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A STUDY ON FAULT DETECTION TECHNIQUES AND CLASSIFICATION ALGORITHMS IN AN OVERHEAD TRANSMISSION LINES

Nadeem Ahmed Tunio[*1], Fatima Tul Zuhra[2], Mohsin Ali Tunio[3], Muhammad Amir Raza[4]

*[*1,3,4]Department of Electrical Engineering, Mehran University of Engineering and Technology, SZAB Campus Khairpur Mir's 66020, Sindh, Pakistan*
[2]Information Technology Department , Shaheed Benazir Bhutto University Sanghar Campus, Sanghar, Sindh, Pakistan

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Corresponding Author: *
Nadeem Ahmed Tunio

Abstract
Transmission lines are very important , vulnerable and exposed part of power system. Continuity of power supply depends on fault free status of transmission lines. Therefore need is to device a robust fault detection and fault classification mechanism with digital relaying system , so as to distinguish between normal and faulty phases and further more to isolate the faulty lines from the rest of grid and further to carry the restoration work quickly . This review provides thourogh overview of various signal processing tools for feature extraction from fault signal keeping FACTS-connected transmission lines considering cross-country and evolving faults . Various fault classification techniques have also been detailed in the context of their fault classification accuracy, memory requirement and computation time , long term depencies , vanishing gradient and receptive field. This literature survey would help researchers to get insight to select an appropriate technique for fault detection and classification in overhead power transmission lines.

1. INTRODUCTION

Electrical power system is growing progressively in its dimensions and thus becoming very complex in its generation, transmission, distribution and on load sides due to integration of renewable resources in the existing power grid. The faults in electrical power system poses technical and financial losses, weaken the reliability level of the power system. Fault occur in various shapes such as short circuit, transient, lighting stroke, fire, snow, wind and directly affect the performance resulting in complete breakdown and collapse of power system. [1] For the safety of the power system, it is imperative to detect and classify faults as fast as possible, since the power system needs to be operated at its maximum capacity on continuous mode. [2]. There are two types of faults that mostly occur in power transmission lines i.e., series and shunt faults[3]. The unsymmetrical faults in transmission lines are very common having damaging effects less as compared to the symmetrical faults. Line to Ground (LG), Line to Line (LL) and Double Line to Ground (LLG) faults are types of unsymmetrical faults. As reported in the literature occurrence of line to ground fault (LG) is reported very high as compared to other fault types in the same category and counts 65-70% of the total faults, where 15-20% of faults count in the category of double line to ground faults[4]. Wind pressure leads line to line faults due to free swinging of conductors, which results into over lapping of conductors on each other, these faults are also termed as unbalanced faults as they produce unbalance currents due to different impedance levels in each phase [2]. Figure 1 shows the details of all such faults.

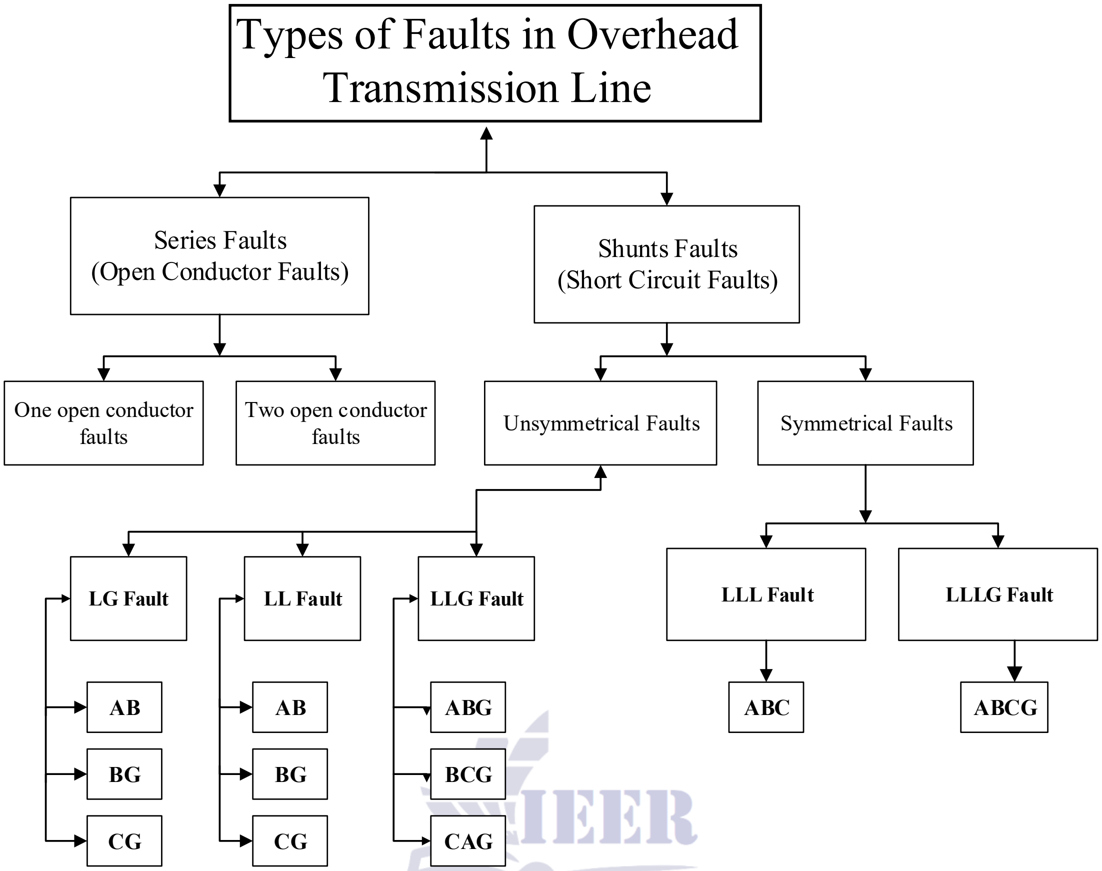


Figure 1: Types of fault reported in overhead power transmission network

Interconnected grid system in few instances is composed of hybrid transmission lines i.e. parts of overhead lines and underground cables. Under such conditions, the protection scheme is different from the only overhead transmission line due to the different velocities of travelling waves in an overhead transmission lines and underground power cables [2, 5]. To evaluate the role of protective devices in such situation is crucial. The protective relay has to act very quickly to detect the fault and accurately localize it, ensuring reliability and quality of power system to remain intact. In case, faults in transmission lines are not properly detected, not cleared in time and power system is not brought back to its normal state , the power quality will degrade. Interruption of power supply due to faults result into finacial and business losses, beside the damages to customers' important and sophisticated equipment [3]. The damage caused by faults depends on their duration and response time of protective relays. Protective relays are intelligent devices (ID), which act once operating limits of currents are violated due to faults and quickly operate in milliseconds to protect the power system, [2]. Modern digital relays are designed on advanced signal processing techniques and are more effective than that of conventional protection relays. Literature review revealed that the conventional protection relays are less effective and far behind in their operation and performance compared to their counterpart digital relays [2, 5].

2. Fault Detection and Classification Methods

There are various studies available in the literature , where the researchers have presented their work regarding automatic features extraction from the fault signal for fault detection and faults classification in transmission lines[4]. There has been lot of work done in this areas for fault detection, and classification using modern signal processing techniques, artificial intelligence, machine learning methods, Global Positioning System (GPS) based on latest communication systems through intelligent electronic devices (IEDs) [6]. Phasor Measurement Unit (PMU) and high-performance computing solutions have also been reported [7]. The only purpose of fault analysis is to detect faults as quickly further to their accurate fault classification [8]. For the reliability of power system, advanced , intelligent supervisory and process based fault diagnosis strategies are essential, which is categorized as shown in Figure 2.

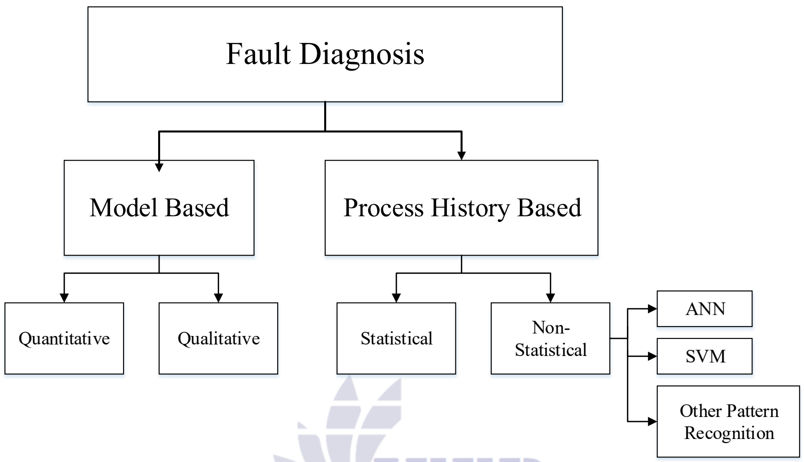


Figure: 2 Process history based fault diagnosis

Model based Fault diagnosis use mathematical model, unfolding the process through already available information obtained from the dynamics of process. Modal based fault diagnosis method has been further classified as quantitative and qualitative model-based methods [5]. The qualitative modeling approach is divided as detailed and simplifies physical methods. The difference in these two is that first technique is applied where analysis of transient faults requires extreme accuracy and precision. The latter is used in cases where the faults change the line parameters[9]. Qualitative based methods are more robust and implemented to explain the exiting state of system using heuristic symptoms [10]. Another type is process-based history methods i.e. pattern recognition entails historical data, which is composed of large volume of experimental data e.g. input/output data set [5]. The relationship between inputs and outputs can be statistical (regression, least square method) and non-statistical or pattern recognition i.e., ANN, SVM etc. based on only these parameters [11]. The process history-based fault detection and classification methods consists of following steps and shown in Figure 3.

1. Measurement
2. Feature extraction
3. Decision
4. Classification

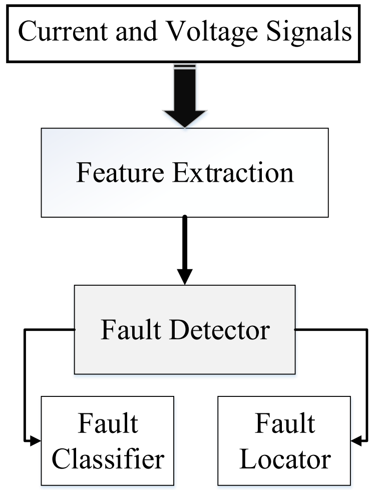


Figure 3: Framework of fault detection, classification and location.

3. Singnal Processing Techniqiues for Feature Extraction from Fault Signal

Fault detection in transmission lines is considered important than fault classification and fault localization[12]. Fault detection distinguishes between faulty and non-faulty lines by comparing extracted features from the disturbed signal with certain set values [13]. In case, the fault detection algorithm is proficient, no separate fault classifiers and locators are used [14-16]. There are many techniques and tools used by the researchers for feature extraction from the fault signal, wavelet-based signal processing method has been proposed for real-time fault detection in transmission lines[17] . The harmonic frequencies generated by FACTS controllers can distort the high frequency pattern of the Travelling Waves (TWs) during a fault. This imposes difficulty for detecting the desired high frequency components for accurate fault location in FACTS compensated transmission lines. It therefore important to incorporate the impact of FACTS devices into fault detection and protection schemes to ensure reliable and secure operation of FACTS-equipped transmission lines [18]. Further more cross-country fault and evolving fault can also be more challenging to detect than traditional faults. These faults are complex because traditional protection methods rely on the assumption that faults occur at a single point and affect all phases equally. Identifying and locating cross-country faults requires advanced techniques that can analyze signals from multiple points along the line. Evolving fault involves multiple fault events occurring in sequence, one after the other, either in the same phase at different locations or in different phases at the same location [19]. These faults are challenging because the initial event can mask the subsequent fault, making it difficult to detect and isolate the actual problem.

Fault must be quickly detected, maintaining accuracy and robustness of fault detection syste. It is however observed that the fault detection time has significant effect on the performance of protection system, in most of the cases fault detection is achieved in 2–10 ms as against 30 ms for fault classification [18, 19]. The case of complexity & technical advancements of power system due to the meddling of harmonics and transient must be considered, while extraction feature of the fault signal [20]. It is necessary that fault detection techniques must rely on computational technique to counter the complexity of fault types[21]. Various feature extraction techniques along with their applications and limitations as explained as follows.

- **Fourier Transform (FT)**

Fourier transform breaks the signal into smaller frequencies of different sinusoids and transform the signal from frequency base to time base and vice versa[21]. This technique is very beneficial and simplified in nature if the signal is static in nature [7]. If the signal is non-stationary or transient, it does not convey the accurate information for feature extraction as some information is lost while transforming the signal from frequency domain to time domain[22].

- **Short time fourier transform (STFT)**

Short time fourier transform prove more attractive and draw a signal into two dimensions i.e., frequency and time[23]. It overcomes the limitation of Fourier Transform for some specific cases but still there is hurdle[24]. Among its other drawbacks , window sizing matters, once the specific size window is selected, it remains same for all frequencies[13]. Short pulses are poorly localized in time with long window and low frequencies can hardly be illustrated with short window while STFT being used for feature extraction from the fault signal[25].

- **Wavelet Transform (WT)**

This has emerged as a new technique, capable to solve the difficulties of Fourier Transform and STFT. Wavelet transform allow use of long-time intervals where error-free low frequency and high frequency data is needed, hence flexible sizing of window and easy frequency- time transformation is possible[26]. WT analyze the fault transient signal, decomposes it in detailed and approximate coefficients as shown in Figure 4 , to obtain enough information for localization and classification of faults. Equation of a signal x (t) in WT is mentioned as under:

$$W\tau, S(t) = \frac{1}{\sqrt{s}} \int_{-\propto}^{\propto} x(t)\psi\left(\frac{t-\tau}{s}\right) dt \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . . Equation(1)$$

m and τ are translating and scale factors. Ψ(t) is the mother wavelet.

Discrete Wavelet Transform (DWT) is type of WT in discrete form, uses samples of data or discrete signals for analysis of fault signal because of increasing use and demand of digital relaying in modern power system, therefore digital fault analysis methods rely on DWT [14, 27]. The DWT of a signal x (t) is defined as:

$$DWT(x, m, n) = \frac{1}{\sqrt{a_0^m}} \Sigma_{\mathrm{m}}\, \Sigma_{\mathrm{n}}\; x(k)\psi\left(\frac{k - nb_0 {a_0}^m}{a_0^m}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . . Equation\ (2)$$

K, m and n are integers. a_0^m and $nb_0{a_0}^m$ are dilation (scale) and translation (time shift) parameters. b_0 and a_0 are constants.

The wavelet singular entropy recovers information from the current signal samples during fault or any other disturbance i.e. power swing [15]. Process it through wavelet transform to derive singular values, used to find out Shannon Entropy, called Wavelet Singular Entropy (WSE) [13].

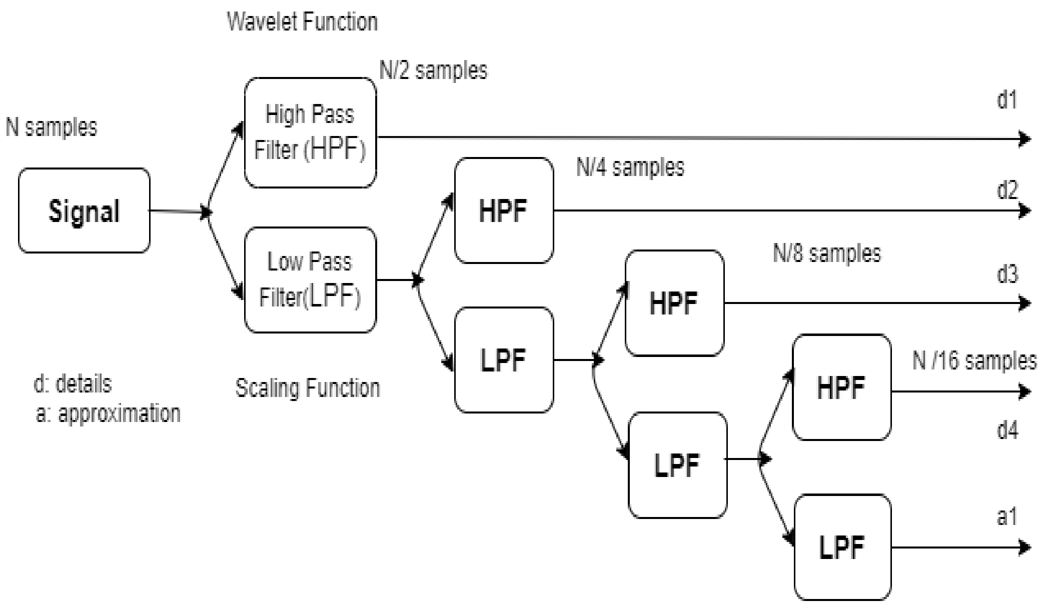


Figure 4: Multi-resolution analysis in DWT

By incorporating DWT into protection schemes, power system operators can enhance fault detection accuracy and reliability in FACTs-equipped transmission lines, ensuring secure and stable operation due to due to multi-resolution analysis capabilities, time-frequency localization, effectiveness in handling non-stationary signals, Feature extraction abilities and Noise reduction potential [28] . Moreover wavelet transforms have emerged as powerful tools for analyzing transient signals generated by cross-country and evolving faults. Their ability to decompose signals into different frequency bands allows for effective extraction of fault features amidst noise and harmonics.

- **Wavelet Packet Transform (WPT)**

WPT uses high frequency contained in faulty signal, to analyse frequency contents, approximate and detailed coefficients are obtained through decomposition technique [15]. Decomposition process takes lot of time in calculation. So to minimize calculation burden the decomposition is performed up to 4 levels [29]. WPT has capability to exhibit relatively better frequency resolution than Discrete Wave Transform [27]. WPT of a signal x (t) is

$$W_b^{n,a} = 2^{a/2} \int f(t)\psi_n(2^{-2}t - b)dt \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{Equation (3)}$$

b and a represents wavelet position and scale. ψ^n, denotes mother wavelet.

- **Stockwell Transform(ST)**

It exhibits combined features of WT and STFT, suitable in case of non-stationary signal, when the window size changes inversely with frequency [30]. ST Possesses capabilities to deliver information, reference to time, frequency and phase angle from the fault signal, beside it is also prone to noise when used for feature extraction compared with other counterpart signal processing techniques [31]. Mathematical expression for S transform for signal $x(t)$ is:

$$S(\tau, f) = \frac{\int_{-\alpha}^{\alpha} x(t) \frac{|f|}{\sqrt{2\pi}} e^{-(\tau-t)^2 f^2}}{2} e^{-j2\pi f t}\ dt \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{Equation}(4)$$

t and f specify time and frequency and T is control parameter used for Gaussian window adjustment.

- **Fast Discrete Orthonormal Stockwell Transform (FDOST)**

Fast Discrete Orthonormal Stockwell Transform (FDOST) is used in situation where better image approximation is required, FDOST has better compression ability and potentially better approximation of the image than other signal processing techniques i.e. DWT and FFT[32, 33]. FDOST has been reported as an effective tool used for feature extraction along with SVM as fault classifier , furthermore FDOST can be sensitive to noise present in the fault signal, which can distort the time-frequency representation and complicate interpretation [34].

- **Principal Component Analysis (PCA)**

Principal Component Analysis (PCA) is used to fit high dimensional data into low dimensional data, to ensure that the variance of the data could be followed in the best possible way [35]. PCA obtains features from faulty signals using either ac voltage or current, wavelet coefficients together with principal components are implemented in order to classify fault type and to locate fault distance[36]. It is a novel approach for feature extraction and fault classification in transmission lines. Feature extraction is achieved from a phase current during 1/4th of a cycle which help it to generate unique signatures for fault analysis [37]. omputational cost and Information loss during dimensionality reduction are few limitations[38].

- **Model Transformation**

This technique is based on modal transformation that considers the general case of an untransposed line. Model transformation is also called Clarke Transformation (CT)[39]. This can be applied for transforming the coupled phase quantities to decoupled modal quantities a, b and c to α, β (two stationary phase components) and 0 (zero sequence components) on basis of fault characteristics by relating the modal components and phase quantities based on eigenvalue/eigenvector theory[40].The main advantage of Clark's transformation over the symmetrical component transformation is that elements are real [35]. Errors due to iinaccurate or varying line parameters and assuming fault signal as stationary affect the feature extraction and fault classification using modal transformation.

- **Independent Component Analysis (ICA)**

ICA is computational technique , belongs to a class of blind source separation (BSS) methods for separating data into underlying informational components, it uses non-Gaussianity concept to obtain independent components[41]. The Independent Component Analysis algorithm is sufficient to identify the faults and locate them in overhead high-voltage power transmission lines with accuracy under situation when the faulty signal is integrated with the noise[42]. Independent component analysis (ICA) combined with both travelling wave (TW) theory and support vector machine (SVM) revealed excellent results in fault location purposes with error rate as less than 1% and accuracy of 100% considering all types of faults[37].

The comparative analysis of all various feature extraction tools along with their advantages and limitations is produced in Table 1.

Table 1: Comparative Analysis of Different Feature Extraction Techniques

Feature	Advantages	Limitations
FT	Very beneficial and simplified in nature if the signal is stationary.	Information is lost while signal transforms from frequency domain in to time domain, If the signal is non-stationary or transient it does not inform the accurate location.
STFT	Technique is simple in implementation with minimum computation time.	Limited space in localizing non stationary signals
	Well suitable for harmonic analysis of signal i.e. periodic or stationary behavior.	Fault classification issues, in cross country faults. Chances of inaccuracy due to frequency leaking. Techniques shows less robustness in case of variations in normal operation conditions.
DWT	It is able to localize signal in time and frequency domain. No need of aliasing and window length required for restoration of original signal. Exhibit accuracy in fault detection and classification.	Choice of mother wavelet is a formidable challenge. Increases the computational time due to higher signal decomposition levels.
Wavelet Singular Entropy (WSE)	Calculating and classifying faults due to complexity, uncertainty of power system, non-linearity is easy, which is unable by routine theory.	They all rest on specified measurement and it's hard to extract features during peak or heavy loading condition.
ST	Good time frequency resolution and noise immunity. Able to convey information of fault signal in time frequency and phase angle.	Does not suitable for real time applications. ST coefficients need to be calculated for each specified time value. Large calculation time and memory required.
PCA	It is simple and fast. Capable to reduce the dimensions of data. Ability to reduce noise.	Covariance matrix is needlessly large in case when number of dimensions is greater than the number of data points.
Modal Transform(MT)	Independent of electrical values and frequency. Single transformation matrix is used for three-phase system. No convolution techniques are required	For complex networks, modal parameters are not reliable.

Independent Component Analysis (ICA).	It is computationally efficient and requires less memory over other blind source separation (BSS) algorithm.	It cannot extract sources properly if the noise is non uniform.

4. Fault Classification Techniques

After the fault is detected it is important to accurately classify the fault in minimum possible time, numerous fault detection mechanisms exist for transmission lines in the literature , that include. Impedance-based techniques:, traveling wave-based techniques, signal-based technique and artificial intelligence-based methods In modern smart grid environment, the complexity of fault location problem increases with the proliferation of unusual topologies such as transmission lines combined with underground cables, series capacitor compensated transmission lines and three-terminal transmission systems[44]. The use of Artificial Intelligence (AI) to improve the fault location accuracy has been attracting many researchers due to its Faster response time and enhanced accuracy [45]. The fault classification techniques used by the researchers are categorized as below and shown in Figure 5.

- Prominent techniques, covers WT based analysis, Artificial Neural Networks and fuzzy logic methods;
- Mixed or hybrid methods containing combination of fundamental techniques;
- Support vector machine, artificial intelligence, phasor measurement units, principal component analysis (PCA) etc. are covered under modern fault classification technique.

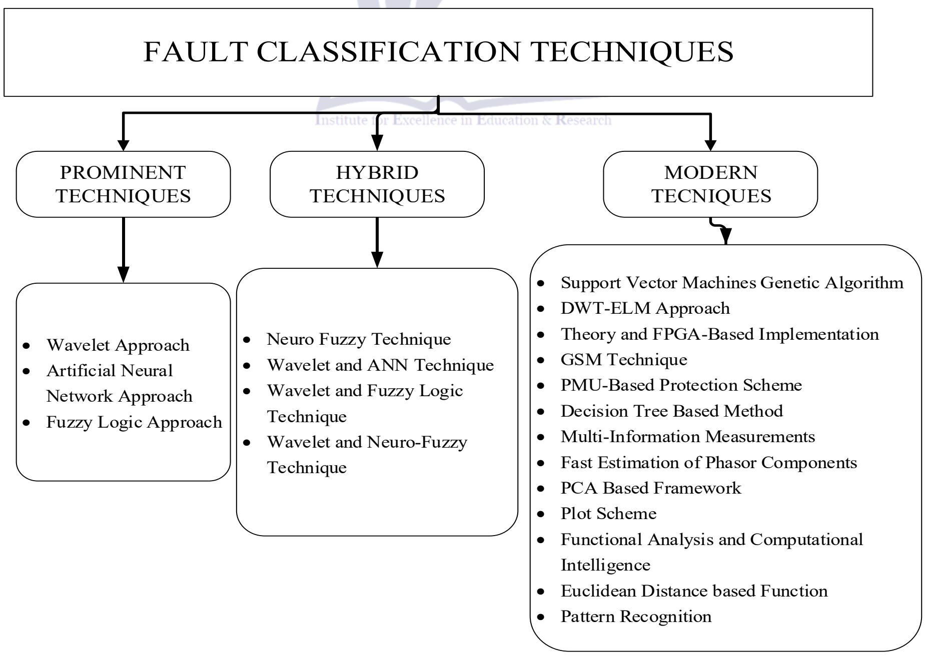


Figure 5: Fault Classification Techniques

A brief review of different AI based fault classification approaches are presented in subsequent section:

- **Artificial Neural Network (ANN)**

ANN has been mostly used for fault analysis in electrical power transmission lines [43]. ANN has been used by the researchers widely for fault detection and classification , it is equally reliable in real time and offline applications because of its adaptive nature and generalization property [13, 27, 32]. ANN requires training for fault signals which are used as an input to get output to detect a fault. ANN has similarity with biological neural system based on-linear statistical models and learning algorithms [12, 44, 45]. ANN has been developed and evolved over a period of time and is extensively used for fault detection, classification and localization in transmission networks[46, 47]. ANN consists of highly distributed interconnections of nonlinear processing elements and can be considered as an adaptable system that can learn relationships through repeated presentation of data, and is capable of generalizing to new, previously unseen data[48-51].

- **Back-Propagation Neural Network (BPNN)**

BPNN is efficiently used for pattern recognition and used for fault identification in power transmission network, with the feedback properties hence the error is controlled [48]. The drawback of BPNN is right selection of number of hidden layers and number of neurons in each layer, if the number of neurons and number of layers is high, it results into enlarged and slower training process [46]. Authors of [47] proposed S transform combined with BPNN as classifier used for fault detection and classification in overhead transmission lines. It is evident that fault classification accuracy is reduced under noisy conditions.

- **Probabilistic Neural Network (PNN)**

PNN is major type of ANN , possessing inbuilt characteristics of pattern recognition consisting of input layer, pattern/hidden layer, summation layer and output layer. It is found that classification ability of PNN is 10% higher than FNN [49]. Major advantage of PNN is that initial weights for initialization is not required[52]. To assure proper functioning of protective devices i.e. relays and circuit breakers, PNN always converges in Bayesian classifier, latter has ability to avoid error or loss of data [53]. PNN learns fast, but the selection of number of layers and number of neurons become uncertain as the network size increases so the training time and memory requirement also increased[54]. Figure 6 shows the layered structure of PNN.

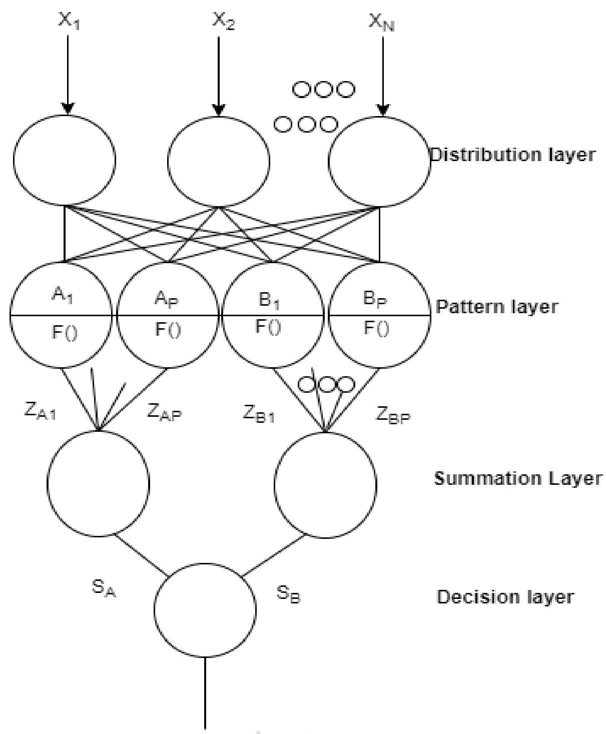


Figure 6 Probabilistic Neural Network (PNN)

- **Feed Forward Neural Network (FFNN)**

FFNN is simplest configuration of all ANN models, has input, hidden and an output layer characterized with single or multi-layer perception and back-propagation learning algorithm. Applications of back propagation (BP) with FNN have been found to select faulty line in power transmission system [55]. The error produced by this method is minimized by adjusting weight and biases of the network [56]. Figure 7 shows the structure of FFNN.

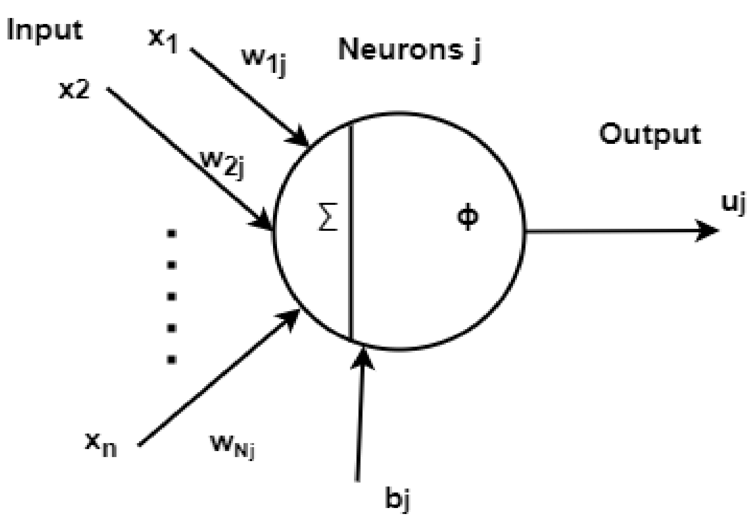


Figure 7 Feed Forward neural network (FFNN)

- **Multilayer Perception (MLP) Network:**

Multilayer Perception is one of the variant of feed-forward ANN, having input layer, hidden layer, and output layer [57]. The weights and biases are initialized with pseudo-random values and are changed through supervised learning methods [58]. The parameters are tuned through gradient descent based back propagation methods. The data is fed or received by the input layer and further passed onto the hidden layer. After processing the data in hidden layer, the targeted information is passed to the output layer with the help of activation function [59]. The number of neurons in each layer causes convergence and divergence issues, therefore impact of computation time depends upon the number of neurons matters in MLP [60].

- **Radial Basis Function Neural Network (RBFNN):**

Radial basis function neural network (RBFNN) composed of 3 layers e.g. input, hidden and output layers similar as having to the ANN[61]. The sequence of data transmission is that processed information of the input layer is forwarded as input to the middle layer i.e. hidden layer. In hidden layer, mean value of hidden layer is adjusted through hidden nodes based on nonlinear radial basis function[62]. RBFNN has been found extensively used algorithm in designing fault models integrated with wavelet features [63]. Figure 8 portrays the layers structure of RBFNN.

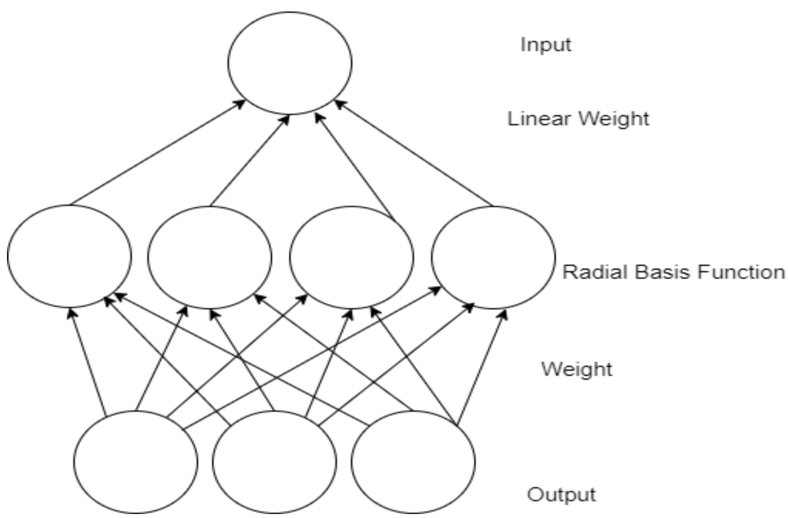


Figure 8. Radial Basis Function Neural Network (RBFNN)

- **Chebyshev Neural Network (ChNN)**

Chebyshev Neural Network belongs to a family of neural networks, which has been used by the researchers for fault analysis [64]. Study of fault classification on Thyristor Controlled Series Compensated transmission line (TCSC) has been conducted with ChNN as fault classifier [19]. Results revealed that ChNN has accuracy level 99.39%, which qualify the use of ChNN in fault analysis while equaled to other similar techniques e.g. MLP Neural Network and Support Vector Machine [67]. Mapping of low dimension data into high dimension space, polynomial based ChNN, functional expansion is also used [65]. Functional expansion block for enhancement of the input patterns by a set of linearly independent functions is used as replacement of middle layer i.e. hidden layer. The numbers of parameters of Chebyshev neural network (ChNN) uses less number of parameters as compared to other conventional multi-layer neural network used for fault classification [66]. Figure 9 shows the data processing flow in ChNN.

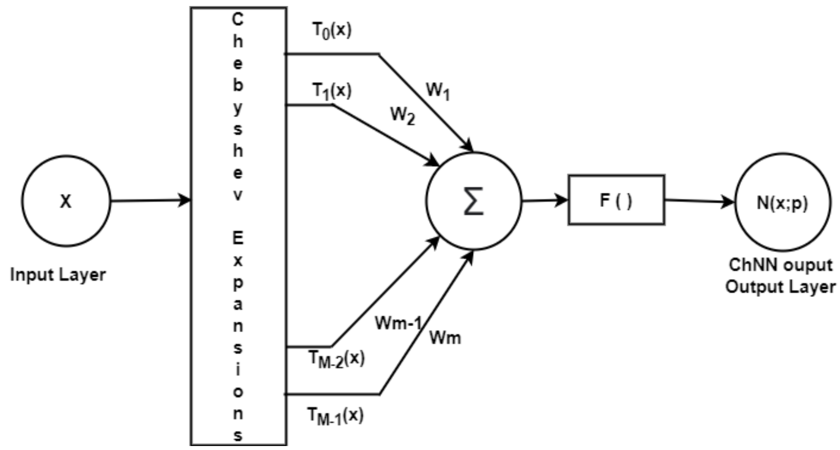


Figure 9 Chebyshev Neural Network (ChNN)

- **Extreme Learning Machine (ELM)**

The concept of extreme learning machine was first proposed by Huang, ELM, is actually a variant of Feed-Forward Neural Network, contains only a single hidden layer [67]. ELM uses analytical approach towards network parameters as against the weights based on the gradient descent training procedure used in MLP [68]. Extreme learning machine does not require tuning of its hidden layer , it is faster and exhibits better performance for fault location and classification in the power system network as compared to conventional function ELM [69, 70]. Figure 10 shows different layers used in ELM for fault classification.

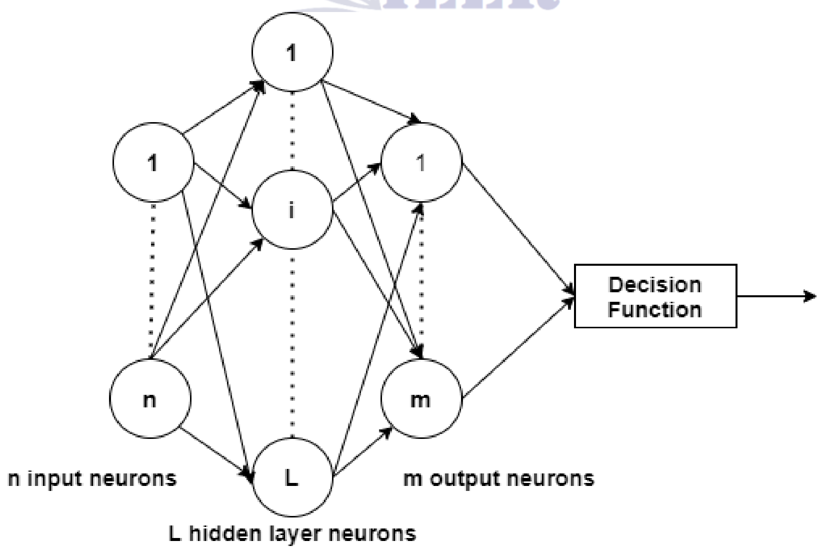
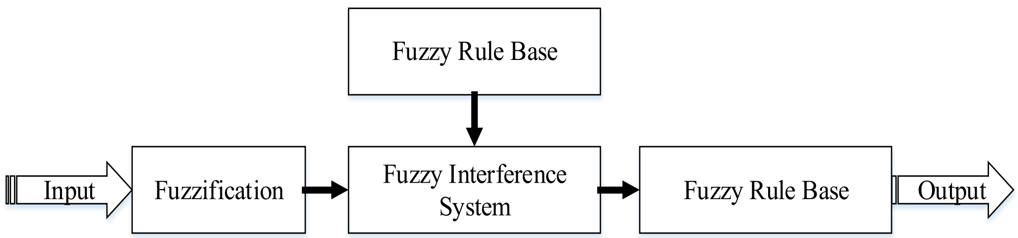


Figure 10 Extreme learning machine (ELM)

- **Fuzy Logic Based Methods**

Fuzzy logics has been widely used for detection, location and classification of faults in electrical power transmission network and is applied by performing an interference operation based on the principle of 'if–then' rules [71].This technique is simpler to control having low computational burden but the drawback of this technique is accuracy in fault detection due to the fault resistance and the fault inception angle [72]. Basic Fuzzy Inference System (FIS) is distributed into three stages First stage is fuzzification followed by fuzzy inference system with fuzzy rule base and defuzzification at the end. Figure 11 shows fuzzy logic system for fault classification. The fuzzification stage calculates membership levels of inputs for different membership functions, these membership functions are then fed to the inference stage where if-then rules are applied [73]. The last stage i.e. defuzzification stage on the basis of information injected by the inference stage provides final decision i.e. the classification decision regarding fault signal as an input and type of fault [74]. The hybrid approach i.e. neuro fuzzy approach which combines ANN and fuzzy logic has been used in the research for fault classification [75, 76].



igure 11 Fuzzy logic system for fault classification

- **Adoptive Neuro Fuzzy Interference System (ANFIS)**

Adaptive Neuro-Fuzzy Inference system has high processing speed, which makes this technique more feasible for real time faults identification and classification in electrical power transmission lines [77]. Every node performs a particular function respect to the applied data set, so named as adaptive network means multilayer network. ANFIS is analogous to neural network and functions as a fuzzy inference system [78]. Accuracy of ANFIS is superior, however due to its if-yes (fuzzy) logic, it takes more time in training the data [71]. Wavelet multi resolution analysis (MRA) is used for feature extraction and ANFIS for fault location in transmission line. When compared to fuzzy inference system (FIS), ANFIS algorithm has proven consistent, reliable and faster (takes less time) than FIS and ANN when fault analysis is conducted during simulation of various faults[79]. It has also been found in the literature that efficiency of this algorithm is affected during processing of the data , further the memory requirement and computation time in AFNIS is high [80]. Figure 12 shows the structure of AFNIS.

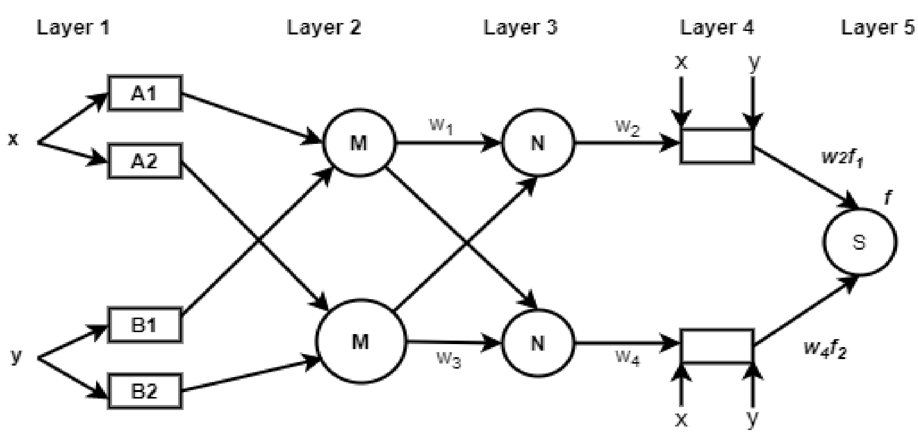


Figure 12 Structure of AFNIS

- **Decision Tree (DT)**

Decision Tree for data mining practice has been used for high dimensional pattern classification, it is tree like graph, capable of making decisions [81]. DT includes three types of nodes as root node, internal node and leaf nodes[82]. DT algorithm used for the recognition of inter grid fault type for exact time measurement of fault inception and odd harmonics computation in the measured signal. DT algorithm is used in FACTs controlled transmission lines for the classification of all shunts faults [83]. In decision tree technique, root node and every internal node under goes tests and thereby decision-making flow goes along the path [84]. Figure 13 shows various nodes involved in DT. Using one-cycle post fault voltage and current signals and zerosequence currents a DT-based fault classification and fault zone identification technique is proposed in [69] for the TCSC compensated transmission line. In that paper, the performance of the DT classifier is compared with SVM classifier. It is demonstrated that the DT-based scheme is superior over SVMbased technique with respect to classification accuracy, computational burden, response time and during noisy operating condition[85]

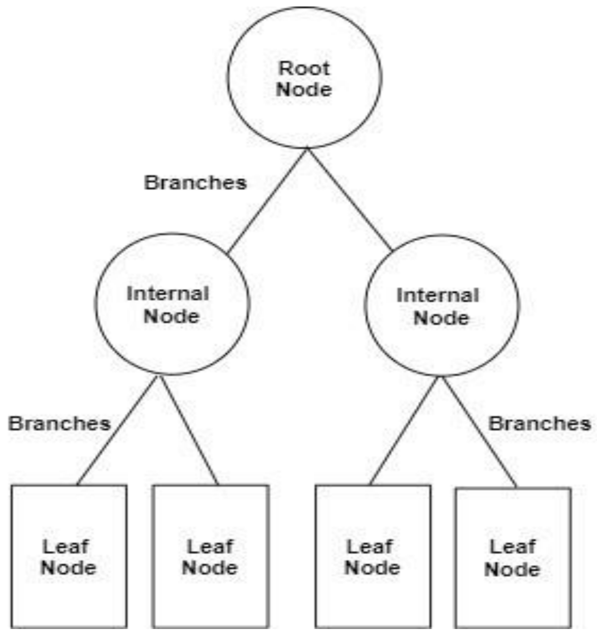


Figure 13 Decision Tree

- **Support Vector Machine (SVM)**

Support vector machine (SVMs) is a machine learning technique, which was developed in 1995 by Cortes & Vapnik. Studies have demonstrated that the SVM based fault diagnosis method is highly accurate and very encouraging for fault location in transmission lines. SVM has characteristics and ability to classify the hidden data based on the model parameters learned during a training phase [29, 86]. Non-linear mapping is basic idea in SVMs to transform given patterns in to a high dimensional features space [87]. SVM has been the area of interest now a days for fault studies in electrical power transmission lines and proved very robust and reliable towards parametric uncertainty[88]. SVM has been used for solving both classification as well as regression problems in the research. These classifiers learn a margin between multiple classes of data in such a way that a maximum separation is achieved between each class and its associated margin, also termed as 'Maximum Margin Classifier. The margin separates the two classes is lying at a maximum distance from two classes[89]. SVM has been used in many studies as non-parametric models of supervised learning and are increasingly being used in transmission line faults diagnosis [90]. In literature SVM has been used for classification of various transmission line faults with greater accuracy and their localization with little error and uncertainty [91]. Figure 14 shows the layers involved in SVM.

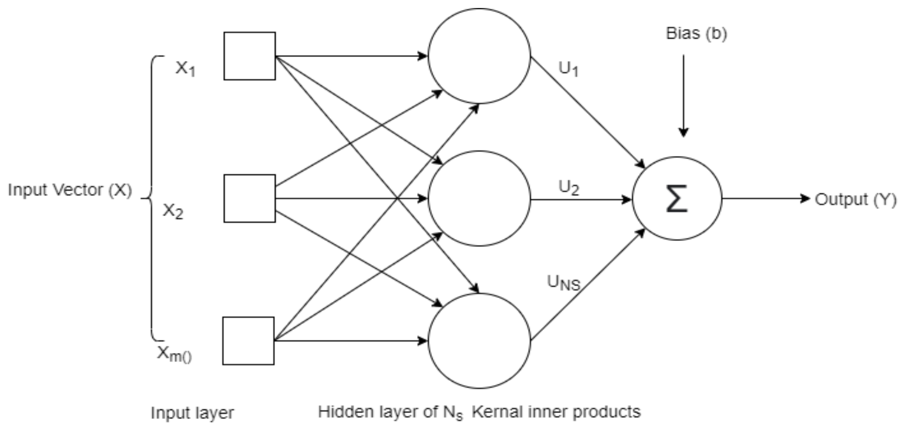


Figure 14 Support Vector Machine (SVM)

In [27], fault classification and section identification task is performed for TCSC compensated transmissionline using SVM, where half-cycle post fault current signals and firing angle of the thyristor are used as inputs to the SVM. The method employs polynomial kernel and Gaussian kernel for training the SVMs. The classification accuracy is above 95% [88].

- **Common Vector Approach (CVA)**

Common Vector Approach (CVA) gives better results during classification of short circuit faults. The CVA has been chosen by the researchers for pattern recognition and fault diagnosis in electrical machines and transmission lines. It is found more efficient than ANN and SVM, when tested its accuracy at various fault parameters i.e. noise levels, fault distances and fault inception angles[92].

- **Bayesian Network**

It is probabilistic graphical model deals with numerous uncertainty problems, when some error or loss of information occurs during data transmission due to non-operation and mal functioning of circuit breakers or relays[93]. Bayesian based model has been increasingly used for fault analysis in overhead electrical power network due to following motives [94, 95].

- **K-Nearest Neighbors (K-NN)**

K-NN is one of the simplest machine learning algorithm based on supervised learning technique. K-NN algorithm stores all the available data and classifies it into a new data , based on the similarity [95]. New data is further classified into a well suited class by using K- NN algorithm [96]. It is a non-parametric algorithm, which means it does not make any assumption on underlying data. K-NN-based algorithm uses only single-end measurements for estimation of the location of all types of faults in parallel lines [97]. Authors [98] proposed scheme that locates the fault with ± 1% error. The accuracy and performance of the algorithm does not depend upon variation in fault parameters, also the number of training patterns does not affect its performance unlike ANN [99]. This method require measurement of voltage and current taken from one end of transmission lines, this helps to precisely locate the fault[100].

- **Hidden Markov Model (HMMs)**

Hidden Markov Model (HMM) is an efficient standard that has ability to recognize and classify the abnormal event directly in a probabilistic way based on the features of faulty waveform [101]. The researchers have used this algorithm as a potential choice for fault classification problems with small, non-linear, and high dimensional sample numbers in transmission lines due to its differentiated ability [99]. Hidden Markov Model algorithm substantially reduces the computational cost by more than 90% in terms of processing time as associated to the conservative classifiers found in the literature [102].

- **Genetic Algorithm (GA)**

Application of genetic algorithm for searching similarity between the recorded post-fault voltage and current transients and stored signals related to the known (previously recorded or simulated) faults has been proved in the literature review [92, 93, 103, 104]. From the research it has been found that discrete wavelet transform and genetic algorithm have been effectively used for fault detection and classification in overhead power transmission lines [20]. GA is valid to handle data which is large, unclear, redundant and noisy, beside able to sort out data which cannot be possible by any linear programming method [53, 105].GA has the property to be trained data off line, which can further be utilized for on line applications. Fault classification is not effected by fault impedance, fault inception angle and distance from the relaying points [78] [106]. Genetic algorithm is very fast, reliable and accurate, further the weights can be modified easily, even during the training process[70].

- **GSM Based Technique**

Global System for Mobile Communications (GSM) is technique for detection and classification of faults in transmission lines . In case of occurrence of fault, a SMS is sent on the mobile to a responsible technical crew via GSM network, fault gets displayed on the display section. Interruption of fault takes place through protective devices e.g. fuses, relays, circuit breakers etc. to clear the fault [99, 107]. GSM based fault detection system avoids human intervention and save human lives, convey message to the concerned responsible personal regarding faults followed by isolation of faulty section of transmission line [108].

- **Wide Area Fault Location Technique:**

This methods is used for accurate fault location of in power transmission lines on the basis of data collected from the monitoring devices fixed at various locations of the network [109].Wide area fault location method is employed for locating transmission line faults through PMUs, which require synchronized voltage and current signals for fault localization[110]. It uses various synchronized voltage measurements to a non-linear estimation problem, worked out by developing an impedance matrix from pre-fault positive and negative sequence network topology using linear least squares methods. Fault resistance does not impact fault accuracy in detection of fault in PMU based fault detection methods [111, 112]. Figure 15 shows fault detection from signal using wide area measurement source.

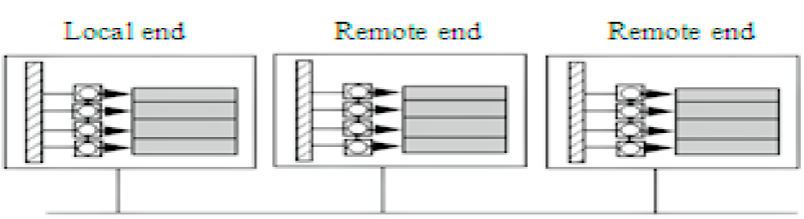


Figure 15 Wide area measurement, source : Adopted from[78].

Utilizing synchronized measurements from phasor measurement units (PMUs) installed at strategic points in the grid enables wide-area protection schemes. These schemes analyze data from across the network, offering enhanced capabilities for detecting and locating cross-country and evolving faults that might evade traditional local protection methods [Wide-Area Backup Protection Scheme for Transmission Lines Considering Cross-Country and Evolving Faults [113].

- **Convolution Neural Network (CNN)**

A deep learning based Convolution Neural Network (CNN) has been used extensively for fault classification in modern days, CNN performs relatively complex tasks with images, sounds, texts and videos requiring huge number data set for training [114]. It exhibit better classification performance due to its deep architecture and characteristics of learning high-level features [115-117]. CNNs leverage their layered structure to progressively unveil hidden patterns and extract highly distinctive features through deeper representation to achieve high efficiency. Convolution Neural Network (CNN) has ability to exhibit better classification performance due to its deep architecture and characteristics of learning high-level features [118]. CNN is composed of several layers which uncover the highly discriminative features while deepening the network [117]. Parameters required for training are also less in CNN [119]. CNNs found well in recognizing patterns and objects in images with some limitations while dealing with sequential data such as limited receptive field, accuracy and generalization. Time series forecasting witnessed a shift towards recurrent neural networks (RNNs) , RNN emerged as the preferred Deep Learning architecture for this task. Since it is notoriously difficult to train basic RNN designs, LSTMs, with their intricate design, emerge as frequent replacements for less sophisticated algorithms [120]. Furthermore, both LSTM and RNN are types of recurrent layers that can be used in conjunction with CNNs to process sequential data within the network architecture [121, 122]. The sequential nature of RNNs and LSTMs makes it difficult to parallelize computations across time steps [29, 123]. Recognizing the limitations of recurrent neural networks (RNNs) in handling long-range dependencies and vanishing gradients, temporal convolutional networks (TCNs) have evolved as a compelling alternative for processing time series data.

For the above discussion , it has been concluded that fault classificatiion algorithm and technique has certain strengths and weaknesses which are Table 2, which is summarized based on the work carried out by the previous researchers in their studies as mentioned in Table 4, Table 5 and Table 6.

Table 2: Weaknesses and Strengths of fault fault classification techniques

Technique	Strength	Weakness
ANN	ANN exhibits accuracy in diagnosing exact fault type. Easily implemented through adjustment of few parameters. Its applications are numerous in real life. ANN learns and no need for reprogramming the algorithm.	For high dimension data, training process is tedious and complex. For non-linear separable pattern classification problem, gradient-based. Back-propagation technique is used. ANN offers slow convergence in the BP, as it depends upon the choice of initial value of weight limitations connected to the network.
PNN	It does not require learning process. Initial weights of the network are not required. PNN is converged with Bayesian classifier to enhance learning time. No connection between learning process and the recalling process.	It requires high processing time for large networks. Difficulty in determining requirement of layers and neurons. Enough memory space requirement to save PNN model.

Fuzzy method	Uncertainty problems are solved using 'if-then' relation.	Large training data requires mandatory experts, which help to determine membership function and fuzzy rules. Robustness is not reported.
ANFIS	Combined or hybrid learning rules are required for tuning of parameters. Convergence in AFNIS faster. The space size required for searching search is also low. Adaptability of ANFIS is proven.	ANFIS is highly complex in computation.
SVM	SVM is a highly accurate approach, SVM works quite well even for non-linearly separable data in base feature space. The probability of misclassification is very low.	It requires for more space and quickness for the testing and training. Complexity is high in classification. It requires large memory.
Decision Tree	It is easy to be interpreted and understood. Compatible with other available decision methods, Rules can be easily set.	Calculation is tedious with increased uncertainty level or a number of outcomes are involved. Over fitting is an issue. Information gain is biased against features which have more levels.
ELM	Contains only one layer i.e. optimize hidden layer. Hidden layer does not require tuning. Adjustment of Weight and bias values is not needed.	Local minima issue Easy over fitting Difficult to find the optimal solution.
Wide-area network	This technique is similarly adopted for monitoring and control operation purposes.	Deployment of PMU in power network is tedious job.
GSM	It is cost effective, rigid, robust and high-speed communication solution covers longer geographical area and distance. Real time monitoring system is actualized	Bandwidth limitation &security
k-NN	Quick calculation time, simple algorithm to interpret, useful for regression and classification, high accuracy.	In case of large data accuracy issue of accuracy matters, requires high memory therefore computationally expensive.
Hidden Markov Model (HMMs)	It is flexible in nature, Markov model follows the concept of memory-less property, i.e., the transition from one state to other state depends only on the present state.	Expensive, both in terms of memory and compute time. As compared to Markov models, HMM requires extensive training on a set of seed sequences and also need large seed.
Deep Learning (DL)	DL minimizes need for feature engineering, as it is most time-consuming against machine learning practice. It possesses adaptive nature characteristics to new problems and can	DL is computationally expensive,

	be implemented with ease with convolutional neural networks, recurrent neural networks, long short-term memory, etc.	
Temporal Convolution Network (TCN)	Efficiency and parallelism, Long term dependencies	Interpretability

Table 3: literature summary showing transmission systems considered for the research along with associated experimental parameters

Reference #	**Type of Transmission line** (OH/UG//Hybrid)	**Transmission line parameters**
[5]	Overhead	400 kV, 50 Hz, distance not mentioned.
[124]	Combined TL	132 kV, 50 Hz, distance not mentioned.
[125]	Overhead	220 kV, 50 Hz, 200 Km
[126]	overhead	735 kV, 60 Hz, 600 Km.
[14]	overhead	11kV, U/G distribution system.
[31]	Overhead	132 kV, 50 Hz, 200 Km.
[68]	Overhead	380 kV, ,50 Hz,600 Km,
[15]	Combined TL.	500 kV/50Hz, 207 km
[127]	Overhead	154 kV, 50 Hz, 28 KM, Simav & Demcri Turkey.
[128]	Overhead	500 kV, 50 Hz, 200 miles.
[129]	Overhead	400 kV, 50Hz, 300 Km.
[13]	Overhead	400 kV, 50 Hz, 100 Km.
[29]	Combined	230 kV, 60 Hz, 160 Km (OH), 32 Km (UG).
[33]	Hybrid TL	400kV, 50 Hz, combined transmission line, 100 Km (OH), 40 Km (UG).
[130]	Overhead	400 kV, 50 Hz, 128 Km
[131]	Overhead	220 kV, 50 Hz.
[10]	Overhead	400 kV, 300 Km, 50 Hz
[23]	Overhead	300 Km, 50 Hz, distance not mentioned.
[11]	overhead	400 Kv, 300 Km, 50 Hz

Table 4: softwares used in previous research for fault detection, classification and localization in transmission lines.

#	Reference(s)	Software used.
1	[5, 14, 130]	PSCAD/EMTDC.
2	[11, 23, 124-127, 129, 132]	MATLAB/SIMULINK
3	[10, 31, 130]	EMTDC/PSCAD
4	[68]	ATP/EMTP/MATLAB.
5	[15]	PSCAD/EMTDC//MATLAB
6	[128]	EMTP
7	[29]	EMTP/ATP
8	[33]	PSCAD/EMTDC
9	[131]	PSCAD

Table 5: Limitation of software used for fault analysis in transmission lines.

S #	Software	Limitations
1	PSCAD	PSCAD is Windows-only. Interface can be challenging to navigate, and modeling very large systems can strain computational resources and lead to performance issues.
2	EMTDC	Building accurate models for complex equipment can be challenging, Simulating very large systems with numerous buses or components can strain computational resources and become time-consuming.
3	MATLAB	Creating detailed power system models with accurate component representations in Simulink can be time-intensive and require significant expertise. Simulating complex faults in extensive power systems can strain computational resources,
4	ATP	ATP primarily detects significant faults like complete power loss or voltage dips beyond a specific threshold. ATP's built-in diagnostic tools might not provide in-depth analysis of the fault event, hindering root cause identification and corrective action planning.
5	EMTP	EMTP's detailed representation of transient phenomena leads to complex calculations, often demanding significant computational resources and time.

Table 6: Techniques used for fault classification in transmission lines corresponding to the literature review with results.

#	Reference #	Classification methods	Accuracy/Remarks
1	[5]	Travelling Wave Fault Locator (TWFL)	High
2	[124]	Travelling Wave Based Algorithm.	Error rate is less than 3%.
3	[125, 126]	ANN	Satisfactory
4	[14]	PNN	High
5	[31]	Transient Recovery Voltage (TVR)	Reliable
6	[68]	ELM	High (99%)
7	[15]	Decision-Tree Based Method	80-80%.
8	[127]	Fuzzy Logic	Convenient and rapid.
9	[128]	Adaptive Neuro-Fuzzy Inference System	>90%
10	[129]	ANN (FFNN & BPNN)	Satisfactory
11	[13]	SVM & MLP	99.62%.
12	[29, 63, 130]	SVM	90-100%.

13	[131]	Principal Component Analysis (PCA)	94.54%
14	[10]	Multi Resolution Analysis (MRA)	High
15	[23]	Genetic Algorithm (GA).	Errors of fault classification is less than 7%.
16	[11]	Common vector approach	99.965%

Table 7: Signal considered as an input for feature extraction corresponding to references.

S #	Reference(s)/Authors	Signal used for feature extraction (i.e. voltage/current/both)
1	[14, 124]	Voltage signal
2	[5, 15, 31, 33, 125, 127-129, 131]	Current signal
3	[10, 11, 13, 29, 68, 126, 129, 130]	Both (voltage & current signals)

5. Key Findings and Way Forward

- **Future Research Directions**

The review presents a comprehensive study of different fault detection and classification, techniqueswhich concludes:

1. The detailed survey confirms large scope for future research in the area of fault detection and classification and in overhead transmission lines due to.
2. Integration of Renewable Energy resources (RSE) with the existing grid and thereby the Fault detection and classification in complex power system .
3. Investigation the effect of noise, fault resistance, ground resistance, location of fault and fault inception angle simultaneously on transient signal for fault detection.
4. Study of deep learning for classification of faults in transmission line.

- **Key Findings and conclusion**

This review intends to serve as a valuable resource offering technical guidance for selecting appropriate fault detection tools and classification algorithms tailored to the evolving complexities of modern grids, particularly those incorporating renewable energy sources. In this paper impact of both FACTS devices on FACTS-equipped transmission lines , cross-country faults and evolving faults into fault detection has been studied. Besides this through overview of various signal processing and feature extraction tools i.e. FT, STFT, DWT, WSE and FDOST while analyzing transients and signal disturbances integrated with noise has neen discussed . This paper details various AI, ML and DL based fault classification techniques which has been presented in terms of their accuracy, computational time and memory requirement . Since researchers are focussing on the use of deep learning algorithm for fault classification in transmission lines due to their efficient image processing, robustness to noise and high accuracy rates compared to other fault classification algorithms, so CNN, RNN and LSTM have also been reviewed for fault classification in transmission lines in this study . Temporal Convolutional Network (TCN) has also been considerd for fault classification in transmission line using time series data considering issues such as long term depencies , vanishing gradient, computation efficiency , memory requirement and receptive field. This work has been done to create an idea to choose the suitable method for fault detection and classification occurring in the transmission lines.

6. Conclusion

Overhead transmission line fault detection and classification algorithms have developed to the point where they no longer rely on more classical techniques of signal processing, such as discrete wavelet transforms, and instead are based on more modern AI-assisted algorithms, such as machine learning ensembles or deep learning models. RF-LSTM voting classifiers, which are higher-order ensemble techniques, can reach accuracies over 99% on a variety of fault types, including line to ground and multi-phase fault, compared to single algorithms, such as KNN or CNNs, because they combine the power of feature extraction and fault pattern recognition. Limitations of the previous studies, including the noise sensitivity, fault initiation angles, and resistance variations, are overcome in these innovations by using methods such as the PCA preprocessing, as well as the hyperparameter optimization by using PSO. In continuous studies, hybrid models with wavelet transforms and LSTMs or transformers are considered to operate in real-time to improve grid stability during renewable energy integration. There are still difficulties with processing noisy field data and multi-label problems, and scalable AI systems offer quicker and more dependable protection relays.

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