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Critical Review of Fault Detection, Fault Classification and Fault Location Techniques for Transmission Network

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Abstract

The fault is an unwanted disturbance in the power system and causes interruption to the normal working condition in the system network. The need to quickly and accurately identify, classify, and locate these faults is of utmost importance. This has propelled a detailed review of the fault analysis 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 qualities, voltage, and current are used in the analysis. Fault detection, fault classification, and fault location are also discussed separately to understand better the methods used in the individual fault analysis. This study gives a critical review that guides understanding the various techniques used in fault analysis, alongside their results, test systems, and gaps in the literature.

Keywords: Fault analysis, Fault detection, Fault classification, Transmission network, Machine learning, Artificial intelligence.

1. Introduction

The transmission line is one of the most important component in the power system, and is more subjected to fault due to its exposure to the environment [1]. One cannot tell when it will occur, it ranges from falling trees on poles, impact of cars to the electric poles, natural disasters, ageing, and so on. Faults are unavoidable in power system. Whenever fault occurs in power system, the system qualities (voltage, current, phase displacement) are affected, it leads to an increase in either of the system quality threshold value. Faults on transmission lines (overhead line) is classified into two, series (open circuit) fault, shunt (closed circuit) fault. Frequently occurring faults on overhead lines is shunt fault [2]. Shunt (short circuit) fault is divided into two; symmetrical faults and unsymmetrical faults. Symmetrical fault also known as balanced faults, it involves the three phase (L-L-L) or three phase to ground (L-L-L-G). Unsymmetrical faults involves; two phase (L-L), a phase to ground (L-G), and two phase and a ground (L-L-G) [3]. Figure 1 shows fault classification on overhead lines.

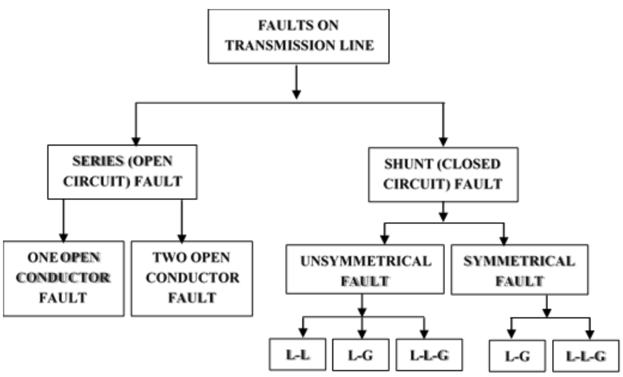

Fig. 1. Fault Classification on Transmission lines.

In as much occurrence of faults on overhead transmission line cann
ot be controlled by humans, it is importance to accurately, and correctly identify, classify and locate faults. A lot of research has been done and still ongoing on fault analysis. Efforts are made to develop smart systems to be able to automatic detect, identify, and locate fault accurately.

Signal processing techniques, machine learning, artificial intelligence (AI) [4], has helped in research to advanced fast recognition, and analysis of faults. Serval barriers has been encountered during research; insufficient real-time data of the system qualities (current and voltage). To obtain to system qualities, feature extraction, i.e. S-Transform, Wavelet Transform, Fourier Transforms, etc. is used [5]. These techniques assure rapid response to faults.

A review of the several techniques used for identification, classification, and location of faults is presented in this paper. A comprehensive review, comparison, and evaluation of the various techniques used for fault identification, fault classification, and faults location is discussed in this paper including the performance indices based on the various techniques used. The order of this paper is as follow. Section 2 discusses signal processing technique, Fault detection techniques, and methods is presented in section 3. Fault classification techniques, and methods is presented in section 4. Section 6 concludes.

2. Signal Processing Technique

The frequency characteristics of the system quantity changes in an occurrence of fault. Signal processing studies the frequency characteristics of time domain signals. Various signal processing techniques has been applied in research for fault analysis especially for fault identification [6][7]. Recently used signal processing technique is discussed below.

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2.1. Wavelet Transform

Wavelet can be seen as converting the available data from time domain to frequency domain without losing any data in the time domain [8]. The wavelet transform is extensively used in fault analysis. There are two wavelet transform; Continuous wavelet transform (CWT) and discrete wavelet transform (DWT). Considering multiple band frequency to finding the current, voltage characteristics discrete wavelet transform is considered [9]. Selection of mother wavelet, and decomposition level is very importance in wavelet transform (WT) implementation used in fault identification, and classification. Various mother wavelet is discussed in [10]. Daubechies4 (db4) mother wavelet is commonly used in power system transient analysis because of its accuracy as compared to other mother wavelet. G. kapoor [11] implemented db4 in fault detection and recognition of faulty phase in a fifteen phase transmission network. [12] Proposes the use of db5 to detect and classify close in and remote end fault in a six phase transmission network.

Discrete wavelet transform (DWT) is mainly used than Continuous wavelet transform (CWT) because of its ease in implementation and requirement for computation above every other advantage.

2.2. Short-Time Fourier Transform (STFT)

Fourier transform is a widely used mathematics tool for frequency domain analysis. Where both frequency, and time coefficient domain are discrete. Discrete Fourier Transform (DFT) is applied and computation is done using Fast Fourier Transform (FFT). STFT is designed to overcome the challenges faced in FT [13]. The characteristics of the frequency amplitude obtained from STFT is used in fault analysis by most researchers [14]. [15] 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.

2.3. Stockwell-Transform (S-Transform)

Analysis from [16] shows S-Transform is a combination of WT and STFT based on their properties. S-Transform gives information on the frequency, time, angle of a signal of study, and also noise has no impact on it [13]. In [17] S-Transform was used to detect fault real time. [18] Proposes the use of S-Transform based detection of fault for improve distance protection performance.

3. Fault Detection

Rapid detection assist in the immediate separation of affected phase to protect the system from possible catastrophic impact of the fault. Fault detection is the first thing that take place before fault classification, or fault location. Based on several techniques especially signal processing features are used for fault detection analysis. Whenever an independent method is used, fault classification and location are activated. Some methods carried out by researcher is discussed below.

Yu Li et al used image fusion based on deep learning for fault detection [19]. The database of three types of imaging (ultraviolet images, infrared images, and visible light images) was collected, processed, and reconstructed by capsule network model resulting in accurate detection and display of fault. Chatterjee & Debnath [20] made use of Sequence Component Analysis (SCA) taking the positive sequence admittance to formulate the algorithm for fault detection. This analysis gives an accurate result even in presence of high impedance, a saturation of the current transformer, and so on. Modified support vector technique was proposed for fault detection in distribution network [21]. This technique was carried out on open circuit faults, considering the potential difference on different node in the distribution network. The input to the system is the root means square voltages. The result of this analysis shows an accurate, robust fault detection system. [22] Proposes a novel algorithm for fault detection in multi-terminal high DC network using the historical current series time data. Different fault detection techniques and methods is shown in Table I considering the method or techniques, input variables, software used, where it was applied (voltage level), results including the performance indices.

The period of fault detection is not directly proportional to the effect of the entire system protection performance that is the fault detection, classification, and location. When compared to fault classification, detection is realized between 2miliseconds to 10miliseconds while that of the latter is 30miliseconds [23].

Table 1. Difference Fault Detection Techniques/ Methods.

	Methods/ Techniques	Signal Variables	Fault Type(s)	Process	Result: Performances Indices
[24]	Linear Discriminant analysis (LDA) and CuttleFish Optimizer (CFO)	Voltage signal	Shunt fault	MATLAB 2013a 181.01 Signal behaviour was extracted using LDA Through CFO learning process based RFA, CFO was used for identifying the faults	Two trials were conducted (50 trials and 100 trials). **50 trials** gave an accuracy of 0.98, specificity 0.96, recall 1.60, precision 0.97. **100 trials** gave accuracy 0.96, specificity 0.98, recall 0.87, precision 0.99
[25]	Discrete wavelet transform (DWT) and Machine Learning tool (MLT)	Current Signal	Shunt Faults	Mother wavelet of db4 is used to decompose the current signal. Based on the extracted feature, statistics measure are applied to obtain statistical feature Artificial Neural Network (ANN) and Multilayer Perception (MLP) network are used for training and detection respectively	Detection of fault shows 100% accurately

[26]	Mathematical Morphology Based and Decision Tree	Current signal	Shunt Faults	ATP/EMTP used for transmission line modelling The Three-Phase current with zero sequence is pre-processed with Morphology Median Filter (MMF) for feature extraction	Accuracy shows 99.98%
[27]	Convolution Neural Network (CNN) based decision	-	Underground Fault	Thermal camera module & Raspberry PI for acquisition Automated decision making was done with CNN Python was used to code for CNN	Accuracy is 93%, Sensitivity is 91%, Specificity is 95%
[28]	Restricted Boltzmann Machine (RBM) and Artificial Neural Network (ANN)	Voltage and Current signal	Shunt Fault	Discrete wavelet transform (DWT) used for current and voltage signal	Accuracy is close to 100%
[29]	Phasor Measurement Units (PMU) and Support Vector Machine (SVM)	Voltage signal	Shunt Fault	PSS/E and MATLAB for testing PMU bus observer was used to obtain the positive sequence and zero sequence voltages	-
[30]	Three-Phase current and a moving average concept	Current signal	Shunt Fault	MATLAB & Simulink with simulation time 100microsecond Sampling frequency is 10kHz	Fault detection less than 1.7ms
[31]	Back Propagation (BP) Neural Network	Voltage and Current signal	Unsymmetrical (Shunt Fault) Fault	PSCAD for modelling and simulation	Accuracy shows 93%
[32]	Artificial Neural Network(ANN)	Voltage and Current signal	Shunt Fault	Modeling was done on PSCAD/EMTDC Simulated fault data were extracted using MATLAB Fault recognition was done using feedforward network with backpropagation	Mean square error of 0.000145 Validation is 0.99998 Testing is 0.99953
[33]	Wavelet Transform (WT) and Artificial Neural Network (ANN)	Voltage Signal	Three Phase fault and Shunt Fault	MATLAB Simulink and Neural network tool box Db4 mother wavelet	Fault detection in very less time

4. Fault Classification

Recent research on fault classification are based on learning algorithm, and classifiers. Fault classification on transmission network is of utmost important, it help the operators know the type of fault that occurred. Recent work on fault classification tend to be focusing on intelligence technique like convolution neural network (CNN), Probabilistic Neural Network (PNN), Feedforward Neural Network (FNN), Support Vector Machine (SVM) [34][35][36]. R. Muzzammel and A. Raza [37], uses Boltzmann Machines Learning (BML) for fault classification. Hybrid methods are also used in fault classification combining both signal processing technique, and artificial intelligence [38][39][40][41]. Data mining techniques are new trends in classifying [42]. [43] Proposes Probabilistic Neural Network (PNN) based fault classification using simulated current signals as input to the neural network. The accuracy based on PNN model is 99.33%. Han, J et al. [44] Proposes an Improved Convolution Neural Network (I-CNN) based fault classification method using simulated data from MATLAB/Simulink. Argumentation of those data was done using CGAN. Result sows an effective classifier of the proposed method.

Principal Component Analysis (PCA) was proposed for fault classification [45]. All fault cases were simulated using the proposed analysis. Proposed method shows an accuracy of 99.41%. Different fault classification methods are shown in Table 2 considering the method or techniques, input variables, software used, where it was applied (voltage level), results including the performance indices.

Table 2. Difference Fault Classification Techniques/ Methods

	Methods/ Techniques	Signal Variables	Fault Type(s)	Process	Result: Performances Indices
[46]	Convolution Neural Network (CNN)	3-Phase Voltage and Current Signal	Short-Circuit Fault	MATLAB/Simulink used for modeling of the system, using 60Hz as frequency Coded on python and keras library with TensorFlow 10-fold validation was considered	Fault Classifier Accuracy is 99.52%
[47]	Principal Component Analysis (PCA) and Probabilistic Neural Network (PNN)	Current Signal	Short-Circuit Fault	Electromagnetic Transient Programming (EMTP) was used for the model of the 150km transmission line Simulated data is analyzed using PCA and PNN Classifier on MATLAB	Fault Classifier accuracy based on the proposed algorithm is 100%

[48]	Convolutional Neural Network	Voltage Signal	Short-Circuit Fault	MATLAB/Simulink was used to model and simulation of the network The fault location, resistance, and also the inception angle was considered and varied during simulation	Accuracy shows 100%
[49]	Hidden Markov Model (HMM)	UFPA dataset	Short Circuit Fault (Unsymmetrical Fault)	Testing and Training was done with HMM Confirmation and validation was done using statistical test	Dataset of between; 200 & 500 has an error rate of 0.02% 100, 300, 600, 700, 900 has an error rate of 0.03% 400, 800, 1000 has an error rate of 0.04%
[50]	Support Vector Machine (SVM)	Voltage Signal	Short Circuit Fault	Fault analysis was simulated using OpenDSS software Python was used as the programming language Training of SVM was done using Gaussian radial basis function (GRBF) IEEE 34 AND 123 Bus was used for testing	Accuracy with IEEE 34 bus containing 48880 of data is 99.99% Accuracy with IEEE 123 bus containing 1 346 310 of data is 99.08%
[51]	Gradient Similarity Visualization (GSV) and Cross-Domain Adaption (CDA) based Convolutional Neural Network(CNN)	voltage and current Signal	Short-Circuit (Unsymmetrical Fault)	The electrical signal (voltage and current) was converted to gradient similarity (GS) based images This GS image serves as input to the CNN	A decrease of 1% accuracy when a noise of 40dB is introduced
[52]	Artificial Neural Network (ANN)	voltage and current Signal	Shunt Fault	MATLAB/Simlink SimPowerSystem was used for modelling of the transmission line Feedforward Neural network (FNN) with backpropagation was used for the analysis of the fault classifier	Performance Indices shows a Mean Square Error (MSE) of 0.00004279 and an accuracy 95.7%
[53]	Backpropagation Neural Network (BPNN)	Voltage and Current Signal	-	MATLAB was used for modeling of the transmission line Simulated voltage and current were extracted and used for the proposed classifier model	Accuracy shows 97.9%
[54]	Decision Tree	Voltage and Current Signal	Short-Circuit Fault	S-Transform was used for feature extraction Features obtained from S-Transform was used as input to the classifier	-
[55]	Discrete Wavelet Transform (DWT) and Adaptive Neuro Fuzzy Interference System (ANIFS)	Current Signal	Short-Circuit Fault	MATLAB/Simulink model of the transmission network DWT is used as feature extraction us dB5 as mother wavelet The feature is then fed to the ANIFS	The accuracy of the Fault Classification shows 99.78%

5. Fault location

Accurate and precise fault location plays a significant part in fast-tracking system restoration, decreasing outage time, and ominously improving system reliability. Fault location can be define as physically determining the location of occurrence of a fault in the power system. Fault location in transmission line is of high increase in the field of research in power system [56]. Diverse scheme and approaches has been used by researchers to tackle the issue of fault location in transmission.

Conventional techniques, over the past years has been used in the fault detection, fault location. The conventional techniques involves trial and error process [57]. The use of foot patrol in search for fault occurrence in small scale areas and the use of vehicles in large scale areas in search for fault location. The conventional process of fault detection, and fault location is time consuming and can cause permanent damage to the power system equipment if the faults is not located on time.

Various techniques has been developed in recent time and has help researchers in the implementation in fault location in transmission network [58]. Fault location method can be categorized into the main and the visualization is seen in Figure 2.

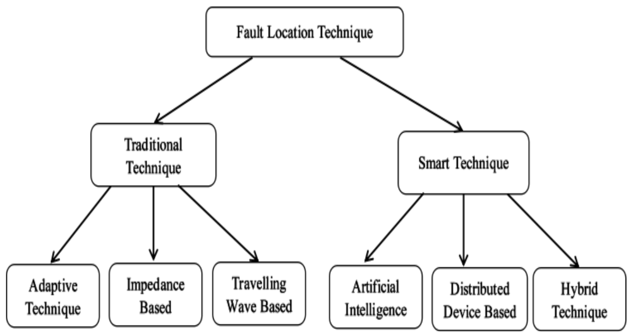

Fig. 2. Techniques for Fault Location (FL).

5.1 Traditional Technique

The tradition technique of fault location are also conventional methods used for fault location. The three common traditional techniques or methods include;

1. Adaptive Technique
2. Impedance Based Technique
3. Travelling Wave Based Technique

Each of the traditional technique is explained in detailed in the next section.

1. Adaptive Technique

Adaptive technique can be traced back to 1960s, the main purpose is to modify the relay setting to the present system state continuously. Many research on fault location has adopted this technique in problem of coordination for protection especially in distributed generation integration. This technique are particular to distributed generators (DG) [59]. When there is a change in the state of the system, i.e., switching, insulation breakdown, generator disconnection, etc., the protective relay re-analyze the settings using the main computer connected [60]. The new analysis done will then be communicated to the individual protective relays to modify its settings. One advantage linked to this technique is the economic cost, which is less expensive.

The re-analysis done by this technique when there is a change in the system is the calculation of the optimum setting, location, size of the generator, the incursion level for reducing failure of the protection and enhancing the network dependability. Practically, obtaining the optimal operating condition is not available all the time. Thevenin equivalent in relation with adaptive technique was proposed by [61], the measured sampled are used to get the Thevenin equivalent parameter and reduces the effect of distributed generators on the protective components, fault calculation online under different scenarios is considered. The operation of the relay works on the principle of current measurement to find possible locations. The limitation of this technique is its dependency on the control centre and communication within the system to make decision.

2. Impedance Based Technique

Impedance based technique is one of the most popular technique 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 [62]. The measured values used in calculation is the voltage and current with line parameter. Based on impedance based technique, the formula for the analytical solution for fault distance based on fault location is shown inequation 1.

$$f_d = \frac{V_f}{I_f + Z_l} \tag{1}$$

Impedance based technique can be further broken down into one ended method and two ended method [58]

- **One Ended Method**: One ended method can be seen in most numerical relays. One ended method uses fundamental frequency of voltage and current to determine the location of the fault [63]. Algorithm in one ended impedance based technique is simple, and does not require any channel for data collection. One limitation of one ended impedance based technique is, it accuracy in terms of estimation in combining the fault resistance and load, error in modelling, non-homogeneity of the system, and relay measurement inaccuracy. A major merit of one ended method is that, one ended method doesn't require any means of communication and can also easily be implemented into digital relays. Mathematically, equation 2 and equation 3 are used in One-end method [63];

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

$$Z_{FS} = \frac{V_S}{I_S} = mZ_L + R_F \frac{I_F}{I_S} \tag{3}$$

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.

- **Two Ended Method:** Compare to one ended method, two ended method make use of the voltage and current of the system at both ends of the network for location of faults. Two ended method measurement compensate the errors from the network and the state of the system based on the analysis gotten from the extraction of the data from both end of the network [64]. The fault location is found when the information obtained from both end of the network is equal. Two ended method can be sub divided into two depending on the data used; synchronized data and unsynchronized data [65].
- Synchronous method: Synchronized method was a primary factor that define a two ended method in fault location. Its solution was based on the analysis between the behaviour of the line viewed from the two ends. The computation of the fault location can be carried out by any of the symmetrical components. From research, it has been seen that negative sequence component is better as compared to the other sequence component (positive sequence, and zero sequence). Negative sequence component is not affected by the current of the load, the mutual coupling, zero sequence line impedance uncertainty, or feed from the tapped load.
- Unsynchronized method: The information obtained from the devices at the two ends may not be synchronized with each other.

3. Travelling Wave Based Technique

Travelling wave based technique is used to overcome the drawback of impedance based technique. Accuracy of travelling wave based technique is higher than that of impedance based technique, it involves majorly the sampling of the acquisition data and synchronization of time [66]. Travelling wave based technique are largely not affected by the mode of operation, type of fault in the system, the current transformer saturation characteristics, etc. Transmission network has largely applied travelling wave based technique especially in research. The system measure relative arrival times of travelling waves produced by faults to approximate fault locations [67].

The concept behind travelling wave based technique is to apply the connection between forward travelling wave propagation and backward wave propagation along the line when there is occurrence of fault [68]. The events of faults such as faults along the line, switching, thunder strokes on the line, induce the transient travelling waves in the transmission line.

When a fault occurs, the initiated travelling wave journeys in the two directions at a speed close to that of light, until it get to the line terminal. The impulse, time difference between the impulse coming in and its reflection or by analyzing the two wave fronts at the respective line terminal, the location of the fault is obtained provided the distance of the conductor, and the velocity propagation known. [69] proposes a single terminal traveling wave based method for fault location in a distribution network.

This proposed technique was used in an unsymmetrical fault specifically line to phase fault with a sampling rate of 10MHz. [59] applied travelling wave technique to the location of fault in a multilateral distributed network, the result of his research shows an exact, fast and accuracy technique, it is not affected by the presence of distributed generations (DGs). [70] uses multi terminal travelling waves based technique in the analysis of fault location for a line to ground fault. Result shows good accuracy with the use of two terminal approach. [71] uses travelling wave based technique in his result for the location of fault where the location is estimated by multiple recorded travelling wave point in the distributed network.

Travelling wave based technique rate of accuracy is dependent on the availability of synchronized data at both end considering a two terminal travelling wave based technique [72]. The accuracy of travelling wave based technique is influenced by inception angle of the fault, fault closed to the fault locator, synchronized device, detection of the travelling waves.

5.2 Smart Techniques

Complexities, unbalanced structure, short distance of the transmission network, unknown fault resistance, laterals, when presence make impedance based technique and travelling wave based technique difficult in application [73]. This technique can be sub divided into three;

1. Artificial Intelligence Technique
2. Distributed Device based Technique
3. Hybrid Technique

1. Artificial Intelligence Technique

Several artificial intelligence technique is been used for fault location such as Artificial Neural Network (ANN), Fuzzy Logic (FL), Genetic Algorithm (GA), Support Vector [74]. Artificial Intelligence technique requires data or information for analysis. Data such as measurement of the feeder, status of the feeder, the status of the station, fault detection data collected by the installed devices along the network, and condition of the atmosphere. Some few techniques will be discussed.

- Artificial Neural Network (ANN) is one of the most used technique under Artificial Intelligence for research in fault location in power system. Artificial Neural network identifies patterns, which enable the network to locate fault(s) in power system [75]. Though, Artificial neural network has to go through a training process for fault location, data are major requirement for the training process. The concept of artificial neural network (ANN) can be visualized in Figure 7, consisting of the input layer, hidden layer and target layer, where mostly voltage and angle are the input for training gotten from the devices installed for measurement and the fault location is the target layer. [76] use Artificial Neural Network for fault location using extracted features obtained with discrete wavelet transform as training parameters for the neural network. The research was carried out on a 735kV transmission network with various distances simulated, the result shows that the proposed system can estimate fault distances based on the fault type. In [77] work, Artificial Neural Network (ANN) was used for fault location, feature extraction was done on a three phase currents with wavelet transform. Result shows a good performance of artificial neural network for locating of faults using different angles, locations and resistance. [78] implemented artificial neural network in IEEE 15 bus system for fault location. Result shows a good performance for fault location.

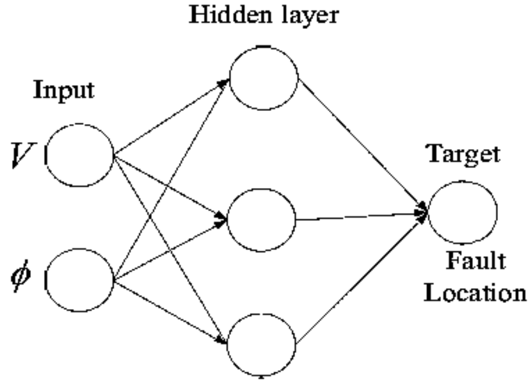

Fig. 7. Basis Concept of Artificial Neural Network (ANN).

- Fuzzy Logic is another technique used in Artificial Intelligence, it is based on possibility instead of probability [79]. The concept of possibility is said to be a number between one and zero, i.e., complete possibility and totally impossible respectively while probability has to done with uncertainty provided statistical data are available. In circumstances when there is no statistical data available, various hypotheses is used by experts. Fuzzy logic technique has a drawback of determining the global minimum using fuzzy function [80]. [81] proposes the detection of high impedance fault using Fuzzy logic [82] presented the application of fuzzy logic in locating faults in power system.
- Support vector machine is another technique used in artificial intelligence. Support vector machine (SVM) are supervised learning algorithm that analyses information using associate learning algorithm [83]. Support vector machine (SVM) is a linear binary classifier and its nature is non probabilistic. The concept of support vector machine (SVM), training are mapped in space [84]. Data point in support vector machine are taken as vector with n-dimension, separated by n-1 hyper planer dimension. [85] presented support vector machine for fault analysis in distribution network. [86] proposes the use of support vector machine for fault location in AC micro grid.
- Genetic Algorithm is another technique used in artificial intelligent for fault location. This technique looks for possible location of fault through crossover, mutation operation, selection to pin point the exact location of the fault.

2. Distributed Device based Techniques

Distributed device based is another technique under smart method for location of fault. Wide area protection is often used under the distributed device based technique. The devices located in the field, system communication in wide area protection can be shared with the distribution network system. The traditional scheme for protection follows a general control, which affect the whole system or network when there is a system failure or fault. Hence, the distributed devices are put in place to overcome the weakness of the traditional protection scheme, where a breakdown at a node leads to the failure of that section [88]. Devices used in distributed protection scheme are, phasor measurement unit (PMU), intelligent electronic devices, (IEDs) and a relay is integrated to improve the fault location. Research have been done on phasor measurement unit (PMU).

[89] applied phasor measurement unit combined with the impedance matrix of the network for fault location in a 14 bus distribution network. The uncertainty on the network

parameter was considered and result shows accuracy in the network. [90] carried out a research using phasor measurement unit (PMU) data in addition of an interval algorithm for fault location in distribution network. IEEE 34-bus was considered for testing the method. Result shows flexibility and stability. [91] proposes a phasor measurement unit (PMU) fault location on a three terminal transmission line. The network is series compensated. Simulation was carried out on DIgSILENT Power Factory and MATLAB. Result shows that the model is suitable for long transmission line, medium transmission line, and short transmission line. [92] validate phasor measurement unit (PMU) for fault location in distribution network. State estimation algorithm was used. IEEE 37 node feeder was used as test for validation and result shows a 90 percent accurate estimation for location of fault. [93] proposes the use of intelligent electronics devices (IDE) for fault location based on sparse measurement. This method was implemented in a 69 bus, 12.66kV distribution network using different fault scenarios. Results shows a good performance for fault location. [94] uses Intelligent electronics devices (IEDs) installed in various station for fault location. The intelligent electronics devices (IEDs) used in the various station were not link with any communication devices either wired or wireless. The aim to locate fault under communication failure.

3. Hybrid Technique

The concept of hybrid technique is the combination of more than one method in fault location. Hybrid technique help to use the strength of individual method in consideration. It help in the accuracy, and speed in the location of fault. Most researcher uses signal processing technique with artificial intelligent technique to extract important features and locate faults based on those features respectively. In [95] work, two hybrid technique was used to predict the location of fault. The first hybrid technique used was discrete wavelet transform (DWT) with Adaptive Neuro-Fuzzy Inference system (ANFIS) and the second hybrid technique used was discrete wavelet transform (DWT) with support vector machine (SVM). A three bus system was used as the test subject. Comparison between the two hybrid systems was carried out to see the best. Sampling rate of 50Hz for both D8 and D9 was used for the wavelet transform and their various coefficient was used as training for both the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Machine (SVM). Serval type of faults were considered including the fault location, fault angle. Etc. [96] combined wavelet transform with extreme learning machine (WT-ELM). 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. Support vector machine (SVM) combined with Artificial Neural Network (ANN) was used to test the accuracy using the wavelet transform data as input to the network. Result shows a good performance. [97] carried out a research on a 20kV 5km underground cable location of fault using wavelet transform (WT) with extreme learning machine (WT-ELM). Signal decomposition was carried out with wavelet transform then feature extraction was done. The extracted feature was inputted to the extreme learning machine. Result shows a least fault locality error of 0.21 percent. [98] presented a fault location system on a 11kV, 60km distribution network using support vector machine (SVM) and radial basis function neural network (RBFNN). Wavelet Transform (WT) was used for pre-processing 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 has 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.

Summary of Related Literature Based on Fault Location

Presented a new algorithm, in locating faults on transmission line. This algorithm uses line parameters given in Partial Differential Equations (PDEs) taken in time domain at both the sending and receiving end. Telegrapher's equation was use for transmission line model, solved with ADM. Result shows high degree of accuracy. [45] Proposes the use of impedance based technique and travelling wave based technique for fault location in a 400kV transmission network. The aim of this study was to analyze the performance of the two technique. Different fault location methods are shown in Table III considering the method or techniques, input variables, software used, where it was applied (voltage level), results including the performance indices.

Table 3. Summary of Fault location Methods

Reference	Methods or Techniques	Signal Variables	Process	Result: Performances Indices
[99]	Adaptive Network Based Fuzzy Interference System (ANFIS)	Current Signal	MATLAB Simulink was used for simulating the three phase transmission line Feature extraction was done Adaptive Network Based Fuzzy Interference System (ANFIS) network is trained using the features	Mean square error (MSE) is achieved between 0.0012 to 0.0022
[100]	Ant Colony Algorithm (ACA) with Radon transform algorithm		The use of traveling wave signal was used and process by radon transform algorithm Ant Colony Algorithm was used for location of the fault	
[101]	Linear Regression (Stepwise Linear) Linear Regression (Stepwise Linear)	Image samples	Pre-processing of the images gotten and feature extraction of the images PSCAD/ EMTDC is used for modelling of the system	Result shows an error of 1.225% for overhead network and 1.304% for underground cable
[102]	Support vector regression (SVM)	Voltage and current signal	Feature extraction was done with wavelet transform Support vector regression (SVM) use the extracted features to train	Single SVM gave a minimum error of 0.0045 and 0.0213

				Multi SVM gave a minimum error of 0.0024 and 0.0070
[103]	Impedance based Technique	Voltage and Current signals	DIgSILENT was used to simulate the model Sampling frequency of 10kHz was used with a 0.2sec simulation time	Result shows error of less than 1%
[104]	Discrete wavelet transform based technique	Current signals	Time domain, impedance, visual inspection were technique used in analysis	Result shows a relative error range of 0.03 p.u.
[105]	Adaptive Convolution Neural network (ACNN)	Three phase voltage and current signal	Feature extraction was done using the pooling layer Extracted features were used as training data Two terminal fault algorithm was used for analysis Adaptive Convolution Neural network Model built with TensorFlow framework	Result shows accuracy of 7.86% with reduced training time of 42.7%
[106]	Discrete Fourier Transform (DFT) and Artificial Neural Network (ANN)	Three phase voltages and current signals	Matlab/ Simulink was used to model and simulate the network for various faults Data pre-processing using Discrete Fourier Transform (DFT) Extracted features were trained using Artificial Neural Network (ANN) using different neurons	Result shows good performance and low error in 99 locations simulated
[107]	Support Vector Machine (SVM) and Similarity Model Matching	Voltage signal	The fault of branch is determine by the SVM fault branch Similarity model with Euclidean distance is used to calculate fault location IEEE-14 network was model to validate the analysis	Result shows a location error with 4%
[108]	Travelling wave and Artificial Neural Network (ANN)	Three Phase current signal	PSCAD/EMTDC was used to verify the accuracy of the system IEEE-30bus system was used Artificial Neural Network was used to train the network	The result shows an absolute error of 0.036km

6. Summary of Discussion

A critical review of fault detection or identification, fault classification, and fault location has been presented in this paper. In addition to representative works, various techniques, methods and procedures are also discussed in detailed.

An overview of feature extraction methods, the foundation for fault identification algorithms, is offered before addressing recent methods utilized in fault detection, classification, and location by researchers. Different transforms, as well as dimensionality reduction approaches, were also discussed. Newly developed theories are also explored, as well as their comparisons to several significant elements of fault detection.

For fault-type classifications, researchers frequently use machine learning-based approaches. Deep learning-based algorithms such as CNN and RBM, in addition to SVM, FIS, ANN, and DT, are recommended for fault classification. From the reviews on the various machine learning algorithms, it can be seen that the advantages of using machine learning algorithm outweigh the traditional or conventional means of fault analysis. Accuracy of the various machine learning algorithms shows a good accuracy as regards the different fault analysis.

The use of AI-based approaches to locate fault is discussed. Due to the rising role of communication and processing in transmission systems, machine learning, particularly deep learning methods, is recommended for future fault location finding methods.

Different artificial intelligence and machine learning-based algorithms are examined in terms of their general strengths and limitations. A tabulated comparison of all three tasks, fault detection, classification, and location, is also discussed, taking into account inputs variables, methods, process and results, The use of AI in the field of power system has proven to be very vital to our smart grid based on the various research that has been carried out.

7. Conclusion

This paper gives a summary of most recent research in the field of power system fault detection and classification. As demand for power raises, there is need for quick detection and identification of fault. Most recent research focuses on Machine Learning (ML) algorithm especially for fault classification. Signal processing technique

A detail review of fault detection, fault classification, and fault location has been discussed in the paper. Various techniques, methods are discussed with prove of recent work carried out by researchers. Artificial intelligence techniques/methods has proven 100% accuracy with less error in both identification, and classification. Future work on latest trend in fault location can be looked into. This work offers foundational knowledge to researchers and scholars in the field of fault analysis.

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