Open Access Research Journal of
Engineering and Technology
Journals home page: https://oarjpublication/journals/oarjet/
ISSN: 2783-0128 (Online)

OARJ OPEN ACCESS RESEARCH JOURNALS

(REVIEW ARTICLE)

Check for updates

A Critical Review of Artificial Intelligence-based Fault Detection, Location and Resolution Techniques in Transmission Networks: A Case Study of the Nigerian 330 kV Transmission Network

Anthony Linus Jack [1], Imo Edwin Nkan [1, *], Unwana Macauley Ekpe [1], Iniobong Ime Essien [1] and Andikan Kenneth Ekpa [2]

[1] *Department of Electrical and Electronic Engineering, Akwa Ibom State University, Nigeria.*
[2] *Department of Electrical/Electronic Engineering, Akwa Ibom State Polytecnic, Nigeria.*

Open Access Research Journal of Engineering and Technology, 2026, 10(02), 127-138

Publication history: Received on 06 May 2026; revised on 12 June 2026; accepted on 15 June 2026

Article DOI: https://doi.org/10.53022/oarjet.2026.10.2.0048

Abstract

An electrical power system is a network that generates, transmits, and distributes electricity from power stations to end users via a transmission line. This power system network is characterized by very lengthy transmission lines which often pass through different environmental topography making it possible for the transmission line to experience fault. A fault is an undesired disruption to the power system that disrupts the system network's regular operation. The need to quickly and accurately identify, classify, and locate these faults is very important as failure to do so will cause damage to the end users and losses to the transmission company. This problem has propelled a detailed review of the fault analysis in transmission network by exploring various scientific and engineering powerful simulation tools and reliable scientific methods like artificial intelligence (AI), machine learning (ML), signal processing techniques, and recent techniques used by researchers. The system quality such as voltage, and current are used in the analysis. Traditional and AI method for Fault detection, fault classification, and fault location are also discussed separately to give a better understanding of each method used in the individual fault analysis. This study presents a comprehensive review that guides the understanding of various techniques used in fault detection, classification and location analysis, alongside their results, test systems, and gaps in the literature.

Keywords: Artificial Intelligence; Fault Detection; Fault Location; Resolution Techniques; Transmission Networks

1. Introduction

An electrical power network comprises generation, transmission and distribution subsystems. While the generation subsystem converts energy derived from primary sources into electricity, the transmission and distribution subsystems respectively transport electricity at high voltages over huge distances and supply power at stepped-down voltages to end users. A significant portion of the Nigerian transmission network comprises 330 kV transmission lines, and these lines are interconnected by transformers, circuit breakers, fuses, isolators, relays, and communication and control devices. While the transformers convert voltages from one level to another, the rest of the components provide the functions of fault detection and isolation, and overall system protection. These functions are especially important because transmission lines are mainly overhead, and the probability of faults occurring is non-negligible due to natural and man-made factors such as falling trees, natural disasters, impact of vehicles, and ageing equipment. Transmission line faults are classified into two types: series or open circuit faults, and shunt or short circuit faults, and over the years, several conventional methods have been developed to detect, locate, and resolve faults. These methods include impedance-based protection schemes, overcurrent protection, differential protection, traveling wave methods, and pilot protection schemes [1]. The conventional methods are widely used but they are beset with peculiar limitations. Fortunately, the application of Artificial Intelligence (AI) has significantly improved the operation of conventional fault

* Corresponding author: Imo Edwin Nkan

detection and transmission system protection techniques. AI-based techniques leverage on Artificial Neural Networks (ANN), Wavelet Transform, Fuzzy Interference, Decision Tree methods, Long Short-Term Memory (LSTM) techniques, Conventional Neural Networks (CNN) and many different hybrid combinations [2]. This paper critically reviews the application of those AI-based fault detection, fault location, and fault resolution techniques in transmission networks, using the Nigerian 330 kV transmission lines as a case study. In achieving this objective, Section 2 presents an overview of the Nigerian 330 kV while Section 3 deals with signal processing techniques relevant to fault detection. Section 4 covers conventional fault classification, detection, and location, and this is followed by a review of the state of the art in harnessing AI techniques to improve fault detection and location in section 5. The future outlook for fault detection and protection of transmission networks is given in Section 6.

2. The Nigerian 330 kV Transmission Network

Construction of the 330 kV section of the Nigerian national grid started in 1968 and was designed to evacuate power from the Kainji hydro station to the eastern parts of the country [3]. The transmission network was subsequently expanded to include other major 330 kV transmission corridors linking key generating stations such as Jebba, Shiroro, Egbin, Afam, Delta (Ughelli), and Sapele to major load centers across the country. The integrated national grid was formed with these interconnections. The transmission network is divided into northern, south-western, and south-eastern sections interconnected through critical transmission lines such as the Jebba-Osogbo, Osogbo-Benin, and Ikeja West-Benin axes. Over the years, additional 330 kV double-circuit lines such as the Ajaokuta-Gwagwalada and Jebba-Kainji routes were developed to improve redundancy, flexibility, and bulk power transfer capability across the grid [4]. Several studies on the Nigerian 330 kV transmission network have consistently identified voltage fluctuation and instability as major operational challenges. These issues are largely attributed to long transmission distances, inadequate reactive power support, and uneven load distribution across the grid. Several researchers have investigated the extent of this problem by analyzing bus voltage profiles under steady-state conditions. For instance, a study of the Nigerian 28-bus 330 kV network reported that six buses violated the acceptable voltage limits of 0.9-1.0 pu, which indicate a significant drop in voltage stability within the system The affected buses included Kano with (0.936895 pu), Gombe with (0.908595 pu), Damaturu with (0.906397) pu, Maiduguri with (0.897593) pu, Yola with (0.9012) pu, Jos with (0.93719) pu [5]. To address these challenges, various solutions have been proposed by different researchers, primarily focusing on reactive power compensation techniques. In particular, the application of Flexible AC Transmission System (FACTS) devices has been widely recommended for improving voltage stability and enhancing power transfer capability. For example, it has been demonstrated that the integration of shunt compensation devices such as Static VAR Compensators (SVC) can effectively regulate bus voltages and reduce voltage deviations across the network [6].

Authors in [7], analyzed the effect of static synchronous series compensators (SSSC) and thyristor-controlled series compensators (TCSC) on the voltage magnitude profile, active power losses, and reactive power losses. Their results indicate that with FACTS devices, the voltage profile of buses can be raised and power losses significantly mitigated. In a similar study, [8], SSSC was used to investigate system responses under the influence of three-phase faults. The power system network was modeled with PSAT software in MATLAB, and faults were introduced on bus 33 while SSSC was installed on line 21-28. The results obtained revealed that with the introduction of SSSC, appreciable damping of power system oscillation was achieved. Also, bus voltage profile was enhanced and this led to dynamic stability of the power system. Other notable studies that investigate the power transfer capability of the Nigerian 33 kV transmission network based on a 58-bus system and utilizing different types of FACTS devices include [9] and [10]. Their results indicate that unified power flow controller (UPFC) enhanced the power transfer capability of the network more than thyristor-controlled series capacitor (TCSC) and interline power flow controller (IPFC).

Fault occurrence is one of the major operational challenges affecting the Nigerian 330 kV transmission network, often leading to equipment damage, supply interruptions, and reduced system reliability. Effective and timely fault detection is therefore critical to maintaining grid stability and ensuring rapid system restoration. Existing studies indicate that the Nigerian 330 kV grid predominantly relies on conventional protection schemes such as overcurrent and distance relays for fault detection and isolation. These methods are widely used due to their relatively low cost, simplicity, and compatibility with the existing (legacy) protection infrastructure [11]. However, despite these advantages, conventional relay-based protection schemes often exhibit limitations, including slower fault detection, poor sensitivity under certain operating conditions, and delayed fault clearance, which can further exacerbate system instability and prolong outages [12], [13]. In response to these challenges, more advanced approaches based on hybrid and intelligent techniques are increasingly being explored. These include the application of artificial intelligence-based methods, which have demonstrated improved fault detection accuracy, faster response times, and enhanced system reliability, thereby reducing overall system downtime [14]. In [12] an intelligent overcurrent relay for real-time protection of distribution network under fault conditions was utilized. The performance of the relay TMS values as obtained were compared to the proposed and classical methods, showing over 18.67 % improvement in the operation times of the relay. In [15], overcurrent relay was used to detect fault in power system network's and also as protection scheme. The adaptive overcurrent protection scheme was applied in the IEEE 33-bus distribution network with and without DGs, for single and multi-DG penetration using both the ETAP and MATLAB software. In [16], support vector machine (SVM), was used for grid fault detection in active distribution networks. Simulated results shows that parameters of a real-life practical photovoltaic (PV) plant give much better output than the traditional reported methods when it comes to fault detection. [17] uses dual-tree complex wavelet transform (DTCWT) based squeeze net (SN) with optimized support vector machine (SVM) to detect fault in an inverter-fed EV. Voltage, current, and speed signals were measured at different faulty conditions, with the extracted data being processed to classified through the sucker-vulture optimization algorithm (SVOA) based SVM. In [18] a novel algorithm for fault detection in multi-terminal high DC network using the historical current series time data was implemented. In [13] fault detection directly proportional to the effect of the entire system was proposed with the protection performance acting effectively in terms of fault detection, classification, and location.

3. Signal Processing Technique

Signal processing techniques for fault detection is a process where signals sensor like current is been transform into a meaningful and moderate data in other to identify abnormalities that indicate a fault present in the power network. Several signal processing techniques can be used to identify signal changes that may indicate anomalies in a power system's operation. Fourier Transform, Wavelet Transform and S-Transform have become very popular and necessary tools in detection of transient’s state in power system network, diagnosis of transmission line faults, classification of faults and identification of the affected phases. Different signal processing techniques have been applied for classifying different types of transmission line faults in power systems. Most widely used signal processing techniques are the Fast Fourier transforms (FFT) and the Short Time Fourier Transforms (STFT). Wavelet transform and Discrete Wavelet Transform (DWT) are dominants signal analysis tool which is broadly used for fault classification in transmission lines. S-transform is an expansion of the concept wavelet transforms; it is a combination of STFT and CWT and it provide excellent time localization of current signals throughout fault conditions. It has suitably and accurately identified power system disturbances in [19, 20]. Recently used signal processing technique is discussed as follows:

3.1. Wavelet Transform

Wavelet transform is a mathematical tool that are used to convert the available data from time domain to frequency domain without losing any data in the time domain. The wavelet transform is extensively used in fault analysis in power system network. There are two wavelets transform namely; Continuous wavelet transform (CWT) and discrete wavelet transform (DWT). When finding the current, and voltage characteristics with respect to multiple band frequency, discrete wavelet transform is considered [21]. For discrete wavelet transform, the signal can be decomposed through high pass filter and low pass filter into an approximate with detail coefficients on them. Approximate coefficient happens to be the smoothed version of the original signal; in contrast the discrete coefficient is the high frequencies that made up the original signal. The approximate coefficients can also be decomposed into another high level of approximate and detail coefficients at the incoming signal of both high-pass filter and low-pass filter where B_1, B_2, and B_3, represents the approximation coefficients (ApCo) of the decomposed signal at each level 1, 2 and 3. Similarly D_1, D_2, and D_3, represents the detail coefficients (DeCo) of the decomposed signal at each level 1, 2 and 3 as seen in Figure 1.

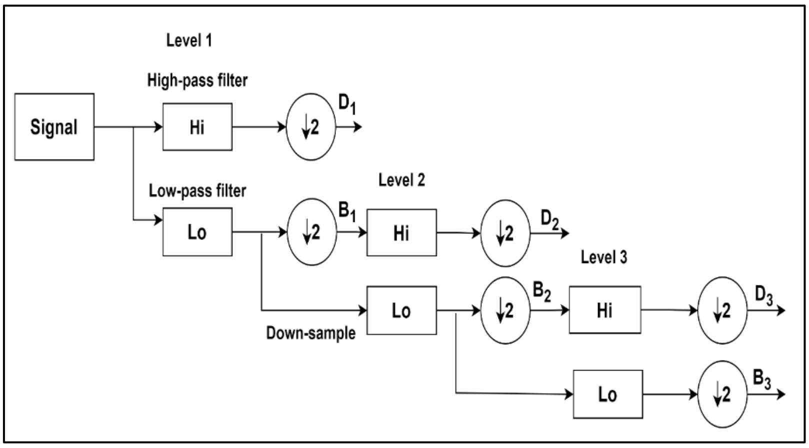

Figure 1 Signal decomposition with high pass and low pass filter.

Selection of mother wavelet, and decomposition level is very importance in wavelet transform. Various mother wavelet has been compared with db10 having the minimum mean square deviation at signal restoration [22]. Four different mother wavelets can be utilized to evaluates the performance of six different machine learning (ML) algorithms for classifying power quality disturbances (PQDs), with statistical features extracted as feature input. Implementation of db4 wavelet for fault detection and recognition of faulty phase in a fifteen-phase transmission network was discussed in [23]. Similarly, db5 mother wavelet can be to detect and classify close in and remote end fault in transmission network.

3.2. Short-Time Fourier Transform (STFT)

In Fourier transform both frequency, and time coefficient domain are discrete. Discrete Fourier Transform (DFT) application and computation is done using Fast Fourier Transform (FFT). STFT is designed to overcome the challenges faced in FT. The characteristics of the frequency amplitude obtained from STFT is used in fault analysis by most researchers. In power system, fault currents and transient disturbances are basically non-stationary, thereby making some researchers to employ STFT to obtain a joint time and frequency representation of the signal. STFT has the ability to extract useful fault features such as amplitude distribution, transient energy, and dominant frequency changes, which are commonly used by many researchers in analysis of fault detection, classification, and high-impedance fault identification in power system [24]. [25], Proposes the use of STFT on DC micro grids for fault detection. STFT was applied to obtain the frequency spectrum from the fault time signal. [24] convert the measured voltage and current signals into time and frequency domains using the short-time Fourier transform (STFT) to produce a time-frequency energy map. In [26], short time Fourier transform (STFT) was proposed as a pre-processing step to acquire time-frequency representation. The vibration images were diagnosed and classify with image classification transformer (ICT), inspired from the transformer's natural language processing. Short Time Fourier Transform can be utilized for transmission line fault detection and classification. It is also used for identification of short duration PQDs which include voltage sags, swells, interruptions, transient oscillations and harmonic distortion. Power quality disturbances can be assessed by Short-Time Fourier Transform, these enhances PQ analysis under dynamic conditions. In [27] short-time Fourier transform was used as mathematical approach for mitigating or reducing harmonics filters in AC transmission system which results in transforming the signal into a domain giving information about time and frequency. [28], discusses various signal processing methods for power quality disturbance (PQ) classification, with short time Fourier transform (STFT) as one of the most effective and reliable methods. The review highlights the strengths and limitations of these techniques, focusing on their effectiveness in addressing non-stationary signal disruptions such as voltage sags, swells, harmonics, and transients. Similarly, [29], compared the performances between the DWT and the short-time Fourier Transform (STFT) in terms of accuracy and processing time for fault detection. In addition to this, the double-detection technique was used to confirm the accuracy of fault detection with results showing that the proposed method is efficient for fault detection and classification.

3.3. Stockwell-Transform (S-Transform)

Analysis in [30] shows that wavelet and short-time Fourier transforms are combined to create the S-transform (ST), which overcomes their limitations in signal processing techniques. S-Transform (ST) has the capability to detect a fault in the power system when influence by noise. Because of this feature, it is very popular in detecting power system faults and power quality disturbances. S-transforms stand out for their capacity to combine local phase information that is absolutely referenced with a frequency-dependent resolution of time-frequency space, a feature that the wavelet transform lacks. The local spectral phase characteristics of the S-transform make it a popular for time-frequency representation. According to [31], who studied fault detection in HVDC transmission line using S-transform technique. Real-time fault detection with different type of faults in HVDC transmission line are simulated using PSCAD. The generated fault signals were analyzed using MATLAB software with S-transform effective detection of transient signal in time-frequency domain. This approach is an expansion of the Wavelet transform technique which is based on a moving and scalable localizing Gaussian window. The location of the fault may be determined by looking at the connection between the signal energy of faults and so-called path characteristic frequencies associated with fault travelling waves, which have a high amplitude around specific frequencies. S-Transform can be used to improve the functionality of existing distance protection by resolving the shortcomings during the fault detection process in case of fault occurrence in systems with a high penetration of power electronics-based generators. Reported results of the operation of commercial distance relays of four different vendors show that all relays experience difficulties during ungrounded faults [32]. [33], proposed a novel S–Transform techniques for identifying power system failures like line to ground, double line to ground, and three line to ground faults. These faults were discovered by using the S–Transform techniques, MATLAB/Simulink software was used to conduct this investigation [34] propose a novel approach for analyzing power system fault based on high frequency noise separately during series arc faults, it also investigates the effectiveness of detection approach for a variety of loads based on S-Transform method. Time-frequency analysis was used to pinpoint the exact location of the transmission line fault in [35]. Transmission line fault identification, classification, and localization are all accomplished with the use of time-frequency transforms like the S-Transform and its variants.

4. Conventional Fault Classification, Detection and Location Techniques

Conventional methods widely used for fault detection, classification and location include:

- Impedance Based Techniques
- Travelling Wave Based Techniques
- Fundamental Frequency Based Techniques

Each of the traditional techniques is discussed in detailed in the subsequent section.

4.1. Impedance Based Technique

Impedance based technique is one of the most popular techniques used in the power network because of its simplicity, and economical value compared to other techniques. The foundational idea behind impedance-based technique is making use of the impedance value (s) from the measurement carried out in the fault location. Impedance based fault location techniques can be further categorized into one ended method and two ended methods

One Ended Method: The majority of numerical relays typically use the one-ended approach for fault location. One-ended method uses the basic frequency components of current and voltage to locate fault. The one-ended impedance-based technique's algorithm is simple and straightforward and doesn't require a communication channel to collect data. Mathematically, equation (1) and equation (2) are used to implement One end method [36].

$$V_S = mZ_L I_S + R_F I_F \tag{1}$$

$$Z_{FS} = \frac{V_S}{I_S} = mZ_L + R_F \frac{I_F}{I_S} \tag{2}$$

where V_S is the source voltage, Z_L is the line impedance, R_F is the resistance of the fault, I_F is the fault current.

In [37], one-ended impedance-based techniques was used to extract faulty line current. The extract faulty features serve as input to Artificial Neural Network (ANN) to locate all type of fault in the transmission line. The one-ended method determined remote end fault current, in order to increase the accuracy of the fault location algorithm. In [38], performance comparison of impedance-based fault location methods was carried out, with impedance parameter of the faulted line section being calculated as a measure of the distance to the fault.

Two Ended Method: Unlike one ended method, two-ended method uses the measurements of voltage and current from both ends of a transmission line to locate fault. By comparing the data from both the sending and receiving ends, two-ended method provides a more accurate estimation of the fault distance compared to the one-ended technique. Mathematically, the two-ended method frequently uses Equations (3) and (4).

$$f_d = \frac{V_S I_R - V_R I_S}{I_S I_R Z_L} \tag{3}$$

Or equivalently, in terms of apparent impedances measured at both ends:

$$Z_{FS} = \frac{V_S + V_R}{I_S + I_R} = f_d Z_L + R_F \frac{I_F}{I_S + I_R} \tag{4}$$

where:

V_S, I_S is the sending end voltage and current

V_R, I_R is the receiving end voltage and current

Z_L is the line impedance

R_F is the fault resistance

f_d is the per-unit distance to the fault along the line

In two-ended method, the fault location is found when the information obtained from both end of the network is equal [39, 40]. In [41] impedance-based fault location algorithms based on two-ends measurements was proposed. The developed rules were employed to obtain an index number of the transmission lines that fault location. These index numbers form the main constraint use in defining the PMU placement to determine the optimal placement of PMUs for state estimation observability and fault location observability.

4.2. Travelling Wave Based Technique

Travelling wave-based technique is used to overcome the limitations of impedance-based technique. Traveling wave-based techniques are more accurate compared to impedance-based techniques; they primarily involve time synchronization and data sampling [42]. The mode of operation, the kind of fault in the system, the current transformer saturation characteristics, etc., have little effect on traveling wave-based techniques compared to impedance-based technique. Several studies have been carried out using a single terminal traveling wave-based method for fault location in a distribution network. This technique normally employed unsymmetrical fault specifically line to phase fault with a sampling rate of 10MHz. [43] applied travelling wave technique to locate fault in a multilateral distributed network, with result showing an exact, fast and accurate, as presence of distributed generations is not affected. Using multi terminal travelling waves-based technique to analyzed fault location have shown good accuracy with the use of two terminal approach [44]. Also, using a combination of single- and double-end techniques and travelling wave fault signature can accurately determine the exact fault location in the transmission network.

4.3. Fundamental Frequency Based Techniques

Fundamental frequency-based fault location techniques are the estimation of fault distance using voltage and current measurements at substations, primarily through impedance calculations or analyzing fault-induced by traveling waves. In [45] traveling-wave natural frequency using 10-ms current data from the single end was proposed. The proposed algorithm depends on peak frequency spectrum corresponding to the first peak as dominant frequency to calculate the fault location. The limitations of the proposed method were overcome in [46]. Fault location technique based on fundamental frequency positive sequence fault are frequently used. In [47]a new single-ended and communication-less method based on positive and negative sequence was superimposed to jointly tackle challenging task on fault location in transmission line.

5. AI Techniques for Fault Classification, Detection and Location

Accurate and precise detection, classification and location of fault type in power systems is very crucial due to the fact that it enables fast and accurate identification of abnormal conditions, they by enabling protection equipment to isolate only the impacted phase of the power system network while maintaining service continuity to un-affected phases. Due to complexity of power systems network, recent researchers on fault detection, classification and location have employed various AI techniques based on learning algorithm, and classifiers to detect, classify and locate fault in power system. In [48], an improved convolution Neural Network based fault detection and classification method with simulated data from MATLAB/Simulink was used to classify all fault type. Argumentation of those data was done using CGAN with result showing an effective classifier of the proposed method. [49] propose a novel self-attention convolutional neural network model for detection and classification of transmission line faults. Convolution neural networks can also be employed in transmission lines to detect and classify all fault types taking into consideration fault inception angles and distances. Probabilistic Neural Network (PNN) and Feedforward Neural Network (FNN) can also be utilized to classify fault. Probabilistic Neural Network (PNN) were employed to classify fault using simulated current signals as input to the neural network. The accuracy based on PNN model was 99.33%.

Support vector machine was used to locate the actual fault distance in a long transmission line [50]. Boltzmann machine learning (BML) techniques was used to detect, classify and locate DC faults with application of traveling waves to produced transmission line faults. Multi-Machine Learning (ML) system architecture was utilized in [51], the proposed techniques use different ML models including Support Vector Machine (SVM) and K-Nearest Neighbours (KNN) to classify transmission line fault. Hybrid methods are also used in fault classification combining both signal processing technique, and artificial intelligence. Data mining techniques has become the new trends in fault classification. In [52] effective data mining tool was used to classify fault in a thyristor-controlled series capacitor compensated line. An advanced machine learning techniques for fault classification were proposed. Advanced digital signal processing (DSP) and time-frequency distribution technique for fault classification was utilized. Results shown that the proposed method was able to classify faults successfully by setting up thresholds obtained via IFDR index for different types of faults. Artificial Neural Network was employed in [53] to detect and classify all types of faults. Feature extraction was done using wavelet transform, the extracted fault current serves as input to Artificial Neural Network (ANN). Result shows a good performance of artificial neural network for locating of faults using different angles, locations and resistance. Also, authors in [54] employed discrete wavelet transform to extract the fault current, in order to train the artificial neural network. Intelligent technique based on artificial neural networks was deployed for precise fault location.

Detection and classification of high impedance fault using Fuzzy logic have proven to be very effective. Fault location can also be achieved using ANFISs [55]. Impedances features including magnitude and phase information of three-phase voltage and current usually serve as inputs for ANFIS training, and based on the result obtain maximum error is about 4% for different fault conditions. ANFIS regression algorithms trained by the BP gradient descent method in conjunction with the least squares' method used the norm entropy of main frequency coefficients (0–62.5 Hz), harmonic coefficients (62.5–500 Hz), and transient coefficients (500–4000 Hz) obtained by six-level DWT using Db4 as mother wavelet severs as inputs for transmission line detection and classification. The average error obtained was 0.25%. Support vector machine can also be utilized for transmission line fault detection and classification. In [56] support vector machine was employed for precise location of fault. The SVM algorithm offers some clear benefits when it comes to resolving location issues. Its prediction time is shorter compare to other techniques [57]. By utilizing the global optimal solution, the target detection classifier's accuracy can be guaranteed. But there are some drawbacks, such as the model of detection is long-established [58]. In term of processing large-scale data set, time complexity and space complexity can increase linearly with respect to the increase in data set [59].

Another smart AI technique used for fault detection, classification and location is distributed device-based. The distributed device-based approach frequently makes use of wide area protection. Devices in the field can communicate with the distribution network system in order to provide wide area protection. Devices employed in distributed protection scheme are, phasor measurement unit (PMU), intelligent electronic devices, (IEDs), digital fault recorders (DFRs), wide area measurement systems (WAMS) and a relay is integrated to improve the fault location.

Research have been carried out on phasor measurement unit (PMU), for instance in [60] phasor measurement unit combined with the impedance matrix of the network was deployed to locate fault in IEEE 14 bus network. [61] uses phasor measurement unit (PMU) in addition to interval algorithm for fault location in distribution network. IEEE 34 bus was deployed as test case, with result showing flexibility and stability. [62] uses phasor measurement unit (PMU), combine with state estimation algorithm to validate fault location in distribution network. IEEE 37 node feeder was used as test case with validation showing 90 % accurate estimation for location of fault. Novel fault localization technique based on Phasor Measurement Units (PMUs) was also discussed. Key objective was to find the distance of the fault occurrence and to locate the fault point along with the latitude and longitude. The results show the effectiveness of the proposed technique to spot the exact fault point in the transmission lines. In [63], phasor measurement units (PMU) and short circuit analysis was proposed for location of fault in distribution network. The proposed method was categorized into two stages; estimation of fault using main feeder and estimation of fault using lateral feeder. The proposed method was verified through various fault situations in a test system. Authors in [64] all deployed phasor measurement units (PMU) in power system for localization of fault. Another distributed device-based technique used in location of transmission line fault is the intelligent electronics devices. [65] proposes the use of intelligent electronics devices for fault location based on sparse measurement. It uses Intelligent electronics devices (IEDs) installed in various station for fault location. The main aim was to locate fault under communication failure. Intelligent electronic devices (IEDs) and sparse measurements tools was used to locate fault-section in a 69-bus, 12.66-kV distribution system with six distributed generations (DGs). Simulation results show that the method is robust for single-phase, double-phase, and double-phase to ground faults with high resistance under noisy condition. In [66] discrete wavelet transforms (DWT) and digital fault recorder (DFR) was combined to locate and capture the first arrival times of the fault-generated by traveling waves. Result shown that the proposed approach performs successfully irrespective of the unknown fault impedance, inception angle, and type. [67], presents a robust fault location method based on K-Means clustering of digital fault recorder (DFRs). The proposed algorithm is tested on both transmission and distribution systems under different fault. Wide-area fault location methods is one of the distributed device-based techniques. In this method, wide-area monitoring system are applied to overcome the adverse situation by providing a viable solution to the fault location problem. In other words, by utilizing the data from a few monitor devices scattered throughout the network, wide-area fault location techniques can accurately identify the fault point within the entire large-scale transmission network. Authors in [68] proposed a synchronized algorithm based on non-linear optimization. By determining the voltage traveling wave arrival time at various sensor nodes in the network and dividing every transmission line at virtual bus nodes, a closed-form expression solution was found. In [69], multiple synchronized voltage measurements were utilized to model the fault location problem as a non-linear estimation problem, which was solved by applying a novel transform based on pre-fault bus impedance matrix to convert the non-linear problem to a linear weighted least-squares problem. Also, fault location without the need for GPS-synchronized sampling of wide-area measurements was proposed in [70].

A linear reformulation of the problem allows for integrating unsynchronized voltage and current measurements, together with two auxiliary variables, into a linear least-squares problem.

Hybrid AI technique is also one of the most used techniques in power system fault detection, classification and location. Most researcher uses the combination signal processing technique with artificial intelligent technique to extract important features detect, classify and locate faults based on those features respectively. Hybrid method which comprises of wavelet technique and artificial neural network was used to detect, classify and locate fault on Nigerian 330kv transmission line. ANN tool box in MATLAB/Simulink R2018a was used to trained the data extracted with wavelet transform. Results showed a Mean Square Error (MSE) of 1.6856e-5 which indicate that the training performance is optimal. line. [71] uses continuous wavelet transform (CWT) and artificial neural network (ANN) to detect, classify and locate faults in a distribution system. To extract the transient signals features more accurately from all the buses, CWT was used. At first, the ANN was trained to detects faulty feeder from the power network, followed by identifying faulty line in the second stage. The final stage uses fault type and fault location to calculated the relaying point with the performance showing more promising as compared to traditionally used algorithms. Work done in [72], two hybrid technique was deployed to predict the location of fault. The first was discrete wavelet transform (DWT) with Adaptive Neuro-Fuzzy Inference system (ANFIS) and the second was discrete wavelet transform (DWT) with support vector machine (SVM). Wavelet transforms can also be combined with extreme learning machine (WT ELM) to detect, classify and locate transmission line fault. Decomposition of the three-phase current was done with the wavelet transform and input to the extreme learning machine was gotten from the output of the decomposed data gotten from the wavelet transform. In [73]Wavelet Transform (WT) was used for preprocessing to acquire the importance features. These features were feed into the SVM and RBFNN for fault distance estimation. Result shows a 0.21 percent fault error locality as compared to other tools used for researchers. Hybrid techniques have some limitation such as large data sets are required, the accuracy of the system is dependent on the amount of dataset, complex decision making in the relay output is required when making use of two methods.

6. Future Outlook on Fault Detection and Protection in Transmission Networks

While existing studies on transmission line and distribution system fault detection, classification, and location have mostly relied on well-established machine learning algorithms, rapid evolution of machine learning and data mining techniques presents more significant opportunities for advancing fault detection and protection schemes. The emergence of deep learning (DL) has introduced more powerful data-driven approaches which is capable of overcoming several limitations associated with conventional protection methods. The foundation of deep learning was established through the use of restricted Boltzmann machines (RBMs) and autoencoders for hierarchical feature extraction from raw data. Although structurally it is a good approach for power system fault detection and classification and similar to multi-layer feedforward neural networks (FNNs), DL models are basically distinguished by their ability to perform unsupervised or semi-supervised feature learning using large volumes of un-labelled data. The significant of this characteristic is to reduces dependence on handcrafted features and helps mitigate over-fitting and convergence to optima, which are common challenges in shallow learning models. Increasing availability in terms of high-resolution measurement data from intelligent electronic devices (IEDs), digital relays, and phasor measurement units (PMUs), combined with advances in computational power, has made the deployment of deep learning models feasible in modern transmission networks. Recent developments in DL have shown substantial improvements in fault detection and classification performance across various domains [74], this indicates strong potential for enhancement of power system fault detection and protection.

Among deep learning architectures, convolutional neural networks (CNNs) have shown more effective in handling multi-channel time-series data [75]. This algorithm aligns naturally with power system fault analysis, since three-phase current and voltage signals are intrinsically synchronized in multi-channel sequences. CNN-based fault detection and classification approaches can effectively capture temporal patterns and inter-phase relationships, which enables more accurate and robust fault classification under complex operating conditions, such as noise, signal distortion, and changing system configurations. Going forward, the integration of deep learning into transmission network protection schemes is expected to support the development of adaptive, intelligent, and self-healing protection systems which is the major limitation in conventional method. Such systems can dynamically adjust the protection settings in order to improve fault discrimination under circumstance of high renewable energy penetration; this enhances resilience against evolving grid disturbances. Furthermore, the combination of deep learning with wide-area measurement systems and high-speed communication technologies will enable faster fault detection, classification and location, it will also coordinate the protection actions, and improved system-wide situational awareness.

In summary, rule-based and static schemes for fault detection and protection in transmission networks will be replaced by data-driven, intelligent protection frameworks in the future. This is due to the reliability, speed, and adaptability requirements of next-generation transmission systems which are expected to be meet large part by deep learning-based techniques that are backed by contemporary sensing and communication infrastructures.

7. Conclusion

This paper gives a detailed summary of most recent research in the field of power system fault detection, classification and location. As demand for power raises due to increase in population, there is need for quick detection, identification, and possibly mitigation of fault in other to protect the end users. Most recent research focuses on Machine Learning (ML) algorithm especially for fault classification. Signal processing technique has also proven to be very active in term of fault detection and classification. A detail review of fault detection, classification, and location has been discussed in the paper. Various techniques, methods are also discussed with prove of recent work carried out by researchers. Artificial intelligence techniques methods have proven 98% accuracy with less error in both identification, classification and localization of fault. Future work on latest trend in fault detection, classification and location can be looked into. This work offers foundational knowledge to researchers and scholars in the field of control and power system for fault analysis.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Mogaru NO. The basics of transmission line protection. In IEEE PES/IAS PowerAfrica, Nairobi, Kenya, 2020.

[2] Kanwal S, Jiriwibhakom S. Artificial intelligence-based faults identification, classification, and localization techniques in transmission lines-A review. IEEE Latin America Transactions. 2023; 21(12): 1290-1305.

[3] Ayamolowo OJ, Buraimoh E, Salau AO, Dada JO. Nigeria electricity power supply system: the past, present and the future. In 2019 IEEE PES/IAS PowerAfrica, 2019.

[4] Okakwu IK, Ogujor EA, Oriaifo PA. Load flow assessment of the Nigeria 330-kV power system. American Journal of Electrical and Electronic Engineering. 2017; 5(4): 159-165.

[5] Egbunike AJ, Anierobi PO. Voltage violation on the 330 kV power network of Nigeria without flexible alternating current transmission device. ANSPOLY Journal of Advanced Research in Science & Technology (AJARST). 2024; 2(1): 16-34.

[6] Ngang NB. Improving voltage stability in Nigerian 330 kV transmission network using intelligent solid state var compensator (SSVC). Journal of Emerging Trends in Engineering and Applied Sciences. 2021; 12(3): 83-90.

[7] Nkan IE, Okoro OI, Awah CC, Akuru UB. Investigating the steady state stability of the Nigerian 48-bus systems using FACTS devices. Nigerian Journal of Technology. 2019; 38(3): 732-743.

[8] Nkan IE, Okoro OI, Akuru UB, Awah CC. Investigating the dynamic stability of the Nigerian 48-bus systems for improved system performance using FACTS. In 2019 International Conference on the Domestic Use of Energy (DUE), 2019.

[9] Natala H, Nkan IE, Obi PI, Okoro OI. Investigation of the transfer capability of the Nigerian 330 kV, 58-bus power system network using FACTS devices. ELEKTRIKA-Journal of Electrical Engineering. 2023; 22(1): 53-62.

[10] Jameson FP, Nkan IE, Okpo EE. Improvement of power transfer capability of Nigeria national grid with TCSC FACTS controller. American Journal of Engineering Research (AJER). 2024; 13(1): 37-43.

[11] Oputa O, Madueme TC. Fault analysis on Nigeria 330 kV transmission system using ETAP," Nigerian Journal of Technology. 2019; 38(1): 202-211.

[12] Unluturk A, Ozer I. Optimization based control of overcurrent relays in distribution network considering real-time measurements: A case study. Applied Energy. 2025; 377: 124439.

[13] Sai Kumar MLS, Kumar J, Mahanty RN. Fault detection during power swing in a TCSC-compensated transmission line based on Clark’s transform and Teager–Kaiser energy operator. Iranian Journal of Science and Technology, Transactions of Electrical Engineering. 2021; 45(1): 47-60.

[14] Nkan IE. Artificial intelligence-based comparative study of high impedance fault detection and localization in the nigerian 330 kV transmission network. Journal of Research and Innovations in Engineering (JORIE). 2025; 10(1): 198-207.

[15] Uma UU, Nmadu D, Ugwuanyi N, Ogah OE, Eli-Chukwu N, Eheduru M, Ekwue A. Adaptive overcurrent protection scheme coordination in presence of distributed generation using radial basis neural network. Protection and Control of Modern Power Systems. 2023; 8(4): 1-19.

[16] Baghaee HR, Mlakić D, Nikolovski S, Dragicević T. Support vector machine-based islanding and grid fault detection in active distribution networks. IEEE Journal of Emerging and Selected Topics in Power Electronics. 2019; 8(3): 2385-2403.

[17] Mestha SR, Prabhu N. Support vector machine-based fault detection in inverter-fed electric vehicle. Energy storage. 2024; 6(1): e576.

[18] Li J, Yang Q, Mu H, Le Blond S, He H. A new fault detection and fault location method for multi-terminal high voltage direct current of offshore wind farm. Applied energy. 2018; 220: 13-20.

[19] Sarna MLA, Hossain MR, Islam MA. Comparative analysis of stft and wavelet transform in time-frequency analysis of non-stationary signals. International Journal of Novel Research in Engineering and Science. 2024; 11(1): 72-78.

[20] Udoh DE, Ekpo DD, Nkan IE. Design and development of a package delivery robot. International Journal of Multidisciplinary Research and Analysis. 2024; 7(6): 2520-2526.

[21] Sun Y, Sun J, Quan X, Liu Y, Ji F, Guo N. A novel transmission line fault location method based on time frequency correlation. In In IOP Conference Series: Earth and Environmental Science, 2021.

[22] Jack AL, Nkan IE, Edem IF, Etim AA. A comparative analysis of different mother wavelets for fault detection and classification in the Nigerian 330 kV transmission network. World Journal of Advanced Engineering Technology and Sciences. 2026; 18(3): 330-340.

[23] Chahinez B, Toufik S, Samah B, Hocine G. Optimal level and base mother wavelet selection for wavelet analysis in wind turbine health monitoring. Algerian Journal of Renewable Energy and Sustainable Development. 2023; 5(2): 191-201.

[24] Yang NC, Yang JM. Fault classification in distribution systems using deep learning with data preprocessing methods based on fast dynamic time warping and short-time fourier transform. IEEE Access. 2023; 11: 63612-63622.

[25] Grcić I, Pandžić H, Novosel D. Fault detection in dc microgrids using short-time fourier transform. Energies. 2021; 14(2): 277.

[26] Alexakos CT, Karnavas YL, Drakaki M, Tziafettas IA. A combined short time fourier transform and image classification transformer model for rolling element bearings fault diagnosis in electric motors. Machine Learning and Knowledge Extraction. 2021; 3(1): 228-242.

[27] Priyadarshini MS, Krishna D, Kumar KV, Amaresh K, Goud BS, Bajaj M, Altameem T, El-Shafai W, Fouda MM. Significance of harmonic filters by computation of short-time Fourier transform-based time–frequency representation of supply voltage. Energies. 2023; 16(5): 2194.

[28] Madgula S, Veeramsetty V, Durgam R. Signal processing approaches for power quality disturbance classification: A comprehensive review. Results in Engineering. 2025; 25: 104569.

[29] Chiradeja P, Ananwattanaporn S, Lertwanitrot P, Ngaopitakkul A, Kunakorn A. Comparative fault detection between DWT and STFT in overcurrent relays. IEEE Access. 2024; 12: 65287-65297.

[30] Beuter C, Oleskovicz M. S-transform: from main concepts to some power quality applications. IET Signal Processing. 2020; 14(3): 115-123.

[31] Singh K, Ukil A. Fault detection in HVDC transmission line by S-transform technique. In 2019 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC) , 2019.

[32] Chavez JJ, Popov M, López D, Azizi S, Terzija V. S-Transform based fault detection algorithm for enhancing distance protection performance. International Journal of Electrical Power & Energy Systems. 2021; 130: 106966.

[33] Agarwal N, Mahela OP, Kumar B. Detection of power system faults in the presence of linear loads using stockwell transform. Journal of Electrical and Electronics Engineering. 2016; 2: 37-45.

[34] Atharparvez M, Purandare KR. Series arc fault detection using novel signal processing technique. In 2018 IEEE Holm Conference on Electrical Contacts, 2018.

[35] Kishor N. Time-frequency based detection of faulted line and fault instant using wide area signals. In 2019 International Conference on Electrical, Electronics and Computer Engineering (UPCON), 2019.

[36] Fan R, Yin T, Huang R, Lian J, Wang S. Transmission line fault location using deep learning techniques. In 2019 North American Power Symposium (NAPS), 2019.

[37] Hashim M, Osman MK, Ibrahim MN, Abidin AF. Investigation of features extraction condition for impedance-based fault location in transmission lines. In 2017 7th IEEE international conference on control system, computing and engineering (ICCSCE), 2017.

[38] Khoa NM, Cuong MV, Cuong HQ, Hieu NTT. Performance comparison of impedance-based fault location methods for transmission line. International Journal of Electrical and Electronic Engineering & Telecommunications. 2022; 11(3): 234-241.

[39] Naidu OD, Pradhan AK. Precise traveling wave-based transmission line fault location method using single-ended data. IEEE Transactions on Industrial Informatics. 2020; 17(8): 197-5207.

[40] Nkan IE, Okpo EE, Akuru UB, Okoro OI. Contingency analysis for improved power system stability of the Nigerian 330 kV, 48-bus system using series FACTS controllers. In International Conference on Use of Energy, 2020.

[41] Dolatabadi SHH, Golshan MEH. Fault location observability rules for impedance-based fault location algorithms. Electric Power Systems Research. 2023; 224: 109771.

[42] Druml G, Skrbinjek O, Hipp W, Leitner W, Schmidt U, Schegner P. Earthfault-localisation in compensated 20-kV-networks based on travelling-waves. In 2019 Electric Power Quality and Supply Reliability Conference (PQ) & 2019 Symposium on Electrical Engineering and Mechatronics (SEEM), 2019.

[43] Kumar R, Saxena D. A literature review on methodologies of fault location in the distribution system with distributed generation. Energy Technology. 2020; 8(3): 1901093.

[44] Abd el-Ghany HA, Elsadd MA, Ahmed ES. A faulted side identification scheme-based integrated distance protection for series-compensated transmission lines. International Journal of Electrical Power & Energy Systems. 2019; 113: 664-673.

[45] He ZY, Liao K, Li XP, Lin S, Yang JW, Mai RK. Natural frequency-based line fault location in HVDC lines. IEEE transactions on power delivery. 2015; 29(2): 851-859.

[46] Elgamasy MM, Izzularab MA, Zhang XP. Single-end based fault location method for VSC-HVDC transmission systems. IEEE Access. 2022; 10: 43129-43142.

[47] Akhavan M, Yazdaninejadi A, Bolandi TG. A new single-ended fault location method based on positive sequence superimposed and pre-fault networks. Electric Power Systems Research. 2026; 250: 112174.

[48] Han J, Miao SH, Yin HR, Guo SY, Wang ZX, Yao FX, Lin YJ. Deep-adversarial-transfer learning-based fault classification of power lines in smart grid. In IOP conference series: Earth and environmental science, 2021.

[49] Fahim SR, Sarker Y, Sarker SK, Sheikh MRI, Das SK. Self-attention convolutional neural network with time series imaging-based feature extraction for transmission line fault detection and classification. Electric Power Systems Research. 2020; 187: 106437.

[50] Ray P, Mishra DP. Support vector machine-based fault classification and location of a long transmission line. Engineering science and technology, an international journal. 2016; 19(3): 1368-1380.

[51] Ghashghaei S, Akhbari M. Fault detection and classification of an HVDC transmission line using a heterogenous multi-machine learning algorithm. IET Generation, Transmission & Distribution. 2021; 15(16): 2319-2332.

[52] Mishra PK, Yadav A, Pansari D. Classification of faults in a TCSC compensated transmission line using data mining algorithm. In 2020 IEEE First International Conference on Smart Technologies for Power, Energy and Control (STPEC) , 2020.

[53] Dashti R, Dashtdar M, Shaker HR. Distribution network fault section identification and fault location using artificial neural network. In 2018 5th international conference on electrical and electronic engineering (ICEEE), 2018.

[54] Chavan JN, Kale AA, Deore SR. Transmission line fault detection using wavelet transform & ANN approach. In 2022 IEEE Integrated STEM Education Conference (ISEC), 2022.

[55] Al Kazzaz SAAS, Ismaeel I, Karam KM. Fault detection and location of power transmission lines using intelligent distance relay. International Journal of Power Electronics and Drive Systems. 2020; 11(2): 726.

[56] Abdullah DM, Abdulazeez AM. Machine learning applications based on SVM classification- A review. Qubahan Academic Journal. 2021; 1(2): 81-90.

[57] Masood AD, Abdulazeez AM, Zeebaree DQ. Machine learning supervised algorithms of gene selection: A review. Machine Learning. 2020; 62(3).

[58] Zebari R, Abdulazeez A, Zeebaree D, Zebari D, Saeed J. A comprehensive review of dimensionality reduction techniques for feature selection and feature extraction. Journal of Applied Science and Technology Trends. 2020; 1(1): 56-70.

[59] Haji SH, Abdulazeez AM. Comparison of optimization techniques based on gradient descent algorithm: A review. PalArch's Journal of Archaeology of Egypt/Egyptology. 2021; 18(4): 2715-2743.

[60] Dashtdar M, Masoud D. Fault location in distribution network based on phasor measurement units (PMU). The Scientific Bulletin of Electrical Engineering Faculty. 2019; 19(2): 38-43.

[61] Fang C, Shi Z, Peng Y, Wu Z, Gu W, Nie P. Fault location in distribution networks using PMU data and interval algorithm. In 2019 9th International Conference on Power and Energy Systems (ICPES), 2019.

[62] Usman MU, Faruque MO. Validation of a PMU-based fault location identification method for smart distribution network with photovoltaics using real-time data. IET Generation, Transmission & Distribution. 2018; 12(21): 5824-5833.

[63] Hong JS, Sim GD, Choi JH, Ahn SJ, Yun SY. Fault location method using phasor measurement units and short circuit analysis for power distribution networks. Energies. 2020; 13(5): 1294.

[64] Conte F, Agostino FD, Gabriele B, Schiapparelli GP, Silvestro F. Fault detection and localization in active distribution networks using optimally placed phasor measurements units. IEEE Transactions on Power Systems. 2022; 38(1): 714-727.

[65] Yang B, Jia K, Liu Q, Zheng L, Bi T. Faulted line-section location in distribution system with inverter-interfaced DGs using sparse meters. IEEE Transactions on Smart Grid. 2022; 14(1): 413-423.

[66] Galvez C, Abur A. Fault location in active distribution networks containing distributed energy resources (DERs). IEEE Transactions on Power Delivery. 2020; 36(5): 3128-3139.

[67] Abur A, Galvez C. Fault location in power networks using a sparse set of digital fault recorders. IEEE Transactions on Smart Grid. 2022; 13(5): 3468-3480.

[68] Marand NJ, Chabanloo RM, Fallah M. Optimal placement of voltage measurements for wide area fault location observability considering the uncertainty of network parameters. Electric Power Systems Research. 2018; 164: 79-88.

[69] Ranjbar AM, Dobakhshari AS. A novel method for fault location of transmission lines by wide-area voltage measurements considering measurement errors. IEEE Transactions on Smart Grid. 2017; 6(2): 874-884.

[70] Dobakhshari AS. Fast accurate fault location on transmission system utilizing wide-area unsynchronized measurements. International Journal of Electrical Power & Energy Systems. 2018; 101: 234-242.

[71] Lala H, Karmakar S, Ganguly S. Fault detection and localization using continuous wavelet transform and artificial neural network-based approach in distribution system. International Journal on Electrical Engineering & Informatics. 2018; 10(2).

[72] Zakri AA, Darmawan S, Ahmad S, Mustafa MW, Usman J. Qualified two-hybrid techniques by DWT output to predict fault location. Indonesian Journal of Electrical Engineering and Informatics (IJEEI). 2020; 8(4): 806-817.

[73] Liu XW. Research on transmission line fault location based on the fusion of machine learning and artificial intelligence. Security and Communication Networks. 2021; 1: 6648257.

[74] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015; 521(7553): 436-444.

[75] Zhang R, Li C, Jia D. A new multi-channels sequence recognition framework using deep convolutional neural network. Procedia Computer Science. 2015; 53: 383-390.