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Review

High-Impedance Fault Diagnosis: A Review

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Abstract: High-impedance faults (HIFs) represent one of the biggest challenges in power distribution networks. An HIF occurs when an electrical conductor unintentionally comes into contact with a highly resistive medium, resulting in a fault current lower than 75 amperes in medium-voltage circuits. Under such condition, the fault current is relatively close in value to the normal drawn ampere from the load, resulting in a condition of blindness towards HIFs by conventional overcurrent relays. This paper intends to review the literature related to the HIF phenomenon including models and characteristics. In this work, detection, classification, and location methodologies are reviewed. In addition, diagnosis techniques are categorized, evaluated, and compared with one another. Finally, disadvantages of current approaches and a look ahead to the future of fault diagnosis are discussed.

Keywords: high-impedance fault; fault detection techniques; fault location techniques; modeling; machine learning; signal processing; artificial neural networks; wavelet transform; Stockwell transform

1. Introduction

High-impedance faults (HIFs) represent a persistent issue in the field of power system protection. Hence, a comprehensive understanding of such faults is a necessity for many engineers in order to innovate practical solutions. The authors of [1,2] introduced an HIF detection-oriented review. Their research defined the HIF problem as a pattern classification task that can be encountered using neural network classifiers trained via features extracted from measurements (i.e., current, voltage, and magnetic field intensity). Mishra et al. [3] further reviewed HIF detection techniques and expanded on mathematical and mechanical approaches. Industrially applied schemes were discussed by the authors of [4] to detect HIFs such as the broken conductor detection method, watt-metric protection relaying, and the ground wire grid approach. HIFs prior to the 2000s were covered by [5]. This article aims to provide an up-to-date comprehensive review on the current HIF detection, classification, and location techniques. The article will be divided as follows: the rest of this section will discuss the HIF definition, hazard, and characteristics; Section 2 will review the up-to-date HIF modeling techniques; Section 3 will discuss the recent HIF diagnosis methodologies attempted by researchers; Section 4 will compare the performance of most novel approaches in HIF detection, classification, and location; and finally, Section 5 will illustrate the conclusions and future recommendations.

1.1. Definition

When an electrical conductor unintentionally comes into contact with a highly resistive medium, it creates what is commonly referred to as a high-impedance fault (HIF). HIFs can be classified into two main types: active and passive, the latter of which occurs in underground conductor insulation deuteriation over a period of time [6], and the other occurs when an overhead conductor breaks and touches highly resistive ground, creating an immediate transient arc [7,8]. The current levels of the resulting phenomena are marginally higher than the normal drawn ampere from the load, hence deeming them impossible to be detected by conventional overcurrent relays [9–16]. Moreover, ground-sensitive relays proved to be unreliable during unbalanced loading conditions [17]. According to [5,6,17], current values can range between 1 and 75 A in 20 kV systems, as shown in Table 1, and it can be observed that the nature of the conductive medium and its humidity affect 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

1.2. Hazards

It has been reported in the literature that 5% to 10% of overall system faults are classified as HIFs [18]. However, this figure only reflects HIFs that further developed into high-current short-circuit faults. Furthermore, [19] stated that conventional relays are blinded to 80% of HIFs occurring in a distribution system which highlights the present level of ambiguity towards HIFs in power system protection schemes. During its undetected state, an HIF is a risk to public safety, since a downed conductor can create hazardous shock, fire, or life-threatening injuries through unintentional human contact [20–23]. Equipment damages due to the presence of HIFs are also considered as a threat to the facility's assets and may cause irreparable damage [24,25].

1.3. Characteristics

HIFs exhibit different characteristics from normal short-circuit faults and are highly complex. Such complexity is due to the following typical traits presented in the literature and shown in Figure 1:

- A- Low current magnitude [26,27] that can be difficult to distinguish from a normal increase or decrease in the electrical load.
- B- Intermittent arcing [28–30] associated with low harmonics and noises in the measurement signals.
- C- Asymmetry and randomness [31] due to the varying fault path which leads to a change in the HIF current magnitude from cycle to cycle.
- D- Nonlinearity [32–34] in the relationship between voltage and current sinusoidal signals during the HIF condition.
- 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.

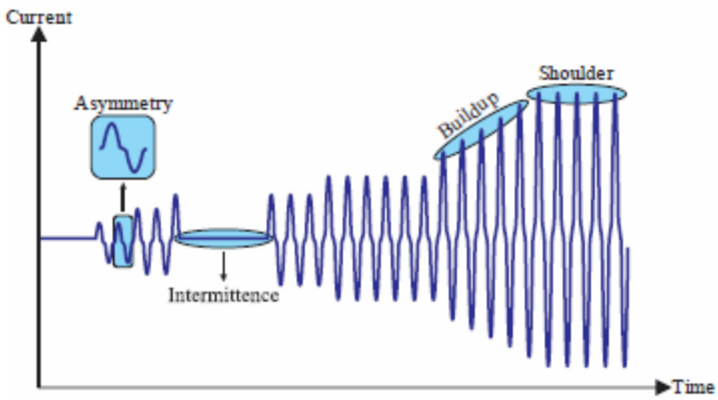

Figure 1. Characteristics of HIFs [26].

2. HIF Modeling

The modeling of HIFs represents the cornerstone for many research papers as the accuracy of the results rely highly on the modeling method's ability to simulate the characteristics of an HIF. Characteristics such as nonlinearity, asymmetry, randomness, intermittence, build-up, and shoulder require elaborate techniques to be modeled in a simulated environment. Hence, this section will discuss the current modeling techniques utilized in the literature.

2.1. Real-Time Models

HIF diagnosis aims to eventually solve a real-world problem. Therefore, utilization of real-world data modeled in a high-current research laboratory is an obvious path to take. In [18], materials such as tree branches, grass, and concrete surfaces were used in dry and wet conditions with utilization of digital data recording equipment to simulate several HIFs and record relevant current and voltage magnitudes. Figure 2 shows the experimental setup performed by [18]. Although this methodology represents the closest approximation to an HIF and provided valuable study data, it can be unpractical for many other researchers due to space limitations. Moreover, laboratories will require expensive high-voltage equipment to replicate the performances of a real HIF and strict safety measures to mitigate any potential dangers from HIF arcing.

(**a**) On grass surface (**b**) On concrete surface

Figure 2. Experimental setup of a downed conductor on a high-impedance surface.

2.2. Simulated Models

The second class of modeling is performed in a simulated environment. This section will explain the three main models used in the literature to simulate HIFs characteristics in electromagnetic transients (EMT) modules.

2.2.1. Single Variable Resistor

This model was proposed by [36–38] to simulate the arcing characteristics of an HIF based on Cassie's and Mayr's [39,40] theories via utilizing the following equation to calculate the arcing resistance R_{Arc}:

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

where R_0 is the system's initial fault resistance, t is time, and τ is the time constant defined by the user. This approach provides a layer of randomness to the simulated HIF. However, asymmetry and nonlinearity aspects of the fault are not represented correctly.

2.2.2. Variable Resistor and Single Inductor

Alternatively, [41] proposed the representation of an HIF shown in Figure 3. Fault resistance R_f can be calculated via the following mathematical equation:

$$R_f = R_0(1 + \alpha\left(\frac{I_f}{I_0}\right)^{\beta}) \tag{2}$$

where α and β are constants defined by the user, I_f is the fault current, and I_0 is the initial fault current. The fault resistance is connected in series with an inductor with a typical value of $Lf = 3$ mH as per [42]. This approach is simple and will reduce the overall computational burden of the experiment, but it is far from a real data representation due to empirical assumptions.

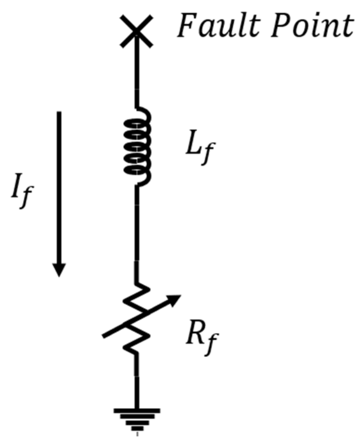

Figure 3. Variable resistor with inductor model.

2.2.3. Two Variable Resistors

In another model proposed by [43,44] using two variable resistors as shown in Figure 4, R_1 is designed to model the HIF asymmetry and nonlinearity between the voltage (V_f) and current (I_f) via calculating their respective ratios as stated by Ohm's law. The values of the current and voltage are sampled over time, where each sample is taken from one complete cycle. Values used in R_1 are from cycles that are similar in amplitude to the preceding cycles so that build-up characteristics are excluded. The current can be calculated via the following equation [45]:

$$I_f = \begin{cases} I_f(n) + \frac{I_f(n+1) - I_f(n)}{V_f(n+1) - V_f(n)} \times \left(V_f - V_f(n)\right), & V_f(n) < V_f < V_f(n+1) \\ I_f(n), & V_f(n) = V_f \end{cases} \tag{3}$$

where $V_f(n)$ and $I_f(n)$ are extracted from the voltage vs. current characteristic curve in sample n. On the other hand, R_2 is designed to represent the build-up and shoulder characteristics of an HIF. The resistance in this variable will start at a high value and decrease over time so that the fault current will eventually reach a steady state value.

The polynomial expression defining R_2 is as follows [45]:

$$R_2 = \begin{cases} b_m \cdot t^m + b_{m-1} \cdot t^{m-1} + \cdots + b_1 \cdot t + b_0, & t < \Delta t \\ 10^{-5}, & t \geq \Delta t \end{cases} \quad (ohms) \tag{4}$$

where m is the polynomial degree, b_m is the coefficient, and Δt is the growing period of the HIF current. The methodology presents a good approach to emulate nonlinearity, asymmetry, build-up, and shoulder features of an HIF. It is worth mentioning that sampling data can vary depending on the surface material and condition. This model is unique in the sense that it is the closest representation to the HIF's build-up and shoulder characteristics. However, the discharged arcing component is not considered.

2.2.4. Two Antiparallel Diodes

Emanuel et al. [46] proposed another model to replicate the unique characteristics of an HIF. As shown in Figure 5, R_1 and R_2 alongside L_1 and L_2 add the nonlinearity dimension to the HIF, and V_p and V_n factor in the discharged arcing voltage of the incident. This model is designed with directional diodes so that if $V_f > V_p$, the fault current will flow from the source to the ground. The opposite will occur at $V_f < V_n$ as the current will flow back to the source, and when $V_n < V_f < V_p$, no current will flow into the system. Other researchers in [47–50] expanded into Emanuel's model by experimenting with a variable resistor, as shown in Figure 6. However, this model lacks the ability to simulate the build-up and shoulder characteristics of an HIF.

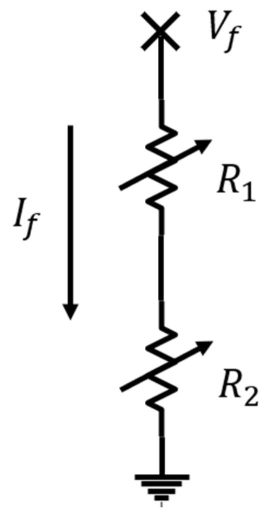

Figure 4. Two variable resistors model.

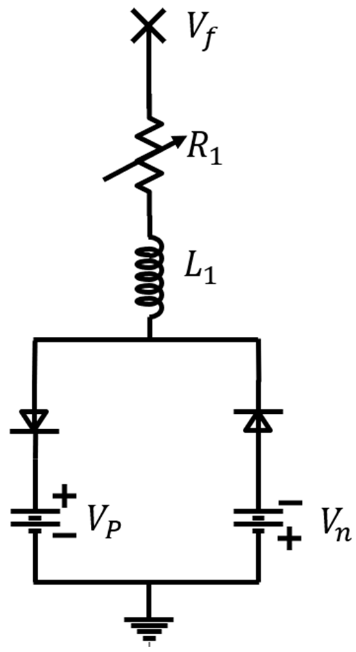

Figure 5. Two antiparallel diodes model.

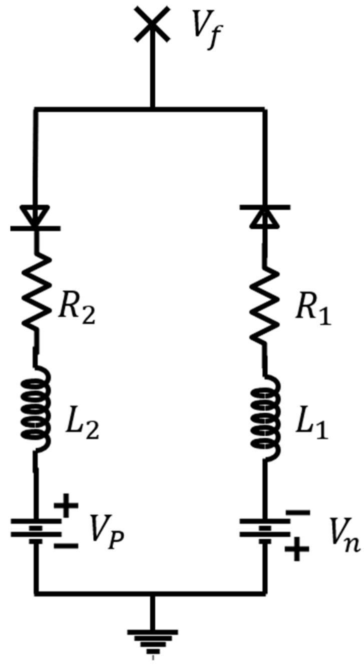

Figure 6. Two antiparallel diodes with resistors and inductors.

3. HIF Diagnosis Techniques

During its undetected state, an HIF is a risk to public safety and eventually the electrical distribution system. Hence, many researchers attempted to identify techniques that can detect, classify, and locate HIFs. This section is going to discuss the recent methodologies used to diagnose HIFs.

3.1. 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:

$$I_a + I_b + I_c = I_{zero\ sequance} = 0 \tag{5}$$

Monitoring $I_{zero\ sequance}$ via a core balanced current transformer (CT) can be referred to in the industry as sensitive ground fault relaying [51]. This method is widely used. However, loads in nature are unbalanced. Therefore, residual current is always present in the system, which will require the relay to be set at a certain tolerance rate to avoid nuisance trips. This tolerance rate may increase the difficulty of HIF detection. The comparison between outgoing and incoming current flows is used in differential protection schemes similar to pipeline leakage detection, where the flow rates are observed. The methodology is sensitive to HIFs. However, the implementation of differential protection in distribution networks is a difficult task as the network may contain various generation points and loading busses.

An alternative technique can be to install a ground grid below the phases of a transmission line, as shown in Figure 7. The method proposed by [4] is intended to capture the falling conductor prior to it being in contact with a high-impedance surface. Once the conductor is in contact with the grid, the overcurrent relay will be able to detect the fault easily and trip the breaker. However, such method is economically infeasible as it requires an additional ground grid mounted at the transmission line poles over lengthy distances. An approach to install a mechanical hook underneath the phase conductors and connected to the natural grid was proposed by [52]. The method will cause a line-to-neutral short circuit in case of a downed conductor, which will trigger the existing overcurrent relays and isolate the line.

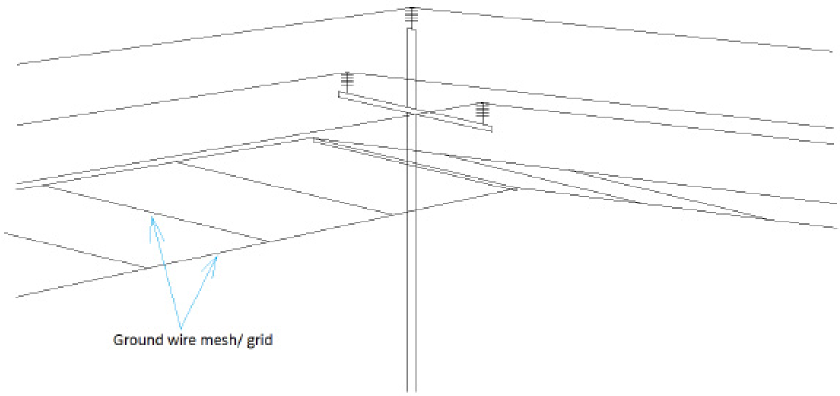

Figure 7. Transmission line ground grid.

3.2. Signal Processing Techniques

To tackle HIFs during the presence of nonlinear loads, [53] presented a fast Fourier transform (FFT)-based approach to analyze electrical currents in single-phase feeders. The method considers the even and odd harmonic components to assess the condition of the electrical distribution system. In the harmonic magnitude vs. time plane, it was observed by the authors that the relevant distance between the third- and seventh-order harmonics clearly changes during an HIF, hence allowing the method to detect HIFs. It is worth noting that such approach is noise-sensitive and will require a noise reduction scheme to achieve desirable results.

A Stockwell transform (ST)-based approach was proposed by [54] to continuously monitor the third harmonic phase angle of the current sinusoidal signal. The variation in third harmonics is correlated with load operations and switching. Therefore, a stabilized value will indicate the presence of an HIF in the system. However, the method may take up to 150 ms to detect the fault which may allow for incident energy build-up.

The authors of [55] introduced a novel approach hybridizing maximum overlap discrete wavelet packet transform (MODWPT) and empirical mode decomposition (EMD). The scheme estimates the change in the inter-harmonic energy content in the fault signal normalized by the pre-fault condition. Such presence indicates the possibility of an existing HIF. The model is unlikely to succeed in real operating conditions for all types of HIFs.

Roy and Debnath [56] proposed an approach utilizing power spectral density (PSD) calculated from a wavelet covariance matrix. The method decomposes current signals up to the third level via wavelet transform. The detailed coefficients are then used to calculate the wavelet transform and PSD for both frequency and time domains. Threshold analysis is applied as the basis for fault detection in the presented approach, but the method was not tested for fault location estimation.

The signal processing-based orthogonal component decomposition of three-phase voltage and current signals method was explored by [57]. The projection of voltage and current components in the plenary function will produce eight components for voltages and eight for the current. The calculated values maintain an absolute value equivalent to zero during normal operating conditions. However, the components may experience variations during a faulty condition, which will lead to HIF detection. While the method is robust in terms of fault detection, its fault distance estimation absolutive error is higher than 10% for half of the cases tested.

3.3. Mathematical Approximation

To estimate the zero-sequence grid capacitance, the authors of [58] implanted an algorithm employing differential equations to estimate the capacitance upstream and downstream of the fault. The calculated values are compared to the expected capacitance during normal operation to detect variations. The method proved to be fast, self-calibrating, and noise-independent. However, it was only introduced for isolated neutral grids. Another estimation method was introduced in [59] to calculate the fault admittance in a medium voltage by relying on field measurements. The method was verified for HIFs with resistance ranging from 100 to 200 kΩ for detecting and locating HIFs.

A state estimation model modified to diagnose HIFs was presented in [60] consisting of elements such as voltage measurements as well as power measurements. The authors were able to prove the efficacy of such an approach in HIF detection. However, faulty line identification results show significant errors while the load is varied. An iterative-based approach for the fault location problem was discussed in [61]. The presented algorithm will estimate an initial location of the fault and fault current and voltage. The weighted least squares (WLS) approach is used to calculate the resistance and reactance estimate of the fault. Afterwards, the estimate is compared with a tolerance rate for convergence, returning the final fault distance, resistance, and reactance. The method requires heavy iterative computational processing and may delay the fault identification time. Ramos et al. [62] employed an analytical WLS state estimator to calculate the fault voltage and current and identify HIFs in distribution networks; the methodology further utilizes the values obtained from the linear regression of the estimated fault distance components.

Monitoring the zero-sequence voltage to reconstruct the declining periodic components via the extended Prony method was the subject of [63]. The methodology aimed to estimate the single-phase to ground fault information with the deployed feeder terminal units. The method's robustness was only proved for single-line to ground fault location estimation.

A searching-based technique was developed in [64]. The method will estimate the fault location based on a comparison of the calculated fault parameters (voltage and current) at certain locations of the feeder and compares it with the reference data for faults in a feeder. Such approach requires a high calculation burden for lower tolerance rates and can be considered only effective at single-feeder distribution lines. Linear prediction was used by [65] to represent time series of signal samples over time. The model uses the energy raising of the linear prediction error to detect HIFs. However, the authors of this research did not consider nonlinear loads existing in the power distribution network.

3.4. Artificial Intelligence-Based Methods

Artificial intelligence-based methods to diagnose HIFs revolve around three main processes: acquisition of data, feature extraction with signal processing techniques, and training using machine learning algorithms. This section will discuss the latest developments in each process.

3.4.1. Data Acquisition

The basis of intelligent-based methods is the measurement signal type used to diagnose HIFs. Various signals were used in the literature, however, current waveforms in HIFs carry over harmonic components that can be distinguished from normal loading situations [1]. The subject measurements were applied in [66,67] to detect and classify HIFs in distribution networks. It is worth noting that current measurements are affected by current transformers ration percentage errors.

On the other hand, a voltage transient spike can be observed due to arcing phenomena in HIFs while considering a fault caused by moving objects such as trees. The movement will introduce air gaps between the conductor and surface which will result in a varying fault impedance. The authors of [68] based their approach on arcing voltage measurements. However, the changes in the voltage waveform are increasingly difficult to capture as the voltage dip is low in case of HIFs. Therefore, many authors such as [69,70] experimented on utilizing both current and voltage waveforms in training the neural network to diagnose HIFs in distribution systems which provided better results. Nevertheless, the approach increases the dataset size for the neural network and will require extensive analysis to limit the training on useful features so that the computational burden can be controlled.

Resistance measurements were used by the authors of [71] to diagnose HIFs. Such measurements, when compared to the original impedance values of a transmission line, will provide an insight to the fault location in the line and reduce the network downtime. The issue is resistance alone cannot represent the nonlinearity, asymmetry, or arcing characteristics of HIFs. Hence, the detection of such faults using this measurement is highly compromised.

The representation of a signal in a defined period of time as an absolute value paired with the phase angle is the objective of synchronized phasor measurement units (SPMUs) [72]. Such measurements provide an accurate representation of current and voltage waveforms in power systems. An application of SPMUs in HIF diagnosis was discussed in [73,74] but the implementation of SPMUs in HIF location considering fault asymmetry and load nonlinearity is subject to further research.

3.4.2. Feature Extraction

Feature extraction using signal processing techniques is an essential tool for the efficient performance in machine learning algorithms. One which is widely used in power quality disturbance application is Fourier transform (FT). This signal processing tool detects the existence of signal frequency components during disturbances [75]. FT is continuous over time; however, discrete Fourier transform (DFT) is commonly used in computational applications and was implemented in [76] for HIF detection. Another form known as fast Fourier transform (FFT) was applied in [77]. However, for HIF diagnosis application, FT can only represent the features in the frequency domain.

Unlike FT, wavelet transform (WT) is an advanced signal processing tool that can represent the features of a signal in the time–frequency domain [78]. This representation is useful in HIF diagnosis applications when represented in discrete format, as shown in [79]. Furthermore, wavelet packet transform (WPT) provides more information in comparison to discrete wavelet transform (DWT) as higher and lower bands of frequency can be decomposed at each decomposition level. Such application was introduced in [80,81] providing satisfactory results in HIF detection and classification. Moreover, the application of multi-wavelet transform (MWT) was discussed in [82]. It was observed that MWT is the extension of scalar wavelet where numerous scaling functions and related multiple wavelets are applied. WT can provide information on the fault during a specified period of time and in decision-making applications, this downfall can compromise the reliability of such applications.

3.4.3. Machine Learning

A neural network (NN) is an interconnection of several processing nodes performing a series of mathematical operations governed by the network's internodal strength, or weight, influenced by an external input referred to as bias attained by a set of historical patterns through the process of adaptation [83–85].

A typical artificial neuron input comprises signals weighted through multiplication factors and summed together alongside the bias to feed a node, as shown in Figure 8, where X represents the inputs, W is the weight, and b is the bias. The resulting value is then compared to a threshold; if the result exceeds the threshold, the node will produce a value output close or equal to one, otherwise it yields zero. The objective of training a neural network is to identify the optimal weights and biases to obtain the desired output.

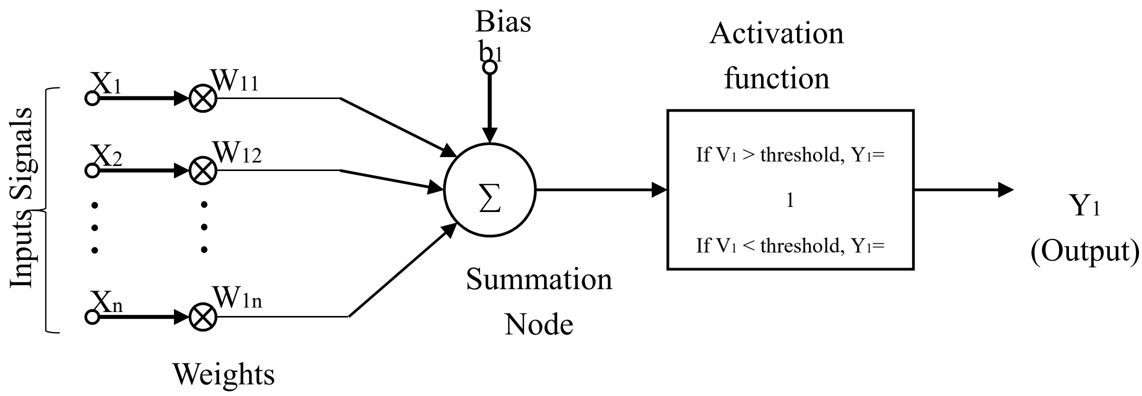

Figure 8. Typical neural network.

A multilayer perceptron neural network (MLP-NN) model was used by [86–88] to diagnose HIFs. The algorithm utilized the effective backpropagation technique to train the network in detecting and classifying faults. However, a technique to choose the accurate number of hidden layers and neurons is required to achieve optimal results with less computational time. Moreover, a hybrid approach using MLP-NN and Gaussian process regression (GPR) was implemented by [80,89]. In the subject research, MLP-NN was used to determine the optimum weights and biases for HIF detection and classification, and on the other hand, GPR plays the role of a linear regressor that aims to approximate the fault location in a transmission line. The authors of [90] utilized MLP-NN in a live experimental setup to diagnose faults in a modeled transmission line. The approach utilized Stockwell transform as a preprocessing and feature extraction tool in the attempts at developing the optimal approach.

4. Comparative Analysis

The presented measurement signals, feature extraction techniques, and machine learning classifiers have distinctive abilities to detect, classify, and locate HIFs. Hence, a comparison was made, as shown in Table 2. The evaluation criteria of such papers can depend on the following [2,31]:

1. Accuracy is used to measure the performance of proposed techniques against the expected results.
2. Dependability and security can measure the precision percentage and miscalculation ratio of HIF diagnosis techniques which are missing in most studies.

It can be observed that in most of the literature, wavelet transform dominates the signal processing techniques. However, other methods utilizing the time–frequency domain such as Stockwell transform have been introduced in recent years.

Table 2. Comparison between existing techniques.

Reference	Measurement Data	Feature Extraction Technique	Machine Learning Classifiers	Experiment Objectives	Accuracy %	Dependability %	Security %
[91]	Voltage and Current	WT	SVM	Detection	91.38	90.04	92.6
[67]	Current	DFT	ANFIS	Detection and Classification	99.64		
[92]	Arc Voltage	EMD	ANN	Detection	99.35		
[71]	Resistance		ANN	Location	99		
[69]	Voltage and Current	WT	ANN	Detection	91.33		
[70]	Voltage and Current	WT	ANN	Detection	95.989		
[93]	Current	WT	SVM	Detection and Classification	96		
[94]	Current	VMD	SVM	Detection and Classification	99		
[95]	Current	TEO	FIS	Detection and Classification			
[82]	Voltage and Current	WT	FLC	Classification	88.89		
[96]	Current	MM	DT	Detection	99.34	100	98.77
[77]	Current	FFT	FLC	Detection			
[79]	Current	WT	ANN	Classification			
[97]	Voltage and Current	ST	ANN	Detection	95.43		
[98]	Current	MG	FLC	Detection	99.4	99.78	99.07
[99]	Voltage and Current		SVM	Detection		100	100
[100]	Current	WT	FLC	Location	99.24		
[87]	Voltage and Current		ANN	Location	99.67		
[101]	Current	MM	DT	Detection	98.33	98.88	100
[102]	Voltage and Current	WT	SVM	Location	99.34		
[86]	Voltage and Current	WT	ANN	Detection			
[80]	Current	WT	ANN+GPR	Location	99.4		
[103]	Current		FLC	Detection and Classification			
[104]	Current	WT	ANN	Detection and Classification	99		
[89]	Voltage and Current	WT	ANN	Detection	96		
[105]	Current	WT	SVM	Detection	99		
[106]	Current	WT	DT	Detection	98.22	95.79	100
[107]	Voltage and Current		ANFIS	Location	99.25		
[108]	Current	WT	ELM	Detection			
[109]	Current	WT	SOMN	Location	91.27		
[110]	Current	ST	ANN	Location	99.15		
[90]	Current	ST	ELM	Detection and Classification	99.3		

5. Conclusions and Future Recommendations

A comprehensive review on HIF detection, classification, and location techniques was discussed in this paper. The review defined the phenomenon of HIFs, where the current levels of the resulting fault are marginally higher than the normal drawn ampere from the load, hence deeming the fault impossible to be detected by conventional overcurrent relays. Such a fault, while undetected, is a risk to public safety since a downed conductor can create hazardous shock, fire, or life-threatening injuries through unintentional human contact. Most challenges in HIF diagnosis result from the unusual characteristics associated with the occurrence of HIFs such as low current magnitude, intermittent arcing, randomness, asymmetry, nonlinearity, build-up, and shoulder.

Moreover, the paper also discussed modeling techniques utilized in the literature for HIFs. The utilization of real-world data modeled in a high-current research laboratory with materials such as tree branches, grass, and concrete surfaces embodies a path to incorporate real-time data into the research. On the other hand, most authors used simulated environments with a single variable resistor, a variable resistor single inductor, two variable resistors, and two antiparallel diodes.

Finally, fault diagnosis techniques were discussed in this review including relay-based methods, signal processing techniques, parameter estimation, mathematical approaches, and artificial intelligence-based methods to diagnose HIFs which revolve around three main processes: acquisition of data, feature extraction, and training using machine learning algorithms.

The presented methodologies in the literature mostly focus on offline systems and will require extensive research to obtain a developed approach. Moreover, the fault clearing time (FCT) of machine learning techniques is still in question since such methodologies will require additional processing time that may increase the risk of hazards resulting from the existence of HIFs.

Highlights on the road ahead for the HIF field are desired. The possible future of the field is outlined as followed:

1. MLP-NN is known to be a universal approximator that helps solve nonlinear problems such as HIFs. The utilization of one hidden layer is widely used in the literature. However, a methodology to determine the optimum number of hidden layers and neurons is still required to increase the effectiveness of neural network-based approaches.
2. Datasets represent the cornerstone of intelligent-based methods. Therefore, scaling, removing outliners, and filtering out noises can improve the learning process of neural networks.
3. Convolutional neural network (CNN) algorithms proved to be capable of training multidimensional data for image processing. An implementation of such techniques to solve the HIF problem can be considered.
4. PMUs are used to measure the magnitude and phase angle of the voltage and current in a distribution grid using a common time source for synchronization. Such measurements provide an additional layer of information to help neural network-based schemes better diagnose HIFs.

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