELING

4.1 High Impedance Fault Modeling Review

A precise simulation of HIFs is essential for the implementation of effective HIF detection techniques. HIF model data should include a variety of characteristics of real life HIFs such as asymmetry, randomness, nonlinearity and dynamic qualities of arcing phenomena.

Generally HIF models are divided into 2 groups; the first group consists of every model that is based on Emanuel model that was proposed in 1990 based on the sparks nature due to contact between the conductor and the ground [48]. The second group refers to other HIF models.

4.1.1 Emanuel Model (1990)

In 1990, Emanuel et al. proposed a HIF model which consists of two DC sources connected in parallel with opposite polarities, each DC source is connected in series with a diode to simulate nonlinearity of voltage and current of HIFs as shown in figure 4.1. This model relies on laboratory measurements and theoretical components.

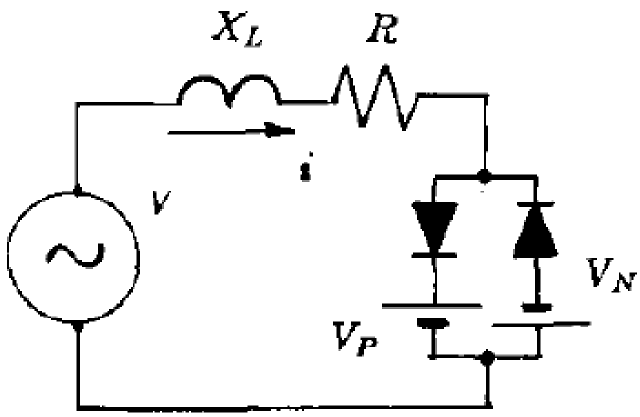

Figure 4.1 : Emanuel HIF model 1990[48]

4.1.2 Improved Emanuel Model (1993)

In 1993 Emanuel model was edited as to consider nonlinearity in earth impedance, so the resistance and inductance of the original Emanuel model were replaced with two nonlinear resistances each connected in series with the dc source and diode on each side [49] as shown in figure 4.2.

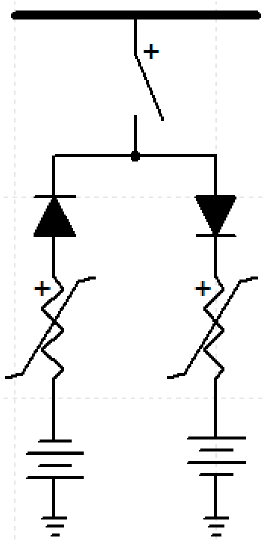

Figure 4.2 : Improved Emanuel model (1993)

4.1.3 David Chan Model (1996)

In 1996 David Chan et al. proposed a new model formed of two time-variable voltage power supplies and a nonlinear impedance along with a Transient Analysis of Control Systems (TACS) controlled switch based on the arc theory [50].

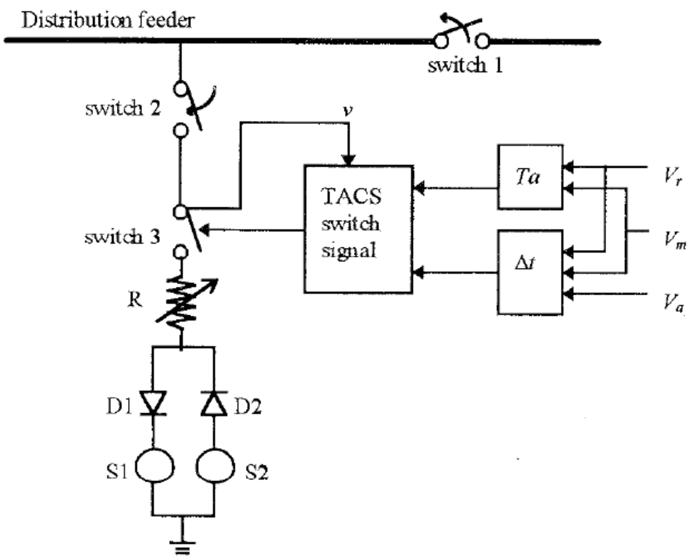

Figure 4.3 : David Can Model (1996)

As shown in figure 4.3, V_r is the input arc re-ignition voltage, V_m is the peak applied voltage and V_r is the arc voltage, T_a is the time between the applied voltage zero crossing and arc re-ignition point and Δt is the time of arc conduction in one half cycle, switches 1 and 2 are conventional time-controlled switches operating in order to disconnect the feeder from the load and connect to the fault path, switch 3 is the TACS controlled switch.

4.1.4 S. R. Nam Model (2001)

In 2001 S. R. Nam presented a HIF model based on nonlinearity, asymmetry as well as buildup and shoulder. This model consists of two series connected time varying resistors (TVR) , a TACS controlling them in (EMTP) Electromagnetic Transient Program as shown in figure 4.4 [51].

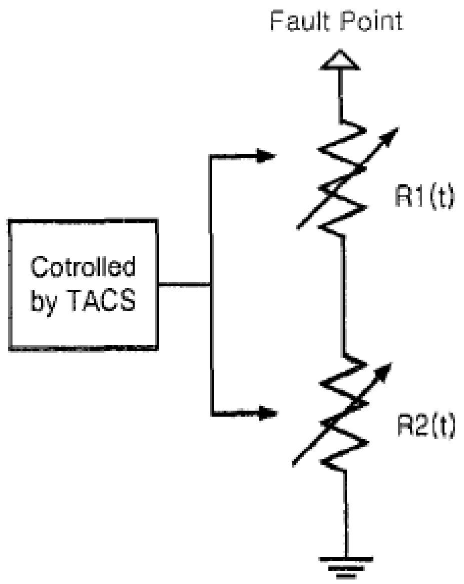

Figure 4.4 : S. R. Nam Model (2001)

One TVR is used to simulate buildup and shoulder characteristics from the waveforms is transient state after HIF, the second TVR is to represent nonlinearity and asymmetry from voltage-current characteristic for one cycle in steady state after HIF occurrence.

4.1.5 T.M Lai Model (2003)

T.M Lai et al. proposed a simplified Emanuel model based on arcing in sandy soil in 2003 as shown in figure 4.5 below. Inception voltage of air in soil and/or between trees and the distribution line is represented by the two DC sources, R1 and R2 are unequal resistances which can represent fault resistances and generate asymmetric fault current. If the phase voltage is higher than DC1 voltage, then fault current flows towards the ground. While when the phase voltage is lower than DC2 voltage, fault current reverses. Phase voltages between DC1 and DC2 are considered non-faulty and fault current does not flow [52].

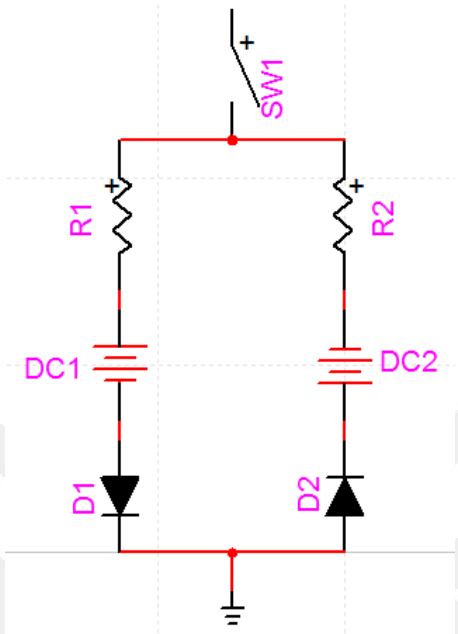

Figure 4.5 : T.M Lai Simplified Model (2003)

4.1.6 Yong Sheng and Steven M. Rovnyak Model (2004)

In 2004, Yong Sheng and Steven M. Rovnyak proposed a model that has a more dynamic and random nature of HIF, as shown in figure 4.6 [53].

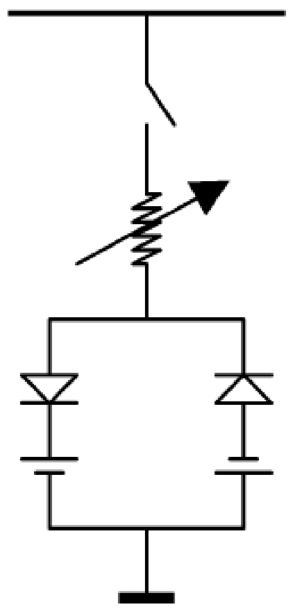

Figure 4.6 : Yong Sheng & Steven M. Rovnyak Model (2004)

This model consists of two DC sources that change amplitudes every half-cycle, two nonlinear resistors and two diodes.

4.1.7 A.R Sedighi Model (2010)

A.R Sedighi proposed a new model consisting of several Emanuel arc models connected in parallel in 2010, as shown in figure 4.7.

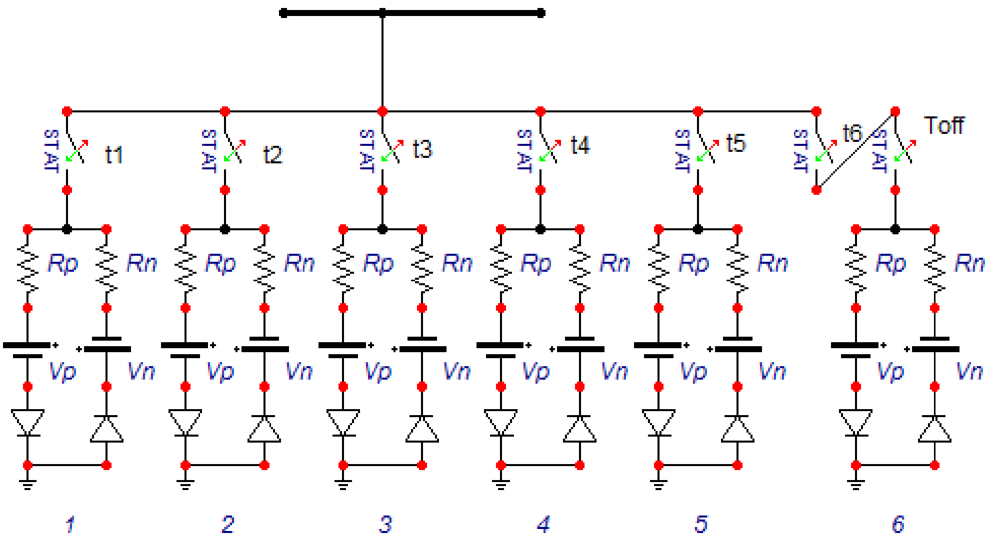

Figure 4.7 : A.R Sedighi Model (2010) [54]

Random state of HIF is produced using STATISTIC switch in EMTP. The state of on and off on arc is shown in the sixth arc model. Arc parameters depend on previously recorded current and voltage data [54].

5. PROPOSED TEST SYSTEM

5.1 Proposed HIF Model

Implementing HIF models and simulating them is not an easy task, since there is no perfect specific model to design HIFs due to their nonlinear and asymmetric characteristic; since HIFs are usually accompanied with an arc, the model should include random and dynamic qualities of arcing. T.M Lai simplified HIF model has been the most widely used model for simulation and experiments in HIF detection techniques, as it combines most of the advantages of other models and maintains simplicity and accuracy.

The proposed model used in this thesis for simulation of HIF detection is based on T.M Lai simplified HIF model that is shown in figure 5.1 below, it includes two DC sources DC1 and DC2, with voltages Vp and Vn respectively, representing the arcing voltage of air in soil and/or between trees and the distribution line; two resistances R1 and R2 placed between two diodes D1 and D2, representing the resistance of trees and/or the earth resistance.

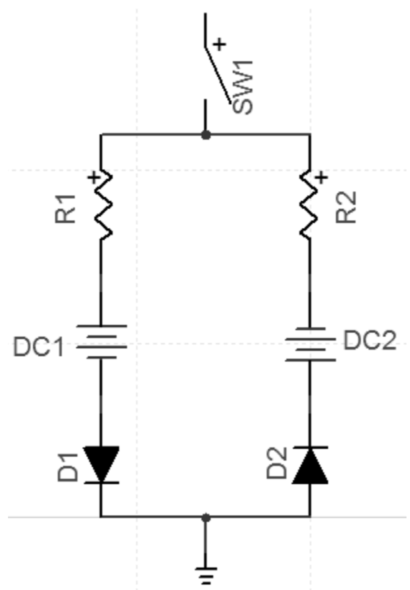

Figure 5.1 : T.M Lai Simplified Emanuel Model

The proposed model is used as a basic model and variable resistances are used as R1 and R2, since the resistance in HIFs is not stable and it keeps on varying up and down, a sample resistance values R1 and R2 are represented in table 5.1 below [55]. From the table it can be seen that the average resistance is between 250 and 260 ohms, and the average variation in resistance is around 10-15%. These values and variation in resistance are interpreted in MATLAB Simulink environment. A custom DC1 and DC2 values are set to 3862V and 3284V respectively. DC sources are inverse-parallel, and the same is applied to the two diodes D1 and D2.

Table 5.1 : Table 1 Simplified Emanuel Model R1&R2 Parameters [55]

R1	R2
205	210
212	222
236	227
245	246
255	271
267	280
270	286
283	289

5.2 Proposed Test System

In order to test and simulate the proposed HIF model and HIF detection technique, a basic distribution system is used as the test system in this study, which consists of a 33kV generator connected to a 33/20kV two winding transformer, transmission lines, and a static load. Properties of the test system are shown below in table 5.2.

Table 5.2 : Table 2 Test System Settings

System Voltage	20KV
System Frequency	50 Hz
Load	800KW
Transmission line length	20km
Transmission line Resistances	0.01273Ω/km
Transmission line Inductances	0.9337mH/km

The single line diagram of the distribution system with and without fault are represented in figures 5.2 and 5.3

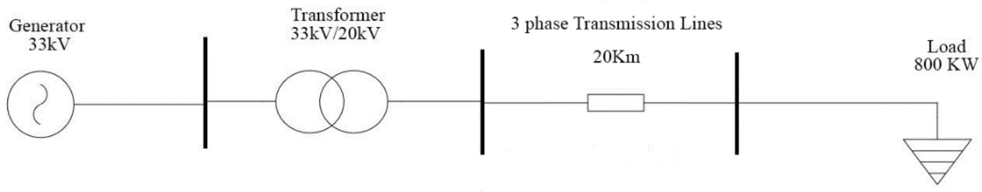

Figure 5.2 : Distribution system in normal condition

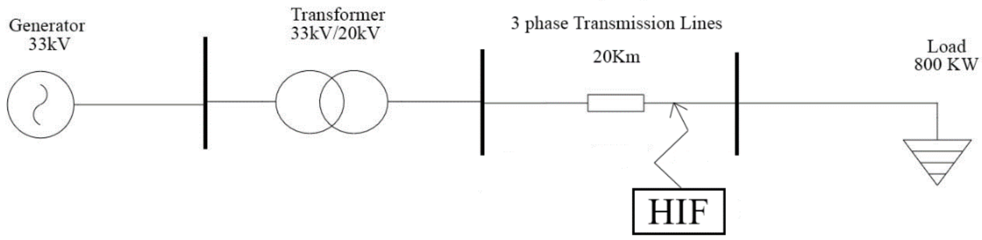

Figure 5.3 : Distribution System with HIF

5.3 Implementation in Simulation Program

For the aim of testing, computer simulation is done by the help of MATLAB R2022b and Simulink.

5.3.1 Implementation of HIF Model in MATLAB

A 33kV source was connected to a 33/20kV transformer, which is connected to a transmission line, then the proposed HIF model is connected to one phase of the transmission line as shown in figure 5.4. Simulation is done to extract the properties and test the efficiency of the model.

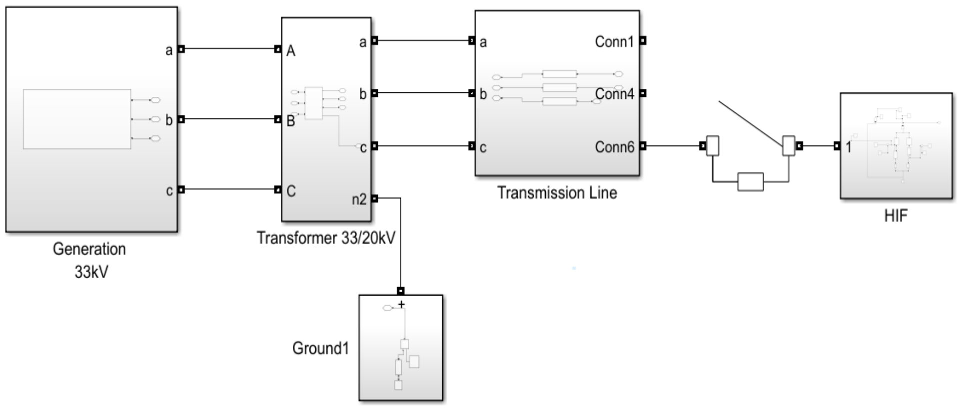

Figure 5.4 : HIF implementation in MATLAB/Simulink

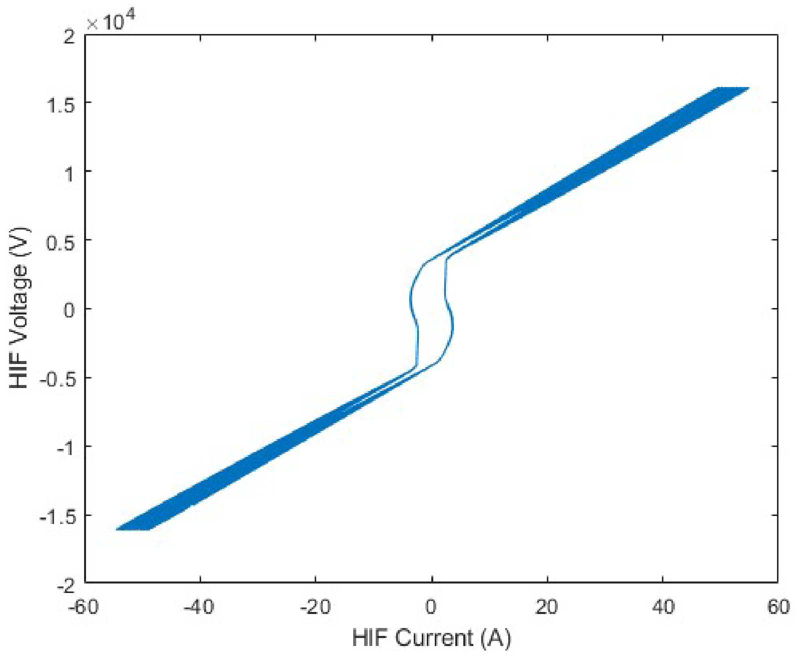

Figure 5.5 : V-I Characteristic of HIF Model

V-I characteristic curve shown in figure 5.5 shows that a nonlinear relationship between voltage and current of the HIF model is present, which is the targeted relation.

Figures 5.6 and 5.7 represent the voltage and current signals of the HIF model.

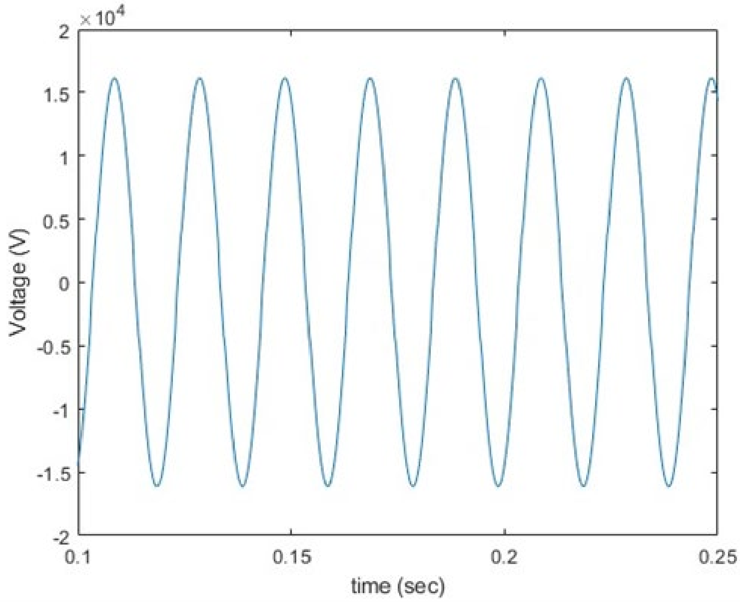

Figure 5.6 : Voltage signal of HIF model

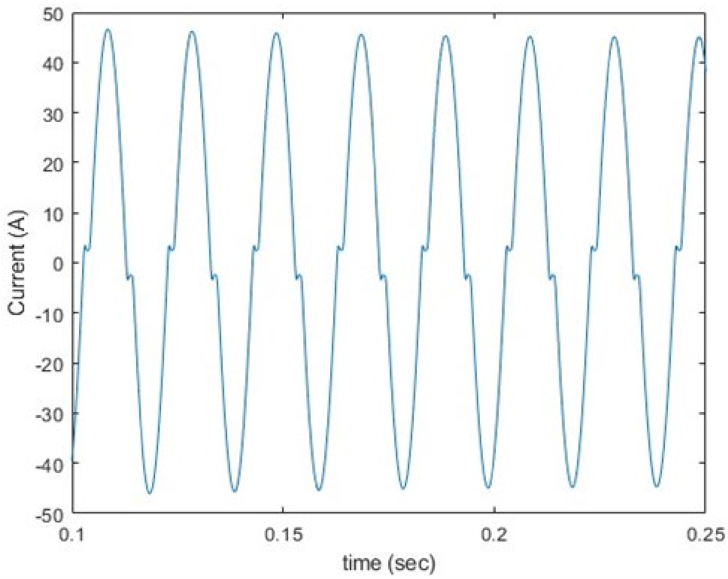

Figure 5.7 : Current signal from HIF model

The random variation of resistance of HIFs introduces asymmetry to the fault current, and due to arc interruption at natural current zero, shoulders are present at zero crossings, which is well observed in the current signal of the HIF model shown in figure 5.7.

5.3.2 Implementation of Test System in MATLAB

In order to simulate and test the proposed system in section 5.2 in MATLAB, a 33kV three-phase source is connected to a two windings 33/20kV transformer that is in turn connected to a V-I measurement block to record three-phase voltage and current. A three phase pi section line block is used to simulate a transmission line of 20 KM length. Another V-I measurement block is connected to the transmission line block and to a static load represented by a three-phase RLC 800KW load. The system is grounded with low resistance grounding to control the ground fault and limit the ground fault current in order to prevent damage to equipment in case of a ground fault by tripping the protective devices. The purpose of low resistance grounding is to immediately cut the power to the circuit in case of fault, it also reduces overvoltage.

Implementation of the test system with and without HIF is displayed in figures 5.8 and 5.9.

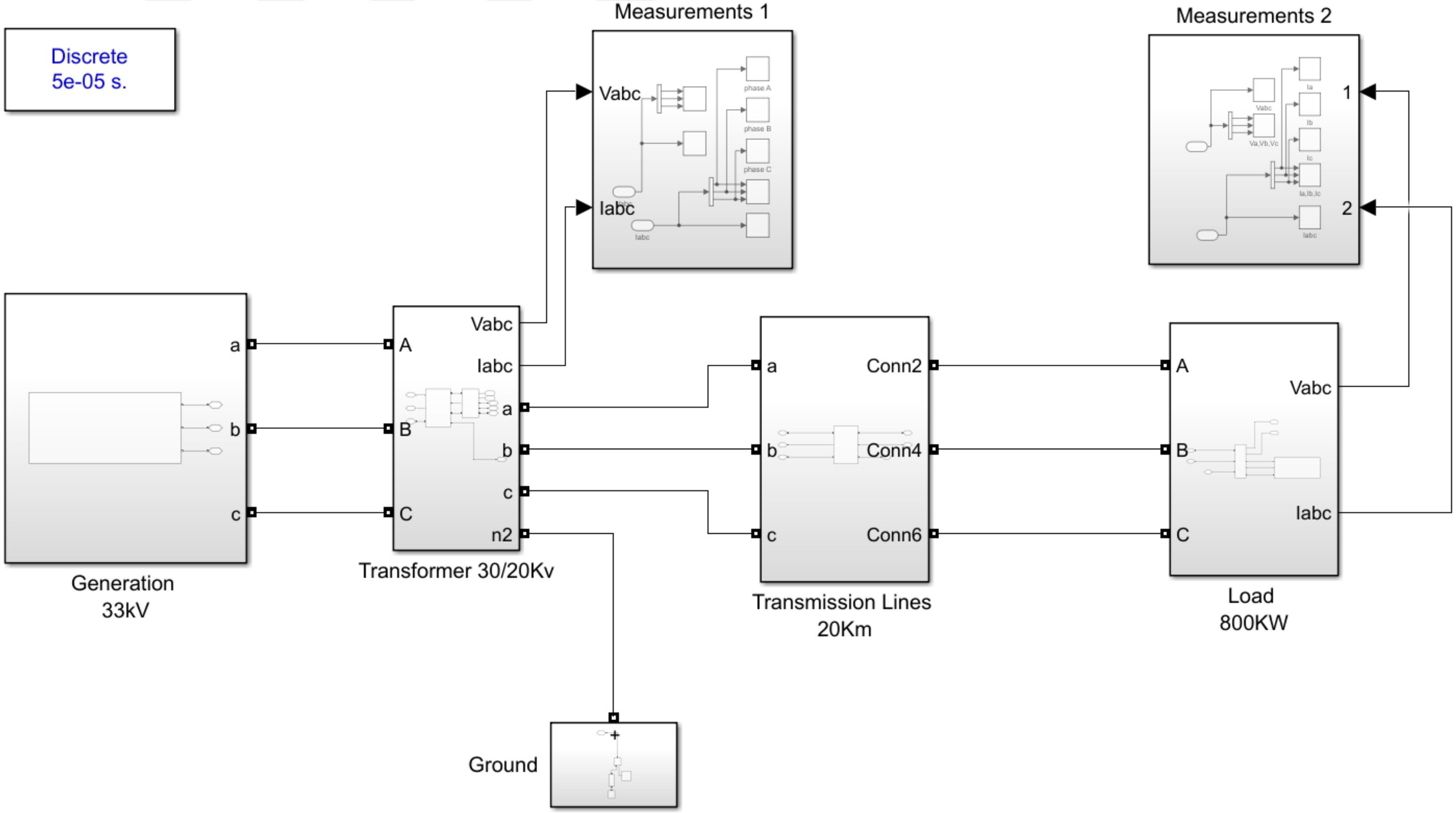

Figure 5.8 : Simulink Distribution System Model (No Fault Condition)

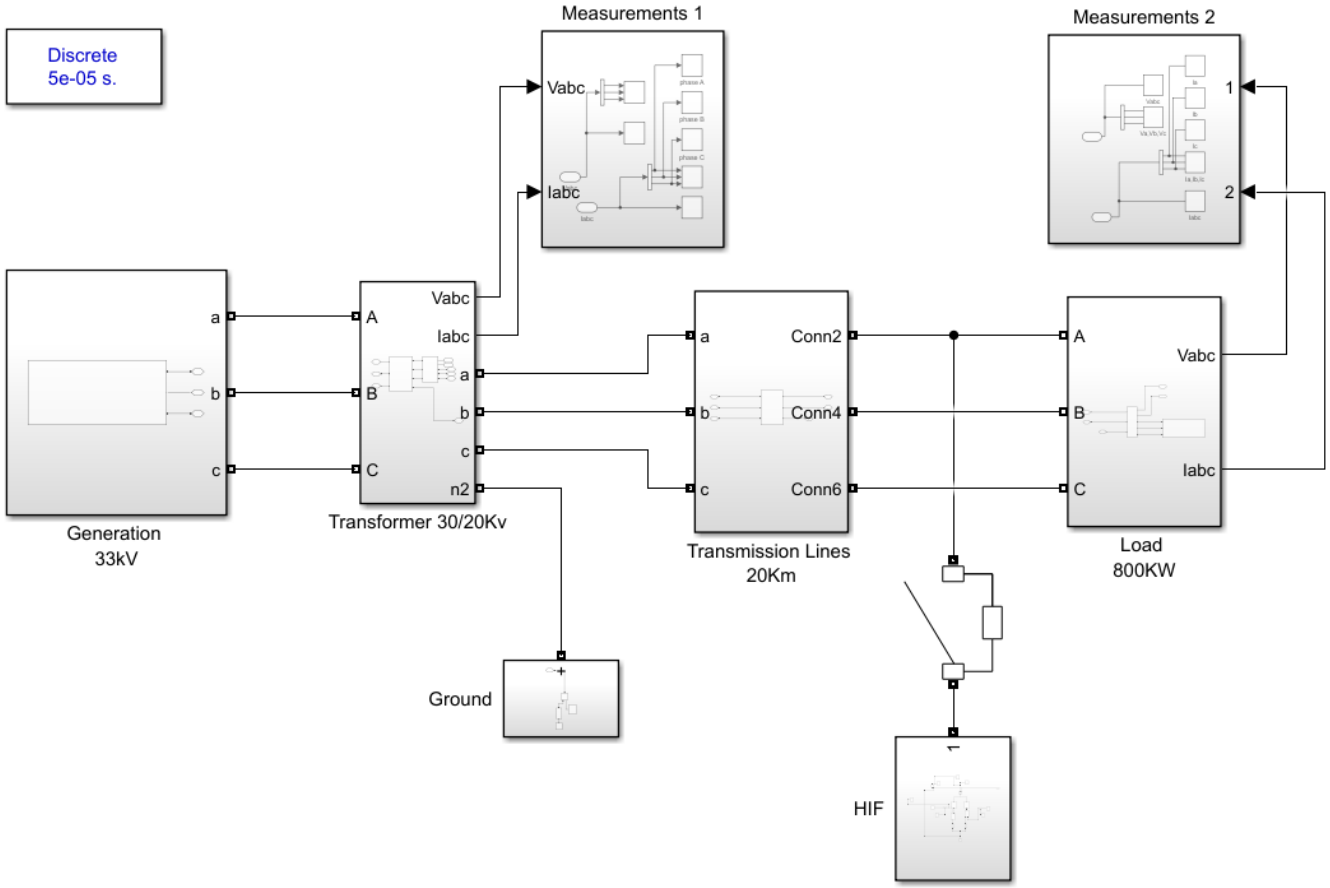

Figure 5.9 : Simulink Distribution System Model (HIF Condition)

5.4 Proposed HIF Detection Method

The proposed algorithm to detect HIFs in this thesis depends on wavelet transform analysis, precisely on discrete wavelet transform (DWT) which is known to be a great technique for analyzing signals in the time-frequency domain, it is capable of providing the time and frequency information simultaneously. Faults such as HIFs have significantly low current values and exhibits highly nonlinear characteristics which leads to presence of harmonics and high frequency components, and wavelet transform is known for being a precise tool for extracting disturbances from a signal which in our case is the high frequency components. WT is also able to provide Multi-Resolution analysis (MRA) in frequency and time, which is a substantial feature for analyzing transient signals and faults. DWT is used instead of CWT, since DWT is simpler yet has a very similar precision and results as CWT with much faster time-frequency analysis. DWT is modelled by using a multistage filter with the mother wavelet as the low pass filter and it's dual as the high pass filter, the results of high pass filters are called approximations and that of low pass filters are called details, in HIF detection details are the point of interest which will be seen further in the next chapter.

As a mother wavelet, the Symlet wavelet was chosen, specifically the 'sym5' is used. The reason of choosing symlet as a mother wavelet is that Symlets are beneficial for preserving energy and aiding in signal analysis. Moreover, they can be effective in extracting important features from signals, making them valuable in applications such as pattern recognition and classification. Furthermore, they are considered versatile and can adapt to different signal characteristics, including signals with abrupt changes and discontinuities, which makes them suitable for analyzing signals that have features such as edges or spikes.

A 5-level MRA decomposition is applied to analyze the current signals and extract its features.

5.4.1 Algorithm Description

The proposed HIF detection algorithm is based on the analysis of the 5th level detail of the DWT performed on the current signals extracted from the transformer secondary winding. The algorithm can be summarized as follows:

1. Extract current signals at transformer secondary for all phases and neutral.
2. Perform DWT/MRA on current signals for all phases and neutral using ‘sym5’ as mother wavelet and a 5-level decomposition
3. Extract and plot detail d5 coefficients of the three phase currents and neutral
4. Calculate energy of detail d5 ED5 for all phases and neutral
5. Plot the area variation curve for the d5 coefficients and integrate and calculate the average slopes of all phases and the neutral.
6. Threshold slope S_{th}=80 is determined by doubling the maximum slope in the normal operating conditions taking into consideration an unbalanced load switching.
7. Compare slopes of the neutral and threshold slope and determine whether a HIF or unbalanced load switching is occurring.
8. In case of HIF, Compare energies and determine if single or double phase to ground HIF.
9. Trip faulty phase(s).

5.4.2 Flowchart

A flowchart of the proposed algorithm is shown in figure 5.10.

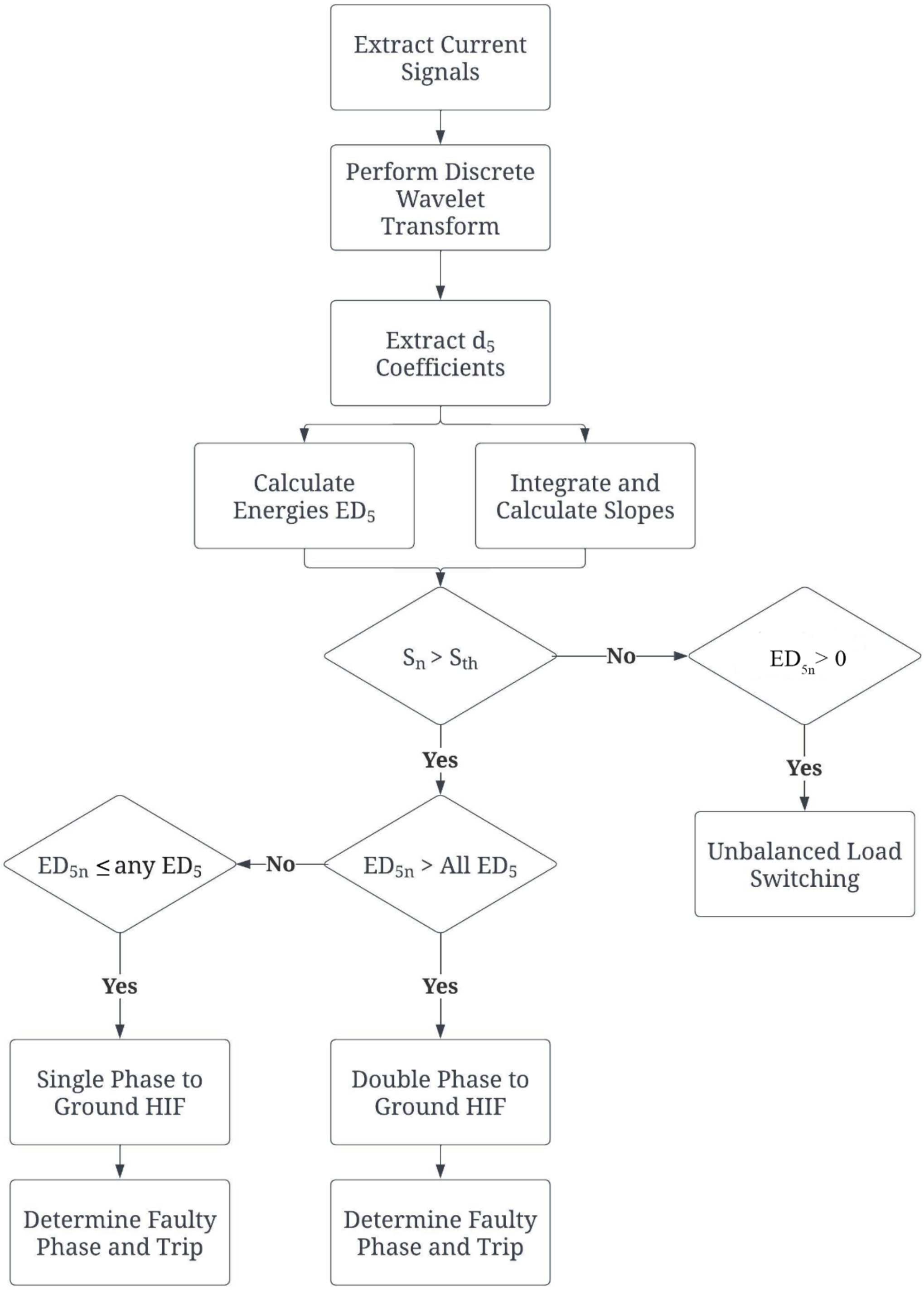

Figure 5.10 : Flowchart of Proposed HIF Detection Algorithm

6. COMPUTER SIMULATION STUDIES FOR TESTING THE PROPOSED METHOD

In this chapter, circuit simulations and results are discussed for normal conditions, unbalanced load switching, and HIF conditions. Testing and simulation of the proposed method on these events was carried out using MATLAB 2022b program for coding along with Simulink for model build up and simulations.

6.1 Verifying The Use of 5-Level MRA

In this section the implemented HIF model discussed in section 5.3.1 is simulated, and DWT with a 5-level MRA using the "sym5" wavelet as the mother wavelet is performed. The results are illustrated in figure 6.1, which shows the approximation and detail coefficients at each level of decomposition.

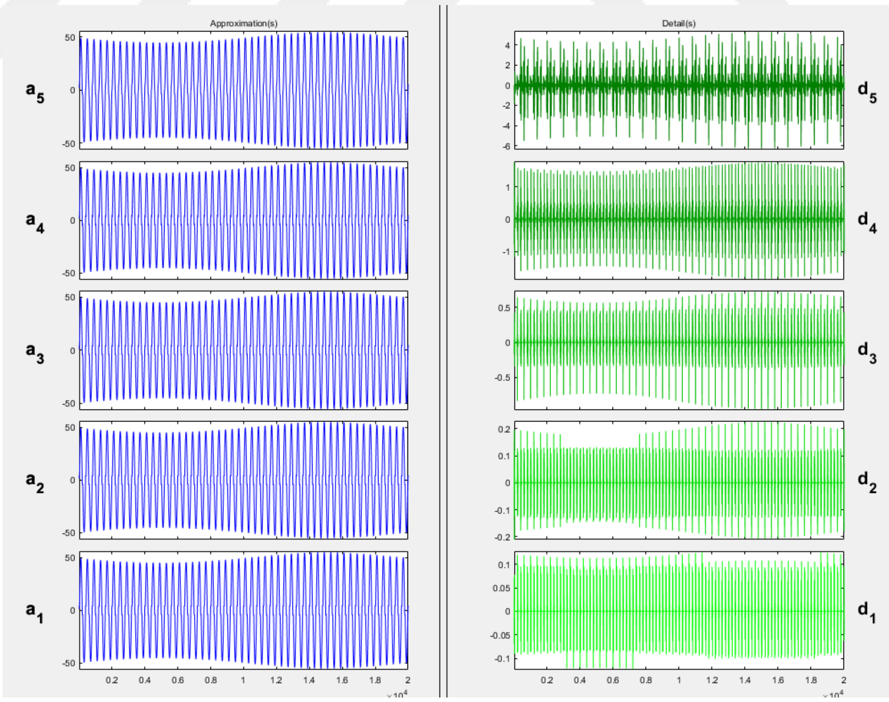

Figure 6.1 : Approximations and details at each level of decomposition

As depicted in figure 6.1, the 5th level detail coefficients reveal the signal disturbances most prominently. Therefore, the fifth level detail coefficients are utilized for monitoring signals in this study.

6.2 Test Cases and Results

6.2.1 Case 1: Normal Operation With No Disturbance (No Fault)

The first case study is the normal conditions of the distributed system, a balanced three phase load of 800kW power is connected to the system and no disturbances of any type is present. D5 coefficients of all phases and neutral at the secondary of the transformer are plotted in figure 6.2, it is clear that no high frequency components are present in this case (no disturbance)

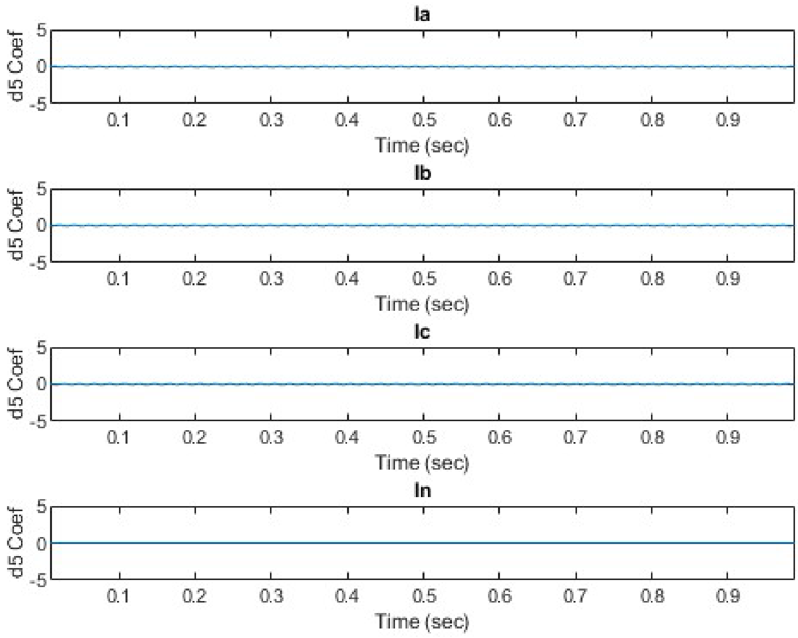

Figure 6.2 : Case 1 d5 coefficients at all phases and neutral under normal operating conditions

After that, area variation curve is calculated and plotted in figure 6.3 and the values are integrated and the slope variation graph is plotted in figure 6.4. The average slope at each phase and the neutral is calculated and the results are as follows: S_a=39.77, S_b=28.72, S_c=36.7, and S_n is nearly equal to zero.

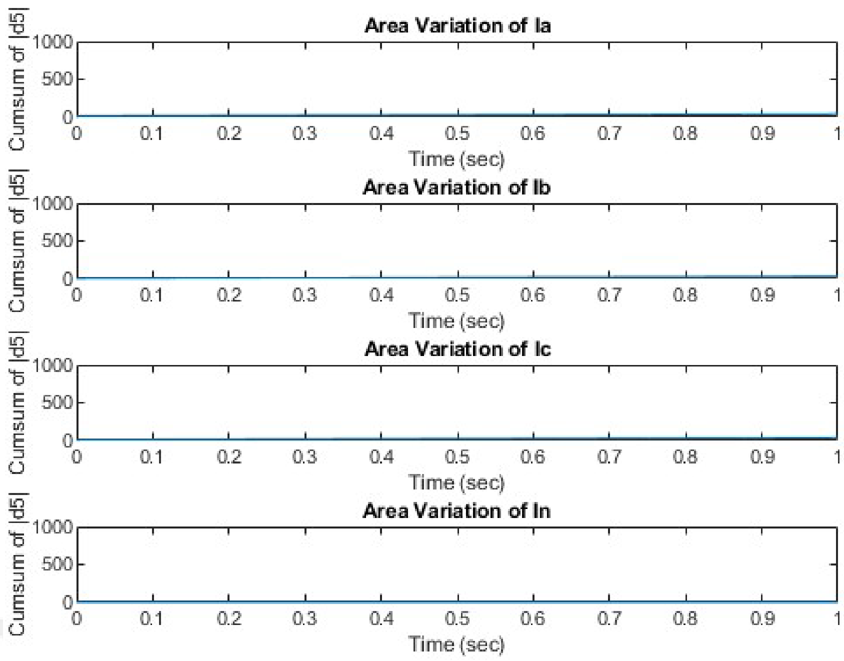

Figure 6.3 : Case 1 Area Variation Curves under normal operating conditions

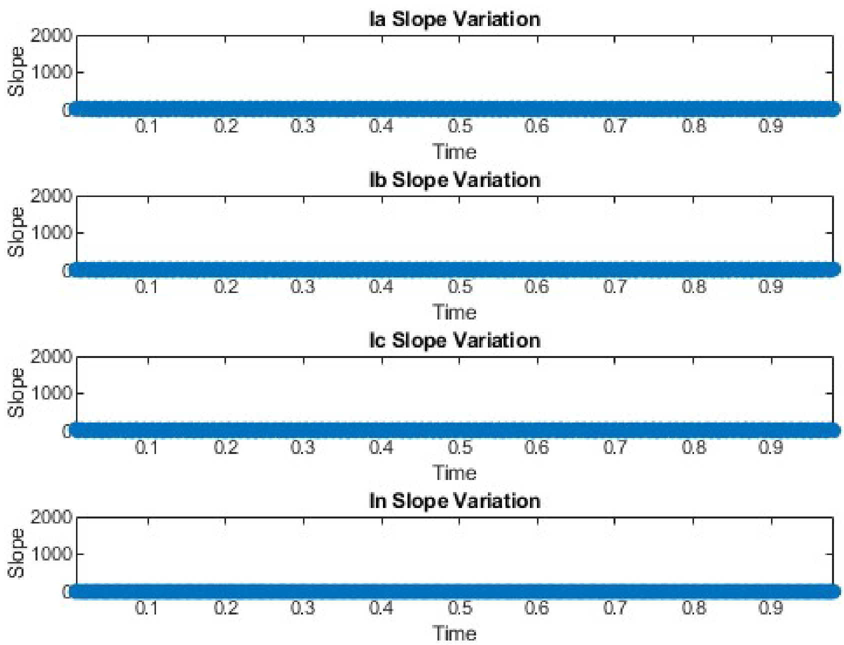

Figure 6.4 : Case 1 Slope Variation Curves under normal operating conditions

Energy levels of details at level 5 decomposition are also calculated and the plot is shown in figure 6.5. Energy levels at each phase and neutral are as follows: ED5a =76.9, ED5b = 8.29, ED5c = 40.3, ED5n = 0.

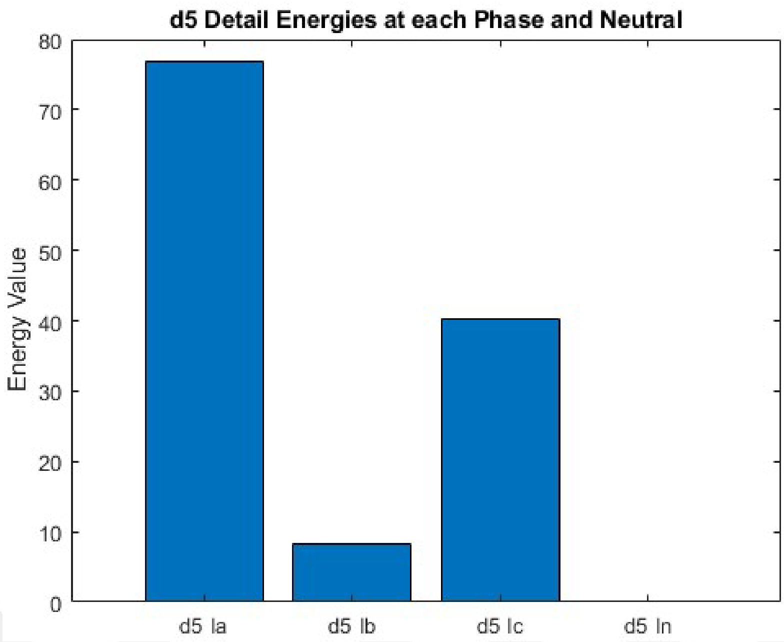

Figure 6.5 : Case 1 Energies at level 5 under normal operating conditions

6.2.2 Case 2: Unbalanced Load Switching

The second case study is an unbalanced load switching condition, balanced three phase load of 800kW of the previous case is switched to an unbalanced load as follows: P_a=1000kW, P_b=500kW, P_c=1300kW at time=0.3 seconds. Then at time=0.6 seconds the load is returned to the balanced condition. D5 coefficients of all phases and neutral at the secondary of the transformer are plotted in figure 6.6. Instantaneous high frequency components are present at the instant of connecting and the instant of disconnecting the unbalanced load.

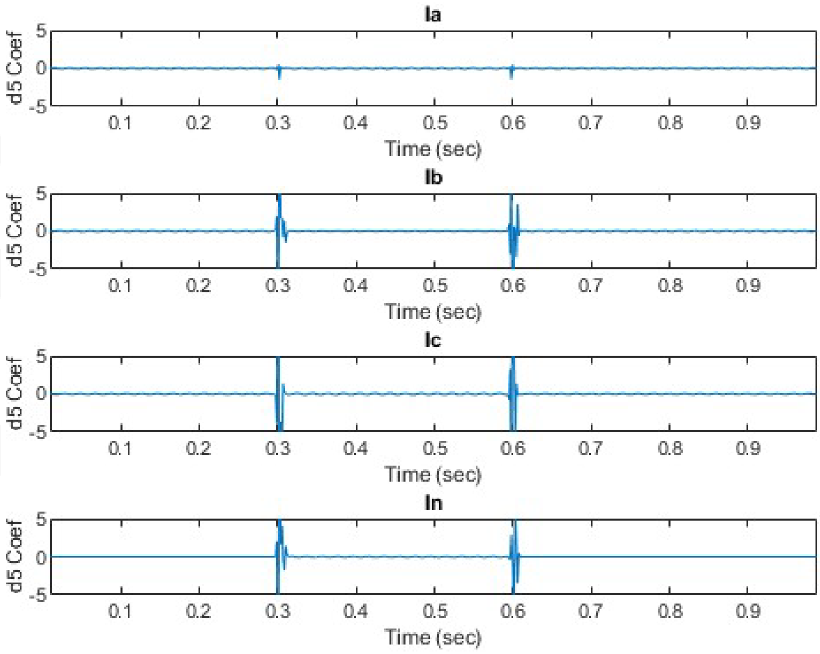

Figure 6.6 : Case 2 d5 coefficients at all phases and neutral under unbalanced load switching

After that, area variation is calculated and its plot is shown in figure 6.7. The values are integrated and the slope variation graph is plotted in figure 6.8. The average slope at each phase and the neutral is calculated and the results are as follows: S_a=31.29, S_b=15.74, S_c=40.4, and S_n=21.9.

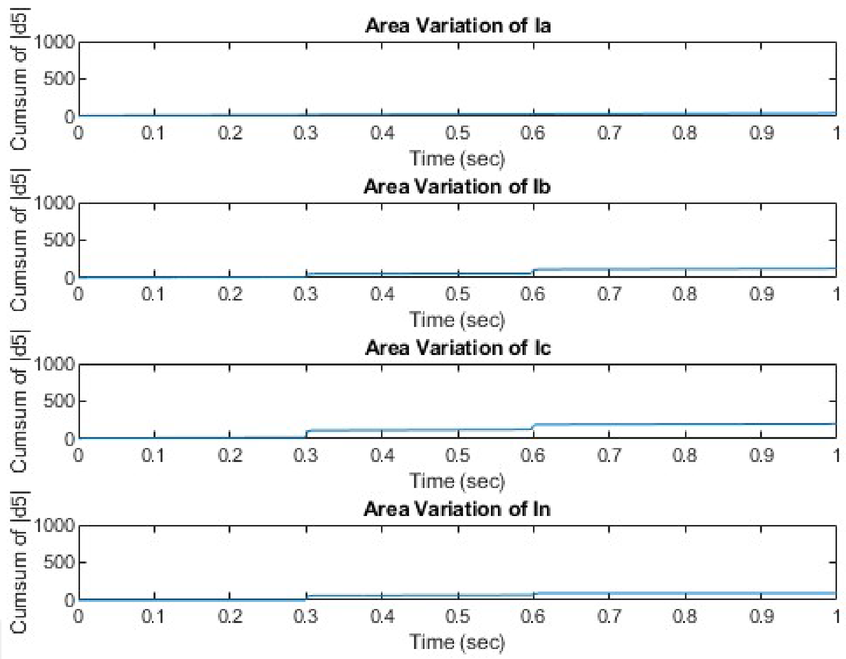

Figure 6.7 : Case 2 Area Variation Curves under unbalanced load switching

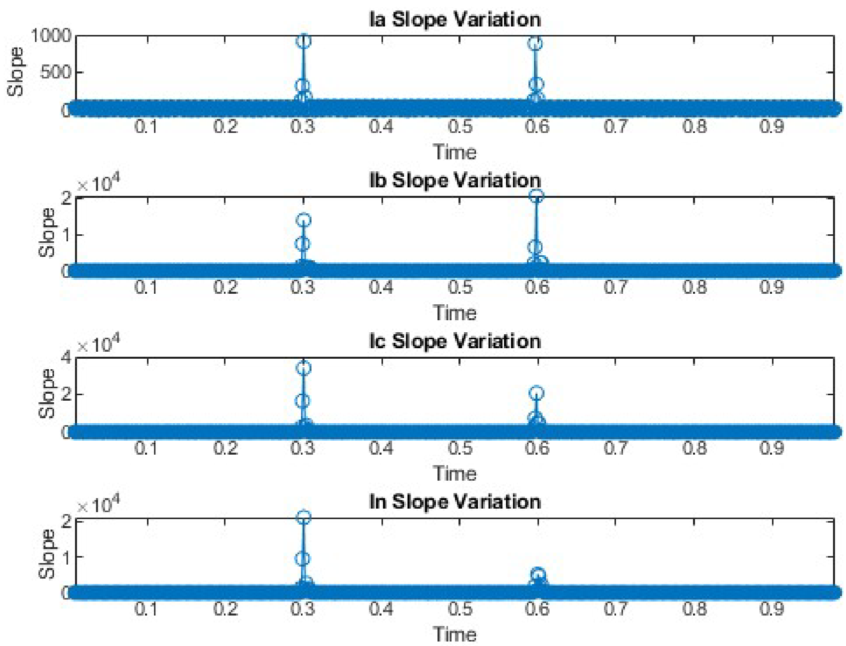

Figure 6.8 : Case 2 Slope Variation Curves under unbalanced load switching

It is observed that a small increase in area variation occurred when switching on and switching off the load, and after that the variation becomes stable. Also slopes had instantaneous increase at switching on and off and then returned to normal.

Energy levels of details at level 5 decomposition are also calculated and the plot is shown in figure 6.9. Energy levels at each phase and neutral are as follows: ED5a = 81.9, ED5b = 1833.5, ED5c = 5001.16, ED5n = 1499.12.

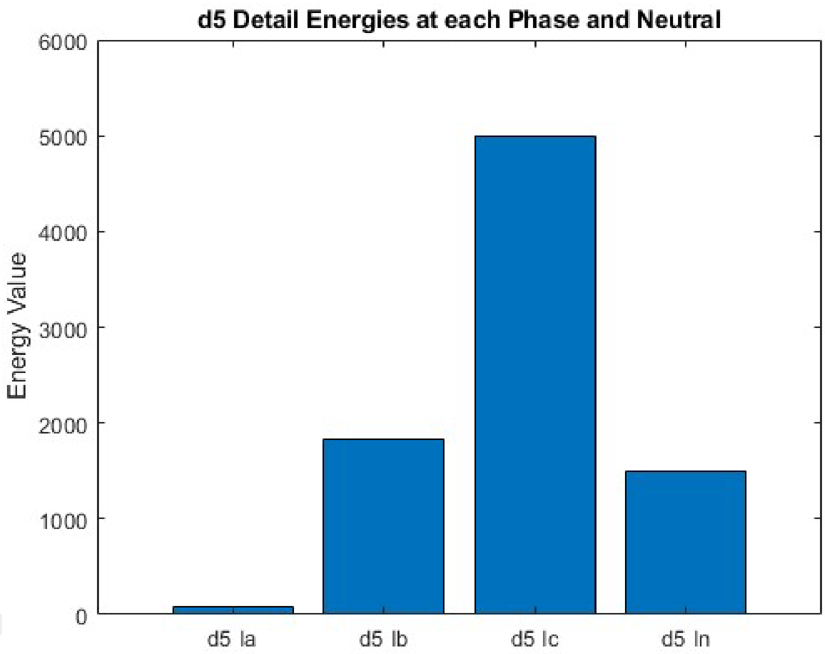

Figure 6.9 : Case 2 Energies at level 5 under unbalanced load switching

As observed energy is present in the neutral due to current flow in it as a result of unbalanced load.

6.2.3 Case 3: HIF at Phase A

The third case study is a HIF condition, a HIF is connected to phase A and fault is introduced to the system at time = 0.5 seconds. The HIF model parameters are as follows: Vp=3862v, Vn=3284v, Rp=250Ω, Rn=260Ω, the resistors are adjusted to have 10% variable change in value. D5 coefficients of all phases and neutral at the secondary of the transformer are plotted in figure 6.10. High frequency components appear in the faulty phase and neutral at the instant of connecting the fault and keep on being present during fault.

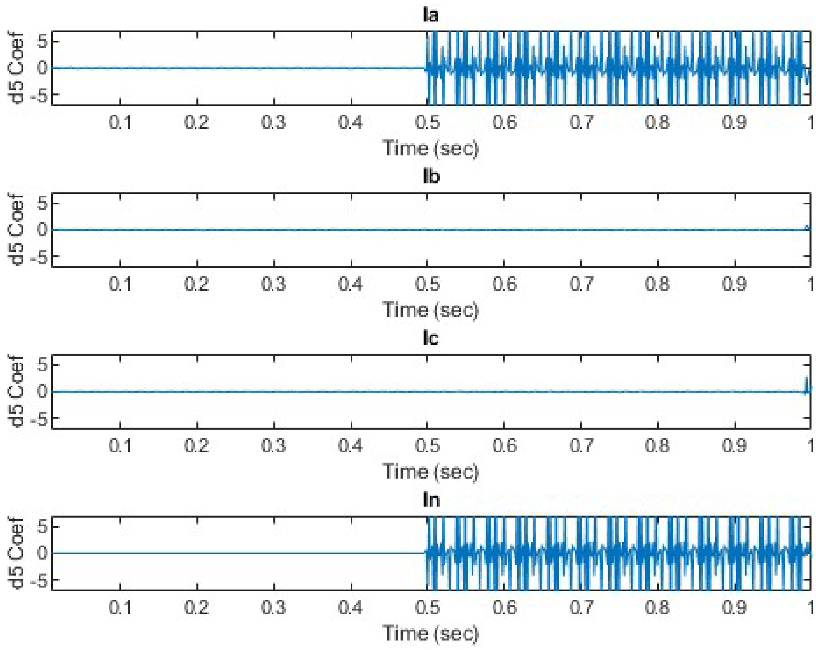

Figure 6.10 : Case 3 d5 coefficients at all phases and neutral under single phase HIF

Then, area variation is calculated and its plot is shown in figure 6.11. The values are integrated and the slope variation graph is plotted in figure 6.12. The average slope at each phase and the neutral is calculated and the results are as follows: S_a=3415, S_b=28.2, S_c=26.8, and S_n=3410.

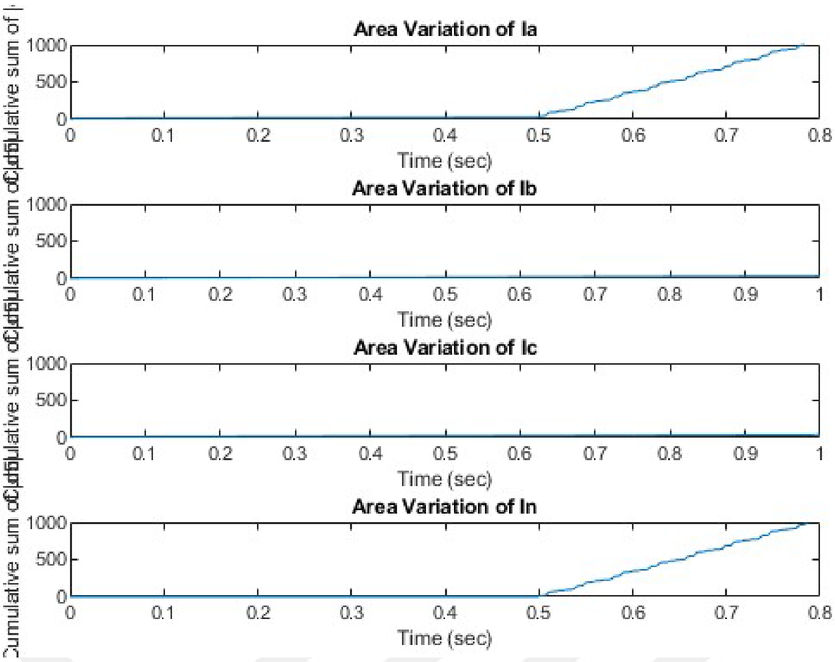

Figure 6.11 : Case 3 Area Variation Curves under single phase HIF

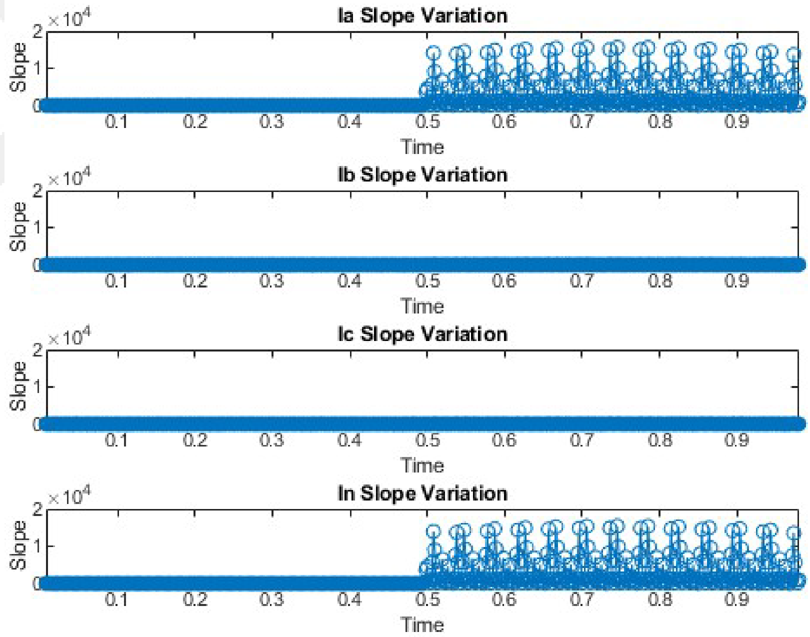

Figure 6.12 : Case 3 Slope Variation Curves under single phase HIF

It is observed that at fault instant, area variation curve of faulty phase and neutral started increasing and kept on increasing during fault. And slopes at faulty phase and neutral increased instantaneously at fault instant and kept fluctuating during fault.

Energy levels of details at level 5 decomposition are also calculated and the plot is shown in figure 6.13. Energy levels at each phase and neutral are as follows: ED5a = 24339.6, ED5b = 8.4, ED5c = 40.4, ED5n = 24165.6.

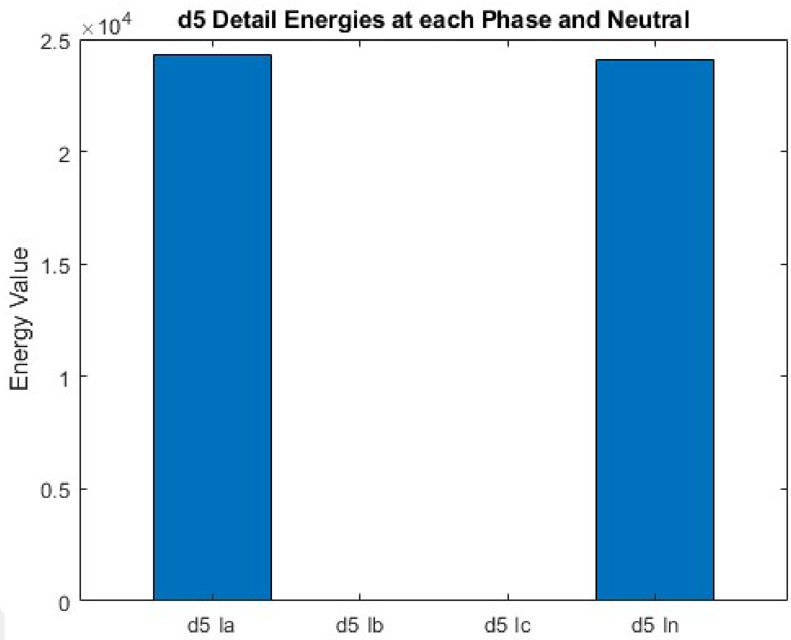

Figure 6.13 : Case 3 Energies at level 5 under single phase HIF

Energy is present in all phases, but is much higher in the faulty phase and neutral due to the presence of high frequency components in their d5 coefficients. Unfaulty phases energies are considered relatively zero because of the huge difference in energies between them and the others. In the case of single phase HIF ED_{5n} and ED_5 of the faulty phase are almost approximately equal to each other.

6.2.4 Case 4: HIF at Phases A and B

The fourth case study is also a HIF condition, two HIF models are connected to phases A and B and are introduced to the system at time = 0.5 seconds. HIF model parameters are the same as in the previous case. d5 coefficients of all phases and neutral at the secondary of the transformer are plotted in figure 6.14. High frequency components appear in faulty phases and neutral at the instant of connecting the fault and keep on being present during fault.

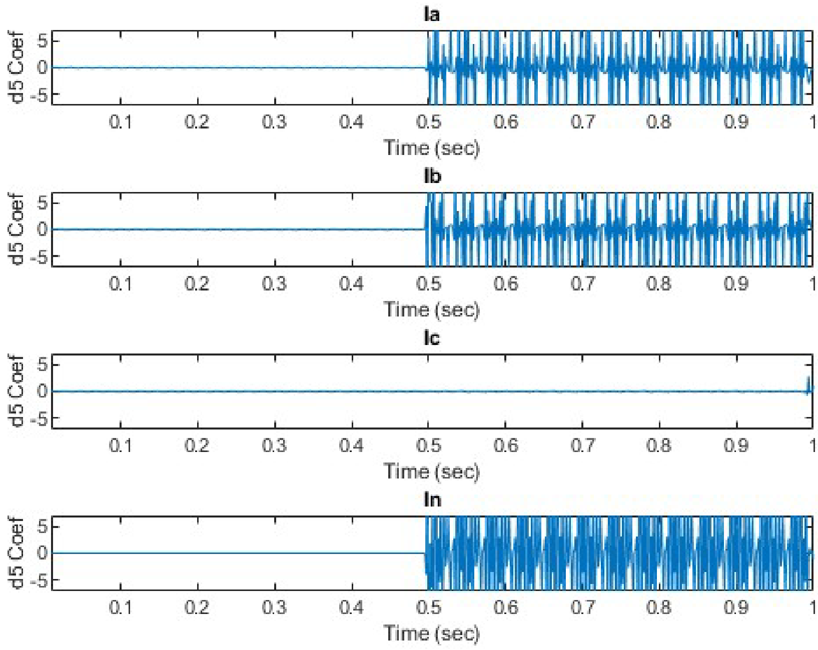

Figure 6.14 : Case 4 d5 coefficients at all phases and neutral under double phase HIF

Area variation is calculated and its plot is shown in figure 6.15. The values are integrated and the slope variation graph is plotted in figure 6.16. The average slope at each phase and the neutral is calculated and the results are as follows: S_a=3434.7, S_b=3612.88, S_c=27.3, and S_n=5558.4.

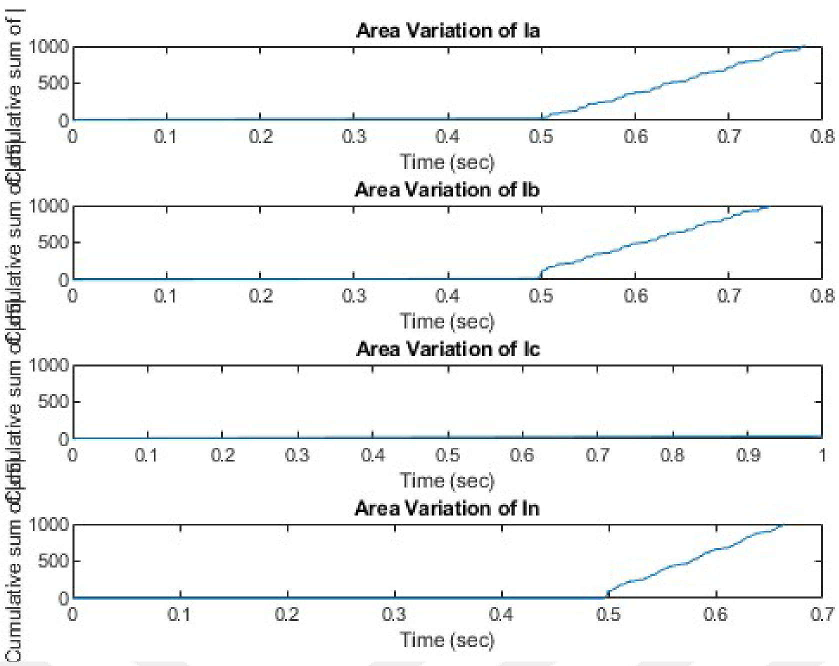

Figure 6.15 : Case 4 Area Variation Curves under double phase HIF

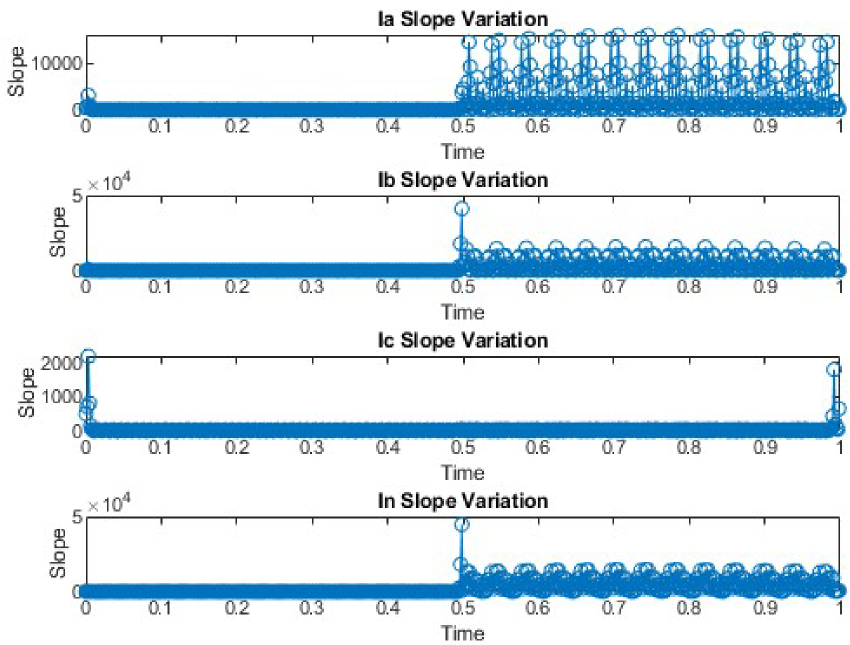

Figure 6.16 : Case 4 Slope Variation Curves under double phase HIF

It is observed that at fault instant, area variation curve of faulty phases and neutral started increasing and kept on increasing during fault. And slopes at faulty phases and neutral increased instantaneously at fault instant and kept fluctuating during fault.

Energy levels of details at level 5 decomposition are also calculated and the plot is shown in figure 6.17. Energy levels at each phase and neutral are as follows: ED5a = 24530.2, ED5b = 30019.7, ED5c = 40.5, ED5n = 44392.2.

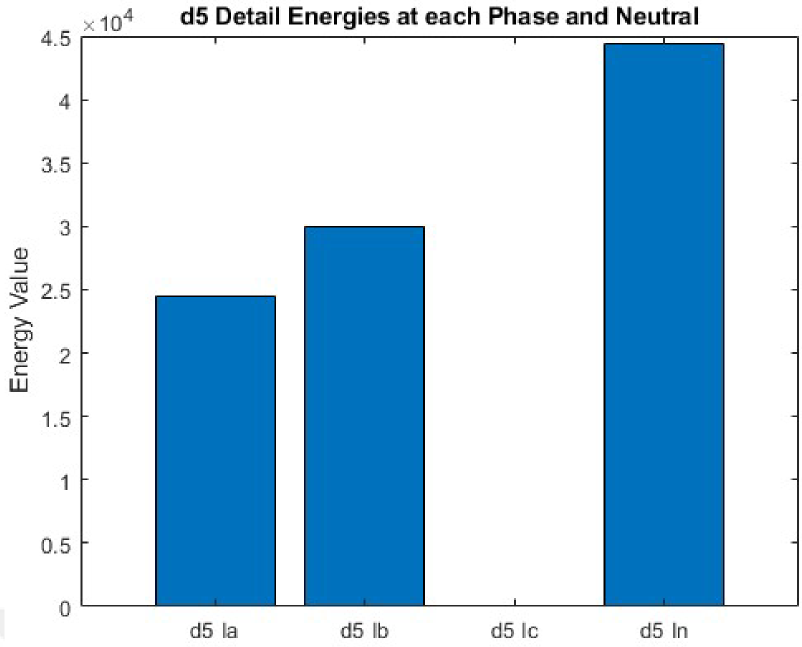

Figure 6.17 : Case 4 Energies at level 5 under double phase HIF

Energy is present in all phases, but is much higher in the faulty phases and neutral due to the presence of high frequency components in their d5 coefficients. The unfaulty phase energy is considered relatively zero because of the huge difference in energies between it and the others. In case of two phase HIF ED_{5n} becomes the highest of all energies ED_5 of other phases.

6.2.5 Case 5: HIF at Phase B

The fifth case study is also a HIF condition, The HIF model parameters were changed as to be as follows: Vp=5193v, Vn=5242v, Rp=400Ω, Rn=420Ω, the resistors are adjusted to have 10% variable change in value. The model is connected to phase B and is introduced to the system at time = 0.5 seconds. Ground resistance was also increased in this case. d5 coefficients of all phases and neutral at the secondary of the transformer are plotted in figure 6.18. High frequency components appear in the faulty phase and neutral at the instant of connecting the fault and keep on being present during fault.

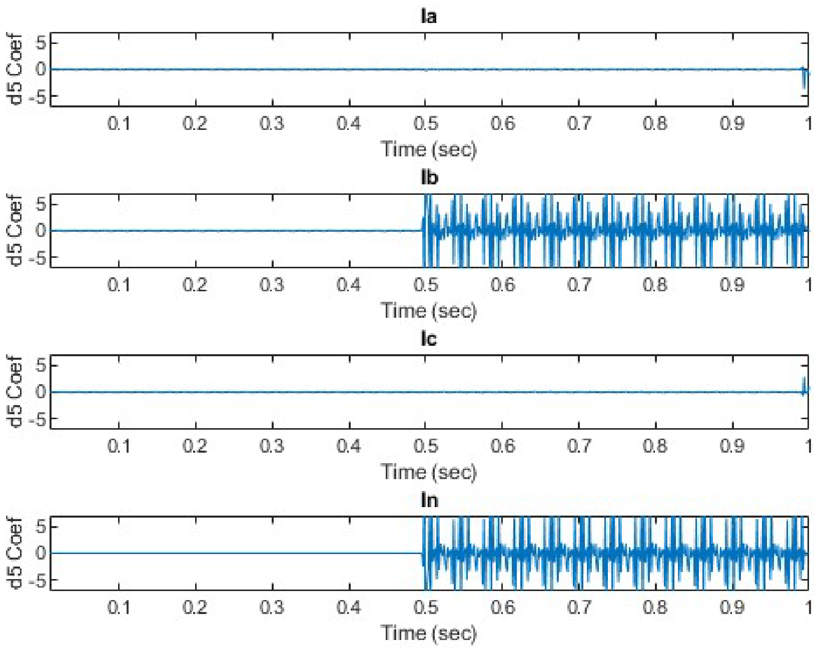

Figure 6.18 : Case 5 d5 coefficients at all phases and neutral under phase B HIF

Area variation is calculated and its plot is shown in figure 6.19. The values are integrated and the slope variation graph is plotted in figure 6.20. The average slope at each phase and the neutral is calculated and the results are as follows: S_a=28.7, S_b=2133.8, S_c=30.4, and S_n=2112.23.

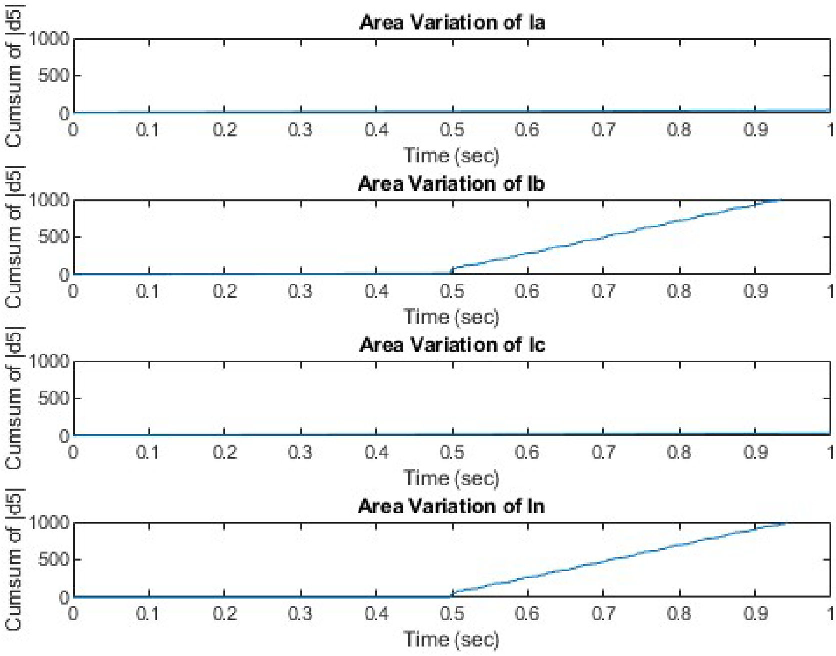

Figure 6.19 : Case 5 Area Variation Curves under phase B HIF

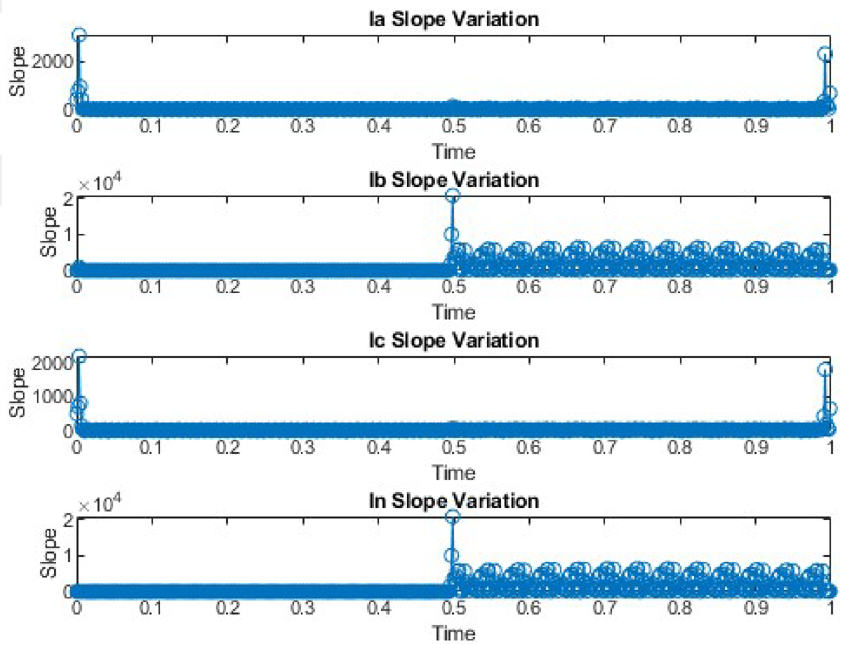

Figure 6.20 : Case 5 Slope Variation Curves under phase B HIF

At fault instant, area variation curve of the faulty phase and neutral started increasing and kept on increasing during fault. And slopes at faulty phase and neutral increased instantaneously at fault instant and kept fluctuating during fault.

Energy levels of details at level 5 decomposition are also calculated and the plot is shown in figure 6.21. Energy levels at each phase and neutral are as follows: ED5a = 77.2, ED5b = 8326.28, ED5c = 30.4, ED5n = 8118.6.

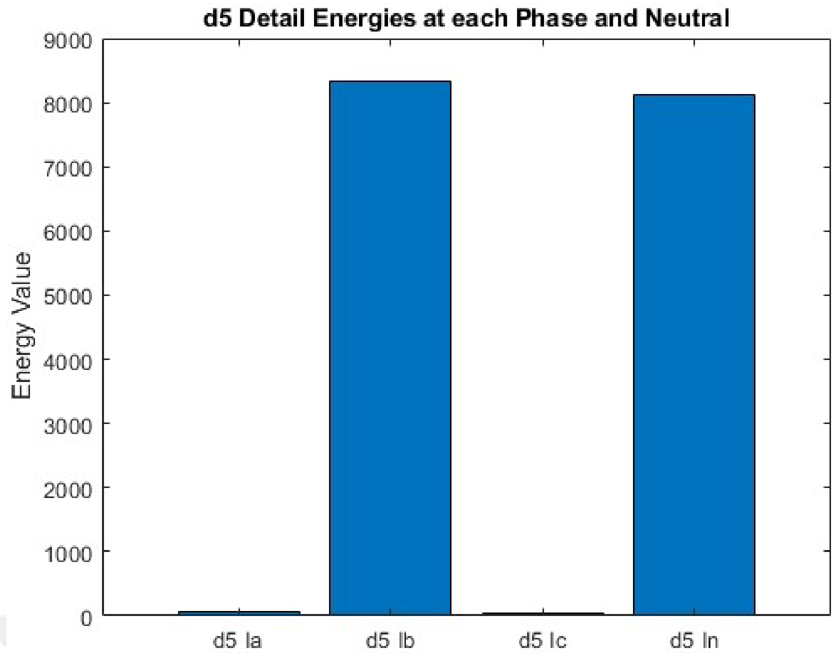

Figure 6.21 : Case 5 Energies at level 5 under phase B HIF

Energy is present in all phases, but is much higher in the faulty phase and neutral due to the presence of high frequency components in their d5 coefficients. The unfaulty phases energies are considered relatively zero because of the huge difference in energies between them and the others. In case of single phase HIF ED_{5n} is approximately equal to ED_5 of the faulty phase.

6.3 Comparative Performance Analysis

6.3.1 Limitations of The Proposed Algorithm

After conducting several tests and simulations, some limitations to the proposed method were detected.

For higher fault current (lower impedance levels) the algorithm worked perfectly without any limitation. But, for lower fault current (higher impedance levels) some issues started appearing. Everything works totally fine and the algorithm gives great results for fault currents above or equal to 10A, which means resistances below 2000Ω. For currents between 5.5A and 10A (2000Ω<R<5000Ω) the algorithm still works but on a risky margin because very low high frequency components are present in the d5 coefficients. While current levels below 5.5A (R>5500Ω) are successful in terms of HIF detection, but high frequency components are very low in the d5 coefficients (around 0, resulting in relatively low average slope levels in the neutral and in addition to very similar energy of details levels in all phases and neutral, resulting in failure in detecting the faulty phase.

An example of the limitation is illustrated below, HIF is injected to phase B, and its resistances are set as follows: Rp=6000Ω, Rn=6100Ω, and voltages of the model are Vp=3862V and Vn=3268V. The results are shown in figures 6.22, 6.23, 6.24 and 6.25.

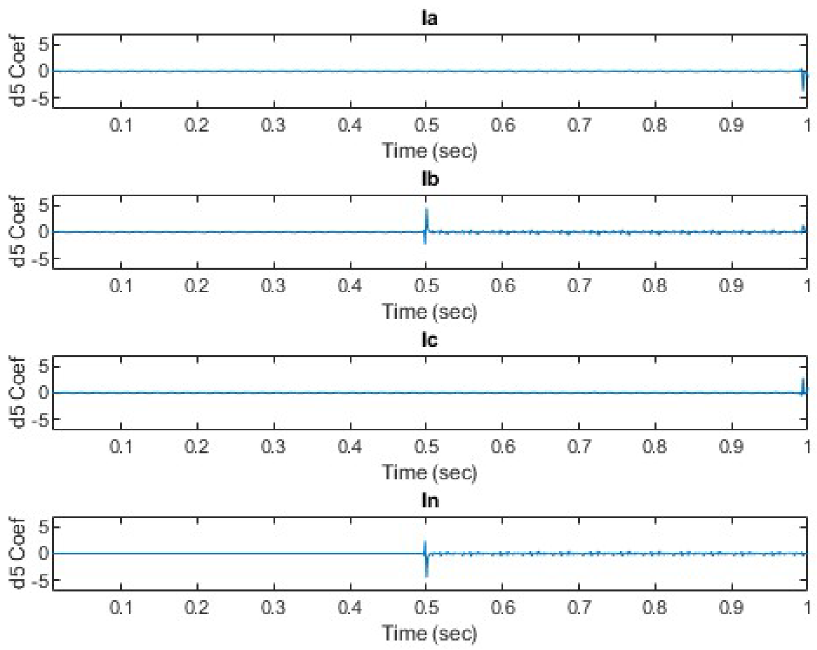

Figure 6.22 : d5 coefficients at all phases and neutral (limitations)

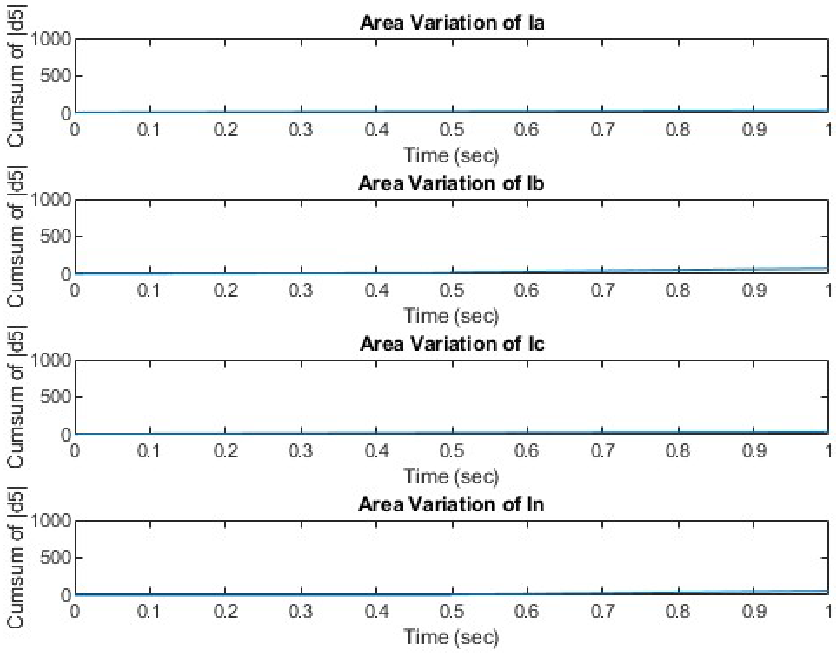

Figure 6.23 : Area variation curves (limitations)

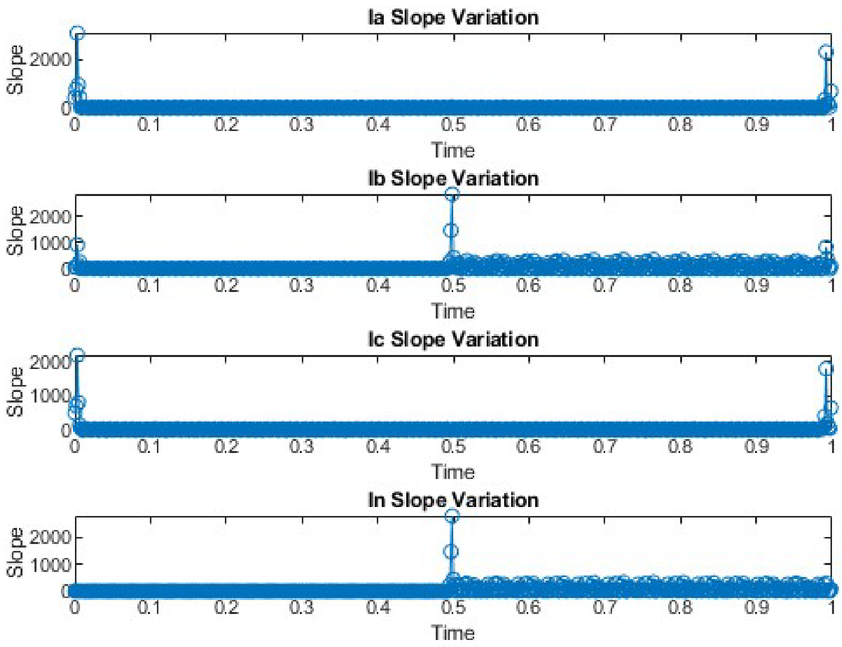

Figure 6.24 : Slope variation curve (limitations)

Average slope at each phase and neutral are as follows: S_a=25.16, S_b=101.5, S_c=24.8, and S_n=95.65.

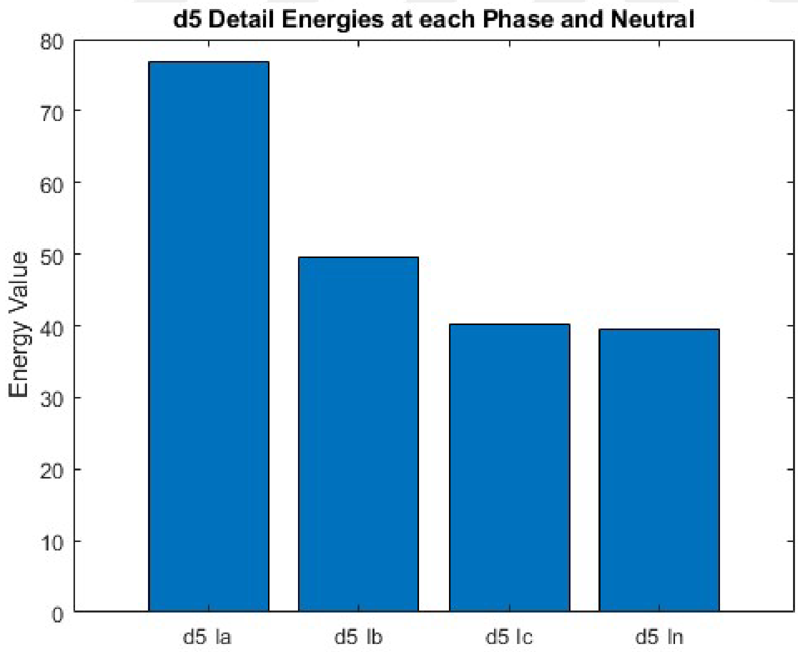

Figure 6.25 : Energies at level 5 (limitations)

Energy levels at each phase and neutral are as follows: ED_{5a} = 76.88, ED_{5b} = 49.67, ED_{5c} = 40.3, ED_{5n} = 39.64.

Fault current in this case was around 4.8A, as seen in figure 6.22 high frequency components are very low, from that the area variation curve in figure 6.23 shows a very slight increase with time resulting in average slope levels relatively low, moreover from figure 6.25 it is clear that all energies at all phases and neutral are relatively small. Faulty phase energy level (Phase B) is lower than that of phase A, which gives false interpretation of the algorithm and the wrong phase would be tripped.

This limitation could be due to many reasons, one of them is that the HIF model may not be very good in responding to high resistance levels as a consequence low current levels. The simplified Emanuel model used in this study is based on arcing in sandy soil, and according [56], HIF current in such cases is around 10A, and according to other references such as [57], HIF current in dry soil is around 20A and for wet soil it is around 40A.

In conclusion, the limitation is most probably from the HIF model that does not properly interpret a HIF in cases of faulty current below 5A.

6.3.2 Comparative Performance

This part compares between the proposed method and other methods and it is divided into two parts: Comparison with conventional protection and Comparison with other algorithms.

6.3.2.1 Comparison With Conventional Protection

Traditional protection devices like overcurrent protection and distance protection face challenges in detecting High Impedance Faults (HIF) for various reasons. For instance, overcurrent protection relies on current level measurements, triggering system shutdown when currents surpass a predefined threshold. However, HIF typically generate low fault currents, rendering the detection inadequate. Distance protection, reliant on analyzing system impedance, encounters difficulties in detecting HIF due to their high impedance values. This can result in overreach or under reach in fault detection, leading to potential misinterpretation between HIF and normal load fluctuations.

6.3.2.2 Comparison With Other Algorithms

Fourier transform for HIF detection in power systems has limitations, it lacks precise time and frequency resolution, posing challenges in identifying the exact occurrence of transient events like HIFs. Furthermore, Fourier assumes signal stationary, but HIFs are often intermittent, resulting in non-stationary behavior that Fourier analysis may struggle to handle effectively. Moreover, the smearing effect in Fourier can spread energy across multiple frequency bins, making it challenging to distinguish between different frequency components and accurately characterize transient event characteristics. Additionally, Fourier's sensitivity to sampling rate may affect accuracy, potentially causing the misinterpretation of signals and missing transient events.

As for Artificial Intelligence (AI) and Machine Learning (ML), such heuristic approaches like genetic algorithm, neural networks and fuzzy logic algorithms can be trained to recognize patterns associated with HIF based on historical data, such methods need extensive training datasets which is expensive. Furthermore, studies employing these methods are very few and still limited.

In studies that leverage wavelet transform analysis to detect HIF, most authors often concentrate on the detection of HIF rather than discrimination. In this study both detection and discrimination of HIF are points of interest, resulting in better precision and better performance for this algorithm.

Comparing limitations between this algorithm and other algorithms is not applicable due to the lack of information about limitations of the other algorithms.

7. CONCLUSIONS AND RECOMENDATIONS

7.1 Contributions

This Master of Sciences research thesis shed the light on a very important and vital issue that may be the most controversial problem in distribution systems, which is the High Impedance Fault. That is because of the difficulties and challenges in the process of detecting such faults, due to the randomness and relatively low fault current they produce. In this study a new HIF detection algorithm is proposed, which is based on wavelet transform, specifically discrete wavelet transform. DWT is used for multiresolution analysis of the current signals extracted at the transformer secondary of the system which are derived from computer simulation.

In the proposed algorithm, discrete wavelet transform with ‘sym5’ mother wavelet and a 5-level multi resolution analysis is done, then the energies of the fifth detail at each phase and the neutral are calculated. Also the area variation graph was extracted along with a slope variation graph, and after that average slopes were calculated and compared to a threshold value to detect if there was a fault or other conditions. Average slope values along with energies of details (ED_5) are used to come up with an algorithm for detecting HIFs. Testing of the proposed method is performed by simulation using MATLAB and Simulink 2022b software.

The simulation results of 5 different cases tested in this thesis, indicate that a potential precise HIF detection algorithm was proposed. The proposed algorithm was successful in differentiating between an unbalanced load switching condition and a HIF situation. Moreover, the proposed method proved to be precise in detecting if a single phase HIF or double phase HIF is occurring from different energy values, in addition to detecting the faulty phase or phases present in the system. Some limitations appeared in simulation which are that the algorithm was able to detect HIF but failed in detecting the faulty phase for low current levels, specifically currents below 5A, which may be due to a modeling problem in the HIF model.

As has been demonstrated in this paper, HIF can be detected by DWT analysis. DWT is considered a relatively simple, fast and easy to implement in real life compared to other techniques, and appears to be applicable in real time detection systems.

Compared to other literature studies based on wavelet transform, this study employs two distinct approaches to detect and discriminate HIF. The first approach involves a 5-level decomposition using Discrete Wavelet Transform/Multiresolution Analysis (DWT/MRA). This decomposition is used to develop a progression for deriving and integrating with respect to time, resulting in average slope values. These values serve as a fault index for detecting HIF. The second approach entails calculating the energy of the 5th level detail coefficients of the DWT/MRA analysis (d5 Coefficients) to discriminate and detect the faulty phase. The combination of these two approaches enhances precision in decision-making. Furthermore, in contrast to other studies, this research considers both fault detection and discrimination, rather than focusing solely on one aspect.

7.2 Future Work

The development and implementation of the HIF detection algorithm proposed in this thesis is still at its first stages. Due to the fact that a HIF is very difficult to be modeled in a perfect way, computer simulation results carried out by MATLAB and Simulink may not be that precise and may be different than real life situations. A real life testing and analysis must be performed in order to verify the precision of the proposed algorithm. Moreover, simulation was done on a simple distribution system, so the algorithm should also be tested on more complicated systems and more sophisticated cases should be considered. Lastly, a future work to find the fault location can be done to increase the reliability of this algorithm.

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