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FAULT DETECTION AND CATEGORIZATION METHODOLOGIES IN POWER TRANSMISSION SECTOR: A REVIEW

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Abstract

Transmission lines are an essential component of the power system network, serving as a critical link in the country's energy system by transferring enormous amounts of electricity at high voltages from producing stations to substations. With an ever-growing demand for electric power as a result of increased industrialization and urbanization, quick and accurate fault investigation is critical for better performance as well as fewer outages in power sector. To be fault-free, transmission lines require real-time monitoring and quick control. The categorization and detection of faulty conditions in power systems has evolved into a critical task. This study provides an in-depth examination of several algorithms that have been developed and deployed in recent years for the categorization and detection of faults in transmission lines.

Keywords: Artificial neural network (ANN), Adaptive neuro-fuzzy inference system (ANFIS), Fault Categorization, Fault Detection, Machine Learning, Power System, Support Vector Machine (SVM)

1. INTRODUCTION

Transmission lines are an essential component of the power sector, serving as a critical link in the country's energy system by transferring enormous amounts of electricity from generating stations to substations at high voltages. Because of industrialization and urbanization, the current electricity grid is a complicated network. Power systems require a high-speed, real-time, precise, and dependable protection system. A fault is just a defect in the power system. Let's compare transmission system faults to human illnesses for clarity. A healthy individual, for example, gets disturbed in his daily life if he encounters any abnormal condition, where abnormal condition refers to diseases such as colds, coughs, fever, heart attacks, cancer, and so on. Similarly, in power transmission systems, when the system quantities (current,voltages, phase angle, etc.) exceed their threshold values as a result of an aberrant situation, this is referred to as a fault[1]MVA is the unit of measurement for fault value. Faults in the electrical power system are imminent, but the transmission line has the greatest fault incidence rate compared to the other key components of the electrical power system since the majority of the overhead transmission line is exposed to atmospheric conditions. Transmission lines account for around 85-87 percent of all power system faults [2]. Faults not only affect system dependability, but they also have a wide-reaching impact on end users.Furthermore, as configurations get more complex, the challenge of preserving transmission line network increases Predicting faults (kind and location) with high accuracy enhances power system stability and operating dependability and aids in the prevention of catastrophic power outages [3]. Faults in power systems can arise for a number of reasons; nevertheless, these faults must be foreseen and diagnosed as soon as possible; otherwise, they might cause a blackout of the entire system, affecting the customer, even if many required protective measures are used in the fault detection.

Faults in the power system can arise for a variety of reasons, but they are primarily classified in two manner. The first one is failure or breakdown at typical voltages due to deterioration in insulation, damage from unforeseeable causes such as a vehicle colliding with poles or towers, or bird short-circuiting, tree falling across the line and another one is failure or breakdown at aberrant voltages due to arcing ground, switching surges or lightning or other causes [3].Overhead transmission system faults are subdivided into two types: shunt faults (short circuit fault) and series faults (open conductor fault). Series faults are easily identified by inspecting each phase voltage. If the voltage measurements climb, it indicates an open conductor fault. These faults are divided into two types: double open conductor faults and single open conductor faults. These are infrequently occurring faults. Short circuits faults are easily identified by monitoring the current in each phase. If the current values rise, it indicates that a short circuit has taken-place [1].Short-circuit faults are classified as either unsymmetrical or symmetrical. Line to ground (LG), double line to ground (LLG) and line to line (LL) faults are unsymmetrical, but triple line to ground (LLLG) and triple line (LLL)faults in overhead transmission networks is shown in Figure 1. The letters A, B, C in this diagram stand for phase A, phase B and phase C respectively and G represent ground. Figure 2 depicts the possibility of different types of transmission line faults.

With the advent of the smart grid, digital technology was introduced, allowing the installation of sensors along transmission lines that can collect live fault data since they offer relevant data that can be utilized to identify transmission line disturbances [4]. For the operational control and performance analysis of smart grids, a large amount of heterogeneous data must be continuously collected by a growing number of distributed low-cost and high-quality sensors, such as RTUs, PMUs, and smart meters, as well as data generated by other measuring devices [5-6]. Traditional time domain approaches are computationally inefficient to fulfil

Figure 1: Various types of Transmission Line fault

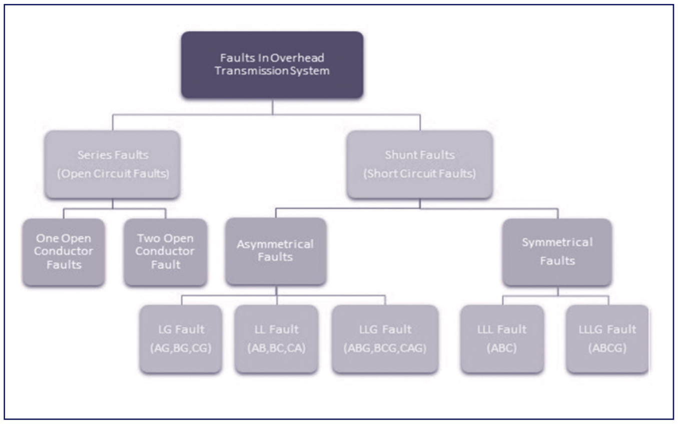
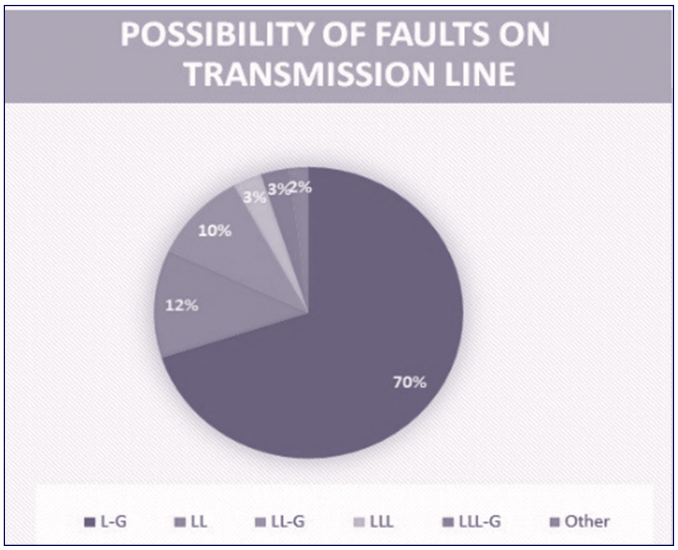


Figure 2: Possibility of faults on line



real-time application demands [7-8]. The study looked at the use of machine learning techniques for fault categorization and localization on transmission lines. We can learn from data without direct programming and behave autonomously whenever exposed to new data. [9]. Various intelligent techniques, such as ANN, fuzzy-based methods, Neuro-fuzzy approach, SVM based approach, Decision tree and combined wavelet-ANN approach, have been developed and applied in transmission systems over the last two decades to address these issues. This study examines the most modern methodologies used in power transmission systems for the detection, categorization, and localization of various faults that occur in transmission networks. This article also compares several fault categorization, detection and localization methods depending on the input, algorithm employed, extracted characteristics, test system and complexity level.

The paper is structured as follows. Sections 2 and 3 give a brief overview of power system Fault categorization and detection, as well as machine learning. Section 4 discusses several fault detections and compares various strategies and while Section 5 and section 6 discusses several fault classifications and compares various strategies, Case study respectively. Section 7 discusses the survey's findings, followed by acknowledgements and references.

2. FAULT DETECTION AND CATEGORIZATION

In the event of a fault, techniques for detecting and categorizing faults rely on changes in current and voltage signals. Techniques range from hand-written rules to expert-defined rules based on threshold values. Hand-coded and expert-defined rules, as well as AI-based technologies such as SVM, fuzzy logic, DT systems, Kernel Nearest Neighbor, and Artificial Neural Network [10], are employed. Several detection characteristics and signal transformations, including as the Fourier Transform, Stockwell transform, and wavelet transformations, have been suggested and used [11]. While local protection equipment like circuit breakers and relays protect critical lines and system buses, the data provided by Phasor measurement units has the potential to improve understanding and situational awareness in a power management centre, as suggested in [12] using the output of a Phasor measurement unit only state estimator for fault classification and detection. The techniques in [13-14] employ decision trees in this context, whereas [15] uses support vector machines. Given the promising results of this research, techniques based on the existence of all measures in full synchronization are detailed.

3. MACHINE LEARNING

Power system fault detection and categorization are crucial for efficient operation. A technique for fault categorization and detection in power systems is created using machine learning. The application of artificial intelligence to power system security is not entirely new, dating back at least to the early 1990s [16]. Machine learning is a branch of artificial intelligence concerned with training computers how to respond in settings for which they were not specifically intended [17-18]. The main goal of machine learning is to develop algorithms that can self-learn by training on massive volumes of data (possibly with known results). Three separate learning strategies are used by machine learning algorithms.

• Unsupervised Learning
• Semi-Supervised Learning
• Supervised Learning

3.1 Unsupervised Learning

Machine learning algorithms to cluster and analyse unlabelled data are used in unsupervised machine learning, also called as unsupervised learning. These algorithms find data groupings or hidden patterns without the need for human input. It is an ideal choice for cross-selling tactics, image recognition, customer segmentation and exploratory data analysis because to its ability to find contrasts and similarities in information. There is no outcome is known and no labelling of input data.

3.2 Semi-Supervised Learning

Semi-supervised learning is a broad category of machine learning methods that employ both unlabelled and labelled data. It is, as the name indicates, a hybrid of unsupervised and supervised learning approaches. In principle, the main notion of semi-supervision is to treat a datapoint differently on the basis on whether or not it has a label: for unlabelled points, the algorithm will minimize the difference in predictions across other comparable training instances; for labelled points, the algorithm will update the model weights using standard supervision.

3.3 Supervised Learning

Artificial intelligence and machine learning are subfields of supervised learning. It is described as the use of labelled datasets to train algorithms that accurately classify outcomes or data. When input data is introduced into the model, it updates its weights as part of the cross predicts -validation process. This type of learning assists firms in dealing with a wide range of real-world circumstances. A model is trained through a learning process that requires predictions to be produced and then corrected if they are erroneous. The training technique will be repeated until the desired outcome is obtained. A certain level of accuracy is achieved on the training data. Input Training data/ information is referred to as training data/information [19].

4. FAULT DETECTION METHODOLOGY

Normally, fault detection happens before categorization and estimation of location. The extracted properties are used to discover faults. When using a self-governing technique for fault detection, the classifier and locator are only activated when the defect has been confirmed. Furthermore, when classifiers and locators can distinguish between healthy and aberrant states, no fault detection techniques are required. This section, however, covers a variety of fault detection approaches.

Negative sequence components were used to discover faults by Joe Air Jiang, Cheng Long Chaung, Yung Chung Wang, Chin Hung Hung, Jiing Yi Wang, Chien Hsung Lee, and Ying Tung Hsiao [20]. A joint fault indicator is formed by convolution of partial differential with regard to (w.r.t.) time of negative sequence components with a triangle wave to limit the potential of inaccurate fault detection (JFI). This defect detection approach based on JFI is robust to both amplitude and frequency variation. A wavelet-based approach for detecting defects in transmission lines in real time is provided [21]. The technique is not exaggerated by the choice of mother-wavelet, and there is no time delay for fault identification for both long and compact wavelets.

Many studies [22-24] have been conducted to identify high impedance faults (HIF), because conventional approaches may fail to detect HIF. D C T Wai and X. Yibin extracted high-frequency data for HIF identification using the Discreate wavelet transform with a quadratic spline mother wavelet [22]. In [23], the wavelet coefficient from the Discrete wavelet transforms and translated scale coefficients are used to detect HIF. Principal component analysis is used to find the mean of DWT coefficients in order to reduce the dimensionality of the features across different frequency bands [24].

Typically, the fault detection time has minimal influence on the overall performance of the protection system, which includes techniques for problem detection, classification, and localisation. Fault detection typically takes 2-10 ms, whereas fault type categorization takes 30 ms. Table 1 compares numerous defect detection methods, taking into account the algorithm employed, complexity level, inputs, used system, features, software used, and outcomes. The complexity of an algorithm is characterized as basic, medium, or complicated based on the number of inputs and rules involved in its development. Furthermore, the level of complexity is influenced by feature training, convergence, testing time, accuracy, and variance, as well as the amount of data required.

5. FAULT CLASSIFICATION METHODOLOGY

Scholars are becoming increasingly interested in developing robust, distinct, and exact fault-type categorization algorithms. The bulk of existing categorization methods depend on classifiers and statistical learning theories [34], with some relying on logical approaches [35]. Advances in machine learning and pattern recognition techniques are critical to the improvement of fault categorization methodologies. The next section examines fault-type categorization approaches in depth.

5.1 Fault Categorization based on Support Vector Machine (SVM)

In 1995, Corinna Cortes and Vladimir Naumovich Vapnik developed the algorithm known as Support Vector Machine (SVM) [36]. A theoretical foundation can be found in [37]. SVM classifiers discover optimum hyperplanes that maximize the difference between two items. Because of its risk-minimizing capabilities, SVM avoids over-fitting and does not fall into local optima, making it an appealing tool for categorization of power system fault in transmission lines. For ready post-fault diagnosis, a knowledge-based technique depends on support vector machines is presented. SVMs are used as an intelligence tool to identify faulty lines originating from substations and to determine their distance from them. SVMs are also compared to radial-based neural networks in datasets representing various transmission system faults. M Sanaye-Pasand et al. and Urmil B. Parikh et al used SVM on series compensated TLs for fault classification, using a separate SVM for ground and three SVMs for three-phases[38,39].The characteristics retrieved by the DWT are fed into SVMs in [40-42]. SVM classifiers in [43,44] were trained using S-transform features. To identify and categorize the errors, N. Shahid, S. A Aleem, N. Zaffer and I.H. Naqvi used a quarter sphere support vector machine (QSSVM) [45].

5.2 Fault Categorization based on Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is a model of information processing that is based on biological neural networks. It is made up of a huge number of highly linked processing components (neurons) that work together to solve issues. Where data characterizing the problem behaviour is available, ANN is an efficient choice for problem solving. It has recently emerged as a sophisticated and accurate solver for power system problems such as

Table1. Comparison of fault detection methods

Reference No.	25	26	27
Authors	M. Ahanch, M. S. Asasi and R. McCann	Wang, H.; Keerthipala, W	Aparnna A; SabeenaBeevi K; Serene Benson; Asif Ali A; Ahamad Dilshad; Deepa S Kumar
Result	100% accuracy for fault detection.	Fault Detection under 10 msec	Accuracy of 99.19 % achieved and Decision Tree has higher accuracy than Navies Bayes and KNN.
Complexity	Medium	Medium	Complex
Simulation tools	PSCAD/EMTDC, MATLAB	PSCAD/EMTDC	PSCAD 2015, MATLAB 2015
Features	1)The Sampling Frequency of 20KHz. 2) Db4 is chosen as the mother wavelet. 3)When difference detail coefficient is level 1 more than predefined threshold value then fault is revealed.	1)Fuzzy controllers and back-propagation are used. 2) FFT is employed to eliminate high harmonic components.	1)5000 Samples per case for infinite bus. 2) 10000 samples per case for WSSC 9-bus system. 3) Test data and Training Data is in the ratio of 70:30. 4)Input data if fed to three different algorithm KNN, DT, Navies Bayes
Test system	100 km, 60 Hz	220 kV, 177.4 km, 50 Hz	24kV line to line voltage,60Hz, 2220 MVA
Input	Current Samples	Fault current and voltage samples	Current and Voltage Signal, Voltage Waveform
Name of Approach	Discrete Wavelet Transform with Harris Hawks ptimisation	Fuzzy-neuro method	Modified CNN (Convolutional Neural Network)
Reference No.	28	29	30
Authors	Silva, K.M.; Souza, B.A.; Brito, N	Tayeb, E.B.	Hong, C.; Elangovan, S
Result	Fault Detection accuracy of 100%.	Highly Satisfactory	Accuracy of fault detection is 99.7% for a single line and 92% for parallel lines.
Complexity	Complex	Medium	Complex
Features	1) 1200 Hz is the sampling frequency. 2) From 1 to -1 are the normalizing voltage and current signals. 3) The mother wavelet is determined to be Db4. 4)Simulating a 720 fault has been researched.	1) There are three distinct layers. Input, Output and hidden layer consist of 6,5 and 4 layers Respectively. 2) Implementation of neural network back propagation	1) A 200 kHz sampling frequency is used. 2) For signals divided into three levels, the mother wavelet Db5 is selected. 3) The simulation of the 3960 faults has been examined. 4) This method employs a neural network based on adaptive resonance theory.
Test system	230 kV,188 km, 60 Hz	220kV, 100km, 60Hz	500 kV, 200miles,50Hz
Input	Current and Voltage signals	Current and Voltage Samples	Current and voltage waveforms
Name of Approach	DWT and ANNs	Artificial Neural Network	WT and self-organized artificial neural network
Reference No.	31	32	33

Authors	Yadav, A.; Swetapadma, A	Gupta, O.H.; Tripathy, M	Perez, F.E.; Orduna, E.; Guidi, G
Result	Fault Detection accuracy of 100%	Fault Detection under 20ms	Fault Detection accuracy of 100%
Complexity	Complex	Complex	Complex
Features	1) Up to three layers of WT are employed to process the present samples. 2) The relay setup covers 90% of the total load.	1) The sampling frequency is one kilohertz. 2) Decisive for low- and high-resistance faults 3) High-speed communication links function well with the pilot relaying strategy.	1) 500 kHz is the sampling frequency. 2) Db4 is selected as the mother wavelet, and current signals are divided into up to three stages using this wavelet. 3) Using this method, a directed zone is obtained. 4) Research has been done on 5328 fault simulation.
Test system	400 kV, 100 km, 50 Hz	400 kV, 300 km, 50 Hz with a Static VAR compensator	500 kV, 864 km, 50 Hz
Input	Current signals	Current andVoltage profiles at both ends of transmission line.	Current signals
Name of Approach	Linear discriminant analysis (LDA) and WT	Superimposed sequence components based integrated impedance (SSCII)	Bayesian classifier and adaptive wavelet

sload forecasting, fault diagnostics, and security evaluation. The applications of ANN in powersystem have been briefly presented by Vidya Sagar S.Vankayala and Nutakki D.Rao [46] and M. Tarafdar Haque and A. M. Kashtiban [47]. Thomas Dalstein and Bemd Kulicke suggested a method for fault analysis of high-speed protective relaying systems based on multi-neural networks. For fault classification, this system employs digital signal processing implementation and a neural network design idea [48]. M. Oleskovicz et al. proposed the ANN approach as yet another methodology for fault categorization and fault localization duties for transmission system protection systems investigated in this research. The method employs current and voltage samples as inputs and aids in the detection of all forms of problems [49]. M. Oleskovicz, D.V. Coury, R. K. Aggarwal suggested a method for studying the hidden link in input patterns utilizing current signals for fault identification, categorization, and localization in a quarter cycle. This method demonstrates that it is capable of producing correct results for various combinations of fault circumstances [50]. Tahar Bouthiba [51] used ANN to design a system for extra high voltage (EHV) transmission lines for fault diagnosis and localization using terminal line data for high-speed protection. Anamika Jain et al. proposed utilizing just current signals obtained at local ends to detect and categorization faults on a double circuit overhead line with a double end in feed [52]. Suhail Muhammad Ali and Muntaser Abdulwahid Salman developed an ANN-based protected relaying pattern categorization technique. This technique reveals that severe three-phase trips on four discretionary locations of unregulated overhead cables are simulated [53]. Eisa Bashier, M. Tayeb Orner and AI Aziz AlRhirn have demonstrated the use of BP that is back-propagation neural system design as an alternative technique for defect analysis. The distance protection plan is separated into multiple neural systems in this study for fault classification in different locations [54]. Moez Ben Hessine et al. devised a method that makes use of the voltage and current of each phase. The artificial neural network's outputs show the presence and type of the fault. The procedure approaches information from current and voltage testing on a terminal-like contribution to the associated ANN for fault classification at each stage [55]. B. Y Vyas, B. Das and R.P Maheshwari [56] employed a Chebyshev neural network (ChNN) to classify faults in TLs. In ChNN polynomials, functional expansion is used to move the original input into higher-dimensional space; the hidden layer is swapped, leaving the network with only one layer [57]. Because of its single-layer structure, ChNN only requires one parameter to be changed, making it easier to implement than other Artificial Neural Network models that produce efficient fault classification results.

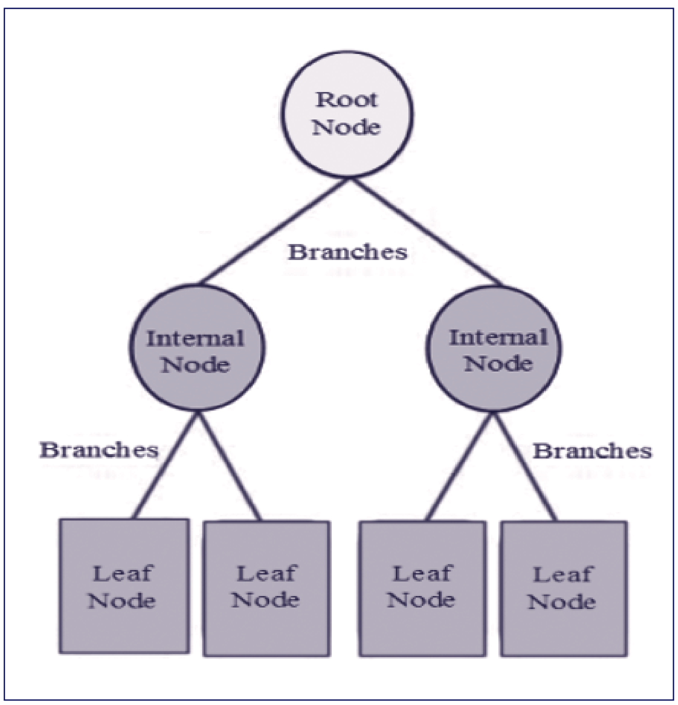
5.3 Fault Categorization based on Bayesian Learner (Naïve Bayes)

Bayesian classifiers are statistical classifiers that use supervised learning methods to predict the likelihood of class membership. The Bayesian classification approach is based on the Bayes theorem, which provides practical learning methods that combine prior knowledge with observed data. A probabilistic learning model is the Bayesian theory of learning [58]. It is employed in decision-making and inferential statistics dealing with probability inference. Because of reciprocal contact between circuits, parallel transmission cables are difficult to secure. To secure a parallel transmission line with inter-circuit faults, fault detection and categorization approaches depend on the Naïve Bayes classifier can be utilized. This classification approach is appropriate for larger data sets since it has greater accuracy and time is less for training process [59-60].

5.4 Fault Categorization based on Decision Tree (DT) Technique

The term decision tree (DT) refers to graphs that can make choices, and its fundamentals are covered in [61, 62]. There are three sorts of nodes in Decision Tree: leaf nodes, internal nodes, and root nodes. For categorization, decision making begins at the root node, and leaf node represented the class label [63]. Using training data, greedy algorithms, such as C4.6, Iterative Dichotomiser 3, regression tree and classification and regression tree (CART), produce a suboptimal decision tree with higher accuracy in a reasonable amount of time [62]. [64] employs a random forest (RF) composed of a finite number of Decision Trees for fault categorization in double and single circuit transmission lines.

Figure 3: Decision tree layout



5.5 Fault Categorization based on ADAPATIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Adjustable Neuro Early in the 1990s, a hybrid intelligent system called the fuzzy interference system was developed with the intention of fusing the best aspects of fuzzy systems with neural networks. It has the potential to utilize the advantages of both in a single framework since it combines the fuzzy logic qualitative approach and adaptive neural network capabilities to improved performance through its learning capability an adaptive network-based fuzzy inference system was utilized by Javad Sadeh and Hamid Afradi [65] to present a novel method for problem identification in transmission networks comprising both overhead lines and underground power cables. For fault classification, section identification, and precise fault localization, a three-stage approach utilizing the Adaptive Neuro Fuzzy interference system network was used. One Adaptive Neuro Fuzzy interference system with four inputs basic three phase currents and zero sequence current was used to identify different fault kinds. Second, an Adaptive Neuro Fuzzy interference system is used for section identification, regardless of whether faults develop in cables or overhead lines. The other eight Adaptive Neuro Fuzzy interference system networks were used to find the faults. Based on a neuro-fuzzy inference system, Thai Nguyen and Yuan Liao [66] proposed an adaptive approach for the categorization of 10 common types of faults in transmission networks. Seven distinct properties are extracted from current waveforms using inter-quartile ranges and correlation coefficients, then used as inputs to the adaptive nervously interference system for classification decision-making. They used two designs for Adaptive Neuro Fuzzy Interference Systems—one with 10 rules and the other with 128 rules—and found that while the 10-rules-based system is easier to use and requires less training time than the 128-rules-based system, the latter is more accurate.

5.6 Fault Categorization Based on K-nearest Neighbors

The KNN or k-NN algorithm, sometimes referred to as the k-nearest neighbors classifier, is a non-parametric supervised learning classifier that makes predictions or classifies the grouping of a single data point using proximity. Although it may be applied to classification or regression issues, it is most frequently employed as a categorization approach since it relies on the idea that similar points can be found nearby. The KNN technique is a safe, supervised machine learning approach that may be utilized to address regression and categorization issues. It is simple to build and comprehend, but when the amount of that information grows in use, it has the severe disadvantage of being significantly slow. Faults may be detected and recognized in distance protection using the k nearest neighbor method. The time of error incidence and the faulty phases are identified in these approaches by computing the gap between each sample and its nearest neighbour in a pre-default frame. For detection and classification methods, the greatest distance value is compared to predetermined threshold values. The main advantages of these approaches are their simplicity, decent accuracy, low computation pressure and speed [67-70].

Table 2 compares several fault-type classification algorithms based on the technique utilized inside the algorithm, complexity level, test system, characteristics, software used, input, and outcomes. In this context, complexity is classified as basic, medium, or difficult based on the number of inputs and rules involved in algorithm construction. Furthermore, the complexity level is determined based on testing duration and feature training, convergence, accuracy & variation, data necessary.

Table 2. Comparison of fault categorization Techniques

Reference No.	69	70	71
Authors	Abdelhadi Recioui, Brahim Benseghier, Hamza Khalfallah	Prerana P. Wasnik, Dr. K. D. Thakur, Dr. N. J. Phadkule	A. Jamehbozorg and S. M. Shahrtash
Result	Fault categorization satisfactorily performed	Fault categorization accuracy of 97%.	Fault categorization accuracy of 100% carried out under 2.5msec.
Complexity	Simple	Simple	Medium
Features	1) Matrixes of samples and training have the same number of columns, which is 35322. 2) When a fault occurs, an algorithm uncovers the hidden data in the current waveform, which is then appropriately converted to uncover the fault signature and define the fault.	1) A total of ten different types of faults were considered. 2) At the generating bus, input is monitored, and output is fault class designated. 3) The fault is found to correspond to the kth minimal distance between marked locations by computing the distance between each labelled sample and the new or untagged sample.	1) A sampling rate of 10 kHz is used. 2) There are 13200 examples in all that are taken into consideration, and the training lasts for 15 minutes. 3) The phasor of odd harmonics up to and including the 19th harmonic is calculated using the half-cycle discrete Fourier transform (HCDFT).
Test system	IEEE-14 Bus system	735kV,300km,60Hz	400kV,100km double circuit transmission line
Input	Current and Voltage samples	Current Value	Current Value
Name of Approach	KNN (Kernel nearest neighbour) (From Waveform)	KNN (Kernel nearest neighbour) (From values)	Decision Tree
Reference No.	72	73	74
Authors	G. Sharma, O. P. Mahela, M. Kumar and N. Kumar	A. Ferrero, S. Sangiova-nni and E. Zappitelli	O. A. S. Youssef
Result	Current based scheme is more effective than voltage-based scheme and Fault classification satisfactorily is performed.	Fault classification under 500 micro second.	With 99% accuracy, the fault categorization time is less than 10 msec.
Complexity	Medium	Medium	Complex
Features	1)Stockwell Transform is used to obtain S-matrix. 2)Sampling Frequency is 2KHz. 3)With the help of DCFI fault is detected.	1) The proposed scheme uses an 8-rule fuzzy set approach. 2) Correct symmetrical current component even when harmonic and exponentially decaying components are present. 3) Simulation of various fault scenarios on a typical Italian HV transmission line.	1) A 4.5 kHz sampling rate is set, and a Db8 mother wavelet is employed. 2) There are four layers in the wavelet. 3) Fault categorization is done online. 4) Fault categorization is quick, reliable, and accurate.
Test system	220kV,50km,60Hz	380kV, 400km, 60Hz	400 kV, 300km, 60 Hz
Input	Current Signal	Current value	Current Signal
Name of Approach	Decision Tree with Stockwell Transform	Fuzzy set	Fuzzy logic and WT based method

Reference No.	75	76	77
Authors	B. Das and J. V. Reddy	G. V. Raju and E. Koley	T. Dalstein and B. Kulicke
Result	Fault categorization accuracy of 97% carried out under 10 msec.	Fault categorization under 10 msec.	7 msec is the fault-type categorization time
Complexity	Medium	Medium	Simple
Features	1)2400 Fault Simulation has been studied. 2) The Half-cycle discrete Fourier transform (HCDFT) technique is used as it is faster than DFT. 3)In terms of prefault power level, fault resistance, and fault inception angle, it has a broad range of efficacy.	1) 3840Hz sampling frequency, i.e., 64 samples per 60 Hz. 2) The signal was subjected to a 2nd order low pass Butterworth filter with a cut-off frequency of 480Hz. 3) Variations in fault resistance, fault location, or inception angle have no impact on the suggested design.	1) The sampling rate is set to 1.1 kHz. 2) There are two hidden layers, 11 output nodes, and 30 input nodes. 3) There are 45000 training patterns.
Test system	400kV,300km, 50Hz	500kV,300km,60Hz	380 kV, 100 km Double circuit
Input	Current Signal	Current Signal	Current and voltage samples
Name of Approach	Fuzzy Logic	Fuzzy logic with STATCOM	FNN
Reference No.	78	79	80
Authors	Subrata K. Sarker, Shahriar Rahman Fahim, S.M. Muyeen, Sajal K. Das, Innocent Kamwa	A. Elbaset, Adel & Hiyama, Takashi	Nguyen, T.; Liao, Y
Result	Fault categorization accuracy is not less than 99.47% and highest is 99.72% in single cycle time	Error is less than 0.2 %.	Fault categorization accuracy is more than 99.92%
Complexity	Complex	Medium	Medium
Features	1) 20KHz sampling rate 2) Db4 mother wavelets are used. 3) Wavelet decomposition tree for input signals up to level 5 4) A 5 x 40-dimensional wavelet detail level coefficient matrix. 5) There are 38115 fault cases considered in total. 6)Free from noise and errors.	1) A total of 9896 fault cases are considered, of which 71% (7040) are used for training purposes and 29% (2856) for testing purposes during the Fault Detection stage. 2) A total of 8860 fault cases are considered, of which 6860 are used for training purposes and 2000 for testing purposes during the fault classification stage.	1) a system of 128 rules with seven inputs and two membership functions. 2) 30.24 kHz is used as the sample frequency. 3) To aid in training, 2660 fault situations were taken into account.
Test system	400kV,100km,50Hz	400kV,200km,50Hz	500 kV, 20 km,50Hz
Input	Current and Voltage Signal	Current and Voltage Value	Current Samples
Name of Approach	Deep Learning	ANFIS	ANFIS

Reference No.	81	82	83
Authors	Rao, P. Srinivasa and Brijesh Naik	Pushkar Tripathi, Abhishek Sharma, G. N. Pillai, Indira Gupta	Jafarian, P. Sanaye-Pasand
Result	Fault categorization satisfactorily is performed.	Accuracy around 100 %	Fault Categorization is 100% accurate
Complexity	Medium	Medium	Medium
Features	1)A sampling frequency of approximately 12.5kHz. 2) The mother wavelet is Daubechies Wavelet db4. 3) Approximately 1000 fault cases are considered. 4) Wavelet MRA approach. The sixth level's sum of detail coefficients is taken from the current signal.	1) A total of 15840 data points is considered, 5840 of which are used for training and another 10,000 for testing. 2) A sampling rate of around 1000Hz. 3) A 5-fold CV is used to modify the SVM parameter connected to the RBF kernel(γ) utilizing regulatory parameter C.	1) The sampling frequency is 160 kHz, and signals are divided into 5 levels. 2) There are 1500 instances of fault. 3) SVM was tested using 700 of the remaining 800 faults after training. 4) To eliminate random noise, the wavelet transform is applied.
Test system	400kV, 300km,50Hz	400kV, 300km,50Hz	230 kV, 330 km, 50 Hz
Input	Current Signal	Current Samples	Current samples
Name of Approach	Pattern Recognition	SVM for TCSC Compensated Transmission Line	Dyadic WT and SVM
Reference No.	84	85	86
Authors	R. K. Aggarwal, A. T. Johns and A. Bennett Q. Y. Xuan, R. W. Dunn	Samantaray, S.R.; Dash, P.	Valsan, S.P.; Swarup, K. S
Result	Mis categorization rate is less than 1%	The accuracy of fault classification is 98.62%, while the accuracy of fault section identification is 99.86%.	Time to categorize a fault is 6 ms, and accuracy is 100%.
Complexity	Simple	Complex	Complex
Features	1) Three sample data windows are used to collect the findings, and the sampling frequency is 800 Hz. 2) There is a significant correlation between the quantity of training sets and the number of Kohonen neurons. A BP network classifier is utilized as a front end to the output layer in supervised learning.	1) A scalable Gaussian window is used for ST with a sampling rate of 1 kHz. 2) The characteristics are standard deviation and energy. 3) Out of 500 datasets, 200 were used for testing and 300 for training.	1) The sampling frequency is 2 kHz. 2) A mother wavelet of type Db6 is employed. 3520 test cases in all were produced. 4) In order to avoid the necessity for multipliers, Karrenbauers transformation is employed.
Test system	Double circuit 128 km Tr Line	300 km long TL. Operate at 230 kV with (TCSC), 50 Hz	400kV,300 km, 50Hz
Input	Current and voltage samples	Current signals	Current signals
Name of Approach	Back-propagation network classifier	ST and PNN	Field-programmable gate array (FPGA) with WT

Reference No.	87	88	89
Authors	Huibin, J	Vyas, B.; Maheshwari, R.P.; Das, B	Gao, F.; Thorp, J.S.; Gao, S.; Pal, A.; Vance, K. A
Result	Fault categorization accuracy of 100%	Fault categorization accuracy of 99.93%	Fault categorization accuracy of 99.98%
Complexity	Complex	Medium	Medium
Features	1) The sampling rate is 500 kHz. 2) Db4 is the mother wavelet. 3) There are 546 fault cases that are taken into account for training.	The sampling rate is 4 kHz.	1) CART is a non-parametric DT learning technique with if-else statements. 2) 2880 fault cases were examined
Test system	500 kV,390 km,50Hz	400 kV,300 km. TCSC is installed at the midpoint	300 km, 345 kV,50 Hz
Input	Current signals	Current signals	Positive sequence voltages
Name of Approach	Bayesian classifier with adaptive wavelet algorithm	Polynomial-based ChNN and discrete wavelet packet transform (DWPT)	CART algorithm

6. CASE STUDY

A case study is considered to understand fault categorization and detection techniques. Consider the below-shown system of a 100km transmission line with the system parameters shown in figure 4.

Source: 60MVA,50Hz,400kV.

Source impedance: 0.2+j2.45.

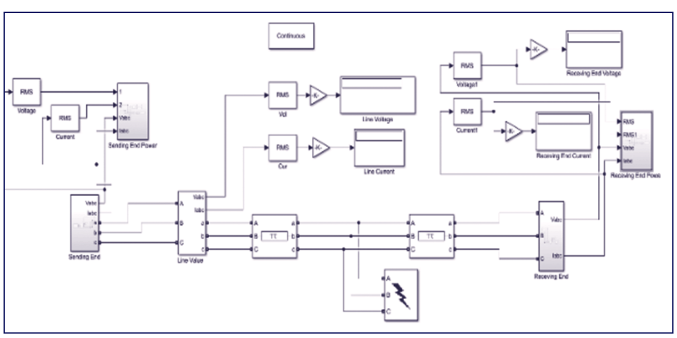
Positive Sequence Resistance: 0.01273Ω/km

Zero Sequence Resistance: 0.3864 Ω/km

PositiveSequenceInductance:0.9337 mH/km

PositiveSequenceInductance:0.9337 mH/km
Zero Sequence Inductance: 4.1264 mH/km
Positive Sequence Capacitance: 12.74 nF/km
Sequence Capacitance: 7.751 nF/km

Figure 4: Transmission line model



Loads: The active and reactive powers of load are 200 MW and 20 MVAr, respectively. [78]

The pattern for the fault detection and Categorization procedure at various locations, accounting for all ten types of faults, including L-G, L-L, L-L-G, L-L-L-G and L-L-L was established using a case study. The outcomes have been found.

Any location along the transmission line is susceptible to faults. The fault's location affects post-fault voltage transients. Therefore, it is crucial to carry out studies to assess how well the suggested design performs at various locations where faults occur. Five fault sites were examined in this analysis, accounting for 20%, 40%, 60%, and 80% of the total length of the transmission line.

The findings are displayed in a table 3, from which the next conclusions are drawn.

1. If I_a greater than threshold value; I_b and I_c approximately at threshold value then Fault AG is occurred.
2. If I_b greater than threshold value; I_a and I_c approximately at threshold value then Fault BG is occurred.
3. If I_c greater than threshold value; I_a and I_b approximately at threshold value then Fault CG is occurred.
4. If I_a and I_b greater than threshold value; I_c approximately at threshold value then Fault ABG is occurred.
5. If I_c and I_b greater than threshold value; Ia approximately at threshold value then Fault BCG is occurred.
6. If I_a and I_c greater than threshold value;I_b approximately at threshold value then Fault ACG is occurred.
7. If I_a and I_b greater than threshold value and V_a and V_b are same; V_c and I_c approximately at threshold value then Fault AB is occurred.
8. If I_c and I_b greater than threshold value and V_b and V_c are same; V_a and I_a approximately at threshold value then Fault BC is occurred.
9. If I_a and I_c greater than threshold value and V_a and V_c are same; V_b and I_b approximately at threshold value then Fault AC is occurred.
10. If I_a, I_b and I_c greater than threshold value then fault ABC occurred,

Table 3: Different fault Incidents

Type of fault	Phase	Distance (km)			
		20	40	60	80
AG	A	**3.5543**	**3.167**	**2.8808**	**2.6689**
	B	0.9292	0.9296	0.9302	0.9306
	C	1.0352	1.0513	1.0666	1.0815
BG	A	1.0353	1.0515	1.0672	1.0818
	B	**3.3277**	**3.0141**	**2.7819**	**2.6052**
	C	0.9291	0.9293	0.9294	0.9301
CG	A	0.9291	0.9294	0.9297	0.9303
	B	1.035	1.0512	1.0664	1.0811
	C	**2.4565**	**2.3715**	**2.2949**	**2.2285**
ABG	A	**3.9476**	**3.8198**	**3.7069**	**3.6047**
	B	**3.6753**	**3.5782**	**3.4803**	**3.3837**
	C	0.9637	0.9823	0.9995	1.0156
BCG	A	0.9639	0.9866	1	1.0162
	B	**3.366**	**3.1245**	**2.2651**	**2.8512**
	C	**2.406**	**2.3452**	**2.3075**	**2.2733**
ACG	A	**3.6151**	**3.2953**	**2.9467**	**2.8911**
	B	0.9691	0.9718	.9996	1.0087
	C	**2.6318**	**2.6769**	**2.7643**	**2.6799**
AB	A	**3.9286**	**3.832**	**3.7399**	**3.652**
	B	**3.354**	**3.2518**	**3.1543**	**3.061**
	C	1.0003	1.0003	1.0003	1.0003
BC	A	1.0003	1.0003	1.0003	1.0003
	B	**2.879**	**2.836**	**2.7944**	**2.7541**
	C	**2.0258**	**1.9836**	**1.9414**	**1.9013**
AC	A	**2.4156**	**2.3298**	**2.2532**	**2.1804**
	B	1.0003	1.0003	1.0003	1.0003
	C	**3.1604**	**3.0868**	**3.0166**	**2.9502**
ABC	A	**3.947**	**3.8572**	**3.7461**	**3.6401**
	B	**3.677**	**3.5904**	**3.5071**	**3.4273**
	C	**2.5038**	**2.4241**	**2.4068**	**2.362**

7. CONCLUSION

This study provides a complete review of fault detection and categorization in transmission lines. A variety of approaches and methodologies are discussed in addition to exemplary works. For fault-type classification, researchers frequently use machine learning-based approaches. Adaptive Neuro Fuzzy interference system-based promising algorithms such as Convolution neural system and Restricted Boltzmann Machine are recommended for fault categorization in addition to Support vector Machine, Naïve Bayes, Artificial Neural Network and Decision Tree. A tabular comparison study on fault detection and categorization is also offered, taking into account characteristics, inputs, complexity, system employed, software tool, and outcomes. This work may give fundamental development for researchers as well as future research directions in this sector.

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