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DOI: https://doi.org/10.64388/IREV10I3-1723403

Predictive Maintenance of High-Voltage GIS Assets for Saudi Smart Grids: Using Partial Discharge Monitoring, Equipment Diagnostics, and Failure-Risk Assessment under Vision 2030

FAISAL ALEEM

Abstract-** High-voltage gas-insulated switchgear (GIS) is central to compact, reliable transmission substations, yet its apparent reliability can conceal insulation defects, mechanical degradation, gas-system anomalies, thermal problems, and ageing mechanisms that become costly when detected only after failure. This review develops a predictive-maintenance framework for GIS assets in Saudi smart grids by integrating partial-discharge (PD) monitoring, multimodal equipment diagnostics, health assessment, and failure-risk prioritisation. Evidence from 2020 to 2025 was synthesised through a structured integrative review of PD sensing and localisation, machine-learning diagnosis, health indices, switchgear condition monitoring, and Saudi smart-grid transformation. The synthesis shows that PD monitoring provides high-value early evidence but should not be treated as a standalone maintenance trigger because interference, sensor position, operating context, defect type, and model uncertainty can materially change interpretation. Stronger decisions emerge when PD evidence is fused with gas, thermal, mechanical, switching-duty, inspection and historical failure information. Health indices create an interpretable bridge between heterogeneous measurements and asset condition, while probabilistic failure-risk assessment adds consequence and criticality to maintenance ranking. Data-driven models can improve defect recognition, especially under complex signal conditions, but field deployment requires explicit treatment of scarce labelled data, domain shift, calibration, explainability, and confidence. The review proposes a closed-loop architecture that connects sensing to diagnosis, risk-ranked intervention, and post-maintenance learning. For Saudi Arabia, the framework supports Vision 2030 priorities by improving grid reliability, reducing forced outages, extending justified asset life, and strengthening local diagnostic and analytics capability.

***Keywords:** gas-insulated switchgear; predictive maintenance; partial discharge; condition monitoring; equipment diagnostics; health index; failure risk; smart grid; Saudi Arabia; Vision 2030*

I. INTRODUCTION

Gas-insulated switchgear combines high-voltage conductors, switching devices, instrument transformers, earthing functions, and insulating gas within grounded metal enclosures. Its compact footprint and environmental isolation make GIS attractive for urban, industrial, and high-value transmission nodes, but the same enclosure that protects live parts can complicate defect observation and corrective access. Failure may originate from insulation contamination, protrusions, free particles, spacer defects, deteriorated contacts, operating-mechanism problems, gas-system abnormalities, or accessory interfaces. Major GIS failure can cause long outages, safety exposure and network constraints, making maintenance quality a resilience issue [1–3].
Traditional periodic maintenance assumes that elapsed time is a reasonable proxy for deterioration. That assumption is weak for GIS because condition evolves through interacting electrical, thermal, mechanical, environmental, and duty-related stress. Health-index studies demonstrate that inspection and diagnostic evidence can be converted into condition states that distinguish assets needing intervention from those that can safely remain in service [1,4]. This supports a shift from calendar-based maintenance towards condition-based and predictive decision making, in which intervention is triggered by observed degradation, forecast failure probability, and network consequence rather than time alone.

Partial discharge is particularly important because it can reveal localised insulation defects before complete breakdown. UHF/VHF, electrical, acoustic, optical and other sensing approaches offer different balances of sensitivity, immunity to interference, localisation capability, installation complexity, and cost [5–11]. Recent studies have also applied deep learning, transfer learning and few-shot methods to GIS PD diagnosis, addressing the practical difficulty that field faults are scarce and laboratory data do not perfectly represent operational substations [6–9]. These advances are valuable, but classification accuracy alone does not create a safe maintenance decision. Uncertainty in calibration, noise, sensor position and localisation must remain visible to engineers [10–13]. Predictive maintenance therefore requires an architecture rather than a single algorithm. PD evidence must be combined with thermal patterns, mechanism condition, gas density or decomposition information, switching history, inspection findings, asset age, environmental exposure, previous defects and maintenance outcomes. The combined evidence must then be translated into health, probability of failure, consequence, and action priority. Fuzzy and conventional health-index approaches show how heterogeneous condition evidence can be made interpretable for maintenance planning [1,4], while broader switchgear research demonstrates the value of temperature monitoring, data-driven condition assessment and risk-ranked scheduling [14–17].

Smart-grid development is being pursued alongside renewable-energy expansion, network digitalisation, greater automation and higher expectations for reliability [18–21]. Predictive GIS maintenance can support this transformation by limiting avoidable outages, using diagnostic resources more selectively, extending service life where evidence justifies it, and building local expertise in sensing, analytics and asset management.

This review therefore focuses specifically on high-voltage GIS assets and the decision chain from defect signal to maintenance action. It does not treat predictive maintenance as synonymous with machine learning. Instead, it examines how monitoring physics, measurement assurance, diagnostic interpretation, health assessment, failure-risk modelling and operational governance must work together. The contribution is a practical, auditable framework scalable from individual bays to a transmission portfolio.

II. AIM, OBJECTIVES AND REVIEW QUESTIONS

The aim of this review is to develop an evidence-based framework for predictive maintenance of high-voltage GIS assets in Saudi smart grids by connecting partial-discharge monitoring, complementary equipment diagnostics, condition assessment, and failure-risk prioritisation within a closed maintenance-learning cycle.

Five objectives guide the analysis. First, the review characterises the principal GIS degradation mechanisms and identifies the observable signals that provide credible early evidence of insulation, gas-system, thermal, contact, and mechanism deterioration. Second, it compares PD sensing, signal processing and localisation approaches according to sensitivity, noise robustness, field deployability, calibration requirements, and diagnostic uncertainty. Third, it examines how multimodal evidence can be transformed into component and bay health indices without hiding severe defects. Fourth, it evaluates data-driven diagnostic methods and their readiness for field use under scarce failures and domain shift. Fifth, it proposes a risk-based implementation roadmap that links diagnostic evidence to probability of failure, consequence, work-order priority, life-extension decisions, and grid outcomes.

Three review questions follow. RQ1 asks which monitoring and diagnostic combinations provide the most defensible evidence for detecting and localising developing GIS defects. RQ2 asks how health indices, uncertainty and asset criticality should be integrated so that diagnostic outputs become risk-ranked maintenance decisions rather than isolated alarms. RQ3 asks which data, governance, capability and operational controls are required to deploy predictive GIS maintenance at Saudi transmission-network scale.

III. REVIEW METHODOLOGY

A structured integrative technical review was selected because the evidence base spans measurement science, high-voltage insulation, signal processing, artificial intelligence, reliability engineering, switchgear maintenance and Saudi smart-grid studies. Direct statistical pooling was inappropriate because studies use different sensors, defects, voltage classes, metrics and field environments. The method therefore emphasised traceable selection, critical comparison and mechanism-based synthesis.

The evidence window was 2020–2025. Search concepts were organised into four blocks: gas-insulated switchgear or high-voltage switchgear; partial discharge, UHF, acoustic, optical, thermal, gas or mechanism diagnostics; condition monitoring, health index, failure probability, risk assessment or predictive maintenance; and Saudi Arabia, smart grid, transmission reliability or Vision 2030. Peer-reviewed journal and conference studies were retained when they provided a reproducible diagnostic method, field or laboratory evidence relevant to GIS, a condition/risk model applicable to switchgear, or Saudi grid context. Related switchgear studies were included only when the maintenance mechanism was transferable.

Quality appraisal considered five questions: whether the sensing or analytical method was described sufficiently; whether the defect, asset or dataset matched the claim being made; whether calibration, uncertainty or validation was addressed; whether performance metrics were interpretable; and whether the findings could reasonably inform field maintenance. Laboratory classification accuracy was not treated as equivalent to operational reliability. Greater weight was given to studies addressing field differences, uncertainty or maintenance consequences [6–13].

The final synthesis used thirty references published within the stated period. Evidence was coded into degradation mechanism, sensing modality, signal assurance, localisation, diagnostic model, health assessment, risk model, maintenance action, and Saudi implementation context. Cross-study comparison focused on weak-defect detection, field transfer, health-index interpretation and conversion of condition evidence into maintenance action.

Two conceptual outputs were developed. The first is a closed-loop architecture connecting asset context, sensing, PD processing, multimodal diagnosis, health and failure-risk modelling, maintenance action, and outcome feedback. The second is a maturity roadmap that stages implementation from trustworthy asset data to portfolio-level predictive scheduling. No primary experimental data are claimed; the figures and tables are analytical syntheses of the reviewed evidence.

IV. SAUDI SMART-GRID CONTEXT AND GIS ASSET CRITICALITY

Saudi power-system development is increasingly shaped by renewable integration, digital control, automation, flexible operation and reliability requirements. Reviews of Saudi smart-grid infrastructure describe a transition that combines smart energy, communication and information layers, while national renewable expansion increases the importance of reliable network interfaces and controllable substations [18,19]. Standards-oriented work also emphasises interoperability and coordinated grid operation as digital and distributed resources expand [20]. Saudi renewable-expansion analysis likewise highlights the importance of grid reliability [21].

Within this environment, GIS assets have high criticality because failure can remove bus sections, transformers, lines or generation connections from service. Criticality depends on topology, redundancy, connected load or generation, safety, restoration options, repair duration and the bay's operational role. A predictive-maintenance programme should therefore maintain a digital asset hierarchy down to compartment and component level, while retaining the network consequence of each failure mode.

Saudi operating conditions can affect sensor performance, thermal interpretation, maintenance access and ageing. The practical lesson is not to import thresholds blindly. Baselines should be established for the actual equipment family, environment, loading and sensor configuration. A PD amplitude change may reflect a defect, changed coupling, or altered interference.

Predictive maintenance should consequently be anchored in asset criticality and evidence confidence. High-criticality GIS may justify continuous UHF

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DOI: https://doi.org/10.64388/IREV10I3-1723403

monitoring, redundant sensors, tighter alarm governance and more frequent model review. Lower-criticality bays may be adequately managed through periodic online surveys combined with routine inspection and targeted diagnostic testing. The objective is to allocate monitoring intensity according to failure consequence, defect detectability and decision value.

V. GIS FAILURE MECHANISMS AND DIAGNOSTIC EVIDENCE

GIS failure mechanisms are heterogeneous, so no single observable can represent asset condition. Insulation defects include metallic protrusions, free or fixed particles, spacer voids, surface contamination, poor interfaces and abnormal field concentration. Mechanical and conductive-path defects include contact deterioration, loosening, alignment problems, drive wear and abnormal operating timing. Gas-system problems include leakage, density decline and decomposition products associated with discharge or arcing. Thermal anomalies can indicate high-resistance contacts, poor joints or abnormal current paths. Each mechanism produces a different evidence signature and a different time horizon to failure.

PD is a high-value precursor because local electrical breakdown can occur repeatedly before insulation collapses. UHF/VHF, acoustic, optical and complementary PD methods offer different balances of sensitivity, interference immunity and localisation capability [5,10,11,24–26]. Acoustic measurements remain sensitive to sensor coupling and placement [10], while optical sensing offers electromagnetic immunity with added installation constraints [25]. Electrical measurements can provide sensitivity and established interpretation but may be vulnerable to substation interference.

Diagnostics should distinguish detection, classification, localisation and severity assessment. Trend persistence and cross-sensor agreement reduce dependence on a single amplitude threshold when operating conditions and interference levels change. Detecting an abnormal pulse establishes that further analysis is needed; it does not prove defect type or urgency. Pattern features, time-frequency representations, phase-resolved behaviour, repetition rate, amplitude trends and multi-sensor arrival times can improve interpretation. Location matters because the same PD pattern has different maintenance implications if associated with an accessible cable termination versus an internal spacer requiring major outage work.

Gas and material evidence can add discrimination. Decomposition-product research illustrates how chemical evidence can complement electrical monitoring [22]. Thermal and mechanism signals likewise provide independent confirmation. Independent corroboration makes a maintenance case more defensible than any isolated threshold.

A practical diagnostic taxonomy should therefore record the suspected failure mode, observable, sensor location, confidence, trend, corroborating evidence and possible consequence. This creates a traceable chain from raw signal to engineering judgement and prevents diagnostic dashboards from becoming collections of disconnected alarms.

VI. PARTIAL-DISCHARGE MONITORING, PROCESSING AND LOCALISATION

The performance of PD monitoring depends as much on measurement assurance as on sensor sensitivity. Field substations contain switching, communication and electromagnetic interference that can overlap PD signals. Denoising, pulse discrimination and baseline characterisation are therefore essential before pattern recognition. Wavelet selection studies show that denoising quality changes with the spectral relationship between signal and noise, so a fixed preprocessing recipe may fail when the interference environment changes [12]. Measurement uncertainty and interference must therefore be represented when interpreting PD magnitude [13].

Calibration is a governance control, not a laboratory formality. Industrial PD calibrator research demonstrates the importance of known charge injection and performance verification for comparable measurements [23]. GIS calibration records should retain sensor type, bandwidth, gain, synchronisation, location and configuration changes. Without this

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DOI: https://doi.org/10.64388/IREV10I3-1723403

metadata, a long-term trend may reflect the monitoring system rather than the asset.

Localisation reduces unnecessary investigation and outage scope. Multi-sensor UHF timing, acoustic time of arrival, cross-correlation and hybrid approaches can estimate source position when propagation paths are understood. GIS cable-terminal research illustrates the value of combining detection positions and physical inspection to identify abnormal regions [5]. Acoustic localisation is sensitive to sensor position [10], while electromagnetic methods face reflections and enclosure geometry. Location should therefore be expressed with a confidence interval or ranked region rather than unjustified precision.

Signal interpretation also requires trend context. A stable low-level pattern may warrant surveillance, whereas a rapidly increasing repetition rate, changing phase distribution or newly corroborated source may justify accelerated investigation. Alarm logic should separate warning, diagnostic escalation and maintenance trigger. Warnings mark deviation; escalation requests additional diagnosis; maintenance triggers require evidence and risk.

Machine learning can improve classification, especially when PD patterns are complex. GIS-specific studies report effective use of deep learning, meta-learning and domain adaptation [6–9]. Their most important contribution for utilities is not merely accuracy but recognition of the field-data problem. Few-shot and domain-adaptation methods explicitly address scarce labelled faults and differences between laboratory and operational distributions. Even so, models should report confidence, preserve representative raw evidence, and be subject to engineering review for high-consequence decisions.

Table 1. Diagnostic modalities and their decision value for GIS predictive maintenance.

Diagnostic modality	Primary evidence	Strength	Main limitation	Maintenance decision value
UHF/VHF PD	Fast electromagnetic discharge pulses	High sensitivity; suited to enclosed GIS	Reflections, coupling and sensor configuration affect response	Early insulation-defect detection and source triangulation
Acoustic/ultrasonic	Mechanical waves from discharge	Useful corroboration and localisation	Strongly dependent on path and sensor placement	Confirms active source and narrows inspection region
Optical sensing	Light/fluorescence response to discharge	Electromagnetic immunity	Installation geometry and cost	Independent confirmation in confined/high-interference locations
Thermal/contact	Temperature rise and thermal pattern	Direct evidence of resistive heating	Load and ambient conditions must be normalised	Contact/joint deterioration and conductive-path risk
Gas/chemical	Density, leakage and decomposition products	Links insulation medium to abnormal activity	Sampling and interpretation may be defect-specific	Gas-system integrity and discharge corroboration
Mechanism/electrical operation	Timing, coil current, travel and switching history	Targets mechanical degradation	Requires comparable operating signatures	Drive/contact mechanism maintenance

Diagnostic modality	Primary evidence	Strength	Main limitation	Maintenance decision value
Health/risk fusion	Condition score, PoF, consequence, confidence	Makes heterogeneous evidence actionable	Poor aggregation can hide severe defects	Risk-ranked inspection, repair, deferment or replacement

VII. MULTIMODAL DIAGNOSTICS AND HEALTH INDICES

A predictive GIS programme needs a common model for evidence produced on different scales. UHF amplitude, acoustic energy, gas density, infrared temperature, operating time, contact resistance, inspection findings and maintenance history cannot be compared directly. Health indices solve this translation problem by mapping measurements to interpretable condition states and combining them at component, compartment and bay levels.

Field-oriented GIS studies show the practical value of this approach. A GIS health-index and risk model used subsystem parameters to distinguish asset states and major-failure risk [2]. Later work introduced conditional factors to improve conventional weighting and scoring, while implementation on operating GIS bays demonstrated how the resulting index can prioritise maintenance [1]. Fuzzy logic can soften rigid thresholds while incorporating operating factors [4].

However, health indices can become misleading if aggregation hides a severe defect. Averaging a critical spacer PD condition with many healthy auxiliary parameters is unsafe. Dominant-defect rules or non-linear penalties should therefore ensure that red-flag evidence remains visible. The model should also distinguish observable condition from invisible ageing. Age, duty, environment and failure history can modify risk, but they should not overwrite direct diagnostic evidence.

Multimodal fusion should follow causal logic. For insulation risk, high-value features may include PD pattern, source location, gas condition, spacer inspection and environmental context. For conductive-path risk, thermal rise, contact resistance, load current and mechanical operating data are more relevant. For mechanism failure, timing, coil current, travel signatures, operation count and maintenance history dominate. Unrelated signals should not be fused merely because they are available.

The health model should retain uncertainty. Each input can carry a confidence level based on calibration status, data completeness, sensor health, diagnostic repeatability and corroboration. A bay with moderate condition but low evidence confidence may deserve targeted testing before a major maintenance decision. This separates uncertainty reduction from physical repair.

VIII. DATA-DRIVEN DIAGNOSTICS AND PREDICTIVE MAINTENANCE

Data-driven methods are increasingly used to extract patterns that are difficult to encode as fixed engineering rules. GIS PD research has applied convolutional networks, recurrent structures, attention mechanisms, meta-learning and domain adaptation [6–9,30]. Improved deep-learning methods can combine spatial and temporal features in acoustic or electrical data [6], while few-shot approaches reduce dependence on large labelled field datasets [7]. Transfer-oriented methods are useful when defect samples are distributed across equipment populations [8,9].

The central deployment problem is distribution shift. Laboratory defects are intentionally created under controlled conditions; operational defects develop with different geometry, noise, ageing and loading. A laboratory model can therefore test well yet remain unreliable in service. Field validation should include unseen substations, equipment families, sensor configurations and interference conditions. Performance should be measured by sensitivity to consequential defects, false-alarm rate, calibration of confidence, and diagnostic lead time, not classification accuracy alone.

Predictive maintenance also extends beyond PD classification. Temperature-monitoring research on switchgear shows that neural networks can relate distributed thermal measurements to health status [14]. Broader reviews show that deep learning can support switchgear fault recognition when data are representative [15]. These methods can be integrated with mechanism timing, gas trends and asset history to forecast deterioration trajectories or identify combinations of weak signals that precede failure.

Explainability matters because maintenance actions have cost and safety implications. Utilities need to know which evidence changed the model output, whether the input is within the training domain, and how stable the recommendation is under plausible measurement variation. Feature attribution, uncertainty bounds and safety overrides can help. Models should also be monitored for drift as sensors age, operating patterns change, or software is updated. The appropriate role of artificial intelligence is therefore decision support. It should not remove measurement traceability, defect physics, or accountable human review. A mature system stores raw and processed evidence, model version, confidence, engineer disposition, maintenance action and confirmed finding so that every intervention becomes new learning data.

IX. FAILURE-RISK ASSESSMENT AND MAINTENANCE PRIORITISATION

Condition is not the same as risk. Risk combines the probability that a failure will occur within a relevant horizon with the consequence if it occurs. A moderately degraded critical bay may deserve higher priority than a poorer bay with strong redundancy. Health-index research already demonstrates the value of translating GIS condition into risk categories [2], while maintenance-prioritisation studies for switching equipment show how condition and operational importance can be combined to rank work [16,17].

Probability of failure should be estimated from multiple evidence layers. The baseline may reflect age, equipment family, service history and known failure modes. Current diagnostics then update the baseline: confirmed PD, deteriorating gas condition, repeated mechanism anomalies or accelerating thermal rise increase probability. Confidence should modify how aggressively the estimate is used. If evidence is sparse or inconsistent, the immediate action may be additional diagnosis rather than repair.

Consequence assessment should include safety, environmental impact, lost load or generation, network security, collateral damage, repair duration, spare constraints and reputational or regulatory exposure. A simple risk matrix is useful for communication but can conceal large differences inside categories. Where data permit, consequence and restoration time should be quantified.

Maintenance priority should also consider intervention effectiveness. Some defects can be corrected during a short planned outage; others require factory support, gas handling, replacement modules or extended isolation. Predictive maintenance seeks a window in which risk is controlled while resources, spares and outage conditions are favourable. Forecast lead time therefore has operational value.

Post-maintenance verification closes the risk loop. The programme should confirm that the diagnostic signature disappeared or stabilised, record the physical defect found, update the health index, and revise failure-model assumptions. Repeated false alarms require investigation; failures without warning require revised sensing or taxonomy. Risk assessment becomes trustworthy only when predictions are systematically reconciled with outcomes.

X. INTEGRATED CLOSED-LOOP GIS PREDICTIVE-MAINTENANCE FRAMEWORK

The reviewed evidence supports a six-stage closed-loop architecture. Stage one establishes the physical GIS context: bay hierarchy, compartment, equipment family, age, switching duty, loading, environment, maintenance history and network criticality. Stage two acquires condition evidence through UHF, acoustic, optical, electrical, thermal, gas and mechanism

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DOI: https://doi.org/10.64388/IREV10I3-1723403

sensing selected according to failure mode and decision value. Stage three processes and localises PD, retaining raw data, preprocessing parameters, confidence and source region. Stage four fuses PD with complementary diagnostics to determine the most plausible defect mechanism and severity. Stage five translates evidence into component health, probability of failure, consequence and confidence-aware risk. Stage six selects inspection, repair, refurbishment, deferment or replacement and records the operational outcome.

Three controls support this sequence. Evidence assurance governs calibration, data quality, synchronisation, sensor health, false-alarm investigation and traceability. Decision governance defines thresholds, escalation rules, engineer approval, work-order creation and exceptions. Portfolio outcome management measures availability, avoided outages, risk reduction, life extension and cost. Figure 1 visualises these relationships.

The architecture separates diagnosis from decision. A diagnostic model can state that a spacer-related PD pattern is probable; the maintenance system must still ask whether the source is confirmed, whether the trend is worsening, what the bay consequence is, whether redundancy exists, and what intervention can remove risk. This prevents uncertain classifications from becoming automatic high-cost outages.

Table 1 summarises diagnostic modalities and decision roles. The key principle is evidence triangulation. When independent measurements support the same failure hypothesis, confidence rises. When they conflict, the system should not average the contradiction away; it should trigger evidence review or targeted testing. In this way, uncertainty becomes a managed state rather than a hidden weakness.

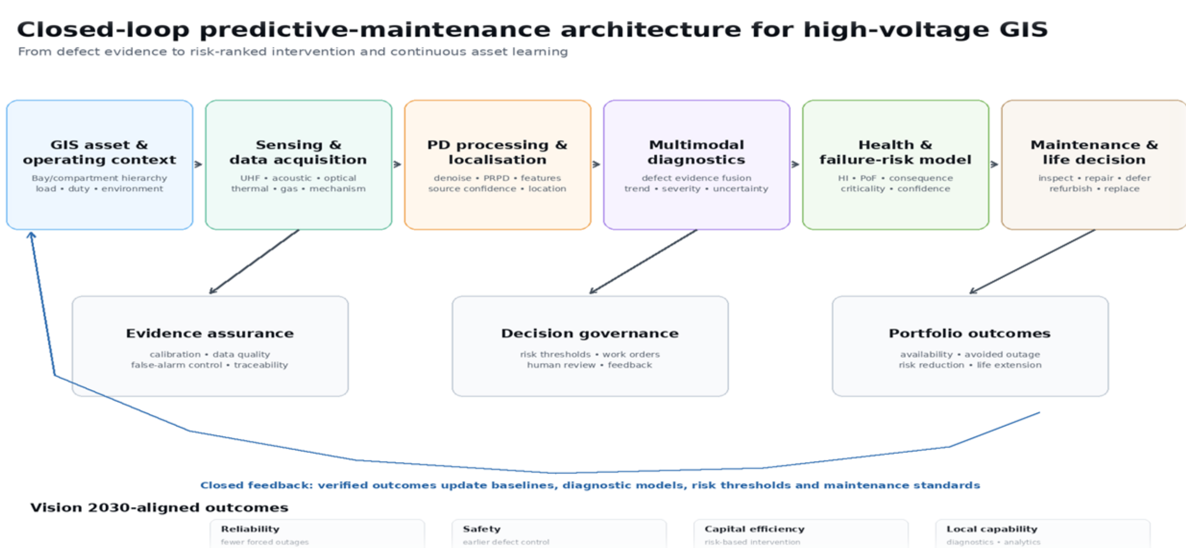

Figure 1. Closed-loop predictive-maintenance architecture for high-voltage GIS assets.

XI. VISION 2030 IMPLEMENTATION ROADMAP

Implementation should proceed in stages because prediction cannot compensate for weak asset data. Stage one establishes the data foundation: unique asset identifiers, compartment hierarchy, installation records, event history, maintenance records, sensor inventory and a common failure taxonomy. The objective is trusted evidence, not advanced analytics.
Stage two standardises diagnostics. Utilities define sensor installation rules, PD baselines, calibration intervals, interference handling, test metadata, alarm classes and methods for confirming defect location. Common practices enable comparison across substations. Stage three creates health and risk fusion.

Condition evidence is mapped to component health, then combined with criticality and consequence to rank interventions. Fuzzy or non-linear health models can support this stage when they remain transparent [1,4].

Stage four introduces predictive scheduling. Deterioration trends and diagnostic confidence are used to estimate lead time, coordinate outages, reserve spares and generate work-order triggers. Data-driven models are deployed only after field validation and drift monitoring. Stage five adds fleet benchmarking, repeated-defect analysis, life-extension evidence and model governance. Figure 2 presents this progression, while Table 2 links stages to controls and outcomes.

For Saudi utilities, governance should align the programme with reliability and localisation objectives. Central engineering functions can own failure taxonomies, calibration standards, model validation and common health-index definitions, while regional teams retain operational judgement and feedback on field conditions. This supports scale while retaining field judgement.

Performance measurement should include early-warning lead time, confirmed-defect detection rate, false alarms, localisation error, diagnostic turnaround time, overdue high-risk work, forced outage reduction, maintenance deferral supported by evidence, and avoided replacement where life extension is justified. Capability indicators should track local training, diagnostic interpretation, sensor maintenance, data engineering and model governance. The Vision 2030 contribution is strongest when predictive maintenance improves both asset outcomes and domestic technical capability rather than simply adding monitoring hardware.

Table 2. Risk-based implementation framework for Saudi high-voltage GIS assets.

Maturity stage	Core controls	Decision enabled	Key performance indicators	Vision 2030-aligned outcome
1. Data foundation	Asset hierarchy, history, failure taxonomy, sensor inventory	Reliable baselines and traceable condition records	Data completeness; asset-ID accuracy; sensor coverage	Trusted digital asset foundation
2. Diagnostic standardisation	PD calibration, noise rules, metadata, localisation confidence	Comparable defect evidence across substations	False-alarm rate; calibration compliance; localisation error	Reliable and scalable diagnostics
3. Health & risk fusion	Component HI, conditional factors, PoF × consequence	Risk-ranked maintenance portfolio	High-risk backlog; confidence; defect confirmation rate	Improved reliability and capital discipline
4. Predictive scheduling	Trend models, lead time, work-order triggers, spares/outage coordination	Timely intervention before forced failure	Warning lead time; overdue risk; planned/forced outage ratio	Higher availability and efficient maintenance
5. Portfolio intelligence	Fleet benchmarking, model drift, post-maintenance learning	Life extension, renewal strategy and model governance	Avoided outage; justified life extension; risk reduction	Local analytics capability and resilient smart grid

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DOI: https://doi.org/10.64388/IREV10I3-1723403

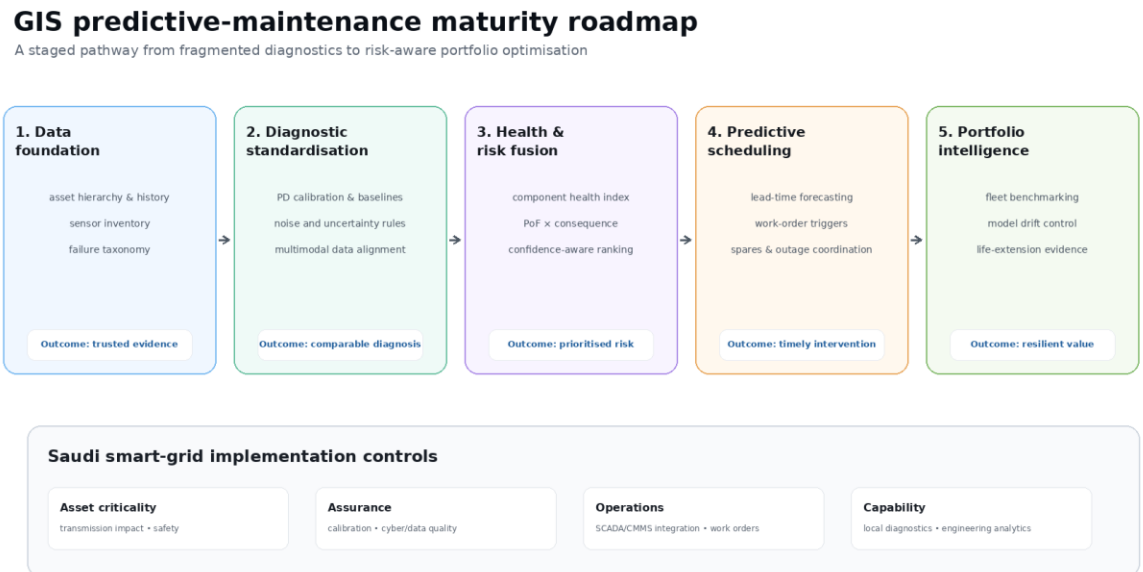

Figure 2. GIS predictive-maintenance maturity roadmap for Saudi smart-grid implementation.

XII. DISCUSSION, RESEARCH GAPS AND IMPLICATIONS

The literature shows rapid progress in GIS PD classification but a slower transition from diagnostic experiments to maintenance systems. A major research gap is field validity. Several advanced models explicitly address limited samples and domain differences [7–9], confirming that laboratory-to-field transfer is not a secondary problem but a central deployment constraint. Future studies should report performance across equipment families, substations and interference environments, including false-alarm consequences.

A second gap is multimodal evidence fusion. PD research is technically mature, yet many studies stop at defect classification. Utilities need models that combine electrical, acoustic, thermal, gas, mechanism and historical evidence according to failure physics. Fusion should explain why evidence supports a mechanism and preserve contradictions. Research on decomposition products in alternative GIS gases suggests additional opportunities for chemical confirmation of discharge processes [22], but operational integration and long-term baselines remain underdeveloped.

A third gap concerns risk calibration. Health indices are practical and interpretable [1,4], but linking health to time-dependent failure probability requires sufficient failure and censored-life data. Related high-voltage insulation studies show that ageing, transient stress and moisture can alter failure evolution [27–29]. Rare catastrophic events make purely statistical estimation difficult. Hybrid approaches that combine population reliability, physics, expert knowledge and current diagnostics are likely to remain necessary. The uncertainty of the resulting probability should be explicit.

A fourth gap is operational integration. Predictive outputs have limited value if they are not connected to work management, outage planning, spares, network criticality and post-maintenance verification. Operational integration should therefore be closed loop. Recent high-voltage asset reviews on high-voltage assets similarly concludes that sensing, diagnostics, life assessment and maintenance need to converge into continuous asset-management feedback, reinforcing the importance of this systems perspective even though its primary asset is cable rather than GIS. For practice, the implication is that utilities should invest first in evidence quality and governance. Calibration, data lineage, asset hierarchy, failure taxonomy and engineer feedback are foundational.

Once these are stable, advanced analytics can scale expert attention and improve timing. The resulting programme is less glamorous than an autonomous prediction platform, but it is more defensible for high-consequence transmission assets.

XIII. LIMITATIONS AND FUTURE RESEARCH

Study heterogeneity limits this review. PD experiments use different defect geometries, sensor bandwidths, signal-to-noise conditions, voltage levels and evaluation metrics, which prevents direct ranking of reported accuracies. GIS failure data are also scarce, and many predictive-maintenance studies concern related switchgear or cable assets rather than complete high-voltage GIS fleets. Saudi-specific GIS evidence remains limited, so some mechanisms are transferred from international studies.

Future research should establish multi-utility field datasets with harmonised labels, calibration metadata and confirmed defect outcomes. Longitudinal studies are needed to relate PD trend changes and multimodal health indices to actual time-to-intervention or failure. Research should also compare probabilistic, fuzzy, physics-informed and machine-learning approaches using the same operational decisions rather than only classification benchmarks. Finally, cybersecure integration with substation automation, historian, enterprise asset management and digital-twin platforms should be evaluated in terms of reliability benefit, decision latency, maintainability and total lifecycle cost.

XIV. CONCLUSION

Predictive maintenance of high-voltage GIS should be understood as an evidence-to-risk discipline rather than a collection of sensors or algorithms. PD monitoring provides valuable early warning, but its maintenance value depends on calibration, interference control, source localisation, trend interpretation and corroboration. Multimodal diagnostics add the physical context needed to distinguish insulation, thermal, gas-system and mechanism defects. Health indices make heterogeneous evidence interpretable, while failure-risk assessment ensures that maintenance priority reflects both condition and network consequence.

The framework connects sensing, diagnosis, health and risk modelling, maintenance action and verified outcomes in a closed loop. Data-driven methods strengthen this chain when they are field validated, confidence aware and governed against domain shift. They do not replace accountable engineering judgement.

For Saudi smart grids, staged implementation can improve reliability while avoiding unnecessary maintenance and premature replacement. Trusted asset data and diagnostic standardisation should precede advanced prediction; risk fusion should precede automated scheduling; and every intervention should feed new evidence back into the models. This progression aligns predictive maintenance with Vision 2030 by reducing forced outages, supporting efficient capital use, extending asset life where justified, and developing local capability in high-voltage diagnostics, analytics and intelligent asset management at scale.

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