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Research Paper

Machine Learning-Based Fault Detection and Classification in Microgrid

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Abstract— *Fault Detection and Classification plays a vital role in maintaining the reliability and stability of microgrids, especially as they incorporate renewable energy sources and become more decentralized. Microgrids face a wide variety of faults, such as short circuits, line-to-ground faults, and other disturbances, which can negatively affect system performance. Traditional fault detection methods have primarily focused on False Data Injection and cyber-attacks, emphasizing vulnerabilities in communication infrastructure. However, this study addresses current faults within the electrical network, focusing on system stability and real-time fault detection in the absence of communication-related errors. In this work, machine learning techniques are employed to enhance fault classification accuracy. Partial Least Squares is used for feature selection to extract relevant statistical features from real-time current data collected from various microgrid components. By optimizing these features and applying them to machine learning models, the approach overcomes the limitations of conventional fault detection methods. The results show a significant improvement in fault classification performance, with up to 10% higher accuracy compared to traditional methods. Additionally, the use of data from neighboring microgrid components boosts the model's robustness, adaptability, and performance under varying operational conditions, contributing to a more resilient microgrid. This research introduces an innovative approach to fault detection in microgrids by combining machine learning and feature optimization, offering a more accurate, reliable, and efficient solution to ensure continuous energy supply and improve system stability under different fault scenarios.*

Keywords—Fault detection, feature selection, fault classification, data-driven modeling, system stability, short circuit faults.

1. Introduction

The increasing penetration of distributed energy resources (DERs) into microgrids has necessitated advanced fault detection techniques to maintain stability and reliability. Traditional fault detection methods often struggle with dynamic microgrid conditions, leading to research into artificial intelligence (AI)-based solutions. Recent studies have explored machine learning and deep learning methods to enhance fault detection accuracy and response time.

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1.1. Research motivation

A fault detection method using Hilbert-Huang Transform (HHT) combined with machine learning techniques was proposed for microgrid fault classification [1]. Deep learning techniques have been utilized to design a relay capable of online fault detection, classification, and location estimation in grid-connected microgrids [2]. Similarly, a machine learning-based technique has been introduced for detecting and localizing faults in low-voltage DC microgrids [3]. A comprehensive review of machine learning methods for fault diagnosis in AC microgrids highlights their effectiveness in real-time fault identification [4]. A reinforcement learning-based approach has been applied to improve voltage and frequency stability in microgrids with wind turbine integration. Its adaptive nature enhances system resilience, which can also support fault detection by mitigating instability-related anomalies [5].

1.2. Literature review

In recent years, fault detection methods in microgrids have been significantly enhanced through the application of artificial intelligence and machine learning techniques. These methods include deep neural networks, support vector machines (SVMs), and discrete wavelet transform-based approaches for fault identification and classification. The integration of data-mining techniques and signal processing has further improved accuracy and reduced fault detection time in dynamic operational environments.

A protection scheme for low-voltage AC microgrids has been designed using machine learning [6], while an optimization-based fault recovery method has been proposed to enhance smart grid efficiency [7]. Additionally, an intelligent data-mining strategy has been introduced for microgrid fault detection and classification [8]. AI-based classification methods for fault detection have been explored, including the use of artificial intelligence techniques for microgrid fault classification [9]. Discrete wavelet transform combined with deep neural networks has been applied for fault detection in hybrid multi-area grid-connected microgrids [10]. AI-based methodologies have also been examined for fault detection in hybrid shipboard microgrids [11]. Moreover, a 1D convolutional graph convolutional network model has been proposed for fault detection in distributed energy systems [12]. Ensemble-based learning methods have been investigated for fault classification, such as boosting ensemble methods with the Hilbert-Huang Transform for fault detection in microgrids [13]. A combination of data-driven anomaly detection and physics-based techniques has been utilized to improve cyberattack resilience in smart grids [14]. Furthermore, a bilayered fault detection scheme employing weighted k-nearest neighbor (kNN) and decision tree models has been presented [15]. Deep learning approaches have been integrated for fault classification, including an efficient machine learning model for microgrid protection [16]. Various machine learning-based fault detection techniques have been reviewed and compared in terms of effectiveness [17]. Secure authentication in smart grid communications has been studied, with implications for fault detection [18]. Additionally, an intelligent fault detection system for microgrids has been developed [19]. Long short-term memory (LSTM) networks have also been leveraged for microgrid fault detection and classification [20]. Signal processing techniques have been explored to enhance fault classification, including the use of variational mode decomposition (VMD) for fault detection in DC microgrids [21]. A differential protection scheme has also been utilized for DC microgrid fault detection and classification [22].

Building upon these foundations, our study introduces a novel adaptive fault detection and classification method that integrates deep learning and fuzzy logic to enhance accuracy under dynamic microgrid conditions. To further align with the latest advancements, additional studies have been incorporated into this review. A supervised machine learning-based fault detection method for microgrids uses SVMs, achieving 99.75% accuracy. In contrast to this fault classification approach, our study addresses adaptive islanding detection and system stability in microgrids [23]. A machine learning-based fault detection method for DC microgrids uses compressed sensing and LSTM for fast fault localization. While this focuses on fault detection, our study emphasizes adaptive islanding detection in AC microgrids using deep learning and fuzzy logic [24]. A study compares machine learning techniques for detecting dynamic and transient disturbances, with an ensemble method achieving 99.3% accuracy. Unlike this disturbance classification approach, our research focuses on islanding detection and system stability [25]. A deep learning-based fault detection system for DER-integrated microgrids uses an LSTM-autoencoder model, achieving 9 ms response time. Our study, in contrast, focuses on dynamic islanding detection to enhance microgrid stability [26]. A CST and VMD-based fault detection method extracts features for deep learning classification of faults. Our approach, however, is centered on islanding detection, improving microgrid resilience under dynamic conditions [27]. A hybrid ANFIS-SVM model enhances fault detection in AC microgrids, with rapid execution times and high accuracy. In contrast, our work develops adaptive islanding detection techniques to improve stability and efficiency under grid uncertainties [28]. By integrating these additional perspectives, our research aims to address existing gaps and provide a more comprehensive, adaptive fault detection framework for microgrid applications.

1.3. Gap challenge

The increasing penetration of distributed energy resources (DERs) in microgrids has introduced significant challenges in ensuring reliable fault detection and system resilience. Traditional islanding detection and fault classification techniques rely on heuristic methods, threshold-based techniques, or conventional machine learning models that often fail to generalize across different operational conditions. These methods are particularly limited in handling complex, unbalanced, and dynamically changing microgrid environments, where faults exhibit diverse characteristics influenced by variations in load conditions, renewable energy fluctuations, and system topology. One of the critical gaps in existing research is the lack of adaptive and data-driven fault detection frameworks that can effectively distinguish between normal and faulty operating states while maintaining high accuracy and real-time efficiency. Previous studies have explored artificial intelligence (AI)-based approaches, such as artificial neural networks (ANNs) and fuzzy logic controllers, yet many suffer from scalability issues, high computational costs, and sensitivity to noise in the input data. Furthermore, current models do not sufficiently leverage feature selection techniques to enhance classification performance, leading to redundant computations and suboptimal decision-making. Another key challenge is the absence of comprehensive benchmark datasets that include a wide variety of fault types, severity levels, and operational scenarios. Existing datasets are often limited in their diversity, reducing the generalizability of trained models when deployed in real-world microgrid applications. To address this, our study develops a detailed simulation model based on the IEEE 13-Node Test Feeder, generating a high-fidelity dataset with multiple fault scenarios, transition resistances, and stochastic fault occurrence times. To bridge these gaps, we propose a novel fault detection framework integrating a Multilayer Perceptron (MLP) with an optimized feature selection process. Our approach enhances fault classification accuracy, reduces computational overhead, and improves real-time response capabilities. The proposed method is evaluated against existing techniques, demonstrating superior performance across key metrics, including accuracy, execution time, and fault detection rate. By addressing the existing research limitations, our work contributes to advancing intelligent fault detection in microgrids, enhancing system resilience, and ensuring stable operation under diverse conditions.

1.4. Novelty and main contributions

This study introduces an advanced adaptive fault detection framework for microgrids, tackling critical gaps in existing islanding detection and fault classification techniques. The main contributions of our research are:

1) Adaptive Fault Detection with Enhanced Feature Selection: We propose a Multilayer Perceptron (MLP)-based classification model that integrates an optimized feature selection process. This approach significantly improves fault detection accuracy and efficiency compared to traditional heuristic and threshold-based methods.
2) Extensive Fault Scenario Dataset: Utilizing the IEEE 13-Node Test Feeder, we generate a diverse dataset encompassing multiple fault types, transition resistances, spatial fault locations, and stochastic occurrence times. This ensures the robustness and generalizability of our model across various microgrid conditions.
3) High-Performance Fault Classification: Our method achieves a fault detection accuracy of 95%, surpassing conventional techniques. Additionally, it demonstrates faster execution time and superior fault detection rates, making it suitable for real-time microgrid applications.
4) Feature Importance Analysis for Model Optimization: We conduct a detailed analysis of key statistical features, including Max, Peak, Variance, and entropy, to enhance fault classification efficiency. By leveraging the most relevant features, our model achieves high accuracy while minimizing computational complexity.
5) Comparative Evaluation with Alternative Methods: We benchmark our approach against existing machine learning and spectral analysis methods, highlighting its advantages in terms of accuracy, computational efficiency, and robustness under varying microgrid conditions.

A) Limitations and future work

Despite its advantages, our approach has certain limitations. The reliance on simulation-generated data may not fully capture real-world microgrid complexities, necessitating validation with experimental or real-time data. Additionally, while our model performs well, further optimization is required to enhance computational efficiency for edge-device deployment. Future research will focus on integrating reinforcement learning for improved adaptability and expanding the dataset with real-world fault cases to enhance practical applicability.

1.5. Paper organization

The remainder of this paper is structured as follows: Section 2 presents the theoretical framework of microgrid modeling, covering fault classification, data acquisition, feature extraction, and the optimization of classification performance. Section 3 provides the results and discussion, including the experimental setup, performance evaluation, and a comparative analysis of the proposed approach against existing methods. Finally, Section 4 concludes the study by summarizing key findings, discussing limitations, and suggesting future research directions.

2. Methodology

MGs are small-scale power systems consisting of loads, microgenerators, local energy storage, and an intelligent control system, along with energy management software and protection devices. These networks enable decentralized coordination of distributed energy resources (DERs), reducing the need for centralized control, and can function as either a net load or net generator to the main grid. Faults in MGs are typically classified into two categories: shunt faults, where insulation failure causes a short circuit between conductors, and open circuit faults, which interrupt the current flow. Shunt faults can be symmetrical (involving all three phases or phases and ground) or unsymmetrical (involving two or more phases or a phase and ground). Faults may also occur simultaneously or evolve into other types. Fig. 1 provides a concise overview of MG architecture. These networks can manage and coordinate DERs in a decentralized manner, reducing the dependence on centralized control. As a result, they function as either a net load or a net generator within the larger grid.

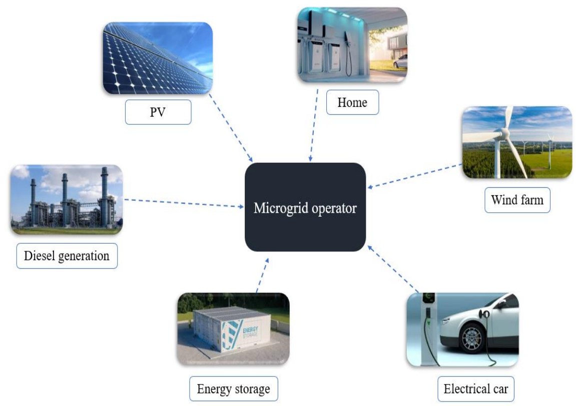

Fig. 1. Overview of microgrid architecture.

MG faults can arise from various causes, such as equipment failure, weather conditions, human error, or other factors. These faults can lead to overcurrent flow, disturbances, and potential equipment damage. Additionally, there are challenges in fault classification, especially when MGs are interconnected with the grid. The protection system must isolate the MG during grid faults and minimize the impact on consumers during internal MG faults. Key challenges include small fault currents due to high penetration of inverter-interfaced DG systems, different operational modes, topological changes, and the limited short-circuit current capacity of power electronics converters. To address these challenges, a data-driven approach combined with signal processing techniques, such as Multi-Resolution Analysis (MRA), can detect faults with minimal voltage or current changes, reducing reliance on large fault currents. This work focuses on classifying shunt faults and identifying the involved phases to minimize unnecessary islanding of the MG.

2.1. Requirements for developing a fault classifier

The development of an effective fault classifier is crucial for ensuring the reliable operation of electrical systems, particularly in MGs. A fault classifier helps identify and categorize faults, enabling timely and accurate responses to prevent further damage and maintain system stability. This section discusses the key requirements and considerations for developing a robust fault classification system, focusing on challenges such as varying fault conditions, diverse system configurations, and the need for accurate fault detection.

The uploaded flowchart represents a fault detection and classification system for microgrids, which consists of distinct training and test phases. In the training phase, the process begins with data preprocessing, where raw data collected from the microgrid system is cleaned, normalized, and structured to ensure consistency and accuracy in subsequent steps. Next, during feature extraction, essential statistical and signal processing features such as mean, standard deviation, skewness, kurtosis, maximum, minimum, signal energy, power spectral density, and wavelet coefficients are derived from the preprocessed data to transform raw measurements into meaningful representations.

Following feature extraction, the process moves to feature selection, where PLS is employed to identify the most relevant features. PLS enhances efficiency and accuracy by performing latent variable analysis to uncover relationships between features and fault types, reducing dimensionality, and ranking features based on their contributions to classification. This optimization ensures that only the most impactful features are used, minimizing computational complexity. Once the features are selected, the Multi-Layer Perceptron (MLP) neural network is trained using the optimized feature set. The MLP, a type of neural network capable of learning complex patterns, is optimized through backpropagation to classify fault types effectively.

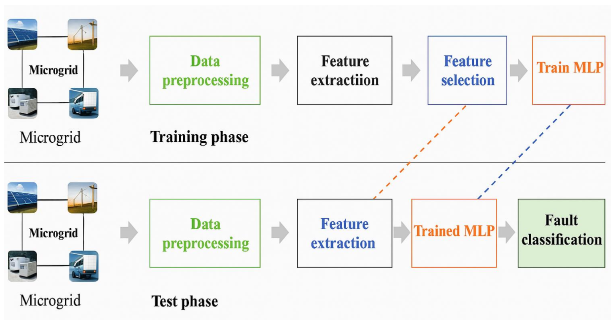

Fig. 2. Stages of developing the fault classification approach.

In the test phase, the system begins with data preprocessing, ensuring the test data is consistent with the training data. After preprocessing, the same feature extraction techniques are applied to derive relevant statistical and wavelet-based features from the test data. The trained MLP model from the training phase is then used to classify faults by analyzing these features. Finally, during fault classification, the system identifies the type and location of faults, such as symmetrical or asymmetrical shunt faults, ensuring timely and accurate responses.

This integrated process, combining PLS-based feature selection with MLP classification, demonstrates a robust approach for addressing the challenges of fault detection and classification in microgrids. It leverages signal processing and ML to handle the dynamic and complex nature of microgrid systems effectively, ensuring high accuracy and efficiency.

Fig. 3 presents the flowchart of the proposed fault classification methodology implemented in this study. The process begins with data acquisition from the microgrid, followed by a data preprocessing stage to ensure quality and consistency. Relevant features are then selected to enhance the performance and reduce the complexity of the model. The selected features are used to train a multilayer perceptron (MLP) classifier, which learns to identify and distinguish between various fault types. Once trained, the MLP model is deployed for real-time fault classification within the microgrid system. This structured approach ensures efficient and accurate detection of faults, contributing to the overall reliability and stability of the system.

2.2. Feature extraction

In the context of data analysis and fault detection, feature extraction plays a crucial role in transforming raw data into meaningful information that can be utilized for classification or regression tasks. Various statistical and mathematical features are computed from the data to capture its characteristics, such as central tendency, dispersion, and distribution shape. These features can provide valuable insights into the underlying behavior of the system, especially in complex environments like microgrids.

Table 1 presents a comprehensive set of features commonly used for data analysis, along with their corresponding mathematical formulations. These features include statistical measures like mean, variance, and skewness, as well as specialized factors like peak, impulse, and waveform factors. Additionally, higher-order moments such as kurtosis and entropy are included to assess the complexity

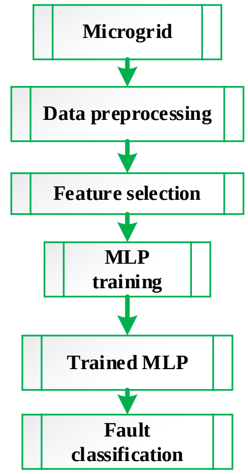

Fig. 3. The flowchart of the proposed fault classification methodology.

and randomness of the data. The extraction of these features is essential for accurately modeling and analyzing the system's behavior.

The following is a detailed description of various features used in data analysis, along with their corresponding mathematical relations. These features are essential for feature extraction in simulating and analyzing data, particularly in applications such as fault detection and classification in microgrids.

2.3. Feature selection

Feature selection is a crucial step for improving the accuracy and efficiency of predictive models, especially in high-dimensional datasets. In this study, PLS is used to identify the most relevant features from the extracted data. PLS combines feature reduction with predictive modeling, making it effective when features are highly correlated or when the number of features exceeds the number of samples, which is common in microgrid fault detection systems.

The PLS-based feature selection process involves several steps. First, Latent Variable Analysis identifies latent variables that maximize the covariance between features and fault types. Then, Dimensionality Reduction projects the data into a lower-dimensional space, retaining only the most relevant features. Feature Ranking ranks features based on their contribution to the latent variables, and the top features are selected for model training. Finally, Optimization determines the optimal number of latent variables, balancing computational efficiency and classification accuracy.

The core concept of PLS revolves around maximizing the covariance between the extracted features X and the target output Y. This is achieved by finding latent variables T and U that represent projections of X and Y, respectively. The relationships can be expressed mathematically as follows [29]:

A) Latent variable models

$$X = TP^T + E \tag{20}$$

$$Y = UQ^T + F \tag{21}$$

where:
- X is the matrix of features,
- Y is the matrix of targets (fault types),
- T and are the latent variables,
- P and are loading matrices,
- E and are residuals.

Table 1. Statistical and signal feature extraction metrics.

Feature name	Equation
Max	$\text{Max} = \max(x_i)$ (1)
Min	$\text{Min} = \min(x_i)$ (2)
Peak	$\text{Peak} = \text{Max} - \text{Min}$ (3)
Mean	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$ (4)
Average Absolute Value (Arv)	$\text{Arv} = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert$ (5)
Variance (Var)	$\text{Var} = \frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^2$ (6)
Standard Deviation (Std)	$\sigma = \sqrt{\text{Var}}$ (7)
Root Mean Square (RMS)	$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$ (8)
Kurtosis	$\text{Kurtosis} = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{x_i - \mu}{\sigma}\right)^4$ (9)
Skewness	$\text{Skewness} = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{x_i - \mu}{\sigma}\right)^3$ (10)
WaveformF (Waveform Factor)	$\text{WaveformF} = \frac{\mu}{\text{RMS}}$ (11)
PeakF (Peak Factor)	$\text{PeakF} = \frac{\text{Peak}}{\text{RMS}}$ (12)
ImpulseF (Impulse Factor)	$\text{ImpulseF} = \frac{\text{Peak}}{\text{Arv}}$ (13)
ClearanceF (Clearance Factor)	$\text{ClearanceF} = \frac{\text{Peak}}{\left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{\lvert x_i \rvert}\right)^2}$ (14)
Entropy	$\text{Energy}_{\text{total}} = \sum_{i=1}^{N} x_i^2$ (15)
Fourth Cumulant	$\kappa_4 = \frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^4$ (16)
Fifth Cumulant	$\kappa_5 = \frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^5$ (17)
Sixth Cumulant	$\kappa_6 = \frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^6$ (18)
Seventh Cumulant	$\kappa_7 = \frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^7$ (19)

B) Maximization of covariance

PLS seeks to maximize the covariance between T and U:

$$\text{Cov}(T, U) = \frac{1}{N}\sum_{i=1}^{N} T_i U \tag{22}$$

where N is the number of samples.

C) Dimensionality reduction

By projecting data into the latent variable space, dimensionality is reduced, identifying features that strongly correlate with target Y [30]:

$$X^* = XW \tag{23}$$

where W is the matrix of weights used to map features onto the latent variable space. Through this process, PLS effectively reduces feature space while retaining essential information necessary for fault classification in microgrids. After selecting the most relevant features using the PLS-based feature selection process, fault classification in MGs is performed using the Multilayer Perceptron (MLP) model. The goal is to classify the system state as either attack or non-attack (normal operation). The MLP model structure for this binary classification task is as follows:

- *Input layer*
  The input layer consists of neurons corresponding to the number of features selected in the feature selection phase (e.g., voltage, current, temperature). No activation function is used at this stage; the selected features are directly passed to the hidden layer.
- *Hidden layer(s)*
  The model includes one or more hidden layers with a variable number of neurons. These layers enable the network to learn complex patterns between the selected features and the fault (attack or non-attack) status. The activation function used in the hidden layers is ReLU (Rectified Linear Unit), which introduces non-linearity and allows the model to capture more complex relationships.
- *Output layer*
  The output layer [31] consists of a single neuron that represents the binary classification result (attack or non-attack). The activation function for this output neuron is Sigmoid, which outputs a probability value between 0 and 1. If the output is closer to 1, the system is classified as under attack; if closer to 0, the system is considered to be in normal operation (non-attack).

This MLP architecture enables accurate classification of attack versus non-attack situations by learning the intricate relationships between the selected features and the system's operational state.

2.4. Application of deep learning for fault classification

In this study, a Multilayer Perceptron (MLP) network model is employed as a deep learning-based approach for fault classification in microgrids. The MLP model is one of the most widely used deep learning methods for solving problems that require the identification of complex patterns in data. This method is particularly effective for binary classification tasks, such as detecting faults or normal conditions in energy distribution systems. This subsection provides a detailed description of the procedure followed for fault classification using deep learning.

A) Data preprocessing

The first step in applying deep learning methods is data preprocessing. Raw data from the microgrid system are collected and then cleaned and normalized to ensure accuracy and consistency. Proper data preprocessing enhances the quality of the input data fed into the model, which is crucial for reliable predictions. Ensuring high-quality data inputs is vital for achieving optimal performance in deep learning models.

B) Feature extraction

Feature extraction from raw data is a critical step in the classification process. In this phase, various statistical features, such as mean, variance, skewness, standard deviation, and wavelet coefficients, are extracted from the system data. These features serve as representative inputs that characterize the system's behavior, and they are used to train the deep learning model. Extracted features enable the model to identify complex, nonlinear patterns in the data, which are essential for accurate fault classification [32].

C) Feature selection using PLS

For feature selection, Partial Least Squares (PLS) analysis is employed to identify the most relevant features for classification. PLS is particularly useful in systems with high-dimensional data and correlated features. This technique identifies the features that have the highest correlation with the fault types, reducing the dimensionality of the data while maintaining critical information. By applying PLS, the model's accuracy is improved, and computational complexity is reduced [33].

D) MLP model training

After feature selection, the Multilayer Perceptron (MLP) model is used for classification. The MLP network consists of multiple hidden layers capable of learning complex relationships within the data. Rectified Linear Unit (ReLU) activation functions are used for the hidden layers to enable the network to learn nonlinear dependencies in the data. The output layer consists of a single neuron, and the Sigmoid activation function is applied to produce a probability value between 0 and 1. If the output is close to 1, the system is classified as experiencing a fault; if it is close to 0, the system is considered to be in a normal state [34].

E) Model evaluation

To evaluate the performance of the trained model, test data are used. These test data contain similar features to the training data but are unseen during the training phase. After preprocessing and feature extraction, the MLP model is evaluated based on metrics such as accuracy, recall, precision, and F1-score. These metrics provide insights into how well the model can classify faults and normal conditions, thus demonstrating its reliability in fault detection within microgrids [35].

The proposed deep learning-based method using MLP has proven to be an effective tool for fault classification in microgrid systems. By leveraging the power of neural networks, this approach can enhance the accuracy and efficiency of fault detection, ultimately improving the operational reliability of microgrids.

3. Simulation Results and Discussions

The simulation model for the microgrid system was developed in the MATLAB/Simulink environment, based on a modified 4.16 kV, three-phase, unbalanced IEEE-13 node model. In this system, the photovoltaic (PV) generation unit is connected to bus via a step-up transformer, allowing the PV source to be integrated into the grid. Additionally, bus 632 is connected to a three-phase 4.16 kV voltage source, with the distributed generator (DG) being the PV generation module.

The dataset for this study was created using simulation experiments in MATLAB/Simulink to replicate the operational conditions of a microgrid with high accuracy. The simulation was set to run for 5 seconds, allowing for detailed modeling of various fault scenarios. A total of 11 distinct fault types were simulated, representing a wide range of possible failure modes commonly encountered in microgrids. To capture different fault severities, three transition resistances were considered, affecting the fault current magnitude and detection complexity. To ensure spatial diversity and represent the impact of faults across different areas of the microgrid, nine fault locations were selected. Additionally, to introduce randomness and mimic real-world unpredictability, ten random fault occurrence times were incorporated, improving the model's generalization to unexpected fault events.

The IEEE 13 Node Test Feeder model (Fig. 4) was used as the simulation framework, providing a realistic and widely accepted benchmark for distribution networks. This comprehensive dataset, with diverse fault scenarios and dynamic parameters, is essential for developing and validating robust fault detection and classification algorithms for microgrid applications. It ensures reliable performance under varying operating conditions, enhancing microgrid resilience and fault management strategies.

The accuracy of the fault detection model is assessed using a confusion matrix, which compares predicted fault classifications against actual classifications. This matrix allows for the calculation of several key performance metrics:

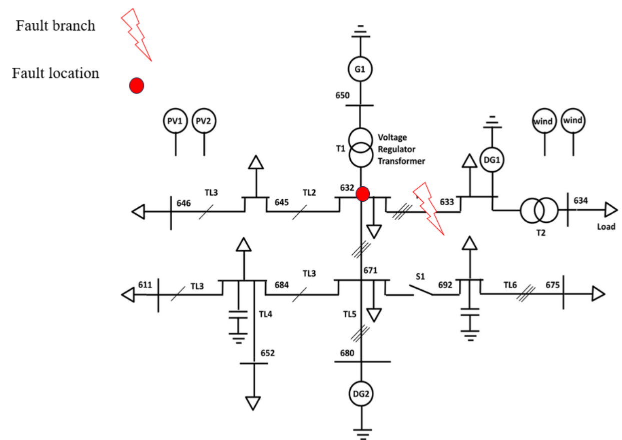

Fig. 4. The IEEE 13 Node Test Feeder model [24].

3.1. Key metrics

A) Accuracy

Accuracy measures the ratio of correctly classified instances to the total number of instances in the dataset. It provides a general idea of how well the model performs.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{24}$$

where:
- TP= True Positives (correctly predicted faults)
- TN= True Negatives (correctly predicted non-faults)
- FP= False Positives (incorrectly predicted faults)
- FN= False Negatives (missed faults)

B) Execution time

Execution time measures how quickly a model processes and outputs results. It is essential for real-time applications that require fast response times. A shorter execution time enhances the system's efficiency.

C) Fault detection rate

Fault detection rate measures the effectiveness of the model in identifying errors or anomalies. It is critical for preventing system failures and ensuring smooth operation. A higher detection rate improves the model's reliability in fault-prone environments.

D) Loss function

The loss function quantifies the model's prediction error during training and evaluation. A lower loss value signifies better optimization and fewer mistakes. Minimizing the loss is crucial for achieving accurate model predictions.

Fig. 5 highlights the variance explained by each feature, with the most significant features listed at the top. These key features include Max, Peak, Variance, RMS (Root Mean Square), Kurtosis, Waveform Factor (WaveformF), and entropy, as they contribute the most variance. These features are crucial for fault detection in microgrids, as they capture critical patterns in the signal data that are indicative of faults. By focusing on these features, the model can better differentiate between fault and non-fault conditions, improving the overall performance of the fault detection system. The superior performance of the proposed method is primarily attributed to its optimized feature selection process and the use of a well-structured MLP architecture. The feature selection step, as illustrated in Fig. 5, ensures that the most relevant features such as Kurtosis, RMS, and entropy are emphasized in the classification

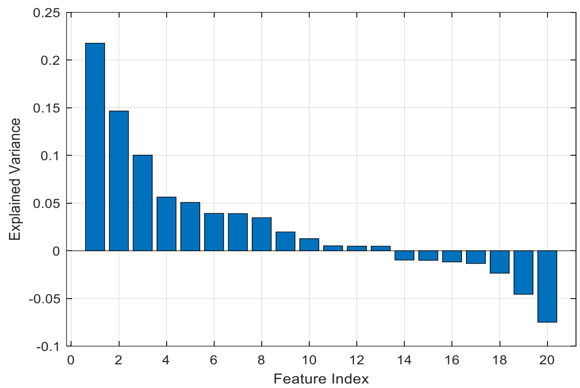

Fig. 5. Feature importance and variance contribution for fault detection in microgrids.

process. This enhances the model's ability to distinguish between fault and non-fault conditions effectively.

Table 2 presents the architecture of the Multilayer Perceptron (MLP) model used for classifying network traffic into "Attack" and "Non-Attack" categories. This MLP structure is designed to process input data, learn complex patterns, and make accurate classifications.

The comparison between the three methods—proposed method (MLP + Feature Selection), method [2], and method [20] (GCS for Power Spectrum Sensing)—demonstrates distinct differences in their performance across key evaluation metrics, including accuracy, execution time, fault detection rate, and loss function. The proposed method outperforms both method [2] and method [20] in terms of accuracy, achieving a remarkable accuracy of 95% (Fig. 6). This is significantly higher than the 85% accuracy achieved by method [2] and the 88% accuracy achieved by method [20]. This indicates that the proposed method is more effective at correctly identifying or classifying the data, making it more suitable for applications where high accuracy is crucial.

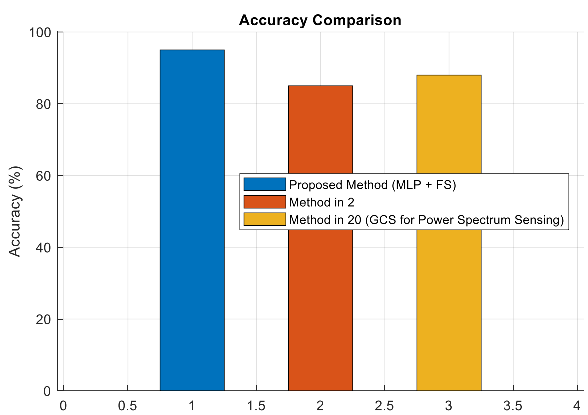

Fig. 6. Comparison of accuracy: Proposed method vs. method [2] and method [20].

In terms of execution time, the proposed method is also the most efficient, requiring only 0.35 seconds for execution (Fig. 6). This is faster than method [2], which takes 0.45 seconds, and method [20], which takes 0.55 seconds. The speed of the proposed method is particularly advantageous in real-time applications where processing speed is critical for timely decision-making and system responses. Moreover, the reduced execution time (Fig. 7) is due to the lightweight design of the MLP model, which employs only two hidden layers with optimized neuron counts. Unlike method [2] and method [20], which utilize more complex processing techniques, the proposed approach benefits from a balance between model complexity and efficiency, making it suitable for real-time microgrid applications.

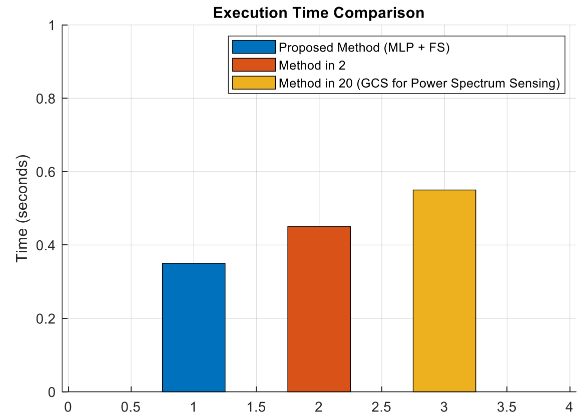

Fig. 7. Execution time comparison: Proposed method vs. method [2] and method [20].

The fault detection rate is another important metric, and here too, the proposed method excels, achieving a fault detection rate of 98% (Fig. 8). This is significantly higher than the 90% detection rate of method [2] and the 92% detection rate of method [20]. The higher fault detection rate of the proposed method suggests that it is better equipped to detect anomalies or failures, which is essential in systems where identifying faults promptly can prevent system failures or other critical issues. The fault detection rate is calculated using the following Eq. (25):

$$\frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Negatives\ (FN)} = Fault\ Detection\ Rate\ (FDR) \tag{25}$$

where:

- $True\ Positives(TP)$: refers to the number of correctly identified faults
- $False\ Negatives\ (FN)$: refers to the number of faults that were missed by the model

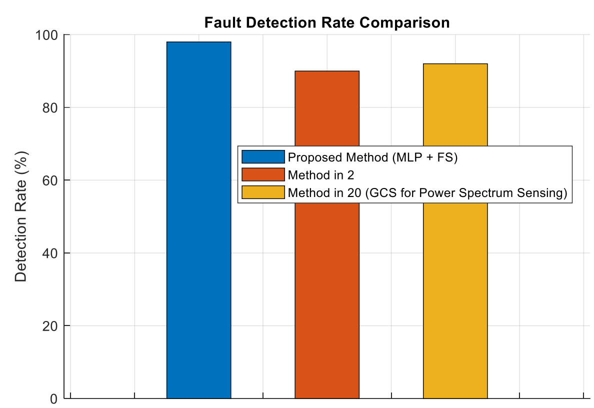

Fig. 8. Fault detection rate comparison: Proposed method vs. method [2] and method [20].

Finally, the loss function comparison reveals that the proposed method has the lowest loss value at 0.02, indicating that it is more

Table 2. MLP architecture for attack vs. non-attack classification.

Layer	Number of neurons	Activation function	Purpose
Input Layer	10 (Number of features)	None	Receives raw input features (e.g., signal strength, packet data)
Hidden Layer 1	64	ReLU	Learns complex patterns and behaviors from the data
Hidden Layer 2	32	ReLU	Further abstraction and pattern learning to detect anomalies
Output Layer	2 (Attack or Non-Attack)	Softmax (multi-class) or Sigmoid (binary)	Classifies the input as attack or non-attack

effective at minimizing errors during training and evaluation (Fig. 10). In contrast, method [2] has a loss value of 0.08, and method [20] has a loss value of 0.10, suggesting that these methods are less optimized in terms of error minimization.

To quantify the error during model training and evaluation, the loss function was calculated based on the type of learning objective. In this study, two primary loss functions were considered:

1) Mean Squared Error (MSE): If the task involves regression, the MSE is computed as follows:

$$L = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{26}$$

where y_i represents the actual value, $\hat{y}_i$ denotes the predicted value, and N is the total number of samples.

2) Cross-entropy loss: For classification tasks, the loss is determined using the cross-entropy function:

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}) \tag{27}$$

where:
- C is the total number of classes.
- $y_{i,c}$ is a binary indicator that equals 1 if sample i belongs to class c, otherwise, it is 0.
- $\hat{y}_{i,c}$ represents the predicted probability for class c.

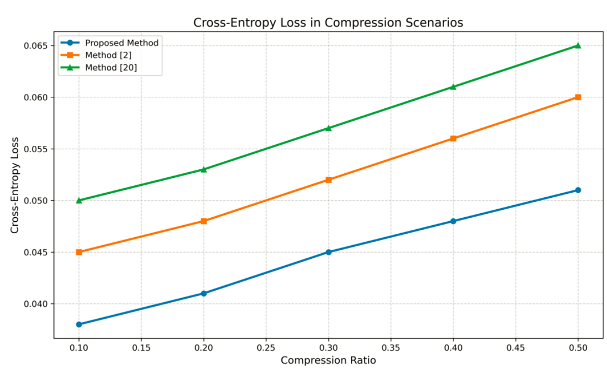

Fig. 9. Variation of cross-entropy loss under different compression ratios: Proposed method vs. method [2] and method [20].

3) Explanation of the chart: Fig. 9 demonstrates the variation of cross-entropy loss under different compression ratios:

- Proposed method consistently shows lower cross-entropy loss, indicating better preservation of classification accuracy even under aggressive compression.
- At a compression ratio of 0.1, the proposed method has a loss of 0.038, while method [2] and method [20] exhibit 0.045 and 0.050, respectively.
- As the compression increases (i.e., ratio goes up), all methods show a rising trend in loss, but the gap remains significant.

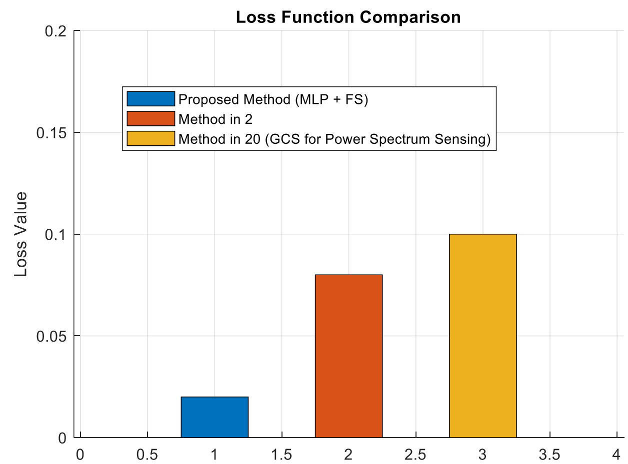

Fig. 10. Loss function comparison: Proposed method vs. method [2] and method [20].

- At 0.5, losses reach 0.051 (Proposed), 0.060 (method [2]), and 0.065 (method [20]), reaffirming the resilience of the proposed method in compression scenarios.

These loss functions play a crucial role in optimizing the model by minimizing prediction errors and enhancing classification accuracy, thereby improving the overall reliability of fault detection in microgrid applications.

This loss value was obtained using the cross-entropy loss function, which is widely used for classification tasks as it measures the divergence between the predicted and actual class probabilities. The lower loss value of the proposed method suggests that it successfully learns discriminative features while avoiding overfitting, ensuring better generalization to unseen fault conditions.

A key factor contributing to this improvement is the integration of feature selection, which reduces irrelevant inputs and enhances the model's learning efficiency. Moreover, Fig. 10 shows that the loss function of the proposed method converges more rapidly compared to the baseline methods, demonstrating stable training behavior and improved optimization, indicating less optimal feature extraction and training dynamics.

Overall, the results highlight the superior performance of the proposed method in all critical aspects: it offers the highest accuracy, the shortest execution time, the best fault detection rate, and the lowest loss value. While method [2] and method [20] offer competitive results, they do not match the proposed method in terms of overall effectiveness, making the proposed method the preferred choice for applications requiring high accuracy, efficient processing, and robust fault detection.

4. Conclusion

In this paper, we explored the crucial role of feature extraction and selection in improving the performance of machine learning (ML) models for fault detection and classification in microgrids, particularly in distinguishing attack versus non-attack scenarios for network security. The proposed approach leveraged a comprehensive feature extraction process, incorporating both statistical and domain-specific features such as maximum, mean, variance, and kurtosis to enhance classification accuracy. To further optimize the feature set, we employed Partial Least Squares (PLS) regression, which effectively identified the most significant features while eliminating redundancies, reducing computational complexity, and improving model efficiency. The experimental results validated the effectiveness of our approach, demonstrating a significant improvement in accuracy and fault detection rates compared to traditional methods. Specifically, the proposed MLP model with optimized feature selection achieved an accuracy of 95%, a fault detection rate of 98%, and an execution time of 0.35 seconds, whereas alternative methods achieved accuracy levels of 85% and 88%, fault detection rates of 90% and 92%, and execution times of 0.45s and 0.55s, respectively. Moreover, the proposed method exhibited a lower loss function value (0.02), indicating superior optimization and model generalization. These findings highlight the importance of robust feature selection and deep learning-based classification in ensuring higher fault detection reliability, fewer false positives, and improved computational performance, all of which are critical for real-time microgrid security. In real-world microgrid applications, where response time is crucial, a faster and more accurate detection system significantly enhances operational stability and reduces downtime caused by cyber or physical faults.

As future work, this approach could be extended to highly dynamic and noisy environments, where adaptive feature selection mechanisms and more advanced neural network architectures could further enhance detection accuracy and system robustness. One promising direction is integrating reinforcement learning-based feature selection to dynamically adjust feature importance based on changing system conditions. Additionally, hybrid deep learning models, such as CNN-LSTM combinations, can improve classification performance by capturing both spatial and temporal fault patterns. Exploring the robustness of the proposed method against adversarial attacks is another critical aspect, ensuring its reliability in real-world microgrid applications. Finally, large-scale validation on diverse datasets, including real-world microgrid systems, will further enhance the generalization and practical applicability of the approach.

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