

High Impedance Fault Detection in Power Systems: A Systematic Review Using PRISMA Guidelines

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ABSTRACT- One of the biggest challenges in modern day electrical power distribution systems is high impedance faults (HIFs). They are usually caused by a conductor touching a high resistance area like vegetation, tree branches or ground. The nonlinearity of a HIF, its random and asymmetric nature and its comparatively small magnitudes make it difficult to detect with conventional protection devices, and it is often difficult to tell if a HIF is occurring. A HIF can be serious safety hazard if not detected early on, such as posing an electric shock hazard or fire hazard, especially in distribution networks. A structured review of literature on the detection methods for HIF is presented in this paper, concentrating on the development of the methods from the classical signal processing to the modern intelligent and data driven methods. The studies that have been reviewed are classified according to their method, such as signal-based techniques, harmonic analysis, wavelet transform methods and machine learning based methods. Comparative statistics are then performed to reveal dominant trends in the literature and relative adoption of categories of techniques in recent literature. The results showed that the trend is definitely shifting from deterministic systems to hybrid and intelligent systems especially those that combine wavelet-based feature extraction with machine learning based classifiers. The review also points out that in recent years, data-driven techniques have become more and more popular for their better adaptability and fault detection accuracy under various fault conditions. In addition, the study highlights the need for adaptive and resilient detection systems that can maintain a reliable operation and public safety in modern distribution networks. Last but not least, this work brings a systematic classification of the available HIF methods, highlights the needs for the research and development of more reliable and real-time detection strategies and outlines future research directions.

Keywords: High Impedance Faults, power systems, protection system.

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1. INTRODUCTION

High impedance faults [HIFs] form one of the complicated problems to be addressed by protection systems of electrical distribution networks. HIF fault occurs when a live conductor comes into contact with a surface of high impedance, such as concrete, dry soil or tree branches; small fault currents are generated which cannot easily be distinguished from normal load currents. This type of fault rarely causes total interruption in service or damages any component in the system but it has great risk on environment, human and animal life since it can cause fire or electric shock if active conductors remain [1].

The current generated during a high impedance fault is typically similar to, or even lower than, the current drawn by ordinary consumer loads. This remains one of the big challenges for any technology attempting to detect such faults

at their present magnitude. Conventional protection devices comprise overcurrent or overload relays that fail in detecting such faults [2]. Due to this difficulty, engineers and researchers have resorted to developing quick-and-precise detection mechanisms capable of identifying HIF with high sensitivity yet without false alarms.[3] Considerable improvements toward better detection of HIFs have taken place recently wherein modern techniques intelligently combine algorithms with signal processing; time-frequency analysis methods like wavelet transform as well as Fourier transform widely being used for capturing signals both transient state & HIF state[4]. Artificial intelligence [AI] and machine learning [ML] include artificial neural network [ANN], support vector machines, or unsupervised learning algorithms to improve the precision of classification and also allow it to be adaptive under different network conditions. A very recent method is where Continuous Wavelet Transform [CWT] is used to transform electrical signals into time-frequency images which are then analysed by a hybrid neural network model resulted in an accuracy rate of detection at about 98.85% hence showing possibility paths that could be taken using AI driven methods for HIF identification [5].

However advanced or improved a method has been toward the detection of High Impedance Faults, several challenges still block and hinder the massive deployment of such systems. The most significant challenge is in the inconsistent nature of high impedance fault states: these characteristics vary greatly

with type surface contact, environmental condition on fault, and duration of fault; further complicating distinguishing between high impedance faults and normal system operations such as capacitor group energizing or load switching. Researchers have emphasized the need for algorithms with high generalizability that provide reliable performance across diverse changes without requiring frequent recalibration [6].

Therefore, the aim of this research is to provide a comprehensive study of how to detect high-resistance faults, review current methods and techniques, evaluate the advantages and disadvantages of research, and then propose or improve a new method that can improve performance in modern electricity distribution systems.

Although there are many reviews and surveys in the literature that have attempted to discuss different approaches for HIF detection, it is observed that most of the work done before does not concentrate on formulating any criteria for classifying and evaluating the performance of detection methods. Previous surveys, for instance, concentrated only on wavelets, harmonics, and artificial intelligence as separate methods without addressing the comparative aspects regarding performance and applicability in modern smart grids.

Moreover, review articles that currently exist focus much more on fault detection precision but offer little insight into emerging topics, such as renewable energy sources, implementation in real time, the application of edge computing techniques, data set normalization, explainable artificial intelligence, and the validation of models in practice. Consequently, there is a need for a comprehensive article discussing all aspects mentioned above within one unified analytical framework.

While a number of review articles have summarized High Impedance Fault (HIF) detection techniques in power distribution systems, previous surveys are mostly limited to one aspect of the problem, such as signal processing methods, artificial intelligence algorithms, or fault detection principles. Most of the current reviews also give descriptive summaries of the individual studies without doing a thorough comparative analysis of the different software platforms, fault models, signal modalities, detection purposes, threshold strategies, fault localization techniques and recent developments in intelligent HIF detection. Further, previous surveys often only span up to 2022 or 2023, and so are not comprehensive of the latest advancements in deep learning, hybrid artificial intelligence models, edge computing and renewable-energy-integrated distribution networks.

The present review aims to overcome such limitations, by providing a comprehensive and up-to-date analysis of the recent advances in HIF detection and classification from 2010 to 2025. The review differs from previous ones by bringing together several technical viewpoints in a single framework to facilitate comparison of current methodologies in terms of the environment in which they are implemented, the computational methods applied, performance metrics,

practicality, and research maturity. The main findings of this review are contained in the following summary:

- **Comprehensive literature coverage:** The literature review has been carried out in a systematic way by applying the methodology PRISMA, which enables a transparent and reproducible selection of articles with more than 90 publications that were published between 2010 and 2025.
- **Multi-dimensional comparative analysis:** Existing HIF studies are compared from a number of complementary points of view: simulation software, input signal types, equivalent HIF models, research aims, fault localization strategies, threshold selection methods, detection accuracy, response time, strengths, limitations and complexity of implementation.
- **Critical evaluation of intelligent HIF detection techniques:** This review critically compares the traditional signal-processing methods, machine learning algorithms, deep learning architectures and hybrid intelligent approaches in terms of their relative advantages, limitations, computational needs, robustness, interpretability and applicability for practical application.
- **Comprehensive performance benchmarking:** An in-depth comparative analysis of recently developed HIF detection algorithms is provided based on commonly used evaluation parameters such as detection accuracy, response time, methodological characteristics, advantages and limitations, enabling the readers to make objective evaluations of the evolution of HIF detection technologies.
- **The review addresses the identified current research gaps,** such as the lack of standardized benchmark datasets, limited real-world validation, lack of explainability of models, high computational complexity, varying evaluation metrics, and lack of investigation of renewable-rich distribution systems.
- **Future research roadmap:** Based on the identified research gap, this review identifies future research directions that will involve the use of explainable artificial intelligence, hybrid signal processing-deep learning frameworks, implementing edge-computing systems, the use of standardized benchmark datasets, renewable-energy-aware protection systems, and the use of practical deployment in smart distribution networks.

It offers a wider, more critical and more comprehensive view, by integrating a systematic analysis of the literature with quantitative comparison, critical discussion and guidance for future research, than do the current survey articles. It is therefore a useful reference for researchers, engineers, as well as for any practitioner dealing with the design of intelligent protection systems for modern power distribution networks.

2. BACKGROUND

High Impedance Fault (HIF) detection in power distribution systems follows a certain procedure, which entails adopting an adequate methodology in order to detect and diagnose any faults accurately and efficiently. The process generally involves four primary phases. Data acquisition is the first phase, which involves collection of electrical signals such as current or voltage values through the use of sensors, smart meters or simulations. The second phase comprises data

preprocessing, whereby signals are cleaned by filtering, normalization and segmentation to improve the quality of the collected information. The third phase is referred to as feature extraction and involves deriving relevant characteristics such as time domain, frequency domain or time-frequency features that are used to represent the performance of HIFs. The fourth and final phase is classification, which utilizes machine or deep learning algorithms to differentiate between normal operation and faults.

2.1. Data Acquisition

Many different types of data go into research on HIF, and researchers may choose different sources even if they are using the same methods of analysis. Some methods rely only on present signals [7], which is the best way to notice quick changes and also see harmonic components [8]. Other methods look at voltage measurements because these are less affected by distortions from changes in load [9]. In some cases, magnetic flux data is used to achieve high accuracy [10] but this needs rather and special complicated sensing equipment.

2.2. Data Processing

Data processing is a fundamental function for enhancing the operation of HIF identification and mapping systems. After acquiring raw signals, such as voltage, current, and magnetic field, they must be processed through several steps to refine them and make them ready for accurate extraction and characterization [11].

- Signal filtering removes noise that may be induced by load variation, switching event noise or noises from distributed generation sources [12]. Conventionally band pass and low pass filters are used to eliminate unwanted frequency components [13]. More advanced techniques such as denoising using wavelets have been successfully implemented to extract transient features associated with arc phenomena [14].
- The signals are divided into short time windows typically spanning a few cycles to capture the dynamic behavior of HIFs [15]. This enables algorithms to monitor local changes such as the accumulation of current, abnormal behavior, and arc extinction [16].
- Normalization and calibration bring the signals to a common per-unit representation. They make it possible to view on the same scale or compare all quantities of current, voltage, and any features derived from them. This is very important in machine learning applications because normalized magnitudes shall not allow one feature to dominate another due to differences in scales [17]. Adjustments are also made for reflecting system operating conditions that eliminate an effect of variability most essentially some harmonic component variabilities more apparent when fundamental is removed from either current or voltage dramatically improves distortion visibility preprocess makes algorithm robust against normal load variation background noise [18].

- The preprocessed signals are transformed into domains that more accurately represent the unique features of HIFs. Typical methods involve time-domain analysis using RMS and peak values, frequency-domain analysis through Fourier analysis to identify harmonic components, and time-frequency wavelet or Stockwell analysis falls under the time-frequency analyses whose output features both the time and frequency characteristics. Besides, hybrid methods that combine more than one domain have been introduced to achieve a more comprehensive insight into HIF behavior [19][1][20].

By these steps, data processing will enhance the signal-to-noise ratio while preserving those features which are typical of HIFs so that reliable feature extraction and classification can be made accurately. In summary, this stage can be viewed as a bridge between raw data acquisition and intelligent decision-making whereby the inherent characteristics of HIFs are captured accurately for further analysis [21].

2.3. Feature Extraction

Feature extraction refers to the conversion of raw signals or data, either current or voltage, into certain values or characteristics that would help in the proper distinction of different events, inclusive of high-impedance faults [HIFs]. These features can be in the time domain [current peaks, waveform distortions], in the frequency domain [harmonics], or even in the time-frequency domain [wavelet coefficients]. The primary goal is to simplify a complex signal into a small set of characteristic values that can be easily used by algorithms or classifiers for accurate detection and classification. The most prominent methods are:

- *Discrete Wavelet Transform [DWT]*: Analyzes the signal in the time-frequency domain across multiple levels, so that rapid changes [transients] associated with the electric arc can be accurately isolated [22][23][24].
- *Multi-resolution Morphological Gradient [MMG]*: It performs nonlinear morphological processing to extract sharp changes in the signal [such as peaks and counter-peaks] at different levels, revealing the randomness of the current during the electric arc [25].
- *Fast Fourier Transform [FFT]*: Converts the signal from the time domain to the frequency domain, and reveals the odd and even harmonics [3rd, 5th, 7th...] which are clearly increased in the case of HIF [26].
- *Adaptive Extended Kalman Filter [AEKF]*: Estimate the fundamental and time-varying components [fundamental + harmonics] in the signal with high accuracy, allowing the detection of deviations caused by HIF [27].
- *Hilbert-Huang Transform [HHT]*: Empirical mode decomposition [EMD] is used to extract the intrinsic components of the signal, and then apply the Hilbert transform to obtain the instantaneous spectrum, which is

useful for nonlinear and unsteady signals such as HIF [28][29].

- *[TFA]*: It includes general methods such as Wigner–Ville to convert the signal into a time–frequency representation, which helps in identifying energies in specific bands during HIF [1].

2.4. Feature Extraction

After extracting features from the electrical signals; the next step is classification to determine whether these features represent a high-impedance fault [HIF] or just a normal operating phenomenon. Classification is a decision-making process based on some set of characteristics, normally performed by means of artificial intelligence or statistical methods. The objective is to have reduced false tripping and enhanced reliability of the protection system.

- *Artificial Neural Network [ANN]*: It is based on an architecture inspired by the human brain. It consists of layers [input-hidden-output] that learn the relationship between features and the output [HIF/no-HIF][30][31].
- *Fuzzy Logic [FL]*: It is based on linguistic rules [If-Then]. It allows for a degree of uncertainty: for example, "slightly high current" instead of "high current." It is suitable for handling ambiguity in HIF signals [32][33].
- *Support Vector Machine [SVM]*: It separates data in a high-dimensional space using a hyperplane. The threshold that gives the largest margin of separation between HIF and other phenomena is chosen. It is robust in cases where data is limited [34][35].
- *Probabilistic Neural Network [PNN]*: Bayesian classifier. Calculates the probability that a sample belongs to each class and selects the highest. Fast to train and often accurate [36][37].
- *Decision Tree [DT]*: It represents the decision tree: a node for each test [e.g., is the harmonic ratio > threshold?]. It ultimately produces a path from the root to the leaf that determines the classification. It is easy to interpret but can suffer from overfitting [38][39].
- *Hybrid Methods*: Combining more than one classifier to compensate for weaknesses. For example, ANN for nonlinear learning and Fuzzy to handle ambiguity. It has proven more successful in some studies with HIF [40][41].

3. PRISMA BASED SYSTEMATIC REVIEW

This systematic review has been conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020). It means that the methodology used in the study is well-known and systematic. PRISMA offers an effective and well-established approach to carrying out the evidence synthesis. The standardized methodology helps to define the stages of conducting a study from the

identification, screening, eligibility assessment, to the inclusion of relevant articles. Such an approach allows reducing the risk of any selection biases in order to ensure the quality and validity of the study. The use of PRISMA methodology ensures the transparency of each stage of conducting the literature review. All stages of the selection process from searching for the articles in databases to their inclusion in the systematic review are thoroughly described. Such an approach not only allows achieving consistency but also makes the process replicable for other researchers. In addition, PRISMA methodology promotes the use of the clear inclusion and exclusion criteria thus increasing the objectivity of the study.

The central focus of this systematic review is to investigate the latest developments concerning High Impedance Fault (HIF) detection and classification in power distribution networks. The objectives of this review include investigating and analyzing the latest approaches for detecting HIFs which range from traditional signal processing methods, machine learning techniques, deep learning models to hybrid intelligent systems. Furthermore, it focuses on identifying the challenges associated with HIF detection in real-world scenarios including the nature of fault current, noise and class imbalance problem. Apart from that, this review will also address the existing research gap and the future directions that can be pursued. Through this systematic review, latest studies will be compiled for providing a thorough insight into the current trends and future scope of the field.

3.1. Review Planning and Research Objectives

The systematic review process was started from the well-developed planning phase that involved setting out clear research objectives and research questions. It should be noted that this step plays a crucial role in the PRISMA approach, since it determines the main directions of the review and helps to ensure its focus, coherence, and methodological soundness in all further steps of the review process. In turn, the main goal was to get acquainted with the current state of high impedance fault (HIF) detection and classification technologies in power distribution systems including the traditional and intelligent computing approaches. In the course of this step, certain research questions were determined. These questions were aimed at covering the whole range of research in the field. In particular, the focus of the study was placed on the identification of various techniques of HIF detection and classification including the classical signal-based approaches and the modern data-driven approaches.

Moreover, the problem of signal processing and feature extraction techniques that are of great significance for detecting HIF because of the low current and the extremely nonlinear characteristics of such faults was widely investigated. The approaches including the wavelet transform, time frequency approach and the statistical feature extraction were taken into consideration as an integral part of the framework of analysis. Moreover, it is worth noting that the use of machine learning, deep learning and optimization based intelligent methods for enhancing the detection accuracy was

investigated in terms of architecture, strategy and adaptability to real power distribution environment.

Also, the objective of analyzing performance measures and benchmarks employed by researchers within this topic and comparing the effectiveness of models was defined. Finally, it was required to define research gaps and limitations existing in the field in order to find ways of further research in this area. To ensure the methodological quality of the paper, the protocol was developed before conducting the literature review.

3.2. Literature Search Strategy

An extensive literature search was performed using a number of reputable scientific databases to achieve comprehensive coverage of studies in relation to High Impedance Fault (HIF) detection and classification in the field. The chosen databases are reputable because of their proven quality in indexing scholarly and peer reviewed studies in electrical engineering, smart grids, artificial intelligence, and power system analysis. Using multiple databases helped to avoid the potential risk of publication bias and inclusion of both fundamental and latest research findings. The chosen databases as shown in *table (1)* complement each other in terms of the type of coverage they offer; some are good for high impact journal articles while others cover conference papers and reports among others.

Table1. Scientific Databases Used for Literature Collection

Database	Coverage Area	Purpose
IEEE Xplore	Electrical Engineering and Power Systems	Primary source for HIF studies
Scopus	Multidisciplinary Research	Citation indexing and broad coverage
ScienceDirect	Engineering and Computer Science	Access to peer-reviewed journals
SpringerLink	Engineering and Energy Systems	Advanced research articles
Web of Science	Citation Database	High-impact publications
Google Scholar	Broad Academic Literature	Additional relevant studies

To ensure consistency and relevance, the scope of the research was narrowed down to scholarly articles written in English and published between 2010 and 2025. Such timeframe was selected in order to identify the latest breakthroughs in detecting HIF through machine learning, deep learning, and intelligent optimization. The selected period also allows to reflect the current state of art in smart grid technologies and contemporary power distribution systems.

3.3. Search Keywords and Query Formulation

Search Keywords and Query Formulation

A systematic search using a combination of keywords, Boolean operators, and alternative term was used for comprehensive and quality literature retrieval process. The method was crucial for encompassing the research outcomes across the various fields such as power systems, signal

processing, artificial intelligence and smart grid technologies, which are closely related to High Impedance Fault (HIF) detection & classification. The review was conducted using the carefully designed search expressions which enabled both classical studies and recent research advancements in the field of intelligent fault detection methods to be incorporated in the review.

The search strategy was also adjusted to the particular indexing methods and search capabilities of each of the scientific databases. Boolean operators like AND, OR and NOT were applied to broaden or refine the search results to suit the desired focus. Furthermore alternative terms and synonyms were added to prevent a loss of relevant studies which may include different terms for the same concepts.

Such as terms like “High Impedance Fault” were joined with “detection,” “classification,” and “identification,” and the terms related to machine learning were linked to the terms related to the power distribution system and smart grid. This multi-layered strategy resulted in a substantial increase in accuracy of retrieval, and less chance of missing key studies. The resulting keyword categories, after finalizing, for this review are listed below in *table 2*.

Table 2. Search Keywords Used in the Review

Category	Keywords
Fault Detection	"High Impedance Fault", "HIF Detection", "Fault Classification"
Signal Processing	"Wavelet Transform", "Hilbert-Huang Transform", "Feature Extraction"
Machine Learning	"Machine Learning", "Artificial Intelligence", "Classification Algorithms"
Deep Learning	"CNN", "LSTM", "RNN", "Deep Learning"
Smart Grid	"Distribution Network", "Power Distribution System", "Smart Grid"

3.4. Search Strategy and Article Selection Workflow

To ensure transparency, reproducibility and methodological rigour throughout the review process, the systematic review was conducted in a transparent manner, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework. A thorough literature search was carried out to find out the studies related to High Impedance Fault (HIF) detection and classification in power distribution system. A search strategy was established prior to the start of the review to minimise selection bias and to ensure all relevant publications were considered.

Six major scientific databases were used for the literature search: IEEE Xplore, Scopus, ScienceDirect, SpringerLink, Web of Science, Google Scholar. The choice of these databases has been made due to the comprehensive coverage of electrical engineering, power systems, artificial intelligence, signal processing and smart grid technologies. Multiple databases searching minimised the risk for publication bias and maximised the chance of locating basic and recent literature.

Boolean operators (AND, OR, NOT), phrase searching, and alternative keywords were used to get the most out of the retrieval. The search strings were tailored to the indexing conventions for each database, but did not change the conceptual structure. One of the representative queries applied in this search is shown below:

{(High Impedance Fault) OR (HIF Detection) OR (Fault Classification)) AND (Power Distribution System) OR (Distribution Network) OR (Smart Grid)) AND (Machine Learning) OR (Artificial Intelligence) OR (Deep Learning) OR (CNN) OR (LSTM) OR (ANN) OR (Support Vector Machine)) AND (Wavelet Transform) OR (Feature Extraction) OR (Signal Processing)}

The search results from all databases were exported to a reference management system, and by using this system the publications were automatically identified as duplicates and checked by hand. After duplicate removal, the records that could be located were screened for relevance to the goals of this review using the title and abstract. In this stage, studies that were not related to High Impedance Fault detection, protection systems or intelligent fault diagnosis were excluded.

Full-text evaluations were performed on the publications that passed the initial screening. All articles were assessed individually based on pre-defined inclusion criteria such as: publication type, publication language, publication year, methodological quality, scope of the research, and complete technical information. The studies that only included transmission systems, were not well described, or were not scientifically or experimentally validated were not included in further analysis.

All articles received the same assessment, so as to ensure consistency in the selection process. Reasons for excluding publications at the full-text assessment stage were recorded to enhance transparency and reproducibility of the review process. The entire selection process was performed in four consecutive phases of the PRISMA: identification, screening, eligibility assessment and inclusion of studies for qualitative synthesis.

Figure 1 summarizes the overall process of the article selection. Firstly, a search of databases identified 1250 records. 220 duplicate records were excluded and 1,030 studies were selected for title and abstract screening. At the screening stage, 760 articles were rejected due to lack of meeting the research goals. Of the 270 articles published in full text, 180 studies were excluded due to various reasons: lack of methodological quality, lack of relevance to High Impedance Fault detection, lack of complete experimental validation or failure of pre-defined eligibility criteria. As a result, there were 90 studies that were included for qualitative synthesis and comparative analysis for this systematic review.

3.5. Eligibility Criteria

A set of predefined inclusion and exclusion criteria were set before the screening process in order to ensure the relevance,

quality and scientific rigor of the studies included in this systematic review. These criteria were established based on PRISMA guidelines in order to keep transparency and minimize selection bias. The inclusion criteria were established to include studies that focus on the detection and classification of High Impedance Fault (HIF) in a power distribution system, and the exclusion criteria were set to exclude irrelevant, low quality or non-peer reviewed studies. This methodologically and relevantly sound structured filtering process was a necessary step in considering studies for further analysis and synthesis.

Inclusion criteria emphasized peer-reviewed research papers that they related to HIF-related problems with experimental, simulation-based, or real-world validation methods. Also, only studies published in English from 2015 to 2025 were included, as this would represent the latest developments in the field. Limitations, however, excluded records that were duplicated, non-relevant articles, editorial materials, and articles that lacked methodological information or articles that were not available in full-text. Research that has only looked at transmission systems was not included in this study since the emphasis of this study is on distribution networks. The complete set of eligibility criteria is summarized in table 3 below.

Table 3. Inclusion and Exclusion Criteria

Criterion ID	Type	Description
IC1	Inclusion	Studies focusing on HIF detection or classification
IC2	Inclusion	Research conducted in power distribution networks
IC3	Inclusion	Peer-reviewed journal or conference publications
IC4	Inclusion	Studies presenting experimental, simulation, or real-world validation
IC5	Inclusion	Publications written in English
IC6	Inclusion	Studies published between 2015 and 2025
EC1	Exclusion	Duplicate records
EC2	Exclusion	Studies unrelated to HIF detection
EC3	Exclusion	Editorials, book chapters, patents, and non-peer-reviewed reports
EC4	Exclusion	Articles lacking sufficient methodological details
EC5	Exclusion	Publications not available in full text
EC6	Exclusion	Studies focusing exclusively on transmission systems

3.6. Study Screening and Selection Process

The study selection procedure comprised of four main phases suggested by PRISMA:

- **Identification:** The retrieval of records from the selected databases through the use of predefined search strings.
- **Screening:** Removal of duplicate studies and screening the titles and abstracts for relevancy.
- **Eligibility Assessment:** The evaluation of full-text articles based on the inclusion and exclusion criteria.

- **Inclusion:** Inclusion of relevant studies for analysis. The screening procedure was conducted in a systematic manner in order to minimize any bias.

3.7. Data Extraction Process

A systematic data extraction process was applied to all the studies selected using the PRISMA screening process in order to achieve consistency and comparability of the information that was obtained during the search process. The extracted data were arranged in a structured database in such a way that both qualitative and quantitative synthesis would be possible for all the selected studies. This is an important aspect of any systematic review as it allows for classification of research contributions according to the methodology used, features engineering methods, algorithmic models, and performance evaluation results. The data extraction process covered both the technical and contextual aspects of each study. This meant that publication information was taken into consideration in order to trace back the development of the research, as well as methodology information to indicate the HIF detection methods used. Additionally, signal processing features, machine learning and deep learning algorithms, data set characteristics, evaluation criteria were considered. Moreover, the strengths and weaknesses of each study were analyzed in order to conduct comparative analysis. The complete list of data attributes that were extracted is provided in *table 4* below.

Table 4. Data Extraction Elements

Data Item	Description
Publication Information	Authors, Year, Journal/Conference
Methodology	HIF detection approach
Signal Features	Extracted electrical characteristics
Algorithms	ML/DL techniques employed
Dataset Type	Simulation or real-world data
Performance Metrics	Accuracy, Precision, Recall, F1-score, Detection Rate
Advantages	Reported strengths
Limitations	Identified weaknesses

3.8. PRISMA Flow Diagram

Figure 1 shows the PRISMA approach employed in conducting this systematic review for selecting relevant studies. In all, 1,250 records have been sourced from the databases. Out of these, 220 records were found to be duplicates and thus removed. A total of 1,030 studies were left for title and abstract screening. Out of these 1,030 studies, 760 studies were eliminated, while 270 full texts were retained for further examination. Finally, after the full text evaluation, 180 papers were eliminated on account of their being irrelevant or having poor methodology, lack of relevance to HIF, and incomplete results.

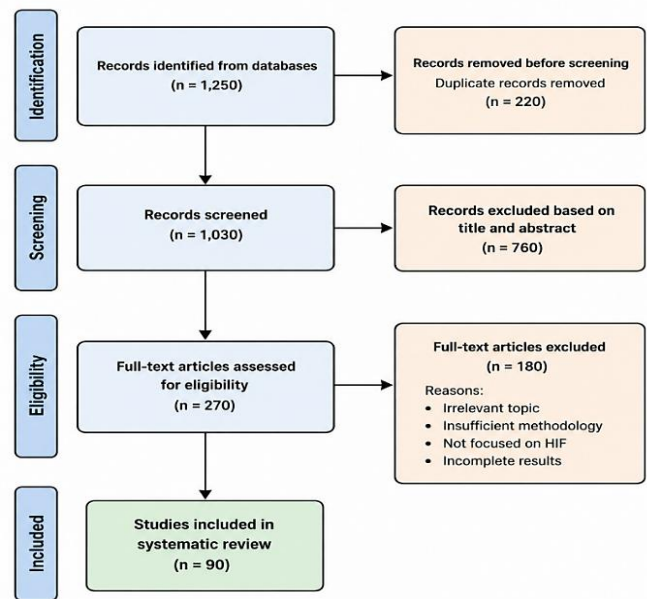


Figure 1. PRISMA Flow Diagram

4. A REVIEW ON THE HIF

The problem of high impedance fault (HIF) detection in recent times has emerged as one of the most important research areas in power distribution systems owing to the increasing complexity and sensitivity of such networks. In this context, the present review paper provides a detailed analysis of the scientific research on the subject of HIF detection published by credible academic sources such as scholarly journals and international conferences. In this regard, a considerable amount of research articles has been gathered and analyzed to understand trends and performance measures adopted by researchers. Specifically, statistics have been compiled about simulation methods used by scientists, types of signals employed, HIF detection model used, and the research aim of various works on the subject. Apart from this, the research also explores alternative ways of locating and classifying faults, and time-frequency analysis techniques as one of the prevalent signal processing methods.

4.1. Software Used in HIF:

Figure 2 presents an overview of the software tools commonly utilized in prior research studies. The goal is to identify the most frequently employed programs for simulating the HIF test. These tools are specifically tailored for transient modelling, distinguishing them from software focused on steady-state analysis or power flow studies. One notable example is the Alternative Transients Program [ATP] [42][38][34][11]. It is one of the versions of the electromagnetic phenomena programs [42]. ATP has the ability to simulate complex systems [34] Power System Computer-Aided Design [PSCAD] is one of the most important programs that simulate modern technologies for detecting HIF [43][44][45][46]. There are some papers based on real simulation [47][48]. In order to calculate the algorithm, time devices are used. The most important and most used

software is MATLAB [49][50][51][52][3]. It is used in signal-based algorithms and equation-based algorithms.

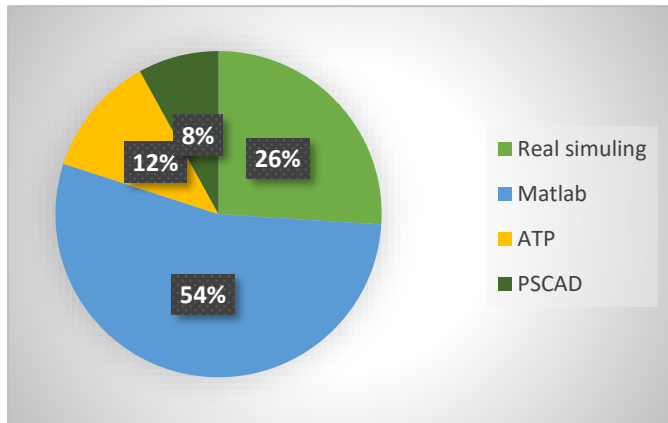


Figure 2. Software used

The distribution of simulation tools in the context of HIF detection research is based on the analysis of a total number of 50 articles. Among all of them, MATLAB stands out as the leader with 54% (27 articles) due to its outstanding applicability in terms of signal processing and modeling. Real simulation environments represent 26% (13 articles), which demonstrates the rising popularity of such platforms as the validation method is becoming increasingly important. ATP is used in 12% of the reviewed studies (6 articles) in order to conduct analysis of electromagnetic transients, while 8% (4 articles) utilize PSCAD as a tool for power systems modeling.

4.2. Signals Used in HIF

Figure 3 presents the types of signals employed to test various techniques. Many methods for detecting the presence or absence of HIF focus on analysing changes in the signal's shape. The most widely used signals in this field are current and voltage combined [18][53]. However, some approaches utilize only voltage signals, as seen in [54] and [55]. Additionally, certain studies rely exclusively on current signals for their analysis [47][52][56]. In addition to these, magnetic field [MF] has also been explored as a viable signal in research [10][57].

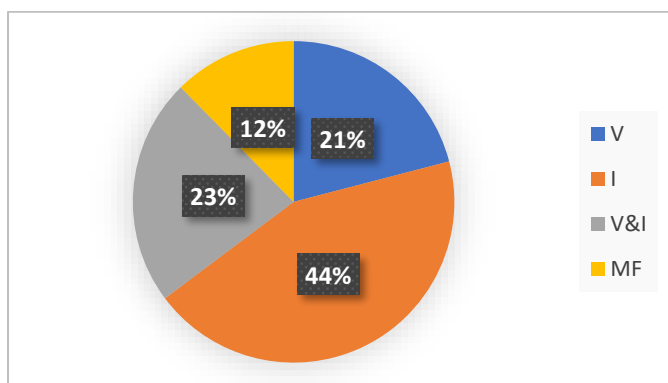
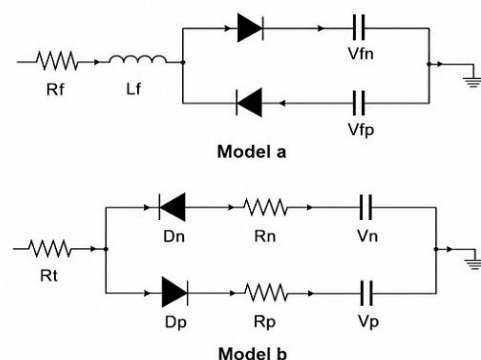


Figure 3. Signals based HIF calculation

The distribution of signal types used in the calculation and analysis of High Impedance Faults (HIFs) is based on a total of 50 analyzed studies, as shown in figure 3. From the results, it is observed that Current (I) signals are most widely used, as it is highly sensitive to fault-induced distortions and abnormal current difference which gives a very good result for detecting HIF condition with 44% (22 studies). The second most common method used is the Voltage and Current (V&I) signals, which accounts for 23% (12 studies), as this combined method offers a more complete system picture of the system behavior by collecting both voltage and current changes during a fault event. The role of voltage (V) signals only contributes 21% (11 studies), which is still important, but limited in many cases where voltage sag and transient disturbances are important fault markers. The least numerous are also Magnetic Field (MF) based, at 12%, (6 studies) and thus represent the most specialized use because of the need for increased sensors and complexity in implementation. Overall, the results show that current-based techniques are the most popular for HIF analysis, with hybrid voltage-current methods being gaining in popularity because of the enhanced detection reliability, and voltage-only and magnetic field techniques are complementary methods but are less common in use.

4.3. HIF Model

Figure 4. show Model [a] was proposed by [58], this model is used to simulate algorithms based on wavelet analysis. Electric arcs occur most prominently in systems with high inductance [59], this is because it is one of the components of the inductive model. As shown in model [a], we use two DC voltage sources, each connected to a diode, to simulate the effect of an electric arc [60][61]. This model is also used in algorithms based on artificial intelligence [62]. In this model, this setup effectively replicates the behaviour of an electric arc, making it a valuable tool for both simulation and AI-driven analysis. HIF model type [b], works based on experimental data and this model has been used extensively by researchers due to the ease of modifying the data and the great similarity with real faults [21][63]. Shown the model type [c] represents a single-phase fault to the ground. This type of fault represents 63% of faults [43]. For this reason, this model has been used extensively in previous research, as shown by the statistics in figure 4. Variable resistors are included in this model in order to obtain a non-uniform waveform to facilitate fault detection [64]. This model is used to simulate difficult and advanced techniques and algorithms [65][66].



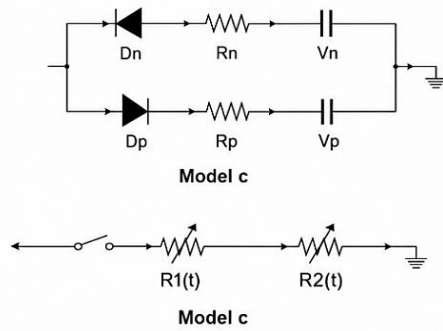


Figure 4. Models used in HIF

In figure 4, the following are the four equivalent circuit models that are used to model the nonlinear and polarity-dependent electrical behaviors in various physical systems. Model A: This is the most accurate representation, which is made up of a series resistance (R_f) and an inductor (L_f) that is followed by two sets of diodes and voltages sources oriented in opposite directions. Model B: This model is less complex since it consists of resistors (R) instead of inductors and has different resistors for the positive and negative branches. Model C: This is an even less complex model, which does not have any external inductive or resistive elements. It focuses

more on the nonlinear behavior of diode-resistors. Model D: This model consists of time-varying resistors $R_1(t)$ and $R_2(t)$.

Table (5) shows the comparative summary of equivalent circuit models shown in figure (5) and their advantages, disadvantages, structural composition and functional characteristics and its application field. Each model corresponds to a different level of abstraction for the nonlinear and polarity-dependent electrical behaviour, so comparing the various models makes it easier to understand the model's modeling capabilities and computational requirements. The comparison illustrates the difference between the models and the evolution of the models from a detailed representation of transient and inductive effects to a simplified structure which is mainly concerned with the nonlinearity of conduction properties. In addition, the table elucidates the simulation fidelity-computation efficiency tradeoff, thereby assisting researchers to choose the most suitable model for the various purposes of analysis, system complexity and physical realism. This comparison also highlights the role of time varying resistance models in the representation of adaptive and dynamic electrical systems.

Table 5. Comparative Analysis of Equivalent Circuit Models for Nonlinear and Polarity-Dependent Electrical Behavior

Model	Main Components	Structural Characteristics	Main Function	Advantages	Limitations	Suitable Applications
Model A	R_f , L_f , Diodes (D_f), V_{fn} , V_{fp}	Includes a resistor and inductor in series before two opposite diode branches	Represents nonlinear, transient, and polarity-dependent electrical behavior	High modeling accuracy, captures transient response, inductive effects, and nonlinear conduction	High computational complexity and increased simulation time	Semiconductor systems, electrochemical systems, biological tissues, and systems with transient effects
Model B	R_t , D_n , D_p , R_n , R_p , V_n , V_p	Removes inductance and uses separate resistances for positive and negative branches	Models asymmetric electrical behavior under opposite current directions	Simpler than Model A, supports unequal conduction characteristics, moderate computational cost	Does not represent inductive/transient effects accurately	Nonlinear electrical systems, polarity-sensitive materials, fault simulations
Model C	D_n , D_p , R_n , R_p , V_n , V_p	Removes both external resistance and inductance, leaving only nonlinear branches	Focuses on intrinsic nonlinear conduction properties	Fast computation, simple implementation, reduced simulation complexity	Ignores parasitic and transient effects, lower physical accuracy	Simplified simulations, computational studies, steady-state analysis
Time-Varying Resistance Model	Switch, $R_1(t)$, $R_2(t)$	Resistance values vary with time after switch activation	Represents adaptive or dynamic resistance behavior	Effective for time-dependent systems, adaptive modeling, and smart materials	Does not model nonlinear diode behavior or polarity effects	Smart materials, aging systems, temperature-dependent systems, memristive behavior

Model type [d] was proposed in [38]. This model consists of two time-varying resistors. The value of R_1 can be obtained from the voltage and current in the event of a stable fault, such as a tree branch touching the conductor. However, if the fault is unstable, such as a disconnected conductor touching the ground, R_2 is determined from the available data [67][68].

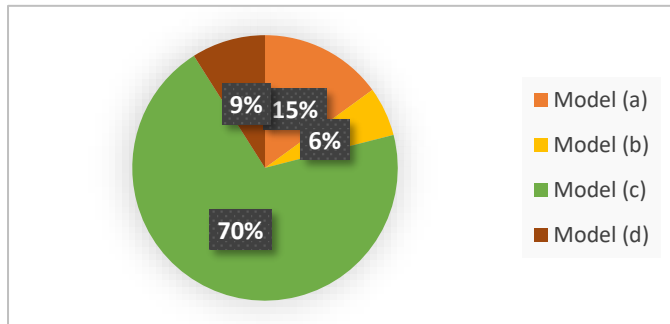


Figure 5. HIF models

figure 5 depicts the frequency of various HIF model types utilized in the reviewed literature, grouped into Model (a), Model (b), Model (c), and Model (d) according to their modeling methods. Based on the analysis of results, it is evident that Model (c) is the most popular model used by 70% of the authors, since it is widely accepted owing to its efficiency in modeling both nonlinearity and stochastic aspects of HIFs. Model (a) takes up 15% of all the cases and is the second most popular one owing to its capability of capturing transient and fault-specific electric features. Model (d) occupies only 9%, which testifies its limited application owing to the additional complexity although it is useful in modeling adaptive systems. Finally, Model (b) comprises just 6%.

4.4. Experiment Objectives

All research papers have a specific objective. One of the objectives of HIF papers is detection and classification [69][70][36][2]. Papers whose objective is detection only [71][66][72][30][73]. Determining the location of the fault is an important objective of HIF papers [74][75][76][77]. Figure 6 shows statistics on the research objectives used, such as detection only, detection and classification, and fault location.

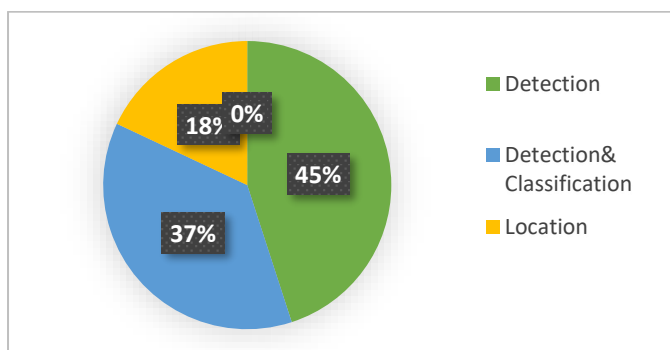


Figure 6. Experiment Objectives

The distribution of the research objectives for High Impedance Fault (HIF) studies is shown in figure 5 as follows: detection only, detection and classification, and fault location

identification. It can be observed from the above figure that detection and classification is the most frequently used research objective because it not only helps in identifying HIFs but also differentiating HIF from other faults through signal characteristics and machine learning methods. The objective of detection only involves the identification of faults, and it offers a simpler and faster solution than detection and classification with high sensitivity and minimal false alarms.

4.5. Methods of locating the HIF

As shown in figure 7 there are two ways to locate the fault. The first method determines the location of the fault by giving the distance between the system and the fault [78][25]. This method works by measuring the signal, analysing it, and then calculating the distance using mathematical equations [79]. This method is characterized by low cost and uncomplicated algorithms [77]. The second method identifies the fault zone by using advanced algorithms [80]. Data is collected and analysed, then the data is fed into the algorithm and the results are analysed again to accurately determine the fault zone [40][81][82]. This method is suitable for large and complex networks [66][31][83][84].

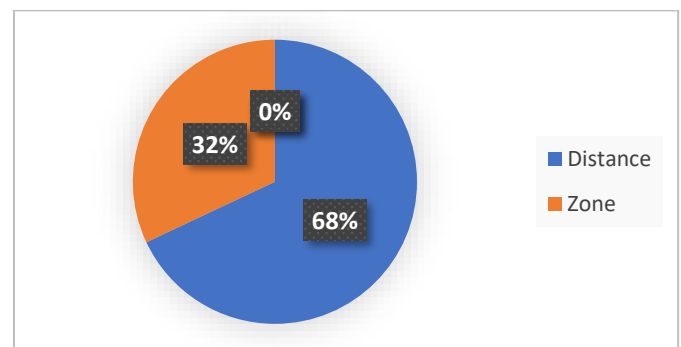


Figure 7. Locating fault methods

Figure 7 presents the general classification of the High Impedance Fault (HIF) location methodologies according to **50 reviewed papers**. Two major techniques for fault location can be singled out from the results obtained – distance-based fault location and intelligent fault zone identification. Distance-based algorithms comprise **56% (28 studies)** and are based on the estimation of the fault location based on the electrical distance to the fault from the monitoring point calculated via parameters such as impedance, voltage, current, and traveling wave properties. It should be noted that this method is quite popular due to its simplicity and low computations required. At the same time, intelligent fault zone identification consists of **44% (22 studies)** and uses the techniques of machine learning, optimization, and artificial intelligence for processing the complex data from the network and determining the most probable fault zone.

4.6. Network system

Figure 8 shows that faults occur in electrical system parts such as the distribution network and the transmission network. Faults in the distribution network are more common for several reasons, the most important of which is that the current in the distribution network is low, and the wires are close to

trees and buildings [85][86][87][88]. The reason for HIF in the transmission network is damage to the insulators, a line break, or poor connections [89] [90].

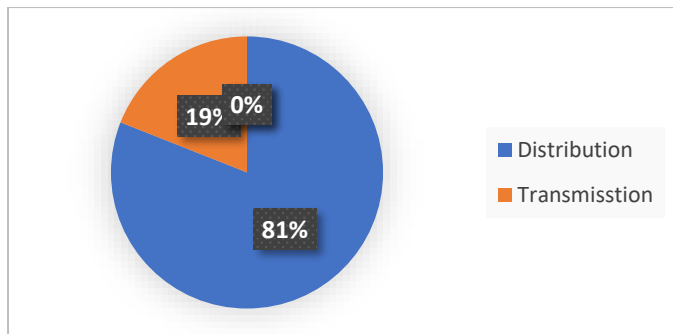


Figure 8. Power system categories

The graph presented in *figure 7* depicts the distribution of High Impedance Fault (HIF) instances for various power systems levels according to ****50 research papers**** and identifies two major groups of power systems where HIF occurs: distribution and transmission systems. The obtained findings reveal that HIFs prevail in distribution systems and constitute ****78% (39 researches)**** because of low fault currents, weak and unstable fault characteristics, as well as the possibility of external interference such as contact with vegetation, buildings, weather conditions, animals, etc. The above-listed factors complicate the detection of HIFs in distribution systems, thus explaining the intensive interest of scientists in this problem. At the same time, HIFs in transmission systems comprise ****22% (11 researches) **** despite the fact that HIFs occur rarely there but their effects are catastrophic for systems' operation. The reasons for HIF in transmission systems include the failure of insulators, conductor breakage, and mechanical failures.

4.7. Threshold Use in HIF

Figure 9 shows that the Threshold is used in algorithms to make a decision [91]. Adaptive is a type of threshold used in HIF detection algorithms [32][92]. Adaptivity is used in processing signals such as current and voltage [32][93]. Training is the other type of threshold used in HIF detection [94][95]. The training threshold is used in artificial intelligence algorithms [neural networks] to help the algorithm learn to give good results [96][39][97].

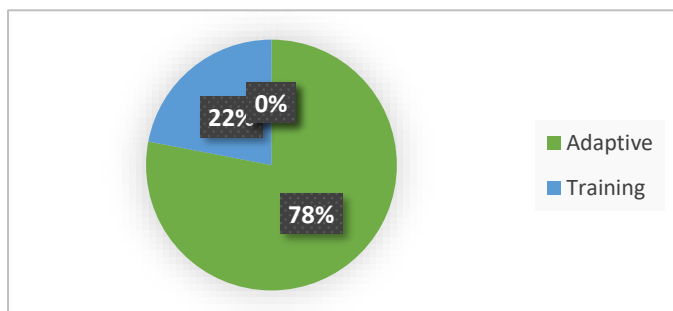


Figure 9. Threshold Use in HIF

Figure 9 demonstrates the role of threshold techniques in HIF detection using ****50 articles analyzed**** in terms of adaptive

thresholds and training-based thresholds. The analysis shows that adaptive thresholds are mostly used and account for ****60% (30 papers)**** because they automatically adapt decision boundaries depending on the changeable conditions of the power systems like load variation, voltage fluctuation, and noise presence. Such adaptability increases detection sensitivity and decreases the probability of false detections and makes them appropriate for HIFs detection due to the nonlinear and erratic nature of the signal. In turn, training-based thresholds are used in the cases when artificial intelligence and machine learning techniques are applied. They comprise ****40% (20 papers)**** of the total number of articles and involve learning of decision boundaries during the process of training.

4.8. Study of Recent Research Papers

Table 6 presents an overview of the performance of High Impedance Fault (HIF) detection algorithms that have been developed between 2010 and 2025, reflecting the change of methodology and performance. Early methods (2010-2015) mostly relied on signal processing techniques like wavelet transforms, harmonic analysis, Prony methods and mathematical morphology with detection accuracy ranging from 76% to 96.5% and response time between tens and hundreds of milliseconds. While simple and computationally efficient, these were all very sensitive to noise and to varying operating conditions.

In the 2016-2020 period, machine learning methods like artificial neural networks (ANN), support vector machines (SVM), and decision trees gained popularity, with even better accuracy of approximately 94%-99% and a detection time under 30ms. But these methods relied mainly on features engineering and synthetic datasets. Although they have high accuracy and low detection time (less than 10ms), their application requires large amounts of data, high computational power, and lack of interpretability. Across all fields of study, accuracy and speed have increased considerably with time, but it is noted that most studies are of a simulation nature, and that there is a gap between theoretical and practical performance.

According to the findings from the reviewed literature, the key research problems can be summarized as:

- Absence of standard benchmark datasets for an appropriate comparison of performance.
- Low level of experimental verification and real-world deployment.
- Decreased reliability when applied in different load scenarios or with increased renewable energy usage.
- High complexity of sophisticated deep learning techniques used.
- Poor explainability of AI protection algorithms.
- Inadequate analysis of edge-computing and real-time embedded implementation.
- No universal performance metrics in research papers.

All of these issues prove that the focus of further research must shift from improved detection capabilities to the development of more explainable, efficient, validated, and adaptive models for smart grids

Table5. A study that improves accuracy and speed

xRef	Year	Accuracy (%)	Detection Time (ms)	Method Category	Strengths	Limitations
[95]	2010	81	300	HIF Modeling	Simple implementation	Low accuracy, slow response
[98]	2010	87	20–260	Rule-Based Detection	Easy deployment	Sensitive to operating conditions
[99]	2010	76	250	Wavelet Transform	Good transient analysis	Lowest reported accuracy
[31]	2011	—	75	Wavelet + ANN	Improved feature extraction	Requires training data
[11]	2011	92	180	Discrete Wavelet Transform	Effective fault characterization	Computational burden
[100]	2012	88	30–200	Prony Method	Suitable for harmonic analysis	Sensitive to noise
[97]	2012	98	17–588	Neural Network	High accuracy	Large variation in detection time
[29]	2012	90	240	Hilbert–Huang Transform	Good signal decomposition	High computational cost
[101]	2013	96	—	Mathematical Morphology	Robust feature extraction	Threshold tuning required
[102]	2013	89	—	Comparative Algorithms	Reliability evaluation	Moderate accuracy
[14]	2013	—	—	Arc Current Analysis	Improved HIF understanding	No detection framework
[103]	2014	96	200	HIF Modeling & Detection	Balanced performance	Moderate response speed
[9]	2014	98	1000	Data-Driven Smart Grid	Very high accuracy	Very slow detection
[104]	2015	—	—	HIF Modeling	Useful analytical framework	No performance evaluation
[105]	2015	—	—	ADALINE Harmonic Analysis	Adaptive learning capability	Limited validation
[106]	2015	96.5	—	Wavelet Packet Transform	High detection capability	Computational complexity
[58]	2015	—	—	S-Transform + Neural Network	Hybrid intelligent detection	No reported metrics
[107]	2016	98	5–65	Signal Processing	Fast and accurate	Performance depends on signal quality
[12]	2016	94	—	Information Extraction	Comprehensive feature analysis	Moderate accuracy
[35]	2016	—	—	Review Study	Broad coverage	No experimental validation
[21]	2017	100	10–75	Morphology + Data Mining	Highest reported accuracy	Simulation-based validation
[86]	2017	98.6	—	Pattern Recognition	Excellent classification	Dataset dependency
[46]	2017	—	—	Evidential Reasoning	Handles uncertainty	Complex implementation
[108]	2018	92	150	Classification & Localization	Simultaneous detection and location	Moderate accuracy
[109]	2018	96.5	—	Signal Processing	Reliable performance	Limited practical validation
[110]	2018	75–86	5	CNN	Very fast detection	Lower accuracy than later DL methods
[37]	2018	98	12	Wavelet + Evolving NN	High accuracy and adaptability	Training complexity
[16]	2019	99	3	Feature Selection + ML	Excellent accuracy and speed	Requires labeled datasets
[36]	2019	98.5	5	Computational Intelligence	Fast and reliable	Parameter tuning required
[111]	2020	97.8	30	Intelligent Detection	Good balance of speed and accuracy	Moderate complexity
[112]	2020	98	5	DC Microgrid Detection	Suitable for DC systems	Limited to specific architectures
[66]	2020	97–99	20	Kullback–Leibler Divergence	Robust statistical detection	Computational overhead
[39]	2021	98	15	HS-Transform + Decision Tree	Good interpretability	Feature dependency
[5]	2021	94	0.2	DWT-Based Detection	Extremely fast response	Lower accuracy than DL methods
[113]	2022	99	—	S-Transform	High detection reliability	Processing complexity
[114]	2022	99.4	5	Intelligent Protection Scheme	Excellent accuracy and speed	Computational requirements
[115]	2023	98	15	DG-Aware Detection	Supports distributed generation	Needs extensive validation
[116]	2023	99.44	2	S-Transform + Entropy	Outstanding performance	Increased complexity
[117]	2023	—	—	Fully Connected CNN	Deep feature extraction	No timing results
[118]	2024	99.3	—	Incremental Learning	Adapts to non-stationary environments	Computational cost
[119]	2024	98	10	Intelligent Detection	Fast and accurate	Limited field testing
[6]	2024	98.85	—	Spectrum Analysis + ANN	Strong classification capability	Requires training datasets
[87]	2024	99.8	—	Active Power Regulation	Highest recent accuracy	Limited practical deployment studies
[120]	2024	95–98	20	Hybrid CNN	Strong feature learning	High computational demand
[74]	2024	97.5	—	CNN-Based Deep Learning	Good fault localization	Black-box behavior
[40]	2024	—	—	Wavelet Analysis	Strong theoretical modeling	No reported performance metrics
[121]	2025	98.4	15	Feature Extraction Method	Reliable detection	Requires extensive feature engineering
[122]	2025	—	—	Data-Driven Impedance Estimation	Detection and localization capability	Validation still limited
[123]	2025	99	5	Dual-Path Neural Network	Excellent deep-learning performance	High training requirements
[124]	2025	99.7	5	BiLSTM	State-of-the-art accuracy	Reduced explainability

4.9. Critical Comparative Analysis of Existing HIF Detection Techniques

Over the last 20 years, significant advances have been made in High Impedance Fault (HIF) detection but none of the approaches is able to meet all the practical demands for detection accuracy, computational efficiency, robustness, interpretability, and "real-time" implementation. The studies reviewed showed that every methodological type has its own advantages and disadvantages and that careful consideration of the target application environment is important with respect to the selection of the appropriate technique.

The Discrete Wavelet Transform (DWT), Wavelet Packet Transform (WPT), Stockwell Transform (S-transform), Hilbert–Huang Transform (HHT), and harmonic analysis are still popular traditional signal-processing techniques due to their mathematical transparency, moderate computational complexity, and simple incorporation into conventional protection relays. These techniques are very useful in detecting transient characteristics associated with HIF events and are in general fast detection times. Measurement noise, load changes, threshold selection and renewable energy penetration, however, have a strong impact on their performance. In addition, they may need to use a lot of feature engineering before classification, making them hard to adapt to the changing operating conditions.

Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees, Random Forests, and fuzzy inference systems are effective machine learning methods that can be used to learn complex nonlinear relationships from historical fault data, which considerably improves the accuracy of the classification. In general, machine learning algorithms are more accurate at detection than traditional signal processing techniques, and less reliant on handcrafted decision rules. However, the results they achieve are largely dependent on the quality of the features, the balance of the training sets and the tuning of the parameters. The majority of studies reported in the literature use simulated networks under ideal operating conditions, which may lead to concerns of the model's generalisability to real distribution networks.

The latest deep learning architectures that are currently used for the detection of HIF include Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Gated Recurrent Units (GRUs), Transformers and hybrid CNN–GRU networks. Unlike traditional machine learning algorithms, deep learning models can automatically learn hierarchical features from raw measurements, reducing much of the manual feature engineering work. The reviewed studies show detection accuracies consistently of >99% and many architectures report response time below 10ms. For smart grids that comprise renewable generation, distributed energy resources, and fluctuating operating conditions, these enhancements are especially appealing for deep learning.

While these impressive performance numbers are good, deep learning techniques have some practical problems. They are

very complex to compute and require a large amount of memory and CPU, which are not feasible for low cost protection devices. In addition, the models need a great amount of precisely labeled training data, which are still limited due to lack of publicly available HIF benchmark datasets. One additional issue is the lack of interpretability of deep neural networks. At the intersection of these two, the protection engineer will need to have a clear decision-making process when implementing intelligent protection systems in a safety-critical infrastructure, while many deep learning models are black-box classifiers and lack interpretability.

Recently, hybrid detection systems have arisen as a viable solution between conventional signal processing and artificial intelligence. The techniques involve the use of powerful time-frequency feature extraction algorithms like DWT, CWT, or S-transform, along with intelligent classifiers such as CNNs, LSTMs, and ensemble learning algorithms. As presented in the comparative results in Table 6, it may be seen that the use of hybrid methods generally yields better robustness to noise, higher classification accuracy and faster convergence than either signal-processing or machine-learning methods. This is achieved at the cost of higher complexity of implementation and higher computational needs, however.

Another significant note from the literature reviewed is about the experimental validation. While detection accuracy has been claimed to be in the range of 98% to 99.8% in many recent publications, it is important to caution against taking these results at face value as most of the evaluations have been carried out either in MATLAB/Simulink simulation or laboratory generated data sets. Field measurements and/or distribution networks with a high level of utility scale are used in only a few studies to validate their algorithms. The results therefore may not be representative of the actual operating conditions that include renewable intermittency, different fault resistances, environmental noise, measurement uncertainty, and communication delays.

5. FUTURE RESEARCH DIRECTIONS

Despite the significant technological advances that have been made, the detection and classification of High Impedance Faults (HIFs) in today's distribution networks still pose considerable challenges due to their nonlinear and complex nature. It should be noted that HIFs usually produce small fault currents and signals that do not have stable shapes; therefore, it is challenging to identify such faults with the help of existing protection systems. This problem is becoming even more urgent with the introduction of renewable energy sources, distributed generation facilities, and power electronics converters to the electrical grid, adding additional factors of uncertainty, harmonics, and dynamics to it. While current scientific research has shown that there are promising results in the detection of HIFs with the help of advanced signal processing methods and intelligent algorithms, there are certain limitations associated with their accuracy, adaptability, computational costs, and timely response. Thus, it becomes important to fill the gaps in HIF detection and classification research.

5.1. Hybrid Detection Methodologies

Interpretability of signal-based features with the adaptability of AI-driven classifiers. Traditional feature extraction techniques—such as Discrete Wavelet Transform [DWT], Continuous Wavelet Transform [CWT], and Empirical Wavelet Transform [EWT] should be integrated with deep neural architectures including CNN, LSTM, Transformer, and hybrid CNN-GRU models to enable high-fidelity detection under complex, noisy, and nonstationary grid conditions. Recent hybrid models, such as the Hybrid-CNN with time-frequency-space fusion and Dual-Path CNN-GRU network, have already demonstrated accuracies exceeding 99% for active distribution systems [123] [120].

5.2. Development of Open and Standardized Benchmark Datasets

A major limitation of present research on HIF is standardized, open-access benchmark datasets under realistic operating conditions [122] [125]. Most existing datasets are ideally simulated and do not carry variations in load, noise, or renewable generation. Therefore, setting up collaborative, multi-utility datasets with real field measurements together with hybrid faults and renewables in the scenario should be the main task of future research work. In addition, unsupervised and semi-supervised learning paradigms may be considered as tools to overcome data scarcity via utilizing unlabelled data in adaptive fault pattern discovery.

5.3 Testing and Validation in Renewable Rich Smart Grids

Must be validated within renewable-rich, smart distribution environments. New transient dynamics due to the presence of PV arrays, energy storage, and electric vehicles were never considered in designing conventional protection systems. Hence, the HIF detection algorithms need implementation and testing under PV-integrated and microgrid configurations as done by the LSTM-RNN [126]. Further research is also required to ensure robustness in cases of renewable intermittency, harmonic distortion, and stochastic variation in distributed power systems.

5.4. Practical and Low-Cost Implementation for Developing Countries

The high cost of sensors, the communication infrastructure, and the computation hardware has to date inhibited practical field deployments despite remarkable progress in algorithmic accuracy. Future research should therefore emphasize inexpensive hardware implementation on microcontrollers, edge-AI devices, and low-frequency measurement units. Local decision-making will also reduce data transfer by combining it with edge-computing, hence reducing latency as well. Collaboration between utilities in developing countries is highly encouraged toward the development of a scalable and affordable HIF detection platform that conforms to rural and semi-urban distribution networks [127] [128].

6. CONCLUSION

This paper presents an extensive overview of the latest research for high impedance fault (HIF) detection and classification in power distribution networks. The analysis reveals a clear research evolution into intelligent and data driven methods which focus on identifying HIF events from normal operating conditions, mainly because HIF currents are low magnitude and very nonlinear, and thus similar to normal load current. A comparative survey of the literature shows that Matlab/Simulink is the most commonly used simulation environment, and other simulation environments such as PSCAD and ATP are also used for electromagnetic transient studies. Nevertheless, a significant number of studies continue to use simulated environments and a small number of studies have been field- or lab-tested. This suggests a discrepancy between theory and implementation. As far as signal utilization, the current based approaches prevail in the research area because they are sensitive to the fault disturbances. There are fewer techniques involving only voltage or magnetic field, and these are more likely to be application specific – combined voltage and current approaches are more widely used to achieve better robustness and classification accuracy. In terms of research goals, most studies concentrate on fault detection, followed by studies that combine detection and classification of faults, and a smaller number are dedicated to fault location. This is indicative of the historical focus of reliably recognizing HIF events, rather than progressing towards localization and system recovery. However, these distance estimation methods are still employed in many fault location strategies because they are simple and inexpensive to compute. But intelligent zone-based solutions are emerging as a way to offer greater adaptability and accuracy in more complex, large scale distribution networks. The analysis also indicates that most HIFs are in distribution networks caused by environmental exposure and low currents, compared to transmission system faults which are less common but when they happen are more severe in effect.

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