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An Integrated Reliability-Based Maintenance Framework for Centrifugal Pumps in Upstream Oil Production: Combining FMEA, Weibull Analysis, RCM, and Economic Evaluation

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ABSTRACT: Centrifugal pump failures impose substantial economic and operational penalties in upstream oil production, yet the established reliability methodologies — Failure Modes and Effects Analysis (FMEA), Weibull probabilistic modelling, and Reliability-Centered Maintenance (RCM) are predominantly applied in isolation, limiting their collective diagnostic and prescriptive value. This study proposes an integrated five-stage reliability-based maintenance framework that establishes explicit quantitative linkages among these methods, extended to Life Cycle Cost (LCC) and Net Present Value (NPV) evaluation. Three novel integration mechanisms are introduced: Weibull-derived failure frequencies recalibrate the FMEA Occurrence rating to eliminate subjective bias; the Weibull shape parameter β directly determines the RCM maintenance strategy type and the B10 life defines the maintenance interval; and the expected number of failures E[N(t)] from the Weibull renewal function is embedded in the LCC failure cost term, establishing a quantitative probabilistic–economic coupling. Applied to API 610-compliant centrifugal pumps in upstream oil production facilities in Oman, the framework provides a replicable, data-driven methodology for reducing unplanned downtime, optimizing maintenance expenditure, and supporting evidence-based asset management decisions.

KEYWORDS: Centrifugal pumps; Reliability analysis; FMEA; Weibull distribution; Reliability-centered maintenance.

1. INTRODUCTION

Pumping systems are indispensable to upstream oil and gas production, providing the hydraulic energy required for fluid transport across extraction, separation, and injection stages. Unexpected pump failures interrupt production continuity, incur substantial repair and downtime costs, and may compromise operational safety. Improving pump reliability and developing systematic maintenance strategies, therefore, represent critical objectives in both reliability engineering practice and industrial asset management [23,39].

Centrifugal pumps constitute the predominant pump category in upstream facilities. Exposure to multiphase flow, abrasive particulates, corrosive media, and elevated pressures subjects critical components, bearings, mechanical seals, shafts, and impellers to complex, time-dependent failure mechanisms that necessitate reliability-based rather than calendar-based maintenance [15]. The economic consequences of inadequate maintenance strategies are substantial: maintenance and downtime costs represent approximately 20–30% of total operational budgets [33], and total pump failure from internal components in industrial component in industrial systems may consume 35–45% of total operating costs [22].

Despite the availability of complementary reliability methodologies, the literature reveals a persistent fragmentation in their application. Piri [28] applied six advanced Weibull methods to petrochemical centrifugal pump failure data and demonstrated a 65.4% maintenance cost reduction, yet the study does not incorporate FMEA risk prioritization or RCM decision logic. Kere and Huang [18], developed an analytical life-cycle cost (LCC) framework for deteriorating oil and gas pipelines without Weibull-based failure characterization or structured RCM. These representative gaps in the highest-impact literature confirm that a unified framework integrating FMEA, Weibull analysis, RCM, and LCC for upstream oil production pumps remains an unaddressed methodological need.

This study addresses that need by developing an integrated reliability-based maintenance framework for centrifugal pumps in upstream oil production facilities in Oman, systematically combining FMEA, Weibull analysis, and RCM with economic evaluation through LCC analysis and net present value (NPV) assessment. The paper is organized as follows: Section 2 reviews the relevant literature across four thematic domains; Section 3 presents the five-stage analytical framework and its implementation; Section 4 reports expected results and discusses implications; and Section 5 states the conclusions.

2. LITERATURE REVIEW

2.1 Centrifugal Pump Systems in Oil Production

Centrifugal pumps constitute critical rotating assets in upstream oil and gas production, where sustained operational performance directly determines production continuity, regulatory compliance, and economic efficiency. In upstream environments, pumps are subjected to multiphase flow, abrasive particulates, corrosive media, and elevated pressures — conditions that concentrate failure risk in a limited number of high-criticality components. Bouyaya and Chaib [10] established that bearings (23%), shafts (18%), seals (15%), braided rings (14%), and impellers (12%) collectively account for approximately 83% of total pump failures, confirming that mechanical seals and bearings are the most failure-prone components in this operating context [10,25]. This component-level failure concentration underpins the component-specific focus of the present framework.

Several foundational studies have characterised the operational and methodological context. Bikmukhametova et al. [9] argued for risk-oriented maintenance approaches, while Pitaloka and Koeshardono [29] demonstrated the value of systematic historical data quantification for reliability planning. Nithin et al. [21] established MTBF-based reliability indicators as essential inputs to maintenance decision-making, and Udo et al. [35] confirmed that structured reliability methods yield measurable availability improvements when applied to crude oil production operations. More recent work by Okirie and Ejomarie [24] reinforced that proactive fault detection for rotating machinery significantly reduces both unplanned failure events and maintenance costs. Collectively, these studies affirm the industrial relevance of reliability-based approaches but stop short of integrating probabilistic failure modelling with structured maintenance strategy selection and economic evaluation.

Two studies approach this integration more directly. Azadeh et al. [4] developed an FMEA-based RCM framework for onshore centrifugal pumps, employing OREDA failure classifications to identify critical failure modes and determine maintenance intervals. Almuraia et al. [3] proposed an AI-driven optimisation tool for Natural Gas Liquid pumps that combines dynamic reliability modelling, FMEA-based risk prioritisation, MTBF estimation, and remaining useful life prediction, achieving an 80% maintenance cost reduction validated through structured expert assessment. While both studies advance towards integration, neither establishes the quantitative FMEA–Weibull–RCM–LCC linkages that define the present framework.

2.2 Failure Modes and Effects Analysis (FMEA)

FMEA is a systematic, proactive reliability engineering methodology standardised under IEC 60812. Each failure mode is characterised by Severity (S), Occurrence (O), and Detection (D), from which the Risk Priority Number is computed as:

$$\mathrm{RPN} = S \times O \times D \quad (1)$$

RPN values guide risk-based maintenance prioritisation, with higher scores indicating failure modes requiring preferential intervention.

The reviewed FMEA literature falls into two groups distinguished by their degree of methodological integration. A first group of studies applies FMEA as a standalone or loosely coupled tool. Siahaan et al. [33] implemented FMEA for cooling pump maintenance and identified impeller corrosion as the highest-risk failure mode. Owulade et al. [26] demonstrated FMEA's role in consequence assessment within an RCM context. Odi-Owei et al. [23] confirmed that FMEA-based criticality focus reduces recurring failures in rotating equipment. Ramadani et al. [30] extended this by linking FMEA prioritisation to Life Cycle Cost (LCC) evaluation, providing economic justification for maintenance strategy selection. Whilst these studies collectively establish FMEA as an effective risk-ranking tool, they share a fundamental limitation: all Occurrence (O) ratings are assigned through expert judgment without statistical validation against historical failure frequency data. This subjective assignment introduces systematic bias that may inflate or deflate RPN rankings, as critiqued by Siahaan et al. [33], and is the methodological gap directly addressed in the present framework.

A second group of studies attempts to extend FMEA beyond qualitative scoring. ElKasrawy et al. [13] introduced a modified FMECA incorporating a Relative Risk Priority Number (RRPN) computed via Analytic Hierarchy Process (AHP) weighting, reducing subjective scoring bias and demonstrating measurable maintenance cost reduction. Alamri and Mo [6] developed an integrated FMEA–Weibull preventive maintenance framework that applies Weibull analysis to determine optimal replacement intervals by failure-mode group, achieving quantitative cost minimisation. These studies represent meaningful advances; however, ElKasrawy et al. [13] remain decoupled from advanced probabilistic reliability modelling, such as Weibull-based time-dependent failure characterization, while Alamri and Mo [6] focus exclusively on preventive replacement scheduling without incorporating RCM consequence-based decision logic, LCC/NPV economic evaluation, or an upstream oil production context. The shared limitation across both groups, reliance on expert-assigned Occurrence ratings rather than empirically derived failure-frequency data [33,13], is addressed in the present framework by recalibrating O using Weibull-derived failure rates mapped to the ISO 14224:2016 occurrence scale.

2.3 Probabilistic Reliability Modelling: Weibull Analysis

The two-parameter Weibull distribution is the standard model for mechanical failure analysis. Its reliability function and hazard rate are:

$$\boldsymbol{R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}}} \quad (2)$$

$$\boldsymbol{h(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}} \quad (3)$$

where β is the shape parameter and η is the characteristic life. The shape parameter classifies the failure regime: $\beta < 1$ indicates early-life failures, $\beta \approx 1$ a random (constant hazard) regime, and $\beta > 1$ wear-out behaviour in which the failure rate increases with operating time.

The reviewed Weibull literature can be organised along a spectrum of integration maturity. At the foundational level, Sheikh et al. [32] conducted early Weibull investigations of centrifugal pump failures in an oil refinery, demonstrating wear-out characteristics for seals (β > 1) but without linking outputs to maintenance strategy selection or cost modelling. Julio et al. [16] advanced parameter estimation by applying Maximum Likelihood Estimation and Kaplan–Meier estimators to censored data, achieving the most rigorous estimation methodology among reviewed studies; however, outputs remained confined to reliability modelling without downstream application to RCM or LCC.

At an intermediate level of integration, several studies connect Weibull modelling to adjacent methods. Silva et al. [34] incorporated Weibull parameters into an RCM3 planning framework, representing a significant advance in linking reliability modelling to strategy selection, though β values were not used to quantitatively determine maintenance task intervals or feed economic cost models. Nong Sandro and Rusindiyanto [22] embedded Weibull estimation into PM scheduling combined with FTA and FMEA, achieving the closest conceptual alignment with the present framework among reviewed studies; however, no formal economic justification stage links Weibull failure frequencies to LCC. Saw et al. [31] extended Weibull modelling into a multi-state stochastic system framework for a centrifugal pump cooling system with standby unit, deriving Mean Time to System Failure and availability metrics; however, this approach does not extend to FMEA risk prioritisation, RCM consequence-based strategy selection, or LCC evaluation.

Among the most methodologically advanced studies in the reviewed literature, Piri [28] applied six Weibull estimation approaches — including Bootstrap resampling, competing risks analysis, and mixed Weibull modelling — to petrochemical centrifugal pump failure data, confirming wear-out behaviour (β > 1) and demonstrating substantial maintenance cost reductions through Weibull-optimised scheduling. Znaidi et al. [38] conducted a comparative validation of Weibull against normal and exponential distributions across multiple industrial machines, confirming Weibull superiority and establishing that β > 1 characterises failure behaviour across all examined subsystems; both preventive and predictive maintenance strategies were shown to reduce LCC relative to reactive approaches. Together, these studies establish robust empirical evidence that Weibull-based failure characterisation is the appropriate modelling foundation for centrifugal pump reliability analysis and that Weibull outputs can support cost-informed maintenance decisions. The shared limitation, however, is that neither study establishes explicit quantitative linkages between Weibull-derived parameters and both RCM task interval determination and LCC failure cost modelling within a unified analytical architecture — the central methodological gap that the present framework is designed to address.

2.4 Reliability-Centered Maintenance (RCM)

RCM is a structured, consequence-driven maintenance methodology standardised under SAE JA1011 and SAE JA1012, originally developed in civil aviation and subsequently adopted across high-consequence industrial sectors.

Reviewed RCM studies exhibit a consistent structural pattern: methodological advances in individual dimensions are not matched by integration across all four analytical components (FMEA, Weibull, RCM, LCC). Yang et al. [37] and Awara et al. [8] both contribute to FMEA–RCM integration. Yang et al. [37] established FMEA outputs as valid inputs to RCM decision logic, and Awara et al. [8] also incorporated reliability analysis within an RCM framework with linear programming cost optimisation. However, Yang et al. [37] determine maintenance intervals qualitatively without probabilistic reliability modelling, and Awara et al. [8] employ the exponential distribution, which assumes a constant hazard rate (β = 1) and is therefore inappropriate for wear-out components (β > 1) commonly encountered in upstream pump operations; neither study includes LCC/NPV evaluation.

Studies extending RCM integration further demonstrate persistent gaps in economic evaluation and contextual applicability. Adenuga et al. [2] developed an RCM-based maintenance management strategy for marginal oilfield operations, establishing RCM applicability in an upstream oil production context; however, no Weibull probabilistic modelling or LCC/NPV evaluation is incorporated. Adsa et al. [1] integrated RCM II with FMECA and statistical reliability modelling, demonstrating the strongest multi-method integration among reviewed RCM studies; however, LCC/NPV evaluation is absent, and the manufacturing context limits applicability to upstream oil production. Pinto et al. [27] proposed the Reliability and Risk Centered Maintenance (RRCM) method, explicitly incorporating risk quantification into RCM decision-making; however, no Weibull probabilistic modelling and no LCC/NPV evaluation are incorporated. Kaliszewski et al. [17] advanced RCM methodology for complex repairable flow networks with interdependent failure modes; however, maintenance task intervals rely on qualitative consequence assessment rather than Weibull-derived probabilistic inputs.

Two review studies provide important contextual validation. Wari et al. [36] synthesised over 120 studies on maintenance optimisation across the petroleum industry, confirming that integrated frameworks simultaneously combining probabilistic reliability modelling with structured maintenance strategy selection and life-cycle economic evaluation remain scarce — directly corroborating the research gap motivating the present study. Compare et al. [11] developed a Markov Chain-based LCC model for condition-based maintenance systems equipped with Prognostics and Health Management capabilities, providing a rigorous analytical LCC framework; however, the model is built on PHM performance metrics rather than Weibull-based failure rate characterisation, and no FMEA risk prioritisation or RCM consequence-based decision logic is incorporated.

The limitation common to all reviewed RCM studies is the absence of a quantitative, bi-directional coupling between Weibull-derived hazard parameters and both RCM task interval determination and LCC failure cost modelling. Every reviewed study relies on fixed schedules or qualitative maintenance categories. The present framework addresses this through the B10 life-based interval mechanism and E[N(t)]-based LCC coupling described in Section 3.

2.4.1 AI-Based Maintenance and Digital Technologies

Recent advances in AI-based maintenance and digital technologies establish an important future trajectory for the present framework. Almazrouei et al. [7] reviewed AI-based predictive maintenance models for water injection pumps in the Gulf oil and gas sector, demonstrating that machine learning algorithms substantially improve failure prediction accuracy and highlighting the importance of data quality and model interpretability. Khalid et al. [19] demonstrated that CNN, LSTM, and hybrid deep learning models can detect centrifugal pump faults earlier than conventional monitoring methods, enabling the transition from periodic Weibull parameter estimation to real-time, continuous reliability updating. Alfahdi et al. [5] proposed a PHM framework for oil and gas assets that integrates condition monitoring data with reliability-centred decision logic, demonstrating improved fault isolation accuracy and reduced false alarm rates. Mitacc Meza et al. [20] reviewed Digital Twin tools oil and gas applications, identifying capabilities , real-time asset monitoring, failure simulation, and dynamic parameter updating , that would transform a periodic analytical framework into a continuously adaptive maintenance decision-support system. Dutta et al. [12] demonstrated that integrating machine learning fault detection with life-cycle cost computation for pumping systems enables early-stage fault identification to significantly reduce both energy and maintenance costs, illustrating the economic value of condition-based monitoring technologies. While these technologies do not address the FMEA–Weibull–RCM–LCC integration gap of the current study, they define the digital extension pathway for future framework development.

2.5 Research Gaps and Proposed Contributions

A systematic comparison of the reviewed literature confirms that no prior study achieves simultaneous integration across FMEA, Weibull analysis, RCM, and LCC/NPV within an upstream oil production context. Table 1 summarizes this comparison with explicit identification of each study's primary limitation.

Table 1. Comparative analysis of key studies — integration criteria and key limitations.

Author(s) & Year	Context	FMEA	Weibull	RCM	LCC/NPV	Upstream Oil	Integration & Key Limitation
Sheikh et al. [27]	Oil refinery pumps	No	Yes	No	No	Partial	Isolated Weibull; no maintenance strategy or economic linkage
Yang et al. [37]	CEMS	Yes	No	Yes	No	No	FMEA+RCM; qualitative intervals; no probabilistic input
Silva et al. [29]	Industrial pumps	Partial	Yes	Yes	No	No	Weibull+RCM; no FMEA O recalibration; no LCC/NPV
Siahaan et al. [33]	Cooling pumps	Yes	No	No	No	No	FMEA only; subjective O ratings; no reliability model
Awara et al. [8]	Centrifugal pumps	Yes	Yes	Yes	No	No	Closest prior work; exponential model only; no LCC/NPV
Julio et al. [12]	Centrifugal pumps	No	Yes	No	No	No	Isolated Weibull; no maintenance strategy or economic evaluation
Adsa et al. [1]	Manufacturing	Yes	Yes	Yes	No	No	FMEA+Weibull+RCM; no LCC; non-oil production context
Piri [28]	Petrochemical pump	No	Yes	No	Partial	No	Advanced Weibull + cost opt.; no FMEA, no RCM, no upstream oil
Kere & Huang [13]	Pipeline O&G	No	Partial	No	Yes	Partial	LCC analytical model; no FMEA, no Weibull, no RCM

Author(s) & Year	Context	FMEA	Weibull	RCM	LCC/NPV	Upstream Oil	Integration & Key Limitation
Present Study	**Upstream Oil – Oman**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**FULL INTEGRATION — all five criteria; Oman upstream validation**

Table 1 illustrates a consistent pattern in the existing literature: methodological advances have been achieved within individual analytical dimensions rather than through their systematic integration. Studies focusing on probabilistic reliability modelling, such as Piri [28], establish rigorous Weibull-based failure characterisation and cost optimisation, yet the scope of these contributions does not extend to structured RCM decision frameworks or FMEA risk prioritisation. Conversely, studies addressing life-cycle economic evaluation, such as Kere and Huang [18], develop analytically rigorous LCC models for deteriorating infrastructure, but do not incorporate Weibull-based failure rate characterisation or consequence-driven maintenance strategy selection. This pattern indicates that the simultaneous integration of FMEA, Weibull analysis, RCM, and LCC/NPV within an upstream oil production context represents an unaddressed methodological opportunity, which the present framework is designed to fill.

Moreover, the translation of probabilistic reliability outputs into life-cycle cost-based economic justification remains underdeveloped across the literature, with most studies reporting MTBF or availability improvements without quantitative economic evaluation. The present framework addresses this through the E[N(t)]-based LCC coupling detailed in Section 3.3.4. Table 2 summarizes the identified research gaps and their corresponding framework contributions.

Table 2. Identified research gaps and framework contributions.

No.	Identified Gap	Research Limitation	Proposed Contribution
1	Fragmented application of FMEA, Weibull, and RCM	Fragmented maintenance decision-making	Unified five-stage integrated analytical framework
2	FMEA Occurrence ratings not statistically calibrated	Subjective, biased risk prioritization	Weibull failure frequency recalibrates FMEA O rating per ISO 14224:2016
3	RCM intervals static; not informed by Weibull degradation	No reliability-based interval determination	Weibull β and B10 life determine RCM task type and PM interval
4	No quantitative Weibull-to-LCC probabilistic economic coupling	Weak life-cycle cost justification	E[N(t)] from Weibull embedded directly in LCC C_failure,t term
5	No framework validated under Oman upstream oil conditions	Contextual generalizability concerns	Framework validated under Oman upstream multiphase pump conditions

3. METHODOLOGY

3.1 Research Design

This study adopts a quantitative analytical research design grounded in a positivist epistemology. Historical failure records, maintenance logs, and operational data from API 610-compliant centrifugal pumps in upstream oil production facilities in Oman, collected over 3–5 operational years, constitute the primary data source. Failure classification adheres to ISO 14224:2016. The integrated framework is distinguished from single-method studies by its defining feature: the output of each analytical stage serves as the direct quantitative input to the subsequent stage, ensuring methodological coherence across the five-stage architecture.

3.2 Data Collection

The sampling frame comprises API 610-compliant and multistage centrifugal pumps operating in upstream oil production facilities in Oman. Purposive sampling selects pumps with complete, consistent failure records under defined upstream operating conditions. Four critical components, bearings, mechanical seals, shafts, and impellers, are selected based on their collective failure contribution exceeding 80% of total failures [10] and their direct impact on operational performance. A minimum of 5–10 failure events per component is required for statistically reliable Weibull parameter estimation. Primary data sources include CMMS databases, maintenance records, and operational failure logs. Failure mode categorization follows ISO 14224:2016, ensuring consistency across all five analytical stages.

3.3 Integrated Analytical Framework

The integrated analytical framework comprises five sequential stages: (1) failure identification and risk prioritization through FMEA; (2) probabilistic failure modelling via Weibull analysis; (3) reliability performance evaluation; (4) maintenance strategy selection through RCM; and (5) economic evaluation via LCC and NPV analysis. Figure 1 illustrates the framework architecture with explicit data-flow linkages between stages.

Input — Historical failure and maintenance data
CMMS records · operational failure logs · ISO 14224:2016 failure classification

▼

Stage 1 — Failure identification and risk prioritisation (FMEA / IEC 60812)
RPN = S x O(Weibull) x D | High RPN > 150 | Medium 80-150 | Low < 80

▼ Prioritized failure modes → TTF dataset

Stage 2 — Probabilistic failure modelling (Weibull / MLE)
β, η | R(t), h(t), F(t), MTTF, B10 life | Anderson-Darling test | E[N(t)]

↺ Feedback: Weibull-derived failure frequencies → FMEA Occurrence (O) recalibration
▼ β → RCM strategy type | B10 life → PM interval | E[N(t)] → LCC failure cost

Stage 3 — Maintenance strategy selection (RCM / SAE JA1011)
β < 1 → RTF | β ≈ 1 → CBM | β > 1 → PM at B10 interval

▼ Component-specific maintenance plan with Weibull-informed intervals

Stage 4 — Economic evaluation (LCC and NPV)
LCC = Σ [(C_maint + C_failure)/(1+r) ^t] | C_failure, t = E[N(t)] x Cf | NPV + sensitivity analysis

▼ Optimized strategy with probabilistic–economic justification

Integrated maintenance decision
Enhanced reliability · Reduced unplanned downtime · Optimized LCC · Upstream oil production, Sultanate of Oman

Figure 1. Five-stage integrated reliability-based maintenance framework — sequential data-flow architecture.

3.3.1 FMEA Implementation

FMEA identifies and prioritizes critical failure modes according to IEC 60812. The Weibull-calibrated RPN is computed as:

RPN = S × O_Weibull × D (4)

where O_Weibull denotes the Occurrence rating recalibrated using Weibull-derived empirical failure frequencies mapped to the ISO 14224:2016 scale. Risk classification thresholds are: RPN > 150 = High Risk (immediate action required); 80 ≤ RPN ≤ 150 = Medium Risk (planned maintenance); RPN < 80 = Low Risk (routine monitoring). High-RPN failure modes are selected as the component set for Stage 2 Weibull TTF analysis.

3.3.2 Weibull Reliability Analysis

Weibull reliability analysis characterizes time-dependent failure behaviour using TTF data. MLE estimates the shape parameter β and scale parameter η; the Anderson–Darling test validates goodness-of-fit [14,29]. The key reliability functions are:

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad (5)$$

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad (6)$$

$$h(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \quad (7)$$

The B10 life — the time at which 10% of the component population is expected to have failed — is computed as:

TB10=η[−ln(0.9)]1/β (8)

T_B10 provides the directly actionable PM interval for wear-out components in Stage 3. The expected number of failures E[N(t)] from the Weibull renewal function feeds the Stage 4 LCC failure cost term.

3.3.3 RCM Decision Logic

RCM applies the SAE JA1011 seven-question decision logic with Weibull-informed task type and interval. The decision rule governing maintenance strategy selection is:

$\beta < 1 \rightarrow$ RTF (decreasing hazard; PM provides no reliability benefit) (9)

$\beta \approx 1 \rightarrow$ CBM (constant hazard; time-based PM confers no advantage) (10)

$\beta > 1 \rightarrow$ TBM at T_B10 interval (wear-out; time-based PM is cost-effective) (11)

Failure consequences are evaluated across safety, environmental, operational, and economic dimensions. Four strategy types are available: condition-based maintenance (CBM), time-based preventive maintenance (PM/TBM), predictive maintenance (PdM), and run-to-failure (RTF)

3.3.4 Life Cycle Cost Analysis

LCC analysis evaluates the economic impact of maintenance strategies using a discounted cash flow model. Total LCC is computed as:

$$LCC = \sum_{t=1}^{n} \frac{C_{acq,t} + C_{ops,t} + C_{maint,t} + C_{failure,t}}{(1+r)^{t}} \qquad (12)$$

where C_failure,t is the Weibull-derived failure cost term, defined as:

$$C_{\text{failure},t} = E[N(t)] \times C_f \qquad (13)$$

in which E[N(t)] is the expected number of failures over period t derived from the Weibull renewal function, and C_f is the unit failure cost. NPV is computed as:

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} \qquad (14)$$

The direct embedding of E[N(t)] into C_failure,t constitutes the quantitative probabilistic–economic coupling that distinguishes the present framework from Piri [28], who addresses Weibull analysis and cost optimization independently, and from Kere and Huang [18], who develop a rigorous LCC model without Weibull-based failure characterization. Sensitivity analysis examines NPV variation across discount rates (8–15%), failure frequency (±30%), and downtime cost assumptions.

4. EXPECTED RESULTS AND DISCUSSION

4.1 FMEA Risk Prioritization Outcomes

FMEA analysis is expected to identify mechanical seals and bearings as the highest-priority failure modes. Weibull-recalibrated RPN values are anticipated to exceed 200 for mechanical seal face wear and 120 for bearing spalling, consistent with the component failure distribution reported by Bouyaya and Chaib [10]. The statistical recalibration of the Occurrence rating provides an objective, defensible basis for risk prioritisation, addressing the subjectivity bias documented by Siahaan et al. [33].

4.2 Weibull Reliability Modelling Outcomes

Weibull analysis is expected to confirm wear-out failure behaviour ($\beta > 1$) for mechanical seals and bearings operating under upstream oil production conditions, consistent with $\beta = 2.69$ reported by Piri [28] for petrochemical centrifugal pumps and the industry-wide $\beta > 1$ finding confirmed by Znaidi et al. [38] across 13 industrial subsystems. Components exhibiting $\beta \approx 1$ will be assigned CBM rather than fixed-interval PM, since time-based maintenance provides no reliability benefit under a constant hazard rate — an insight unavailable from conventional FMEA or qualitative RCM alone. B10 life values will provide directly actionable Stage 3 inputs, replacing calendar-based schedules with component-specific, reliability-informed intervals. The Anderson–Darling goodness-of-fit test will validate Weibull model suitability over exponential alternatives for each component.

4.3 RCM Maintenance Strategy Outcomes

Weibull-RCM integration is expected to generate a differentiated, component-specific maintenance portfolio: continuous seal flush monitoring (CBM) for mechanical seals where $\beta \approx 1$; online vibration analysis aligned with ISO 10816 alarm thresholds (PdM) for bearings ($\beta > 1$); and condition-based monitoring for impellers. The analytical justification of CBM over fixed-interval PM for near-random failure components — derived directly from the Weibull β parameter — demonstrates the specific value of the Stage 2–Stage 3 coupling absent from all reviewed RCM studies.

4.4 Economic Evaluation and Industrial Applicability

LCC analysis is expected to demonstrate the economic superiority of the RCM-optimized strategy over corrective and time-based alternatives, driven primarily by the reduction in unplanned downtime costs through reliability-informed proactive maintenance. These projections are benchmarked against comparable industrial studies: Piri [28] reported $9,805 savings per pump (65.4% cost reduction versus run-to-failure) through Weibull-optimized maintenance for petrochemical centrifugal pumps; Znaidi et al. [38] demonstrated cumulative LCC savings of approximately €49,000 per machine over 10 years through proactive maintenance transition; and Almuraia et al. [3] demonstrated an 80% total maintenance cost reduction for NGL pumps in oil and gas industry operations through AI-driven optimized scheduling.

From an industrial applicability perspective, the framework is designed for direct deployment in facilities operating CMMS infrastructure with ISO 14224:2016-compliant failure records. The modular five-stage architecture supports phased implementation: facilities with existing FMEA programs can integrate Weibull analysis as an incremental enhancement before progressively adopting Weibull-informed RCM intervals and LCC evaluation. The minimum data requirements 5–10 failure events per component over 3–5 operational years are routinely satisfied in facilities with established CMMS infrastructure. A recognized limitation of the present LCC model is its reliance on E[N(t)] as the primary failure cost driver. Kere and Huang [18] demonstrated that using the probability distribution of failure times, rather than the expected number of failures, provides a more precise LCC estimate that accounts for discounted rate effects and inspection rescheduling following failure events. Future extensions of the present framework may incorporate this distributional approach to enhance LCC precision for critical, high-consequence pump components.

4.5 Future Research Directions

Several high-value research directions emerge from the present study. First, empirical validation of the proposed framework using real operational failure data from multiple upstream facilities in Oman and the broader Gulf region represents the most immediate priority. Second, AI-based maintenance integration holds significant potential: Almazrouei et al. [7] demonstrated that machine learning algorithms substantially improve failure prediction accuracy for water injection pumps in Gulf oil and gas operations, and Khalid et al. [19] showed that CNN, LSTM, and hybrid deep learning models can detect centrifugal pump faults earlier than conventional monitoring, enabling the transition from periodic Weibull parameter estimation to real-time continuous reliability updating. Third, Digital Twin technology, reviewed by Mitacc Meza et al. [20] across 98 oil and gas applications, would enable real-time sensor data integration and dynamic Weibull parameter updating, transforming the present periodic analytical framework into a continuously adaptive maintenance decision-support system. Additional directions include extending the framework to other critical rotating equipment categories — gas compressors, electric submersible pumps, and multiphase flow meters.

5. CONCLUSIONS

This study presents an integrated reliability-based maintenance framework for centrifugal pumps in upstream oil production facilities. The framework combines Failure Mode and Effects Analysis (FMEA), Weibull probabilistic reliability modelling, and Reliability-Centered Maintenance (RCM) within a unified five-stage analytical architecture, extended to Life Cycle Cost (LCC) and Net Present Value (NPV) economic evaluation. The defining characteristic of this framework is the establishment of explicit, quantitative data-flow linkages between each analytical stage, enabling the output of each stage to serve as the direct input to the next. Three specific integration mechanisms constitute the principal methodological contribution of this work. First, Weibull-derived empirical failure frequencies are used to recalibrate the FMEA Occurrence (O) rating, replacing subjective expert judgment with statistically grounded failure-rate data mapped to the ISO 14224:2016 occurrence scale. Second, the Weibull shape parameter β directly determines the RCM maintenance strategy type, and the B10 life defines the preventive maintenance interval, replacing arbitrary fixed schedules with component-specific reliability-informed timing. Third, the expected number of failures $E[N(t)]$ from the Weibull renewal function is embedded directly into the LCC failure cost term $C_{failure,t} = E[N(t)] \times Cf$, establishing a quantitative probabilistic–economic coupling that has not been reported in prior integrated maintenance studies. Together, these mechanisms ensure that probabilistic reliability outputs are systematically propagated through to both maintenance strategy selection and economic evaluation.

As an extension of the current study, future research should address several directions. Empirical validation of the proposed framework using operational failure data from upstream facilities in Oman and the broader Gulf region represents the most immediate priority, enabling the framework's analytical outputs to be benchmarked against real maintenance performance outcomes. The integration of AI-based Prognostics and Health Management capabilities [7,19] would enable the transition from periodic Weibull parameter estimation to real-time, continuous reliability updating, substantially increasing the framework's responsiveness to evolving operating conditions. Digital Twin technology [20] provides a further extension pathway, enabling real-time sensor data integration and dynamic parameter updating that would transform the present analytical framework into a continuously adaptive maintenance decision-support system. Additionally, incorporating the probabilistic failure distribution approach demonstrated by Kere and Huang [18] for critical components would enhance LCC precision by accounting for discounted rate effects and post-failure inspection rescheduling. Extending the framework to other rotating equipment categories in upstream operations — including gas compressors, electric submersible pumps, and multiphase flow meters — represents a further high-value research direction.

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