J. Inst. Eng. India Ser. B (August 2021) 102(4):855–877
https://doi.org/10.1007/s40031-020-00530-0

REVIEW PAPER

Transmission Line Faults in Power System and the Different Algorithms for Identification, Classification and Localization: A Brief Review of Methods

Alok Mukherjee[1] · Palash Kumar Kundu[2] · Arabinda Das[2]

Received: 29 September 2020 / Accepted: 20 December 2020 / Published online: 6 January 2021

Abstract Transmission lines are one of the most widely distributed engineering systems meant for transmitting bulk amount of power from one corner of a country to the farthest most in the other directions. The expansion of the lines over different terrains and geographic locations makes these most vulnerable to different kinds of atmospheric calamities which more often develops faults in line. It is imperative to remove the faulty line at the earliest to restrict undue outflow of bulk power through the faulted point as well as restore system stability earliest to resume normal power flow operation. Here lays the importance of having a robust fault identification, classification and localization algorithm which would be successfully able to drive as well as actuate the digital relaying system. Researchers have worked out several methodologies in developing improved power system protection algorithms which would be able to serve to eliminate faults immediately on occurrence of the same. A brief yet exhaustive review has been presented in this article including the several methodologies adopted by numerous researchers for developing effective fault diagnosis schemes, mentioning about the highlights as well as the shortcoming of each of the methods. This compact and effective survey of literature works would help researchers to take up appropriate techniques for different purposes of transmission line fault analysis.

Keywords Transmission line · Fault identification · Fault classification · Fault location

✉ Arabinda Das
adas_ee_ju@yahoo.com

Alok Mukherjee
alokmukherjee.ju@gmail.com

Palash Kumar Kundu
palashm.kushi@gmail.com

[1] Government College of Engineering and Ceramic Technology, Kolkata 700010, India

[2] Department of Electrical Engineering, Jadavpur University, Kolkata 700032, India

Introduction

Fault identification, classification and localization have been practiced by scientists with a very high efficiency since very long. People are using diverse topologies and algorithms for serving the same purpose. Long transmission lines are the cheapest and the most efficient modes of carrying huge amount of power over miles of distances. Hence, these transmission lines are extended over several miles and are one of the most exposed engineering systems to the environment. Environmental calamities like storm, snow, rain, wind, ice, etc., often cause major short circuits among the intermediate lines, as well as in between the lines and the ground. Other minor but natural problems like animals, birds and even growing plants and vegetation also cause short circuit many times. Hence, these lines are very often subjected to various faults. As mentioned before, the two major roles of the protection algorithm, i.e., fault classification and prediction of fault location. Classification of the fault is of primary importance for detection of the faulted phase and disruption of power through the same. This helps to ensure protection of the connected equipments and the associated personnel as well as for immediate restriction of unnecessary drainage of power. Four major classes of faults occur in practice in a three-phase transmission network. These are single line to ground fault or SLG fault, line to line fault or double line fault denoted as LL or DL fault, double line to ground fault mentioned as LLG or DLG fault and triple line fault, i.e., LLL or 3L fault. Each of these faults, except for the LLL fault, is further classified according to the short-circuiting phases: SLG faults are subclassified as SLG-AG, SLG-BG and SLG-CG faults, DL faults are subclassified as DL-AB, DL-BC and DL-CA faults and DLG faults are subclassified as DLG-ABG, DLG-BCG and DLG-CAG faults.

Identification of fault location is also of utmost importance for restoration of stability of the power system at the earliest possible time and for resuming normal power flow. Faults are often of two types in nature; either these are temporary or permanent types of faults. Temporary faults are very common in transmission lines. These are often caused due to some sudden events like falling of leaves, large branches of trees, of due to wing, rain or snow during the atmospheric hazards or sometimes due to passage of birds or other animals in between the lines which causes sudden short circuit in between the lines or between the line and ground. These temporary faults are of least importance from the perspective of power system protection and analysis. But permanent faults cause serious trouble in restoration of normal power flow. These faults do not wear away until and unless some manual intervention forcefully removes the cause of fault. In order to do so, the knowledge of fault location is very much essential. This helps the working personnel to detect the fault location almost accurately and hence, identify the cause of fault almost at the exact location without hovering through a large distance along the faulted transmission line. This helps in removal of fault very easily. Thus, it saves useful time for resuming power flow through the lines and starts to restore normalcy of operation in power shredded portions in a zone.

In this article, several articles have been studied extensively illustrating the development of the different methodologies for developing different fault diagnosis methods. The vital outcomes of the different research works and their methodologies and contribution to this field of power system fault analysis are also highlighted for each article. Research in this field of power system protection, more precisely in the field of fault analysis, has been practiced by scientists since very long back. Researchers have investigated a number of different methods throughout ages for identification, classification and finally prediction of fault location of faults in a transmission line [1–5]. Primitive and conventional methodologies incorporate distance relaying schemes which primarily use impedance relays and Mho relays for distance estimation. Massive advancement of soft computing methods and artificial intelligence (AI), especially during the last few years, has paved the way for soft computation-based digital relaying schemes, which have almost replaced the conventional prototypes of distance relays. These digital relays are much faster and accurate and hence, enable earlier detection of correct fault line. This further enables detection and isolation of the faulty line much earlier than the old prototypes. The following section discusses about the different effective methodologies adopted by different researchers in the field of transmission line fault analysis.

Different Methodologies of Fault Analysis

Aleem, S. A. et al. (2014) in [1] and Chen, K. et al. (2016) in [2] have described a comprehensive review of the different methods used for different types of fault detection, classification and prediction of location in transmission and distribution systems existing in the contemporary literature works. Mishra, D. P. et al. (2017) in [3] have provided another well-structured review of the different methodologies of fault analysis in recent research works. Besides, they have also provided a comprehensive comparative analysis of the different fault parameters and numerical representations of the outcomes obtained from different research works. Prasad, A. et al. in their two articles [4, 5] have also illustrated the different prevalent techniques used in this field of fault analysis and research with good illustrations. All these review works have highlighted the pros and cons of the different fault analysis methods.

Impedance measurement-based method as motioned before along with traveling wave-based analysis is the conventional methods often used for the overall diagnosis of fault in a transmission line [3]. These methods are very old and contain large error, especially for fault localization, primarily due to several factors like fault impedance, shunt and series components of line impedance, source and load parameters, power line noise and variation in fault inception angle. Prasad, A. et al. have mentioned about the three major types of fault diagnosis techniques:

(i) *Prominent techniques*, which include wavelet transformation-based analysis (WT), artificial neural network (ANN) and fuzzy logic approach;

(ii) *Hybrid techniques* which contain various combinations of these fundamental techniques and finally,

(iii) *Modern techniques* like support vector machine (SVM), different artificial intelligence (AI)-based methods, phasor measurement unit (PMU), principal component analysis (PCA)-based approaches and many others.

These methodologies are discussed in detail with some of the reported advantages and disadvantages in the next sections.

Artificial Neural Network (ANN)-Based Fault Analysis

Artificial neural network or ANN has been conventionally applied in different sectors of fault analysis with a huge success. This method is one of the most widely used methods from the group of artificial intelligence and quite rightly has immense importance in developing efficient power system fault analysis schemes. A typical ANN model consists of three primary layers: input layer, hidden layer and output layer.

There are several advantages of ANN which enable its extensive uses in developing fault analysis algorithms. ANN is very effective in designing the fault diagnosis models. The most effective advantage of ANN is its inherent ability to learn by itself. It requires the adjustment of only a few parameters to adjust. ANN updates the associated path weights during training process; hence, ANN is insensitive toward loss of data due to updating of weights. Besides, parallel processing of data is another advantage itself, which altogether allows for its ease of implementation for serving real-life problems like fault analysis. ANN suffers from some shortcomings as well [3] lead by the requirement of training the ANN structure using with large and distributed data for accurate weight updating and development of the ANN structure. The associated and unavoidable high training time is also a major hindrance of its use, especially training becomes complicated for multi-dimensional analysis. The gradient-based back-propagation (BP) algorithm often sticks to a local optimum solution. This occurs more for nonlinear separable problem meant for pattern recognition-based classification. This also causes slow convergence of the method. Convergence of ANN also depends on the choice of initial values of weights; hence, initialization plays a major role in determining ANN performance. Besides, ANN also suffers from the disadvantage of reproducibility of the same output.

Several research works are found in this regard executed using ANN methodology [6–10]. Jain, A. et al. (2009) have described a ANN-based fault localization method for a double end fed double-circuit transmission line using one cycle post-fault three-phase current signal of both the circuits, but of one terminal only [6]. This work achieves an average error of fault localization of about 1.472%, where maximum error reaches nearly 7%. An effective fault detection and classification method has been presented by Hessine, M. B., et al. (2014) in [7] where each phase current and voltage of transmission line is treated separately. The fault class is determined from the four outputs of the ANN structure where the first three output parameters indicate presence of fault in each the three phases and the fourth parameter is meant for detecting ground fault. Variation in fault resistance is considered for both of these works [6, 7]. The work by [8] explains diverse ANN structures for single- and double-circuit two-terminal transmission line faults. A tool, termed as SARENEUR, has been used to select the best ANN structures with training time less than a minute for both single- and double-circuit lines. Fault classification error is zero for single-circuit lines and smaller than 1% for double-circuit lines. The mean error of fault location is also found to vary between 0.015% and 0.4%. Sanaye-Pasand, M. et al. (2003) in [9] has shown the use of ANN as a pattern classifier for protective relaying in power system and faulted phase selection, i.e., classification. Besides, the authors have also shown that the performance of classifier remains unaffected by the changing network conditions or different fault parameters. A hardware implementation-based work has been proposed by Ezquerra, J. et al. (2011) in [10] who used field-programmable gate array (FPGA) for implementation of ANN-based transmission line fault-location system. The ANN model, for both fault classification and localization process, was trained again using SARENEUR application tool. The error fault location is found only as 0.03% for a single-phase fault as reported by the authors for the 'La Lomba–Herrera' 380 kV, 189.3 km overhead transmission line. More importantly, prototype hardware has been developed in this work. Modern advancement of ANN has progressed to machine learning and deep learning-based analysis which has made useful progress in this research of fault diagnosis.

Wavelet Transform-Based Fault Analysis

Wavelet transform (WT) has tremendous influence on fault analysis and research. WT basically analyzes the frequency of the fault transient signals and decomposes the waveform into subsequent detailed and approximate coefficients, which bear vital information regarding the location and class of fault. In this way, WT extracts key features from the fault waveforms at different levels of decomposition. Sometimes wavelet entropy is also used directly for the analysis of fault. WT is very accurate and identifies the fault features using the decomposed frequency components of a fault waveform; although WT suffers from its inherent disadvantage of progressively increasing complexity of analysis, especially for increasing levels of decomposition of the fault signal.

Similar to ANN, several researchers have paid attention toward WT-based fault analysis algorithms [11–15]. WT has been employed in [11] to decompose fault signals into different frequency bands, followed by further processing using multiresolution analysis or MRA for the development of a real-time digital distance protection algorithm for transmission line. Jiang, H. et al. (2012) in [12] presents a wavelet-based scheme for fault localization in smart grid. The features from fault signal are extracted by computing the maximum WT coefficients (WTCs), further processed using a newly designed hybrid clustering algorithm for multi-bus system. Along with transmission line faults, the presented method also studies the effectiveness of the so designed WT-based algorithm for detection of generator fault, load fault and transformer fault as well. A WT- and transient-based protection relaying topology has been presented by Janıcek, F. et al. (2007) in [13]. The WT coefficient-based discrimination on the direction of relay is studied in this article. The relay responses for different classes of faults as well as system conditions are investigated here to examine accuracy of response in all cases. The authors of [14] present a four-bus, meshed system to investigate their proposed WT-based high speed, computationally efficient scheme which is found to yield a classifier accuracy 99.53%, as well as an average fault localization error of 0.217% with a maximum error of less than 3%, which is high in accuracy in contemporary analysis. A micro-grid connected power system protection algorithm is presented by Shekar, S. C. et al. (2019) in [15] using a wavelet-based analysis of transient fault current signals. Multiresolution analysis (MRA) is used with wavelet detailed coefficients of Mother Biorthogonal 1.5 wavelet.

Discrete wavelet transform (DWT) is the discrete variation in WT, which has become enormously accepted for analyzing discrete or sampled signals. Nowadays, in an era of digital communication and analysis, digital relaying systems have possessed an increasing demand for DWT methods. Most of the WT-based modern and digital fault analysis methods rely upon DWT analysis [16–19], which describe DWT-based fault detection method for transmission line faults. Devi, S. et al. (2016) in [16] have justified the effectiveness of using DWT with dB4 mother wavelet and a moving window for fault detection. The method computes the detail and approximate coefficients for the development of the algorithm. The detail coefficients with the highest level of decomposition, kept at dB4 level, are used for discrimination of faults and no-fault and develop algorithm for classification. Swetapadma, A., et al. (2015) in [17] have presented a DWT-based fault-location algorithm using current and voltage signals measured at one end. This method yields accurate prediction of location with an error of $\pm$ 1% only; although the detection time is a marginally on the higher side with one cycle pre-fault and two cycles post-fault signals. One of the most important outcomes of the work is that this method does not require fault classification prior to location estimation, which is a common practice. The authors of [18] have developed a simple comparative rule base using the mean of the approximate coefficient values of the three phases for the 132 kV 200 km long line. Upendar, J. et al. (2008) in [19] have used another AI-based tool like genetic algorithm as the basic analyzer of the features extracted using DWT for developing a transmission lines classifier. A huge number of 1,209,600 observations were used in this method for testing and validating the algorithm which is huge in itself. The range of variation in accuracy of classification is found varying between 98.66% and 100%, whereas the average overall accuracy is found approximately as 99.77%.

It is very common practice to associate wavelet analysis to combine with ANN to produce accurate fault protection schemes [20–26], although the disadvantages of both methods exist in the developed hybrid model. In these cases, wavelet transform is used to extract fault features from the fault waveforms and ANN is used to analyze these fault features in terms of wavelet coefficients to develop fault diagnosis models. Beg, M. A. et al. (2013) in [20] present a method to distinguish between the different transients arising out of different switching operations, different types of line faults and line switching using DWT of d1 and d5 level only to produce an overall efficiency of classification of 96.79%, with 96.15% for non-fault cases and 97.47% for fault transients. Signal acquisition time although is on the higher side for this work with three cycles of post-fault duration. Wavelet entropy-based ANN fault analysis architecture is presented in [21]. The authors obtained an average error of localization of 1.72% and worst error of 3.25% using Db4 decomposition level; fault resistance although is kept static at 10 Ω. Bhowmik, P.S. et al. (2009) in [22] have described novel topology using a combined DWT and back-propagation neural network BPNN.

DWT-linear discriminant analysis or LDA-based fault analysis scheme is proposed by Yadav, A. et al. (2015) in [23]. Quarter cycle current signal is analyzed using DB-4 wavelet up to level 3. The effect of nonlinear high impedance fault as well as CT saturation is also nullified in this scheme. The detection and classification efficiency is found as 100% and within one cycle time. Another important feature of this work is that it is able to analyze faults up to 99% of line length which is quite an important contribution in this field of study.

Wavelet energy entropy-based analysis is proposed with effective outcomes. He, Z. et al. (2010) in [24] have worked with wavelet singular entropy (WSE) and it uses the first half cycle of the post-fault signal for the analysis. The authors have used db4 mother wavelet and four-scaled WT. Sequence components of current and voltage signals are studied to develop the algorithm which is able to classify faults with 100% accuracy, even with the incorporation of dynamic fault resistance. Another quite similar wavelet entropy-based work for fault analysis is proposed by El Safty, S. et al. (2009) in [25]. Multi-level wavelet analysis has been adopted in several research works for accurate identification of the dynamic characteristics of the transient oscillations and extracts useful features; although inherent power line noise and the different harmonics of line voltage and currents often incorporate inaccuracies in prediction of outcomes.

Hybrid Methods of Fault Analysis Using WT and ANN

Wavelet packet transform (WPT) methodology is another way of using wavelet analysis in developing power system fault analyzer as adapted in [26, 27]. The authors in [26] have used WPT with ANN architecture for estimation of fault location. The method produces highly accurate results with only 0.14% of worst deviations, especially with the use of energy of current signal as input to the proposed ANN model; although, nothing much is mentioned about the variation in fault resistance. A two-terminal HV transmission line is studied by Adly, A. R. et al. (2019) in [27] using similar methods in spectral domain using db6 wavelet packet, i.e., using level 7 of decomposition to obtain the energy coefficients; although this high level of decomposition increases the computational burden many folds. The key feature of this work is that the proposed scheme is based on an adaptive threshold level and no special adjustment is required for different transmission systems. One WPT-based approach for fault detection has been proposed in [28], even during power swing for a hybrid transmission line. Another WPT-based fault analysis is proposed in [29] by Ray, P. et al. (2013) using a hybrid methodology combining with ANN in series-compensated transmission line. Maximum localization error of less than 0.35% with a mean error of less than 0.25% is achieved by the authors. Fault resistance has been kept dynamic, and the signal acquisition time is also moderate at one cycle post-fault.

A directional protection scheme is proposed by Yadav, A. et al. (2015) in [30] using similar hybrid localization model for a double-circuit transmission lines with single-end data. The maximum error found is 0.6665% with dynamic variation in fault resistance fault inception angles and two others. A different methodology using rough membership neural network (RMNN) has been proposed by He, Z. et al. (2014) in [31] using BPNN and wavelet analysis. The mother wavelet used here is Daubechies 4 (db4), since it owns a good time resolution with accurate detection of the fast fault transients to yield an overall classifier accuracy of 99.4%. Another different topology using DWT and Chebyshev neural network (ChNN) is proposed by Vyas, B. et al. (2014) in [32] for a thyristor-controlled series-compensated line. The work uses half cycle post-fault three-phase current signals with db1 mother wavelet at first level of decomposition to obtain 99.81% classifier accuracy. Most of the works mentioned above analyzed the fault signals using several levels of decomposition. Higher-order decomposition levels make the analysis more complicated.

Application of Radial Basis Function Neural Network (RBFNN) for Fault Analysis

Radial basis function neural network or RBFNN contains three layers similar to the ANN architecture. These are again denoted as input layer, hidden and output layer. The output signals from the input layer are thrown to the hidden layer as input where nonlinear radial basis function neuron action takes place. The output again contains linear neuron architecture [3].

RBFNN has often used as a key method for the development of fault models using the wavelet features. Research works of [33, 34] illustrate similar works using RBFNN. Samantaray, S. R. et al. (2007) in [33] presents a distance relaying scheme for estimation of fault location using radial basis function neural network (RBFNN); although the fault classification is done using support vector machine (SVM). Localization error is found to vary with minimum value of 0.51% for a LLL-G fault and maximum of 1.87% in case of a LL fault, with dynamic fault resistance. The work uses one cycle pre-fault and one cycle post-fault signal. Patel, B. et al. (2018) in [34] also proposes wavelet packet entropy and RBFNN-based analysis for fault detection, classification and localization technique for HVAC transmission line. The work considers the dynamics of alternator and also considers the effect of transformers.

Fuzzy Inference System Applied in Fault Analysis

Fuzzy inference system is often applied independently without being combined with ANN or wavelet analysis. The chief advantage of fuzzy analysis is that it is able to solve uncertainty problems using 'if–then' type of relations. But fuzzy-based analysis is less robust. Besides, development of fuzzy membership function requires good expertise [3]. The articles [35, 36] are two among the several literature works illustrating the application of fuzzy inference system or FIS applied in the field of power system fault analysis. A fuzzy multi-sensor data fusion-based latest fault-location prediction algorithm is proposed by Jiao, Z. et al. (2018) in [35] for transmission line fault localization. FIS and weighted covariance fusion (WCF) are applied in combination to obtain fast and accurate location outcomes. Yadav, A. et al. (2015) in [36] have described a performance improvement technique for directional relaying and complete fault analysis including fault classification and fault-location schemes for transmission lines using FIS model, with protection range of up to 95% of line length. The worst performance is found as a percentage error of -3.521% for a LLG fault. Fault resistance is also kept dynamic, as well as inception angle. The authors have also validated this fault-location scheme using χ^2 test with 5% level of significance.

Fuzzy adaptive resonance theory (ART) neural network has been also used independently to develop efficient fault diagnosis schemes [37, 38]. Vasilic, S. et al. (2005) in [37] have described a self-organized, supervised fuzzy adaptive resonance theory (ART) neural network algorithm for classification of power system faults by introducing advanced pattern recognition approach for the classification of transmission line faults. This method is based on application of fuzzy logic with the help of neural network. The improved algorithm ART2 is found to produce excellent results, with nearly zero errors, in terms of fault classification, compared with ART1 method, even with dynamicity of different fault parameters. A real-time fault analysis tool for monitoring operation of transmission line protective relaying scheme is proposed in [38] using fuzzy ART neural network and synchronized sampling method. Fault detection accuracy of 100% is attained, whereas the maximum error of localization is found to be 0.720% using one cycle fault signal data. Fault distance variation is kept in the range of 5–95%, whereas fault resistance is also kept dynamic.

Hybrid Methods Using WT, ANN, Fuzzy Logic Inference and SVM for Fault Analysis

Combination of WT, ANN and fuzzy logic or any paired combination of these has often proved successful in developing hybrid models for fault diagnosis [39, 40]. Reddy, M. et al. (2007) in [39] and Meyur, R. et al. (2016) in [40] have proposed two such analyses using wavelet-fuzzy combined approach for transmission line fault analysis. In [39], authors have presented wavelet multiresolution analysis (MRA) for classification and fuzzy logic for prediction of fault location. The authors use about one cycle of fault waveform, and the maximum location prediction error is restricted to 6.5%. The authors of [40] obtained an average location error of about 0.152%, and the maximum error is found near 0.76%. But this analysis for fault classification requires three cycles of nominal frequency, which is on the higher side compared with some of the contemporary analyses. Also, neither [39] nor [40] has commented on the variation in fault resistance. Goli, R. et al. (2015) have also proposed another fuzzy-wavelet-based combined approach transmission line protection mythology with the presence of flexible AC transmission device like SVC in [41].

ANN too is often used with fuzzy logic inference to develop hybrid method to develop adaptive neuro-fuzzy inference system or ANFIS topology which has been used by several researchers to develop efficient protection schemes [42–47]. Parameter tuning in ANFIS becomes accurate using the hybrid model, which leads to reduction in the search space dimension, producing faster convergence; although this method is computationally much heavier than the other similar hybrid methods [3]. A combined transmission system made with combination of overhead transmission lines and underground cable is examined using wavelet and neuro-fuzzy-based fault-location predictor algorithm in [42] by Jung, C.K. et al. (2007). Neuro-fuzzy analysis is used for fault localization utilizing detailed coefficients from WT. Half cycle current signals are used in this work with dynamic fault resistance to obtain maximum location prediction error of 0.3306 km for the cable part and 0.2551 km for the overhead line. An ANFIS-based fault diagnosis scheme is proposed by Eristi, H. (2013) in [43] which uses one cycle post-fault signal of a series-compensated transmission line with dynamic allocation of fault resistance with variation in other parameter. The overall classifier accuracy is found as 99.301%, whereas average and worst location error are found to be less than 0.25% and 1.288%, respectively. A comparative analysis is described in by Reddy, M. J. et al. (2007) in [44] between FIS and ANFIS topologies for prediction of fault location. The maximum error of fault location is found as 6.36% using the FIS model and 3.67% using ANFIS model, showing the superiority of ANFIS over FIS model, which is a significant contribution of their proposed work. A parallel transmission line model is investigated by Swarup, K. S. et al. (2007) in [45] using WT-based ANFIS. Time frequency analysis-based pattern recognition approach is adopted in this work to produce 100% classifier accuracy. A novel fault classification analysis using correlation coefficients and inter-quartile ranges of current signals and adaptive neuro-fuzzy inference system is proposed in [46] using dynamic fault resistance separately for grounded faults and non-grounded faults. The overall classification accuracy obtained is more than 96% for all cases. The maximum location error as described in [47] by Sadeh, J. et al. (2009) for the overhead line and the underground cable is found as 0.0277 (about 24.9 m) and 0.038 (about 3.8 m), respectively, for SLG faults, and the same for LLL fault is 0.0081 (about 7.3 m) and 0.071 (about 7.1 m), respectively. The overall maximum location error is found below 0.07% using one cycle post-fault signal. Another wavelet-based artificial neural network method for ultrafast detection of transmission line faults is presented by the Abdullah, A. (2017) in [48]. DWT analysis is used for extracting fault features from the high-frequency components of the two aerial modal currents. A feature vector is developed with the wavelet coefficients which are used to train the neural network.

Combination support vector machine or SVM with wavelet has proven effective in several research works [49, 50]. The authors of [49] have used WT to decompose the fault signals and extract fault features, which are used for training an SVM network. Two kernel functions: polynomial and Gaussian radial basis function (RBF) are used. Classifier accuracy is found to vary within 91.6667% to 100%, with the obtained accuracy of 94.1358% for SLG, which occupy almost 85% of the total faults. A high-frequency transients-based fault analysis scheme for the multi-terminal transmission lines is presented by Jafarian, P. et al. (2012) in [50] using dyadic wavelet transform to decompose the signal into different component frequency bands, followed by computation of spectral energy of each such band and finally, SVM-based classification is performed. The maximum classifier accuracy obtained is 100% using Gaussian and polynomial kernel function. A critical fault detection analysis and fault time for a flexible AC transmission system like UPFC incorporated transmission line is presented by Mishra, S. K. et al.(2019) in [51]. The method uses discrete wavelet transform (DWT) using db4 mother wavelet and discrete Fourier transform (DFT) methods for estimating spectral energy (SE) of the fault signals. The method is also able to detect fault within 20 ms, which is less than one cycle of power–frequency signal.

Support Vector Machine (SVM)-Based Approaches of Fault Analysis

Support vector machine (SVM) is another method used extensively in power system analysis since very early ages. SVM is very effective and accurate in identification, classification as well as localization of transmission line faults even independently [50–54]. SVM is effective even for data set which is not linearly separable. Besides, the dimension of space remains almost unaffected by the upper bound generalized error. But the primary shortfall of SVM is that SVM requires a very large and diverse data set both for training and testing purpose. Besides, the computational burden of SVM is much higher than several similar schemes, which also trigger the requirement of a large volume of memory [3]. Chothani, N. G. et al. (2011) in [52] have illustrated an algorithm for fault zone identification for busbar protection using SVM technique. The method uses one cycle post-fault current signals of all the lines as an input to SVM classifier model. An overall classification accuracy of more than 99% is achieved here. Gaussian RBF kernel gives the highest accuracy of 99.833%. Effect of CT saturation is also considered, along with variation in fault resistance. Apart from the development of an SVM for fault diagnosis scheme, Ravikumar, B. et al. (2008) in [53] have also compared SVMs with radial basis function neural networks (RBFNN) regarding analysis of different faults on transmission system. Authors of [54] have obtained an average localization error of only 0.015%, whereas the maximum error is recorded as low as 0.7% only, even with varying fault resistance. But the requirement of two cycles of post-fault waveform for analysis is marginally higher than some of the comparative literature works. Faults in transmission line with multiple generators connected have been investigated by Reddy, M. J. B. et al. (2016) in [55]. The method used for the analysis is discrete orthogonal Stockwell transform or DOST. This article further makes a comparative analysis of ANFIS, ANN and SVM-based analysis to demonstrate the superiority of SVM over some of the computational intelligence analyses for fault localization. Moravej, Z. et al. (2012) in [56] uses hyperbolic S-transform and learning machines for extracting fault features using one cycle post-fault transient current and voltage signals, followed analyzing the so obtained features using SVM and regression-based method. The method produces classification accuracy of 99.21%, district detection of 98.11% and location relative error of 2.48E − 3% for the 100 km line. Fault resistance is again kept dynamic.

A hybrid methodology combining SVM with and several is proposed by Jiang, J. A. et al. (2011) in [57] where the authors have proposed a multiple hybrid framework for fault detection, classification and location for transmission line. The proposed framework contains several arithmetical algorithms like negative-sequence component (NSC), wavelet transform (WT), principal component analysis (PCA), support vector machines (SVMs) and adaptive structural neural networks (ASNNs). The average detection accuracy of this work is found to be 99.9%. The average sensitivity and specificity of fault classification are obtained as 99.78% and 99.87%, respectively, and average fault-location error is about 0.47% only with a maximum error of 0.84%, using one cycle time period of fault data. But this method becomes extremely heavy as well as time complex as it uses so many different algorithms.

A combined SVM- and WT-based approach has been presented by Ekici, S. (2012) in [58] for classification and localization of transmission line faults. Error of classification is found less than 1% for all fault classes, and the average and maximum error of fault localization is found less than 0.26% and less than 0.95 km, respectively, using half cycle pre-fault and half cycle post-fault signal, as well as fault resistance is also kept dynamic.

SVM and fuzzy logic reasoning (FLR) have been combined to develop a method for transmission line fault detection and classification by Yusuff, A.A. et al. (2011) in [59]. The authors have suggested a determinant-based feature extraction principle using single-end measurements of the time shift invariant property of sinusoidal waveform. Data window of 1/4, 1/2 and one cycle of post-fault signal has been considered here for comparing the performances of three classifier models based on SVM, FLR and J48 keeping varying fault resistance.

A multi-class SVM approach for fault classification is presented in [60]. The authors have used wavelet decomposition information of post-fault current transients as input to SVM for classifier to obtain a classifier accuracy of above 98.8%. Yusuff, A. A. et al. (2014) in [61] have proposed stationary wavelet transform (SWT) for developing a filtering scheme and determinant function feature (DFF) to extract distinctive fault features, support vector machine (SVM) for developing fault classifier model and support vector regression (SVR) for accurate fault-location analysis. The relative location error is found as 2.10E − 03% with a maximum deviation of 0.4 km. SVM often becomes less effective with abruptly increased power line noise as well as when target classes seem to overlap. SVM also suffers from high analytical complexity, as well as it necessitates correct tuning of some of the model parameters. Another application of SVM method has been proposed by Vyas, B. Y. et al. (2016) in [62] for fault classification in transmission lines compensated with thyristor-controlled series devices. The method uses pattern recognition features of support vector machine to good effect for classifying faults.

Principal Component Analysis (PCA)-Based Fault Analysis

Multivariate statistical analysis like principal component analysis (PCA) is another useful tool used for classification and localization of faults. PCA is useful to identify the key directions of variation in a set of signals and find out the principal components decreasing order of importance. In this way, PCA effectively reduces a large multivariate data to the most important directions, making further analysis simple and fast. Hence, PCA is used in different engineering fields for identifying the major affecting parameters. Another advantage of PCA is that since PCA considers only the most important directions of variations, the effect of noise is reduced naturally. But, on the contrary, the development of the principal components uses linear combination of the original features, which is quite a broad approximation leading to reduced accuracy. Besides, if in any case, the number of dimensions exceeds the number of data points in a system, covariance matrix becomes very large [3]. PCA is effectively used for power system fault analysis either directly or in combination with other methodologies. The authors of [63–67] have proposed PCA-based fault classifier as well as localizer algorithm. A PCA-ratio-based fault classifier scheme is developed in [63], whereas a multiple linear regression (MLR)-based fault localizer scheme is proposed by Mukherjee, A. et al. (2020) in [64]. The analysis is made using the principal component index (PCI) so developed using the post-fault transient signals. These analyses use closest match analysis to obtain the minimum distance from the test signal PCI and each of the training fault prototypes which are the ten different fault classes. PCA-based classifier and localizer model is proposed by Alsafasfeh et al. in [65, 66]. Alsafasfeh, Q. H. et al. (2012) in [65] used PCA as the basic analysis tool and uses quarter cycle post-fault signal which is appreciable. The maximum localization error obtained is 2.7%. Symmetrical pattern and PCA-based framework are illustrated in [66], again using quarter cycle post-fault signal to develop the fault signature patterns using symmetrical components and PCA. The method yields 100% classifier accuracy, as well as considers variation in fault resistance. Mukherjee, A. et al. (2020) in [67] have proposed another direct application of PCA for localization of transmission line faults using the index values developed using the PCA algorithm aided by best fit analysis.

Hybrid PCA methods are very much useful for fault analysis and development of fault diagnosis methods. PCA is effectively combined with another excellent feature extraction, as well as pattern recognition technique: probabilistic neural network or PNN. Sinha, A. K. et al. (2011) in [68] illustrates a combined methodology of PCA and PNN techniques, aided by WT. WT is used to extract distinguishing features, which are used with PCA algorithm to reduce the data dimensionality and obtain principal components. These are further fed to PNN architecture to develop final classifier model which yielded accuracy level in a range of 98–100%. Another modified ratio analysis-based fault classification method is discussed again by Mukherjee, A. et al. (2020) in [69]. This method further compares the results of this direct PCA-based classifier method with another method which additionally uses probabilistic neural network or PNN in combination with PCA. The PCA scores are fed to a PNN architecture designed for fault classification. Both of these analyses are found to yield 100% classifier accuracy which proves effectiveness of PCA, even with variation in fault resistance.

Jafarian, P. et al. (2010) in [70] have proposed a traveling wave-based protection technique using complex wavelet transform (WT), followed by principal component analysis (PCA) to identify the dominant pattern of these signals. This hybrid methodology shows the effectiveness of combining WT and PCA together for fast identification of faults, mostly being conducted inside the protected zone. Authors of [71] have described another traveling wave-based distance protection scheme using PCA. In this method, an ultra-high speed transmission line protection algorithm is described. Wave front shape is characterized for the different internal and external faults. PCA along with ANN is used for feature extraction and implementation of these features with pattern recognition approach. PCA is applied with DWT for classification of fault originated transients in high-voltage network in [72]. The authors illustrate different types of capacitor switching, load switching, and various classes of line faults and faults due to energization and de-energization of line producing an overall efficiency of 95%.

Govender, P. et al. (2013) in [73] examines the impact of lightning, fire and birds on the power line and describes an ANN-based system to identify the exact cause of fault using features of PCA. Guo, Y. et al. (2012) presents transmission line fault detection and classification method using features of PCA and modeling the classifier model using SVM in [74]. PCA has been used to reduce the dimensionality as well as to find violating points of the fault signals and used later to construct SVM networks. Pattern recognition approach is used to distinguish the faulty phase directly. The method produces a maximum error of 1.1497%. PCA is also combined with a number of the above methodologies simultaneously in [75] for effective fault diagnosis. A novel hybrid framework for rapid detection and localization of a fault is proposed by Jiang, J. A. et al. (2011) in [75]. The method uses negative-sequence current and voltage components for fast fault detection, multilevel WT, PCA and SVM for fault classification and adaptive structure neural networks for fault location. This method yielded 99.9% fault detection accuracy, and the average fault-location error is around 0.61%, using one cycle data. But this method becomes too complex as it uses several algorithms.

Traveling Wave-Based Analysis

Traveling waves (TW) are often used in developing effective fault classification and localization methods [76–78], but response time required depends on the time of travel of the wave. Two-terminal TW-based fault localization is presented by Lopes, F. V. et al. (2017) in [76]. This method depends on the time difference between the first incident wave and the consecutive reflection from the point of occurrence of fault, at both line ends; and hence, data synchronization is not required of line parameters. The maximum error of localization is found even less than 270 m for the designed 200 km line and the average error was found as 31 m with a standard deviation of 36 m, which could be treated as a highly effective result; although like other TW-based analyses, this method requires variable time which depends on the location of the fault, hence is a variable factor. Besides, the range of fault resistance used is not mentioned clearly. Hasheminejad, S. et al. (2016) in [77] have described another TW-based protection algorithm for parallel transmission lines using Karenbauer's phase to modal transform and Teager energy operator. High accuracy of about 0.9% maximum error and 0.15% minimum error is obtained here, which are again highly effective. Ma, G. et al. (2016) have discussed about a basic traveling wave theory-based method for fault location, using WT as a supporting methodology in [78]. The maximum relative error is found as 0.65% for a two-phase fault. A fast identification method for DC transmission line faults is proposed by Tang. L. et al. in (2019) in [79] using the fault-induced traveling waves. The method uses traveling wave features from single-end only. Besides, fast identification method for lighting disturbances is also proposed by the authors, which is able to detect in less than 1.2 ms. Another traveling wave frequency analysis has been proposed by Akmaz, D. et al. (2018) in [80] for prediction of fault location in transmission line. The method incorporates transformation of the time domain signal into frequency domain using the fast Fourier transform (FFT), followed by analysis of the same using an advanced form for supervised learning method like extreme learning machine for developing the localizer scheme.

Time–Frequency Domain Approaches for Fault Localization

Time–frequency domain analysis of transmission line faults is a common practice. Power spectrums are obtained on frequency domain analysis, especially using Fourier transform-based analysis. These power spectrums have often been practiced, especially for estimating the fault locations. The high-frequency fault transients developed immediately after the fault contain the most vital information regarding the fault type, location and others. This information is mostly hidden in the fault transient frequencies, which are investigated in time domain or frequency domain analysis, leading to power spectrums [75–83]. Hence, these power spectrums contain major information regarding the fault parameters.

Mamiş, M. S. et al. (2013) have used fast Fourier transform (FFT) for mapping the time domain signals to frequency domain, and further in developing power spectrum model [81]. Further, they have used the frequency of the first fault generated harmonic obtained using one cycle post-fault transient signal for predicting fault location using traveling wave theory of transmission line. The average and maximum errors are obtained as 1.369% and 4.21%, respectively, although the maximum error is marginally higher. Fault resistance is also kept dynamic. Song, G.

et al. (2014) have presented a novel method for locating VSC-HVDC transmission line faults using one terminal current data and traveling wave theory [82]. The average and maximum error of 0.183% and 0.64% were found, respectively. The analysis uses data window of only 5 ms, which is analogous to quarter cycle of signal in AC equivalent system and fault resistance is also kept dynamic again. A protection scheme for phase-to-phase faults based on spectrum characteristic of the post-fault high-frequency transients is presented in [83]. The difference of fundamental natural frequencies at both the ends of the line is used for identification of internal or external fault. A time–frequency-based analysis is proposed in [84] using S-transform along with complex window to generate frequency contours, i.e., S-contours. These time–frequency patterns with varying window are described as fault signatures, which enable development of fault classifier model using pattern recognition-based approach. Fault resistance is again varied in this work. Radojevic, Z. M. et al. (2006) describes a numerical spectral domain algorithm using arc voltage amplitude and fundamental and third harmonics of voltages and currents phasors taken at the terminal [85]. Spectral analysis of the input phase voltages and line currents signals is developed in addition to facilitate the development of fault analyzer. Authors of [86] illustrate a model-based approach, ESPRIT and its application to a number of simulated voltage waveforms to identify the parameters of oscillatory transients during disturbance. Gopakumar, P., et al. (2015) in [87] describes a real-time protection methodology for a self-healing grid in smart power grids. Frequency domain analysis using FFT of variations in EVPA and ECPA during fault is considered here, and phasor measurement unit (PMU) is also incorporated. A multi-class SVM classifier is also been used for this purpose. The accuracy of line identification in a multi-bus model is very high using fundamental and harmonics, even for variation in fault resistance; although use of FFT and SVM simultaneously along with PMU for acquiring signal data makes the analysis more complex. Dash, P. K. et al. (2015) have developed a cumulative sum average technique (CUCUM) in [88] which is used to detect the instant of fault occurrence. Energy of the vital frequency components is computed using fast frequency filtering S-transform (FFST) or sparse S-transform for fault classification. Fault resistance is also varied. This FFST shows a fault detection and classification reliability higher than 97% for high impedance faults (> 250 Ω) and 100% for low impedance faults. Fault localization error is also found low as 0.3%. Fault classification time is also found mostly less than 10 ms. Krishnanand, K.R. et al. (2015) in [89] suggested a pattern recognition approach for current differential relaying for power transmission lines. This method uses spectral energy and fast discrete S-transform. The highest error reported in this work is 2.4561E − 02 per unit which is excellent. Variation in fault resistance is also considered. Half cycle before the CUSUM detection point and half cycle after that point are used independently to compute the change in energy content of the differential and average signals.

Time-Synchronized Methods of Analysis, Phasor Measurement Unit (PMU)-Based Analysis

Time-synchronized fault analysis methods are also gaining immense popularity with days. One such method is proposed by Dutta, P. et al. (2014) in [90], where the authors use synchronized sampling of voltage and current signals. This method uses the IEEE 118-bus model to perform the multi-bus analysis, as well as is able to detect and classify fault within 7 ms of fault inception which is very fast, even less than half cycle time. Two groups of dynamic fault resistance: 0-160Ω and 200-10,000Ω are used to study normal and high resistance faults. Classifier accuracy is found as 100%, and the location error is restricted to 3%.

Phasor measurement unit or PMU-based application is an ideal example of similar time-synchronized technology which helps in fault analysis by detecting electrical signals simultaneously at both ends [91–96]. A PMU-based fault-location scheme is proposed by Jiang, Q. et al. (2012) in [91] which studies voltage signals of large transmission networks. The authors use IEEE 39-bus system and ZJP 76-bus system to implement the same. Maximum localization error is obtained as 0.8%, with classifier accuracy of 100% is achieved with variable fault resistance. Another PMU-based fault detection and location methodology is proposed by Barman, S. et al. (2018) in [92] for large transmission system. One objective of this work is to accomplish the work using minimum number of PMUs. This work is further validated on the IEEE 14, 30, 39 and 118-bus systems for different fault conditions. The results show a classification error of less than 0.01% with fault resistance dynamic again. Gopakumar, P., et al. (2015) in [93] describes a synchronous phasor angle measurement-based adaptive fault identification and classification scheme for smart grids. FFT is used here to analyze the phase angles obtained from PMUs. This helps in developing frequency spectrum coefficients, containing fault classifying features. Support vector machine (SVM) is further employed to develop fault classifier simultaneously. An optimal phasor measurement unit or PMU-based fault localization method is proposed by Devi. M.M. et al. (2018) in [94]. This work is validated using a 49-bus system to obtain a maximum localization error of 0.19% for symmetrical fault and 0.012% for unsymmetrical fault with dynamic fault resistance; although the required number of post-fault cycles is not reported clearly. But these methodologies often require major hardware support like synchronized time-based GPS system, etc., which makes the system costly. Sequence component analysis has been a major tool of fault analysis since long and has been practiced since the earlier days. Another innovative fault-location method has been proposed by Lee, Y. J., et al. (2019) in [95] for estimation of fault location in a multi-terminal nonhomogeneous transmission lines. The method uses synchronized voltage and current phasors which are recorded using synchronized data collection device like phasor measurement units or other intelligent electronic devices. The authors have used graph theory-based indices in addition to optimal calculation data window for the purpose. A method of remote monitoring for real-time transmission line fault detection and classification has been proposed by Gopakumar, P. et al. (2018) in [96]. The method incorporates PMU measurement method for acquiring the fault signals.

Probabilistic Neural Networks or PNN-Based Analysis

Probabilistic neural networks or PNN, being a major variant of ANN architecture, has inherent property of pattern identification hence has been used effectively in power system fault classification [97–101]. PNN has immense capability of pattern recognition, for which, it is applied extensively in such problems, like the fault classification. Initialization of the architecture with initial weights is not required in PNN, which is a major advantage of PNN; besides, PNN always converges in Bayesian classifier, hence often used with such [3]. PNN learns fast, as well as it is also insensitive to outliers, but similar to other neural network models, training time as well as memory requirement becomes large for a large network and the selection of layers and neurons becomes doubtful at times [3].

The authors of [97] have described a very fundamental way of developing PNN-based fault classifier model, by easy explanation of the basic architecture of PNN and the Parzen's method of density estimation which often used in several PNN-based works for the estimation of the probability density function (pdf). The authors found the classification accuracy of 100%, compared with BP network which they found to yield 90% accuracy. Another hybrid methodology using WT and PNN is developed in [98] for classification to obtain accuracy of 100%. Raval, P. D. et al. (2016) in [99] investigates fault in a series-compensated multi-terminal EHV transmission line using PNN architecture to obtain 100% classifier accuracy with PNN-2 architecture. Variation in ground fault resistances is also incorporated for the examined double split transmission line. A fault analysis method is proposed by Roy, N. et al. (2015) in [100] using S-transform-based PNN for classification and BPNN for fault localization with dynamic fault resistance. The authors obtained an average classifier accuracy of 99.6% and the same is obtained as 98.7% using noise corrupted signals. The localizer model produced a maximum error of 4.46% and the same again of 4.35% for with noisy signals. Moravej, Z. et al. (2015) in [101] have proposed an effective combined method for symmetrical faults identification in the presence of power swing. This method again uses S-transform (ST) and probabilistic neural network (PNN) to obtain average accuracy for detection of power swing (C1) and fault during power swing (C2) is 95.5% and 90.93%, respectively, using half cycle current signal. C1 and C2 are also classified with accuracy 100% and 90%, respectively, with dynamic fault resistance.

Variants of Neural Network Applied for Fault Analysis

Different other forms of neural network and its association with other topologies have been investigated to justify their effectiveness. Different analyses have been carried out using ANN or its variations with numerous other techniques [102–106]. Cui, H. et al. (2015) in [102] have illustrated generalized regression neural network architecture for predicting fault location in a HVDC transmission line, which yielded a mean error of localization below 0.05 km and the maximum error is also found just higher than 0.3 km, although the status of fault resistance or the required number of cycle of signal required for analysis has not been mentioned in detail.

WT and the adaptive resonance theory (ART) have been hybridized in [103]. This ART2-based method has produced classification accuracy of 99.91%, compared with 99.88% as obtained with ANN. The location error is found even lower than 1.5% based on the inverse interpolation method and examining all classes of faults and with dynamic fault resistance.

The authors of [106] have investigated the application of HS-transform and radial basis function neural network in this field. The change in energy and standard deviation of current and voltage signals are computed using S-transform of one cycle ahead and one cycle back from the fault instant. The location error found is lowest for LG fault which is 0.89% and goes highest up to 1.89% for LLG fault.

Vyas, B. et al. (2014) in [105] have investigated improved artificial intelligence techniques for fault classification in [98]. The authors use this methodology for thyristor-controlled series-compensated transmission lines with half cycle post-fault current signal. Polynomial-based Chebyshev neural network (ChNN) and discrete wavelet packet transform (DWPT) are used as the basic building blocks of the algorithm, which although increases computational burden to some level. Classification accuracy achieved is 99.39% justifying the effectiveness of ChNN as an improved machine learning method against the multilayer perceptron NN and SVM.

A particle swarm optimization or PSO and ANN-based fault classification scheme are proposed by Upendar, J. et al. (2010) in [106]. An average classification accuracy of 99.91% is achieved in this process even with dynamic fault resistance. It is observed that testing cases of the PSO-based network yielded a successful prediction rate of up to 99.91%, compared with BPNN (99.88%) and SVM (96.01%)-based methods tested in this work, which concluded that the PSO-based method performed better than the designed SVM and BPNN.

Extreme learning machine (ELM)-based neural networks have also been examined in research. Among the key advantages of ELM network, the presence of a single optimized hidden layer lies in front. Besides, this hidden layer does not require tuning, as well as the weight and bias adjustment are not essential at all; yet ELM suffers from major shortcomings like the presence of local minima, ease of over-fitting, as well as complicatedness in reaching the optimal solution [3]. The authors of [107] have proposed an innovative self-learning machine learning-based feature extraction algorithm termed as summation-wavelet extreme learning machine (SW-ELM). The authors have also claimed that their proposed method is able to diagnose faults within a single cycle to produce accurate classification of about 95% as well as precise location estimation with only 1.3%–4.8% of error. Besides, this method is also found to remain unaffected by the variation in fault resistance and inception angle. Another transmission line fault localization method is proposed by Mirzaei, M. et al. (2018) in [108] using another advanced analysis of the neural network: deep neural networks, which are gaining immense popularity with the massive advancement of soft computational analysis.

Correlation-Based Analysis of Fault Signals

Correlation-based analysis is another effective tool to identify interrelation between voltage and currents of each phase in different classes of faults, since these parameters seem to vary during the transients. Accordingly, this method is applied with good effect in this field of research [109-106]. Yu-Wu, C. et al. (2010), Haomin, C. et al. (2014) and Zheng, Z. et al. (2012) illustrate a very popular statistical method of correlation coefficient analysis for fault treatment in transmission line for classification, as well as for localization of faults to some extent [109–111]. Correlation coefficient is an important statistical tool which identifies the interdependence of two variables. The voltage and currents of the three phases are investigated using this analysis, and the correlation coefficients are obtained, based on which classifier algorithm is developed. The affected phase voltage or current is disturbed maximum from the healthy condition. Hence, correlation of the faulted signal from the healthy one produces correlation coefficient much less than unity. This is investigated in several research works of this class of research for developing fault classifier model. Besides, fault current shoots to a very high level abruptly on occurrence of a fault, whereas voltage level seems to drop from the no-fault level. This again produces a much less than unity value of correlation coefficient while investigated between voltage and current waveforms of the directly faulted phases. This method of investigation is followed in several research works to develop a direct threshold-based fault classifier model. Dasgupta, A. et al. (2015) in [112] and Chatterjee, B. et al. (2020) in [113] use cross-correlation analysis in a similar way to develop fault identification and classification topologies. The authors of [112] have used k-nearest neighbor analysis to map the correlation values to identify faults. The authors of [113] have further incorporated fuzzy inference along with cross-correlation method to classify transmission line faults. Another cross-correlation-based method is investigated in Bhattacharjee, A. et al. (2019) in [114] where Elman back-propagation neural network is used to detect as well as estimate fault location of single line to ground faults. Correlation-based method is also used in combination with other feature extraction methodologies like traveling wave analysis by Zhang, G. et al. (2016) in [115] or frequency spectrum-based characteristics by Zhu, K. et al. (2018) in [116] to develop effective fault analysis methods. Lei, A. et al. (2018) in [117] have proposed an efficient correlation-based ultra-high-speed directional relay for very fast detection of power line faults. The authors of [118] have proposed another fault diagnosis methodology for localization of transmission line faults using correlation analysis method applied with traveling wave theory. This is an example of correlation analysis used for localization of transmission line faults. Shu, H. et al. (2020) illustrates another correlation-based method of analyzing single pole-to-ground fault of MMC-HVDC transmission lines based on capacitive fuzzy identification techniques [119].Other methods of using correlation-based techniques have also been proposed in [120, 121]. These analyses have shown the effectiveness of a simple statistical technique line correlation to develop simple yet effective computational methods for fault analysis.

Other Latest Methods of Fault Analysis

Upendar, J. et al. (2012) in [122] have proposed a fault classifier and localizer algorithm implementing decision tree-based modeling with classification and regression tree (CART), DWT and ANN. Key features from the faulted signals are extracted using DWT, and the statistical CART is used to classify the type of fault with 99.97% accuracy compared with 99.88% as obtained using BPNN architecture. Localization error is mostly less than 1.5%, which is quite high accuracy, especially with dynamic fault resistance. Application of two excellent methods of artificial intelligence (AI) like ANN and genetic algorithm (GA) has combined together to develop effective hybrid method like genetic algorithm-generalized neural network or GA-GNN for fault classification in a three-phase transmission system by Sharma, S. K. et al. (2019) in [123]. Radial Basis Function (RBF), SVM and Scaled Conjugate Gradient (SCALCG) basis neural network method have been applied to develop a hybrid model for locating fault location on Extra High Voltage (EHV) transmission line [124]. The maximum and minimum error of fault location has been 1.93 km and 0.0001 km, respectively.

Time reversal-based analysis has also been conducted or locating faults in transmission line [125, 126]. An electromagnetic time reversal-based method is studied by Razzaghi, R. et al. (2013) in [125] for developing an efficient fault localization algorithm for different faults occurring in power system networks. Codino, A. et al. (2017) in [126] have proposed another time reversal-based method for transmission line fault location considering different media for the forward and the backward propagation phases. The authors also show that the proposed method provides high localization accuracy of faults in the range of $\pm$ 1 m for frequency higher than 1.22 MHz and $\pm$ 100 m for frequency higher than 0.071 MHz with single observation point. Fast discrete orthogonal S-transform or FDOST entropy-based intelligent digital relaying scheme for detection, classification and localization of faults on the hybrid transmission line is presented by Patel, B. (2018) in [127]. FDOST is used effectively for feature extraction; SVM is used for classifier model and support vector regression (SVR) model for pattern recognition of faults, which is used for classification and prediction of location of faults. Fault resistance is varied dynamically with addition of noise to obtain maximum location error of 0.477 km with an average deviation of 0.077 km for the 140 km hybrid line and using half cycle post-fault signal. The classifier accuracy is also obtained as 99.53%. A comparative analysis of two excellent methods like ANN and traveling wave has been described by Maheshwari, A. et al. (2019) in [128] for developing effective fault localization schemes for transmission lines. Liu, Y., et al. (2017) in [129] have presented a dynamic state estimation-based fault localization method for transmission line faults using instantaneous sampled values instead of phasors which enables estimation of the fault location. This method shows improved accuracy, significantly for short duration faults.

A real-time fast mathematical morphology-based feature extraction technique is presented by Godse, R., et al. (2020) for detection as well as classification of faults in transmission lines [130]. Morphological median filter is investigated to extract unique fault features, followed by analyzing the same using a decision tree fault classifier. Classification accuracy of 99.9819% is achieved using this method having reduced computational intricacy, more importantly, using even less than a quarter cycle of the fault waveform. Another mathematical morphology-based fault detection method for double-circuit transmission line has been proposed by Kapoor, G. (2018) in [131]. Fault current of three-phase fault signals of both circuits is measured at relay locations for analysis with mathematical morphology analysis.

A very traditional method of fault analysis like sequence network-based fault-location scheme has been well established in recent methodologies [132, 133]. Ghorbani, A. et al. (2019) have proposed a negative-sequence network-based scheme for detecting location of fault in a double-circuit multi-terminal transmission lines [132]. It is shown that fault location estimated is possible using only one element for each transmission line. The insensitivity of fault resistance and infeed current on its performance is also demonstrated. A maximum error of 1.9% is obtained by the authors using this method. A positive sequence superimposed network-based transmission line protection system is developed by Ji, L. et al. (2019) in [133] using a new single ended method during auto-reclosing. The proposed method uses local measurement data only and is able to quantify the negative effects of fault resistance, fault distance and unknown remote end source impedance. An average and maximum location error of less than 0.62% and less than 1.36% are achieved, respectively, using one cycle of fault waveform with varying fault resistance. Fan, R. et al. (2018) have described an ensemble Kalman filter (EnKF)-based fault localization technique [134]. Two different categories of faults: AG and BC faults are analyzed to obtain an average fault-location error of 0.159 km, and a maximum error of 0.242 km for AG fault and similarly 0.109 km and 0.199 km for BC fault, with variable fault resistance and half cycle post-fault waveform.

Phasor analysis-based power system fault analysis method has also been proposed by scientists in this field of research. A similar approach is prescribed by Gajare, S. et al. (2016) in [135] and is experimented using this topology on a multi-circuit series-compensated transmission lines. This method uses phasor data from intelligent electronic devices (IEDs) at both ends. The method computes errors for untransposed transmission lines, considering error in line parameters, complex fault impedance, error in data and error in synchronization. The maximum location error obtained is 0.0965% for overall untransposed lines, 1.2120% with 10% error in voltage data and 1.9282% error in current data; 0.5333% and 1.2380% maximum error for 10 ns and 1 µs synchronization time error. Fault resistance is also kept variable in this research work. The authors of [136] explain another dynamic phasor modeling-based analysis for asymmetrical faults with unbalanced polyphase power systems. The advantage of using dynamic phasors is that these are capable for fast numerical simulations, since these tend to vary slowly even for an abrupt change of instantaneous quantities.

A three-terminal transmission line is investigated by Gaur, V.K. et al. (2017) to develop new faulty section identification and fault localization technique [137]. This method is designed to estimate the fault resistance too along with fault location. The error for fault location and fault resistance is found to remain within ± 1.5% and ± 3.5%, respectively, even for wide variation in system and fault parameters. Dobakhshari, A. S. et al. (2014) in [138] have presented linear weighted least-squares (WLS) method for fault-location estimation by synchronized voltage measurement technique using positive sequence only. One advantage of this method is that it does not require the prior knowledge of classification. The predicted fault-location error is found to remain far below 1%; hence, this method obviates the need to deal with CT saturation and unreliable zero-sequence parameters of the line. A novel fault detection method is proposed by Tong et al. (2020) in [139] for transmission lines, based on pilot impedance method. The authors have shown that the method is insensitive to variation in fault location, fault type, fault resistance and presence of weak source. The method is also found to produce reliable performance, even during power swing as well as during open-phase operation. Bagged tree ensemble classifier, another latest technology, has been successfully implemented to develop a novel analysis method for classification of different categories of faults in a series capacitor compensated transmission line by Mishra, P. K. et al. (2018) in [140].

Swetapadma, A. et al. (2016) have proposed a decision tree-based scheme within half cycle of power swing for a double-circuit line with dynamic fault resistance [141]. DFT is used for the signal processing purpose. This presented scheme effectively detects the fault with 100% accuracy as well as yields 99.99% classifier accuracy. An independent component analysis (ICA)-based approach is presented by Almeida, A. R. et al. (2017) in [142] using hybrid method with traveling wave (TW) theory and support vector machine (SVM) for localizing and classifying faults in high-voltage transmission line. The location error is found below 1%, and classification accuracy of 100% is achieved; although combination of three methodologies makes the analysis more complicated. A wide area measurement-based fault detection and localization method for transmission line is presented by Das, S. et al. (2017) in [143] using only voltage signals from WAMS and bus admittance matrix of the network. The authors have also shown that the method is independent of fault type, fault location as well as fault resistance. A cumulative sum (CUSUM)-based approach for fault detection is presented in Dash, P. K. et al. (2014) in [144]. Fast discrete S-transform (FDST) is used to extract spectral energies from current signals, thus precisely identifying fault before or after the STATCOM and compute the fault location using half cycle pre-fault and half cycle post-fault signal. Localization error is found mostly below 1% for faults before STATCOM and 2% for cases with STATCOM present in the fault loop. Apart from this, fault-location errors are mostly found within a bound of 2–3% and are found to vary from 0.02 to 2.52% for different fault resistance and other conditions.

Class-dependent feature (CDF) and two-Tier multilayer perceptron network-based robust transmission line fault classification analysis has been presented by Mahmud, M. N. et al. (2018) in [145]. The accuracy level is tested in this work with CDF and two-Tier MLP network for three different noise levels of the fault signal: with no noise, 20 dB and 30 dB noise level. The method shows that a highest average classifier accuracy of 99.36% is achieved. A method for prediction of fault location in a double-circuit series-compensated transmission line has been presented by Sahani, M. et al. (2019) in [146]. The method uses parameter optimized variational mode decomposition (POVMD) and weighted P-norm random vector functional link network (WPRVFLN) for estimating fault location.

Adaptive wavelets-based classifier is presented by Perez, F. E. et al. (2011) in [147] using DWT and probability analysis method such as the Bayesian linear discrimination analysis. This model classifies different faults with an accuracy level of 100% and most importantly, using only (1/10) cycles of post-fault signals, which is a vital outcome of this work. Fault resistance is also kept variable. A different type of classification scheme using image classification-based transmission line fault detection method has been presented by Wang, Y. et al. (2019) in [148] which uses deep quality-aware fine-grained categorization learning method. Analog relaying schemes have been used traditionally using these methods. Advancement of soft computational techniques has given abrupt rise to digital relaying methods. Digital sequence component-based methods have come out with accurate outcomes. Magnetic measurement-based fault detection schemes have come up with effective measures to extract fault features. These have used variation in magnetic flux for detecting the same as proposed in by Kazim, M. et al. (2019) in [149] where the authors describe a new approach of non-contact magnetic-based measurement system for detecting and localizing short circuit using highly sensitive and energy-efficient magnetic sensors which detect the variations in magnetic field levels along the lines. Laboratory experiments were conducted by the authors, and they produced error of less than 5% even for worst case; although the additional sensors require additional cost. The authors of [150] have described a fault-location prediction algorithm for a compensated transmission line with series connected FACTS devices. Recursive algorithm is used in this work and applied at both ends. The error is found mostly below 0.5%; although this method does not use the compensator device model for governing its operating mode to compute the voltage drop during fault. Zhong, Y. et al. (2013) in [151] have presented a novel distance protection algorithm for the estimation of fault location on the lumped transmission line model.

A Comparative Quantitative Analysis of Different Methods in Literature

A comparative analysis is shown here with the different state-of-the-art methodologies for classification and localization of transmission line faults in power system network. An overview of Table 1 gives a better idea about the different methods of fault analysis executed by different researchers over the years. The analysis of comparison primarily focuses on the level of accuracy reached in classifying faults, as well as prediction of fault location, number of power–frequency cycle required for analysis and the methods used for computation of fault parameters; hence, these values are mentioned in the table for respective research works.

Conclusion

In this article, a brief and overall review of the different methodologies adopted for analyzing power system faults is presented. The different techniques investigated by several researchers for detection, classification and localization of especially the transmission faults are described here, analyzing their major advantages as well as shortcomings. The accuracy of classification as well as localization obtained by various methods is also reported while explaining the methodologies.

Literature works show that traditional methods like artificial neural network (ANN), wavelet transform (WT) and fuzzy inference system (FIS) have tremendous influence over fault analysis methods. These methods have been proved extremely accurate for fault diagnosis over the years, yet suffer from respective disadvantages. ANN and other similar supervised models need intense training using diversely distributed data hence make the analysis complex, as well as time consuming due to the requirement of adequate training time. WT has developed good mathematical tools and waveform analysis methods for fault diagnosis. But, WT becomes computationally intricate progressively with increase in the level of decomposition. Besides, selection of mother wavelet is another issue faced in different research works; although WT is extremely efficient to extract minor details in a signal, hence used in abundance in fault signal analysis. Development of the rule bases for FIS sometimes becomes difficult and introduces inaccuracy in analyzer design. It is observed that many researchers prefer hybrid combination of these fundamental techniques. Many analyses show that WT is used to extract fault features and supervised learning method like ANN or membership function based techniques like FIS are used to develop suitable fault analysis models using the extracted features. Combinations of these methods are found to yield efficient fault analyzers; although at the cost of heavier computational burden. Different other advanced forms and variants of ANN and various hybrid methodologies combining these tools together have yielded excellent results, especially over the past two decades. Probabilistic neural network or PNN has come up with admirable results of fault analysis, particularly for fault classification due to its inherent capability of pattern recognition; although, PNN also suffers from requirement of severe training for achieving high accuracy of the fault analyzer model. Support vector machine (SVM)-based methods are very accurate; especially SVM-based classifiers of faults achieve very high accuracy. But SVM often loses accuracy under high noisy environment when fault signals are affected by severe noise, apart from being computationally heavy. SVM-based classifiers analyze fault signals in a binary way: this puts the test signals either above or below the classifying hyper plane, instead of the class probability analysis done in case of PNN classifiers.

Principal component analysis or PCA is a statistical method used in this research which enables reduction of memory requirement by cutting down the dimensionality of data as well as finds the major directions from a multivariate data; which, in turn, reduces the computational burden as well as memory requirement, since it considers only the major directions of variation in the data in descending order of importance. This also helps to reduce the effect of noise in signals in computation. But PCA considers the derived components as the linear combination of fault features, which introduce minor inaccuracy.

Table 1 Comparative analyses of different fault localization schemes

References	Methods used	Line length (km)	Fault resistance (Ω)	Percentage error (PE)	Number of cycles required
[6] Jain, A. et al. (2009)	ANN	100	0–100	Average PE found from table is 1.472%, maximum PE 7%	One cycle
[14] Valsan, S. P. et al. (2009)	WT	4-bus system	10–1000	Average error of 0.217% with the maximum error less than 3%; overall classification accuracy 99.53%	Less than one cycle
[17] Swetapadma, A., et al. (2015)	DWT-ANN	100	0–100	Percentage error in fault-location estimation within ± 1%	One cycle of pre-fault and two cycles of post-fault signals
[21] Dasgupta, A. et al. (2012)	Wavelet entropy and ANN	150	10	Location accuracy of 98.28%, i.e., error of 1.72%, maximum PE 3.25%	1/2 cycle pre-fault and 1/2 cycle of post-fault
[23] Yadav, A. et al. (2015)	WT and linear discriminant analysis (LDA)	100	0–100	Detection and classification accuracy 100%	1/4 cycle
[24] He, Z. et al. (2010)	Wavelet singular entropy (WSE)	300	0–300	Classification overall accuracy 100%	1/2 cycle
[29] Ray, P., et al. (2013)	WT–ANN and WPT–ANN-based hybrid method	300	0–45	Maximum error of less than 0.35% and mean error of less than 0.25%	One cycle
[30] Yadav, A. et al. (2015)	Wavelet and ANN	300	3–99	Minimum % error is − 0.0007 and maximum % error is 0.6665	–
[31] He, Z. et al. (2014)	Wavelet transforms and rough membership neural network (RMNN) classifier	200	0–500	Average success classification rate of 99.4%	1/4 cycle
[32] Vyas, B. et al. (2014)	(DWT and Chebyshev neural network (ChNN)	300	0–50	Classification accuracy 99.81%	1/2 cycle
[33] Samantaray, S. R. et al. (2007)	Wavelet and SVM for classification; RBFNN (radial basis function neural network) with recursive least-square algorithm for location	330	0–200	The classification rates are above 97%; location error calculated for all kinds of fault is below 2%	One cycle ahead and one cycle after the fault inception
[36] Yadav, A. et al. (2015)	Fuzzy inference system (FIS)	200	0–100	Fault-location error within 1 km mostly	Less than 1/2 cycle
[39] Reddy, M. et al. (2007)	Wavelet-fuzzy	300	0.001	Average PE found from table is 2.655% and Maximum PE 6.5%	One cycle
[40] Meyur, R. et al. (2016)	Wavelet-adaptive network-based fuzzy inference	300	–	Average PE found from table is 0.152% and Maximum PE 0.76%	Three cycles of nominal frequency
[42] Jung, C. K. et al. (2007)	Wavelet and neuro-fuzzy system	14 + 6.06 (line + cable)	0–200	Maximum location error for cable is 0.3306 km, and for overhead line 0.2551 km	1/2 cycle
[43] Eristi, H. (2013)	WT and ANFIS	320	0.1–50	Average location error less than 0.25% maximum location error of 1.288%, classification error 99.301%	About one cycle
[44] Reddy, M. J. et al. (2007)	WT, FIS and (ANFIS)	300	0.001–100	Maximum fault-location error varies − 3.67% to + 3.33%	–
[47] Sadeh, J. et al. (2009)	ANFIS	90-km overhead 10-km cable	0–100	Maximum location error below 0.07%	Within one cycle

Table 1 continued

References	Methods used	Line length (km)	Fault resistance (Ω)	Percentage error (PE)	Number of cycles required
[49] Bhalja, B. et al. (2008)	WT and SVM	128	0–100	Highest classifier accuracy of 98.5185%	–
[50] Jafarian, P. et al. (2012)	Dyadic WT and SVM	330	0.01–50	Maximum classification accuracy is 100% of Gaussian and polynomial kernel function	1/4 cycle
[52] Chothani, N. G. et al. (2011)	SVM	100	0–50	The Gaussian RBF kernel gives the highest accuracy of 99.833%	One cycle
[54] Salat, R. et al. (2004)	SVM	200	2–25	Minimum error 0.015% for LLL fault, maximum PE 0.7%	Two cycle
[56] Moravej, Z et al. (2012)	Hyperbolic S-transform and SVM	100	1–50	Classification accuracy 99.21% location relative error 2.48E−3	1/2 cycle
[58] Ekici, S. (2012)	SVM and WT	360	10–1000	Classification error is below 1%; average location error < 0.26%, maximum error < 0.95 km	1/2 cycle pre-fault and 1/2 cycle post-fault
[61] Yusuff, A. A. et al. (2014)	Stationary wavelet transform (SWT), determinant function feature (DFF), SVM and SVR	361.297	0.001–50	Classification accuracy of 100% location accuracy: % relative error for fault location is 2.10E−03%	1/4 cycle
[65] Alsafasfeh, Q. et al. (2012)	PCA	100	5–100	Minimum error 0.3% and maximum error of 2.7%	1/4 cycle
[76] Lopes, F. V. et al. (2017)	Traveling waves	200	50	Average error equal to 31 m, i.e., 0.0155%; maximum error < 270 m, i.e., 0.135%	Variable
[81] Mamiş, M. et al. (2013)	Spectrum	240	0.1–50	Average PE found from table is 1.369%, maximum PE 4.21%	One cycle (20 ms)
[82] Song, G. et al. (2014)	Frequency	225	0–100	Average PE found from table is 0.183%, maximum PE 0.64%	5 ms data window, 1/4 cycle AC equivalent
[88] Dash, P. K. et al. (2015)	Fast frequency filtering ST (FFST) along with a cumulative sum (CUSUM) average and fast Gauss–Newton (FGN) algorithm	230	5–200	Fault detection and classification reliability > 97% for high impedance faults (> 250 Ω) and 100% for low impedance faults fault-location accuracy is of the order of 0.3%	Classification time < 10 ms in most cases
[89] Krishnanand, K. R. et al. (2015)	Spectral energy, fast discrete S-transform, CUSUM algorithm	308	0.1–100	Maximum location error of 2.4561E−02 per unit	Half cycle before and after the CUSUM detection point (CSDP)
[90] Dutta, P. et al. (2014)	Synchronized V and I samples	IEEE 118-bus	0–100/ 200–10,000	Fault-location accuracy is within 3% except for one case	Within 7 ms of fault
[94] Devi, M. M. et al. (2018)	Phasor measurement units	Multi-bus (49-bus)	10–50	Maximum error of 0.19% for symmetrical fault, and 0.012% for unsymmetrical fault	–
[100] Roy, N. et al. (2015)	S-transform-based PNN and BPNN	300	0–100	4.46% without noise and 4.35% with noise	–
[101] Moravej, Z. et al. (2015)	S-transform (ST) and PNN methods	300	5–100	Power swing and symmetrical fault during power swing are classified with accuracy 100 and 90%, respectively	1/2 cycle

Table 1 continued

References	Methods used	Line length (km)	Fault resistance (Ω)	Percentage error (PE)	Number of cycles required
[103] Upendar, J. et al. (2010)	Adaptive resonance theory (ART) neural network for classification and inverse interpolation for location	300	0–200	Classification accuracy 99.91% and location errors lower than 1.5%	–
[104] Samantaray, S. R. et al. (2006)	Hyperbolic S-transform (HS-transform) and radial basis function neural network (RBFNN)	300	0–200	Fault-location error varies from 0.89 to 1.89%	One cycle ahead and one cycle back from the fault inception
[105] Vyas, B. et al. (2014)	Polynomial-based Chebyshev neural network (ChNN) and discrete wavelet packet transform (DWPT)	300	0–50	Classification accuracy 99.39%	1/2 cycle
[106] Upendar, J. et al. (2010)	PSO-based multilayer perceptron neural network and wavelet transform	300	0–200	99.91% Average fault classification accuracy	–
[107] Chen, Y. Q. et al. (2017)	Extreme learning machine (ELM)	100	0–200	Absolute fault-location errors of between 1.3 and 4.8%; average classification accuracy of 98% or above	One cycle
[122] Upendar, J. et al. (2012)	Classification and regression tree (CART), WT, ANN	300	0–200	Overall classification accuracy 99.97% using CART, 99.88% using BPNN, and location error is less than 1.5%	Two full cycles (0–720 degree)
[127] Patel, B. (2018)	FDOST entropy	140 (100 + 40)	0–100	Average error below 0.077 km maximum error below 0.477 km	1/2 cycle
[132] Ghorbani, A. et al.(2019)	Negative-sequence network	Multiple lines	0–300	Maximum error of 1.9%	–
[133] Ji, L. et al. (2019)	Positive sequence superimposed network	100	0.1–200	Average error below 0.62% Maximum error below 1.36%	One cycle
[134] Fan, R. et al. (2018)	Ensemble Kalman filter	200	0.01–15	AG fault: average error of 0.159 km, maximum error of 0.242 km, BC fault: average error of 0.109 km, maximum error of 0.199 km	1/2 cycle
[135] Gajare, S. et al. (2016)	Phasor data from intelligent electronic devices (IEDs) at both ends	500	0.001–100	Maximum error 0.0965%; worst error of 1.9282% with 10% error in current data, 5.0369% with 10% line parameter error	Pre-fault phasors calculated at a cycle pre-fault and phasors during fault obtained from second cycle
[137] Gaur, V.K. et al. (2017)	Time-synchronized and superimposed of fault signals	(310 + 60 + 50) km	Estimation parameter	Fault location and fault resistance remains within ± 1.5% and ± 3.5%, respectively	1/2 cycle
[138] Dobakhshari, A. S. et al. (2014)	Weighted least-squares (WLS) method	9-bus and 22-bus test systems	2–50	Fault-location error is less than 1%	One cycle starting two cycles after fault inception

Table 1 continued

References	Methods used	Line length (km)	Fault resistance (Ω)	Percentage error (PE)	Number of cycles required
[141] Swetapadma, A. et al. (2016)	Decision tree-based scheme	100	0–100	Classification accuracy is 99.99%	1/2 cycle
[142] Almeida, A. R. et al. (2017)	Independent component analysis (ICA), TW, SVM	200	20–240	Fault-location error < 1% classifier accuracy 100%	–
[144] Dash, P. K. et al. (2014)	Cumulative sum (CUSUM) and fast discrete S-transform (FDST)	300	5–200	Fault-location error is varying from 0.02 to 2.52%	1/2 cycle pre-fault and 1/2 cycle post-fault
[147] Perez, F. E. et al. (2011)	Adaptive wavelet algorithm (AWA) and Bayesian linear discrimination analysis for classification	390	0–40	Classification accuracy is 100%	1/10 cycle

Traveling wave and frequency analysis-based methods are also used effectively. Fourier transform-based analysis helps in developing frequency spectrums which bear major information regarding faults. Apart from these, entropy-based methods, correlation and regression analysis, time synchronous analysis of fault signals and several others have been proved effective in this regard. Phasor measurement unit (PMU) has come up over the last few years with excellent results of fault localization. But time synchronous analysis methods like PMU requires measurement of fault signals from both ends of the system simultaneously, which require additional hardware support, which further involves enhanced costing. Several other effective methods have also come up in the last few years especially with the rapid advancement of soft computational analysis as discussed earlier.

All these above methods of fault analysis are mentioned in brief in this article, both qualitatively as well as quantitatively. Citations are duly mentioned along with corresponding key features and outcomes of each of the research works. This is done with an aim to help researchers to develop an overall idea of research in this field, as well as identify the suitable method for serving the intended purpose regarding fault analysis for detection, classification and localization of power system faults, occurring in the transmission lines.

References

1. S.A. Aleem, N. Shahid, I.H. Naqvi, Methodologies in power systems fault detection and diagnosis. Energy Syst. **6**(1), 85–108 (2014)
2. K. Chen, C. Huang, J. He, Fault detection, classification and location for transmission lines and distribution systems: a review on the methods. High Voltage **1**(1), 25–33 (2016)
3. D.P. Mishra, P. Ray, Fault detection, location and classification of a transmission line. Neural Comput. Appl. **30**(5), 1377–1424 (2017)
4. A. Prasad, J.B. Edward, K. Ravi, A review on fault classification methodologies in power transmission systems: Part—I. J. Elect. Syst. Inf. Technol. **5**(1), 48–60 (2018)
5. A. Prasad, J.B. Edward, K. Ravi, A review on fault classification methodologies in power transmission systems: Part-II. J. Elect. Syst. Inf. Technol. **5**(1), 61–67 (2018)
6. A. Jain, A.S. Thoke, R.N. Patel, Double circuit transmission line fault distance location using artificial neural network, in 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC) (pp. 13–18). IEEE (2009)
7. M.B. Hessine, H. Jouini, S. Chebbi, Fault detection and classification approaches in transmission lines using artificial neural networks, in MELECON 2014–2014 17th IEEE Mediterranean Electrotechnical Conference (pp. 515–519). IEEE (2014)
8. J. Gracia, A.J. Mazon, I. Zamora, Best ANN structures for fault location in single-and double-circuit transmission lines. IEEE Trans. Power Delivery **20**(4), 2389–2395 (2005)
9. M. Sanaye-Pasand, H. Khorashadi-Zadeh, Transmission line fault detection & phase selection using ANN, in International Conference on Power Systems Transients (pp. 1–6) (2003)
10. J. Ezquerra, V. Valverde, A.J. Mazon, I. Zamora, J.J. Zamora, Field programmable gate array implementation of a fault location system in transmission lines based on artificial neural networks. IET Gener. Transm. Distrib. **5**(2), 191–198 (2011)
11. A.H. Osman, O.P. Malik, Transmission line distance protection based on wavelet transform. IEEE Trans. Power Delivery **19**(2), 515–523 (2004)
12. H. Jiang, J.J. Zhang, D.W. Gao, Fault localization in smart grid using wavelet analysis and unsupervised learning, in 2012 Conference Record of the Forty Sixth Asilomar Conference on Signals, Systems and Computers (ASILOMAR) (pp. 386–390). IEEE (2012)
13. F. Janıcek, M. Mucha, M. Ostrozlık, A new protection relay based on fault transient analysis using wavelet transform. Journal of Electrical Engineering **58**(5), 271–278 (2007)
14. S.P. Valsan, K.S. Swarup, Wavelet transform based digital protection for transmission lines. Int. J. Electr. Power Energy Syst. **31**(7–8), 379–388 (2009)
15. S.C. Shekar, G. Kumar, S.V.N.L. Lalitha, A transient current based micro-grid connected power system protection scheme using wavelet approach. International Journal of Electrical and Computer Engineering **9**(1), 14 (2019)

16. S. Devi, N.K. Swarnkar, S.R. Ola, O.P. Mahela, Detection of transmission line faults using discrete wavelet transform, in 2016 Conference on Advances in Signal Processing (CASP) (pp. 133–138). IEEE (2016)
17. A. Swetapadma, A. Yadav, All shunt fault location including cross-country and evolving faults in transmission lines without fault type classification. Electr. Power Syst. Res. **123**, 1–12 (2015)
18. M. Choudhury, A. Ganguly, Transmission line fault classification using discrete wavelet transform, in 2015 International Conference on Energy, Power and Environment: Towards Sustainable Growth (ICEPE) (pp. 1–5). IEEE (2015)
19. J. Upendar, C.P. Gupta, G.K. Singh, Discrete wavelet transform and genetic algorithm based fault classification of transmission systems, in 15th National Power Systems Conference, IIT Bombay (pp. 323–328) (2008)
20. M.A. Beg, M.K. Khedkar, S.R. Paraskar, G.M. Dhole, Feed-forward Artificial Neural Network-Discrete Wavelet Transform Approach to Classify Power System Transients. Electric Power Components and Systems **41**(6), 586–604 (2013)
21. A. Dasgupta, S. Nath, A. Das, Transmission line fault classification and location using wavelet entropy and neural network. Electric Power Components and Systems **40**(15), 1676–1689 (2012)
22. P.S. Bhowmik, P. Purkait, K. Bhattacharya, A novel wavelet transform aided neural network based transmission line fault analysis method. Int. J. Electr. Power Energy Syst. **31**(5), 213–219 (2009)
23. A. Yadav, A. Swetapadma, A novel transmission line relaying scheme for fault detection and classification using wavelet transform and linear discriminant analysis. Ain Shams Engineering Journal **6**(1), 199–209 (2015)
24. Z. He, L. Fu, S. Lin, Z. Bo, Fault detection and classification in EHV transmission line based on wavelet singular entropy. IEEE Trans. Power Delivery **25**(4), 2156–2163 (2010)
25. S. El Safty, A. El-Zonkoly, Applying wavelet entropy principle in fault classification. Int. J. Electr. Power Energy Syst. **31**(10), 604–607 (2009)
26. S. Ekici, S. Yildirim, M. Poyraz, Energy and entropy-based feature extraction for locating fault on transmission lines by using neural network and wavelet packet decomposition. Expert Syst. Appl. **34**(4), 2937–2944 (2008)
27. A.R. Adly, R.A. El Sehiemy, M.A. Elsadd, A.Y. Abdelaziz, A novel wavelet packet transform based fault identification procedures in HV transmission line based on current signals. International Journal of Applied **8**(1), 11–21 (2019)
28. B. Patel, P. Bera, Fast fault detection during power swing on a hybrid transmission line using WPT. IET Gener. Transm. Distrib. **13**(10), 1811–1820 (2019)
29. P. Ray, B.K. Panigrahi, N. Senroy, Hybrid methodology for fault distance estimation in series compensated transmission line. IET Gener. Transm. Distrib. **7**(5), 431–439 (2013)
30. A. Yadav, A. Swetapadma, A single ended directional fault section identifier and fault locator for double circuit transmission lines using combined wavelet and ANN approach. Int. J. Electr. Power Energy Syst. **69**, 27–33 (2015)
31. Z. He, S. Lin, Y. Deng, X. Li, Q. Qian, A rough membership neural network approach for fault classification in transmission lines. Int. J. Electr. Power Energy Syst. **61**, 429–439 (2014)
32. B.Y. Vyas, R.P. Maheshwari, B. Das, Improved fault analysis technique for protection of Thyristor controlled series compensated transmission line. Int. J. Electr. Power Energy Syst. **55**, 321–330 (2014)
33. S.R. Samantaray, P.K. Dash, G. Panda, Distance relaying for transmission line using support vector machine and radial basis function neural network. Int. J. Electr. Power Energy Syst. **29**(7), 551–556 (2007)
34. B. Patel, P. Bera, B. Saha, Wavelet packet entropy and RBFNN based fault detection, classification and localization on HVAC transmission line. Electric Power Components and Systems **46**(1), 15–26 (2018)
35. Z. Jiao, R. Wu, A new method to improve fault location accuracy in transmission line based on fuzzy multi-sensor data fusion. IEEE Transactions on Smart Grid **10**(4), 4211–4220 (2018)
36. A. Yadav, A. Swetapadma, Enhancing the performance of transmission line directional relaying, fault classification and fault location schemes using fuzzy inference system. IET Gener. Transm. Distrib. **9**(6), 580–591 (2015)
37. S. Vasilic, M. Kezunovic, Fuzzy ART neural network algorithm for classifying the power system faults. IEEE Trans. Power Delivery **20**(2), 1306–1314 (2005)
38. N. Zhang, M. Kezunovic, A real time fault analysis tool for monitoring operation of transmission line protective relay. Electr. Power Syst. Res. **77**(3–4), 361–370 (2007)
39. M.J. Reddy, D.K. Mohanta, A wavelet-fuzzy combined approach for classification and location of transmission line faults. Int. J. Electr. Power Energy Syst. **29**(9), 669–678 (2007)
40. R. Meyur, D. Pal, N.A. Sundaravaradan, P. Rajaraman, K.V.V.S. Srinivas, M.J.B. Reddy, D.K. Mohanta, A wavelet-adaptive network based fuzzy inference system for location of faults in parallel transmission lines, in 2016 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES) (pp. 1–6). IEEE (2016)
41. R. Goli, A.G. Shaik, S.S.T. Ram, Fuzzy-Wavelet Based Double Line Transmission System Protection Scheme in the Presence of SVC. J. Inst. Eng. (India) Ser. B **96**(2), 131–140 (2015)
42. C.K. Jung, K.H. Kim, J.B. Lee, B. Klöckl, Wavelet and neuro-fuzzy based fault location for combined transmission systems. Int. J. Electr. Power Energy Syst. **29**(6), 445–454 (2007)
43. H. Eristi, Fault diagnosis system for series compensated transmission line based on wavelet transform and adaptive neuro-fuzzy inference system. Measurement **46**(1), 393–401 (2013)
44. M.J. Reddy, D.K. Mohanta, A wavelet-neuro-fuzzy combined approach for digital relaying of transmission line faults. Electric Power Components and Systems **35**(12), 1385–1407 (2007)
45. K.S. Swarup, N. Kamaraj, R. Rajeswari, Fault diagnosis of parallel transmission lines using wavelet based ANFIS. International Journal of Electrical and Power Engineering **1**(4), 410–415 (2007)
46. T. Nguyen, Y. Liao, Transmission line fault type classification based on novel features and neuro-fuzzy system. Electric Power Components and Systems **38**(6), 695–709 (2010)
47. J. Sadeh, H. Afradi, A new and accurate fault location algorithm for combined transmission lines using adaptive network-based fuzzy inference system. Electr. Power Syst. Res. **79**(11), 1538–1545 (2009)
48. A. Abdullah, Ultrafast transmission line fault detection using a DWT-based ANN. IEEE Trans. Ind. Appl. **54**(2), 1182–1193 (2017)
49. B. Bhalja, R.P. Maheshwari, Wavelet-based fault classification scheme for a transmission line using a support vector machine. Electric Power Components and Systems **36**(10), 1017–1030 (2008)
50. P. Jafarian, M. Sanaye-Pasand, High-frequency transients-based protection of multiterminal transmission lines using the SVM technique. IEEE Trans. Power Delivery **28**(1), 188–196 (2012)
51. S.K. Mishra, L.N. Tripathy, A critical fault detection analysis & fault time in a UPFC transmission line. Protection and Control of Modern Power Systems **4**(1), 3 (2019)

52. N.G. Chothani, B.R. Bhalja, U.B. Parikh, New fault zone identification scheme for busbar using support vector machine. IET Gener. Transm. Distrib. **5**(10), 1073–1079 (2011)
53. B. Ravikumar, D. Thukaram, H.P. Khincha, Application of support vector machines for fault diagnosis in power transmission system. IET Gener. Transm. Distrib. **2**(1), 119–130 (2008)
54. R. Salat, S. Osowski, Accurate fault location in the power transmission line using support vector machine approach. IEEE Trans. Power Syst. **19**(2), 979–986 (2004)
55. M.J.B. Reddy, P. Gopakumar, D.K. Mohanta, A novel transmission line protection using DOST and SVM. Engineering Science and Technology, an International Journal **19**(2), 1027–1039 (2016)
56. Z. Moravej, M. Khederzadeh, M. Pazoki, New combined method for fault detection, classification, and location in series-compensated transmission line. Electric Power Components and Systems **40**(9), 1050–1071 (2012)
57. J.A. Jiang, C.L. Chuang, Y.C. Wang, C.H. Hung, J.Y. Wang, C.H. Lee, Y.T. Hsiao, A hybrid framework for fault detection, classification, and location—Part I: concept, structure, and methodology. IEEE Trans. Power Delivery **26**(3), 1988–1998 (2011)
58. S. Ekici, Support Vector Machines for classification and locating faults on transmission lines. Appl. Soft Comput. **12**(6), 1650–1658 (2012)
59. A.A. Yusuff, A.A. Jimoh, J.L. Munda, Determinant-based feature extraction for fault detection and classification for power transmission lines. IET Gener. Transm. Distrib. **5**(12), 1259–1267 (2011)
60. V. Malathi, N.S. Marimuthu, Multi-class support vector machine approach for fault classification in power transmission line, in 2008 IEEE International Conference on Sustainable Energy Technologies (pp. 67–71). IEEE (2008)
61. A.A. Yusuff, A.A. Jimoh, J.L. Munda, Fault location in transmission lines based on stationary wavelet transform, determinant function feature and support vector regression. Electr. Power Syst. Res. **110**, 73–83 (2014)
62. B.Y. Vyas, R.P. Maheshwari, B. Das, Pattern recognition application of support vector machine for fault classification of thyristor controlled series compensated transmission lines. J. Inst. Eng. (India) Ser. B, **97**(2), 175–183 (2016)
63. A. Mukherjee, P. Kundu, A. Das, Identification and Classification of Power System Faults using Ratio Analysis of Principal Component Distances. Indonesian Journal of Electrical Engineering and Computer Science **12**(11), 7603–7612 (2014)
64. A. Mukherjee, P.K. Kundu, A. Das, Power system fault identification and localization using multiple linear regression of principal component distance indices. International Journal of Applied Power Engineering **9**(2), 113–126 (2020)
65. Q.H. Alsafasfeh, I. Abdel-Qader, A.M. Harb, Fault classification and localization in power systems using fault signatures and principal components analysis. Energy Power Eng. **4**, 506–522 (2012)
66. Q. Alsafasfeh, I. Abdel-Qader, A. Harb, Symmetrical pattern and PCA based framework for fault detection and classification in power systems, in 2010 IEEE International Conference on Electro/Information Technology (pp. 1–5). IEEE (2010)
67. A. Mukherjee, P.K. Kundu, A. Das, Transmission Line Fault Location Using PCA-Based Best-Fit Curve Analysis. J. Inst. Eng. India Ser. B (2020). https://doi.org/10.1007/s40031-020-00515-z
68. A.K. Sinha, K.K. Chowdoju, Power system fault detection classification based on PCA and PNN, in 2011 International Conference on Emerging Trends in Electrical and Computer Technology (pp. 111–115). IEEE (2011)
69. A. Mukherjee, P.K. Kundu, A. Das, Application of Principal Component Analysis for Fault Classification in Transmission Line with Ratio-Based Method and Probabilistic Neural Network: a Comparative Analysis. J. Inst. Eng. India Ser. B **101**(4), 321–333 (2020)
70. P. Jafarian, M. Sanaye-Pasand, A traveling-wave-based protection technique using wavelet/PCA analysis. IEEE Trans. Power Delivery **25**(2), 588–599 (2010)
71. E. Vázquez-Martınez, A travelling wave distance protection using principal component analysis. Int. J. Electr. Power Energy Syst. **25**(6), 471–479 (2003)
72. M.A. Beg, M.K. Khedkar, S.R. Paraskar, G.M. Dhole, Classification of fault originated transients in high voltage network using DWT–PCA approach. International Journal of Engineering, Science and Technology **3**(11), 1–14 (2011)
73. P. Govender, N. Pillay, K.E. Moorgas, Fault classification on high voltage power lines using principal component analysis and feed-forward artificial neural networks, in 2013 IEEE International Conference on Industrial Engineering and Engineering Management (pp. 1550–1554). IEEE (2013)
74. Y. Guo, K. Li, X. Liu, Fault diagnosis for power system transmission line based on PCA and SVMs, in International Conference on Intelligent Computing for Sustainable Energy and Environment (pp. 524–532). Springer, Berlin, Heidelberg (2012)
75. J.A. Jiang, C.L. Chuang, Y.C. Wang, C.H. Hung, J.Y. Wang, C.H. Lee, Y.T. Hsiao, A hybrid framework for fault detection, classification, and location—part II: implementation and test results. IEEE Trans. Power Delivery **26**(3), 1999–2008 (2011)
76. F.V. Lopes, K.M. Dantas, K.M. Silva, F.B. Costa, Accurate two-terminal transmission line fault location using traveling waves. IEEE Trans. Power Delivery **33**(2), 873–880 (2017)
77. S. Hasheminejad, S.G. Seifossadat, M. Razaz, M. Joorabian, Traveling-wave-based protection of parallel transmission lines using Teager energy operator and fuzzy systems. IET Gener. Transm. Distrib. **10**(4), 1067–1074 (2016)
78. G. Ma, L. Jiang, K. Zhou, G. Xu, A Method of line fault location based on traveling wave theory. International Journal of Control and Automation **9**(2), 261–270 (2016)
79. L. Tang, X. Dong, S. Shi, Y. Qiu, A high-speed protection scheme for the DC transmission line of a MMC-HVDC grid. Electr. Power Syst. Res. **168**, 81–91 (2019)
80. D. Akmaz, M.S. Mamiş, M. Arkan, M.E. Tağluk, Transmission line fault location using traveling wave frequencies and extreme learning machine. Electr. Power Syst. Res. **155**, 1–7 (2018)
81. M.S. Mamiş, M. Arkan, C. Keleş, Transmission lines fault location using transient signal spectrum. Int. J. Electr. Power Energy Syst. **53**, 714–718 (2013)
82. G. Song, X. Chu, X. Cai, S. Gao, M. Ran, A fault-location method for VSC-HVDC transmission lines based on natural frequency of current. Int. J. Electr. Power Energy Syst. **63**, 347–352 (2014)
83. S.F. Huang, X.G. Wang, A protection scheme for phase-to-phase faults based on spectrum characteristic of fault-generated high-frequency transient signals, in 2009 IEEE Power & Energy Society General Meeting (pp. 1–5). IEEE (2009
84. S.R. Samantaray, P.K. Dash, G. Panda, Transmission line fault detection using time-frequency analysis, in 2005 Annual IEEE India Conference-Indicon (pp. 162–166). IEEE (2005)
85. Z.M. Radojevic, J.R. Shin, New one terminal digital algorithm for adaptive reclosing and fault distance calculation on transmission lines. IEEE Trans. Power Delivery **21**(3), 1231–1237 (2006)
86. M.H. Bollen, E. Styvaktakis, I.Y.H. Gu, Categorization and analysis of power system transients. IEEE Trans. Power Delivery **20**(3), 2298–2306 (2005)

87. P. Gopakumar, M.J.B. Reddy, D.K. Mohanta, Adaptive fault identification and classification methodology for smart power grids using synchronous phasor angle measurements. IET Gener. Transm. Distrib. **9**(2), 133–145 (2015)
88. P.K. Dash, S. Das, J. Moirangthem, Distance protection of shunt compensated transmission line using a sparse S-transform. IET Gener. Transm. Distrib. **9**(12), 1264–1274 (2015)
89. K.R. Krishnanand, P.K. Dash, M.H. Naeem, Detection, classification, and location of faults in power transmission lines. Int. J. Electr. Power Energy Syst. **67**, 76–86 (2015)
90. P. Dutta, A. Esmaeilian, M. Kezunovic, Transmission-line fault analysis using synchronized sampling. IEEE Trans. Power Delivery **29**(2), 942–950 (2014)
91. Q. Jiang, X. Li, B. Wang, H. Wang, PMU-based fault location using voltage measurements in large transmission networks. IEEE Trans. Power Delivery **27**(3), 1644–1652 (2012)
92. S. Barman, B.K.S. Roy, Detection and location of faults in large transmission networks using minimum number of phasor measurement units. IET Gener. Transm. Distrib. **12**(8), 1941–1950 (2018)
93. P. Gopakumar, M.J.B. Reddy, D.K. Mohanta, Fault detection and localization methodology for self-healing in smart power grids incorporating phasor measurement units. Electric Power Components and Systems **43**(6), 695–710 (2015)
94. M.M. Devi, M. Geethanjali, A.R. Devi, Fault localization for transmission lines with optimal Phasor Measurement Units. Comput. Electr. Eng. **70**, 163–178 (2018)
95. Y.J. Lee, T.C. Lin, C.W. Liu, Multi-terminal nonhomogeneous transmission line fault location utilizing synchronized data. IEEE Trans. Power Delivery **34**(3), 1030–1038 (2019)
96. P. Gopakumar, B. Mallikajuna, M.J.B. Reddy, D.K. Mohanta, Remote monitoring system for real time detection and classification of transmission line faults in a power grid using PMU measurements. Protection and Control of Modern Power Systems **3**(1), 16 (2018)
97. F. Mo, W. Kinsner, Probabilistic neural networks for power line fault classification, in Conference Proceedings. IEEE Canadian Conference on Electrical and Computer Engineering (Cat. No. 98TH8341) (Vol. 2, pp. 585–588). IEEE (1998)
98. K.H. Kashyap, U.J. Shenoy, Classification of power system faults using wavelet transforms and probabilistic neural networks, in Proceedings of the 2003 International Symposium on Circuits and Systems, 2003. ISCAS'03. (Vol. 3, pp. III-III). IEEE (2003)
99. P.D. Raval, A.S. Pandya, Accurate fault classification in series compensated multi-terminal extra high voltage transmission line using probabilistic neural network, in 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT) (pp. 1550–1554). IEEE (2016)
100. N. Roy, K. Bhattacharya, Detection, classification, and estimation of fault location on an overhead transmission line using S-transform and neural network. Electric Power Components and Systems **43**(4), 461–472 (2015)
101. Z. Moravej, J.D. Ashkezari, M. Pazoki, An effective combined method for symmetrical faults identification during power swing. Int. J. Electr. Power Energy Syst. **64**, 24–34 (2015)
102. H. Cui, N. Tu, Generalized regression neural networks based HVDC transmission line fault localization, in 2015 7th International Conference on Intelligent Human-Machine Systems and Cybernetics (Vol. 1, pp. 25–29). IEEE (2015)
103. J. Upendar, C.P. Gupta, G.K. Singh, Fault classification scheme based on the adaptive resonance theory neural network for protection of transmission lines. Electric Power Components and Systems **38**(4), 424–444 (2010)
104. S.R. Samantaray, P.K. Dash, G. Panda, Fault classification and location using HS-transform and radial basis function neural network. Electr. Power Syst. Res. **76**(9–10), 897–905 (2006)
105. B. Vyas, R.P. Maheshwari, B. Das, Investigation for improved artificial intelligence techniques for thyristor-controlled series-compensated transmission line fault classification with discrete wavelet packet entropy measures. Electric Power Components and Systems **42**(6), 554–566 (2014)
106. J. Upendar, C.P. Gupta, G.K. Singh, G. Ramakrishna, PSO and ANN-based fault classification for protective relaying. IET Gener. Transm. Distrib. **4**(10), 1197–1212 (2010)
107. Y.Q. Chen, O. Fink, G. Sansavini, Combined fault location and classification for power transmission lines fault diagnosis with integrated feature extraction. IEEE Trans. Industr. Electron. **65**(1), 561–569 (2017)
108. M. Mirzaei, B. Vahidi, S.H. Hosseinian, Fault location on a series-compensated three-terminal transmission line using deep neural networks. IET Sci. Meas. Technol. **12**(6), 746–754 (2018)
109. C. Yu-Wu, G. Yu-Hong, Fault phase selection for transmission line based on correlation coefficient, in 2010 International Conference on Computer Application and System Modeling (ICCASM 2010) (2010))
110. C. Haomin, L. Peng, G. Xiaobin, X. Aidong, C. Bo, X. Wei, Z. Liqiang, Fault prediction for power system based on multidimensional time series correlation analysis, in 2014 China International Conference on Electricity Distribution (CICED) (pp. 1294–1299). IEEE (2014)
111. Z. Zheng, J. Liu, H. Yu, Fault location on transmission line using maximum correlation coefficient method, in 2012 Annual Report Conference on Electrical Insulation and Dielectric Phenomena (pp. 226–229). IEEE (2012)
112. A. Dasgupta, S. Debnath, A. Das, Transmission line fault detection and classification using cross-correlation and k-nearest neighbor. International Journal of Knowledge-based and Intelligent Engineering Systems **19**(3), 183–189 (2015)
113. B. Chatterjee, S. Debnath, Cross correlation aided fuzzy based relaying scheme for fault classification in transmission lines. Engineering Science and Technology, an International Journal **23**(3), 534–543 (2020)
114. A. Bhattacharjee, A. Dasgupta, Cross-correlation based distance estimation of single line to ground faults using Elman back-propagation neural network, in 2019 3rd International conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 1230–1235). IEEE (2019)
115. G. Zhang, H. Shu, Y. Liao, Automated double-ended traveling wave record correlation for transmission line disturbance analysis. Electr. Power Syst. Res. **136**, 242–250 (2016)
116. K. Zhu, W.K. Lee, P.W. Pong, Fault-line identification of HVDC transmission lines by frequency-spectrum correlation based on capacitive coupling and magnetic field sensing. IEEE Trans. Magn. **54**(11), 1–5 (2018)
117. A. Lei, X. Dong, V. Terzija, An ultra-high-speed directional relay based on correlation of incremental quantities. IEEE Trans. Power Delivery **33**(6), 2726–2735 (2018)
118. D. Lin, P. Jun, T. Jun, Fault location for transmission line based on traveling waves using correlation analysis method, in 2008 international conference on high voltage engineering and application (pp. 681–684). IEEE (2008
119. H. Shu, N. An, B. Yang, Y. Dai, Y. Guo, Single Pole-to-Ground Fault Analysis of MMC-HVDC Transmission Lines Based on Capacitive Fuzzy Identification Algorithm. Energies **13**(2), 319 (2020)
120. M.H. Musa, Z. He, L. Fu, Y. Deng, A correlation coefficient-based algorithm for fault detection and classification in a power transmission line. IEEJ Transactions on Electrical and Electronic Engineering **13**(10), 1394–1403 (2018)

121. X.N. Lin, M. Zhao, K. Alymann, P. Liu, Novel design of a fast phase selector using correlation analysis. IEEE Trans. Power Delivery **20**(2), 1283–1290 (2005)
122. J. Upendar, C.P. Gupta, G.K. Singh, Statistical decision-tree based fault classification scheme for protection of power transmission lines. Int. J. Electr. Power Energy Syst. **36**(1), 1–12 (2012)
123. S.K. Sharma, GA-GNN (Genetic Algorithm-Generalized Neural Network)-Based Fault Classification System for Three-Phase Transmission System. J. Inst. Eng. (India) Ser. B **100**(5), 435–445 (2019)
124. K. Gayathri, N. Kumarappan, Accurate fault location on EHV lines using both RBF based support vector machine and SCALCG based neural network. Expert Syst. Appl. **37**(12), 8822–8830 (2010)
125. R. Razzaghi, G. Lugrin, H. Manesh, C. Romero, M. Paolone, F. Rachidi, An efficient method based on the electromagnetic time reversal to locate faults in power networks. IEEE Trans. Power Deliv. **28**(3), 1663–1673 (2013)
126. A. Codino, Z. Wang, R. Razzaghi, M. Paolone, F. Rachidi, An alternative method for locating faults in transmission line networks based on time reversal. IEEE Trans. Electromagn. Compat. **59**(5), 1601–1612 (2017)
127. B. Patel, A new FDOST entropy based intelligent digital relaying for detection, classification and localization of faults on the hybrid transmission line. Electr. Power Syst. Res. **157**, 39–47 (2018)
128. A. Maheshwari, V. Agarwal, S.K. Sharma, Comparative Analysis of ANN-Based FL and Travelling Wave-Based FL for Location of Fault on Transmission Lines. J. Inst. Eng. (India) Ser. B 1–10 (2019)
129. Y. Liu, A.S. Meliopoulos, Z. Tan, L. Sun, R. Fan, Dynamic state estimation-based fault locating on transmission lines. IET Gener. Transm. Distrib. **11**(17), 4184–4192 (2017)
130. R. Godse, S. Bhat, Mathematical morphology-based feature-extraction technique for detection and classification of faults on power transmission line. IEEE Access **8**, 38459–38471 (2020)
131. G. Kapoor, Mathematical morphology based fault detector for protection of double circuit transmission line. ICTACT Journal of Micro Electronics **4**(2), 589–600 (2018)
132. A. Ghorbani, H. Mehrjerdi, Negative-sequence network based fault location scheme for double-circuit multi-terminal transmission lines. IEEE Trans. Power Delivery **34**(3), 1109–1117 (2019)
133. L. Ji, X. Tao, Y. Fu, Y. Fu, Y. Mi, Z. Li, A New Single Ended Fault Location Method for Transmission Line Based on Positive Sequence Superimposed Network During Auto-Reclosing. IEEE Trans. Power Delivery **34**(3), 1019–1029 (2019)
134. R. Fan, Y. Liu, R. Huang, R. Diao, S. Wang, Precise fault location on transmission lines using ensemble Kalman filter. IEEE Trans. Power Delivery **33**(6), 3252–3255 (2018)
135. S. Gajare, A.K. Pradhan, An accurate fault location method for multi-circuit series compensated transmission lines. IEEE Trans. Power Syst. **32**(1), 572–580 (2016)
136. A.M. Stankovic, T. Aydin, Analysis of asymmetrical faults in power systems using dynamic phasors. IEEE Trans. Power Syst. **15**(3), 1062–1068 (2000)
137. V.K. Gaur, B. Bhalja, A new faulty section identification and fault localization technique for three-terminal transmission line. Int. J. Electr. Power Energy Syst. **93**, 216–227 (2017)
138. A.S. Dobakhshari, A.M. Ranjbar, A novel method for fault location of transmission lines by wide-area voltage measurements considering measurement errors. IEEE Transactions on smart grid **6**(2), 874–884 (2014)
139. X. Tong, H. Wen, A novel transmission line fault detection algorithm based on pilot impedance. Electr. Power Syst. Res. **179**, 106062 (2020)
140. P.K. Mishra, A. Yadav, M. Pazoki, A novel fault classification scheme for series capacitor compensated transmission line based on bagged tree ensemble classifier. IEEE Access **6**, 27373–27382 (2018)
141. A. Swetapadma, A. Yadav, Data-mining-based fault during power swing identification in power transmission system. IET Sci. Meas. Technol. **10**(2), 130–139 (2016)
142. A.R. Almeida, O.M. Almeida, B.F.S. Junior, L.H.S.C. Barreto, A.K. Barros, ICA feature extraction for the location and classification of faults in high-voltage transmission lines. Electr. Power Syst. Res. **148**, 254–263 (2017)
143. S. Das, S.P. Singh, B.K. Panigrahi, Transmission line fault detection and location using wide area measurements. Electr. Power Syst. Res. **151**, 96–105 (2017)
144. P.K. Dash, J. Moirangthem, S. Das, A new time–frequency approach for distance protection in parallel transmission lines operating with STATCOM. Int. J. Electr. Power Energy Syst. **61**, 606–619 (2014)
145. M.N. Mahmud, M.N. Ibrahim, M.K. Osman, Z. Hussain, A robust transmission line fault classification scheme using class-dependent feature and 2-Tier multilayer perceptron network. Electr. Eng. **100**(2), 607–623 (2018)
146. M. Sahani, P.K. Dash, Fault location estimation for series-compensated double-circuit transmission line using parameter optimized variational mode decomposition and weighted P-norm random vector functional link network. Appl. Soft Comput. **85**, 105860 (2019)
147. F.E. Perez, E. Orduna, G. Guidi, Adaptive wavelets applied to fault classification on transmission lines. IET Gener. Transm. Distrib. **5**(7), 694–702 (2011)
148. Y. Wang, Q. Li, B. Chen, Image classification towards transmission line fault detection via learning deep quality-aware fine-grained categorization. J. Vis. Commun. Image Represent. **64**, 102647 (2019)
149. M. Kazim, A.H. Khawaja, U. Zabit, Q. Huang, Fault Detection and Localization for Overhead 11-kV Distribution Lines With Magnetic Measurements. IEEE Trans. Instrum. Meas. **69**(5), 2028–2038 (2019)
150. J. Sadeh, A. Adinehzadeh, Accurate fault location algorithm for transmission line in the presence of series connected FACTS devices. Int. J. Electr. Power Energy Syst. **32**(4), 323–328 (2010)
151. Y. Zhong, X. Kang, Z. Jiao, Z. Wang, J. Suonan, A novel distance protection algorithm for the phase-ground fault. IEEE Trans. Power Delivery **29**(4), 1718–1725 (2013)