International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V71I8P229

Volume 71 Issue 8, 333-347, August 2023

Review Article

Intelligent Fault Detection Technique for a Distribution Network with Distributed Generation Sources - Status Review

Sipho P Lafleni[1], Mbuyu Sumbwanyambe[2] , Tlotlollo S Hlalele[3]

[1,2,3]*Department of Electrical Engineering, University of South Africa, Johannesburg, South Africa.*

[1]*Corresponding Author : 54337852@mylife.unisa.ac.za*

Received: 03 March 2023 Revised: 12 May 2023 Accepted: 07 August 2023 Published: 15 August 2023

Abstract *- Distributed generation (DG) are gaining popularity in power systems due to its environmental and economic benefit versus other technologies. Despite the benefits of DG and their operation, discussions need to be done on the potential problems and impact of the increased penetration when they get integrated into the grid. This discussion is vital for distribution engineers and designers as studies have shown that the application of local DG into distribution grids has consequences for the protection system and protection issues concerning distributed generation. The primary purpose of power system protection is to ensure the safe operation of power systems hence the safety of the people and types of equipment. This review paper aims to explore the different fault detection techniques and their evolution in implementation over the past three decades. This review study is required to investigate the different algorithms implemented for distribution network faults detection methods in power systems networks and micro-grid networks.*

Keywords *- Distribution generation, Protection system, Fault detection, Algorithms, Distribution network.*

1. Introduction

Electrical protection systems in modern DN are becoming progressively multi-functional and intricate because of the rapid advancement of both technology and scientific knowledge. The capacity to identify and diagnose faults is one of the most significant capabilities required for the deployment of current protection systems in power systems. While designing and maintaining a system, the fault diagnosis of the protection system quickly becomes vital. Protection system fault diagnostics use operational data to detect, isolate, and identify faults. In order to properly diagnose a problem, there are three primary steps to take: (1) determining whether or if the equipment is normal; (2) identifying the impending breakdown and its root cause; and (3) forecasting fault development trends. Because of this, fault diagnosis can simply be thought of as a challenge involving pattern recognition in relation to the condition of spinning machinery. Artificial intelligence (AI), which is a potent tool for pattern identification, has gained a considerable deal of attention from a large number of researchers and shows promise in applications relating to the recognition of faults in the electrical distribution network. Given the diversity and volume of the reaction signals, it is almost impossible to recognize fault patterns straightforwardly. Because of this, the fundamental components of a typical fault diagnostic system typically include the following: data processing (feature extraction) and fault detection [2-4]. The pre-processing of input patterns by feature extraction algorithms is the foundation on which the vast majority of common intelligent fault diagnosis systems are constructed[5]. This pre-processing is done with the intention of allowing input patterns to be represented by low-dimensional feature vectors, which makes it simpler to match and compare [6].

Using condition indicators derived from system data, a decision model is trained to assess test data to establish the system's present state, allowing for the development of an algorithm for problem detection and diagnosis. Several intelligence (AI) tools and techniques have been employed, including approaches based on classification, statistical learning, probability, and more conventional optimization (mathematical and convex).[7]. Fault detection of DN has made extensive use of classifiers and statistical learning methods like a k-nearest neighbor algorithm [8], Fuzzy Logic, wavelet transform[9, 10], support vector machine (SVM) [11], and artificial neural network (ANN)[12]. Fault diagnosis is another area where deep learning methods have recently been employed [13].

This work intends to provide a thorough review of the three decades to the most up-to-date findings in the study and development of AI approaches to fault detection in DN with DGs from both theoretical and practical perspectives. This paper's remaining sections are structured as follows. The fundamental principle behind various AI approaches is presented in Section 2. In Section 3, we will look at how artificial intelligence has been used in the field of malfunction diagnostics for DN with and without DGs in the last three decades until today. In Section 4, we talk about discussion, constraints, and emerging trends. Section 5 offers some last thoughts on the study's continuums and evolution.

2. First Literature Review

2.1. Distributed Generation

In the early years of the electrical industry, distributed generation—small-scale energy generating—was used to provide electricity to customers close to the generation plant. Nowadays, it is recognized that each utility's approach to protecting the distribution network relies on the issue and their preferred method of solving it. Utility protection plans vary according to operational needs; thus, connecting DG units to the grid is still important without jeopardizing supply dependability, safety, or quality. The issue is that because "grids are currently planned in a top-down way [14] with predetermined power flows," the majority of electrical networks were not built to manage distribution generation. Depending on the design, power can often flow unidirectional from higher voltage levels to lower voltage levels but bidirectional within a voltage level [14]. To maximize the reliability and availability of the electricity being delivered and to always work safely, the protective system must be adequately selective [15]. The grid's short-circuit power and current path are improved by adding DG. The degree of DG penetration and the kind of interface devices substantially influence the protection system. The main goal of protection coordination is to establish selectivity or keep healthy parts apart from faulty parts to maintain stability [16]. Several articles demonstrate how DG safeguards distribution networks.

Fault conditions in the DN can occur due to natural commotion such as lighting strikes, Tornados and hurricanes, but situations like falling trees onto the line or even Human incidences such as crashing aero-planes or vehicle collisions on supporting structures. These conditions can create the following types of unsymmetrical or asymmetrical faults, which are namely single line to ground (L-G), line to line (L-L), double line to ground (L-L-G) and double line to ground (LL-G) faults.

3. Theory Background of AI Fault Detection Methods

Recent history had shown fast developments of faults techniques in diagnosis, detection and classification due to growth in signal processing of hardware, artificial intelligence, global position system and communication, which had opened opportunities to many researchers in the study shortfall of the traditional DN when interconnected to the grid. Due to the difficulty in data acquisition, intelligent electronic devices are deployed instead of traditional measuring, like current transformers and voltage transformers, to obtain large data pools. Big data makes it possible for researchers to develop modern and intelligent fault detection techniques.

3.1. Logic Flow

Suppose no machine learning base algorithms are being applied. In that case, logic flow-based algorithms at component levels have been proposed in [17] using combinational logic and fuzzy logic method for fault detection. For realistic conditions, [18] has proposed a performance evaluation fault detection system based on data from the IEEE 9 bus model with a three-step logic flow. In [19], data is extracted from two ends of a transmission line with three-phase faults implementation done in the detection, classification and location steps of the fault. In cases whereby a HIF detection method for distribution systems is implemented, [20] describes in detail the logic flow to solve HIF systems.

Even though in the period of 2000-2010, grid diversity of energy mix was seen as a futurist implementation and authors such as [21] proposed fault detection techniques with measurement parameters that can be obtained using current transformers. The opportunities of integrating Wireless Sensor Networks in Smart Grid as a tool in the logic flow process of fault detection has been prominent as the traditional technology had been seen as a disadvantage due to their cost when required in a smart grid [22]; summarizes the opportunities and challenges in wireless communication, when it is described due to the requirement of a robust data transmission method to function. In [23] conclusion is discussed that without a robust data transmission infrastructure, the distribution network of the Smart Grid of the future cannot operate. The Smart Grid has the capacity to accommodate significant amounts of DG. However, new DG connectivity standards will be required. Furthermore, with the use of data transmission and distributed processing, DGs of any scale may be intelligently monitored, controlled, and assessed.

3.2. Fuzzy Logic

Fuzzy logic is an effective modelling technique for regulating intricate, non-linear systems. In application, which implements artificial intelligence (AI) systems, fuzzy logic imitates human reasoning and cognition. Fuzzy logic is a method of making decisions that are based on a developed rule base with a number of contradictory and gray factors. It is developed from ideas that recognize and use the gray area between two extremes and is determined by logical equations rather than complicated differential equations.[24]. An explanation is given for simplicity as in Fig 1, which shows a form of intelligent fault detection process cycle.

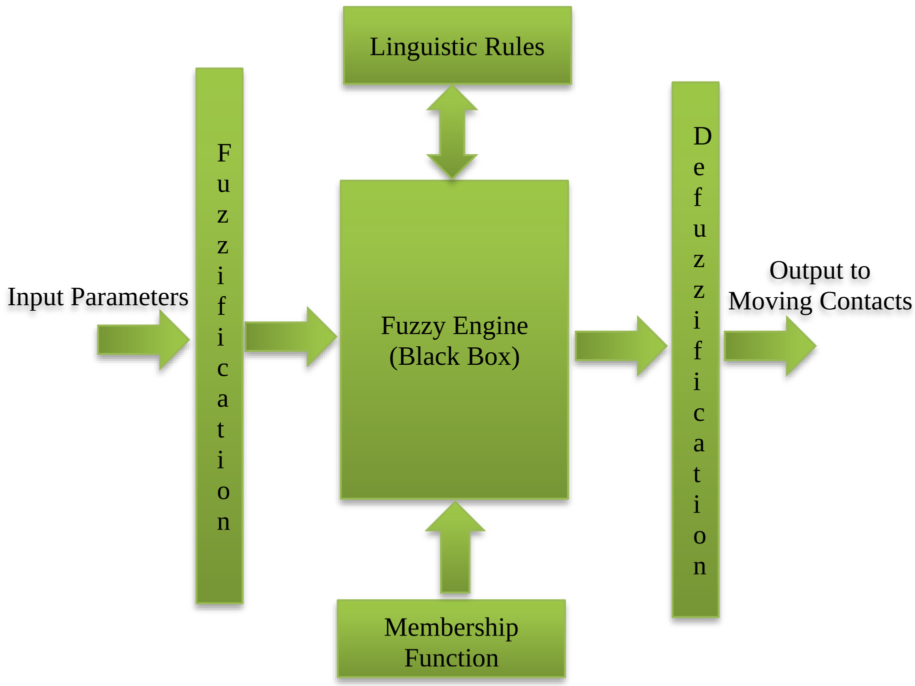

Fig. 1 Fuzzy logic intelligent fault detection process[25]

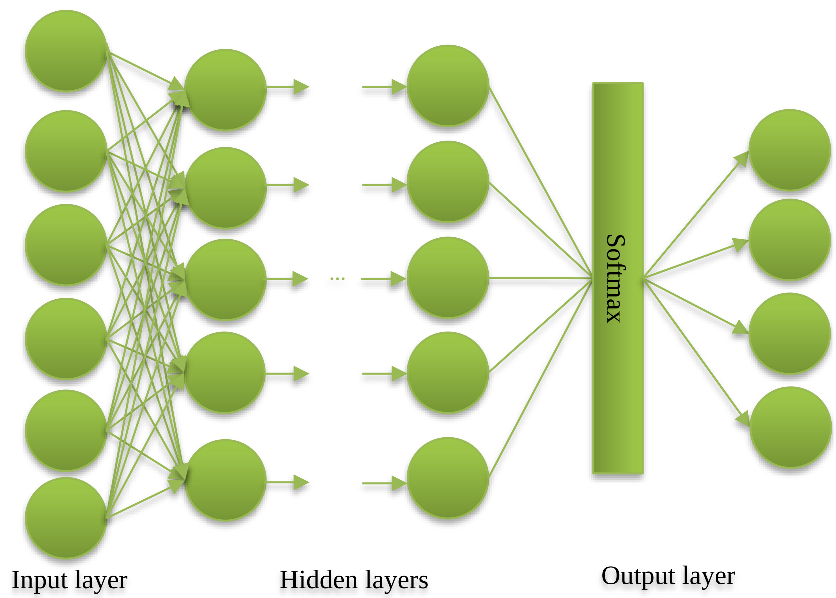

Fig. 2 The typical topology of a neural network for doing classification[26]

3.3. Artificial Neural Network

One of the clever methods employed for defect detection in distribution systems is using artificial neural networks (ANNs). Due to ANN's pattern recognition abilities, errors may be easily pinpointed. However, in order to find the problem in the relationship between the input data and the predicted output, they require training. A neural network that is used for classification problems is made up of four layers: the input layer, hidden layer, softmax layer, and output layer, the voltage and current of the three-phase neural network are trained using the input values to a processing unit, which in our instance are six inputs. The three phases, A, B, and C, of the three-phase distribution system line voltages and currents make up three of the four total outputs of the neural network in the distribution line, with the fourth being ground. The pattern usage for the pattern recognition technique is a procedure for figuring out abnormal and normal conditions in the electrical power distribution system that is based on the function of brain and nervous system studies, as shown in Figure 2.

Feature scaling of the following kind can be used to standardize input data prior to being transmitted into the input layer, as is common practice for data-driven fault diagnostic techniques, ensuring that all values fall within the range [26]:

$$X' = \frac{x - min(x)}{max(x) - min(x)} \tag{1}$$

The following nonlinear transformations equation is performed on the input data in the hidden layers to produce increasingly refined representations (features):

$$h_1 = \sigma(\omega_{1x} + b_1) \tag{2}$$

$$h_l = \sigma(\omega_l h_l + b_l), l = \{2 \dots d \tag{3}$$

Where X ϵ R^{n_x} is the input vector h_l ϵ R^{nhl} is the hidden representation, W_l ϵ $R^{nhl\ X\ nhl-1}$ is the weight matrix, b_l ϵ R^{nhl} is the bias vector and d is the number of hidden layers. It is important to remember that n_{hl} (the amount of neurons in each hidden layer) with d are hyperparameters whose values must be established before neural networks can be trained. To make the aforementioned nonlinear transformation is used in this work, and the rectified linear unit (ReLU), which is defined as:

$$\sigma(x) = max(0, x) \tag{4}$$

The output of the last hidden layer undergoes the transformation depicted in h_1 by equation (2) without the activation function:

$$h_s = \omega_s h_d + b_s \tag{5}$$

In addition, the softmax layer uses the following softmax function to determine the values of each output neuron.

$$y_j = \frac{esp(h_s, j)}{\sum_{j=1}^{n_{hs}} esp(h_s, j)} \tag{6}$$

3.4. Support Vector Machine (SVM)

The SVM class of learning machines has effectively solved Pattern Recognition (PR) issues [28]. Maximizing the margin in classification problems is equivalent to a conventional framework; minimization of the weight vector provides better control over the problem's generalization. The answer is found in the form of a sparse set of support vectors. Whether the separation surface is linear or non-linear, it must be realized in the input space for classification to take place. Linear combinations of kernels related to Support Vectors may be used to define the separation function in Support Vector classification, as seen here:

$$f(x) = \sum_{zj \in s} \alpha_j y_j\, k(x_j, x) + b \tag{7}$$

Training patterns are denoted by x_i class labels by y_i ϵ {+1, -1}} and the collection of Support Vectors is indicated by S. Therefore, the dual formulation results in:

$$\min_{0 \le \alpha : \le c} = \sum_{ij} \alpha_j Q_{ij} \alpha_j - \sum_i \alpha_i + b + \sum_i y_i \alpha_i \tag{8}$$

Where a_i the respective coefficients, b is an offset matrix, and a_i are related coefficients. In the inseparable situation, the symmetric positive definite kernel is denoted as $Q_1 = y_1 y_j \mathrm{K}\ (x_i, x_j)$ Karush-Kuhn-Tucker (KKT) dual conditions can be written as;

$$g_i = \frac{\partial w}{\partial w} = \sum_i Q_{ij}\ \alpha_j + \boldsymbol{y}_i b - 1 = y_i f(x_i) - 1 \tag{9}$$

$$\frac{\partial w}{\partial w} = \sum_i y_{ij}\ a_j = 0 \tag{10}$$

This partitions the training set into S, the support vector set (0<a_i<C, g_i=0), E the error set (a_i=C, g_i<0) and R the well-classified set (a_i=0, g_i>0)

3.5. Discrete Wavelet Transform (DWT)

To decompose a signal into a collection of "wavelet," basis functions over time and frequency, the wavelet transform (WT) is used [29]. For identifying different frequency components in a signal, the wavelet transform makes use of the growth and shrinkage of basic functions. By using a wavelet transform, a signal may be broken down into its component frequencies. This is because the mother wavelet is the basis function, and it makes use of the dilation and translation characteristic. Here, we retrieve the signal's low-frequency component by using wide windows, whereas small windows reflect discontinuities.

$$Wf(m, n) = 2^{m/2} \int f(t) \varphi(2^{-m} t - n) dt \tag{11}$$

To where m corresponds to the frequency and n to the duration. The typical formula for a wavelet series is

$$f(t) = \sum_{k=\infty}^{k=\infty} c_k \emptyset(t - k) + \sum_{k=-\infty}^{\infty} d_{ik}\, \emptyset(2^i t - k) \tag{12}$$

$$\emptyset(x) = \sqrt{2} \sum_n h_0\ \Phi\ (2x - n) \tag{13}$$

Where h_1 the high pass is the filter coefficient, and Φ(x) is the wavelet function.

4. Three-Decade Span of AI in Power System Protection

4.1. Artificial Neural Network

4.1.1. Artificial Neural Network: 2000-2009

ANN is one of the earliest AI approaches; ANNs have been used in the field of power engineering research for quite some time. This type of model in fault detection and diagnosis continues to be revolutionary in its outcome, and verification of its application is mentioned by [30, 31]. A study done by [32] suggests an innovative technique for identifying and categorizing transmission-line faults using oscillography data. In [33], the oscillography data is applied as instantaneous current/voltage samples, in which artificial neural networks have been fed as systems inputs. Neural networks and GAs have issues with training, making it challenging to implement in a practical setting, according to [34], in which the author further offered a solution of Bayesian networks-based method of approach for power systems fault diagnosis. The Bayesian network-based method showed improved results compared to previous approaches, as illustrated in [35] and [36]. An ANN for effective problem diagnosis in a deregulated distribution system with high impedance faults (HIF) is suggested in the research[37]. The operation, control, and protection of the system are all affected by new difficulties brought on by this new environment.

4.1.2. Artificial Neural Network: 2010-2019

Artificial Neural Networks (ANNs) are used as the identification technique of choice for defect detection in PV arrays. Its operation and definition are written by [38], also defining its methodology in its operation. In terms of power system engineering, [39] shows that the NN architecture of a neural network is used to identify faults in a power transmission line system. Its ultimate goal is to provide a comprehensive architecture for distance protection, with each zone separated by neural networks. The faults being tested are namely single phase, two phases, and both phases to the ground are taken into account.

The author, through various examples, explains in [40] an innovative approach to identifying faulty sections and pinpointing faults in power system distribution networks using a hybrid of Discrete Wavelet Transform (DWT) and artificial neural networks (ANN).

There have been studies have also been done on Fault Detection and Localization in DC Microgrids Using Artificial Neural Networks, as the article in [41] introduces an innovative technique that uses artificial neural networks (ANNs) for fault detection and localization in a micro-grid with a low voltage DC bus. It further states that a more reliable DC microgrid can be attained with the suggested technique applied in [41] thanks to its ability to rapidly detect problems on the DC bus and isolate them without de-energizing the entire system. The neural network is trained using real-world DC bus short circuit examples to guarantee its accuracy. The use of online condition monitoring and protection technology is necessary due to difficulties in discovering and detecting high impedance faults in power distribution networks, it has significantly impacted positively, and this is especially true in systems that make use of dispersed generation, this is true and shown in [42] where a technique is offered for locating and identifying HIFs in DG-based distribution systems that are nonlinear in its application. To further show a variety of methodologies in [43], an investigation into the effects, on fault detection, of using a variety of neural network structures and types of data inputs. By using an artificial neural network, an intelligent fault classification technique is being built [44] with the isolation model that artificial intelligence and advanced signal processing are based on.

4.1.3. Artificial Intelligent 2020-2023

Recent presentations have shown how models of artificial intelligence (AI) can be used to devise answers to problems with adaptive system protection, and authors like [45] evaluate the approach in detection and classification for fault conditions. It is important to highlight that in order to train and test AI models, these methods make use of the available data. In validating the statement, Authors such as [46] use DNNs, or deep neural networks, a type of artificial neural network (ANN) made up of numerous hidden layers of neurons positioned between the inputs and outputs. An intelligent fault detection method is described in Reference [47], which offers quick information on the fault's kind, phase, and position for the sake of MG protection. The defect detector used in the solution is developed with the help of the discrete wavelet transform and deep neural networks (NNs).

4.2. Support Vector Machine

4.2.1. Support Vector Machine: 2000-2009

The strategy based on artificial neural networks and support vector machines for finding defects in radial distribution systems is described by [48], with SVM being clearly defined. Studies conducted after big power outages worldwide found that faults in the protection system were to blame or miss-co-ordination was another cause. This has highlighted the requirement for further post-fault and remedial research utilizing intelligent/knowledge-based systems to enhance protective coordination. After a fault in a surrounding line that feeds into the same substation can be more accurately diagnosed using this method. The possible benefit includes enhanced fault monitoring and diagnostics for safer power system operation, which has been studied successfully [49]. By giving attention to technology development with a viewpoint of preventing catastrophe before any breakdown, [50] employs the moment approach and statistical aspects of thermal pictures to identify malfunctions in electrical equipment. In which a thermography-based technique is applied for intelligent defect identification in electrical equipment, which has been presented using the support vector machine (SVM) as a classifier and the Zernike moment as an image feature. The combination between SVM and other Intelligent techniques is also possible to employ in fault detection and classification, as demonstrated by [48] for radial distribution systems. This [51] research uses a support vector machine (SVM) to detect the faulty line from a substation and its distance. SVMs using RBF kernels may learn the link between voltages and currents, as well as fault source and location. Although measurements recorded during a failure in actual power systems are limited, we find that they give useful information on substation status and fault location. This article explains how to process them to construct an effective fault diagnostic system.

4.2.2. Support Vector Machine: 2010-2019

In this decade, SVM is an intelligent tool for locating the section of faulty lines; SVM is a modern machine learning technique built on the foundation of statistical learning theory. In [52, 123], the findings show that the proposed strategy may be put to use in the real world for smart grid distribution fault diagnosis. It is shown in [54] that such intelligent systems rely fundamentally on knowledge discovery in data techniques, which can significantly boost their performance. Even though the SVM detection method has shown great performance capability in power applications systems different to DN with DGs, studies such as [55] demonstrate a possibility of integrating these detection methods with power systems networks like transmission lines. Using a support vector machine (SVM) classifier and Wavelet Transformation, the research [56] introduces a technique for fault classification in power systems. In[52], the author, in this paper, describes a malfunction identification and localization method for DG-penetrated power distribution networks. The proposed method uses support vector machines to aid the fault diagnostic process. At this stage of protection of the electrical grid in modern DN, the limitations of conventional protection schemes are still present, and hence authors like [57, 58] write about an approach how to Evaluate the Performance of the Support Vector Machine (SVM) Approach for Distributed Generation Fault Detection. Then authors like [59] demonstrate or introduce a unique pattern recognition-based technique for identifying high-impedance failures (HIFs) in distribution networks has been developed in which HIFs include, but are not limited to, damaged conductors and arcs. Many methods have been presented for HIF fault in the past, such as those presented in [60] and showed many disadvantages, but in the 2010-2020 era, authors such as [61] had presented ways to counter the disadvantage in [59, 60].

Suggested that a technique be developed that makes use of an algorithm that is based on machine learning (ML), namely support vector machine (SVM) [62]. The proposed SVM-based approach is designed to solve the important challenge of discriminating between islanding and grid fault occurrences. This allows the system to achieve better precision in islanding identification while simultaneously detecting grid failures more realistically. In this article [63], a technology known as Modified Multi-Class Support Vector Machines (MMC-SVM) is created to concurrently detect and classify several forms of open-circuit failures that might occur in power distribution systems. [64] developed a unique strategy based on PSO methods designed to optimize input characteristics concurrently and SVM characteristics to classify the various fault types seen in the distribution network. Single phase-to-ground faults (AG, BG, and CG), line-to-line faults (AB, AC, and BC), double line-to-ground faults (ABG, ACG, and BCG), and three-phase short-circuit faults (ABC) are only a few of the ten categories into which these fault types can be divided.

4.2.3. Support Vector Machine 2020-2023

A method is proposed by [65] in which single-line, double-line, and triple-line HIFs were detected using the suggested technique in a typical distributed generating system. While faults occur, the other phases' current signals are studied to see how they change. [66] evaluate numerous intelligent fault detection techniques in networks with DGs integrated with advantages and disadvantages being evaluated. The artificial intelligent techniques that can be implemented for such diversified networks are Artificial Neural Network (ANN), Support Vector Machine (SVM), Fuzzy Logic, Genetic Algorithm (GA), and matching method are all examples of machine learning techniques. In a Distribution Network (DN), you can obtain another class of faults which is called (HIF) which can be difficult to deal with due to the low value of the current since it is usually not detected by accustomed overcurrent-based protection devices[67].

4.3. Wavelet Transform

4.3.1. Wavelet Transform 2000-2009

[68] Can define knowledge of discrete wavelet transformation. In power system applications, WT, a strong new mathematical tool, may be utilized as a quick and very effective alternative to the accustomed Fourier transform for the purpose of analyzing the waveforms of power system transients[69]. Issues in the distribution system are extremely difficult to circumvent, and a fault diagnostic technique for power distribution systems is proposed in the study of [70] for fault detection and classification procedure. In several published papers, many papers have also introduced the wavelet transform as a useful technique for analyzing disturbances in power systems. In addition, [71] proposes a method based on the dyadic wavelet transform as a method for locating faults in transmission lines. The coefficient of discrete approximation of the dyadic wavelet transform with the Haar wavelet is used as an index in this method's description of transmission line fault detection and faulted-phase selection [122]. Application of wavelet in power systems has shown gradual growth in the number of publications as shown by [73] by indication of the percentage of publications that have been made in each field; also, it has been noticeable that the field of protection and the field of

power quality are the two fields that have produced the most works.

Since dispersed generators are linked to a low or medium-voltage distribution system [74] was hypothesized that a method that would use a network of cooperative relay agents would be the most effective way to find and isolate problematic portions in a Distribution network that utilized distributed generators. The study in [75] proposes decentralized multi-agent protection for the DG systems capable of HIF detection, fault identification, and coordinate DG system protection systems. In condition monitor units, the new digital protection schemes are relay agents that can seek information from other agents, interact with equipment, and protect autonomously and cooperatively. The wavelet packet analysis extracted fault characteristics in multi-agent network protection to prevent normal load current effects.

Although underground cables are more reliable than overhead lines, in [76], a method is presented for finding faults in underground distribution systems. Discrete Wavelet Transform (DWT), based on a traveling wave, is used to find the high-frequency parts of the underground distribution system and figure out where the problems are. The study in [77] describes a new technique for detecting phase-to-ground faults in main distribution networks. This paper provides a unique fault detection technique for imbalanced distribution systems.

4.3.2. Wavelet Transform 2010-2019

The current practice is to disconnect DG units as soon as feasible to allow traditional protection devices like fuses, sectionalizes, and reclosers to work correctly to avoid difficulties with the protection system. A problem detection system and a directed comparison scheme have been developed using high-frequency transient signals. [78], It utilizes the DWT based on the Daubechies wavelet function to extract differentiating properties from fault-generated high-frequency current transient signals. The work proposed by [79] shows a protective strategy for identifying faults with and without DGs based on Wavelet Transforms. Each bus implements this, as faults are simulated, and the fault currents are analysed with Haar wavelet to yield single-level decomposition detail coefficients. The method for fault categorization stated by [80] consists of two distinct logics, depending on whether or not the fault includes ground. This is critical, as the features of a defect affecting the ground differ significantly from those of a fault that does not involve the ground, which must be addressed independently. Other authors, such as [10,81-85], present a precise method for fault detection and classification of fault kinds and faulted phase(s) in distribution networks.

This study by the author [86] describes a power distribution network short circuit fault feature extraction, detection, and classification method. Transient fault currents measured at the network source terminal are DWT-analyzed to extract characteristics. With the IEEE 13-Bus and IEEE 34-Bus systems used as a proven platform, a data mining-driven solution based on discrete wavelet transform (DWT) is proposed for high impedance fault (HIF) identification in active distribution networks [87]. Through the breakdown of two fault current signal cycles and the extraction of statistical features from DWT detail coefficients at each level, DWT extracts time-frequency characteristics. Correlation coefficients replace fault signal decomposition. This research analyses series compensated long transmission line fault detection and classification using artificial neural networks, and wavelet transform[88]. The suggested method finds the ground current signal by sampling three-phase current signals one cycle before fault and atleast a single cycle post fault.

4.3.3. Wavelet Transform 2020-2023

Establishing strategies that could deal with numerous unpredictable or complex scenarios in the diversified grid and load demand, renewable energy production, and fault information ambiguity has become a challenge to overcome in distribution network protection systems. With the help of machine learning instruments and signal processing strategies, this article by [89] outlines a method for defect identification in the dynamic distribution grid. Signal processing methods include the Hilbert-Huang transform (HHT) and the discrete wavelet transform (DWT) while machine-learning tools include feedforward neural networks (FFNN). Author[90] uses Advanced signal processing and machine learning technologies which are offered for defect location and classification based on prior information. The tool receives a three-phase current measurement as input, and output releases information on the fault's classification and location. An algorithm has been developed by [91]. While in his study, creating a model that uses the MATLAB/Simulink environment based on the discrete wavelet transform, multi-scale approximation analysis, and artificial neural networks is also implemented. The fault detection and classification procedures in distribution networks may be carried out with high levels of efficacy, speed, and dependability using this model. Similar articles are written, such as [92-95], for high-impedance failures, also known as HIFs, which are known to have an effect on the protection of distribution systems. This is especially true for microgrids and distribution networks that contain distributed generators (DGs) and have variable operation approaches.

4.4. Fuzzy Logic

4.4.1. Fuzzy Logic 2000-2009

In the recent decade of the 21st century, they have seen a sharp increase in the number of papers on the use of fuzzy logic in power systems, particularly for control-related issues. But [96] is stated that at the beginning of the last decade, a family of fuzzy-based algorithms was used to protect power systems. In this study[97], the author presents a quick fault detection method for power systems that takes advantage of fuzzy logic to locate the offending circuit. The values of CB and relay in CE-Nets are described using the system's established binary and coordinative relations. The author uses fault sections which are diagnosed using sagittal diagrams. Then, as suggested in this work, the failure or erroneous alarms of relays and circuit breakers are analyzed using the alarm data and the estimated fault section to cope with the uncertainties placed on the fault section diagnostics of power systems. In terms of both membership and malfunction or false alarm, the suggested system gives the fault section candidates[98, 99]. A fuzzy-logic-based multi-criteria approach is used by [100] in showing a new way to classify faults in power transmission systems in real-time. A fault-type identification technique based on fuzzy logic has been suggested by [101] in which use this technique, just three observations—three measurements of line current—are required, and the suggested method can precisely identify each of the ten types of short-circuit defects. [102] Examining a medium voltage test system bus bars, transformers, and line sections describes and verifies the fault detection method[102]. To find errors in these networks, a blend of fuzzy logic and genetic algorithms (GAs) is used and turned out to be fast, accurate, and reliable, and it worked well in various system conditions. The study mentioned above demonstrates how fuzzy logic and neural networks may be used to provide an advanced pattern recognition method for categorizing transmission line defects. The method uses [103] to increase the algorithm's selectivity for a range of real situations that were not always anticipated during training.

4.4.2. Fuzzy Logic : 2010-2019

In [104, 121], the author states that a new time-frequency method for finding power islands in systems with many generators is described, similarly to the paper [106, 107] Failure Identification in Smart Grids. This related study [108] offers a state-of-the-art method for identifying power system faults. The different fault types in distribution lines with DGs present, and different fault locations, are investigated and verified [109]; recent developments in fault detection are reviewed in [110]. Transmission line fault detection and classification using fuzzy logic is shown by [111] to be successful and efficient across various fault scenarios. This method can not only identify and categorize faults but also provide real-time, automated protection. This study by [112] focuses on fuzzy logic defect diagnosis. Phase and neutral current magnitudes define fuzzy fault identification criteria. The IEEE 34-Node Radial Test model is utilized for all substation measurements.

4.4.3. Fuzzy Logic: 2020-2023

Utilizing AI algorithms have been suggested in this research literature by using data collected by sensors and smart meters in the smart grid; the suggested technique is tested on the IEEE 37-bus system for fault detection, classification, characterization, and localization[113]. Even though the author[114] is not implementing DN with DG, in this work, he provides a fuzzy logic-based control strategy, an artificial intelligence technique, for determining the cause of transmission line problems. For DG-integrated distribution lines, this paper by [115, 116] proposes a fuzzy-based intelligent fault detection and classification scheme. We use two distinct fuzzy inference systems (FIS) to simulate the defect detection process. The first FIS identifies the high magnitude of fault current associated with normal shunt faults; the second FIS identifies the small magnitude of current owing to the occurrence of HIF.

5. Discussion, Constraints, and Emerging Trends

It has been described how different AI algorithms can diagnose and categorize abnormal situations in distribution networks with distribution generation. It is evident that they have been used to diagnose a variety of power system faults. In conclusion, they each have strengths and flaws of their own. The fuzzy logic rules are set in plain language, which is a benefit for formalizing human reasoning. The three fundamental components that make up a fuzzy-logic system are fuzzification, fuzzy inference, and defuzzification. To distinguish between different types of faults, fuzzy logic can be employed for fault identification in which the fuzzy logic system has some advantages over the other AI techniques; while the fuzzy logic system can provide results by specifying a few rules, other techniques require extensive modelling processes.

An Artificial Neural Network (ANN) is a computational model that imitates the structure of the human brain. Like the human brain, the model is made up of simple processing elements that are connected in a complex layer structure. This allows the model to approximate a complex non-linear function with multiple inputs and outputs. Hence is visible to note that the architectures of Artificial Neural Networks (ANNs) have made notable progress in the realm of fault detection applications. Deep learning methodologies, including deep neural networks and convolutional neural networks, have been utilized for the purpose of automatically extracting high-level features. Scholars have directed their attention towards enhancing fault detection performance by optimizing network architectures, regularization techniques, and training algorithms.

The wavelet transform has been proven to be an excellent technique for investigating and evaluating the signals in consideration[117]. The observed distorted signal may be resolved using the wavelet transform into a variety of different time–frequency domains [118]. The wavelet transform may be used to find various frequency components in a measured signal through the expansion and contraction of fundamental functions. The signal is broken down into a variety of frequency bands after going through the wavelet transform. The mother wavelet, which makes advantage of the dilation and translation characteristic, serves as the basis for the function.

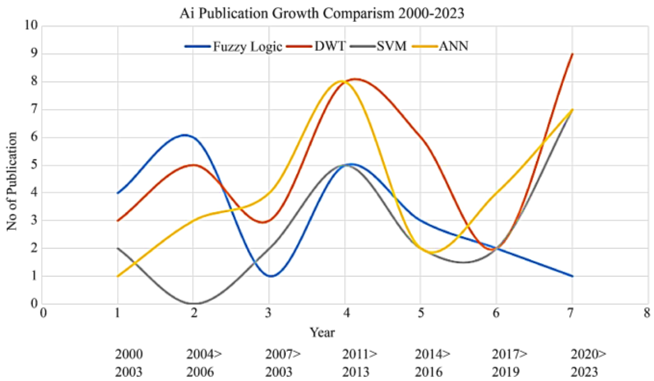

Fig. 3 Publication of AI techniques for fault detection with and without DG

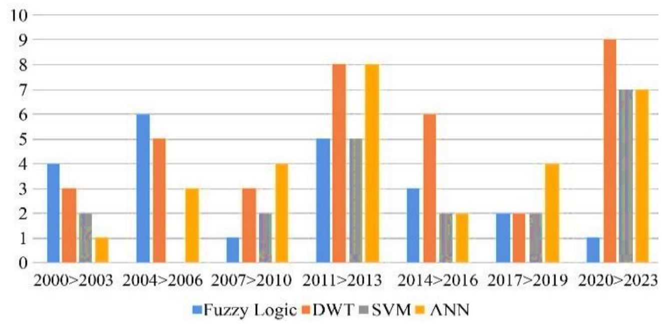

Fig. 4 Consistency trend of various intelligence techniques in fault detection in power systems

Using a support vector machine (SVM) for classification essentially requires training and testing data made of numerous examples. Because of this, SVM has demonstrated outstanding performance in generalization, even with a small amount of training data. Furthermore, data from two or more categories may always be separated by a hyperplane due to its correct nonlinear relationship in mapping using kernel-level functions. [119]. As a consequence, it can perform classification tasks with an excellent degree of precision for the purpose of defect detection and classification.

The scholarly inquiry has concentrated on enhancing the efficacy of Support Vector Machines (SVMs) through the utilization of diverse kernel functions, investigating ensemble techniques, and tackling concerns associated with imbalanced datasets. The utilization of support vector machines (SVM) in conjunction with feature selection methodologies and hybrid methodologies has been investigated as a means of improving the efficacy of fault detection.

In general, ANN, DWT, SVM, and deep learning techniques tend to perform better when handling multiple levels of dimensions and continual features. The performance of various algorithms might vary significantly from one another depending on the application.

The following graphic in Figures three (3) and four(4) provides a summary comparison of publications that compare AI approaches from each of the three decades, as referenced in section IV because there is no one learning algorithm that can consistently perform better than other algorithms across all datasets. Therefore, the publications chosen for the review either use a single learning method or combine it with another learning algorithm.

This chart has been created to compare the development or evolutionary growth or fatigue of AI technology within the category of power system protection or within power systems with dispersed generation integrated. The publications are either journal articles or conference proceedings. Because of this, especially in the past several years, fuzzy algorithms have shown significant signs of weariness in their application in power system protection as a single algorithm.

On the other hand, DWT, SVM, and ANN algorithms are now seeing an increase in the number of publications they get. It is not to imply that these strategies represent the future; rather, recently, researchers have been applying combinations of all four of these methods in an effort to better. From the analysis of figure 3 and 4, we can summarize various techniques such as Support Vector Machines (SVM), Fuzzy Logic, Discrete Wavelet Transform (DWT), and Artificial Neural Networks (ANN), have been widely employed for detecting faults in electrical distribution networks that incorporate distribution generation, since the year 2000. The field of fault detection systems in distribution networks has seen notable progress in various aspects, such as performance, feature extraction, hybridization, and network architectures. These advancements have resulted in more precise and dependable techniques for detecting faults; hence, the growth trend acknowledges that.

6. Conclusion

AI approaches can handle electrical power system protection data in the future; thus, they need greater attention. AI distribution and transmission protection approaches are evolving beyond the applications listed above.

As illustrated by [120], Without considering the complete diagnostic system, fault diagnostic systems are often built by combining certain components, such as data collection, feature extraction, and reduction of dimensionality, with fault detection. Deep learning may merge feature extraction and pattern recognition. Diagnostic systems that are integrated and automated should be given top priority. Designing and creating hybrid systems for applications involving distribution systems seems necessary since intelligent diagnosis is likely to be the next frontier of fault diagnostic research. This will allow us to benefit from the unique qualities of various algorithms also the development of deep learning. Notably, the selection of an AI approach depends on the particular needs of the distribution network, the data at hand, and the level of operator experience. When trying out several methods to discover the best answer, keep in mind that certain strategies can be more suited for various situations.

References

[1] Johan Driesen, Pieter Vermeyen, and Ronnie Belmans, "Protection Issues in Microgrids with Multiple Distributed Generation Units," *Power Conversion Conference-Nagoya, IEEE,* pp. 646-653, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[2] Venkat Venkatasubramanian et al., "A Review of Process Fault Detection and Diagnosis: Part III: Process History Based Methods," *Computers & Chemical Engineering,* vol. 27, no. 3, pp. 327-346, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[3] Andrew K.S. Jardine, Daming Lin, and Dragan Banjevic, "A Review on Machinery Diagnostics and Prognostics Implementing Condition-Based Maintenance," *Mechanical Systems and Signal Processing,* vol. 20, no. 7, pp. 1483-1510, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[4] Amin Ghaderi et al., "High-Impedance Fault Detection in the Distribution Network using the Time-Frequency-Based Algorithm," *IEEE Transactions on Power Delivery,* vol. 30, no. 3, pp. 1260-1268, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[5] Yann Qi Chen, Olga Fink, and Giovanni Sansavini, "Combined Fault Location and Classification for Power Transmission Lines Fault Diagnosis with Integrated Feature Extraction," *IEEE Transactions on Industrial Electronics,* vol. 65, no. 1, pp. 561-569, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[6] Kunjin Chen, Caowei Huang, and Jinliang He, "Fault Detection, Classification and Location for Transmission Lines and Distribution Systems: A Review on the Methods," *High Voltage,* vol. 1, no. 1, pp. 25-33, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[7] Dhivya Elavarasan et al., "Forecasting Yield by Integrating Agrarian Factors and Machine Learning Models: A Survey," *Computers and Electronics in Agriculture,* vol. 155, pp. 257-282, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[8] K. Gangwar, and A. Gafoor Shaik, "Fault Detection, Location in Hybrid Distribution Network Using Machine Learning Algorithm," *Location in Hybrid Distribution Network Using Machine Learning Algorithm,* 2022. [Google Scholar]

[9] Sudarshan Khond, Vijay Kale, and Makarand Sudhakar Ballal, "A Combined Data Mining and Machine Learning Approach for High Impedance Fault Detection in Microgrids," *IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy, IEEE,* pp. 1-7, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] K. De Kerf et al., "Wavelet-Based Protection Strategy for DC Faults in Multi-Terminal VSC HVDC Systems," *IET Generation, Transmission & Distribution,* vol. 5, no. 4, pp. 496-503, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[11] Bernhard Schölkopf, and Alexander J. Smola, *Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*, MIT Press, 2002. [Google Scholar] [Publisher Link]

[12] Ke-Lin Du, and M. N. S. Swamy, *Neural Networks and Statistical Learning*, Springer Science & Business Media, 2013. [Google Scholar] [Publisher Link]

[13] Rachna Vaish et al., "Machine Learning Applications in Power System Fault Diagnosis: Research Advancements and Perspectives," *Engineering Applications of Artificial Intelligence,* vol. 106, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[14] Peter Dondi et al., "Network Integration of Distributed Power Generation," *Journal of Power Sources,* vol. 106, no. 1-2, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[15] J. Driesen, and R. Belmans, "Distributed Generation: Challenges and Possible Solutions," *IEEE Power Engineering Society General Meeting,* 2006. [CrossRef] [Google Scholar] [Publisher Link]

[16] Ashwini D. Udgave, and H.T. Jadhav, "A Review on Distribution Network Protection with Penetration of Distributed Generation," *IEEE 9th International Conference on Intelligent Systems and Control,* pp. 1-4, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[17] Weiqiang Chen, and Ali M. Bazzi, "Logic-Based Methods for Intelligent Fault Diagnosis and Recovery in Power Electronics," *IEEE Transactions on Power Electronics,* vol. 32, no. 7, pp. 5573-5589, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[18] Stavros Ntalampiras, "Fault Diagnosis for Smart Grids in Pragmatic Conditions," *IEEE Transactions on Smart Grid,* vol. 9, no. 3, pp. 1964-1971, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[19] M. Kezunovic, and B. Perunicic, "Automated Transmission Line Fault Analysis using Synchronized Sampling at Two Ends," *IEEE Transactions on Power Systems,* vol. 11, no. 1, pp. 441-447, 1996. [CrossRef] [Google Scholar] [Publisher Link]

[20] Jie Gao et al., "A High-Impedance Fault Detection Method for Distribution Systems Based on Empirical Wavelet Transform and Differential Faulty Energy," *IEEE Transactions on Smart Grid,* vol. 13, no. 2, pp. 900-912, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] B. Don Russell, and Carl L. Benner, "Intelligent Systems for Improved Reliability and Failure Diagnosis in Distribution Systems," *IEEE Transactions on Smart Grid,* vol. 1, no. 1, pp. 48-56, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[22] Vehbi C. Gungor, Bin Lu, and Gerhard P. Hancke, "Opportunities and Challenges of Wireless Sensor Networks in Smart Grid," *IEEE Transactions on Industrial Electronics,* vol. 57, no. 10, pp. 3557-3564, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[23] V. K. Sood et al., "Developing a Communication Infrastructure for the Smart Grid," *IEEE Electrical Power & Energy Conference,* pp. 1-7, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[24] A C Kurniawan et al., "Application of Fuzzy Logic to Electrical Protection Devices," *Journal of Physics: Conference Series,* vol. 1501, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[25] S. Samonto et al., "Fuzzy Based Intelligent Fault Protection Schemes: A Critical Review to Explore the Future," *SSRN Electronic Journal,* 2020. [Google Scholar]

[26] Seongmin Heo, and Jay H. Lee, "Fault Detection and Classification using Artificial Neural Networks," *IFAC-PapersOnLine*, vol. 51, no. 18, pp. 470-475, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[27] Vikramaditya Jakkula, *Tutorial on Support Vector Machine (SVM),* School of EECS, Washington State University, vol. 37, 2006. [Google Scholar] [Publisher Link]

[28] N. Saravanan, and K. I. Ramachandran, "Incipient Gear Box Fault Diagnosis using Discrete Wavelet Transform (DWT) for Feature Extraction and Classification using Artificial Neural Network (ANN)," *Expert Systems with Applications,* vol. 37, no. 6, pp. 4168-4181, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[29] M. A. Awadallah, and M. M. Morcos, "Application of AI Tools in Fault Diagnosis of Electrical Machines and Drives- An Overview," *IEEE Transactions on Energy Conversion,* vol. 18, no. 2, pp. 245-251, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[30] M. Sanaye-Pasand, and H. Khorashadi-Zadeh, "Transmission Line Fault Detection & Phase Selection Using ANN," *International Conference on Power Systems Transients,* pp. 1-6, 2003. [Google Scholar] [Publisher Link]

[31] K. M. Silva, B. A. Souza, and N. S. D. Brito, "Fault Detection and Classification in Transmission Lines based on Wavelet Transform and ANN," *IEEE Transactions on Power Delivery,* vol. 21, no. 4, pp. 2058-2063, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[32] R.N. Mahanty, and P.B. Dutta Gupta, "Application of RBF Neural Network to Fault Classification and Location in Transmission Lines," *IEE Proceedings-Generation, Transmission and Distribution,* vol. 151, no. 2, pp. 201-212, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[33] Zhu Yongli, H. Limin, and Lu Jinling, "Bayesian Networks-Based Approach for Power Systems Fault Diagnosis," *IEEE Transactions on Power Delivery,* vol. 21, no. 2, pp. 634-639, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[34] Xiao Liu, Haijun Li, and Lin Li, "Building Method of Diagnostic Model of Bayesian Networks based on Fault Tree," *Seventh International Symposium on Instrumentation and Control Technology: Sensors and Instruments, Computer Simulation, and Artificial Intelligence,* vol. 7127, pp. 529-534, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[35] Luis E. Garza Castañón et al., "Fault Diagnosis of Industrial Systems with Bayesian Networks and Neural Networks," *MICAI 2008: Advances in Artificial Intelligence,* pp. 998-1008, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[36] A.S. Bretas, and N. Hadjsaid, "Fault Diagnosis in Deregulated Distribution Systems using an Artificial Neural Network," *IEEE Power Engineering Society Winter Meeting, Conference Proceedings,* vol. 2, pp. 821-823, 2001. [CrossRef] [Google Scholar] [Publisher Link]

[37] Syafaruddin, E. Karatepe, and T. Hiyama, "Controlling of Artificial Neural Network for Fault Diagnosis of Photovoltaic Array," *16th International Conference on Intelligent System Applications to Power Systems*, pp. 1-6, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[38] Eisa Bashier M Tayeb, "Faults Detection in Power Systems using Artificial Neural Network," *American Journal of Engineering Research,* vol. 2, no. 6, pp. 69-75, 2013. [Google Scholar] [Publisher Link]

[39] Adeyemi Charles Adewole, Raynitchka Tzoneva, and Shaheen Behardien, "Distribution Network Fault Section Identification and Fault Location using Wavelet Entropy and Neural Networks," *Applied Soft Computing,* vol. 46, pp. 296-306, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[40] Qingqing Yang et al., "Artificial Neural Network Based Fault Detection and Fault Location in the DC Microgrid," *Energy Procedia,* vol. 103, pp. 129-134, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[41] Fabricio Lucas et al., "High Impedance Fault Detection in Time-Varying Distributed Generation Systems using Adaptive Neural Networks," *International Joint Conference on Neural Networks,* pp. 1-8, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[42] Luciana C. Acácio et al., "Evaluation of the Impact of Different Neural Network Structure and Data Input on Fault Detection," *IEEE PES Innovative Smart Grid Technologies Conference - Latin America (ISGT Latin America)*, pp. 1-5, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[43] Majeed Rashid Zaidan, "Power System Fault Detection, Classification and Clearance by Artificial Neural Network Controller," *Global Conference for Advancement in Technology*, pp. 1-5, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[44] Shahriar Rahman Fahim et al., "A Deep Learning Based Intelligent Approach in Detection and Classification of Transmission Line Faults," *International Journal of Electrical Power & Energy Systems,* vol. 133, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[45] Amir Reza Aqamohammadi et al., "Deep Neural Network with Hilbert–Huang Transform for Smart Fault Detection in Microgrid," *Electronics,* vol. 12, no. 3, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[46] Priya Singh, Nitin Singh, and Niraj Kumar Choudhary, "Fault Detection and Classification in Microgrid using Wavelet Transform and Artificial Neural Network," *Advances in VLSI, Communication, and Signal Processing,* vol. 683, pp. 17-31, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[47] D. Thukaram et al., "Artificial Neural Network and Support Vector Machine Approach for Locating Faults in Radial Distribution Systems," *IEEE Transactions on Power Delivery,* vol. 20, no. 2, pp. 710-721, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[48] B. Ravikumar, D. Thukaram, and H. Khincha, "Application of Support Vector Machines for Fault Diagnosis in Power Transmission System," *IET Generation, Transmission & Distribution,* vol. 2, no. 1, pp. 119-130, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[49] Abolfazl Rahmani, Javad Haddadnia, and Omid Seryasat, "Intelligent Fault Detection of Electrical Equipment in Ground Substations using Thermo Vision Technique," *2nd International Conference on Mechanical and Electronics Engineering*, pp. V2-150-V2-154, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[50] D. Thukaram, H. P. Khincha, and B. Ravikumar, "An Intelligent Approach using Support Vector Machines for Monitoring and Identification of Faults on Transmission Systems," *IEEE Power India Conference*, pp. 184-190, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[51] Rimjhim Agrawal, and D Thukaram, "Identification of Fault Location in Power Distribution System with Distributed Generation using Support Vector Machines," *IEEE PES Innovative Smart Grid Technologies Conference*, pp. 1-6, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[52] Modu Abba Gana, Ishaku Abdul Dalyop, and Musa Mustapha, "Assessment of Reliability of Distribution Network with Embedded Generation," *SSRG International Journal of Electrical and Electronics Engineering,* vol. 7, no. 2, pp. 34-37, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[53] Ping Yang, and Sui Sheng Liu, "Fault Diagnosis for Boilers in Thermal Power Plant by Data Mining," *ICARCV 2004 8th Control, Automation, Robotics and Vision Conference,* vol. 3, pp. 2176-2180, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[54] Manohar Singh, B.K Panigrahi, and R. P. Maheshwari, "Transmission Line Fault Detection and Classification," *International Conference on Emerging Trends in Electrical and Computer Technology*, pp. 15-22, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[55] Hanif Livani, and Cansın Yaman Evrenosoğlu, "A Fault Classification Method in Power Systems using DWT and SVM Classifier," *PES T&D*, pp. 1-5, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[56] Mollah Rezaul Alam, Kashem M. Muttaqi, and Abdesselam Bouzerdoum, "An Approach for Assessing the Effectiveness of Multiple-Feature-Based SVM Method for Islanding Detection of Distributed Generation," *IEEE Transactions on Industry Applications,* vol. 50, no. 4, pp. 2844-2852, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[57] Ramón Pérez, and Carmen Vásquez, "Fault Location in Distribution Systems with Distributed Generation using Support Vector Machines and Smart Meters," *IEEE Ecuador Technical Chapters Meeting*, pp. 1-6, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[58] M. Sarlak, and S. M. Shahrtash, "SVM-based Method for High-Impedance Faults Detection in Distribution Networks," *COMPEL-The International Journal for Computation and Mathematics in Electrical and Electronic Engineering,* vol. 30, no. 2, pp. 431-450, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[59] B. Mike Aucoin, and B. Don Russell, "Distribution High Impedance Fault Detection Utilizing High Frequency Current Components," *IEEE Transactions on Power Apparatus and Systems,* vol. 101, no. 6, pp. 1596-1606, 1982. [CrossRef] [Google Scholar] [Publisher Link]

[60] S.R. Samantaray, B.K. Panigrahi, and P.K. Dash, "High Impedance Fault Detection in Power Distribution Networks using Time–Frequency Transform and Probabilistic Neural Network," *IET Generation, Transmission & Distribution,* vol. 2, no. 2, pp. 261-270, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[61] Hamid Reza Baghaee et al., "Support Vector Machine-Based Islanding and Grid Fault Detection in Active Distribution Networks," *IEEE Journal of Emerging and Selected Topics in Power Electronics,* vol. 8, no. 3, pp. 2385-2403, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[62] Fazel Mohammadi, Gholam-Abbas Nazri, and Mehrdad Saif, "A Fast Fault Detection and Identification Approach in Power Distribution Systems," *International Conference on Power Generation Systems and Renewable Energy Technologies*, pp. 1-4, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[63] Ming-Yuan Cho, and Thi Thom Hoang, "Feature Selection and Parameters Optimization of SVM Using Particle Swarm Optimization for Fault Classification in Power Distribution Systems," *Computational Intelligence and Neuroscience*, vol. 2017, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[64] Ali Ahmadi, Ebrahim Aghajari, and Mehdi Zangeneh, "High-Impedance Fault Detection in Power Distribution Grid Systems based on Support Vector Machine Approach," *Electrical Engineering,* vol. 104, pp. 3659-3672, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[65] S. S. Gururajapathy, H. Mokhlis, and H. A. Illias, "Fault Location and Detection Techniques in Power Distribution Systems with Distributed Generation: A Review," *Renewable and Sustainable Energy Reviews,* vol. 74, pp. 949-958, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[66] C. G. Wester, "High Impedance Fault Detection on Distribution Systems," *Rural Electric Power Conference Presented at 42nd Annual Conference*, p. c5-1, 1998. [CrossRef] [Google Scholar] [Publisher Link]

[67] Tim Edwards, "*Discrete Wavelet Transforms: Theory and Implementation*," 1991. [Google Scholar] [Publisher Link]

[68] K. L. Butler-Purry, and M. Bagriyanik, "Characterization of Transients in Transformers using Discrete Wavelet Transforms," *IEEE Transactions on Power Systems,* vol. 18, no. 2, pp. 648-656, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[69] Rodrigo Hartstein Salim et al., "Hybrid Fault Diagnosis Scheme Implementation for Power Distribution Systems Automation," *IEEE Transactions on Power Delivery,* vol. 23, no. 4, pp. 1846-1856, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[70] Joe-Air Jiang et al., "A Fault Detection and Faulted-Phase Selection Approach for Transmission Lines with Haar Wavelet Transform," *IEEE PES Transmission and Distribution Conference and Exposition*, vol. 1, pp. 285-289, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[71] S. Sreedevi, and G. Angeline Ezhilarasi, "Optimal Allocation of Multiple Distributed Generators Based on Hybrid Technique for Reduction of Power Loss," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 10, no. 7, pp. 1-21, 2023. [CrossRef] [Publisher Link]

[72] R. M. de Castro Fernandez, and Horacio Nelson Díaz Rojas, "An Overview of Wavelet Transforms Application in Power Systems," *Proceedings of 14th PSCC, Sevilla, Session*, vol. 1, pp. 1-8, 2002. [Google Scholar] [Publisher Link]

[73] N. Perera, and A. D. Rajapakse, "Agent-based Protection Scheme for Distribution Networks with Distributed Generators," *IEEE Power Engineering Society General Meeting*, p. 6, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[74] Zeng Xiangjun et al., "Multi-Agents based Protection for Distributed Generation Systems," *IEEE International Conference on Electric Utility Deregulation, Restructuring and Power Technologies*, vol. 1, pp. 393-397, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[75] A. Ngaopitakkul et al., "Identification of Fault Locations in Underground Distribution System using Discrete Wavelet Transform," *Proceedings of the International Multi Conference of Engineers and Computer Scientists*, vol. 2, 2010. [Google Scholar]

[76] Rodrigo Hartstein Salim, Karen Rezende Caino de Oliveira, and Arturo Suman Bretas, "Fault Detection in Primary Distribution Systems using Wavelets," *International Conference on Power Systems Transients*, 2007. [Google Scholar] [Publisher Link]

[77] J. G. Moreno, F. E. Pérez, and E. A. Orduña, "Protection Functions for Distribution Networks with Distributed Generation Applying Wavelet Transform," *Sixth IEEE/PES Transmission and Distribution: Latin America Conference and Exposition*, pp. 1-5, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[78] Mahmood Shaik, M. Nageswara Rao, and Shaik Abdul Gafoor, "A Wavelet based Protection Scheme for Distribution Networks with Distributed Generation," *International Conference on Emerging Trends in Electrical Engineering and Energy Management*, pp. 33-37, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[79] K. Saravanababu, P. Balakrishnan, and K. Sathiyasekar, "Transmission Line Faults Detection, Classification, and Location using Discrete Wavelet Transform," *International Conference on Power, Energy and Control*, pp. 233-238, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[80] A.C. Adewole, and R. Tzoneva, "Fault Detection and Classification in a Distribution Network Integrated with Distributed Generators," *IEEE Power and Energy Society Conference and Exposition in Africa: Intelligent Grid Integration of Renewable Energy Resources*, pp. 1-8, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[81] Behrooz Moeil et al., "Distinction of Permanent and Transient Faults in Microgrids using Wavelet Transform," *Journal of Applied Environmental and Biological Sciences*, vol. 3, no. 10, pp. 41-51, 2013. [Google Scholar] [Publisher Link]

[82] Prakash K. Ray et al., "Disturbance Detection in Grid-Connected Distributed Generation System using Wavelet and S-Transform," *Electric Power Systems Research*, vol. 81, no. 3, pp. 805-819, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[83] Majid Jamil, Rajveer Singh, and Sanjeev Kumar Sharma, "Fault Identification in Electrical Power Distribution System using Combined Discrete Wavelet Transform and Fuzzy Logic," *Journal of Electrical Systems and Information Technology*, vol. 2, no. 2, pp. 257-267, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[84] Flavio B. Costa, Antonello Monti, and Samara C. Paiva, "Overcurrent Protection in Distribution Systems with Distributed Generation based on the Real-Time Boundary Wavelet Transform," *IEEE Transactions on Power Delivery*, vol. 32, no. 1, pp. 462-473, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[85] X. G. Magagula et al., "Fault Detection and Classification Method using DWT and SVM in a Power Distribution Network," *IEEE PES Power Africa*, pp. 1-6, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[86] Youness Mohammadnian, Turaj Amraee, and Alireza Soroudi, "Fault Detection in Distribution Networks in Presence of Distributed Generations using a Data Mining–Driven Wavelet Transform," *IET Smart Grid*, vol. 2, no. 2, pp. 163-171, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[87] Papia Ray et al., "Fault Detection and Classification of a Transmission Line using Discrete Wavelet Transform & Artificial Neural Network," *International Conference on Information Technology*, pp. 178-183, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[88] Md Shafiullah, Khalid A. AlShumayri, and Md. Shafiul Alam, "Machine Learning Tools for Active Distribution Grid Fault Diagnosis," *Advances in Engineering Software*, vol. 173, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[89] Yordanos Dametw Mamuya et al., "Application of Machine Learning for Fault Classification and Location in a Radial Distribution Grid," *Applied Sciences*, vol. 10, no. 14, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[90] Naval Kishor Sah, and Prabhat Kumar Pankaj, "Distribution System Fault Detection and Classification using Wavelet Transform and Artificial Neural Networks," *Proceedings of 11th IOE Graduate Conference*, vol. 11, pp. 69-75, 2022. [Google Scholar] [Publisher Link]

[91] Mohammed Yahya Sulimano, and Mahmood Taha Alkhayyat, "High Impedance Fault Detection in Radial Distribution Network using Discrete Wavelet Transform Technique," *Archives of Electrical Engineering*, vol. 70, no. 4, pp. 873-886, 2021. [Google Scholar] [Publisher Link]

[92] Tapaswini Biswal, and S.K. Parida, "High Impedance Fault Detection in Microgrid System using Discrete Wavelet Transform and Support Vector Machine," *Second International Conference on Power, Control and Computing Technologies, IEEE*, pp. 1-6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[93] Fabricio Lucas et al., "Fault Detection in Smart Grids with Time-Varying Distributed Generation using Wavelet Energy and Evolving Neural Networks," *Evolving Systems*, vol. 11, pp. 165-180, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[94] N Vineeth, and P. Sreejaya, "High Impedance Fault Detection in Low Voltage Distribution Systems using Wavelet and Harmonic Fault Indices," *IEEE International Conference on Power Electronics, Smart Grid and Renewable Energy*, pp. 1-6, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[95] W. Rebizant, and K. Feser, "Fuzzy Logic Application to Out-of-Step Protection of Generators," *Power Engineering Society Summer Meeting, Conference Proceedings*, vol. 2, pp. 927-932, 2001. [CrossRef] [Google Scholar] [Publisher Link]

[96] Hong-Chan Chin, "Fault Section Diagnosis of Power System Using Fuzzy Logic," *IEEE Transactions on Power Systems*, vol. 18, no. 1, pp. 245-250, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[97] Hyun-Joon Cho, and Jong-Keun Park, "An Expert System for Fault Section Diagnosis of Power Systems using Fuzzy Relations," *IEEE Transactions on Power Systems*, vol. 12, no. 1, pp. 342-348, 1997. [CrossRef] [Google Scholar] [Publisher Link]

[98] S. Min, S. Lee, and J. Park, "An Expert System for Fault Section Diagnosis in Power Systems using the Information Including Operating Times of Actuated Relays and Tripped Circuit Breakers," *Proceedings of the KIEE Conference*, pp. 125-127, 2000. [Google Scholar] [Publisher Link]

[99] O. A. S. Youssef, "Combined Fuzzy-Logic Wavelet-based Fault Classification Technique for Power System Relaying," *IEEE Transactions on Power Delivery*, vol. 19, no. 2, pp. 582-589, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[100] B. Das, and J. V. Reddy, "Fuzzy-Logic-based Fault Classification Scheme for Digital Distance Protection," *IEEE Transactions on Power Delivery*, vol. 20, no. 2, pp. 609-616, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[101] Dipti Srinivasan et al., "Automated Fault Detection in Power Distribution Networks using a Hybrid Fuzzy–Genetic Algorithm Approach," *Engineering Applications of Artificial Intelligence*, vol. 13, no. 4, pp. 407-418, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[102] S. Vasilic, and M. Kezunovic, "Fuzzy ART Neural Network Algorithm for Classifying the Power System Faults," *IEEE Transactions on Power Delivery*, vol. 20, no. 2, pp. 1306-1314, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[103] P.K. Dash, Malhar Padhee, and T.K. Panigrahi, "A Hybrid Time–Frequency Approach based Fuzzy Logic System for Power Island Detection in Grid Connected Distributed Generation," *International Journal of Electrical Power & Energy Systems*, vol. 42, no. 1, pp. 453-464, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[104] S. Anudevi, and Vinayak N. Shet, "Distribution Network with Optimal DG Placement and Protection Impacts: Review Analysis," *SSRG International Journal of Electrical and Electronics Engineering*, vol. 4, no. 2, pp. 12-16, 2017. [CrossRef] [Publisher Link]

[105] Vito Calderaro et al., "Failure Identification in Smart Grids Based on Petri Net Modeling," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 10, pp. 4613-4623, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[106] Alexandros Mouzakitis, "Classification of Fault Diagnosis Methods for Control Systems," *Measurement and Control*, vol. 46, no. 10, pp. 303-308, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[107] Pituk Bunnoon, "Fault Detection Approaches to Power System: State-of-The-Art Article Reviews for Searching a New Approach in the Future," *International Journal of Electrical and Computer Engineering*, vol. 3, no. 4, p. 553, 2013. [Google Scholar] [Publisher Link]

[108] Moslem Dehghani, Mohammad Hassan Khooban, and Taher Niknam, "Fast Fault Detection and Classification based on a Combination of Wavelet Singular Entropy Theory and Fuzzy Logic in Distribution Lines in the Presence of Distributed Generations," *International Journal of Electrical Power & Energy Systems*, vol. 78, pp. 455-462, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[109] Aboelsood Zidan et al., "Fault Detection, Isolation, and Service Restoration in Distribution Systems: State-of-the-Art and Future Trends," *IEEE Transactions on Smart Grid*, vol. 8, no. 5, pp. 2170-2185, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[110] Shuma Adhikari, Nidul Sinha, and Thingam Dorendrajit, "Fuzzy Logic based on-Line Fault Detection and Classification in Transmission Line," *SpringerPlus*, vol. 5, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[111] Ramón Perez et al., "Fault Diagnosis on Electrical Distribution Systems Based on Fuzzy Logic," *International Conference on Swarm Intelligence*, vol. 10942, pp. 174-185, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[112] Felix Ghislain Yem Souhe et al., "Fault Detection, Classification and Location in Power Distribution Smart Grid Using Smart Meters Data," *Journal of Applied Science and Engineering*, vol. 26, no. 1, pp. 23-34, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[113] Rishabh Verma, and M. A. Ansari, "Fault Detection and Classification Using Fuzzy Logic Controller and ANN," *Micro-Electronics and Telecommunication Engineering*, Springer Nature Singapore, vol. 373, pp. 25-35, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[114] Subhamita Roy, and Sudipta Debnath, "PSD based High Impedance Fault Detection and Classification in Distribution System," *Measurement*, vol. 169, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[115] B.K. Chaitanya, and Anamika Yadav, "An Intelligent Fault Detection and Classification Scheme for Distribution Lines Integrated with Distributed Generators," *Computers & Electrical Engineering*, vol. 69, pp. 28-40, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[116] K K Shukla, and Arvind K. Tiwari, *Efficient Algorithms for Discrete Wavelet Transform: With Applications to Denoising and Fuzzy Inference Systems*, Springer Science & Business Media, 2013. [Google Scholar] [Publisher Link]

[117] Purva Sharma, Deepak Saini, and Akash Saxena, "Fault Detection and Classification in Transmission Line using Wavelet Transform and ANN," *Bulletin of Electrical Engineering and Informatics,* vol. 5, no. 3, pp. 284-295, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[118] Yashima Ahuja, and Sumit Kumar Yadav, "Multiclass Classification and Support Vector Machine," *Global Journal of Computer Science and Technology,* vol. 12, no. 11, pp. 15-19, 2012. [Google Scholar] [Publisher Link]

[119] Erxuan Chai et al., "Artificial Intelligence Approaches to Fault Diagnosis in Power Grids: A Review," *Chinese Control Conference*, pp. 7346-7353, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[120] Pukar Mahat, Zhe Chen, and Birgitte Bak-Jensen, "Review on Islanding Operation of Distribution System with Distributed Generation," *IEEE Power and Energy Society General Meeting,* pp. 1-8, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[121] K. M. Silva et al., "Haar Wavelet-Based Method for Fast Fault Classification in Transmission Lines," *IEEE/PES Transmission & Distribution Conference and Exposition,* pp. 1-5, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[122] N. Shahid et al., "Support Vector Machine based Fault Detection & Classification in Smart Grids," *IEEE Globecom Workshops*, pp. 1526-1531, 2012. [CrossRef] [Google Scholar] [Publisher Link]