

Original Research Article

Risk-Based Asset Management Framework for Enhancing High Voltage Power Infrastructure Reliability in Saudi Energy Networks

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Abstract: The electricity system in Saudi Arabia is currently being expanded and is at the same time becoming more digitally monitored, although the high-voltage transformers, substations, transmission lines, switchgear and protection systems remain long-life assets whose failure can have severe implications for reliability and economic performance. This review presents a risk-based asset management framework aimed at improving the reliability of high-voltage power infrastructure within Saudi energy networks. Evidence published between 2020 and 2025 has been brought together covering the areas of transformer condition monitoring, health indices, dissolved-gas analysis, machine learning, predictive maintenance, life-cycle planning, risk assessment and the modernisation of the Saudi grid. The review applies a structured integrative method which stresses clear eligibility criteria, critical comparison and thematic synthesis rather than making up screening statistics. The findings indicate that asset decisions can be made more defensible if condition data is transformed into a health state and then combined with the probability and consequences of failure, with uncertainty taken into account, before being linked to specific actions such as inspection, maintenance, refurbishment, replacement or continued monitoring. The proposed framework thus includes five interconnected layers: asset evidence, condition state, risk quantification, intervention decisions and portfolio governance. Special attention is paid to the conditions under which the Saudi infrastructure operates, such as high ambient temperatures, exposure to dust, rapid growth in demand, the integration of renewable energy, the geographically dispersed nature of the infrastructure and the increasing reliance on digital monitoring. The framework contributes to improved reliability by directing limited maintenance resources towards those assets that have the highest risk trajectory rather than just those that are the oldest. It also points out the need for further research in the areas of fleet-scale data quality, uncertainty calibration, interpretable artificial intelligence, cybersecurity, climate stress modelling and local validation. The approach thus offers a practical basis for utility companies that wish to implement transparent, auditable and reliability-focused asset management in line with the requirements of Saudi energy transition.

Keywords: High-Voltage Power Infrastructure; Risk-Based Asset Management; Power System Reliability; Transformer Condition Monitoring; Health Index; Dissolved Gas Analysis.

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1. INTRODUCTION

The high-voltage power infrastructure is built with a view to lasting service, but its reliability relies on components that wear out due to the combined effects of electrical, thermal, mechanical, environmental, and operational stresses. Since power transformers are so important, this is because they are expensive to acquire, hard to replace quickly, and are located at key points in the network. For this reason, recent literature regards maintenance not as a routine activity scheduled on a calendar basis but as an asset-management issue in which the technical condition, the probability of failure, the consequences, the cost, and the remaining life have to all be taken into account [1–5]. This change is significant for Saudi Arabia since the country's growing electricity demand, the increasing integration of renewable energy, the introduction of digital substations, the need for interconnections, and the existence of large-scale development projects are all placing greater operational demands on assets that vary considerably in age, loading history, environmental exposure, and the extent of monitoring. A reliability strategy that is based solely on time-based maintenance will result in the excessive servicing of low-risk equipment while at the same time failing to give adequate priority to degradation that has high consequences.

The evidence for making more selective decisions comes from condition monitoring. Nowadays, transformer programs make use of dissolved-gas analysis (DGA), measurements of oil quality, thermal indicators, partial-discharge sensing, frequency-response analysis, dielectric response, vibration analysis, records of load history, and visual inspection. Reviews of the various monitoring technologies indicate that no single measurement can describe the full condition of the equipment; reliable interpretation depends on data fusion and a understanding of the failure mechanisms [7–11]. DGA is still a key diagnostic method for oil-immersed transformers since the gases produced by thermal and electrical faults contain information regarding early insulation problems, but the traditional ratio methods may result in ambiguous or unresolved classifications. In view of this, recent studies have combined DGA with probabilistic methods, machine learning, and structured health indices in order to improve consistency [12–16]. However, these techniques are of no use unless the output of the models stays linked to engineering meaning and has clear decision thresholds.

Health indices deal with this issue by converting the diverse information about the condition of assets into a standard condition score which can then be used for comparing fleets. Since 2020, research has demonstrated a growing focus on

operating history, temporal deterioration, uncertainty, and the use of machine-learning methods to represent condition [4,15–18]. It should be noted, though, that a health index is not a risk index; two assets that have the same level of health may call for different actions if one supplies a vital industrial load, has little redundancy, or would result in a long restoration time. Risk-based asset management therefore goes beyond condition assessment by incorporating both the probability of failure and the consequences of failure and by examining how risk changes when intervention is delayed. This distinction ensures that expenditure on maintenance is linked to reliability exposure rather than merely to the age of the asset.

The fact that the Saudi situation makes this kind of integration particularly important is evident. Research into the Kingdom's developing power grid has shown that there are problems associated with the integration of renewable energy, issues concerning voltage control, microgrid standards, short-term load forecasting, and the expansion of data-intensive smart grid structures [26–30]. Although high levels of solar irradiance help to boost renewable energy production it also results in operating patterns that can change the loading of transformers and voltage conditions. High temperatures cause insulation to age more quickly when the thermal limits are frequently reached, and dust in the air can have an effect on insulators, cooling surfaces, sensors and outdoor equipment. Because of the long distances involved in transmission and the widespread location of demand centres the impact of failures can be greater where there is little redundancy or when replacement parts are difficult to get. Digital monitoring can help to reduce uncertainty, but it also brings with it dependencies on data quality and cybersecurity. A framework that is focused on Saudi conditions therefore should link the local stressors to equipment health, system criticality and portfolio decisions rather than simply importing uncalibrated general thresholds.

The review meets this need by bringing together the most recent evidence and presenting it as a practical framework for high-voltage infrastructure. The work does not involve the development of a new failure-prediction algorithm; rather, it sets up a clear decision-making structure in which diagnostic tests, health indices, predictive models, engineering judgment, considerations of economic impact, and governance controls can all be incorporated. The framework is constructed in such a way that it remains useful even when the level of data availability varies from one substation to another and from one type of asset to another. It enables the use of simple engineering assessments when there is limited evidence, while at the same

time permitting the use of probabilistic or machine-learning models when validated data are available. This step-by-step method is meant to alleviate two common flaws in asset analytics: viewing model accuracy as the ultimate goal and considering a combined condition score as enough reason to carry out maintenance spending.

2. Aim, Objectives and Review Questions

This review is intended to establish an asset management framework based on risk that will transform information regarding condition and operational performance into prioritised intervention measures focused on reliability for high-voltage power infrastructure within Saudi energy networks. The study has five objectives: to (1) summarise the more recent methods used for monitoring the condition of high-voltage assets and assessing their health; (2) determine the main technical, operational, environmental and consequence factors needed for making risk-informed decisions; (3) compare the different maintenance approaches based on time, condition, prediction and risk; (4) define an auditable data-to-decision architecture appropriate for the conditions in Saudi networks; and (5) identify the implementation gaps that need to be dealt with prior to large-scale deployment. The review also poses three questions: first, which streams of evidence are most effective in supporting the estimation of condition and failure risk? Second, how should probability, consequence, uncertainty and criticality be combined in a way that does not conceal engineering judgment within a single unclear score? Third, what organisational and data capabilities are necessary in order to turn risk analytics into tangible improvements in reliability?

3. REVIEW METHODOLOGY

A structured integrative review approach was chosen since the subject area involves engineering diagnostics, maintenance optimization, reliability analysis, machine learning, and the modernisation of the Saudi grid. The protocol adopts the clear line of reasoning that has been used in recent technical reviews and does not include any unsubstantiated statements regarding the number of databases or the number of studies screened. The review focused on literature published between 2020 and 2025, giving particular attention to studies in peer-reviewed journals and at conferences that dealt with power-transformer asset management, high-voltage condition monitoring, health indices, DGA, prognostics, predictive maintenance, maintenance optimisation, risk assessment, or the operating conditions of Saudi smart grids. The three papers that had been uploaded were used as a basis for the scholarly structure, for the level of methodology described, for the comparative tables, and for the way

the framework was presented; the substantive claims from these papers were not incorporated into the manuscript.

The search concepts were divided into four groups: those relating to assets (such as power transformer, high-voltage equipment, substation, and transmission asset), those relating to condition (including condition monitoring, health index, DGA, partial discharge, thermal monitoring, and remaining useful life), those relating to decision-making (such as asset management, maintenance optimization, predictive maintenance, risk-based maintenance, and criticality), and those relating to region (for example, Saudi Arabia, the Saudi grid, smart grid, and renewable integration). Logical combinations of these concepts were applied in order to find relevant research in the major scholarly discovery databases. In order to be included, a study had to be directly relevant to condition, risk, reliability, or maintenance decision-making; it had to have been published within the specified time period; it had to provide enough methodological detail to allow the contribution to be interpreted; and it had to be bibliographically traceable. Any studies that concentrated only on low-voltage consumer devices, on mechanical assets unrelated to the topic, or on general artificial-intelligence applications without a plausible link to power assets were excluded.

Each source that was kept was assigned a code based on a standard analytical framework. The first code indicated the asset or subsystem in question. The second code specified the type of evidence, for example oil chemistry, electrical tests, thermal measurements, acoustic or optical sensing, loading, weather exposure, inspection, or failure history. The third code named the analytical method, this including rule-based diagnostics, health indices, fuzzy logic, probabilistic models, machine learning, optimization, and multi-criteria decision methods. The fourth code recorded the decision output: fault classification, condition grade, remaining life, failure probability, maintenance interval, risk category, or replacement priority. The fifth code noted the implementation limitations, particularly those relating to data scarcity, lack of external validation, interpretability, changing operating conditions, or the absence of consequence modelling. This coding structure enabled studies using different algorithms to be compared on the basis of their decision value rather than just their predictive performance.

The evaluation of quality focused on traceability, engineering validity, and the relevance of the decisions involved. More emphasis was placed on studies that included descriptions of the input variables, validation data, uncertainties or limitations, as well as the link between the model's

output and a maintenance decision. Since transformer-failure datasets are generally imbalanced and specific to a particular site, high accuracy figures alone were not considered to be adequate proof of practical usefulness. The approach combined reviews with empirical studies: the reviews showed the range of existing methods, while the empirical papers demonstrated in practice how specific diagnostics or risk models perform. All the references listed in the final version were checked in the DOI records, and citations to sources outside the 2020–2025 period were not used in the manuscript even if earlier works had introduced historically important concepts.

The process took place in three stages. In the first stage, the evidence was divided into four

categories: condition acquisition, condition interpretation, risk quantification, and decision optimisation. In the second stage, the cross-cutting themes identified were data quality, multi-sensor fusion, interpretability, uncertainty, consequence, economic trade-offs, and local environmental adaptation. In the third stage, these themes were combined into a five-layer framework, incorporating feedback from actual field results to calibrate the model. This method is suitable for a review whose aim is conceptual integration rather than a meta-analysis since the literature contains diverse assets, datasets, outcome metrics, and validation methods. The framework is therefore given as a decision architecture which needs to be locally calibrated, not as a general numerical model.

Structured review workflow used for evidence synthesis

The protocol emphasizes reproducibility, source traceability and transparent eligibility criteria without inventing screening counts or unsupported selection statistics.

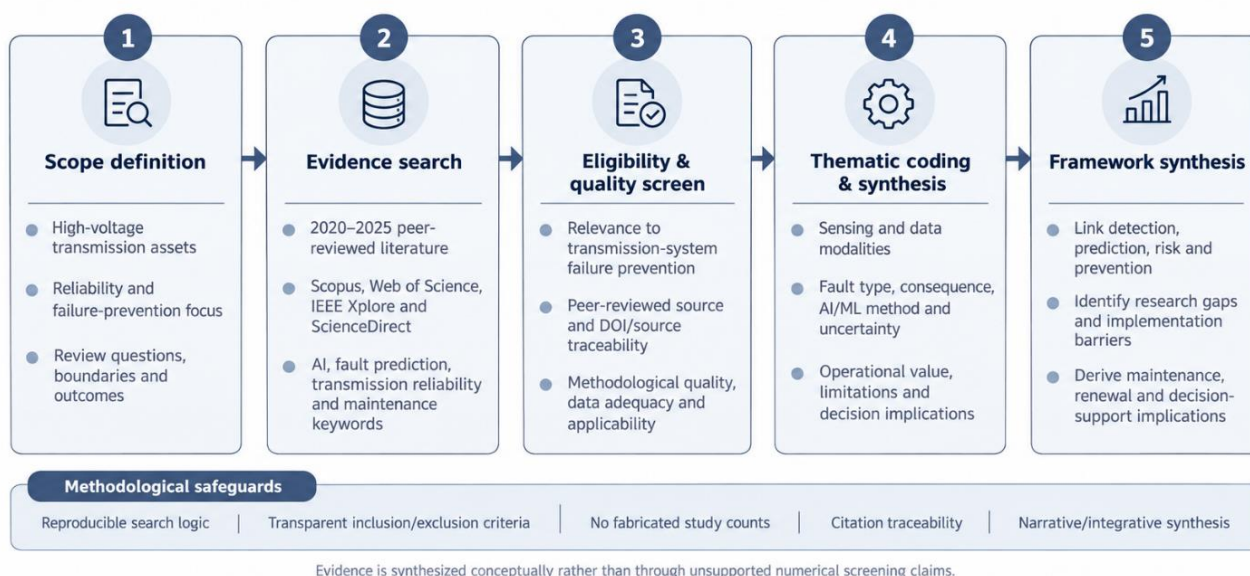


Figure 1: Structured review and synthesis workflow

4. Saudi High-Voltage Infrastructure Context

The management of high-voltage assets in Saudi Arabia should be considered in the context of a network that is at the same time expanding, moving towards decarbonization, and becoming more digital. Research into the integration of renewable energy has found that voltage problems, variability, protection issues, and the need for operational coordination are continual challenges as the amount of inverter-based resources increases [27]. Saudi studies of the distribution network also indicate that a high level of photovoltaic generation can cause local voltage to rise and that this situation then requires active control [26]. At the transmission and substation levels, such changes influence loading patterns, reactive power requirements, switching

frequency, and the thermal load experienced by transformers and other primary equipment. Asset-management models which assume that the historical duty levels are stable thus fail to reflect the higher levels of stress that will occur if the operating conditions change more rapidly than the maintenance policies are revised.

Environmental exposure is also a factor; when the ambient temperature is high it decreases the thermal headroom and can cause the insulation in transformers to age more quickly if the transformers are working near or above the thermal ratings indicated on their nameplates. Dust and contamination mean that the external insulation condition, the effectiveness of the cooling system, and

the maintenance of the sensors become more important. Transmission corridors that are used for long-distance transmission result in logistical exposure since the length of time taken to restore service may be as much determined by access, the availability of spare parts, and the need for heavy transport as it is by the failed component itself. Such considerations should be included in consequence models, not just in the technical condition ratings. A transformer that is only moderately degraded at a substation in an urban area with a high level of redundancy may involve less network risk than a healthier asset serving a location with a weak meshing structure and a long replacement lead time.

Studies into smart grids in Saudi Arabia have shown that there has been simultaneous progress in both data and communications capabilities. The use of hybrid deep learning for short-term load forecasting shows how locally trained analytics are able to capture Saudi demand patterns [29], and research into IoT-enabled smart grids underscores the importance of securing data exchange and the connected monitoring infrastructure [30]. These findings have direct relevance to asset management; online DGA, intelligent electronic devices, weather stations, digital protection records, supervisory-control data, and inspection platforms can only reduce uncertainty if the timestamps, asset identifiers, calibration states, and data ownership are reliable. For this reason, the framework presented here considers data confidence and cybersecurity as part of risk governance rather than as secondary issues relating to information technology.

5. Condition Assessment, Health Indices and Failure Evidence

The initial stage in risk-based asset management is the acquisition of evidence. With regard to power transformers, the literature on condition monitoring always recommends a multi-parameter method [7–11]. DGA picks up the chemical traces linked to thermal and electrical faults; the oil quality and the amount of moisture show the condition of the insulation environment; winding and dielectric tests show both electrical and mechanical degradation; thermal monitoring shows how well the transformer performs in terms of loading and cooling; partial-discharge measurements detect local insulation activity; and vibration or acoustic techniques can provide additional information about the mechanical state. When choosing sensors, one should base the decision on the possible failure modes rather than on the availability of technology. A utility will not benefit much from fitting high-frequency sensors whose output does not influence a specific maintenance decision.

The second layer transforms evidence into a condition state. Health-index methods are worthwhile since they allow for the standardisation of diverse measurements when comparing fleets. Guo and Guo [4] illustrated the advantages of combining operating history with test data, and Zaldivar and Romero [16] showed that different health-index formulations can lead to different classifications of the same fleet. Bohatyrewicz and Banaszak [17] also stressed the importance of monitoring changes in the health index over time rather than depending on isolated snapshots. These results suggest that a version of the approach used in Saudi Arabia should keep the original component scores and the trend data rather than storing only the final index. The index should be seen as a structured summary that is interpretable, not as a replacement for the diagnostic evidence from which it was derived.

The use of artificial-intelligence techniques can enhance the diagnostic process if they are incorporated into this engineering framework. Applications of machine learning to DGA have demonstrated better identification of fault patterns than those based on strict ratio limits [12–14]. Graph-based and deep-learning methods are also capable of showing the relationships between various condition indicators [15]. Recent reviews indicate that transformer prognostics are now increasingly incorporating random forests, neural networks, ensemble methods, and remaining-life estimation [5,6]. Yet the performance of the models is very much dependent on the quality of the labels, the balance of the classes, the similarity of the fleet, and the stability of the operating conditions. A model developed from the fault history of one utility might perform badly if it is applied to different oil types, various loading regimes, different maintenance practices, or varying environmental conditions. Local validation is therefore a necessity for ensuring reliability rather than merely an optional stage of research.

Physics-informed methods provide a promising solution to this issue of transfer. For instance, physics-informed neural networks have been applied in order to reconstruct transformer temperature fields while incorporating the heat-transfer constraints [20]. They are appealing for use in high-voltage infrastructure since they are able to maintain physically reasonable behaviour even when the amount of data is limited. In a similar way, maintenance-interval optimisation can take into account imperfect maintenance and the variation in costs over the lifetime of an asset [23]. The practical takeaway is that risk-based asset management should not favour one particular analytical approach; rule-based engineering, statistical reliability, fuzzy logic, machine learning, and physics-informed

models can all coexist provided that their outputs are calibrated to the same condition and decision states.

Every condition estimate must be accompanied by a measure of data confidence since missing sensors, out-of-date laboratory results, inconsistent naming, changes in maintenance procedures, and unrecorded replacements of components can lead to a false sense of precision. To this end, the suggested framework assigns a confidence level to each health assessment; in order

to achieve a high level of confidence, recent online and offline evidence showing consistent trends is required; medium confidence might be based on incomplete evidence; and low confidence should prompt an inspection or test before approving a decision to carry out a costly replacement. This straightforward approach ensures that uncertainty is not concealed within a numerical risk score and makes actions aimed at improving the data visible in the maintenance portfolio.

Table 1: Evidence streams and their role in risk-based asset management.

Asset domain	Evidence	Risk mechanism	Analytical treatment	Decision use
Transformer insulation	DGA, moisture, oil quality, dielectric response	Thermal/electrical degradation; aging	DGA rules, ML, health index	Fault classification; inspection priority
Windings & core	FRA, impedance, vibration, current signatures	Mechanical deformation; looseness; short circuits	Trend comparison; signal analytics	Testing, outage inspection, refurbishment
Bushings / external insulation	Capacitance/tan delta, thermal imaging, visual contamination	Insulation deterioration; hot spots; pollution	Thresholds + trend analysis	Cleaning, testing, replacement
Cooling and loading	Top-oil/hot-spot temperature, fans/pumps, load history	Accelerated thermal aging; cooling failure	Thermal model; anomaly detection	Derating, repair, maintenance timing
System consequence	Capacity, redundancy, customers, restoration lead time	Outage severity and recovery exposure	Criticality / consequence scoring	Portfolio priority and contingency

6. Risk Quantification and Maintenance Decision Logic

Risk quantification starts by dividing the probability of failure from the consequence of failure. The probability is determined by factors such as the asset's health status, the trend of its degradation, its age, the loads it carries, its defect history, the environment it is in, and the experience of other similar assets. The consequence takes into account the network topology, the criticality of the customers and the industry, safety considerations, environmental exposure, the replacement lead time, the duration of the outage, the complexity of the repair, and the financial impact. It is important to make this distinction since condition and criticality address different questions; an asset that is in a poor condition might warrant close monitoring instead of immediate replacement if there is redundancy, while an asset that is in a moderate condition but has serious consequences if it fails might warrant earlier action. Increasing research into risk assessment of transformers is in favour of using multi-dimensional criteria rather than ranking according to a single parameter [18,25].

A good way to approach this is through a two-stage risk model. In the first stage, a health-based

probability band is estimated rather than assuming that the limited amount of failure data is enough to allow exact annual probabilities to be assigned to each unit. In the second stage, the consequences are assessed by means of a standard criticality model. The results from these two stages are then combined to form a risk category, and the trend of this category is kept under observation over time. Once enough fleet data are available, the probability bands can be adjusted to match the actual observed failure frequencies; in cases where data are scarce, Bayesian updating, survival models, or expert-based ranges may be employed. The framework must retain the confidence interval or the uncertainty associated with the category so that those making decisions can tell the difference between an asset that is truly high risk and one that has a high score due to lack of information.

Decisions based on risk should be turned into specific actions. An asset that is deteriorating and carries credible evidence of this kind may need an immediate inspection, a reduction in load, maintenance, contingency planning, or the start of replacement procurement. A medium-risk asset should have targeted diagnostics carried out and its review periods shortened. A low-risk asset should

continue to be monitored in the normal way and unnecessary maintenance should be avoided since such maintenance can itself lead to defects. As shown in the literature on predictive maintenance in the power industry, the economic value of using advanced analytics comes from altering the timing and focus of interventions, not just from the ability to predict [1]. Smart asset-management systems do likewise by stressing the combination of online and offline evidence so that diagnostic information can be used by decision-making processes that do not require specialist knowledge [3].

Maintenance optimization includes a life-cycle viewpoint. Although time-based maintenance is still useful for statutory duties, for known wear mechanisms, and for low-cost inspections, it is inefficient when used uniformly across diverse fleets. While condition-based maintenance improves the accuracy of targeting it can still fail to take account of the consequences of a system's failure. Predictive maintenance can forecast deterioration or failure, but such a forecast only becomes operationally significant when it is turned into a risk-informed action. It is for this reason that risk-based maintenance stands above the other approaches: it uses information on condition and prediction to determine how limited resources can achieve the greatest improvement in reliability. Studies into the optimization of maintenance intervals show that reliability constraints and varying costs can be combined explicitly [23], and life-cycle economic analysis shows the advantage of considering long-term ownership rather than just the immediate cost of repair [24].

The final stage is portfolio optimization. Assets should not be approved for significant spending on their own since budgets, outage periods, spare parts, specialist teams, and network projects all have interdependencies. Although a portfolio approach can rank different actions according to the amount of risk reduction they achieve per unit of cost, this ranking must still take into account engineering constraints and minimum reliability requirements. For the networks in Saudi Arabia, portfolio analysis also needs to take the strategic development timelines into consideration. An asset that needs replacing as part of a substation expansion might be suitable for temporary monitoring instead of major refurbishment, and a transformer serving a new industrial area might qualify for accelerated renewal even if its current health rating is not the worst among the fleet. Governance therefore has to ensure that both the quantitative risk evidence and the documented engineering justification are maintained.

7. Proposed Risk-Based Asset Management Framework

The framework suggested organises these findings into five interconnected layers. The first layer, Asset Evidence, gathers information on condition, operation, environment, events, and maintenance. The second layer, Condition State, turns these inputs into evaluations of possible failure modes, health indices, trends in degradation, and estimates of remaining life, each accompanied by a data-confidence rating. The third layer, Risk Model, incorporates the probability of failure, the consequences of failure, criticality, and uncertainty. The fourth layer, Decision Layer, converts risk into actions such as inspection, maintenance, refurbishment, replacement, derating, contingency, or monitoring and deferring. The fifth layer, Governance, is responsible for managing portfolio budgets, reliability indicators, data standards, cybersecurity, audit trails, and the feedback from completed work. The architecture is shown as a closed loop in Figure 2 since the results of maintenance and actual failures have to be used to update the future thresholds and model parameters.

This design intentionally stops direct access going from the raw sensor output to the final decision. First, online monitoring generates evidence; the diagnostic logic then checks whether this evidence is in line with a known degradation mode; the health assessment decides on the severity and trend; risk analysis assesses the system's importance; and governance decides if the recommended action is feasible and justified. It is important to have this separation in the case of safety-critical infrastructure since each of the stages can be examined on its own. Whenever an artificial-intelligence classifier is altered, there is no need to rebuild the consequence model. If the network topology changes, the criticality can be updated without having to retrain the diagnostic model. The modular approach also allows for a step-by-step rollout among utilities that have different levels of digital maturity.

A basic and workable implementation for transformers could start by using existing DGA results, oil test data, the loading levels, the age of the equipment, the maintenance history and the records of inspections. A transparent health index should assign condition ratings, and a simple consequence model should take into account capacity, redundancy, the criticality to customers, the replacement lead time, safety, and exposure to the environment. The matrix produced in this way could be used to prioritise more intensive testing and contingency planning. When the level of data maturity increases, it would be possible to incorporate online DGA, thermal sensors, partial-discharge monitoring,

weather data, automated event logs and machine-learning prognostics. However, the order in which this is done is important: data governance and decision rules must be established before any additional sensors are bought, because otherwise utilities could end up with a large amount of data but no clear way of improving reliability.

Another design principle is that of temporal risk. Although static red-amber-green displays are easy to understand they can conceal changes that occur over time. To address this, the system keeps a record of the past history of an asset's health, risk, and confidence level. An asset which is rapidly moving from a low to a medium risk category may warrant greater attention than one that is steadily at a medium risk level. It is important that trend analysis should be able to tell the difference between slow ageing of insulation and sudden changes caused by through-faults, overloads, deterioration of the cooling system, or environmental events. Temporal risk also aids in deciding when interventions should take place: in the case of slow deterioration and a planned network outage six months in the future, delaying action may be reasonable; but if the risk is increasing, it may be unacceptable to wait for the planned outage.

A third principle is that of escalation taking into account uncertainty. When there is a high level of consequence together with low confidence regarding the data, the better course of action is usually to obtain more information rather than to carry out an

immediate replacement. Techniques such as targeted DGA, thermal inspection, electrical testing, or getting a specialist's assessment can reduce uncertainty at a fairly low cost. On the other hand, if both the level of condition evidence and the consequence are high and the confidence in them is strong, then carrying out repeated diagnostic tests can amount to an unjustified delay. This approach treats inspection as an active means of managing risk and enables the distinction to be made between the value of the information and the value of physical intervention.

In the end, the framework calls for measurable performance indicators. Examples of such indicators are risk-weighted forced-outage exposure, the percentage of critical assets that have current condition assessments, the number of high-risk assets lacking approved mitigation measures, the average time between risk escalation and taking action, the rate of unplanned transformer outages, the maintenance cost per unit of risk reduced, and the calibration of forecast against observed failure rates. These measures are more informative than simply counting completed maintenance tasks since they link activities to reliability outcomes. A well-developed program should also monitor model drift, missing-data rates, false alarms, and cybersecurity incidents which affect the monitoring systems. Taken together, these metrics enable senior management to determine whether the investment in digital asset management is actually reducing operational exposure or is simply leading to greater analytical complexity.

Risk-Based Asset Management Architecture for High-Voltage Infrastructure

A structured decision workflow linking engineering evidence, condition assessment, risk evaluation, intervention planning, and governance feedback.

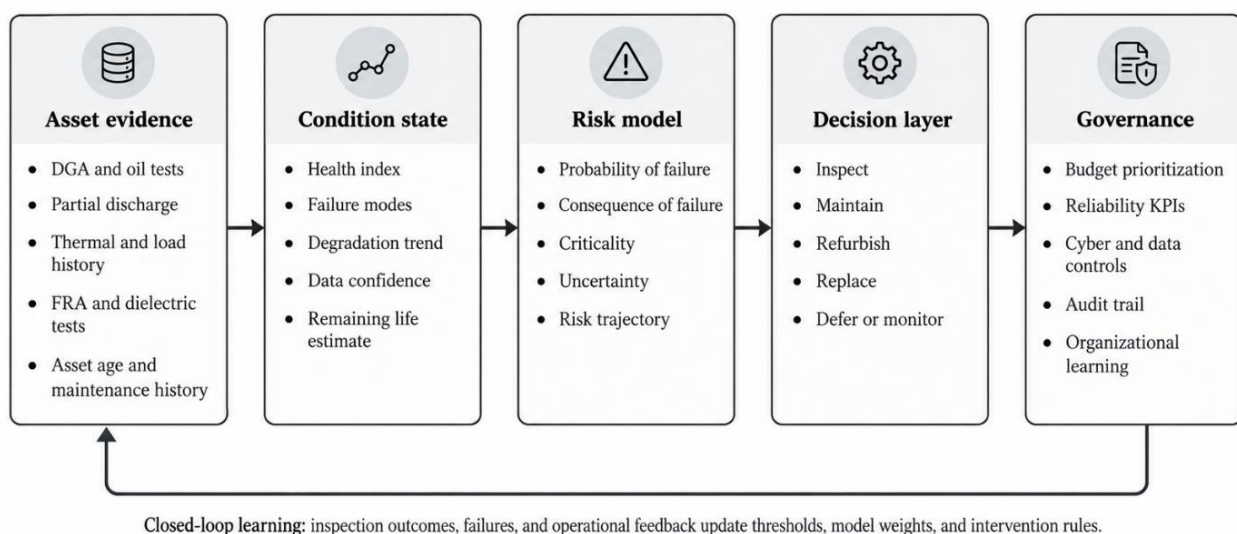


Figure 2: Five-layer risk-based asset management architecture with closed-loop learning

Table 2: Framework layers, outputs, and decision functions

Layer	Core content	Key output / KPI	Primary decision
1. Asset evidence	Condition, operation, environment, events, maintenance	Completeness; recency; sensor/test validity	Acquire missing evidence; validate data
2. Condition state	Health index, failure modes, degradation trend, RUL	Condition grade; trend; confidence	Diagnose and quantify severity
3. Risk model	Probability $\times$ consequence + uncertainty	Risk category; trajectory; confidence band	Escalate, inspect, or accept risk
4. Decision layer	Maintenance, refurbishment, replacement, derating	Expected risk reduction; cost; outage need	Select intervention and timing
5. Governance	Portfolio, KPIs, cybersecurity, audit trail	Risk backlog; model drift; data quality	Fund, approve, monitor, recalibrate

8. DISCUSSION

The available literature shows a clear trend moving from periodic maintenance towards condition- and risk-informed management, but it also highlights a persistent gap in implementation. A number of studies focus on optimising a diagnostic or predictive task without showing how the results affect actual maintenance decisions. This issue is especially evident in machine-learning research, where classification accuracy is often reported on curated datasets while the cost of false alarms, faults being missed, missing data, and the ability of the approach to be applied across a fleet is given less consideration. In order to overcome this gap, the framework requires all analytical outputs to be linked to a specific decision and makes confidence levels explicit. This approach is in line with recent reviews of asset management which stress the integration of diagnosis, health assessment, and life management rather than the use of separate algorithms [2,5].

Localization is the key research need for Saudi networks. Although international transformer models offer useful approaches, the threshold values and risk weights must be adjusted in light of the local equipment designs, the ambient conditions, the loading patterns, the maintenance practices, and the consequences for the network. Saudi studies have already shown that local-specific aspects of load forecasting, the integration of renewable energy, voltage behaviour, and digital-security issues differ from the general assumptions [26–30]. This approach should also be followed in the case of asset health. A model should not be regarded as ready for deployment until it has been tested using data from a representative sample of the Saudi fleet and has been examined by engineers who are familiar with the operational context.

The degree to which implementation is carried out also relies on careful change management. Asset owners should record the reasons for selecting thresholds, identify who is authorised to override the automated recommendations, specify how often the models are

recalibrated, and state what evidence is needed before an intervention is postponed. This kind of governance is particularly important when analytics are shared among business units because.

9. Research Gaps and Practical Implications

The following six research gaps should be given priority. Firstly, the utilities in Saudi Arabia need to have standardized asset identifiers together with detailed longitudinal records of asset condition in order that the data from laboratories, SCADA systems, protection systems, maintenance activities, and failure incidents can be reliably linked. Secondly, since maintenance actions frequently prevent the kind of event that a predictive model is attempting to learn, the assignment of failure labels must be governed. Thirdly, uncertainty calibration should become a standard practice since risk scores that do not include a measure of confidence may lead to a false sense of precision. Fourthly, environmental stress models should be developed to assess the combined impact of heat, dust, loading, and the variability in operations caused by renewable energy on degradation. Fifthly, cyber resilience must be incorporated into the online monitoring system since compromised or unavailable data could lead to incorrect asset decisions. Sixthly, portfolio studies should examine how risk-based prioritization affects reliability, cost, spare parts strategy, and outage planning over a number of years.

The practical implementation can be carried out in stages. The utilities could start by establishing a common asset taxonomy, a minimum condition dataset, consequence categories, and decision thresholds for one particular high-value asset class, for example transformers operating at 132 kV or above. A pilot project should compare the current maintenance priorities with those recommended by the framework and note the reasons for any disagreements. In the following phase, online monitoring and predictive models should only be introduced where they deal with uncertainties that have already been identified. Governance must involve periodic reviews of the thresholds, independent validation of the models, a cybersecurity

assessment, and an auditable record of any overrides. Thus, this step-by-step method reduces technology risk while generating evidence regarding reliability and economic benefit before the approach is widely adopted.

10. Limitations

The review does have some limitations. Instead of calculating a pooled effect size, it has combined a variety of studies since the methods, the groups of assets, and the criteria used for validation are not sufficiently similar to allow a reliable meta-analysis. The period covered in the review was deliberately restricted to the years 2020 to 2025, which means that older foundational standards and traditional risk-based maintenance studies have been excluded. The framework has not been calibrated using a Saudi utility's confidential database of failures and equipment conditions, and therefore the numerical thresholds in it should not be regarded as validated local limits. Lastly, the framework is mainly based on evidence that is centred on transformers since the recent literature is most robust in this area; future work should involve the development of asset-specific modules for circuit breakers, gas-insulated switchgear, cables, overhead lines, reactors, instrument transformers, and protection systems while maintaining the same risk-governance structure.

11. CONCLUSION

Risk-based asset management is able to enhance the reliability of high-voltage infrastructure by changing the unit of decision from the maintenance interval to the risk trajectory. Evidence examined between 2020 and 2025 indicates that current transformer management already includes most of the necessary technical elements such as multi-sensor monitoring, DGA analytics, health indices, prognostics, machine learning, maintenance optimization, and life-cycle assessment. The main difficulty, however, lies in integration: condition has to be linked to failure probability; probability must be combined with consequence; uncertainty must stay visible; and the resulting risk must lead to a specific intervention that can be audited and evaluated. For Saudi energy networks, the integration should be adjusted to take into account high-temperature operation, dust exposure, changing load patterns, the integration of renewable energy, the dispersed nature of the infrastructure, and the growing digital monitoring capabilities. The suggested five-layer framework—comprising asset evidence, condition state, risk model, decision layer, and governance—offers a practical approach to achieving this integration. Its key idea is that the most reliable maintenance decision does not have to be to address the oldest or most deteriorated asset first, but rather to act at the point where there is credible evidence

showing the largest potential improvement in reliability. A step-by-step implementation that starts with data governance and the use of clear transformer risk models can establish this approach before more sophisticated analytics are brought in. Future research should validate the framework using data from the Saudi fleet, quantify the uncertainty, benchmark the level of risk reduction over time, and apply the architecture to other high-voltage asset types.

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