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RISK-BASED MAINTENANCE IN AGING ENERGY INFRASTRUCTURE: ANALYTICAL PERSPECTIVES ON MACHINE LEARNING APPROACHES

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ABSTRACT
The growing reliability, safety and environmental risks associated with aging energy infrastructure- such as power transmission systems, oil and gas piping, nuclear plants and offshore systems- are increased as systems continue to be used beyond their designed design life in a state of increased uncertainty. Conventional maintenance approaches, which rely mostly on isochronic schedules or states of condition have not been effective in dealing with low likelihood, high-consequence failures of such assets. Risk-Based Maintenance (RBM) has thus become an imperative decision structure, which blatantly incorporates the probability of failure, severity of consequences, and asset criticalness. Meanwhile, machine learning (ML) has become a popular data-driven degradation modelling, fault detection and predictive maintenance tool. Nevertheless, the speed of ML application proliferation has exceeded the pace of their inclusion in the systematic risk-centric maintenance theory. This is an analytical summary of ML methods of RBM in aging energy infrastructure and focuses on conceptual integration, as opposed to algorithmic benchmarking. It looks at the role played by supervised learning, deep learning, probabilistic ML, and reinforcement learning in the various aspects of RBM, and the various challenges posed by the data imbalance, non-stationary degradation, weak interpretability, and weak connection to physical failure. This analysis shows that high predictive accuracy does not always result in effective maintenance decisions out of the context of explicit risk integration, consequence modelling and human supervision. This review makes it clear that ML is a decision-support enabler rather than a substitute to probabilistic risk assessment by merging knowledge in the energy domain and methodological paradigm. The study also ends by outlining major research priorities, such as physics-informed and hybrid probabilistic ML, digital twins, explainable AI and cyber-resilient maintenance analytics.

KEYWORDS: *Risk-Based Maintenance, Aging Energy Infrastructure, Machine Learning-Enabled Asset Management, Probabilistic Risk Assessment, Predictive and Condition-Based Maintenance*

1. INTRODUCTION
The energy facilities, such as power grids, oil and gas pipelines, nuclear plants and offshore platforms, are becoming used past their designed lifespan and become susceptible to progressive degradation processes, such as corrosion, fatigue, aging of insulation, and structural weakening. These aging effects increase risks of reliability, safety, environmental protection and economic sustainability especially since failures in the energy systems tend to spread to other systems rather than being confined (Frangopol & Tsompanakis, 2014; Adewoyin, 2022; Hanson et al., 2024). These risks are further enhanced by climate stressors, increased exploitation of the assets, and the increased complexity of the systems, and make the traditional approaches to the assets management inadequate when working with modern energy systems (Tesfamariam et al., 2018; Mahmood et al., 2023).

The problem of aging is reflected yet just as significant ways in every sector of energy. The transmission, distribution network operates with a growing number of failures due to the aging lines, substations, and cables, whereas the oil and gas pipelines and offshore premises are subjected to corrosion-related and mechanically induced degradation in adverse conditions (Yeboah & Enow, 2018; Asaye, 2025; Amaechi et al., 2022). The requirements are of particular rigor with nuclear energy systems, as they have little room to fail and have strong regulatory control (Erhueh et al., 2024; Opoku & Adeoye, 2025). Traditionally, the methods of maintenance have been based on age-based or time-based interventions based on the assumption of predictable wear and tear. Nevertheless, broad evidence indicates that this practice is becoming less effective with heterogeneous and long-lived assets and may cause inefficient maintenance allocation and high risk of failure (Lawoyin et al., 2023; Belodedenko et al., 2023).

The literature has responded by moving to models of Risk-Based Maintenance (RBM) and Condition-Based Maintenance (CBM) frameworks that directly incorporate the failure likelihood, consequences severity, asset criticality and lifecycle cost. Machine learning (ML) has become one of the facilitators of these models, enabling degradation modeling, fault detection, and predictive maintenance in the energy domain due to the development of sensing and data analytics (Gomez et al., 2019; Manninen et al., 2022; Sundsgaard, 2025). However, there remains a desperate gap on the subject of the limited adoption of ML outputs into formal risk-based decision-making frameworks. Most studies emphasize predictive accuracy more than quantification of uncertainty, consequence modeling, and actionable decision assistance and have low efficacy in safety-critical and aging systems (Kabir et al., 2018; Tesfamariam et al., 2018; Han et al., 2024). To fill this gap, it is necessary to analytically and theoretically incorporate ML

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into RBM and make sure that data-driven information complements, not substitutes, probabilistic risk determination and informed maintenance decision-making processes.

2. CONCEPTUAL FOUNDATIONS OF RISK-BASED MAINTENANCE

Risk-Based Maintenance (RBM) is at its core based on the fact that risk is formally defined as the product of failure probability and severity of consequence and not as the failure likelihood. When applied to energy infrastructure, risk does not just represent an opportunity where an asset fails, but it also represents the extent of technical impact, economic impact, safety and environmental impact (Frangopol & Tsompanakis, 2014; Tesfamariam et al., 2018; Kabir et al., 2018). The degradation mechanisms encountered by aging energy assets are characterized by uncertainties, which are dependent on material specifics, operating conditions, exposure to the environment, and past maintenance activities, and therefore, accurate failure prediction is impossible (Belodedenko et al., 2023; Asaye, 2025). Consequently, RBM takes a probabilistic approach, acknowledging that uncertainty plays a central role in infrastructure degradation and it cannot be eradicated but it should be modeled explicitly. Such a probabilistic basis of RBM is what stands in opposition to deterministic maintenance philosophy and establishes the theoretical foundation of the risk-informed decision-making under uncertainty (Gomez et al., 2019; Han et al., 2024).

RBM is conceptually different to Reliability-Centered Maintenance (RCM) and Condition-Based Maintenance (CBM) within the larger context of maintenance. RCM is based on the identification of failure modes and specifying maintenance actions to maintain system functions, yet it tends to consider consequences qualitatively and operate under relatively stable operating conditions (Yeboah & Enow, 2018; Ajenifuja, 2024; Samuel & Chukwunweike, 2023). CBM, in its turn, uses the condition monitoring data to initiate maintenance correction when asset health indicators pass specific thresholds, although it often does not provide a clear means of adding consequence severity or system level risk (Sundsgaard, 2025; Mortensen, 2024). The degradation mechanisms, modeling the failure modes, and modeling the consequences of the system are explicitly linked in the RBM model to facilitate maintenance decisions that prioritize assets based on their contribution to the system-wide risk, as opposed to individual condition or age (Adewoyin, 2022; Manninen et al., 2022; Eskandarzade et al., 2020).

One of the key purposes of RBM is the prioritization of risks with limited maintenance funds, which is especially acute in old energy infrastructure. A scarcity of financial and human resources leads to the need to make challenging trade-offs, with the asset managers putting resources into areas of maintenance that will provide the highest returns in terms of risk reduction (Lawoyin et al., 2023; Alquraidi & Awad, 2024). The role of asset criticality in the process is decisive since the occurrence of highly interconnected or safety-critical components, including transmission lines, substations, pipelines, and nuclear systems, may be the cause of cascading failures with extensive consequences (Manninen et al., 2022; Mahmood et al., 2023; Zhang et al., 2025). Therefore, RBM frameworks focus on prioritizing consequences, introducing service disruption, safety risks, environmental risks and regulatory risks non-compliance into maintenance planning (Kabir et al., 2018; Tesfamariam et al., 2018; Gomez et al., 2019).

Analytically, probabilistic property of RBM has critical implications to machine learning use in maintenance decision-making. Although ML models can offer useful learning about degradation behavior and risk of failure, deterministic predictions are also inadequate to risk based decision making, especially in aging energy systems, where failure data is sparse, behavior is non-stationary, and the effects of failure are high (Papakonstantinou et al., 2024; Gaye et al., 2025.; Wang, 2025). To make sound decisions in the face of uncertainty, risk modeling needs not only point estimation, but also uncertainty quantification and consequence integration (Han et al., 2024; Kabir et al., 2018). This weakness is particularly severe in strongly regulated and safety-critical areas, including nuclear energy, pipeline systems, and power transmission networks, where the requirements of regulatory frameworks necessitate conservative, transparent and defensible risk assessment (Erhueh et al., 2024; Opoku & Adeoye, 2025; Panful et al., 2025). Therefore, RBM offers the conceptual prism in which ML outcomes are supposed to be projected, not as a decision, but as a probability to be fed into a more comprehensive risk-informed maintenance system.

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Table 1. Comparison of Maintenance Paradigms

Paradigm	Decision Basis	Risk Explicit?	Data Intensity	Suitability for Aging Assets	Key References
Age-Based Maintenance	Fixed time or usage intervals	No	Low	Low - assumes uniform degradation, ignores uncertainty and failure consequences	Frangopol & Tsompanakis (2014); Yeboah & Enow (2018); Lawoyin et al. (2023)
Reliability-Centered Maintenance (RCM)	Failure mode and functional analysis	Limited (qualitative)	Moderate	Moderate - identifies failure modes but limited in dynamic risk prioritization	Yeboah & Enow (2018); Ajenifuja (2024); Samuel & Chukwunweike (2023)
Condition-Based Maintenance (CBM)	Condition indicators and thresholds	Implicit	High	Moderate -effective for degradation detection but weak in consequence modeling	Sundsgaard (2025); Mortensen (2024); Meier (2023)
Risk-Based Maintenance (RBM)	Probability × consequence, asset criticality	Yes (explicit)	Moderate - High	High - suited for aging, safety-critical, and interconnected energy assets	Adewoyin (2022); Gómez et al. (2019); Manninen et al. (2022); Tesfamariam et al. (2018); Hanson et al. (2024)

3. CHARACTERISTICS OF AGING ENERGY INFRASTRUCTURE

The main characteristic of the aging energy infrastructure is the extensive physical degradation processes which are developed over long operation periods and under the conditions of very strong variability. In power grids, pipelines, offshore systems, and nuclear systems, the most common aging processes are corrosion, fatigue cracking, insulation, wear, and embrittlement of materials, which typically interact with each other in a nonlinear way (Frangopol & Tsompanakis, 2014; Adewoyin, 2022; Asaye, 2025). Exposure to the environment, operational loading, and history of maintenance all have a strong impact, and such mechanisms result in an asset-specific and time-varying deterioration pathway (Amaechi et al., 2022; Belodedenko et al., 2023; Han et al., 2024). Consequently, any age-related degradation processes of energy assets are non-stationary, which is a major breach of a basic assumption of several data and machine learning models that assume the stability of statistical characteristics over time. Furthermore, such system failures are usually infrequent but high-stakes phenomena with heavy-tailed failure distributions that pose significant challenges to traditional learning strategies that are usually trained on regular operating data only (Mahmood et al., 2023; Kabir et al., 2018).

Besides the physical degradation, the aging infrastructure of energy sources is characterized by serious data-related issues that only make the implementation of ML more complex. Most of the assets are based on legacy monitoring systems with low sensing resolutions, inconsistent data logging processes, and a high frequency of data gaps because of sensor failures, retrofitting constraints, or changes in the data acquisition standards with time (Meier, 2023; Mortensen, 2024; Papakonstantinou et al., 2024). Historical data is prone to bias and approximate and drifting sensors introduce uncertainty that can invalidate assumptions of independent and identically distributed (IID) data, which most supervised learning models are based upon (Sundsgaard, 2025; Wang, 2025). Moreover, the fact that energy assets may have long service life, and the data history may be short and disjointed. (Asaye, 2025; Alquraidi & Awad, 2024). These properties complicate the generalization of models and raise the chances of overfitting, especially when the ML models are trained without the clear regard of uncertainty and the quality of the information (Gaye et al., 2025).

Another characteristic of aging energy infrastructure is the heterogeneity and interdependence of resources in multifaceted networked systems. The heterogeneity of energy networks network expressions is that they can contain dozens of ports with different designs, ages, materials, and operating regimes, which inevitably results in an extremely heterogeneous nature of the degradation patterns of the same system (Manninen et al., 2022; Lawoyin et al., 2023; Zhang et al., 2025). A failure in one part of a network, e.g., transmission lines, substations, pipeline, or control systems can spread through networks, causing cascading failures of systems and increasing risk at the system level (Tesfamariam et al., 2018; Gomez et al., 2019). These interdependencies also breach the independence assumptions typically assumed in ML models and point to the weakness of asset-level predictions on their own. In turn, non-stationary degradation, sparse and biased information, assortment of assets, low-frequency catastrophic occurrences of machines, network dependencies are the features of aging energy infrastructure that indicate the necessity of risk-based, probabilistic models where machine learning is not a decision-maker but an analytical instrument to support decisions.

4. EVOLUTION OF MACHINE LEARNING IN MAINTENANCE DECISION-MAKING

Energy infrastructure maintenance decisions have shifted their focus towards more and more probabilistic and data-driven paradigms as opposed to schedule-driven deterministic approaches. The initial models were based on constant failure rates, mean time to failure, and interventions due to age and utilized the assumption of stationary degradation mechanisms and minimal uncertainty (Frangopol & Tsompanakis, 2014; Yeboah & Enow, 2018). With the limitations of deterministic models becoming clear especially of aging assets which are subject to variable and uncertain conditions, a shift in research to probabilistic reliability and risk-based methods was undertaken. The use of statistical regression, survival analysis, and hazard models allowed estimating the probability of failures and the remaining useful life and clearly take into account the uncertainty, which is a crucial conceptual development in the field of maintenance planning in energy systems (Tesfamariam et al., 2018; Kabir et al., 2018; Gomez et al., 2019).

The increased access to condition monitoring data and computing resources then prompted the use of machine learning (ML) in maintenance. Initial ML applications were the continuation of classical regression and classification engines that were capable of being more flexible in modeling the operation of degradation and fault behavior in power grids, pipelines, and industrial equipment (Meier, 2023; Mortensen, 2024; Dokic & Kezunovic, 2018). As ML methods were advancing, studies began to work on ensemble learning, deep learning and reinforcement learning methods with the ability to model nonlinear degradation dynamics and assist with sequential maintenance decisions (Sundsgaard, 2025; Mohanachandran et al., 2025; Zhou et al., 2025; Xu & Zhang, 2026). Although predictive models became more precise, a large majority of ML-based studies continued to concentrate on the accuracy of predictions because they tended to be black-box, with little interpretability, and they also ignored uncertainty (Papakonstantinou et al., 2024).

One of the specific analytical differences that come up in this evolution is the difference between prediction, prognostics and decision support. Whereas ML models have been found to be useful in predicting the probability of failure, as well as predicting degradation curves; they often fall short of aiding maintenance choices that explicitly consider probability, the severity of consequences, cost, and system-wide risk (Wang, 2025; Manninen et al., 2022). Risk-based maintenance involves combining probabilities of failures derived by ML with consequence modeling and asset importance, but these connections are not firmly established in most of the literature (Kabir et al., 2018; Tesfamariam et al., 2018; Hanson et al., 2024). Subsequently, more and more studies discuss the development of ML-enhanced risk-based maintenance models, in particular, in safety-relevant and regulated sectors, where deterministic forecasts do not suffice to make resilient decisions under uncertainty, like nuclear energy, power transmission, and offshore.

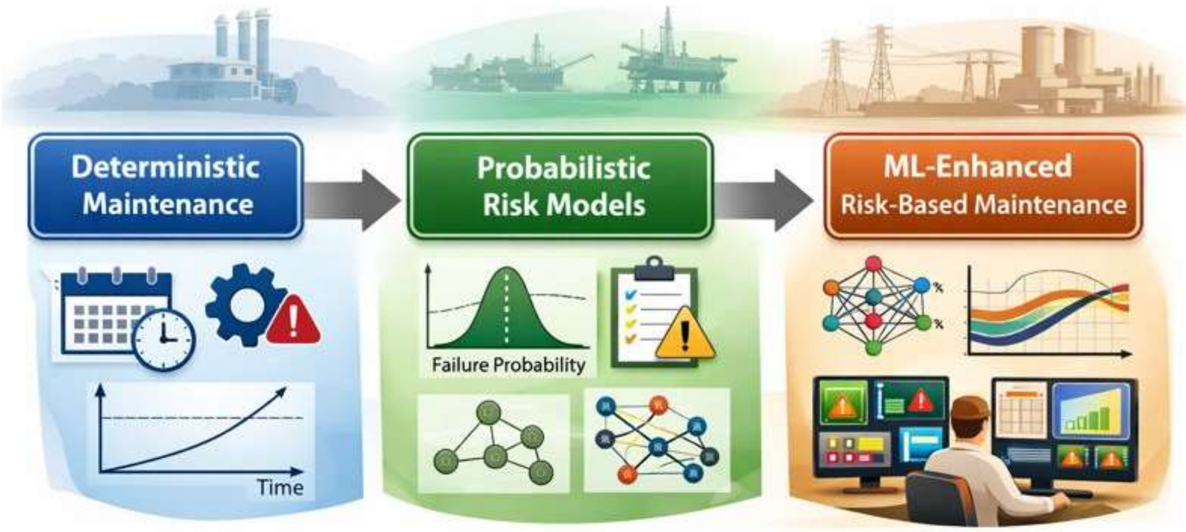

Figure 1. Evolution of Maintenance Decision Models

5. ANALYTICAL PERSPECTIVES ON MACHINE LEARNING TECHNIQUES FOR RISK-BASED MAINTENANCE

5.1 Supervised Learning for Risk Estimation

Random Forests, Gradient Boosting and Support Vector Machines (SVMs) are examples of supervised learning methods that were among the first and most popular initially and broadly used ML methods in estimating risks associated with maintenance in energy infrastructure. These approaches are especially effective with tabular data that integrates check findings, working conditions, and asset characteristics and allows estimating the risks of failures or conditions of various assets in different populations (Dokic & Kezunovic, 2018; Meier, 2023; Mortensen, 2024). Ensemble-based techniques in general, as well as infrastructure system

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degradation have been shown to be robust to noisy data and nonlinear interactions, thus appealing to infrastructure systems with heterogeneous degradation drivers (Mohanachandran et al., 2025).

Regarding the RBM, the main advantage of the supervised learning method is that it can be used to estimate a probability of risk, in particular, when the risk model is trained to predict the likelihood of failure or rather risk scores, but not binary outcomes (Gomez et al., 2019; Manninen et al., 2022). Partial interpretability can also be provided by tree-based ensembles by feature importance measures which can be used to prioritize maintenance as well as provide regulatory justification in energy markets requiring transparency (Alvarez et al., 2021; Hanson et al., 2024). The uses of these properties have made their usage in power networks, pipeline integrity management and monitoring industrial assets.

Nevertheless, monitored learning models have significant deficiencies in their use by aging energy infrastructure. This makes their extrapolation capacity to unobserved regimes of degradation limited, especially in end-of-life behaviour of assets where failures are uncommon but disastrous (Asaye, 2025; Papakonstantinou et al., 2024). Unbalanced data sets that are primarily normal operation states further distort predictions to low-risk results, which is not very reliable in decision making with high consequences (Gaye et al., 2025). Consequently, whereas the use of supervised learning can be useful in estimating the probability of failure, it cannot be applied alone to achieve full RBM without the explicit treatment of uncertainties and the integration of consequences (Kabir et al., 2018).

5.2 Deep Learning for Degradation Modeling

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks represent deep learning (DL) methods that have been used to dominant extent to characterize more intricate degradation processes in sensor-saturated energy products. Such techniques are especially useful in the extraction of features of high-dimensional data streams of vibration, thermal images, and time-series readings in power systems, offshore platforms, and rotating machinery (Sundsgaard, 2025; Olojede et al., 2025; Erhueh et al., 2024). DL models can be trained on raw data to learn hierarchical representations, eliminating the need to perform manual feature engineering and they can also learn to capture nonlinear temporal interactions between successive degradation.

On the analytical level, deep learning improves the prognostic ability, allowing to predict the degradation history and the remaining useful life instead of merely estimating the condition (Wang, 2025; Yahaya et al., 2023). This renders DL especially appealing to CBM and predictive maintenance in energy infrastructure that has continuous monitoring systems. In offshore and nuclear energy applications, it has been suggested that diagnostics and control schemes, enabled by DL, can be used to assist with the early identification of faults and operational resilience (Opoku et al., 2025; Adeoye et al., 2025; Mohammad Fadzil et al., 2024).

Although there are these benefits, deep learning presents great challenges to the use of RBMs. High model complexity and large parameter space are prone to overfitting, particularly in aging infrastructure settings where the failure data are not dense and non-stationary (Papakonstantinou et al., 2024; Asaye, 2025). In addition, the predictions made by DL models do not have high interpretability and can only be incorporated in risk-based decision-making systems that demand the transparent explanation of maintenance decisions (Hanson et al., 2024). Deep learning is therefore most useful when incorporated in hybrid or probabilistic RBM configurations as opposed to it being an independent decision-making entity.

5.3 Bayesian and Probabilistic Machine Learning

Bayesian and probabilistic ML methods such as Bayesian network and Gaussian process, have been found to be most similar representations of the theoretical basis of the RBM as they explicitly model uncertainty. The approaches allow modeling the probability of failures as probability distributions instead of deterministic estimates, making it possible to make risk-sensitive decisions in the face of uncertainty (Kabir et al., 2018; Tesfamariam et al., 2018). Bayesian networks, specifically, have been highly applicable in the representation of causal relationships between degradation mechanisms, mode of failure, and outcomes of infrastructure systems (Eskandarzade et al., 2020; Gomez et al., 2019).

One of the essential analytical strengths of probabilistic ML is its capacity to combine the learning based on data with the expert knowledge, which is a crucial need in aging energy infrastructure where the data alone cannot be sufficient (Frangopol & Tsompanakis, 2014; Han et al., 2024). Risk models can be made as expert knowledge, which can be encoded by a prior distribution, or network structure in a way that risks models do not collapse when data is sparse or incomplete. It is particularly useful in the regulated and safety-critical systems like nuclear facilities, pipelines, and transmission systems (Erhueh et al., 2024; Opoku & Adeoye, 2025).

Nonetheless, when trained on huge and high-dimensional asset systems, probabilistic ML models can be vulnerable to scalability and calculation problems (Alquraidi & Awad, 2024). Their application can also need heavy domain experience in specifying relevant priors and causal structures, and thus cannot be widely applicable. However, in the perspective of RBM, probabilistic ML has the most consistent method of implementing the outputs of ML into formal risk evaluation, especially when there is a need to conduct consequence modeling and make decisions throughout the lifecycle (Tesfamariam et al., 2018; Hanson et al., 2024).

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5.4 Reinforcement Learning for Maintenance Policies

Reinforcement learning (RL) is an even more recent development in maintenance analytics, and instead of focusing on prediction, it focuses on making sequential decision-making under uncertainty. The conceptual characteristics of RL frameworks make them a highly suitable model of maintenance as a dynamic system where actions can affect future system conditions, costs, and risks, thus fitting well in the long-term maintenance planning of ageing infrastructure (Zhou et al., 2025; Xu & Zhang, 2026). RL has been used in energy systems to maximize inspection time, repair-time, and replacement-time in case of stochastic degradation.

Using a RBM lense, RL has the possibility of optimizing maintenance policies cumulatively in terms of cumulative risk and lifecycle cost as opposed to predictive accuracy within a short time. The goals of risk-based asset management match those of RL by learning about the policies achieving trade-offs between immediate maintenance costs and future consequences of failures (Wang, 2025; Manninen et al., 2022). This renders RL very appealing in case of intricate energy networks that share the assets and have long-term planning.

However, the implementation of RL in actual energy infrastructural settings is still restricted by substantial problems. It is not an easy task to define proper reward functions that are risk- and safety-constrained and prevalent exploration methods in RL cannot always be applied in safety-critical systems (Panful et al., 2025; Hanson et al., 2024). Also, the data and simulation fidelity required to implement RL training is challenging to attain with aging assets with sparse failure histories. Consequently, RL can only be considered an encouraging but yet an immature aspect of ML-enhanced RBM as opposed to a fully-fledged solution.

Table 2. Machine Learning Paradigms Mapped to Risk-Based Maintenance Functions

ML Class	Primary RBM Function	Key Strength	Key Limitation	Key References
Supervised Learning (Random Forests, Gradient Boosting, SVMs)	Failure probability estimation; asset risk scoring	Robust with tabular and heterogeneous data; partial interpretability through feature importance	Limited extrapolation under non-stationary aging processes; biased by rare failure data	Dokic & Kezunovic (2018); Meier (2023); Mortensen (2024); Mohanachandran et al. (2025)
Deep Learning (CNNs, LSTMs)	Degradation modeling and prognostics (RUL prediction)	Captures nonlinear temporal and high-dimensional sensor patterns; automated feature learning	Overfitting in sparse failure datasets; low explainability	Sundsgaard (2025); Olojede et al. (2025); Yahaya et al. (2023); Erhueh et al. (2024)
Bayesian & Probabilistic ML (Bayesian Networks, Gaussian Processes)	Risk quantification and uncertainty modeling	Explicit uncertainty representation; integration of expert knowledge	Computational complexity; scalability challenges	Kabir et al. (2018); Tesfamariam et al. (2018); Gómez et al. (2019); Eskandarzade et al. (2020)
Reinforcement Learning	Sequential maintenance policy optimization	Long-term, risk-aware decision support under uncertainty	Reward definition; safety constraints; deployment challenges	Zhou et al. (2025); Xu & Zhang (2026); Manninen et al. (2022); Hanson et al. (2024)

6. RISK INTEGRATION: FROM PREDICTION TO DECISION

An unusual weakness in the literature on machine learning-based maintenance is the subconscious belief that high predictive accuracy would be directly associated with making better maintenance decisions. Practically, even the risk-optimal interventions may not be achieved when the accurate predictions of the conditions of the assets (or their probability of failure) are made because in the case of the aging energy infrastructure, failures are uncommon yet have devastating consequences (Kabir et al., 2018; Tesfamariam et al., 2018; Papakonstantinou et al., 2024). Statistical metrics, including accuracy, precision or mean error, which are not indicative of the asymmetric cost of false negatives, safety impacts or system-wide effects of failure are common measures used to evaluate ML models (Gaye et al.; Wang, 2025). Consequently, prediction-based methods can implicitly give more emphasis to assets that have more abundant data or of smaller frequency minor faults, whereas ignoring low-probability, high-consequence failure modes, which are the focus of risk-based maintenance (Hanson et al., 2024; Han et al., 2024).

In order to close this gap, the outputs of ML need to be systematically incorporated into the formal risk assessment frameworks and not seen as decision-endpoints. Risk matrices in RBM are the inputs of predicted probabilities of the failure or health indices, each paired with likelihood and extent of consequences on several dimensions, such as cost, safety, environmental impact, and service continuity (Gomez et al., 2019; Manninen et al., 2022). Energy systems in the case of pipelines, transmission networks, and nuclear infrastructure, consequence modeling is especially important because any malfunction can cause a cascading effect, breach of regulations, and environmental harm (Mahmood et al., 2023; Opoku & Adeoye, 2025). Risk integration thus necessitates integrating the ML derived probability estimates with consequence models and lifecycle cost calculations in order to be able to prioritize on limited maintenance budgets (Lawoyin et al., 2023; Alquraidi & Awad, 2024). In its absence, ML-based maintenance is still reactive and disjointed, and it is not concise with the goal of RBM to reduce the risk of the entire system.

Outside quantitative integration, multi-criteria decision analysis (MCDA) and human-in-the-loop control are required to support the effective risk-based decision-making in the energy infrastructure. The maintenance decisions will have to consider competing goals, such as reducing risks, cost-effectiveness, regulatory compliance, and operational feasibility that cannot be addressed using automated prediction only (Tesfamariam et al., 2018; Manninen et al., 2022). The human knowledge will be essential in confirming the outputs of the models, uncertainty interpretation, and additional contextual knowledge that history does not usually reveal, especially in aging or refurbished properties (Frangopol & Tsompanakis, 2014; Kabir et al., 2018). In addition, safety-critical systems, including nuclear energy, pipelines, and transmission systems, have regulatory acceptance requirements that mandate the maintenance decision to be transparent, explainable, and defensible to restrict the usage of opaque, completely autonomous, ML solutions (Erhueh et al., 2024; Panful et al., 2025). In turn, ML-enabled RBM should be viewed as a decision-support paradigm, in which the role of machine learning is to inform, rather than to substitute, the probabilistic risk assessment and human judgment.

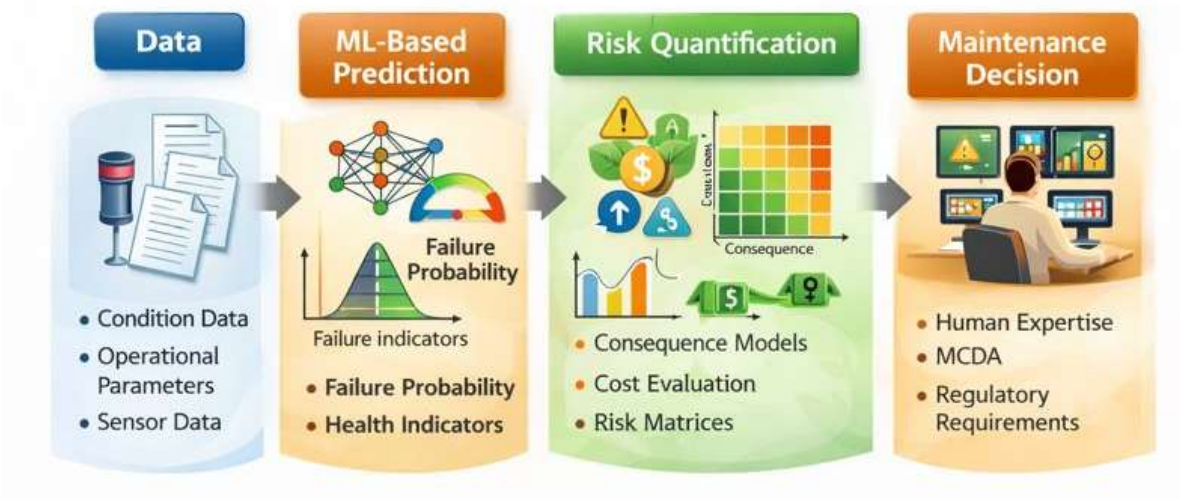

Figure 2. ML-Enabled Risk-Based Maintenance Decision Pipeline

7. SECTOR-SPECIFIC INSIGHTS ACROSS ENERGY DOMAINS

Aging infrastructure in power transmission and distribution systems is largely influenced by exposure to stress factors of the environment over a long period, growing variability of loads, and growing network interdependencies. The mechanisms of degradation in overhead transmission lines, underground cables, and substations include conductor fatigue, insulation aging, and mechanical wear, and the failures usually propagate at a fast rate among the interconnected grids (Yeboah & Enow, 2018; Manninen et al., 2022; Zhang et al., 2025). The availability of data in power systems is high, given that many sensors, smart meters, and supervisory control systems are deployed, allowing using supervised and deep learning models to detect faults and monitor the conditions (Dokic & Kezunovic, 2018; Olojede et al., 2025). Nonetheless, the transferability of ML models across regions and type of assets is still limited by the fact that the network topology, age distributions of assets, and operating practices vary which requires local calibration in risk-based maintenance models (Meier, 2023; Mortensen, 2024).

In the case of oil and gas pipelines, corrosion, mechanical damages, material defects and exposure to the environment are the leading risks of the aging process and the failure can be related to serious environmental and safety impacts. The typical characteristics of pipeline systems are long distance operation, heterogeneous materials, coating, and operating conditions, and therefore a significantly variable degradation path is expected (Adewoyin, 2022; Asaye, 2025; Han et al., 2024). Data availability in comparison to power systems is usually uneven and it is characterized by periodic inspection data, sparse failure records and outdated monitoring technologies, limiting purely data-driven approaches to ML (Jones et al., 2025; Mohammad Fadzil et al., 2024). Although ML models are potentially useful in integrity evaluation and anomaly detection, they can be transferred to site-specific environmental and operational conditions, which supports the integration of probabilistic and risk-based models that integrate ML predictions with consequence models and expert opinions (Kabir et al., 2018; Mahmood et al., 2023).

The existence of extreme safety requirements, hostile operating environments and the existence of strict regulatory oversight characterize nuclear energy systems and offshore renewable infrastructure, and risk profiles are therefore influenced. The cost of failure in nuclear systems is too high and that is why it requires exceptionally conservative maintenance strategies, which drives interest in Self-correcting control schemes, robotics-assisted inspection, and AI-driven diagnostics to support predictive maintenance with very strict safety requirements (Erhueh et al., 2024; Opoku & Adeoye, 2025; Adeoye et al., 2025). Wind and tidal systems,

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which are examples of offshore renewable assets, are prone to corrosions and accelerated aging in the hostile marine environment, inaccessibility, and high maintenance expenses, and are commonly supported by condition monitoring and digital twins to plan maintenance (Amaechi et al., 2022; Yahaya et al., 2023). Data sparsity, few failure samples, and constant technological changes in both areas also limit the explicit applicability of ML models in other fields. This means that the risk-specific driving factors and regulatory environment used in one energy sector cannot be blindly applied to another without a strict risk contextualization (Frangopol & Tsompanakis, 2014; Hanson et al., 2024; Alquraidi & Awad, 2024).

8. CRITICAL GAPS, LIMITATIONS, AND OPEN CHALLENGES

One of the greatest constraints of machine learning-based risk-based maintenance (RBM) of aging energy infrastructure is the issues associated with data, namely extreme class imbalance and the lack of failures. Historical data are usually dominated by benign conditions, and failures, particularly catastrophic ones are rare, unlabeled, or missing, which spans to unbalanced ML models that underestimates low-probability high-consequence risks (Asaye, 2025; Papakonstantinou et al., 2024; Gaye et al., 2025; Kabir et al., 2018). The latter is compounded by the fact that long-lasting asset lifetime and relatively short or discontinuous data history do not provide sufficient information to learn late-life degradation behavior by the ML models, and the inability to predict the reliability of assets that grow old and operate under different conditions than those assumed in their design (Frangopol & Tsompanakis, 2014; Alquraidi & Awad, 2024).

The misalignment of the ML evaluation practices with the risk-based decision needs is also equally important. The numerous studies largely depend on accuracy-based measures that do not reflect asymmetric costs of risks, safety effects, and systemic costs of failure, which does not reveal the fact that the existence of the ML models can lead to a better maintenance decision under the uncertainty situation (Tesfamariam et al., 2018; Wang, 2025). They are exacerbated by limited model interpretability, the lack of scalability between ML and physical degradation processes, scaling complications to support heterogeneous networks of assets, and increased cyber-security and cyber-physical risks of increased digitalization (Belodedenko et al., 2023; Manninen et al., 2022; Zhang et al., 2025; Panful et al., 2025). Taken together, these loopholes restrict credibility, regulatory approval, and feasible application of ML in the systems of RBM.

9. FUTURE RESEARCH DIRECTIONS

Future studies should focus on combined modeling mechanisms that are more consistent with machine learning and physical and probabilistic theory of RBM. Models based on physics-informed machine learning and hybrid Bayesian-deep learning provide a promising opportunity toward being able to achieve better generalisation with thinly sampled and non-stationary data, including uncertainty quantification, and enabling both prediction and explicit correlation with the degradation processes and assessment of risk. The methods are most applicable in an aging asset where uncertainty, as opposed to accuracy in prediction, prevails in making maintenance decisions.

Simultaneously, the current progress in digital twins, transfer learning, and explainable AI (XAI) is required to ensure scalable and reliable implementation of RBMs. Digital twins can assist in real-time risk-conscious maintenance planning with the help of ML and probabilistic models whereas transfer learning provides chances to address the problem of data scarcity across asset classes in the conditions of the appropriate contextualization of asset criticality and severity of consequences. Regulatory acceptance, human-in-the-loop decision-making, and cyber-resilient maintenance systems of safety-critical energy are also impossible without the development of XAI and secure ML frameworks. All these directions are aimed at ML-enhanced RBM models that are interpretable, probabilistic, scalable, and in enforcement of real-world risk management requirements.

10. CONCLUSIONS

With this review, a risk-focused approach to maintenance decision-making in the aging energy infrastructure has been promoted, stating that the efficient management of long-lasting, safety-critical assets cannot be achieved through mere stepwise enhancement in predictability. As the energy system grows old and works under a lot of uncertainty, the maintenance decision should be based on probabilistic risk theory, which clearly incorporates the probability of failure, severity of the consequences, the criticality of the assets, and the interdependence of the system. Risk-Based Maintenance (RBM) offers the conceptual framework of such a decision-making, making it possible to prioritize with limited resources and to match the goals of safety, environment, and reliability. In this respect, machine learning acts as a strong analytical enabler, yet only to the extent its results are analysed in the prism of risk and not considered as self-solving solutions. The crux that comes out of this synthesis is that no prediction in the absence of risk integration can be applied to manage complex, high-consequence realities of the aging of energy infrastructure.

The consequences of this point of view reach into policy implications, operations practice implications, and future research implications. The results indicate to policymakers and regulators that it is time to shift the focus off technology-based discourse to more governance constructs that focus on transparency, uncertainty control, and justifiable risk-based choices in ML-based maintenance systems. To asset owners and operators, the review suggests the need to incorporate ML tools in systematic RBMs that include human judgment, consequence modelling, and lifecycle factors instead of using the automated predictions. To researchers, the synthesis suggests a research agenda on physics-informed and probabilistic machine learning, explainable and secure analytics, and decision-oriented evaluation measures which indicate risk reduction in the real world. Taken together, these implications support the idea that the ultimate value of machine learning in maintenance is not to displace conventional risk theory, but to build up its use to the current mutating demands of aging power infrastructure.

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