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Maintenance Strategy Optimization Using Failure Rate Analysis and Risk-Based Inspection: Review, Gap Analysis, Framework Development, and Case Study

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ABSTRACT

Optimizing maintenance in asset-intensive industries requires integrating reliability, safety, and cost under uncertain, time-dependent degradation. Conventional strategies often fail to capture stochastic failure behavior, limiting predictive capability and leading to suboptimal inspection and replacement decisions. Although Risk- Based Inspection (RBI) enhances asset prioritization, its implementation often relies on static assumptions, fragmented data structures, and limited adaptability. A review of maintenance optimization, failure-rate modeling, and RBI applications reveals key gaps: isolated deployment of Reliability-Centered Maintenance (RCM), Total Productive Maintenance (TPM), and RBI; insufficient integration of predictive analytics; limited quantification of cost–risk–reliability trade-offs; and inadequate modeling of system-level interdependencies. These gaps constrain the evolution toward dynamic, risk-informed maintenance systems. This study proposes an Integrated Reliability-Centered Framework (IRCF) that unifies probabilistic reliability modeling, RBI principles, and predictive condition monitoring in a continuous, data-driven architecture. The framework integrates time-dependent failure rate estimation, quantitative risk assessment, and Remaining Useful Life (RUL) prediction, with feedback mechanisms that dynamically update risk rankings and inspection intervals. Application of the IRCF to a feedwater centrifugal pump station in a steam generation system reduced downtime by ~25% and maintenance costs by ~20%, while enhancing safety through risk-prioritized interventions. Inspection intervals derived from Probability of Failure (PoF) and RUL metrics optimized resource allocation and minimized unnecessary preventive maintenance.

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Abbreviations

Abbreviation	Full Term	Short Definition
AIM	Asset Integrity Management	Structured management of asset safety and reliability.
API	American Petroleum Institute	Organization issuing industry inspection and maintenance standards.
CBM	Condition-Based Maintenance	Maintenance triggered by equipment condition monitoring.
CM	Corrective Maintenance	Repair after failure occurrence.
FMEA	Failure Modes and Effects Analysis	Method to identify failure modes and their impacts.
FTA	Fault Tree Analysis	Root-cause analysis using logical failure modeling.
HSE	Health, Safety, and Environment	Integrated safety and environmental management framework.
IRCF	Integrated Reliability-Centered Framework	Hybrid framework integrating reliability and risk-based maintenance.
KPI	Key Performance Indicator	Metric used to measure performance.
MTBF	Mean Time Between Failures	Average time between system failures.
MTTR	Mean Time To Repair	Average time required to repair a failure.
NPSH	Net Positive Suction Head	Pressure margin to prevent pump cavitation.
OEE	Overall Equipment Effectiveness	Measure of equipment availability, performance, and quality.
PdM	Predictive Maintenance	Data-driven failure prediction approach.
PM	Preventive Maintenance	Scheduled maintenance to prevent failures.
PoF	Probability of Failure	Likelihood of failure within a given period.
RBI	Risk-Based Inspection	Inspection planning based on risk assessment.
RCM	Reliability-Centered Maintenance	Maintenance strategy based on system reliability analysis.
RUL	Remaining Useful Life	Estimated time remaining before failure.
TPM	Total Productive Maintenance	Proactive strategy to maximize equipment effectiveness.

Introduction

Industries with high safety, environmental, and economic risks have been early adopters of risk-based asset management strategies to ensure operational continuity, safety, and environmental protection. In the oil and gas sector, Risk-Based Inspection (RBI) frameworks safeguard pipelines, pressure vessels, offshore platforms, and other critical assets. Failures can lead to explosions, hydrocarbon releases, environmental damage, and significant financial losses, making proactive, risk-informed approaches essential for reliability and regulatory compliance [1,2]. Power generation—including nuclear, thermal, and renewable plants—uses RBI to prioritize inspections of boilers, turbines, generators, and electrical systems under strict safety standards. Manufacturing sectors also adopt RBI to enhance equipment reliability, reduce unplanned downtime, and improve operational efficiency. Industrial assets face operational stress, environmental exposure, and aging, which can cause failures and escalate costs if unmanaged. Effective maintenance mitigates these risks, sustaining production, safety, and long-term asset performance.

Asset Integrity Management (AIM)

Asset Integrity Management (AIM) is critical in high-risk sectors such as energy, petrochemicals, mining, and infrastructure. AIM provides a structured, lifecycle-oriented approach to maintain functionality, prevent failures, and improve performance. Integrating technical, operational, and managerial disciplines, AIM reduces unplanned downtime, mitigates risks, and ensures compliance with regulations and stakeholder expectations. The ISO 55000 series emphasizes aligning asset management with organizational objectives and strategic planning [3,4]. Modern AIM emphasizes proactive, risk-informed, and data-driven strategies. High-risk assets require predictive and preventive maintenance, while low-risk equipment may follow run-to-failure approaches [5-7]. AIM also supports sustainable operations by reducing energy use, emissions, and waste, contributing to circular economy goals [8]. Three methodologies underpin AIM: RBI, Reliability-Centered Maintenance (RCM), and Total Productive Maintenance (TPM). RBI prioritizes inspections based on probability and consequence of failure (PoF and CoF), RCM focuses on functional failures and root-cause analysis, and TPM engages operators in equipment health management to maximize efficiency [1,9-13]. Integration can provide synergistic benefits, though siloed implementation and governance gaps often limit effectiveness [14-16].

Maintenance Strategies and Evolution

Industrial maintenance strategies include corrective, preventive, and condition-based approaches. Table 1 summarizes key strategies, highlighting objectives, decision criteria, advantages, applications, and data requirements. Approaches range from reactive run-to-failure to proactive, predictive, and risk-informed methods, with RCM optimizing policies per asset and TPM maximizing overall equipment effectiveness (OEE). Figure 1 shows alignment of strategies with asset criticality, emphasizing proactive approaches that enhance reliability, availability, maintainability, and safety (RAMS) and support sustainability [17-21]. RBI structures inspection and maintenance based on failure probability and consequence, improving safety, efficiency, and resource allocation. Many implementations, however, rely on static assumptions, simplified datasets, and limited adaptability. Table 2 lists analytical tools used in RBI, including FMEA, risk matrices, fault tree analysis (FTA), Weibull modeling, condition monitoring, and software platforms. Probabilistic methods enable dynamic inspection planning, focusing on high-risk components while avoiding unnecessary interventions for low-risk assets.

Study Objectives and Contribution

Despite advances in maintenance optimization, failure-rate modeling, and RBI, gaps remain: fragmented methodology implementation, incomplete datasets, limited predictive models, neglected system interdependencies, human and organizational constraints, technological barriers to AI-driven RBI, and lack of unified frameworks. Addressing these gaps is essential to achieve proactive, risk-informed, and cost-effective maintenance strategies that enhance safety, reliability, and operational performance in complex industrial systems.

This study proposes an Integrated Reliability-Centered Framework (IRCF) combining probabilistic failure modeling, RBI, and predictive monitoring to optimize maintenance, improve risk management, and enhance resource allocation. Figure 2 illustrates the simplified framework. The paper is organized as follows: Section 2 reviews maintenance strategies, failure-rate modeling, and RBI, Section 3 identifies key challenges and research gaps, Section 4 presents the proposed methodology and IRCF, Section 5 demonstrates an industrial case study, and Section 6 concludes with findings and future directions.

Table 1: Comparative Classification of Maintenance Strategies

#	Strategy	Decision Basis	Objective	Key Advantage	Context	Data Required
1	Reactive (Run-to-Failure)	Functional failure	Restore after breakdown	Low cost, minimal planning	Low-criticality assets	None
2	Time-Based (TBM)	Fixed interval	Reduce failure risk	Predictable schedule	Stable-life assets	Operating hours, schedule
3	Condition-Based (CBM)	Condition monitoring	Maintain on degradation	Avoids unnecessary work	Sensor-equipped equipment	Sensor readings, inspections
4	Predictive (PdM)	Prognostic/ statistical models	Prevent failure via RUL	Optimized timing, less downtime	High-value systems	Historical & real-time sensor data, models
5	Risk-Based Inspection (RBI)	Risk (PoF × Consequence)	Prioritize inspections	Enhances safety, efficient resources	Critical process assets	PoF, consequence, risk metrics
6	Reliability-Centered (RCM)	Functional failure + reliability	Optimize maintenance policies	Systematic, function- oriented	Complex systems	Failure modes, reliability data, FMEA
7	Total Productive (TPM)	Performance + operators	Maximize OEE, reduce downtime	Proactive, organization-wide	Manufacturing lines	Performance metrics, operator feedback

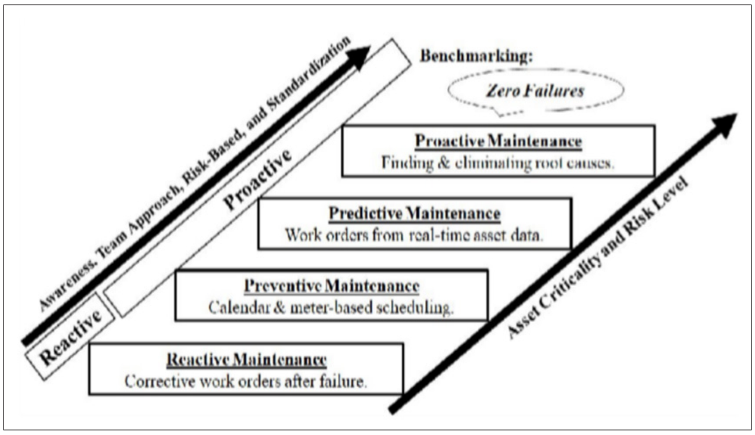

Figure 1: Maintenance & Inspection Policies

Table 2: Core Analytical Tools for RBI/M

#	Tool / Method	Purpose	Key Advantage	Application	Data Required
1	FMEA	Identify potential failures	Prioritizes critical risks	Design review, maintenance planning	Expert judgment, failure records
2	FTA	Identify root causes	Systematic, quantitative	Complex/safety-critical systems	Schematics, failure probabilities
3	Risk Matrices / Ranking	Rank assets by likelihood & impact	Simplifies prioritization	Inspection scheduling, asset management	Failure data, consequence criteria
4	Weibull Analysis	Model time-to-failure	Forecasts the component life	Rotating/critical equipment	Historical failures, operating hours
5	Condition Monitoring (CM)	Detect anomalies	Enables timely interventions	Motors, pumps, rotating machinery	Sensor data (vibration, temperature, pressure)
6	Software Platforms	Integrate monitoring & decision-making	Streamlines workflow, supports reporting	Asset management, PdM programs	Sensor & historical data

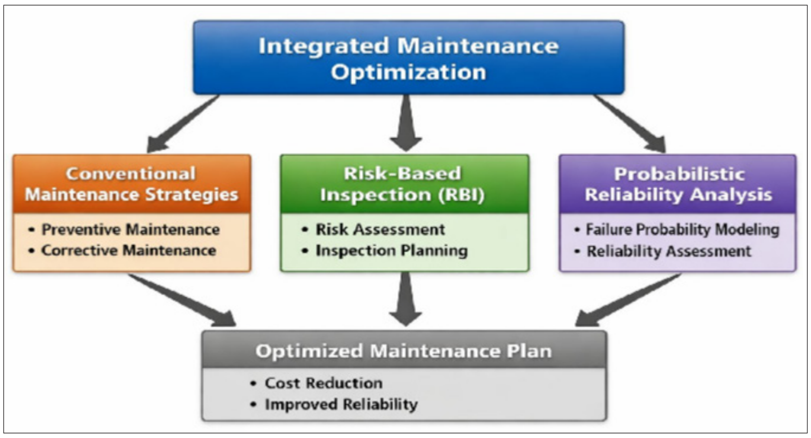

Figure 2: Simplified Framework of the Proposed Integrated Maintenance Optimization

Literature Review

This review systematically examines literature published between 2007 and 2026 from Scopus, Web of Science, and ScienceDirect. A structured search used keywords and Boolean operators such as “maintenance optimization,” “failure rate analysis,” “risk-based inspection,” “reliability engineering,” and “asset integrity management” to identify studies on maintenance strategies, reliability modeling, and inspection methodologies. Only peer-reviewed journal articles, conference proceedings, and review papers in English were included, while duplicates, non-technical reports, and studies lacking methodological rigor were excluded. Selected studies were analyzed to identify key trends, theoretical approaches, and methodological frameworks, emphasizing probabilistic reliability modeling, maintenance scheduling strategies, and integration of failure rate analysis with risk-based inspection. This review provides a comprehensive synthesis, highlighting critical research gaps, emerging methodologies, and opportunities for developing a reliability-based framework for maintenance optimization and RBI-informed decision-making.

Risk-Based Inspection (RBI)

Risk-Based Inspection (RBI) is a key methodology in Asset Integrity Management (AIM), widely applied in high-risk industries such as oil and gas, petrochemical, energy, and critical infrastructure. Unlike reactive or fixed-interval maintenance approaches, RBI prioritizes inspection and maintenance based on the Probability of Failure (PoF) and Consequence of Failure (CoF). This enables organizations to focus on high-risk components, optimize resources, reduce unnecessary interventions, and extend asset service life, effectively shifting maintenance from reactive to proactive, risk-informed strategies. RBI is formalized through API standards, particularly API 581 (2008) and API 580 (2016), which provide structured procedures for risk evaluation and management of static equipment such as pressure vessels, piping, and storage tanks. These standards guide the calculation of failure probabilities, assessment of consequences, and prioritization of inspections, enhancing safety, regulatory compliance, and cost-effectiveness [22]. RBI often applies the Pareto principle, where a small subset of components accounts for the majority of potential failures [23,24]. Comprehensive assessments also consider technical, operational, environmental, and human factors [25].

RBI assessments can be qualitative, quantitative, or semi-qualitative. Qualitative approaches rely on expert judgment, quantitative methods employ probabilistic and statistical models, and semi-qualitative techniques combine both to improve robustness and predictive accuracy [26]. High-quality input data— including historical failures, inspection logs, operational parameters, and design specifications—are critical for effective risk evaluation API 580, 2016 [27]. Table 3 summarizes key RBI studies, highlighting advanced optimization and predictive modeling techniques such as multi-objective and bi-objective genetic algorithms, dynamic Bayesian networks, and neural networks to balance inspection cost, risk reduction, and safety [28-32]. AI and condition monitoring systems further support dynamic, data-driven inspection scheduling [9,33].

RBI has been applied to a variety of assets, including offshore and subsea pipelines, high-energy piping systems, underground pipelines, bridges, and gas stations, addressing critical degradation mechanisms such as corrosion, fatigue, wall thinning, and internal defects [34-38]. Dynamic, semi- quantitative, and knowledge-based approaches have enhanced inspection prioritization, lifecycle cost optimization, and operational safety, particularly for sensitive or hard-to-access assets [1,39-41].

In practice, RBI dynamically adjusts inspection schedules according to assessed risk, focusing on high-priority components while minimizing unnecessary inspections for low-risk assets, thereby improving reliability, reducing unplanned downtime, and supporting strategic maintenance decisions [22,42-47]. Integration with Reliability-Centered Maintenance (RCM) and Total Productive Maintenance (TPM) further enhances operational efficiency [48].

Recent advances leverage AI and analytics, including logistic regression, dynamic Bayesian networks, and neural networks, to model degradation, estimate failure likelihood, and identify emerging risks [32,49,50]. Offshore, subsea, and high-energy systems account for variable pressures, corrosion, fatigue, and hydrodynamic loading, while early detection and prioritization reduce unplanned outages [34,38,51].

A typical RBI workflow includes data collection, risk assessment, risk ranking, and optimized inspection planning (API 580, 2016) Figure 3. Emerging trends focus on multi-objective optimization with genetic algorithms, AI-driven predictive inspections and asset-specific solutions for wall thinning and corrosion [9,28,29,33,35,36]. Key challenges include data quality, integration with other maintenance strategies, and adoption of predictive technologies [16,14].

Table 3: Summary of Key Literature on Risk-Based Inspection (RBI)

#	Author(s)	Key Contributions
1	Javid [29]	Multi-objective RBI using genetic algorithms to optimize inspection cost and risk reduction.
2	Almeida de Rezende et al. [34]	RBI for offshore mooring chains integrating fatigue and corrosion models.
3	Huang et al. [30]	RBI for pipelines using Dynamic Bayesian Networks for inspection interval optimization.
4	Babaeian et al. [35]	Semi-quantitative RBI for gas stations, wall thinning as critical failure mechanism.
5	Aditiyawarman et al. [9]	AI integration in RBI for predictive risk management.
6	Zhang et al. [33]	CMS integration in RBI for dynamic inspection and lifecycle cost reduction.
7	Eskandarzade et al. [36]	RBI framework for underground pipelines integrating damage progression modeling.
8	Sözen et al.	RBI for pipelines with internal defects under variable pressure conditions.
9	Abdallah et al. [1]	Review of U.S. bridge inspections emphasizing RBI modernization.
10	Hameed et al. [37]	RBI strategies for offshore pipelines with corrosion and fatigue-driven failures.
11	Javid [28]	Bi-objective optimization for balancing safety and economic performance in RBI.
12	Yang & Frangopol [52]	Comparison of static and adaptive RBI approaches for structural systems.
13	Song et al. [51]	RBI framework for high-energy piping systems in power plants.
14	Agistina et al. [22]	API 581-based RBI methodology for geothermal facilities.
15	Abubakirov et al. [31]	Dynamic Bayesian networks to optimize inspection intervals in pipelines.
16	Febriyana et al. [41]	RBI for monitoring offshore pipeline damage.
17	Melo et al. [40]	Risk-based framework for undiggable pipelines.

18	Rachman & Ratnayake [32]	Neural networks for RBI screening in hydrocarbon facilities.
19	Arzaghi et al. [38]	Dynamic RBI for subsea pipelines with evolving risks.
20	Kamsu-Foguem [39]	Knowledge-based RBI for sensitive petroleum production systems.
21	Seo et al. (2015)	Risk assessment framework for subsea pipelines.

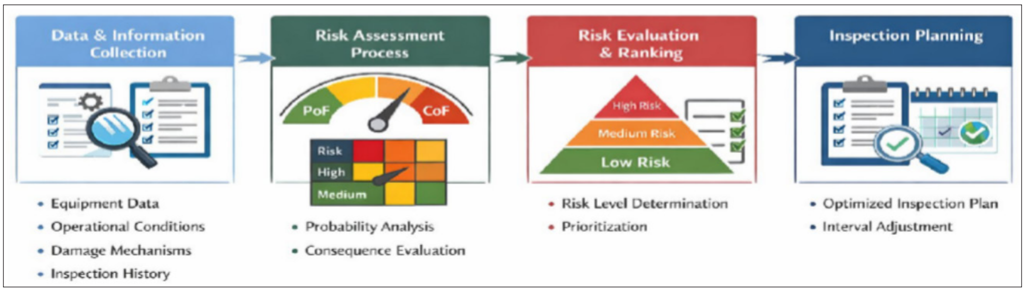

Figure 3: RBI Implementation Steps

Reliability-Centered Maintenance (RCM)

Reliability-Centered Maintenance (RCM) is a structured methodology that prioritizes maintenance based on asset functions, potential failure modes, and their consequences. Unlike conventional reactive or fixed-interval maintenance strategies, RCM focuses on critical assets to reduce downtime, extend service life, improve operational efficiency, and enhance safety and regulatory compliance [48,53]. By aligning maintenance with strategic objectives, RCM ensures that resources target components whose failure would have the greatest operational, financial, or safety impact, enabling a risk-informed, performance-oriented approach to asset management.

The RCM process, illustrated in Figure 4, involves identifying systems and their primary functions, performing a Failure Mode and Effects Analysis (FMEA) to determine potential failures and consequences, selecting appropriate maintenance tasks (preventive, predictive, or corrective), and defining inspection intervals. Feedback loops using operational data, inspection results, and historical failures allow continuous refinement of maintenance plans, increasing adaptability and predictive capability. Table 4 highlights key studies demonstrating RCM applications, methodologies, and outcomes across industries, showing the practical relevance of RCM in enhancing reliability and efficiency.

RCM has been implemented across transportation, manufacturing, power generation, healthcare, petrochemical, and water treatment sectors. For instance, Liu et al. optimized high-speed rail maintenance to reduce costs while improving reliability, and Qaid et al. applied a fuzzy-FMECA framework for criticality- driven, data-informed maintenance in manufacturing [53,54]. Hybrid RCM models, such as those applied in power generation, combine traditional RCM with quantitative risk assessment to improve operational efficiency and cost-effectiveness [55,56].

Integration with digital technologies and predictive analytics has further enhanced RCM. Introna & Santolamazza demonstrated the use of IoT, digital twins, and Industry 4.0/5.0 tools to enable proactive maintenance decision-making [57]. Da Silva et al. proposed the Reliability-Risk-Centered Maintenance (RRCM) framework, combining RCM and Risk-Based Maintenance (RBM) to optimize reliability, safety, and cost trade-offs. Fuzzy logic and case-based reasoning have been applied to support adaptive, risk-informed decisions in complex industrial systems [48,58].

The practical benefits of RCM are significant. Cahyati et al. reported up to a 70% reduction in maintenance costs, Liu et al. and Enjavimadar & Rastegar improved preventive maintenance effectiveness, and Afefy et al. demonstrated the value of extending RCM to non-critical assets [11,59,60,61]. Applications across pumps, boilers, pumped storage plants, and hospital equipment illustrate its versatility and cost-effectiveness [56,62-64].

Despite these advantages, challenges remain, including limited data availability, partial integration with complementary approaches such as RBI and Total Productive Maintenance (TPM), and context-specific implementation barriers. Future research should focus on developing unified, adaptive, and risk-informed frameworks that integrate RCM with predictive monitoring, AI analytics, and real-time feedback to enhance reliability, cost-effectiveness, and safety across industrial operations [11,48,65,66].

Table 4: Key Literature on Reliability-Centered Maintenance (RCM)

#	Author(s)	Key Contributions / Applications
1	Liu et al. [53]	RCM for high-speed rail: modeled asset deterioration and optimized maintenance.
2	Qaid et al. [54]	Fuzzy-FMECA framework for criticality-based, data-driven manufacturing maintenance.
3	Asghari & Jafari [61]	Enhanced pump MTBF and operational performance in water treatment plants.
4	Cahyati et al. [59]	Industrial plant RCM: 70% maintenance cost reduction via reliability analysis.
5	Introna & Santolamazza [57]	RCM integrated with Industry 4.0/5.0 technologies for predictive maintenance.
6	Jiang et al. [56]	Optimized RCM for pumped storage plants, improving maintenance efficiency.
7	Rodríguez-Padial et al. [58]	Combined RCM with case-based reasoning and fuzzy logic for risk-based decision-making.
8	Sembiring [63]	Cost-effective RCM strategies for boiler systems.
9	Da Silva et al. [48]	RRCM framework: integrates RCM with RBM to optimize cost-reliability trade-offs.
10	Al-Farsi & Syafiie [67]	Structured 10-step RCM model for cement manufacturing.
11	Liu et al. [60]	Applied RCM to mechanical equipment for improved preventive maintenance.
12	Enjavimadar & Rastegar [61]	RCM in electricity networks: reduced maintenance costs and improved reliability.
13	Elijaha [68]	Hybrid RCM-RBM strategy for petrochemical pumps.
14	Rosita & Rada [69]	Manufacturing RCM application to reduce downtime and improve reliability.
15	Alrifaey et al. [55]	Hybrid RCM model for power generation, improving cost-effectiveness.
16	Prasetyo & Rosita [70]	RCM for systematic maintenance in manufacturing.
17	Shamayleh et al. [64]	RCM in hospital equipment management, reducing downtime vs. preventive maintenance.
18	Afefy et al. [11]	RCM inclusion of non-critical assets, optimizing performance and reducing costs.

Figure 4: RCM Implementation Steps

Challenges and Research Gaps in Maintenance Optimization, Failure Modeling, and RBI

Risk-Based Inspection (RBI) is a core methodology within Asset Integrity Management (AIM), particularly for high-risk, asset-intensive industries such as oil and gas, petrochemical, energy, and critical infrastructure. RBI enhances operational safety, reliability, and continuity by prioritizing inspection and maintenance activities based on the Probability of Failure (PoF) and Consequence of Failure (CoF). By focusing on high-risk components, RBI optimizes resource allocation, minimizes unnecessary interventions, and extends asset service life. Unlike traditional time- or condition-based maintenance strategies, RBI enables organizations to anticipate failures and implement proactive, risk-informed maintenance programs.

RBI methodologies are formalized through standards such as API 581 (2008) and API 580 (2016), which provide structured guidance for assessing and managing risks in pressure vessels, piping, storage tanks, and other static equipment. These standards facilitate the calculation of failure probabilities, assessment of consequences, and prioritization of inspection and maintenance activities, supporting safety, regulatory compliance, and cost efficiency [22]. Central to RBI is the integration of failure likelihood and consequence severity to identify critical components, often following the Pareto principle, where a small subset of components accounts for most potential failures [23,24]. Comprehensive risk assessment also considers technical, operational, environmental, and human factors, reflecting the complexity of modern industrial systems [25].

RBI assessments are typically qualitative, quantitative, or semi-qualitative. Qualitative methods rely on expert judgment and operational experience, quantitative approaches apply probabilistic and statistical models to estimate failure likelihood and consequences, semi-qualitative methods combine both for improved robustness and predictive accuracy [26]. High-quality input data—including historical failure records, inspection logs, operational parameters, and environmental conditions—are critical for effective implementation API 580, 2016 [27]. Incomplete or fragmented datasets reduce predictive accuracy, potentially leading to over- or under-maintenance and increased risk of unplanned downtime [49].

RBI has been successfully applied in refineries, petrochemical plants, offshore platforms, power generation facilities, and geothermal operations [42]. Unlike deterministic inspection strategies with fixed intervals, RBI dynamically adjusts inspection schedules according to risk, prioritizing critical assets while minimizing unnecessary interventions on low-risk components [43-45]. Predictive capabilities are further enhanced using advanced statistical and AI-based techniques, including logistic regression, dynamic Bayesian networks, and artificial neural networks, enabling proactive detection of potential failures and optimized inspection planning [32,49,50]. Offshore and subsea systems have adapted RBI to complex conditions, such as variable pressure, corrosion, and fatigue, while high- energy piping systems and power plants benefit from early detection and prioritization of critical maintenance activities [34,38,51].

Despite these advancements, several technical and methodological gaps remain. Weak integration of probabilistic failure modeling with inspection planning can lead to over-maintenance of low-risk assets or under-maintenance of critical components. Insufficient consideration of cost–risk–reliability trade-offs remains a major limitation, as RBI frameworks often prioritize safety and reliability without systematically incorporating economic factors [28,29]. Conventional RBI models also lack adaptive, real-time updating mechanisms, relying on historical data and periodic reassessments, which may not capture rapidly changing operational conditions or evolving degradation patterns, particularly in offshore platforms, subsea pipelines, and high-energy process equipment [34,51]. Limited adoption of advanced condition-monitoring technologies further constrains predictive accuracy and increases the risk of unplanned downtime [36,49].

Additional gaps include insufficient attention to system-level interdependencies, where failures in one component can cascade and impact others. Human and organizational factors, including reliance on expert judgment, resistance to change, and limited training, also restrict effective implementation [1,39]. Technological challenges persist in AI-driven RBI 4.0 adoption, such as model calibration, standardization, and integration of heterogeneous data [33,35]. Strategically, the lack of unified frameworks integrating RBI with Reliability-Centered Maintenance (RCM) and Total Productive Maintenance (TPM), along with regulatory variability, limits the adoption of holistic, adaptive maintenance strategies [14,16].

Table 5 and Figure 5 highlight the main challenges and research gaps in maintenance optimization, failure modeling, and Risk-Based Inspection (RBI), including incomplete or inconsistent datasets, fragmented implementation of RBI, RCM, and TPM, limited adaptive and predictive models, and insufficient consideration of cost–risk–reliability trade-offs. Other critical issues involve neglected system-level interdependencies, reliance on expert judgment, organizational resistance to change, technological barriers to AI-driven RBI 4.0 adoption, and the lack of unified, integrated frameworks. Addressing these challenges is crucial for developing proactive, risk-informed, and cost-effective maintenance strategies that enhance safety, reliability, and operational performance across complex industrial systems.

In conclusion, addressing these challenges requires advanced probabilistic modeling, multi-objective optimization, AI-driven adaptive RBI, enhanced condition monitoring, and integrated standardized frameworks. Closing these gaps enhances predictive accuracy, reduces unplanned downtime, improves operational and financial performance, and allows organizations to implement fully proactive, risk-informed, and cost-efficient maintenance strategies. Future research should focus on developing unified frameworks that integrate RBI, RCM, TPM, and real-time analytics, enabling dynamic maintenance management capable of responding to evolving industrial risks while maintaining safety, reliability, and cost-effectiveness.

Table 5: Key Challenges and Research Gaps in Maintenance Optimization and RBI

#	Category	Challenge / Research Gap	Description
1	Data Limitations	Incomplete/inconsistent data	Missing or fragmented operational and failure records reduce predictive accuracy.
2	Integration Gaps	Disconnected RBI, RCM, TPM	Independent methods prevent system-wide optimization and coordinated decisions.
3	Analytical Limitations	Limited adaptive models	Models lack dynamic updating and fail to capture time-dependent degradation.
4	Cost–Risk–Reliability	Weak multi-objective integration	Safety, reliability, and economic factors are rarely optimized jointly.
5	System-Level Issues	Ignored interdependencies	Component-focused analysis overlooks cascading and systemic failures.
6	Organizational Factors	Reliance on expert judgment	Subjective decisions and resistance to change hinder implementation.
7	Technological Gaps	AI/RBI 4.0 adoption challenges	Data heterogeneity, calibration, and standardization limit advanced analytics.
8	Strategic Gaps	Lack of unified frameworks	Absence of integrated, dynamic approaches constrains scalable deployment.

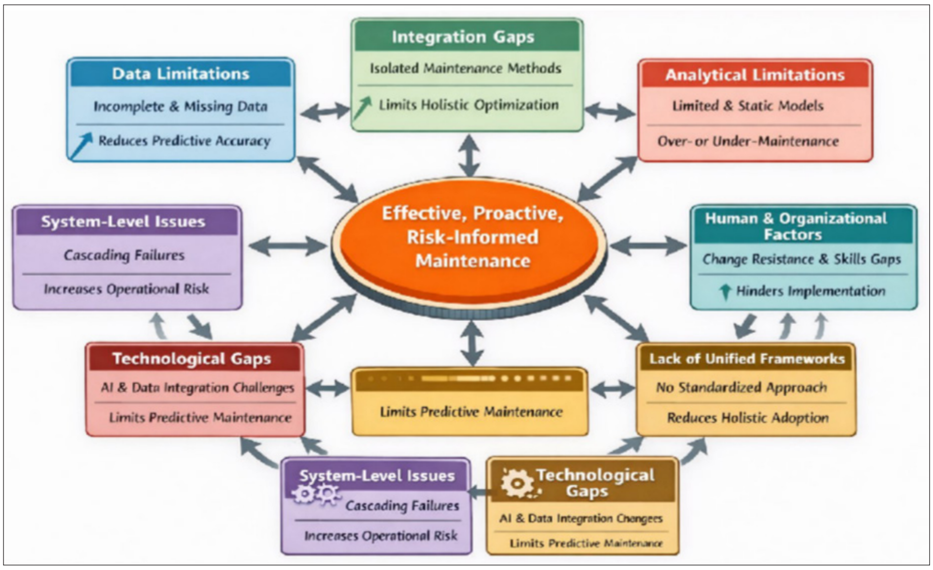

Figure 5: Key Challenges and Research Gaps in Maintenance and RBI

Integrated Reliability-Centered Framework

High-risk industrial assets operate under conditions of uncertainty, operational variability, complex degradation mechanisms, and exposure to mechanical, thermal, chemical, and environmental stressors. Failures in such systems can cause severe safety incidents, environmental hazards, regulatory non-compliance, and substantial financial losses. Traditional maintenance strategies—primarily corrective and time-based preventive approaches—provide structure but often fail to address stochastic failures, time-dependent degradation, and risk-based prioritization. Fixed inspection intervals and reliance on historical averages frequently result in reactive maintenance, inefficient resource allocation, excessive downtime, and compromised reliability.

To overcome these limitations, this study proposes an Integrated Reliability-Centered Framework (IRCF) that unifies conventional maintenance, Risk-Based Inspection (RBI), and probabilistic reliability modeling into a cohesive, adaptive decision-making system. The IRCF shifts maintenance management from deterministic scheduling to dynamic, risk-informed optimization. By integrating qualitative risk assessment with quantitative reliability analysis, inspection intervals and maintenance priorities continuously adapt to operational conditions and degradation dynamics. Embedded predictive monitoring enables proactive interventions, enhances system resilience, extends asset life, and optimizes life-cycle costs while ensuring safety and regulatory compliance.

The framework is based on the principle that effective maintenance planning must simultaneously consider failure likelihood, consequence severity, degradation behavior, and real-time condition information. Integrating these factors transforms maintenance planning from static scheduling into adaptive, reliability-centered decision-making that evolves with asset performance and operational variability.

Integrated Reliability-Centered Framework

The IRCF enhances conventional RBI by integrating qualitative, quantitative, and predictive approaches to establish a comprehensive, reliability-centered maintenance strategy. Traditional RBI prioritizes maintenance based on Probability of Failure (PoF) and consequence severity but often relies on static assumptions or simplified data, limiting adaptability in dynamic operational environments. Common challenges include predictive uncertainties, incomplete degradation models, human judgment errors, inconsistent compliance, and suboptimal inspection intervals.

Key analytical tools employed in the framework include:

- Failure Modes and Effects Analysis (FMEA): identifies potential failure modes, operational impacts, and severity of consequences to support risk prioritization.
- Risk Matrices: classify components by likelihood and consequence severity, enabling informed prioritization and resource allocation.
- Fault Tree Analysis (FTA): traces failure pathways and root causes to identify critical vulnerabilities and inter-dependencies.
- Probabilistic Reliability Models: Weibull, exponential, and log-normal distributions model stochastic failure behavior, estimate Remaining Useful Life (RUL), and quantify risk.
- Condition Monitoring and Predictive Analytics: real-time monitoring captures operational variability and component health, feeding into dynamic PoF and RUL calculations.

Figure 6 illustrates the integration of conventional maintenance, RBI, and probabilistic modeling into a unified decision-making framework. Historical maintenance and operational data establish baselines, RBI evaluates component criticality, probabilistic modeling predicts failures and estimates RUL, and continuous feedback dynamically updates PoF and risk assessments to guide proactive maintenance decisions. A key feature is dynamic PoF assessment, which quantifies failure likelihood under variable operational and environmental conditions. Statistical reliability models combined with hazard function analysis account for aging, wear, environmental stressors, and operational variability. Integrating PoF with RBI principles ensures maintenance resources target components with the highest operational or safety risk, minimizing unnecessary interventions and enhancing system resilience. The framework is structured into three interrelated tiers:

1. **Risk Assessment Tier**

- Conducts qualitative and semi-quantitative analyses (FMEA, risk matrices, FTA) to identify critical components, failure modes, and consequences.
- Generates hierarchical risk maps to guide probabilistic modeling and predictive maintenance.

2. Reliability Analysis Tier

- Applies probabilistic modeling to estimate PoF and RUL.
- Optimizes inspection intervals using hazard functions and reliability metrics while accounting for operational and environmental variability.

3. Predictive Maintenance Tier

- Integrates real-time condition monitoring, predictive analytics, and software platforms to dynamically update PoF and RUL.
- Enables proactive, risk-informed interventions and continuous adaptive learning.

Figure 7 illustrates the tiered structure and information flow, while Figure 8 depicts the adaptive feedback mechanism that continuously updates PoF, inspection schedules, and maintenance priorities based on operational and inspection data. Figure 9 demonstrates Weibull, exponential, and log-normal distributions capturing diverse failure behaviors over time, supporting accurate PoF estimation, optimized inspection intervals, and proactive maintenance scheduling. Figure 10 shows a decision matrix integrating component criticality, PoF, and consequence severity for systematic maintenance prioritization. Table 6 summarizes the framework's components, analytical methods, required data, and expected outcomes.

Application Steps of the Integrated Reliability-Centered Framework

The IRCF is applied to a high-risk industrial system to demonstrate methodological feasibility, operational coherence, and performance improvement. Implementation follows a structured, iterative process, integrating qualitative risk assessment, probabilistic modeling, and predictive maintenance within a closed-loop architecture. Table 7 and Figure 11 outline the seven-step application process:

Step 1: Define Scope, Boundaries, and Objectives

- Identify critical assets, system boundaries, and operational constraints.
- Define objectives: reliability enhancement, downtime reduction, cost optimization, and regulatory compliance.
- Establish KPIs such as MTBF, asset availability, maintenance cost per unit, and safety incident frequency.

Step 2: Data Collection and Baseline Assessment

- Gather maintenance records, failure logs, inspection reports, operational parameters, and degradation indicators.
- Identify data gaps and establish baseline reliability profiles.

Step 3: Qualitative Risk Assessment

- Apply FMEA, risk matrices, and FTA to identify high-risk components and critical failure pathways.
- Generate hierarchical risk maps to guide probabilistic modeling and predictive maintenance integration.

Step 4: Probabilistic Reliability Modeling

- Select appropriate distributions (Weibull, exponential, log-normal) and calibrate using historical and operational data.
- Define target reliability levels for critical assets to guide maintenance planning and risk mitigation.
- Derive hazard functions, estimate PoF and RUL, and optimize inspection intervals.

Step 5: Predictive Maintenance Integration

- Integrate sensors and predictive analytics for real-time monitoring.
- Dynamically update PoF and RUL, recalibrate hazard models, and adjust inspection schedules based on operational conditions.
- Consolidate outputs into a risk-informed maintenance plan.

Step 6: Continuous Feedback and Performance Evaluation

- Monitor KPIs including reliability, downtime, costs, and safety performance.
- Iteratively update PoF, RUL, and inspection intervals based on operational feedback.
- Incorporate lessons learned into organizational procedures and knowledge systems.

Step 7: Outcomes and Benefits

- Enhanced reliability and extended asset life.
- Reduced unplanned downtime and improved operational continuity.
- Optimized maintenance expenditure and resource allocation.
- Improved safety and regulatory compliance.
- Sustainable, adaptive, data-driven maintenance practices.

In conclusion, the Integrated Reliability-Centered Framework provides a comprehensive, adaptive methodology for industrial maintenance. By integrating qualitative risk assessment, probabilistic modeling, and predictive monitoring within a closed-loop system, it links failure behavior, risk exposure, and maintenance decision- making. Its adaptive feedback mechanism transforms maintenance planning into a continuous learning process, ensuring responsiveness to operational variability and environmental uncertainty. The IRCF advances conventional RBI, providing a foundation for optimized inspection intervals, enhanced reliability, improved safety, and sustainable asset management in high-risk industrial environments.

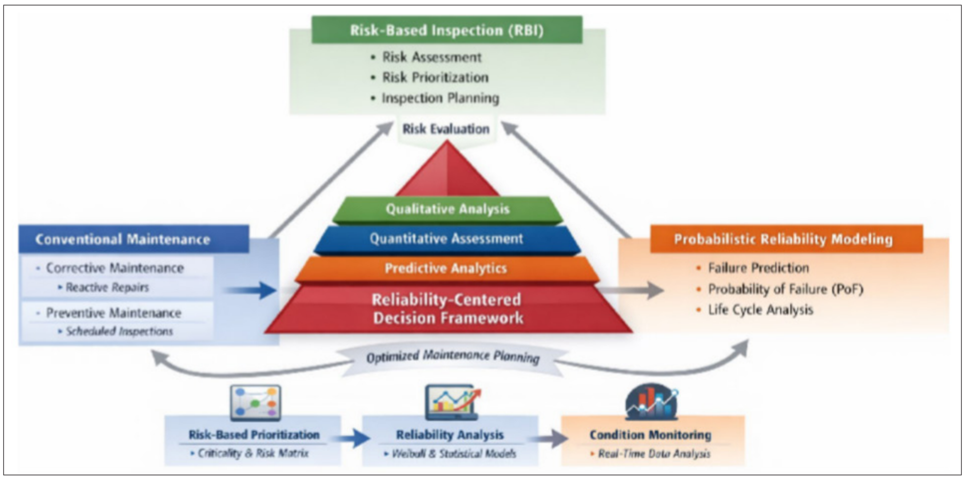

Figure 6: Integrated Reliability-Centered Framework Overview for RBI and Maintenance

Table 6: Integrated Reliability-Centered RBI/M Framework

#	Component	Purpose	Methods	Data	Outcomes
1	Conventional Maintenance	Baseline interventions	Performance analysis, work orders	Maintenance & downtime logs	Baseline insights, recurring failures
2	Risk Assessment	Identify critical components & failures	FMEA, Risk Matrices, FTA	Component specs, operational data	Prioritized high-risk assets
3	Reliability Analysis	Quantify PoF & RUL, optimize intervals	Weibull, exponential, log-normal, hazard analysis	Failure history, operational/ environmental data	Optimized inspections, PoF & RUL predictions
4	Predictive Maintenance	Monitor real-time condition	Sensors, analytics, software	Real-time operational data	Dynamic PoF updates, predictive interventions
5	Adaptive Feedback	Continuous model updates	Iterative updating, Bayesian learning	Operational & inspection data	Adaptive planning, improved accuracy
6	Decision Matrix	Integrate criticality, PoF & consequence	Multi-criteria decision analysis	PoF, consequence severity	Focused resources, improved safety
7	Implementation Workflow	Stepwise framework deployment	7-step methodology	Complete asset dataset	Risk-informed, adaptive maintenance
8	Overall Benefits	Framework impact	Integration of all tiers	Operational & maintenance data	Enhanced reliability, safety, cost-efficiency, and sustainability

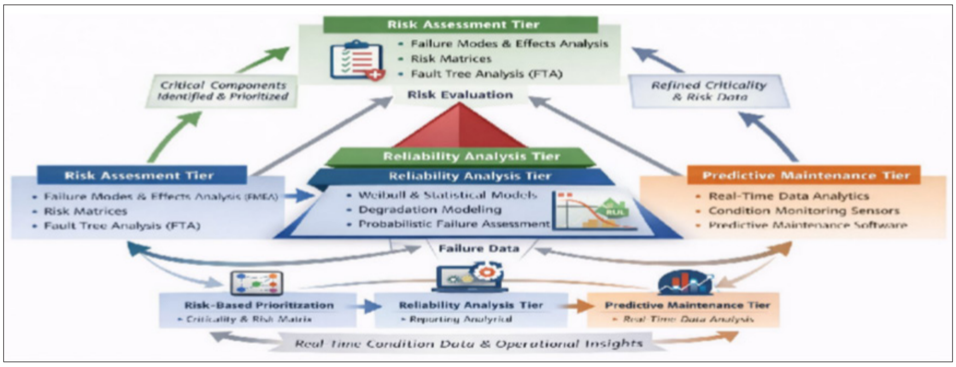

Figure 7: Three-Tier Structure of the Reliability-Centered Framework

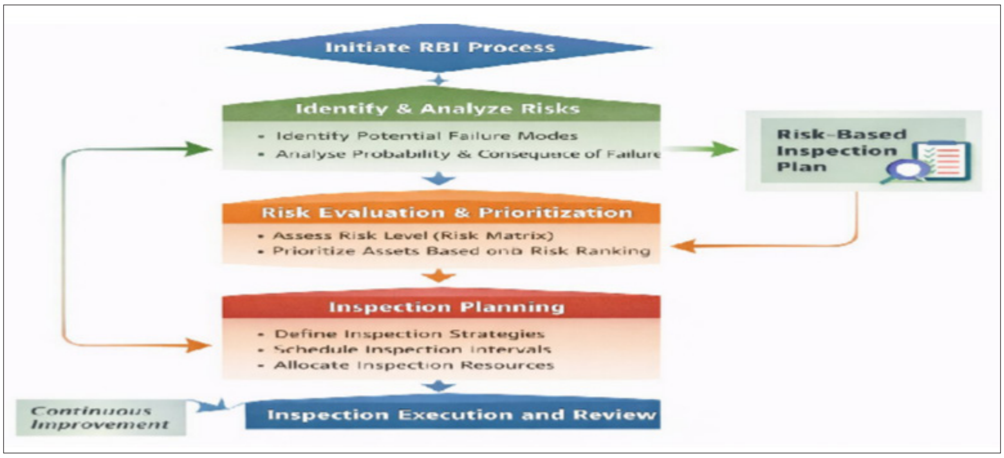

Figure 8: Adaptive Feedback Mechanism for Dynamic Maintenance Planning

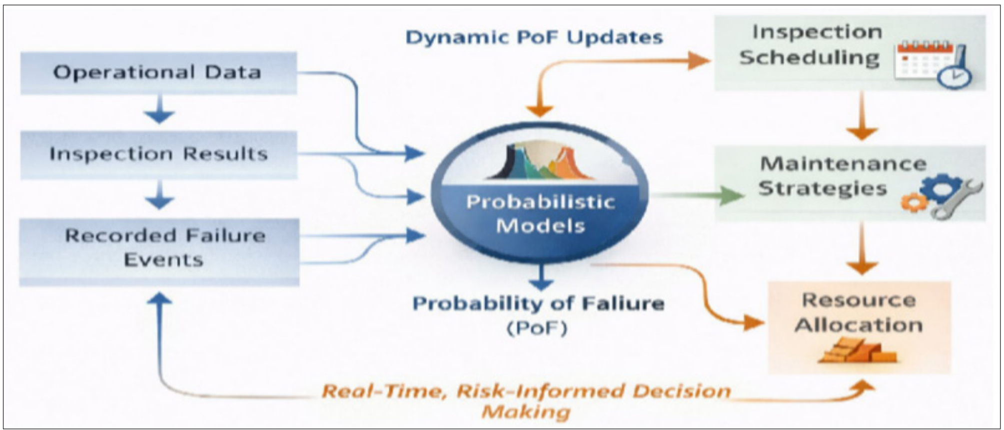

Figure 9: Probability of Failure (PoF) Modeling of Critical Components

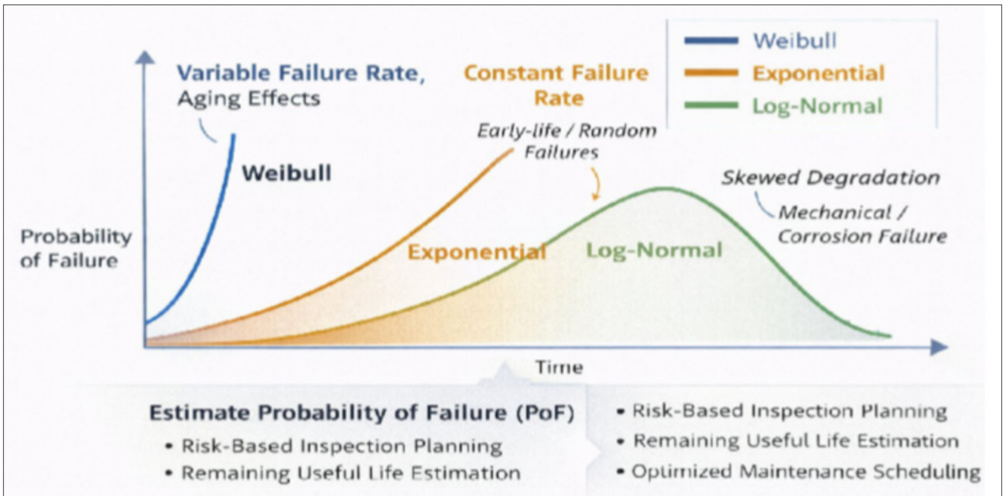

Figure 10: Maintenance Prioritization Decision Matrix

Table 7: Steps of the Integrated Reliability-Centered RBI/M Framework

#	Step	Objective	Key Activities	Expected Outcomes
1	Define Scope	Set boundaries and priorities	Identify critical assets, objectives, and KPIs	Focused assets, clear KPIs
2	Data Collection	Establish baseline	Gather failure, inspection, operational, and environmental data	Validated dataset, prioritized components
3	Qualitative Risk Assessment	Identify high-risk items	Apply FMEA, risk matrices, and FTA	Risk map, prioritized failures
4	Reliability Modeling	Quantify failure likelihood	Calibrate distributions, estimate PoF/RUL, optimize intervals	Accurate PoF/RUL, optimized inspections
5	Predictive Maintenance	Enable proactive actions	Integrate sensors, apply analytics, update models	Adaptive inspections, reduced downtime
6	Continuous Feedback	Maintain the learning system	Monitor KPIs, update models, and incorporate feedback	Improved predictive accuracy, enhanced resilience
7	Outcomes & Benefits	Achieve sustainable, risk- informed maintenance	Consolidate insights, implement interventions, evaluate performance	Higher reliability, lower downtime, optimized costs, improved safety

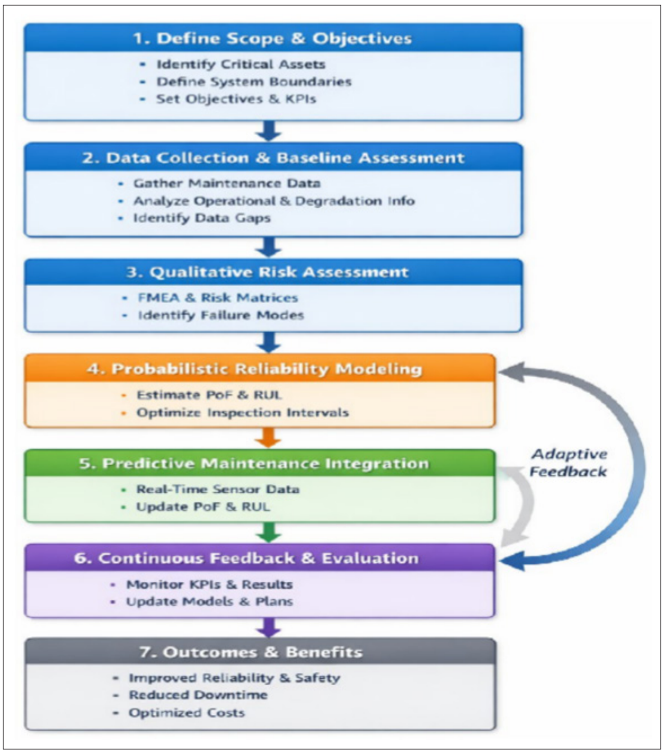

Figure 11: Flowchart of Application steps of the Integrated Reliability-Centered RBI/M Framework

Case Study: Application of the Integrated Reliability-Centered Framework (IRCF)

This case study demonstrates the practical application of the Integrated Reliability-Centered Framework (IRCF) at a feed-water centrifugal pump station with four units in a steam system at a petrochemical facility in Egypt. The station supplies steam to turbines, process heaters, and other critical systems. Failures of pump units or associated components can lead to production downtime, safety hazards, environmental risks, and regulatory non-compliance, highlighting the necessity for predictive, risk-informed maintenance strategies. This study illustrates how integrating Risk-Based Inspection (RBI), probabilistic reliability modeling, and predictive monitoring enhances the maintenance of high-risk industrial assets.

System Overview

Pump Unit Components

- Centrifugal pumps: impeller, bearings, mechanical seals, casing, shaft coupling
- Electric motors: rotor, stator, bearings, cooling system, alignment coupling
- Valves: inlet, outlet, check, pressure relief

- Pipelines: feed-water lines prone to corrosion, vibration, thermal stress, and scaling

Operational Conditions
- 4 identical feed-water centrifugal pumps supplying water to the steam boiler system.
- Configuration: N+1 redundancy (3 pumps running, 1 standby).
- Continuous 24/7 operation with variable load cycles
- Intermittent high-load periods increase thermal and vibration stress
- Pipelines exposed to cyclic pressure and temperature fluctuations, accelerating fatigue and corrosion

Baseline Challenges
- Frequent valve leaks reduce efficiency
- Motor overheating due to misalignment or lubrication failures
- Pump seal wear is causing unplanned shutdowns
- Limited condition monitoring (vibration, temperature, lubrication, corrosion)
- Maintenance schedules based on historical averages rather than real-time operating conditions

Maintenance Objectives
- Ensure continuous, reliable operation
- Minimize unplanned downtime and maintenance costs
- Extend asset life through predictive, risk-informed strategies
- Maintain safety, regulatory compliance, and environmental protection

Main Steps of IRCF Implementation
The IRCF framework integrates qualitative risk assessment, probabilistic reliability modeling, and predictive maintenance into a three-tiered structure with a seven-step methodology, enabling adaptive, risk-informed maintenance for critical components.

Tier 1 – Risk Assessment
Step 1: Define Scope, Boundaries, and Objectives
- Scope: four pump units, motors, valves, and pipelines
- Boundaries: entire station, including inlet/outlet lines, control valves, and instrumentation
- Objectives: improve reliability, reduce downtime, optimize costs, and ensure compliance
- KPIs: MTBF, system availability, maintenance cost per unit, safety incidents, energy efficiency

Step 2: Data Collection and Baseline Assessment
- Collected maintenance logs, inspection reports, operational data, and historical failure records
- Historical failure data over 5 years is available.
- Baseline Issues: valve leaks (2–3/year), motor overheating (~1/year/unit), pump seal wear (1–2/year/unit)
- Gaps Identified: pipeline corrosion trends, vibration/temperature monitoring, lubrication data, predictive failure information
- Baseline reliability profiles established for probabilistic modeling

Step 3: Qualitative Risk Assessment
- Applied FMEA, risk matrices, and FTA to identify high-risk components
- High-risk components: pump impellers, motor bearings, critical valves, corrosion-prone pipelines

Table 8 summarizes component prioritization with failure modes, root causes, consequences, risk levels, and maintenance priorities, providing the foundation for PoF estimation, RUL calculation, and risk-informed inspection scheduling

Tier 2 – Reliability Analysis
Step 4: Probabilistic Reliability Modeling [71]
- Use statistical distributions based on component behavior
- Weibull distribution: pumps and motors (wear-out failures)
- Exponential distribution: valves and pipelines (random failures)
- Log-normal distribution: components with variable environmental degradation
- Target reliability level (80%) for critical assets to guide maintenance planning and risk mitigation.
- Calculate Probability of Failure (PoF) using hazard functions.
- Estimate Remaining Useful Life (RUL) to guide inspection scheduling.

Hazard functions quantify Probability of Failure (PoF) over time, accounting for load cycles, vibration, temperature, and environmental stresses. Remaining Useful Life (RUL) estimates optimize inspection intervals and prioritize preventive interventions.

Table 9 presents component prioritization with PoF, RUL, suggested inspection intervals, and key risk focus. High-criticality components such as pump impellers and motor bearings are inspected frequently (every 4–6 months), while medium-risk components are inspected at longer intervals (12–18 months), ensuring adaptive, predictive, and resource-efficient maintenance.

Tier 3 – Predictive Maintenance
Step 5: Predictive Monitoring Integration
- Sensors continuously monitor vibration (motors, pump shafts), temperature (motors), flow/pressure (valves/pipelines)
- Real-time analytics update PoF and RUL for proactive interventions
- Example: a vibration spike in Motor 2 triggered immediate bearing inspection, preventing catastrophic failure

Step 6: Continuous Feedback and Performance Evaluation
- Monitored KPIs: reliability, unplanned downtime, maintenance costs, safety incidents
- Feedback loops dynamically update hazard models, PoF, and RUL estimates
- Lessons learned incorporated into operational procedures and knowledge systems

Step 7: Outcomes and Benefits
- Prevented pump cavitation and motor bearing failures
- Reduced unnecessary valve maintenance by ~20%
- Decreased unplanned downtime by ~15%
- Focused maintenance on high-risk components improved operational efficiency
- Risk-informed interventions ensured safety, regulatory compliance, and cost optimization

Table 10 shows that before implementing the IRCF, maintenance was predominantly reactive, characterized by frequent pump downtime, motor overheating, and unpredictable valve failures, which contributed to high maintenance costs and minor safety incidents. Fixed inspection schedules did not account for operational stress or component degradation, limiting the effectiveness of preventive measures. These challenges underscore the need for a proactive, risk-informed maintenance framework like IRCF to enhance reliability, optimize costs, and improve overall safety and operational performance.

Before-and-After IRCF Performance

Post-IRCF KPIs show measurable improvements. Table 11 and Figure 12 compare key performance indicators (KPIs) before and after the implementation of the Integrated Reliability-Centered Framework (IRCF), highlighting significant improvements across all monitored parameters. Pump downtime was reduced by approximately 25%, reflecting fewer operational interruptions, while motor overheating incidents decreased by 50–100%, indicating more effective monitoring and early fault detection. Valve failures also declined by 30–50%, demonstrating enhanced reliability and targeted maintenance. Maintenance costs were lowered by around 20% due to optimized interventions and reduced emergency repairs. Safety incidents were cut by 50–100%, showing improved risk management and compliance. Additionally, inspection intervals shifted from fixed schedules of 6–12 months to dynamic, risk-informed intervals ranging from 4–18 months, optimizing resource allocation and maintenance planning.

Overall, these results illustrate the IRCF's effectiveness in transforming reactive maintenance into a proactive, predictive, and cost-efficient strategy. These results confirm that IRCF converts traditional reactive maintenance into a predictive, adaptive, and reliability-centered approach, enhancing reliability, operational efficiency, safety, and long-term sustainability. In conclusion, the IRCF is a data-driven framework that enhances high-risk industrial maintenance by integrating risk assessment, reliability modeling, and predictive monitoring. It prioritizes critical assets, reduces unplanned downtime, and optimizes maintenance costs—demonstrated at a feedwater pump station with ~25% less downtime, ~20% lower costs, and fewer safety incidents. Dynamic inspection intervals based on probability of failure (PoF) and remaining useful life (RUL) enable timely, cost- effective interventions, making IRCF a scalable solution for industries seeking greater reliability, efficiency, safety, and sustainability.

Table 8: Component Prioritization with Risk Assessment and Maintenance Priority

#	Component	Failure Mode	Root Cause	Consequence	Risk Level	Maintenance Priority
1	Pump impeller	Cavitation	High flow velocity, low NPSH	Bearing overload, downtime	High	1
2	Motor bearing	Overheating	Misalignment, lubrication failure	Motor failure, downtime	High	2
3	Inlet valve	Leakage	Seal wear, corrosion	Pressure drop, efficiency loss	Medium	3
4	Pipeline section	Corrosion	High temperature, water chemistry	Leak, environmental risk	Medium	4

Table 9: Component Prioritization – PoF, RUL, and Suggested Inspection Intervals

Component	Criticality	PoF (%)	RUL (months)	Suggested Inspection Interval	Key Risk Focus
Pump impellers	High	25	18–24	6 months	Cavitation and wear prevention
Mechanical seals	High	20	18–24	6 months	Leakage and wear control
Motor bearings	High	30	12–18	4 months	Vibration and temperature monitoring
Shaft coupling	Medium	10	36	12–18 months	Alignment and vibration checks
Inlet/Outlet valves	Medium	15	24–30	12 months	Seal wear and corrosion
Pipelines	Medium	10	36+	18 months	Corrosion-prone sections

Table 10: Key Performance Indicators (KPIs) Before IRCF Implementation

#	KPI	Pre-IRCF Value	Observed Challenges	Suggested Inspection Interval	Key Risk Focus
1	Pump downtime (hours/year/unit)	48–60	Frequent stoppages caused by impeller wear, seal leakage, and cavitation disrupt operations.	6 months	Cavitation and wear prevention
2	Motor overheating incidents/unit	1–2/year	Delayed detection led to unplanned repairs and production interruptions.	6 months	Leakage and wear control
3	Valve failures	2–3/year	Failures were unpredictable, causing minor efficiency losses and reactive maintenance.	4 months	Vibration and temperature monitoring
4	Maintenance cost ($/unit/year)	35,000–40,000	High emergency repair expenses and redundant inspections increased overall costs.	12–18 months	Alignment and vibration checks
5	Safety incidents	1–2 minor/year	Safety risks were addressed reactively, with potential regulatory non-compliance.	12 months	Seal wear and corrosion
6	Inspection intervals	Fixed (6–12 months)	Did not account for operational stress or degradation trends, limiting inspection effectiveness.	18 months	Corrosion-prone sections

Table 11: Key Performance Indicators (KPIs) Before and After IRCF Implementation

#	KPI	Before IRCF	After IRCF	Improvement (%)
1	Pump downtime (hours/year/unit)	48–60	35–40	~25%
2	Motor overheating incidents/unit	1–2/year	0–1/year	50–100%
3	Valve failures	2–3/year	1–2/year	30–50%
4	Maintenance cost ($/unit/year)	35,000–40,000	28,000–32,000	~20%
5	Safety incidents	1–2 minor/year	0–1 minor/year	50–100%
6	Inspection intervals	Fixed (6–12 months)	Dynamic (4–18 months)	Optimized

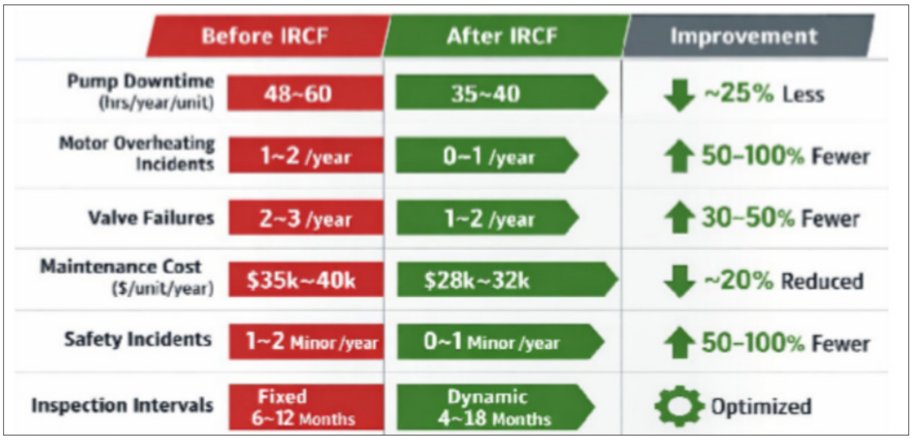

Figure 12: Comparative KPI visualization before and after IRCF implementation

Conclusion and Future Work

This study presents the Integrated Reliability-Centered Framework (IRCF), which integrates conventional maintenance practices, Risk-Based Inspection (RBI), and probabilistic reliability modeling into an adaptive, risk-informed system for high-risk industrial assets. A review of maintenance optimization, failure rate modeling, and Risk-Based Inspection (RBI) frameworks reveals critical gaps, including incomplete or inconsistent datasets, fragmented application of RBI, RCM, and TPM, limited adaptive and predictive models, and inadequate integration of cost–risk–reliability trade-offs. Additional challenges encompass neglected system-level interdependencies, overreliance on expert judgment, organizational resistance to change, technological barriers, and the absence of unified, integrated frameworks. Addressing these gaps is essential for developing proactive, risk-informed, and cost-effective maintenance strategies that enhance safety, reliability, and operational performance across complex industrial systems.

By combining qualitative risk assessment, probabilistic modeling, and real-time predictive monitoring, the IRCF dynamically estimates Probability of Failure (PoF), forecasts Remaining Useful Life (RUL), and optimizes inspection intervals. Its tiered architecture—comprising risk assessment, reliability analysis, and predictive maintenance layers—ensures that maintenance resources are focused on components with the highest operational or safety impact. The framework's adaptive feedback mechanism continuously updates priorities based on operational data, inspection results, and evolving degradation trends. Implementation at a feedwater centrifugal pump station demonstrated measurable improvements: pump downtime decreased by approximately 25%, maintenance costs were reduced by 20%, and safety incidents were significantly minimized. Dynamic, risk-informed inspection intervals allowed proactive maintenance of high-criticality components while avoiding unnecessary interventions on lower-risk assets, effectively transforming traditional reactive maintenance into a predictive, reliability-centered system.

In conclusion, the IRCF provides a robust, adaptive, and sustainable framework for modern industrial maintenance. By integrating reliability-centered principles with risk-informed decision-making, it improves asset performance, enhances safety, and supports long-term operational resilience. The framework offers a practical and scalable pathway for organizations to implement proactive, cost-effective, and risk-informed maintenance strategies across complex industrial systems. Future work should focus on expanding AI-driven predictive capabilities, integrating real-time condition monitoring, and applying multi-objective optimization to further enhance dynamic decision-making, improve predictive accuracy, and extend the framework's applicability across diverse industrial environments.

Theoretical Implications: The IRCF advances reliability engineering by demonstrating how qualitative risk assessment, probabilistic modeling, and predictive monitoring can be integrated into a dynamic framework, enhancing understanding of stochastic failures and operational variability.

Practical Implications: For industrial practitioners, the framework provides a structured methodology to optimize maintenance planning, improve inspection accuracy, allocate resources efficiently, and strengthen asset lifecycle management.

Managerial Implications: Managers gain decision-support tools for strategic resource allocation, proactive risk mitigation, and improved operational readiness, fostering a safety-focused, reliability-centered organizational culture.

Study Limitations: Framework effectiveness depends on the availability and quality of historical and real-time data, comprehensive sensor coverage, and expertise in probabilistic modeling. Limitations in data quality or organizational readiness may reduce predictive accuracy and hinder adoption.

Future Research Directions: Future research should focus on enhancing the Integrated Reliability-Centered Framework (IRCF) through the integration of digital twins for real-time monitoring and predictive simulations, enabling proactive maintenance planning. Incorporating AI-driven analytics can improve Probability of Failure (PoF) and Remaining Useful Life (RUL) predictions, automate risk-informed inspection scheduling, and uncover hidden operational patterns. Multi-objective optimization can balance reliability, cost, and risk, while expanding IRCF across diverse industrial sectors and leveraging Industry 4.0 technologies—such as IoT sensors, cloud analytics, and edge computing—can increase scalability, adaptive decision-making, and operational resilience, strengthening IRCF as a predictive, reliability-centered framework for modern industrial systems.

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Generative Artificial Intelligence Statement: The authors used the free version of ChatGPT to refine the writing quality of some paragraphs. No generative artificial intelligence (GenAI) was used in creating the manuscript content.

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References

1. Abdallah AM, Atadero RA, Ozbek ME (2022) A state-of-the-art review of bridge inspection planning: current situation and future needs. Journal of Bridge Engineering 27: 03121001.
2. Amrina E, Firda S (2024) Evaluation model of total productive maintenance implementation for cement plant. In AIP Conference Proceedings 2710.
3. Odili PO, Daudu CD, Adefemi A, Ekemezie IO, Usiagu GS (2024) Operational readiness and assurance (OR&A) in asset integrity: strategies for excellence in facility management. Engineering Science & Technology Journal 5: 581-596.
4. Gomaa AH (2025) Asset Management Excellence: A Roadmap for Integrating Lean Six Sigma and ISO 55001 to Achieve Operational Excellence. Intelligent and Sustainable Manufacturing 2: 1-19.
5. Gomaa AH (2023) Maintenance process improvement framework using lean six sigma: A case study. International Journal of Business & Administrative Studies 9: 1-25.
6. Gomaa AH (2024a) Enhancing proactive maintenance of critical equipment by integrating digital twins and lean six sigma approaches. International Journal of Modern Studies in Mechanical Engineering (IJMSME) 10: 20-35.
7. Gomaa AH (2024b) Improving shutdown maintenance management performance using lean six sigma approach: A case study. International Journal of Applied and Physical Sciences IJAPS 10: 1-14.
8. Samadhiya A, Agrawal R (2024) Total productive maintenance and sustainability performance: resource-based view perspective. Benchmarking: An International Journal 31: 2177-2196.
9. Aditiyawarman T, Kaban APS, Soedarsono JW (2023) A recent review of risk-based inspection development to support service excellence in the oil and gas industry: An Artificial Intelligence Perspective. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering 9: 010801.
10. Ben-Daya M (2000) You may need RCM to enhance TPM implementation. Journal of Quality in Maintenance Engineering, MCB UP Ltd 6: 82-85.
11. Afefy IH, Mohib A, El-Kamash AM, Mahmoud MA (2019) A new framework of reliability centered maintenance. Jordan

Journal of Mechanical & Industrial Engineering 13.
12. Adesta EYT, Prabowo HA, Agusman D (2018) Evaluating 8 pillars of Total Productive Maintenance (TPM) implementation and their contribution to manufacturing performance. IOP Conference Series: Materials Science and Engineering, IOP Publishing 290: 012024.
13. Ardi M, Sutanto A, Susilawati A (2023) Analysis of effectiveness of cut size line machines based on total productive maintenance (TPM) and analytical hierarchy process (AHP)-A case study. Journal of Ocean, Mechanical and Aerospace-science and engineering 67: 109-117.
14. Shannon N, Trubetskaya A, Iqbal J, McDermott O (2023) A total productive maintenance & reliability framework for an active pharmaceutical ingredient plant utilising design for Lean Six Sigma. Heliyon 9.
15. Prasanna NKK, Akula S, Desai TN (2011) December. Integration of maintenance strategies for improved asset reliability and availability. In 2011 IEEE International Conference on Industrial Engineering and Engineering Management 1514-1518.
16. Mkandawire BO, Ijumba NM, Whitehead H (2011) Application of maintenance tools and strategies in integrated risk management of critical physical assets. International Journal of Agile Systems and Management 4: 261.
17. Gomaa AH (2022) Enhancing maintenance management of critical equipment using digital twin. Comprehensive Research and Reviews in Engineering and Technology (CRRET) 11: 45-55.
18. Gu D, Nie R, Han W, Chen G, Jia L (2023) Research on preventive maintenance strategy of Coating Machine based on dynamic failure rate. Operation and Reliability 25.
19. Biswas J (2024) Total productive maintenance: an in-depth review with a focus on overall equipment effectiveness measurement. International Journal of Research in Industrial Engineering 13: 376-383.
20. Flagg MI, Amadi NS (2024) Utilization of total productive maintenance techniques for quality improvement of electrical workshop by technical colleges in Rivers State. International Journal of Modern Innovations and Knowledge 5: 1-11.
21. Khan AI, Islam N (2024) Utilizing data analytics for predictive maintenance in manufacturing: A systematic review on achieving operational excellence. Innovatech Engineering Journal 1: 56-67.
22. Agistina A, Budiasih E, Pramoso A (2021) Determination of risk Level, remaining life prediction, and risk-based inspection planning based on API 581. In IOP Conference Series: Materials Science and Engineering 1034: 012116.
23. Drożyner P, Veith E (2002) Risk based inspection methodology overview. Diagnostyka 27: 82-88.
24. Sitko J, Mikuš R, Božek P (2018) Analysis of device failure in the mechanical production plant. Multidisciplinary Aspects of Production Engineering 1.
25. Zhou X, Xu A, Yan B, Sun Y, Chen W, et al. (2024) Research on the integrated failure analysis method of safety and security of fieldbus transmitters. Measurement and Control 57: 1038-1050.
26. Sadri A, Tibbo M, Naghizadeh M, Climenhaga B, Santini R, et al. (2023) Implementing Risk-Based Inspection (RBI) and Life Cycle Monitoring into Refractory Lining Management of Pyrometallurgical Furnaces. In Conference of Metallurgists 835-853.
27. Slimane SB, Andrawus J, Iyalla I (2023) Modelling System Failure of a Typical Hydraulic Power Unit within a Subsea Production Control System. In SPE Nigeria Annual International Conference and Exhibition D021S012R006.
28. Javid YJPS (2021) A bi-objective mathematical model to determine risk-based inspection programs. Process Safety and Environmental Protection 146: 893-904.
29. Javid Y (2024) Efficient risk-based inspection framework: Balancing safety and budgetary constraints. Reliability Engineering & System Safety 253: 110519.
30. Huang Y, Qin G, Yang M (2023) A risk-based approach to inspection planning for pipelines considering the coupling effect of corrosion and dents. Process Safety and Environmental Protection 180: 588-600.
31. Abubakirov R, Yang M, Khakzad N (2020) A risk-based approach to determination of optimal inspection intervals for buried oil pipelines. Process Safety and Environmental Protection 134: 95-107.
32. Rachman A, Ratnayake RC (2018) Artificial neural network model for risk-based inspection screening assessment of oil and gas production system. In ISOPE International Ocean and Polar Engineering Conference ISOPE-I.
33. Zhang WH, Qin J, Lu DG, Liu M, Faber MH (2023) Quantification of the value of condition monitoring system with time- varying monitoring performance in the context of risk-based inspection. Reliability Engineering & System Safety 231: 108993.
34. Almeida de Rezende F, Videiro PM, Volnei Sudati Sagrilo L, de Oliveira MC, dos Santos GYM (2024) A tool for reliability-based inspection planning of mooring chains. In International Conference on Offshore Mechanics and Arctic Engineering 87790: V002T02A036.
35. Babaeian A, Eslami A, Ashrafizadeh F, Golozar MA, Samadzadeh M, et al. (2023) Risk-based inspection (RBI) of a gas pressure reduction station. Journal of Loss Prevention in the Process Industries 84: 105100.
36. Eskandarzade M, Shahrivar R, Ratnayake RC, Bukhari UN (2022) An optimal approach for semiquantitative risk-based inspection of pipelines. Journal of Pipeline Systems Engineering and Practice 13: 04022017.
37. Hameed H, Bai Y, Ali L (2021) A risk-based inspection planning methodology for integrity management of subsea oil and gas pipelines. Ships and offshore structures 16: 687-699.
38. Arzaghi E, Abaei MM, Abbassi R, Garaniya V, Chin C, et al. (2017) Risk-based maintenance planning of subsea pipelines through fatigue crack growth monitoring. Engineering Failure Analysis 79: 928-939.
39. Kamsu-Foguem B (2016) Information structuring and risk-based inspection for the marine oil pipelines. Applied Ocean Research 56: 132-142.
40. Melo C, Dann MR, Hugo RJ, Janeta A (2019) A framework for risk-based integrity assessment of unpiggable pipelines subject to internal corrosion. Journal of Pressure Vessel Technology 141: 021702.
41. Febriyana P, Haryadi GD, Widodo A, Tauviqirrahman M, Suprihanto A, et al. (2019) Evaluation for detecting and monitoring of offshore pipeline damage based on risk-based inspection method. In AIP Conference Proceedings 2097.
42. Botsaris PN, Naris AD, Gaidajis G (2010) A Risk Based Inspection (RBI) preventive maintanance programme: a case study. In Engineering Asset Lifecycle Management: Proceedings of the 4th World Congress on Engineering Asset Management (WCEAM 2009), 28-30 September 2009 London: Springer London 902-911.
43. Tan Z, Li J, Wu Z, Zheng J, He W (2011) An evaluation of maintenance strategy using risk based inspection. Safety science 49: 852-860.
44. Soares WA, Vasconcelos VD, Rabello EG (2015) Risk-based inspection in the context of nuclear power plants (No.

INIS- BR--15950). Associacao Brasileira de Energia Nuclear (ABEN), Rio de Janeiro, RJ (Brazil).
45. Reza MA, Zaman MB, Siswantoro N (2023) Maintenance Strategy for Pressure Vessel at Offshore Platform Using RBI Method. International Journal of Marine Engineering Innovation and Research 8:795-801.
46. Topalis P, Korneliussen G, Hermanrud J, Steo Y (2012) Risk based inspection methodology and software applied to atmospheric storage tanks. In Journal of Physics: conference series 364: 012125.
47. Saranya R, Sneha M, Sridevi R (2023) An Analysis of Manufacturing Machine Failures and Optimization Using Replacement Year Prediction. In International Conference on Data Science, Computation and Security 311-324.
48. Da Silva RF, Melani AHDA, Michalski MADC, De Souza GFM (2023) Reliability and risk centered maintenance: A novel method for supporting maintenance management. Applied Sciences 13: 10605.
49. Andrejiova M, Grincova A, Marasova D (2018) Failure analysis of rubber composites under dynamic impact loading by logistic regression. Engineering Failure Analysis 84: 311-319.
50. Converso G, Gallo M, Murino T, Vespoli S (2023) Predicting failure probability in Industry 4.0 production systems: a workload-based prognostic model for maintenance planning. Applied Sciences 13: 1938.
51. Song JS, Lok V, Yoon KB, Ma YW, Kong BO (2021) Quantitative risk-based inspection approach for high-energy piping using a probability distribution function and modification factor. International Journal of Pressure Vessels and Piping 189: 104281.
52. Yang DY, Frangopol DM (2021) Risk-based inspection planning of deteriorating structures. Structure and Infrastructure Engineering 18: 109-128.
53. Liu G, Liu L, Li Q, Wang Q, Zhang H (2024) Reliability-centered maintenance scheduling optimization for high- speed railway facilities with multi-level tasks. In International Conference on Traffic and Transportation Studies 51-60.
54. Qaid A, Ahmad R, Mustafa SA, Mohammed BA (2024) A systematic reliability-centred maintenance framework with fuzzy computational integration–A case study of manufacturing process machinery. Journal of Quality in Maintenance Engineering 30: 456-492.
55. Alrifaey M, Sai Hong T, As'arry A, Elianddy Supeni E, Ang CK (2020) Optimization and selection of maintenance policies in an electrical gas turbine generator based on the hybrid reliability-centered maintenance (RCM) model. Processes 8: 670.
56. Jiang Q, Li X, Yang L, Ma Y, Li H (2024) Innovation and application of reliability-centered maintenance technology for pumped storage power plant. In Journal of Physics: Conference Series 2694: 012014.
57. Introna V, Santolamazza A (2024) Strategic maintenance planning in the digital era: A hybrid approach merging Reliability- Centered Maintenance with digitalization opportunities. Operations Management Research 1-24.
58. Rodríguez-Padial N, Marín MM, Domingo R (2024) Improvement of industrial maintenance plans through assistance-driven reliability-centered maintenance and case-based reasoning Design. Electronics 13: 639.
59. Cahyati S, Puspa SD, Himawan R, Agtirey NR, Leo JA (2024) Optimization of preventive maintenance on critical machines at the Sabiz 1 plant using reliability-centered maintenance method. Sinergi (Indonesia) 28: 355-368.
60. Liu Y, Tang Y, Wang P, Song X, Wen M (2023) Reliability-centered preventive maintenance optimization for a single-component mechanical equipment. Symmetry 16: 16.
61. Enjavimadar M, Rastegar M (2022) Optimal reliability-centered maintenance strategy based on the failure modes and effect analysis in power distribution systems. Electric Power Systems Research 203: 107647.
62. Asghari A, Jafari SM (2024) Investigating the Influence of reliability-centered maintenance on water treatment plant pumps (Case study: Guilan water treatment plant). Journal of Water and Wastewater, Ab va Fazilab (in persian) 35: 86-102.
63. Sembiring AC (2024) Analysis of boiler machine maintenance using the reliability-centered maintenance method. JKIE Journal Knowledge Industrial Engineering 11: 1-8.
64. Shamayleh A, Awad M, Abdulla AO (2020) Criticality-based reliability-centered maintenance for healthcare. Journal of Quality in Maintenance Engineering 26: 311-334.
65. Harsanto B, Yunani A (2023) Electric power distribution maintenance model for industrial customers: Total productive maintenance (TPM), reliability-centered maintenance (RCM), and four-discipline execution (4DX) approach. Energy Reports 10: 3186-3196
66. Al-Farsi N, Syafiie S (2023) Reliability centered maintenance application for the development of maintenance strategy for a chemical plant. In International Conference on Mathematical and Statistical Physics, Computational Science, Education, and Communication (ICMSCE 2022) 12616: 211-214.
67. Gelaw MT, Azene DK, Berhan E (2024) Assessment of critical success factors, barriers and initiatives of total productive maintenance (TPM) in selected Ethiopian manufacturing industries. Journal of Quality in Maintenance Engineering 30: 51- 80.
68. Elijaha PT (2021) Modeling effective maintenance strategy using reliability centered maintenance with risk maintenance. FUPRE Journal of Scientific and Industrial Research (FJSIR) 5: 38-56.
69. Rosita KKM, Rada MV (2021) Equipment reliability optimization using predictive reliability centered maintenance. In 2021 IEEE 8th International Conference on Industrial Engineering and Applications (ICIEA) 348-354.
70. Prasetyo YT, Rosita KKM (2020) Equipment reliability optimization using predictive reliability centered maintenance: a case-study illustration and comprehensive literature review. In 2020 7th International Conference on Frontiers of Industrial Engineering (ICFIE) 93-97.
71. Chiagorom VC, Osuchukwu LC (2023) Assessing Pump Reliability: a Case Study of Port Harcourt Refinery. ASRIC Journal on Engineering Sciences 3: 68-76.