www.idosr.org Arionget, 2026

©IDOSR PUBLICATIONS

ISSN: 2579-079X

International Digital Organization for Scientific Research IDOSR JST/26/1220000
IDOSR JOURNAL OF SCIENCE AND TECHNOLOGY 12(2):58-62, 2026.
https://doi.org/10.59298/IDOSR/JST/26/122.5862

Artificial Intelligence for Predictive Analytics in Nigeria's Energy Sector: A Review, Use-Case Map, and Implementation Roadmap

Arionget Jemima

Department of Pharmacoepidemeology Kampala International University Uganda
Email: jemima.arionget@studwc.kiu.ac.ug

ABSTRACT

Nigeria's energy sector faces persistent challenges: demand–supply imbalance, grid instability, high technical/commercial losses, fuel supply constraints, and operational downtime across electricity and hydrocarbons. Predictive analytics (forecasting, anomaly detection, predictive maintenance, and risk prediction) powered by Artificial Intelligence (AI) can materially improve planning, reliability, revenue assurance, and asset performance. This review synthesizes the main AI methods used for predictive analytics, maps high-value use cases across Nigeria's electricity and oil & gas value chains, and proposes a practical implementation roadmap tailored to local data realities (e.g., metering gaps, limited SCADA coverage, fragmented systems). Evidence from Nigeria-focused studies and sector reports indicates strong opportunity in (i) load and renewable generation forecasting, (ii) outage/fault prediction and grid event early warning using SCADA/EMS and feeder data, (iii) ATC&C loss and theft analytics leveraging meter/billing/feeder reconciliation, and (iv) predictive maintenance for rotating equipment, pipelines, and processing facilities. Key barriers are data availability/quality, interoperability, cybersecurity, skills, and governance. The paper concludes with a phased strategy emphasizing data readiness, prioritized pilots, MLOps, regulatory alignment, and responsible AI.

Keywords: Nigeria, predictive analytics, AI, machine learning, load forecasting, predictive maintenance.

INTRODUCTION

Predictive analytics refers to the application of statistical methods, machine learning, and domain rules to historical and near–real-time data to estimate future states. In operational contexts, "future states" may include near-term demand (e.g., load in the next hour), equipment health (e.g., probability of transformer failure in the next week), technical performance (e.g., expected losses on a feeder), and risk events (e.g., likelihood of a pipeline leak or impending process upset). Unlike descriptive analytics (what happened) or diagnostic analytics (why it happened) [1], predictive analytics asks a forward-looking question: what is likely to happen next, and when? For critical infrastructure sectors such as power and oil & gas, this ability is not merely an academic exercise; it is an operational advantage that can be translated into concrete outcomes, fewer outages, better dispatch and scheduling, improved maintenance planning, reduced losses, enhanced safety, and more predictable cashflows. In energy systems, the case for predictive analytics is particularly strong because the sector is asset-intensive, reliability-sensitive, and increasingly data-rich [2]. Power systems depend on coordinated generation, transmission, and distribution, with continuous balancing of supply and demand under constraints of equipment condition, network losses, and weather-driven variability. Oil & gas operations similarly involve complex assets and processes such as wells, flowlines, pipelines, compressors, separators, refineries, and storage facilities where equipment health and process stability directly influence production volumes, operating costs, emissions, and safety risk. In both sectors, failures are costly: they trigger downtime, repair expenses, environmental incidents, customer dissatisfaction, regulatory penalties, and reputational damage. Predictive analytics creates value by shifting operations from reactive response (fix after breakdown) to proactive planning (prevent, predict, and optimize) [3].

Nigeria's energy landscape intensifies this need. On the electricity side, the Nigerian Electricity Supply Industry (NESI) faces persistent pressures to improve reliability, reduce technical and commercial losses, and strengthen revenue collection to support reinvestment. The system's performance is increasingly scrutinized using measurable indicators, and regulatory monitoring frameworks emphasize operational and commercial performance, reinforcing the requirement for evidence-based improvement strategies [4]. At the same time, grid modernization efforts such as the expansion and integration of Supervisory Control and Data Acquisition/Energy Management Systems (SCADA/EMS), smart metering, feeder monitoring, and improved reporting are gradually creating a stronger digital foundation. These layers are critical enablers of predictive analytics at scale because predictive models depend on data availability (volume, variety, velocity), data quality (accuracy, completeness), and reliable telemetry (consistent streaming from field devices).

On the hydrocarbons side, Nigeria's oil & gas industry is also repositioning around digitization, automation, and advanced analytics as levers for improved efficiency and value creation. In upstream and midstream operations, predictive analytics can support production forecasting, well performance monitoring, corrosion and integrity management, leak detection, and downtime minimization. In downstream operations, it can improve demand planning, refinery yield optimization, asset maintenance, and logistics scheduling [5]. Across the value chain, it can contribute to safety assurance and environmental risk reduction by identifying weak signals that precede incidents. As competitive pressures, cost constraints, and sustainability expectations grow, the incentive to turn operational data into predictive insight becomes stronger. However, the transition from "data exists" to "data creates value" is not automatic. Predictive analytics requires deliberate governance, capable technical and institutional frameworks, and a fit-for-purpose pipeline: data capture → cleaning/integration → feature engineering → model development → validation → deployment → monitoring and continuous improvement [6]. In Nigeria, gaps often emerge at multiple points along this pipeline, including fragmented data systems, poor data fidelity, limited sensor coverage, constrained ICT infrastructure, talent shortages, and weak alignment between analytics outputs and operational decision-making. These constraints create a practical research and implementation problem: how can predictive analytics be adopted and scaled to deliver measurable reliability, efficiency, and commercial gains within Nigeria's electricity market and oil & gas operations? [7]

Despite ongoing reforms and modernization initiatives, Nigeria's energy systems continue to experience significant operational inefficiencies and performance shortfalls. In the electricity sector, reliability challenges, equipment failures, load forecasting errors, network losses, and maintenance backlogs contribute to frequent service disruptions and reduced quality of supply. Commercial performance challenges such as revenue leakage, metering gaps, and collection inefficiencies further undermine the financial viability required for sustained infrastructure investment [8]. While regulatory reporting frameworks and SCADA/EMS integration efforts indicate a shift toward measurable performance management and improved observability, many utility decisions remain reactive, driven by immediate faults rather than predictive insight.

Similarly, Nigeria's oil & gas sector faces recurring challenges related to asset integrity, unplanned downtime, leak and spill risks, production variability, and cost pressures. Although digitization and analytics are increasingly emphasized as strategic priorities, implementation is often uneven, constrained by data silos, inconsistent instrumentation, limited interoperability, inadequate cybersecurity readiness, and shortages of specialized analytics skills. Consequently, the potential of predictive analytics to reduce failures, optimize maintenance, improve planning accuracy, and enhance safety is not fully realized [9].

The core problem, therefore, is the limited practical deployment and institutionalization of predictive analytics across Nigeria's power and oil & gas operations, despite clear operational needs and emerging digital enablers. Without a structured approach to predictive analytics adoption, grounded in sector realities, data maturity, and decision workflows, Nigeria risks continuing cycles of reactive maintenance, avoidable losses, and suboptimal performance outcomes [10]. This study aims to assess how predictive analytics can be designed, implemented, and used to strengthen operational reliability and commercial efficiency across Nigeria's electricity market and oil & gas operations. Specifically, it focuses on (i) identifying high-impact use-cases with the greatest operational and financial returns such as outage prediction, transformer health forecasting, feeder loss estimation, and leak detection so that analytics investments target problems that materially affect uptime, safety, and revenue; (ii) evaluating data readiness and the enabling digital infrastructure required to support robust modeling, including the availability, quality, and interoperability of systems such as SCADA/EMS, metering platforms, condition monitoring tools, and operational databases; and (iii) proposing a practical framework for embedding predictive models into routine decision-making processes, including maintenance scheduling, dispatch planning, integrity management, and performance reporting. The study is significant operationally because it supports a shift from reactive to proactive operations, improving fault localization, reducing outage frequency and duration, optimizing maintenance, strengthening asset integrity, and minimizing unplanned shutdowns. Commercially, it can enhance revenue protection by reducing technical and non-technical losses, improving energy accounting, and prioritizing interventions for high-loss feeders and underperforming assets, while in oil & gas it reduces downtime costs and stabilizes production and cash flows. Regulators and policymakers benefit from actionable, forward-looking performance metrics that enable evidence-based oversight and risk-informed planning. Safety and environmental gains include fewer catastrophic failures, improved spill prevention through early leak detection, and reduced public hazards from electrical faults. Academically, the study contributes context-specific knowledge on adoption pathways, organizational constraints, and capacity needs for sustainable predictive analytics in Nigeria's energy sector.

Scope and approach of this review

This review examines how predictive analytics can be applied to strengthen performance, reliability, and decision-making in Nigeria's two most consequential infrastructure domains: the electricity sector and the oil & gas sector. For electricity, the review spans the full value chain—generation, transmission, and distribution alongside metering, revenue protection, and customer operations, where predictive models can support load forecasting, outage prediction, asset health monitoring, loss detection, and service quality improvement [11]. For oil & gas, it covers upstream production facilities, pipeline networks, midstream processing plants, and downstream storage and distribution systems, where analytics can help anticipate equipment failure, detect leaks and corrosion risk, optimize maintenance schedules, and reduce unplanned downtime and safety incidents. Methodologically, the review synthesizes Nigeria's sector performance realities and the practical data sources that enable prediction, including SCADA/EMS streams, smart and conventional meter data, billing and customer records, IoT and process sensors, asset registers, and environmental data such as weather and satellite observations. It also maps the AI/ML techniques most relevant to these tasks, drawing on Nigeria-relevant evidence from academic and technical studies as well as regulatory and industry reporting [12]. Finally, the review translates findings into an actionable implementation roadmap and a governance checklist addressing data quality, cybersecurity, model risk, compliance, and organizational readiness.

Nigeria energy context: constraints that shape AI design

Nigeria's energy context imposes practical constraints that should shape AI design toward "data-first" value. On the electricity distribution side, high Aggregate Technical, Commercial and Collection (ATC&C) losses limit revenue and reduce network observability; for example, sector reporting based on the regulator's Q2 2025 data indicates DisCos recorded ~37.9% ATC&C losses versus a ~20.5% target benchmark, signalling that near-term AI ROI is likelier in revenue protection, theft detection, loss mapping, and basic feeder visibility than in sophisticated optimization that assumes clean telemetry [13]. At the same time, metering scale-up through programmes such as the National Mass Metering Programme (NMMP) is improving customer data density and billing transparency like foundational inputs for forecasting, segmentation, and anomaly analytics. For renewables, Nigeria's growing solar interest makes variability management non-optional: higher PV penetration increases balancing and voltage-management needs, strengthening the case for probabilistic forecasting and automated anomaly detection, with Nigeria-focused studies showing machine learning can improve PV forecasting accuracy for planning and dispatch decisions. Finally, in oil and gas, uptime, integrity, and safety priorities make predictive maintenance and asset-health analytics strategically valuable, reducing unplanned downtime, optimizing turnarounds, and preventing incidents across upstream and midstream operations [14].

Predictive analytics tasks and AI methods used in energy

Predictive analytics in the energy sector focuses on anticipating demand, system behavior, and operational risks so utilities and operators can plan, optimize, and prevent losses. A core task is forecasting, covering electricity load from hour-ahead to year-ahead, renewable generation from solar/wind/hydro, and financial variables such as price, revenue, and collections; where datasets exist, models may also predict gas supply and fuel availability to support dispatch planning. Another major area is failure prediction and predictive maintenance, where algorithms monitor assets transformers, breakers, feeders, turbines, pumps, compressors, and rotating machinery- to estimate fault likelihood and remaining useful life (RUL), enabling maintenance before breakdowns [15]. Anomaly detection is equally critical for identifying energy theft and non-technical losses, meter tampering, sensor drift, data quality problems, leak detection, and abnormal operating regimes. Energy analytics also includes risk prediction, such as estimating outage probability for feeders/substations, providing early warning for grid disturbances, and detecting safety near-miss patterns. These tasks are powered by AI methods ranging from classical machine learning (regression, random forests, gradient boosting like XGBoost/LightGBM) to deep learning (LSTM/GRU, temporal CNNs, Transformers), probabilistic forecasting (quantile/Bayesian/conformal approaches), graph learning (GNNs for topology-aware prediction), and hybrid physics–AI digital-twin models, with unsupervised techniques (clustering, autoencoders, isolation forests) often driving anomaly use cases, especially where labeled events are limited, as in Nigeria [16].

Power system operations (generation + transmission)

AI can deliver high-value predictive capabilities across Nigeria's power and energy value chain, spanning generation–transmission operations, distribution networks, renewable integration, and oil & gas. In bulk power operations, national/regional load forecasting using historical demand, weather, calendar effects, economic proxies, and major-event indicators improves dispatch efficiency, reduces reliance on spinning reserves, and strengthens outage planning; Nigeria-focused research using ANN/ANFIS has already shown such models are feasible with local datasets. On the grid, event prediction frequency excursions, overload risk, and voltage violations can provide early warning for preventive control when fed by SCADA/EMS telemetry, breaker status, and real-time frequency/voltage streams, with expanding SCADA/EMS integration improving observability [17]. Predicting generator availability and derating from plant sensor tags, maintenance logs, fuel constraints, and past derating events supports unit commitment and maintenance scheduling. The strongest near-term ROI is typically in DisCos: feeder-level load and overload prediction enables targeted upgrades and transformer protection; outage prediction and fault localization accelerate restoration and reduce SAIDI/SAIFI; and ATC&C analytics and theft detection using meter reads, billing/vending data, feeder energy balance, and geospatial layers support revenue recovery, hotspot ranking, and customer-level default risk segmentation. For renewables, solar PV forecasting using irradiance proxies, satellite cloud cover, and inverter telemetry reduces curtailment and instability, while hybrid mini-grid predictive control optimizes batteries and genset fuel use. In oil & gas, predictive maintenance and leak-risk models enhance safety, uptime, and environmental protection [18].

Data architecture for predictive analytics in Nigeria's energy sector

A practical data architecture for predictive analytics in Nigeria's energy sector should unify operational, commercial, asset, and external datasets into a single analytics-ready layer that supports forecasting, loss reduction, reliability, and asset health decisions. Core inputs include SCADA/EMS (where available) for real-time telemetry, alarms, and events across transmission and parts of generation/distribution; AMI/smart meters and prepaid vending platforms for interval consumption trends, voltage events, and tamper flags; and billing/CRM/collections systems for customer attributes, arrears status, and payment behavior [19]. Asset registries and GIS provide the physical network context such as transformer locations, feeder topology, switching points, and maintenance history while IoT condition-monitoring (vibration, partial discharge, thermal imaging) offers early indicators of equipment degradation. Weather and satellite data (irradiance, cloud cover, temperature, humidity) strengthen PV output forecasting, temperature-sensitive demand estimation, and outage risk prediction. In practice, predictable constraints must be engineered into the pipeline: missing data and irregular sampling require robust imputation, anomaly-aware preprocessing, and confidence scoring; topology uncertainty demands investment in feeder mapping before topology-aware analytics; and label scarcity for failures or theft requires semi-supervised approaches paired with targeted field verification loops. Fragmented systems should be integrated using a lean lakehouse design and standardized identifiers linking customer–meter–transformer–feeder. Implementation should follow a staged roadmap: Phase 0 (8–12 weeks) establishes data readiness, unique IDs, a minimal canonical model, and data-quality KPIs; Phase 1 (3–4 months) delivers quick-win pilots (load forecasting, theft/loss hotspots, PV forecasting) with dashboards and field validation; Phase 2 (4–6 months) operationalizes models via MLOps, drift detection, and human-in-the-loop workflows; and Phase 3 (6–18 months) scales to probabilistic forecasting, graph analytics, and digital twins. Because models increasingly influence dispatch, disconnection, inspections, and maintenance, governance must be explicit, with data access controls and audit logs, cybersecurity hardening of OT/IT interfaces (especially SCADA/EMS), explainability for high-stakes decisions, routine bias checks, and disciplined model documentation, approval, rollback, and monitoring [20].

CONCLUSION

A unified, analytics-ready data architecture is foundational to making predictive analytics practical and scalable in Nigeria's energy sector. By integrating SCADA/EMS telemetry, metering and prepaid signals, billing/CRM behavior, and asset–GIS context like augmented with IoT condition monitoring and weather/satellite inputs, utilities can move from reactive operations to proactive forecasting, targeted loss reduction, improved reliability, and smarter asset-health decisions. However, value depends on engineering for real-world constraints: missing and irregular data must be treated systematically, topology uncertainty must be reduced through credible mapping, and label scarcity must be addressed through semi-supervised learning backed by field verification. A phased implementation roadmap enables quick wins while building durable capability, from data readiness and pilot use cases to MLOps-driven operationalization and advanced analytics such as probabilistic forecasting, graph methods, and digital twins. Finally, strong governance cybersecurity, access control, auditability, explainability, bias checks, and rollback readiness- ensures models remain trustworthy, safe, and accountable in high-stakes utility decisions.

REFERENCES

1. Zito, F., Cutello, V., Pavone, M.: Data-driven forecasting and its role in enhanced decision-making. Eng. Appl. Artif. Intell. 154, 110934 (2025). https://doi.org/10.1016/j.engappai.2025.110934
2. Govea, J., Gaibor-Naranjo, W., Villegas-Ch, W.: Transforming Cybersecurity into Critical Energy Infrastructure: A Study on the Effectiveness of Artificial Intelligence. Systems. 12, (2024). https://doi.org/10.3390/systems12050165
3. Lu, H., Xie, D., Cheng, Y.F.: Methane emissions from the oil and gas supply chain: Characteristics and mitigation. Nexus. 2, 100087 (2025). https://doi.org/10.1016/j.ynexs.2025.100087

4.Haron N H, Mahmood R, Amin N M, Ahmad A, Jantan S R., (2025). An Artificial Intelligence Approach to Monitor and Predict Student Academic Performance. *Journal of Advanced Research in Applied Sciences and Engineering Technology, 44, (1), 105-119.* **DOI:** *https://doi.org/10.37934/araset.44.1.105119*

5.Obele, D.J.D.: ARTIFICIAL INTELLIGENCE ADOPTION IN NIGERIA'S OIL AND GAS INDUSTRY: CHALLENGES, OPPORTUNITIES, AND IMPACT ON OPERATIONAL EFFICIENCY. BW Acad. J. 2, (2025)

6.Li, P., Chen, Y., Guo, X.: Digital transformation and supply chain resilience. Int. Rev. Econ. Finance. 99, 104033 (2025). https://doi.org/10.1016/j.iref.2025.104033

7.Echegu D. A., Artificial Intelligence (AI) in Customer Service: Revolutionizing Support and Engagement. IAA Journal of Scientific Research 11(2):33-39, 2024. https://doi.org/10.59298/IAAJSR/2024/112.3339

8.Gbenga-Dada, O.: The Role of Digitilisation in Improving Nigeria's Power Sector, https://ng.andersen.com/the-role-of-digitilisation-in-improving-nigerias-power-sector/, (2025)

9.Hussain, M., Zhang, T., Seema, M.: Adoption of big data analytics for energy pipeline condition assessment - A systematic review. Int. J. Press. Vessels Pip. 206, 105061 (2023). https://doi.org/10.1016/j.ijpvp.2023.105061

10. Alum, E.U., Ugwu, O.PC. Artificial intelligence in personalized medicine: transforming diagnosis and treatment. *Discov Appl Sci* **7**, 193 (2025). https://doi.org/10.1007/s42452-025-06625-x

11. Shahverdi, N., Saffari, A., Amiri, B.: A systematic review of artificial intelligence and machine learning in energy sustainability: Research topics and trends. Energy Rep. 13, 5551–5578 (2025). https://doi.org/10.1016/j.egyr.2025.05.021

12. Adedoyin Adesuji*1, 2: ARTIFICIAL INTELLIGENCE APPLICATIONS IN PIPELINE MONITORING AND MAINTENANCE: A PATHWAY TO SUSTAINABLE OIL AND GAS OPERATIONS IN NIGERIA. WORLD J. Eng. Res. Technol. 12, 19–34 (2026). https://doi.org/10.5281/zenodo.18440992

13. Ghazouani M, Fandi F Z, Zaher N, Ounacer S, Karim Y, Aziza C, Azzouazi M (2024). Enhancing Immersive Virtual Shopping Experiences in the Retail Metaverse Through Visual Analytics, Cognitive Artificial Intelligence Techniques, Blockchain-Based Digital Assets …*Engineering Applications of Artificial Intelligence, 305-318.*

14. Mucomole, F.V., Silva, C.A.S., Magaia, L.L.: Parametric Forecast of Solar Energy over Time by Applying Machine Learning Techniques: Systematic Review. Energies. 18, (2025). https://doi.org/10.3390/en18061460

15. Ezeonwumelu, J. O. C., Uhama, K. C., Ugwu, O. P. C., Ugwuanyi, A. C., Tambwe, P. R. (2024). The Impact of Artificial Intelligence and Machine Learning on Pharmacy Practice. Research Invention Journal of Research in Medical Sciences 3(1):10-15.

16. Mastoi, M.S., Wang, D., Ma, N., Hassan, M., Shafiullah, M., Bashir, T., Hassan, A., Flah, A.: AI-driven control and optimization for renewable energy integration in smart grids: Challenges, applications, and future research directions. Energy Strategy Rev. 64, 102049 (2026). https://doi.org/10.1016/j.esr.2026.102049

17. Li, B., Wang, J.: Economic Dispatch Methods for Smart Grid Based on Improved SPEA2 and Improved NSGA2. Front. Energy Res. 9, (2021). https://doi.org/10.3389/fenrg.2021.767721

18. Mukisa, N., Zamora, R., Lie, T.T.: Energy Business Initiatives for Grid-Connected Solar Photovoltaic Systems: An Overview. Sustainability. 14, (2022). https://doi.org/10.3390/su142215060

19. George U A, Kolawole A O, Ebenezer E (2023). Critical review on the application of artificial intelligence techniques in the production of geopolymer-concrete. *SN Applied Sciences, 5, (8), 217.*

20. Escalona, M.-J., Koch, N., Garcia-Borgoñon, L.: Lean requirements traceability automation enabled by model-driven engineering. PeerJ Comput. Sci. 8, e817 (2022). https://doi.org/10.7717/peerj-cs.817

CITE AS: Arionget Jemima (2026). Artificial Intelligence for Predictive Analytics in Nigeria's Energy Sector: A Review, Use-Case Map, and Implementation Roadmap. IDOSR JOURNAL OF SCIENCE AND TECHNOLOGY 12(2):58-62, 2026. https://doi.org/10.59298/IDOSR/JST/26/122.5862