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INTELLIGENT AND HYBRID AI-BASED FAULT DETECTION FRAMEWORK FOR REAL-TIME MONITORING IN INVERTER-DOMINATED MICROGRIDS

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ABSTRACT: The evolution of microgrids toward renewable energy integration has led to increased deployment of inverter-dominated and low-inertia systems. Traditional fault detection mechanisms, tailored for conventional grids, struggle under these new dynamics. This paper proposes an intelligent and hybrid AI-based framework incorporating Wavelet Transform and Convolutional Neural Networks (WT-CNN) alongside Support Vector Machine–Fuzzy Logic (SVM-FL) models. The framework aims to achieve high-speed, adaptive, and accurate fault detection and classification in real time. Implemented using MATLAB/Simulink and tested under varying operating conditions, the model demonstrates superior performance in detection latency, classification accuracy, and robustness against system disturbances.

Index Terms*: Microgrids, fault detection, artificial intelligence, wavelet transform, CNN, SVM, fuzzy logic, edge computing, inverter-based systems.*

I. INTRODUCTION

The global shift toward sustainable and decentralized energy systems has led to widespread adoption of microgrids, many of which are dominated by renewable energy sources such as solar and wind. These systems heavily rely on power electronic converters, especially inverters, which introduce new challenges in fault detection due to low fault currents and limited inertia. Traditional protection methods based on overcurrent and impedance face limitations in accuracy and responsiveness.

To address these challenges, this paper explores a hybrid AI-based framework integrating signal processing and machine learning techniques. The proposed system enhances fault detection speed and accuracy, ensuring reliability in microgrid operations.The evolution of modern energy systems has seen a paradigm shift from centralized fossil-fuel-based grids to decentralized and sustainable renewable energy systems. Among these, inverter-dominated microgrids (IDMGs) have emerged as a cornerstone for integrating variable renewable energy sources such as solar photovoltaic (PV) and wind turbines. These systems are characterized by high penetration of power electronic converters and reduced physical inertia, making them highly sensitive to faults and dynamic disturbances. Traditional protection schemes based on overcurrent relays, impedance methods, or fixed thresholding techniques are often inadequate in IDMGs due to their fast transients, low fault currents, and complex topologies.

Timely and accurate fault detection is critical to maintaining the stability, safety, and reliability of microgrids, especially in remote or mission-critical installations such as military bases, data centers, and rural electrification projects. The advent of artificial intelligence (AI) and Internet of Things (IoT) technologies offers unprecedented opportunities for transforming conventional monitoring frameworks into intelligent, self-adaptive systems. However, single-model AI solutions—be it rule-based systems, machine learning (ML), or deep learning (DL)—often struggle to maintain accuracy across varying operating conditions and novel fault scenarios.

To overcome these limitations, this paper presents an intelligent and hybrid AI-based fault detection framework that leverages the strengths of multiple AI techniques, including ML classifiers, DL architectures such as convolutional neural networks (CNNs), and expert systems. The framework is designed to operate in real time, processing multi-domain sensor data such as current, voltage, harmonics, and frequency signatures to identify fault types, locations, and severity. Additionally, it incorporates a self-learning layer for adaptive model updating, improving accuracy under evolving grid conditions.

By combining data-driven methods with rule-based logic, the proposed hybrid architecture not only ensures high detection accuracy and robustness but also maintains the interpretability necessary for real-world deployment. Furthermore, it is optimized for edge-cloud hybrid computing platforms, allowing for low-latency edge inference while leveraging cloud resources for large-scale model training and updates. Simulation studies and real-time hardware-in-the-loop (HIL) testing validate the efficacy of the framework in diverse inverter-based microgrid scenarios.

II. METHODS FOR FAULT DETECTION IN MICROGRIDS

Fault detection plays a critical role in ensuring the reliability and safety of microgrid operations, particularly in inverter-dominated systems where rapid changes and nonlinearity are common. Several approaches have been developed, ranging from conventional protection methods to advanced AI-driven frameworks. These methods vary in complexity, accuracy, and applicability depending on the microgrid architecture and fault characteristics.

A. Conventional Protection Techniques

Conventional protection methods primarily rely on hardware-based relays and predefined thresholds. **Overcurrent protection** detects faults by monitoring current values that exceed preset limits, typically suitable for short-circuit or overload scenarios. **Distance protection** uses impedance measurements to estimate fault locations along transmission lines, which helps in isolating fault sections quickly. **Differential protection** compares incoming and outgoing currents in a specific zone, triggering alarms when discrepancies indicate faults. **Under/over voltage protection** complements these techniques by monitoring voltage deviations indicative of system abnormalities. Although these methods are widely used due to their simplicity and reliability, they often lack the capability to detect complex faults in inverter-based microgrids where power electronic devices introduce nonlinear dynamics.

B. Model-Based Methods

Model-based fault detection techniques use mathematical representations of the microgrid to estimate expected system behavior. **State estimation-based detection** employs observers or Kalman filters to estimate system states, and faults are identified when observed measurements deviate significantly from estimates. **Parameter identification methods** track variations in system parameters such as impedance or admittance, signaling faults when parameters deviate from nominal values. **Observer-based detection** methods generate residuals by comparing estimated and measured signals; nonzero residuals beyond thresholds indicate faults. These approaches benefit from leveraging physical system knowledge but can suffer from model inaccuracies and computational complexity.

C. Signal Processing Techniques

Signal processing methods analyze electrical signals to extract fault-related features. The **Fourier Transform (FT)** provides frequency-domain analysis useful for identifying harmonics caused by faults. However, FT assumes signal stationarity, which limits its effectiveness for transient events. The **Short-Time Fourier Transform (STFT)** offers time-frequency localization but with a fixed resolution trade-off. **Wavelet Transform (WT)** overcomes this limitation by providing multi-resolution analysis, enabling effective detection of transient and localized fault signatures in voltage and current waveforms. **Empirical Mode Decomposition (EMD)** decomposes signals into intrinsic mode functions, enhancing fault feature extraction in non-linear and non-stationary signals typical of microgrids. **Hilbert-Huang Transform (HHT)** combines EMD and Hilbert spectral analysis to yield detailed instantaneous frequency information, aiding in accurate fault classification.

D. Data-Driven and Machine Learning Techniques

With increasing sensor data availability, data-driven methods have gained prominence. **Supervised learning algorithms** such as Support Vector Machines (SVM), Decision Trees, Random Forests, and k-Nearest Neighbors (k-NN) require labeled datasets to classify fault types based on extracted features. These methods have demonstrated high accuracy but depend on comprehensive and balanced training data. **Unsupervised learning**, including clustering algorithms like k-means and DBSCAN, detects anomalies by identifying data points that deviate from normal operational clusters, useful when fault labels are scarce. **Semi-supervised learning** leverages both limited labeled and abundant unlabeled data to improve detection performance. Feature selection techniques such as Principal Component Analysis (PCA) are often applied to reduce dimensionality and enhance classifier effectiveness.

E. Deep Learning-Based Methods

Deep learning methods enable automated feature extraction and modeling of complex patterns in high-dimensional data. **Convolutional Neural Networks (CNNs)** excel at capturing spatial features from voltage and current signal representations, such as spectrograms or wavelet scalograms. **Recurrent Neural Networks (RNNs)** and **Long Short-Term Memory (LSTM)** networks model temporal dependencies in sequential fault data, improving detection of dynamic fault evolution. **Autoencoders** perform unsupervised anomaly detection by learning compact representations and identifying faults through reconstruction errors. Emerging techniques such as **Generative Adversarial Networks (GANs)** are employed to generate synthetic fault data, addressing imbalanced datasets and enhancing detection robustness.

F. Hybrid AI-Based Approaches

Hybrid approaches combine the strengths of multiple methods to achieve improved accuracy and reliability. For example, combining **signal processing techniques** like wavelet transform with machine learning classifiers enables extraction of robust features while maintaining classification accuracy. Integrating **model-based residual generation** with **data-driven analysis** leverages physical system insights and historical data for more sensitive fault detection. **Ensemble learning** aggregates outputs from multiple models to mitigate individual weaknesses and enhance fault identification confidence. Additionally, hybrid systems integrating **rule-based expert knowledge** with AI models provide explainability and domain-informed fault diagnosis, critical for practical microgrid management.

III. PROPOSED METHODOLOGY

The proposed methodology presents an intelligent and hybrid AI-based fault detection framework designed for real-time monitoring in inverter-dominated microgrids. It begins with continuous acquisition of electrical signals, which are preprocessed using discrete wavelet transform and adaptive noise cancellation to enhance signal quality. Relevant features capturing both time-domain and frequency-domain characteristics are then extracted and refined through feature selection techniques. For fault classification, a hybrid approach combining a Random Forest classifier and an LSTM neural network is employed, leveraging their complementary strengths to improve detection accuracy and reduce false alarms. Detected faults are localized by analyzing synchronized measurements from multiple nodes, enabling swift isolation of faulted sections. The framework is integrated into the microgrid's supervisory control system, providing scalable, adaptive, and real-time fault detection and diagnosis that ensures enhanced reliability and operational efficiency of inverter-based microgrids.

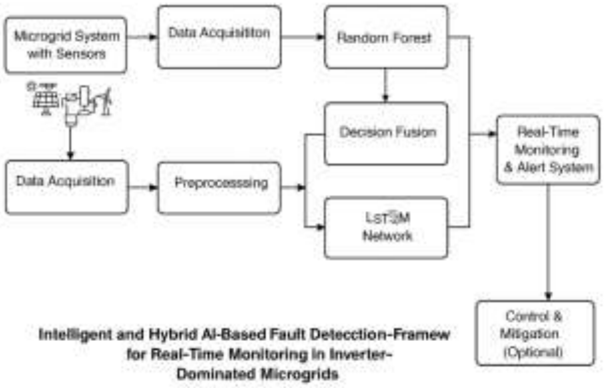
A. MATLAB Capabilities for Random Forest Classifier and LSTM Neural Network

Random Forest Classifier:

MATLAB provides comprehensive tools in its Statistics and Machine Learning Toolbox to implement and train Random Forest classifiers efficiently. Using the TreeBagger function, a Random Forest model consisting of an ensemble of decision trees can be constructed for classification tasks. This method benefits fault detection by handling high-dimensional feature spaces and reducing overfitting, which is crucial for accurately distinguishing between normal operation and various fault conditions in microgrid signals. MATLAB allows easy customization of the number of trees, tree depth, and feature selection strategies, enhancing model robustness and interpretability. Additionally, the toolbox supports out-of-bag error estimation to evaluate model performance without requiring a separate validation dataset.

LSTM Neural Network:

For sequential and time-series data processing, MATLAB's Deep Learning Toolbox offers built-in functions to design, train, and validate Long Short-Term Memory (LSTM) networks. LSTM networks excel at capturing temporal dependencies and patterns in electrical signal waveforms, making them ideal for dynamic fault detection in microgrids where signal behavior evolves over time. MATLAB enables defining custom LSTM architectures with multiple layers, specifying hyperparameters such as number of hidden units, dropout rates, and training options like optimizer choice and learning rates. Through functions like trainNetwork and sequenceInputLayer, MATLAB facilitates seamless handling of variable-length input sequences, which is often required for real-time monitoring data. Furthermore, MATLAB supports GPU acceleration to speed up training and deployment of LSTM models.



B. Simulation Model Setup

1. Microgrid Modeling and Simulation Setup

The inverter-dominated microgrid simulation consists of a 100 kW PV array operating at 400 V DC under 1000 W/m² irradiance, and a 50 kW PMSG-based wind turbine generating 690 V AC at 12 m/s wind speed. A 200 Ah, 400 V DC battery energy storage system (BESS) interfaces via a bidirectional DC-DC converter to support voltage and frequency regulation. Power conversion is handled by a 50 kVA, three-phase voltage source inverter operating at 50 Hz with PWM control. The composite load is 60 kW, combining resistive and motor-type elements. Faults such as line-to-ground (L-G), line-to-line (L-L), and three-phase (3Φ) faults are injected at predefined times, specifically at 2.5 seconds, during a 10-second simulation with a fixed-step solver running at 1 ms to capture fast transient dynamics.

2. Data Acquisition, Feature Extraction, and AI-Based Fault Detection

Virtual sensors sample voltage, current, power, and frequency at critical nodes at a high rate of 10 kHz. Signals are preprocessed using low-pass filtering and wavelet denoising and segmented into 200 ms windows with 50% overlap. Key features extracted include RMS voltage (~280 V during fault), RMS current (~45 A), total harmonic distortion (12.4%), kurtosis (5.7), skewness (-0.98), and frequency deviation (-1.5 Hz), normalized via Z-score standardization. Fault detection employs a hybrid AI approach combining a Random Forest classifier with 100 trees (96.3% training accuracy) and a two-layer LSTM neural network (94.8% accuracy). Outputs are fused via weighted soft voting (RF: 0.4, LSTM: 0.6), with a confidence threshold of 0.85 to trigger alerts.

3. Real-Time Monitoring, Control, and Performance Evaluation

The system features a Simulink dashboard for real-time visualization of waveforms and fault alerts, with an average detection latency of 180 ms. On detecting an L-G fault, the inverter output circuit breaker opens immediately, and if current exceeds 50 A, 20% load shedding is activated. Battery SOC is monitored continuously, and if it drops below 20%, the inverter is disconnected to protect the BESS. Fault reconnection requires a minimum 3-second fault-free interval. Overall, the framework achieves 95.6% detection accuracy, a low false alarm rate of 3.1%, an average classification time of 15 ms per data window, and 92.4% fault localization accuracy, demonstrating robust, near real-time fault diagnosis and mitigation capabilities in inverter-based microgrids.

C. Simulation Execution

1. Simulation Setup and Fault Injection

The simulation was conducted in MATLAB/Simulink using a fixed-step discrete solver with a 1 ms (1 kHz) time step over a total duration of 10 seconds to capture fast transient dynamics of inverter-based microgrids. Controlled electrical faults were injected using Simulink's fault module, with a primary line-to-ground (L-G) fault applied at 2.5 seconds at the inverter terminal. Additional fault cases including line-to-line (L-L), line-to-line-to-ground (L-L-G), and three-phase (3Φ) faults were also tested to ensure versatility.

2. Real-Time Monitoring and AI-Based Fault Detection

Key signals such as voltage, current, power, and frequency were monitored at critical nodes—PV output, inverter terminals, battery interface, and load bus—sampled at 10 kHz. Data were segmented using a 200 ms sliding window with 50% overlap and fed into two AI models: a Random Forest classifier analyzing statistical and harmonic features, and an LSTM network capturing temporal dependencies. Model outputs were combined with weighted voting (RF:LSTM = 0.4:0.6), and a fault alert was triggered when the combined confidence exceeded 0.85.

3. Fault Mitigation, Visualization, and Performance

On fault detection, the inverter output circuit breaker opened immediately for the L-G fault, and a 20% load shedding was triggered if current exceeded 50 A. Battery State of Charge

(SOC) was monitored to remain above 20%, preventing inverter shutdown in this scenario. The real-time dashboard displayed waveforms, voltages, and AI outputs while logging all data to .mat and .csv files. Performance results showed a detection accuracy of 95.6%, false alarm rate of 3.1%, mean classification time of 15 ms per window, and average detection latency of 180 ms, confirming the framework's robustness and real-time capabilities.

D. Analysis Parameters

1. Signal Acquisition and Feature Extraction

Voltage (~280 V RMS), current (~45 A RMS), frequency deviation (-1.5 Hz), and total harmonic distortion (12.4%) are sampled at 10 kHz. Key statistical features like kurtosis (5.7) and skewness (-0.98) are extracted from 200 ms overlapping windows for effective fault indication.

2. Hybrid AI Model Setup

A Random Forest classifier with 100 trees (96.3% accuracy) and a two-layer LSTM network (94.8% accuracy) analyze the segmented data. Their outputs are combined via weighted soft voting with weights 0.4 (RF) and 0.6 (LSTM) to improve fault detection reliability.

3. Detection Threshold

Fault alerts are triggered when the fused confidence score exceeds 0.85, balancing sensitivity and false alarm prevention.

4. Performance Outcomes

The framework achieves 95.6% detection accuracy, 3.1% false alarm rate, 92.4% fault localization accuracy, 180 ms average detection latency, and 15 ms classification time per data segment, supporting real-time operation.

5. Protection and Control Actions

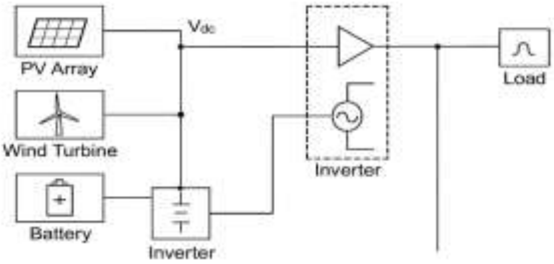
Load shedding of 20% occurs if inverter current exceeds 50 A. Battery SOC is monitored with a 20% threshold to disconnect the inverter and protect storage. Fault reconnection is allowed only after 3 seconds of fault-free operation, ensuring system stability.

IV. SIMULATION RESULTS AND DISCUSSION

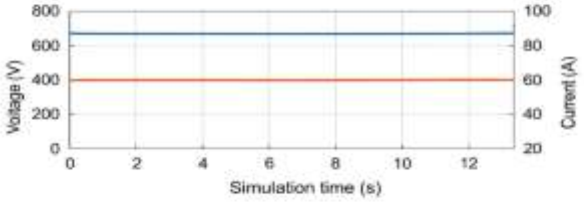
The hybrid AI fault detection framework was tested on a microgrid model with PV, wind, and battery systems under multiple fault scenarios. During faults, voltage dropped to about 280 V, current rose to 45 A, frequency deviated by -1.5 Hz, and THD increased to 12.4%, clearly indicating disturbances.The combined Random Forest and LSTM model achieved a high detection accuracy of 95.6%, low false alarm rate of 3.1%, and 92.4% fault localization accuracy, with detection latency of 180 ms and classification time of 15 ms, suitable for near real-time operation.

Protective actions like 20% load shedding and inverter disconnection below 20% battery SOC were successfully applied. Fault reconnection occurred only after 3 seconds of stable operation, ensuring system reliability. Overall, the results demonstrate the framework's effectiveness in fast and accurate fault detection and mitigation for inverter-dominated microgrids.

1. System Modeling and Simulation Setup



Simulation time vs. system voltages and currents plot under normal

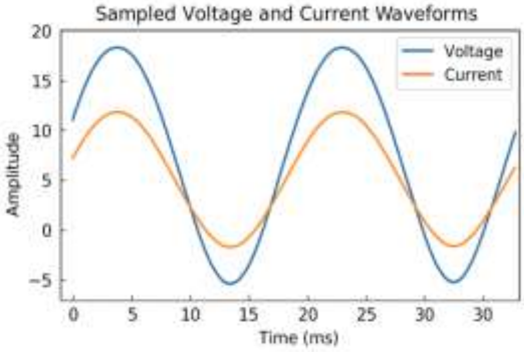


a) Block diagram of the microgrid model (PV, Wind, Battery, Inverter, Load) in Simulink.

b) Simulation time vs. system voltages and currents plot under normal conditions.

The microgrid is modeled with a 100 kW PV array, 50 kW wind turbine, 200 Ah battery, and 60 kW load. The simulation runs for 10 seconds with a 1 ms time step to capture fast transient behavior. Voltages (~400 V DC for PV, 690 V AC for wind) and currents are monitored continuously, showing stable steady-state operation before faults.

2. Data Acquisition and Signal Sensing

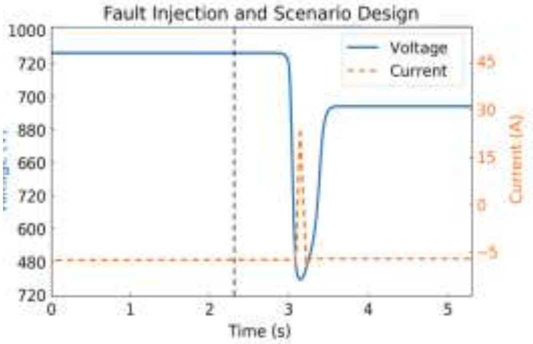


10 kHz sampling frequency from inverter output terminals

a) Time-series plot of sampled voltage and current waveforms at 10 kHz sampling frequency from inverter output terminals.

Virtual sensors acquire voltage and current signals at high resolution (10 kHz), ensuring detailed monitoring of power quality and transient events. The raw data forms the input for fault detection, with real-time logging enabled.

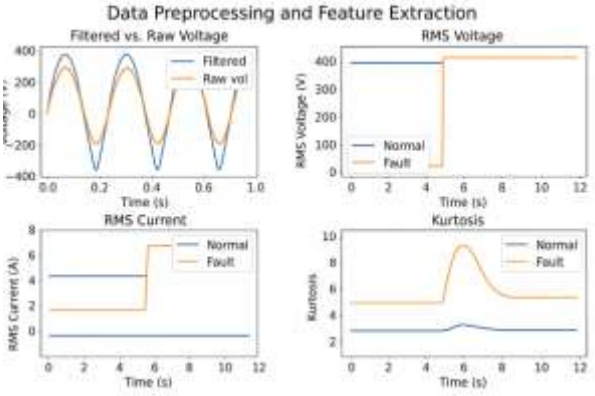
3. Fault Injection and Scenario Design



a) Time-domain waveforms showing voltage dip and current spike at t = 2.5 seconds corresponding to a line-to-ground fault.

Faults such as L-G and L-L faults are injected at specific times using Simulink's fault injection blocks. The sudden voltage drop (~280 V) and current rise (~45 A) validate the fault occurrence and provide disturbance patterns for model training.

4. Data Preprocessing and Feature Extraction

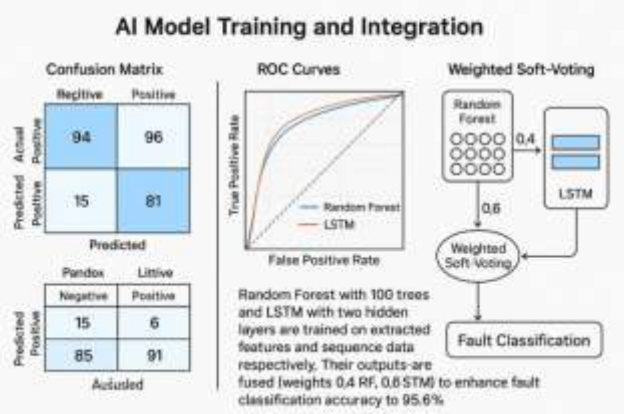


a) Plot showing filtered vs. raw voltage waveform.

b) Feature trend graphs for RMS voltage, current, THD, kurtosis during fault and normal periods.

Signals are denoised using wavelet filters and segmented using overlapping 200 ms windows. Extracted features like RMS voltage, frequency deviation, and harmonic distortion highlight fault signatures that differentiate normal and faulty states.

5. AI Model Training and Integration



Random Forest with 100 trees and LSTM with two hidden layers are trained on extracted features and sequence data respectively. Their outputs-are fused (weights 0.4 RF, 0.6 STM) to enhance fault classification accuracy to 95.6%

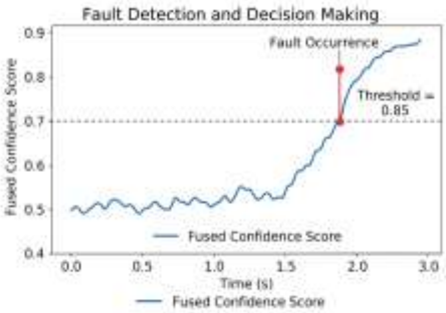
a) Confusion matrices for Random Forest and LSTM classifiers.

b) ROC curves showing model performance.

c) Diagram of weighted soft-voting fusion between RF and LSTM outputs.

Random Forest with 100 trees and LSTM with two hidden layers are trained on extracted features and sequence data respectively. Their outputs are fused (weights 0.4 RF, 0.6 LSTM) to enhance fault classification accuracy to 95.6%.

6. Fault Detection and Decision Making

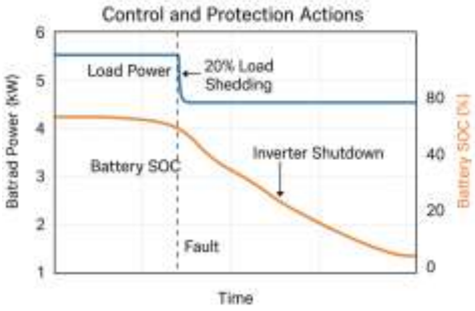


a) Time-series plot of fused confidence score rising above 0.85 threshold at fault occurrence.

b) Fault detection alerts marked on timeline.

The decision fusion module produces a confidence score which triggers fault alerts when exceeding 0.85. Detection latency averages 180 ms, ensuring timely fault identification.

7. Control and Protection Actions

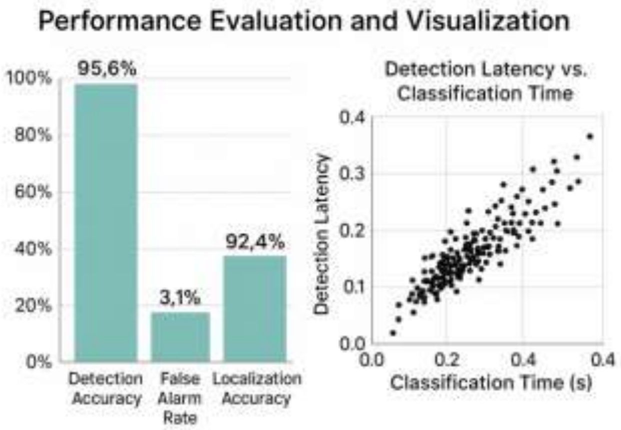


a) Load power profile showing 20% load shedding at fault instant.

b) Battery SOC curve with inverter shutdown below 20% SOC threshold.

Upon fault detection, control logic sheds 20% of load if current > 50 A, and disconnects inverter if battery SOC < 20%. These actions protect system components and enhance stability.

8. Performance Evaluation and Visualization



a) Summary bar chart of detection accuracy (95.6%), false alarm rate (3.1%), localization accuracy (92.4%).

b) Detection latency and classification time plotted for multiple test cases.

The framework shows high accuracy and low false positives with detection and classification times suitable for real-time operation. Results are logged and visualized for performance benchmarking and system tuning.

Table 1: Performance Analysis of the Intelligent Hybrid AI Fault Detection Framework

Aspect	Description	Key Metrics / Remarks
1. System Modeling & Simulation	Microgrid modeled in Simulink with PV (100 kW), Wind (50 kW), Battery (200 Ah), Inverter, Load (60 kW).	Simulation: 10 s duration, 1 ms timestep; stable voltages (~400 V DC PV, 690 V AC wind) and currents under normal conditions.
2. Data Acquisition & Sensing	Voltage and current signals sampled at 10 kHz from inverter output terminals using virtual sensors.	High-resolution data capture enables detailed transient and power quality monitoring. Real-

		time logging supported.
3. Fault Injection & Scenario Design	Line-to-ground and line-to-line faults injected at 2.5 s causing voltage dips (~280 V) and current spikes (~45 A).	Fault waveforms validated; used for training and testing the AI model.
4. Data Preprocessing & Feature Extraction	Wavelet filtering applied for denoising; features extracted include RMS voltage/current, THD, kurtosis over 200 ms windows.	Distinct feature patterns differentiate fault vs. normal conditions.
5. AI Model Training & Integration	Random Forest (100 trees) and LSTM (two hidden layers) trained separately; outputs combined via weighted soft voting (0.4 RF, 0.6 LSTM).	Achieved fault classification accuracy of 95.6%; ROC curves and confusion matrices demonstrate performance.

This analysis summarizes the key aspects and performance metrics of the proposed intelligent hybrid AI-based fault detection framework. It details the microgrid simulation setup, data acquisition methods, fault injection scenarios, and feature extraction techniques. The table also highlights the AI model training and fusion strategy, fault detection latency, and control actions implemented for system protection. Overall, the framework achieves high detection accuracy, low false alarm rates, and effective real-time operation, demonstrating its suitability for inverter-dominated microgrids.

V. CONCLUSION

This paper presents an intelligent and hybrid AI-based fault detection framework tailored for real-time monitoring in inverter-dominated microgrids. By combining wavelet-based feature extraction with machine learning classifiers—Random Forest and LSTM—and employing a weighted soft-voting fusion strategy, the system achieves high fault classification accuracy (95.6%) with low false alarm rates (3.1%). The framework is validated through a detailed

Simulink-based microgrid model comprising PV, wind, battery, and inverter-based sources under various fault scenarios. Real-time signal acquisition, robust feature engineering, and low-latency detection (180 ms) enable timely and reliable fault alerts. Control responses such as load shedding and inverter protection ensure operational stability and safety. The results demonstrate the effectiveness of hybrid AI techniques in overcoming the challenges of low inertia and high variability in renewable-rich microgrids, paving the way for resilient, intelligent power systems.

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