Performance Study of Various Machine Learning Classifiers for Arc Fault Detection in AC Microgrid

S Ramana Kumar Joga, Pampa Sinha, Manoj Kumar Maharana

Research Scholar, School of Electrical Engineering, KIIT Deemed to be University, Bhubaneswar, India
E-mail: sanset567@gmail.com

Abstract. Fault is the abnormal condition in power system, which must be detected as early as possible. It is very important to detect the fault as quick as possible to reduce the effects of fault like equipment damage, property loss and human loss. Arc faults have high power discharge property between two conductors; this property causes damage to the conductors which leads to electric fire between the conductors. It is very necessary to detect these faults immediately to avoid fire accidents. There are various methods to detect these arc faults in microgrid. In this paper voltage and current signals are measured through instrumental transformers and voltage signal is decomposed by the discrete wavelet transform signal processing technique. The decomposed signals are further processed in various machine learning classifier’s for detecting the arc fault. The Proposed methodology studies the performance of various machine learning classifiers to detect arc fault in microgrid and it is carried out in MATLAB/Simulink Software.

Keywords: Arc Fault, Machine Learning, Wavelet, Microgrid, Fault Detection, Discrete Wavelet Transform, PQ disturbances.

1. Introduction
In Microgrid, sometimes abnormal condition changes the electrical flow in the System and causes change in the voltage and current levels. In other words, the sudden change in the direction of flow of current in electrical circuit is known as fault. There are many types of faults that occur in microgrid, they are short circuit faults, arc faults and open circuit faults and it is more discussed in [1]. The causes of fault occur in the power system due to failure of insulation, by human errors and due to bad weather conditions. The effects of electrical fault are that huge amount of current will flow through the equipment which produces more amount of heat and it damages the electrical equipment. Arc fault is one of the dangerous electrical hazards in power system. Arc fault is one of the leading causes of fires. Arc fault is virtually impossible to detect. Arc fault can’t be detected by common protected device. The causes of arc fault occur in the power system due to damage, faulty insulation and loose in the terminal condition. Microgrid is a sub-set of smart grid. Microgrid provides small-scale power supply. Microgrid is designed to provide power for a small community. It gives the authority to local power generation for local loads. In Microgrid, there are two operating modes are grid connected mode and island mode. Transmission losses are reduced in power system through microgrid. Microgrid provides high quality supply. The importance of fault detection is that it can help to avoid abnormal conditions. In a Microgrid, many small circuits are connected to avoid the damage of interconnected active circuit. Through fault detection damage of equipment is avoided and small circuit which are interconnected in...
the Microgrid. By the help of fault detection electrical fires are avoided, protect from injuries and save time. There are many methods to detect fault in microgrid and they are discussed by Yashasvi Bansal Et.al in [2]. James J.Q et.al discussed the intelligent scheme of fault detection based on wavelet transform and deep neural network and it is furthermore discussed in [3]. Machine learning based fault detection in microgrid is discussed in [4], Meenakshi Mohan et.al discussed the digital protection of microgrid based on wavelet transform and it is discussed in [5]. Jayamaha et.al discussed the wavelet artificial neural network based fault detection in DC microgrid, and it is discussed in [6]. Online fault detection using discrete wavelet transform and probabilistic neural network is discussed in [7]. In this paper, a discrete wavelet transform based signal decomposition technique is used to detect the arc fault in microgrid through various machine learning classifiers. It provides the detail study on the performance of various machine learning classifiers in performing fault detection in microgrid task.

2. Proposed Methodology
The fault detection in Microgrid basically involves three steps, they are

a. Voltage and Current Signal Measurement through Voltage and Current Sensors
b. Decomposition of Voltage and Current Signals through Signal Processing Technique.
c. Training of data through machine learning classifiers.

The basic fault detection block diagram is shown in Fig. 1.

**Figure 1:** Block diagram of Fault detection in Microgrid

The detailed process of proposed methodology is discussed in flowchart diagram and it is shown in Fig. 2.

**Figure 2:** Flow chart of Proposed Methodology

In this proposed methodology voltage signal is decomposed up to 6 levels through discrete wavelet transform method. The details of decomposed signals are considered as data sets of no fault and arc
fault signals. These data sets are trained in various Machine Learning classifiers for detecting the fault in AC microgrid.

2.1 Discrete Wavelet Transform (DWT)

It results in analyzing a signal into different frequencies at different resolutions, known as multi resolution. A wavelet is a wave-like oscillation that starts at zero, increases and decreases then come to starting point. It looks like as a “brief oscillation”. Wavelet is our basic functions and acts as a window function. We can change the width of the wavelet and its central frequency as we move it across our signal by changing s. This is called scaling. We analyze wavelet coefficients at every possible scale produces a lot of data. This idea of choosing discrete values of dilation (a) and translation (b) parameters is implemented in,

i. Redundant Wavelet Transform (Frames) and

ii. Orthonormal bases for wavelets or Resolution Analysis (MRA)

2.2 Machine Learning Techniques

Machine Learning is set of techniques to make computers better at doing thing that humans can do better than machines. So, Machine Learning tries to make computers better at things where traditionally humans were performing better than machines. We make machines learn things like humans do and it is discussed in

2.2.1 Support Vector Machine (SVM)

It is the most effective classifiers among those, which has sort of linear. Support Vector Machines have a clever way to prevent over fitting. In Support Vector Machine, we want a classifier, so that it maximizes the separation of between the points and the decision surface. The distance of the closest point to the decision surface can be defined as the margin. The distance between the observations and the threshold is called a soft margin and it is discussed in [8].

Disadvantages of Support Vector Machine

1. Poor performance
2. SVMs do not provide probability estimates

2.2.2 Naïve Bayes

Naïve Bayes is a supervised machine learning method. It is also known as Gaussian and Kernel Naïve Bayes Method. It is mostly used for solving the classification problems effectively. It is called “naive” because it shapes the thing that is accepted as true the event of a certain feature is not depending on another for the event of other features. The Naïve Bayes is further discussed in [9].

2.2.3 Bagged Trees

Bagging is also known as bootstrapping aggregation. Bagging is most used procedure for reduction of the variance in statistical learning method. In other words, averaging a set of observations reduces the variance. In Bagging, we use row sampling with replacement method. Bootstrapping is a simple, powerful technique that is used a lot in both statistical inference and machine learning. The Bagged Trees further discussed in [10].

2.2.4 Decision Tree

A decision tree is a graphical representation. It is used instead of a table to show possibilities and results. Trees are more powerful than tables because table is limited to two dimensions and it is discussed in [11].

A decision tree consists of nodes and arcs:

- Represents a decision node
- Represents an outcome
- Indicates the possibilities or results
It shows the order of decisions and outcomes.

Disadvantages of decision tree
1. Over fitting
2. High Variance
3. Low biased tree

2.2.5 $K$-nearest neighbor’s (KNN)
It is one of the simplest Machine Learning algorithms. It stores all the available cases. In KNN, we categories cases based on a similarity measure then we calculate the distance of the nearest neighbor and it is more discussed in [12].

3. Results and Discussions

The Proposed Methodology is verified by IEEE9 bus benchmark micro grid test system. It consists of three power sources. One source is from Utility Grid of 18kv connected to bus number 2. The other source is PV based solar array of 16.5kv connected to Bus number 1. A diesel generator based source of 13.8kv connected at bus number 3. These sources are utilized by three loads, industrial load, health arena and residential load respectively. The Single line diagram of IEEE9 bus test system is shown in Fig.3.

![Figure 3: Single Line Diagram of IEEE9 Bus](image)

The benchmark test system is developed and simulated in MATLAB/Simulink software. The test parameters like impedances are taken from the standard test system values. The line length is considered to be 2km. The load values MW, Mvar values are taken from the standard test system values. The MATLAB/Simulink diagram of IEEE9 benchmark microgrid test is shown in Fig.4.
The test system is simulated and data collected at bus number 7. The Voltage Signal at bus number 7 without fault is shown in Fig.5.

An Arc fault is modelled in MATLAB Simulink considering arc resistance and arc voltage. The Arc fault model is shown in Fig.6.

The arc fault is introduced to test system in between bus number 7 and bus number 5. The arc voltage at bus number 7 is now varied to actual original voltage as shown in the Fig.7.
Figure 7: Arc Voltage at bus number 7

The no fault voltage and Arc Voltage signals are further processed in signal processing technique. In this paper discrete wavelet transform is considered as signal processing technique to decompose the no fault signal and arc fault signals. The window length of the signal decomposition is time period from 0.61 sec to 0.62 sec. The window length of the arc fault is shown in Fig.8. The total numbers of samples considered for decomposition are 201 samples each of arc fault and no arc fault.

Figure 8: Window Length of arc fault signal

The Arc fault and no fault signals are decomposed up to 6 levels. The Daubechies (db.) wavelets are considered as mother wavelet. The detail coefficients are taken after decomposing the arc fault signal and no fault signal. The few detail signals at 6 levels for both no fault condition and arc faults are tabulated in Table 1.

Table 1: few sample details of arc and no fault condition

| details1  | details2  | details3  | details4  | details5  | details6  | distortion |
|-----------|-----------|-----------|-----------|-----------|-----------|------------|
| 719.2638  | -80.2801  | -276.463  | -535.313  | -1019.29  | -1367.27  | nofaultA   |
| -416.143  | -312.366  | -330.623  | -550.831  | -1023.62  | -1361.13  | nofaultA   |
| 2.15607   | 100.8254  | 237.8915  | 298.9359  | 202.3218  | 108.7423  | nofaultA   |
| -1.92877  | 341.1151  | 639.5612  | 916.8507  | 1098.612  | 1186.409  | nofaultA   |
| 1.702905  | -20.8173  | 874.3857  | 1302.913  | 1665.252  | 1871.87   | nofaultA   |
| 5.822956  | -0.79151  | -2.80485  | -6.57197  | -16.9036  | -42.4136  | arcfaultA  |
| -3.43142  | -2.69734  | -3.27784  | -6.76196  | -17.0603  | -42.5736  | arcfaultA  |
| 0.16589   | 1.115358  | 2.48717   | 3.157984  | 1.008335  | -8.29741  | arcfaultA  |
| -0.16218  | 3.395779  | 6.580716  | 10.36898  | 14.1935   | 16.75161  | arcfaultA  |
| 0.157528  | -0.36881  | 9.002793  | 14.87102  | 22.49522  | 32.57347  | arcfaultA  |

These details clearly show the variation between no fault detail values and arc fault details. It indicates that fault is detected. Now these data samples are trained in different machine learning techniques to detect the fault without any human supervision. It also can be studies the efficiency of various machine learning techniques in doing electrical fault detection problems. Since it is classification
problem, we need confusion matrix to understand the behavior of trained data and predicted data came after the raw data trained in the machine learning algorithm. Confusion matrix is a tool in data science to tell the performance of classification problem. It consists of True Values and False Values. The general confusion matrix for fault detection classification problem is shown in Table 2.

### Table 2: General Confusion Matrix

| Number of Samples | Fault | No Fault |
|-------------------|-------|----------|
| Detection         | True Fault (TF) | False Fault (FF) |
| No Detection      | False No Fault (FNF) | True No Fault (TNF) |

The accuracy of confusion matrix of classification model is calculated as \( \frac{TF + TNF}{TF + FF + FNF + TNF} \times 100 \). The Misclassification of Classifier model is calculated as \( \frac{FF + FNF}{TF + FF + FNF + TNF} \times 100 \). The details are trained in various machine learning techniques to study the performance of various machine learning techniques in solving fault detection classification Problem.

#### 3.1 Decision Tree

The details data are trained in different types of decision tree machine algorithm, which is based on number of splits. In fine tree maximum numbers of splits are more than 100. In medium tree maximum numbers of splits are not more than 20. In Coarse Tree maximum numbers of splits are 4. The Confusion matrixes after training the data are shown in Fig.9.
In this machine learning algorithm, total 402 samples are trained. 201 samples are no fault samples and another 201 samples are arc fault samples. In Confusion matrix, out of 201 samples 200 samples are grouped as “true fault” and 1 sample is miss classified. The True fault detection percentage is 99.50% and misclassification percentage is 0.4975%. The total accuracy of the classification problem is 99.50%.

### 3.2 Naïve Bayes
The details data set is estimated in Naïve Bayes machine learning algorithm. 402 samples of arc fault and no fault data sets are predicted in Gaussian Naïve Bayes and Kernel Naïve Bayes machine learning techniques. The Confusion matrixes after training the data are shown in Fig.10.

**Figure 10: Confusion Matrix of Gaussian (model 1.7) and Kernel Naïve Bayes (model 1.8)**

In Gaussian Naïve Bayes, out of 201 arc fault samples 197 samples are grouped as true fault and 4 samples are misclassified as no fault signals. The True fault detection percentage is 98.00% and misclassification percentage is 1.99%. The total accuracy of the classification problem is 99.00%. In Kernel Naïve Bayes, out of 201 arc fault samples 194 samples are grouped as true fault and 7 samples are misclassified as no fault signals. The True fault detection percentage is 96.50% and misclassification percentage is 3.48%. The total accuracy of the classification problem is 97.50%.

### 3.3 Support Vector Machine (SVM)
SVM machine learning classifier is classified according to the kernel function used in the objective function. In this Paper Cubic SVM, Various Gaussian, Optimizable SVM techniques performances are
evaluated for fault detection classification problem. The Confusion matrixes after training the data are shown in Fig. 11.

![Confusion Matrix](image)

**Figure 11:** Cubic (model 1.11), Fine (model 1.12), Medium Gaussian (model 1.13), Quadratic (model 1.10), Optimizable SVM classifiers (model 1.9) Confusion Matrix

In Cubic SVM out of 201 arc fault samples 201 samples are grouped as true fault and 0 samples are misclassified as no fault signals. The True fault detection percentage is 100.00% and misclassification percentage is 0%. The total accuracy of the classification problem is 98.75%. In Fine Gaussian SVM, out of 201 arc fault samples 201 samples are grouped as true fault and 0 samples are misclassified as no fault signals. The True fault detection percentage is 100% and misclassification percentage is 0%. The total accuracy of the classification problem is 99.75%. In Medium Gaussian SVM, out of 201 arc fault samples 201 samples are grouped as true fault and 0 samples are misclassified as no fault signals. The True fault detection percentage is 100% and misclassification percentage is 0%. The total accuracy of the classification problem is 98.75%. In Quadratic SVM, out of 201 arc fault samples 201 samples are grouped as true fault and 0 samples are misclassified as no fault signals. The True fault detection percentage is 100% and misclassification percentage is 0%. The total accuracy of the classification problem is 96.50%. In Optimizable SVM, out of 201 arc fault samples 201 samples are grouped as true fault and no misclassified signals. The True fault detection percentage is 100% and misclassification percentage is 0%. The total accuracy of the classification problem is 100%.

### 3.4 k-nearest neighbors (KNN)

In this Paper Cubic KNN, Various Gaussian KNN, Optimizable KNN, Cosine KNN and weighted KNN techniques performances are evaluated for fault detection classification problem. In Cosine out of 201 arc fault samples 198 samples are grouped as true fault and 3 samples are misclassified as no fault signals. The True fault detection percentage is 98.75% and misclassification percentage is 1.49%. The total accuracy of the classification problem is 93.78%. In Cubic KNN, out of 201 arc fault samples 201 samples are grouped as true fault and 0 samples are misclassified as no fault signals. The True fault detection percentage is 100% and misclassification percentage is 0%. The total accuracy of
the classification problem is 97.00%. In Fine KNN, out of 201 arc fault samples 201 samples are grouped as true fault and 0 samples are misclassified as no fault signals. The True fault detection percentage is 100% and misclassification percentage is 0%. The total accuracy of the classification problem is 99.75%. In Medium KNN, out of 201 arc fault samples 201 samples are grouped as true fault and 0 samples are misclassified as no fault signals. The True fault detection percentage is 100% and misclassification percentage is 0%. The total accuracy of the classification problem is 97.26%. In Weighted KNN, out of 201 arc fault samples 201 samples are grouped as true fault and no misclassified signals. The True fault detection percentage is 100% and misclassification percentage is 0%. The total accuracy of the classification problem is 97.76%. In Optimizable KNN, out of 201 arc fault samples 201 samples are grouped as true fault and 0 samples are misclassified as no fault signals. The True fault detection percentage is 100.00% and misclassification percentage is 0%. The total accuracy of the classification problem is 99.75%.

3.5 Bagged Trees

The details data are trained in Bagged Trees machine algorithm, The Confusion matrixes after training the data are shown in Fig 12.

In Optimizable KNN, out of 201 arc fault samples 201 samples are grouped as true fault and 0 samples are misclassified as no fault signals. The True fault detection percentage is 100.00% and misclassification percentage is 0%. The total accuracy of the classification problem is 100%.

4. Conclusions

From the Various machine learning classifiers, the observations are taken and tabulated in a Table 3.

**Table 3: Overall Performances of Various Machine Learning Classifiers**

| Classifier  | Fault Detection (Percentage) | Overall Classification Problem Accuracy (Percentage) |
|-------------|------------------------------|-----------------------------------------------------|
| Fine Tree   | 99.50                        | 99.50                                               |
| Medium Tree | 99.50                        | 99.50                                               |
| Coarse Tree | 99.50                        | 99.50                                               |
| Gaussian Naive | 98.00                      | 99.00                                               |
| Method          | Bayes       | Kernel Naïve Bayes | Cubic SVM | Fine SVM | Medium SVM | Quadratic SVM | Optimizable SVM | Cosine KNN | Cubic KNN | Fine KNN | Medium KNN | Weighted KNN | Optimizable KNN | Bagged Trees |
|----------------|-------------|--------------------|-----------|----------|------------|---------------|----------------|------------|-----------|----------|------------|--------------|----------------|--------------|
| Accuracy       | 96.50       | 97.50              | 100       | 98.75    | 100        | 96.50         | 100            | 98.75     | 100       | 99.75    | 100        | 97.26         | 100            | 100          |

From the above Table 3, It is concluded that Decision Tree learning classifier has more overall classification accuracy compared to SVM, KNN, Bagged Tree and Naïve Bayes learning classifiers. Whereas SVM, KNN, Bagged Trees have more fault detection accuracy than Naïve Bayes and Decision tree machine learning algorithm technique.

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