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Integrating Wireless Sensor Networks and IoT for Intelligent Power Line Monitoring: A Theoretical Review of the Power Line Monitoring Systems Framework

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Review Article

Abstract

The persistent challenges of fault detection, downtime, and infrastructure vulnerability in sub-Saharan Africa's power grids necessitate a shift toward intelligent, distributed monitoring systems. This theoretical review investigates the foundational models and frameworks underpinning the Distributed Power Line Monitoring System (PoLiMoS), with a specific focus on enhancing fault detection, predictive maintenance, and operational resilience in sub-Saharan Africa's power grids, a wireless sensor and IoT-based platform designed for predictive maintenance and real-time monitoring of overhead power lines. It explores critical domains including Wireless Sensor Networks (WSNs), Internet of Things (IoT) architectures, predictive maintenance, smart grid reliability engineering, human–machine interaction, edge computing, and energy harvesting, to evaluate the feasibility of a decentralised, solar-powered, and cloud-integrated monitoring framework. The study critically evaluates each theoretical model's strengths, limitations, and applicability within the PoLiMoS context, especially in rural or resource-constrained environments. Findings reveal that while robust theoretical support exists for decentralised sensing, cloud analytics, and edge intelligence, practical deployment demands adaptations in energy management, environmental resilience, and cybersecurity. Lightweight predictive models such as Bayesian Linear Regression are identified as more suitable for real-time edge processing in PoLiMoS compared to computationally intensive deep learning alternatives. Furthermore, the system's reliance on solar-powered sensor nodes and rugged hardware enclosures aligns with environmental adaptation theory for deployment in harsh climates. This review not only validates PoLiMoS' multidisciplinary foundation but also highlights critical gaps in existing frameworks particularly in long-term reliability, cost-efficiency, and contextual scalability, paving the way for future hybrid architectures tailored to developing regions.

Keywords: *Edge Computing, Internet of Things (IoT), Predictive Maintenance, Smart Grid, Wireless Sensor Networks (WSNs), Power Line Monitoring System (PoLiMoS).*
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1. Introduction

The need for reliable and intelligent energy infrastructure in developing economies has never been more urgent. Power outages resulting from undetected faults in overhead transmission lines cause significant economic and safety challenges. Traditional inspection techniques, including manual patrol and aerial surveys, have proven to be labor-intensive, time-consuming, and limited in accuracy, particularly in rural or difficult-to-access areas [1]. As energy demand rises and networks expand, it is essential to develop smarter systems capable of real-time fault detection, anomaly prediction, and autonomous system reconfiguration.

In this context, the integration of Wireless Sensor Networks (WSNs) [2], Internet of Things (IoT) technologies, and predictive maintenance algorithms have gained significant research interest [3,4]. These technologies enable proactive monitoring and data-driven decision-making, thus shifting maintenance paradigms from reactive to predictive. Ali *et al*. [5] provides an in-depth analysis of the technologies and standards that form the IoT technology stack. It presents a layered architecture approach, discussing current research and open challenges at every layer. The article also explores the role of middleware platforms in IoT application development and integration, and provides steps towards IoT stack optimization. It also investigates the interfacing of Fog/Edge Networks to the IoT technology stack. However, the proposed Power Line Monitoring System (PoLiMoS) system, designed as a distributed and non-invasive power line monitoring infrastructure, fits into this shift by embedding intelligence at the edge through sensor nodes and leveraging cloud analytics for centralized monitoring.

The relevance of theoretical frameworks in guiding such designs cannot be overstated. Theories underpinning WSN communication protocols, data compression, and energy optimisation play a vital role in the architecture of sensor networks [2,6]. Likewise, IoT reference architectures and smart grid reliability models define the functional layers and interoperability between physical devices and software applications [7,8]. A comprehensive theoretical foundation not only improves system robustness and scalability but also enhances the replicability of such solutions across varying geographies.

This review explores foundational theories, models, and frameworks relevant to PoLiMoS. It highlights the theoretical gaps and critiques current approaches while validating the significance of hybrid systems combining physical sensing, edge analytics, cloud integration, and user interfacing. The focus is on enhancing resilience, accuracy, and responsiveness in power infrastructure, with special attention to applications in Nigeria and sub-Saharan Africa more broadly [9].

2. Theory Discussion

This section explores the major theoretical paradigms that inform the design and deployment of the PoLiMoS system. The subsections delve into key themes such as sensor network theory, IoT architectures, predictive modeling, reliability engineering, and human–machine interaction. In addition, new emerging domains including edge computing, energy harvesting, and environmental adaptation are presented as part of the broader framework in which PoLiMoS operates.

2.1 Wireless Sensor Networks

WSNs serve as the backbone of the PoLiMoS architecture, enabling distributed sensing and real-time data communication across distant power poles. Key theoretical foundations include network topology optimisation, energy-aware routing algorithms, and fault-tolerant clustering models. These theories ensure that even under node failure or environmental disturbances, the system remains operational and resilient. The Industrial Revolution 4.0 has significantly impacted the world, with WSNs being a crucial component. WSNs are deployed for critical real-time applications that need stringent fault tolerance (FT) to avoid catastrophic situations. The underlying FT scheme is a critical requirement for WSN algorithms. Owing to the evolving IoT systems, enhancements in FT mechanisms are needed to guarantee maximum network reliability and integrity. FT schemes consist of three stages, including detection, diagnosis, and recovery of error. Analytics has led to the development of new FT schemes and Techniques based on AI and cloud-based methods. Adday *et al.* [10] survey provides a detailed classification and analysis of FT schemes and their components, analyzing existing techniques based on eight constraints. It also proposes an enhanced categorization based on new metrics, such as sensor node engagement, overall fault-tolerant approach performance, and algorithm placement.

WSNs are composed of spatially distributed autonomous devices that employ sensors to cooperatively sense physical or environmental status. For PoLiMoS, the design leverages multi-hop communication, fault tolerance, and hierarchical routing strategies such as low energy adaptive clustering hierarchy (LEACH) and power efficient gathering in sensor information systems (PEGASIS) [11]. These protocols are crucial for minimizing energy consumption while maximizing network lifetime, which is particularly critical in remote environments where physical maintenance is challenging.

Energy efficiency remains the cornerstone of WSN theory. Recent models suggest incorporating energy harvesting mechanisms, such as small solar panels, into nodes to achieve energy-neutral operations [12]. Additionally, advances in self-organising networks and adaptive clustering algorithms improve the resilience of sensor networks in harsh environments, allowing for better handling of node failures or signal degradation [3].

Security in WSNs is another emerging research area, as unauthorised access or tampering could compromise data integrity. Lightweight encryption techniques and node authentication protocols have been proposed in recent works [13], and their integration into PoLiMoS enhances trustworthiness, especially for critical infrastructure monitoring.

2.2 Internet of Things (IoT) Integration

The PoLiMoS system also aligns with IoT frameworks where interconnected devices share data to enable automated decision-making. Theoretical models such as the IoT Reference Architecture and cloud-fog-edge computing hierarchy justify the use of cloud storage and real-time dashboards for data visualisation in PoLiMoS. IoT middleware platforms like FIWARE and Node-RED provide scalable and interoperable layers, relevant to PoLiMoS' deployment.

Middleware platforms are crucial in IoT systems, managing intermediary communications among devices and applications. In the energy sector, IoT devices integrate network assets into a large distributed system, improving energy efficiency, renewable energy generation, and reducing maintenance costs. However, existing solutions face issues like vendor lock-ins. Alfalouji *et al*. [14] review literature and surveys on IoT middleware platforms in energy systems to provide tools for future, efficient, flexible, and interoperable solutions. Experts primarily use IoT middleware for visualisation, monitoring, and comparative analysis of energy consumption, with energy optimisation as a trending application. Non-functional requirements like security and privacy also play a significant role.

The IoT paradigm enables heterogeneous devices to connect, communicate, and coordinate with minimal human intervention. The integration of PoLiMoS into cloud-based platforms draws from the IoT reference architecture that defines layers such as perception, network, middleware, and application [15]. Each layer is essential to ensure the smooth flow of data from sensors to decision systems. Cloud platforms such as Amazon Web Services (AWS) IoT, Google Firebase, and open-source FIWARE offer real-time dashboards, anomaly detection, and automated alerts. The fog computing model, positioned between edge and cloud, reduces latency and enhances fault isolation by processing data locally before it is transmitted to the cloud [16]. This is particularly useful in PoLiMoS where low-latency is required for timely intervention. Despite these advantages, IoT systems face challenges including scalability, interoperability, and security risks [1]. PoLiMoS addresses these concerns through modular hardware design, standardized communication protocols like MQTT, and password-protected dashboards. These align with current best practices in industrial IoT systems.

2.3 Predictive Maintenance and Fault Detection

Electrical grid maintenance is significantly important due to its direct influences on the reliability, performance, and cost-effectiveness of the grid [17]. These maintenance approaches can be categorised into five levels: reactive, planned, proactive, predictive, and prescriptive [18]. Figure 1 illustrates each type of maintenance along with its unique characteristics. As can be seen from Figure 1, the reliability of the electrical grid improves progressively as maintenance shifts from reactive to prescriptive levels.

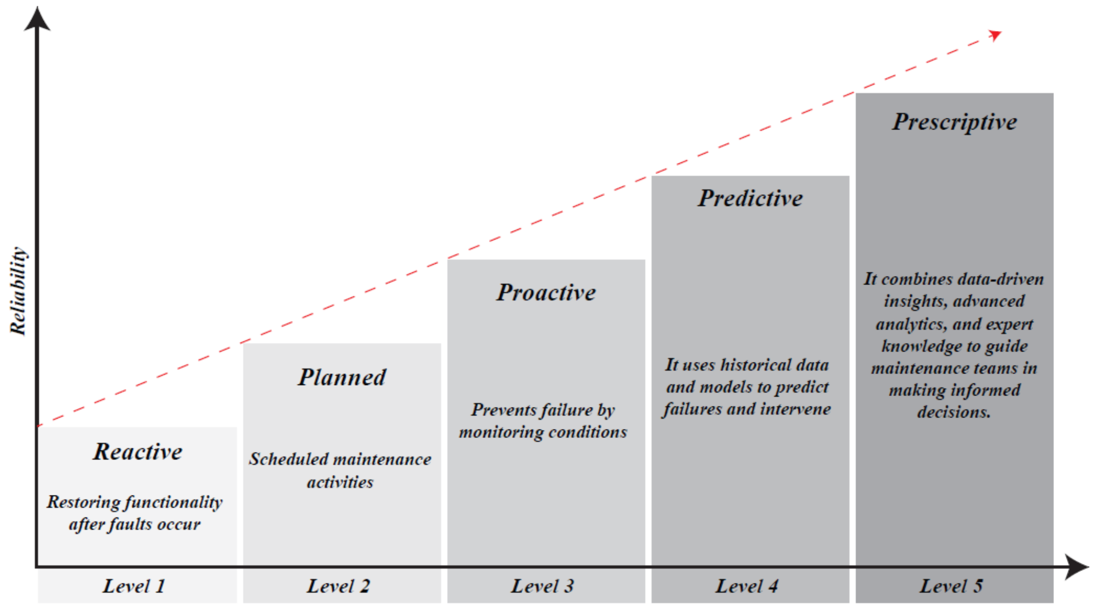

Figure 1: Categorical levels of electrical grid maintenance [19]

Constant faults in power distribution networks (PDN) are a significant issue that prevents quality power from reaching consumer units when it is due. Component fault detection and inventory are significant challenges faced by electricity transmission and distribution utility organisations, particularly in developing countries. Traditional methods are inefficient, insecure, and untimely, leading to a significant problem in monitoring and managing electricity assets. Detecting faults using automated machine learning techniques, such as parametric monitoring, offers a reliable, efficient, and fast solution to power quality problems. Ibitoye *et al*. [20] provides, an overview of machine learning methods for fault detection in PDN, discussing their pros and cons, such as artificial neural networks (ANNs), deep learning (DL) techniques, support vector machines (SVM), k-nearest neighbor (KNN), and decision trees (DT). Further research directions are suggested for effective machine learning-enabled systems of fault detection in power grids.

Maduako *et al*. [21] explores, the use of oblique unmanned aerial vehicle (UAV) imagery and deep Convolutional Neural Networks (CNNs) for automatic faulty unit inspection and documentation in an Electric Power Transmission Network (EPTN). The Single Shot Multibox Detector (SSD) is used for localisation, detection and classification of faults leveraging aerial image patches with ground truth. The SSD Rest50 architecture variation performed best, having a mean Average Precision (mAP) of 89.61%. All SSD-based methods achieve high precision rates and low recall rates in faulty components detection, acceptable balance levels of F1-score achieved. The hybridisation of UAV imagery and computer vision presents a low-cost approach for easy and timely electricity asset inventory, especially in developing countries. The study also provides guidance on deep learning architecture, training samples, data augmentation effects, and intra-class heterogeneity.

Predictive Maintenance (PdM) has been addressed using Machine Learning (ML) and Deep Learning (DL) solutions in recent years. This involves monitoring and logging industrial equipment events, such as temporal behavior and fault events, using records from sensors installed in different parts of an industrial plant. However, progress is slow due to challenges and the performance of applications depends on the chosen method. Davari *et al.* [22] surveyed, existing ML and DL techniques for handling PdM in the railway industry, discussing main approaches, task types, methods, evaluation metrics, equipment or process, and datasets. Various time-series prediction algorithms do exist [19]. Table 1 presents the existing algorithms with their brief description.

Table 1: Existing Time-series Algorithms

S/N	Algorithm	Full Name / Description
1	ARIMA	Autoregressive Integrated Moving Average – A statistical model for analyzing and forecasting time series data.
2	Seasonal ARIMA	Seasonal ARIMA (SARIMA) – Extension of ARIMA that supports modeling seasonal effects.
3	Exponential Smoothing	A technique that applies exponentially decreasing weights to past observations.
4	Prophet	A time-series forecasting model developed by Facebook, suitable for trend and seasonality decomposition.
5	LSTM	Long Short-Term Memory – A deep learning recurrent neural network model ideal for sequential data.
6	SVM	Support Vector Machine – A machine learning algorithm that can be adapted for regression tasks in time-series prediction.

Predictive maintenance draws from the Prognostics and Health Management (PHM) model and Bayesian Network Theory emphasising early detection and risk forecasting. In PoLiMoS, the ML algorithm applied for pole orientation prediction is grounded in the Residual Life Prediction (RLP) model and Time Series Forecasting using LSTM or ARIMA. These models underpin the system's preventive maintenance logic. Predictive maintenance relies on the real-time analysis of sensor data to forecast equipment failure, thus avoiding unplanned downtimes. The PHM framework offers a methodology for predicting component health status based on observed conditions [23]. In PoLiMoS, this involves analysing gyroscope data to determine tilt angle deviations that precede pole collapse.

Time-series forecasting algorithms, particularly LSTM networks, are widely used in predictive maintenance for their capacity to learn temporal dependencies [24]. Digital technologies have revolutionised the maintenance of electrical systems, enabling the use of time-series prediction to improve maintenance practices. Mirshekali *et al.* [19] explores, various time series that can be used to support maintenance role in electrical grids, focusing on different methods and components of the grid. The digitisation of electrical grids has supported the collection of diverse time-series data from network elements. The paper presented an overview of how these data and historical-fault data can be used for the purpose of maintenance in electrical grids, presenting various maintenance levels and time series employed in different grid components. However, for computational efficiency, Bayesian linear regression and threshold-based classification methods can be equally effective when processing is conducted at the edge node. Table 2 presents a comparison of common predictive models used in fault detection systems.

Table 2: Comparison of Predictive Maintenance Models

Model	Accuracy	Processing Complexity	Real-Time Capability	Suitability for PoLiMoS
LSTM	High	High	Moderate	Partial
ARIMA	Moderate	Moderate	High	High
Bayesian Linear Regression	Moderate	Low	High	High

The table shows that Bayesian methods, although less complex, are more suitable for edge deployment in resource-constrained environments such as rural Nigeria.

2.4 Smart Grid Monitoring and Reliability Engineering

Smart grid theory supports real-time monitoring, decision support systems, and demand-response mechanisms. Markov decision processes and stochastic reliability modeling (Zhang et al., 2022) provide analytical tools to assess MTTR and MTBF (Mean Time Between Failures) in infrastructure like powerlines, validating PoLiMoS' objective of reducing downtime. Smart grid theory also emphasises adaptive control, real-time fault detection, and enhanced reliability. Reliability engineering introduces metrics like MTBF (Mean Time Between Failures) and MTTR (Mean Time To Repair), which are critical in assessing the performance of monitoring systems like PoLiMoS [8]. These metrics are used to quantify how quickly faults are detected, acknowledged, and rectified.

The Markov Decision Process (MDP) is a commonly used framework for modeling stochastic reliability in smart grids. MDPs allow decision-makers to evaluate optimal policies for system restoration given uncertain future states [25]. By integrating real-time sensor data with probabilistic models, PoLiMoS can predict and respond to power disruptions more effectively. Taher *et al.* [25] analyses the reliability of an underground vault system (UVS) for distribution substations using a continuous Markov process. The system consists of five major subsystems: Transformer, Circuit Breakers, Sensors, and Bus Bars. A Markov-based matrix is used to identify state probabilities and overall reliability. The UVS's reliability is found to be 77.66% over its 20-year operational period. Recent work has also explored the use of digital twins in grid monitoring, virtual replicas of physical systems updated in real time [9]. Although not implemented in PoLiMoS' current version, this approach could enhance its predictive capabilities and provide a broader situational awareness.

2.5 Human–Machine Interaction (HMI) and Visualisation

The integration of web-based platforms for remote inspection and data visualisation aligns with cognitive load theory in Human-Machine Interface (HMI) and interactive dashboard design frameworks. These theories promote user-friendly visualisation interfaces, vital for field technicians and power administrators interacting with PoLiMoS. A core aspect of PoLiMoS is its user-friendly web-based monitoring dashboard. This interface adheres to cognitive load theory, ensuring users are not overwhelmed with excessive or complex information [26]. Effective HMI design involves minimalistic layouts, colour-coded alerts, and context-aware notifications. Visual analytics frameworks for infrastructure systems emphasise real-time data plotting, heat maps for fault concentration, and temporal trends [27]. These visual tools improve situational awareness and reduce response time in field operations.

In contemporary control systems, a HMI display module is essential for the management, control, and monitoring of a complex systems through interactive interfaces. Grandhi [28] aims to improve water level monitoring systems by integrating HMI display modules with passive IoT optical fibre sensor networks. The research uses Fiber Bragg Grating (FBG) sensors for high sensitivity and reliability, providing real-time data visualisation and advanced feature extraction. The Approach includes deployment of FBG sensors across water bodies, data capturing using an IoT gateway, and using HMI modules for user-friendly interfaces. The work employed signal conditioning, feature extraction, and machine learning algorithms for data accuracy and predictive analytics. System robustness is ensured through testing and validation.

In recent years, advancements in Intelligent and Connected Vehicles (ICVs) have led to a significant increase in the amount of information to the driver through Human–Machine Interfaces (HMIs). To prevent driver cognitive overload, the development of Adaptive HMIs (A-HMIs) has emerged. (Tufano *et al*. [26] introduced, a multiobjective optimisation methodology for adaptive strategies in Autonomous Highway Management (A-HMIs). The methodology is designed for an A-HMI that monitors the Driver-Vehicle-Environment (DVE) system, schedules actions, and selects appropriate presentation modalities. The goal is to minimise driver workload and action queuing. The methodology evaluates how applications' requests impact the driver's cognitive load and waiting queue. The paper solves offline optimization procedures for scheduling requests of five applications, including forward collision warning, system interaction, turn indicators, infotainment volume increase, and phone calls. The approach streamlines scheduling rules and prevents driver cognitive overload.

Data visualization is crucial in smart grid (SG) and low carbon energy systems, but research on information design, technology, and visualization tools is limited. Chen and Chen [27] reviews data visualization in power and energy systems, discussing applications like smart grid, electric vehicles, and building energy consumption. It discusses design principles for large screen, personal computer, and mobile device interfaces, and the application of 3-D technologies, animations, and AR&VR. Interactive visualizations not only support monitoring but also serve as training tools. Technicians and stakeholders can simulate fault scenarios, improving their preparedness. These considerations make HMI not just a technical requirement but a critical usability component of PoLiMoS.

2.6 Edge Computing and Localised Intelligence

Edge computing refers to processing data near the source of generation rather than relying on centralised servers. In PoLiMoS, parent nodes can process orientation data locally and determine whether to trigger alerts, which reduces latency and network load. This approach is supported by distributed computing theory, which proposes decentralised architectures for time-sensitive applications [6]. Research has shown, that local processing reduces response times by over 40% in smart grid environments [16]. PoLiMoS can benefit from low-power microcontrollers such as ESP8266 with onboard memory to store and analyze orientation thresholds, enabling near-instantaneous anomaly reporting without relying on the cloud.

2.7 Energy Harvesting and Sustainability Models

Sustainable monitoring systems require minimal dependency on external power. Energy harvesting models such as solar, piezoelectric, or RF harvesting ensure continuous operation in isolated locations. The PoLiMoS hardware integrates solar panels and rechargeable batteries to achieve autonomy. According to Singh *et al*. [12], WSN nodes with energy harvesting can increase operational lifespan by over 300%. Adaptive duty cycling, a method where sensors alternate between sleep and active states, further extends battery life [3,2]. Incorporating these models makes PoLiMoS particularly relevant for developing regions where grid access for sensor nodes is unavailable.

2.8 Environmental Adaptation and Deployment Strategies

Environmental adaptation theory in WSNs emphasises the need for robust deployment in variable conditions such as extreme heat, rainfall, and wind. Hardware must be weatherproofed, and software must account for noise in sensor readings. Research by González Rivero *et al.* [29] highlights the necessity of calibrating sensors according to local climatic patterns. The deployment of PoLiMoS in Nigeria must consider these factors, including dust interference and tropical storms. PoLiMoS uses rugged enclosures, filtered gyroscopes, and humidity-resistant connectors to enhance survivability in the field. These adaptations align with principles of resilient systems engineering.

3. Comparison and Critique of Theories and Models

While WSNs and IoT frameworks offer a strong foundation for distributed monitoring, they are often challenged by energy constraints, latency issues, and hardware limitations, especially in rural or underdeveloped environments [30]. The PoLiMoS system addresses these through solar-powered modules and low-energy transceivers, though scalability remains a concern. The predictive maintenance models, while powerful, rely on extensive historical data for training. In new deployments like PoLiMoS, this may introduce inaccuracies or overfitting [31]. However, real-time data acquisition through child-parent node communication improves model adaptability. In cloud-based smart grid systems, security and data integrity remain under-theorised in literature relative to their real-world implications [1]. PoLiMoS partially mitigates this through localised data processing at the parent node level, though integration with encrypted cloud APIs would be beneficial.

Regarding visual inspection vs. sensor-based systems, theories favoring automated image processing such as UAV and computer vision, boast higher accuracy in detecting surface-level anomalies [32], but are limited by weather and visibility. Nguyen *et al.* [33] presented a novel autonomous vision-based power line survey system using UAV and optical images as primary data sources. The system addresses three main challenges in deep learning: limited training data, class imbalance, and small components and faults detection. Four medium-sized datasets are created for training, and imbalanced classes were addressed by data augmentation techniques. The system uses a SSM detector and deep Residual Networks for small component detection and classification. The speed and accuracy of the system was established through field test.

Defects in high voltage transmission line components pose a great threat to humans and the environment due to continuous exposure to harsh environmental conditions. The very common components are broken wires rope, cracked insulators, and corroded power line joints. Siddiqui [34] presents, a real-time aerial power line monitoring system that uses a deep learning-based framework to detect and analyse high voltage transmission line components like insulators, splitters, damper-weights, and power lines. The system uses a Jetson TX2 embedded platform for real-time detection and localisation from live video captured by a remotely controlled drone. The detected components are then analysed using novel defect detection algorithms. Results show the system is robust against cluttered environments and outperforms similar research in terms of defect detection precision and recall. The automatic defect analysis system can reduce manual inspection time. PoLiMoS uses physical orientation data, which may capture faults even under obscured conditions, suggesting a complementary rather than competing approach.

Theoretical models explored in the previous section provide a solid foundation for designing distributed powerline monitoring systems like PoLiMoS. However, each model has strengths and limitations that must be critically evaluated in relation to the system's goals, namely real-time monitoring, low power consumption, cost-effectiveness, and environmental adaptability. WSNs, though highly efficient for data acquisition and communication, often suffer from limited transmission ranges and high energy consumption during prolonged operation. While clustering protocols like LEACH enhance energy efficiency, they are not inherently fault-tolerant unless combined with redundancy strategies [11]. Furthermore, the reliability of wireless communication in harsh environments, such as areas with dense vegetation or high electromagnetic interference, remains an open challenge.

IoT architectures enhance scalability and remote access but are prone to security vulnerabilities, particularly in open transmission environments [1]. The lack of encryption in many low-cost sensor modules used in developing countries exposes systems to data tampering. Middleware interoperability is also a significant concern, especially when integrating sensors from multiple vendors. For PoLiMoS, standardising communication protocols such as MQTT and adopting open IoT frameworks like FIWARE is a step in the right direction but may require further hardening.

Predictive models offer valuable foresight but their implementation in edge-based systems is limited by processing power and memory constraints. As seen in Table 3, complex models like LSTM deliver high prediction accuracy but demand significant computational resources, making them more suitable for cloud-based analysis. Lightweight models such as Bayesian Linear Regression or Threshold Analysis offer reduced accuracy but are more practical for embedded systems.

Table 3: Summary of Theory Strengths and Weaknesses in PoLiMoS Context

Theoretical Domain	Strengths	Weaknesses	Implication for PoLiMoS
Wireless Sensor Networks	Decentralised, scalable, energy-efficient	Limited range, vulnerable to node failure	Needs redundancy and energy harvesting
IoT Frameworks	Real-time remote access, layered design	Security risks, middleware complexity	Requires encryption and protocol standardisation
Predictive Maintenance	Preventive action, reduced downtime	High processing demands, training data dependency	Edge-friendly algorithms are needed
Smart Grid Reliability	Quantifiable performance metrics	Assumes ideal data streams	Needs adaptive modelling with real-time data

Theoretical Domain	Strengths	Weaknesses	Implication for PoLiMoS
HMI & Visualization	Enhances usability and response	User overload in poorly designed UIs	Minimalist design is required for technicians
Edge Computing	Reduces latency, local intelligence	Limited by device specs	Prioritise critical functions at the edge
Energy Harvesting	Enables off-grid operation	Seasonal inconsistency	Must include battery buffers
Environmental Adaptation	Increases resilience	Requires custom design	Higher upfront hardware cost

In addition, a gap exists between theory and practice regarding long-term deployment. Many models assume controlled environments and short-term simulations, whereas PoLiMoS must perform in real-world Nigerian conditions for extended durations. Real deployment introduces challenges like sensor drift, environmental wear, vandalism, and data loss all of which are rarely addressed in theoretical works [9,29]. Lastly, cost and maintainability are rarely factored into high-level theoretical frameworks. For instance, while digital twins provide exceptional diagnostic power, they are computationally and financially intensive, thus unsuitable for PoLiMoS' resource-constrained target regions unless open-source and edge-integrated alternatives are adopted

4. Conclusion

The theoretical review illustrates that the PoLiMoS system builds upon robust, multi-disciplinary frameworks ranging from WSN and IoT to predictive analytics and smart grid monitoring. By integrating these models, the project offers a practical alternative to traditional powerline monitoring strategies, particularly for developing regions. However, limitations in energy efficiency, data modeling accuracy, and cybersecurity must be addressed to fully realise the theoretical potential. Future iterations should incorporate adaptive AI models, encrypted communication protocols, and hybrid inspection methods. The PoLiMoS initiative, grounded in these theories, advances the discourse on intelligent infrastructure and demonstrates a locally adaptable solution with global relevance.

The theoretical models and frameworks reviewed in this study provide valuable insights into the development and deployment of distributed monitoring systems like PoLiMoS. By integrating WSNs, IoT architectures, predictive maintenance, edge computing, and human-centric design, the PoLiMoS system exemplifies a multidisciplinary approach to addressing the challenges in Nigeria's power transmission network. A significant theoretical implication is the need for hybrid models that combine the lightweight features of embedded systems with the analytical strength of cloud computing. This calls for more research into dual-layered architectures where low-level anomaly detection is performed on-site, while advanced diagnostics are carried out remotely. The reviewed theories also highlight the importance of contextual adaptation, recognising that models effective in one geographic or climatic context may not perform well in another.

Moreover, the critique reveals gaps in current theoretical frameworks, particularly around security, long-term deployment resilience, and cost-efficiency. The PoLiMoS project, by focusing on localised deployment, environmental adaptation, and predictive modeling tailored to available computational resources, presents a unique opportunity to validate and extend these theoretical models.

In summary, while existing theories provide a robust starting point, their application in resource-limited and environmentally challenging regions like sub-Saharan Africa requires strategic modifications. The PoLiMoS initiative contributes not only to technological innovation but also to the theoretical advancement of intelligent infrastructure monitoring systems tailored for the Global South.

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