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Predictive Maintenance and Condition Monitoring in Critical Power and Energy Infrastructure

TUNJI S. ADARAMOLA[1], SAMUEL FADERO[2], EDIKAN NSE GIDEON[3]
[1]*Nestle Nigeria Plc, Abaji plant, Abuja, Nigeria*
[2]*SanlamAllianz Life Insurance Ltd, Lagos Nigeria*
[3]*Independent Researcher, Lagos, Nigeria*

Abstract- This review examines the development, technologies, applications, and implementation requirements of predictive maintenance and condition monitoring across critical power and energy infrastructure. Its purpose is to determine how contemporary asset-management approaches can improve reliability, safety, operational continuity, lifecycle value, and resilience in increasingly complex energy systems. The study adopts a structured narrative review of established scholarly literature published up to 2018, synthesising evidence on maintenance philosophies, degradation mechanisms, sensing technologies, data architectures, diagnostic analytics, machine learning, digital twins, remaining-useful-life estimation, cybersecurity, and economic evaluation. The findings show a decisive transition from reactive and interval-based maintenance towards condition-based, predictive, and risk-informed decision-making. Effective implementation depends on the coordinated use of vibration, thermal, electrical, chemical, acoustic, and operational data, supported by interoperable communication networks, secure storage, rigorous data-quality management, signal processing, statistical analysis, and physics-based models. Machine learning and digital twins strengthen fault detection and prognostics, although their value is constrained by scarce failure data, model uncertainty, legacy-system incompatibility, cybersecurity exposure, workforce limitations, and weak economic justification. Applications across conventional generation, transmission, distribution, renewable-energy, and storage assets demonstrate that predictive methods can reduce unplanned outages, improve maintenance prioritisation, extend asset life, and enhance service resilience. The review concludes that predictive asset management should be treated as an integrated organisational capability rather than a stand-alone technological intervention. It recommends phased deployment focused on high-criticality assets, stronger data governance, validated and explainable models, secure interoperable architectures, workforce development, and lifecycle-based investment appraisal. Future research should prioritise affordable edge analytics, uncertainty-aware prognostics, climate-responsive degradation models, standardised datasets, and cybersecure digital-twin frameworks suited to diverse operating contexts.

Keywords: predictive maintenance, condition monitoring, critical infrastructure, asset reliability, digital twins, operational resilience.

I. INTRODUCTION

1.1 Criticality, Complexity, and Reliability Requirements of Power and Energy Infrastructure

Power and energy infrastructure constitutes a socio-technical system upon which healthcare, transportation, telecommunications, water supply, finance, manufacturing and public administration depend. Its criticality derives not merely from the electricity or fuel delivered, but from the scale of disruption following service loss. Modern energy networks operate as interdependent infrastructures in which physical, cyber, geographic and organisational relationships can transmit disturbances beyond the initially affected asset. A transformer failure, communication malfunction or fuel-supply interruption may consequently propagate across sectors, creating cascading effects that are disproportionate to the initiating event (Rinaldi, Peerenboom & Kelly, 2001).

The complexity of this infrastructure arises from the interaction of heterogeneous assets with different ages, technologies, operating environments and failure characteristics. Conventional generators, transformers, transmission corridors, substations, distributed resources, inverters, storage systems and supervisory platforms must function coherently despite uncertain demand, equipment deterioration and changing network configurations. Interdependency modelling demonstrates that infrastructure behaviour cannot be understood adequately through isolated component analysis because feedback loops, shared resources and cross-sector dependencies reshape both failure propagation and recovery trajectories (Ouyang, 2014). Reliability management must therefore consider the system as a dynamic network rather than a collection of independent machines.

Digitalisation has further transformed the technical architecture of power systems. Smart grids combine two-way electricity flows with communication, sensing, automation and distributed control, thereby improving observability and operational flexibility while introducing additional interfaces and potential failure pathways (Fang et al., 2012). This cyber-physical structure increases the importance of accurate condition data, time synchronisation, interoperable communication and secure control. Reliability is consequently dependent on both the integrity of electrical equipment and the availability of information required for protection, control and restoration. Analytical frameworks must capture structural, functional and dynamic complexity if vulnerability estimates are to support defensible investment and maintenance decisions (Zio, 2016).

Reliability requirements extend beyond avoiding routine interruptions. Critical systems must possess adequacy, security, robustness and recoverability under component failures, operational errors, cyber incidents and high-impact natural hazards. Comparative assessment of electricity systems indicates that resilience depends on the diversity and adaptability of the energy conversion chain, rather than installed generation capacity alone (Molyneaux et al., 2012). Extreme weather can simultaneously damage multiple assets, restrict access for repair crews and prolong restoration, making conventional independent-failure assumptions inadequate for risk management (Panteli & Mancarella, 2015).

Resilient performance therefore requires the capability to anticipate disruption, absorb its effects, adapt operationally and restore priority services promptly. Research on extreme-event performance emphasises network hardening, topology reconfiguration, distributed resources, automation and coordinated restoration as complementary measures for limiting service degradation (Bie et al., 2017). These requirements make asset health visibility indispensable. Condition monitoring can reveal incipient insulation breakdown, thermal stress, vibration anomalies, lubrication degradation, corrosion and abnormal electrical signatures before these defects develop into functional failures.

The integration of renewable and distributed resources introduces further reliability considerations. Variability, converter dependence, storage degradation and bidirectional flows alter protection coordination and system operating states. Reliability assessment of renewable microgrids shows that planning must jointly evaluate interruption frequency, energy not supplied, expected outage cost and lifecycle performance when determining an appropriate generation-storage configuration (Adefarati& Bansal, 2017). Predictive maintenance is especially valuable in this context because fixed service intervals may not reflect weather exposure, cycling intensity or rapidly changing loading conditions.

Reliability challenges are particularly consequential in African power systems, where limited reserve margins, ageing networks and constrained maintenance resources can magnify the economic effects of equipment unavailability. Evidence from Ethiopia demonstrates that unreliable electricity reduces firm performance and encourages costly self-generation, illustrating how infrastructure failures transfer operational burdens to consumers and industry (Abdisa, 2018). In Nigeria, integrating solar generation into small-scale manufacturing has been presented as a response to unstable grid supply, but the dependable operation of such decentralised assets still requires effective inspection, fault detection and lifecycle maintenance practices (Sunday &Omoegun, 2018).

1.2 Evolution from Reactive and Preventive Maintenance to Predictive Asset Management

Maintenance practice in critical power and energy infrastructure has evolved from a corrective function into an integrated asset-management discipline concerned with reliability, risk, lifecycle value and operational continuity. Reactive maintenance permits equipment to operate until functional failure occurs. Although economical for inexpensive, non-critical

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items, it is inappropriate for generators, transformers, turbines, switchgear and storage assets whose failure can trigger outages, safety incidents and secondary damage. Recognition of its organisational consequences established maintenance as a strategic activity (Tsang, 2002).

Preventive maintenance emerged as an organised response to the disruption associated with run-to-failure practices. Inspections, lubrication, overhauls and component replacements are performed according to calendar intervals, operating hours or manufacturers' recommendations. Scheduled intervention improves planning, yet assumes that deterioration correlates with age or usage. Identical components may degrade differently because of loading, environmental stress, installation quality and operating history. Preventive regimes can therefore produce unnecessary maintenance, premature replacement and avoidable shutdowns. Experience from Nigeria's Egbin Thermal Power Plant shows that preventive programmes require disciplined scheduling, trained personnel, adequate spares and reliable documentation (Oyedepo & Fagbenle, 2011).
The limitations of time-based intervention encouraged condition-based maintenance, in which action is triggered by evidence of deterioration. Measurements including vibration, temperature, oil quality, acoustic emissions, insulation condition and electrical signatures allow operators to identify abnormalities before loss of function. This approach reduces intrusive inspection and directs resources towards assets displaying measurable degradation. Its effectiveness depends on sensor accuracy, suitable alarm thresholds and the ability to distinguish operational variability from fault development. The integration of machinery diagnostics and prognostics provided the basis for converting condition information into defensible maintenance actions (Jardine, Lin & Banjevic, 2006).

Digital communication and networked information systems extended condition-based maintenance into e-maintenance. Remote sensors, supervisory platforms, computerised maintenance-management systems and shared databases enabled information to be collected, transmitted and analysed across dispersed facilities. Energy operators could combine live measurements with work orders, failure histories, asset criticality and resource availability. This improved coordination while supporting remote expertise and faster responses to emerging defects (Muller, Crespo Marquez &Iung, 2008).

Prognostics shifted the central question from whether an asset was faulty to how its condition would evolve and when it might become unable to perform its required function. Statistical, physical and data-driven models were used to estimate failure probability and remaining useful life. These estimates allowed interventions to be scheduled before critical deterioration while avoiding premature maintenance. Prognostic capability therefore transformed condition-based maintenance from a diagnostic activity into a forward-looking planning process (Peng, Dong & Zuo, 2010).

Prognostics and health-management frameworks subsequently integrated sensing, feature extraction, fault diagnosis, health assessment, degradation forecasting and decision support. For power and energy infrastructure, this architecture enables machine-level evidence to be evaluated alongside network redundancy, demand conditions, safety consequences and maintenance windows. Interventions can then be prioritised according to system importance rather than technical condition alone, aligning maintenance activity with reliability objectives (Lee et al., 2014).

Machine learning accelerated this transition by identifying nonlinear and multivariate patterns hidden from conventional thresholds. Classification algorithms can learn from operational histories to distinguish normal behaviour from developing failure modes and generate warnings across prediction horizons. Nevertheless, performance depends on representative training data, robust feature selection and careful management of false alarms. An inaccurate predictive system may overlook a dangerous defect or produce excessive recommendations, undermining confidence in automated decision support (Susto et al., 2015).

The transition is especially demanding in developing industrial contexts. Evidence from Kenya shows that maintenance maturity may be constrained by weak strategy formulation, limited performance measurement, inadequate training and uneven technology adoption. Predictive asset management cannot therefore be achieved through sensor installation alone. It requires governance, workforce development, data discipline and investment models suited to ageing infrastructure and constrained maintenance budgets (Muchiri et al., 2017).

Mature predictive asset management combines condition assessment, degradation modelling, remaining-useful-life estimation and risk-based optimisation. Its objective is not merely to forecast failure, but to determine the intervention timing and scope that best preserve safety, availability and lifecycle value under uncertainty. Reliable outcomes depend on the analytical chain, from data acquisition and health-indicator construction to degradation-stage recognition and prognostic interpretation. This progression represents a shift from repairing failed assets or servicing them at fixed intervals towards anticipating deterioration and coordinating maintenance with operational priorities (Lei et al., 2018).

1.3 Role of Condition Monitoring in Infrastructure Reliability and Operational Resilience

Condition monitoring occupies a central position in the reliability management of power and energy infrastructure because it converts asset behaviour into evidence for decision-making. Measurements of vibration, temperature, current, insulation quality, oil chemistry and acoustic response allow deterioration to be distinguished from normal variability. For motors and generators, combining electrical and mechanical signatures supports recognition of bearing defects, winding faults, eccentricity and rotor abnormalities before these conditions interrupt service (Nandi, Toliyat& Li, 2005).

Reliability improvement arises when monitored degradation is linked to failure mechanisms, alarm thresholds and maintenance priorities. Rotating electrical machines may remain functional while defects progress beneath conventional protection limits; therefore, online surveillance provides a wider intervention window than trip-based protection. Effective monitoring should employ measurements required to identify credible failure modes, while integrating complementary signals where individual indicators are ambiguous (Tavner, 2008).

At the infrastructure level, condition information supports availability, maintainability and risk-based resource allocation. Evidence from Nigeria's Afam thermal power station demonstrates that maintenance decisions become more defensible when equipment condition is considered alongside reliability, repairability, operational consequence and lifecycle cost. Such integration enables resources to be directed towards assets whose deterioration presents the greatest threat to generation continuity (Eti, Ogaji& Probert, 2007).

Condition monitoring also strengthens resilience by improving preparedness before disruptions and accelerating response when abnormalities occur. In South African research on liquid-immersed transformers, networked sensing was designed to detect developing faults early and preserve insulation through improved cooling control. Continuous visibility of transformer health can reduce catastrophic failures, support controlled intervention and maintain operational capacity during periods of elevated system stress (Van der Walt &Doorsamy, 2018).

Renewable-energy infrastructure presents additional monitoring requirements because loading, weather exposure and remote siting produce variable degradation patterns. Wind-turbine surveillance combines vibration, lubricant, electrical, temperature and supervisory-control data to identify faults across gearboxes, bearings, generators, blades and converters. Multi-source monitoring therefore protects reliability while enabling operators to plan maintenance around accessibility, wind conditions and production requirements (Tchakoua et al., 2014).

Operational resilience ultimately depends on converting condition data into accurate diagnosis and sufficiently early action. Advanced wind-turbine monitoring illustrates the value of signal processing, model-based analysis and data-driven classification for detecting weak fault signatures before substantial performance loss. However, resilience gains require reliable sensors, validated models, competent interpretation and communication between monitoring, operations and maintenance teams, ensuring that warnings lead to proportionate interventions rather than unmanaged alarms or delayed decisions (Hossain, Abu-Siada&Muyeen, 2018).

1.4 Aim, Objectives, Scope, and Organisation of the Review

This review aims to critically examine the evolution, application, and strategic significance of predictive maintenance and condition monitoring within critical power and energy infrastructure. It seeks to clarify how contemporary maintenance philosophies contribute to asset reliability, operational continuity, safety, cost control, and resilience across increasingly complex and interconnected energy systems.

The objectives are to evaluate the conceptual foundations of reactive, preventive, condition-based, predictive, and prescriptive maintenance; assess the principal sensing, diagnostic, prognostic, and data-analytics techniques used to identify degradation; examine their application across generation, transmission, distribution, renewable-energy, and storage assets; and analyse the organisational, economic, cybersecurity, workforce, and regulatory factors that influence successful implementation. The review also aims to identify persistent methodological limitations, including inadequate failure data, model uncertainty, interoperability constraints, and difficulties in transferring diagnostic models across different operating environments.

The scope encompasses conventional power plants, substations, transformers, rotating machinery, transmission lines, wind turbines, photovoltaic systems, inverters, microgrids, and battery-energy-storage facilities. Particular attention is given to the integration of sensor networks, industrial Internet of Things platforms, machine learning, digital twins, and remaining-useful-life estimation within asset-management decision processes.

The paper is organised progressively. It begins with the reliability context and maintenance evolution, followed by condition-monitoring technologies and analytical methods. It then examines sector-specific applications, implementation barriers, economic value, cybersecurity concerns, and emerging research priorities before synthesising the principal findings and practical recommendations. This structure supports a balanced assessment of technological capability, implementation readiness, and long-term infrastructure value across operating contexts.

II. FOUNDATIONS OF PREDICTIVE MAINTENANCE AND CONDITION-BASED ASSET MANAGEMENT

2.1 Maintenance Strategies, Terminology, and Decision-Making Frameworks

Maintenance strategy denotes the governing logic through which an organisation determines whether, when and how intervention should be undertaken on an asset. In critical power and energy infrastructure, terminology must be applied precisely because approaches embody different decision triggers, information requirements and risk implications. Reactive maintenance restores function after failure; preventive maintenance intervenes according to predetermined intervals; condition-based maintenance responds to observed deterioration; predictive maintenance forecasts future condition; and prescriptive maintenance recommends an optimised action. Strategy selection should reflect asset function, criticality, failure behaviour, redundancy and operational consequence.

Reactive maintenance remains rational for inexpensive, non-critical and replaceable items where failure consequences are negligible. It becomes unsuitable when breakdown can interrupt generation, destabilise networks, damage adjacent equipment or compromise safety. Nigerian industrial evidence demonstrates that excessive dependence on breakdown maintenance produces avoidable downtime, energy losses and weak equipment performance, while structured preventive programmes require failure analysis and root-cause investigation (Eti, Ogaji& Probert, 2006). The decision is not whether reactive work can be eliminated, but where its use is defensible.

Time-based preventive maintenance uses calendar periods, operating hours, starts or duty cycles as intervention thresholds. It offers predictable labour and spare-parts planning, yet may cause premature replacement when age is a poor proxy for condition. Condition-based maintenance instead evaluates measured health indicators and initiates work when deterioration reaches a defined threshold. The distinction lies in whether decisions are governed by elapsed exposure or observed asset state, with each method requiring different inspection, modelling and information capabilities (Ahmad & Kamaruddin, 2012).

Predictive maintenance extends condition-based practice by estimating degradation trajectories, failure probability or remaining useful life. Its value is realised only when forecasts improve intervention timing and reduce risk-adjusted cost. Maintenance should therefore be treated as a contributor to productivity and profitability, not merely as an engineering expense, because availability, quality losses, energy use and maintenance expenditure interact within lifecycle performance (Alsyouf, 2007). Prescriptive maintenance advances further by comparing feasible responses and recommending the action that best satisfies reliability, cost, safety and operational constraints.

Reliability-centred maintenance provides a functional decision framework rather than a single maintenance type. It identifies required functions, functional failures, failure modes, consequences and technically effective tasks before assigning corrective, scheduled, condition-directed or redesign actions. Total productive maintenance complements this logic through operator involvement, autonomous care, defect elimination and organisational ownership of equipment effectiveness, linking maintenance strategy to human capability and continuous improvement (Ahuja & Khamba, 2008).

Strategy selection is intrinsically multi-criteria. Cost alone cannot represent consequences involving personnel safety, environmental damage, regulatory exposure, service interruption and cascading system effects. The Analytic Hierarchy Process enables decision makers to structure these criteria, weight their relative importance and compare alternative policies transparently, as demonstrated in maintenance selection for process infrastructure (Bevilacqua & Braglia, 2000). Fuzzy extensions are useful where expert judgements are linguistic, uncertain or incomplete and where a portfolio of strategies is preferable to a uniform policy (Wang, Chu & Wu, 2007).

Risk-based maintenance prioritises assets through the combined assessment of failure likelihood and consequence. A quantitative framework integrates risk estimation, risk evaluation and maintenance planning, allowing resources to be concentrated where risk reduction is greatest (Khan &Haddara, 2003). Hybrid approaches can combine risk assessment with AHP and goal programming to reconcile safety and cost objectives under resource constraints (Arunraj & Maiti, 2010).

Decision quality must be evaluated through indicators aligned with corporate and operational objectives. Measures of availability, reliability, planned-work compliance, maintenance cost, safety, downtime and schedule effectiveness should reveal whether the selected strategy produces intended outcomes. A structured performance framework prevents local optimisation and links maintenance activities to production capability and organisational value (Muchiri et al., 2011).

Table 1. Comparative decision framework for selecting maintenance strategies in critical power and energy infrastructure

Maintenance strategy or framework	Primary decision trigger	Information requirement	Most appropriate application	Principal limitation
Reactive maintenance	Functional failure	Minimal condition information	Low-cost, redundant and non-critical components	Unplanned downtime and potentially severe secondary consequences

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Time-based preventive maintenance	Calendar interval, operating hours or duty cycles	Age, usage and maintenance history	Assets with predictable age-related deterioration	Premature replacement and unnecessary planned outages
Condition-based maintenance	Measured deterioration threshold	Reliable sensors, inspections and diagnostic limits	Assets with observable degradation mechanisms	Sensor uncertainty and ambiguous condition indicators
Predictive maintenance	Forecast failure probability or remaining useful life	Historical and real-time condition data, prognostic models	High-value assets with progressive degradation	Data scarcity, model error and false alarms
Prescriptive maintenance	Optimised response to predicted condition	Prognostic results, costs, constraints and operational priorities	Complex assets with several feasible intervention choices	High analytical and integration requirements
Reliability-centred maintenance	Functional consequences and failure modes	Asset functions, failure analysis and consequence assessment	Systems containing assets of different criticalities	Resource-intensive analysis and implementation
Total productive maintenance	Equipment-effectiveness losses and operator observations	Production, quality, maintenance and workforce information	Facilities requiring operator participation and continuous improvement	Strong dependence on organisational culture
Risk-based maintenance	Combined failure likelihood and consequence	Reliability, safety, environmental and financial risk data	Safety-critical and high-consequence infrastructure	Sensitive to uncertain probability and consequence estimates

2.2 Asset Degradation, Failure Mechanisms, and Health Indicators

Asset degradation in critical power and energy infrastructure is a progressive loss of functional capability caused by interacting electrical, thermal, mechanical, chemical and environmental stresses. Failure rarely originates from a single mechanism; loading history, design margins, defects, contamination and maintenance quality combine to accelerate deterioration. In oil-filled transformers, elevated temperature, moisture and oxygen promote cellulose depolymerisation and oil oxidation, weakening dielectric and mechanical integrity while increasing susceptibility to partial discharge and breakdown (Saha, 2003).

Transformer oil condition provides a health signal because acidity reflects oxidation and ageing by-products. Excessive acid content encourages sludge formation, reduces heat transfer and increases internal temperature, thereby accelerating insulation decay. Evidence from a Nigerian distribution network demonstrates that acidity testing can differentiate serviceable oils from units requiring intervention and reveal conditions associated with overheating and fire risk (Adekoya &Adejumobi, 2017).

Because indicators represent different degradation timescales, health assessment should combine short-term fault evidence with long-term ageing measures. A South African transformer framework integrates dissolved-gas analysis, oil quality, paper degradation, ancillary-component condition and network exposure into plant health and risk indices, enabling assets to be ranked for inspection, maintenance or replacement (Singh & Swanson, 2018).

Power-electronic converters experience distinct failure processes driven by thermal cycling, electrical overstress and material fatigue. Repeated junction-temperature variation can degrade semiconductor dies, bond wires, solder layers and capacitors. Relevant indicators include on-state voltage, thermal resistance, leakage current and capacitor equivalent series

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resistance, although monitoring methods must remain sensitive without disturbing converter operation (Yang et al., 2010).

Wind turbines exhibit coupled structural, mechanical and electrical degradation. Gear wear, bearing fatigue, lubrication loss, blade cracking, generator faults and converter deterioration generate changes in vibration, temperature, acoustic emission, lubricant debris and electrical output. Effective diagnosis requires component-specific indicators interpreted against variable speed, wind loading and environmental conditions (Qiao & Lu, 2015).

Battery-energy-storage assets degrade through capacity loss, resistance growth and electrochemical side reactions influenced by temperature, charge rate, depth of discharge and cycling history. State of health, available capacity, internal resistance and remaining useful life provide complementary indicators for distinguishing temporary operating effects from irreversible ageing (Zhang & Lee, 2011).

Health indicators must be interpretable, repeatable and sensitive to incipient deterioration. Physicochemical transformer diagnostics, including dissolved gases, moisture, acidity, interfacial tension and furan compounds, are most effective when trends are evaluated collectively rather than as isolated thresholds, permitting degradation severity and failure proximity to be assessed with greater confidence (N'cho et al., 2016).

III. CONDITION-MONITORING TECHNOLOGIES AND INFRASTRUCTURE DATA ACQUISITION

3.1 Sensor-Based Monitoring, Inspection, and Diagnostic Technologies

Sensor-based monitoring, inspection and diagnostic technologies provide the observational foundation of predictive maintenance in critical power and energy infrastructure. Their principal function is to convert physical, electrical, chemical and operational behaviour into measurable evidence of degradation. A dependable monitoring architecture therefore combines appropriate transducers, disciplined data acquisition, signal conditioning, diagnostic interpretation and maintenance response. Technology selection must follow credible failure modes rather than sensor availability, because an instrument that measures an accessible parameter may still offer little sensitivity to the defect that threatens service continuity.

Vibration monitoring is particularly valuable for turbines, generators, pumps, compressors, gearboxes and wind-turbine drivetrains. Accelerometers and velocity or displacement transducers reveal imbalance, misalignment, looseness, bearing damage and gear defects through changes in amplitude, phase and spectral content. Low-cost microelectromechanical accelerometers can also support blade monitoring where conventional piezoelectric devices are too expensive or intrusive; experimental work involving a Nigerian researcher demonstrated their integration for identifying changes in wind-turbine blade dynamics (Esu et al., 2014). Nevertheless, variable speed, structural resonance and environmental excitation require operating-condition normalisation before an alarm is interpreted as damage.

Thermal inspection supplies complementary evidence because abnormal resistance, friction, cooling failure and overload commonly appear as localised temperature rise. Infrared thermography permits non-contact examination of switchgear, busbars, cable joints, photovoltaic modules, bearings and rotating equipment while assets remain energised. Its diagnostic value depends on emissivity, viewing angle, atmospheric attenuation, reflected radiation and load at the time of inspection; consequently, thermal images should be compared with similar components and operating states rather than judged by temperature alone (Bagavathiappan et al., 2013).

Electrical insulation demands techniques capable of detecting incipient dielectric deterioration. Partial-discharge monitoring uses electrical, acoustic, optical or ultra-high-frequency sensors to capture local discharge activity in transformers, generators, cables and gas-insulated equipment. Pulse magnitude, repetition rate, phase-resolved patterns and source location can indicate voids, surface tracking or insulation contamination, although electromagnetic interference and multiple simultaneous sources complicate interpretation (Bartnikas, 2002).

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Transformer diagnostics additionally combine dissolved-gas analysis, moisture, oil quality, winding resistance, dielectric response and frequency-response analysis. This multi-parameter approach is necessary because no single test represents the condition of windings, insulation, bushings, tap changers and cooling systems simultaneously (Abu-Elanien& Salama, 2007).

Renewable-energy assets require similarly integrated surveillance. Wind-turbine monitoring combines vibration, acoustic emission, oil-debris analysis, generator-current signatures, strain measurement and supervisory control and data acquisition records. Each technique possesses different sensitivity, coverage and installation cost; their combined use improves fault localisation across blades, bearings, gearboxes, generators and power converters (García Márquez et al., 2012). Existing SCADA measurements offer a comparatively economical diagnostic layer because deviations among power, wind speed, temperatures and control variables can expose abnormal performance without extensive additional instrumentation (Yang, Court & Jiang, 2013).

Inspection technologies also reduce human exposure to hazardous or inaccessible infrastructure. Mobile robots equipped with cameras, thermal imagers, electromagnetic sensors and manipulators can travel along distribution lines to inspect conductors, fittings and insulators. Their deployment improves measurement repeatability and access, but practical performance depends on obstacle negotiation, mechanical stability, energy supply, communications and compatibility with live-line environments (Katrasnik, Pernuš& Likar, 2010).

At system scale, phasor measurement units and frequency disturbance recorders provide time-synchronised observations of voltage, current, phase angle and frequency across wide geographic areas. Egyptian experience with wide-area monitoring illustrates how distributed sensing and reliable communications can support disturbance recognition and situational awareness on high-voltage networks (Eissa et al., 2015). Diagnostic effectiveness ultimately depends on sensor calibration, placement, sampling rate, synchronisation, noise control and data validation. Multi-sensor corroboration is preferable where fault signatures overlap, while inspection intervals and alarm thresholds should reflect asset criticality, degradation speed and consequence of missed detection. Periodic inspection and continuous monitoring should not be treated as competing practices: online sensors provide temporal continuity, whereas targeted offline tests and visual examination offer diagnostic depth, verification, and access to variables that cannot be measured economically during normal operation. These requirements ensure that monitoring technology produces actionable asset-health information rather than an unmanaged accumulation of measurements.

Table 2. Comparative application of sensor-based monitoring and diagnostic technologies in critical power and energy infrastructure

Monitoring or inspection technology	Principal measurements	Applicable infrastructure assets	Detectable conditions or faults	Principal strength	Major constraint
Vibration monitoring	Acceleration, velocity, displacement and frequency spectra	Turbines, generators, motors, pumps, bearings and gearboxes	Imbalance, misalignment, looseness, bearing wear and gear damage	Sensitive to developing mechanical defects	Results are affected by speed, load and structural resonance
Infrared thermography	Surface-temperature distribution and thermal gradients	Switchgear, busbars, cable joints, transformers,	Overheating, loose connections, overload,	Non-contact inspection of energised equipment	Accuracy depends on emissivity, loading and

		photovoltaic modules and bearings	cooling failure and abnormal friction		environmental conditions
Partial-discharge monitoring	Electrical pulses, acoustic emissions, optical signals and UHF activity	Transformers, generators, cables and gas-insulated switchgear	Voids, insulation contamination, surface tracking and dielectric deterioration	Detects incipient insulation defects	Noise and multiple discharge sources complicate localisation
Transformer oil and gas analysis	Dissolved gases, moisture, acidity, dielectric strength and contaminants	Oil-immersed power and distribution transformers	Thermal faults, arcing, partial discharge and insulation ageing	Provides evidence of internal transformer condition	Sampling, laboratory delay and interpretation uncertainty
SCADA-based monitoring	Power, temperature, wind speed, pressure, current and control variables	Wind turbines, power plants, substations and renewable-energy installations	Performance deviation, component overheating and control-system abnormalities	Uses existing operational measurements	Low sampling rates may conceal rapidly developing faults
Robotic and visual inspection	Optical images, thermal images, electromagnetic readings and geometric measurements	Transmission lines, distribution conductors, towers and insulators	Corrosion, cracked fittings, conductor damage, contamination and thermal anomalies	Improves access and reduces human exposure	Mobility, communications and obstacle-crossing limitations
Wide-area synchrophasor monitoring	Voltage, current, frequency and phase angle	Transmission networks and interconnected power systems	Oscillations, instability, generator trips and regional disturbances	Provides time-synchronised system-level awareness	Requires reliable timing, communications and data coordination
Multi-sensor diagnostic systems	Combined mechanical, electrical, chemical and operational indicators	High-value or safety-critical energy assets	Overlapping and interacting degradation mechanisms	Improves diagnostic confidence through corroboration	Greater cost, integration complexity and data-management burden

3.2 Data Integration, Communication, Storage, and Quality Management

Data integration is the connective process through which measurements from sensors, supervisory control and data acquisition platforms, smart meters, protection systems, maintenance records and environmental services are transformed into a coherent representation of asset condition. In critical power and energy infrastructure, integration must preserve time, location, equipment identity, units and operating context; otherwise, accurate measurements may produce misleading diagnostic patterns. Data-quality management therefore begins with explicit definitions of accuracy, completeness, consistency, timeliness and accessibility, supported by repeatable assessment and improvement procedures (Batini et al., 2009).

Communication architecture determines whether condition information reaches analytical and operational users within the required decision window. Smart-grid applications impose different requirements: protection messages demand low latency and high availability, whereas meter readings and maintenance files tolerate delay but require dependable delivery and scalability. Fibre optics, power-line communication, cellular systems, wireless sensor networks and radio technologies should consequently be selected according to bandwidth, range, interference, security and criticality rather than adopted uniformly (Gungor et al., 2011).

Interoperability is equally important because energy assets are commonly supplied by different vendors and installed across several technological generations. Communication networks must support heterogeneous devices while maintaining common semantics and service quality. Layered architectures, standard interfaces and protocol gateways can connect field equipment, substations, control centres and enterprise systems, but excessive protocol conversion introduces delay, configuration errors and opportunities for data loss. A scalable infrastructure must therefore reconcile coverage, latency, reliability and cybersecurity across wide-area and local operational domains (Yan et al., 2013).

Storage design must accommodate the volume, velocity and variety created by continuous monitoring. Waveforms, alarms, inspection images, maintenance narratives and operational time series possess different retention and processing requirements. Distributed databases, data lakes and cloud platforms can provide scalable capacity, while edge computing permits filtering, compression and preliminary diagnosis near the asset. However, aggregation policies must retain sufficient signal detail for later fault investigation, because aggressive compression or premature summarisation may remove weak degradation signatures (Tu et al., 2017).

Analytical value depends on preprocessing. Time stamps should be synchronised; duplicated records removed; missing observations identified; sensor drift corrected; and anomalous values distinguished from genuine fault evidence. Streaming and historical datasets must also be linked so that models can compare present behaviour with seasonal, loading and maintenance contexts. Big-data architectures support descriptive, predictive and prescriptive analysis, but reliable decisions require transparent workflows from collection and cleansing to feature extraction, modelling and visualisation (Zhang, Huang & Bompard, 2018).

The Nigerian operating environment illustrates why architecture must reflect infrastructure realities. Automated distribution systems require digital monitors, communication links, supervisory interfaces and remote-control capability, yet their effectiveness depends on dependable telecommunications, equipment compatibility and trained operators. Where connectivity is intermittent, local buffering, redundant communication paths and controlled data reconciliation are necessary to prevent gaps from being mistaken for healthy operation or equipment inactivity (Olagoke, Dahiru & Salawu, 2018).

Data governance must finally protect confidentiality, integrity, availability and accountability without obstructing time-critical operations. Authentication, encryption, access control, secure updating, audit trails and network segmentation should extend from field sensors to central repositories. Cyber compromise can alter measurements, suppress alarms or corrupt historical records, thereby undermining predictive models and maintenance priorities. Security and quality management must therefore be designed together, with provenance, validation rules, retention schedules and recovery arrangements ensuring that asset-health information remains trustworthy throughout its lifecycle (El Mrabet et al., 2018).

IV. FAULT DIAGNOSIS, PROGNOSTICS, AND INTELLIGENT MAINTENANCE ANALYTICS

4.1 Signal Processing, Statistical Analysis, and Physics-Based Diagnostic Methods

Signal processing transforms raw measurements into diagnostic evidence by separating fault-related behaviour from operational noise and sensor artefacts. In power and energy infrastructure, time-domain statistics including mean, root-mean-square amplitude, crest factor, variance and kurtosis indicate changing vibration, current or acoustic behaviour. Interpretation should remain conditional on load, speed and operating regime because a statistically unusual signal is not necessarily a defect. Spectral kurtosis is valuable for locating transient, non-stationary energy within frequency bands, improving the visibility of weak impulsive faults concealed by broadband noise (Antoni, 2006).

Frequency-domain analysis uses Fourier spectra, order tracking and harmonic relationships to associate responses with rotating speed, electrical frequency or component geometry. Bearing and gearbox faults generate repetitive impacts that modulate structural resonances; envelope analysis can demodulate these responses and reveal characteristic defect frequencies. Effective diagnosis requires sampling, anti-aliasing, windowing and sensor placement, since leakage, resonance and transmission-path effects can distort spectra. Bearing diagnostics therefore combine spectral interpretation with knowledge of machine construction and operating conditions rather than treating peaks as definitive evidence (Randall & Antoni, 2011).

Time-frequency techniques are required where assets operate under changing speed, wind, load or switching conditions. Short-time Fourier transforms, wavelets and decompositions represent how frequency content evolves, enabling transient faults and regime changes to be localised. Wind-turbine diagnosis illustrates this requirement because aerodynamic variability, drivetrain dynamics and control actions produce non-stationary signals; interpretation draws upon vibration, oil, temperature, electrical and supervisory data rather than one channel alone (Hameed et al., 2009).

Statistical diagnostic methods convert extracted features into evidence about health states. Threshold models, probability distributions, regression, clustering and classification can distinguish normal variability from degradation when training and validation data represent credible operating ranges. Transformer dissolved-gas analysis demonstrates how gas features can support nonlinear classification of partial discharge, arcing and thermal faults, although confidence remains sensitive to sample quality, class boundaries and limited fault examples (Bacha, Souahlia&Gossa, 2012).

Physics-based diagnosis compares observed behaviour with predictions derived from conservation laws, thermal networks, electrical circuits, mechanical dynamics or degradation equations. Faults are detected through residuals between measured and modelled outputs, while residual structure assists isolation. This approach offers interpretability and can operate with limited failure data, but reliability depends on parameter accuracy and treatment of uncertainty, disturbances and model mismatch (Isermann, 2005).

Mechanism-based models link monitored loads to fatigue, creep, wear, corrosion or thermal ageing. They permit accumulated damage and service-life consumption to be estimated under actual duty rather than nominal schedules. For gas-turbine and energy assets, load-based maintenance can distinguish severe exposure from harmless utilisation, although uncertain material properties and boundary conditions must be propagated into decisions (Tinga, 2010).

Practical implementation requires analytical sophistication proportional to infrastructure capability. Nigerian and South African research integrating vibration and temperature sensors shows how local processing, threshold logic and remote communication can establish economical diagnostic visibility for conventional machines. Such systems are valuable when calibration, baseline development, alarm verification and maintenance feedback are institutionalised, ensuring that processed indicators lead to defensible intervention rather than technical displays (Adeyeri, Mpofu & Kareem, 2016).

4.2 Machine Learning, Deep Learning, Digital Twins, and Remaining Useful Life Estimation

Machine learning has expanded predictive asset management by enabling condition data to be converted into classifications, anomaly scores, degradation estimates and maintenance priorities. Supervised algorithms learn relationships between labelled observations and known health states. Their practical value depends on representative fault examples, feature engineering and validation under operating conditions different from those used during training. In high-voltage infrastructure, support vector regression has demonstrated how radio-frequency measurements can be mapped to partial-discharge locations, providing a Nigerian-supported contribution to substation diagnostics (Iorkyase et al., 2018).

Unsupervised and semi-supervised approaches are particularly relevant where failures are rare and historical records represent normal operation. Clustering, autoencoders and novelty-detection models establish behavioural baselines and identify deviations without requiring complete fault labels. However, an anomaly does not automatically identify a failure mechanism, and models may respond to changes in load, weather, control settings or sensor calibration. Predictive systems therefore require contextual variables, engineering review and feedback from completed maintenance work to prevent transitions from being treated as incipient defects.

Deep learning reduces dependence on manually designed features by learning hierarchical representations from vibration, current, temperature, acoustic and operational time series. Convolutional networks are effective in extracting local patterns, while recurrent and long short-term memory architectures represent temporal dependencies and degradation histories. Their advantages become significant when datasets are large, heterogeneous and labelled; nevertheless, computational burden, opaque decision logic and sensitivity to domain shift restrict direct deployment in safety-critical energy systems (Khan & Yairi, 2018).

Remaining useful life estimation translates condition evidence into the expected time or usage before an asset reaches a defined failure threshold. Statistical approaches model degradation and uncertainty through lifetime distributions, stochastic processes, filtering and Bayesian updating. Their outputs should be expressed as probability distributions or confidence intervals rather than single deterministic dates because loading, environmental exposure and measurement uncertainty alter degradation trajectories. No universally superior model exists; suitability depends on available histories, failure definitions and the behaviour of the monitored asset (Si et al., 2011).

Hybrid statistical and machine-learning methods can improve prognostic stability. A bearing framework combining a Weibull failure representation with an artificial neural network illustrates how degradation indicators and lifetime behaviour may be fused to estimate residual life. This African-European contribution matters within energy infrastructure because bearings underpin turbines, generators, pumps and wind drivetrains, although transfer between machines requires comparable loading, sensor placement and failure progression (Ben Ali et al., 2015).

Deep convolutional prognostics permit normalised multichannel measurements to be processed directly, allowing temporal features to emerge during training. Such methods can estimate asset life without handcrafted signal descriptors, but their accuracy must be tested against unseen units, alternative duty cycles and realistic prediction horizons. Evaluation should penalise late warnings more strongly where delayed intervention could cause severe service or safety consequences (Li, Ding & Sun, 2018). Deep architectures applied to rotating components similarly demonstrate the value of representation learning for extracting health information from condition-monitoring datasets while highlighting the need for robust training populations and transparent uncertainty treatment (Deutsch & He, 2018).

Digital twins extend prognostics by maintaining a dynamic virtual representation of a physical asset. Sensor observations update the model, while simulations examine current condition, alternative operating scenarios and maintenance actions. A functional twin requires more than a static three-dimensional model: it needs traceable asset identity, bidirectional data exchange, calibrated behavioural models and defined update frequencies. Near-real-time coupling can reduce the delay between physical change and analytical interpretation, supporting condition-aware operation and intervention planning (Uhlemann, Lehmann &Steinhilper, 2017).

For critical power infrastructure, digital twins can combine engineering models, operational histories, environmental conditions and learned degradation patterns across the asset lifecycle. This convergence supports virtual testing, fault reproduction, performance forecasting and risk-informed maintenance scheduling. Yet trustworthy deployment requires model verification, cybersecurity, semantic interoperability and continuous reconciliation between virtual predictions and physical observations. Digital-twin value therefore arises from disciplined

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integration of physical knowledge and data analytics rather than visualisation alone (Tao et al., 2018).

V. APPLICATIONS ACROSS CRITICAL POWER AND ENERGY ASSETS

5.1 Conventional Generation Plants and Electromechanical Equipment

Conventional generation plants remain dominated by tightly coupled thermal, hydraulic, electrical and mechanical subsystems whose reliability depends on the condition of a small number of high-criticality assets. Gas and steam turbines, generators, boilers, pumps, compressors, motors, condensers and cooling systems operate under thermal loading, pressure variation, vibration, contamination and transients. Predictive maintenance must therefore combine equipment-level monitoring with plant-performance assessment so that deteriorating efficiency, abnormal behaviour and failure mechanisms are distinguished from changes in demand.

Gas turbines require evaluation of compressor efficiency, exhaust-temperature spread, fuel flow, pressure ratio, shaft speed and vibration. Fouling, erosion, seal leakage, blade damage and combustion abnormalities can appear as subtle departures from corrected performance baselines. Performance-based health monitoring combines thermodynamic models, trend analysis and diagnostic algorithms to isolate component deterioration and estimate its operational significance, allowing maintenance to be planned before heat-rate penalties or mechanical damage become unacceptable (Tahan et al., 2017).

Evidence from Nigerian gas-turbine stations demonstrates why asset-level diagnostics must be interpreted alongside plant indices. Low capacity factors, energy shortfalls and poor availability can reflect equipment failures, maintenance delays, fuel constraints and system-level limitations. Tracking reliability, utilisation and availability provides a contextual layer for determining whether declining output arises from internal degradation or external restrictions, thereby preventing maintenance teams from treating every production deficit as a machine fault (Oyedepo, Fagbenle &Adefila, 2015).

Steam and hydro turbines are exposed to fatigue, erosion, cavitation, corrosion, thermal distortion and shaft-line instability. Hydro units additionally encounter sediment abrasion, pressure pulsation and water-hammer effects that damage runners, guide vanes, seals and bearings. Monitoring vibration, shaft displacement, acoustic emission, temperature and hydraulic performance supports early recognition of these mechanisms, but diagnostic interpretation must account for operating head, load, flow regime and transient duty (Dorji & Ghomashchi, 2014).

Large generators require coordinated surveillance of electromagnetic, thermal and mechanical condition. Partial-discharge activity, stator temperature, air-gap behaviour, rotor flux, cooling performance and bearing vibration provide complementary evidence of winding insulation deterioration, eccentricity, loose components and rotor defects. Partial-discharge measurements are valuable for identifying progressive insulation defects, although noise separation, pattern recognition and long-term trending are essential before intervention is justified (Stone, 2005).

Auxiliary induction motors drive pumps, fans, mills and compressors whose loss can constrain or trip an entire generating unit. Smart wireless sensing combined with motor-current signature analysis can identify stator, rotor, bearing and supply-related abnormalities while supporting remote surveillance of dispersed equipment. Its non-intrusive character is advantageous where permanent vibration systems are impractical, although variable loading, electromagnetic interference and communication reliability must be controlled to prevent false classifications (Guesmi et al., 2015).

Pumps should be assessed through vibration, pressure, flow, power consumption and suction conditions because cavitation, blockage, impeller damage, misalignment and bearing wear often generate overlapping symptoms. Classification methods based on vibration features can distinguish several operating states, yet reliable application requires representative baselines and controlled consideration of speed, hydraulic duty and mounting condition. Diagnostic outputs should be linked to process consequences, since a small efficiency loss may be economically significant in continuously operated feedwater or

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cooling-water services (Sakthivel, Sugumaran &Babudevasenapati, 2010).

Acoustic-emission monitoring extends diagnostic sensitivity to crack initiation, friction, impacts and lubricant-film breakdown in bearings, gearboxes, pumps and turbine structures. High-frequency stress waves may reveal damage earlier than conventional vibration measurements, particularly in slowly rotating machinery. However, attenuation, sensor coupling and background process noise complicate localisation, making acoustic emission most effective when combined with vibration, temperature and lubricant evidence (Mba & Rao, 2006).

Plant-wide implementation also requires dependable monitoring of instrumentation and protection channels. Nuclear-generation experience shows that online validation can identify sensor drift, response degradation and calibration problems without waiting for scheduled outages. Redundant measurements, analytical models and process relationships can test whether channels remain trustworthy, thereby protecting both diagnostic accuracy and safe operation. Similar principles apply across conventional plants, where unreliable sensors can conceal genuine deterioration or create false maintenance demands under demanding plant operating conditions (Hashemian, 2011).

Table 3. Asset-specific condition-monitoring priorities in conventional generation plants

Plant asset or system	Dominant degradation and failure mechanisms	Principal monitoring variables and technologies	Predictive maintenance decision supported
Gas turbine	Compressor fouling, blade erosion, seal leakage, combustion instability and thermal fatigue	Exhaust-temperature spread, pressure ratio, fuel flow, vibration, shaft speed and corrected performance	Compressor washing, combustion tuning, borescope inspection or hot-section maintenance
Steam turbine	Rotor imbalance, blade fatigue, seal wear, thermal distortion and bearing deterioration	Shaft vibration, axial displacement, differential expansion, steam temperature, pressure and bearing temperature	Load restriction, balancing, alignment correction, bearing inspection or planned overhaul
Hydro turbine	Cavitation, sediment erosion, runner cracking, pressure pulsation and seal deterioration	Vibration, acoustic emission, hydraulic pressure, efficiency, shaft displacement and water quality	Runner inspection, cavitation mitigation, seal replacement or operating-point adjustment
Generator	Stator insulation ageing, partial discharge, rotor eccentricity, cooling failure and loose windings	Partial-discharge activity, stator temperature, rotor flux, air-gap measurements and bearing vibration	Insulation testing, rewinding assessment, cooling-system maintenance or rotor inspection
Boiler and pressure system	Tube creep, corrosion, erosion, overheating, scaling and leakage	Tube temperature, pressure, chemistry, wall thickness, acoustic leak detection and thermal imaging	Tube replacement, chemical cleaning, water-treatment correction or outage inspection
Centrifugal pump	Cavitation, impeller damage, blockage, misalignment, seal leakage and bearing wear	Vibration, suction and discharge pressure, flow, motor power, temperature and acoustic signals	Impeller inspection, alignment, seal replacement, bearing maintenance or hydraulic correction
Auxiliary induction motor	Broken rotor bars, winding faults, eccentricity, bearing damage and supply imbalance	Motor-current signatures, vibration, temperature, voltage balance and wireless sensor data	Bearing replacement, winding inspection, power-quality correction or motor change-out

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Condenser and heat exchanger	Fouling, scaling, corrosion, tube leakage and declining heat-transfer performance	Temperature approach, pressure drop, vacuum, flow, water chemistry and thermal efficiency	Tube cleaning, leak testing, water-treatment adjustment or bundle repair
Instrumentation and protection channels	Sensor drift, calibration loss, response degradation and communication failure	Redundant-sensor comparison, analytical redundancy, calibration trends and response testing	Channel calibration, sensor replacement, communication repair or protection-system verification

5.2 Transmission, Distribution, Renewable-Energy, and Energy-Storage Systems

Transmission, distribution, renewable-energy and storage systems present a maintenance environment defined by geographic dispersion, exposure and constrained interruption windows. Their reliability depends on assets ranging from conductors, cables and transformers to photovoltaic arrays, wind turbines, converters and battery packs. Predictive maintenance must integrate condition, network consequence and operating context, because identical defects may carry different risks depending on redundancy and customer criticality.

Transmission networks require surveillance capable of identifying deterioration before faults propagate across systems. Nigerian evidence from the Benin transmission network shows how failure frequency, outage duration and availability indices reveal weak elements that merit targeted maintenance. Reliability analysis becomes more valuable when interruption records are linked to inspections, protection events, weather exposure and repair histories, enabling operators to distinguish recurrent degradation from isolated disturbances (Airoboman, Ogujor&Okakwu, 2017).

Overhead-line management combines conductor-temperature sensing, weather measurements and loading forecasts. Static ratings assume conservative conditions, whereas dynamic line rating estimates permissible current from wind speed, ambient temperature, solar radiation and conductor behaviour. Machine-learning-assisted prediction can extend this approach to short-term forecasting, but erroneous inputs may create unsafe ratings. Predictive maintenance should examine thermal excursions, sag, vibration, corrosion and fitting condition alongside transfer capacity (Aznarte& Siebert, 2017).

Power transformers remain critical interfaces between transmission and distribution. Health-index methods consolidate dissolved-gas analysis, oil quality, insulation ageing, load history and component condition into a score for maintenance and replacement planning. Such indices support portfolio prioritisation, but weighting systems must reflect local failure experience and consequence severity. A deteriorated transformer serving a non-redundant substation may warrant earlier intervention than a similar unit in a resilient configuration (Jahromi et al., 2009).

Distribution systems require rapid fault detection and accurate location because radial structures can expose many customers to one defect. Impedance-based, travelling-wave and knowledge-based methods can shorten restoration times, although distributed generation changes fault-current magnitude and direction. Diagnostic frameworks must incorporate topology, protection settings, smart-meter observations and switching status, while teams verify recurrent faults associated with vegetation, contamination, cable deterioration or defective joints (Shafiullah &Abido, 2017).

Photovoltaic infrastructure combines modules, strings, connectors, inverters, protection equipment and sensors whose faults may reduce energy yield without shutdown. Open circuits, mismatch, shading, hot spots, grounding defects and inverter abnormalities require electrical, thermal and model-based diagnostics. Effective systems compare measured production with weather-normalised expectations and classify deviations before inspection, preventing irradiance variability, soiling or sensor error from being misinterpreted as equipment failure (Mellit, Tina & Kalogirou, 2018).

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Wind-energy maintenance is influenced by accessibility and logistics. Field data from offshore turbines show that failure rates, restoration time and costs vary among subsystems, making failure counts inadequate for prioritisation. Gearboxes, generators and converters impose different consequences because vessel availability, lifting requirements and weather windows affect repair duration. Condition monitoring should therefore be integrated with spare-parts strategy, access forecasting and consequence-based scheduling (Carroll, McDonald & McMillan, 2016).

Energy-storage systems introduce technology-specific ageing and safety considerations. Lithium-ion battery health is represented through capacity retention, internal resistance and power capability, yet these indicators respond differently to temperature, cycling depth, charge rate and calendar ageing. Experimental measurements, equivalent-circuit models, observers and data-driven estimators provide partial visibility. Reliable state-of-health assessment requires calibrated measurements and uncertainty bounds so that balancing, derating, replacement and end-of-life decisions are not based on one unstable indicator (Berecibar et al., 2016).

Storage portfolios may include pumped hydro, compressed air, flywheels, thermal storage and electrochemical chemistries with different degradation mechanisms. Asset-management plans must align monitoring with technology: rotating machinery requires surveillance, reservoirs and pressure systems require inspection, and batteries require thermal and electrochemical control. System value depends on available energy, efficiency, cycle life, response reliability and sustained availability during grid contingencies (Luo et al., 2015).

VI. IMPLEMENTATION CHALLENGES, CYBERSECURITY, ECONOMIC VALUE, AND FUTURE RESEARCH DIRECTIONS

Implementing predictive maintenance across critical power and energy infrastructure is constrained by technical, organisational and institutional conditions that are more difficult than algorithm development itself. Legacy generators, substations, pipelines, renewable plants and storage installations often contain incompatible sensors, proprietary communication protocols and incomplete maintenance histories. Retrofitting such assets can require outages, specialised engineering and calibration before reliable baselines are established. Deployment also depends on leadership, workforce competence, cross-functional cooperation and sustained funding. Evidence from multiple infrastructure sectors shows that projects are more likely to endure when they are designed around maintenance decisions, supported by user-centred interfaces and embedded within operational processes rather than treated as isolated data initiatives (Golightly, Kefalidou& Sharples, 2018).

Data scarcity and model transferability remain central analytical barriers. Catastrophic failures are rare, labels may be uncertain, and equipment populations often differ in age, manufacturer, loading and environment. Models trained on one plant may therefore produce false alarms or missed detections elsewhere. Practical implementation requires data-governance rules, sensor validation, uncertainty reporting and phased trials that compare predictive recommendations with engineering judgement. In remote or resource-constrained energy systems, barriers extend to inadequate communications, limited technical support, financing constraints and weak institutional coordination. Remote-community analysis indicates that successful technology deployment must jointly address social acceptance, technical suitability, economics, environmental conditions and policy support rather than assume that hardware performance alone determines sustainability (Akinyele, Belikov & Levron, 2018).

Cybersecurity becomes inseparable from maintenance when sensors, historians, cloud services and remote diagnostic platforms are connected to industrial control systems. Compromised measurements can conceal degradation, manufacture false alarms, alter maintenance priorities or create unsafe control actions. Conventional information-technology controls cannot be transferred uncritically because operational technology prioritises availability, safety and deterministic performance. Effective protection requires network segmentation, authenticated devices, controlled remote access, secure software updating, anomaly monitoring, recovery procedures and security metrics suited to industrial environments. Research has identified the lack of control-system-specific metrics and the unresolved relationship between security, safety and operational continuity as weaknesses in cybersecurity governance (Knowles et al., 2015).

Economic value must be demonstrated through lifecycle outcomes rather than reductions in maintenance expenditure. A defensible business case should include avoided outages, reduced secondary damage, improved energy efficiency, deferred replacement, labour utilisation, spare-parts optimisation and the cost of false predictions. These benefits must be compared with sensors, communications, software, cybersecurity, training, model maintenance and integration costs. Economic assessment should connect condition information with production, quality and accounting data because maintenance value is realised through its effects on the wider operating system. Integrated vibration-based maintenance research shows that inadequate maintenance and poorly justified intervention both impose business costs, making value measurement essential for investment decisions (Al-Najjar, 2007).

Implementation priorities vary across regional contexts. In Botswana and comparable sub-Saharan systems, smart-grid and virtual-power-plant deployment is limited by infrastructure deficits, investment requirements, regulatory uncertainty, technical skills and consumer participation. These factors are equally relevant to predictive asset management because diagnostic intelligence depends on dependable digital and physical networks (Prasad &Samikannu, 2018). Future research should consequently prioritise affordable edge analytics, interoperable architectures, uncertainty-aware prognostics, cybersecure digital twins, explainable artificial intelligence and methods that learn from limited or imbalanced failure data. Greater attention is also required for climate-driven degradation, human–automation collaboration, standardised benchmarking datasets and economic evaluation under developing-economy constraints. Field-scale longitudinal studies should test whether predictive systems remain accurate, trusted and financially beneficial after deployment, while regulatory frameworks should clarify data ownership, algorithm accountability, cybersecurity obligations and acceptable evidence for maintenance decisions.

VII. CONCLUSION

This review has demonstrated that predictive maintenance and condition monitoring have become indispensable to the reliability, safety, efficiency, and resilience of critical power and energy infrastructure. The study's aim was achieved by examining the conceptual progression from reactive and preventive maintenance toward condition-based, predictive, and prescriptive asset management, while evaluating the technologies, analytical methods, applications, and implementation conditions that shape contemporary practice.

The findings show that effective maintenance depends on more than sensor deployment. Reliable outcomes require the integration of high-quality condition data, robust communication systems, secure storage architectures, appropriate signal-processing techniques, statistical reasoning, physics-based models, machine learning, digital twins, and remaining-useful-life estimation. Across conventional generation plants, transmission and distribution networks, renewable-energy installations, and storage systems, the value of predictive maintenance lies in its capacity to detect incipient deterioration, reduce unplanned outages, prioritise interventions, extend asset life, and support risk-informed decision-making. The review also identified persistent barriers, including fragmented legacy systems, poor data quality, limited failure histories, cybersecurity exposure, model uncertainty, workforce shortages, interoperability constraints, and difficulties in demonstrating economic value. These challenges are especially significant in developing economies, where ageing infrastructure and constrained investment increase the consequences of delayed or poorly targeted maintenance.

It is therefore recommended that infrastructure operators adopt phased, risk-based implementation strategies focused initially on high-criticality assets. Investments should prioritise interoperable sensing, data governance, cybersecurity, workforce development, and model validation under local operating conditions. Regulators and policymakers should promote common technical standards, secure data-sharing frameworks, and incentives for digital modernisation. Future research should advance explainable and uncertainty-aware artificial intelligence, physics-informed digital twins, affordable edge analytics, standardised datasets, and climate-responsive degradation models. Ultimately, predictive asset management should be treated as an integrated organisational capability that combines engineering judgement, digital intelligence, economic discipline, and resilient operational planning. Such integration will strengthen service continuity while protecting communities, industries, and economies.

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