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Machine Learning Framework for Detection, Classification and Zone Location of Fault in Transmission Line

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***Abstract* - For reliable and high-speed protective relaying, fault classification is required, followed by digital distance protection. As a result, a thorough examination of these procedures is required. The vast array of power systems and applications necessitates the development of appropriate fault classification algorithms in power transmission systems in order to improve system efficiency and avert catastrophic damage. Using Machine Learning methods, this project suggested an effective methodology for detecting faults, classifying fault types, and locating fault zones in transmission lines, which could be applied in numerical relays. The entire system is capable of detecting no-fault conditions, three types of line-to-ground faults, line-to-line faults, and double line-to-ground faults, as well as signaling the fault zone. Each transmission line has been divided into three zones to help find the fault. With the aid of confusion matrix parameters, the algorithm is constructed and analyzed in MATLAB.**

***Index Terms* - Fault Detection, Fault Classification, Transmission Lines, Machine Learning.**

I.INTRODUCTION

The most important responsibility in the protection of the power system is to protect transmission lines from exposed faults. Protective relaying is used to recognize anomalous signals that indicate defects in a power transmission system. Fast and precise fault classification is critical in a transmission line for high-speed protective relaying. Transmission line protection against uncovered deficit is the most basic task in power system assurance. Faults in overhead wires are a rare occurrence, caused by a variety of factors including weather, human error, fires, and mechanical failures such as rotating machines and transformers. These problems result in intrusion to electric streams, hardware harms and even cause passing of people, winged creatures, and creatures. These issues are hazard to the congruity of power supply. Fault is nothing but an abnormal condition [1]. Recent technological advancement in machine learning techniques creates an interest to engineers to do research in this area. Earlier various researchers have proposed different schemes for fault classification. The problem is raised, whenever a new user starts his research in this area, he/she may get confusion to select the method to classify the nature of the fault. Because, so many researchers have already developed different methods but each method have their own advantages and disadvantages [2].

Providing uninterrupted electric power to end-users is a difficult undertaking for power system operators. Although human control over fault infiltration is impossible, it is critical to reliably identify, categories, and localize the fault location. The methods for detecting, classifying, and locating faults in power transmission networks have been extensively explored. Efforts are underway to develop an intelligent protection system capable of properly detecting, classifying, and locating defects. Researchers have been able to adopt a more thorough and dedicated approach in studies related to signal processing techniques, artificial intelligence (AI), and machine learning (ML) because to advancements in signal processing techniques, AI, and ML with conventional fault protection strategies [1] [2].

There are two types of faults in overhead transmission systems: series (open conductor) faults and shunt (short circuit) faults. By analyzing each phase voltage, series problems can be easily discovered. When the voltage readings rise, it means there is an open conductor defect. There are two types of open conductor faults: one open conductor faults and two open conductor faults. These are flaws that only happen once in a while. Short circuit problems can be easily found by looking at the current in each phase. When the current values rise, it means a short circuit has occurred. Asymmetrical and symmetrical faults are the two forms of short circuit faults. Asymmetrical faults line to ground (LG), line to line (LL), and double line to ground (LLG), and symmetrical faults are triple line (LLL) and triple line to ground (LLLG) faults. The development of an efficient, precise and accurate real-time fault detection system using machine learning, based on measurements of bus voltages and current injections, in an electrical transmission and distribution network, is basic need. Numerous automated algorithms have been proposed till date to alleviate this procedure and make it more efficient, each having its own strengths and weaknesses. The coherence of each algorithm depends on how accurately it identifies the network topology and pin points fault locations [2].

II. LITERATURE SURVEY

Overhead lines are the easiest to examine in a power system since the problem is usually self-evident, such as when a tree falls over the line or when a utility shaft breaks and the conductors fall to the ground. The accuracy with which it recognizes and classifies faults is one of the most important aspects of overhead line protection. In a recent study, the following fault categorization strategies were discussed:

The fault identified [3] in less time so that trip command can be initiated to the dc breaker. The dc lines are economical for long length so at far end distance fault identification is essential. The converter control in dc transmission lines control the power and provides synchronous interconnection between two ac systems. The factors considering the effect of fault location and fault resistance are considered for the accuracy, reliability and selectivity. The detailed simulation study of transmission line faults with linear and non-linear loads [4] has been carried out in MATLAB/Simulink environment. The simulation results show the impacts of faults on the system voltages and load currents. A relaying algorithm based on Artificial Neural Network (ANN) technique presented [5] for the protection of transmission line. ANN configuration has been found to be the best one and has an accuracy of 100% for fault detection and classification in both training and testing phases with the relay operating time of 12.5 ms. An algorithm presented [6] for detection and classification of transmission line faults using time-frequency analysis (Stock-Well Transform) on current signal obtained from both the ends of transmission line with successfully testing for types of fault, fault impedance, fault incidence angle and fault location. A novel scheme proposed [7] for fault detection, classification and location which compensate for phase angle error due to line charging current using synchronized phasor measurements in SMART GRID. Also proposed algorithm is highly encouraging with symmetrical as well as unsymmetrical faults. Fault location estimation is independent of fault resistance. Authors focused [8] on detecting, classifying and locating faults on electric power transmission lines achieved by using artificial neural networks. Simulation results have been provided to demonstrate that artificial neural network based methods are efficient in locating faults on transmission lines and achieve satisfactory performances.

A strategy proposed [9] to detect nontechnical losses using a multivariate control chart that establishes a reliable region for monitoring the measured variance. The numerical results demonstrate the selectivity and efficiency of the proposed methodology applied for monitoring a real distribution network. A new approach for detection, discrimination of faults for five terminal transmission line protection [10] adopted in presence of PV and Wind Energy system. This scheme is tested for various types of faults in multi terminal transmission system in presence of hybrid generation and it is found effective for detection of faults with various fault inception angle, fault impedance at different distances. An efficient algorithm presented [11] to detect unsymmetrical faults, classify the fault type and locate the fault zone in transmission lines using Artificial Neural Network (ANN), which could be implemented in numerical relays. A Hybrid Wavelet Singular Entropy and Fuzzy System Based Fault Detection and Classification on Distribution Line with Distributed Generation is implemented [12]. Simulation study shows that, the developed scheme works accurately for huge number of fault cases. A wavelet based alienation technique proposed [13] for the detection and classification of faults on transmission lines at different fault locations and different fault incidence angles. A fault detection and classification in a long transmission line which is series compensated [14] using artificial neural network and wavelet transform. The results indicate that the proposed scheme can correctly classify every possible fault with large variations in system conditions. The detection of power system faults in the presence of wind power generation is presented [15] in which faults considered such as line to ground (LG), double line (LL), double line to ground (LLG) and three phase fault involving ground (LLLG).

III. PROPOSED WORK

The entire working process of the presented method is shown in Fig. 1. As shown in figure, the presented model consists a series of processes which are discussed in the figure.

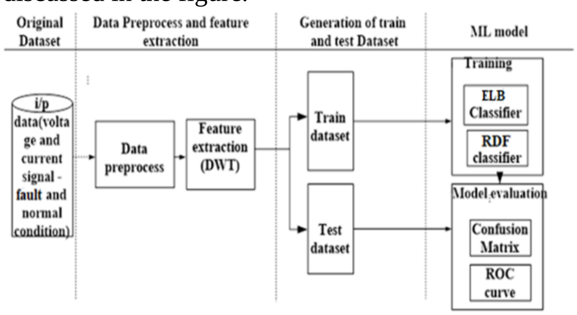


Fig 1: Proposed Block Diagram

1. Original Dataset

In our prototype model we develop a system on MATLAB Simulink for a specific three phase transmission line and distribution system using MATLAB Simulink model. By using fault block in simulink we are going to assign different types of fault on transmission line like LG, LL, LLG etc and that variation is observed in terms of instantaneous voltage and current signal. Thus this data is acquired and stored for further process.

2. Data Preprocess and Feature Extraction

Pre-processing is a valuable technique for improving the performance and speed of a protection mechanism by extracting useful information from signals and reducing the input data dimension. For feature extraction, the proposed protection strategy uses the Discrete Wavelet Transform (DWT), which is achieved in the stages below. To begin, the suggested system model is simulated in order to get instantaneous voltage and current samples at the relay points. Second, the obtained voltage and current signals. Voltage and current data are retrieved and processed by the DWT using multi decomposition analysis to generate approximate voltage and current signal coefficients. To train the fault detector/classifier, 3-level approximation coefficients of voltage and current signals are employed as features, coupled with statistical parameters collected from the same signal in terms of maximum and minimum of a signal, mean, standard deviations, entropy, root mean square and variance of a signal.

The decomposition of signal is repeated to further increase the frequency resolution and the approximation coefficients decomposed with high and low pass filters and then down sampled. This is represented as a binary tree with nodes representing a subspace with a different time-frequency localization. The tree is known as a filter bank. The architectural diagram of 3 level wavelet decomposition of a signal is as shown in fig 2.

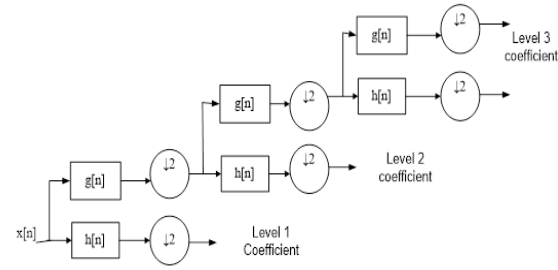


Fig 2: A Multilevel (3 level) filter bank

3. Generation of train and test data

We used a machine learning algorithm to generate the train and test datasets. Machine Learning (ML) is the science of getting computers to learn from and make predictions on data without being explicitly programmed. It arose from the field of artificial intelligence (AI). In other words, rather than following strictly static programme instructions, machine learning algorithms build a model from example inputs in order to make data-driven predictions or decisions. Because we have input and output data, we used a supervised machine learning approach in our proposed work. We have considered two algorithms for our project after consulting the literature review, Ensemble Learning Boosting and Random Decision Forest algorithms.

3.1 Ensemble Learning Boosting

Ensemble Learning Boosting (ELB) classifiers are supervised learning models that analyses input data and classify them according to pattern. This classifier builds a model by using training dataset and categorizes it into two classes. The algorithm then assigns new examples of testing dataset to one of the two classes. ELB classifier thus finds the best hyper plane that separates the two groups and thus classifies the data. Boosting is a general ensemble method that creates a strong classifier from a number of weak classifiers. This is done by building a model from the training data, then creating a second model that attempts to correct the errors from the first model. Models are added until the training set is predicted perfectly or a maximum number of models are added. Boosting is a sequential process, where each subsequent model attempts to correct the errors of the previous model. The succeeding models are dependent on the previous model. Thus, the boosting algorithm combines a number of weak learners to form a strong learner. The individual models would not perform well on the entire dataset, but they work well for some part of the dataset. Thus, each model actually boosts the performance of the ensemble.

3.2 Random Decision Forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random decision forests correct for decision trees' habit of overfitting to their training set. Most of the options depend on two data objects generated by random forests. When the training set for the current tree is drawn by sampling with replacement, about one-third of the cases are left out of the sample. This oob (out-of-bag) data is used to get a running unbiased estimate of the classification error as trees are added to the forest. It is also used to get estimates of variable importance. After each tree is built, all of the data are run down the tree, and proximities are computed for each pair of cases. If two cases occupy the same terminal node, their proximity is increased by one. At the end of the run, the proximities are normalized by dividing by the number of trees. Random Forests grows many classification trees. To classify a new object from an input vector, put the input vector down each of the trees in the forest. Each tree gives a classification, and we say the tree "votes" for that class. The forest chooses the classification having the most votes (over all the trees in the forest)

4. ML Model

Here, we used two algorithm ELB and RDF. For every machine learning algorithm implementation, first training need to be performed and after successful validation of trained model, test dataset is predicted for output class i.e. faulty or normal condition. In model evaluation phase, validation of test model is performed using confusion matrix and receiver operating characteristics plot.

IV. RESULTS AND DISCUSSION

The proposed work is implemented on a Windows 10 laptop with an Intel Core i5 processor and 8GB of RAM. The Signal Processing, Statistics and Machine Learning toolkit, and SimPower System Toolbox were used to construct the Simulink model and write the programming code in MATLAB R2018b software. As indicated in the diagram below fig 3, the suggested Simulink model of a Three-Phase Series Compensated Network of a 735-kV transmission system is employed as a test case scenario in the transmission line.

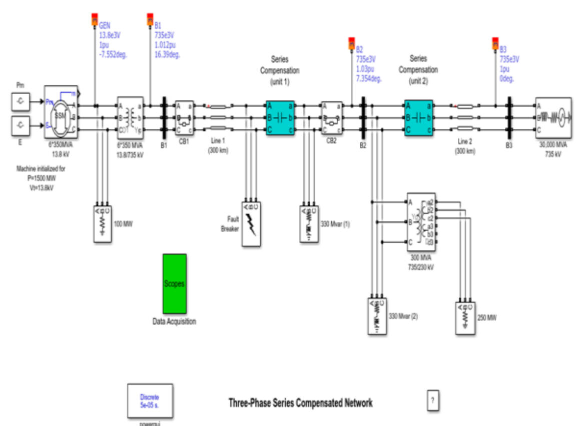


Fig 3: Proposed Matlab Simulink model

A three-phase, 50 Hz, 735 kV power system transmitting power from a power plant consisting of six 350 MVA generators to an equivalent network through a 600 km transmission line. The transmission line is split in two 300 km lines connected between buses B1, B2, and B3. In order to increase the transmission capacity, each line is series compensated by capacitors representing 40% of the line reactance. Both lines are also shunt compensated by a 330 Mvar shunt reactance. The shunt and series compensation equipment's are located at the B2 substation where a 300 MVA 735/230 kV transformer with a 25 kV tertiary winding feeds a 230 kV, 250 MW load. The series compensation subsystems are identical for the two lines. Voltages and currents are measured in B1, B2, and B3 blocks for fault detection, classification and zone detection. In testing phase, several fault conditions are tested listed on table 1. The test case sample of ABG fault condition is observed and tested on proposed system. Test input voltage and current signal and its decomposed signal after 3 level DWT is as shown in fig 4 and 5. Accordingly its predicted output with time required for testing it as shown in fig 6 and 7. Similarly for normal condition, results are shown in fig 8, 9, 10 and 11. Table 1 showed various tested fault and normal condition actual and predicted for fault detection, classification and its equivalent zone. Table 2 described the confusion matrix of proposed system algorithms in which how much number of test signals are predicted for output classes with its equivalent accuracy with respective algorithms. Table 3 defined the time required for training and testing phase for respective algorithms.

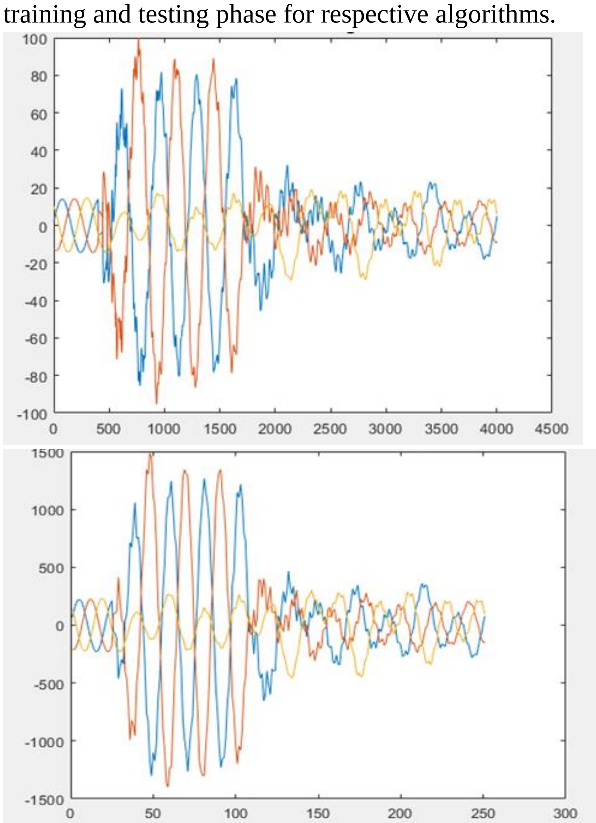


Fig 4: Test Current signal with its third level DWT decomposed signal for ABG fault

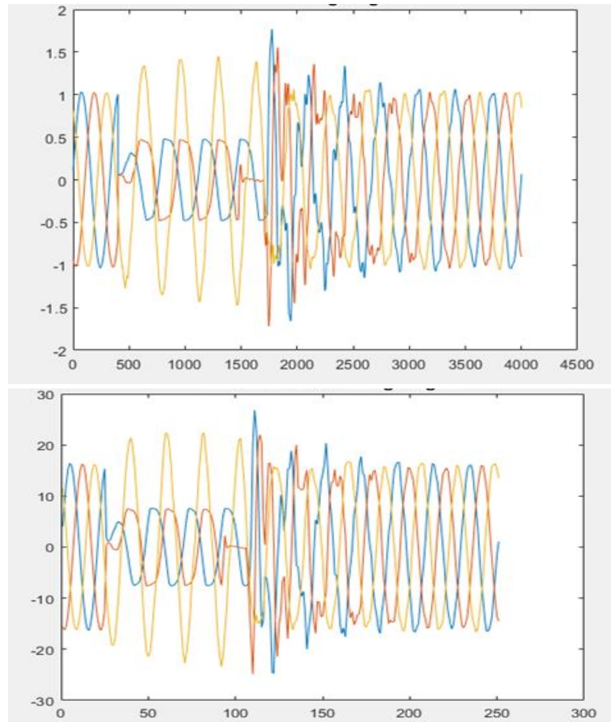


Fig 5: Test Voltage signal with its third level DWT decomposed signal for ABG fault

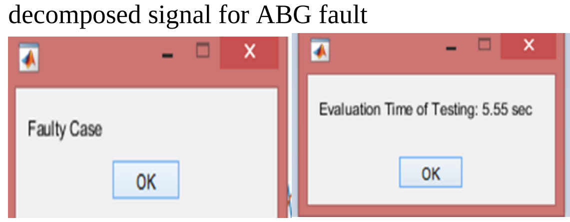


Fig 6: Predicted output with time required for testing phase using ELB for fault case

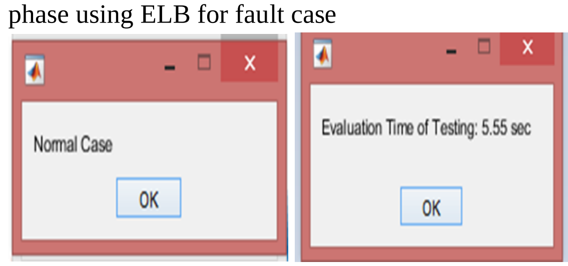
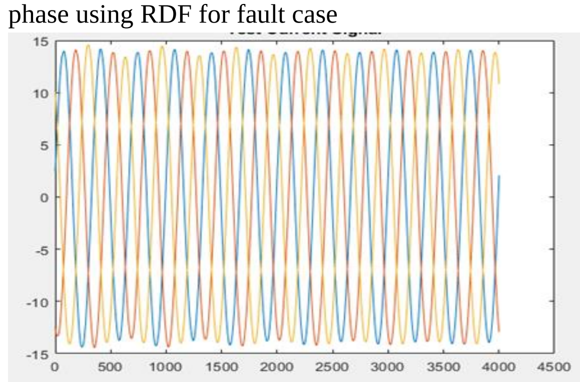


Fig 7: Predicted output with time required for testing phase using RDF for fault case



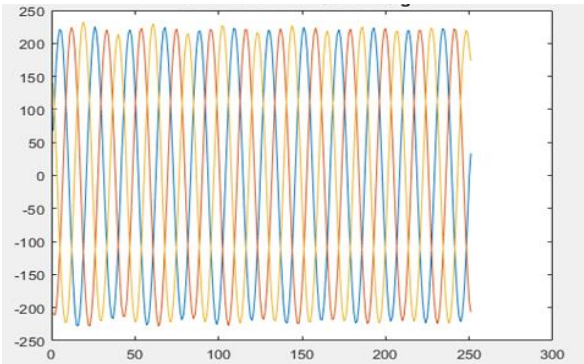


Fig 8: Test Current signal with its third level DWT decomposed signal for Normal condition

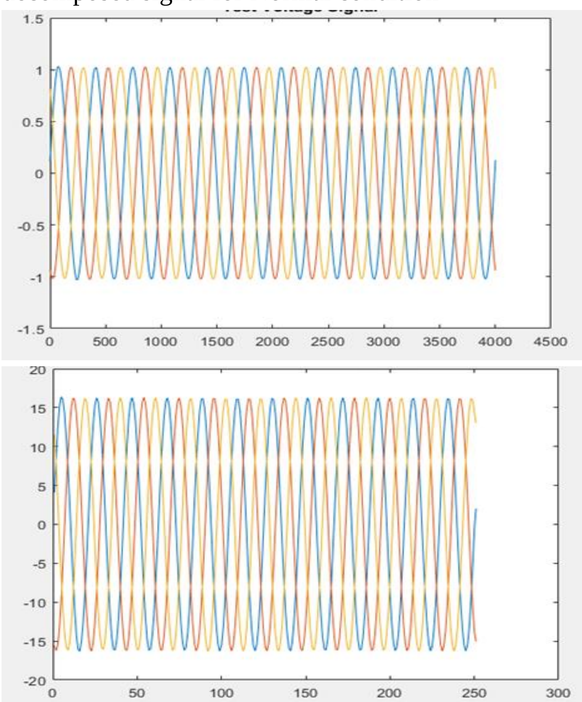


Fig 9: Test Voltage signal with its third level DWT decomposed signal for Normal condition

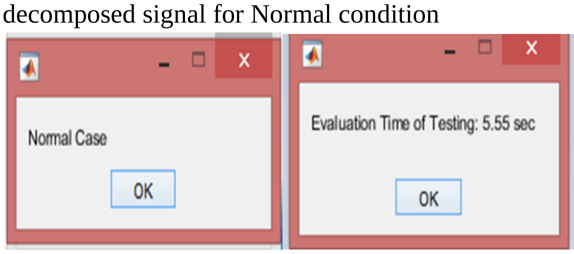


Fig 10: Predicted output with time required for testing phase using ELB for fault case

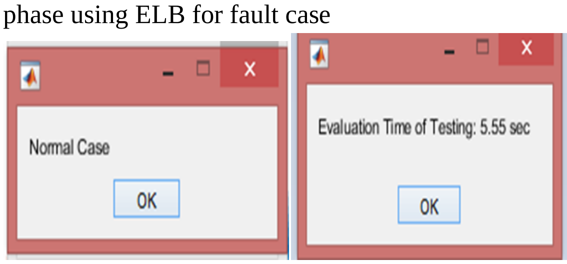


Fig 11: Predicted output with time required for testing phase using RDF for fault case

Table 1: Various Test Fault Condition & its Predicted Output

Sr.no	Scenario	Actual output	Predicted output	
			ELB	RDF
1	A-G Fault	Fault	Fault (zone-1)	Fault (zone-1)
2	A-B-C Fault	Fault	Fault (zone-1)	Fault (zone-1)
7	L-G fault	Fault	Fault (zone-1)	Fault (zone-1)
10	L-L-L Fault	Fault	Fault (zone-1)	Fault (zone-1)
11	A-B fault	Fault	Fault (zone-1)	Normal
12	B-C fault	Fault	Fault (zone-1)	Fault (zone-1)
13	A-B-G fault	Fault	Fault (zone-2)	Fault (zone-2)
14	A-C-G fault	Fault	Fault (zone-2)	Fault (zone-2)
15	A-B-C-G fault	Fault	Fault (zone-2)	Fault (zone-2)
16	A-B-C-G fault	Fault	Fault (zone-3)	Fault (zone-3)
17	B-C fault	Fault	Normal	Fault (zone-3)
18	A-C fault	Fault	Fault (zone-3)	Fault (zone-3)
19	B-C-G fault	Fault	Fault (zone-3)	Fault (zone-3)
20	Normal	Normal	Normal	Normal

Table 2: Performance evaluation of proposed system using confusion matrix

Classifier	Events	Predicted Events		Accuracy
		Faulty	Normal	
ELB	Faulty	11	1	93.33%
	Normal	0	3	
RDF	Faulty	10	1	86.66%
	Normal	1	3	

Table3: Evaluation Time required for Training and

Sr.no	Method	Training Time	Testing Time
1	ELB	0.72sec	0.12sec
2	RDF	1.16sec	0.15sec

V. CONCLUSION

The approaches for fault classification, as well as their main aspects, were presented in this paper. Each technique has its own set of advantages, such as a shorter execution time and higher forecast accuracy. For fault-type classifications, machine learning-based approaches are the most effective and commonly used. Using wavelet features of currents and voltages in the three phases during fault, the proposed system can detect, categories, and localize unsymmetrical faults on transmission lines. The results reveal that the created algorithm is capable of accurately detecting and locating the defect. The proposed model eliminates the need for human manipulation. Using Machine Learning in our system has a lot of benefits. Furthermore, under various test case scenarios, this system can be expanded to multiple failure kinds and zones. Deep learning techniques can be employed for accurate categorization if the test case scenario is a complex transmission system. Due to the rising role of communication and computation in transmission systems, machine learning, especially deep learning approaches, is advocated for future defect detection methods.

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