

Intelligent Condition Monitoring for Mission-Critical Electrical Infrastructure: Integrating Sensors, Data Analytics, and Predictive Diagnostics

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Abstract

Mission-critical electrical infrastructure increasingly requires maintenance strategies capable of identifying degradation before it progresses into disruptive or catastrophic failure. This review examines the role of intelligent condition monitoring in strengthening asset reliability through the coordinated application of sensor technologies, data analytics, and predictive diagnostic methods. A structured narrative review approach was adopted to synthesise relevant engineering literature on electrical asset failure mechanisms, sensing modalities, condition assessment, prognostics, digital monitoring architectures, and implementation challenges. The review considered transformers, substations, rotating machinery, renewable-energy systems, protection infrastructure, and associated cyber-physical environments.

The findings show that effective condition monitoring depends on integrating complementary electrical, thermal, vibration, acoustic, optical, and environmental measurements with analytical methods capable of extracting meaningful health indicators. Statistical analysis, anomaly detection, health-index modelling, machine learning, digital twins, and remaining useful life estimation substantially improve the ability to distinguish transient operating variations from progressive equipment deterioration. Integrated SCADA, Industrial Internet of Things, edge-computing, and secure communication architectures further enhance real-time visibility and support maintenance decisions across distributed assets. However, implementation remains constrained by data quality, interoperability limitations, legacy-system compatibility, cybersecurity exposure, model explainability, workforce capability, and insufficient field validation.

The review concludes that intelligent monitoring is most effective when sensing, analytics, diagnostics, cybersecurity, and maintenance governance operate as an integrated decision-support ecosystem rather than as isolated technologies. It recommends greater emphasis on interoperable architectures, uncertainty-aware prognostics, explainable artificial intelligence, secure edge analytics, standardised condition data, and multi-site validation under diverse operating environments. These priorities can support earlier intervention, reduce unplanned outages, improve asset utilisation, and strengthen the resilience and lifecycle performance of critical electrical systems.

Keywords: condition monitoring; predictive diagnostics; electrical infrastructure; sensor technologies; prognostics; digital twins

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1. Introduction

1.1 Reliability Demands in Critical Electrical Systems

Mission-critical electrical systems underpin facilities and services in which loss of power can rapidly translate into safety hazards, process interruption, data loss, equipment damage, or wider service disruption. Their reliability requirement therefore extends beyond simple continuity of supply to encompass power quality, protection integrity, fault tolerance, restoration capability, and the ability to detect deteriorating asset conditions before functional failure. In developing grids, the growth of distributed and alternative energy resources further increases operational complexity because network operators must manage bidirectional flows, variable generation, and new interfaces without compromising stability; modelling of hydrogen integration, for example, illustrates the broader system-planning implications of introducing new energy carriers into national grids (Adeniji et al., 2019).

Reliability is particularly dependent on the performance of medium-voltage distribution assets, where insulation defects, grounding deficiencies, switching failures, conductor deterioration, and protection maloperation can propagate into sustained outages. Effective grounding design is consequently fundamental because it provides a controlled path for fault current, constrains dangerous potential rise, and supports dependable operation of protective devices under abnormal conditions (Shittu et al., 2020). Load allocation is equally important: poorly balanced or inadequately coordinated hybrid installations can increase thermal and electrical stress, reduce operating margins, and create conditions that accelerate component degradation, making

optimized load distribution a practical reliability requirement rather than solely an efficiency objective (Sunday & Omoegun, 2019).

The operational consequences of unreliability are especially pronounced where feeders support industrial, commercial, healthcare, communications, data-processing, transportation, or public-service loads. Evidence from Nigerian distribution networks shows that reliability assessment using interruption-duration and interruption-frequency measures can expose material differences in feeder performance and provide a quantitative basis for maintenance planning and service improvement (Adesina, Ogunbiyi & Jimada-Ojuolape, 2024). Similar evidence from South African medium-voltage networks demonstrates that structured deficiency identification and risk-based maintenance can reduce outage frequency, duration, and associated power losses, reinforcing the importance of linking reliability targets to asset condition and maintenance prioritisation (Ramere & Laseinde, 2024).

For critical equipment, reliability increasingly depends on observability. Power transformers, for instance, experience interacting electrical, thermal, mechanical, and dielectric stresses that may remain latent until an advanced failure state is reached. Continuous sensing of current, voltage, temperature, moisture, dissolved gases, partial discharge, and related variables enables abnormal behaviour to be detected while intervention remains feasible (Samimi & Dadashi Ilkhechi, 2020). Partial-discharge activity is especially significant because progressive insulation deterioration can precede severe transformer failure; systematic detection and interpretation of such signals therefore strengthen early diagnosis and reduce exposure to catastrophic outages (Hussain, Refaat & Abu-Rub, 2021).

Condition information becomes more valuable when it is translated into asset-level risk. Health-index approaches combine monitoring data, degradation models, statistical evidence, and expert judgement to estimate breakdown probability and remaining lifetime, enabling maintenance and replacement decisions to be prioritised according to actual condition rather than fixed schedules alone (Foros & Istad, 2020). This principle aligns closely with the reliability demands of mission-critical infrastructure, where unnecessary intervention can itself introduce operational risk, while delayed intervention can permit incipient defects to mature into service-threatening failures.

Modern reliability management therefore requires an integrated progression from sensing to diagnosis, prognosis, and intervention. Online and offline transformer-monitoring methods demonstrate how dissolved-gas analysis, thermal measurements, vibration assessment, dielectric testing, and related techniques can reveal degradation mechanisms and support earlier maintenance decisions (Jin et al., 2022). Within mission-critical electrical infrastructure, such intelligence provides the foundation for condition-based maintenance, predictive diagnostics, dynamic risk assessment, and resilient operational planning, allowing reliability to be managed continuously as an observable and actionable engineering state rather than treated retrospectively as an outage

statistic. This shift is essential as infrastructure becomes interconnected, digitally controlled, heavily loaded, and intolerant of prolonged service interruption.

1.2 Evolution of Intelligent Condition Monitoring

Intelligent condition monitoring has evolved from periodic inspection and reactive repair toward continuous, data-driven surveillance capable of identifying degradation before functional failure. Early maintenance regimes largely depended on scheduled servicing and operator judgement, whereas contemporary practice increasingly combines embedded sensing, automated acquisition and analytical models to support predictive intervention. This transition reflects the growing cost of unplanned downtime and the operational consequences of failure in electrically dependent infrastructure. Sunday et al. (2020) demonstrate this progression from reactive practices toward predictive maintenance, highlighting the value of condition information in anticipating equipment deterioration.

The next phase of development was enabled by programmable automation. Industrial controllers increasingly transformed monitoring from isolated measurements into coordinated process supervision, allowing operating variables, alarms and control responses to be captured within integrated digital environments (Sunday & Omoegun, 2022). SCADA subsequently expanded this capability by linking field devices, communication networks and supervisory interfaces, creating platforms for real-time visualization, remote control and increasingly sophisticated analytics (Omoegun et al., 2024).

Sensor proliferation has also changed the architecture of maintenance intelligence. In a South African processing environment, sensor-derived vibration data and statistical thresholds were used to identify abnormal equipment behaviour and support pre-failure maintenance decisions, illustrating the practical movement from descriptive monitoring toward condition-based intervention (Ngoma, Mativenga & Pretorius, 2020). Such developments are increasingly reinforced by intelligent sensors, Industrial Internet of Things connectivity and machine-learning methods capable of transforming high-frequency operational data into actionable maintenance knowledge (Pech, Vrchota & Bednář, 2021).

1.3 Review Aim, Scope, and Objectives

This review examines the development and application of intelligent condition monitoring across mission-critical electrical infrastructure, with emphasis on the integration of sensing technologies, data analytics, and predictive diagnostic techniques. Its principal aim is to evaluate how these complementary capabilities can improve the reliability, operational resilience, safety, and

maintenance efficiency of electrical assets whose failure could result in substantial technical, economic, or service consequences.

The scope encompasses critical electrical equipment and systems including transformers, switchgear, substations, generators, rotating machinery, protection systems, industrial power networks, renewable-energy installations, and digitally controlled distribution infrastructure. Particular attention is directed toward the acquisition of condition data through electrical, thermal, vibration, acoustic, environmental, and other sensor modalities, together with the analytical processes required to transform these measurements into meaningful indicators of equipment health. The review also considers the growing role of supervisory control systems, Industrial Internet of Things architectures, machine learning, artificial intelligence, digital twins, anomaly detection, fault classification, and prognostic modelling within modern maintenance environments.

The review pursues four interrelated objectives. First, it examines the reliability demands and principal degradation mechanisms associated with mission-critical electrical assets. Second, it evaluates the sensing and data-acquisition technologies used to identify emerging abnormalities and deteriorating operating conditions. Third, it assesses analytical and predictive diagnostic approaches for fault detection, condition assessment, degradation forecasting, and maintenance decision support. Finally, it critically evaluates integrated monitoring architectures, implementation barriers, cybersecurity concerns, interoperability requirements, and future research priorities. Collectively, these objectives provide a structured basis for understanding how intelligent condition monitoring can support earlier intervention, reduce unplanned outages, strengthen asset management, and advance more resilient electrical infrastructure.

2. Mission-Critical Electrical Infrastructure and Failure Risks

Mission-critical electrical infrastructure comprises interconnected assets whose reliable operation is indispensable to the continuity of essential industrial, commercial and public services. Transformers, substations, switchgear, generators, protection systems, uninterruptible power supplies, renewable-energy interfaces and distribution networks operate under electrical, thermal, mechanical and environmental stresses that can progressively erode performance. In Nigeria, the increasing incorporation of solar-generation systems into industrial installations illustrates how distributed generation expands system complexity by introducing additional conversion equipment, protection interfaces and operating states that must remain coordinated under fluctuating conditions (Sunday & Omoegun, 2018).

Failure risk is rarely attributable to a single mechanism. Electrical insulation degradation, thermal ageing, excessive loading, moisture ingress, short circuits, partial discharge, contact deterioration and mechanical deformation may interact over prolonged operating periods before culminating in functional failure. Transformer lifecycle evidence from Kenya demonstrates that ageing insulation and prolonged service exposure require systematic condition assessment because apparently serviceable equipment may contain progressive defects capable of precipitating disruptive failure (Mharakurwa, 2022). Temperature management is similarly important across electrically driven auxiliary systems, since inefficient thermal control can increase energy demand and equipment stress, thereby narrowing operational safety margins (Sunday et al., 2019).

Transformers represent particularly consequential points of vulnerability because their failure can interrupt large sections of transmission or distribution infrastructure. Fault-detection research demonstrates that incipient electrical and thermal abnormalities must be identified rapidly because delayed isolation may escalate equipment damage, increase repair expenditure, and expose adjacent assets and personnel to secondary hazards (Abbasi, 2022). These risks justify monitoring strategies that evaluate evolving condition rather than relying solely upon fixed maintenance intervals.

Digital substations introduce additional dimensions of vulnerability. Their dependence on intelligent electronic devices, networked sensors, and communication systems creates cyber-physical pathways through which measurement errors, communication failures, or malicious interference may compromise protection performance. IoT-enabled adaptive protection consequently requires resilient architectures capable of maintaining dependable distributed-energy-resource integration under both physical disturbances and digital threats (Shittu et al., 2024). Digital-twin representations further enable evolving substation conditions to be compared with modelled behaviour, supporting real-time recognition of deviations before they develop into significant operational events (Shittu et al., 2023).

Renewable-energy infrastructure presents comparable challenges because variable generation, power-electronic interfaces and geographically distributed assets create dynamic operating conditions. AI-enabled digital twins can support predictive maintenance by continuously relating operational observations to asset models, thereby strengthening early recognition of degradation and optimizing intervention schedules (Shittu & Shittu, 2024). At the wider infrastructure level, electrical reliability also intersects with energy efficiency and transportation-dependent economic systems, meaning that failures can propagate beyond individual equipment boundaries and impair interconnected services (Opara et al., 2024).

3. Sensor Technologies for Asset Condition Monitoring

Sensor technologies constitute the primary interface between physical electrical assets and intelligent condition-monitoring systems, converting otherwise latent deterioration processes into measurable signals that can support diagnosis, prognosis, and maintenance intervention. Effective monitoring therefore depends not simply on installing sensors, but on selecting measurement principles that correspond to expected failure mechanisms, operating environments, and asset criticality. In Nigerian electrical applications, infrared thermography provides a particularly valuable non-contact approach because abnormal thermal patterns can reveal overloaded conductors, deteriorated connections, insulation deficiencies and other developing defects without interrupting equipment operation (Ukiwe, Adeshina & Tsado, 2023).

Electrical and electromechanical assets frequently require multiple sensing modalities because degradation seldom manifests through a single observable variable. Vibration sensing is especially important for motors, generators, bearings and other rotating machinery, where mechanical imbalance, misalignment, looseness and bearing degradation alter vibration signatures. LabVIEW-based monitoring demonstrates how acquired vibration signals can be processed and visualised to support condition assessment and early recognition of mechanical abnormalities before they develop into functional failures (Omoegun et al., 2023). Vibro-acoustic analysis extends this principle to power transformers, where structural vibrations and acoustic signatures can provide information concerning winding, core and mechanical conditions while reducing reliance on invasive inspection (Secic, Krpan & Kuzle, 2019).

Acoustic sensing is also valuable for identifying insulation deterioration. Partial discharge generates transient acoustic emissions that can be detected by appropriately positioned sensors, while differences in signal arrival times can assist with locating discharge sources within transformer structures. Such localisation improves maintenance precision by moving diagnostics beyond confirmation of abnormal activity toward identification of the probable defect region (Rathod, Kumbhar, Bhalja, 2022).

Optical technologies provide another important sensing pathway for high-voltage environments. Fibre-optic sensors offer electrical insulation, electromagnetic immunity, small dimensions and the potential for internal installation, enabling temperature, strain, vibration, dissolved-gas and partial-discharge measurements under conditions in which conventional electronic sensors may experience interference (Ma et al., 2021). These characteristics make optical sensing especially attractive for mission-critical transformers requiring continuous observation under intense electromagnetic fields.

Sensor-based monitoring is equally relevant to electrically dependent auxiliary infrastructure. HVAC equipment, for example, can be instrumented to track operating variables whose deviations

indicate inefficient performance or developing faults, allowing maintenance personnel to identify abnormal conditions through measured evidence rather than waiting for loss of functionality (Sunday & Omoegun, 2022). More broadly, combining heterogeneous sensing channels can improve diagnostic robustness because complementary measurements capture different manifestations of equipment degradation. Sensor-fusion techniques can integrate multiple data streams into richer representations of asset condition and thereby improve classification performance when individual signals are ambiguous or noisy (Cinar, 2022).

Connectivity has further transformed sensors from isolated measurement devices into distributed components of intelligent monitoring architectures. IoT-enabled systems can acquire transformer temperature, humidity, gas concentration and other environmental measurements and communicate them remotely for continuous supervision and automated analysis (Hasır, Cekli & Uzunoğlu, 2021). Evidence from South Africa similarly indicates that IoT frameworks are increasingly enabling real-time transformer monitoring, remote data acquisition and predictive maintenance while improving access to condition information across geographically dispersed electrical networks (Msane, Thango & Ogudo, 2024).

The analytical value of sensing ultimately depends on sensitivity, calibration, sampling frequency, placement, environmental robustness and data quality. Artificial-intelligence integration can further enhance interpretation by allowing complex sensor outputs to be classified and converted into actionable diagnostic information, demonstrating the wider potential of intelligent sensing systems to distinguish subtle abnormal patterns within high-volume measurement streams (Olorunkosebi, Ayinde & Kofi, 2023). For mission-critical infrastructure, sensor selection should therefore be treated as an engineering architecture decision: electrical, thermal, vibration, acoustic, optical and environmental measurements must be strategically combined so that emerging failure mechanisms become observable sufficiently early to permit reliable diagnostic and maintenance action.

4. Data Analytics for Electrical Health Assessment

Data analytics transforms condition-monitoring measurements into evidence about asset health, degradation, and emerging failure risk. For mission-critical electrical infrastructure, this function begins with disciplined data preparation because sensor streams may contain missing values, drift, noise, and operating-state variability that can distort diagnosis. Anomaly detection based on auxiliary features and density-based clustering demonstrates how valid equipment abnormalities can be distinguished from invalid outliers before subsequent assessment, thereby preserving diagnostically meaningful deviations while improving data quality (Liu et al., 2020).

Once data integrity is established, descriptive and statistical methods provide the first analytical layer. Statistical process control offers a structured means of tracking variation, establishing control limits and identifying departures from expected behaviour, principles that can be transferred to electrical health surveillance where measured parameters evolve around operating baselines (Akanbi, Ganiu & Sunday, 2022). Multi-criteria analytics are equally important because electrical assets rarely deteriorate through one indicator; approaches that combine several condition variables into a prioritisation structure illustrate how heterogeneous evidence can be consolidated for intervention decisions (Alaka et al., 2023).

Transformer health assessment demonstrates this progression clearly. Statistical analysis integrating chemical, mechanical and electrical parameters can convert disparate diagnostic observations into health indices and fault-criticality measures, enabling emerging deterioration to be ranked according to severity rather than treated as isolated test results (Soni & Mehta, 2022). Enhanced health-index methods can also reduce diagnostic complexity while retaining sensitivity to insulation deterioration and loading-related ageing, thereby supporting practical assessment where complete datasets are unavailable (Da Silva et al., 2021). Comparative health-index techniques based on weighted sums, fuzzy inference and clustering further show that analytical method selection can materially affect condition classification and maintenance ranking (Zaldivar & Romero, 2022).

Machine learning extends assessment from rule-based interpretation toward pattern recognition across high-dimensional condition data. Data-driven thermal modelling enables expected transformer temperature behaviour to be learned from historical operating measurements, so deviations between predicted and observed temperatures can signal incipient thermal faults requiring investigation (Doolgindachbaporn et al., 2022). In South African research, regression-based analysis combined with frequency-response measurements has likewise demonstrated how statistical modelling can strengthen interpretation of transformer winding condition and distinguish structural changes that warrant engineering attention (Thango et al., 2022).

The value of analytics is ultimately determined by its connection to operational decisions. Forecasting frameworks developed for complex operational systems demonstrate the importance of converting historical data into forward-looking indicators rather than relying exclusively on retrospective performance description (Akin-Oluyomi & Akhigbe, 2023a). Data-driven performance indicators likewise support comparison across multiple sites or assets, which is essential when utilities must rank maintenance needs across geographically distributed infrastructure (Akin-Oluyomi & Akhigbe, 2023b).

For mission-critical electrical systems, an effective analytical architecture therefore links acquisition, preprocessing, feature extraction, anomaly detection, health-index computation, machine-learning inference, and risk prioritisation. The objective is not merely to generate more

data, but to convert heterogeneous observations into interpretable evidence about present condition and probable degradation trajectories. This capability is especially important where equipment failure can interrupt healthcare, industrial control, communications, transport, or services with limited tolerance for downtime. Such an architecture supports earlier intervention, more defensible maintenance prioritisation and continuous reassessment as operating conditions change over asset lifecycles.

Table 1. Analytical pathway for electrical health assessment

Analytical Stage	Typical Data Inputs	Principal Technique	Health Information Produced	Maintenance Application
Data validation	Sensor streams, SCADA records	Cleaning and anomaly screening	Reliable condition dataset	Prevent false diagnostics
Feature extraction	Temperature, vibration, gases, electrical signals	Statistical and signal analytics	Condition-sensitive indicators	Detect emerging deviations
Condition assessment	Multiple diagnostic parameters	Health indices and multicriteria models	Asset health classification	Rank asset condition
Intelligent diagnosis	Historical and real-time measurements	Machine learning and regression	Fault probability and patterns	Identify incipient failures
Predictive assessment	Time-series condition histories	Forecasting and trend modelling	Degradation trajectory	Anticipate deterioration
Decision support	Health, risk and operational data	Risk prioritisation analytics	Intervention priority	Schedule maintenance efficiently

Table 1: Author’s synthesis of the data-analytics pathway linking condition measurements to maintenance decisions in mission-critical electrical infrastructure.

5. Predictive Diagnostics and Failure Prognostics

Predictive diagnostics extends condition monitoring beyond recognition of abnormal behaviour by determining probable fault mechanisms, estimating their progression, and identifying when deterioration may threaten functional integrity. Within mission-critical electrical infrastructure, this capability is particularly valuable because transformers, induction machines, converters, generators and auxiliary equipment may exhibit measurable degradation long before service

failure. Prognostics and health management therefore integrates fault detection, diagnosis and future-state prediction into a unified framework capable of supporting maintenance decisions before critical thresholds are exceeded (Biggio & Kastanis, 2020).

Diagnostic reasoning begins with distinguishing normal operational variability from patterns associated with identifiable defects. Root-cause analysis and design-of-experiments approaches provide structured mechanisms for tracing recurrent equipment deterioration to influential technical variables, thereby reducing the likelihood that maintenance merely addresses symptoms while underlying causes persist (Akanbi et al., 2023a). Systematic failure-reduction methodologies further strengthen this process by linking recurring faults to measurable process variation and corrective actions that progressively reduce failure frequency (Akanbi et al., 2023b).

Prognostics advances this reasoning by estimating degradation trajectories and remaining useful life (RUL). Stochastic approaches based on Wiener, gamma, inverse Gaussian, and Markov processes provide mathematical mechanisms for representing uncertain deterioration and estimating the time remaining before defined failure thresholds are reached (Du et al., 2021). For power transformers, probabilistic forecasting combined with Bayesian state estimation can incorporate uncertainty in loading and operating conditions to produce lifetime distributions rather than deterministic end-of-life estimates, strengthening risk-informed planning (Aizpurua et al., 2022).

Artificial intelligence has substantially expanded diagnostic and prognostic capability. Deep-learning architectures can extract degradation features from heterogeneous time-series measurements, although generalisation, interpretability, scarce failure examples and changing operating regimes remain important barriers to dependable deployment in safety-critical applications (Fink et al., 2020). In induction machines, expert-based, physics-based and machine-learning methods provide complementary routes for detecting faults and estimating asset health, reinforcing the value of hybrid approaches where different evidence streams are available (Huang et al., 2024).

Renewable-energy assets present similar prognostic requirements because variable operating conditions influence converters, bearings, batteries and generator components. Health indicators and RUL estimation can support maintenance scheduling by distinguishing temporary operating excursions from persistent degradation processes that require intervention (Saidi & Benbouzid, 2021). Predictive insight is most useful when integrated into reliability-centred maintenance, where intervention is prioritised according to failure consequences, asset condition and operational significance rather than calendar intervals alone (Olutimehin & Ganiu, 2022).

Maintenance execution must also accommodate operational capacity. Workforce allocation and line-balancing principles illustrate how maintenance requirements can be coordinated with

resource availability and production demands so that interventions do not create unnecessary operational disruption (Akanbi, Ganiu & Sunday, 2022). For mission-critical electrical infrastructure, predictive diagnostics should therefore connect sensor evidence, fault classification, degradation modelling, RUL estimation and maintenance planning within a continuous decision loop capable of updating predictions as new condition data become available.

Table 2. Predictive diagnostic and prognostic decision pathway

Stage	Analytical Purpose	Typical Methods	Principal Output	Maintenance Value
Fault detection	Identify abnormal behaviour	Thresholds, anomaly models	Abnormal-state alert	Early warning
Fault diagnosis	Determine defect type	Classification, root-cause analysis	Fault identity	Targeted intervention
Severity assessment	Evaluate degradation magnitude	Health indices, trend analysis	Condition state	Risk ranking
Degradation modelling	Characterise fault progression	Statistical and physics-based models	Degradation trajectory	Failure anticipation
RUL estimation	Estimate remaining service time	Stochastic, ML and Bayesian models	Remaining useful life	Maintenance timing
Decision optimisation	Select intervention strategy	Risk and reliability models	Maintenance priority	Reduced downtime

Table 2: Author’s synthesis of the progression from fault detection to prognostic maintenance decision-making in mission-critical electrical infrastructure.

6. Integrated Architectures for Intelligent Monitoring

Intelligent condition monitoring reaches its full operational value when sensing, communications, analytics, diagnostics and maintenance decision-making are integrated within a coherent architecture. In mission-critical electrical infrastructure, such architectures must connect field-level measurements with higher-level intelligence while preserving low latency, interoperability, cybersecurity and continuity of service. Rather than treating monitoring devices as independent

instruments, modern architectures establish an end-to-end information pathway through which asset condition can be continuously observed, interpreted and translated into operational action.

At the physical layer, transformers, switchgear, generators, converters and auxiliary systems generate electrical, thermal, mechanical and environmental measurements. Industrial Internet of Things architectures provide the connectivity required to aggregate these heterogeneous data streams, while edge computing moves selected processing closer to field assets, reducing latency, communication bandwidth and dependence on remote cloud services (Qiu et al., 2020). This is particularly important for protection-sensitive infrastructure, where an abnormal condition may require near-real-time classification rather than delayed remote processing.

Above the sensing and edge layers, SCADA provides supervisory visibility and control across geographically dispersed electrical assets. Secure exchange between SCADA nodes becomes fundamental because corrupted or manipulated measurements may produce inappropriate operating decisions. Blockchain-assisted architectures offer mechanisms for preserving data integrity, traceability, and trusted exchange across interconnected power-system components (Opara et al., 2022). Fog-based architectures further distribute computation between field and cloud environments, although authentication, key management, intrusion detection, and privacy protection must be incorporated by design to prevent increased connectivity from enlarging the attack surface (Ferrag, Babaghayou & Yazici, 2020).

Integrated monitoring increasingly requires cybersecurity to coexist with interoperability rather than function as an independent layer. Smart-grid architectures incorporate communications, advanced metering, SCADA and networked control devices, creating numerous interfaces through which cyber compromise may affect physical electricity operations (Achaal et al., 2024). Attribute-based access control can strengthen such architectures by restricting information and functions according to authenticated roles and permissions, thereby limiting inappropriate access to sensitive operational resources (Shittu & Nabil, 2023).

Digital twins provide an additional architectural layer by maintaining virtual representations of physical electrical assets. When continuously updated using sensor measurements, these models can support condition assessment, load forecasting, simulation and maintenance planning before actions are executed on physical equipment (Zhang & Lv, 2022). End-to-end predictive-maintenance platforms similarly demonstrate the value of integrating fragmented operational datasets, analytics and field-level action within a common digital environment rather than maintaining disconnected diagnostic tools (Christou et al., 2020).

Cyber-physical situational awareness strengthens this integration by linking asset criticality, operational state and potential threats so that monitoring systems can distinguish routine anomalies from events capable of affecting essential infrastructure functions (Alrowaili & Saxena, 2023).

Governance is also necessary because integrated monitoring introduces responsibilities involving data ownership, access privileges, configuration control, auditability and compliance; structured IT-governance principles can therefore provide institutional mechanisms for managing complex digital environments (Fadero et al., 2018).

Distributed energy resources further increase architectural complexity. Peer-to-peer microgrids illustrate how decentralised generation, digital communication and transactional mechanisms can coexist within interconnected energy environments, requiring monitoring systems capable of supervising both physical power flows and digital exchanges (Shittu et al., 2021). The resulting architecture should therefore operate as a layered cyber-physical system in which sensing establishes visibility, edge and communication technologies transport and preprocess information, analytics derive health intelligence, digital twins simulate future conditions, and secure decision-support platforms coordinate maintenance responses.

Table 3. Integrated architecture for intelligent electrical monitoring

Architecture Layer	Principal Components	Core Function	Monitoring Contribution
Physical asset layer	Transformers, switchgear, generators, DERs	Electrical operation	Source of condition states
Sensing layer	Thermal, vibration, electrical, acoustic sensors	Data acquisition	Captures degradation indicators
Edge/fog layer	Gateways, embedded processors, local analytics	Low-latency processing	Filters and analyses local data
Communication layer	IIoT, Ethernet, wireless, industrial protocols	Data transmission	Connects distributed assets
Supervisory layer	SCADA, HMI, alarm systems	System oversight	Enables real-time supervision
Analytics layer	AI, anomaly detection, prognostics	Health interpretation	Diagnoses and predicts failures
Digital-twin layer	Virtual asset and grid models	Simulation and forecasting	Tests future operating conditions
Security layer	Encryption, access control, blockchain, IDS	Cyber protection	Preserves integrity and availability
Decision layer	CMMS, dashboards, maintenance workflows	Operational response	Converts intelligence into action

Table 3: Author's synthesis of a layered architecture integrating sensing, communications, analytics, digital twins, cybersecurity and maintenance decision support for mission-critical electrical infrastructure.

7. Implementation Challenges and Future Research

The transition from conventional maintenance toward intelligent condition monitoring presents implementation challenges extending beyond sensor installation and analytical accuracy. Mission-critical electrical infrastructure frequently combines legacy equipment, proprietary communication protocols, ageing protection systems, and emerging digital technologies. Achieving interoperability among these components requires substantial engineering effort, particularly where historical assets were not designed for continuous data exchange. Digital-twin research similarly identifies inconsistent definitions, fragmented architectures, insufficient standards and limited performance metrics as persistent barriers to scalable industrial deployment (Sharma et al., 2022).

Data availability and quality constitute another fundamental constraint. Predictive models require representative measurements across normal, degraded and faulty operating states, yet severe electrical failures are comparatively rare and historical maintenance records may be incomplete. Machine-learning condition monitoring is consequently affected by class imbalance, sensor noise, changing operating regimes, model-selection uncertainty and limited transferability between machines or sites (Surucu, Gadsden & Yawney, 2023). Future research should therefore prioritise transfer learning, semi-supervised approaches, synthetic fault-data generation and physics-informed learning capable of reducing dependence on large labelled failure datasets.

Cybersecurity becomes increasingly consequential as sensors, SCADA platforms, edge devices, cloud services and digital twins become interconnected. Greater connectivity creates additional pathways for false-data injection, denial-of-service attacks, malware and manipulation of control functions. Smart-grid security research demonstrates that future monitoring architectures will require adaptive intrusion detection, secure communications, authentication and coordinated defence mechanisms capable of addressing evolving cyber threats without degrading operational availability (Ghiasi et al., 2023).

Human and organisational readiness are equally important. Advanced monitoring platforms may fail to deliver their intended benefits when engineers and maintenance personnel lack confidence in automated recommendations or insufficiently understand the underlying analytical processes. Technology-adoption frameworks therefore emphasise workforce readiness as an essential component of successful digital transformation, particularly when new systems alter established roles, decision processes and technical responsibilities (Akhigbe, Falemi & Akin-Oluyomi,

2024a). Capability development should correspondingly encompass sensor engineering, data analytics, cybersecurity, reliability analysis and interpretation of AI-supported diagnostics across distributed operations (Falemi, Akhigbe & Akin-Oluyomi, 2020).

Implementation also requires governance structures that connect technical monitoring outputs with enterprise-level risk decisions. Integrating operational analytics with risk-management processes can help organisations determine which predicted failures justify immediate intervention, deferred maintenance or asset replacement according to safety, economic and service consequences (Akhigbe, Falemi & Akin-Oluyomi, 2024b). Within African infrastructure environments, institutional capacity, leadership and policy implementation may additionally influence whether technological transformation progresses from pilot initiatives to sustained operational systems (Enaifoghe, Dlamini & Agwuna, 2020).

Conclusion

This review has demonstrated that the reliability of mission-critical electrical infrastructure increasingly depends on the capacity to detect, interpret, and anticipate equipment deterioration before it develops into disruptive failure. The study achieved its objectives by examining the reliability demands and principal failure risks affecting critical electrical assets, evaluating the sensing technologies used for condition surveillance, assessing analytical and prognostic methods for transforming operational data into actionable intelligence, and examining integrated architectures that connect monitoring, diagnostics and maintenance decision-making.

The findings show that no single technology is sufficient for dependable condition assessment. Electrical, thermal, vibration, acoustic, optical and environmental sensors provide complementary perspectives on asset behaviour, while advanced analytics improve the interpretation of complex and high-volume measurements. Health indices, anomaly detection, machine learning, degradation modelling and remaining useful life estimation collectively strengthen the transition from reactive and time-based maintenance toward condition-based and predictive strategies. Digital twins, SCADA, Industrial Internet of Things platforms, edge computing and secure communication architectures further enable continuous asset visibility and more coordinated maintenance decisions across distributed electrical systems.

The review also establishes that technological sophistication alone does not guarantee successful implementation. Data quality, interoperability, cybersecurity, legacy-system integration, workforce capability, model explainability and organisational governance remain decisive constraints. Poorly validated predictive models or insecure monitoring architectures may introduce new operational risks even while attempting to reduce conventional equipment failures.

Accordingly, future deployments should adopt layered and interoperable architectures in which sensing, analytics, cybersecurity and maintenance governance are designed as mutually dependent functions. Utilities and operators should prioritise field validation, standardised data structures, explainable diagnostic models, uncertainty-aware prognostics and multidisciplinary workforce development. Future research should also emphasise multi-site validation under diverse operating conditions and establish transparent benchmarks for diagnostic accuracy, false alarms, computational latency, lifecycle cost and resilience. These measures will strengthen the practical translation of intelligent condition monitoring into safer, more reliable and economically sustainable electrical infrastructure.

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