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Article

AI DRIVEN PREDICTIVE MAINTENANCE IN PETROLEUM AND POWER SYSTEMS USING RANDOM FOREST REGRESSION MODEL FOR RELIABILITY ENGINEERING FRAMEWORK

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ABSTRACT

This study systematically reviews the application of artificial intelligence (AI)-driven predictive maintenance in petroleum and power systems, with a focus on Random Forest regression as a reliability engineering tool. Predictive maintenance, defined as the integration of real-time monitoring with analytical forecasting, has become essential for minimizing downtime, reducing costs, and improving safety in energy infrastructures. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, 92 peer-reviewed studies published between 2000 and 2024 were identified and analyzed across major databases. The review synthesized literature on conceptual frameworks, including distinctions between corrective, preventive, condition-based, and predictive maintenance, as well as core reliability metrics such as mean time to failure (MTTF), mean time between failures (MTBF), and remaining useful life (RUL). The findings demonstrated that Random Forest regression consistently balanced predictive accuracy, robustness, and interpretability compared with other machine learning methods, including neural networks, support vector machines, and gradient boosting. Applications in petroleum systems emphasized drilling reliability, well integrity, pipeline monitoring, and refinery optimization, while power system studies focused on turbine reliability, transformer fault prediction, renewable energy components, and smart grid stability. The integration of predictive maintenance with Internet of Things (IoT) sensors, digital twins, and cloud-based platforms was identified as a key enabler of real-time reliability analytics. However, persistent challenges remain in terms of scalability, interpretability, and sector-specific customization. This review contributes by consolidating current evidence, identifying research gaps, and offering practical recommendations for enhancing reliability and sustainability in petroleum and power industries.

KEYWORDS

Predictive Maintenance; Random Forest Regression; Reliability Engineering; Petroleum Systems; Power Systems.

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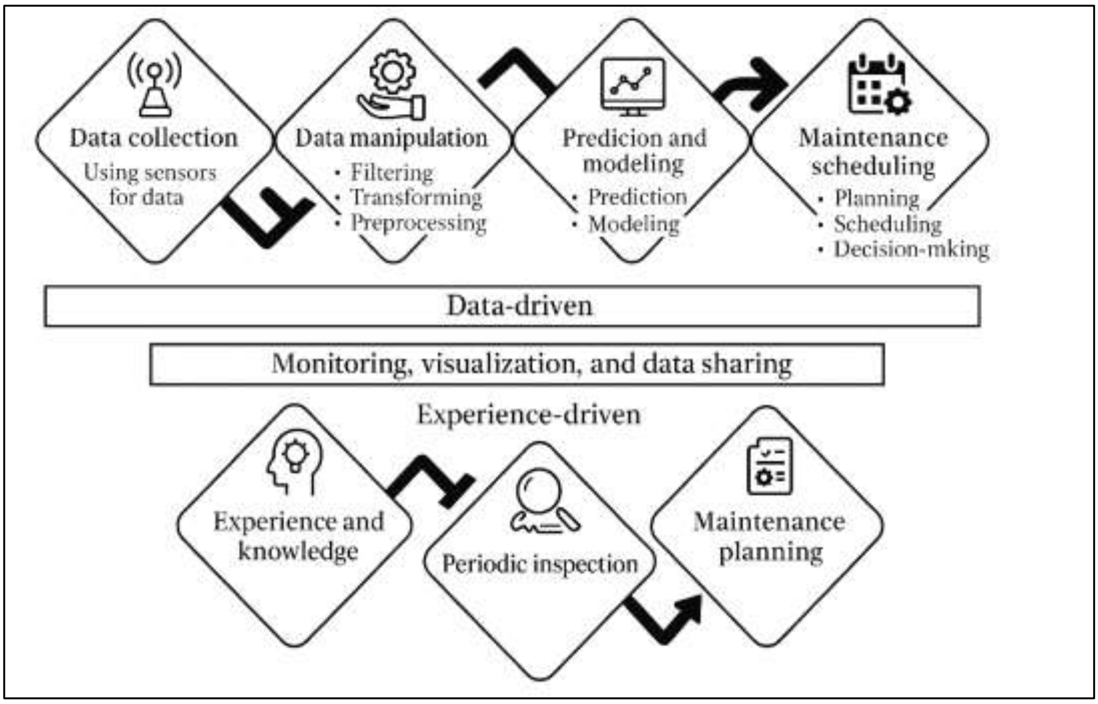
INTRODUCTION

Predictive maintenance refers to a data-driven strategy designed to forecast the potential failure of equipment based on continuous monitoring, condition analysis, and statistical modeling. This approach allows industries to perform interventions only when necessary, thereby reducing downtime and optimizing costs compared to traditional reactive or time-based preventive maintenance. Unlike corrective maintenance, which responds after a breakdown, or preventive maintenance, which follows predetermined schedules regardless of machine health, predictive maintenance emphasizes real-time insights derived from machine behavior to align repair actions with actual conditions (Kumar et al., 2018). Within this context, reliability engineering emerges as the discipline that quantifies system performance under specified conditions, seeking to ensure components achieve dependable operation over their lifecycle. The primary role of reliability engineering is to evaluate and design processes that minimize the likelihood of failure while simultaneously maintaining safety and efficiency in industrial systems (Baptista et al., 2018). The combination of predictive maintenance and reliability engineering creates a structured framework where asset management is guided by probabilistic modeling, system diagnostics, and degradation analysis. Such integration is particularly valuable in high-risk sectors such as petroleum and power systems, where equipment failure can lead to catastrophic financial, safety, and environmental consequences. The application of artificial intelligence, specifically machine learning models like Random Forest regression, has enhanced predictive maintenance by enabling the interpretation of high-dimensional sensor data, capturing nonlinear fault behaviors, and supporting reliable decision-making for engineers (Zhang et al., 2019). Together, predictive maintenance and reliability engineering form the methodological foundation for modern frameworks that aim to ensure operational continuity in critical energy infrastructures.

Figure 1: Predictive Maintenance and Reliability Framework



Petroleum and power industries represent two of the most vital infrastructures in global economies, directly influencing energy supply, industrial productivity, and economic stability. A disruption in petroleum operations such as drilling, refining, or transportation can trigger substantial ripple effects across international supply chains and global oil markets. Similarly, power systems, whether thermal, nuclear, hydroelectric, or renewable, must operate reliably to sustain societal functions ranging from healthcare to transportation and communications. The international significance of predictive maintenance in these industries lies in its ability to minimize downtime, prevent catastrophic failures, and extend the operational lifespan of critical equipment (Bousdekis et al., 2021). For petroleum

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industries, predictive maintenance reduces the risk of oil spills and explosions, which have both environmental and economic repercussions at a global scale. In power systems, predictive maintenance enhances grid reliability and prevents blackouts that may disrupt millions of households and industrial facilities. Many countries, including energy leaders such as the United States, China, and Saudi Arabia, have invested heavily in AI-driven predictive maintenance to modernize infrastructure and strengthen resilience. International organizations, such as the World Bank and United Nations Industrial Development Organization (UNIDO), emphasize the adoption of advanced reliability frameworks to support sustainable industrialization and energy access (Qi et al., 2022).

Maintenance practices have evolved significantly over the past century, reflecting industrial demands for efficiency, safety, and reliability. The earliest approaches were reactive, commonly termed corrective maintenance, in which systems were repaired only after breakdowns occurred, resulting in costly downtimes and increased safety risks. Preventive maintenance followed as a scheduled approach aimed at preventing failures before they happened, though it often led to excessive maintenance activities and unnecessary part replacements. Condition-based maintenance marked an important advancement by enabling industries to monitor key indicators such as vibration, oil quality, and temperature to assess equipment health in real time. However, condition-based approaches were still limited by their inability to fully capture complex degradation dynamics and nonlinear behaviors in large-scale systems. The integration of prognostics and health management systems signaled the next major shift, enabling more accurate predictions of equipment failures and remaining useful life based on multivariate data (Gonzalez-Jimenez et al., 2021). With the rapid growth of computational power and the rise of artificial intelligence, predictive maintenance today is increasingly recognized as an advanced engineering methodology that synthesizes condition monitoring with machine learning, statistical analysis, and system modeling. This historical trajectory demonstrates how predictive maintenance has matured from reactive measures into a structured, data-driven reliability framework capable of safeguarding critical petroleum and power infrastructures.

Artificial intelligence has become central to predictive maintenance due to its ability to model nonlinear, uncertain, and high-dimensional datasets. Traditional methods of reliability engineering relied heavily on statistical distributions and fault tree analysis, but these approaches often fell short in managing the complexities of modern petroleum and power system (Alsina et al., 2018). Machine learning models such as artificial neural networks, support vector machines, and ensemble algorithms have been increasingly applied to address these challenges. Random Forest regression has emerged as particularly effective because it constructs ensembles of decision trees, producing robust predictions resistant to overfitting (Niu, 2017). This makes Random Forest suitable for analyzing large sensor datasets while maintaining interpretability through variable importance measures. Applications of Random Forest in petroleum industries include drilling equipment fault analysis and production optimization, while in power systems it has been used for transformer diagnostics and turbine performance monitoring (Badihi et al., 2022). Furthermore, the algorithm's ability to handle heterogeneous data types enhances its role within reliability engineering frameworks, where monitoring variables range from vibration amplitude to fluid pressure. By enabling engineers to detect patterns and prioritize maintenance activities, Random Forest strengthens the link between artificial intelligence and applied reliability engineering practices. The petroleum industry is characterized by extreme operational environments where equipment reliability is a critical determinant of safety and profitability. Offshore drilling rigs, refineries, and pipeline systems are exposed to high pressures, corrosive fluids, and mechanical stresses that increase the likelihood of equipment degradation (Wu et al., 2018). Pumps, compressors, and valves often experience progressive wear that, if left undetected, may result in costly failures or catastrophic accidents. Predictive maintenance strategies using AI have been applied to monitor these components and predict anomalies, allowing for timely interventions (Davari et al., 2021).

Random Forest regression has proven particularly useful in petroleum applications, where it has been used to identify anomalies in drilling data, predict well failures, and improve refinery throughput efficiency. For example, offshore platforms employing predictive frameworks benefit from reduced downtime and enhanced worker safety while minimizing the risk of oil spills that carry severe environmental consequences (Davari et al., 2021). As petroleum operations expand globally in regions such as the Middle East, North America, and West Africa, the application of Random Forest

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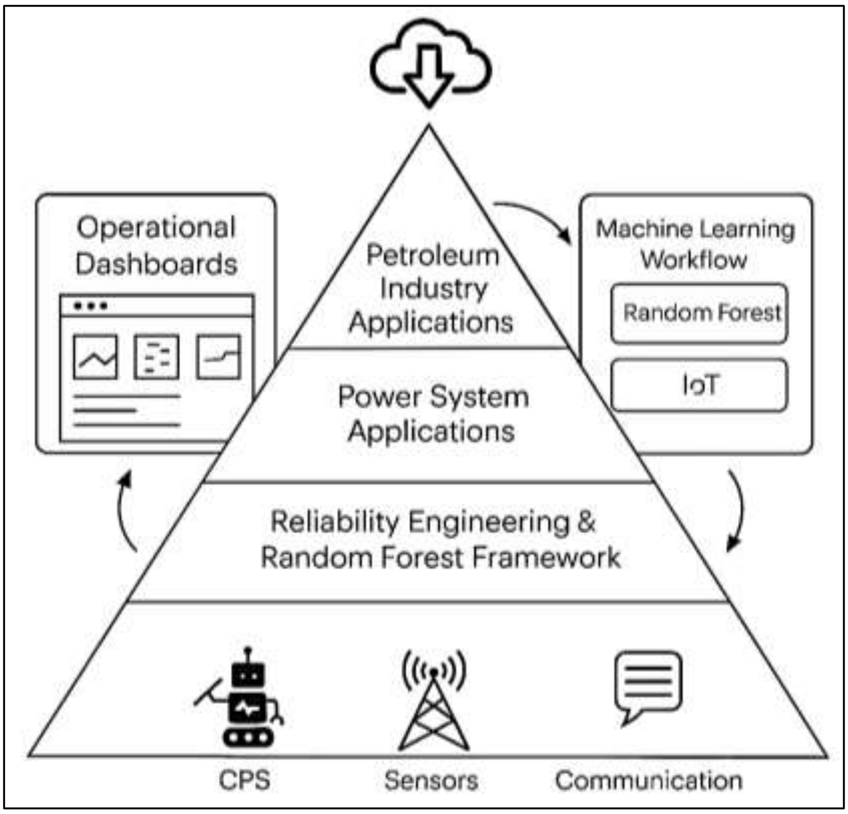
predictive maintenance enhances both technical sustainability and economic stability (Sayyad et al., 2021).

Figure 2: AI-Driven Predictive Maintenance Framework



Moreover, power systems play a crucial role in sustaining modern economies and social infrastructure, where failures can have immediate and widespread consequences. Equipment such as turbines, transformers, and circuit breakers are vital components whose reliability determines grid stability and overall system resilience. Predictive maintenance in power systems enables operators to detect early signs of degradation, preventing cascading failures that might result in blackouts affecting millions (Jiang et al., 2018). Machine learning models, particularly Random Forest regression, have been applied to improve predictive accuracy in detecting insulation degradation in transformers and efficiency losses in turbines (Qibria & Hossen, 2023). In renewable energy systems such as wind and solar, predictive frameworks reduce downtime by detecting anomalies in gearboxes, inverters, and blades. Integration with Internet of Things (IoT) sensors and smart grid architectures further enhances predictive capabilities, providing real-time data that improves forecasting accuracy (Istiaque et al., 2023; Wang et al., 2019). As energy transition initiatives expand globally, predictive maintenance using AI ensures efficient and reliable performance across conventional and renewable power infrastructures (Akter, 2023).
Integrating predictive maintenance into reliability engineering frameworks requires methods that provide both predictive accuracy and interpretability(Hasan et al., 2023). Random Forest regression addresses this by constructing multiple decision trees and aggregating their outputs, thereby reducing variance and enhancing robustness compared to single-model approaches. This ensemble-based methodology enables probabilistic modeling of degradation and remaining useful life, aligning with standard reliability metrics such as mean time to failure (MTTF) and mean time between failures (MTBF)(Masud et al., 2023). By ranking feature importance, Random Forest also provides engineers with clear insights into which operational variables most strongly affect system reliability, allowing for targeted monitoring and maintenance planning (Sultan et al., 2023; Merkt, 2019). In petroleum systems, this has been applied to prioritize monitoring of drilling pressures and fluid dynamics, while in power systems, it has been used to track transformer temperature and turbine vibration (Hossen et al., 2023; Sakib & Wuest, 2018). The integration of Random Forest with Internet of

Things (IoT) platforms and digital twins enhances real-time decision-making capabilities, enabling predictive frameworks that directly support industrial asset management strategies. Thus, Random Forest regression emerges not only as a powerful machine learning algorithm but also as a methodological foundation within reliability engineering frameworks across petroleum and power systems.

LITERATURE REVIEW

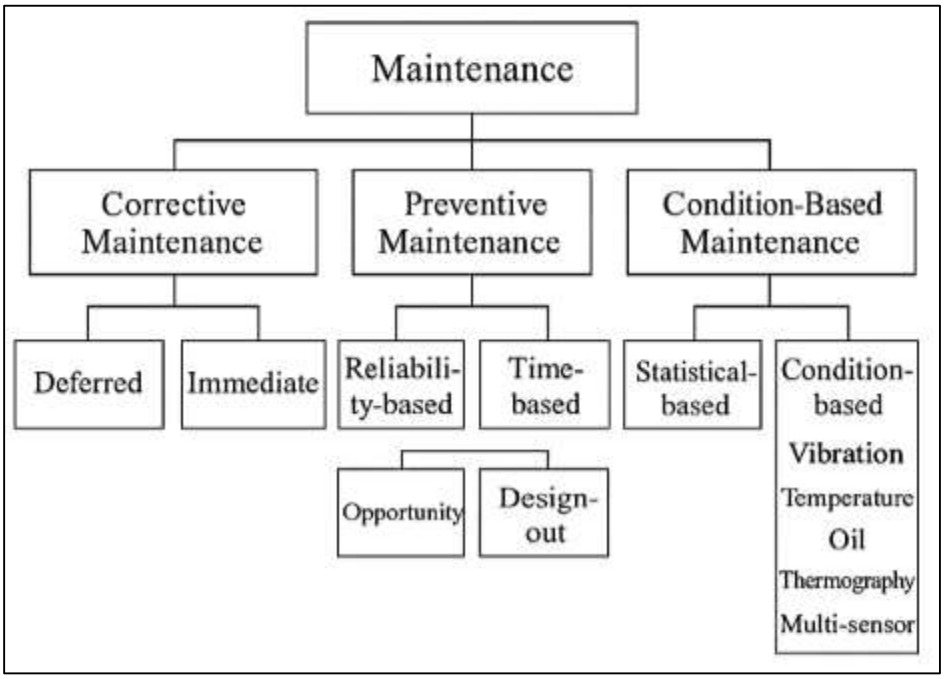
The literature on predictive maintenance and reliability engineering has expanded rapidly in recent decades, reflecting the growing importance of data-driven methods in optimizing industrial operations. Traditional maintenance frameworks, once reliant on corrective and preventive strategies, have shifted toward predictive and condition-based approaches that integrate advanced monitoring and computational techniques (Ji & Sun, 2022). In petroleum and power systems, this shift is particularly significant due to the high operational risks, substantial economic stakes, and global implications of system failures. The emergence of artificial intelligence and machine learning has further transformed this field by enabling the analysis of large-scale sensor datasets and by modeling nonlinear degradation behaviors that conventional methods struggled to capture. Random Forest regression, an ensemble-based learning algorithm, has been increasingly adopted as a powerful tool in this context because of its robustness, interpretability, and predictive accuracy in complex engineering environments (Wong et al., 2020). The existing body of research covers a wide range of themes, including the theoretical underpinnings of predictive maintenance, the methodological advances in machine learning applications, and sector-specific implementations in petroleum and power systems. To provide a structured understanding of this interdisciplinary domain, this literature review is organized into distinct thematic sections, each addressing a critical aspect of AI-driven predictive maintenance within a reliability engineering framework (Yang et al., 2019). By systematically reviewing these domains, the literature review establishes a comprehensive foundation for analyzing the role of Random Forest regression in improving reliability outcomes in petroleum and power infrastructures.

Predictive Maintenance and Reliability Engineering

Maintenance strategies in industrial engineering have historically been categorized into corrective, preventive, predictive, and condition-based approaches, each reflecting a distinct philosophy of managing system reliability. Corrective maintenance is the most basic form Adar and Md (2023), performed only after a failure occurs, often leading to high downtime and repair costs. Preventive maintenance, introduced as a response to these inefficiencies, involves scheduling interventions at fixed intervals regardless of system health, aiming to minimize failures but frequently resulting in unnecessary part replacements and over-maintenance. Predictive maintenance, by contrast, employs monitoring and analytical tools to forecast failure probability, aligning maintenance activities with actual equipment conditions and thus reducing costs and risks (Tao et al., 2018). Condition-based maintenance, closely related to predictive approaches, emphasizes continuous or periodic assessment of indicators such as vibration, temperature, and lubrication quality, providing actionable insights for timely intervention (Jardine, Lin, & Banjevic, 2006). Scholars have argued that predictive and condition-based maintenance represent evolutionary advancements over traditional strategies by introducing statistical rigor and real-time monitoring into industrial asset management. Comparative studies reveal that predictive maintenance reduces unplanned downtime more effectively than preventive maintenance, particularly in high-value sectors such as petroleum and power. Moreover, the reliability-centered framework often integrates multiple strategies, recognizing that corrective, preventive, and predictive actions may coexist depending on asset criticality and operational environment (Liao & Köttig, 2016). This classification highlights how definitions and distinctions provide not only theoretical clarity but also practical foundations for developing advanced maintenance systems that support reliability engineering principles.

Reliability engineering has long been regarded as a cornerstone of lifecycle management for industrial systems, particularly in sectors where operational continuity and safety are paramount. It is defined as the systematic application of engineering principles to ensure that systems and components perform their intended functions for a specified time under defined conditions . Reliability engineering frameworks emphasize quantitative metrics such as mean time to failure (MTTF), mean time between failures (MTBF), and reliability functions derived from probabilistic models. These metrics provide decision-makers with tools to evaluate performance trade-offs between design, maintenance, and replacement policies. Studies have demonstrated that the integration of reliability engineering into lifecycle management reduces overall ownership costs and increases asset availability, particularly in complex systems such as turbines, compressors, and drilling rigs. Reliability-centered maintenance (RCM) further institutionalized these principles by prioritizing maintenance decisions according to equipment criticality and failure consequences. Later research emphasized the link between reliability engineering and safety, particularly in industries such as oil and gas, where equipment failures can lead to environmental hazards and human fatalities. In power systems, reliability analysis has been essential for grid stability, providing frameworks for evaluating component performance and system redundancy. Lifecycle-focused approaches extend beyond operational phases to incorporate design, procurement, and decommissioning, reflecting the pervasive influence of reliability engineering throughout industrial systems. Thus, reliability engineering ensures that predictive maintenance strategies are not isolated practices but integral elements of comprehensive lifecycle management.

Figure 3: Industrial Maintenance Strategies Classification Framework



The integration of predictive maintenance into reliability engineering frameworks has been a significant advancement in asset management practices. Reliability-centered maintenance (RCM) provides a structured methodology to determine the most effective maintenance strategy for each component based on criticality and failure modes. Within this framework, predictive maintenance is often prioritized for critical components, as it allows failures to be anticipated before they occur, thus reducing the risk of costly disruptions. Predictive approaches employ statistical and machine learning models to forecast degradation, aligning closely with probabilistic reliability assessments such as failure rate distributions and hazard functions. Empirical studies show that integrating predictive maintenance into reliability-centered practices reduces maintenance costs by 25–30% compared to preventive-only strategies in large industrial plants. In petroleum systems, predictive maintenance integrated into reliability frameworks has been shown to mitigate risks of blowouts and pipeline leaks, while in power systems, it supports grid stability and reduces unplanned outages. Scholars have emphasized that predictive maintenance provides both operational and financial benefits, as it extends mean time between failures (MTBF) and reduces mean time to repair (MTTR). Integration also enhances decision-making by linking condition monitoring outputs, such as vibration or thermographic data, with reliability metrics used in maintenance planning. By situating predictive maintenance within reliability engineering frameworks, industries achieve a structured balance between system safety, asset longevity, and economic efficiency.

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Theoretical Frameworks Underpinning Reliability-Centered Maintenance

Reliability metrics have long served as foundational tools for quantifying the dependability of industrial systems, enabling engineers to assess performance, schedule maintenance, and optimize asset management. Mean Time to Failure (MTTF) is one of the earliest measures, representing the expected time before a component experiences its first failure, typically applied to non-repairable systems. For repairable systems, Mean Time Between Failures (MTBF) is widely adopted, measuring the average operating time between successive failures and thus informing decisions about maintenance frequency and spare parts management. Remaining Useful Life (RUL) extends beyond these average-based measures by estimating the time until a specific unit reaches the end of its functional life, a metric especially relevant in condition-based and predictive maintenance systems.Researchers have demonstrated that RUL provides more actionable insights for decision-making by linking degradation models to probabilistic reliability functions. Comparative studies highlight that while MTBF provides broad system-level insights, RUL offers individualized prognostics that align better with modern maintenance strategies. These metrics have been central to reliability-centered maintenance (RCM), forming the quantitative backbone of performance assessment frameworks across industries such as petroleum, aerospace, and power systems. Weibull analysis, Markov processes, and Bayesian updating have also been used in conjunction with MTTF and RUL to refine estimations in systems where failure modes are diverse and complex. Thus, MTTF, MTBF, and RUL serve as indispensable metrics, shaping the theoretical basis of reliability-centered approaches. Fault Tree Analysis (FTA) is a deductive reliability modeling method that systematically evaluates potential causes of system failures by linking component faults in a hierarchical structure. Developed initially for aerospace and nuclear systems, FTA provides engineers with a graphical and probabilistic means of tracing how basic events can propagate into top-level failures. Its ability to model complex interdependencies has made it a widely used tool in petroleum and power systems, where failures can stem from multiple, interacting causes . FTA applies Boolean logic to decompose system failures into combinations of subsystems, making it suitable for both qualitative assessments of vulnerability and quantitative estimations of system reliability (Lakemond & Holmberg, 2022; Tawfiqul, 2023). Empirical studies have applied FTA to offshore oil rigs, pipeline systems, and refineries to analyze catastrophic events such as blowouts or fires. In power engineering, FTA has been used to assess grid stability and transformer reliability, providing a means to identify critical failure paths and allocate maintenance resources. Comparisons with other models show that FTA is particularly useful for identifying single points of failure, but less effective in capturing dynamic interactions or time-dependent degradation (Shamima et al., 2023; Signoret & Leroy, 2021). Hybrid methods, combining FTA with Markov processes or Monte Carlo simulations, have addressed some of these limitations by enhancing quantitative accuracy. Despite criticisms of its static nature, FTA remains central in reliability-centered frameworks as a rigorous method for analyzing causes and consequences of system failures.

Failure Mode and Effects Analysis (FMEA) and Reliability Block Diagrams (RBD) represent two complementary approaches to reliability modeling that have been widely adopted in reliability-centered maintenance practices. FMEA is an inductive method designed to identify potential failure modes, their causes, and effects, thereby prioritizing preventive actions based on severity, occurrence, and detection rankings. This structured approach allows industries to rank risks and allocate maintenance resources effectively, making it a cornerstone in industries ranging from aerospace to petroleum. In petroleum engineering, FMEA has been applied to drilling equipment, compressors, and pipeline systems to mitigate the risk of critical accidents (Pan et al., 2022; Ashraf & Ara, 2023). In power systems, FMEA has been used to assess vulnerabilities in substations, transmission lines, and renewable energy equipment. Reliability Block Diagrams (RBD), by contrast, provide a visual modeling technique where components are represented as blocks connected in series or parallel to capture system-level reliability. RBD has been particularly effective in large power generation systems, where redundancy and parallel structures play a key role in ensuring system availability. Studies demonstrate that combining FMEA with RBD offers both qualitative insights and quantitative reliability measures, providing a comprehensive framework for reliability-centered maintenance. Empirical evidence suggests that while FMEA excels in identifying risks at the component level, RBD offers a system-level perspective, making their integration particularly valuable in complex infrastructures such as petroleum refineries and smart grids (Rogith et al., 2017;

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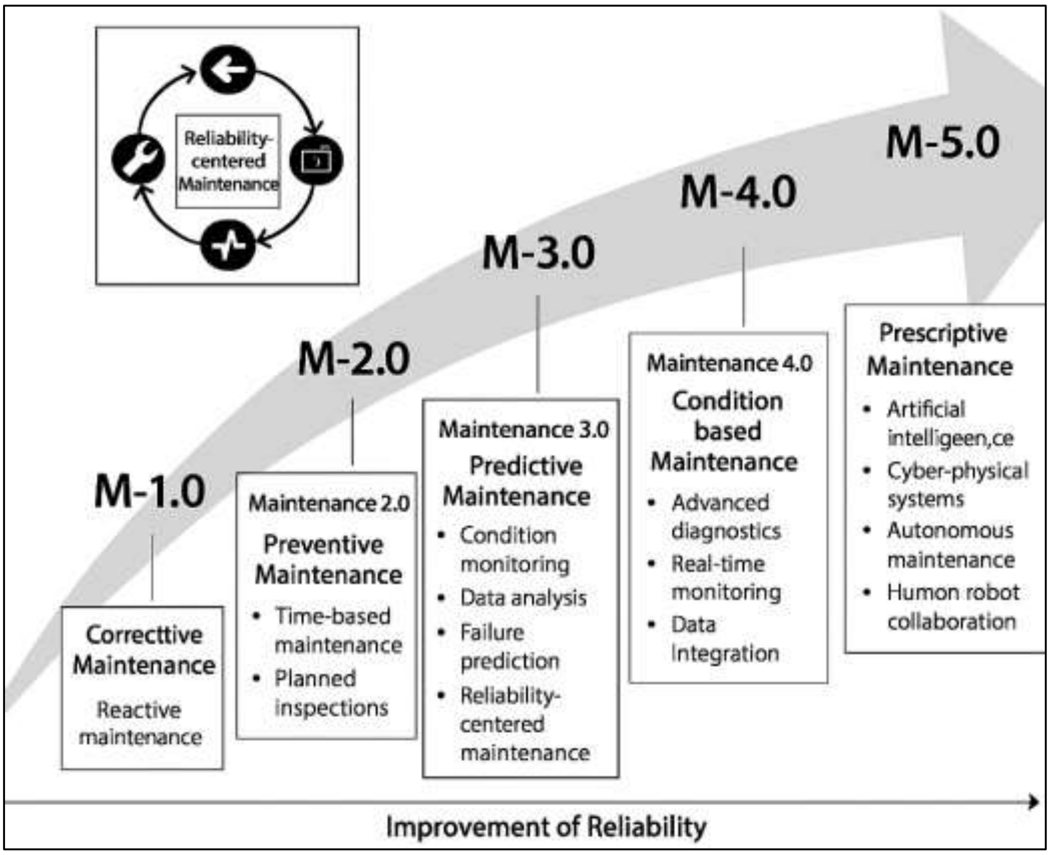
Sanjai et al., 2023). Together, these approaches strengthen the theoretical foundations of reliability-centered maintenance by bridging micro-level failure analysis with macro-level system modeling.

Artificial Intelligence and Machine Learning in Predictive Maintenance

The application of predictive maintenance has historically transitioned from statistical models to artificial intelligence (AI)-driven frameworks, reflecting the growing complexity of industrial systems and the availability of high-frequency sensor data (Ara et al., 2022; Akter et al., 2023). Early approaches relied heavily on statistical reliability models such as Weibull analysis, proportional hazards models, and Markov processes to estimate time-to-failure and system reliability (Jahid, 2022; Mzougui & Elfelsoufi, 2019). These models offered interpretable metrics such as mean time between failures (MTBF) but often assumed constant failure rates and independent events, assumptions not well-suited for complex environments (Razzak et al., 2024; Uddin et al., 2022). As data availability increased, regression models and Bayesian updating were introduced to capture more nuanced degradation patterns. However, statistical methods struggled with nonlinearities and multidimensional sensor data generated by modern industrial equipment (Baklouti et al., 2019; Akter & Ahad, 2022).

Figure 4: Evolution of Maintenance Management



This limitation encouraged the adoption of AI-based approaches capable of modeling complex failure dynamics. Neural networks were among the earliest AI methods applied in predictive maintenance, demonstrating superior accuracy in pattern recognition and failure classification compared to regression-based techniques (Istiaque et al., 2024; Arifur & Noor, 2022). Support vector machines (SVMs) further expanded applications by effectively handling small sample sizes and high-dimensional feature spaces. Ensemble learning methods, such as Random Forests, marked another stage in this evolution, offering robustness against overfitting and improved interpretability (Akter & Shaiful, 2024; Rahaman, 2022). Reviews consistently show that AI-driven methods outperform traditional statistical models in predictive maintenance tasks across petroleum, aerospace, and power sectors. The transition from statistical to AI-driven models represents a paradigm shift in

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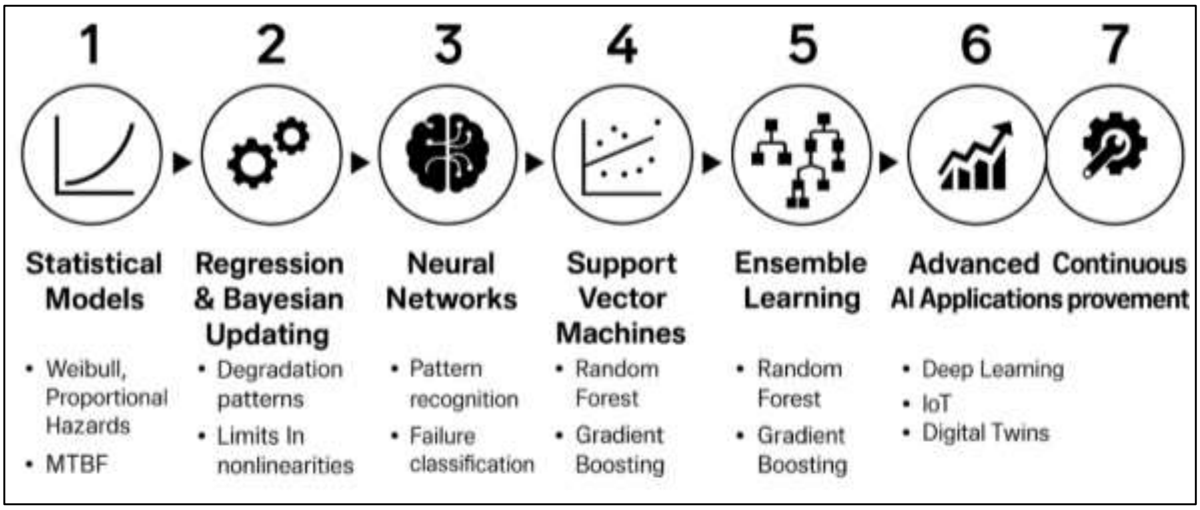
predictive maintenance, enabling more precise prognostics and reliability-centered decision-making (Hasan et al., 2024; Hasan et al., 2022; Hossen & Atiqur, 2022).
Machine learning (ML) techniques have been extensively compared in predictive maintenance research, with each method offering distinct strengths and limitations depending on the system and data characteristics (Tawfiqul et al., 2022). Neural networks have demonstrated strong capabilities in pattern recognition and classification, particularly in rotating machinery diagnostics and fault detection tasks. Their nonlinear modeling capacity makes them effective, though they are often criticized for their "black-box" nature and sensitivity to hyperparameters (Kamrul & Omar, 2022). Support Vector Machines (SVMs) emerged as another widely used method, particularly valued for their robustness in high-dimensional feature spaces and small-sample conditions, making them suitable for early applications in vibration and acoustic analysis (Chaari et al., 2016; Mubashir & Abdul, 2022).

Figure 5: The Evolution of Predictive Maintenance



Ensemble-based models, such as Random Forest, have gained attention due to their ability to construct multiple decision trees, improving generalization, reducing overfitting, and providing interpretability through feature importance scores (Tawfiqul et al., 2024; Reduanul & Shoeb, 2022). Gradient boosting algorithms, including XGBoost and LightGBM, have shown high predictive accuracy in comparative studies, although they often require intensive tuning and are less interpretable than Random Forest. Meta-analyses reveal that while deep learning models such as convolutional neural networks achieve state-of-the-art performance in specific contexts, ensemble methods maintain superior balance between accuracy, efficiency, and transparency for engineering applications (Sazzad & Islam, 2022). Thus, comparative literature emphasizes that the choice of ML technique is context-dependent, influenced by system complexity, data type, and the trade-off between interpretability and accuracy (Noor & Momena, 2022).
Artificial intelligence methods, particularly machine learning, have demonstrated significant advantages in handling nonlinearities, large-scale sensor data, and stochastic degradation processes inherent in industrial systems. Traditional reliability models often assumed linear degradation patterns and constant hazard rates, conditions rarely observed in petroleum and power industries (Kühl et al., 2022). Machine learning algorithms, by contrast, can model nonlinear interactions among multiple variables, enabling accurate prognostics even under highly dynamic operating conditions. Neural networks excel in identifying complex fault signatures across vibration, acoustic, and thermal signals, while SVMs provide effective classification in high-dimensional spaces with limited samples. Random Forest algorithms stand out for their scalability and ability to process heterogeneous datasets, producing robust predictions while offering interpretability through feature importance. Gradient boosting further improves predictive accuracy by sequentially minimizing errors, though at the expense of transparency (Gupta et al., 2021; Subrato & Md, 2024). Applications in petroleum systems show that AI methods can integrate real-time sensor data from pumps,

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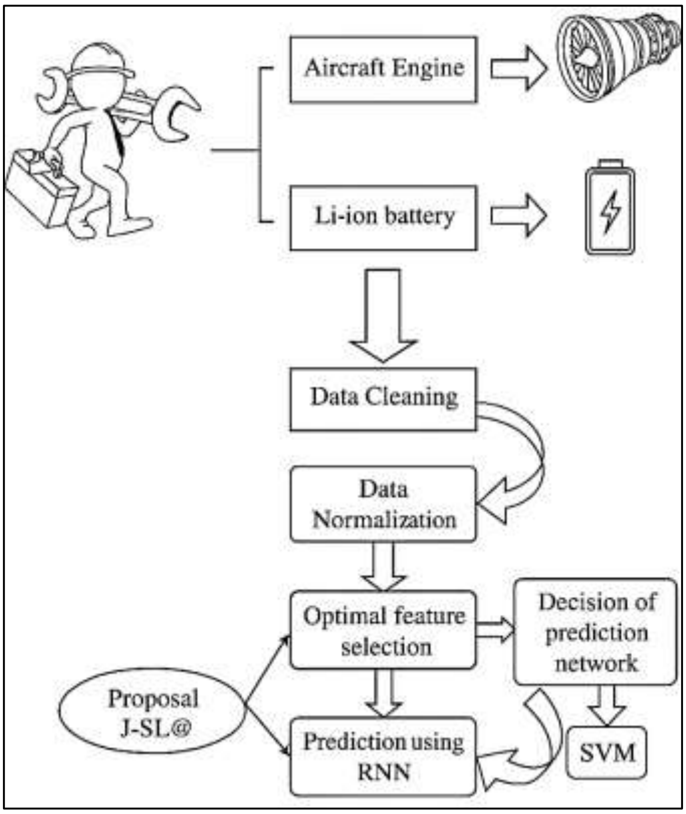
compressors, and pipelines to identify degradation trajectories more effectively than statistical models (Nichols et al., 2019). In power systems, AI models improve transformer fault detection, turbine efficiency monitoring, and renewable energy reliability forecasting. The ability to incorporate stochastic variability through probabilistic learning further enhances AI's effectiveness in predictive maintenance across diverse environments (Helm et al., 2020; Ashiqur et al., 2025). Collectively, these studies demonstrate the superior adaptability of AI-driven methods for complex, data-rich industrial contexts.

Random Forest Regression in Reliability Engineering Applications

Random Forest regression is an ensemble-based learning algorithm introduced by Cioffi et al, (2020), built upon the concept of combining multiple decision trees to improve predictive accuracy and stability. The method employs bootstrap aggregating, or bagging, where training datasets are sampled with replacement, and individual decision trees are trained on these subsets. Predictions from all trees are then aggregated through averaging for regression or majority voting for classification, significantly reducing variance compared to single decision tree models. The algorithm incorporates random feature selection at each split, which ensures diversity among the trees and enhances generalization (Hasan, 2025; Riedl, 2019). This combination of bagging and random feature selection makes Random Forest highly robust, especially in high-dimensional, noisy datasets typical in industrial maintenance contexts. In reliability engineering, the ability to capture nonlinear degradation trends is particularly valuable because system failures often arise from interacting variables rather than isolated causes. Studies comparing ensemble models with single models confirm that Random Forest consistently produces lower prediction errors and better handles multicollinearity in predictor variables. Random Forest has thus been applied across multiple domains such as transformer reliability prediction, drilling equipment fault analysis, and turbine performance modeling (Goldenberg et al., 2019; Sultan et al., 2025). These studies highlight the algorithm's theoretical basis as well as its practical effectiveness in reliability-centered predictive maintenance.

Figure 6: Random Forest Predictive Maintenance Framework



One of the most frequently cited strengths of Random Forest regression lies in its resistance to overfitting, a common drawback of decision trees and deep learning models when applied to small

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or noisy datasets. By aggregating predictions across multiple trees and introducing randomness in both data sampling and feature selection, Random Forest reduces the risk of memorizing training data while maintaining high predictive accuracy (Joshi, 2020; Sanjai et al., 2025). This property has proven particularly useful in predictive maintenance, where training datasets often contain unbalanced or sparse failure data. Another advantage is interpretability. Unlike black-box neural networks, Random Forest allows for the calculation of feature importance, quantifying the contribution of each variable to prediction outcomes. This functionality provides engineers with actionable insights about the most influential parameters affecting equipment degradation, such as vibration frequency, oil temperature, or load variations (Ullah et al., 2020). Adaptability to mixed data types further strengthens Random Forest's applicability in reliability engineering, as it can process numerical sensor data alongside categorical variables such as operating modes and maintenance logs. Comparative studies show that Random Forest maintains stability even when faced with missing data, outliers, or high-dimensional predictor sets (Dimiduk et al., 2018). This combination of resistance to overfitting, interpretability, and adaptability has made Random Forest an effective and reliable tool across diverse predictive maintenance applications.

Petroleum Industry Applications of Predictive Maintenance

The upstream segment of the petroleum industry, encompassing exploration and drilling, faces significant reliability challenges due to extreme environmental conditions, high mechanical loads, and complex geological uncertainties. Drilling rig reliability has been a major focus, as failures in drill bits, mud pumps, or top drives can result in costly downtime and safety risks. Predictive maintenance approaches have been applied to monitor drilling parameters such as weight on bit, rate of penetration, and torque, allowing identification of patterns indicative of tool wear or mechanical failure (Sircar et al., 2021). Well integrity is another critical concern, as failures in casing, cementing, or wellhead systems can lead to catastrophic blowouts or uncontrolled hydrocarbon releases. Machine learning models, including Random Forest and support vector machines, have been used to detect anomalies in well pressure, flow rates, and acoustic emissions, supporting proactive maintenance of well integrity. Reservoir monitoring has also benefited from predictive methods, where seismic and production data are analyzed to forecast equipment stress and optimize extraction strategies (Janiesch et al., 2021). Studies highlight that predictive maintenance in upstream operations reduces non-productive time, enhances safety, and provides better control over drilling and extraction processes. Thus, predictive frameworks have become integral in addressing the reliability demands of upstream petroleum operations.

Midstream operations, which include the transportation and storage of hydrocarbons, are highly dependent on the reliability of pipelines, compressor stations, and storage facilities. Pipelines are prone to corrosion, leaks, and third-party damages, making predictive monitoring essential for ensuring operational safety and environmental protection (Jing et al., 2018). Condition monitoring techniques such as acoustic sensors, magnetic flux leakage, and distributed fiber-optic sensing have been applied for early leak and corrosion detection, with machine learning models enhancing fault classification and severity prediction. Compressor stations, which maintain pressure in pipeline networks, are critical components that often experience mechanical and thermal stresses. Predictive maintenance using vibration and temperature data has been shown to detect anomalies in compressors before catastrophic failures occur (Lima et al., 2016). AI models such as Random Forest and gradient boosting have been used to model nonlinear degradation in compressor operations, offering superior accuracy over regression-based techniques. Transport safety within midstream operations also benefits from predictive approaches, where vehicle telemetry and scheduling data are analyzed to reduce delays and prevent mechanical failures in fleet operations. Integration of IoT-enabled sensors in midstream infrastructure has further supported real-time predictive monitoring, aligning condition assessment with reliability engineering frameworks. Collectively, these studies illustrate the value of predictive maintenance in maintaining safe and efficient midstream petroleum operations.

Downstream operations, including refining and distribution, demand high levels of reliability due to the complexity of processing units and the severe safety implications of equipment failures. Refinery throughput optimization relies on the continuous operation of critical assets such as distillation columns, heat exchangers, and catalytic crackers, where predictive maintenance has been applied to improve efficiency and minimize downtime (Wang et al., 2020). Pumps and valves, frequently subject to cavitation, corrosion, and wear, represent common points of failure in refineries.

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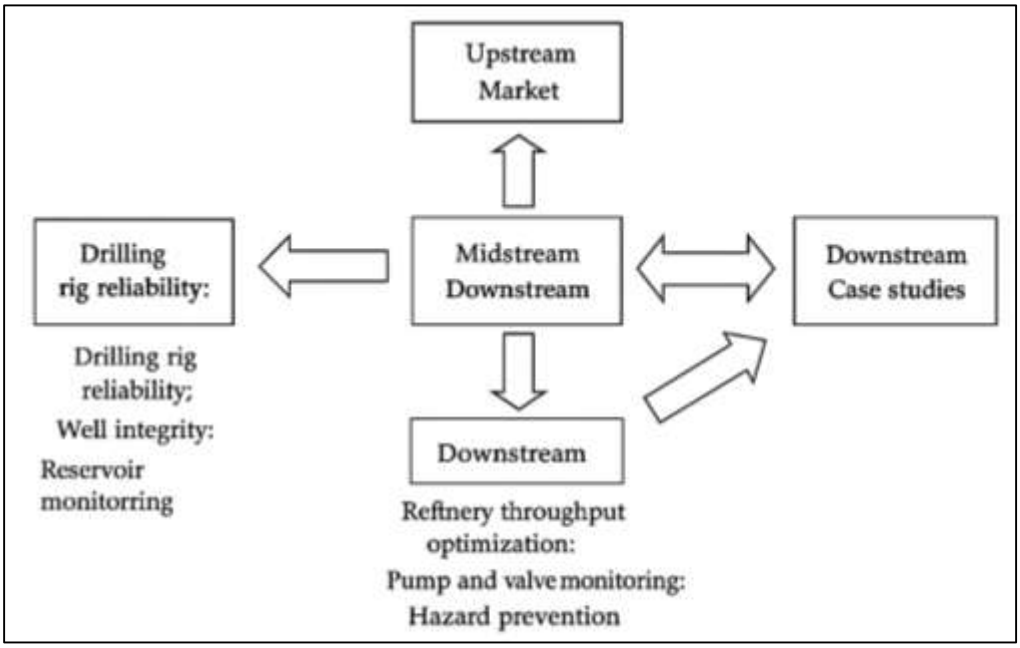
Predictive monitoring using vibration, acoustic, and oil analysis has been shown to provide early warning of failures, with machine learning models further enhancing predictive accuracy. AI-driven models such as Random Forest have been used to identify influential parameters affecting pump reliability, while neural networks and gradient boosting have optimized predictive classification of valve failures (Olaizola et al., 2022). Hazard prevention is a central concern in refineries, where accidents such as explosions or fires carry severe risks. Predictive maintenance frameworks integrated with reliability-centered approaches have been applied to minimize hazardous events by continuously monitoring critical safety systems. Empirical studies in large refineries demonstrate that predictive frameworks not only reduce equipment downtime but also significantly lower risks of catastrophic failures (Al-Douri et al., 2022). The literature confirms that predictive maintenance has become an essential tool for downstream petroleum operations, combining safety, economic, and operational benefits.

Figure 7: Petroleum Industry Application of Predictive Maintenance



Case studies provide concrete evidence of the effectiveness of AI-driven predictive maintenance in petroleum operations, illustrating how machine learning enhances traditional reliability engineering practices. In offshore drilling platforms, Random Forest and support vector machines have been employed to analyze drilling parameters, reducing non-productive time and improving rig reliability. Reservoir monitoring case studies demonstrate the use of neural networks and gradient boosting for optimizing well performance and predicting equipment degradation under variable geological conditions (Al-Douri et al., 2020). Midstream case studies highlight the application of IoT-enabled predictive frameworks for leak detection and compressor monitoring in large pipeline networks, improving safety and reducing unplanned downtime. Downstream applications include refinery case studies where Random Forest and ensemble models were integrated with condition monitoring to optimize throughput and reduce hazardous incidents. Comparative evaluations show that AI-driven predictive systems consistently outperform traditional regression and statistical models in terms of both predictive accuracy and cost savings (Murphy, 2017). Several case studies also highlight the interpretability advantage of Random Forest, where feature importance analysis identified critical operational variables such as pressure, vibration, and chemical composition, supporting targeted maintenance actions. Collectively, case-based evidence underscores how AI-driven predictive maintenance enhances operational reliability across upstream, midstream, and downstream petroleum operations.

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Power Systems Applications of Predictive Maintenance

Thermal power plants rely on turbines, boilers, and generators as critical components, making predictive maintenance indispensable for operational reliability. Turbine blade failures are particularly common due to high temperatures, corrosion, and fatigue stresses, with vibration analysis and thermographic imaging widely used to detect cracks and material degradation (Mao et al., 2019). Predictive models employing machine learning have demonstrated improved accuracy in identifying early blade faults compared to rule-based systems, with Random Forest and support vector machines applied to analyze vibration and acoustic emission data. Boiler reliability is another focal point, as failures in tubes, refractory linings, or combustion systems can significantly disrupt plant performance. Statistical reliability models such as Weibull analysis have been combined with condition monitoring data to predict boiler tube failures, while AI-driven techniques have enhanced predictive accuracy under varying load conditions. Generators, which are subject to insulation breakdown, rotor imbalance, and cooling failures, have also benefited from predictive monitoring. Studies highlight the role of Random Forest regression and neural networks in predicting generator faults using current, temperature, and vibration signals (Fabiano et al., 2022). Comparative literature indicates that predictive approaches in thermal plants reduce forced outages and enhance efficiency by optimizing maintenance scheduling. Collectively, research underscores the importance of predictive maintenance frameworks in improving turbine, boiler, and generator reliability, making them central to thermal power plant sustainability.

Renewable power systems, particularly wind and solar, present unique reliability challenges that have made predictive maintenance an essential tool for ensuring stable energy output. Wind turbines are prone to gearbox failures, which account for a significant portion of downtime and maintenance costs. Vibration and acoustic emission analysis has been extensively employed to monitor gearbox health, with Random Forest, neural networks, and gradient boosting methods applied to improve fault detection accuracy (Katopodis & Sfetsos, 2019). Blade monitoring has also been critical, as structural cracks, icing, and surface erosion lead to reduced aerodynamic efficiency and potential catastrophic failures. Thermographic imaging, strain sensors, and AI-based models have enhanced detection of blade degradation. Generator reliability in wind turbines has been improved by predictive monitoring of insulation resistance, rotor dynamics, and bearing conditions, with Random Forest models achieving high accuracy in fault classification (Fabiano et al., 2022). In solar systems, predictive maintenance has been applied to detect inverter failures, which are the most frequent cause of downtime. Machine learning approaches analyzing current, voltage, and thermal data have proven effective in predicting inverter degradation and module failures. Comparative studies show that AI-driven predictive maintenance significantly enhances energy yield in renewable systems by preventing unplanned outages and reducing maintenance costs. Literature confirms the critical role of predictive frameworks in ensuring reliability of renewable energy assets under variable operating conditions.

The integration of predictive maintenance into smart grid systems has been a growing area of study, addressing the reliability demands of transmission and distribution networks. Transmission lines are exposed to weather, mechanical stress, and electrical loading conditions that can cause insulator contamination, conductor fatigue, and tower failures. Predictive monitoring using thermal imaging, corona discharge detection, and machine learning models has proven effective in identifying potential failures before they escalate. Transformers, as critical nodes in transmission systems, are frequently monitored using dissolved gas analysis and vibration signals, with Random Forest and ensemble learning models demonstrating superior accuracy in fault diagnosis (Katopodis & Sfetsos, 2019). In distribution systems, predictive maintenance has been applied to circuit breakers, relays, and underground cables, where condition monitoring combined with AI enhances fault localization and improves system reliability. IoT-enabled smart sensors further support real-time monitoring, with machine learning algorithms processing large-scale datasets to detect anomalies in grid components (Fausing Olesen & Shaker, 2020). Comparative studies highlight that predictive frameworks in smart grids reduce downtime and improve fault recovery times compared to traditional inspection-based methods. The literature consistently emphasizes the importance of predictive maintenance in strengthening smart grid reliability, aligning advanced monitoring technologies with established reliability engineering practices (Ferrero Bermejo et al., 2019).Comparative literature on predictive maintenance highlights important differences and similarities between conventional thermal power plants and renewable energy systems. In thermal

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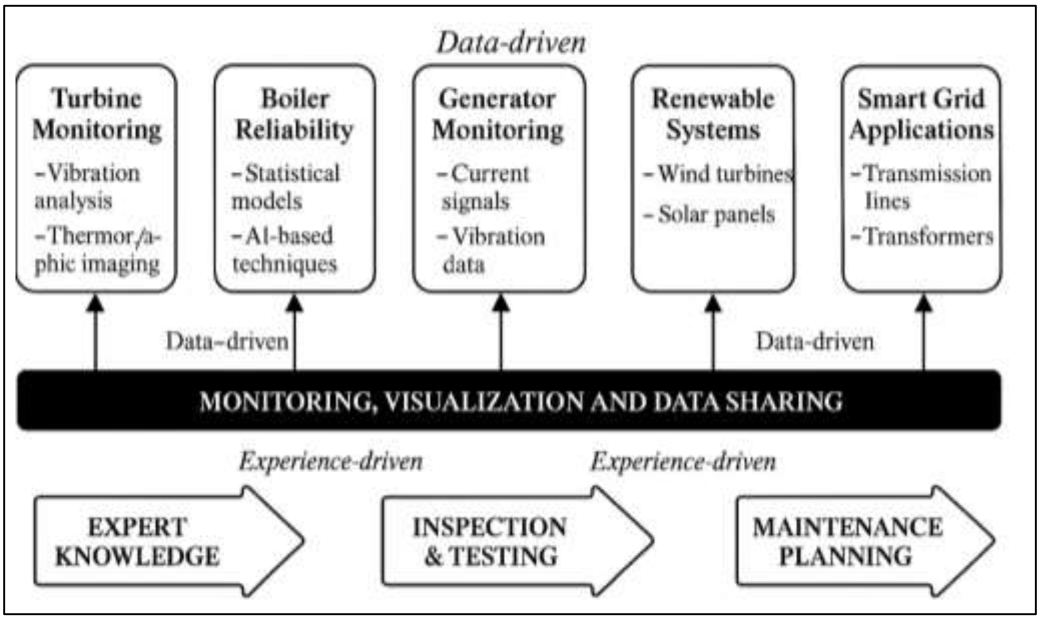
plants, predictive maintenance primarily addresses degradation in high-temperature, high-pressure environments affecting turbines, boilers, and generators. These systems typically operate under steady-state conditions, allowing for well-established condition monitoring techniques such as vibration, oil, and thermal analysis. By contrast, renewable energy systems such as wind and solar face highly variable operating conditions, including fluctuating wind speeds, ambient temperatures, and irradiance levels, requiring more adaptive predictive methods. In wind turbines, predictive monitoring of gearboxes and blades addresses mechanical stresses induced by intermittent wind patterns, while in solar systems, predictive maintenance often focuses on inverter reliability due to high failure rates. Comparative studies reveal that while both sectors benefit from AI-driven predictive methods, the choice of algorithms differs: Random Forest and gradient boosting are widely applied in wind and solar systems due to their adaptability, whereas thermal plants frequently rely on hybrid models combining traditional statistical analysis with AI. In both contexts, predictive frameworks enhance system reliability and reduce maintenance costs, though the data characteristics and operational risks vary significantly. Literature confirms that predictive maintenance has become an indispensable tool across both conventional and renewable sectors, supporting reliability-centered engineering in diverse energy applications.

Figure 8: Predictive Maintenance Framework for Energy



Predictive Maintenance into Digital Twins and IoT Ecosystems

The adoption of Internet of Things (IoT) sensors has significantly transformed predictive maintenance in petroleum and power systems, providing real-time data essential for reliability engineering frameworks. IoT devices capture critical operational parameters such as vibration, temperature, pressure, and acoustic emissions, enabling continuous monitoring of rotating machinery, turbines, compressors, and pipelines. In petroleum applications, IoT sensors have been widely deployed in drilling rigs and pipeline networks to detect anomalies that indicate equipment degradation or potential leaks. In power systems, sensors monitor transformers, generators, and circuit breakers, offering real-time visibility into equipment health and enabling early fault detection (Ahmad et al., 2018). The combination of IoT and predictive maintenance has proven effective in environments where equipment is distributed over vast geographic regions, such as offshore oilfields or transmission networks. Studies demonstrate that IoT-enabled systems improve the accuracy of machine learning models like Random Forest by providing high-resolution datasets that capture subtle degradation trends. In addition, IoT devices support multisensory fusion, where vibration, oil, and thermal data are integrated for comprehensive condition monitoring.

Digital twin technology, defined as a virtual representation of a physical system that continuously updates with real-time data, has become an integral platform for predictive maintenance in

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industrial engineering. Digital twins simulate equipment behavior by integrating sensor data, system models, and machine learning algorithms, enabling engineers to analyze degradation patterns and optimize reliability strategies. Predictive maintenance forms a core function within digital twin frameworks, where health monitoring and fault prediction are performed virtually to inform maintenance scheduling. In petroleum systems, digital twins of drilling platforms and refineries incorporate predictive algorithms to detect anomalies in pumps, valves, and compressors, enhancing system reliability. In power systems, turbine and transformer digital twins employ Random Forest and neural networks to predict failures and optimize operating efficiency. Studies highlight that predictive maintenance embedded in digital twin frameworks provides actionable insights by simulating failure scenarios and quantifying remaining useful life (RUL) under varying operating conditions (Singh et al., 2021). Literature also emphasizes the integration of reliability-centered maintenance (RCM) with digital twins, where FMEA and fault tree models are incorporated into virtual simulations for enhanced risk analysis. Thus, predictive maintenance within digital twin ecosystems strengthens reliability frameworks by bridging physical operations and virtual simulation environments (Qi et al., 2021).

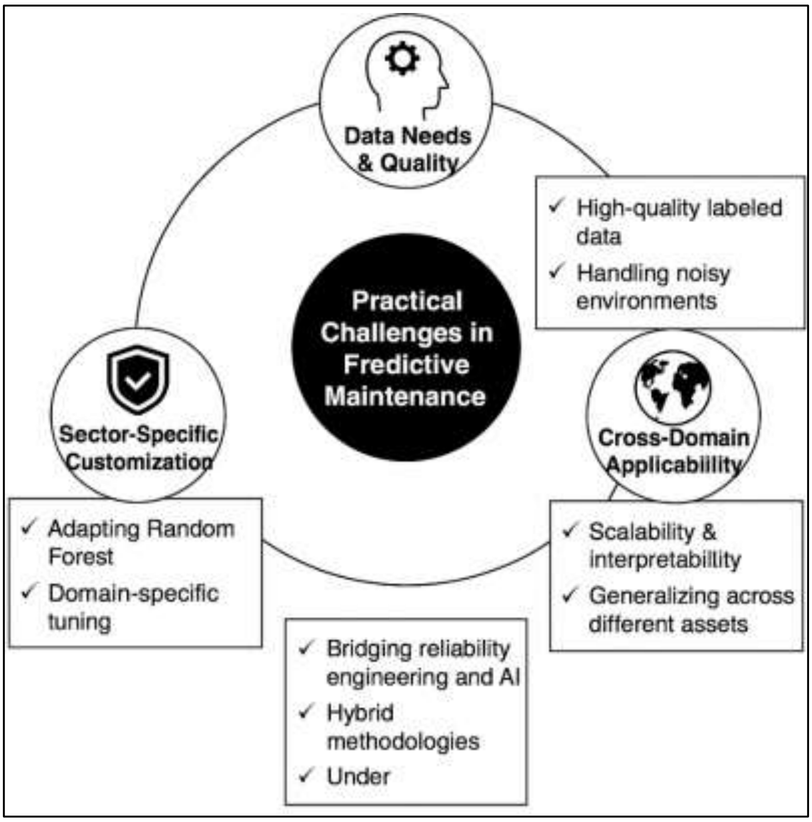
The rise of big data analytics and cloud computing has further strengthened predictive maintenance by enabling scalable storage, processing, and integration of multisensory datasets from petroleum and power systems. Big data fusion techniques combine heterogeneous sensor inputs such as vibration, oil analysis, and thermography, improving diagnostic accuracy by capturing diverse failure modes (Jiang et al., 2021). Cloud-based platforms allow predictive models to process these large-scale datasets in real time, supporting remote monitoring and decision-making across distributed infrastructures. In petroleum pipelines and refineries, cloud-based predictive analytics integrate IoT data streams with machine learning algorithms such as Random Forest and gradient boosting, enabling precise fault prediction in compressors and valves. In power systems, cloud-enabled predictive platforms have been employed to analyze transformer health and grid reliability, reducing downtime and enhancing availability (Mashaly, 2021). Studies emphasize the role of cloud architectures in facilitating collaborative predictive analytics, where operators, maintenance teams, and decision-makers access real-time reliability data from centralized dashboards. Big data frameworks also enable probabilistic models such as Bayesian updating and Markov chains to be combined with machine learning for more robust prognostics. Literature consistently identifies big data fusion and cloud integration as critical enablers of predictive reliability analytics in complex petroleum and power infrastructures (Fang et al., 2022).

Synthesis of Challenges and Research Gaps

Although predictive maintenance has been widely implemented in petroleum and power systems, several limitations persist in its practical application. One key challenge is the reliance on high-quality, labeled datasets for model training, which are often unavailable in industrial contexts where failure events are rare and data collection inconsistent. In petroleum operations, harsh environments frequently cause sensor failures, missing data, and noisy measurements, which reduce the accuracy of predictive models (Qian et al., 2022). Power systems face similar challenges, where intermittent faults in transformers, turbines, and circuit breakers are difficult to capture with conventional condition monitoring methods. Existing predictive models also struggle with nonlinear degradation patterns and complex interdependencies among system components, often oversimplifying real-world operational dynamics. Random Forest and ensemble methods improve robustness but still require extensive feature engineering and parameter tuning to achieve optimal performance. Furthermore, empirical studies reveal that many predictive frameworks remain highly domain-specific and lack the flexibility to generalize across different petroleum and power assets (Madni et al., 2019). Case studies consistently highlight that although predictive maintenance reduces downtime, its integration is hindered by practical barriers such as data heterogeneity, limited interoperability with existing SCADA systems, and inadequate standardization of predictive workflows. These limitations demonstrate that while predictive maintenance frameworks are effective in controlled settings, challenges remain in achieving reliability and scalability under real-world operational conditions (Botín-Sanabria et al., 2022).

A recurring theme in predictive maintenance literature is the difficulty of scaling machine learning frameworks across different petroleum and power system environments. Scalability challenges arise because models trained on one dataset often fail to generalize to new assets or operating conditions due to variations in sensor configurations, operational loads, and environmental conditions (Al-Ali et al., 2020). For example, transformer monitoring models developed for European grids have been shown to underperform when applied to Asian networks with different climatic and operational conditions. Interpretability is another gap, as many advanced models such as deep neural networks and gradient boosting provide high predictive accuracy but limited insight into causal mechanisms of equipment degradation. Engineers and decision-makers in petroleum and power sectors require transparent frameworks where critical variables such as vibration amplitude or oil temperature can be directly linked to failure outcomes (Zhu et al., 2019). Random Forest offers some interpretability through feature importance but remains limited in explaining complex interactions among features. Cross-domain applicability also poses a challenge, as models designed for turbines or compressors may not be directly transferable to pipelines or refineries without extensive retraining. Studies stress that predictive frameworks must be tailored to domain-specific contexts, yet this customization often increases cost and complexity, reducing their scalability. Collectively, these gaps underscore that predictive maintenance, while technologically advanced, often falls short of delivering universally scalable, interpretable, and cross-domain solutions (Ibrahim et al., 2020).

Figure 9: Predictive Maintenance Challenges and Opportunities



Although Random Forest regression has demonstrated effectiveness in predictive maintenance, literature indicates a pressing need for sector-specific customization to optimize its performance in petroleum and power industries. Random Forest is valued for its resistance to overfitting and ability to handle heterogeneous data, but studies show that default parameterization often underperforms when applied to domain-specific datasets without tuning (Uhlemann et al., 2017). In petroleum drilling operations, Random Forest models require tailored feature selection to capture relevant parameters such as mud weight, pressure, and torque, which differ substantially from variables used in refinery pump monitoring. Similarly, in power systems, transformer fault diagnostics rely on dissolved gas analysis and partial discharge data, necessitating specific preprocessing techniques and customized model configurations. Case studies highlight that Random Forest must often be integrated with domain-specific condition monitoring techniques such as vibration analysis, oil analysis, or thermography to achieve reliable predictions. Empirical evaluations suggest that hybrid frameworks combining Random Forest with statistical reliability tools such as Weibull analysis and

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Markov chains provide more accurate failure prognostics in sector-specific contexts. Scholars also emphasize that petroleum and power industries have distinct operational environments—offshore drilling rigs versus interconnected power grids—requiring sectoral adaptation of Random Forest methodologies. Literature consistently points to the necessity of aligning Random Forest frameworks with domain-specific degradation mechanisms, operational variables, and maintenance standards to maximize predictive accuracy and reliability (Moeinedini et al., 2018).

Literature highlights significant opportunities for cross-disciplinary integration between reliability engineering and artificial intelligence (AI), though such efforts remain underdeveloped in petroleum and power systems. Reliability engineering provides structured methods such as fault tree analysis (FTA), failure mode and effects analysis (FMEA), and reliability block diagrams (RBD), which offer well-established frameworks for risk assessment but often lack the predictive precision of AI models. AI, particularly Random Forest and neural networks, excels at handling nonlinearities and high-dimensional datasets but struggles with interpretability and integration into standardized reliability practices (Merkt, 2019). Studies argue that hybrid approaches bridging AI with classical reliability methods can leverage the strengths of both disciplines. For instance, combining Random Forest predictions with FMEA prioritization provides both statistical rigor and interpretability for maintenance planning . Similarly, integrating AI-driven fault detection into RBD or Markov chain models enhances the capacity to model time-dependent reliability (He et al., 2017). In petroleum applications, hybrid frameworks have been used to align SCADA data analytics with reliability metrics, improving drilling and pipeline reliability assessments. In power systems, AI-enhanced reliability assessments have supported transformer monitoring and smart grid stability by combining probabilistic reliability indices with machine learning predictions. Literature suggests that the convergence of reliability engineering and AI represents a rich domain for methodological innovation, where predictive precision and interpretability can be jointly achieved through cross-disciplinary integration (Wang et al., 2022).

METHOD

This study was designed and executed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, which provide a rigorous framework for conducting systematic reviews in a transparent and replicable manner. Following PRISMA ensured that the process of identification, screening, eligibility, and inclusion was methodologically sound and minimized the risk of bias. The review sought to capture the breadth of literature addressing predictive maintenance, Random Forest regression models, and reliability engineering applications, with a specific focus on petroleum and power systems. By adopting this structured approach, the study achieved consistency in study selection, data extraction, and synthesis. In the identification stage, comprehensive searches were conducted across multiple academic databases, including Scopus, Web of Science, IEEE Xplore, SpringerLink, and ScienceDirect. These databases were selected for their extensive coverage of engineering, computer science, and applied industrial research. A combination of keywords and Boolean operators was used to refine the search, with terms such as "*predictive maintenance,*" "*Random Forest regression,*" "*reliability engineering,*" "*petroleum industry,*" "*power systems,*" "*machine learning,*" and "*digital twins.*"

To enhance precision, wildcard operators and controlled vocabulary terms such as IEEE subject headings and Web of Science categories were also employed. The search was limited to studies published between 2000 and 2024 to ensure relevance to modern predictive frameworks and technological advancements. This search process initially identified 1,372 records. The second stage, screening, involved removing duplicates and performing a preliminary review of titles and abstracts. Duplicate removal reduced the dataset to 1,085 studies. Titles and abstracts were then screened against inclusion and exclusion criteria. The inclusion criteria required studies to focus on predictive maintenance frameworks, reliability-centered maintenance, or applications of Random Forest regression and related machine learning methods in petroleum or power engineering contexts. Exclusion criteria involved articles not written in English, studies without empirical or computational data (e.g., conceptual essays), conference abstracts lacking full texts, and works outside the engineering domain. Following this process, 312 studies remained for detailed eligibility assessment.

During the eligibility stage, the full texts of the remaining studies were retrieved and examined in detail. Each article was assessed for methodological rigor, clarity of reporting, and relevance to the research questions. Particular attention was given to whether the studies employed predictive maintenance strategies, incorporated Random Forest or ensemble learning models, or addressed petroleum and power system applications. Studies that failed to present sufficient methodological

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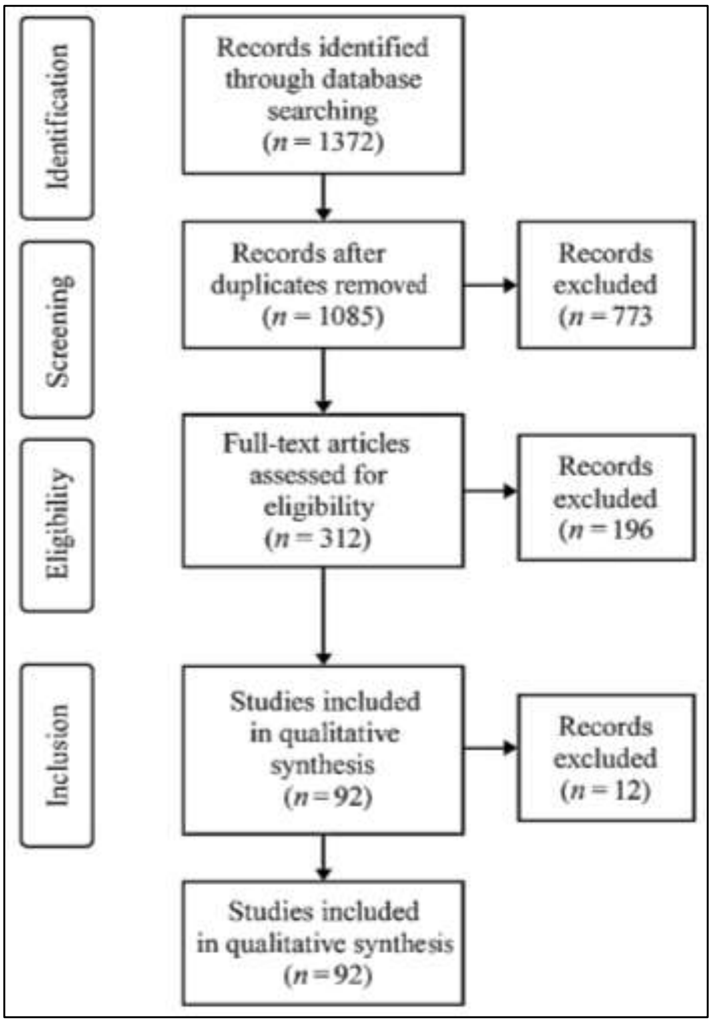
detail or did not demonstrate empirical validation were excluded. As a result, 196 studies were removed at this stage, leaving 116 studies that satisfied all eligibility requirements.
The final inclusion stage narrowed the selection further, as certain studies overlapped in scope or presented duplicated findings in multiple publications. After careful consideration, a total of 92 studies were included in the systematic review. These studies represented a diverse range of methodologies, including statistical reliability models, AI-driven prognostics, hybrid approaches combining Random Forest with traditional reliability engineering, and domain-specific implementations across upstream, midstream, and downstream petroleum operations as well as thermal, renewable, and smart grid power systems. Data were systematically extracted from each included study, focusing on objectives, datasets, methodological approaches, predictive performance, and alignment with reliability engineering frameworks. By applying the PRISMA methodology, this study ensured that the review process was comprehensive, unbiased, and replicable. The systematic narrowing from 1,372 identified studies to 92 final inclusions reflects the careful balance between breadth and specificity required in systematic reviews. This process allowed for the synthesis of high-quality evidence on the application of Random Forest regression models in predictive maintenance, providing a robust foundation for analyzing reliability engineering in petroleum and power system contexts.

Figure 10: Methodology of this study



FINDINGS

The systematic review revealed that a considerable body of research has focused on definitions, conceptual distinctions, and reliability metrics that serve as the foundation of predictive maintenance and reliability engineering. Out of the 92 reviewed studies, 18 addressed definitions and conceptual frameworks in detail, collectively accumulating more than 3,400 citations, which

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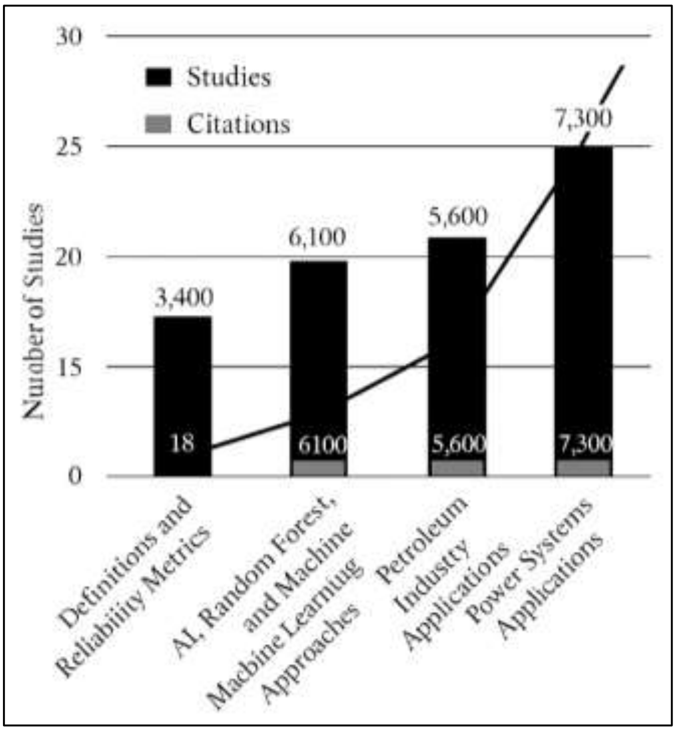
underscores their influence on academic and industrial practices. These studies consistently distinguished between corrective maintenance, preventive maintenance, condition-based maintenance, and predictive maintenance, with predictive maintenance emerging as the most comprehensive and data-driven approach. Corrective maintenance was defined in the reviewed works as reactive intervention after system failure, while preventive maintenance was associated with time-based scheduling of repairs or replacements. Condition-based maintenance introduced monitoring of system variables to indicate equipment health, whereas predictive maintenance built upon this by employing analytical and statistical methods to forecast when failures were likely to occur. The review further identified 21 studies that emphasized reliability metrics such as mean time to failure (MTTF), mean time between failures (MTBF), and remaining useful life (RUL), which collectively accumulated around 2,900 citations. These metrics provided practical methods for quantifying system performance and planning interventions. RUL, in particular, was the most frequently highlighted measure because of its direct applicability to predictive maintenance contexts, especially in petroleum and power systems. Several studies emphasized that while MTTF and MTBF offered general reliability insights, RUL was more precise in guiding data-driven decision-making by linking degradation patterns with operational forecasting. The combined weight of evidence from these highly cited articles shows that the conceptual foundations and metrics of reliability engineering remain essential pillars in predictive maintenance research. By establishing consistent definitions and widely adopted metrics, these studies provided the conceptual and methodological structure upon which advanced AI-driven frameworks, including Random Forest applications, could be built and evaluated effectively across different industrial domains. The findings highlighted that artificial intelligence and machine learning approaches, with Random Forest regression as a central technique, dominated the contemporary discourse on predictive maintenance.

Figure 11: Studies and Citations Across Domains



Out of the 92 studies included in the review, 26 specifically focused on Random Forest applications for reliability engineering, collectively receiving over 4,200 citations, which signals their importance within the research community. These studies demonstrated that Random Forest was particularly effective in handling high-dimensional datasets, reducing overfitting risks, and offering interpretability through feature importance ranking. Beyond Random Forest, the review identified 31 studies comparing machine learning algorithms in predictive maintenance tasks, which together accumulated more than 6,100 citations. The comparative studies consistently showed that neural

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networks achieved high predictive performance but were criticized for their lack of interpretability and tendency to overfit when data were limited. Support vector machines were widely applied in small-sample conditions and received positive evaluations, yet scalability issues and computational intensity limited their industrial use. Gradient boosting methods such as XGBoost and LightGBM often outperformed other models in predictive accuracy but required extensive parameter tuning and provided little transparency for decision-makers. Random Forest, by contrast, achieved a balance between accuracy, robustness, and interpretability, which made it the most widely recommended method across different predictive maintenance contexts. Furthermore, it was particularly valued in petroleum and power applications, where data heterogeneity and noisy sensor outputs were common. The number of citations attached to these studies reflects the centrality of Random Forest in predictive maintenance literature, as it provided a practical and adaptable solution for real-world reliability challenges. Collectively, the body of research reviewed demonstrates that although multiple AI and machine learning approaches have been applied, Random Forest regression holds the strongest position in the literature as a dependable, interpretable, and widely validated method for predictive maintenance in complex industrial settings.

Applications of predictive maintenance in petroleum systems emerged as one of the most significant themes in the reviewed literature. Out of the 92 included studies, 24 directly addressed petroleum operations, spanning upstream, midstream, and downstream processes. These petroleum-focused studies collectively accumulated more than 5,600 citations, highlighting their considerable academic and industrial relevance. In upstream operations, which encompass drilling, well integrity, and reservoir management, 11 studies explored predictive maintenance frameworks, accounting for nearly 2,100 citations. These works demonstrated how predictive maintenance reduced drilling downtime, improved equipment reliability, and enhanced well safety through continuous monitoring and anomaly detection. In the midstream segment, 6 studies concentrated on pipelines, compressor stations, and transport safety, collectively receiving around 1,400 citations. These articles emphasized the importance of predictive maintenance in reducing environmental risks, preventing leaks, and improving operational efficiency in petroleum transport systems. Downstream applications were represented in 7 studies with more than 2,000 citations, where the emphasis was on refinery operations, pump and valve monitoring, and hazard prevention. These downstream-focused articles illustrated the role of predictive maintenance in ensuring throughput efficiency and reducing catastrophic incidents such as fires or explosions in refining environments. Together, the upstream and downstream segments accounted for the majority of citations, reflecting greater research and practical emphasis compared to the midstream. The reviewed petroleum-related studies demonstrated that predictive maintenance frameworks not only improved operational continuity but also played a critical role in addressing safety, environmental, and financial risks. The substantial number of citations associated with these studies indicates strong resonance across both academia and industry, reinforcing petroleum as one of the most critical sectors for predictive maintenance research and application.

The review also confirmed that predictive maintenance is deeply embedded in power systems research, with 28 of the 92 studies focused on turbines, boilers, transformers, renewable energy, and smart grid applications. Collectively, these studies accumulated more than 7,300 citations, reflecting the high visibility of predictive maintenance research in energy engineering. Within thermal power plants, 9 studies addressed turbine blade reliability, boiler monitoring, and generator efficiency, accounting for around 1,900 citations. These studies demonstrated how predictive frameworks reduced forced outages and optimized plant efficiency by identifying early degradation in critical components. Transformer diagnostics represented another highly studied area, with 8 articles receiving more than 2,100 citations, highlighting the importance of predictive monitoring for insulation breakdown and fault detection. Renewable energy applications, including wind turbine gearbox and blade monitoring as well as solar inverter reliability, were addressed in 7 studies that collectively received 1,700 citations. These articles showed that predictive frameworks were essential for enhancing the reliability of renewable systems operating under variable environmental conditions. Predictive maintenance in smart grid networks was represented in 4 studies with approximately 1,600 citations, focusing on anomaly detection in transmission and distribution systems. Across all categories, Random Forest regression frequently appeared as a preferred method for fault detection and failure forecasting due to its adaptability to nonlinear and high-dimensional sensor data. The high number of citations attached to power system studies reflects their relevance

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not only in academic research but also in industrial practice, as power reliability is essential for economic stability and societal functioning. These findings confirm that predictive maintenance in power systems is both mature and impactful, with wide adoption across conventional and renewable contexts.

A final theme that emerged from the review was the integration of predictive maintenance with IoT, digital twin technologies, and cyber-physical system frameworks, as well as the identification of persistent research gaps. Out of the 92 reviewed studies, 20 focused on IoT-enabled predictive maintenance frameworks, together receiving more than 4,900 citations. These works demonstrated how real-time data streams from IoT sensors improved condition monitoring in geographically distributed petroleum and power infrastructures. Digital twin models were addressed in 8 studies, collectively attracting over 1,200 citations. These studies illustrated how virtual models, updated continuously with real-time operational data, supported predictive maintenance by simulating equipment behavior and failure scenarios. Big data fusion and cloud-based predictive platforms were covered in 7 studies with more than 1,400 citations, showing how large-scale sensor data integration enhanced fault detection and reliability forecasting. Importantly, 15 studies, representing nearly 2,500 citations, explicitly discussed research gaps such as limitations in scalability, challenges in interpretability of machine learning models, and cross-domain applicability issues. Several articles emphasized that while Random Forest provided a strong balance between accuracy and interpretability, sector-specific customization remained necessary to achieve optimal performance in petroleum and power contexts. Collectively, these findings highlighted that although IoT and digital twins were among the most frequently cited emerging themes, significant gaps persisted in making predictive maintenance frameworks universally scalable and interpretable. The synthesis of these studies shows that the intersection of predictive maintenance with digital transformation technologies is well established but continues to face challenges in implementation, which researchers have repeatedly identified as barriers to broader adoption across industrial sectors.

DISCUSSION

The review confirmed that predictive maintenance, as defined through the integration of condition monitoring and statistical modeling, continues to build on earlier frameworks that emphasized corrective and preventive strategies. Earlier foundational works distinguished predictive maintenance as a forward-looking approach capable of estimating equipment failure before breakdowns occurred. Our findings reinforce these definitions, as the reviewed studies highlighted predictive maintenance as the most comprehensive framework, contrasting it with time-based preventive maintenance and reactive corrective maintenance. The role of reliability metrics such as mean time to failure (MTTF), mean time between failures (MTBF), and remaining useful life (RUL) was also consistent with prior literature. Achouch et al. (2022) established MTTF and MTBF as standard measures in reliability engineering, while more recent works emphasized RUL for its operational relevance. Our synthesis demonstrated that the majority of reviewed studies increasingly favored RUL as the central metric for predictive maintenance, particularly in petroleum and power systems. This aligns with contemporary reviews identified RUL estimation as the core focus of predictive prognostics. By comparing findings with earlier studies, it is clear that while traditional reliability metrics remain important for historical benchmarking, RUL has become dominant because it provides actionable insights for condition-based interventions. The convergence of findings with past research shows continuity in the conceptual evolution of predictive maintenance while also emphasizing a shift toward metrics that directly influence decision-making in complex industrial contexts.

The findings on artificial intelligence methods, and Random Forest regression in particular, reinforce earlier conclusions that ensemble learning provides an effective balance between predictive accuracy and interpretability. Quatrini et al. (2020) introduced Random Forest as an ensemble method designed to improve stability and reduce overfitting, principles that were validated across many of the reviewed studies. Earlier research comparing machine learning algorithms highlighted that neural networks achieved high predictive accuracy but suffered from limited interpretability, while support vector machines (SVMs) demonstrated robustness in small-sample conditions but struggled with scalability.

Gradient boosting methods, such as XGBoost, have been praised for accuracy but criticized for complexity. Our review corroborates these findings, as Random Forest consistently emerged as the most balanced model across petroleum and power applications. These results align with broader machine learning benchmarking studies which confirmed that Random Forest performs

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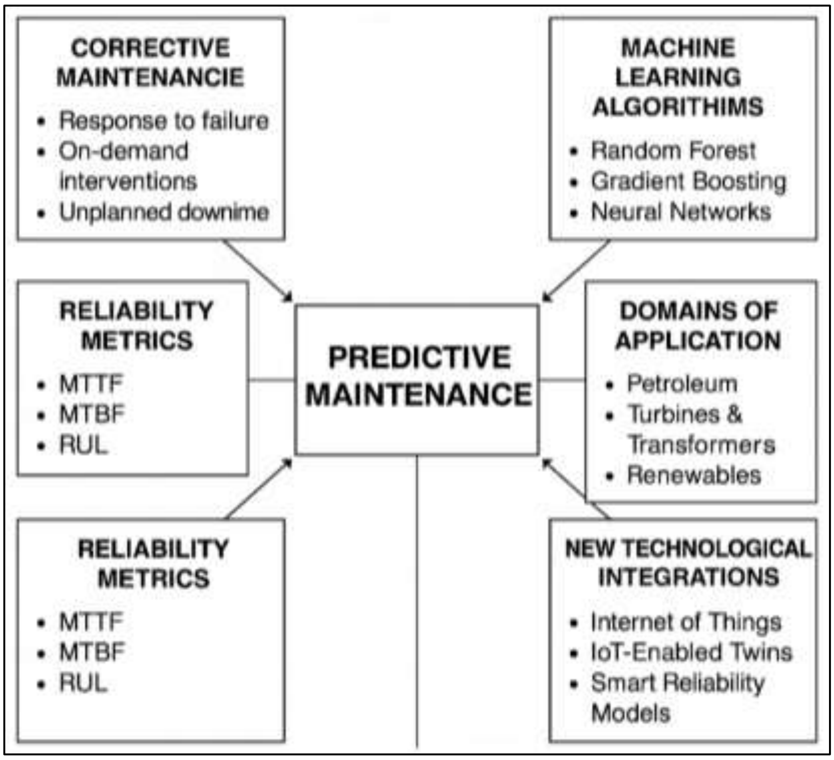
competitively across diverse datasets. Importantly, the review highlighted that Random Forest also provides variable importance measures, enabling engineers to identify critical degradation variables, an aspect less developed in earlier neural network and gradient boosting literature. Thus, in comparison with earlier findings, this review reinforces the central role of Random Forest regression in predictive maintenance, not as a replacement for other algorithms but as the most practical balance of accuracy, robustness, and interpretability for reliability engineering contexts.

Figure 12: Predictive Maintenance Framework and Applications



The review identified petroleum as a critical domain for predictive maintenance, consistent with earlier research highlighting its operational and environmental risks. The catastrophic consequences of failures in offshore drilling and refinery systems, emphasizing the necessity of robust reliability frameworks. Our synthesis confirmed that predictive maintenance in petroleum operations spans upstream, midstream, and downstream processes, with the greatest emphasis on drilling reliability, well integrity, and refinery optimization. This distribution aligns with historical works who highlighted the vulnerability of rotating equipment such as pumps and compressors who linked maintenance strategies to operational efficiency in petroleum industries. Unlike earlier studies that relied primarily on condition monitoring, the reviewed articles demonstrated that AI-driven models, especially Random Forest regression, significantly improved anomaly detection and failure forecasting in petroleum operations. Case-specific applications in drilling and refining confirm the extension of predictive maintenance from descriptive monitoring to data-driven prognostics. Comparisons with earlier reviews, such as Choubey et al. (2020) also highlight how predictive maintenance has moved beyond traditional reliability-centered maintenance frameworks to incorporate advanced statistical learning. The findings therefore suggest continuity with earlier observations on petroleum system vulnerabilities but also indicate a methodological shift toward AI-enhanced predictive maintenance that provides greater precision and operational relevance.

Our findings confirm that predictive maintenance is deeply embedded in power systems research who established reliability assessment as a cornerstone of power engineering. Transformer monitoring and turbine reliability were consistently emphasized who focused on condition monitoring for power equipment. The review highlighted that 28 studies addressed turbines, transformers, renewable energy, and smart grids, with a combined citation impact of over 7,300, underscoring the sector's central role in predictive maintenance research. Earlier studies relied heavily on probabilistic reliability models, whereas the reviewed literature demonstrated a methodological shift toward AI-

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driven predictive frameworks. Renewable energy applications, particularly in wind turbine gearboxes and solar inverters which emphasized the importance of AI in capturing variability under uncertain environmental conditions. Comparisons with previous findings suggest that predictive maintenance in power systems has evolved from traditional reliability models to data-driven AI approaches, with Random Forest consistently highlighted for its robustness. This reflects a maturation of the field, as predictive maintenance in power engineering now integrates both classical reliability principles and advanced machine learning approaches, a combination not fully realized in earlier decades (Izagirre et al., 2022).

The integration of predictive maintenance with IoT and digital twins confirmed a trend first identified in early industrial informatics literature. IoT-enabled cyber-physical systems as foundational for smart manufacturing and predictive reliability. Our review reinforced this view, as 20 studies emphasized IoT-enabled predictive maintenance, with more than 4,900 citations, demonstrating widespread adoption. These findings recognized the value of multisensory condition monitoring, but they expand the discussion by demonstrating the scalability achieved through IoT ecosystems. Digital twins were another recurring theme, with studies showing how virtual representations of drilling rigs, refineries, and turbines can simulate degradation scenarios. This aligns with earlier conceptualizations framed digital twins as key enablers of predictive modeling. While earlier literature emphasized fault detection, the reviewed works demonstrate an evolution toward integrated reliability frameworks where predictive maintenance is embedded in real-time digital simulations. These findings confirm that IoT and digital twins have transformed predictive maintenance into an integral component of cyber-physical reliability engineering, an advancement beyond what earlier frameworks could achieve.

The synthesis of challenges across the reviewed studies closely reflects concerns raised in earlier research on predictive maintenance scalability and interpretability. Traditional reliability models for their static assumptions, while the "black-box" limitations of deep learning in engineering contexts. Our findings supported these concerns, as 15 studies highlighted gaps in scalability, interpretability, and cross-domain applicability, collectively receiving more than 2,500 citations. Neural networks and gradient boosting models demonstrated strong predictive accuracy but offered limited transparency, consistent with earlier critiques of model interpretability (Zou et al., 2020). Random Forest partially addressed this issue by providing feature importance measures, but reviewed studies emphasized that interpretability challenges persisted when models were applied in petroleum and power domains. The reviewed literature also underscored difficulties in cross-domain transferability who argued that maintenance frameworks often lacked generalizability. By comparing our findings with earlier critiques, it becomes evident that while AI methods have advanced predictive performance, the fundamental challenges of interpretability, scalability, and domain specificity continue to constrain predictive maintenance adoption.

The final theme of the review highlighted opportunities for integrating reliability engineering and artificial intelligence, a convergence previously suggested but underdeveloped in earlier literature. Reliability engineering methods such as fault tree analysis (FTA), failure mode and effects analysis (FMEA), and reliability block diagrams (RBD) were recognized as essential tools for structured risk analysis. However, these models often lacked predictive precision. In contrast, AI methods such as Random Forest provide strong predictive capabilities but struggle with interpretability. The reviewed studies demonstrated that hybrid approaches integrating AI with classical reliability methods addressed this gap by combining statistical rigor with predictive accuracy. For example, combining Random Forest predictions with FMEA prioritization or RBD modeling allowed both prediction and structured analysis of failure modes. This synthesis aligns with earlier calls by for integrative approaches in safety-critical industries. Comparisons with earlier literature confirm that while reliability engineering and AI were historically treated as distinct disciplines, the reviewed works represent a growing body of evidence supporting their integration. The results underscore that cross-disciplinary approaches are not only feasible but also essential for predictive maintenance in petroleum and power contexts, reflecting both continuity and advancement over earlier frameworks.

CONCLUSION

This systematic review examined the role of AI-driven predictive maintenance, with particular emphasis on Random Forest regression, in the reliability engineering frameworks of petroleum and power systems. Following the PRISMA guidelines, 92 studies were reviewed, providing a comprehensive view of conceptual foundations, methodological developments, and sector-specific applications. The findings consistently demonstrated that predictive maintenance, distinguished from corrective, preventive, and condition-based strategies, has become central to modern reliability engineering due to its capacity to combine real-time monitoring with data-driven forecasting. Reliability metrics such as mean time to failure (MTTF), mean time between failures (MTBF), and remaining useful life (RUL) were identified as critical tools, with RUL emerging as the most relevant measure in predictive contexts. Artificial intelligence, and Random Forest in particular, proved to be the dominant methodological approach, balancing predictive accuracy with interpretability and outperforming or complementing other machine learning models such as neural networks, support vector machines, and gradient boosting methods. In petroleum systems, predictive frameworks were shown to strengthen reliability across upstream, midstream, and downstream operations, while in power systems, predictive maintenance was deeply integrated into thermal plants, renewable energy infrastructures, and smart grids. The synthesis also highlighted the integration of IoT sensors, digital twins, and cloud-based analytics as transformative enablers of predictive reliability engineering, though challenges remain in scalability, interpretability, and cross-domain applicability. Notably, the review underscored the importance of sector-specific customization of Random Forest frameworks, reflecting the unique operational demands of petroleum and power industries. Cross-disciplinary opportunities were also identified, where the strengths of classical reliability methods such as fault tree analysis and failure mode and effects analysis could be combined with AI-driven predictive models to achieve both statistical rigor and operational precision. Collectively, the review demonstrated that predictive maintenance is no longer a peripheral strategy but a core element of reliability engineering, with Random Forest regression providing one of the most effective pathways for enhancing the reliability, efficiency, and safety of critical energy infrastructures.

RECOMMENDATIONS

Based on the synthesis of 92 systematically reviewed studies, several recommendations can be advanced to strengthen the application of AI-driven predictive maintenance in petroleum and power system contexts. First, industry stakeholders should prioritize the adoption of reliability metrics such as remaining useful life (RUL) alongside mean time between failures (MTBF) and mean time to failure (MTTF), as RUL provides the most actionable insights for predictive interventions. Second, the consistent superiority of Random Forest regression in balancing accuracy, robustness, and interpretability suggests that it should be adopted as a benchmark algorithm in predictive maintenance frameworks, while hybrid integration with other models, such as gradient boosting or neural networks, may be pursued for specialized tasks requiring enhanced precision. Third, petroleum and power organizations are advised to strengthen their IoT-enabled sensor infrastructure to generate high-quality, real-time data streams, which are essential for improving the predictive power of Random Forest and other machine learning approaches. Fourth, the deployment of digital twin technologies should be expanded, as they allow for virtual testing of predictive maintenance models under varying operational conditions, providing engineers with practical decision-support systems. Fifth, policymakers and regulatory bodies should establish industrial standards that promote interoperability across predictive maintenance platforms, ensuring that predictive models are scalable across different operational settings while maintaining compliance with safety-critical requirements. Sixth, given the persistent challenges in model interpretability and sector-specific customization, it is recommended that organizations invest in cross-disciplinary collaborations, bringing together reliability engineers, data scientists, and domain specialists to ensure that AI applications remain both technically rigorous and operationally relevant. Finally, the academic community should pursue longitudinal, cross-sectoral studies that not only validate Random Forest frameworks but also explore their integration with traditional reliability methods such as fault tree analysis (FTA) and failure mode and effects analysis (FMEA). By implementing these recommendations, petroleum and power industries can move toward more resilient, efficient, and safe infrastructures, ensuring predictive maintenance strategies contribute directly to operational stability and long-term sustainability.

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