Machine Learning Framework For Power System Fault Detection And Classification

Baskar. D, Dr. Selvam. P

Abstract: The modern power system requires real-time monitoring and fast control to be protected from faults on transmission lines. The detection and classification of faulty conditions in power systems is a task of crucial importance for reliable operation. The traditional fault diagnosis methods rely on the manual feature extraction of engineers with prior knowledge that has been proposed by several researchers for fault detection and classification. It is highly necessary to identify faults in any analog circuit to ensure the circuit's reliability. Early diagnosis of faults in a circuit can help to maintain the system significantly by avoiding potentially harmful damage from the fault. Automatically and accurately identifying the incipient micro-fault in the power system, especially for fault orientations and severity degree, is still a significant challenge in the field of intelligent fault diagnosis. Intelligent fault diagnosis methods based on machine learning become a research hotspot in the fault diagnosis field. In this paper, various machine learning algorithms are discussed.

Index Terms : Power System, Machine Learning, Fault Detection, Fault Classification.

1 INTRODUCTION

The power transmission network is the most vital link in the country's energy system as it carries massive quantities of power from generators to substations at high voltages. The modern power system is a complex network that demands a high-speed, accurate, and reliable system of protection. Faults in the power system are inevitable, and there are usually higher overhead transmission line failures connected to other major components. Not only do they influence the system's reliability, but they also have a widespread effect on end-users. Additionally, as the configurations become more complex, the complexity of protecting transmission line configurations increases, predicting faults (type and location) with considerable accuracy, therefore, improves the power system's operational reliability and stability and helps prevent colossal power failure. With 85%-87% of power system failures occurring on distribution lines [1], power quality has become a significant concern in power system engineering in recent years. Faults in power systems may arise due to various reasons however these faults must be predicted and diagnosed as early as possible if not it may sometimes lead to the blackout of the entire systems following which it affects the customer even though a lot of necessary protection devices are employed in the detection of faults. Still, it is necessary to predict the faults in advance to overcome the above-said problems. Digital technology was introduced with the introduction of a smart grid enabling the installation of sensors along the transmission lines that can capture live fault data because they present useful data that can be used to detect disruptions in transmission lines [2]. A considerable amount of heterogeneous data continuously collected by the growing number of distributed low-cost and high-quality sensors, such as Remote Terminal Units, Phasor Measurement Units, and smart meters, along with those generated by other measuring devices [3-4] is required for the operational control and performance analysis of smart grids. Conventional time-domain techniques are inefficient in computational terms and may not meet real-time application specifications [5-6]. Application of machine learning algorithms on the transmission line for fault classification and location identification has been explored in this research. We can learn without direct programming from the data and, once exposed to new data, can respond independently [7]. Most researchers believe that the approach of machine learning (ML) such as artificial neural networks (ANNs), decision trees (DTs), deep learning models, etc. is capable of providing interesting information on safety in power systems. [8-14]. With the introduction of the smart grid, the operation, monitoring, and regulation of the power system is becoming smarter and supported by machines. In line with the fundamental goal and point of view of smart power grids, recognition of transmission line fault patterns and clearance of faults must be done more intelligently, judiciously, and automatically, with less intrusion from the operator.

The innumerable extent of power systems and application requires improving suitable fault classification techniques in power transmission systems, increasing system efficiency, and avoiding significant damage. The paper analyzes the scientific literature and summarizes the most relevant approaches that can be applied in power transmission systems to fault identification methodologies. The research presented in this paper

- *Baskar D, Research Scholar, Department of Electrical & Electronics Engineering, Vinayaka Mission's Kirupananda Variyar Engineering College, Vinayaka Mission's Research Foundation (Deemed to be University), Salem, Tamil Nadu, India*
- *Dr. Selvam P, Professor & Head, Department of Electrical & Electronics Engineering, Vinayaka Mission's Kirupananda Variyar Engineering College, Vinayaka Mission's Research Foundation (Deemed to be University), Salem, Tamil Nadu, India*

2 POWER GENERATION

2.1 Generation

The generation process involves the conversions of available energy in different forms into electrical energy. The chief sources of energy available for generation in various forms are

- Thermal Energy.
- Solar Energy.
- Hydro Energy.
- Wind Energy.
- Nuclear Energy.
- Tidal Energy.
- Fuels

All the above said forms of energy could be converted into electrical energy by the use of suitable arrangements. Due to the need to reduce greenhouse gas emissions and introduce mixed energy sources, electricity production is increasing dramatically around the globe. The power network faces tremendous transmission and distribution challenges due to unpredictable regular and seasonal fluctuations [15].

2.2 Transmission and Distribution
The bulk powers generated in generating stations are connected to the distribution system through the transmission line by which various power grids are connected. Electrical power generated at the voltage level of 11 kV to 25 kV is stepped up to the transmission level in the range of 66 to 765 kV or even higher in some countries such as 1200 kV. This electricity is transmitted by electrical transmission and distribution (T&D) lines for consumption [16].

2.3 Sub Station
At the gantry and in the intermediate places in the transmission line, it is necessary to change some characteristics (i.e., a.c to d.c voltage, Frequency, etc.) of power supply to achieve a smart efficiency towards the receiving end. The assembly of required apparatus such as a transformer, etc. are used for this purpose. Likewise, at the receiving end near the consumers' localities, the voltage may be stepped down to the recruitment level. All these activities are done in the substation. Even in some utility, it is required to convert a large quantity of a.c. Power to d.c. Power. So it clear that the type of equipment needed in the substation is depended upon the particular service requirement. If the sub-transmission network is optimally designed, it will, on the one hand, adequately supply the distribution system loads and, on the other hand, result in the efficient design of the transmission network [17].

2.4 Faults
Basically, the power system equipment or appliances are so designed in such a manner to perform a continuous required function except in case of preventive maintenance or due to lack of external sources. The fault is the random character that may appear in the power system, and due to this inability to perform the required function, since the fault can occur at any situation and any location in the power system, the fault is random.The balanced three-phase a.c.is the steady-state operating mode of a power system, due to adverse external and internal changes in the system, the above condition is disrupted. In any case, if the insulation of the system fails in the following particular locations such as Phase conductors or Phase conductor and earth or any earthed screens surrounding the conductors, the fault will occur. Leading causes of faults: Faults in the power system occurs due to the numerous causes mainly it is categorized in two ways as follows

1. Breakdown or failure at typical voltages because of deterioration of insulation, damage due to unpredictable causes such as an unfortunate tree falling across the line, vehicles colliding with towers or poles, short-circuiting by birds.
2. Breakdown or failure at abnormal voltages because of Lightning or Switching surges, Arcing ground.

TABLE 1: *POSSIBILITY OF FAULTS ON DIFFERENT EQUIPMENT IN POWER SYSTEMS*

Equipment	Percentage %
OH lines	50
Cables	10
Transformers	9-12
Switchgear	13-15
Control equipment	2-3
Instrument Transformer(CTs and PTs)	1-2
Miscellaneous	8-10

In most cases, the possibility of failure or breakdown occurs in the overhead lines due because of the greater length of the conductor exposure to the atmosphere. Transmission network or Transmission lines of the power system used for the transportation of the bulk power from the sending end to receiving end (i.e., from the generating station to the load center) are because of its characteristics in nature it is always exposed to the all atmospheric condition either the temperature is high or low it is designed as per recruitment using the sag calculation by the due course this transmission line has the highest fault rate when compared to the other equipment is in the power systems. The practical study of power system failures is a critical issue in many power system research, such as network scheduling, equipment design, and alignment of protective systems [18].

2.5 Categories of Fault
In most cases, the possibility of failure or Short circuit fault is the most essential and dangerous common fault that probably occurs in the power system as already discussed this type of faults are occurred because of breakdown or failure in the insulation of current-carrying phase conductor relative to earth or in the insulation between the phases.
The fault that occurred due to a short circuit in the three-phase a.c. Power circuit is

- The Line to Line fault (L-L).
- Single line to ground fault (L-G).
- Double Line to ground fault (L-L-G).
- Phase to Phase and third Phase to ground fault.
- All the three phases to ground (L-L-L-G).
- All three phases short-circuited (L-L-L).

TABLE 2: *POSSIBILITY OF SHORT CIRCUIT FAULTS IN OH LINES.*

Type of Fault	Percentage %
Single line to ground fault (L-G).	65-70
Line to Line fault (L-L).	10-15
Double Line to ground fault (L-L-G).	8-10
Phase to Phase and third Phase to ground fault.	2-3
All the three phases to ground (L-L-L-G).	2-3
All the three phases short circuited (L-L-L).	2-3

On the type, as mentioned earlier of a fault, the first four types are said to an unbalanced operating condition because it involves only one or two-phase, and hence, it is referred to as unsymmetrical faults. i.e., in short, different current in the three phases. The last two types of faults occurred in all three phases, and so it is known as symmetrical faults i.e. equal fault current in the three phases with 120°. On compared to the all the above faults, the line to ground(L-G) fault is the most common fault that occurred in the OH lines, whereas the balanced three-phase fault is the rare one, but it is the severe fault which occurred due to the carelessness operating personnel. Fault analysis is essential for secure and high-speed protective relaying supported by digital distance protection. Therefore, a proper evaluation of these methods is required [19].

3 FAULT DETECTION AND CLASSIFICATION

The techniques for detecting a faults and classifying them make use of changes in current and voltage signals in case of fault. Techniques range from hand-coded expert-defined rules based on certain thresholds to artificial intelligence-based techniques such as ANNs, vector supporting machines, and blurred decision systems. The methods vary from hand-coded and expert-defined rules based on certain thresholds to artificial intelligence-based techniques, such as support vector machines, fuzzy decision systems, ANNs [20]. Several characteristics and signal transformations were suggested and used for detection purposes, such as Fourier and wavelet transformations. [21]. While protection of critical lines and system buses is ensured with local protection equipment such as relays and circuit breakers, the data made available by PMUs offer the potential to increase understanding and situational awareness in a power management center as also suggested in[22] using the output of a PMU-only state estimator for detection and classification of faults. In this context, the approaches in [23-24] use decision trees, and [25] employs support vector machines for this purpose. Such methods presume, as discussed above, the complete presence of all the measurements in full synchronization, given the promising results provided in these works. In the scope of this work, we have experimented with two fault detectors for the output of a PMU-only state estimator: one based on ANN and the other based on support vector machines. Because of the observed superior performance of ANN and space limitations, we restrict our discussion and findings with ANNs in the following to detect and identify faults. Further work is ongoing for a comparison of different machine learning-based techniques for power system fault detection and classification.

4 MACHINE LEARNING

Detection and classification faults in power systems are a vital activity for efficient operation. Classification and detection of faults in power systems based on machine learning is proposed. The protection of power systems based on artificial intelligence is not entirely new and dates back to at least the early 1990s [26-27]. Machine Learning is a twig of Artificial Intelligence concerned with "teaching" computers how to act without being explicitly programmed for every possible scenario [28-29]. The central concept in Machine Learning is developing algorithms that can self-learn by training on a massive number of inputs (possibly with known results). The three different learning styles in machine learning algorithms are

- Supervised Learning
- Unsupervised Learning
- Semi-Supervised Learning

4.1 Supervised Learning

A model is trained through a process of learning in which predictions must be made and corrected if those predictions are wrong. The training process continues until a desired degree of accuracy is reached on the training data. Input information/data is called training information/data and has a known spam / not-spam label or result at one time [30].

4.2 Unsupervised Learning

By deducting the structures present in the input data, a model is prepared. This may be for general rules to be extracted. It may be through a mathematical process that redundancy can be systematically reduced, or similar data can be organized. There is no labeling of input data, and there is no known result.

4.3 Semi-Supervised Learning

There is a desired problem of prediction, but the model needs to learn the structures and make predictions to organize the data. Input data is a combination of instances that are marked and unlabeled.

5 MACHINE LEARNING TECHNIQUES FOR FAULT CLASSIFICATION

Classification is a crucial step in fault prediction. The list of various classification algorithms that were widely used in the literature [31] of decision support systems presented for different domains and have been used to develop our classifiers are

- Support Vector Machine.
- Bayesian Learner (Naïve Bayes).
- Sequential Minimal Optimization (SMO).
- Logistic Regression.
- Decision Tree.
- K Nearest Neighbor (K NN).

5.1 Support Vector Machine

Post-fault studies of recent major power failures worldwide reveal, to some extent, responsibility for malfunctioning and/or inappropriate protection system coordination. When a significant power disruption occurs, safety and control action is needed to avoid the deterioration of the power system, restore the system to a healthy state, and minimize the impact of the disruption. Nonetheless, this has suggested that additional post-fault and corrective research using intelligent / knowledge-based systems need to enhance security coordination. A knowledge-based method is provided using support vector machines (SVMs) for ready post-fault diagnosis. SVMs are used as an intelligence tool to identify the faulty line arising from the substation and to find the distance from it. SVMs are also compared in datasets with radial-based neural networks that correspond to different transmission system faults. For post-fault evaluation of any relay mal-operation (a faculty or incorrect operation) following a disruption in the adjacent line connected to the identical substation, the approach is particularly important. This can help improve the process of fault monitoring/diagnosis, thereby ensuring secure power systems operation [32-34].In this research, a single vector support machine is used to identify ten types of shunt faults and fault location regression model, which removes manual work.

5.2 Bayesian Learner (Naïve Bayes)

Bayesian classifiers are statistical classifiers that use supervised methods of learning to predict the probability of class membership. Bayesian classification is based on the theorem of Bayes, which offers practical learning algorithms that combine prior knowledge with observed data. The Bayesian theory of learning is a probabilistic model of learning [35]. It is applied to decision-making and inferential statistics dealing with the inference of probability. Due to the mutual coupling between circuits, parallel transmission lines are difficult to protect. Fault detection and classification techniques based on the Naïve Bayes classifier may be used to secure a parallel transmission line with inter circuit faults. This is a suitable classification method for more massive data sets, as it takes less time and higher accuracy for the training process [36-37].

5.3 Sequential Minimal Optimization (SMO)

Training a support vector machine needs the solution of the sizeable quadratic programming optimization problem. SMO splits this major quadratic programming problem into a series of minor quadratic programming problems. Such small quadratic programming problems are analytically solved, which prevents using a time-consuming optimization of numerical quadratic programming as an inner loop. Since matrix calculation is bypassed, SMO scales in training set size for different test problems around linear and quadratic. The standard chunking SVM algorithm scales in the defined size of the learning between linear and cubic. The calculation time of SMO is determined by SVM analysis, which makes SMO the fastest for linear SVMs and sparse data sets. SMO can be stronger at least a thousand times quicker than the chunking algorithm in real-world sparse information sets [38-39].

5.4 Logistic Regression

In case the dependent variable is dichotomous (binary), logistic regression is the appropriate regression analysis to perform. Logistic regression is a statistical method, like all regression analyses. Logistic regression is rarely used in the diagnosis of power distribution failure, while the neural network has been widely used in reliability research on power systems [40-43]. In logistic regression, the dependent variable Y with interested outcome values are 1 and 0.

$$\text{Log it}(Y=1)=\ln[P(Y=1)/P(Y=0)]=\alpha+\beta X \quad (1)$$

α and β are unknown parameters to be estimated/defined using the training data using the maximum likelihood method [35].

$$P(Y=1)=1/1+e-(\alpha+\beta X) \quad (2)$$

Finally, by comparing the measured probability with the predefined threshold, the class label is applied to that test case.

5.5 Decision Tree (DT)

The design of the decision tree is straightforward, and we can easily follow a tree structure to explain how to make a decision. The fault type is recognized utilizing a decision-tree algorithm (DT) [44]. DT may be the most advanced technology to divide sample data into a collection of decision rules. Decision trees are often referred to as category trees for classification problems. The innumerable extent of power systems DT has recently been found to be highly successful in applications such as online dynamic safety evaluation [45], transient stability [46], and islanding detection [47]. DT can identify and recognize transmission line failures reliably [48]. It is applied in the power transmission network for fault detection. This defines the exact starting time of the fault with the moving waves triggered by the detector of fault and fault. Information from one side of the protected line is required for this process, and decision-making was carried out in just 2 ms, which is the best time of earlier approaches.

5.6 K nearest neighbor (KNN)

The K-nearest Neighbors algorithm is a secure, supervised algorithm for machine learning which can be used to solve problems of classification and regression. It's easy to implement and understand, but as the scale of that information increases in use, it has a significant drawback of becoming substantially sluggish. It is possible to detect faults and recognize them in distance protection based on the k-NN algorithm. In these methods, the time of error occurrence and the defective phases are determined by calculating the interval separating each sample and its nearest neighbor in a pre-default frame. The maximum distance value is compared with predefined threshold values for detection and classification procedures. Simplicity, low calculation pressure, reasonable precision, and speed are the key advantages of these methods [49-52]. The k-NN algorithm is a method of non-parametric classification that can produce high classification precision in non-normal and unknown distribution problems. K closest points separating the data and the sample are identified for a particular sample. The Euclidean distance is commonly used, where the components of one point are used to equate the components of another point. A data matrix consisting of N rows and M columns is the basis of the k-NN algorithm. Parameters N and M are, respectively, the number of data points and the dimension of each data point. A query point is given using the data matrix, and within this data matrix, the nearest k points are searched, which are the closest to this query point. In general, the Euclidean distance in the data matrix is calculated between the query and the rest of the points. N Euclidean distances are reached after this operation, symbolizing the distances between the query and each corresponding point in the data set. Then the k closest points to the query can be searched simply by sorting the distances in ascending order and finding the k points with the smallest distance between the data set and query.

6 PERFORMANCE METRICS

"True" Positive Rate, "False" Positive Rate, True Negative Rate, and False Negative Rate are the four labels obtained from the confusion matrix that is used to determine the efficiency of various machine learning approaches. The performance metrics used in this work include accuracy, precision, recall, f-measure. The trueness of the analytical result to the actual value is defined as accuracy. The probability of the sample data test is correctly performed is called precision. The recall is the probability that a sample data test is positive. F-measure (F1 score) is a measure of a test's accuracy and is defined as the weighted harmonic mean of precision and recall. The formulas used for these performance evaluations are given below.

$$\text{Accuracy} = (TP + TN)/\text{Total} \quad (3)$$

$$\text{Precision} = TP/(TP+FP) \quad (4)$$

$$\text{Recall} = TP/(TP+FN) \quad (5)$$

$$\text{F-measure} = 2TP/(2TP + FP + FN) \quad (6)$$

Where TP is the "true" positive value, TN is the "true" negative value, FP is the "false" positive value, and FN is the false negative value.

7 CONCLUSION

To ensure efficient and reliable power flow, transmission lines must be secured. Fault identification and classification are the essential safety functions of transmission lines. Considering applications for machine learning, the complex difficulties of the power system have become more comfortable to handle. Traditional methods are not computationally feasible solutions as they have an inadequate ability to handling massive amounts of data (including bits of different data sets) from units of measurement such as smart meters and units of phasor analysis. Protection of the power system includes the method of identifying and correcting faults until fault currents create damage to utility facilities or property of the consumer. There is an opportunity to enhance fault detection techniques in distribution systems, where the amount of measurements is increasing. Using powerful machine learning techniques to predict fault could result in improving the power transmission system protection procedures. It will also reduce the time necessary to clear the faults, especially for a long transmission line, thereby increasing the reliability and efficiency of the overall power system. The paper gives a summary of the sophisticated algorithms and methods utilized to provide solutions to the difficulties of the power system. This study shows that supervised classifications of machine learning are used more than other methods that suggest classification algorithms yield more benefit to engineering problems in this area. It is concluded that applying machine learning to electrical engineering not only simplifies the problem but also ensures more reliable and accurate performance. Future work should suggest using the real network or real-time simulation data to validate the implemented process. Furthermore, a comparative analysis of different machine learning techniques is being prepared in terms of performance, complexity, and training time for identification and classification of power system failures.

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