Artificial Intelligence Based Faults Identification, Classification, and Localization Techniques in Transmission Lines-A Review

Shazia Kanwal, *Student Member, IEEE,* and Somchat Jiriwibhakorn, *Member, IEEE*

***Abstract*—An overview of the many methods used for fault detection, classification and location in the power system, particularly in transmission lines, is provided in this review, it also includes an experimental result of adaptive neuro-fuzzy inference system -based fault detection, fault classification and fault location. Being in operation outdoor environment, transmission lines are more vulnerable to various faults which may lead to system collapse in severe cases. Therefore, to ensure the reliable and safe operation of power system it is imperative to critically monitor the faults in transmission lines. In this regard, researchers around the globe have developed several techniques and constantly putting efforts to further improve the protection efficacy. The brief yet thorough analysis and comparison of the artificial intelligence-based techniques, hybrid methodologies and most recent approaches in the context of power system faults have been discussed and presented. In addition, the research work and the experimental results of an adaptive neuro-fuzzy inference system-based techniques have also been discussed for IEEE-9 bus system. The mean square error for testing data of ANFIS-based fault detection, classification, is zero and for fault location Mean square error is 5.32km. This piece of work could be helpful in the development of a comprehensive understanding of various artificial intelligence-based techniques within the realm of fault detection, classification and localization in transmission lines.**

***Index Terms*—Artificial Intelligence-based techniques, Adaptive neuro fuzzy inference system, Fault identification and Fault location, Hybrid methods, Transmission line.**

I. Introduction

Power system is expanding in faster pace in size to meet the rising electricity requirement, hence resulting in more system complexities from various aspects [2]. The electric power system comprises of three main entities: the generating system, which produces electric power; the transmission system, which transports electric power from the source of supply to regional substations usually over high voltage and the distribution system, which distributes electric power to local consumers.

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Shazia Kanwal is a Ph.D. student in the department of Electrical Engineering, School of Engineering, King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand (e-mail: 65016006@kmitl.ac.th).
Somchat Jiriwibhakorn is associate professor at the department of electrical engineering, King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand(e-mail: somchat.ji@kmitl.ac.th).

Transmission line faults are the primary threats to the delivery of electrical power in the system [3]. Transmission line faults must be identified and fixed in order to keep the power system stable and reliable and prevent an interruption in service to consumers. The transmission line is more prone to faults due to its exposure to the environment [3]. Transmission systems frequently experience unexpected failures due to a variety of unpredictable causes. The most frequent causes of faults in overhead lines are contaminated insulators, ice and snow loading, lighting, partial discharges (corona), punctured or broken insulators, falling trees, and wind. Transmission line faults can be categorized into two groups: series faults and shunt faults. Shunt faults are further divided into symmetrical and asymmetrical faults. Symmetrical faults include triple line faults (ABC) and triple line to ground faults (ABC-G), whereas asymmetrical faults include a single line to ground faults (A-G, B-G, C-G), line to line faults (AB, BC,CA) and double line to ground faults (AB-G, BC-G, CA-G) [4] as shown in Fig. 1.

The protection method must quickly identify the issue, categorize its nature, and predict its position in order to prevent serious electrical system damage. For the purpose of identifying the faulty phase and preventing a power outage, the classification of the fault in transmission lines is crucial. This promotes prompt control of the unwanted power drain and helps to assure the protection of linked equipment. For the quickest possible restoration of the electrical system's stability and to resume regular power flow, pinpointing the location of the fault is also important [5].

For a very long time, scientists have effectively used fault identification, categorization, and localization methods. Various topologies and techniques have been developed and implemented so far to achieve optimal protection against line faults. Therefore, power utility companies have a difficult task in choosing a specific fault categorization approach. Various fault analysis topics, such as the identification, categorization, and predicting location of faults in transmission lines in power systems transmission lines have advanced rapidly during the past 20 years [6].

This paper provides review of various techniques, presented by a researcher for precise fault identification, classification, and fault localization in power systems, notably in transmission lines.

In recent years new deep learning method, Long Short-Term Memory (LSTM) is gaining more attention in a variety of electrical engineering applications. This paper also presents a brief overview of the recently popular LSTM approach. Moreover, advantages and limitations of all techniques have been discussed and experimental results of Adaptive Neuro-Fuzzy Inference System (ANFIS)-based fault detection and classification in IEEE-9 bus system have displayed. In the following section, many efficient approaches are further described.

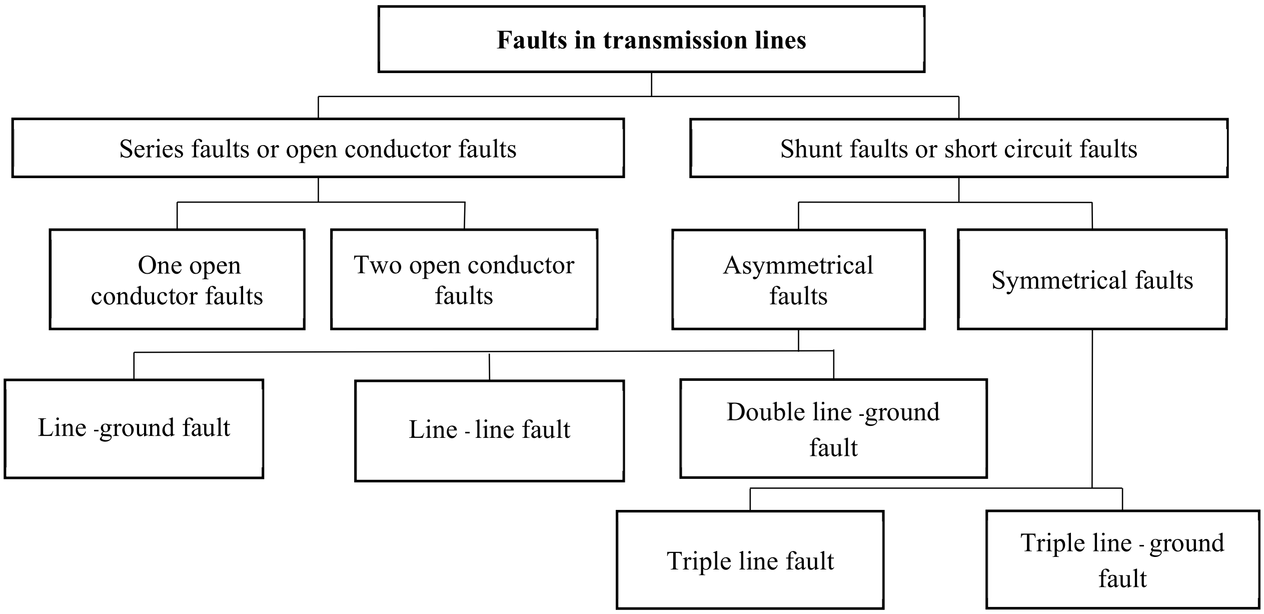

Fig. 1. Types of faults in transmission lines.

II. Different Techniques Of Fault Analysis

In recent academic efforts, authors in [5] has presented a well-organized assessment of the various fault analysis approaches. Additionally, they have included a thorough comparative study of the various fault characteristics as well as numerical representations of the findings from other research articles. Similarly, authors in [1],[7] provides clear demonstrations of several common methodologies utilized in the area of fault analysis. All these reviews have outlined the advantages and disadvantages of the various fault analysis methods. Along with a comprehensive review of fault analysis techniques, [1] presented three main divisions of fault techniques as demonstrated in Fig.2:

Prominent techniques include fundamental techniques of fault analysis, such as artificial neural network, wavelet transform-based fault analysis, and the fuzzy logic technique, hybrid techniques include all those techniques which are a combination of basic techniques, modern techniques include Artificial Intelligent (AI) based methods, LSTM, the Phasor Measurement Unit (PMU), and Support Vector Machine (SVM). These methods are discussed in detail in the following sections with updated research.

A. *Prominent Fault Analysis Methods*

Prominent methods are well-known techniques, often used for fault classification, detection, and prediction of location in transmission lines. There are three prominent fault analysis methods which are discussed in below sections.

1) Fault Analysis Based on Wavelet Transform (WT):

Research in fault analysis is more influenced by wavelet transform. Fundamentally, WT examines the frequency of the fault transient signals and divides the waveform into a series of precise and approximate coefficients that include vital details about the fault's location and type. This is how WT obtains important characteristics from fault waveforms at various decomposition stages. Wavelet entropy is occasionally applied directly to fault analysis. Although WT has the intrinsic disadvantage of steadily growing complexity of analysis, especially for higher levels of decomposition of the fault signal, it is quite accurate and can identify fault features utilizing the decomposed frequency components of a fault waveform.

Wavelet transform is a useful method for investigating and analyzing faults [4][8-15]. In [8] for a multi-terminal transmission line system, WT has been utilized to acquire the estimated and detailed differential current and voltage coefficients and two-level decomposition is used with mother wavelet. In [9] wavelet approach fault analysis for micro-grid is proposed for a transient fault current signal, to identify, differentiate, and locate faults in the transmission network. The process of Multiresolution Analysis (MRA) is utilized.

In recent times Discrete Wavelet Transform (DWT) approaches in relaying systems have increased. The majority of WT-based analytic techniques used today rely on DWT analysis. In [4] the current signals from transmitting end for each phase are subsequently decomposed up to level 5 using DWT and MRA to produce detail coefficients. The normalized values of each phase's coefficients are compared to the system's threshold values in order to identify and classify problems on transmission lines. Further, the discrete version of WT is used with the mother wavelet for the identification of fault by the author in [10] over a moving window of 32 samples. The detail coefficients and approximation coefficients have been added together. To identify transmission line faults, the approximation and detail coefficients for each fault have been shown. The detail coefficients' relative maximum values are used to distinguish between the various fault kinds. With the assistance of DWT and the multi resolution analysis, the author in [11] created a new approach utilizing currents from one end of the transmission wire to address the abnormalities in the system. Utilizing MRA, DWT is used to divide current signals into several frequency bands and determine the kind of fault based on the results.

In order to create precise fault protection algorithms, wavelet analysis, and fuzzy logic are frequently combined. In [12] for

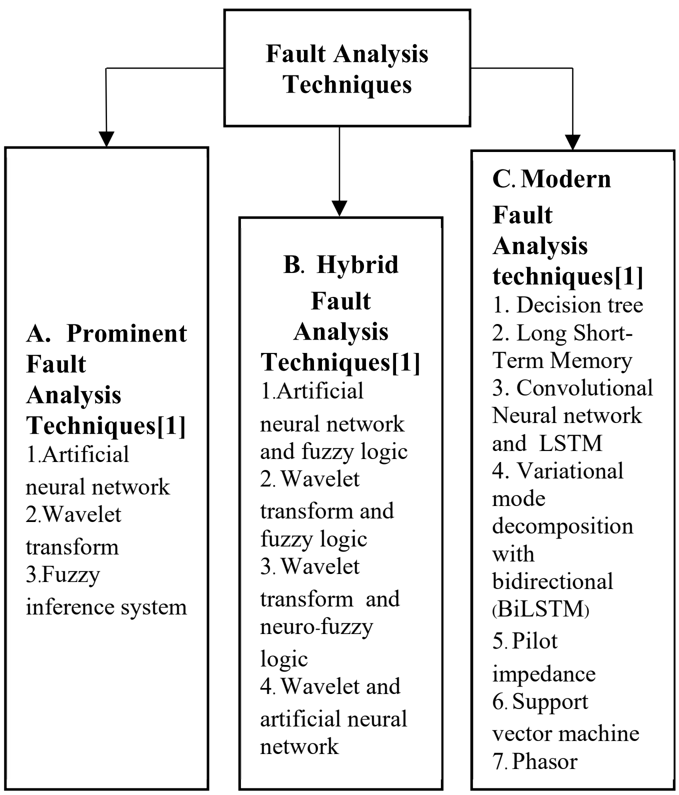

Fig. 2. Fault analysis techniques in transmission lines [1-36].

asymmetrical distribution systems with distributed generation, the use of wavelet singular entropy and fuzzy logic is employed for fault detection and classification to identify islanding and take preventive action. To locate and classify the fault, indicators are constructed based on wavelet singular entropy in positive components and three-phase currents. In [13] the IEEE-34 bus system is simulated to measure the current signal at bus 800 throughout the course of 12 cycles, with faults added at the fifth cycle. The current signals are separated into high and low frequencies up to level 3 using the discrete wavelet transform with db-4 wavelet. Different kinds of power system failures are identified and categorized using the fault index peak values. A rule-based decision tree is used to classify the faults.

2) Fault Analysis Based on Artificial Neural Network (ANN): Artificial intelligence (AI) based neural network technique is most often employed, for creating effective power system fault investigation tools. In ANN fundamental architecture, there are three layers namely, Input, output, and hidden layers. One of the advantages of ANN is its ability to learn on its own. Only a small number of parameters need to be adjusted. During the training process, ANN updates the weights; another benefit of ANN is parallel data processing, which makes it simple to implement real-time issues like fault analysis. ANN has several drawbacks as well; lengthy training time are unavoidable, particularly for analyses of multidimensional problems. One of ANN's drawbacks is that it needs big, dispersed data to update weights in the ANN structural model, and for multidimensional analysis, high training time is unavoidable [14]. Additionally, ANN has the drawback of reproducibility of the same result. As shown in Fig. 3. ANN works on following steps:

a) Data acquisition and preprocessing dataset
b) Network training
c) Testing the network

Various ANN-based types of research have been found for fault analysis. To identify and categorize the fault using a feed-forward method, the author provided an ANN-based model in [15]. The model is trained using three phase root mean square voltages and currents for each of eleven fault scenarios. It took 21000 samples to train the network. The output parameters taken for the ANN structure are in total four, which are used to define the location of fault, fault class, ground fault, and indicate the existence of fault. The calculated mean square error (MSE) is 0.082101.

In [16] a feed-forward ANN with a back-propagation technique is used to create a fault detector and classifier. The classifier and detector are trained using the values of the instantaneous current and voltage. The performance is evaluated through the mean square error (MSE) and confusion matrix of the classifier and detector, the accuracy for the detector is 100% and MSE of 8.5571e-7, classifier's accuracy is 88%, and its MSE is 0.63035.

In [17] the location of the fault is determined using an extended ANN-based efficient and reliable transmission line fault investigation, the Global Positioning System (GPS), and the Global System for Mobile Communication (GSM) is utilized. Along with the matching pre-fault values, the voltage, and current samples for each of the three phases are recorded. The ratio of the voltage and current, in each phase, before and after the occurrence of the fault, serves as the neural network's training inputs. This network's mean square error for training, testing, and validation have been calculated to be 0.0013561, which is less than the target MSE of 0.01.

3) Fault Analysis based on Fuzzy Inference System (FIS) FIS is also common in fault detection, classification, and localization. The advantage of a fuzzy inference system is the use of 'if-then' rules to address uncertainty in issues. The

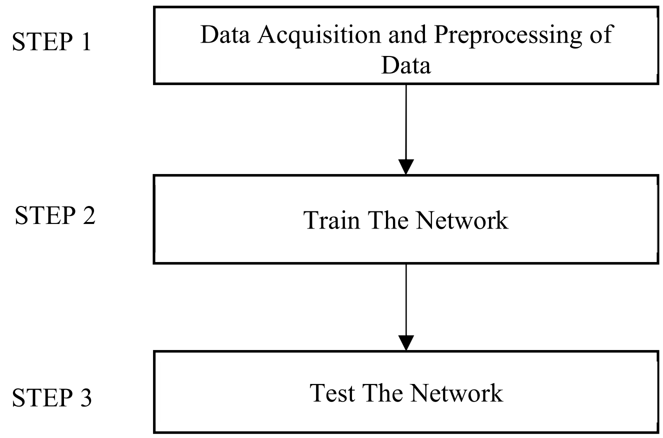

Fig. 3. ANN implementation steps.

disadvantage of the system is the design of fuzzy membership functions requires significant competency [5].

Fuzzy systems, often known as fuzzy logic, are logical frameworks for formalizing and standardizing approximative reasoning. With the ability to generate precise answers from specific or even approximative knowledge and data, it is comparable to human decision-making. Fuzzy logic uses reasoning that is comparable to human reasoning. Fuzzy logic underlies how the human brain works, and we may use this technology to simulate human behavior in machines.

Fuzzification improves the ability to represent complicated issues at low or moderate solution costs by enhancing expressive power, generality, and modeling capabilities. Fuzzy logic permits a specific degree of ambiguity during an analysis and is valuable in many applications because it reduces issue complexity.

Author in [18] fuzzy multi-sensor data fusion for the localization of faults in transmission lines. Weighted Covariance Fusion (WCF) and FIS are combined for speedy and accurate location findings. To create a model and assess the suggested approach, electromagnetic transient simulations are performed. A transmission line of 500 kV between bus 25 and 26 in an IEEE 39 power system is utilized to demonstrate the effectiveness of the approach, with a 2kHz sample frequency. The fraction of instances with the fusion result error was computed, and it is less than 1%. A fuzzy logic-based method for the classification and detection of directed phase-to-phase faults in three-phase transmission lines at bus 8 of the IEEE 9 bus bar typical grid was developed in [20]. Different failure types in both the forward and backward directions were simulated. This study demonstrated that the suggested approach was easy to apply and effective in precisely identifying and categorizing the types of defects within around one cycle.

B. Hybrid Based Fault Analysis Using ANN,FIS and WT

Three prominent fault analysis techniques, wavelet transform, ANN, and the fuzzy inference system are combined in hybrid techniques. Hybridization aims to address the weaknesses of one approach while maximizing the benefits of the other by properly combining them together. Hybrid methods are the results of combining one or more prominent fault analysis techniques.

Hybrid models for fault investigation, that combine WT, ANN, and fuzzy logic have frequently been successful in fault detection, classification, and localization. Wavelet and artificial neural network techniques combine to integrate the best aspects of both approaches as used in [21]. The authors suggested a directional protection plan employing WT and ANN techniques using single-end data, with variation in inception angles and fault resistance. The maximum and minimum error found is 0.6665% and 0.0178% respectively. In [22] adaptive WT technique is presented, which utilizes db6 wavelet, for generating coefficients, this WT method is based on threshold, therefore, this is not applicable to all other systems.

In [23] discrete wavelet transform with MRA and artificial neural network with a Taguchi method have been presented. This study suggests fault detection, classification, and prediction of fault location based on Taguchi, the input dataset to the ANN is the differences in the wavelet entropies of the three-phase voltages, three-phase currents, and wavelet entropies of the neutral current under fault conditions. For the training of ANN orthogonal dataset is produced using Taguchi's method.

In [24] fault detection and classification are accomplished using DWT-ANN approaches. To extract features, the three-phase current signal of the transmission line is decomposed using DWT up to the fifth detail level, and fault classification and fault detection are completed by using maximum and minimum coefficient values of db4 and db5, respectively. The classification accuracy is achieved as 90.60%. In order to create an adaptive neuro-fuzzy inference system or ANFIS, ANN is frequently combined with fuzzy logic inference. To provide effective security models, researchers utilized the ANFIS technique. A similar hybrid technique is used in [25] to predict the fault's location using the three-line impedances of the three phases as input to the ANFIS. Approximation coefficients are used to compute line impedances.

The maximum error of fault location is found to be 1.5%. The comparative study of ANN and ANFIS fault detection and fault location has been done in [26] percentage error in both techniques is found to be 0.25%. However, the mean error of ANFIS is less than ANN. The accuracy for the fault classification for both techniques is found to be 99.9%. Wavelet-based ANN is used for fault detection in ultra-high transmission lines [27]. High-frequency details of the local current signal at one end of the transmission line are used to classify transients, categorize transients and faults, and detect the causes of the transients on the protected and adjacent lines. DWT is used to extract high-frequency components. A feature vector is developed and used to train ANN.

1) ANFIS-based Fault Analysis in IEEE-9 Bus System

Fault detector , fault classifier and fault locator is designed using ANFIS. The fault analysis approach is based on using voltage and current waveforms at the transmission line between bus 7 and bus 8 in IEEE 9 bus system as shown in Fig.4. The post fault values of three phase voltage and current at bus number 7 is captured and used as input to the ANFIS for the fault detector , fault classifier and fault locator. In this technique, fuzzy clustering is used to generate fuzzy inference system with 100 clusters for all three models, each input variable has one "gaussmf" input membership function for each fuzzy cluster. And since we used Sugeno system therefore, the output membership function is linear MF for each output variable in each cluster.

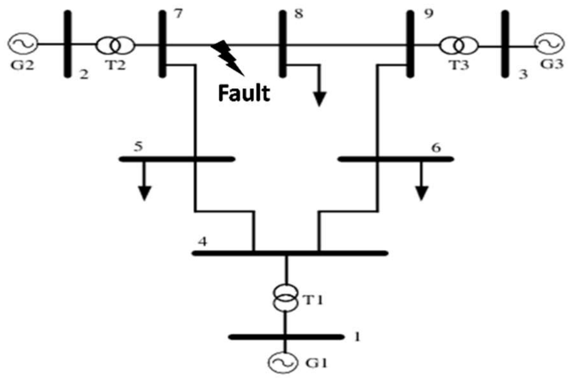

Fig. 4. IEEE-9 bus system.

Methodology followed in ANFIS based fault detection is given bellow:

a) Select the area in the power system for study, in this study the area between bus seven and bus eight has been selected as shown in Fig.4
b) Generate fault between bus 7 and bus 8, capture the values of voltage and current values from one end.
c) Apply all fault conditions, AG, BG, CG, AB, BC, CA, ABG, BCG, CAG and no fault
d) Change the fault position, and collect faulty signal's voltage and current (rms)values
e) Normalization of the data
f) Select the structure of ANFIS
g) Choose input and target data
h) Train ANFIS with the dataset
i) Test the models
j) Compute the Mean square error for ANFIS based detector , classifier and for location

Sample data set is given in Table III. The total data set used is 1840 collected using 40 different cases. 80 percent of the data is used for training and 20 percent is used for testing. The structure of ANFIS model used in for this application is given in the Fig.6. Mean square error have computed for the testing of the ANFIS based models. The results are computed using MATLAB [47] toolbox. The MSE , RMSE and R^2 for fault detection, classification and location for training and testing are displayed in table IV . The MSE for fault detection and classification is almost zero this technique is perfect for detection and classification. For location MSE is also acceptable. However, it can be improved by adding more features and by combining it with WT or other methods such as LSTM.

C. Fault Analysis Using Modern Techniques

Modern AI techniques have had an effect on almost all scientific disciplines. Businesses and industries are already being disrupted and transformed by it. The top economies and IT firms in the world are competing to enhance modern AI learning. It has already outperformed humans in a number of fields, including disease diagnosis and disaster prediction. Hutcher et al introduces the LSTM in 1997 as a powerful, recurrent neural network (RNN) architecture for time series modeling and forecasting. Experiments with artificial data have shown that LSTM leads to more successful runs and learn faster compared to other recurrent network methods. LSTM is also capable of solving complex long and time-consuming tasks, that previous methods were unable to solve. LSTM has been able to overcome major limitations and shortcomings of recurrent neural networks, such as the problem of vanishing gradient, by allowing gradients to pass unaltered. While traditional neural networks focus on learning the static relationship between inputs and outputs of the network, LSTM can retain knowledge or information of previous modes and trained for high-dimensional data that requires memory or need previous knowledge [37].

LSTM addresses the problem of vanishing gradient structure; it has the ability to remember patterns over a long period of time which is one of advantages of LSTM. Information in LSTM flows through cell states, which helps retain necessary information while forgetting the rest. LSTM is proficient at learning dependencies even if they are separated by large time steps [34]. There are four important units in LSTM that all work together to solve complex problems, memory unit, input gate, output gate and forget gate as shown in Fig.5. The signal flows through the memory cell while being in control of input, output and forget gate. These gates are controllers for making sure what is stored, written, and read. In Fig.5. h, C, and X are inputs and outputs of the LSTM cell at the step time of 't' and 't-1'. Operator X and operator + show element-wise multiplication and element-wise summation. Symbol 'σ' is a sigmoid function and tanh is hyperbolic tangent.

Equations (1)-(6) which represents the mathematical expressions used in the LSTM cell with the gates are given below [28][39].

$$f_t = \sigma\left(W_f x_t + W_f h_t - 1 + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i x_t + W_i h_t - 1 + b_i) \tag{2}$$

$$o_t = \sigma(W_o x_t + W_o h_t - 1 + b_o) \tag{3}$$

$$a_t = tanh(W_a x_t + W_a h_t - 1 + b_a) \tag{4}$$

$$c_t = f_t * c_t - 1 + i_t * \sigma(W_c x_t + W_c h_t - 1 + b_c) \tag{5}$$

$$h_t = o_t * \sigma_h(c_t) \tag{6}$$

Where f_t, i_t, o_t, are forget, input, and output gate vectors, a_t is hidden vector and W_t, W_i, W_o, W_a are the weights of respective input and output gates for the training of the data. The symbol b_f , b_i , b_o , b_a ,represents the output bias values. Recurrent neural networks using LSTMs are capable of tracking long-term dependencies. Since they rely on context and former states, they are excellent for learning from sequence incoming data and developing models. The LSTM cell block keeps track of important information from earlier states. The input, forget, and output gates, respectively, control fresh data entering the cell, what stays in the cell, and the cell values utilized in the LSTM block's computation of the output.

Various studies have been done by researchers to evaluate the performance of LSTM in transmission lines identification, classification, and localization of faults. The use of the frequency response analysis (FRA) approach to locate and categorize transmission line problems according to their impedance is covered in [31]. The FRA technique is employed to evaluate the effects of fault location and impedance on frequency-domain voltage and current data. The interpretation of the FRA results, however, is seen to be the method's weak point. Support vector machine (SVM), decision tree (DT), k-Nearest Neighbors (k-NN), convolutional neural network (CNN), long short-term memory (LSTM), and a hybrid model of convolutional LSTM (C-LSTM) are some of the machine learning and deep learning techniques used to solve this problem. These techniques can accurately categorize various transmission line fault types and locations, including asymmetric and symmetric faults. This research applies faults with different impedances to six segments of an IEEE standard transmission line system and computes their frequency response curves (FRCs) as input datasets for the recommended networks. Different statistical performance assessment criteria are used to examine the outcomes of each network. The capacity of the recommended models to classify the type and location of high impedance faults (7000 and 9000 Ohms) for early detection is finally proved.

In terms of locating and categorizing transmission line faults, the hybrid model of C-LSTM performed better than the other models, which included SVM, DT, k-NN, CNN. Using voltage and current readings from a single transmission line end, a mixed convolutional neural network with an LSTM structure is trained to estimate the fault location [29]. Convolutional function, pooling layers, and LSTM structure are employed in the proposed network to retain translation invariance and capture the temporal correlation of the input data. To effectively train the neural network and avoid over-fitting, advanced deep learning techniques including adaptive moment estimation and dropout are applied. Numerous studies that prove the accuracy and performance of the suggested technique in locating faults serve as evidence of its efficacy. In a large-scale, multi-machine power system, a data-driven method for fault detection, identification, and diagnosis in transmission lines is suggested in [28]. The method entails the creation of three deep learning models based on LSTM for the two-area four-machine power system transmission lines. These models are utilized for intelligent fault diagnosis, classification, and localization. The suggested models rely on characteristics that self-extract over time directly from the voltage and current input patterns, negating the need for additional procedures. In order to represent the behavior of the system, the given sequential learning algorithms extract the most spatiotemporal information from the sequential features, resulting in the greatest classification and prediction accuracy and resilience.

The fault type classification (FTC) and faulty region identification (FRI) models exhibit great accuracy in fault detection and fault type classification, particularly in recognizing the kind of the fault. Through a statistical analysis, the mean and standard deviation of the fault location distance prediction error have been used to examine the accuracy and reliability of the findings acquired from predictions. The

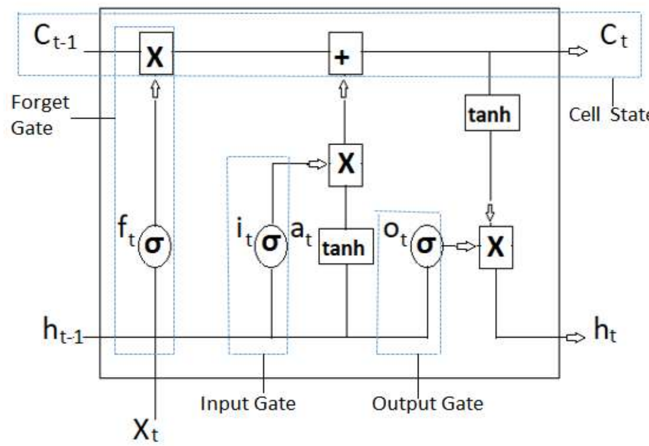

Fig. 5. LSTM cell structure [6].

outcomes show how precise, dependable, and highly efficient the suggested LSTM-based models are for finding, categorizing, and locating problems in power systems transmission lines.

Authors in [38] proposes new relaying scheme for bipolar line commutated converter high voltage direct current ((LCC HVDC) transmission lines that detect faults, identifies the pole of fault, and estimates the fault's location using features from rectifier end DC current and voltage signals. The scheme uses LSTM, a deep learning method, as a classifier and predictor for fault detection, pole identification, and location estimation. The proposed method has been tested with varying faults types location, resistance, and noisy signals and has demonstrated a 100% sensitivity and reliability, with an error in location estimation within 1%. The proposed method does not require a communication link and can work with low sampling frequency, making it more proficient compare to other methods.

In [32], a novel method for identifying insulated overhead conductor (IOC) faults in accordance with partial discharge is described. It is based on discrete wavelet transform (DWT) and long short term memory network (LSTM). First, DWT denoises the raw signal. Second, DWT decomposes the denoised signal and extracts characteristics on several layers. Finally, LSTM finds the IOC fault. When tested on the ENET open data set and compared to other classification algorithms, this strategy can increase the detection accuracy of IOC fault. Likewise, in [33], authors suggest a technique for diagnosing transmission line faults based on variational mode decomposition (VMD) along with bidirectional LSTM (BiLSTM). A completely linked layer, a softmax layer, and a bidirectional LSTM layer are all parts of the bidirectional long-term and short-term memory network. Following line fault extraction, the zero-sequence current is subjected to variational modal decomposition, and the average accuracy of LSTM and VMD is 97.4% which shows the higher efficiency of BiLSTM technique.

Another study on fault classification in transmission lines using a Long Short-Term Memory (LSTM) network is presented in [40]. The research entails simulating a 400 kV, 100-kilometer transmission line and generating fault signals for ten different types of failures. The fault signals are pre-processed, and the post-fault current signals are supplied into the LSTM network, which has been trained to recognize various sorts of defects. The suggested model is tested with white Gaussian noise with Signal-to-Noise Ratios (SNR) of 20 dB and 30 dB, and it achieves a promising classification accuracy of 100%, 99.77%, and 99.55% for ideal, 30 dB, and 20 dB noise, respectively. The results are compared with four different methods, and the LSTM network outperforms them with the highest classification accuracy. The study concludes that the proposed LSTM network method has the capability to classify fault signals with high accuracy. Further for on-line transmission line fault diagnosis, LSTM network with a calibration training filter is combined in [41].

The LSTM network is a multilayer recurrent neural network that is well-suited for complex time-series classification problems. However, the large number of units in LSTM makes the training progress time-consuming, and it is not suitable for on-line diagnosis devices. To address this issue, researchers in [41] introduced filter-enhanced calibration method to accelerate the calibration training of LSTM. The filter selects samples having the same pattern as the signal under diagnosis, which reduces the training complexity. The proposed filter calibrated LSTM (FC-LSTM) is compared with other neural networks and machine learning algorithms on an on-line test model. The experimental results show that FC-LSTM has better classification accuracy and a very short time delay compared to other algorithms. The proposed method can be used for on-line transmission line fault diagnosis, where the parameters of the transmission line are always varying with time, and the diagnosis devices require frequent calibration training on the network. The proposed filter-enhanced calibration method can reduce the training complexity and accelerate the calibration training of LSTM, making it suitable for on-line diagnosis devices. High Impedance Fault (HIF) in solar Photovoltaic (PV) integrated power systems cannot be ignored [42].

LSTM based research includes simulating an IEEE 13-bus system in MATLAB/Simulink and integrating 300 kW solar PV plants for analysis. For feature extraction, three-phase current signals were used in both non-faulty and faulty circumstances. The Discrete Wavelet Transform approach was used to obtain the energy value information from each phase for training and testing the classifiers. In recognizing HIF in PV integrated power networks, the suggested LSTM classifier achieved an overall classification accuracy of 91.21% and a success rate of 92.42%. The prediction outcomes were compared to those of other well-known classifiers. As we know the false alarm impacts the performance of fault detection, to overcome this issue, [43] present deep learning framework for early failure detection. To evaluate system variance and estimate distribution, the framework makes use of deep neural networks and long short-term memory networks. The suggested circular indirect alarm evaluation approach gathers deviation values and only verifies fault occurrence once a predetermined level of confidence is reached. The efficacy and dependability of the model are demonstrated by experimental findings employing bearing data sets from the actual world.

In other study [44], authors proposes a machine learning-based algorithm using LSTM recurrent neural networks and autoencoder networks to detect DC faults and monitor load conditions in naval pulse loads. The algorithm extracts frequency-domain features of load current using wavelet transform for network training and produces signal classification and reconstruction of the pulse load. The proposed load monitoring solution can be applied to any load profile exhibiting repetitive transients during normal operation, and any faults should result in large reconstruction errors for protective action. The solution addresses the concern that pulse loads drawing large currents in short periods of time may be indiscernible from faults in next-generation warships.

Similarly, a new method for real-time fault detection and classification in PV systems using a hybrid deep learning model is introduced in [45]. The model combines the Equilibrium Optimizer Algorithm (EOA) and Long Short-Term Memory (LSTM) approaches and utilizes the Wavelet Packet Transform (WPT) as a data preprocessing technique. The model automatically extracts fault features from preprocessed data without requiring previous knowledge and improves the speed and accuracy of fault detection and classification. The proposed model was evaluated on a 250-kW grid-connected PV system.

A new method that uses pilot impedances, gathered from the positive, negative, and zero sequence current values and voltages from both ends of the transmission line, is presented in [30]. LSTM-based unique technique has been established for carrying out multiple relaying tasks for categorization and for the fault prediction in bipolar line commutated converter(LCC) in transmission line [34].

Other than LSTM there are various modern method such as Phasor Measurement Units (PMU) based techniques and support vector machine. In order to concurrently detect and categorize various open-circuit fault types in power distribution systems, the Modified Multi-Class Support Vector Machines (MMC-SVM) technique is proposed in [35]. While taking into account the effects of variation in the voltage of various nodes in power distribution networks, simulation is carried out on the IEEE 13 bus test system. PMU-based fault location for double circuit transmission lines in modal domain is presented in [36]. A 100km double circuit transmission line, with a 220 kV model used to investigate the proposed scheme, and fault cases were simulated.

The network distribution system (NDS), which connects numerous circuits with electricity and high-speed communication technologies, is replacing the conventional Radial Distribution System (RDS) for the distribution of power. The NDS has benefits such as higher terminal voltage, increased facility utilization, and increased hosting capacity. Accurate fault direction identification is crucial since the current protection coordination mechanism created for the RDS is insufficient for fault occurrences in the NDS. Authors in [46] presents a communication-based protection coordination approach that may be used in fault circumstances within an NDS, along with a fault direction detection method using the waveform of the fault current based on an LSTM neural network. Another latest technique for fault detection have been discussed in [38] , This technique has suggested a decision tree-based strategy for a double-circuit line with dynamic fault resistance within half cycle of power swing. For signal processing, Discrete Fourier transform (DFT) is employed. This proposed method delivers 99.99% classification accuracy while fault detecting accuracy is about 100% accuracy.

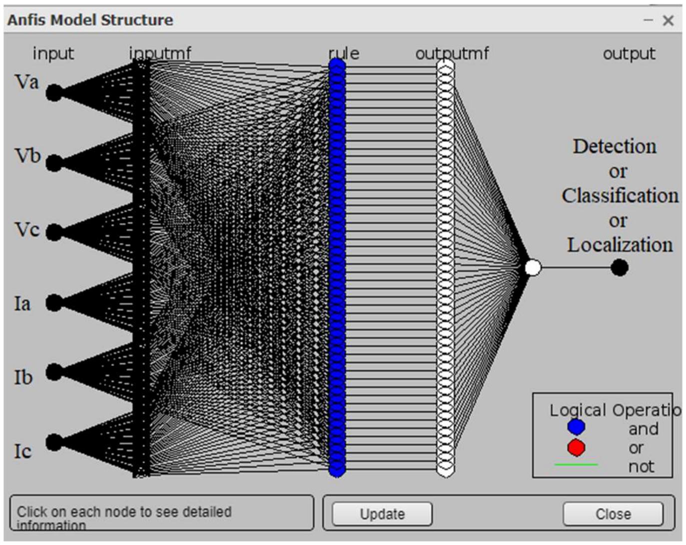

Fig.6. ANFIS model structure [47].

III. Comparative Analysis of Classification, Detection and Location of Fault

For the power system to work effectively and efficiently, accurate fault detection, fault classification, and location of the fault in the system are vital. Researchers have developed many methods for fault classification, detection, and localization of in transmission system under various fault conditions. There are many factors that are considered and extracted in [1-45] for identification and locating faults in transmission lines, such as current, voltage, impedance and in some cases approximate and detailed coefficients, extracted from the current signal, were taken as observation for the fault analysis techniques.

A comparative study of various fault analysis techniques has been done in Table I, the system taken for simulation, and the parameters such as transmission line length, fault resistance, and system voltages are mentioned too. AI-based approaches for fault identification and location are more adaptable and are less likely to be affected by fault or line parameters. AI-based fault identification and localization will become more important among fault diagnosis techniques as a result of ever-improving computing and communication capabilities. Modern AI learning techniques like LSTM could perform better than those already in use. Therefore, in the future, for fault diagnosis researchers may consider modern AI techniques, such as LSTM approach.

The advantages and limitations of various fault techniques have been discussed in Table II.

The benefits of ANN make it possible to employ it extensively in the creation of fault analysis algorithms. When creating models for fault diagnostics, ANN is particularly useful. The ability of ANNs to naturally learn on their own is their most useful advantage. Additionally, the parallel processing of data is a benefit, which altogether enables its simplicity of implementation for real-world issues like fault analysis. However, the need to train the ANN structure utilizing big and scattered data in order to construct the ANN structure and update the weights accurately is one of the flaws that affects ANN. WT is quite accurate and can identify fault features utilizing the decomposed frequency components of a fault waveform. However, it has the intrinsic disadvantage of constantly growing complexity of analysis, especially for higher levels of decomposition of the fault signal. The main benefit of fuzzy analysis is that uncertain problems can be solved utilizing 'if-then' rules. However, fuzzy analysis is less reliable. Additionally, for fuzzy membership function construction requires high experience. ANFIS is a hybrid of fuzzy logic and neural networks that is capable of modeling complex systems. ANFIS-based methods have been used for fault detection in transmission lines due to their ability to handle uncertainty and nonlinearity in data. However, ANFIS-based methods require the selection of suitable fuzzy rules and the optimization of fuzzy sets, which can be time-consuming. Therefore, it could produce better results if used with modern AI techniques such as WT or LSTM.

Modern AI learning technique particularly LSTM has gained significant attention worldwide in modern artificial intelligence approaches. The approach has been widely used in a variety of power system applications and has yielded remarkable results. Several attempts have been made to classify transmission line faults using various deep learning approaches. However, the LSTM, has not been highlighted in the literature. The LSTM has reduced the complexity of updating each weight compared to the backpropagation method. LSTM provides a wide variety of input-output biases, therefore there is no need for adjustment. The gradient vanishing problem faced by traditional RNN is successfully addressed by peculiar structure of LSTM, therefore, information retains for a long period in the LSTM network due to the rescaling sigmoid activation and tangential hyperbolic functions. LSTM is simple but effective in its performance when compared to conventional approaches, which demand specialized operator engagement and experience to properly establish the algorithm's unique parameters. LSTM can be a remarkable technique for the field of fault detection, classification and predicting fault location in transmission lines. Phasor Measurement Units (PMUs): PMUs measure the phasor quantities of the power system, including voltage and current phasors. PMU-based methods have been used for fault detection in transmission lines due to their ability to capture the transient behavior of the system during a fault. However, PMUs are expensive and require a large number of installations. Support Vector Machines (SVMs): SVM is a machine learning algorithm that is commonly used for classification problems. SVM-based methods have been used for fault detection in transmission lines due to their ability to handle high-dimensional data and their robustness to noise. However, SVM-based methods require the selection of suitable kernel functions and parameters, which can affect their performance.

Overall, each method has its strengths and weaknesses, and the choice of the appropriate method depends on the specific application and the characteristics of the data. A combination of these methods may be used for fault detection in transmission lines to improve the accuracy and robustness of the system.

IV. Challenges and Future Research Perspectives

The development in the field of artificial intelligent techniques for fault diagnosis is extraordinary, however, there are few challenges which are still unresolved and need to address, such as:

1) Dataset has a significant impact on the fault identification and classification, however due to unavailability of real dataset from real systems researchers are convinced to use the simulated data.
2) The simulated data is theoretically good enough to produce significant results, however it is still not able to produce real time scenarios such as voltage fluctuation and current fluctuation.
3) The simulated data for testing AI systems are unable to recognize problems like imbalanced data, which would appear in real-time data. This needs to be investigated independently because it is significant for real-world applications.
4) Nearly all AI-based techniques have been applied to fault-diagnosis. In addition, fault diagnosis applications can explore modern AI learning techniques like LSTM and other more sophisticated learning techniques that are being used by researchers in other power system applications.
5) Utilization of Internet of thing (IoT) can be considered for real time data acquisition for fault detection, identification and localization in transmission lines.
6) Digital twin technology can be considered to create virtual models of power systems that can be used to simulate and predict the behavior of the actual power system. This technology can be used to identify potential faults and optimize power system performance.
7) Although modern AI fault analysis techniques such as LSTM, SVM, CNN have made significant progress, it is still in its early stages. There is an enormous potential for utilizing current algorithms and architectures, as well as exploring further optimization methods to handle the fault analysis issues. Currently, issues such as overfitting, and training times, is faced during training of data. However, if possible, ways to overcome these obstacles are discovered then the modern AI techniques will be capable of dealing with all kinds of applications.
8) Hybrid methods such as ANFIS, ANFIS with WT and LSTM can be implemented to produce better result in fault analysis.

V. Conclusions

An overview of the many methods used for fault investigation in the power system, particularly in transmission lines, is provided in this review, it also includes an experimental result of ANFIS based fault detection, fault classification and fault location in IEEE-9 bus system. Numerous methods developed by various researchers for fault localization, classification, and detection of transmission line faults are briefly presented, along with their main benefits and drawbacks. A survey of the literature indicates that models for fault analysis such as the artificial neural network, the fuzzy inference system, and wavelet transform have a significant impact on fault analysis techniques. Analyses of ANN and other models employing supervised learning techniques require extensive training utilizing a variety of data, which makes them more complex and time-consuming. For fault diagnosis, WT is a useful set of mathematical tools, a model, and a signal analysis technique. However, as decomposition increases, WT becomes complex. The if-then rule-based FIS approach can create complexity and analyzer inaccuracy. No precise inputs are necessary for FIS because it is robust rule-based system. Researchers prefer to employ hybrid models to maximize the benefits of techniques. In many fault analyses, researchers employ WT to extract fault features before applying ANN supervised learning approaches. Combining all of these strategies results in fault analyzers that are accurate and efficient. In recent years' new techniques have been introduced by researchers such as fault analysis techniques based on SVM and LSTM. SVM is also accurate; in particular, fault classifiers based on SVM have very high accuracy. PMU emerged as one of the accurate fault localization methods. LSTM has reduced the complexity of updating each weight compared to the backpropagation method. ANFIS based method has been tested for IEEE 9 bus system, the performance of this technique is best for fault detection and classification, however for location it can be improved further by adding WT or LSTM with ANFIS.

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TABLE I
COMPARATIVE ANALYSIS OF FAULT ANALYSIS TECHNIQUES

Reference	Voltage (kV)	Fault resistance (Ohms)	Line length (km)	Algorithm	Task Performed	Results and Implications
[8] 2020	345	0-200	100-200	Wavelet Transform(WT)	Detect, locate, and classify the fault	High speed and more accurate (no missing fault class). Only three faulty sections have been defined, it can be extended.
[9] 2019	575	N/A	60	Discrete Wavelet Transform (DWT)-Multiresolution Analysis (MRA)	Detect, locate, and classify the fault	Tested with microgrid, results are independent of fault inception angle, impedance and distance.
[4] 2017	220	18	90	Discrete Wavelet Transform, and MRA	Detect and locate the fault	Decomposition level 5 is used with WT.
[10] 2016	25	N/A	100	Discrete Wavelet Transform	Detect the fault	Fourth level decomposition is used and detail coefficient of faulty and healthy coefficient are use for differentiation.
[12] 2016	66	N/A	25	Wavelet singular entropy(WSE) and fuzzy logic(FL)	Detect and classify the fault	Classification and detection accuracy for WSEFL is 100% , time taken to distinguish and islanding is 10ms.
[13] 2018	N/A	N/A	IEEE 34-bus system	Discrete Wavelet Transform and Decision Tree	Detect and classify the fault	Fault index has been used to differentiate faulty and healthy lines
[11] 2016	400	100-500	200	Discrete Wavelet Transform (DWT)-Multiresolution Analysis (MRA)	Classify the fault	Threshold value of detail coefficient has set to differentiate the faults. This may not be applicable if the other parameters are changed.
[15] 2021	11	N/A	200	ANN-Feed Forward	Detect and classify the fault	The MSE for classification of fault is 0.082 is fair, correlation coefficient(R) is 0.82 , this could be improved using normalization or hyperparameter tunning.
[16] 2018	500	1,5,10,25,50	200	ANN-Feed Forward and Backpropagation	Detect and classify the fault	Accuracy of fault detectors 100% and fault classifier is 88% this can be improved using hyperparameter tunning.
[17] 2019	N/A	0.25,0.5,0.75,1, 5,10,25, 50	300	ANN with GPS and GSM	Fault location	Max correlation coefficient is 0.99329,MSE for LL-G fault is 0.0013561 is improved when the hidden neurons are increased.
[18] 2018	500	0-100	IEEE 39-bus system	Fuzzy Multi-Sensor Data Fusion	Fault location accuracy	Fuzzy multi-sensor data fusion technique is new in fault location in power systems. Data from distance relays are used. Error is below 1%.
[19] 2021	138	N/A	68	Fuzzy Logic	Detect and classify the fault	Series fault detection is carried out with FIS and frequency domain transformation is used to extract components of current signal; DWT could further improve if replaced in frequency domain transformation.
[20] 2021	230	N/A	IEEE 9-bus system	Fuzzy Logic	Detect and classify the fault	faults in forward and reverse directions have been simulated using fuzzy. This could generate wide range of possibilities for model to learn.
[21] 2015	400	3,5,7,25,50,75,99	300	Wavelet Transform and ANN	Fault location	Directional fault section identification and location have been done using DWT and ANN with improved performance of 0.001% average error .
[22] 2019	500	10,100	300	wavelet packet transform (WPT)	Detect and classify the fault	For extraction of current coefficient wavelet db6 and 7 level decomposition is used , which will increase the complexity of computation, new approach is based on adaptive threshold value which is not needed to vary for other transmission lines.
[23] 2019	69	N/A	microgrid	DWT and ANN	Detect, locate, and	Micro controller based Static switch is used and verified for fault detection method with WT and ANN.

					classify the fault	
[24] 2017	220	N/A	200	DWT and feed-forward back propagation ANN	Detect and classify the fault	Augmented global relay parameters have been introduced to detect and classify the faults which is more accurate in detection of faults from power swing.
[25] 2020	400	0-50	430	WT and ANFIS	Fault location	First level decomposition has been used which could lead to more time for process. Fault locator is immune to fault inception angle (FIA) and fault resistance (FR).
[26] 2018	400	N/A	450	ANN, ANFIS	Locate and classify the fault	Hyperparameter and other options are not consider for comparison. The GUI is more interesting for visual display of signal and for comparison.
[27] 2017		0,20,100, 1000	IEEE 118-bus system	DWT and ANN	Detect and classify the faults	Faults; lightning , switching, have been classified with DWT feature vector with ANN.
[28] 2021	Two area four machine system	N/A	220	Long Short-Term Memory(LSTM) based Deep Recurrent Neural Network(DRNN)[28]	Detect, locate, and classify the fault	Min percent error for LG fault location is 0.004% and max is 0.632% with LSTM. With large-scale multi-machine power systems, the faulty region identification (FRI) and fault type classification (FTC) models have been validated.
[29] 2019	320	0.01-20	200	CNN-LSTM, Multi layer perceptron(MLP), single ended impedance method	Fault location	CNN-LSTM based transmission fault location is accurate then other conventional methods, average location error for CNN-LSTM is 0.126km, for MLP it is 1.661km, single ended impedance technique is 2.020km.
[30] 2020	500	0,300,500,1000	IEEE 39-bus system	pilot impedance	Fault detection	This method is immune to fault resistance, fault type and fault location and it can perform well during power swing and open operations.
[31] 2022	230	1,50,100,500,1000,3000,5000	IEEE 6-bus system	k-NN,CNN,LSTM, CNN-LSTM	Classify and locate the fault	C-LSTM outperformed than k-NN, CNN and LSTM with MSE 0.5303 for fault type, and for fault location MSE is 0.1768..
[33] 2020	195-231	N/A	200	VMD and Bidirectional LSTM	Fault detection	Average accuracy for VMD-LSTM is 97% fault diagnosis.
[34] 2021	±500 HVDC	0-100	1100	LSTM	Detect, locate, and classify the fault	The fault location error is within 1%. Works well with low sampling frequency. Accuracy is 99%.
[35] 2019	IEEE 13-bus system	N/A	IEEE 13-bus system	Modified Multi-Class support Vector Machines (MMC-SVM)	Detect and classify the fault	Dataset sample are less, the accuracy is 88.75% for fault detection and 98% for fault identification.
[36] 2016	220	N/A	100	Phasor measurement unit(PMU)	Fault location	PMUs have been used to collect the current data from both end of double circuit lines, using PMU in real time would be cost effective.
[38] 2016	400	0,50,100	5-95km	DFT with decision tree	Fault detection and classification	Accuracy of fault detection is 100% and fault classifier is 99.99% accuracy.
[40] 2020	400	N/A	100	Long Short-Term Memory(LSTM)	Fault classification	LSTM's performance is better for classification with average accuracy of 99.77%.
[41] 2019	500	NA	300	filter calibrated LSTM (FC-LSTM)	Fault classification	Use of calibration filter have reduced the training complexity. LSTM has highest classification accuracy rate across all methods with a precision increase of 4.82% to 9.34%.
[42] 2021	IEEE 13 bus system	20-150	IEEE 13 bus system(PV integrated)	Recurrent Neural Network(RNN) based Long Short-Term Memory(LSTM)	Fault detection, fault classification	LSTM classifier achieved an overall classification accuracy of 91.21% and a success rate of 92.42% for HIF.

TABLE II
ADVANTAGES AND LIMITATIONS OF VARIOUS FAULT ANALYSIS TECHNIQUE

Fault analysis technique	Advantages	Limitations
Artificial Neural Network (ANN)[15-17] ,[23]	1.ANNs have better generalization ability 2.ANNs are simple to use and have a few adjustable parameters [6]. 3. Implementation of ANNs is easier[14].	1. Extending trained ANNs for another task is complex 2. The ANNs training procedure is difficult for high-dimension problems [6].
Fuzzy Inference System [18-20]	1. No precise inputs are needed. 2. Utilizes "if-then" principle. 3. Knowledge-based method.	1. Unable to learn by its own. 2. Expertise are needed to define "if-then" rules. 3. Less robust.
Wavelet Transform [8-13]	1. Computationally very fast. 2. Small wavelets can be employed to extract fine details of the signal.	1. Computational complexity increases with increasing levels of decomposition of the faulty signal. 2. Threshold values are needed, which need to be change for varying system parameters.
Adaptive Neuro Fuzzy Inference System (ANFIS)[25-26]	1. Nonlinearity and organized knowledge representation. 2. Ability to adapt. 3. Hybrid model can adjust the parameter more accurately. 4. Faster convergence.	1. High computational complexity. 2. With the increment of if-then rules the computational complexity also increases.
Support Vector Machine (SVM)[35]	1.More effective in high dimensional areas. 2. High accuracy of fault classification. 3. When the quantity of dimensions exceeds the quantity of datasets, it works well.	1.SVM could not be effective for large datasets. 2. The SVM will perform poorly when there are more attributes for each data point than there are training datasets.
Support Vector Regression (SVR)[35]	1. Generalization and accurate prediction capability. 2. Implementation of SVR is easier. 3. Requires less computing than other regression methods.	1.SVR not effective for large datasets. 2.The SVM perform poorly when there are more attributes for each data point than there are training datasets.
Phasor Measurement Units (PMUs)[36]	1. Controlling of bus and monitoring of transmission lines is easier using PMUs for fault location. 2. Optimized location technique for PMUs placement can reduce the cost.	1. PMUs at every bus for the fault location is expensive. 2. Placement of PMUs in the network is complex.
Long-Short Term Memory (LSTM) Technique[38-42]	1. LSTM is able to learn and remember information for long time. 2. Ability to overcome the vanishing gradient problem [39].	1. LSTM need more time to train for the input data.

TABLE III
SAMPLE DATA SET FOR THE ANFIS BASED FAULT DETECTION, CLASSIFICATION AND FOR LOCATION

	Input data(rms)						Output data		
Fault case	**Va**	**Vb**	**Vc**	**Ia**	**Ib**	**Ic**	**Detection**	**classification**	**Location**(km)
AG	0.1311	0.6292	0.6068	2.1012	0.3729	0.3622	1	1	25,50,75,100
BG	0.606	0.1213	0.6297	0.3651	2.0097	0.3712	1	2	25,50,75,100
CG	0.63	0.6069	0.1616	0.3717	0.3642	1.5324	1	3	25,50,75,100
AB	0.2912	0.3291	0.6116	2.305	2.0751	0.3619	1	4	25,50,75,100
BC	0.6116	0.2981	0.3451	0.3619	1.7722	1.4873	1	5	25,50,75,100
CA	0.3487	0.6116	0.2997	1.4149	0.3619	1.7019	1	6	25,50,75,100
ABG	0.1178	0.1282	0.6235	2.1606	2.176	0.3723	1	7	25,50,75,100
BCG	0.6235	0.1087	0.1312	0.3709	2.0516	1.6206	1	8	25,50,75,100

CAG	0.1459	0.6237	0.1367	2.0298	0.3716	1.5825	1	9	25,50,75,100
No fault	0.611627	0611627	0.611627	0.361749	0.361749	0.361749	0	0	25,50,75,100

TABLE IV
ANFIS TRAINING AND TESTING RESULT

	Training			**Testing**		
ANFIS	Detection (fault, no fault)	Classification (Asymmetrical faults)	Location (km)	Detection (Fault, no fault)	Classification (Asymmetrical faults)	Location (km)
MSE	0.00	0.00	0.95	0.00	0.00	5.32
RMSE	0.00	0.00	0.974	0.00	0.005	2.31
R^2	1	1	0.99	1	1	0.99

REFERENCES

[1] A. Prasad, J. B. Edward, and K. Ravi, "A review on fault classification methodologies in power transmission systems: Part—I," *J. Electr. Syst. Inf. Technol.,* vol. 5, no. 1, pp.48-60, May. 2018, doi: 10.1016/j.jesit.2017.01.004.

[2] F. A. -García, E. S. Manzano, M. A. Montero, A. Alcayde, and F. M. -Agugliaro, "Power transmission lines: worldwide research trends," *Energies*, vol. 15, no.16, August. 2022, doi: 10.3390/en15165777.

[3] J. Owolabi, and O. Pius, "A Comparative study of symmetrical method and artificial neural network in faults detection in power transmission lines," *Int. j. innov. res. technol. sci. eng.,* vol. 7, no 5, pp.1362-1366, May. 2022, doi: 10.5281/zenodo.6716134.

[4] B. Masood, U. Saleem, M. N. Anjum, U. Arshad, "Faults detection and diagnosis of transmission lines using wavelet transformed based technique," in *Proc. 2017 IEEE Jordan Conf. Appl. Elect. Eng. Comput. Technol.,* Aqaba, Jordan, 2017, pp. 1-6, doi: 10.1109/AEECT.2017.8257776.

[5] A. Mukherjee, P. K. Kundu, and A. Das, "Transmission line faults in power system and the different algorithms for identification, classification and localization: A brief review of methods," *J. Inst. Eng. (India): B,* vol. 102, no. 4, pp. 855-877, August. 2021, doi: 10.1007/s40031-020-00530-0.

[6] K. Chen, C. Huang, and J. He, "Fault detection, classification and location for transmission lines and distribution systems: a review on the methods," *High Voltage*, vol. 1, no. 1, pp. 25-33, April .2016, doi: 10.1049/hve.2016.0005.

[7] A. Prasad, J. B. Edward, and K. Ravi, "A review on fault classification methodologies in power transmission systems: Part-II," *J. Elect. Syst. Inf. Technol.,* vol. 5, no. 1, pp. 61-67, May. 2018, doi: 10.1016/j.jesit.2016.10.003.

[8] A. R. Adly, et al, "A novel protection scheme for multi-terminal transmission lines based on wavelet transform," *Elect. Power Syst. Res.*, vol. 183, June. 2020, doi: 10.1016/j.epsr.2020.106286.

[9] S. C. Shekar, G. R. Kumar, and S.V.N.L. Lalitha, "A transient current based micro-grid connected power system protection scheme using wavelet approach," *Int. J. Elect. Comput. Eng.*, vol. 9, no. 1, pp. 14-22, February. 2019, doi: 10.11591/ijece.v9i1.

[10] S. Devi, N. K. Swarnkar, S. R. Ola, and O. P. Mahela, "Detection of transmission line faults using discrete wavelet transform," in *Proc. 2016 Conf. Adv. Signal Process.*, Pune, India, June. 9, 2016, pp. 133-138.

[11] A. Prasad, and J.B. Edward, "Application of Wavelet Technique for Fault Classification in Transmission Systems," *Procedia Comput. Sci.*, vol. 92, pp. 78-83, 2016, doi: 10.1016/j.procs.2016.07.326, doi: 10.1109/CASP.2016.7746152.

[12] M. Dehghani, M.H. Khooban, and T. Niknam, "Fast fault detection and classification based on a combination of wavelet singular entropy theory and fuzzy logic in distribution lines in the presence of distributed generations," *Int. J. Elect. Power Energy. Syst.,* vol. 78, pp. 455-462, June. 2016, doi: 10.1016/j.ijepes.2015.11.048.

[13] A. Malhotra, O.P. Mahela, and H. Doraya, "Detection and classification of power system faults using discrete wavelet transform and rule based decision tree," in *Proc. 2018 Int. Conf. Comput, Power & Commun. Technol.,* Greater Noida, India, September. 28-29, 2018, pp. 142-147, doi: 10.1109/GUCON.2018.8674922.

[14] D. P. Mishra, and P. Ray, "Fault detection, location and classification of a transmission line," *Neural Comput. Appl.,* vol. 30, no. 5, pp. 1377-1424, September. 2018, doi: 10.1007/s00521-017-3295-y.

[15] M. R. Bishal, et al, "ANN Based Fault Detection & Classification in Power System Transmission line," in *Proc. 2021 Int. Conf. Sci. Contemp. Technol.*, Dhaka, Bangladesh, 2021, pp. 1-4, doi: 10.1109/ICSCT53883.2021.9642410.

[16] S.Upadhyay, S. Kapoor, and R. Choudhary, "Fault classification and detection in transmission lines using ANN," in *Proc. 2018 Int. Conf Inventive Res. Comput. Appl.,* Coimbatore, India, July. 11-12, 2018, pp. 1029-1034, doi: 10.1109/ICIRCA.2018.8597294.

[17] O. E. Obi, O. A. Ezechukwu, and C. N. Ezema, "An Extended Ann-Based High Speed Accurate Transmission Line Fault Location for Double Phase To earth Fault on Non-Direct-Ground," *Int. J. Eng. Sci. Technol.*, vol. 1, no.1, pp. 31-47, 2019, doi: 10.29121/IJOEST.v1.i1.2017.04.

[18] Z. Jiao, and R. Wu,"A New Method to Improve Fault Location Accuracy in Transmission Line Based on Fuzzy Multi-Sensor Data Fusion," *IEEE Trans. Smart Grid,* vol. 10, no. 4, pp. 4211-4220, July. 2018, doi: 10.1109/TSG.2018.2853678.

[19] T. R. Althi, E. Koley, and S. Ghosh, "Fuzzy Logic based Fault Detection and Classification scheme for Series Faults in Six Phase Transmission Line," in *Proc. 2021 7th Int. Conf. Elect. Energy Syst.*, Chennai, India, February. 11-13, 2021, pp. 479-483, doi: 10.1109/ICEES51510.2021.9383768.

[20] R. M. S. Dawood, M. Al-Greer, and G. Pillai, "Fuzzy Logic Based Scheme for Directional Overcurrent Detection and Classification for Transmission Line," in *Proc. 2021 56th Int. Univ. Power Eng. Conf.*, Middlesbrough, United Kingdom, August. 31, 2021 – September. 3, 2021, pp. 1-6, doi: 10.1109/UPEC50034.2021.9548215.

[21] A. Yadav, and 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. Elect. Power Energy Syst.,* vol. 69, pp. 27-33, July. 2015, doi: 10.1016/j.ijepes.2014.12.079.

[22] A. R. Adly, R. A. E. Sehiemy, M. A. Elsadd, A. Y. Abdelaziz, "A novel wavelet packet transform based fault identification procedures in HV transmission line based on current signals," *Int. J. Appl. Power Eng.*, vol. 8, no. 1, pp. 11-21, April. 2019, doi: 10.11591/ijape.v8.i1.pp11-21.

[23] Y.-Y. Hong, and M. T. A. M. Cabatac, "Fault Detection, Classification, and Location by Static Switch in Microgrids Using Wavelet Transform and Taguchi-Based Artificial Neural Network," *IEEE Syst. J.*, vol. 14, no. 2, pp. 2725-2735, July. 2019, doi: 10.1109/JSYST.2019.2925594.

[24] S. Affijulla, and P. Tripathy, "A Robust Fault Detection and Discrimination Technique for Transmission Lines," *IEEE Trans. Smart Grid,* vol. 9, no. 6, pp. 6348-6358, May. 2017, doi: 10.1109/TSG.2017.2709546.

[25] M. Paul, and S. Debnath., "ANFIS based single line to ground fault location estimation for transmission lines," in *Proc. Michael Faraday IET Int. Summit 2020* , [online], October . 3-4, 2020, doi: 10.1049/icp.2021.1077.

[26] S. Panda, D. Mishra, and S. Dash, "Comparison of ANFIS and ANN Techniques in Fault Classification and Location in Long Transmission Lines," in *Proc. 2018 Int. Conf. Recent Innov. Elect., Electronics, Commun. Eng.,* Bhubaneswar, India, July. 27-28, 2018, doi: 10.1109/ICRIEECE44171.2018.9008605.

[27] A. Abdullah, "Ultrafast Transmission Line Fault Detection Using a DWT-Based ANN," *IEEE Trans. Ind. Appl.*, vol. 54, no. 2, pp. 1182-1193, November. 15, 2017, doi: 10.1109/TIA.2017.2774202.

[28] S. Belagoune, N. Bali, A. Bakdi, B. Baadji, K. Atif, "Deep learning through LSTM classification and regression for transmission line fault detection, diagnosis and location in large-scale multi-machine power systems," *Measurement,* vol. 177, June. 2021, Art. no. 109330, doi: 10.1016/j.measurement.2021.109330.

[29] R. Fan, T. Yin, R. Huang, J. Lian and S. Wang, "Transmission Line Fault Location Using Deep Learning Techniques," *2019 North American Power Symposium (NAPS)*, Wichita, KS, USA, 2019, pp. 1-5, doi: 10.1109/NAPS46351.2019.9000224.

[30] X. Tong, and H. Wen, "A novel transmission line fault detection algorithm based on pilot impedance," *Elect. Power Syst. Res.*, vol. 179, Feb. 2020, Art.. no. 106062, doi: 10.1016/j.epsr.2019.106062.

[31] A. Moradzadeh, H. Teimourzadeh, B. M. Ivatloo, K. Pourhossein, "Hybrid CNN-LSTM approaches for identification of type and locations of transmission line faults," *Int. J. Elect. Power Energy Syst.*, vol. 135, Feb. 2022, Art. no. 107563, doi: 10.1016/j.ijepes.2021.107563

[32] N. Qu, Z. Li, J. Zuo and J. Chen, "Fault Detection on Insulated Overhead Conductors Based on DWT-LSTM and Partial Discharge," *IEEE Access,* vol. 8, pp. 87060-87070, May. 2020, doi: 10.1109/ACCESS.2020.2992790.

[33] Z. Wan, L. Hui, and L. Yongkang, "Research on Fault Diagnosis of Transmission Lines based on VMD and Bidirectional LSTM," in *Proc. 2020 7th Int. Forum Elect. Eng. Auto.,* Hefei, China, Sep. 25-27, 2020, pp. 445-450, doi: 10.1109/IFEEA51475.2020.00099.

[34] A. Swetapadma, S. Chakrabarti, A. Y. Abdelaziz, , H. H. Alhelou, "A Novel Relaying Scheme Using Long Short Term Memory for Bipolar High Voltage Direct Current Transmission Lines," *IEEE Access*, vol. 9, pp. 119894-119906, Aug. 24, 2021, doi: 10.1109/ACCESS.2021.3107478.

[35] F. Mohammadi, G. -A. Nazir, M. Saif, "A Fast Fault Detection and Identification Approach in Power Distribution Systems," in *Proc. 2019 Int. Conf. Power Gen. Syst. Renew. Energy Technol.,* Istanbul, Turkey August. 26-27, 2019, pp. 1-4, doi: 10.1109/PGSRET.2019.8882676.

[36] S. V. Unde and S. S. Dambhare, "PMU based fault location for double circuit transmission lines in modal domain," in *Proc. 2016 IEEE Power Energy Soc. Gen. Meet.,* Boston, MA, USA, pp. 1-4, July. 17-21, 2016, doi: 10.1109/PESGM.2016.7741819.

[37] S. Hochreiter, and J. Schmidhuber, "Long Short-term Memory," *Neural Computation*, Vol. 9, Dec. 1997, pp. 1735-80, doi: 10.1162/neco.1997.9.8.1735.

[38] A.Swetapadma, A. Yadav, "Data-mining-based fault during power swing identification in power transmission system," *IET Sci.Meas & Technol,* vol. 10, pp. 130-139, 2016, doi: 10.1049/iet-smt.2015.0169.

[39] A. Shrestha and A. Mahmood, "Review of Deep Learning Algorithms and Architectures," in *IEEE Access*, vol. 7, pp. 53040-53065, 2019, doi: 10.1109/ACCESS.2019.2912200.

[40] A.M.S.Omar, et al. "Fault classification on transmission line using LSTM network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 20, no. 1 pp. 231-238, Oct, 2020, doi:10.11591/ijeecs.v20.i1.pp231-238.

[41] M. Li, Y. Yu, T. Ji and Q. Wu, "On-line Transmission Line Fault Classification using Long Short-Term Memory," *2019 IEEE 12th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED)*, Toulouse, France, 2019, pp. 513-518, doi: 10.1109/DEMPED.2019.8864831.

[42] V. Veerasamy *et al*., "LSTM Recurrent Neural Network Classifier for High Impedance Fault Detection in Solar PV Integrated Power System," in *IEEE Access*, vol. 9, pp. 32672-32687, 2021, doi: 10.1109/ACCESS.2021.3060800.

[43] W. Lu, Y. Li, Y. Cheng, D. Meng, B. Liang and P. Zhou, "Early Fault Detection Approach With Deep Architectures," in *IEEE Transactions on Instrumentation and Measurement*, vol. 67, no. 7, pp. 1679-1689, July 2018, doi: 10.1109/TIM.2018.2800978.

[44] Y. Ma, D. Oslebo, A. Maqsood and K. Corzine, "DC Fault Detection and Pulsed Load Monitoring Using Wavelet Transform-Fed LSTM Autoencoders," in *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 9, no. 6, pp. 7078-7087, Dec. 2021, doi: 10.1109/JESTPE.2020.3019382.

[45] M. Alrifaey *et al*., "Hybrid Deep Learning Model for Fault Detection and Classification of Grid-Connected Photovoltaic System," in *IEEE Access*, vol. 10, pp. 13852-13869, 2022, doi: 10.1109/ACCESS.2022.3140287.

[46] W-H.Kim, J-Y. kim, W-K.chae,G.Kim, C-K.lee, "LSTM-based fault direction estimation and protection coordination for networked distribution system," *IEEE Access*, vol. 10, pp. 40348–40357, April. 2022, doi: 10.1109/ACCESS.2022.3166836.

[47] The MathWorks, Inc. (2022). *MATLAB version: 9.7.0 (R2019b)*.

Shazia Kanwal (student member, IEEE) received her B.S. and M.Sc degree in electronics from Sir Syed University of Engineering and Technology, Karachi, Pakistan and King Mongkut's University of Technology, North Bangkok, Thailand respectively. Currently, she is working toward the D.Eng. degree in electrical engineering at King Mongkut's Institute of Technology Ladkrabang (KMITL). Her interests include artificial intelligent based fault analysis in transmission lines.

Somchat Jiriwibhakorn (member, IEEE) received his B.Sc. and M.Sc. degrees in electrical engineering from King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand, in 1994 and 1997, respectively, and his Ph.D. degree in electrical engineering from Imperial College London, UK, in 2000. He was an associate professor from 2006 to present at the department of electrical engineering, KMITL. His research interests include power system stability, power system optimization, power system planning and forecasting, and applications of neural networks and ANFIS in power engineering.