SIMULATION-BASED EVALUATION OF MACHINE LEARNING ALGORITHMS FOR FAULT DETECTION IN MICROGRIDS

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Abstract. Microgrids fault detection is essential to ensure stable and uninterrupted operation, especially as renewable energy sources and distributed generation become more widespread. In this study, a single-source AC microgrid was modeled in MATLAB/Simulink to examine the effect of different short-circuit conditions, comprising Single phase to Ground, two phase, two phase to Ground and three phase/Three phase to Ground faults. By simulating these faults in different load conditions as well as different fault impedances (specifically the low impedance ranging between 0.001 and 10 Ohms) we were able to produce a dataset comprising of different features including voltages, currents, and other features extracted therein. The dataset was then utilized to test different artificial intelligence algorithms to provide a reliable basis for classification of faults and demonstrate the relative advantages of such approaches. Among the tested algorithms, Random Forest achieved the highest accuracy (82%), outperforming, Multi-Layer Perceptron, Decision Tree and long short-term memory. The future work will be extended to include high-impedance faults and real-time hardware in the loop validation, thereby contributing to the development of adaptive protection schemes for modern microgrids.
Keywords: *microgrid protection system, fault identification, fault classification, intelligent learning algorithms, model based algorithms*

Introduction

The concerns raised by greenhouse gas emissions, climate change, and thus the need for sustainable alternatives to fossil fuels, have consequently led to a steep hike in the demand for renewable energy source (Sortomme et al., 2008). The integration of Distributed Energy Resources (DERs), comprising wind turbines, photovoltaic solar system, energy storage element, and small-scale generation units, into a single controllable entity has resulted in the evolution of microgrids (Zaben et al., 2024; Brearley and Prabu, 2017; Ton and Smith, 2012). They allow the integration and control of DERs and thus it is important to properly regulate them. By definition, a microgrid is a small energy system that can operate locally either in the islanded (isolated) mode or in conjunction with the utility grid. It not only includes the generation units (or DERs) and the loads, but also the communication infrastructure, making the system flexible but more vulnerable to faults (Parhizi et al., 2015; Ustun et al., 2012; El-Zonkoly, 2011). Unlike conventional power systems where current flows in a single direction, microgrids allow two-way power flow due to the presence of multiple DERs. This, combined with the fluctuating nature of renewable resources, creates major challenges for existing protection scheme. Traditional protection based on overcurrent relays and reverse power flow detection is often inadequate in microgrids, primarily because inverter-based sources limit fault current magnitudes (Cano et al., 2024). Other factors such as the diversity of network topologies, different grounding practices, and the variability in DER penetration levels make the protection coordination more complex

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and difficult (Lin et al., 2019; Kar et al., 2017; Kuncheva, 2014). Consequently, conventional schemes often suffer delays in detecting faults, maloperation, or even a total failure in some cases. *Figure 1* reflects the summary of these issues. To establish a theoretical foundation for the simulated analysis, the three phase voltages under balanced conditions can be expressed as equation (1) to equation (3) where are the phase voltages respectively, is the amplitude of peak voltage, is the frequency (in Hertz) and is time (in sec).

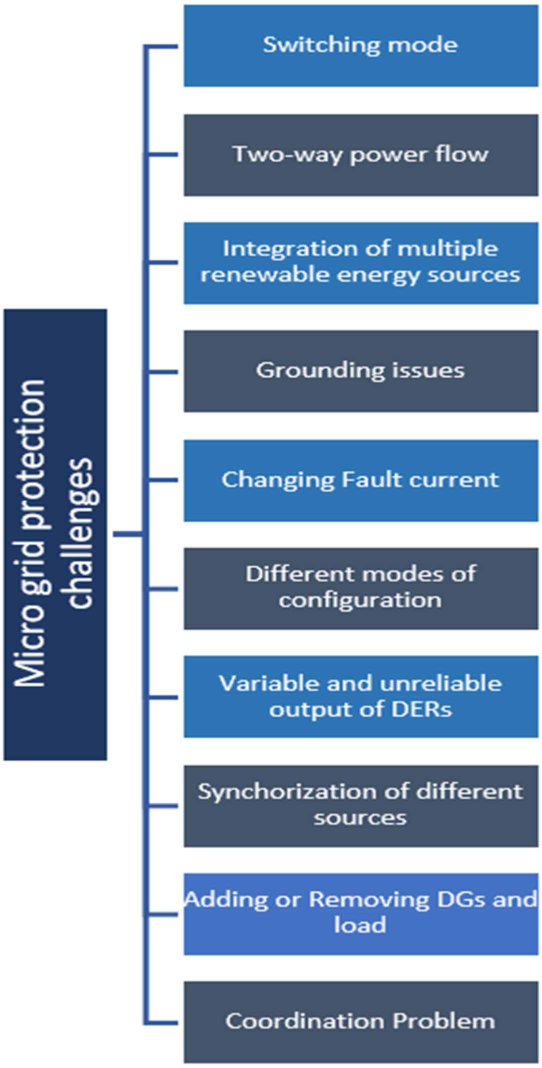

Figure 1. *Micro-grid protection challenges.*

When a single phase to ground (LG) fault occurs on phase a, the corresponding fault current is given by equation (4) where Z1 is the positive sequence impedance, Z2 is the negative sequence impedance and Z0 is the zero-sequence impedance respectively, and is the fault impedance. This implies that fault impedance and network sequence parameters affect the fault current's magnitude, providing the analytical foundation for the simulated current distortions examined in later sections. Due to these challenges, researchers have studied novel techniques for locating faults and their classification (Altaf et al., 2022; Rezaei and Uddin, 2021). It has been realized that the adoption of a

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single technique for the purpose of classification and detection of faults has always proved to be insufficient. Therefore, it will be essential to consider the adoption of intelligent protection schemes that utilize a variety of techniques for effective recognizing, categorizing, and localization of faults (Saha et al., 2019). The Machine learning (ML) and Deep Learning (DL) techniques have especially gained increased popularity in recent years thanks to their functionalities of detecting patterns in the complicated current and voltage patterns and self-adaption to the nonlinearity system behavior, with greater accuracy.

In this context, the novelty of our work is four-fold. We first offer a complete simulation of an AC microgrid in MATLAB/Simulink together with the pre known short-circuit fault scenarios, namely Single phase to Ground (LG), Two phase (LL), Two phase to Ground (LLG) and three phase (LLL) / Three phase to Ground (LLLG). It has been carried out to study the dynamic behavior of voltage and current signals and several other extracted features from such signals. Second, we create a dataset by conducting the simulation under various fault scenarios, fault impedances, and load conditions. Third, we then test several ML and DL algorithms such as Multilayer Perceptron, Support Vector Machine, Decision Trees, Random Forest and Long Short-Term Memory networks. Fourth and finally, we compare our results against recent research literature such that the merits and demerits of various classifiers may be critically evaluated. It is noted that the analysis indicates that Random Forest has provided the maximum classification accuracy. Unlike previous studies that focus on individual fault types or fixed impedances, this study investigates multiple low-impedance fault conditions across varied loads and fault locations in a unified MATLAB-based microgrid model. The generated dataset enables a comparative analysis of multiple ML techniques under consistent operating conditions. By integrating simulation-based studies with open-source evidence, this work derives theoretical and practical insights into the application of ML and DL algorithms for microgrid fault detection.

Classification of fault in power system

Power systems faults occur when the current diverted away from its designated path due to insulation breakdown, equipment failure, or outside disruptions such as lightning strikes and adverse weather conditions (Gururajapathy et al., 2017). Both the reliability and the stability of the network, are compromised by such occurrences, and if they do not address properly, may result in equipment damage or prolonged service interruption. From a broad perspective, power system faults are generally classified into two categories: series faults and shunt faults. Series faults, also known as open-circuit faults are most commonly incurred by the opening of conductors in single-phase, double-phase, or three-phase lines. Although these faults do not often produce high fault currents, they significantly create imbalance in the system and overall reliability. Shunt faults, in contrast, occur when conductors make unintended contact with each other or with the ground, leading to large fault currents. Shunt faults are further classified into four main types: namely Single phase to Ground (LG), Two phase (LL), Two phase to Ground (LLG) and three phase (LLL) / Three phase to Ground (LLLG) faults. The most severe of these are the three-phase faults because all the wires are involved and the faults will have the highest current values in most cases. Such severe disturbances have the potential to destabilize the system and induce equipment failure (Paithankar and Bhide, 2022). For mathematical representation, the faulted conditions in a triple-phase

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system are characterized by the utilization of symmetrical components. The sequence currents relations for the most common fault types are summarized as in Eq. (1) to Eq. (3). The major fault categories that are considered in this study are depicted in *Figure 2*, which illustrates the fundamental types of disturbances that are encountered in AC power systems. This classification also serves as the major reference for the subsequent analysis and provides the foundation for introducing machine learning methods for recognizing and precisely diagnosing fault conditions.

$$LG\ fault: I_0 = I_1 = I_2 \quad \text{Eq. (1)}$$
$$LL\ fault: I_0 = 0, I_1 = -I_2 \quad \text{Eq. (2)}$$
$$LLG\ fault: I_1 + I_2 + I_0 = 0 \quad \text{Eq. (3)}$$

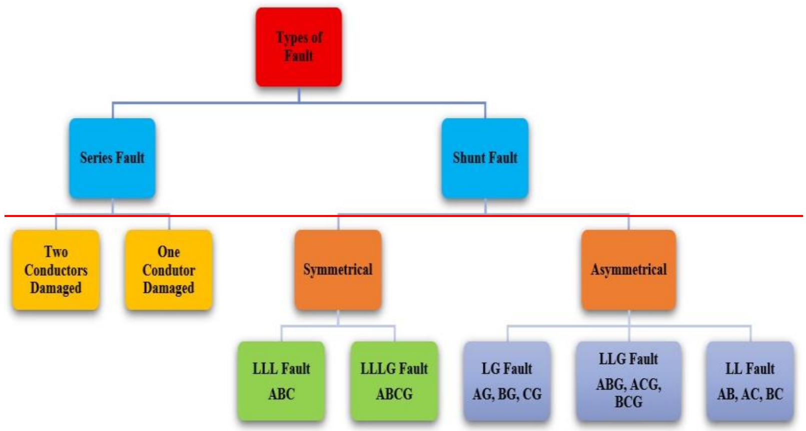

Figure 2. *Types of faults.*

ML techniques for fault analysis

The addition of distributed energy resources (DERs) and variable loads makes microgrids even more sensitive to disturbances so that the rapid and precise detection of faults becomes unavoidable. Traditional protection schemes are frequently unable to address the challenge due to the bidirectional character of powers and dampened levels of fault currents in inverter-dominated grids. Machine learning (ML) has very recently been proposed as a promising alternative, having the characteristic of discriminating faults directly from the current and voltage measurements. With learning, the ML schemes are provided with the capabilities of discerning subtle nonlinear relations, adapting to the variable system conditions, and refining the accuracy in the classification of faults when compared to traditional schemes. The most well-known ML methods are described below along with their pros and cons in the security of microgrids. In the following sub-sections, some explanations are given with these methods and their usages in the fault detection issue.

Multilayer Perception (MLP)

The perceptron is a type of artificial neuron that function as a linear classifier, producing binary outputs. The multilayer perceptron (MLP) is a feedforward neural network, as information travel only in one direction without forming cycle. It comprising an input layer, one or more hidden layers, and an output layer. It works in two stages, forward propagation (prediction) and backward propagation (learning),

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minimize the loss function by adjusting weights and biases. In fault classification, MLP handle complex dataset efficiently. wavelet packet transform (WPT) employed (Haykin, 2009) to extract features from the voltage and current signals, for this purpose two key preprocessing methods such as dimensionality reduction and discretization to enhance classifier performance. In that study, the MLP achieved high classification accuracy of 92.22% without feature reduction, but performance declined when dimensionality reduction was applied, highlighting the importance of feature selection strategies. Another work (Jamali et al., 2020) used an MLP with seven output neurons to identify both the occurrence and type of fault in a six-bus microgrid. Input was considered as Discrete Fourier Transform (DFT) based Features extracted from current and voltage signals. The architecture possessed 64 hidden neurons, trained over 1000 epochs, achieving 90.3% accuracy. However, this study was limited merely to symmetrical faults, overlooking other fault types. *Figure 3* illustrates the MLP architecture employed in this work.

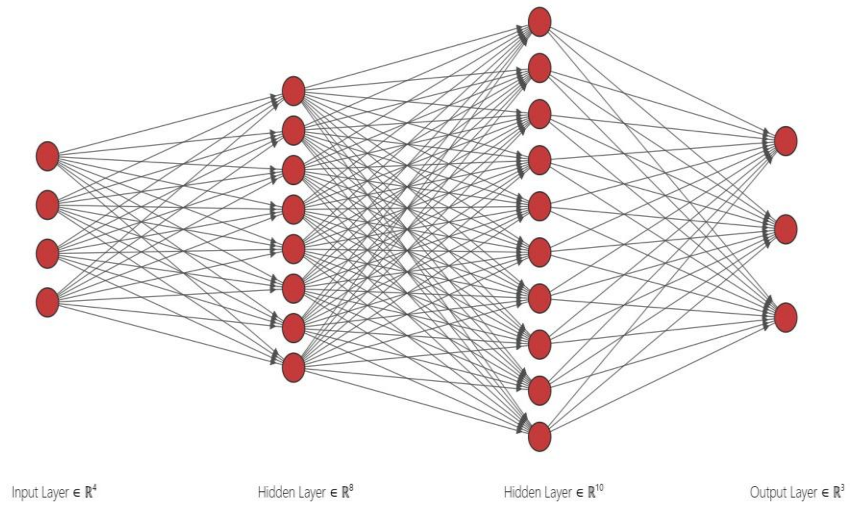

Figure 3. *Multilayer Perceptron (MLP).*

Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised ML technique designed for classification and regression problem (Abdelgayed et al., 2018). Its basic idea is to construct an optimal hyperplane which can distinguish classes with maximum margin. The data points around the separating hyperplane that are also referred to as support vectors, play a crucial role in ascertaining the optimal decision. When non-linearly separable data need to be mapped into linearly separable data SVM uses kernel function to map these data into higher dimensions. In microgrid applications, SVM has been utilized both for classification and fault location. For example, (Jamali et al., 2020) proposed fault location in a six-bus microgrid using SVM, achieving 99.5% detection accuracy based on raw RMS measurements of current and voltage without any feature extraction. The major advantage of SVM is that it can work in high dimensional feature spaces effectively and can handle non-linear data effectively. However, challenges include the selection of an appropriate kernel, slow training on large datasets due to its non-parametric nature and sensitive to feature scaling (Abdelgayed et al., 2018). *Figure 4* demonstrates the concept of SVM classification.

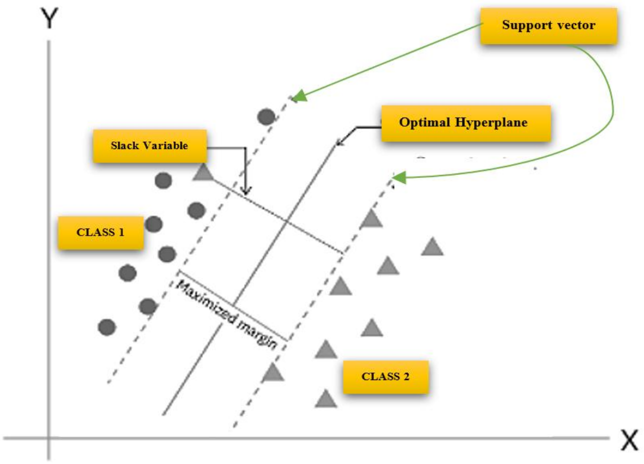

Figure 4. *Support Vector Machine.*

Decision tree

Decision Trees (DTs) are supervised learning algorithms designed for both classification and regression tasks. They have a root node, internal nodes, and leaf nodes operate in a hierarchical frame work. The process begins at the root node, where data are split at each node based on attribute conditions until decision is reached at the leaf node. The process of pruning helps reduce overfitting by eliminating redundant branches (Lin et al., 2019). In microgrid fault detection, new classifier such as the J48 decision tree (an extension of the C4.5 algorithm) have been employed. One study (Dougherty, 2012) used J48DT for fault zone detection, applying feature extraction methods including RMS values, power factor, sequence components, and total harmonic distortion (THD). The wrapper method for feature selection resulted in higher performance than filter-based technique. Accuracy levels of approximately 89% were achieved across training, validation, and test datasets (Sridharan and Sugumaran, 2025). Additionally, studies have combined DT with Discrete Wavelet Transform (DWT) for the purpose of feature extraction, enhancing classification accuracy (Kar et al., 2017; Mishra et al., 2016). *Figure 5* shows the structure of a decision tree.

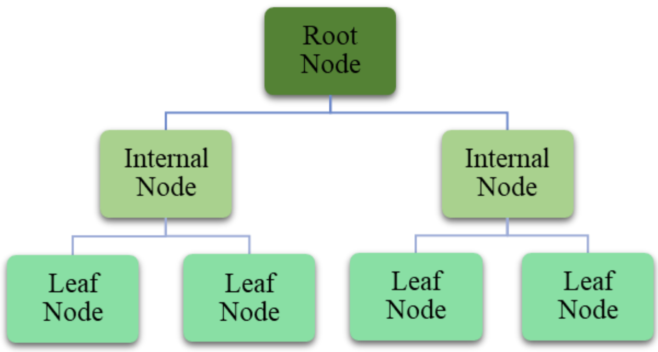

Figure 5. *Decision tree.*

Random forest

Random Forest (RF) is a form of ensemble learning method where predictive accuracy is enhanced by combining the multiple trees for making decisions. An individual tree is learned using the random subset of the data and attributes, and majority vote determines the final classification. RF would result in reliable microgrid fault detection. In (Kar et al., 2017), the method achieved 99.9% accuracy in detecting faults. The result show that integrated RF with DWT-based feature extraction, reporting 99% fault detection accuracy and 94% accuracy in fault type classification. RF is immune to overfitting and does not require feature scaling, but it can be computationally intensive when dealing with large numbers of trees. *Figure 6* presents clustering property of RF.

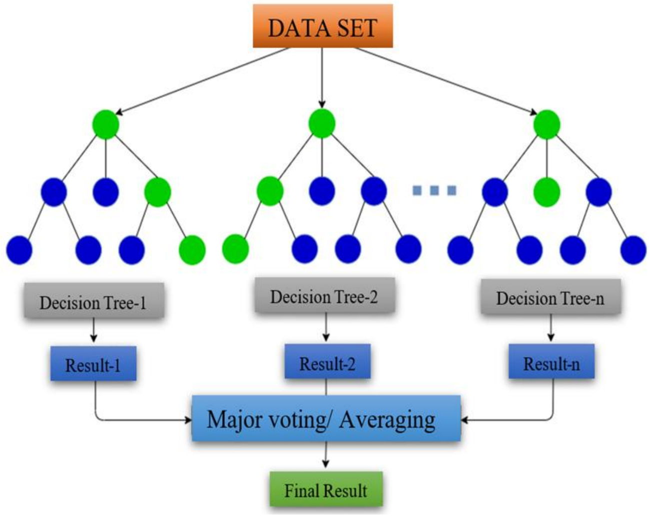

Figure 6. *Random forest.*

Deep learning based LSTM network

Long Short-Term Memory (LSTM) networks, is an amended form of recurrent neural networks (RNNs), are developed to work for sequential data and retain long-term dependencies (Veerasamy et al., 2021). Their architecture includes memory cells regulated by input, forget, and output gates that manage the flow of information. LSTMs are used in power systems for tasks such as load prediction and fault detection due to their capability to process time-series data. They are particularly effective in capturing temporal patterns that conventional ML models may overlook. For example, (Roy et al., 2023) highlights the multitask learning ability of LSTMs in handling complex datasets. Advantages of LSTM include overcoming the vanishing gradient problem and strong performance on sequence prediction tasks. However, they are computationally intensive, prone to overfitting, and require large amounts of training data. *Figure 7* depicts the LSTM cell structure.

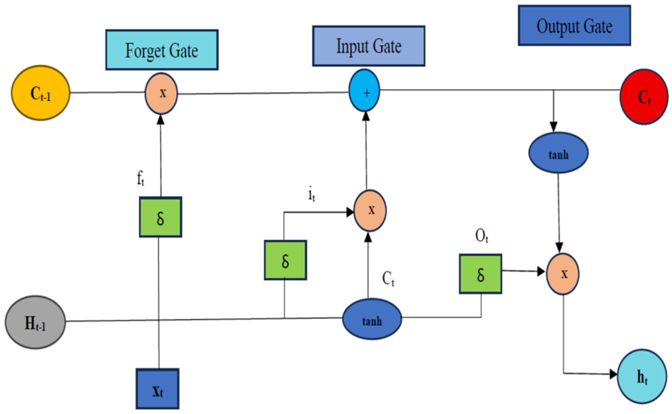

Figure 7. *LSTM cell structure.*

Performance comparison of various ML technique

The performance of the ML algorithms for the purpose of detecting faults in microgrids relies on several factors such as the nature of the extracted features, the nature of the dataset, and classifier construction. Here, in this research compared using simulation outcomes five popular ML techniques that were later assessed relative to values reported in the literature. *Table 1* gives a comparison between accuracy reported in the literature and the results obtained in this research work. The comparison outcomes reveal that Random Forest delivered the best accuracy for the synthetic dataset (~82%), in agreement with studies in the literature where RF has been popular for its reliability and resilience. LSTM also delivered a commendable performance (~81%), in agreement with its propensity for voltage and current waveform sequence variation feature capture. Conversely, moderate performances were given by Decision Tree and MLP models where DT proved highly sensitive to limited dataset variation. SVM delivered stable performance (~82%), albeit sensitive to careful parameter selection. Even though the absolute values of accuracy here were below some baselines in the literature, the result confirms the same relative ranking that ensemble schemes (RF) and recurrent network models (LSTM) are generally superior to single classifiers. It is a result of the nature of dataset size, feature abstracting schemes, and the fact that most baselines in the literature are implemented using the larger or aggregate sets of datasets, whereas this work is implemented using a single simulated microgrid system.

Table 1*. Comparison of classification performance in literature vs. this study.*

Technique	Key Features Used	Accuracy (Literature / This Study)	Accuracy (This Study)	Strengths	Limitations
MLP	Voltage/current signals (WPT, DFT)	90–92% (Jamali et al., 2020; Haykin, 2009)	~79%	Handles non-linear data, effective on unseen cases	Sensitive to dataset size; may overfit small samples
SVM	RMS values of current & voltage	95–99% (Jamali et al., 2020; Abdelgayed et al., 2018)	~82%	Performs well in high-dimensional space, robust to non-linearity	Requires kernel tuning; computationally heavy for large data
DT	RMS, power factor, THD, sequence components	87–89% (Sridharan and Sugumaran, 2025; Lin et al., 2019; Dougherty, 2012)	~76%	Simple, interpretable; fast training	Prone to overfitting; unstable with small data variations

RF	DWT features + ensemble voting	94–99% (up to 99.9%) (Kar et al., 2017; Mishra et al., 2016; Kuncheva, 2014)	~82%	Reduces overfitting, strong accuracy on complex datasets	Computationally intensive with many trees
LSTM	Time-series current/voltage sequences	92–98% (Veerasamy et al., 2021)	~81%	Captures temporal patterns; avoids vanishing gradient	High training cost; requires larger datasets

Materials and Methods

A two-step procedure has been followed here. For the initial step, a MATLAB/Simulink model of an AC microgrid has been created to generate a series of short-circuit fault cases. For the second step, the waveforms so generated were categorized using the machine learning (ML) schemes programmed into the programming language Python.

$$V_a = V_p \sin 2\pi f t \qquad \text{Eq. (4)}$$

$$V_b = V_p \sin(2\pi f t - 120°) \qquad \text{Eq. (5)}$$

$$V_c = V_p \sin(2\pi f t + 120°) \qquad \text{Eq. (6)}$$

$$\text{fault current}(\mathrm{I_f}) = \frac{V_a}{Z_1 + Z_2 + Z_0 + 3Z_f} \qquad \text{Eq. (7)}$$

Microgrid modeling and fault scenarios

The microgrid model was established in MATLAB R2023a/Simulink and consisted of a three-phase source rated at 150 kVA and operating at 60 Hz, supplying a balanced RL load of approximately 80 kVA. The distribution feeder was represented with practical resistance and inductance values, while inverter-based distributed generation was integrated to reflect realistic system dynamics. Low-impedance short-circuit faults were applied at different buses of the network, covering Single phase to Ground (LG), Two phase (LL), Two phase to Ground (LLG) and three phase (LLL)/Three phase to Ground (LLLG) conditions. Each fault has been initiated between 0.3 seconds to 0.8 seconds between the one-second simulation time span, while the fault resistance has been varied between 0.01 Ω and 0.1 Ω and the inception angles have been varied between 0° and 90°. Such varied ensured that the developed dataset comprises a broad spectrum of fault activities. The system was designed on MATLAB/Simulink is shown in Figure 8, which illustrates the primary source, transmission line for distribution, load, and corresponding components that are used for simulation.

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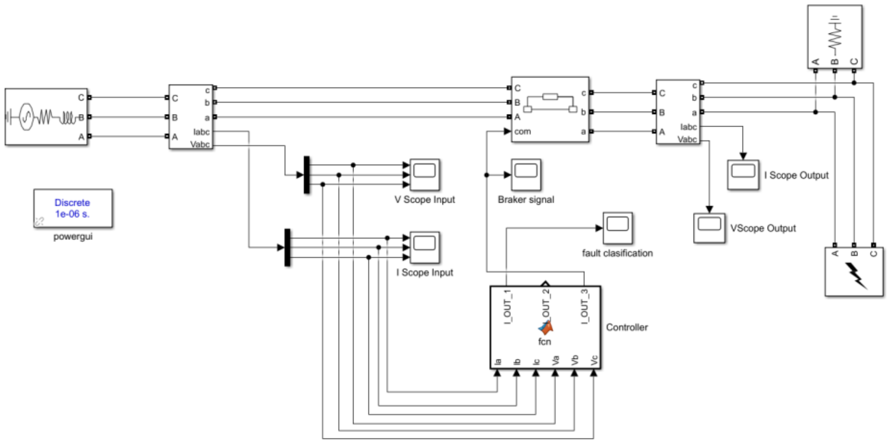

Figure 8. *MATLAB simulation.*

Results and Discussion

Data acquisition and waveform analysis

Three-phase current and voltage waveforms for their normal and faulted states were also captured. The waveforms exhibited definite patterns for each kind of fault. For instance, LG faults showed a fall in faulted-phase voltage and a sudden spike in its current, while the LLG faults showed unsymmetrical distortions in two phases. For the LL faults, two of the phase voltages fell sharply, while the three-phase and the three-phase-to-ground faults resulted in near-complete voltage collapse and huge current surges in all phases. Representative examples of these behaviors are presented in Figures 9–20, which illustrate voltage and current distortions under different fault conditions. These results confirm that the severity and type of fault are directly reflected in waveform variations, providing the foundation for feature extraction and ML-based classification. In preprocessing the dataset for analysis, a number of features were extracted from the retrieved signals. They consisted of the root mean square (RMS) measurements of the voltage and current, the frequency-domain features by the Fast Fourier Transform (FFT), statistical features of the mean and the standard deviation. Time-domain descriptors such as also the peak amplitudes and waveform distortions were recovered. Mathematically, the parameters were evaluated by the standard terms given in the Eq. (8) to Eq. (12). These formulations quantitatively capture the time- and frequency-domain characteristics of voltage and current signals, providing a discriminative feature set for ML-based fault classification.

$$X_{RMS} = \sqrt{\left(\frac{1}{N}\sum x^2(n)\right)} \qquad \text{Eq. (8)}$$

$$\mu = \left(\frac{1}{N}\right)\sum x(n) \qquad \text{Eq. (9)}$$

$$\sigma = \sqrt{\left(\frac{1}{(N-1)}\sum (x(n)-\mu)^2\right)} \qquad \text{Eq. (10)}$$

$$THD = \frac{\sqrt{V_2^{2}+V_3^{2}+\cdots+V_n^{2}}}{V_1 \times 100} \quad \text{Eq. (11)}$$

$$X(k) = \sum x(n)\, e^{\frac{-j2\pi kn}{N}} \quad \text{Eq. (12)}$$

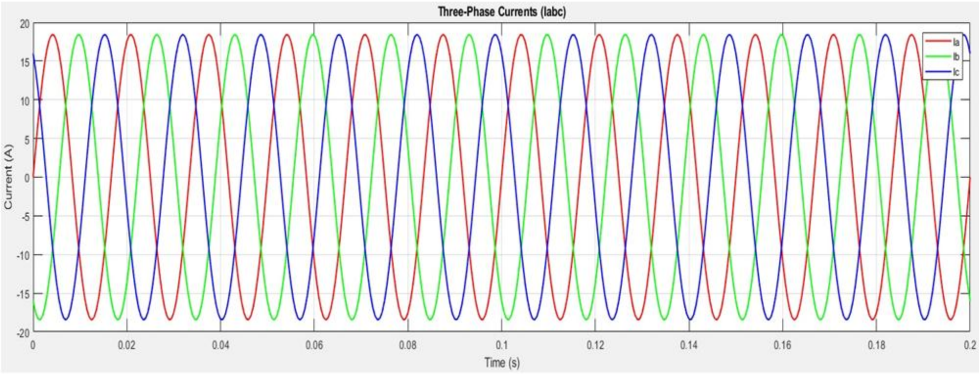

Figure 9. *Three-phase current waveform under normal condition (no-fault).*

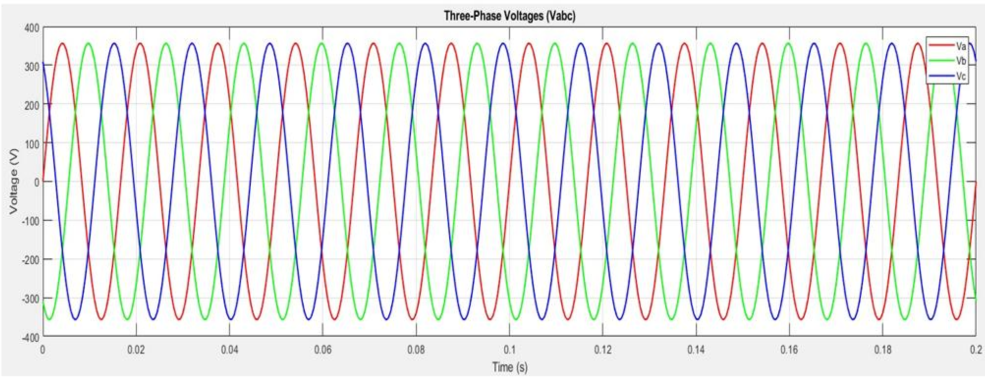

Figure 10. *Three phase voltage waveforms under normal condition (no-fault).*

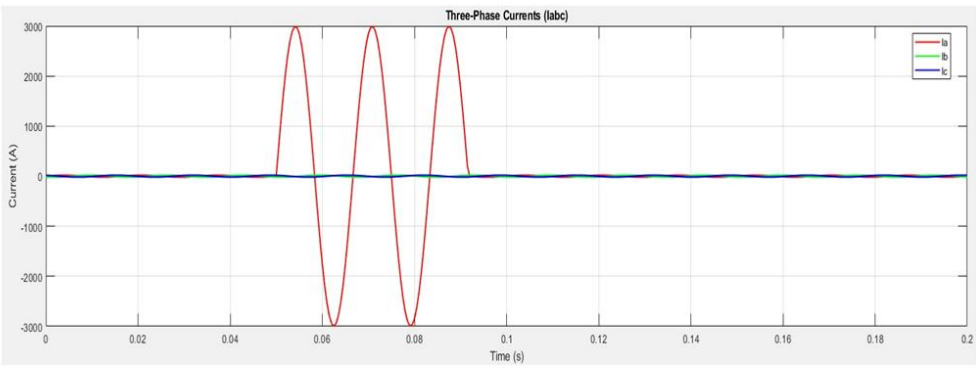

Figure 11. *Current waveform under line-to-Ground (LG) fault.*

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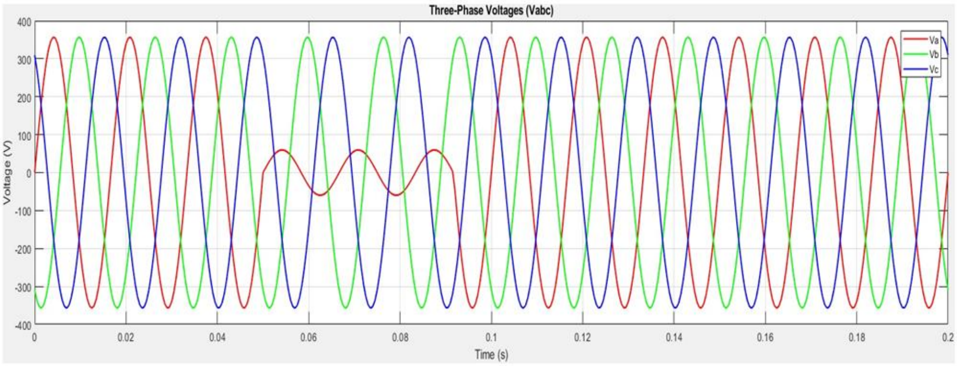

Figure 12. *Voltage waveform under Line-to-Ground (LG) fault.*

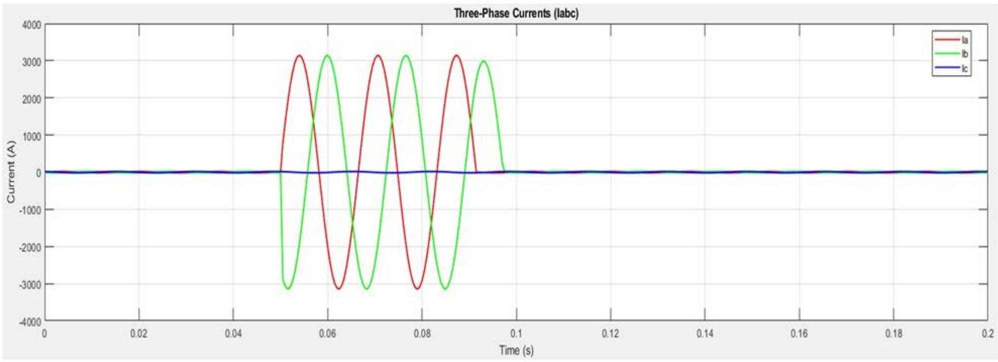

Figure 13. *Current waveform under Double Line-to-Ground (LLG) fault.*

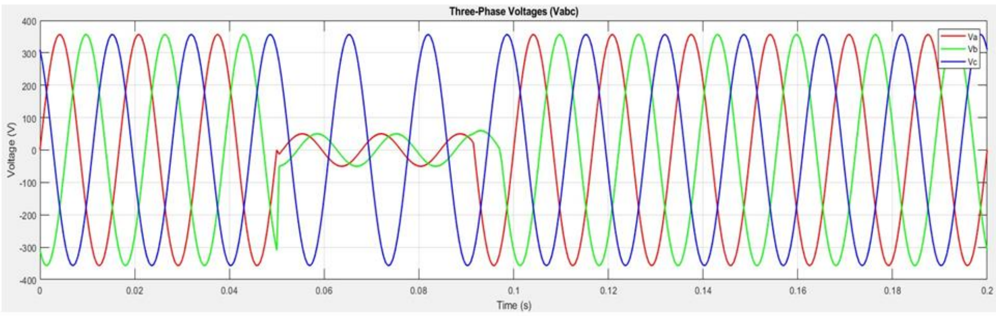

Figure 14. *Voltage waveform under Double Line-to-Ground (LLG) fault.*

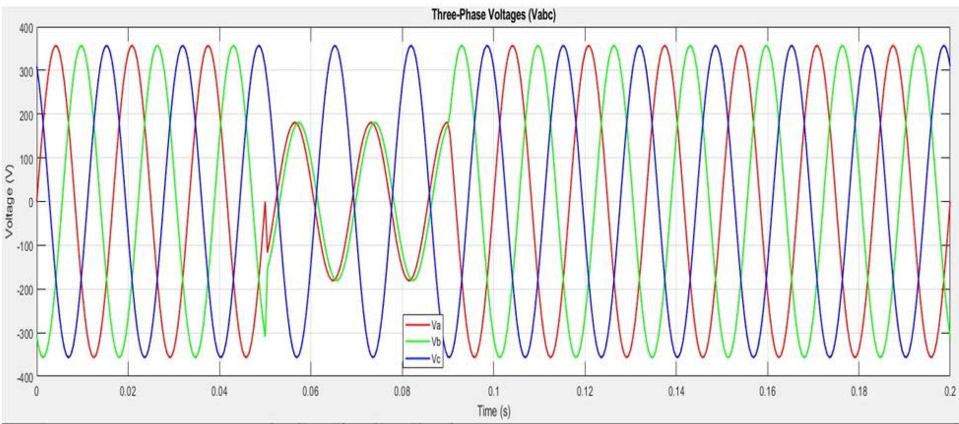

Figure 15. *Voltage waveform under Line-to-Line (LL) fault.*

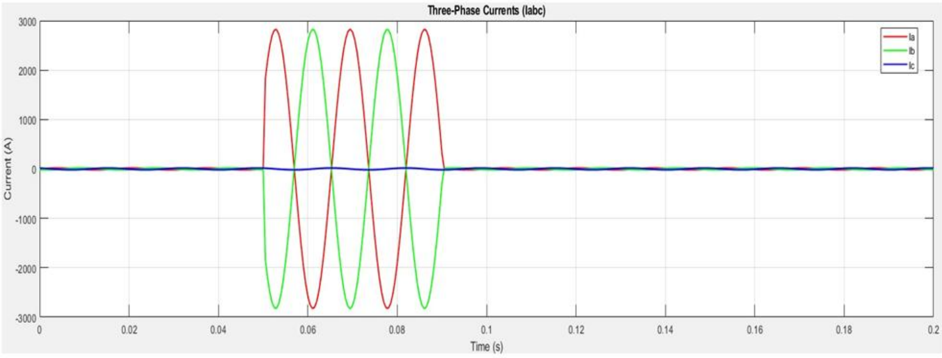

Figure 16. *Current waveform under Line-to-Line (LL) fault.*

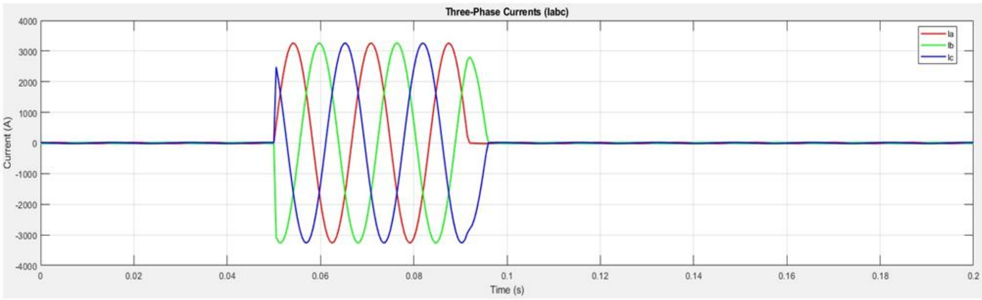

Figure 17. *Current waveform under Three-Phase (LLL) fault.*

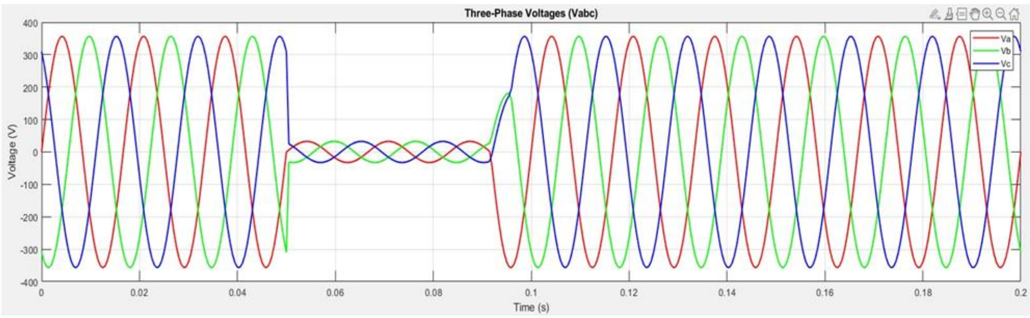

Figure 18. *Voltage waveform under Three-Phase (LLL) fault.*

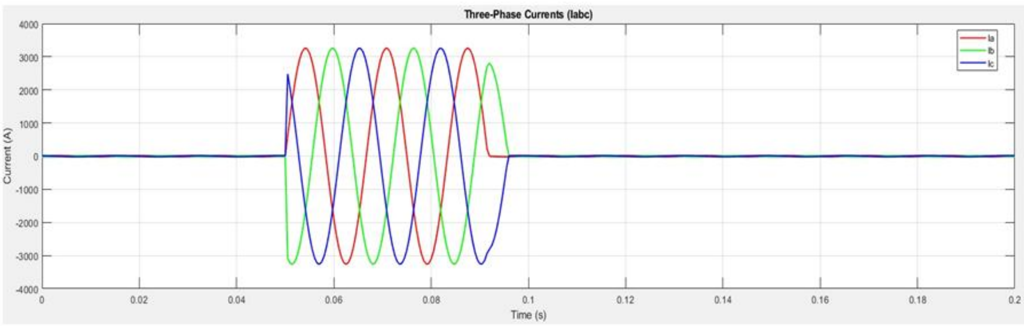

Figure 19. *Current waveform under Three-Phase-to-Ground (LLLG) fault.*

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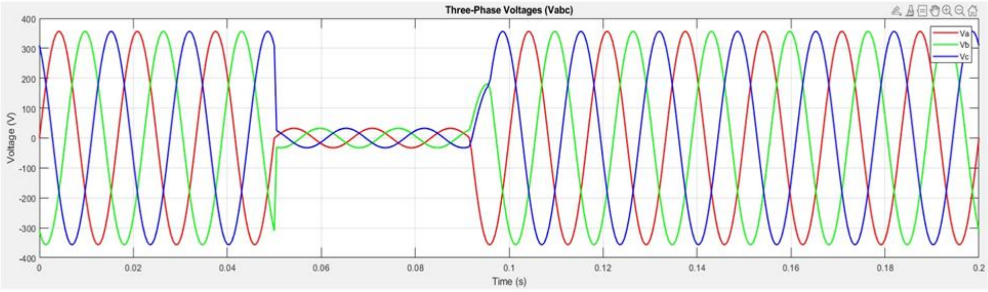

Figure 20. *Voltage waveform under Three-phase-to-Ground (LLLG) fault.*

Machine learning framework

The data comprised approximately 2000 labeled specimens for normal operation and five faults' categories. For the purpose of increased generalization, all the specimens were normalized and divided into training sets (70%), verification sets (15%), and test sets (15%). There were five classifiers employed here: Multilayer Perceptron, Support Vector Machine, Decision Trees, Random Forest and Long Short-Term Memory networks. The mathematical formulas for the machine learning models were established as the Eq. (13) to Eq. (21) in order to indicate their mechanisms for making decisions. These expressions are the definitive mathematical comprehension of how each algorithm processes and categorizes the microgrid fault data. All the machine learning models were designed and trained under the MATLAB R2023a environment. The individual classification learner toolbox was employed for DT, RF, MLP, and SVM models, and the deep learning toolbox for the execution of LSTM. Tree depth, estimators number, hidden layer size, learning rate, and epochs for training were all experimentally calibrated by repeated trials and cross-validation to minimize avoiding overfitting and optimizing classification performance. All extracted features were normalized between 0 and 1 to ensure uniform scaling and to prevent bias toward variables of higher magnitude. Hyperparameter such as tree depth, number of estimators, learning rate, and training epochs were optimized through repeated cross-validation to balance accuracy and computational cost while minimizing overfitting.

$$f_{SVM}(x) = sign\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right) \quad \text{Eq. (13)}$$

$$Gini = 1 - \sum_{i=1}^{C} p_i^2 \quad \text{Eq. (14)}$$

$$y_{RF} = mode\{h_1(x), h_2(x), \cdots, h_T(x)\quad \text{Eq. (15)}$$

$$w_{ij}(t+1) = w_{ij}(t) - \eta \frac{\partial L}{\partial w_{ij}} \quad \text{Eq. (16)}$$

$$f_t = \sigma(W_f[h_{t-1,}x_t] + b_f) \quad \text{Eq. (17)}$$

$$i_t = \sigma(W_i[h_{t-1,}x_t] + b_i) \quad \text{Eq. (18)}$$

$$o_t = \sigma(W_0[h_{t-1}, x_t] + b_0) \quad \text{Eq. (19)}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_C[h_{t-1}, x_t] + b_C) \quad \text{Eq. (20)}$$

$$h_t = o_t \odot \tanh(C_t) \quad \text{Eq. (21)}$$

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Evaluation metrics

The classifier's performance was assessed by the standard measures depicted by Eq. (22) to Eq. (25) in order to obtain a complete evaluation. Accuracy estimated the percentage of properly classified sample sets, while precision and recall estimated the accuracy of fault type identifications. The F1-score, being the harmonic mean of the precision and the recall rate, proved especially efficient in managing potential class imbalances. Further confusion matrices were also constructed for the sake of plotting the results of the classification for all the fault levels. The above-described metrics were also uniformly employed for the test dataset in simulation and the performance comparison given in next section, facilitating a just appraisal of the classifiers and their applicability for microgrid fault detection.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{Eq. (22)}$$

$$Precision = \frac{TP}{TP + FP} \quad \text{Eq. (23)}$$

$$Recall = \frac{TP}{(TP + FN)} \quad \text{Eq. (24)}$$

$$F1 - Score = \frac{2 \times (Precision \times Recall)}{(Precision + Recall)} \quad \text{Eq. (25)}$$

Analytical validation of fault signal

To confirm simulation results, the waveform responses were checked against theoretical fault equations that were developed in Section 2. The current level for a single line-to-ground fault provided by Eq. (26) was around thrice the normal phase current in synchronism with. The voltage asymmetry that also existed when double-line-to-ground faults were present also followed the theoretical relationship. Accordingly, the analytical and simulation data correspondence verifies the analytical model implemented using MATLAB/Simulink and confirms the dataset that has been employed for classification purposes using machine learning.

$$I_f = \frac{v_a}{Z_1 + Z_2 + Z_0 + 3Z_f} \quad \text{Eq. (26)}$$

Conclusion

The research work included the simulation analysis of fault detection and classification for AC microgrids through the machine learning approach. A MATLAB/Simulink model has also been established for the simulation of voltage and current waveforms for the scenarios such as LG, LL, LLG, LLL, and LLLG. The waveforms were processed to extract representative features that served as input to various ML classifiers. Comparative analysis confirmed that ensemble and deep learning models (RF and LSTM) were more resilient to non-linear and noisy waveform feature, whereas single classifier such as DT and MLP were more sensitive to dataset size and feature variation (Zaben et al., 2024; Roy et al., 2023; Veerasamy et al., 2021; Lin et al., 2019; Kar et al., 2017; Mishra et al., 2016). Figure-based waveform

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distortions also validated that fault severity directly influences classifier accuracy. The comparison results confirmed that the waveform-based features represent a stable base for discriminating fault categories. Among the studied methods, the Random Forest demonstrated the maximum accuracy for the simulation dataset, testifying to its efficiency and reliability to perform with a wide spectrum of feature sets. Long Short-Term Memory networks also demonstrated competitive performance where it thrived in recognizing patterns of sequential waveforms over time. Decision Tree, SVM, and MLP were characterized by average accuracy but sensitivity to the dataset's size and feature selection strategies. The experiment outcomes indicate that the ensemble methods and the deep learning models are better for the purpose of microgrid fault detection than the single classifiers while their computational intensity may impede real-time applicability. Based on comparison of simulation results with benchmarks provided in the literature, the paper showed consistency in the patterns of the performance and the promising potential of RF and LSTM as competitive alternatives for Smart microgrid protection schemes (Zaben et al., 2024; Roy et al., 2023; Veerasamy et al., 2021; Lin et al., 2019; Kar et al., 2017; Mishra et al., 2016). The research will be further enhanced for high-impedance and time-varying faults, for hybrid ML–DL techniques, and for testing the performance in a hardware-in-the-loop or real-time environment. Future work will extend toward hybrid ML-DL architectures and hardware-in-the-loop validation to enable real-time adaptive protection for smart microgrids. Developments of this nature will further reinforce the resilience and adaptability of the microgrid protection system towards facilitating intelligent and reliable fault detection for the future power network.

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Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

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