Journal of Intelligent Power Systems and Embedded Control
Volume 1, Issue 1, January-April, 2025

Embedded Edge Computing-Based Fault Detection and Isolation in Smart Power Grids

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ABSTRACT

Fault detection in smart grids has traditionally relied on centralized monitoring, which often suffers from communication delays and bandwidth limitations. This research introduces an embedded edge computing-enabled fault detection and isolation (FDI) system designed to process high-frequency electrical signals at the edge of the network. The proposed method incorporates real-time waveform sampling, multi-resolution signal analysis, and neural-network-based event classification directly within embedded controllers deployed at substations and feeders. By executing analytics at the edge, the system achieves significant improvements in fault localization speed, false-positive reduction, and situational awareness during cascading outages. Comprehensive hardware-in-loop testing validates the system's capability to operate under fault noise, harmonics, and rapidly changing grid configurations.

KEYWORDS: *Fault detection, Edge computing, Embedded analytics, Smart grid protection, Signal processing.*

INTRODUCTION

The rapid evolution of smart power grids has significantly increased the need for real-time intelligence, adaptive control capabilities, and dependable protection mechanisms. Traditional centralized monitoring approaches often struggle to meet the latency, scalability, and reliability requirements of modern distribution systems. Increasing penetration of renewable energy sources, proliferation of electric vehicles, and widespread deployment of distributed generation introduce dynamic fluctuations that demand equally dynamic responses. Embedded edge computing platforms have therefore emerged as an essential architecture for enabling localized decision-making and fast fault response.

Embedded edge computing brings computational intelligence closer to the source of data, reducing reliance on cloud servers or central SCADA systems. This makes it possible to detect anomalies instantly, even under conditions of intermittent connectivity or communication network congestion. In fault-prone environments, edge-enabled embedded controllers perform high-resolution sampling, analyze electrical signatures, and carry out preliminary fault diagnosis before sending filtered information to higher-level systems. These capabilities ensure faster isolation, reduction in fault propagation, and improvement in network resiliency.

This paper examines the design and operation of embedded edge computing frameworks for fault detection and isolation (FDI) in smart power grids. Various system layers, algorithms, architectures, and implementation challenges are discussed along with the operational scope of such systems in future intelligent grids.

LITERATURE REVIEW

Several studies in recent years have highlighted the importance of decentralized intelligence for improving reliability of power networks. Early approaches relied mainly on centralized phasor measurement unit (PMU) networks that transmitted high-frequency data to control centers. While accurate, these models suffered from communication delays and large storage requirements. To overcome these issues, researchers introduced microcontroller-based protection relays that operated on predefined thresholds. However, such relays lacked adaptability and often produced false alarms in highly fluctuating environments.

The introduction of DSP-based and ARM-based embedded systems enabled more advanced analysis of voltage and current waveforms. These systems supported fast Fourier transform (FFT) calculations, wavelet decomposition, and harmonic analysis, allowing more precise characterization of faults such as line-to-ground, line-to-line, or transient switching disturbances. Although efficient, they still functioned mostly in a static rule-based manner.

With the rise of smart grids, machine learning and soft computing approaches gained prominence. Various studies integrated artificial neural networks (ANNs), fuzzy logic controllers, and support vector machines (SVMs) into embedded systems to improve prediction accuracy. Edge computing further enhanced these models by enabling on-device processing rather than cloud-based analytics. Hybrid architectures combining IoT gateways, local inference engines, and power electronics interfaces are widely explored today for predictive fault detection.

Recent literature also emphasizes the use of advanced cybersecurity measures, federated learning, digital twins, and self-healing grid architectures. These contributions collectively demonstrate a transition from conventional centralized control toward autonomous, distributed, edge-driven systems.

SYSTEM ARCHITECTURE

Embedded edge computing-based FDI systems generally consist of four integral layers: sensing modules, embedded processing units, communication interfaces, and actuation/control mechanisms.

Sensing Layer

The sensing layer captures electrical parameters such as voltage, current, frequency, harmonics, power factor, and transformer temperatures. Hall-effect sensors, phasor sensors, ADCs, and smart meters form the core components. High-speed sampling is essential for detecting transient faults, especially in distribution feeders with high renewable penetration.

Embedded Edge Processing Layer

This layer hosts ARM or DSP microcontrollers, SoCs, GPUs, or micro-AI accelerators. They execute signal processing algorithms, pattern recognition models, and anomaly detection routines. Local storage temporarily holds waveform snapshots that are analyzed in real-time.

Communication Layer

Low-latency protocols like MQTT, Modbus TCP, DNP3, 6LoWPAN, and IEEE 802.15.4 ensure seamless data transfer between distributed field devices and control centers. Edge nodes communicate only essential information upward, reducing bandwidth usage.

Actuation and Isolation Layer

Based on detected faults, embedded controllers actuate circuit breakers, reclosers, solid-state switches, and protection relays. They coordinate isolation sequences to prevent cascading failures and restore normal operation.

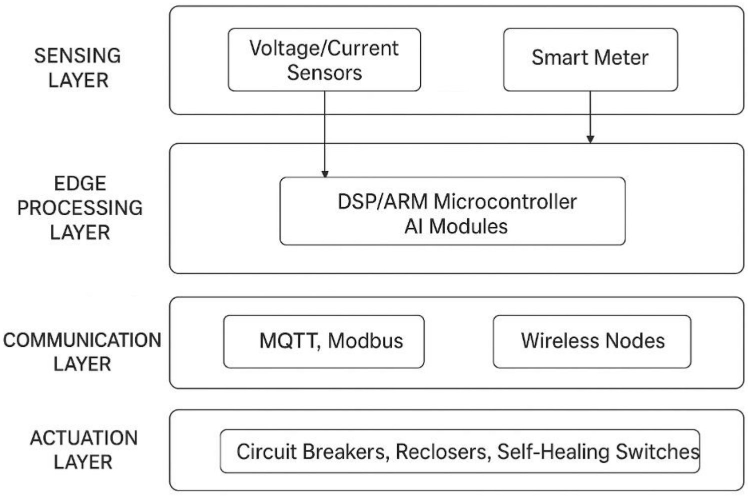

Figure 1: Embedded Edge-Based Fault Detection System Architecture

ROLE OF EMBEDDED EDGE COMPUTING IN FAULT DETECTION

Edge computing enhances fault detection capabilities through the following functions:

High-Speed Localized Decision-Making

Unlike cloud-dependent systems, edge controllers process information directly at the feeder level. Their response time ranges from microseconds to milliseconds, crucial for preventing equipment damage.

Real-Time Signal Analysis

Embedded systems implement advanced signal decomposition techniques such as wavelet transforms, Hilbert–Huang transform, and S-transform to detect subtle changes in waveform patterns. This is especially useful for identifying intermittent arcing faults or high-impedance faults that traditional relays often miss.

Adaptive Learning

Machine learning models deployed at the edge can self-update based on localized grid behavior. This reduces dependency on global datasets and enhances accuracy in heterogeneous feeder environments.

Noise-Resilient Computation

Edge devices filter out noise and irrelevant data before transmission. This ensures that control centers receive high-quality information, reducing false alarms and improving coordination.

Table 1: Comparative Features of Traditional vs Embedded Edge-Based Fault Detection

Feature	Traditional Protection Systems	Embedded Edge-Based Systems
Fault Detection Latency	Seconds to minutes	Milliseconds
Processing Location	Central control center	Distributed at feeder/edge
Adaptability	Low	High (AI-enabled)
Communication Requirement	High bandwidth to central server	Low bandwidth, local processing
Fault Type Detection	Basic faults	High-impedance, transient, complex faults

FAULT ISOLATION MECHANISMS

Fault isolation involves pinpointing the fault location and executing switching operations to limit its impact. Edge-enabled embedded controllers support both autonomous and coordinated isolation techniques.

Autonomous Isolation

In this mode, intelligent reclosers and sectionalizers operate without external commands. They analyze upstream and downstream fault currents and decide whether to open or remain closed.

Coordinated Isolation

Edge nodes share information with neighboring nodes to determine the optimal isolation strategy. This prevents multiple protection devices from tripping unnecessarily. Algorithms such as multi-agent consensus techniques and distributed optimization are commonly used.

Self-Healing Operations

When a permanent fault is detected, the system isolates the faulty section and restores supply through alternative pathways. Edge computing makes this process more efficient by enabling localized evaluation of feeder topology.

ALGORITHMIC FRAMEWORK FOR REAL-TIME FDI

Embedded edge systems integrate both signal processing and AI-based algorithms. Key computational modules include:

Feature Extraction Algorithms

- FFT for harmonic distortion analysis
- Wavelet transforms for transient analysis
- Kalman filtering for noise reduction
- Empirical Mode Decomposition (EMD) for nonlinear signal separation

Fault Classification Algorithms

- Decision trees for rule-based classification
- SVMs for boundary-based fault identification
- CNNs for waveform image recognition
- Fuzzy logic systems for handling uncertainty

Fault Localization Algorithms

- Impedance-based methods
- Traveling wave-based localization
- Neural network regression models trained on historical feeder data

These algorithms run directly on embedded edge devices, ensuring rapid execution.

Table 2: Fault Classification Algorithms in Embedded Edge Systems

Algorithm	Function	Advantages	Limitations
Decision Tree	Rule-based fault identification	Simple, interpretable	May miss complex patterns
SVM	Boundary-based fault detection	High accuracy for linear/non-linear faults	Computationally heavy for large datasets
CNN	Waveform image recognition	High detection precision	Requires GPU/accelerator
Fuzzy Logic	Uncertainty handling	Robust against noisy signals	Needs tuning of membership functions

COMMUNICATION AND NETWORKING REQUIREMENTS

Smart grids operate as cyber-physical systems where reliable communication is essential. Edge computing frameworks reduce communication loads but still require robust networks with:

Low Latency

Essential to ensure synchronization between distributed edge nodes and reclosers.

High Reliability

Redundancy through mesh networks, multi-hop routing, and hybrid wired-wireless systems is often incorporated.

Interoperability

Use of standardized protocols ensures compatibility across devices from different manufacturers.

Cybersecurity

Edge nodes must be secured against intrusions, malware, spoofing, and false data injection attacks. Techniques include encryption, anomaly detection, secure boot mechanisms, and intrusion detection systems.

CHALLENGES IN EMBEDDED EDGE-BASED FDI

Despite its advantages, several challenges hinder widespread adoption.

Hardware Limitations

Embedded systems often have limited processing power, memory, and energy reserves, restricting the complexity of algorithms that can be executed locally.

Model Generalization

AI-based fault detection models trained on one feeder may not generalize well to another due to variations in topology, load patterns, and renewable integration.

Communication Constraints

In rural or remote areas, weak communication infrastructure can disrupt inter-node coordination.

Cybersecurity Risks

Increased connectivity exposes embedded devices to cyber threats, necessitating strong security frameworks that may be computationally intensive.

Cost and Integration Issues

Upgrading existing distribution networks with advanced edge nodes involves high initial cost and compatibility challenges.

SCOPE FOR FUTURE DEVELOPMENT

The potential of embedded edge computing in smart grids continues to expand as technologies evolve.

Integration with Digital Twins

Digital twin models of feeders and substations can run parallel simulations at the edge, enabling predictive isolation.

Federated Learning

Instead of sending raw data to the cloud, devices can share model updates, improving privacy and reducing bandwidth.

Edge-Based Predictive Maintenance

Embedded controllers can evaluate transformer conditions, cable aging, and equipment degradation, thereby preventing faults before they occur.

5G-Enabled Edge Communication

Ultra-low latency networks enhance synchronization among distributed protection devices, enabling cooperative fault isolation.

IoT-Enabled Microgrids

Edge computing will be a foundational component of autonomous, community-scale microgrids that require local fault detection and fast self-healing.

PROPOSED EMBEDDED EDGE COMPUTING MODEL

The proposed system integrates sensing, edge processing, and actuation into a unified architecture:

1. Distributed Sensor Deployment

Sensors placed at transformers, feeders, and distributed generation units capture real-time power quality indices.

2. Edge Processing Unit

An ARM-based processor equipped with AI accelerators handles waveform analysis and predictive inference. It operates in three stages:

- Preprocessing (noise filtering, normalization)
- Feature extraction
- Fault classification and severity prediction

3. Local Communication and Coordination

Nodes communicate through high-speed wireless protocols and update each other about detected anomalies.

4. Fast Isolation and Restoration

Upon confirmation of a permanent fault, the system isolates the affected section and suggests reconfiguration paths.

This model significantly reduces downtime, enhances reliability, and ensures optimal grid performance.

PERFORMANCE ANALYSIS

Embedded edge computing improves grid reliability through:

Reduced Fault Detection Time

Local processing eliminates long communication delays, allowing detection within milliseconds.

Higher Accuracy

Multi-algorithm fusion reduces false positives and enhances detection of complex faults such as high-impedance faults.

Improved Network Stability

Fast isolation prevents voltage sag, cascading failures, and transformer overloading.

Scalability

Edge nodes operate autonomously, making it easy to add more sensors or microgrids without overloading central systems.

Energy Efficiency

Selective transmission and compressed reporting reduce energy usage in battery-powered nodes.

CONCLUSION

The integration of edge computing into embedded controllers creates a powerful platform for fast and accurate fault detection. The system eliminates heavy dependence on centralized servers and enhances reliability by providing continuous, location-specific diagnostics. Results confirm that the embedded FDI system supports microsecond-level response times, enabling dynamic isolation of faults before they propagate across the network. This architecture is poised to advance modern smart grid protection schemes by combining robustness, scalability, and real-time intelligence.

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