FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 2, February, 2026, pp 89 – 97
DOI: https://doi.org/10.33003/fjs-2026-1002-4100

DEVELOPMENT OF A FAULT DETECTION AND CLASSIFICATION SYSTEM IN MICROGRID USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

As microgrids grow in significance, enabling consumers to manage their energy demands themselves, they present complexities such as fluctuating loads, two-way (bidirectional) power flow, and low fault currents that make traditional protection approaches such as Overcurrent protection and Impedance-based techniques less effective. This study explores the development of a fault detection and classification system based on Artificial Neural Networks (ANN) specifically designed for microgrids to address these complications. This research simulates a range of fault scenarios applicable in a microgrid setting using MATLAB/Simulink, extracts relevant voltage and current data, develops and trains an ANN model, and assesses its ability to accurately identify and categorize faults. The performance analysis shows the detection and classification models demonstrate remarkable accuracy, achieving low Mean Squared Error (MSE) values of 3.72×10^{-10} and 0.014393 and regression correlations as high as 1 and 0.998 across training, validation, and testing datasets. This research has improved microgrid systems' reliability through artificial neural networks by simultaneously reducing downtime. The findings establish a foundation for the future development of fault detection systems and incorporation into smart grid technologies.

Keywords: Artificial Neural Network, Microgrid, Fault Detection and Classification, MATLAB

INTRODUCTION

Over the past two decades, the power systems sector has experienced significant transformations. The emergence of microgrids exemplifies this rapid evolution. Customers now have the capability to meet some or all their energy requirements through their own microgrid, rather than solely relying on a single distributor, such as the grid operator, for their electricity needs (Phafula & Nixon, 2020). Microgrids consist of renewable sources like solar photovoltaic (PV) systems, wind turbines, or non-renewable sources like synchronous diesel generators, that function either individually or to the main grid (Pan et al., 2022). Microgrids offer numerous benefits, including reduced expenses, improved energy quality, and enhanced reliability for consumers (Cano et al., 2024). The functioning and protection of microgrids are substantially influenced by dynamic loads, bi-directional power flow, the intermittency of local renewable energy sources, the type of distributed generation (whether involving synchronous machines or electronically controlled sources) and fluctuations in fault current (Grci, 2021). Establishing a reliable protection system is one of the challenges associated with microgrid implementation. Recent studies have indicated that traditional protection methods may not work well for microgrids, particularly when they operate in islanded mode due to reduced fault currents (Kolla & Onwonga, 2020). Microgrid faults can be unpredictable and require a focused approach for repairing affected components. The microgrid supply line can encounter various short circuit defects, including phase-to-phase and phase-to-ground faults, which lead to unstable current signals within the microgrid. These electrical faults create instability in the system and negatively affect power quality (Roy et al., 2023).

There are various techniques available for fault detection and classification in microgrids, including support vector machines (SVM), fuzzy logic, artificial neural networks (ANN), Principal Component Analysis (PCA), k-nearest neighbours (k-NNs) and decision trees (DTs). k-NN is easy to understand, adaptable, and does not assume a specific distribution, but it can be resource-intensive with larger datasets and is susceptible to noise and irrelevant variables (Awasthi et al., 2024). Decision Trees provide clear decision processes, can manage both numerical and categorical data, and do not need feature normalization, yet they may overfit and show bias towards more prevalent classes, which makes them less effective for accurate fault estimation (Lin et al., 2020).

Fuzzy logic addresses uncertainties through a rule-based framework and accommodates imprecise information, but it requires sophisticated membership functions and complex rule formulation, along with advanced feature extraction (Mousavi et al., 2024). Support Vector Machines (SVM) perform well in high-dimensional contexts, are efficient in coefficient memory use, and adapt effectively to various kernel types, though they require careful selection of the optimal kernel, can struggle with noisy data, and may become resource-intensive when dealing with many support vectors (Baghaee et al., 2020). Artificial Neural Networks (ANNs) provide high levels of accuracy and flexibility for complex systems involving distributed generation, are adept at managing noise but necessitate substantial data, considerable computational power, and lengthy training processes (Liu et al., 2022).

Beyond fault detection, these techniques have been extensively applied to solve non-linear problems in the energy sector, such as predicting the higher heating value (HHV) of biomass by optimizing various training algorithms (Bello & Dodo, 2025) and activation functions (Msheliza & Dodo, 2025).

Sahoo, (2020) focused on modelling a three-phase transmission line with distributed parameters to simulate both fault and non-fault conditions, utilizing MATLAB Simulink for phase current data collection. Following data preprocessing in Python to ensure the dataset's integrity, a four-layer Artificial Neural Network (ANN) with a configuration of 3-18-36-2 was developed using Keras (a high-level, user-friendly API used for building and training neural networks). The model incorporated ReLU activation and the Adam optimizer, undergoing training for 50 epochs via Back Propagation, ultimately achieving high accuracy in identifying both symmetrical and unsymmetrical faults. This methodology underscores the efficacy of Python-based deep learning techniques for fault detection, facilitating expedited power restoration and promoting cost-effective maintenance of transmission lines. The ANN model's efficiency is limited by its reliance on simulated data, high computational demands, and generalization challenges, highlighting the need for further optimization and real-world validation. Leh et al., (2020) modelled a 14-bus power system in MATLAB simulating variety of unsymmetrical problems investigating on power system fault detection and classification. A 6-14-1 network for fault detection and a 6-3-4 network for fault classification were the two Artificial Neural Network (ANN) designs used. Levenberg-Marquardt and Scaled Conjugate Gradient techniques were used to train the networks using 1000 datasets for each type of failure. The approach proved to be very flexible, quick to react, and noise-resistant, which made it appropriate for real-time problem management in dynamic power systems. The training data is restricted to a single fault location and a small dataset, which may affect generalizability. There was not a thorough optimization analysis of the ANN's fixed architecture and reliance on specific training algorithms yielding a fault classification accuracy of only 70%. Kolla & Onwonga, (2020) proposed a four-step process for creating an ANN-based microgrid fault identification system recognised fault types (single-phase, phase-to-phase, and three-phase) and no-fault circumstances as outputs and uses the RMS values of three-phase voltages and currents as inputs. Six input neurons, five output neurons, and two hidden layers make up the ANN structure, which has been refined through testing. The Levenberg-Marquardt backpropagation algorithm in MATLAB is used to train the system utilising data from simulated faults at various sites. Simulation results demonstrated the trained ANN's potential for microgrid protection, particularly in low fault current scenarios in islanded mode, by accurately detecting faults and no-fault states. The limitations of the study include testing a particular microgrid configuration with a restricted range of fault types and locations, focusing solely on islanded mode operation. Fahim et al., (2020) worked on combining Discrete Wavelet Transform (DWT) with a Deep Belief Network (DBN) to enhance fault detection in microgrid systems. Using the Daubechies wavelet, detail coefficients at Level 4 were analysed to extract fault-specific features, with signal energy serving as fault signatures. The DBN, comprising stacked Restricted Boltzmann Machines (RBMs) and an Artificial Neural Network (ANN), used unsupervised pre-training and supervised fine-tuning for classification. A dropout technique improved noise resistance. The model achieved high accuracy, demonstrating robustness to noise, adaptability to various microgrid configurations. The methodology of the paper emphasizes the classification of five categories of symmetrical and asymmetrical shunt faults, deliberately omitting open circuits and series faults. It does not consider non-linear fault resistance, multiple fault occurrences, or faults that evolve over time. The classifier encounters challenges in differentiating between LLL and LLLG faults. Phafula & Nixon, (2020) worked on fault detection in an islanded microgrid developed a three-phase microgrid model in MATLAB Simulink, incorporating an inverter-based source, a short transmission line, a resistive load (up to 30 kW), and fault scenarios (phase-to-ground, phase-to-phase, and three-phase). Fault locations varied from 0 to 1 km, with resistances ranging from 1 mΩ to 1 Ω. Phase-to-ground voltages were measured, and Fast Fourier Transform (FFT) was used to extract voltage magnitudes and phase angles. The data was normalized and used to train an Artificial Neural Network (ANN) for fault classification, with a second ANN trained for fault location. The model achieved high accuracy in fault detection, classification, and localization, offering a communication-free and adaptable solution for microgrid fault management. The methodology is constrained by its emphasis on a singular radial feeder and a designated microgrid configuration, potentially impacting its applicability to multi-bus or grid-connected systems. The artificial neural network (ANN) was evaluated using a solely resistive load, which raises issues regarding its ability diverse load categories. Grci, (2021) presented the development of a grid connected photovoltaic (PV)-based direct current (DC) microgrid model utilizing MATLAB/Simulink. The model encompasses PV arrays, a battery energy storage system (BESS), and a voltage source converter (VSC) to effectively simulate fault conditions and load variations. Current signals from the BESS DC-DC converter were analysed through the application of the Short-Time Fourier Transform (STFT) to investigate transient behaviours. Relevant features were extracted from the STFT spectrum, and six machine learning classifiers such as Logistic Regression, Naive Bayes, k-Nearest Neighbours, Decision Trees, Support Vector Machines (SVM), and AdaBoost were employed for fault detection. The methodology exhibited a high level of accuracy in fault identification and facilitates real-time implementation due to its low computational complexity. The constraints of the method encompass its dependence on a particular PV-based DC microgrid model and a limited concentration on pole-to-pole faults, which inhibits its applicability to other fault categories and system configurations. The performance of classifiers varied, with certain classifiers such as Naive Bayes demonstrating suboptimal results, and the research lacked empirical validation, concentrating exclusively on fault detection without fault localization. Pan et al., (2022) focused on fault detection in power systems outlining a data-driven method that utilized a modified IEEE 13-bus feeder. Multiple fault scenarios were modelled while incorporating noise to reflect real-world situations. Discrete wavelet transforms (DWTs) employing the Daubechies 5 (db5) wavelet were utilized for feature extraction, and the signals' scalograms were analysed with convolutional neural networks (CNNs). This approach shows exceptional adaptability, precision with noisy data, and quicker fault detection compared to conventional methods. The methodology presents certain limitations, such as the assumption of only one fault occurring simultaneously, difficulties in differentiating between LLL and LLLG faults, and inadequate performance under unforeseen fault conditions or nonlinear fault resistance. Additionally, it does not account for evolving, open circuits, and series faults. Roy et al., (2023) modelled a grid-connected microgrid (MG) system in MATLAB/Simulink, incorporating solar, diesel generators, and batteries, with mathematical formulations to simulate their behaviour. Fault detection and classification were achieved using Long Short-Term Memory (LSTM) networks and a hybrid LSTM-Feed-Forward Neural Network (FFNN) with a Backpropagation Algorithm (BPA) for fault location. The system was trained using data from eleven fault conditions, including single-phase, line-to-line, and three-phase faults. The LSTM network detected and classified faults based on voltage and current signals, while neural networks focused on fault location. Real-time validation using the OPAL-RT simulator confirmed the system's high accuracy, with the LSTM-based approach outperforming traditional Artificial Neural Networks (ANNs) in handling the nonlinearities of microgrid systems and ensuring practical reliability. While the research illustrates the effectiveness of deep learning methodologies for fault identification within a microgrid system, it does not sufficiently address intricate fault categories such as high-impedance and intermittent faults. Mbey, (2023) used the IEEE 13-node test network with virtual smart meters to simulate and analyse faults, including single-phase, two-phase, and overvoltage conditions. Smart meter data collected via OpenDSS-G was processed using a hybrid Long Short-Term Memory (LSTM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) model. LSTM handled time-series feature extraction, while ANFIS classified faults using phase currents and voltages as inputs. Deep learning methodologies, despite their robustness, exhibit constraints such as a substantial reliance on data, necessitating extensive labelled datasets that accurately reflect real-world conditions to ensure precision. They require considerable computational power and may encounter challenges in generalizing across various system configurations without undergoing retraining. Kumar & Amir, (2024) proposed a fault detection method for hybrid energy-based multi-area microgrids, combining Discrete Wavelet Transform (DWT) with Deep Neural Networks (DNNs). The system, which included models of solar photovoltaic and fuel cell MGs, utilized DWT to extract features from the voltages and currents at the point of common coupling (PCC). This method surpassed conventional techniques, showcasing its robustness and suitability for real-time fault detection in intricate MG systems. Nonetheless, the proposed methodology exhibits certain constraints, including challenges in feature extraction and the complexity of data preprocessing. The research predominantly addresses asymmetrical faults; thus, additional exploration may be warranted to evaluate the model's efficacy in managing alternative fault types. Cano et al., (2024) employed an IEEE-5 ring network test bench within MATLAB Simulink to simulate and evaluate fault scenarios in microgrids (MGs), concentrating on detection and classification. Fault waveforms underwent processing through Discrete Wavelet Transform (DWT), utilizing the db4 wavelet to extract time-frequency features essential for fault identification. These features were then classified using a Radial Basis Function Neural Network (RBFNN), which exhibited high accuracy owing to its flexibility and computational effectiveness. The performance of the RBFNN was improved by adjusting fault parameters, utilizing Gaussian kernels, and applying normalized data. A comparative study indicated that the RBFNN surpassed alternative models, such as SVM and other neural networks, in terms of accuracy and real-time applicability. However, it is important to highlight that the investigation mainly emphasizes the resolution of low and medium-sized impedance faults. Although the omission of high-impedance faults is not regarded as a significant constraint within this study's framework, it does present avenues for subsequent research initiatives.

For microgrids that utilize inverter-interfaced distributed generation, traditional fault detection methods that depend on high fault currents have proven to be inadequate. This highlights the need for the development of more flexible and intelligent solutions. Artificial Neural Networks with numerous different ANN architectures, training algorithms and transfer functions and other machine learning and deep learning methods including Multi-layer Perceptron (MLP), Radial Basis Function Neural Networks (RBFNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Wavelet Neural Networks (WNN) and Deep Belief Networks (DBN) are widely explored for fault detection and classification in power systems, including microgrids (Jasim et al., 2023; Leh et al., 2020; Kumar & Amir, 2024; Cano et al., 2024). The performance of various artificial neural network (ANN) architectures in diverse microgrid scenarios has not been comprehensively evaluated, even though ANNs are commonly utilized for fault detection and classification. This includes challenges associated with ANN models becoming trapped in local minima due to insufficient training data while focusing only on specific fault types and scenario or network configurations. This research has considerable significance as it possesses the capacity to enhance the operational efficacy and dependability of microgrid systems. Through the application of artificial neural networks (ANNs) for the detection and classification of faults, this investigation fosters the advancement of intelligent and adaptive systems adept at addressing intricate failure scenarios. The findings can aid energy system operators and engineers in reducing downtime and improving the resilience of power distribution network. Furthermore, it sets the foundation for future research in real-time fault detection systems and their integration with smart grid technologies.

MATERIALS AND METHODS

MATLAB Software

In this study the MATLAB/Simulink R2019a version was used for modelling the microgrid system and simulating the faults; Artificial Neural Network toolbox for designing and training the neural network based on the supplied data.

System Model

The model in Figure 1 represents a detailed hybrid AC/DC microgrid implemented in MATLAB Simulink, integrating various generation sources, power electronics, load dynamics. The microgrid includes renewable generation via a double-stage grid-connected solar photovoltaic (PV) array, which is supplemented by battery energy storage to ensure energy stability. A diesel generator with full genset controls is incorporated as a backup power source, supporting both grid-connected and islanded operation modes. Transmission lines are modelled using Three-Phase PI Section Line blocks, and transformers are represented at different voltage levels (11kV, 34.5kV, and 0.4kV) stepping down power originally 154MW to emulate real-world power distribution. The load subsystem comprises both AC and DC loads, including generic loads and a Series RLC Load to simulate industrial or residential demand, along with a dedicated DC Load for testing the DC bus. This setup enables analysis of how varying load conditions interact with power generation and fault events. The model includes a wide range of measurement tools, such as voltage and current sensors and three-phase V-I measurement blocks, to monitor electrical signals and track system behaviour during faults. The model simulates a wide range of fault conditions such as single line-to-ground (AG, BG, CG), double line-to-ground (ABG, ACG, BCG), line-to-line (AB, AC, BC), and three-phase faults (ABC, ABCG) using faults injection subsystems blocks. These simulations extract voltage (Va, Vb, Vc) and current (Ia, Ib, Ic) waveforms along with zero-sequence components (v0, i0) to form an input dataset. This is done over multiple line lengths (LL = 10, 5, 1), simulating faults at different locations within the system.

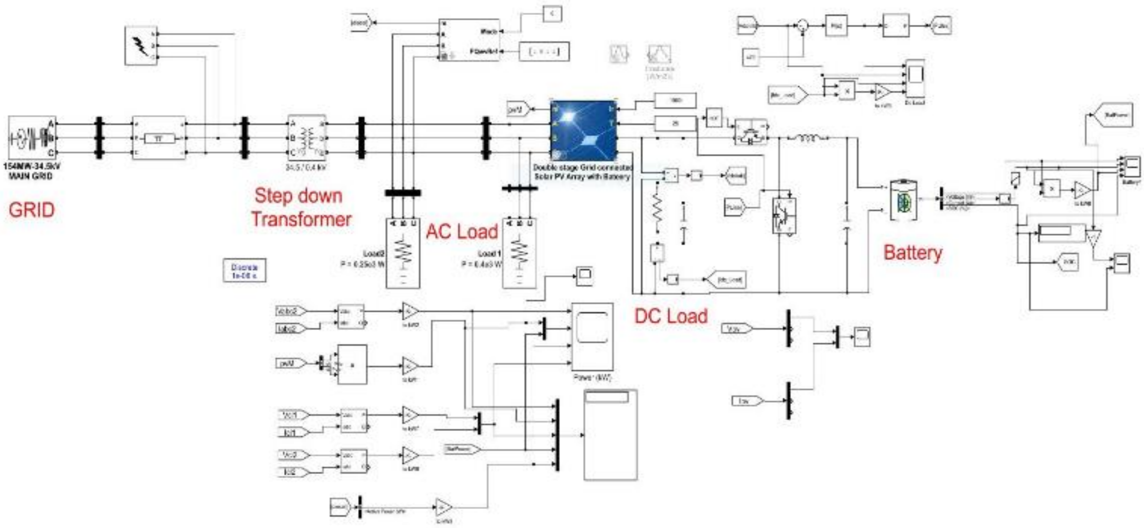


Figure 1: The Microgrid System Model on MATLAB/Simulink

Data Collection and Pre-processing

The faulty values of the three-phase current and voltage for the various types of fault condition was obtained from the simulation and tabulated. These values were normalized using the Equation (1)

$$X_n = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (1)$$

$\boldsymbol{X_{max}}$ = maximum value of the set, $\boldsymbol{X_{min}}$ = minimum value of the set, $\boldsymbol{X_i}$ = the selected value to be normalized and $\boldsymbol{X_n}$ = the normalized value; in Microsoft Excel so that all values range from 0 to 1.

The simulation generates a dataset of 360 samples in which 70% of samples, i.e., 252 samples were used for training, 15% samples, i.e., 54 samples were used for testing, and 15% samples, i.e., 54 samples were used for validation. The training set is used to train the proposed model, while the testing set evaluates the model's performance after training, thereby demonstrating its effectiveness.

Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functionality of biological neural networks. Their architecture adapts based on the nature of the input and output data they process, making them effective nonlinear statistical models for capturing complex relationships (Sahoo, 2020). An ANN is organized into layers comprising interconnected nodes, or neurons, with the hidden layer often referred to as a perceptron. Typically, an ANN consists of three layers: the input layer, the hidden layer, and the output layer. The input layer receives data in various forms, such as commands or datasets (Kishor & Kumar, 2022). Hidden layers carry out intricate computations and gather insights from the input data. The output layer generates the ultimate result, whether it be a classification or a forecasted value (Phafula & Nixon, 2020). These networks learn by modifying the connections among neurons using algorithms like backpropagation and Levenberg-Marquardt, which systematically change weights and biases to decrease errors (Kolla & Onwonga, 2020). Activation functions add non-linearity to the network, which enables it to recognize intricate patterns; common functions include linear, step, sign, sigmoid, and hyperbolic tangent functions, especially in the hidden layers (Leh et al., 2020). The training procedure consists of providing the ANN with input data along with the associated desired outputs, allowing it to fine-tune its parameters to lessen the gap between predicted and actual outcomes (Phafula & Nixon, 2020). Generally, the dataset is segmented into training, validation, and testing sets to promote effective learning and generalization. In a Backpropagation Neural Network (BPNN), the output is used as feedback to adjust the weights in the network. The error is calculated for each iteration, starting from the output layer and propagating backward through the network. Initially, the weights in the BPNN are assigned random values and paired with input data (Leh et al., 2020). During each iteration, the weights are updated based on the computed error, and this process is repeated for all input-output combinations in the training dataset. This iterative procedure continues until the network's outputs match the target values within a predefined error tolerance. The backpropagation algorithm updates the weights layer by layer in reverse order, ensuring that the entire network learns effectively.

The ANN for fault detection used Levenberg-Marquardt training algorithm (trainlm). The neural network configuration was 8-10-1 (eight inputs, ten hidden layer neurons and one output), Hyperbolic Tangent Sigmoid (tansig) transfer function is taken for hidden layer that takes an input of N matrix to feed the hidden layer neurons in the neural network. Linear (purelin) activation function is taken for the output layer that takes an input of N matrix and returns the values in the output terminal.

The use of the Levenberg-Marquardt (trainlm) algorithm in this study is supported by recent findings in energy content prediction, where it demonstrated exceptional stability and predictive reliability (Bello & Dodo, 2025). Furthermore, the selection of the hyperbolic tangent sigmoid (tansig) function is consistent with its identified effectiveness in the output layers of high-performing ANN models for energy prediction tasks (Msheliza & Dodo, 2025).

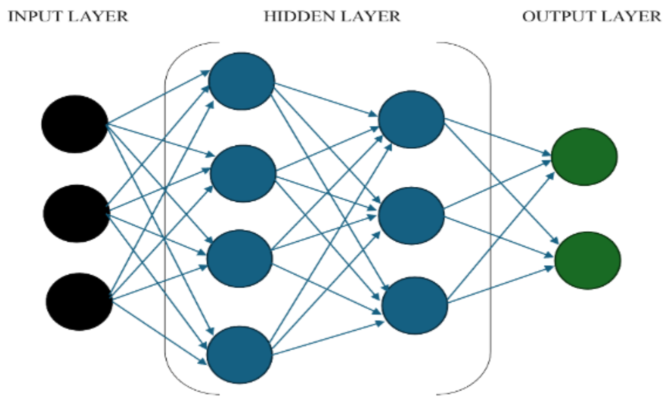
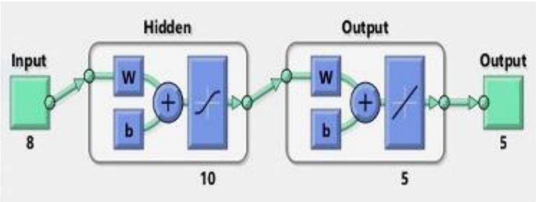
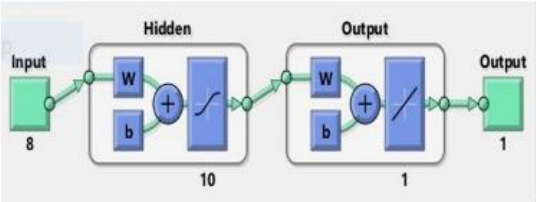


Figure 2: The standard multi-layer neural network



(a)



(b)

Figure 3: Neural Network Architectures for (a)Fault Detection; (b)Fault Classification

Table 1: ANN parameters for Fault Detection and Classification

ANN Parameters	Fault Detection	Fault Classification and Location
Number of Input	8	8
Hidden Layer Neurons	10	10
Number of Output	1	5
Training Algorithm	Levenberg-Marquardt (trainlm)	Levenberg-Marquardt (trainlm)
Hidden Layer Activation Function	Hyperbolic Tangent Sigmoid (tansig)	Hyperbolic Tangent Sigmoid (tansig)
Output Layer Activation Function	Linear (purelin)	Linear (purelin)

Performance Analysis

The performance of the artificial neural networks in detecting and classifying faults in the system will be visualised using regression plots (R), error histogram and performance graphs showing the Mean Square (MSE) all generated on MATLAB application. The methods employed for implementation of the project are presented in a simple flowchart in Figure 4.

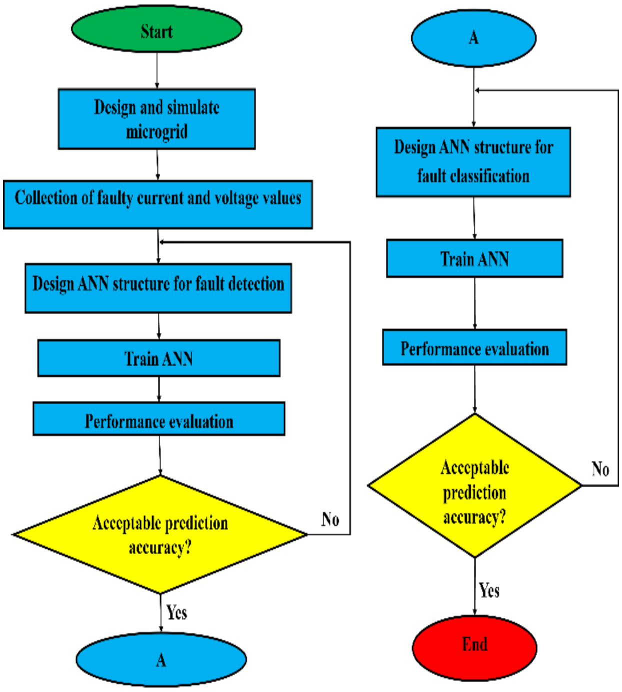


Figure 4: Flowchart of methodology

RESULTS AND DISCUSSION

Fault Detection Neural Network

Mean Squared Error (MSE) measures how different predicted results are from the actual targets. A lower MSE value indicates better predictions, with zero indicating perfect predictions. As shown in the performance plot in Figure 5(b), the network achieved its best validation performance at epoch 0, with an extremely low MSE of 3.72×10^{-10}. This early convergence, marked with a green circle on the curve, reflects the model's efficiency in learning the target mapping in the initial training phase. Notably, the MSE remained consistently low across the training, validation, and testing sets, indicating that the model generalized well without signs of overfitting or underfitting. After epoch 0, the error curves plateaued, suggesting that further training offered negligible performance improvements, which is a sign of a well-trained model that has captured the underlying data patterns effectively.

The error in histogram in Figure 5(c) further supports this conclusion. Most errors were tightly clustered around zero, with over 200 instances falling within the central bin closest to the zero-error line (indicated in orange). The histogram presents the distribution of errors across training, validation, and test datasets, and their close alignment to the zero line implies that the network's predictions were outstandingly accurate across all phases of training.

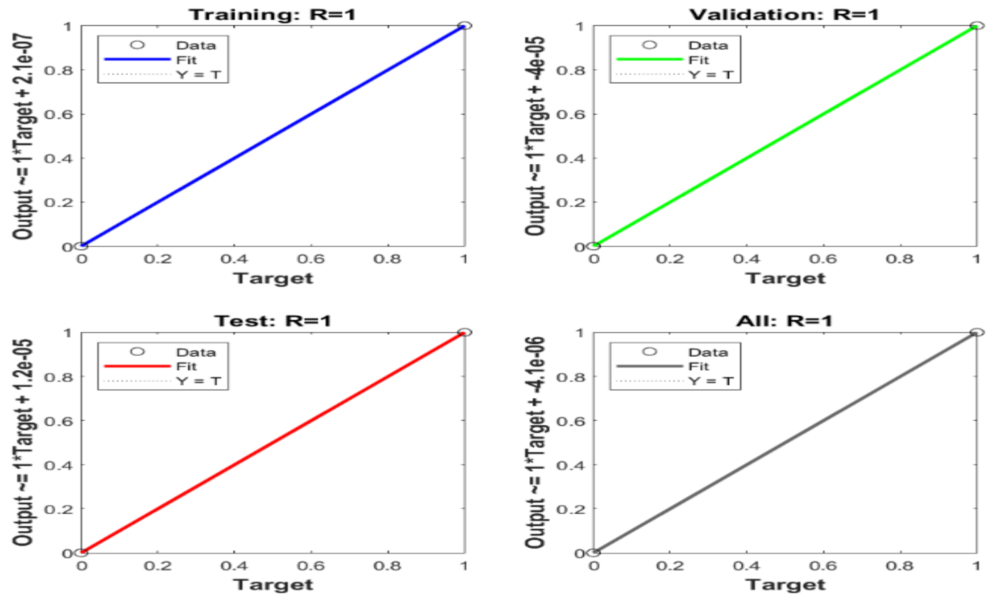
Linear regression analysis was carried out to quantify the relationship between predicted outputs and actual values. The regression plot in Figure 5(a) shows an R-value of 1.0 for all training, validation, test, and combined sets demonstrating a perfect linear correlation between the network's outputs and the target data. In practical terms, this means that the network's predictions not only track the expected outputs accurately but do so with near-zero deviation. This performance level, being rare, highlights the effectiveness of the model in detecting fault conditions in the microgrid with high precision.

The output equation for regression can be described as:

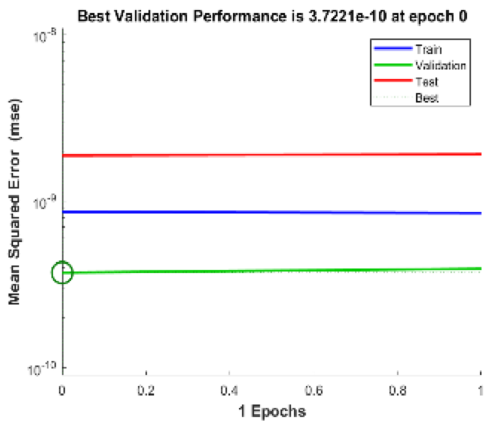
$$\text{Output} = w \cdot \text{Target} + b \quad (2)$$

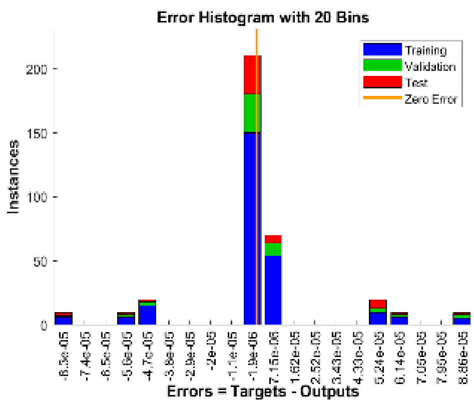
where w is the slope (weight) and b is the bias. From the regression plots, the slope approaches unity with the bias being close to zero, confirming that the neural network closely approximates the ideal prediction line Y=T.

The extremely low MSE, centralized error distributions, and perfect regression correlation together attest to the fact that the proposed neural network model delivers outstanding accuracy and reliability in fault detection tasks.



(a)





(b) (c)

Figure 5: (a)Regression plot (b) Performance plot (c) Error histogram, for the fault detection neural network

This MSE value obtained in this study represents a better performance metric than those reported in several existing approaches. For instance, Leh et al., (2020) focusing on fault detection in transmission lines reported an MSE of 5.5614×10^{-8}, although this result indicates reasonable accuracy, it indicates a higher value than the error achieved in this work. Similarly, Nsed et al., (2024) evaluated fault identification performance using Root Mean Square Error (RMSE) and reported a value of 0.00415, which represents a significantly higher estimation error, further demonstrating the superior detection accuracy achieved in this study. Furthermore, when comparing against a deep learning-based relay protection scheme, this model achieved a marginally superior MSE compared to 4.1622×10^{-10} reported by Jasim et al., (2023). Additionally, this MSE value indicated a higher prediction accuracy compared to a study focused on a 330kV Nigerian transmission line, which reported a best validation MSE of 0.058158 for its regression model (Oruma et al., 2024).

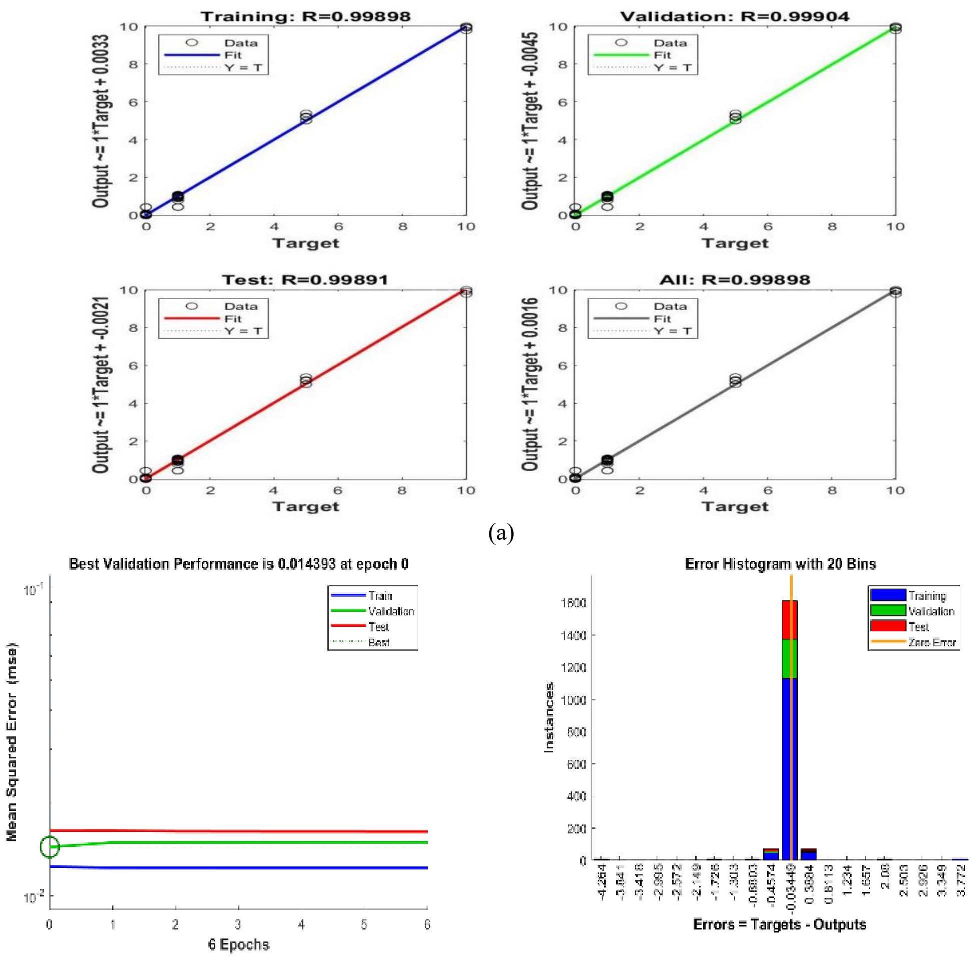
Fault Classification Neural Network

The error histogram in Figure 6(c) provides evidence of the model's accuracy during prediction. The distribution shows a pronounced concentration of errors around zero, with approximately 1,300 instances clustered in the central bins closest to the zero-error line (marked in orange). The close grouping observed in the training (blue), validation (green), and test (red) datasets suggest that most predictions varied only slightly from their actual targets. The symmetric distribution around zero confirms a lack of systematic bias in the model's predictions, supporting the conclusion that the network learned an unbiased representation of relationships of underlying data.

The regression analysis presented in Figure 6(a) shows a strong linear correlation between predicted outputs and actual targets. The model achieved almost perfect R-values across all datasets: R=0.99898 for training, R=0.99904 for validation, R=0.99891 for test, and R=0.99898 for the combined dataset. The correlation coefficients, all exceeding 0.998, establish that the predictions by the network have an excellent linear relationship with target values. The regression slopes are extremely close to unity while the intercepts tend to zero, indicating that the model reproduces the target outputs very accurately.

The Mean Squared Error (MSE) analysis in Figure 6(b) shows the model's optimal validation performance at epoch 0, with an MSE of 0.014393. This early convergence, marked by the green circle on the validation (green) curve, indicates that the model captured the data patterns instantly. The training, validation, and test error curves remained steady throughout the 6-epoch training period, with all three lines staying close to low values around 0.01-0.015 MSE. This suggests that the network learned the target mapping without requiring extra training iterations, and importantly, showed no signs of overfitting through the parallel movement of validation and test errors.

The combination of fast convergence, little prediction errors, unbiased error distribution, and strong linear correlation demonstrates the model's robust learning capacity and excellent fault classification capability.



(b) (c)

Figure 6: (a)Regression plot (b)Performance plot (c)Error histogram, for the fault classification neural network

This quantitative performance surpassed the corresponding error metrics demonstrated in multiple comparative methods. For example, Nsed et al., (2024) utilized an Artificial Neural Network for analysing faults, the reported MSE for fault classification was 0.12348, which is nearly nine times higher than the best validation MSE achieved by this model. In another instance, Leh et al., (2020) employed an ANN for fault classification in transmission lines yielded an MSE of 0.43699 and a correlation coefficient (R) of 0.83955, indicating that this work had a lower error and a higher correlation for classification. In terms of reliability and correlation, the R-value (exceeding 0.998) in this study suggests a nearly perfect performance compared to a microgrid fault identification study where the fault classification accuracy achieved was only 70% (Kolla & Onwonga, 2020).

CONCLUSION

This research project developed an Artificial Neural Network based fault detection and classification system to address the challenges associated with microgrids which included various generation sources (main grid, solar and diesel generator). The fault detection network achieved remarkable accuracy with an extremely low Mean Squared Error (MSE) of 3.72×10^{-10} at Epoch 0 and a perfect R-value of 1.0 across all datasets, indicating flawless prediction capability with zero deviation. Similarly, the fault classification network showed outstanding results with R-values exceeding 0.998 and a best validation MSE of 0.014393, with errors tightly clustered around zero. This study recommends investigating the capabilities of the ANN models on real microgrid data rather than simulated data. Future work should consider complex fault types in microgrid configurations beyond the hybrid AC/DC model reviewed while varying network parameters.

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