A Review on Diagnosis of High-Impedance Faults

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1.Introduction

High-impedance faults (HIFs) are a recurring problem in power system protection. As a result, many engineers must have a thorough awareness of such flaws in order to create viable remedies. The authors of [1, 2] presented an HIF detection-focused review. The HIF problem was characterised in their research as a pattern classification job that may be faced utilising neural network classifiers trained using features collected from measurements (i.e., current, voltage, and magnetic field intensity). Mishra et al. [3] built on mathematical and mechanical methods to HIF detection strategies. The authors of [4] explored industrially applicable strategies for detecting HIFs, such as the broken conductor detection method, watt-metric protection relaying, and the ground wire grid methodology. Prior to the 2000s, HIFs were covered by [5]. This article seeks to give an up-to-date complete assessment of current HIF detection, categorization, and localization approaches.

The article will be divided as follows: The rest of this section describes the definition, hazards, and characteristics of HIF. Section 2 gives an overview of current HIF modeling techniques. Section 3 describes new HIF diagnostic methods attempted by researchers. Section 4 compares the performance of the newest approaches in HIF detection, classification, and localization. Section 5 describes conclusions and future recommendations. If a conductor accidentally comes into contact with a high impedance material, what is called a high impedance fault (HIF) occurs. HIFs fall into two types: active and passive. The former arises as a result of subterranean conductor insulation determination over time [6,7], while the latter happens when an overhead conductor breaks and contacts extremely resistive ground, resulting in an abrupt transient arc [7,8]. The current levels of the ensuing events are slightly greater than the typical drawn ampere from the load, making them hard to detect by traditional overcurrent relays [9–16]. Furthermore, ground-sensitive relays were found To be unstable under imbalanced loading circumstances [17]. According to [5, 6, 17], current values in 20 kV systems can range between 1 and 75 A, as indicated in Table1, and it can be shown that the type of the conductive material and its humidity impact the HIF current.

Table 1. High-impedance fault (HIF) current on various surfaces.

Surface	**Current (A)**
Reinforced concrete	75
Wet grass	50
Wet sod	40
Dry grass	25
Dry sod	20
Wet sand	15
Dry asphalt	<1
Dry sand	<1

According to the research, HIFs account for 5% to 10% of all total system defects [18]. This statistic, however, only includes HIFs that progressed to high-current short-circuit problems. Furthermore, [19] noted that traditional relays are oblivious to 80 percent of HIFs happening in a distribution system, highlighting the current degree of uncertainty in power system safety mechanisms regarding HIFs. An HIF poses a concern to public safety when it is unnoticed, because a dropped conductor can cause hazardous shock, fire, or life-threatening injuries through unintended human contact [20–23]. Damage to equipment caused by the presence of HIFs is also seen as a hazard to the facility's assets and may result in permanent damage [24, 25].

HIFs differ from regular short-circuit failures in their characteristics and are quite complicated. This intricacy is attributable to the following typical characteristics, as given in the literature and depicted in Figure 1:

A- Low current magnitude [26, 27] that might be difficult to differentiate from a typical rise or decrease in electrical load.

B- Intermittent arcing [28–30] caused by low harmonics and noise in measuring signals.

C- Asymmetry and randomness [31] owing to the variable fault route, which causes the HIF current magnitude to alter from cycle to cycle.

D- During the HIF condition, there is nonlinearity [32–34] in the connection between voltage and current sinusoidal signals.

E- Build-up and shoulder [35] where the current magnitude of an HIF gradually increases during several cycles until it reaches a steady state condition.

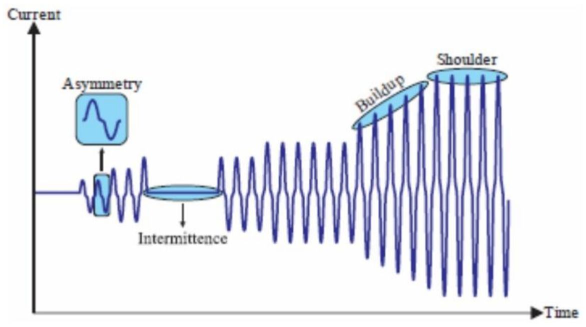

Figure 1. Characteristics of HIFs [26].

2. HIF Modeling

Many research publications rely heavily on HIF modelling since the correctness of the results is greatly dependent on the modelling method's capacity to reproduce the properties of an HIF. Nonlinearity ,asymmetry, unpredictability, intermittence, build-up, and shoulder require sophisticated methodologies to be modelled in a simulated system. As a result, this section will go through the current modelling methodologies used in the literature.

The goal of HIF diagnosis is to one day address a real-world problem. As a result, using real-world data modelled in a high-current research laboratory is a sensible route to follow. In [18], materials like as tree branches, grass, and concrete surfaces were utilised in dry and wet situations to imitate different HIFs and record important current and voltage magnitudes using digital data recording equipment. The experimental setup has been used by [18]. Despite the fact that this approach is the closest approximation to an HIF and offered excellent study data, it may be impractical for many other researchers due to space constraints. Furthermore, laboratories will require costly high-voltage equipment to simulate the performance of a real HIF, as well as stringent safety procedures to reduce any possible threats from HIF arcing.

The second layer of modeling is implemented in a simulation environment. This section explains the three main models used in the literature to simulate the properties of HIF in an electromagnetic relay module (EMT).

Single Variable Resistor

This model was proposed by [36–38] to simulate the arc discharge characteristics of a HIF based on the theory of Cassie and Mayr [39,40] using the following equation to calculate the arc resistance where R0 is the initial error of the resistance system, t is the time, and τ is the user-defined time constant. This approach provides a random layer for the simulated HIF. However, the asymmetrical and non-linear aspects of the defect are not accurately represented.

$$R_{Arc}(t) = \frac{R_0}{1 - e^{-t/\tau}}$$

Alternatively, [41] proposed the depiction of HIF shown in Figure 2. Fault tolerance Rf can be calculated using the following formula:

$$R_f = R_0\left(1 + \alpha\left(\frac{I_f}{I_0}\right)^{\beta}\right)$$

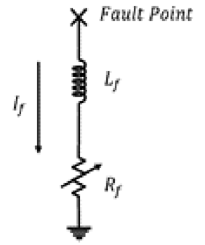

Figure 2. Variable resistor with inductor model.

In another model presented by [43, 44], R1 has HIF asymmetry and voltage (Vf) and current (If) by calculating their respective ratios according to Ohm's law, as shown in Figure 3. R1 is intended to mimic the non-linearity between. Current and voltage readings are sampled Figure 3. Two variable resistors model. over time and each sample is from one complete cycle. The value used can be calculated from cycles that are similar in amplitude to the previous cycle, thus excluding build-up characteristics. The current can be calculated as clearly explained in [45].

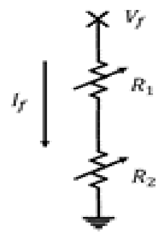

Figure 3. Two variable resistors model.

Emanuel et al. [46] presented an additional model to emulate the unique properties of an HIF. As indicated in Figure 4, R1 and R2 contribute the nonlinearity dimension to the HIF, while Vp and Vn factor in the incident's discharged arcing voltage. This model is built with directed diodes so that the fault current flows from the source to the ground if Vf>Vp. The opposite will occur at Vf <Vn, as current will flow back to the source, and no current will flow into the system when Vn<Vf<Vp. Figure 5 shows how other researchers in [47–50] expanded on Emanuel's concept by experimenting with a variable resistor. This model, however, lacks the capacity to simulate.

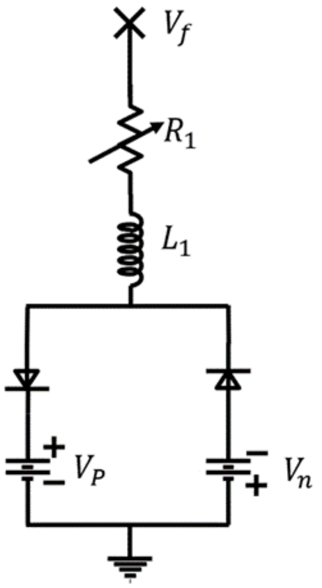

Figure 4. Two antiparallel diodes model.

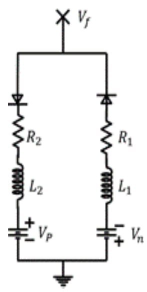

Figure 5. Two antiparallel diodes with resistors and inductors.

3. HIF Diagnosis Techniques

An HIF poses a risk to public safety and, eventually, the electrical distribution system when it is undiscovered. As a result, numerous researchers sought to discover ways for detecting, classifying, and locating HIFs. This section will go through the most modern approaches for diagnosing HIFs.

Traditional Methods

In a balanced three-phase system, the summation of the currents in all phases is equal to zero as per the following equation:

Ia + Ib + Ic = Izero sequance = 0

Controlling zero sequence current using a core balanced circuit using the current transformer is also known as the sensitive ground fault relaying [51]. This technique is extensively utilised. Loads in nature, on the other hand, are imbalanced. As a result, residual current is constantly present in the system, requiring the relay to be tuned to a specific tolerance rate to minimise nuisance trips. This tolerance rate may make HIF identification more challenging. In differential protection techniques, such as pipeline leakage detection, the comparison of outgoing and incoming current flows is employed. The approach is HIF-sensitive. However, implementing differential protection in distribution networks is complicated due to the network's multiple generating sites and loading buses.

In the work proposed in [4], a way for capturing the falling conductor before it makes contact with a high-impedance surface is discussed. When the conductor makes contact with the grid, the overcurrent relay may immediately identify the fault and trigger the breaker. However, such a solution is economically unfeasible since it necessitates the installation of an extra ground grid at transmission line poles across long distances. [52] advocated installing a mechanical hook beneath the phase conductors and connecting it to the natural grid. In the event of a downed conductor, the procedure will result in a line-to-neutral short circuit. Paper [53] introduced a Fast Fourier Transform (FFT) -based technique for studying single-phase feeder currents to address HIF in the presence of non-linear loads. This approach evaluates the state of the distribution system, taking into account the even and odd harmonic components. The authors found that the critical spacing between the 3rd and 7th harmonics varied significantly in the magnitude-to-time plane of the harmonics during HIF, enabling an approach to detect HIF. Note that such techniques are noise sensitive and require a noise reduction scheme to achieve the desired result.

The method proposed in [54] proposes a stockwell transformation (ST) -based method for constantly monitoring the phase angle of the third harmonic of a sinusoidal current input. Fluctuations in the third harmonic are related to load activity and switching. As a result, stable values indicate the presence of HIF in the system. However, this approach can take up to 150 milliseconds to detect a defect, allowing the accumulation of incident energy.

The author of [55] proposed a unique method that combines maximum overlap discrete wavelet packet transform (MODWPT) with empirical mode decomposition (EMD). This technique calculates the change in the amount of inter-harmonic energy of the fault signal after it is normalized by the pre-failure state. The existence of such an entity represents the possibility of an existing HIF. For all types of HIF, it is unlikely that the model will succeed under actual operating conditions.

Roy and Debnath [56] proposed a method for calculating the power spectral density (PSD) using the wavelet covariance matrix. The wavelet transform is used to decompose the power signal to the third level. Then use the exact coefficients to calculate the wavelet transform and PSD in both the frequency domain and the time domain. The proposed strategy uses threshold analysis as the basis for fault detection, but the system has not been validated for fault location estimation.

The author of [57] studied the orthogonal component decomposition of three-phase voltage and current waveforms by signal processing. The projection of the voltage and current components in the plenary function yields eight voltage and eight current components. During normal operation, the calculated value maintains an absolute value equal to zero. However, in a flawed situation, the component may fluctuate and HIF may be detected. Although this approach is robust when it comes to fault identification, the absolute inaccuracy in estimating fault distance is over 10% in half of the assessed situations.

Mathematical Approximation

The authors of [58] used differential equations to determine the capacitance upstream and downstream of the fault to estimate the zero-sequence grid capacitance. To discover discrepancies, the estimated values are compared to the anticipated capacitance during normal operation. The approach was found to be rapid, self-calibrating, and noise-free. However, it was only made available for isolated neutral grids. Another estimating approach based on field measurements was developed in [59] to determine fault admittance in a medium voltage. The approach was validated for identifying and finding HIFs with resistances ranging from 100 to 200 k.

The authors in [60] offered a state estimate model that was adjusted to diagnose HIFs and included features such as voltage and power data. The authors were able to demonstrate the effectiveness of such a strategy in HIF identification. However, when the load is altered, incorrect line identification results in severe inaccuracies. The paper [61] discusses an iterative method to the fault finding problem. The method given estimates the location of the fault start and the current and voltage of the fault. The weighted least squares (WLS) method is used to measure fault resistance and reactance. It then compares the estimates to the convergence tolerance and returns the final fault distance, resistance, and reactance. This approach requires extensive iterative processing and can result in longer error detection times. Ramos et al. [62] An analytical WLS state estimator was used to calculate fault voltage and current to identify the HIF in the distribution network. This approach also uses values derived from the linear regression of the predicted obstacle distance component.

Using the enhanced Prony approach, we reconstructed the decaying periodic component by monitoring the zero voltage. The technique needs to estimate single-phase ground fault information using an attached feed-in clamp. The robustness of this approach has only been demonstrated to determine the location of single-phase ground faults.

The authors in [64] devised a strategy based on searching. The approach estimates the fault site by comparing the estimated fault characteristics (voltage and current) at various locations of the feeder to the reference data for faults in a feeder. Such a technique necessitates a large computation overhead for lower tolerance rates and is only applicable to single-feeder distribution lines. [65] employed linear prediction to describe time series of signal samples across time. The model detects HIFs by increasing the energy of the linear prediction error. However, the authors of this study did not take into account nonlinear loads in the power distribution network.

Artificial Intelligence-Based Methods

The three primary stages of artificial intelligence-based systems for diagnosing HIFs are data collecting, feature extraction using signal processing techniques, and training using machine learning algorithms. This section will go through the most recent advances in each step.

Data Acquisition

The sort of measuring signal employed to diagnose HIFs serves as the foundation for intelligent-based techniques. In the literature, several signals were utilised; nevertheless, current waveforms in HIFs carry over harmonic components that can be separated from typical loading scenarios [1]. In [66,67], the subject measurements were used to detect and categorise HIFs in distribution networks. It is worth mentioning that current measurements are influenced by the percentage mistakes of current transformers.

If you look at the defects caused by moving objects such as trees, you can notice the temporary voltage spikes caused by the HIF arc. This movement creates an air gap between the conductor and the surface, changing the fault impedance.

The authors of [68] have developed their method based on arc voltage measurements. However, the small drop in HIF makes it increasingly difficult to detect changes in the voltage waveform. As a result, many authors, including [69,70], tried to identify the HIF of the distribution system using both current and voltage waveforms in neural network training with excellent results.

The authors of [71] employed resistance measures to diagnose HIFs. When such data are compared to the original impedance values of a transmission line, they offer information about the location of the issue and decrease network downtime. The problem is that resistance alone cannot reflect HIF nonlinearity, asymmetry, or arcing. As a result, utilising this measurement to detect such errors is significantly compromised.

The goal of synchronised phasor measurement units (SPMUs) is to describe a signal over a predetermined time period as an absolute value linked with the phase angle [72]. In power systems, such measurements offer an accurate picture of current and voltage waveforms. The use of SPMUs in HIF diagnosis was described in [73,74], however the use of SPMUs in HIF localization with fault asymmetry and load nonlinearity need more investigation.

Feature Extraction

Feature extraction using signal processing techniques is a critical tool for machine learning algorithms to work efficiently. The Fourier transform is commonly utilised in power quality disturbance applications (FT). During disturbances, this signal processing tool determines the presence of signal frequency components [75].

Although FT is continuous over time, discrete Fourier transform (DFT) is widely utilised in computational applications and was employed in [76] for HIF identification. In [77], another variant known as the fast Fourier transform (FFT) was used. FT, on the other hand, can only express characteristics in the frequency domain for HIF diagnostic applications.

In contrast to FT, wavelet transform (WT) is a sophisticated signal processing method that can encode signal properties in the time–frequency domain [78]. When given in discrete format, as illustrated in [79], this model is beneficial in HIF diagnostic applications. Furthermore, as compared to discrete wavelet transform (DWT), wavelet packet transform (WPT) delivers more information since higher and lower frequency bands may be deconstructed at each decomposition level.

This type of application was first established in [80,81], and it produced good results in HIF detection and categorization. Furthermore, the use of multi-wavelet transform (MWT) was described in [82].

It was discovered that MWT is a scalar wavelet extension with several scaling functions and associated multiple wavelets are utilised During a fault, WT can offer information about the fault.

Machine Learning

A neural network (NN) is a connection of multiple processing nodes that perform a series of mathematical operations obtained through the tuning process that are modified by external inputs called biases and are guided by the strength or weight between the nodes of the network [. 83-85].

The work proposed in [86–88] employed a multilayer perceptron neural network (MLP-NN) model to diagnose HIFs. To train the network in identifying and categorising defects, the approach used the effective backpropagation technique. To get optimal outcomes in less computing time, a strategy for selecting the correct number of hidden layers and neurons is necessary.

Furthermore, [80,89] devised a hybrid technique combining MLP-NN and Gaussian process regression (GPR). MLP-NN was used in the study to identify the best weights and biases for HIF detection and classification, whereas GPR is a linear regressor that seeks to approximate the position of a fault in a transmission line.

The authors of [90] used MLP-NN to identify errors in a live experimental setting.

4. Comparative Analysis

The measurement signals, feature extraction approaches, and machine learning classifiers given here offer specific capabilities for detecting, classifying, and locating HIFs. As a result, a comparison was performed, as indicated in Table 2. The following [2, 31] might influence the grading criteria of such papers:

1. Accuracy is used to compare the performance of proposed procedures to the predicted outcomes.

2. Reliability and security may be used to calculate the precision % and miscalculation ratio of HIF diagnostic procedures, which are lacking in most research.

The wavelet transform dominates signal processing techniques in the majority of the literature. Other time–frequency domain approaches, such as the Stockwell transform, have been presented in recent years.

Reference	Measurement Data	Feature Extraction Technique	Machine Learning Classifiers	Experiment Objectives	Accuracy %
[69]	Voltage and Current	WT	ANN	Detection	91.33
[70]	Voltage and Current	WT	ANN	Detection	95.989
[67]	Current	DFT	ANFIS	Detection and Classification	99.64
[92]	Arc Voltage	EMD	ANN	Detection	99.35
[71]	Resistance		ANN	Location	99
[91]	Voltage and Current	WT	SVM	Detection	91.38
[93]	Current	WT	SVM	Detection and Classification	96
[94]	Current	VMD	SVM	Detection and Classification	99
[82]	Voltage and Current	WT	FLC	Classification	88.89
[77]	Current	FFT	FLC	Detection	
[79]	Current	WT	ANN	Classification	
[87]	Voltage and Current		ANN	Location	99.67
[86]	Voltage and Current	WT	ANN	Detection	
[80]	Current	WT	ANN+GPR	Location	99.4
[89]	Voltage and Current	WT	ANN	Detection	96
[90]	Current	ST	ELM	Detection and Classification	99.3

Table 2. Comparison between existing techniques

5. Conclusions and Future Recommendations

This publication provided a complete assessment of HIF detection, classification, and localization strategies. This review defines a phenomenon in HIF where the resulting fault current level is slightly higher than the normal amperage drawn from the load, making it difficult for traditional overcurrent relays to detect faults.

Although such problems have not been diagnosed, public safety is assured that accidental contact with the human body can cause dangerous electric shock, fire, or life-threatening injuries if the ladder falls. Concerns arise. Specific properties related to HIF development such as B. Low current, intermittent arc discharge, unpredictability, asymmetry, non-linearity, accumulation and shoulder represent most of the obstacles in HIF diagnosis.

In addition, this study examined the modeling methods used in the HIF literature. Using real-world data modeled in high-current laboratories using materials such as tree branches, grass, and concrete surfaces is an example of how to incorporate real-time data into your research. Most authors, on the other hand, used simulation settings with a single variable resistor, a single variable resistor, inductor, two variable resistors, and two antiparallel diodes.

Finally, this review covers three major processes: data acquisition, feature extraction, and training, including relay-based methods, signal processing techniques, parameter estimation, mathematical approaches, and artificial intelligence-based methods for diagnosing HIF. I explained the failure diagnosis technology centered on it. Uses machine learning algorithms.

The approaches described in the literature are primarily focused on offline systems and requires additional research to reach a mature methodology. In addition, the error elimination time (FCT) of the machine learning approach is still under debate. Such a methodology requires additional processing time and increases the potential for danger due to the presence of HIF.

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