



Apply Machine Learning Algorithms For Early Detection And Diagnosis Of Faults In Microgrid Networks

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Abstract: The study explores fault prediction within a Microgrid by comparing a hybrid model with individual algorithms like decision trees, logistic regression, and gradient boosting. The hybrid model's design integrates the strengths of these diverse algorithms, enabling it to effectively capture both linear and non-linear data patterns. This results in more accurate and robust predictions. In terms of performance, the hybrid model achieves a higher Area under the Curve (AUC) score, which reflects its superior ability to distinguish between true positives and false positives. This performance boost is due to the hybrid model's capacity to reduce both bias and variance, thereby balancing the trade-offs between sensitivity (true positive rate) and specificity (true negative rate). Unlike complex models prone to over fitting, such as deep decision trees, or simpler models like logistic regression that may under fit, the hybrid approach strikes an optimal balance. When evaluating classification accuracy, the hybrid model demonstrates superior performance, achieving a 94% accuracy rate. While individual models like logistic regression, decision trees, random forests, support vector machines (SVM), and neural networks each offer varying levels of accuracy, the hybrid model outperforms them by combining their unique strengths. This ensemble approach ensures more reliable and accurate fault predictions, making the hybrid model a powerful tool for managing Microgrid operations. The findings underscore the hybrid model's ability to generalize across different datasets and distributions, further enhancing its prediction accuracy. By effectively managing the trade-offs between bias and variance, the hybrid model provides a more comprehensive understanding of complex data relationships, leading to improved fault prediction in microgrids.

I. INTRODUCTION

In power system operations, detecting and locating faults are critical procedures to ensure system protection, smooth operation and service restoration. Successfully detecting faults aids in the proper operation of protective relays which isolate faults and de-energize the faulted section of the grid.

While fault detection and location techniques have been studied extensively in transmission and distribution systems, in this work, we consider the problem of Fault classification answers the question: given that a fault has occurred, what type of fault has occurred? Accurate real-time fault classification can support superior grid operation by reducing the likelihood of relay operations on non-faulted phases.

The protection of Microgrid can prove to be challenging as they have a variety of modes of operation and diverse power generation technologies. Traditional relaying schemes used in distribution grids may fail to protect a microgrid especially when the distributed energy sources are interfaced with power electronic devices such as inverters, which severely limit the fault current.

Given that micro grids rely on distributed generation sources at the loads, for stable operation, it is essential to avoid losing generation capacity while isolating faults. In order for microgrids to sustain operation during the unbalanced faults, several factors need to be considered such as the internal protection

schemes of inverters which are currently designed to trip during unbalanced conditions in order to meet the current islanding protection requirements. However, in order to design and operate a truly smart microgrid, then it must be equipped with distributed energy sources that can operate through

Unbalanced faults. Failing which, any asymmetrical fault (irrespective of its location and duration) may result in an islanded microgrid to shut down. Thus, a smart microgrid must ensure operation of sound phases during unbalanced faults which account for the majority of faults that occur in the system [1].

Selective phase tripping requires fault type classification by the microgrid protection system. Faults in microgrids present a complex classification and detection problem. With the advent of new machine learning methods and supervised learning methods, these challenges may be more effectively addressed. Machine learning methods are based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention. The ability to automatically apply complex mathematical calculations to big data – over and over, faster and faster - gives these algorithms potential to identify patterns in the data which would be otherwise an impossible task for humans. The availability of high-resolution/high-volume data, due to the proliferation of intelligent electronic devices in smart grids, paves ground to implement more accurate and intelligent machine learning methods for fault classification in microgrids.

For this study secondary data has been collected. From the website of KSE the monthly stock prices for the sample firms are obtained from Jan 2010 to Dec 2014. And from the website of SBP the data for the macroeconomic variables are collected for the period of five years. The time series monthly data is collected on stock prices for sample firms and relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

II. LITERATURE REVIEW

Intelligent fault detection and classification stems from the convergence of advancements in the fields of signal processing techniques, artificial intelligence, data science and sensor technologies such as Internet of Things (IoT), which have enabled researchers to apply these concepts to expand the horizon of traditional fault protection techniques in power systems. In the last decade, rapid growth of interest and advancements in smart grid and related concepts such as microgrids has fuelled research into developing an intelligent fault diagnosis system that can classify and locate faults with a high level of accuracy. This section briefly summarizes the significant related works and detailed literature survey on fault classification using deep learning techniques including study of the existing published material.

In recent years, data driven and signal processing approaches have become increasingly popular for fault detection and classification in microgrids. Artificial neural networks and other machine learning algorithms such as; support vector machines, decision trees (DT), and Nearest Neighbours (KNN) are some of the commonly used algorithms in such studies. In addition, signal processing techniques such as Fourier Transforms and wavelet transforms have widely been utilized to pre-process the signals to extract the features for analysis. For instance, in the work presented by Yu et al. [2], the authors use discrete wavelet transform (DWT) to extract features from the branch current signals. These features are used to detect faults and are further fed into a neural network comprising of gated recurrent units for fault classification. The authors tested their proposed scheme on the CERTS microgrid test bed and the IEEE-34 bus system and achieved high accuracy in fault classification. Jayamaha et al. [3] apply similar principles for fault detection in DC microgrids. Here, the relative wavelet energy of the signals is extracted using DWT based Multi-resolution analysis (MRA) of the input signals. A simple feed forward neural network is used for classifying the input features. High et al. [4] propose a modular ANN for fault classification and location that consists of training multiple networks for each type of fault. This approach helps to reduce the training time and computational complexity of the network as each network is only required to learn one type of fault and need not be trained all the available data. However, this scheme only identifies the four types of faults and cannot identify the faulted phases. Wavelets transforms have been widely used in the field of fault detection and classification due to their ability to enhance the differentiability between faulted and non-faulted data by projecting the data in the time-frequency domain. The application of wavelet transform in conjunction with machine learning techniques to fault classification has been further illustrated in various works [5]– [8].

In addition to neural networks, decision trees and K- nearest neighbours are popular algorithms employed for the purpose of fault classification. Li et al. [5] use two decision trees to detect and classify faults in transmission lines based on fifteen features extracted using DWT and were able to achieve a classification

accuracy of 94% using random forest method. However, the method suffers from major drawbacks as 12% of the line to line to ground faults was classified as line to ground faults. Also, the method fails to identify the faulted phases. Decision trees were also used by Jamebozorg et al. [9] to classify faults in transmission lines. Abnegated et al. [7] use a semi-supervised machine learning approach is proposed to handle both labelled and unlabelled data by co-training decision trees and KNN classifiers to classify faults in both transmission and distribution systems including microgrids.

The application of convolutional neural networks (CNN) to fault classification is an interesting approach in the sense that here signals are not directly used as inputs to the classifier.

In most cases, the signals are transformed into images based on some extracted features, which are then used to train the CNN. In the work done by Guo et al. [10], the authors employ the Hilbert-Huang transform to construct an energy matrix from the time-frequency pieces. The energy matrix is then transformed into an image by proportionally transforming the values of the matrix to the colour values in a colour map. The authors reported high accuracy using this approach. A similar approach was adopted by Y. Li et al. [11] to classify single phase earth faults in distribution networks. CNNs have also been used Liao et al. [12] for voltage sag estimation and classification where the inputs to the CNN were matrices of selected variables formed using the concept of system area mapping. Bagheri et al. [13] propose a method for voltage dip classification using CNN. Here, the authors employed the deep learning technique in an effective two-dimensional transform domain, under space-phaser model, for efficient extraction and characterization of features that are independent of the duration and sampling frequency of dip recordings.

In addition to the techniques discussed, some other novel approaches to fault classification are as follows. Alsafasfeh et al. [14] use principal component analysis to classify faults based to the phase current values in only one-fourth of a cycle. Chain Tanya and Yadav [15] experimented with the application of fuzzy inference system to detect and classify high impedance faults. Here, two different fuzzy inference systems (FIS) are modelled in each phase to detect the fault. The first FIS identifies the high magnitude of fault current associated with normal shunt faults; and the second FIS identifies the small magnitude of current owing to occurrence of high impedance faults. In the work done by Mishra and Yadav [16] a classification scheme based on Discrete Fourier Transform and fuzzy logic is used. Finally, Salim et al. [17] present a hybrid method for fault detection and classification based on wavelets and ANN that has been implemented by a Southern Brazilian power distribution company, thereby justifying the advantages and feasibility for this approach.

III. BACKGROUND MICROGRID

3.1 Review of Microgrid Technology

In the current centralized energy system, electric power is transmitted from the power generation sites to the consumers through an electric Microgrid. However, many alternative power systems models are emerging in response to the new challenges of increase in electricity demand and reducing global emissions of greenhouse gases. The constant increase in demand for electric power and better quality of supply has compelled utilities to rethink the current energy system as it pushes it limits in terms of size and complexity. Our constant pursuit of a more environmentally sustainable grid has necessitated the adoption of grid architectures that leverage the distributed nature of renewable energy sources. As such Microgrid have emerged as increasingly popular solution to the centralized system due to their feasibility and adaptability for a variety of needs such, campuses, remote communities, island networks and standalone

Microgrids offer several economic and technical benefits that include:

- They minimize the risk of price volatility, outages, load growth, etc. which benefits both the utility operator as well as the customer.
- Reduce energy loss in the system as the energy sources are present closer to the loads, the need to transmit energy over long distances is reduced thereby reducing energy loss in transmission lines.
- They improve voltage quality and power factor due to increased control of reactive power in the system.
- Reduce overall load on the grid especially during peak hours. They also help utilities postpone or delay major system upgrades.
- Reduce energy costs for consumer by not only reducing the energy drawn from the grid, they can also provide a revenue stream to the consumers.

- Finally, Microgrids, improve the environment by promoting the use of renewable energy sources and making the energy grid more sustainable.

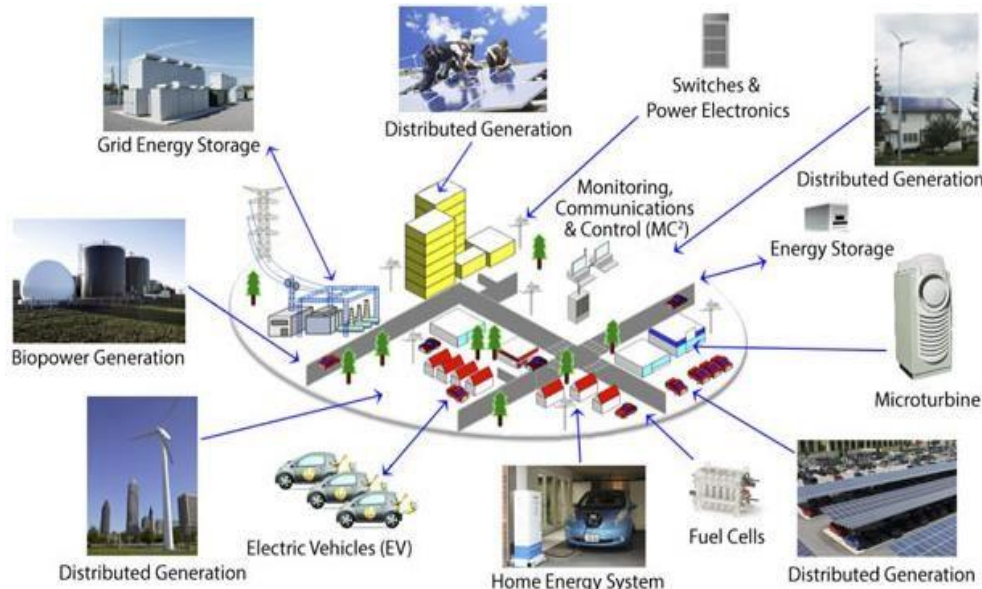


FIGURE 1. A typical microgrid and its components.

When two or more faults occur at the same instant, then such faults are called Simultaneous faults. They may be of the same type or of different types that may or may not occur at the same location. A broken overhead line conductor that falls to earth is a simultaneous single-phase open-circuit and single-phase short-circuit fault at the same location.

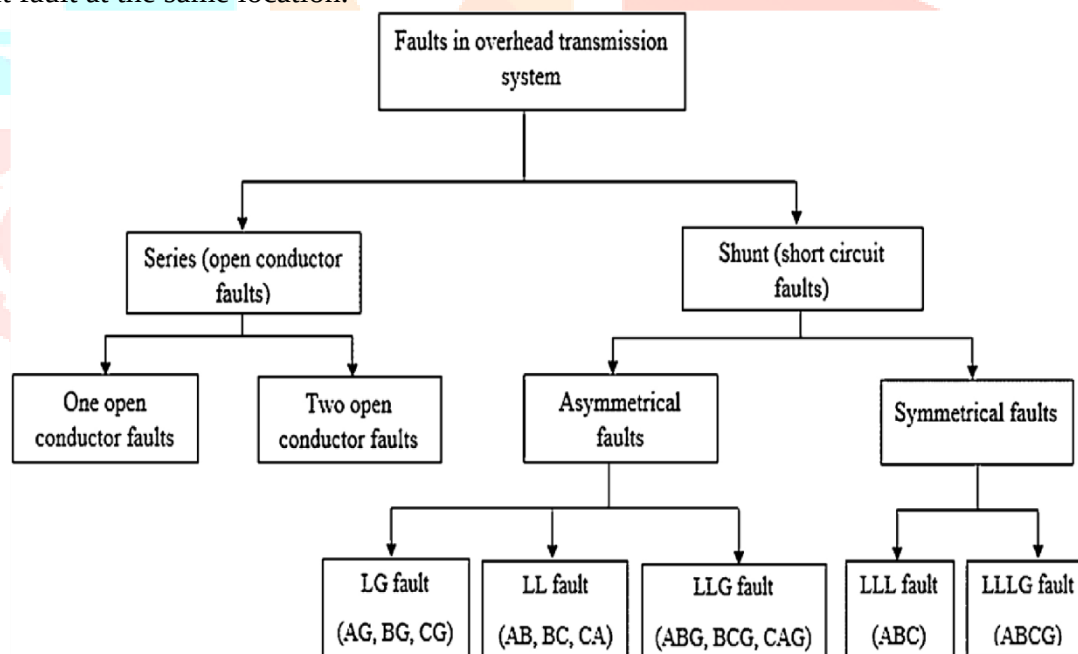


FIGURE 2. Classification of power system faults.

Causes of Electrical Faults

Electrical faults in power distribution systems, or microgrids, can be caused by a variety of reasons which may include:

- Weather conditions:** It includes lightning strikes, heavy rains, heavy winds, salt deposition on overhead lines and conductors, snow and ice accumulation on transmission lines, etc. These environmental conditions interrupt the power supply and also damage electrical installations.
- Equipment failures:** Various electrical equipment like generators, motors, transformers, reactors, switching devices, etc. causes short circuit faults due to malfunctioning, ageing, insulation failure of cables, and winding. These failures result in high current to flow through the devices or equipment which further damages it.

- **Human errors:** Electrical faults are also caused due to human errors such as selecting improper rating of equipment or devices, forgetting metallic or electrical conducting parts after servicing or maintenance, switching the circuit while it is under servicing, etc.
- **Smoke from fires:** Ionization of air, due to smoke particles surrounding the overhead lines result in sparks between the lines or between conductors to insulators. This flashover causes insulators to lose their insulating capacity due to high voltages.

IV. RESEARCH METHODOLOGY

A. Challenges Posed by Microgrids

Microgrids offer several challenges to the standard fault protection techniques employed in traditional distribution systems which are designed for radial architectures with unidirectional power flows, based usually on fuses and current limiters to face faults. When a microgrid is interconnected with the grid, the protection system must make sure that the microgrid is isolated in case of a fault in the main grid and in case of a fault in the microgrid, the minimum number of consumers are affected.

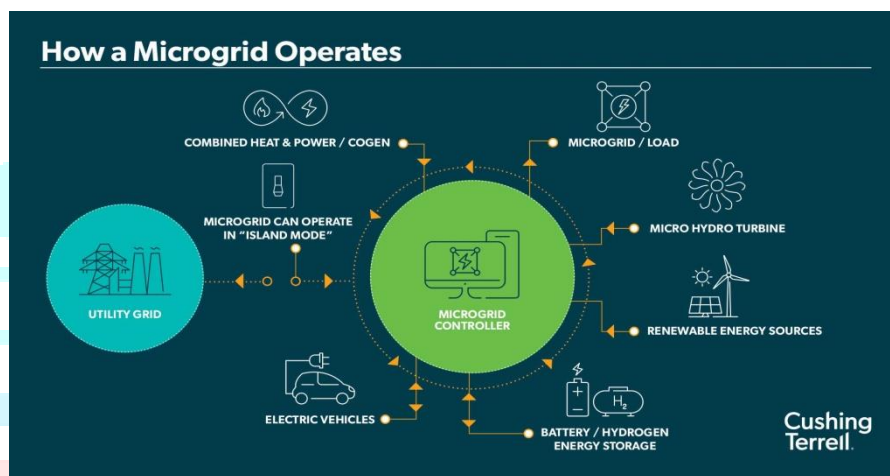


Figure 3 Process Microgrid Operates

The major challenges faced by the protection system in a microgrid are:

- Smaller and intermittent magnitude of fault currents due to high penetration of inverter interfaced DERs.
- Different modes of operation i.e. grid connected and islanded mode which may produce different levels of fault current.
- Topological changes within the microgrids due to connections and disconnections of generators, storage systems and loads.
- The intermittent nature of DERs means that the assessing the level of fault current may prove to be challenging.
- Presence of generation and storage technologies that connects by means of power electronic devices. The capacity of these inverters to generate short circuit current is very limited, not being able to produce more than 1.2 to 2 times the generator rated current in case of a fault. These figures contrast with much higher values provided by conventional synchronous generators.

Thus, a data driven approach combined with signal processing techniques could help in overcoming the above challenges as it does not rely on set thresholds used in traditional protection systems. Using signal processing techniques such as MRA allows us to detect faults with the smallest change in voltage or current thus reducing our dependence on large magnitude of fault currents for detection. In this work, we consider the classification of shunt faults, i.e. given that a fault has occurred, we aim to identify the phases involved which will allow the control system to trip only the faulted phases so as to avoid unnecessary islanding of the microgrid.

4.1.2 Wavelet Transforms

Analysing digital signals in different domains of representation allows us to better understand its salient features such as its periodicity, autocorrelation and power spectrum of the signal which may be hard to extract from any single domain. Wavelets are an effective tool for analysing and processing signals. Wavelet transforms, allow us to represent the signal in the time-frequency domain in the form of a set of

wavelet coefficients that can be manipulated to achieve various signal processing effects. Wavelets have been used widely in fields such as computer vision, music and digital signal processing to analyse and transform data.

A wavelet is any wave that satisfies certain conditions.

B. Continuous Wavelet Transform

The continuous wavelet transforms (CWT) was developed in order to provide better time frequency resolution as compared to STFT. Similar to STFT, the wavelet analysis is performed by multiplying the signal with a function and computing the transform for different segments of the time-domain signal. However, unlike in STFT, the width of the window (basis function) is changed for every spectral component providing better resolution at different frequencies. The wavelet transform $W_x(a, s)$ of a continuous-time signal $x(t)$ is defined as

$$W_x(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad \dots\dots\dots (1)$$

Here, the wavelet transform is computed as the inner product of $x(t)$ and the translated and scaled versions of a single function $\psi(t)$. The bandwidth and centre frequency of the wavelet can be varied by changing the scaling parameter a . thus, when a is fixed, the transformation is nothing but the convolution of $x(t)$ with the time-reversed and scaled wavelet.

When transforming a signal into different domains of representation, it should be ensured that the signal can be perfectly reconstructed from its representation without which the representation may be meaningless. For the wavelet transform, the condition that must be met in order to ensure perfect reconstruction is

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{|\omega|} d\omega < \infty \quad \dots\dots\dots (2)$$

where $|\psi(\omega)|$ denotes the Fourier transform of the wavelet. This condition is known as the admissibility condition for the wavelet (t). As such, in order to satisfy the above equation, the wavelet must satisfy:

$$\psi(0) = \int_{-\infty}^{\infty} \psi(t) dt = 0 \quad \dots\dots\dots (3)$$

Moreover, $|\psi(\omega)|$ must decrease rapidly for $|\omega| \rightarrow 0$ and for $|\omega| \rightarrow \infty$. These two conditions imply that the average value of the wavelet in time domain must be zero and it must be oscillatory.

4.1.3 Discrete Wavelet Transform

To overcome the above challenges, the discrete wavelet transforms (DWT) was introduced. Discrete wavelets can only be scaled and translated in discrete steps and provide sufficient information for analysis (decomposition) and synthesis (reconstruction) of the signal, while reducing the computational time. The DWT is considerably easier to implement as compared to the CWT.

$$d_{j,k} = \frac{1}{\sqrt{|a_0^j|}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-kb_0a_0^j}{a_0^j} \right) dt \quad \dots\dots\dots (4)$$

In the above equation, j and k are integers reflecting the level and location respectively, and $b_0 > 1$ is a fixed dilation step. The effect of discretizing the wavelet is that the time-scale space is now sampled at discrete intervals. When discrete wavelets are used to transform a continuous signal, the result will be a series of wavelet coefficients, and it is referred to as the wavelet series decomposition.

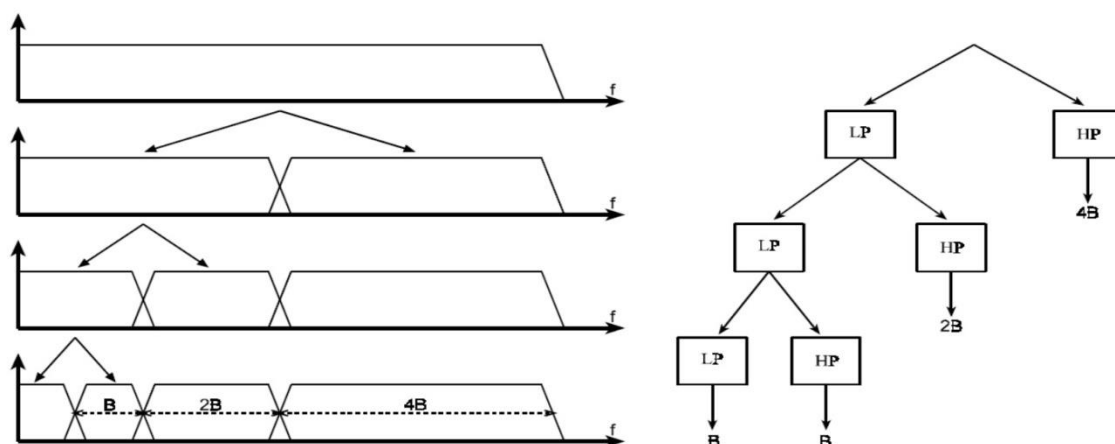


FIGURE 5. Three level decomposition of a signal showing the frequencies being split after each level of decomposition [24]

The output of the high pass filter is called the approximation coefficients and the output of the lowpass filter are called the detail coefficients. This procedure, also called sub-band coding, is repeated with the detail coefficients until such only two samples are left in the signal. At each level, the sub-sampling will lead to half the time resolution and half the frequency band thus doubling the frequency resolution. This procedure can be visualized as shown in Figure 4.

Mathematically, the multi resolution decomposition of a signal $x(t)$ at level M can be achieved by

$$x(t) = \sum_k a_{M,k} \frac{1}{\sqrt{2^M}} \varphi\left(\frac{t}{2^M} - k\right) + \sum_j \sum_k d_{j,k} \psi\left(\frac{t}{2^j} - k\right) \dots\dots\dots (5)$$

In this work we use DWT to filter the noise from the signal to improve the classification accuracy. A detailed implementation of the procedure is explained in the following chapter.

II. DESIGN AND IMPLEMENTATION

E. Methodology

This section provides an overview of the proposed method to classify faults in microgrids using neural networks. The method is designed such that it addresses the challenges posed by microgrids as discussed in the previous chapter. It is designed so as to be scalable and adaptable to microgrids of different sizes that operate at different voltages to be able to provide classification with high accuracy and confidence and facilitate its safe operation, in case of a fault. The goal is to employ deep learning methods to identify fault types in a microgrid rather than hard coding the values.

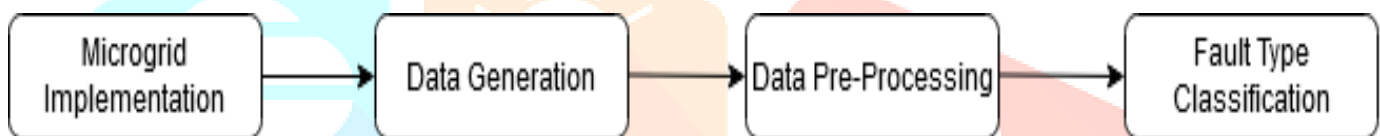


FIGURE 4. Methodology followed in this work.

F. Microgrid Implementation

For the purpose of this research we designed and implemented a microgrid that is a modified version of the IEEE 13 bus feeder [32]. The one-line diagram of which, is shown in Figure 11. It is an unbalanced system that models many of the typical characteristics of a standard distribution network described below:

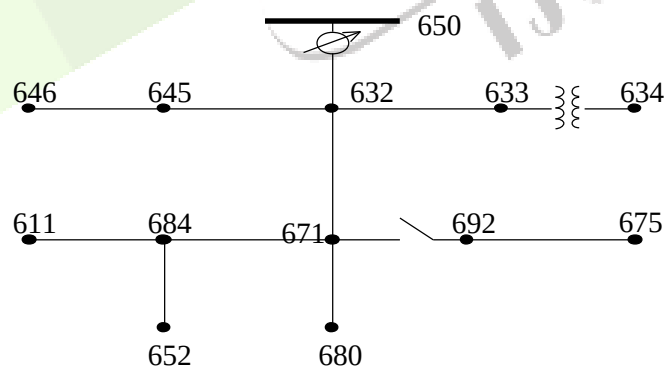


FIGURE 6. One-line diagram of the IEEE 13 bus feeder.

- Three-phase, two-phase, and single-phase lines and cables with significant mutual coupling.
- Delta and star-connected loads and distributed loads in three types—constant power, constant current, and constant impedance (ZIP types).
- Two three-phase transformers and a circuit breaker.

The feeder is short and highly loaded operating at 4.16 kV, 60 Hz. It consists of both overhead and underground lines with different phase configurations connected to unbalanced and distributed loads [33]. To test the performance of the proposed scheme on various types of DGs in microgrids, we modify the above network to include two PV-DGs in the system at nodes 680 and at node 602 which, lies at the end of an added distribution line connected to node 633. A battery-energy storage system (DG- BESS) is connected at node 675. The Point of Common Coupling (PCC) is modelled as a three-phase voltage source in the star configuration with a ground connection.

Variable loads are also added to the same nodes connected as the PV-DGs. The ‘Grid Connected PV Array’ block and the ‘Grid Connected Energy Storage Block’ as found in Simulink Microgrid library [34] are used to implement the PV-DGS and DG-BESS. The energy storage block is a system level model that can be used for hybrid - phasor electro-magnetic transient studies. The block is set to voltage control mode in the islanded operation of the microgrid and current control mode when the microgrid is grid connected. The microgrid has several types of loads i.e. constant current, constant impedance and constant power in star or delta configuration. In addition to the spot loads, a distributed load is present between nodes 632 and 671. The parameters of the spot loads are provided in Table 1.

The parameters of the DG-BESS are provided in Table 2. The storage system is operated in current control mode or voltage control mode depending on whether the microgrid is in grid connected mode or in Islanded mode respectively.

TABLE 1. Parameters of the DG-BESS Model

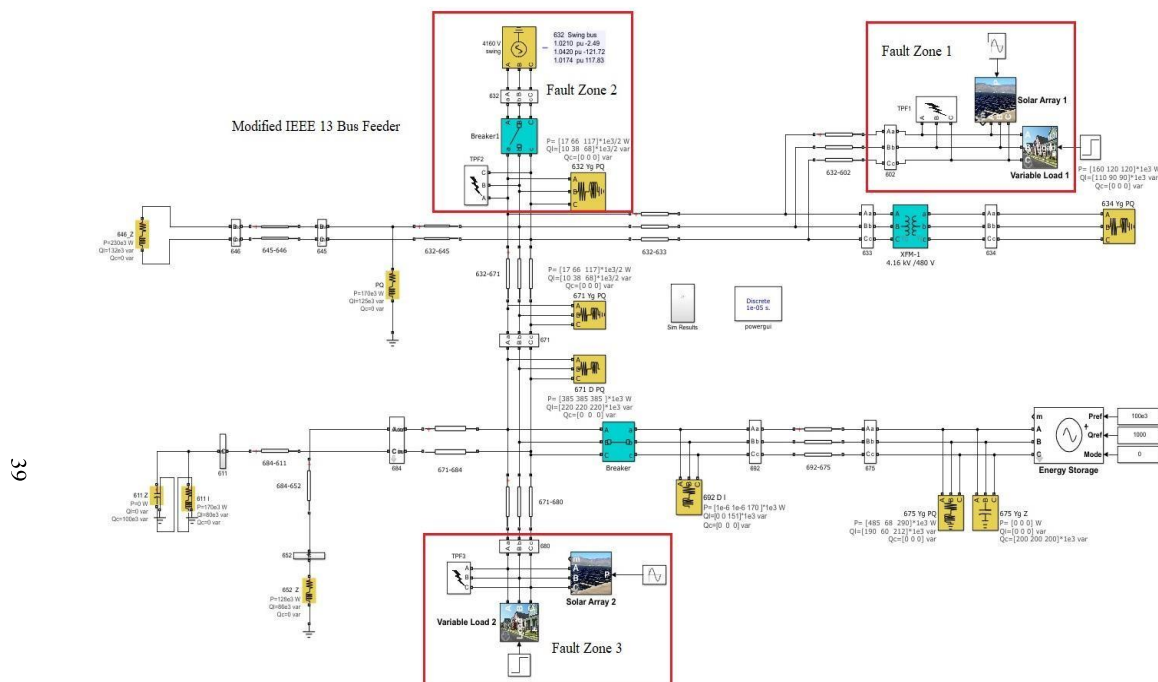
Parameter		Value
Nominal Voltage		4610 kV
Nominal Frequency		60 Hz
Rated Power	500 kW	
Overall system efficiency	96%	
Recharge Rate	50%	
Initial SOC	80%	
Mode of Operation	Voltage Control/ Current Control	
Power	500 kW	

The parameters of the grid connected PV array and the transformer are provided in tables 3 and 4 respectively.

TABLE 2. Parameters of Grid Connected PV Array

Parameter	Value
Nominal Voltage	4610 kV
Nominal Frequency	60 Hz
Power	500 kW

The complete IEEE -13 bus feeder as implemented in MATLAB/Simulink is shown in Figure



1. Data Generation

Before the classifier can be used to classify faults, their learning parameters need to be trained as explained in the previous chapter. To obtain the data to train and test the proposed neural networks in the MATLAB environment, eleven types of faults with various conditions are simulated. The fault conditions including fault type, fault resistance, and fault inception angle are considered in simulations. Three-phase voltage and the three-phase line currents are measured in the simulation models.

TABLE 3. Configuration of the Fault Cases Simulations

Parameter	Configuration	Count
Faults Simulated	AG, BG, CG, ABG, ACG, BCG, AB, AC, BC, ABC, ABCG	11
Fault Inception Angles	0°, 60°, 90°, 135°, 180°, 225°, 270°, 315°	8
Fault resistances	0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1 ohm	7
Fault Locations	Zone 1, Zone 2, Zone 3	3
Mode of Operation	Grid Connected / Islanded	2

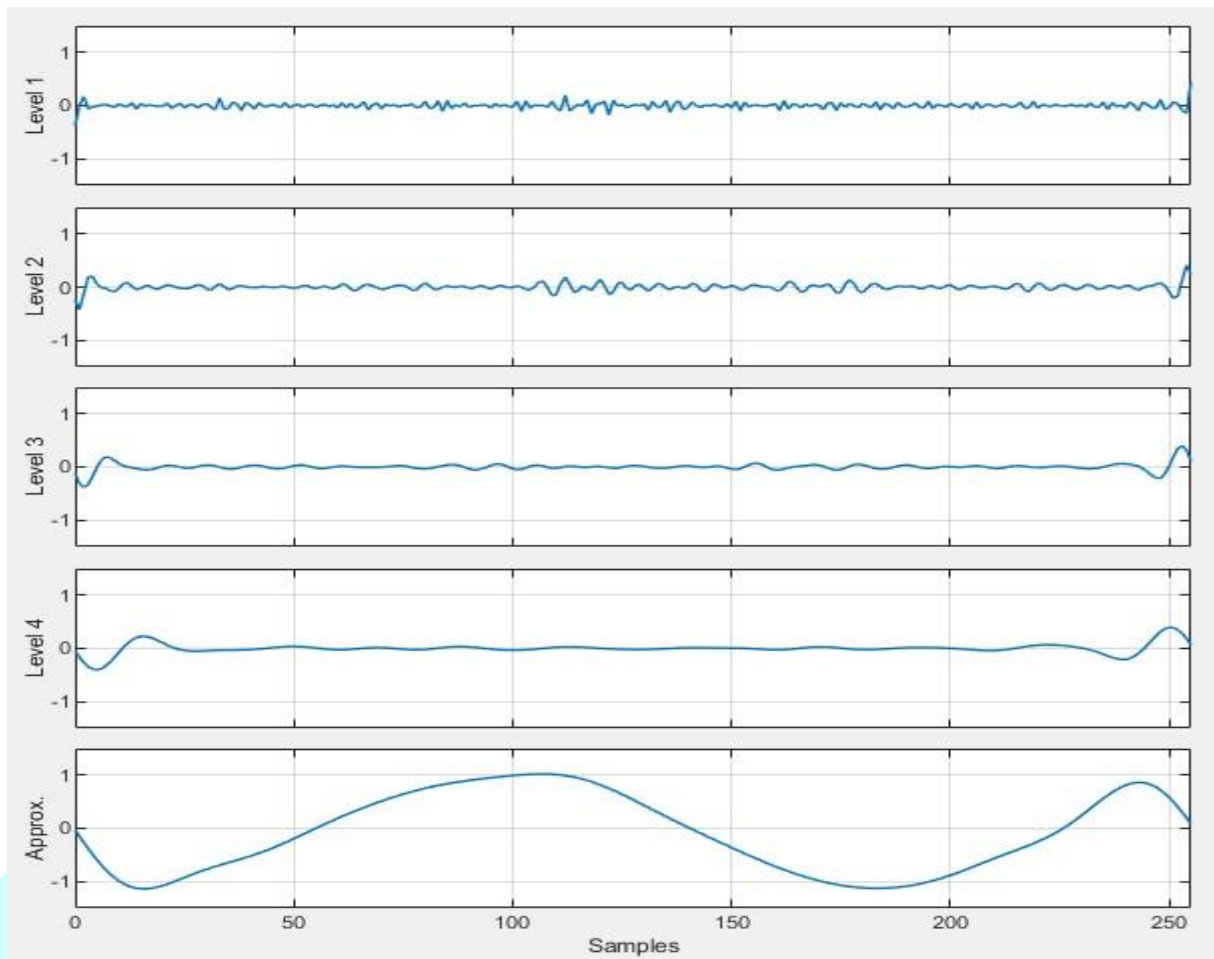


FIGURE 7 Decomposition of the signal into 4 levels of detail coefficients and the approximation coefficients using Daubechies (db10) mother wavelet.

TABLE4.Relative Energy of Signals in the Approximation Coefficients After Different Levels of Decomposition for Smelts and Daubechies Wavelet Families

Wavelet Number	Symlets	Daubechies
1	n/a	89.62
2	93.73	93.73
3	94.33	94.33
4	94.51	94.51
5	94.60	94.60
6	94.64	94.64
7	94.67	94.67
8	94.69	94.69
9	n/a	94.71
10	n/a	94.72

Thus, based on the above analysis it can be seen that db10 had the maximum relative energy and was therefore selected as the chosen mother wavelet. The processed fault signal is shown in Figure 15.

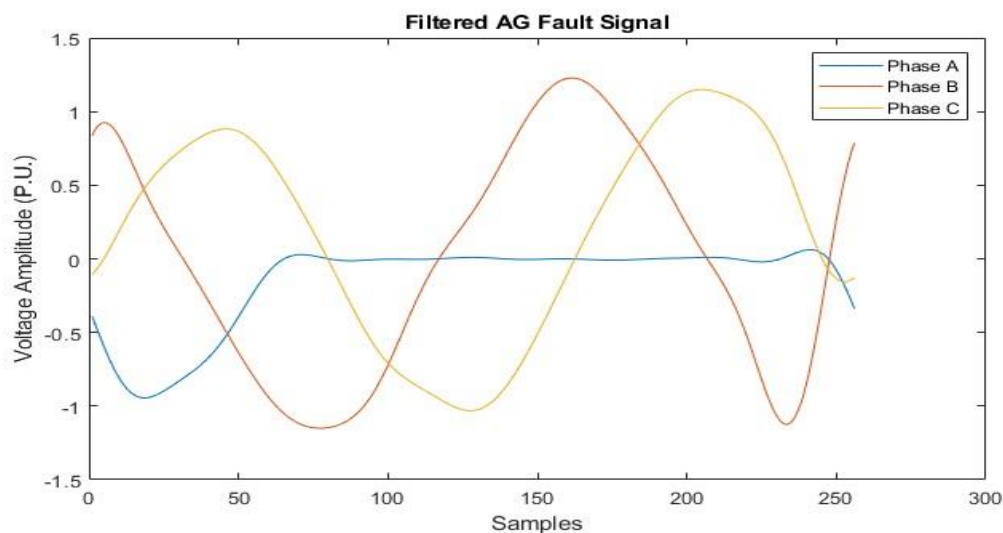
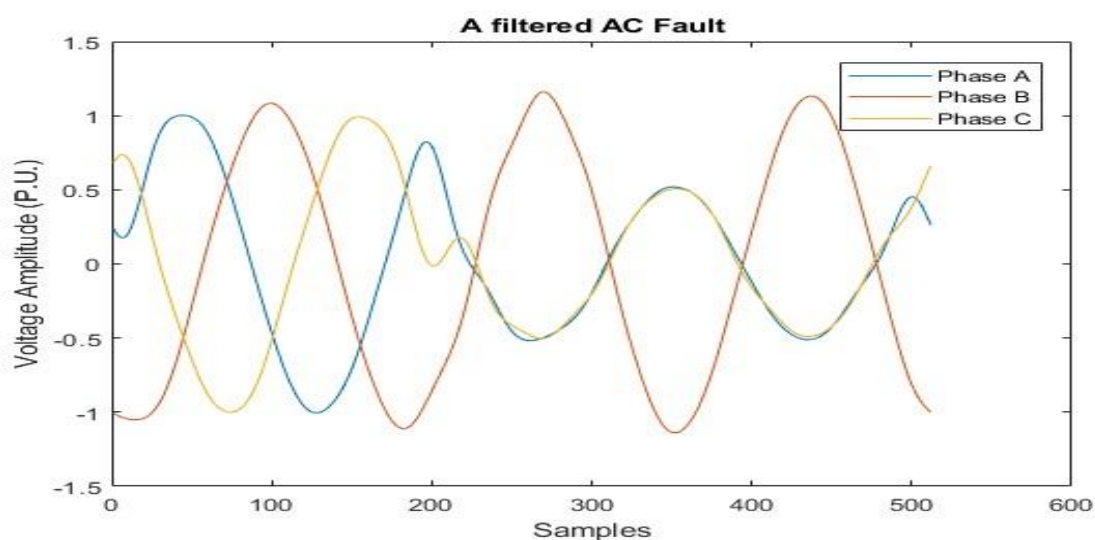
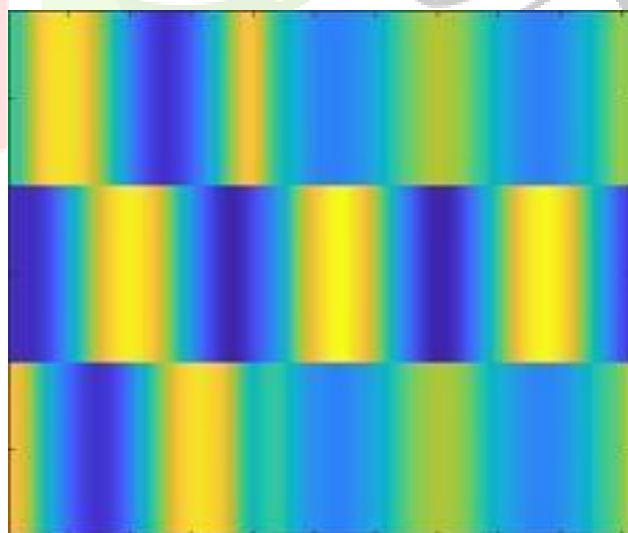


FIGURE 5.6. Filtered AG fault signals.

Thus, the final product after processing the signals are filtered sequences of the 3phase voltages containing 1 cycle after the fault inception. These sequences are used as data to train and test the LSTM neural networks.



1. (a)



2. (b)

FIGURE 8 The figure (a) shows an example of an AC fault and (b) shows the image of the same fault obtained using the *images* function in MATLAB.

The outputs of the last fully connected layer are passes through a SoftMax layer which limits the outputs into the range of 0 to 1. This is done so as to reflect the probabilities of an input belonging to each class.

The last layer is the classification layer which provides the final outputs. The multiclass cross entropy is used as the loss function.

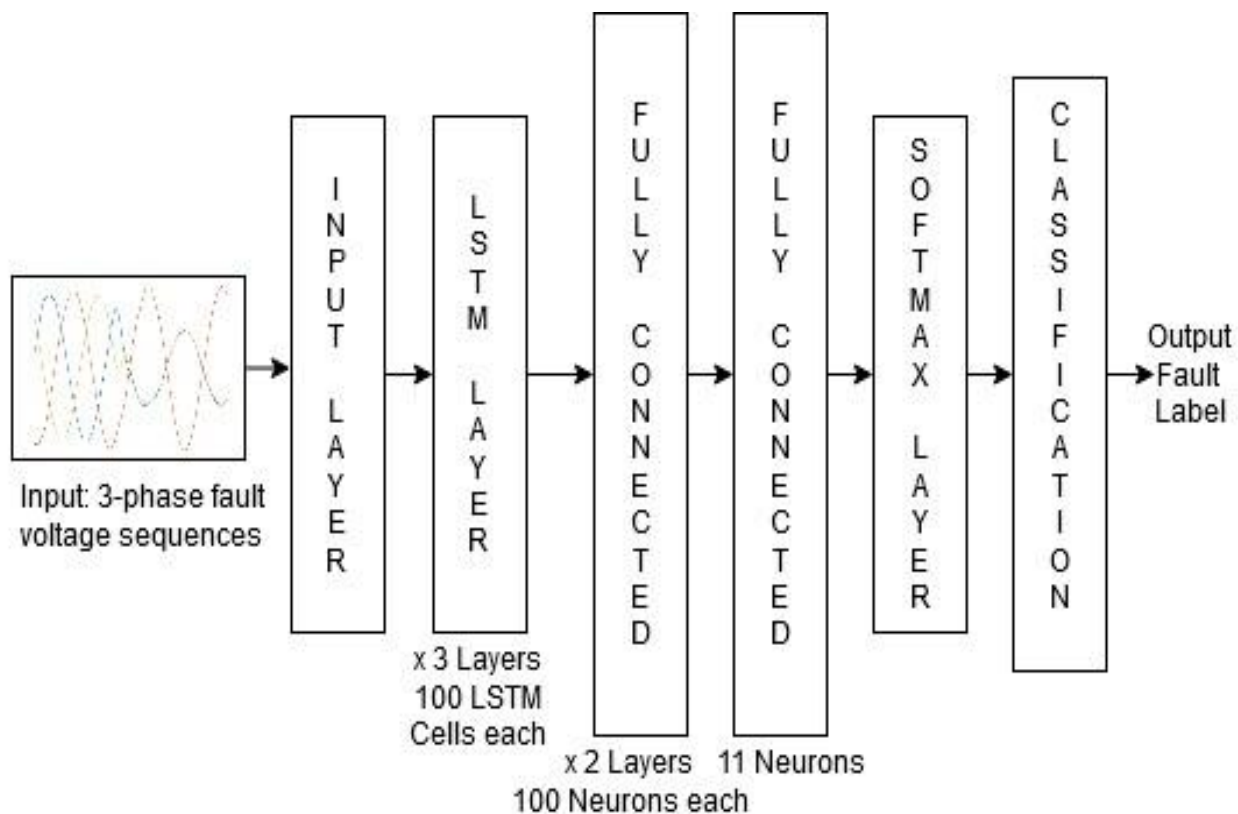


FIGURE 9. Architecture of the LSTM Network.

The parameters of the network used are shown in Table 7.

Parameter	Value
Number of Layers	5
Number of Neurons per layer	100
Initial Learn rate	0.001
Validation frequency	10
Max epochs	200
Mini Batch size	16

IV. RESULTS AND DISCUSSION

This section discusses the various methods and parameters used to evaluate the performance of the model. For multi class classification problems, a confusion matrix is often used to evaluate, quantify and visualize the performance of a classifier on the test data for which the true values are known. A confusion matrix is a table that summarizes the results of a classification problem, by presenting the count of correct and incorrect predictions for each class. It thus, not only reveals the errors being made, it also reveals the type of errors [38]. Figure 19 shows a sample confusion matrix for two classes.

	Predicted Class 1	Predicted Class 2
Actual Class 1	True Positive	False Negative
Actual Class 2	False positive	True Negative

FIGURE 10. A sample confusion Matrix for two classes.

G Method 1: LSTM Model

In the first case, we test the model on the data generated when the microgrid is in the islanded mode, results of which are shown in Table 10. The table presents the precision, recall and F1-score for each of the eleven types of faults for three different noise levels. While, the model is able to classify all single phase and two-phase faults correctly, it struggled to distinguish between the three phase faults and three phases to ground faults. This, could be attributed to the fact that the two types of faults have very similar signatures.

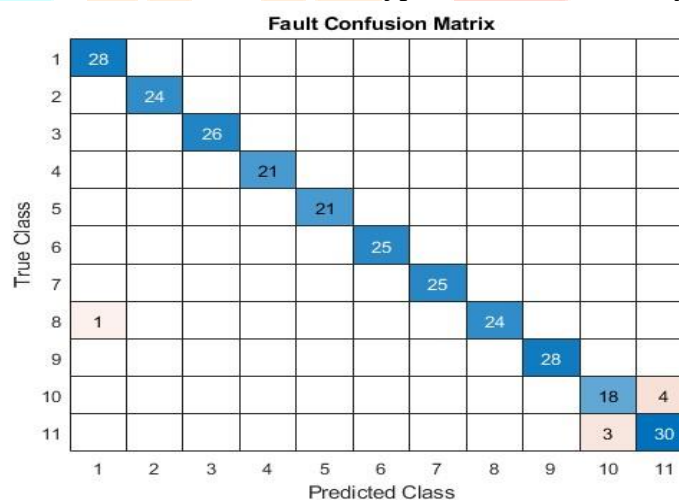


FIGURE 11 Confusion matrix for classification results with microgrid in the islanded mode using LSTM network.

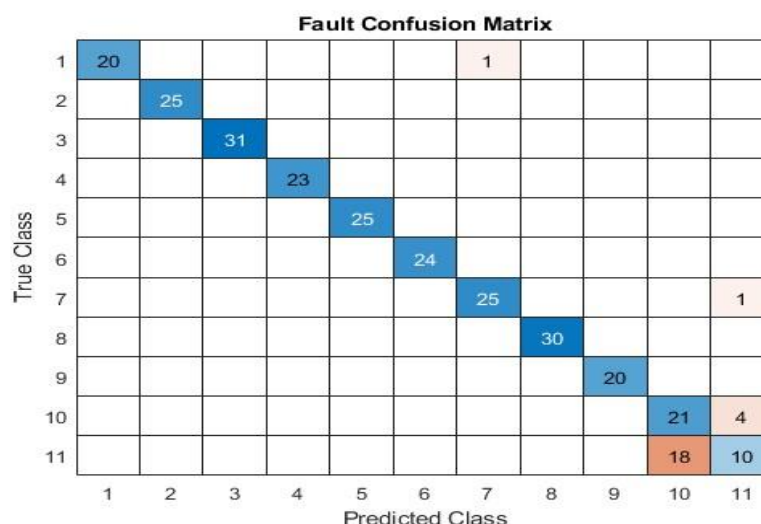


FIGURE 12 Confusion matrixes for classification results with microgrid in the grid connected mode using LSTM network.

In both the above cases, the results showed high F1-scores for all faults barring ABC and ABCG faults across all noise levels. The model is trained and tested on one cycle of post fault 3 phase voltage data and takes 0.685 seconds to classify a fault. Table 12 provides the computation time of various processes involved. The overall validation and test accuracy of the model in both grids connected mode and islanded mode for different noise levels is provided in Table 13.

TABLE 9. Computation Time for Various Processes for Method 1

Process	DWT based Pre-processing	Model Training	Fault Classification
Avg. Time (sec)	0.0531	453.2	0.685

CONCLUSION AND FUTURE WORK

The research presented in this thesis studies the application of two types of neural networks for the purpose of classifying faults in Microgrid. The data for training the neural networks was generated by implementing a modified IEEE 13 bus network connected with DERs and battery storage systems. An effort was made to generate signals that reflect real world data by adding AWGN and AIGN noise to the signals. The noisy signals were further processed using DWT based MRA. To assess the performance of the models, they were tested on three levels of noisy data. The simulations showed that the LSTM networks provide superior performance by achieving high accuracy as compared to the CNN model. The CNN model performed well but required twice the amount of data as the LSTM network to provide a comparable performance. The research showed that a practical, data-based approach can be implemented to for the protection of Microgrid from electrical faults.

A lot of research can be conducted to make the proposed approach much more robust and practical in the future. As faults are often accompanied by arcing, the impact of the non-linear fault resistance can be studied on the performance of the model. Furthermore, the method can be extended to detect and classify ‘evolving faults’ i.e. faults that begin in one phase and spread to other phases subsequently. In this work, we assumed only a single fault on the system at any given time, however, further research can be done to study the impact of multiple faults in different parts of the Microgrid on the proposed methods. Finally, data-based approaches are limited by the data that they are trained on and may fail to perform in cases where the fault conditions do not match the training data, thus a way to handle such cases must be found to make the proposed scheme truly practical.

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