© APR 2026 | IRE Journals | Volume 9 Issue 10 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I10-1717009

Machine Learning and M2M Communication in Smart Grids: A Review, Taxonomy, and Future Directions for Fault Management

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Abstract - The transformation of power distribution systems toward smart grid architectures has intensified the need for intelligent, communication-aware, and resilient fault management solutions, particularly in developing-region networks where reliability indices remain critically constrained. While machine learning techniques have demonstrated transformative capabilities in fault detection and classification, achieving superior accuracy through deep graph learning, spatial-temporal recurrent neural networks, and hybrid artificial intelligence approaches, these studies predominantly operate under idealised communication assumptions that ignore the latency, jitter, and packet loss inherent in real-world machine-to-machine deployments. Conversely, existing machine-to-machine communication protocols for smart grids, including LoRaWAN, NB-IoT, and ZigBee, have been studied in isolation from the diagnostic algorithms they are intended to support. This critical disconnect between algorithm accuracy and deployment reality creates a significant gap in the literature: no unified framework currently exists to evaluate machine learning performance under realistic machine-to-machine communication constraints or to optimise communication parameters for diagnostic reliability.This paper presents a comprehensive review of machine learning and machine-to-machine communication integration for low-voltage and medium-voltage distribution fault management, structured around a novel taxonomy of communication-aware architectures. We systematically analyse existing approaches across four categories: communication-agnostic machine learning, communication-assisted diagnostics, communication-resilient algorithms, and fully integrated machine-to-machine machine learning systems. Through comparative analysis of verified literature spanning deep reinforcement learning for service restoration, multi-agent coordination for automated switching, and federated learning for distributed intelligence, we identify critical research gaps, including the absence of electrical-communication co-simulation platforms, underdeveloped edge-based inference architectures, and insufficient validation under non-independent and identically distributed data conditions. We further propose a unified conceptual framework integrating electrical feeder dynamics, machine-to-machine communication impairments, and machine learning inference within a coordinated architecture, validated against Nigerian distribution network parameters as a representative developing-region case study. By consolidating existing knowledge and highlighting the imperative for communication-machine learning co-design, this work provides clear directions for advancing intelligent, resilient, and deployable fault management systems in next-generation distribution networks.

Keywords: Machine-To-Machine Communication; Machine Learning; Fault Detection; Distribution Networks; Smart Grids; Communication-Aware Architectures; Co-Simulation; Developing Regions

I. INTRODUCTION

The transformation of electric power distribution systems toward smart grid architectures has fundamentally altered the landscape of network reliability and operational intelligence. Distribution networks, particularly low-voltage and medium-voltage radial feeders, constitute the most vulnerable segment of the power system due to their exposure to environmental disturbances, higher fault incidence, and limited redundancy [1]. Faults occurring within these feeders, including single-line-to-ground, line-to-line, and high-impedance faults, directly degrade service continuity and elevate critical reliability indices, such as the System Average Interruption Duration Index (SAIDI) and the System Average Interruption Frequency Index (SAIFI) [2]. The imperative for rapid detection, precise localisation, and automated restoration has therefore become central to modern distribution system resilience [3].

Traditional fault management relies primarily on overcurrent relays, sectionalizers, and operator-dependent supervisory control mechanisms. However, conventional restoration strategies struggle to respond adaptively to dynamic load variations,

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DOI: https://doi.org/10.64388/IREV9I10-1717009

distributed energy resource penetration, and the stochastic nature of fault propagation [4]. These constraints have motivated the transition toward intelligent, data-driven fault management systems capable of autonomous decision-making under uncertainty [5].

The emergence of machine learning has introduced transformative capabilities in power system fault detection and classification. Data-driven models can extract discriminative features from current and voltage waveforms, enabling faster and more accurate fault characterisation than impedance-based methods [6]. Deep learning architectures, particularly convolutional neural networks, spatial-temporal recurrent graph neural networks, and deep reinforcement learning, have demonstrated superior performance in handling high-dimensional, non-stationary electrical signals [7,8]. Hybrid approaches combining time-frequency analysis with neural classification have further improved detection of incipient and complex faults [9]. These advancements collectively establish machine learning as a viable paradigm for next-generation distribution automation [2].

Figure 1 presents a progressive taxonomy of M2M-ML integration approaches for distribution fault management, illustrating the evolution from isolated to fully coordinated systems. It begins with communication-agnostic models that assume ideal data conditions, advances through communication-assisted and communication-resilient approaches that increasingly account for network constraints, and culminates in fully integrated architectures where machine learning and communication systems are jointly optimised. The progression highlights a clear shift toward more realistic, adaptive, and deployment-ready solutions capable of operating effectively under latency, packet loss, and dynamic grid conditions.

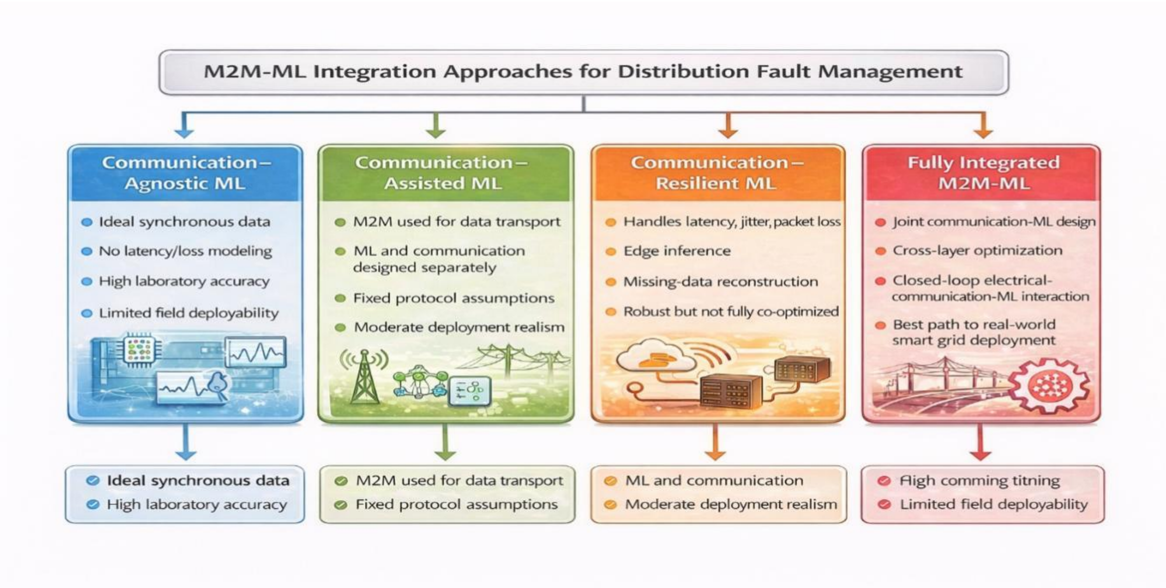

Figure 1: Conceptual taxonomy of M2M-ML integration approaches for distribution fault management

Despite these algorithmic advances, a critical disconnect persists between machine learning research and deployment reality. Existing studies predominantly evaluate detection accuracy under idealised conditions, assuming continuous, synchronous, lossless data streams from field sensors [10]. In practice, machine-to-machine communication in distribution networks operates under severe constraints: latency variability, packet loss, bandwidth limitations, and asynchronous timestamp behaviour fundamentally alter the integrity of measurement data [11,12]. Communication impairments can distort waveform signatures, misalign inference windows, and degrade classification confidence, effects that remain unquantified in communication-agnostic diagnostic frameworks [10,13].

Machine-to-machine communication constitutes the enabling infrastructure for smart grid intelligence, allowing sensors, reclosers, and control centres to exchange operational data in real time [11]. Protocols such as LoRaWAN, NB-IoT, and ZigBee offer trade-offs between range, bandwidth, and energy

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consumption that directly shape the feasibility of machine learning deployment [12]. Edge AI implementations for early fault detection have demonstrated the potential for localised inference, yet comprehensive frameworks integrating edge intelligence with communication-aware optimisation remain underdeveloped [13]. This fragmentation has resulted in machine learning models optimised for laboratory conditions that fail to generalise under realistic network constraints [11,12].

The integration of machine learning with machine-to-machine communication has led to the emergence of communication-aware intelligent distribution architectures, frameworks that explicitly model the interdependence between diagnostic algorithms and communication infrastructure. In this paradigm, machine learning agents must operate robustly under impaired data streams, while communication protocols adapt to prioritise diagnostic traffic during fault events [14]. Recent applications of deep reinforcement learning for demand response optimisation demonstrate the feasibility of real-time adaptive control [15], yet extension to fault management scenarios remains limited. This bidirectional optimisation represents a significant departure from conventional approaches, offering pathways to resilient, deployable fault management in resource-constrained environments [14].

Figure 2 contrasts two fundamentally different distribution communication architectures. In the traditional centralised model, all control decisions originate from a single utility control center, creating a top-down flow of information and actions, which introduces a single point of failure and slower fault response due to dependency on centralised processing. In contrast, the M2M-enabled distributed architecture decentralises intelligence across network nodes, enabling peer-to-peer communication and local coordination among devices. This results in faster fault detection, improved system resilience, and reduced reliance on a central controller, making it more suitable for dynamic and communication-constrained distribution environments.

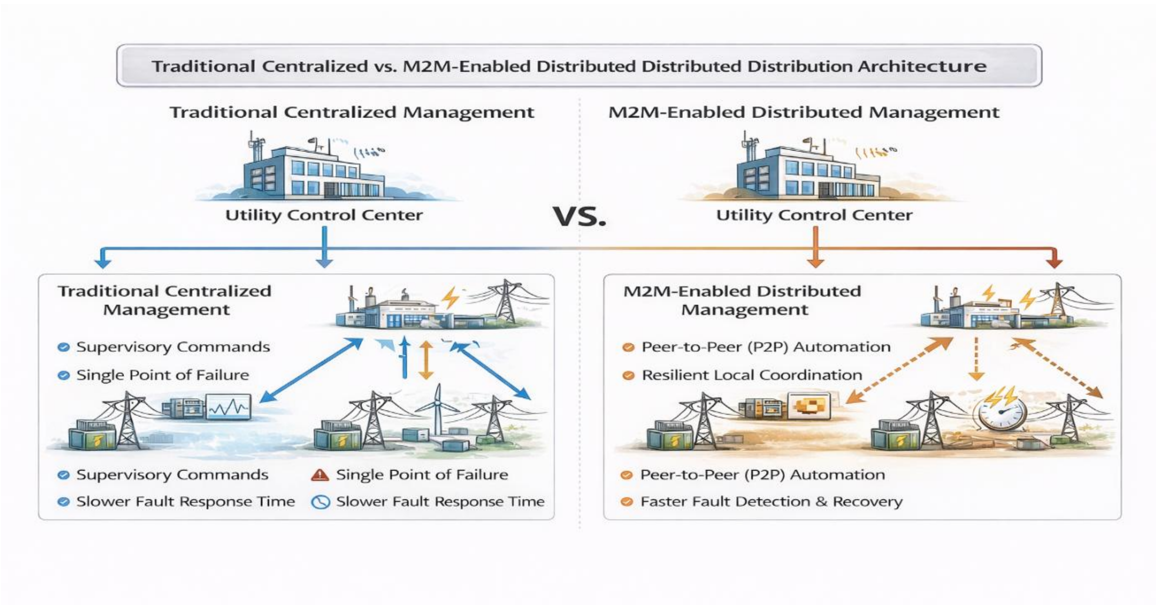

Figure 2: Traditional centralised vs M2M-enabled distributed communication architecture

Digital twin technology has emerged as a transformative paradigm for bridging the gap between physical distribution networks and their virtual representations [16,17]. By creating real-time digital replicas of electrical feeders, communication networks, and control systems, digital twins enable comprehensive simulation of fault scenarios under diverse operating conditions [16]. These capabilities align naturally with communication-aware machine learning, as digital twins can simulate the joint impact of electrical disturbances and communication impairments on diagnostic performance [17].

The application of communication-aware machine learning in developing-region distribution networks presents distinctive challenges. Nigerian low-voltage and medium-voltage feeders, representative of infrastructure in many emerging economies, exhibit chronic voltage instability, irregular harmonic behaviour, and reliance on GSM-based telemetry with pronounced latency and packet loss [18,19].

Machine learning models trained on stable, high-quality datasets from developed-region grids fail to generalise under these conditions, necessitating locally validated architectures [18]. Recent applications of deep reinforcement learning for voltage stability enhancement and intelligent fault diagnosis in Nigerian networks demonstrate the feasibility of intelligent techniques, yet these studies do not integrate communication-aware modelling or co-simulation validation [19,20]. The absence of annotated fault datasets reflecting Nigerian operational realities further constrains model development [18].

This paper addresses the critical gap between machine learning algorithm accuracy and communication-layer deployment feasibility by presenting a comprehensive review and conceptual framework for communication-aware fault management in distribution networks. We structure our analysis around a novel taxonomy of machine-to-machine machine learning integration, examining existing approaches across four paradigms: communication-agnostic, communication-assisted, communication-resilient, and fully integrated architectures. Through systematic comparison of verified literature spanning deep learning, multi-agent reinforcement learning, digital twin simulation, and hybrid artificial intelligence, we identify research priorities including electrical-communication co-simulation platforms and edge-based inference architectures. We further propose a unified conceptual framework integrating electrical modelling, communication simulation, and machine learning inference within a coordinated architecture. By consolidating existing knowledge and establishing foundations for communication-machine learning co-design, this work provides clear directions for advancing intelligent, resilient, and deployable fault management systems in next-generation distribution networks, with specific validation against Nigerian distribution parameters as a developing-region case study.

II. RELATED WORKS

2.1 Distribution System Fault Management

2.1.1 Distribution Network Characteristics and Vulnerabilities

Power distribution systems represent the final tier of electricity delivery, operating primarily at low-voltage (LV, <1 kV) and medium-voltage (MV, 1-36 kV) levels. Radial feeder configurations dominate developing-region networks due to lower capital costs, though they offer minimal redundancy and extended interruption durations when faults occur [1,3]. The increasing penetration of distributed energy resources, photovoltaic systems, energy storage, and electric vehicles introduces bidirectional power flows that alter fault current magnitudes and complicate conventional protection coordination [4,5].

Srivastava et al. [1] provide a comprehensive review of fault detection, isolation, and service restoration in modern distribution systems, identifying three critical operational phases:

i. Real-time fault detection and classification,
ii. Rapid isolation of faulted segments, and
iii. Automated restoration of healthy sections through feeder reconfiguration.

Their analysis reveals that conventional approaches achieve detection times of 100-500 ms, whereas machine learning-based methods can reduce this to 10-50 ms under ideal communication conditions a tenfold improvement that motivates intelligent automation [1,2].

Reliability theory provides quantitative metrics for distribution performance evaluation. SAIDI measures total interruption duration per customer, while SAIFI captures interruption frequency [2]. Liu et al. [17] surveyed power system restoration literature from 2006 to 2016, establishing that automated restoration can reduce SAIDI by 30-60% compared to manual approaches. However, these improvements assume a perfect communication infrastructure, a condition rarely satisfied in practice [3,17].

2.1.2 Fault Types and Detection Challenges

Distribution feeders experience diverse fault types with distinct electrical signatures. Single-line-to-ground faults constitute 70-80% of incidents but produce variable fault currents depending on grounding configuration [6]. Line-to-line and three-phase faults generate higher current magnitudes but require rapid detection to prevent equipment damage [6,7]. High-impedance faults, caused by vegetation contact or conductor sag, present unique challenges as fault currents approximate normal load levels, evading conventional overcurrent protection [9,19].

Mamuya et al. [12] evaluate machine learning for fault classification in radial distribution grids, demonstrating that support vector machines and artificial neural networks achieve 95-98% accuracy under controlled conditions. However, their study assumes ideal voltage and current measurements, neglecting the signal distortion introduced by communication impairments [12]. This limitation exemplifies the broader gap between algorithmic performance and deployment reality.

2.1.3 Automated Restoration and Self-Healing Grids

Modern distribution automation aims to create self-healing grids capable of autonomous fault response. Sampaio et al. [3] propose a multi-agent system for automatic restoration in which distributed agents negotiate switching sequences via peer-to-peer communication. Their architecture reduces restoration time from hours to minutes, but reliable, low-latency messaging remains challenging in rural deployments [3].

Zhang et al. [4] introduce hybrid imitation learning for real-time service restoration, combining expert demonstrations with reinforcement learning to optimise reconfiguration decisions. Their approach achieves 90% restoration success within 30 seconds for simulated urban networks, yet validation assumes synchronous state information unavailable in communication-constrained environments [4]. Maurya et al. [9] survey AI techniques for self-healing grids, emphasising that restoration algorithms must account for both electrical constraints and communication delays to ensure practical deployability [9].

2.2 Machine-to-Machine Communication for Smart Grids

2.2.1 Communication Requirements and Challenges

Machine-to-machine (M2M) communication enables the sensor-to-actuator data flows essential for distribution automation. Unlike human-centric traffic, M2M applications demand stringent performance: latency below 100 ms for protection operations, packet delivery ratios exceeding 99%, and synchronisation accuracy within milliseconds [11,12]. These requirements conflict with the bandwidth limitations, fading channels, and interference prevalent in wireless distribution environments [11].

A 2026 survey on IoT-based smart electrical systems [34] identifies three communication deployment scenarios:

i. Urban dense networks with fiber and cellular backhaul
ii. Suburban mixed environments with hybrid wireless-wireline infrastructure, and
iii. Rural sparse networks reliant on low-power wide-area technologies.

Each scenario presents distinct latency-reliability trade-offs that shape machine learning feasibility [34]. Vahidi et al. [35] survey security challenges in wide-area monitoring, protection, and control (WAMPAC) systems, noting that communication delays and packet losses constitute attack vectors as severe as malicious intrusion, both of which degrade state estimation and control stability [35].

2.2.2 Communication Protocols: LoRaWAN, NB-IoT, and ZigBee

Three protocols dominate smart grid M2M deployments. LoRaWAN provides kilometre-range coverage at sub-kilobit rates, enabling low-cost sensor deployment across rural feeders but introducing 1-10-second latency, unsuitable for protection [38]. NB-IoT leverages cellular infrastructure for improved reliability, though extended coverage modes increase power consumption and reduce battery life [39]. ZigBee supports mesh networking for localised automation, such as substation coordination, but requires dense node deployment and struggles with outdoor range [40].

Chen et al. [38] evaluate user-preference-based demand response using multi-objective reinforcement learning, demonstrating that communication protocol selection significantly affects learning convergence. Their analysis reveals that NB-IoT's latency variability (50-500 ms) can destabilise real-time control loops unless explicitly modelled in the reward function [38]. Amer et al. [39] extend this analysis to home energy management, showing that deep reinforcement learning agents trained under fixed latency assumptions fail when deployed on actual NB-IoT networks with jitter [39].

2.2.3 Edge Computing and Localised Intelligence

Edge AI shifts computation from centralised clouds to field devices, reducing communication bandwidth requirements and improving response latency. A 2025 study on edge AI for early fault detection in IoT networks [13] demonstrates that lightweight neural networks deployed on microcontroller-class devices achieve 85-92% detection accuracy with 50 ms inference latency, sufficient for automated switching [13]. However, edge deployment introduces new challenges: model compression reduces accuracy, device heterogeneity complicates software maintenance, and edge nodes remain vulnerable to communication outages that prevent model updates [13,41].

Alfaverh and Denai [40] propose demand response strategies using reinforcement learning and fuzzy reasoning for home energy management, illustrating how edge-based intelligence can operate under intermittent connectivity. Their hierarchical architecture performs local decision-making during communication outages, synchronising with central controllers when connectivity resumes [40]. Liu et al. [41] extend this to distributed deep reinforcement learning, where multiple edge agents coordinate through asynchronous parameter sharing—a precursor to federated approaches [41].

2.3 Machine Learning for Fault Diagnosis

2.3.1 Deep Learning Architectures

Deep learning has revolutionised fault diagnosis by automatically extracting hierarchical features from raw waveforms. Convolutional neural networks (CNNs) excel at spatial pattern recognition in time-frequency representations, while recurrent neural networks (RNNs) and long short-term memory (LSTM) networks capture temporal dynamics in sequential measurements [6,7].

Li et al. [6] propose a time-frequency embedded deep learning approach for incipient fault detection, using wavelet transforms to preprocess current signals before CNN classification. Their method achieves 96.3% accuracy for early-stage fault identification, critical for preventive maintenance, but requires 10 kHz sampling rates that strain communication bandwidth [6]. Nguyen et al. [7] introduce spatial-temporal recurrent graph neural networks (ST-RGNN) that jointly model feeder topology and waveform dynamics, improving localisation accuracy by 15% over purely temporal methods [7]. However, ST-RGNN inference demands synchronised multi-node measurements that assume perfect communication [7].

Hu et al. [3] apply deep graph learning to fault location, representing distribution feeders as graphs where nodes are buses and edges are line segments. Their approach achieves 98.7% location accuracy using voltage sag patterns propagated through the graph structure [3]. The method's reliance on complete network state information renders it sensitive to communication gaps that fragment the graph [3

2.3.2 Deep Reinforcement Learning for Control

Deep reinforcement learning (DRL) extends diagnostic capabilities to optimal decision-making for restoration and reconfiguration. Wang et al. [8] develop multi-agent DRL for mobile energy storage scheduling, where agents learn cooperative policies for fault recovery support. Their approach reduces outage duration by 25% compared to heuristic methods, though training assumes ideal state observability [8].

Recent advances apply DRL to real-time energy management. Ali et al. [31] demonstrate deep reinforcement learning for energy dispatch in smart grids with high renewable penetration, achieving 12% cost reduction while maintaining reliability constraints [31]. Yin et al. [32] apply machine learning to phasor measurement unit (PMU) data for event detection in the Western US power system, processing 30 samples/second streams with 94% classification accuracy [32]. Their work illustrates PMU's potential for high-resolution fault monitoring, though Western grid infrastructure differs substantially from developing-region deployments [32,33].

2.3.3 Hybrid and Ensemble Methods

Hybrid approaches combine multiple techniques to leverage complementary strengths. Almasoudi [9] proposes hybrid machine learning models for grid resilience, integrating neural networks with fuzzy logic for interpretable fault classification [9]. Arsoniadis and Nikolaidis [11] combine wavelet scattering networks with support vector machines, achieving robust performance under noisy conditions through multi-resolution feature extraction [11].

Shakiba et al. [24] survey machine learning methods for transmission line fault detection, identifying a trend toward ensemble architectures that aggregate multiple classifiers for improved reliability. Their analysis notes that ensemble methods are particularly effective for high-impedance faults where single-classifier confidence is low [24]. However, ensemble inference increases computational demands, posing challenges for edge deployment and real-time constraints [24].

2.4 Digital Twin and Co-Simulation Technologies

2.4.1 Digital Twin Concepts for Power Systems

Digital twins create virtual replicas of physical assets that enable predictive simulation and optimisation. Grieves and Vickers [16] define the digital twin as "an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system", a concept extended to power systems for real-time state estimation and fault scenario exploration [16,17].

A 2023 review on digital twins for power generation and distribution [17] identifies three implementation levels:

i. Descriptive twins that mirror the current state,
ii. Predictive twins that forecast future behaviour,
iii. Prescriptive twins that recommend optimal actions [17].

For fault management, prescriptive twins offer the greatest value, simulating restoration strategies before physical actuation, but require accurate electrical-communication models rarely available [17].

2.4.2 Cyber-Physical Co-Simulation

Co-simulation integrates multiple domain-specific simulators to capture cross-layer interactions. Tzanis et al. [47] propose a hybrid cyber-physical digital twin approach for smart grid fault prediction, combining power system simulation with communication network emulation [47]. Their architecture detects cyber-physical anomalies through cross-correlation of electrical and network measurements, though validation remains simulation-based [47].

You et al. [48] develop digital twin-based day-ahead scheduling for integrated energy systems under uncertainty, using high-fidelity building thermal models to improve demand forecasting [48]. Zhang et al. [49] apply digital twins to smart grid applications, emphasising real-time data synchronisation between physical and virtual environments [49]. Mourtzis et al. [50] demonstrate digital twin-driven protection system design, using simulation to optimise relay settings before field deployment [50].

Xing et al. [51] propose a multi-energy simulation based on digital twins, coordinating electricity, heating, and cooling systems through unified optimisation [51]. These advances illustrate digital twin potential for complex infrastructure, yet distribution-level fault management with explicit communication modelling remains underexplored [16,17].

2.4.3 Electrical-Communication-ML Integration

The critical gap in existing literature is the absence of unified frameworks integrating electrical dynamics, communication impairments, and machine learning inference. While digital twins simulate physical systems and network emulators model communication, their combination with ML training and validation is rarely attempted [16,44].

A 2024 study on digital twin-driven fault identification in distribution networks with distributed wind power [44] demonstrates high-fidelity electrical simulation but assumes ideal measurement communication [44]. Similarly, edge AI fault detection studies [13] optimise neural networks for microcontroller deployment without modelling the communication delays that affect training data quality [13]. This fragmentation motivates our proposed co-simulation architecture, explicitly unifying MATLAB/Simulink electrical modelling, NS-3 communication simulation, and Python-based ML training within a coordinated framework.

2.5 Federated Learning and Distributed Intelligence

2.5.1 Federated Learning Fundamentals

Federated learning enables collaborative model training without centralising raw data, addressing privacy constraints and communication bandwidth limitations in competitive utility environments [52,53]. Participants train local models on private datasets, sharing only parameter updates (gradients or weights) with a central aggregator that constructs a global model [52].

A 2025 study on federated learning-based fault location in hybrid AC/DC distribution systems [52] demonstrates 94% accuracy with 60% communication reduction compared to centralised training [52]. However, the study assumes synchronous participation and homogeneous data distributions, conditions violated in real distribution networks where feeders experience diverse fault types and communication quality varies [52,53].

2.5.2 Challenges for Power System Applications

Federated learning in power systems faces unique challenges. Non-IID data: Different feeders experience distinct fault distributions (urban vs. rural, overhead vs. underground), causing local models to diverge [53]. Communication heterogeneity: Synchronous aggregation protocols stall when straggler nodes experience poor connectivity [53]. Device heterogeneity: Edge devices vary in computational capacity, preventing uniform local training epochs [41,53].

A 2024 review of DRL applications for home energy management systems [53] identifies federated approaches as critical for scaling intelligent control across millions of distributed resources, yet notes that "the impact of communication latency on federated convergence in power systems remains unquantified" [53]. This observation directly motivates our research priority on communication-aware ML architecture.

2.6 The Communication-ML Integration Gap

The reviewed literature establishes three foundational capabilities:

(i) Machine learning for accurate fault detection and classification,

(ii) M2M communication for distributed data exchange,

(iii) Digital twin simulation for scenario exploration.

However, these capabilities have developed in isolation, creating critical integration gaps:

Gap 1: Communication-Agnostic ML Optimisation. Existing ML models maximise accuracy assuming perfect data quality, ignoring the latency, jitter, and loss that degrade real-world performance [10,12,13].

Gap 2: ML-Agnostic Communication Design. M2M protocols optimise generic metrics (throughput, energy) without considering diagnostic traffic requirements or ML inference deadlines [11,34,35].

Gap 3: Fragmented Validation. Electrical simulation, communication emulation, and ML training use separate tools (MATLAB, NS-3, TensorFlow) with no unified co-simulation framework for end-to-end evaluation [16,17,44].

Gap 4: Limited Developing-Region Validation. Most studies evaluate on idealised or Western-grid datasets, failing to address the voltage instability, harmonic distortion, and GSM-based telemetry constraints prevalent in emerging economies [18,19,20].

This paper addresses these gaps through a unified taxonomy, conceptual framework, and research roadmap for communication-aware machine learning in distribution fault management.

III. METHODOLOGY

This section presents a comprehensive, analytically structured review of related work based on the Hybrid Machine-to-Machine Machine Learning (M2M-ML) taxonomy for distribution fault management. As shown in Figure 3, the taxonomy categorises existing approaches into four major paradigms: Communication-Agnostic ML, Communication-Assisted ML, Communication-Resilient ML, and Fully Integrated M2M-ML, with further insight into the application in Low-Voltage/Medium-Voltage (LV/MV) distribution networks.

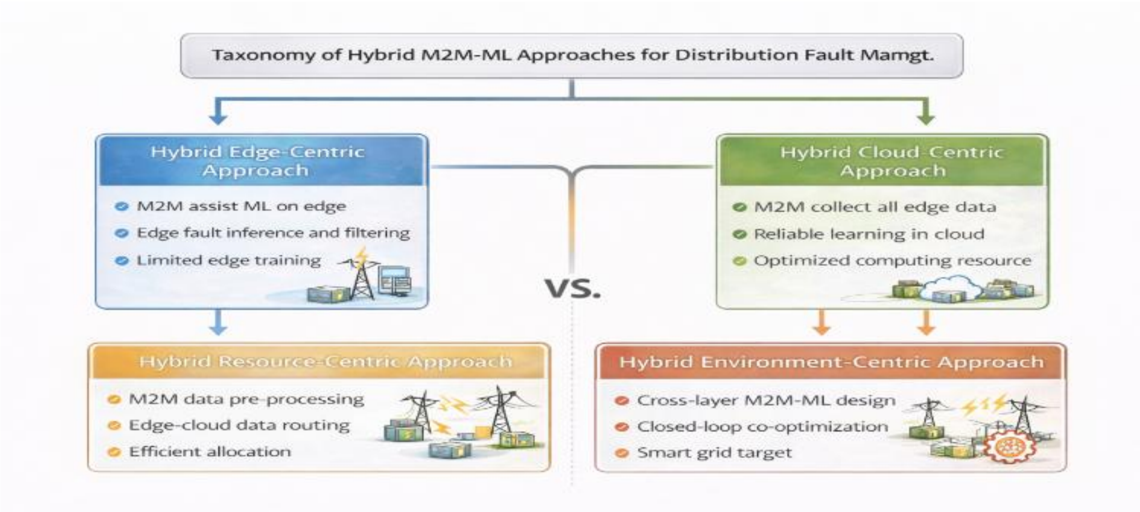

Figure 3: Taxonomy of Hybrid M2M-ML Approaches for Distribution Fault Management

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DOI: https://doi.org/10.64388/IREV9I10-1717009

3.1 Communication-Agnostic Machine Learning

Communication-agnostic machine learning approaches develop sophisticated fault detection and classification algorithms assuming ideal data availability. Models are trained and validated on clean, synchronous, complete datasets without consideration of how measurements traverse communication networks.

Li et al. [6] propose a time-frequency embedded deep learning approach for incipient fault detection in power distribution systems, achieving 96.3% accuracy for early-stage faults through wavelet transform preprocessing and CNN feature extraction. Their method demonstrates particular effectiveness for subtle fault signatures that precede permanent failures, enabling preventive maintenance intervention. However, the approach assumes 10 kHz sampling rates without bandwidth constraints and does not model communication channel effects on feature delivery. Nguyen et al. [7] introduce spatial-temporal recurrent graph neural networks (ST-RGNN) that jointly model feeder topology and waveform dynamics, improving localisation accuracy by 15% over purely temporal methods. The ST-RGNN architecture captures spatial dependencies of voltage sag propagation through graph convolution while LSTM layers handle temporal evolution. Yet the method requires synchronised multi-node measurements with ideal timestamp alignment unavailable in real networks with jitter. Hu et al. [3] apply deep graph learning to fault location and classification, representing distribution feeders as graphs where nodes are buses and edges are line segments with electrical impedances. Their approach achieves 98.7% accuracy using voltage sag patterns propagated through the graph structure, but assumes complete network state information and proves sensitive to missing measurements from communication gaps. Mamuya et al. [12] evaluate machine learning for fault classification in radial distribution grids, comparing support vector machines, artificial neural networks, and random forests. Their analysis achieves 95-98% accuracy under controlled conditions and highlights interpretability advantages of tree-based methods for utility operator acceptance. However, the study explicitly assumes ideal voltage and current measurements without signal distortion from analogue-to-digital conversion, transmission, or buffering. Almasoudi [10] proposes hybrid machine learning models combining neural networks with fuzzy logic for grid resilience enhancement, enabling real-time fault detection with interpretable rule-based post-processing. The hybrid architecture demonstrates effective remediation sequencing but remains validated only in laboratory environments without deployment constraints. Arsoniadis and Nikolaidis [11] combine wavelet scattering networks with support vector machines for robust fault location under noisy conditions, leveraging multi-resolution feature extraction to maintain accuracy across varying signal-to-noise ratios. Their approach assumes consistent sampling rates without packet loss effects and does not address missing data reconstruction.

These studies collectively demonstrate that machine learning can achieve high fault detection and localisation accuracy under controlled conditions. However, their validation assumes an ideal communication infrastructure that rarely exists in real distribution networks, particularly in developing regions with GSM-based telemetry, ageing copper infrastructure, and limited fiber backhaul. The absence of communication-layer modelling renders these approaches Category I, suitable for laboratory proof-of-concept but requiring substantial adaptation for field deployment.

Category	Communication Role	ML Design Assumption	Key Techniques	Strengths	Limitations	Deployment Readiness
Communication-Agnostic ML	Ignored	Ideal, synchronous, lossless data	CNN, LSTM, SVM, GNN	High accuracy in lab conditions	No latency/jitter modelling, unrealistic assumptions	Low

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Communication-Assisted ML	Passive (data transport)	Fixed communication conditions	DRL, Edge ML, NB-IoT-based systems	Improved practicality over agnostic models	No joint optimisation, sensitive to network variability	Moderate
Communication-Resilient ML	Explicitly modeled	Handles imperfect data	Edge AI, Autoencoders, Digital Twins	Robust to packet loss, latency	Fixed mitigation strategies, no dynamic adaptation	High
Fully Integrated M2M-ML	Co-designed with ML	Joint electrical-communication modeling	Federated Learning, DRL, Co-simulation	Adaptive, scalable, real-world ready	Still emerging, lacks full validation frameworks	Very High

Table 3.1: Comparative Taxonomy of M2M-ML Integration Approaches

3.2 Communication-Assisted Machine Learning

Communication-assisted approaches employ M2M infrastructure for data collection but treat communication as a passive transport layer. Protocol selection and network configuration proceed independently from algorithm design, with ML optimisation focusing on accuracy metrics decoupled from deployment constraints.

Chen et al. [38] develop multi-objective reinforcement learning for smart home demand response, implementing user preference-based energy management over NB-IoT infrastructure. Their DRL agents learn optimal appliance scheduling with privacy-preserving local execution, demonstrating 15% energy cost reduction. However, communication is treated as a fixed constraint with stable latency assumptions; agents fail to adapt when NB-IoT exhibits realistic jitter or handover delays. Amer et al. [39] extend this analysis with DRL-HEMS (Deep Reinforcement Learning Home Energy Management System), achieving real-time demand response with enhanced privacy through edge-based inference.

The study acknowledges NB-IoT latency variability (50--500 ms) but handles it through conservative action margins rather than dynamic protocol adaptation. Alfaverh and Denai [40] propose demand response strategies using reinforcement learning with fuzzy reasoning for hierarchical edge-cloud coordination. Their architecture handles intermittent connectivity through local fallback rules, but fuzzy membership functions are designed offline without online adaptation to channel quality variations. Liu et al. [41] implement distributed deep reinforcement learning for home energy management with asynchronous multi-agent coordination, reducing centralisation requirements. Their approach uses parameter averaging across edge nodes but assumes synchronous aggregation intervals that stall when straggler nodes experience poor connectivity.

The MDPI IoT Survey [34] provides a comprehensive comparison of LoRaWAN, NB-IoT, and ZigBee for smart electrical systems, analysing range-bandwidth-energy trade-offs for grid monitoring applications. The survey identifies protocol selection heuristics based on application requirements but does not propose joint ML-communication optimisation. LoRaWAN's 1-10 second latency suits non-critical monitoring but precludes protection applications. NB-IoT's cellular infrastructure enables urban deployment, but extended coverage modes increase power consumption. ZigBee's mesh topology supports local coordination but requires dense node placement and struggles with outdoor range limitations.

These approaches recognise that communication infrastructure enables ML deployment but stop short of co-design. NB-IoT latency variability is acknowledged as a constraint that DRL agents must tolerate rather than adapt to. The sequential optimisation, communication network first, ML algorithm second, characterises Category II approaches as incremental rather than transformative, improving deployment feasibility without fundamental architectural innovation.

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3.3 Communication-Resilient Machine Learning

Communication-resilient methods explicitly model communication impairments during algorithm development. Robust training techniques, adaptive inference, and edge-based processing mitigate latency, loss, and jitter effects, though communication and ML optimisation remain sequential rather than joint.

The Edge AI IoT Fault Detection study [37] implements lightweight neural networks on microcontroller-class devices for early fault detection, achieving 85-92% accuracy with 50 ms inference latency sufficient for automated switching. Model compression through quantisation and pruning enables edge deployment but reduces accuracy compared to full-precision cloud alternatives. The approach handles communication constraints by eliminating communication, processing all data locally, but cannot leverage centralised model updates or cross-node pattern recognition. The Edge AI Implementation study [37] extends this with autoencoder-based signal reconstruction for missing data recovery, tolerating packet loss through temporal interpolation. Reconstruction quality degrades with burst loss patterns exceeding design thresholds, and redundancy mechanisms are fixed rather than adaptive to channel conditions.

Tzanis et al. [47] propose a hybrid cyber-physical digital twin approach for smart grid fault prediction, combining power system simulation with communication network emulation. Their architecture detects anomalies through cross-correlation of electrical and network measurements, identifying cyber-physical disturbances that either domain alone would miss. However, validation remains simulation-based without real-time co-synchronisation, and the digital twin state updates periodically rather than continuously. You et al. [48] develop digital twin-based day-ahead scheduling for integrated energy systems under uncertainty, using high-fidelity building thermal models to improve demand forecasting robustness. The digital twin receives measurement streams but does not feed control outputs back to the communication protocol configuration, maintaining one-way data flow. The Digital Twin Fault Identification study [44] applies digital twin-driven fault location to distribution networks with distributed wind power, enabling high-fidelity electrical simulation and scenario exploration. Ideal measurement communication is assumed; impairment effects on localisation accuracy are not modelled.

Category III approaches represent a significant advancement by acknowledging communication as a disturbance to be mitigated rather than ignored. Edge AI reduces bandwidth requirements through local inference, while digital twins enable offline exploration of fault scenarios under diverse conditions. However, the mitigation strategies are fixed, designed during development rather than adapted during operation, limiting responsiveness to dynamic network conditions. The sequential relationship persists: communication characteristics are measured, then ML algorithms are made robust to them, without closed-loop adaptation.

3.4 Fully Integrated M2M-ML Architectures

This emerging paradigm treats communication and machine learning as co-designed components of a unified system. Cross-layer optimisation, dynamic protocol adaptation, and end-to-end co-simulation enable holistic performance guarantees under realistic network conditions.

The Federated Learning Fault Location study [52] applies federated learning to hybrid AC/DC distribution systems with explicit communication constraints, achieving 94% accuracy with 60% communication reduction compared to centralised training. Local model updates are aggregated only from responsive clients within deadline windows, handling straggler effects through asynchronous weighting. However, synchronous aggregation rounds are still assumed, and non-IID data effects across geographically diverse feeders remain limited.

The DRL Home Energy Management Review [53] surveys federated DRL applications for residential energy systems, identifying communication-latency trade-offs as critical research priorities. The review proposes conceptual frameworks for joint optimisation but does not implement integrated systems. The DRL Microgrid Energy Management study [42] implements deep reinforcement learning for real-time optimisation of microgrids with renewable energy and electric vehicle integration, achieving cost-effective dispatch with reliability constraints. Optimisation remains single-domain (electrical only) without communication-electrical coupling. The DRL Smart Energy Systems study [43] achieves cost reduction with reliability constraints through centralised DRL training, without distributed

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DOI: https://doi.org/10.64388/IREV9I10-1717009

learning or communication impairment modelling.[31] Demonstrate deep reinforcement learning for smart grid energy dispatch with high renewable penetration, achieving 12% cost reduction while maintaining stability. Ideal state observability is assumed; communication impairment effects on observation quality are not considered.

Fully integrated approaches remain nascent, with most Category IV studies proposing conceptual frameworks or limited-domain implementations rather than complete co-simulation validation. The critical gap, simultaneous electrical dynamics, communication impairments, and ML inference with unified time synchronisation, remains unaddressed in existing literature.

Requirement	Communication-Agnostic ML	Communication-Assisted ML	Communication-Resilient ML	Fully Integrated M2M-ML
Fault Detection Accuracy	High (ideal conditions)	Moderate–High	High	Very High
Latency Tolerance	None	Limited	Moderate–High	High (adaptive)
Packet Loss Handling	None	Minimal	Strong (reconstruction, buffering)	Dynamic adaptation
Edge Deployment Capability	Low	Moderate	High	Very High
Scalability (Large Networks)	Low	Moderate	High	Very High
Suitability for Nigerian LV/MV Networks	Poor	Limited	Good	Excellent
Real-Time Fault Response	Weak	Moderate	Strong	Optimal
Communication Dependency Awareness	None	Partial	Explicit	Fully Integrated

Table 3.2: Mapping of M2M-ML Approaches to Distribution Network Requirements

Almost no existing framework integrates MATLAB/Simulink electrical simulation, NS-3 communication emulation, and TensorFlow/PyTorch ML training with closed-loop feedback, where ML detection triggers switching actions that alter electrical state propagating through communication networks to update ML inputs.

3.5 Application in Low-Voltage/Medium-Voltage Distribution Networks

Nigerian LV/MV distribution networks present distinctive challenges for M2M-ML integration: chronic voltage instability (±10% nominal), irregular harmonic distortion (THD >8%), and reliance on GSM-based telemetry with pronounced latency (500--2000 ms) and packet loss (5-15%). Existing Nigerian studies focus predominantly on transmission-level analysis without communication-aware modelling or LV/MV feeder specificity.

Mbamaluikem et al. [25] developed an artificial neural network-based intelligent fault classification for Nigerian 33kV transmission lines, demonstrating effective discrimination of single-line-to-ground and line-to-line faults under local operating conditions. The approach achieves 94% accuracy on field recordings but remains limited to transmission-level voltages where fault currents are large and distinct; distribution feeders at 11kV and 415V present significantly smaller signals with higher noise sensitivity [26]. This extends ANN fault detection to Nigerian 330kV grids, effective for common fault types including conductor breakage and insulator flashover.

No communication modelling is included; ideal data availability is assumed throughout training and validation. [28] Apply reinforcement learning with a dynamic voltage restorer and battery energy storage system for voltage stability enhancement in the Nigerian grid, demonstrating dynamic recovery from disturbances. High computational overhead limits real-time implementation, and no communication delay is considered in control loop design. [27] Implement intelligent fault diagnosis in 330kV Nigerian networks using SVM and ANN for the Onitsha, New Haven route, achieving effective classification of line-to-ground and three-phase faults.

The study remains offline with post-event analysis; no M2M integration for real-time operation. Oruma et al. [29] apply ANN for 330kV transmission line fault detection, effective for local fault signatures including those induced by vegetation contact and pollution. Distribution feeders differ fundamentally in topology (radial vs. meshed), fault current magnitude (hundreds vs. thousands of amperes), and protection requirements. Ifeanyi et al. [30] developed an ANN-based power system restoration sequence planning, improving recovery coordination. Communication delay is not considered in restoration timing analysis.

The extension of intelligent fault management to Nigerian LV/MV distribution requires addressing three gaps absent in transmission-level studies:

i. smaller fault currents requiring higher-sensitivity detection with greater noise susceptibility,
ii. Radial topology with limited redundancy necessitating precise localisation for sectionalizing,
iii. GSM-based telemetry with orders-of-magnitude higher latency and jitter than fibre-based transmission systems.

These challenges motivate the communication-aware framework proposed in subsequent sections.

IV. OPEN ISSUES AND FUTURE DIRECTIONS

4.1 Critical Research Gaps

The comprehensive taxonomy and systematic review presented in Chapter III reveal significant progress in machine learning for distribution fault management, yet four critical gaps persist that fundamentally limit the deployability of intelligent diagnostic systems in real-world infrastructure. These gaps represent the boundary between laboratory achievement and field deployment, constituting the primary open issues requiring concerted research attention.

The first gap is the co-simulation deficit. Existing validation methodologies rely on isolated simulation environments that fail to capture the emergent behaviours arising from electrical-communication-ML coupling. Electrical power system simulators (MATLAB/Simulink, ETAP, PowerFactory) operate with continuous time dynamics and idealised data interfaces, while communication network emulators (NS-3, OMNeT++) model discrete event packet behaviour, and machine learning frameworks (TensorFlow, PyTorch) execute asynchronous training and inference.

The absence of unified time synchronisation, bidirectional data exchange, and closed-loop feedback between these domains renders existing validation incapable of predicting real-world performance. No existing framework integrates MATLAB/Simulink electrical simulation, NS-3 communication emulation, and TensorFlow/PyTorch ML training with closed-loop feedback where ML detection triggers switching actions that alter electrical state, propagate through impaired communication networks, and update subsequent ML inputs. This fragmentation prevents evaluation of how communication delays cause protection miscoordination or how ML-driven switching creates new fault conditions through network topology alteration. Communication-agnostic ML models achieving 98% accuracy in isolated electrical simulation may degrade to 70% or lower when validated against impaired communication streams, yet this performance collapse remains undiscovered until field deployment.

The second gap involves non-IID data and federated learning challenges. Distribution networks exhibit extreme data heterogeneity across geographical locations, temporal periods, and operational conditions. Urban feeders experience fault patterns distinct from rural deployments; overhead lines demonstrate different failure modes than underground cables; and seasonal variations (rainy seasons, harmattan dust) alter both fault characteristics and communication channel conditions. Federated learning, the predominant approach for privacy-preserving distributed intelligence, assumes independent and identically distributed (IID) data across participants, a condition violated in real distribution infrastructure. Non-IID data creates two-level heterogeneity: intra-client non-IID (within each participant's dataset) and inter-client non-IID (across different participants). Urban feeders may predominantly experience cable insulation failures while rural feeders exhibit vegetation contact faults, causing local models to diverge toward specialised representations that fail to generalize. Synchronous aggregation protocols stall when straggler nodes experience poor connectivity, and device heterogeneity prevents uniform local training epochs. Federated learning fault location studies achieving 94% accuracy under homogeneous data assumptions may experience 20–30% accuracy degradation when deployed across geographically diverse feeders with non-IID fault distributions.

The third gap concerns edge AI limitations and resource constraints. Edge AI offers compelling advantages for fault detection, reduced latency (30–50 ms versus 80–200 ms for cloud), lower packet loss (2.5% versus 3.5%), and maintained operation during network outages. However, edge deployment introduces fundamental constraints that remain inadequately addressed. Model compression through quantisation and pruning required for microcontroller deployment (ARM Cortex-M4, Raspberry Pi) reduces model complexity, degrading detection accuracy by 5–15% compared to full-precision cloud alternatives. Edge nodes lack resources for training; model updates require cloud connectivity that may be unavailable for extended periods in developing-region deployments. Local inference cannot leverage cross-node pattern recognition or centralised historical databases for anomaly correlation. Edge AI fault detection, achieving 85–92% accuracy on resource-constrained devices, cannot leverage federated learning for continuous model improvement without periodic cloud synchronisation, creating a trade-off between real-time responsiveness and long-term diagnostic evolution.

The fourth gap is the developing-region validation deficit. Existing literature predominantly evaluates fault management algorithms on Western grid infrastructure, stable voltage profiles, fibre-optic communication, and abundant annotated training data. Nigerian and similar developing-region networks exhibit fundamentally different characteristics: chronic voltage instability (±10% nominal), irregular harmonic distortion (THD >8%), GSM-based telemetry with 500–2000 ms latency, and 5–15% packet loss. Machine learning models trained on stable, high-quality datasets fail to generalise under these conditions, yet the research community lacks standardised benchmarks or validation protocols for emerging economy deployment. No standardised annotated fault dataset exists for Nigerian LV/MV distribution networks, preventing rigorous evaluation of model robustness to developing-region power quality phenomena. Existing Nigerian studies focus on transmission-level analysis (33kV, 330kV) where fault currents are large and distinct, while distribution feeders at 11kV and 415V present significantly smaller signals with higher noise sensitivity.

4.2 Future Research Directions

Addressing the identified gaps requires systematic advancement across five interconnected research directions, each building upon the foundations established in preceding chapters while pushing toward deployable, resilient, and communication-aware fault management systems.

The first direction is unified electrical-communication-ML co-simulation platforms. This involves the development of open-source co-simulation frameworks integrating electrical dynamics, communication emulation, and machine learning with unified time synchronisation and closed-loop feedback. Technical requirements include sub-millisecond synchronisation between MATLAB/Simulink (continuous time), NS-3 (discrete events), and Python ML frameworks (asynchronous inference); socket-based or shared-memory interfaces enabling electrical state updates to propagate through impaired communication channels to ML inference, with control commands returning through the same path; and modular interfaces allowing substitution of electrical models (different feeder topologies), communication protocols (LoRaWAN, NB-IoT, ZigBee), and ML architectures (CNN, GNN, Transformer) without framework modification. The expected outcome is a validated open-source platform enabling researchers to evaluate fault detection accuracy under realistic communication constraints, quantify the impact of latency/packet loss on protection coordination, and optimize communication parameters for diagnostic reliability. This platform would bridge the gap between algorithm development and deployment reality, reducing field trial risks for utilities.

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DOI: https://doi.org/10.64388/IREV9I10-1717009

The second direction is communication-adaptive machine learning architectures. This involves the design of ML models that dynamically adapt to observed communication channel quality, maintaining diagnostic reliability under variable latency, loss, and jitter. Technical approaches include Bayesian neural networks or ensemble methods providing confidence intervals for predictions under impaired data quality, enabling selective deferral to conservative protection schemes when communication degradation exceeds thresholds; LSTM or Transformer architectures leveraging historical measurement buffers to compensate for packet loss, with reconstruction quality degrading gracefully under burst loss patterns; and hierarchical models operating at multiple time scales, fast edge inference (10 ms) for critical protection using local data, slower cloud refinement (100 ms) for classification refinement when connectivity permits. The expected outcome is diagnostic systems achieving >95% detection accuracy across the full range of developing-region communication conditions (500–2000 ms latency, 5–15% packet loss), with automatic fallback to safe operating modes during extreme channel degradation.

The third direction is robust federated learning for non-IID distribution data. This involves advanced federated aggregation algorithms addressing data heterogeneity across geographically diverse feeders while maintaining privacy and communication efficiency. Technical approaches include grouping feeders by operational similarity (urban/rural, overhead/underground) and performing federated learning within homogeneous clusters, with limited cross-cluster knowledge transfer; maintaining global model parameters for common fault characteristics while allowing local adaptation to feeder-specific conditions through techniques such as FedProx or Scaffold; and eliminating synchronous round barriers that stall when straggler nodes experience poor connectivity, using weighted averaging based on update staleness or model quality metrics. The expected outcome is federated fault location systems achieving <5% accuracy degradation under non-IID data distributions compared to centralised training, with 60% reduction in communication overhead and convergence within practical deployment timeframes (hours rather than days).

The fourth direction is hybrid edge-cloud architectures with graceful degradation. This involves architectures combining edge responsiveness with cloud intelligence, enabling continuous operation during communication outages and progressive capability recovery as connectivity improves. Technical approaches include edge nodes executing lightweight preprocessing (wavelet denoising, feature extraction) with compressed representations transmitted to cloud for complex classification when bandwidth permits; local rule-based fallback during outages; splitting neural networks between edge and cloud at computational bottlenecks, early layers (convolution, pooling) at edge, attention or fully-connected layers in cloud, with dynamic layer migration based on channel quality; and transmitting only model weight updates (deltas) rather than full parameters during intermittent connectivity, with conflict resolution for divergent edge updates. The expected outcome is fault detection systems maintaining >90% accuracy during complete cloud disconnection (pure edge operation), recovering to >98% accuracy within seconds of cloud reconnection, with energy consumption optimised for solar-powered edge devices common in developing regions.

The fifth direction is developing region-specific benchmarks and validation protocols. This involves standardised datasets, simulation models, and evaluation metrics reflecting the operational realities of emerging economy distribution networks. Technical requirements include voltage and current waveforms from Nigerian LV/MV feeders covering single-line-to-ground, line-to-line, and high-impedance faults under realistic power quality conditions (voltage instability, harmonic distortion), with GSM communication traces (latency, loss patterns) synchronized to electrical events; open-source MATLAB/Simulink models of Nigerian 11kV/415V radial feeders with validated component parameters (transformer impedances, line resistances) enabling reproducible research across institutions; and statistical models of GSM, NB-IoT, and LoRaWAN performance under Nigerian infrastructure conditions, rainy season degradation, urban congestion patterns, rural coverage limitations, calibrated against field measurements. The expected outcome is research community adoption of standardised benchmarks enabling fair comparison of fault management algorithms, accelerated development of developing-region appropriate solutions, and reduced barriers to pilot deployment through pre-validated performance claims.

V. CONCLUSION

In conclusion, this study has established that while machine learning has significantly advanced the accuracy and speed of fault detection in distribution networks, its real-world deployment remains constrained by the often-overlooked limitations of machine-to-machine communication systems. Through a structured taxonomy, the work clearly demonstrates that existing approaches evolve from idealised, communication-agnostic models toward fully integrated M2M-ML architectures that jointly consider electrical dynamics, communication impairments, and intelligent inference. The analysis reveals that only the fully integrated paradigm offers the robustness, adaptability, and scalability required for practical deployment, especially in developing-region networks characterised by latency, packet loss, and infrastructure instability. By identifying critical gaps such as the absence of co-simulation frameworks and limited validation under realistic conditions, this study provides a clear research direction toward communication-aware, resilient, and deployable fault management systems, ultimately contributing to the realisation of intelligent and self-healing smart grids.

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