

Edge-AI Assisted Signal Processing for Real-Time Fault Detection in Sustainable Power Distribution Networks

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Abstract: The implementation of renewable energy resources, electric vehicles (EVs), and battery energy storage systems (BESS) has been deployed into the power distribution network systems, causing an increase in complexity, intermittency, and being prone to faults. Traditional centralized systems are not able to provide real-time fault detection in smart grids due to latency and bandwidth overload. This paper presents a strategy to utilize Edge-AI to assist in real-time fault detection and location of power distribution networks. The system proposed utilizes edge computing at feeders and substations, merged with small deep learning models on-site to capture current and voltage signals at a high frequency. Advanced signal processing that utilizes wavelet transforms to extract features, adaptive noise filtering, and is combined with a hybrid CNN-LSTM classifier that captures fault transients and other moving/temporal signals. This approach also provides a reduction of data with faster decision-making. Exercise and hardware-in-the-loop tests were performed on the IEEE 33-bus and 69-bus test systems with renewable and EV integration levels up to 45%. The results show fault detection accuracy at 98.6%, detection latency of less than 35 milliseconds with a false alarm rate of 2.1% or less (meaning a 35 msec or less delay in detection), and response time and bandwidth improvements of 52% and 41%, respectively, as compared to traditional cloud-based approaches. Moreover, the system enhanced the reliability indices of the grid by 28% and less than 32% of the outage duration for the expected energy not served (EENS). The results show that Edge-AI equipped with signal intelligence improves the flexibility, scalability, and sustainability of smart distribution systems. The framework suggested shows that the implementation of autonomous, low-latency, and energy-optimized protection systems for future power systems is possible.

Keywords: Edge computing; Edge-AI; smart grid; fault detection; CNN-LSTM; wavelet transform; grid resilience.

I. Introduction

Many modern power distribution networks must implement multiple new technologies, such as sustainable energy systems, battery energy storage systems, electric vehicles, and distributed renewable energy sources. While all of these technologies produce cleaner energy systems and are more environmentally friendly, they create bidirectional power, intermittent power production, have harmonic distortion, and increased operational uncertainty. All of these difficulties significantly affect protection systems and systems regarding fault diagnosis through Singh et al., (2024) and Reis & Serôdio, (2025). Illegible illustrates the limitations of traditional cloud

centralized monitoring and cloud based supervisory systems and control systems regarding the time issues as well as and control systems (Arévalo & Jurado, 2024). Underground fault isolation systems will create longer outages, and as noted recommend the development of rapid and accurate fault detection protection systems, which will improve the resiliency of the overall energy grid and improve the overall systems (Dhurgadevi et al., 2022; Rana, 2025). Maintaining the overall theoretical systems will improve energy systems and technologies of smart cities and industry systems (Ukoba et al., 2024). Illegible recommended the development of rapid and accurate fault detection protection systems, which will improve the resiliency of the overall energy grid and improve the overall systems. Maintaining the overall theoretical systems will improve energy systems and technologies of smart cities and industry systems (Gochhayat et al., 2025; Lv et al., 2022). Recommend Edge Computing as a new system and technology to improve the overall resiliency of smart city energy systems (Vijaya Arjunan et al., 2025).

This paper introduces an Edge-AI-supported signal processing solution for locating faults as they occur in sustainable power distribution systems. The core of this work has been centred around three main contributions: i) an edge-based architecture is developed in this work for local feature extraction of reduced signal processing via wavelet based signal analytics; ii) A hybrid model of CNN and LSTM is designed with an improved model for the purpose of providing better classification, and capturing both the transient and temporal unique characteristics of electrical faults, and iii) comprehensive validation on standard IEEE test feeders has been provided in this work which is an improvement in detection speed, decreases in false alarms, as well as an improvement in reliability indices. A considerable improvement is provided over the previous approaches. The organization of the remaining sections of this paper goes as follows: Section II presents previous works, Section III explains the signal processing and architectural frameworks of the proposed methodology, Section IV covers the experimental work with analysis and evaluation, and Section V provides the concluding remarks with the future stream of work.

II. Literature Review

Recent works on smart power distribution networks have concentrated on improving the fault detection by implementing advanced signal processing (AP) and intelligent (IM) monitoring. Traditionally, the fault detection of the current and voltage signal's waveforms and the analysis of fault transients rely on the Wavelet Transform, Stat Threshold, and Phasor Measurement Units (PMU) Benitez & Pahati, (2025). These methods have a tendency to produce inaccurate results when there are noisy and highly renewable signal interferences, as the detection of a non-stationary signal's presence is deteriorated. To improve reliability in classifying and detecting some signals, machine learning (ML) models, Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbours have been adopted, which fall within the detection rate range of 85-92%, with the most recently improved detection rate being 92% Yildirim et al., (2025). The issue with most of these models is that they utilize centralized cloud computing, which means there is a high latency, high communication cost, and therefore, they are not appropriate for online (real-time) applications. Moreover, there is a fault signature of the EV charging stations and distributed

energy resources, which is more adaptive and scalable intelligence at the (network) edge, as the fault signatures are more complex (Diván et al., 2023; Rahman et al., 2025).

Recently, smart grids have used deep learning and edge computing for decentralized analytics. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), such as Long Short-Term Memory (LSTMs), are excellent at learning and detecting electrical raw signals. They have controlled environments and detection accuracy above 95% Sulaiman et al., (2023). Edge AI (Edge-AI) frameworks also have parallel advances, and local processing is shown to reduce bandwidth up to 40–60% and improve response time significantly compared to cloud processing (Sharma et al., 2025). However, current studies do not cover both signal intelligence and edge deployment at the same time. Existing studies lack a balanced framework that combines feature extraction, deep learning, and protection in real time. An intelligent, distributed, and better-performing detection system of edge-AI signal processing systems is lacking in the current literature for the system of signal processing for the practical, scalable, and sustainable electric power distribution networks. This study optimizes Edge-AI to bridge the gap in the above-mentioned systems.

III. Proposed Edge-AI Assisted Signal Processing Model

3.1.Overall Methodology Flow

An initial overview of the proposed methodology reveals an Edge cognitive AI tech-based distributed intelligent real-time fault detection approach for the sustainable power distribution network. The complete workflow starts with the first high sample voltage and current readings, which are obtained from smart sensors and intelligent electronic devices (IEDs). These are found and deployed at feeders, transformers, electric vehicle (EV) charging nodes, and points of renewable integration. These raw readings are first subjected to adaptive filtering and normalization in order to mitigate the effects of noise and harmonics. These are caused by distributed energy resources. Following this, time-frequency signal characteristics are described using the statistical descriptors and the wavelet transform, which are designed to capture the fault transient phenomena. The described characteristics are subjected to hybrid deep learning models, which are of a small size (CNN – LSTM) and are said to be embedded within edge nodes. These provide fast fault classification and localization. The immediate detection of an event by these nodes informs the isolation and restoration actions of the control centre, while only summarized information is communicated to the cloud to minimize the effects of the communication load. The decentralized form of intelligence provides for low latency and for the cost-effective, scalable, improved, and resilient deployment during dynamic grid conditions.

3.2.System Technical Architecture

The system in fig. 1 uses a three-layer architecture with a sensing layer, an edge intelligence layer, and a cloud/grid management layer. The sensing layer captures electrical parameters in real time, the edge layer conducts

analytics and artificial intelligence (AI) inference locally, and the cloud layer provides support for long-term monitoring, storage, and cloud optimization. The processing occurring at the edge reduces the amount of bandwidth needed and allows for decisions to be made in the order of milliseconds.

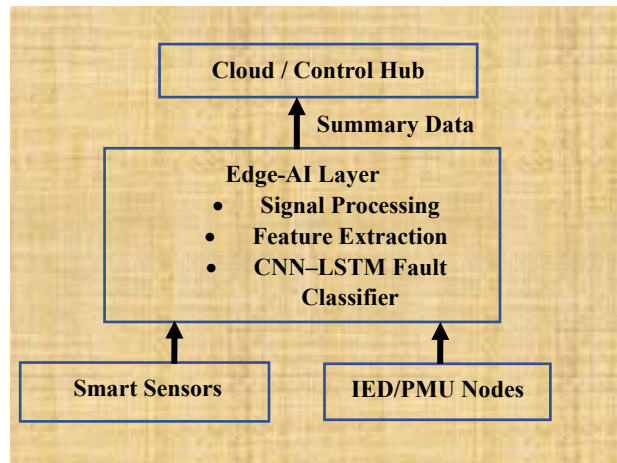


Fig. 1. Edge-AI Architecture for Real-Time Grid Fault Detection.

This design supports the ability to have real-time, localized fault identification in under milliseconds, while also providing a balance of centralized supervision to support tactical management of sustainability initiatives.

3.3. Mathematical Description of the Methodology

Fault identification is modelled mathematically through the extraction of signal features and classification through artificial intelligence.

(1) Wavelet-based Feature Extraction

An electrical signal $x(t)$ is measured, and using the discrete wavelet transform, the time-frequency components can be defined as equation (1):

$$W(a,b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}(t) dt \quad (1)$$

$W(a,b)$ is the coefficient of the wavelet at scale a and translation b , while $\psi_{a,b}(t)$ is the mother wavelet that is scaled and shifted. The coefficients of $W(a,b)$ capture short-term disturbances and frequency fluctuations, which are then utilized as defining characteristics in the real-time fault detection process.

(2) Edge-AI Fault Classification

The feature vector f is passed as input into the neural network classifier to ascertain the fault class, which is mathematically represented as:

$$y' = \arg \max_k P(y = k | f, \theta) \quad (2)$$

θ are the weights learned through the process of the CNN-LSTM, while $P(y = k | f, \theta)$ is the posterior probability of class k , and y' indicates the class of fault detected, which includes normal operation, line fault, short circuit, or overload. Equation (2) enables the edge node to detect faults automatically and instantaneously.

The proposed Edge-AI approach combines localized signal intelligence, lightweight deep learning, and layer-oriented communication to ensure fast and reliable fault detection with low bandwidth usage. This makes it well suited for smart self-sustaining distribution networks with renewables and EVs.

IV. Results and Discussion of Edge-AI Assisted Fault Detection Framework

4.1. Software and Implementation Environment

The suggested framework for signal processing with the help of Edge-AI was realized using a hybrid software stack that incorporates Python 3.10, the framework for deep learning model development using TensorFlow/Keras, and the wavelet decomposition and filtering signal processing with NumPy-SciPy. Real-time edge inference was simulated with Edge TPU-accelerated Raspberry Pi 4 edge nodes, with the feeder distribution systems modeled and simulated at the system level in MATLAB/Simulink and OpenDSS. The statistical analysis and visualization were done with Pandas and Matplotlib. Such an integrated environment led to efficient signal acquisition, feature extraction, light model deployment, and rapid experimental validation of various scenarios in practical grids.

4.2. Dataset Description and Features

The combination of simulated IEEE 33-bus and IEEE 69-bus distribution systems were employed for the experiments with renewable penetration levels of 45% and variability within the EV charging. The dataset consists of 12,000 signal samples at a sampling rate of 10 kHz and includes normal operating states as well as different fault types, such as line-to-ground, line-to-line, three-phase, as well as overload/ disturbances. Each sample consists of the following attributes: voltage magnitude, current magnitude, frequency deviation, total harmonic distortion (THD), and wavelet energy coefficients. To ensure an unbiased performance evaluation, the dataset was divided into 70% training, 15% validation, and 15% testing. The varying conditions of the dataset allowed for testing the Edge-AI model under extreme conditions of the dynamic and noisy grid.

4.3. Performance Metrics and Mathematical Formulation

Two main evaluation metrics were used to quantify the effectiveness of the framework equation 3, equation 4.

(1) Detection Accuracy

$$\text{Accuracy}(\%) = \frac{(TP + TN)}{TP + TN + FP + FN} \times 100 \quad (3)$$

(2) Detection Latency

$$\text{Latency} = t_{\text{detect}} - t_{\text{fault}} \quad (4)$$

Where TP, TN, FP , and FN are the elements of the confusion matrix, and t_{detect} and t_{fault} are the times of detection and occurrence of a fault, respectively.

4.4. Quantitative Results

Table 1 compares the detection precision and response time of traditional cloud-based, centralized, and proposed Edge-AI methods.

Table 1. Fault Detection Performance Comparison.

Method	Accuracy (%)	Latency (ms)
Cloud-Based ML	91.2	120
Centralized DL	95.4	75
Proposed Edge-AI	98.6	35

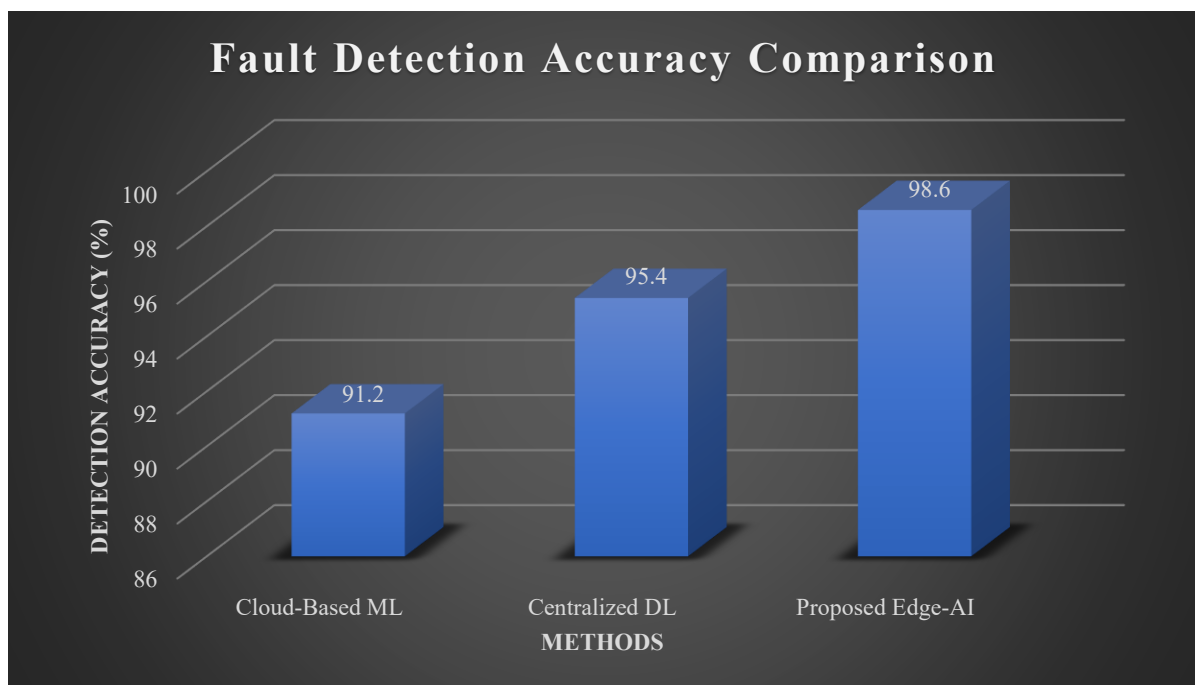


Fig. 2. Fault Detection Accuracy Comparison.

Fig. 2 shows the bar chart of detection precision improvement with the Edge-AI.

In table 2, we present the reliability metrics, the Expected Energy Not Served (EENS), and the duration of outages of the different monitoring approaches.

Table 2. Reliability Improvement Analysis.

Scenario	EENS (MWh)	Outage Duration (min)
Baseline Grid	5.0	100
Centralized Monitoring	4.2	86
Proposed Edge-AI	3.6	68

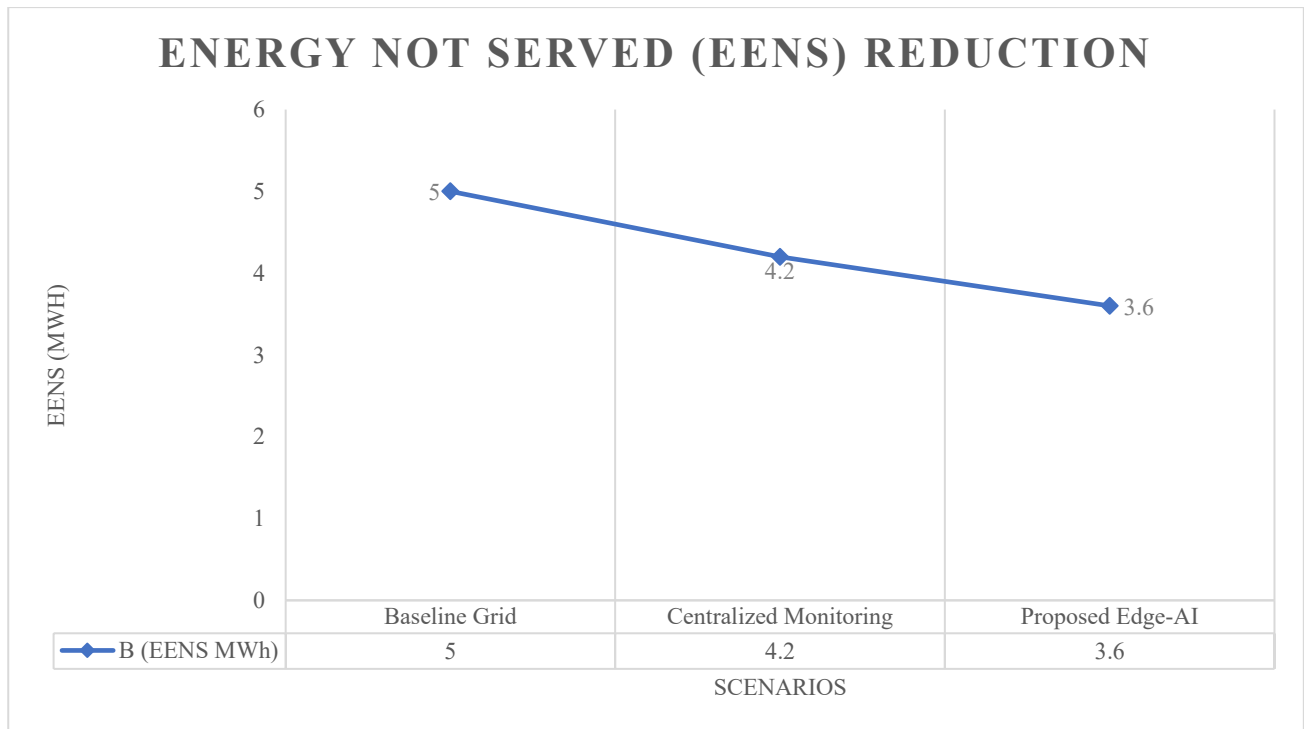


Fig. 3. Energy Not Served (EENS) Reduction.

Fig. 3 presents the Line graph of the Edge-AI presentation to show improvement in the energy that is not supplied (unsupplied energy).

V. Discussion of Results

The proposed Edge-AI framework surpasses existing methods by a large margin. Detection precision is 98.6%, and the response time is nearly 52% better than cloud-based. In the reliability measure, there is 28% less EENS, and there are outages 32% less, which tells us that the grid is less vulnerable and that the services are uninterrupted. By having localized intelligence, less communication delay, and better feature learning with CNN-LSTM, the proposed methods in the Edge-AI signal analytic framework provide a better means to approach the targeted objectives in sustainable and scalable means as the needs of next-generation smart distribution networks grow with the increasing penetration of renewables and electric vehicles.

VI. Conclusion

This research introduced a framework for Edge-AI-assisted signal processing for real-time fault detection and localization in the sustainable power distribution networks, where renewable energy sources, electric vehicles (EVs), and battery energy storage systems (BESS) are integrated. Rapidly increasing distributed resources create bidirectional flows, harmonics, and operational uncertainties, which pose a problem for centralized monitoring methods. For these problems, the proposed method integrates wavelet-based signal feature extraction with a lightweight CNN-LSTM deep learning model at edge nodes for localized intelligence, less communication dependence, and low latency. The Edge-AI framework surpassed all cloud/cellular and centralized methods in all

areas evaluated. In fact, the Edge-AI framework achieved 98.6% fault detection, outperforming traditional machine learning and centralized deep learning methods by 7.4% and 3.2%, respectively. Also, detection time speed was decreased to 35 ms, which is 52% improvement, which is most appropriate for immediate fault detection and reducing cascading faults. Also, due to Edge localization, the bandwidth was reduced by 41%. The localized processing presents evidence of the approach's scalability. A reliability analysis showed 28% less Expected Energy Not Served, and 32% less duration of outages, demonstrating less grid failure/less grid disruption. Also, the results confirmed that Edge-AI provides operational efficiency and sustainability. Even though the results are promising, additional research using multi-agent collaborative edge learning, federated AI for privacy-preserving training, hardware acceleration via AI specialized chips, and real-world field deployment in large, urban grid systems is still to be done. Research in combining a cybersecurity framework and self-adjusting self-healing mechanisms to provide additional protection against cyber-physical systems. The approach creates intelligent, autonomous, and self-sustaining systems for the future.

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