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IoT-Based Fault Detection in Distribution Lines

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Abstract

Quickly detecting and pinpointing faults in electrical distribution lines are important for shortening the duration of service interruption, reducing maintenance costs, and increasing safety. In this work, we propose realistic architecture for an Internet-of-Things (IoT)-enabled fault detection system designed for distribution networks. To continually assess electrical characteristics including voltage, current, frequency, temperature, and line status, the suggested architecture combines low-cost, dispersed sensor nodes placed along feeders and important network points. These sensor nodes connect to edge devices via dependable wireless protocols, where they execute initial data preprocessing, filtering, and anomaly detection to minimize latency and bandwidth consumption. Deployed at the edge gateway or in the cloud, advanced machine learning (ML)-based analytics are utilized for fault detection, classification (e.g., line-to-ground, line-to-line, open conductor), and severity estimation. The architectural proposal fuses low-cost sensor nodes as down to the network, edge-based data preprocessing and cloud or edge gateway-oriented ML based analytics. We discuss the elements of the system, the data flow, fault detection and classification techniques (both rule-based and ML-based), as well as potential approaches to fault localization. Finally, we present high-level sketches of an experimental plan and discuss the trade-offs involved. The idea is to help utilities transition from reactive maintenance to real-time monitoring and active fault management.

Keywords: Distribution lines, fault detection, IoT, machine learning, smart grid edge computing

INTRODUCTION

Electrical distribution systems deliver power to end users; however, they remain far from being immune to different types of faults – both due to various forms of vegetation contact (with objects like trees, etc.), insulation decay, lightning or overloading (caused by severe weather impacts or minor animals which accidentally cut off circuits) and aging facilities. The susceptibility of the system is further increased by external events like storms, strong winds, heavy rains, and falling debris [1–4]. Occasionally, small animals and birds inadvertently cause outages by damaging insulation or bridging wires. Fault probability is also greatly increased by aging infrastructure such as damaged transformers, connectors, and poles. Prolonged service outages, equipment damage, financial losses, and major safety risks like electrical fires or electrocution threats can all be caused by these failures. Therefore, increasing system dependability and operational resilience requires better fault detection and monitoring systems. Those sorts of mistakes can lead to outages, wrecks, and even safety hazards [5, 6].

Conventional fault detection and response generally rely on manual examination or regular visits, which result in the delay of discovering faults and causes long time down.

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Recent smart grid concepts advocate an intelligent distribution network, characterized by the deployment of sensor-based monitoring solutions and state-of-the-art analytics. IoT devices, inside edge computing and machine learning can provide continuous real-time monitoring – resulting in fault detection that is faster, more accurate and scalable than the customary approach. several recent studies support the feasibility of this approach.

In this paper, we propose an end-to-end IoT system designed for distribution lines. Our design highlights cost effectiveness, scalability, and extensibility to constraints encountered in the real world such as constrained communication, data bandwidth, and fault types.

LITERATURE REVIEW

In recent years several works have investigated (a)IoT/(a)ML based approaches for fault detection in power grids:

- A real project in "Line Fault Detection and Alert System Using IoT" monitors the parameters, such as voltage, current, and temperature on the distribution line through deployed sensors, when the abnormalities are found by this system then sends an alert in real time with GPS to locate the fault.
- In a recent survey on ML-based methods for fault detection in distribution grids, it is reported that algorithms, such as ANN, SVM, decision trees, and deep learning models, show an appealing level of performance with respect to the accuracy in detecting, classifying, and even locating faults.
- Another recent paper presents an end-to-end architecture of sensor-rich distribution networks, edge computing and ML for real-time fault detection and predictive maintenance.
- On a more advanced front, detection of challenging fault scenarios (i.e., high impedance faults and incipient [slow-developing] faults) can be approached through time–frequency domain techniques, wavelet-based transformers, or deep learning networks integrated with recurrent networks.
- These results demonstrate that IoT + ML hybrids can provide a substantial enhancement compared to traditional relay-based or manual systems, especially when applied in complex distribution networks with incomplete instrumentation.

PROPOSED SYSTEM ARCHITECTURE

Overview and Design Goals

The model consists of three layers:

- *Edge Sensing Nodes:* These are low-cost IoT sensor nodes installed at various locations (such as feeder heads, transformers, critical poles, and sectionalizing points) along the distribution lines.
- Communication network – light but strong communication (LoRaWAN, NB-IoT / LTE-M; GSM fallback) at edge nodes to gateways / to cloud.
- *Analytics Layer:* Rule-based fast detection at the edge for instant alerts and cloud/edge-based machine learning for more accurate fault detection, classification, and localization.
- Specific design targets involved low-power (~10 µW to ~10 mW), scalability, and cost-effectiveness up/downwards from 1000 s down to 1 s of nodes, tolerance for intermittent communication (e.g., due to high-impedance faults), various types of faults ranging from conventional short-circuits to more subtle ones, such as high-impedance or partial-discharge related.

Hardware and Sensing Design

- *Sensors:* Current measurement CTs (current transformers) or Rogowski (Voltage dividers for voltage measurement) /PT, Optional PD/Insulation-condition sensors Temperature and ambient sensors. Other options to monitor the environment, overheating, and thermal anomalies. The level of partial discharge measurement provides a means to detect insulation degradation or when insulation failure begins.

- *Controller:* A microcontroller (e.g., ESP32 for SynDicEDGS, or an industrial IoT gateway/µPMU providing more synchronized measurements) for data acquisition, preprocessing, and buffering of events, and communication.
- *Power & Enclosure:* In remote poles, nodes can be powered by solar + battery and encased in an IP-rated enclosure to remain sturdy as well as low maintenance.

Nodes constantly sample low-rate data (e.g., RMS voltage/current 1–5 seconds) and transition to high resolution sampling (Waveform capture several kHz for short window) on event triggers such as sudden current surge, voltage drop, PD pulse, etc.

FAULT DETECTION AND LOCALIZATION METHODS

Edge-Based Rule Detection (Low Latency)

Near-immediate alerts are possible by using flat rules-based logic, running on device edges to trigger on things like:

- Large voltage dips or surges.
- Sudden current peaks or zero sequence current bursts.
- Temperature shock in the form of jumps, or PD pulses (if there are sensors).

These triggers produce alert packets + timestamp (GPS-synced) sent by one-hop to gateway/maintenance center. With this, you will get timely feedback for trivial errors without waiting for cloud analysis.

Machine Learning Based Classification and Fault Detection

- For improved sensitivity conditions – particularly for low level or high impedance faults – the system employs a Machine Learning (ML) classification on retrieved high-resolution waveform data.
- *Feature Extraction:* Features can be extracted from the captured waveforms, such as time domain characteristics (peak waveform current, RMS value change and duration of fault), statistical parameters (kurtosis, skewness, and entropy), and time-frequency domain wavelet transform-based or other method-derived features. These multi-domain feature sets have proven to be robust in discriminative diverse fault types.
- *ML Models:* Various models can be utilized; the following may depend on data and computation resources available:
  - *Conventional Classifiers:* SVM, Random Forest, Decision Trees – appropriate if features are handcrafted. Some of these have been successfully employed for HIF sensing.
- *Deep Learning Techniques:* 1D-CNN, recurrent networks (e.g., LSTM, could be improved with wavelet-embedded cells) – applicable when waveform data is rich and fault signatures are complex or non-stationary. In recent work, in Yin and Wei (2020), Wani et al. (2021), Kavousi-Fard (2021), Magesh et al. (2023) [7–10], very promising results have been obtained when considering time-frequency embedded LSTM for incipient fault detection.

These ML based detectors can be deployed to the cloud/edge gateways and generate alerts or evoke maintenance workflows [11].

Fault Localization

Discovering a fault is one thing but bringing service back up means – knowing where the fault is. The following localization strategies are supported by the designed system, depending on the existing infrastructure:

- *Synch Time-Difference of Arrival (TDOA):* For µPMUs or GPS-time-synced nodes, the propagation time for a fault wave across the sensors can be used to triangulate location from Figure 1.

- *Pattern-Based Triangulation:* without µPMUs – through matching triggers at several nodes in sequence and magnitude. For instance, a node which first detected the anomaly or relation of magnitudes or series of voltage/current disturbances.
- *Impedance-Based Estimation:* use pre-fault load/line impedance models and monitor voltage/current changes to estimate location. Most effective if synchronized measurements and line model are available.
- Hybrid strategies that incorporate several of the methods are likely to be most effective, particular in complex branched distribution feeders and/or systems with distributed generation.

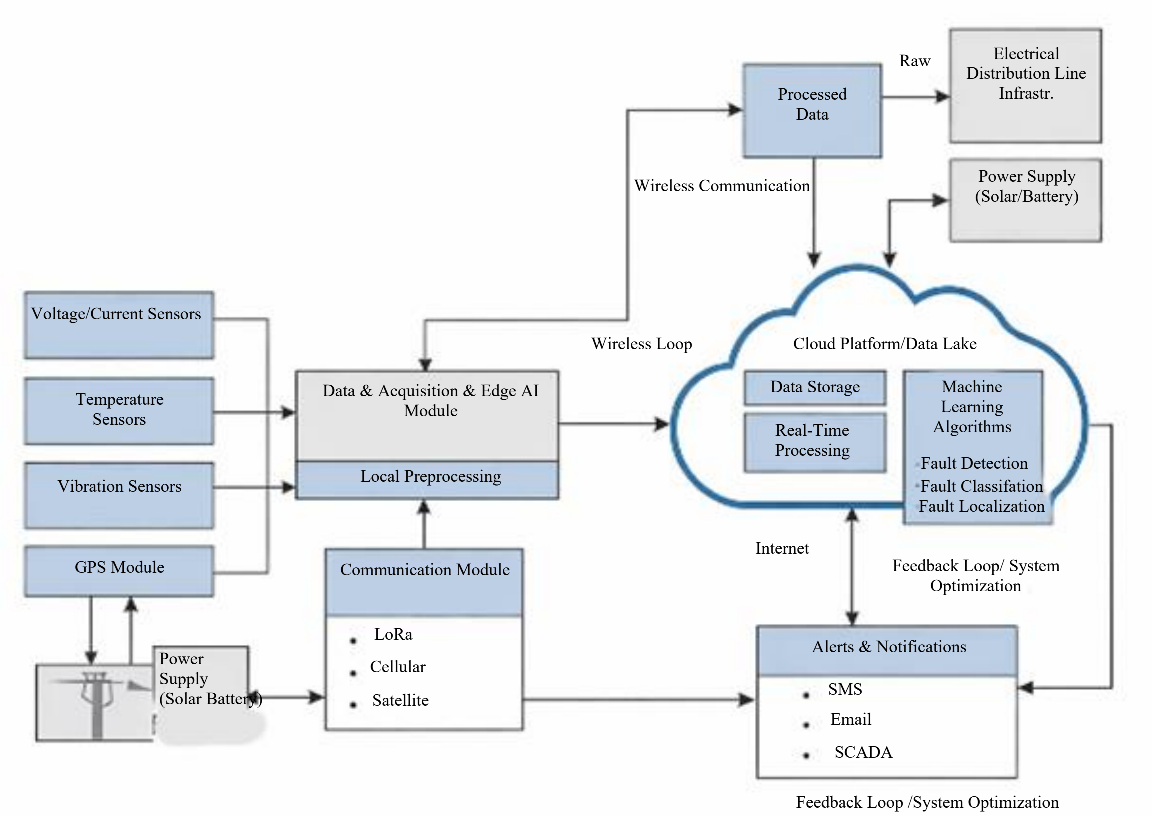

Figure 1. Proposed IOT-based fault detection system architecture.

DATA PIPELINE AND SYSTEM INTEGRATION

- *Edge Preprocessing:* Baseline removal, filtering, event detection – decreases volume of raw data and triggers only valuable captures.
- *Communication:* The event data (e.g., alerts, compressed waveform snapshots, metadata) is transmitted through secure links (e.g., MQTT over TLS) to a gateway/cloud. Telemetry upload (RMS values, temperature, health checks) of the subject performed routinely at scheduled intervals.
- *Storage:* Telemetry typically in a time-series database (e.g., InfluxDB / TimescaleDB) and waveform data in object storage (S3-like) or file server.
- *Analytics:* Streaming engine (e.g., Apache Kafka / MQTT broker + stream processor) for near real-time ML inference; batch processing for retraining and model updates; dashboards for operators and OMS; automatic notifications (SMS/email) for maintenance staff.
- *Security Measures:* Mutual TLS authentication for devices, firmware signing and secure over-the-air updates, device attestation – to ensure no tampering or fake alerts.

EXPERIMENTAL EVALUATION PLAN

We recommend a phased approach to testing and quantifying the performance of our system:

- Lab testing & simulation Physically simulate various fault types (phase-to-phase, phase-to-ground, high-impedance, insulation degradation, partial discharge) under different loads and noise using hardware-in-the-loop (HIL) or test bench. Use this for labeled dataset and test for latency, detection accuracy and false-positive/ false-negative rates for ML training.
- *Pilot Field Deployment:* Instrument a feeder section (e.g., 5–10 poles/nodes) within an actual distribution network. Run the system for a few months to collect natural faults and events, log detection events, classification results, and localization accuracy.
- *Scalability & Operation:* Estimate communication bandwidth consumption, storage cost, resistance under network disconnections, maintenance burden and power consumption (in the case of solar-powered nodes), up time of system.
- *Mechanisms to Monitor:* Detection accuracy (precision/recall), F1-score, false alarm rate, localization error (meters; mean & 95th percentile), detection latency (time from fault occurrence until alert generation) and system availability.

EXPECTED BENEFITS AND TRADE-OFFS

Benefits

- Real-time fault identification and alerting, reducing downtime and increasing safety.
- More sensitive to subtle faults (e.g., high-impedance or partial discharge) – often overlooked by conventional protection schemes.
- Shortened manual patrols and inspections, reduced maintenance cost
- Data-driven analytics for predictive maintenance and grid-aging condition monitoring.
- *Scalable:* It is applicable to large distribution networks with inexpensive sensor nodes.

Trade-offs and Challenges

- In case of detecting the subtlest fault (e.g., HIF) sensitivity of the sensor, quality of measurements and quality/quantity of training samples are very important concerning accuracy detection. Performance could be restricted when using inexpensive sensors.
- *Bandwidth and Storage:* If events are frequent, the requirement for high-resolution waveform capture may be resource-intensive. Hybrid approaches (edge filtering + selective upload) can help, but the design needs to be cautious.
- *Communication Reliability:* In remote or rural feeders where cellular / LPWAN coverage is low, data loss may occur due to latency.
- *Security and Reliability IoT:* The devices are subject to interference, counterfeiting or defects need of secure authentication and firmware update.
- Integrating with legacy infrastructure and grid operations (e.g., the SCADA/OMS system) may be further effort.

CONCLUSION AND FUTURE WORK

We present a holistic framework for the detection of faults in distribution lines based on IoT – integrating low-cost sensors, edge computing, secure communications and ML-based analytics. This approach provides a path for utilities to move from reactive, manual fault management to proactive real-time monitoring and maintenance.

As Future Work, We Recommend

- Improvements on ML models through transfer learning and federated learning across feeders/regions to reduce overfitting.
- *With Addition of Self-Healing:* interfacing with sectionalizing/reclosing automation for partial automatic restoration upon fault detection.
- Such as insulation condition monitoring (e.g., PD sensors, thermal imaging) to predict faults before they appear.
- Investigating adaptive sampling and edge-based ML inference to minimize bandwidth and latency; to calculate the system ROI due to large roll out.

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