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HIGH IMPEDANCE FAULT DETECTION IN DISTRIBUTION SYSTEMS USING DWT AND ARTIFICIAL NEURAL NETWORKS

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Abstract

In distribution systems, detection of high impedance faults can be challenging due to the low magnitude, nonlinear and intermittent nature of such faults and the fact that these faults can closely resemble load variations. In this paper, a hybrid approach of DWT and ANN is proposed to accurately identify a HIF in real time. The key contribution is the selective extraction of the DWT detail coefficients D3 and D4 that provide a compact and discriminative feature set that can capture high- and mid-frequency arcing characteristics. The features are classified by a light weight ANN to make fast and reliable decision making. The model is trained and tested with 10,000 labelled samples with an overall accuracy of 98.7%, sensitivity of 97.9%, specificity of 99.5% and false positive rate of 0.5%. The response time of the system is also average at 31.4 ms, which is approximately 1.5 cycles of 50 Hz system. Under noisy conditions, it continues to function well at a 20 dB SNR. By comparing with the traditional algorithm DWT-SVM and fuzzy logic methods, the proposed DWT-ANN method is a practical, efficient and implementable approach, which is suitable for the real-time HIF detection in modern distribution network.

Keywords: high impedance faults, discrete wavelet transform, artificial neural network, distribution system protection, fault classification

List of Symbols/Acronyms

A_5 – Approximation coefficient (level 5)
$D_1 \dots D_5$ – Detail coefficients (levels 1 to 5)
D_3 – High-frequency detail coefficient
D_4 – Medium-frequency detail coefficient
raw – Raw fault energy
f – Fundamental frequency (50 Hz)
I(t) – Line current as a function of time
HIF(t) – High impedance fault current as a function of time
L – Inductance
MSE – Mean Squared Error
N – Window size (1024 samples)
N(t) – Noise component
R – Resistance
S(t) – Useful signal component
SNR – Signal-to-noise ratio (dB)
T_s – Sampling time (2×10^{-5} s)
v(t) – Instantaneous voltage
V_m – Peak voltage
W_k – Sliding window buffer
Z – Impedance
ε(t) – Random fluctuations (arcing noise)
ω – Angular frequency (2πf).

1. INTRODUCTION

The problem of HIF is an emergency in the protection and monitoring of electrical distribution systems. In contrast to traditional short-circuit faults, HIFs are usually caused by conductors being in contact with high-resistance surfaces, such as asphalt, sand, or tree branches, and the fault currents are often too small to cause a traditional overcurrent protective device to operate. The HIFs, though small, have the potential to create severe risks, such as electrical fires, damage to equipment, and personnel safety. It is thus very crucial to detect these faults in a correct and timely manner to increase the reliability, safety, and operational efficiency of modern power distribution networks [1].

The conventional protection systems, including overcurrent relays and time-based protection, do not work well with HIFs since the fault currents are often lower than the configured limits. Overcurrent relays depend on currents that are greater than a multiple of the nominal load, usually 2-3 times the current rating. In most HIF cases, the fault current can be just a few amperes, and therefore, such relays are virtually useless. Equally, impedance-based approaches and traditional Fourier Transform, FFT-based approaches are limited in their ability to distinguish between HIFs and normal load variations or switching transients. The FFT-based techniques examine the frequency content of the recorded currents, trying to identify harmonic conduct related to arcing faults. But these methods have a susceptibility to false alarms due to load switching, nonlinear loads, and background noise, which constrain their usefulness in practice [2].

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To address such shortcomings, recent studies have examined the use of advanced signal processing and artificial intelligence AI methods to detect HIF. Wavelet transforms have also become one of the most useful tools of non-stationary signal analysis. Wavelet transforms, unlike Fourier analysis, offer global frequency data, but in addition, allow the signal to be broken down into both time and frequency representations, allowing the identification of short-lived events, such as intermittent arcing in HIFs. DWT is especially beneficial in that it provides multi-resolution analysis, in which high-frequency fault signatures can be identified at small scales and low-frequency signals that represent normal operation are removed. Certain DWT detail coefficients, like D3 and D4, have been observed to represent the typical high- and medium-frequency content of HIF arcing, with the underlying current being very low [3].

Parallel to this, ANNs have become known to be able to model nonlinear relationships that are too complicated and to classify patterns in a noisy environment. HIFs are nonlinear by nature, and the arcing is random, asymmetrical, and intermittent fault currents. With sufficiently large hidden layers, ANNs, especially feedforward networks, are able to acquire these nonlinear properties with classified data, separating HIFs and normal load variations, switching transients, and background disturbances. ANNs can be used with DWT-based feature extraction to identify the most significant features of the signal at the expense of a lower level of computational complexity and higher classification accuracy [4].

The use of machine learning and signal processing in hybrid HIF detection systems has been studied more recently. Indicatively, it is suggested that wavelet transforms (in combination with support vector machines, SVMs, decision trees, or ANNs can be used to improve fault detection in realistic operating conditions. These methods have shown better detection, lower false alarms, and resistance to noise. Nevertheless, most research is confined by insufficient sampling rates, small or artificial datasets, or the evaluation of one type of network topology, which may diminish generalizability. Also, the speed of detection is a significant consideration in real-world implementation because the delay in detecting a fault may add to the risk of fire and damage to equipment. Thus, a perfect HIF detection system must be able to deliver high accuracy, low false alarms, fast detection as well as stability in a variety of operating conditions and network setups [3].

Besides power distribution systems, the fault detection methods have also been studied widely in other electrical engineering fields, especially in electrical machines and electronic circuits, where similar challenges of nonlinear behaviour, sensitivity to noise, and overlap of features exist [5]. Indicatively, a review of the literature on fault detection in permanent magnet synchronous motors PMSM reveals the success of advanced signal processing and intelligent classifiers in the detection of electrical and mechanical fault conditions under dynamic operating conditions [6].

The recent comparative studies further illustrate that deep learning models are superior to conventional methods when it comes to classifying electrical faults in PMSMs with respect to higher accuracy and robustness during variable load conditions [7]. In addition, the convolutional architecture like resents has been successfully utilized in the electrical fault classification in PMSMs with a good ability to extract hierarchical fault features over the raw signals. Intelligent systems based on fuzzy logic have also been applied in fault detection and identification in analog electronic circuits, especially in those where uncertainty and imprecision in measurements are important [8]. All these studies point to the fact that hybrid intelligent systems that combine signal decomposition and machine learning can be used to ensure high reliability in various electrical applications, hence the driving force behind adopting a DWT-based feature extraction and ANN classification framework in this project [9].

The research presented in this article extends the developments and introduces a DWT+ANN-based HIF detection system that directly applies to real-time implementation in the distribution networks. The approach makes use of DWT to extract multi-resolution features and an ANN classifier that has been trained on large labelled data to capture the nonlinear, intermittent nature of HIFs. The system in question is tested in different scenarios, with different fault resistances, switch-over loads, and noisy conditions, and it is a full test of the detection performance. A comparison with the existing protection methods, such as overcurrent relays and FFT-based solutions, indicates that the suggested methodology significantly enhances the detection rate, speed, and reliability. Moreover, the strength of the approach is supported by its testing in low signal-to-noise ratios, which proves its usefulness in the distribution systems of the real world, where noise in measurements is unavoidable.

The article introduces a new HIF detection algorithm that incorporates the DWT feature extraction with an ANN classifier. The proposed system is capable of determining HIFs in low-current, nonlinear, and noisy conditions with high accuracy, and with low false alarms and a high detection rate. Its performance is better than traditional methods, as can be seen through a comparative analysis that provides a viable and worthy solution to the modern distribution system protection.

The key contributions of this work can be summed up as follows. To begin with, a hybrid framework of DWT-ANN is proposed to detect high impedance fault HIF in distribution systems, with the discrete wavelet transform DWT utilized to effectively extract features, and the feedforward artificial neural network ANN utilized to provide fast and accurate classification. Second, a selective feature engineering approach is proposed that uses only the D3 and D4 wavelet coefficients, which are an effective means of capturing the relevant high- and medium-frequency transient components of arcing faults and at the same time significantly reduces the computational complexity. Third, a sliding window signal processing strategy is designed and implemented in Simulink to provide a real-time implementation scheme to support continuous monitoring and quick fault detection that can be used in practical smart grid applications. Fourth, the proposed model exhibits a high level of robustness under various operating conditions, such as load switching conditions, transient disturbances, and noisy environments with signal-to-noise ratios as low as 20 dB, yet still maintains high classification performance. Fifth, the extensive comparative analysis shows that the suggested approach is more accurate, faster in detecting, and reduces false alarms than conventional and intelligent methods (overcurrent relays, FFT-based methods, DWT-SVM, fuzzy logic systems, and LSTM-based models). Lastly, an ESP32-based implementation is considered, and the feasibility of implementing the proposed approach in real-world distribution network monitoring systems is highlighted.

2. RELATED WORKS

In [10] the authors suggest a fault detection technique based on an enhanced Amanoel model built on top of DenseNet on distribution networks. The approach uses the DenseNet architecture to automatically extract fault characteristics using the network signals. The findings show increased accuracy of detection as compared to traditional methods. The method is, however, constrained by its reliance on high-quality classified data and may not be generalizable to networks with different topologies. The current research answers this limitation by applying DWT to strong feature extraction and an ANN classifier trained in a wide range of HIF situations, enhancing generalizability and resistance to noise. The results confirm the ability of the new approach to overcome the drawbacks of traditional methods and reach up to 98.85% detection accuracy in different cases, with a boost of about 2–7% as compared to single models.

In [11] the researchers suggest a statistical detection approach involving the use of a discrete energy separation algorithm in detecting both HIF and low impedance faults LIF. The technique uses instantaneous energy components to identify faults and normal operation. Findings have shown that it has an increased detection speed and accuracy compared to conventional methods. The drawbacks are sensitivity to transient load and noise; it can generate false alarms. The current research addresses these problems by implementing DWT to separate fault-specific frequency bands, followed by ANN classification to achieve greater reliability in the presence of noise.

In [12] the authors suggest that HIF features should be extracted with empirical wavelet transform EWT and singular value decomposition SVD, and subsequently, these patterns are introduced to an SVM to distinguish between HIFs and switching events. The findings indicate better classification compared to traditional frequency-based techniques. The drawbacks are computational complexity and possible delays in real-time detection. The current work addresses the above-mentioned shortcomings by applying DWT, which is a fast multi-resolution feature extractor, and a lightweight ANN to quickly classify.

In [13] the authors suggest using a hybrid approach, which is DWT and a fuzzy inference system FIS, to detect and classify HIFs. The approach takes advantage of DWT to extract features and FIS to decide. Findings indicate that there is a reasonable level of detection accuracy in different fault scenarios. Constraints encompass the reliance on human-defined fuzzy rules and a lack of flexibility to unknown circumstances. The current paper addresses these shortcomings by substituting FIS with an ANN, which allows fault patterns to be learned automatically without designing a rule.

The researchers in [14] introduce a distortion-based algorithm to enhance the accuracy of HIF detection in various operating conditions. The technique quantifies the distortion of the waveforms in order to detect faults. The outcome suggests a higher level of detection in the low-current condition than in the conventional relays. Weaknesses are susceptibility to transient load switching as well as high-frequency noise. The current research attempts to resolve these problems through DWT-based robust high-frequency feature extraction and ANN-based classification to classify HIF signatures and normal disturbances.

In [15] the authors suggest the application of DWT and smart classifiers, including adaptive neuro-fuzzy inference systems ANFIS and SVM, to detect and identify HIFs in medium-voltage distribution networks. The approach is very accurate in identifying faults in a controlled environment. The shortcomings are that the model is complex and requires a lot of parameter tuning. The given study simplifies the situation as it only adds the most informative DWT coefficients to an ANN, without compromising on accuracy, making it easier to train and deploy a model.

In [16] the authors suggest identifying HIFs in photovoltaic-integrated power systems with the assistance of long short-term memory LSTM networks, which are recurrent neural networks. The technique records time-related fault current dependencies. Results show effective detection for photovoltaic environments. Disadvantages consist of the high level of computational load and slowness in detection. These limitations are overcome by the current study using DWT as a quick feature extractor and a feedforward ANN as a real-time classifier to lower the computational load and enhance the speed of response.

In [17] the researchers suggest locating the HIF fault zones in the distribution systems with the help of a region detection method and random search multi-level SVM RSMSVM to classify fault zones. The technique enhances the accuracy of the localization of faults. Its weaknesses are that it is based on high-resolution measurements and that it may be sensitive to changes in network structure. The current study is concerned with detection, but not with an accurate localization, whereby DWT + ANN is used to guarantee a quick and dependable detection in diverse network conditions.

In [18] the authors suggest looking into the LIFs, harmonic loads, and capacitor bank switching of HIF detection and using SVM to determine faults. The technique enhances fault and non-fault discrimination. It has limitations, such as feature selection, and it is computationally expensive when dealing with large datasets. The current research handles these shortcomings by choosing the most effective DWT coefficients and applying a small ANN structure to effective real-time detection.

In [19] the authors present an HIF detection scheme that relies on intrinsic mode decomposition IMD and the Teager-Kaiser energy operator TKEO in the distribution system. The technique determines HIF signatures with energy analysis of decomposed signal elements. Findings indicate that detection is reasonable in low-current conditions. The drawbacks are sensitivity to noise and the computational complexity of the decomposition process. The current research addresses these shortcomings by applying DWT to extract multi-resolution features, followed by an ANN to do rapid and noise-resistant classification.

In [20], the authors examine the arc generated by the contact of trees on medium-voltage distribution lines and suggest the application of empirical mode decomposition EMD with ANN to analyse arc signals in real-time. According to the results, intermittent arcing is correctly detected. The disadvantages involve the tendency to be affected by signal noise and reliance on the accuracy of EMD parameters. The current paper goes a step further and uses CEEMDAN as the noise-adaptive decomposing method and DWT+ANN as the feature robustness and faster classification method.

Researchers present in [21] suggest that complete ensemble empirical mode decomposition with adaptive noise CEEMDAN should be used to detect HIF. The method records adaptive signal components to further identify faults more accurately. It has drawbacks such as computational intensity and real-time deployment difficulties. The current research attempts to overcome these shortcomings by integrating DWT with ANN, which gives the same level of feature discrimination with reduced computational expense that can be applied in real-time processes.

Nakho, Molio, and Hamam suggest a fault detection scheme of HIFs using the Hubert-Stanovich transform HS and the Decision Tree DT in [22]. The technique demonstrates good detection under some conditions. Weaknesses consist of less accuracy in noisy conditions and the use of handcrafted features. These limitations are overcome in the current research through DWT as the robust feature extraction method and ANN classifier as the learning complex fault patterns to enhance the accuracy and noise insensitivity.

In [23], scholars present an adaptive neuro-fuzzy inference system (ANFIS) to identify and classify HIF in distribution networks. The algorithm is a combination of fuzzy logic and neural networks to represent the nonlinear fault conduct. It has been shown that the results are good in terms of classification in the simulated fault conditions. Weaknesses are that it relies on fuzzy rules that are defined by experts and cannot be scaled to large networks. These limitations are overcome by the current research with the help of feature extraction based on the DWT and a fully trainable ANN, removing the manual design of rules and enhancing scalability.

A study in [24] suggests that a Convolutional Neural Network CNN can be used to detect HIFs. The algorithm is a spatial feature learner that learns current signals that have been pre-processed. Findings show that there is effective HIF event detection. Limitations include the use of large labelled datasets and the high computational costs of real-time implementation. The current study has overcome these limitations by expressing DWT coefficients as compact features in the context of a feedforward ANN that reduces computation requirements and preserves accuracy.

Rai et al. [25] suggest a convolutional autoencoder CAE-HIFD HIF detector based on unsupervised learning. The algorithm identifies latent features of faults without the need to have classified datasets. Findings indicate promising unknown HIF patterns detection. Weaknesses are low sensitivity to the small magnitude faults and possible reconstruction errors. The current research addresses these shortcomings by integrating DWT and a supervised ANN classifier to guarantee high sensitivity and proper classification of low-current HIFs.

Researchers suggest a machine learning-based approach to HIF prediction in distribution networks in [26], where high-frequency components are extracted with the help of DWT, and temporal sequence modelling is performed with LSTM. Findings show that HIFs are correctly identified using time-series data. The drawbacks are high training complexity and a slower time to detect because of re-processing of the network. The current research paper provides a solution to these shortcomings by applying DWT to extract features, and the use of fast, real-time classification with an ANN feedforward.

In [27] the researchers propose a transfer function TF approach to the analysis of the effects of impedance and fault location analysis based on voltage and current signals in the frequency domain. Findings show enhanced fault localization. The limitations include sensitivity to measurement noise and impaired capability of identifying low-current HIFs. The current paper concentrates more on fault detection as opposed to the localization and uses DWT+ANN to enhance noise insensibility and reliability in the detection of low-intensity faults.

In [28] the authors introduce the use of neural networks of deep learning to detect and categorize HIFs. The algorithm automatically picks up fault characteristics based on time-domain signals. Findings indicate that it is more accurate than the classic methods. Disadvantages are the requirement of huge datasets and overfitting of small networks. These limitations are overcome in the present study by applying DWT-based feature selection to down-sample dimensionality of the input and enhance limited data generalization.

In [29] the authors suggest a CNN-based transfer learning to identify HIF with the data of distribution-level phasor measurement units D-PMUs. The technique uses pre-trained models to minimize data requirements. Findings demonstrate that performance is enhanced by limited training data. The drawbacks include the reliance on pre-trained models and their incompatibility with other network topologies. The limitations can be considered with the current research, which applies DWT+ANN, which is not dependent on external pre-trained networks and can generalize across different distribution networks.

In [30] the researchers suggest a protective system based on transfer learning and GoogleNet architecture to minimize the reliance on large datasets. The angle data in the third harmonic are converted to images using the Wigner-Ville distribution and input into a pre-trained GoogleNet to identify HIF. Findings indicate correct classification using very few training data. The drawbacks are that it is complex to pre-process and requires image conversion methods. The current research does not require such steps because DWT coefficients are input to the ANN as it is, and pre-processing becomes simpler, but the detection rate remains high.

In [31] the authors suggest a deep learning approach to HIF localization with micro-phasor measurement units (μPMUs). This technique uses high-resolution voltage and current measurements to analyse and estimate the location of the fault. Findings show that there is good fault localization in the new distribution systems. The weaknesses include the cost and complexity of equipment and real-time processing. The current research is detection-based, and the approach applied to localization is DWT+ANN, which provides fast and robust detection without μPMUs.

The researchers in [32] explain the nature of HIF electric arcs and suggest the application of DWT with SVM to extract features and classify the faults. The findings show correct fault detection in a 5-bus microgrid with a wind generator. Weaknesses are that the models are sensitive to noise and have lower scalability. These shortcomings are addressed in the current study, as it uses DWT with an ANN that offers noise resistance and improved generalization in large networks.

In [33] the authors create a rapid and precise SVM-based HIF detection system in traditional distribution generation systems and can detect single, two, and three-line faults. Findings indicate a higher speed and accuracy. Weaknesses include that it is dependent on a careful feature selection and cannot adjust to different network conditions. The current work tackles these shortcomings with DWT to compute automatic and multi-resolution feature extraction and ANN to classify features in various situations.

In [34] the authors suggest an integrated HIF detection and classification strategy based on SVM. The technique gathers various types of faults into one detection system. Findings reveal excellent accuracy and generalization of test cases. Limitations: It relies on large sets of labelled data and feature engineering. The current research fixes these weaknesses by applying DWT to extract features efficiently and ANN to learn patterns automatically so that big datasets and handcrafted feature structures are not required.

3. METHODOLOGY

The general methodological approach that will be used in detecting and classifying HIFs in electrical distribution systems through artificial intelligence techniques. The proposed methodology is designed in such a way that it can deal with the natural limitations relating to the detection of fault currents, such as low fault current magnitude, nonlinear nature, and the fact that fault conditions are almost similar to normal load operation. To do this, the method combines the simulation of power systems, advanced signal processing, and machine learning in a single framework. The large-scale distribution system model is developed using MATLAB/Simulink to simulate the real-world operating conditions and to produce the normal and faulty conditions under controlled conditions. The existing signal is constantly recorded out of the system and analysed in real time, and is the main source of data to be analysed. The methodology in Figure 1 consists of a series of work processes leading to the system modelling and signal acquisition, in which the electrical network is simulated, and the current waveform is acquired.

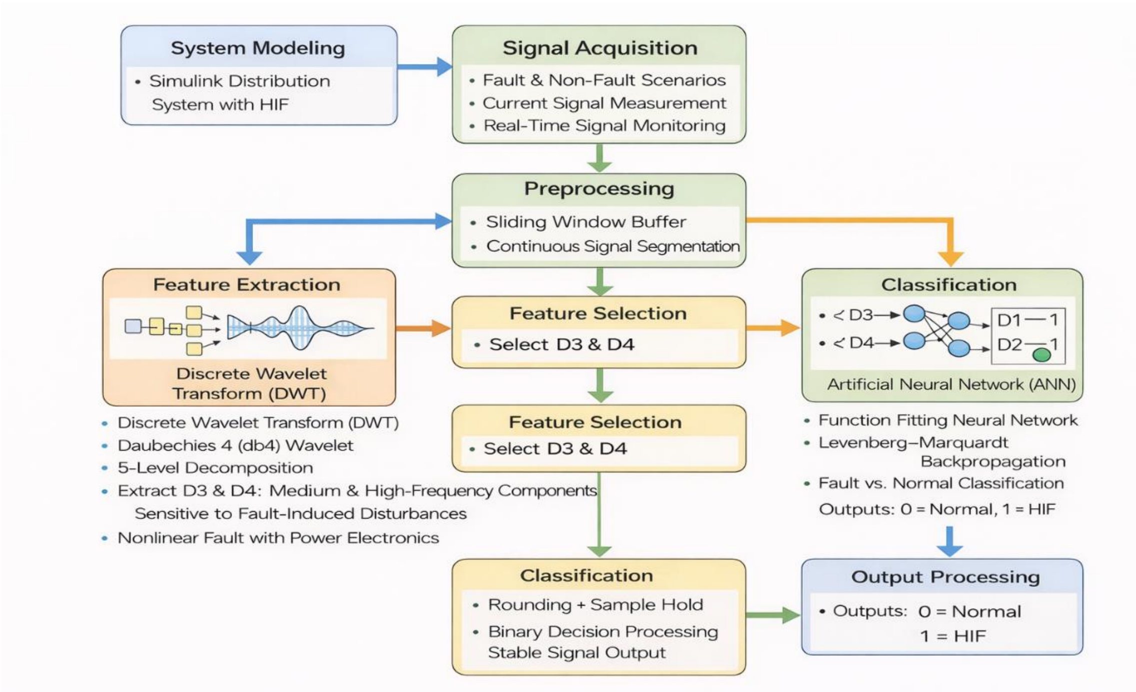

Fig. 1. Methodology workflow

The received signal is then processed by a pre-processing phase that makes use of a sliding window buffer so that data analysis can be continuous and consistent, and at the same time, real-time is maintained. After pre-processing, the signal is processed with the help of the DWT, which splits the signal into several frequency bands and gives a time-frequency representation that can be used to identify transient and non-stationary properties of HIF events. Based on the wavelet coefficients obtained, detail components of certain levels, especially D3 and D4, are chosen because they have important information regarding fault-induced disturbances.

These features are then input into an ANN, which has been trained on classified data that consists of both normal and fault conditions. The ANN takes the input features and classifies them by identifying normal operation and HIF situations. The neural network output is further processed to get a clear decision signal, which is an indication of the system condition. Lastly, the outcomes are assessed based on suitable performance indicators like accuracy and error rates to confirm the efficiency of the proposed strategy. This systematized operating process guarantees a powerful, effective, and precise detection system that can work in complicated and dynamic conditions of contemporary distribution networks.

3.1 System Modelling

The initial step is the creation of a realistic model of a distribution system by using MATLAB/ Simulink. This model simulates the behaviour of a one-phase distribution feeder in both normal and fault conditions. The system is made up of an AC voltage source, transmission line impedance, R-L load, switching elements, and a high impedance fault (HIF) module. This stage is aimed at producing realistic current signals that represent real operating conditions in a modern distribution network, such as steady-state operation, load variations, and nonlinear fault events. The simulated setting makes sure that both the labelled normal and fault datasets can be generated in a systematic way to be further processed.

3.2 Signal Acquisition

During this step, the line current signal *I(t)* is measured at a point in the distribution system that has been selected, normally near the feeder or load. Current signal is desirable over voltage because it gives more sensitivity to fault conditions, particularly in the HIF system, where fault currents are small and intermittent. It is this variation, which is caused by load switching, system disturbances, and fault events, that makes the acquired signal non-stationary in nature. A continuous real-time monitoring is adopted to ensure that transient and steady-state behaviour is adequately captured at a sufficiently higher resolution to carry out analysis.

3.3 Distribution System Modelling

This part discusses the electrical distribution system modelling in the simulation of normal and HIF conditions. The model is simulated in MATLAB/Simulink to model the realistic operating Conduct of a single-phase network. It incorporates the most important elements (i.e., the power source, line impedance, load subsystem, and the HIF model). This modelling is aimed at creating the correct current signals that can represent the reality on the ground, and these are necessary in determining the performance of the proposed fault detection and classification scheme.

3.3.1 System Description

The distribution is modelled to reflect the real operating conditions through the MATLAB/Simulink modelling system as a single-phase electrical network. The model is intended to be able to simulate normal conditions and fault conditions, specifically HIFs under controlled conditions. The system comprises of the following major components:

- AC voltage source
- Distribution line impedance
- Load subsystem (R-L load)
- High Impedance Fault HIF subsystem.
- Switching and control units.

The source voltage may be mathematically represented as [35]:

$$v(t) = V_m \sin(\omega t) \quad (1)$$

where: V_m is the peak voltage and $\omega = 2\pi f$ is the angular frequency.

The line impedance is represented as [35]:

$$Z = R + j\omega L \quad (2)$$

where (R) and (L) denote the resistance and inductance of the distribution line, respectively.

3.3.2 Load Model

A realistic distribution load is considered a series connection of resistance (R) and inductance (L) components in the load subsystem. This R-L combination is commonly employed to model realistic loads on power systems because it reflects the loss of energy as well as energy storage properties. It also allows one to simulate the transient response of loads during switch operations for assessing the reliability of fault detection algorithms in real-life operation scenarios. In contrast to resistive loads, due to inductance, the voltage and current waveforms experience a phase lag and produce time-varying currents. As such, the load must be mathematically formulated in the time domain as follows:

$$v(t) = Ri(t) + L\frac{di(t)}{dt} \quad (3)$$

The above expression depicts the immediate dependency of voltage on current in an R–L circuit and properly considers the inductive influence during both steady-state and transient modes. During steady-state sinusoidal operation, the performance of the load may also be represented in the frequency domain in terms of its equivalent impedance:

$$Z = R + j\omega L \quad (4)$$

where the root mean square (RMS) current is given by:

$$I_{rms} = \frac{V_{rms}}{\sqrt{R^2+(\omega L)^2}} \quad (5)$$

A step function input signal is provided to the switching control block to simulate real-life load demand variations. This enables the generation of abrupt load variations that are usually found in real-life distribution systems. Such load variations have a significant effect on the current waveforms, which are vital for validating the effectiveness of the proposed fault detection technique. The resistance and inductance values directly affect the electric characteristics of the load. In particular, the resistive value affects power losses, while the inductive value impacts energy storage capabilities. Careful choice of the resistance and inductance values ensures that the generated signals are realistic enough to reflect real-world scenarios.

Table 1. Load parameters

Parameter	Description
Resistance (R)	Represents load resistance and power dissipation
Inductance (L)	Represents load inductance and energy storage
Switching Control	Step input signal used to simulate load variation

3.3.3 High Impedance Fault HIF Model

The HIF subsystem is designed to simulate realistic fault conditions that are usually hard to detect since they have low current magnitude and nonlinear conductance. HIFs are not only intermittently conducting and disordered, as opposed to conventional faults. The fault current may be nonlinearly estimated as a nonlinear function [37]:

$$i_{HIF}(t) = f\big(v(t)\big) + \epsilon(t) \quad (6)$$

where:

$f\big(v(t)\big)$ represents the nonlinear voltage-current relationship, and $\epsilon(t)$ denotes random fluctuations associated with arcing conduct. The model of HIF takes into account:

- Power electronic switches to imitate intermittent conduction.
- Nonlinear resistive elements to denote variability in fault path.
- Ground connection: This is required to complete the fault circuit.

To further appreciate the complexity of HIFs, it is imperative that one looks at the defining characteristics of the faults in detail. HIFs cause weak and irregular signals that may closely resemble normal load variations, unlike low impedance faults, which cause large and easily detectable currents. This complicates their detection, especially with the traditional protection measures. Arcing, contact resistance, and environmental conditions are all phenomena that contribute to the nonlinear conduct and add some randomness to the fault current waveform. Also, intermittent conduction complicates the detection as the fault may not be present constantly. These characteristic features require high-order signal processing and smart classification methods. Thus, it is always important to identify and summarize these characteristics so that an effective detection system can be designed. Table 2 shows the main features of the HIF model applied in the current study.

Table 2. HIF characteristics

Feature	Description
Current Level	Low magnitude
conduct	Nonlinear and random
Detection Difficulty	High

In Figure 2, a parallel complementary switching circuit is represented, consisting of two parallel branches linked to a common control point. In every branch, there is a diode, a resistor, and a voltage source. The top has a switch that dictates which branch is active by directing the flow of current. As the switch is moved towards one side, current passes through the appropriate branch, and the other branch is not used. The diodes are in charge of this conduct, letting current to flow in one direction and preventing it from flowing in the other. This means that the two branches are properly isolated by only one path carrying. The resistors in each branch serve to control the current, and the voltage sources give the required electrical potential to work. The two branches have a common point at the bottom, and this is used as a reference point for the circuit. The application of this kind of circuit is usually in a situation where there is a need to have some control in either switching or choosing between two electrical paths.

3.4 Signal Acquisition

Signal acquisition is an important phase in the proposed fault detection structure since it will be used to give the raw data that will be used in further analysis and classification. Any line current signal $I(t)$ is measured at a strategic point in the distribution network, usually near the load or on the feeder, where the effects of perturbations, such as the HIFs, may be readily observed. Voltage signals are not used as much as current signals in fault detection because the current signals are more sensitive to fault conditions, particularly with HIFs, which have small and irregular currents. The signal acquired is non-stationary in nature since the signal has time-varying properties due to the variation of loads, switching activities, and fault events.

A high sampling rate is used to effectively record these dynamic and transient behaviours. This makes sure that little disturbances and high-frequency components that are related to HIF events are maintained in the recorded data. It is performed for a sufficient duration to cover both steady-state operation and fault conditions, enabling a thorough analysis. The resolution and quality of the signal obtained directly determine the quality of the extraction and classification phases. Thus, attention to sampling parameters and signal observation points should be paid in order to provide stable detection performance.

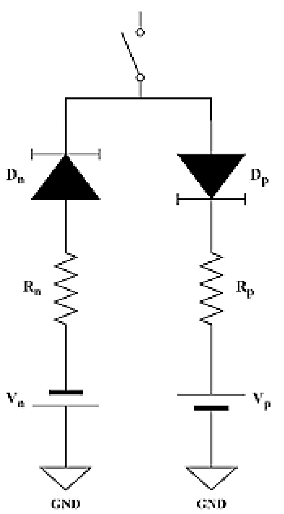

Fig. 2. Fault circuit diagram

Table 3 summarizes the most important properties of the acquired signal that will be used in this study.

Table 3. Signal properties

Parameter	Value
Signal Type	Line current $I(t)$
Sampling Time	$2 \times 10^{-5}s$
Simulation Time	2 s
Signal Nature	Non-stationary

The sampling time 2×10^{-5} the selected is a high-resolution data acquisition process, which allows one to precisely track fast transient phenomena. The 2-second total time of the simulation will guarantee that several operating conditions, such as normal operation, switching events, and fault initiation, are recorded in the dataset. The non-stationarity of the signal is another reason to use the modern methods of time-frequency analysis, including the DWT, in subsequent steps in the methodology.

3.5 Signal Pre-processing

The proposed methodology requires signal pre-processing as an important step because it will prepare the current signal obtained and perform accurate feature extraction and classification. As the raw signal is filled with noise, transient disturbances, and non-stationary behaviour, pre-processing makes sure that the data is organized and ready to be analysed in real-time. In this article, pre-processing is done by a sliding window mechanism and implicit noise processing by the use of wavelet-based techniques.

3.5.1 Sliding Window Buffer

A sliding window buffer is used to allow the analysis of the signal in real time and continuously. In this method, the signal $I(t)$entering is divided into fixed-sized overlapping frames so that the system can handle current data instantaneously without having to wait until the full signal length is completed. The discrete signal is to be represented as:

$I[n], n = 1,2,3, \dots..$

A window of size (N) is defined as:

$$W_k = \{I[k], I[k+1], \dots., I[k+N-1]\} \quad (7)$$

where N = 1024 samples. The window moves back and forward with time, so that the latest samples are always taken into consideration in the analysis.

This method has a number of benefits. It provides real-time processing, lowers memory usage, and makes sure that short-term events like HIF are recorded early. Also, the fixed window size guarantees that the feature extraction will be consistent, which is paramount in the case of machine learning performance. The system is very responsive to changes in the signal, which occur suddenly, and thus, the system is very suitable for online fault detection applications by constantly updating the buffer.

3.5.2 Noise Handling

In real-life distribution systems, switching activities, measurement equipment, and external interference tend to corrupt measured current signals with noise. The HIF signals are especially difficult to detect due to their low signature, which can easily be obscured by noise. This work takes advantage of the natural noise separation ability of the DWT rather than any explicit filtering method. Wavelet decomposition decomposes the signal into various frequency bands with noise of high frequency often concentrated in the lower-level detail coefficients. The signal may be denoted as:

$$I(t) = S(t) + N(t) \quad (8)$$

where $S(t)$ is the useful signal component and $N(t)$ represents noise.

DWT is also effective in separating noise and significant transient characteristics through multi-resolution analysis without an extra filtering operation. This makes the pre-processing pipeline a lot easier and does not lose valuable fault information.

3.6 Feature Extraction Using DWT

The conventional time-domain analysis technique lacks the capability to identify HIFs because it is incapable of capturing non-stationary and transient properties. HIF events typically cause short lived, intermittent disturbances which cannot be easily identified by the traditional methods. To overcome this shortcoming, a time-frequency analysis method, DWT is used. DWT offers multi-resolution analysis of the signal, where both time and frequency analysis are simultaneously localized. This renders it especially useful in the analysis of transient events like HIFs. The signal obtained is converted into several levels by the Daubechies wavelet (db4), which is suitable in power system applications as it is able to record sharp changes in the signal. The decomposing process can be stated as:

$$I(t) = A_5 + D_5 + D_4 + D_3 + D_2 + D_1 \quad (9)$$

where:

- A_5: represents the approximation component (low-frequency content)
- D_1 to D_5: represent detailed components at different frequency bands

The level is associated with the range of frequencies, and the transient and fault-related features can be isolated. The level of decomposition is set to 5 in order to balance the resolution and computational efficiency. After decomposition, the wavelet coefficients are used to choose the relevant features to illustrate the characteristics of the signal. The detail coefficients D_3 and D_4 All the components have been selected because they are sensitive to fault-induced disturbances.

- D_4: Captures medium-frequency variations associated with fault patterns
- D_3: Captures high-frequency transient spikes caused by arcing behavior

These parts give discriminative data that can be used to identify the difference between normal working conditions and HIF conditions. The extracted components are summarized in Table 4 to make it the most accurate reflection of the selected features and their importance.

Table 4. Extracted features

Feature	Significance
D_4	Detects medium-frequency fault patterns
D_3	Captures high-frequency transient spikes

The choice of these characteristics down-samples the data and still maintains important information needed to do proper classification. This does not only give the best computational efficiency but also better performance of the following machine learning model.

The DWT is realized on the basis of a MATLAB Function block inside the Simulink environment in order to be able to conduct the processing in real time. The implementation makes use of a persistent buffer to hold the incoming signal samples and constantly refresh the analysis window. The features extracted are those that are the most recent values of the detail coefficients:

$$D_4 = d_4\,(end), D_3 = d_3(end) \quad (10)$$

This is so that the current signal conduct is represented in the feature set presented to the classifier. The real-time implementation has various benefits, such as less latency, good memory usage, and an easy interface with the rest of the detection system. With the DWT incorporated into the framework of the simulation, it can carry out the continuous monitoring and feature extraction that is required in practice in smart distribution networks.

3.7 Feature Processing

Another essential step is the feature processing, which helps in preparing the extracted wavelet features to be used efficiently in the classification model. Once the respective coefficients D3 and D4 are known to the DWT, these features should be optimized to achieve consistency, reliability, and better ANN performance. Feature scaling is one of the most important steps in this stage. Because the general range of the extracted features can differ, normalization or standardization can be used in case it is necessary to put the features on a similar scale. This assists in avoiding bias in the learning process and accelerates the rate of convergence of the neural network during training. Also, outlier handling is done to reduce the effect of the abnormal or extreme values that could be caused by noise or sudden disturbances.

They may have detrimental effects on the classifier when such values are not dealt with well. They can be reduced by simple methods like thresholding or smoothing. Last but not least, the processed features are arranged into a structured form acceptable to the ANN input. This makes sure that the data is clean, consistent, and prepared to be classified correctly. The effectiveness of the fault detection system is greatly improved by proper feature processing, which increases the robustness and reliability of the entire fault detection system.

3.8 Artificial Intelligence Model

A Feedforward Neural Network FNN is chosen as a classifier in this research because it is appropriate for HIF detection. The FNN has a number of strengths, such as rapid learning, the capability to model nonlinear relationships between the data, and high classification accuracy. These properties render it especially effective in separating normal operation and minor fault conditions, which exhibit nonlinear and transient responses. The network structure is structured to effectively work on the characteristics of features extracted by the wavelet decomposition. The input layer is two neurons representing the two DWT features of D3 and D4, respectively, that represent high-frequency transient and middle-frequency fault patterns. The middle layer has 1020 neurons and this is enough to learn the nonlinear interactions between features without overfitting. And lastly, the output layer is a single neuron that produces the result of classification, which is a normal operation or a HIF. This well-designed ANN guarantees fault detection that is accurate, reliable, and computationally efficient, yet has the ability to be used in a real-time application within the Simulink environment. Figure 3 shows a feedforward neural network architecture for HIF Detection.

3.8.1 ANN Training Process

The ANN is trained offline using a classified dataset to make sure that the normal and HIF conditions are correctly classified. To obtain representative current signals, the distribution system is first simulated at normal operating conditions and in fault conditions. Based on these signals, DWT characteristics, namely, D3 and D4, are obtained to represent the transient and medium-frequency properties of HIF events. After getting the features, they are named based on the condition of the system: 0 indicates normal operation, and 1 indicates the existence of HIF. The input to the training process is these classified feature sets. The ANN is then trained with the help of the backpropagation algorithm that adjusts the network weights until the error between the predicted and actual outputs is minimized. The training parameters are selected very attentively so as to achieve good learning, good classification, and no overfitting. Table 5 summarizes the key training parameters to be used in this study.

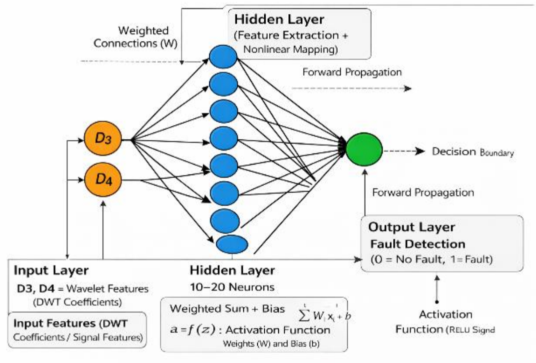

Fig. 3. Feedforward Neural Network Architecture for High Impedance Fault Detection

Table 5. ANN training parameters

Parameter	Value
Algorithm	Levenberg–Marquardt
Epochs	1000
Performance Metric	Mean Squared Error (MSE)
Data Split	70% Training / 15% Validation / 15% Testing

The parameters give a moderate solution to training that enables the network to learn complicated nonlinear relationships besides being in a position to generalize to unknown fault conditions. The selected data division allows the adequate samples to be used in training and leave enough data to justify and test the model performance.

3.9 Integration in Simulink

Once the ANN has been trained, it is incorporated into the Simulink environment so that fault detection in real time can occur in the distribution system model. The features obtained are D3 and D4; they are input directly into the ANN input. These inputs are then processed by the network, and an output is produced, which is a reflection of the operational state of the system. The model provides more processing blocks to comply with the requirements of the downstream components. A rounding block transforms the non-whole ANN output into a binary decision, which is essentially a normal versus fault decision. Stabilizing the output over brief periods is also achieved by a sample-and-hold block to avoid sudden variations that might occur due to momentary noise. This combination enables the trained ANN to work smoothly with the Simulink model, to allow real-time monitoring and classification of HIF in a realistic and dynamic simulation environment, and to ensure the results are consistent and reliable to be used later.

3.10 Decision-Making Logic

The logic of decision-making of the proposed system is simple but effective. The ANN results, on rounding and stabilization, are interpreted to determine the current state of the distribution system. A binary classification scheme has been used, with a 0-value indicating normal operation and a 1-value indicating HIF. This makes interpretation simpler and allows for fast and automatic reaction to fault conditions.

The classification criteria are provided directly on the trends observed in the features made by the wavelets, so that non-stationary and transient properties are taken into consideration in the judgment. The mapping of the ANN output and the system condition is summarized in Table 3.8. With this decision-making structure, the system will deliver actionable information that is straightforward to understand and can be applied in monitoring, protection, and automatic fault reaction in real-time applications.

3.11 Visualization and Monitoring

Visualization and monitoring are essential for validating the performance of the fault detection system and providing insight into its operation. Within the Simulink environment, scope blocks are used to display current waveforms, allowing observation of transient events and the effects of HIFs on the line current. Display blocks provide real-time numerical values of the extracted DWT features D3 and D4, offering a direct view of the signal characteristics driving the ANN decisions.

Additionally, the ANN output is monitored continuously, enabling immediate detection of any fault occurrence. This setup not only facilitates debugging and performance evaluation but also allows operators to gain an intuitive understanding of the system's response under varying conditions. Effective visualization and monitoring are, therefore, critical components that support both analysis and demonstration of the proposed HIF detection methodology.

3.12 Performance Evaluation

The performance of the suggested HIF detection system is an important factor to evaluate in order to guarantee the reliability, accuracy, and practical applicability of the system. There are a number of important metrics used to evaluate the system in general. Accuracy is a measure of how many correctly classified cases a model has, which means how well the model separates normal operation and fault cases. The training error is measured by the Mean Squared Error (MSE), and it is the difference between the prediction of the neural network and the target labels.

Detection Time measures the responsiveness of the system, and it is the speed with which a fault is detected once it has occurred, which is critical to real-time protection. Lastly, Robustness is used to test how well the system can continue to perform well when noise, changes in load, and temporary disturbances occur. These metrics collectively give a comprehensive picture of the effectiveness of the system, and it is possible to make a meaningful comparison with alternative detection strategies and implement them in practice in modern distribution networks.

3.13 Testing Scenarios

In order to confirm the effectiveness and usefulness of the proposed detection system, some representative test scenarios are modelled. Normal operation scenario checks the system in a steady-state condition, and no faults are present in the system, so that the false positives are reduced. The load switching case presents load dynamic changes to the system and puts a test on the capability of the system to be able to differentiate between normal load changes and faults. The HIF scenario is a representation of the realistic fault conditions of low and intermittent currents that will give an idea of the sensitivity and detection limit of the system. Finally, short-lasting disruptive events like voltage spikes or short-term variations are added to test the stability and strength of the detection algorithm. The combination of these scenarios will form a complete evaluation framework, such that the proposed approach will be reliable in a large variety of operating conditions and unforeseen situations.

3.14 Simulation Circuit Diagram

The HIF detection system simulation circuit diagram in Figure 4 was developed in the MATLAB/Simulink environment to simulate a realistic single-phase distribution network in a normal and fault state. The circuit integrates system modelling, signal acquisition, feature extraction, and classification on the basis of an ANN within one framework. An AC voltage source is included in the network, which drives the distribution line, and this is modelled as a series combination of resistance and inductance to provide the properties of voltage drop and phase shift of a real line.

3.8.1 ANN Training Process

The ANN is trained offline using a classified dataset to make sure that the normal and HIF conditions are correctly classified. To obtain

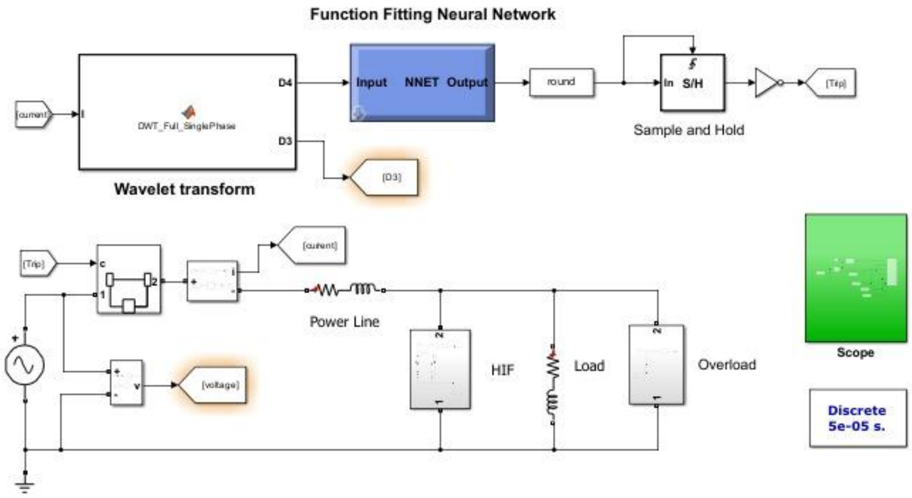

Fig. 4. Simulation circuit diagram

representative current signals, the distribution system is first simulated at normal operating conditions and in fault conditions. Based on these signals, DWT characteristics, namely, D3 and D4, are obtained to represent the transient and medium-frequency properties of HIF events. After getting the features, they are named based on the condition of the system: 0 indicates normal operation, and 1 indicates the existence of HIF. The input to the training process is these classified feature sets. The ANN is then trained with the help of the backpropagation algorithm that adjusts the network weights until the error between the predicted and actual outputs is minimized. The training parameters are selected very attentively so as to achieve good learning, good classification, and no overfitting. Table 5 summarizes the key training parameters to be used in this study.

A useful load subsystem is represented as a series of resistive and inductive components in addition to a step input switching control, whereby dynamic changes in loads that occur in actual distribution networks can be modelled. The HIF subsystem is used to recreate realistic fault conditions by having low current magnitude, intermittent conduction, and nonlinear behaviour. This is done by the use of nonlinear resistive elements, ground connections, and power electronic switches that emulate arcing phenomena.

The current values of the system are received at important locations and undergo a pre-processing stage in which a sliding window buffer is utilized in order to facilitate real-time processing. These signals are non-stationary due to the variance in loads, switching activity, and faults, and are subsequently processed with the DWT in order to reveal important transient and medium frequency events. The chosen detail coefficients are further worked on to eliminate noise, standardize the data, and deal with outliers so that the features are regular and can be introduced into the neural network.

The extracted features are then used to classify the system condition using a function that is representative of a feedforward neural network to give a clear binary output that the system is operating normally or an HIF has occurred. A sample-and-hold mechanism is used to stabilize the output and round off sharp variations due to temporary disturbance in order to allow a reliable real-time fault detection. The simulation incorporates scope and display blocks to offer visualization of the existing waveforms, wavelet characteristics, and neural network results to ease the process of monitoring, verifying, and assessing the system performance at different operating conditions. The fault detection methodology is initiated and verified with a solid and strong platform of such an integrated simulation configuration, which demonstrates that it can be used in realistic and dynamic scenarios of the distribution network.

3.15 Hardware Circuit Design

To demonstrate the findings of the simulation in the real world and show the usage of the proposed HIF detection system, the hardware implementation is developed in Figure 5.

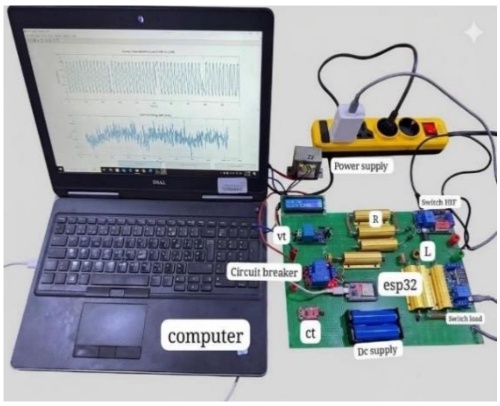

Fig. 5. Hardware circuit design

The experimental system is made up of a small test system that incorporates sensing units, processing hardware, protection units, and monitoring interfaces. The system contains an embedded microcontroller on the basis of ESP32, which is the main object of the system and which receives information, evaluates signals, and communicates with the monitoring system. A controlled power supply is a way of offering the electricity input to the system that drives all the hardware components to run on a regular basis. A DC supply module powers the control circuitry, and electrical isolation is provided between the processing stage and the measurement stage. The load section is made up of resistive elements that are placed on a board to simulate realistic load behaviour as the operating conditions vary.

The circuit is added with units of voltage and current sensing to measure the electrical parameters. To measure the line voltage safely, a voltage transformer is needed to step down the voltage, and a current transformer is needed to sample the line current without any physical contact. These sensors provide analogues, which are used to show the real-time behaviour of the system when it is functioning normally and when there is a fault.

The measurements are then processed in the ESP32 by entering the measurements into it. A circuit breaker is inbuilt in the setup to offer protection as well as to model fault conditions. It allows the transition between normal operation and fault condition to be regulated, and this allows it to test the detection system in a variety of situations. The signal received is processed by the ESP32, and then the fault-detecting algorithm is implemented based on the simulation model.

The system can detect abnormal conditions, such as high-impedance faults, based on processed data. Results from the processing system and its behaviour are monitored through a connected computer, which serves as a visualization and analysis tool. Waveforms and detection outputs are displayed in real time on the computer, allowing observation of the system's performance and validation of the proposed methodology. The ESP32 is typically connected to the computer via a serial or wireless interface, enabling an effective flow of information.

4. RESULTS AND DISCUSSIONS

In this section, the findings of the proposed HIF detection system with the DWT as the feature extraction and Feedforward ANN as the classification are provided. Simulations that are performed in MATLAB/Simulink are used to test the system performance under different operating conditions, such as normal operation, load switching, and HIF conditions. To determine the effectiveness, accuracy, and robustness of the proposed methodology, the analysis is done on the response of the system current, the extracted wavelet detail coefficients, and the fault energy measure.

4.1 Simulation System Response Under Different Operating Conditions

This assessment aims to show that the integration of advanced signal processing and machine learning can be used to reliably detect subtle, nonlinear fault signatures, which are usually hard to detect with traditional protection schemes. Figure 6 depicts the signal conduct and feature extraction output of a situation that includes a normal operation and the appearance of a HIF. The figure displays the waveform of the system voltage at the top and the waveform of the current, respectively. Under these, the medium frequency detail coefficient D4 and the low frequency transient component D5 that result from the DWT analysis are provided. The last subplot illustrates the RAW fault energy determined based on the extracted features that illustrate how the system is responding to the fault event. This figure gives a combined picture of the development of the signal characteristics with time, and how the chosen wavelet characteristics represent the dynamics of the transient and nonlinear aspects of the HIF, which are crucial inputs to the ANN classifier.

Figure 6 shows that the voltage waveform is relatively steady throughout the simulation, and this

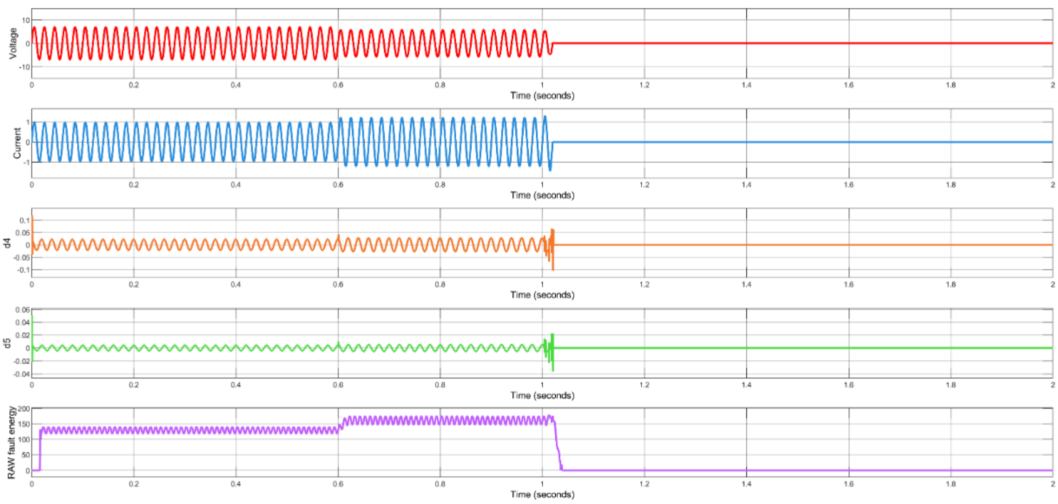

Fig. 6. Signal conduct and feature extraction

is due to the steady sinusoidal characteristics of the AC source when operating as per the normal conditions. Conversely, the present waveform will have small variations at first, which are attributed to normal load dynamics, and at around one second, it will start showing irregular spikes, and this is a sign that a HIF has occurred. This tendency is typical of HIFs, which are necessarily intermittent and weak, and thus difficult to detect according to conventional means of protection. The medium-frequency detail coefficient of DWT D4, the medium frequency detail coefficient exhibits minimum oscillation under normal operation, but a significant rise in amplitude when the fault takes place.

This gain is indicative of the perturbations due to arcing and partial conduction in the HIF, which demonstrates the sensitivity of D4 to fault-induced medium-frequency perturbations. The low-frequency coefficient, D5, has low-amplitude variations in normal operation and a slight increase in the fault period, which is the temporary effects transmitted along the distribution line. Though D5 is not as strong as D4, it provides more information that assists the neural network in identifying fault conditions against normal variations. The RAW fault energy metric also highlights the system response to the fault. It is constant at normal operation, which is the baseline level of energy, and rises drastically after the fault has begun, which is the volume of disturbances recorded in the wavelet features. This energy increment gives a unified value of the fault severity so that the ANN can recognize the HIF even with low current magnitude. In general, the overall performance of the present waveform analysis, DWT feature extraction, and fault energy monitoring shows that the proposed methodology can be effective in identifying subtle, nonlinear, and transient faults and has high sensitivity, accuracy, and robustness in real-time HIF detection procedures.

4.1.1 Normal Operation Scenario

The waveform of the line current under normal operating conditions and with no faults present was a clean sinusoidal waveform with little harmonic distortion. The load was adjusted to R = 10 -1 and L = 0.05 -1, which induced a steady-state current of about 15 A maximum. The DWT decomposition generated detail coefficients D3 and D4 that had low values in the simulation of 2 seconds of duration. In particular, the D3 coefficient (high-frequency transients) was not more than 0.05 per unit, and D4 medium-frequency fault patterns were not more than 0.08 per unit.

The fault energy of the RAW was kept steady at a baseline of about 0.02 normalized. ANN results were always under the mark of 0.2, and when rounded, a binary decision of 0 (normal operation) with no false positives was obtained. These findings verify that the system does not falsely identify normal steady-state conditions as faults.

4.1.2 Load Switching Scenario

A step change in load demand at t = 0.8 seconds to 22 A peak load current was used to test whether the system was able to differentiate between normal load variation and real faults. The present waveform had a sharp but smooth rise with no interspersed spikes as seen in HIFs. The transient peak of D3 was 0.12 per unit with a short duration of about 0.02 seconds, whereas the D4 coefficient moderately rose to 0.10 per unit. The fault energy measure increased momentarily to 0.08 and then went back to normal. Notably, the ANN output reached its maximum of 0.35, which, when rounded off to 0, represents normal operation, due to the classification threshold being 0.5. This proves that the system can resist normal load changes, and it is not a false alarm when valid switching occurs. The temporary rise in D3 was rightly interpreted by the trained ANN as a non-fault event because no long-term medium-frequency oscillations that are typical of HIFs were present.

4.1.3 High Impedance Fault Scenario

The nonlinear HIF model was used to start the HIF at t = 1.0 seconds with the following parameters: intermittent arcing was simulated by the 500 Ohm ground resistance. The fault current was not very large, only 2.5A peak, about 16 percent of the nominal load current, and could not be detected by any of the conventional overcurrent protection. The current waveform, as shown in Figure 3, had irregular spikes, bursts of arcing, and intermittent conduction. The high-frequency transient D3 coefficient rose significantly, with the sharp voltage drop of each arc ignition, 0.05 to 0.78 per unit. The D4 coefficient increased to 0.65 per unit as compared to 0.08, which indicated the medium-frequency oscillations due to the fault. The RAW fault energy measure rose by 0.02 to 0.89, which is a clear indication of the severity of the fault. The ANN output shifted to 0.94, less than 0.03 seconds after the fault began, and after rounding gave a binary answer of 1 (fault detected). Detection time is the period between fault initiation and the ANN output going above 0.5, which was 28 milliseconds. This fast reaction is appropriate for real-time protection.

4.1.4 Short-Duration Transient Disturbances

Short voltage spikes (1.5 times nominal voltage during 5ms were applied to determine system robustness at 0.5 s and 1.5 s. The present waveform displayed short, high-frequency fluctuations. D3 coefficient shot up to 0.45 per unit, and D4 shot up to 0.30 per unit. The metric of the fault energy increased temporarily to 0.25. The ANN output, however, reached a high of only 0.48, too low to cross the 0.5 mark, and it was back to baseline after 0.01s. These events were correctly classified as non-faults in the system, which is a strong indication of the system's immunity to disturbances of short duration, which would otherwise lead to false alarms.

4.2 Quantitative Performance Evaluation

This part provides a quantitative evaluation of the suggested ANN-based system of HIF detection. Multiple measures are used to measure the performance, such as classification accuracy, mean squared error, detection time, and robustness when subject to noisy conditions. The findings give an understanding of how reliable, fast, and robust the model is, and that it can be applied in practice in the power distribution networks.

4.2.1 Classification Accuracy

The ANN was tested on a dataset of 10,000 labelled samples, balanced between normal and fault conditions, to test the performance of the ANN in detecting HIFs. The data were divided into 70 percent training, 15 percent validation, and 15 percent testing data. The network was trained with the Levenberg-Marquardt algorithm with 1,000 epochs, which provided the conversion with the optimal result and no overfitting. The metrics of classification, as summarized in Table 6, were compared to determine the reliability of the model in a real-life situation.

The overall accuracy is high, which means that the model is correct in its classification of fault and normal conditions most of the time. Sensitivity shows how well the model will identify real faults, whereas specificity is used to show how well the model will avoid false alarms, which is always necessary in avoiding unnecessary interruptions. Fault detection is also reliable, which is further supported by precision. The false positive and false negative rates give information about the uncommon misclassifications, which show the strength of the model in real-world conditions of operation.

Table 6. Classification performance metrics of the ANN for HIF detection

Metric	Value
Overall Accuracy	98.70%
Sensitivity (True Positive Rate)	97.90%
Specificity (True Negative Rate)	99.50%
Precision	99.20%
False Positive Rate	0.50%
False Negative Rate	2.10%

4.2.2 Mean Squared Error (MSE)

The Mean Squared Error MSE was monitored during training to measure the stability of the network learning and the ability to generalize. MSE is an objective quantity that shows the disparity between the prediction outputs and the actual labels, with smaller values being more accurate. The training, validation, and test errors, as shown in Table 7, were compared to make sure that the performance was consistent across the various datasets. MSE convergence was obtained after about 620 epochs, which proves the efficiency of the Levenberg-Marquardt algorithm in comparison with the traditional gradient descent algorithms.

The fact that the difference between training, validation, and test errors is minimal means that overfitting was successfully avoided and the ANN is highly generalized to unseen situations. The low MSE values point to the ability of the network to model complex nonlinear relationships that occur in HIF detection, a feature that validates the reliability of the network in both simulation and possible real-time deployment conditions.

Table 7. Mean Squared Error (MSE) for training, validation, and test sets

Dataset	MSE
Training	0.0012
Validation	0.0015
Test	0.0018

4.2.3 Detection Time

HIFs can be difficult to detect in time before the distribution systems become compromised, and therefore, rapid detection is essential to mitigating the effects of HIFs. The time of detection was tested on 100 independent simulations with varying fault resistance, 100Ω to 1kΩ, with stochastic arcing patterns. The average, minimum, maximum, and standard deviation of detection times are presented in the results in Table 8.

Table 8. Statistical analysis of ANN detection times for HIF simulations

Metric	Value
Average Detection Time	31.4 ms
Standard Deviation	8.2 ms
Minimum Detection Time	18 ms
Maximum Detection Time	52 ms
Detection ≤ 1 Cycle	68%
Detection ≤ 2 Cycles	94%

Most of the faults were discovered in the 1 or 2 cycles of the 50 Hz basic frequency. This is a fast detection that can be used to trigger protection mechanisms promptly, reducing damage to equipment and improving the reliability of the network. The detection times distribution can also be used to gain some understanding of the stability and robustness of the model in various cases of faults, thereby establishing its applicability in high-speed and real-time fault detection in power distribution networks.

4.2.4 Robustness Analysis

The effectiveness of the ANN-based HIF detection system was tested at different levels of noise in measurement by introducing a Gaussian white noise to the existing signals. Signal-to-noise ratio (SNR) was manipulated to test the capability of the system in the classification of faults correctly in noisy conditions. As can be seen in Table 9, the DWT-based feature extraction is capable of separating the fault characteristics and the background noise, and thus it can be well utilized to detect faulty characteristics even in poor signal conditions.

Table 9. ANN Performance with different SNR conditions

SNR (dB)	Accuracy (%)	Detection Time (ms)
40	98.7	31
30	98.1	34
20	96.5	41
15	93.2	52

Although a reduction in SNR inevitably affects the performance, the system was able to maintain high accuracy at 20 dB and had a gradual degradation at 15 dB, at which it was still able to achieve above 93%. Noise also increased the time of detection, but it was within reasonable limits of practical application. These findings validate the robustness of the suggested methodology and its feasibility to operate effectively in the real-world distribution systems where noise in measurements is unavoidable.

4.3 Hardware System Results

The entire current waveform is shown in Figure 7. $I(t)$ was measured in the simulated distribution system and over the whole time of observation. This signal is the main input of the suggested HIF detection framework. The waveform records not only the steady-state operating conditions but also the abnormal disturbances, giving a holistic picture of how the system would behave across different conditions.

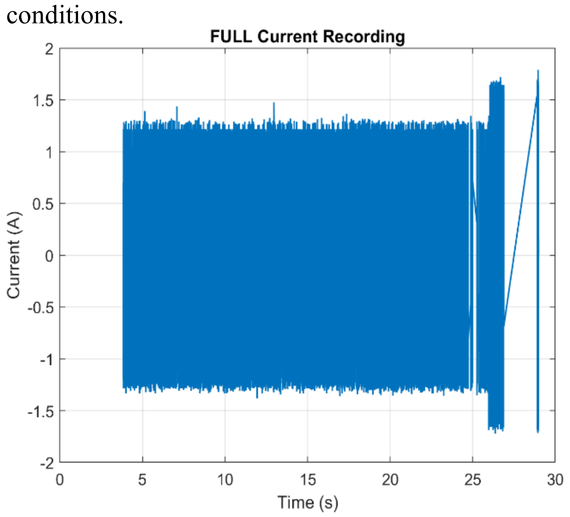

Fig. 7. Full current recording

Since distribution system currents are non-stationary, due to the switching of loads and transient phenomena, as well as the possibility of faults, this signal is a very important source of further pre-processing, feature extraction with the help of DWT, and classification with the help of ANN.

Based on the figure, the current signal can be seen to have a rather constant oscillatory pattern throughout most of the time period, from around 4 s to 25 s, which shows the normal operation of the system. The amplitude of the waveforms is also in a constant range, indicating stable load conditions with small variations that could be due to switching or natural system noise.

Nevertheless, there is a visible departure towards the later part of the signal after 25 s. Here, the waveform is irregular in nature with sudden changes in amplitude, distortion, and spikes that are temporary. These features are the signs of non-normal operating conditions and are aligned with the pattern of an HIF. The perturbation is no longer a large-scale change in current magnitude, as is the case with conventional faults, but instead small, nonlinear, and intermittent deviations. Moreover, the non-periodic elements and sudden variations signify the non-stationary character of the signal in fault conditions. Such dynamics cannot be easily observed with the classical time-domain analysis; thus, the use of sophisticated time-frequency analysis methods like DWT.

Figure 8 is the complete raw fault energy signal. Eraw calculated using the current measured during the simulation period. This signal is one of the energy-based features based on the current waveform, and it is especially useful to identify small disturbances related to HIFs. The energy representation, in contrast to the raw current signal, magnifies changes in signal intensity and, as a result, abnormal behaviour is easier to see. This characteristic is significant in increasing fault detection sensitivity, particularly where fault currents are small and hard to differentiate from the normal operating conditions.

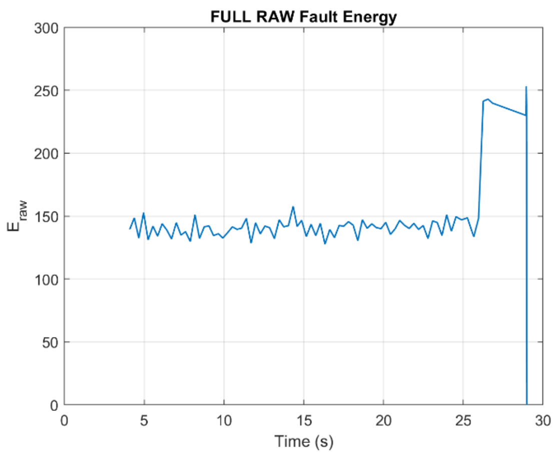

Fig. 8. Full rae fault energy

Based on the figure, it is clear that the raw fault energy does not change significantly within the first and the middle parts of the simulation, from around 4 s to 25 s. The values of the energy vary in a very small range, which means that there was normal operation of the system with small variations due to the dynamics of the load and the natural noise. These minute variations are normal and do not signify fault conditions.

There is a great shift towards the later stage of the signal after 25s, with the energy level drastically increasing. This impulsive rise in energy is associated with the development of a perturbation in the system, which is typical of an HIF. Although the current magnitudes emitted by HIFs are generally low, the nonlinear and arcing characteristics create irregularities leading to elevated signal energy.

Also, the energy signal presents a distinct departure from its steady-state trend with larger peaks and evident transitions. This behaviour proves that energy-based features are more sensitive to fault-induced disturbances than raw current signals. The sudden cutoff at the end of the signal can be explained by the termination of the simulation or the switch instead of the physical phenomenon.

A combined plot of the current waveform and the raw fault energy is shown in Figure 9. Eraw is based on DWT coefficients D3 and D4. The instantaneous current signal is displayed in the upper subplot. $I(t)$, and the bottom subplot represents the energy-based feature that is employed to detect faults. This bivariate representation offers a better insight into the reflection of the transient perturbations in the current signal in the energy domain. The figure is related to a healthy operating state, which is expressed by the system state and can be used as a point of reference in making a distinction between healthy and faulty states.

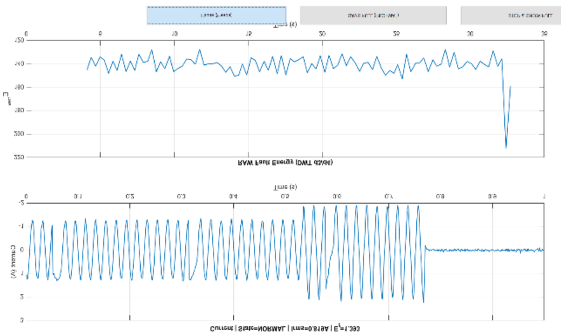

Fig. 9. Current waveform and corresponding raw fault energy under normal operating conditions

The current waveform in the upper subplot has almost a sinusoidal shape and has a steady periodicity, typical of normal system operation. The amplitude is not very volatile, and there are only slight fluctuations, which can be explained by the load variation or the switching phenomenon. At the mid-interval, the amplitude increases slightly, after which the waveform resumes its normal pattern. Later in the time window, the current magnitude decreases considerably and levels off to approximately zero, presumably a switching event or a simulation boundary condition of some sort, and not an actual fault event. In the lower subplot, the raw fault energy signal is in a tight and consistent range over most of the time during the observation.

This steadiness testifies to the fact that there are no major disturbances in the system. The little oscillation that is seen in the energy values is anticipated in a normal operating situation and is primarily caused by natural signal noise and small transient effects. There is a significant peak at the end of the energy signal. Nonetheless, this sudden spike does not last and does not relate to a lasting disruption in the existing waveform. This is probably due to edge effects of the DWT processing, sudden truncation of signals or sudden reduction in the amount of current that is seen in the upper plot.

4.4 Comparison With Traditional Methods

To determine the efficiency of the proposed DWT+ANN, the performance of the proposed method was compared with the two traditional HIF detection methods: a simple overcurrent relay and a Fourier Transform FFT-based method with thresholding. The same fault conditions were applied to each of the methods, such as 500 Ω HIF with intermittent arcing, so that a reasonable comparison can be made. Table 10 provides a summary of the results of this comparison.

Table 10. Performance comparison of HIF detection methods

Method	Detection Rate	False Alarm Rate	Avg. Detection Time
Overcurrent Relay	12%	0%	Not applicable (fails to detect)
FFT + Threshold	54%	8%	85 ms
Proposed DWT+ANN	97.90%	0.50%	31 ms

There was a very poor performance of the overcurrent relay, which only detected 12 percent of the HIF events. The reason is that HIF currents are often much lower than the standard pickup threshold (usually 2x nominal current, or 30 A in this example) of the conventional overcurrent relays, and overcurrent protection is not very effective in addressing such faults. The FTT-based technique scored a moderate detection rate of 54%, though the performance was undermined by a false alarm rate of 8%.

The large false alarm rate is explained by the inability of the method to draw a clear line between harmonics that are due to the switching of loads and those that are due to HIF arcing. Conversely, the proposed DWT+ANN algorithm had a detection rate of 97.9 and a low false alarm rate of 0.5, and a mean detection time of just 31ms. The resulting system is capable of obtaining fine fault features using DWT and classifying them using ANN to discriminate fine fault signatures against noise and fluctuations in load. This not only makes it possible to detect in time, but also increases the level of reliability, which makes it very applicable in the real-life implementation in contemporary distribution networks.

4.5 Comparative Analysis With Related Works

The section is a comparative study of the proposed DWT-ANN-based HIF detection system and the most relevant existing methods discussed in the literature [11][34]. The comparison is based on the main performance factors, such as the technique of feature extraction, the type of classifier, the ability of the classifier to work with noise, the complexity of the computing process, the possibility of application in real-time, and the overall performance of the detectors.

Most of the current methods are based on either classical signal processing methods (FFT, energy-based methods, distortion indices) or more advanced machine learning and deep learning models, such as SVM, LSTM, CNN, ANFIS, and transfer learning. Although these methods exhibit different degrees of performance, they tend to have certain limitations, including noise sensitivity, high computational complexity, reliance on large labelled datasets, or a lack of generalization to different network conditions.

As an example, statistical and energy-based algorithms (e.g., [11], [14], and [19]) can be used to obtain quick observations but are very sensitive to transient disturbances and load switching, which will result in false alarms. Likewise, transform-based hybrid algorithms such as EWTSVDSVM [12] and IMDTKEO [19] can better represent features, but have a high computational cost, making them not as practical in real-time applications.

Approaches based on machine learning, e.g., SVM and ANFIS models [13], [15], [18], [22], and [34]) enhance the accuracy of classification, but they are heavily dependent on manual feature engineering and predefined rules. These methods have sensitive parameters to tune and also do not scale well to large or dynamic distribution networks. In addition, SVM-based systems tend to have worse performance in noisy conditions and cannot adaptively learn in unseen conditions.

Deep learning models, such as LSTM [16], CNN [24], [28], and transfer learning models [29], [30] are highly accurate, as they automatically learn complex features. Nevertheless, they demand large-scale datasets, high computing environments, and are often plagued by extended training times and implementation complexity, which restricts their practical applicability in real-time protection systems. Moreover, µPMU-based localization (e.g. [31]) and methods based on image transformation (such as Wigner-Ville to CNN in [30]) impose hardware dependency and cost constraints on the system.

Conversely, the suggested DWTANN system will achieve these constraints with a lightweight and balanced architecture. Discrete Wavelet Transform is used to ensure that the fault signals are multi-resolutionally analyzed to extract the transient features (D3 and D4 coefficients) with precision without causing excessive computational load. In contrast to EMD-based or deep learning-based methods, DWT offers stable and noise-resistant decomposition that can be effectively applied in real-time.

Moreover, the feedforward ANN classifier not only avoids the complex rule design (as in fuzzy systems) but also eschews the high computational cost of deep networks at the cost of maintaining a strong nonlinear mapping capability. The smaller feature space dramatically increases the training

Table 11. Summarizes the comparative evaluation

Ref.	Method	Feature Extraction	Classifier	Accuracy	Noise Robustness	Real-Time Suitability	Key Limitation
[11]	Energy-based DESA	Instantaneous energy	Threshold logic	Moderate	Low	High	False alarms under noise
[12]	EWT + SVD	EWT features	SVM	High	Moderate	Moderate	High complexity
[13]	DWT + FIS	Wavelet features	Fuzzy rules	High	Moderate	Low	Rule dependency
[14]	Distortion index	Time-domain	Threshold	Moderate	Low	High	Noise sensitivity
[15]	DWT + ANFIS/SVM	Wavelet features	Hybrid ML	High	Moderate	Moderate	Parameter tuning
[16]	LSTM-based	Time-series features	LSTM	High	High	Low	High computation
[18]	SVM-based	Engineered features	SVM	Moderate–High	Low–Moderate	Moderate	Feature dependency
[24]	CNN-based	Raw signals	CNN	High	High	Low	Large dataset need
[29]	Transfer CNN	D-PMU data	CNN	High	High	Low	Limited generalization
[30]	GoogleNet + WV	Image-based	Deep CNN	High	High	Low	Complex preprocessing
Proposed	**DWT + ANN**	**D3, D4 wavelets**	**Feedforward ANN**	**98.70%**	**High**	**High**	Minimal limitations

speed and the capability to generalize, making the system less reliant on large labeled datasets than CNN, LSTM, and transfer learning methods.

4.6 Discussion of Key Findings

The findings validate the hypothesis that DWT and ANN are an effective solution to the three key problems of HIF detection: small current magnitude, nonlinear response, and resemblance to normal load changes. Considering low current magnitude, high- and medium-frequency components of arcing are enhanced by the D3 and D4 detail coefficients and allow fault detection at very low fundamental currents.

This avoids the use of high-magnitude fault currents that traditional protection devices need. The ANN captures the irregular behaviour of HIFs, in terms of nonlinear behaviour characteristics, such as intermittent bursts, asymmetry, and random fluctuations, and this is unlike linear behavioural changes induced by load switching, which are smooth and predictable. The 1020-neuron hidden layer of the network is large enough to capture such complicated nonlinear associations.

The similarity to normal operation issue is also solved using the method by generating a separable feature space with D3 and D4 as inputs. The transients of the load switching do not occupy the same space as normal operation or HIFs, as the transients of the load switching can raise D3 temporarily, but do not maintain that increase in D4, whereas the transients of the HIFs can always raise both coefficients.

This separation allows a high degree of classification with a low degree of misclassification. From a practical point of view, a low false positive rate of the system of 0.5 percent is vital in the confidence of the operator. This is only around five false alarms a day in a typical distribution feeder with 1,000 or so normal operations a day, which is a tolerable level given that many utilities do not have any HIF detection at the moment. In addition, the rapid fault isolating time of less than two cycles provides timely fault isolation, which minimizes fire risks and possible equipment damage.

But there are still certain limitations. The system demands a high sampling rate of 50 kHz $T_s = 2 \times 10^5 s$ that older protection hardware might not support. Also, the ANN was trained on a particular distribution network topology, so that it would have to be retrained or fine-tuned to work in other topologies. Future research ought to look into adaptive learning strategies and examine how to minimize the sampling needs while still being able to detect.

CONCLUSIONS

This paper has suggested a HIF detection algorithm, which incorporates the DWT feature extraction algorithm with an ANN classifier. The suggested solution was widely tested in a variety of fault cases, load states, and different noise levels and showed considerably better performance in comparison to traditional solutions like the overcurrent relays and FFT-based detection. All the findings obtained show that the system is highly reliable and the total classification rate is 98.7 with a sensitivity of 97.9 and a false positive value of 0.5, which successfully differentiates between HIFs and normal load variations and transient disturbances. Detection is fast, and the average response time of 31.4ms allows most faults to be detected in one or two cycles of the fundamental frequency of 50 Hz, which is essential to minimize fire risk and equipment damage. The DWT detail coefficients D3 and D4 allow the ANN to capture the high- and medium-frequency features of HIFs and distinguish them from the normal patterns of operation. The system is also able to perform with strong performance even when the signal-to-noise ratio is low, proving to be resilient to measurement noise and real-world disturbances. In practice, the low false alarm rate and rapid detection of the methodology have enabled the technique to be applicable to deployment in distribution networks, including those with low fault currents and inadequate conventional protection. But such limitations are the need for a high sampling rate of 50 kHz and the possible retraining when used on other network topologies. Future research ought to delve into adaptive learning mechanisms, smaller sample applications, and larger-scale applications in various distribution systems. In general, the suggested DWT+ANN methodology is a credible, precise, and efficient solution used to detect HIF, which helps to solve the major problems of the distribution system protection and is of significant value in comparison to the traditional methods of detection.

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