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Reliability Optimization and Component Replacement Scheduling for Compressed Air Systems in Indonesian Navy PKR-Class Vessels Using FMECA and Weibull Analysis

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ABSTRACT

Compressed air systems are critical auxiliary systems aboard Indonesian Navy PKR-Class vessels, providing essential compressed air for main engine starting and various operational functions. This study addresses the frequent failure rate of compressed air systems, which experiences approximately 2 failures per 100 operational hours, significantly impacting vessel operational readiness. A comprehensive reliability optimization approach was developed by integrating Failure Mode, Effects, and Criticality Analysis (FMECA) with Weibull distribution analysis to identify critical components and determine optimal replacement intervals. Multi-expert assessment involving four independent evaluators identified five critical components from 14 assessed components: Lamellar Valve (RPN=8.14), Solenoid Valve 2nd stage (RPN=7.64), Solenoid Valve 1st stage (RPN=7.48), Safety Valve (RPN=7.16), and Non-Return Valve (RPN=6.99). Pre-optimization reliability analysis revealed critically low reliability levels ranging from R(t)=0.434 to R(t)=0.533. Through optimization using three-parameter Weibull distribution and Excel Solver, component-specific replacement intervals were established ranging from 145 to 457 days, achieving post-optimization reliability levels exceeding R(t)=0.95 for all critical components. Economic analysis demonstrated cost-effectiveness with Cost-Benefit Ratio (CBR) values below 1.0 for all components, indicating 20-33% cost savings compared to reactive maintenance approaches. The optimized maintenance strategy projects an 84.9% reduction in annual maintenance costs, from IDR 339,427,200 to IDR 51,426,953 per vessel, while improving system availability from 92% to over 99%. This research contributes a practical, data-driven framework for naval vessel auxiliary system maintenance optimization, demonstrating significant economic benefits and operational reliability improvements applicable to maritime defense operations..

1. Introduction.

Naval vessel operational readiness is fundamentally dependent on the reliability of auxiliary systems that support main propulsion and weapon systems. Among these auxiliary systems, the compressed air system occupies a critical position due to its essential role in providing high-pressure air (40 bar) for main engine starting, pneumatic control systems, and emergency operations (Júnior & Pereira, 2023; Ceylan, 2023). For Indonesian Navy PKR-Class (Perusak Kawal Rudal - Missile Guard Destroyer) vessels, which serve as frontline combatants in territorial water security and defense operations, any degradation in compressed air system reliability directly translates to reduced operational capability and mission effectiveness.

Recent operational data from PKR-Class vessels reveals a concerning reliability trend. The compressed air system expe-

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riences failure approximately 2 times per 100 operational hours, resulting in an estimated system availability of only 92% (Azhari et al., 2024; Cullum et al., 2018). This failure rate substantially exceeds acceptable standards for mission-critical naval auxiliary systems, where minimum availability targets typically range from 95% to 99% (Daya & Lazakis, 2023). The consequences of compressed air system failures are severe and multifaceted. Primary impacts include inability to start main engines, compromised pneumatic control system functionality, extended vessel downtime during critical operational periods, increased emergency maintenance requirements, and significant lifecycle cost escalation through reactive maintenance approaches (Jimenez et al., 2020; Cipollini et al., 2018).

The root causes of these reliability challenges are complex and interconnected. Current maintenance practices for PKR-Class compressed air systems predominantly follow time-based preventive maintenance schedules with fixed six-month intervals, applied uniformly across all components regardless of their criticality or actual degradation patterns (Vera-García et al., 2019). This approach fails to account for component-specific failure characteristics and may result in either premature replacement of serviceable components or delayed replacement of degraded critical components. Furthermore, the absence of systematic reliability analysis and criticality assessment prevents informed resource allocation and maintenance prioritization (Daya & Lazakis, 2023; Liu et al., 2024).

While extensive literature exists on reliability analysis and maintenance optimization for industrial systems, several critical gaps remain in the application of these methodologies to naval vessel auxiliary systems, particularly for compressed air systems in operational military contexts. First, previous research on naval vessel maintenance predominantly focuses on main propulsion systems and electronic equipment, with limited attention to auxiliary pneumatic systems despite their critical operational importance (Cipollini et al., 2018; Coraddu et al., 2016). Second, existing FMECA applications in maritime contexts typically rely on single-expert assessments or limited validation, potentially introducing subjective bias and reducing the credibility of criticality rankings (Certa et al., 2017; Gupta et al., 2021). Third, while Weibull analysis is widely employed for reliability modeling, the integration of FMECA-identified critical components with Weibull-based replacement interval optimization remains underexplored in naval applications (Okaro & Tao, 2016; Budimir et al., 2025).

This research addresses these gaps by developing and implementing a comprehensive, integrated methodology that combines multi-expert FMECA with three-parameter Weibull distribution analysis, specifically tailored for compressed air systems in PKR-Class naval vessels. The study's significance extends beyond immediate operational improvements for Indonesian Navy vessels. Methodologically, the research advances reliability engineering practice by demonstrating the effectiveness of multi-expert consensus in reducing assessment bias and improving criticality identification accuracy. Economically, the documented cost-benefit analysis provides empirical evidence supporting the business case for transitioning from reactive to predictive maintenance strategies in resource-constrained military contexts. Operationally, the optimized maintenance schedules directly enhance fleet readiness and mission capability by reducing unexpected failures and improving system availability.

This research aims to develop and validate a comprehensive reliability optimization framework for compressed air systems in Indonesian Navy PKR-Class vessels through five integrated objectives. First, to identify and prioritize critical components through systematic FMECA incorporating multi-expert assessment from manufacturer, fleet command, shore facility, and ship-level perspectives. Second, to characterize failure distribution patterns and reliability parameters of critical components using three-parameter Weibull analysis based on operational failure data. Third, to determine optimal component replacement intervals maximizing reliability while considering operational constraints and resource availability. Fourth, to evaluate economic feasibility and cost-effectiveness of optimized maintenance strategies using Cost-Benefit Ratio (CBR) analysis comparing planned preventive against reactive corrective maintenance. Fifth, to validate practical applicability and implementation feasibility through comparative analysis with current maintenance practices. The research scope concentrates on the WP65L air compressor system and associated components (valves, cylinders, pistons, filtration elements) aboard PKR-Class vessels operating within the Indonesian Navy's eastern fleet command area, with failure data spanning multiple maintenance cycles providing sufficient statistical basis for analysis.

Several limitations constrain the generalizability and interpretation of findings that require explicit acknowledgment. The analysis assumes historical failure data accurately represents future failure patterns under similar operational conditions, which may not hold if operational intensity or environmental conditions change significantly. Component quality consistency is assumed based on approved supplier procurement, though counterfeit or substandard parts could invalidate reliability predictions. The independence assumption in component failure analysis may not capture cascading failures or system-level interactions, while cost estimates rely on historical procurement and maintenance records that may vary with market conditions and supply chain dynamics. Additionally, the optimization assumes proper installation and maintenance procedures, recognizing that variations in maintenance quality could affect actual reliability outcomes. These limitations are addressed through sensitivity analysis, confidence interval quantification, and conservative assumption selection to ensure findings remain robust across reasonable scenario variations.

2. Literature Review.

2.1. Theoretical Foundations of FMECA.

Failure Mode, Effects, and Criticality Analysis (FMECA) represents a systematic, proactive approach to identifying potential failure modes within a system, evaluating their effects on system performance, and prioritizing them based on criticality for focused mitigation efforts (Lawson, 1983; Modarres et al., 2017). The methodology evolved from military reliability standards and has become a cornerstone of reliability engineering across industrial sectors. FMECA's fundamental strength lies in its structured framework for translating qualitative expert knowledge into quantitative risk metrics through the Risk Priority Number (RPN), calculated as the product of Severity (S), Occurrence (O), and Detection (D) ratings.

Recent methodological developments have significantly enhanced FMECA's robustness and objectivity. Certa et al. (2017) introduced Dempster-Shafer Theory to address epistemic uncertainty in FMECA assessments, demonstrating improved risk quantification for fishing vessel propulsion systems. This approach acknowledges and systematically manages the inherent uncertainty in expert judgments, particularly valuable when historical failure data is limited. Gupta et al. (2021) advanced fuzzy logic integration with FMECA, enabling more nuanced representation of linguistic variables in expert assessments and reducing the discretization artifacts inherent in traditional integer scales. Their case study of industrial centrifugal pumps demonstrated improved discrimination between components with similar traditional RPN scores.

The integration of network theory and data - driven approaches represents another significant advancement. Wang et al. (2019) proposed complex network-based FMECA to identify hidden interdependencies and cascade failure patterns not apparent in traditional component-by-component analysis. Antomarioni et al. (2022) combined association rules and social network analysis with FMECA for onshore platforms, revealing failure mode correlations that informed more effective maintenance strategies. Kalathil et al. (2020) compared Dempster-Shafer and fuzzy FMECA approaches in LNG storage facilities, finding that method selection should be guided by data availability and uncertainty characteristics.

Despite these advances, challenges remain in FMECA implementation. The subjectivity of expert assessments, particularly when experts have divergent backgrounds and experiences, can introduce bias (Braglia et al., 2003). The geometric mean approach to RPN calculation, while mathematically elegant, may mask important distributional characteristics when expert opinions diverge significantly (Carpitella et al., 2018). The criticality threshold selection (e.g., RPN ≥ 7.0) often lacks rigorous justification and may be context-dependent. These considerations informed the design of the multi-expert assessment protocol employed in this research.

2.2. *Weibull Distribution in Reliability Engineering.*

The Weibull distribution's flexibility and versatility have established it as the preeminent model for lifetime data analysis in reliability engineering (McCool, 2012; Gómez et al., 2023). Its three-parameter form, f(t) = (β/η)((t-γ)/η)∧(β-1)exp(-((t-γ)/η)∧-β), accommodates diverse failure patterns through the shape parameter (β), scale parameter (η), and location parameter (γ). The shape parameter's interpretation is particularly valuable: $\beta < 1$ indicates infant mortality or decreasing failure rate, $\beta \approx 1$ suggests random failures, and $\beta > 1$ characterizes wear-out or increasing failure rate (Ebeling, 1997; Jardine & Campbell, 2001).

Recent methodological developments have expanded Weibull analysis capabilities. Shama et al. (2023) introduced modified generalized Weibull distributions to model complex failure patterns with multiple inflection points, demonstrating improved fit for electronic component degradation data. Ahmad and Ghazal (2020) developed exponentiated additive Weibull distributions for systems exhibiting competing failure mechanisms, achieving better characterization than traditional mixture models. Wang et al. (2021) proposed generalized-X family distributions incorporating Weibull as a special case, offering enhanced flexibility for reliability applications with limited data.

Parameter estimation methodology has also evolved significantly. Li et al. (2025) addressed the challenging zero-failure data scenario common in high-reliability systems, developing Bayesian estimation approaches that incorporate prior knowledge while acknowledging limited failure observations. Zhang (2020) proposed maximum likelihood estimation refinements for zero-failure contexts, enabling reliability inference for high-quality products without requiring accelerated testing. Zhu (2020) advanced block censoring analysis for two-parameter Weibull, improving estimation efficiency for incomplete lifetime data typical in operational settings.

Wu et al. (2024) examined mixture Weibull distributions for components with multiple failure modes using expectation-maximization algorithms, demonstrating improved prognostic accuracy for mechanical systems. Their work highlights the importance of matching distributional assumptions to underlying failure physics. For compressed air system components, the dominance of mechanical wear and fatigue suggests that single-mode Weibull with $\beta > 1$ is typically appropriate, though mixture models may be necessary for components exhibiting competing failure mechanisms.

2.3. *Integrated FMECA-Weibull Approaches in Maritime Applications.*

The integration of FMECA criticality identification with the Weibull - based reliability modeling represents a powerful synergy for maintenance optimization, combining qualitative risk assessment with quantitative lifetime prediction (Qiu et al., 2018; Catic & Glišović, 2019). This integration addresses a fundamental limitation of standalone FMECA, which identifies critical components but provides limited guidance on optimal replacement timing, while Weibull analysis offers precise lifetime modeling but lacks systematic criticality prioritization.

Okaro and Tao (2016) pioneered this integration for subsea compression systems, demonstrating that FMECA - identified critical components could be analyzed using Weibull methods to optimize design and achieve target reliability levels under operational stresses. Their study achieved a 52% reliability improvement by identifying under-designed components through integrated analysis and implementing targeted design modifications. This work established the feasibility of the integrated approach but focused primarily on design optimization rather than maintenance scheduling.

Júnior and Pereira (2023) extended this methodology to vessel pneumatic equipment, combining FMECA with Fault Tree

Analysis to identify critical failure modes and implementing Air Dryer systems to mitigate moisture-related degradation. Their case study demonstrated significant reliability improvements and maintenance cost reductions, validating the practical applicability of integrated analysis in maritime contexts. However, their work did not employ Weibull analysis for replacement interval optimization, relying instead on manufacturer recommendations.

Recent maritime applications have increasingly incorporated condition-based maintenance (CBM) with integrated reliability analysis. Jimenez et al. (2020) developed predictive maintenance models for vessel machinery using machine learning to process sensor data, achieving improved failure prediction compared to time-based approaches. Cipollini et al. (2018) demonstrated CBM effectiveness for naval propulsion systems with minimal feedback, using data-driven approaches to identify degradation patterns. Coraddu et al. (2016) applied machine learning to improve CBM of naval propulsion plants, highlighting the value of integrated data analytics and reliability modeling.

The risk-based maintenance (RBM) paradigm represents a mature framework for integrating reliability analysis with operational decision-making. Cullum et al. (2018) developed RBM scheduling methodologies for naval vessels, demonstrating cost-effectiveness compared to traditional preventive maintenance while maintaining or improving availability. Their work emphasized the importance of balancing reliability targets with resource constraints, particularly relevant in military contexts where maintenance budgets are limited. Azhari et al. (2024) applied Reliability Centered Maintenance (RCM) to vessel machinery in Indonesian commercial shipping, showing significant cost reductions and reliability improvements through systematic criticality analysis and interval optimization.

2.4. Economic Analysis and Optimization in Naval Maintenance.

The economic justification for reliability-based maintenance strategies is critical for organizational acceptance and resource allocation (Dere & Deniz, 2021). Cost-Benefit Ratio (CBR) analysis provides a structured framework for comparing preventive maintenance costs against expected costs of reactive maintenance following failure, accounting for failure probabilities and consequence costs (NAVAIR 00-25-403, 2005). The fundamental premise is that when CBR < 1, preventive replacement is economically justified because the amortized cost of planned maintenance is less than the expected cost of failure-driven maintenance.

Dere and Deniz (2021) examined compressed air system energy efficiency on ships, demonstrating that optimal pressure management could reduce energy consumption and fuel costs by 58.2% while simultaneously decreasing CO2 emissions. Their work highlighted the often-overlooked operational cost component of compressed air systems, beyond maintenance costs. The integration of energy efficiency considerations with reliability analysis presents opportunities for holistic system optimization.

Fu and Zhu (2023) developed joint age-based system replacement and component reallocation policies, demonstrating that strategic component reallocation between systems can enhance resilience while minimizing costs. Their optimization framework considered system-level interactions and component degradation patterns, achieving improved cost-effectiveness compared to component-by-component replacement strategies. Fu et al. (2019) earlier established the theoretical foundations for optimum periodic component reallocation and system replacement, providing mathematical frameworks that balance replacement costs, residual life, and system reliability requirements.

Poppe et al. (2018) proposed hybrid condition-based maintenance policies for continuously monitored components with two degradation thresholds, demonstrating cost - effectiveness through delayed replacement until approaching critical degradation levels. Their work is particularly relevant for high-value components where premature replacement represents significant economic waste. Chen et al. (2022) conducted maintenance cost-based importance analysis under different maintenance strategies, revealing that optimal strategies are highly context-dependent and require careful consideration of cost structures, failure consequences, and operational constraints.

The application of these economic frameworks to naval contexts introduces unique considerations. Military operational requirements often prioritize availability and mission capability over pure cost minimization, creating multi-objective optimization problems (Baker et al., 2020). Budget constraints in defense contexts may impose hard limits on maintenance expenditures, requiring careful prioritization and phasing of improvements. The extended supply chains for military-specific components and the potential for supply disruptions introduce additional economic uncertainties that must be considered in optimization formulations.

2.5. Research Positioning and Contribution.

This research positions itself at the intersection of three critical domains: FMECA criticality analysis, Weibull-based reliability modeling, and economic optimization for naval applications. The literature review reveals that while each domain is well-developed individually, their integration for compressed air systems in operational naval vessels remains underdeveloped. Previous maritime applications have primarily focused on main propulsion systems or commercial vessels, with limited attention to military auxiliary systems operating under high-stress conditions with stringent availability requirements.

The primary contributions of this research relative to existing literature are threefold. Methodologically, the multi-expert FMECA protocol incorporating manufacturer, fleet command, shore facility, and ship-level perspectives provides enhanced credibility and reduced bias compared to single-expert assessments common in previous studies. The integration of FMECA-identified critical components with three-parameter Weibull optimization explicitly addresses the gap between criticality identification and replacement timing determination. The comprehensive economic analysis including CBR evaluation, annual cost projections, and sensitivity analysis provides practical decision - support tools often absent in academic reliability studies.

Theoretically, this research extends reliability engineering frameworks to the unique context of naval auxiliary systems, where operational requirements, maintenance constraints, and cost structures differ substantially from commercial maritime or industrial applications. The explicit consideration of operational readiness requirements alongside cost minimization represents an advancement beyond purely economic optimization formulations. Practically, the documented implementation pathway and validation against current maintenance practices provides actionable guidance for naval maintenance organizations considering transitions to reliability-based maintenance strategies.

3. Research Methods.

3.1. Research Design and Framework.

This research employs a sequential mixed-methods design integrating qualitative expert assessment with quantitative reliability modeling and optimization. The overall research framework, depicted in Figure 1, comprises four primary phases: system characterization and data collection, multi-expert FMECA execution, Weibull distribution analysis and reliability modeling, and optimization with economic evaluation. This sequential structure ensures that each phase builds upon validated outputs from preceding phases, enhancing the rigor and traceability of the analysis.

The research philosophy is grounded in pragmatism, emphasizing practical problem-solving and actionable outcomes for operational decision-making. This pragmatic orientation informed methodological choices prioritizing practical applicability over purely theoretical elegance. The validation strategy incorporates both internal consistency checks and external validation through comparison with operational performance data and expert review of findings. The research timeline spans 18 months, encompassing data collection, analysis, optimization, and validation phases.

3.2. System Description and Operational Context.

The compressed air system investigated in this research is installed aboard PKR-Class vessels, which serve as the Indonesian Navy's primary surface combatants for maritime patrol, surveillance, and limited anti-surface warfare missions. The system architecture consists of two WP65L-type reciprocating air compressors manufactured by Sauer Compressors, strategically positioned in the main engine room and diesel generator room to ensure redundancy. Each compressor is designed to deliver 40 bar compressed air, stored in high-pressure receivers for distribution to consuming systems.

The primary consumers of compressed air include the main diesel engine starting system, which requires high-pressure air for direct start capability; pneumatic control systems for valve actuation throughout the vessel; emergency systems including emergency diesel generator starting; and auxiliary systems such as pneumatic tools and cleaning equipment. System operating parameters include nominal pressure of 40 bar, storage capacity of 2000 liters across multiple receivers, compressor capacity of 65 m^3/hour free air delivery, and operational temperature range of 5-45°C ambient.

The critical importance of the compressed air system stems from its role in main engine starting, which represents a single-point-of-failure risk for vessel propulsion. Unlike commercial vessels with alternative starting methods, PKR-Class vessels rely exclusively on compressed air for main engine start, making system reliability paramount for operational capability. This dependency motivates the intensive reliability analysis undertaken in this research.

3.3. Data Collection Strategy.

Data collection was conducted through three complementary approaches: historical failure data extraction, structured expert interviews, and questionnaire-based FMECA assessments. Historical failure data was obtained from Planned Maintenance System (PMS) databases, ship logbooks, and maintenance records spanning 36 months of operational history across the PKR-Class fleet. This dataset encompassed 247 recorded failure events across all compressed air system components, providing statistical basis for reliability analysis.

Expert participants were selected through purposive sampling to ensure diverse perspectives and comprehensive system knowledge. The expert panel comprised four independent evaluators: a technical representative from MTU AIR Ltd (equipment manufacturer) with design and specification expertise; the Materiel Maintenance Officer from Fleet Command II representing fleet-level maintenance management and operational requirements; the Chief of Material Maintenance at Naval Base Command V representing shore-based repair facility capabilities and standards; and the Head of Engineering Department aboard KRI GNR-332 representing ship-level operations and field maintenance experience.

Structured interviews were conducted individually with each expert to explain the FMECA methodology, establish common understanding of severity, occurrence, and detection scales, and gather preliminary insights on critical failure modes. Interview duration averaged 90 minutes per expert, with sessions recorded and transcribed for analysis. Questionnaires were subsequently distributed to experts for independent assessment of each component's failure modes using standardized rating scales.

3.4. FMECA Methodology.

The FMECA execution followed a systematic six-step protocol adapted from MIL-STD-1629A and refined based on recent best practices in maritime applications (Modarres et al., 2017; Júnior & Pereira, 2023). Step one involved system definition and functional analysis, wherein the compressed air system was decomposed into functional subsystems (compression, storage, distribution, control) and components. Functional relationships and failure propagation pathways were mapped using functional block diagrams.

Step two encompassed failure mode identification for each component, drawing on historical failure data, manufacturer

FMEA documentation, and expert knowledge. For each component, potential failure modes were identified, failure mechanisms and root causes were documented, and failure detection methods were specified. This process resulted in identification of 14 distinct component-failure mode combinations warranting detailed analysis.

Step three involved failure effects analysis, systematically evaluating the consequences of each failure mode on local component function, subsystem performance, and system-level mission capability. Effects were categorized as immediate (occurring within minutes of failure), intermediate (developing over hours), and long-term (cumulative degradation over days orweeks). This temporal dimension is particularly important for naval applications where mission timelines may be brief but critical.

Step four executed criticality assessment through independent expert evaluation. Each expert rated failure modes using standardized scales: Severity (S) from 1 to 10, where 1 indicates no effect on system function and 10 indicates catastrophic effect with potential loss of vessel or life; Occurrence (O) from 1 to 10, where 1 indicates remote likelihood (< 1 in 10,000) and 10 indicates very high frequency (≥ 1 in 10); and Detection (D) from 1 to 10, where 1 indicates certain detection before impact and 10 indicates no detection capability before failure effect manifests.

The Risk Priority Number (RPN) was calculated using the geometric mean approach: RPN = (S × O × D)∧(1/3). This formulation provides more balanced weighting compared to arithmetic multiplication, which can be dominated by extreme values in any single dimension (Carpitella et al., 2018). Individual expert RPNs were averaged across the four-expert panel to produce final RPN values for each component-failure mode combination.

Step five established criticality thresholds through analysis of RPN distribution and consideration of resource constraints. Components with RPN ≥ 7.0 were classified as critical, representing the top 35.7% of assessed components. This threshold was selected based on natural clustering in the RPN distribution and practical considerations of maintainable scope for detailed reliability analysis. Step six involved prioritization and documentation, ranking components by final RPN and preparing detailed failure mode documentation for subsequent Weibull analysis.

3.5. *Weibull Distribution Analysis.*

Weibull analysis was conducted for each FMECA-identified critical component using Weibull++ 6 software (ReliaSoft Corporation). The analysis followed a five-phase protocol: data preparation and validation, distribution selection and parameter estimation, goodness-of-fit assessment, reliability function derivation, and uncertainty quantification.

Data preparation involved extracting component - specific time-to-failure (TTF) data from historical records. For each critical component, individual failure event times were recorded along with relevant operating conditions. Data quality was assessed through completeness checks, outlier detection using Grubbs' test, and censoring identification. Right-censored observations (components still operating at data collection cutoff) were explicitly handled using appropriate likelihood functions.

Distribution selection evaluated multiple candidate distributions including exponential (1 and 2 parameter), Weibull (2 and 3 parameter), lognormal, and normal distributions. Maximum likelihood estimation (MLE) was employed for parameter estimation, with the log-likelihood function optimized using Newton-Raphson iteration. For the three-parameter Weibull distribution, parameters were estimated as: shape parameter β indicating failure rate pattern; scale parameter η representing characteristic life; and location parameter γ defining failure-free operating period.

Goodness - of - fit assessment employed multiple criteria: Anderson-Darling test statistic for overall fit quality; likelihood ratio tests comparing nested models; Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for model comparison accounting for parameter count; and probability plots with confidence bounds for visual assessment. The three-parameter Weibull distribution was selected for all critical components based on superior fit across these criteria.

Reliability functions were derived from estimated Weibull parameters: R(t) = exp(-((t-γ)/η)∧β) for reliability; F(t) = 1 - R(t) for cumulative failure probability; f(t) = (β/η)((t-γ)/η)∧(β-1)exp(-((t-γ)/η)∧β) for probability density; and λ(t) = (β/η)((t-γ)/η)∧(β-1) for instantaneous failure rate. These functions enable prediction of component behavior across the operational lifetime.

Uncertainty quantification employed Fisher information matrix inversion to derive parameter variance-covariance matrices. Confidence bounds on reliability functions were calculated using the delta method, providing 90% two-sided confidence intervals for reliability predictions at specified operating times. Monte Carlo simulation with 10,000 iterations validated analytical confidence bounds and assessed sensitivity to parameter uncertainty.

3.6. *Optimization Methodology.*

Optimization of component replacement intervals integrated reliability targets with operational and economic constraints. The optimization framework employed Microsoft Excel Solver with the Generalized Reduced Gradient (GRG) Nonlinear algorithm. For each critical component, the optimization problem was formulated as:

Maximize: R(t_r) = exp(-((t_r - γ)/η)∧β)
Subject to:

- R(t_r) ≥ 0.95 (minimum acceptable reliability)
- t_r ≤ MTBF (replacement before expected failure)
- t_r ≥ γ + ε (replacement after failure-free period plus margin)
- CBR < 1 (economic feasibility constraint)

The minimum reliability constraint of 0.95 was established based on naval auxiliary system standards and consultation with

Fleet Command maintenance planners. This target ensures that fewer than 5% of components fail before scheduled replacement, balancing reliability assurance with resource efficiency. The MTBF constraint prevents replacement intervals that exceed the expected component lifetime, which would increase failure risk. The lower bound ensures replacement occurs after the failure-free period with a safety margin $\varepsilon = 10$ days.

The optimization algorithm iteratively adjusted replacement interval t_r to maximize reliability while satisfying all constraints. Convergence criteria required objective function change less than 10∧-6 and constraint violation less than 10∧-8. Multiple starting values were tested to ensure global optimum identification and avoid local optima. Sensitivity analysis examined the impact of ±10% variations in Weibull parameters on optimal intervals, assessing robustness to parameter uncertainty.

For components where the reliability constraint was binding (optimization stopped at $R(t_r) = 0.95$), the replacement interval represents the maximum feasible interval under reliability requirements. For components achieving $R(t_r) > 0.95$, the interval represents the optimal balance between reliability margin and practical implementation considerations such as maintenance window alignment and spare parts inventory management.

3.7. *Economic Analysis Methodology.*

Cost-Benefit Ratio (CBR) analysis quantified the economic feasibility of optimized replacement strategies compared to reactive maintenance. The CBR formulation adapted from NAVAIR 00-25-403 (2005) is:

$$\mathbf{CBR = [MTBF \times ((C\_BF \times N\_S) + (C\_AF \times (1 - N\_S)))] / [(C\_AF \times t\_r) \times (N\_S + (K \times (1 - N\_S)))]}$$

Where MTBF represents mean time between failure estimated from Weibull distribution as $MTBF = \gamma + \eta \times \Gamma(1 + 1/\beta)$, where Γ denotes the gamma function; C_BF represents cost of planned replacement before failure including component cost, labor cost at standard rates, no operational downtime cost (scheduled during maintenance windows), and administrative overhead; C_AF represents cost of unplanned replacement after failure including component cost, labor cost at emergency rates (typically 1.5× standard), operational downtime cost based on vessel day rate, emergency logistics and mobilization costs, and potential secondary damage costs.

N_S represents survival probability at replacement interval, calculated as $N\_S = R(t\_r)$ from Weibull analysis; t_r represents proposed replacement interval from optimization; and K represents ratio of premature failure consequences to normal failure consequences, estimated as $K = 1.5$ based on emergency response cost multipliers.

Cost data was obtained from multiple sources including procurement records from Fleet Command II supply management system covering 36 months of component purchases, maintenance labor cost standards from Naval Base Command V accounting 2024 rates and multipliers, vessel operating cost allocations from Indonesian Navy budget documentation, and expert estimates for indirect and consequence costs validated with structured interviews.

Annual cost projections compared optimized preventive maintenance against current reactive approaches. Current annual maintenance cost was estimated as (annual operating hours / 100) × 2 failures × average corrective maintenance cost. Optimized annual maintenance cost was calculated as $\Sigma(365 / t\_ri) \times C\_BF\_i$ for all critical components i. The difference represents projected annual savings per vessel, which was then scaled to fleet level considering 10 PKR-Class vessels for total fleet impact assessment.

Sensitivity analysis examined CBR robustness to cost variations including ±25% variation in component costs reflecting procurement price volatility, ±50% variation in failure consequence costs acknowledging uncertainty in operational impact valuation, and ±20% variation in labor costs reflecting potential wage adjustments. This analysis identified conditions under which CBR remains below 1.0, establishing the economic robustness of optimized strategies.

3.8. *Validation and Quality Assurance.*

Multiple validation mechanisms ensured research quality and findings credibility. Internal validation included cross - checking failure data across multiple sources (PMS database, logbooks, maintenance records) to ensure consistency; verification of Weibull parameter estimates through alternative software (R survival package) confirming convergence to identical parameter values; sensitivity analysis demonstrating that optimal intervals remained stable under ±10% parameter variations; and expert review of optimization results with Fleet Command maintenance planners confirming practical implementability.

External validation comprised comparison of predicted failure rates from Weibull models against historical failure frequencies, with observed rates falling within 90% confidence intervals for all components; validation of CBR estimates through consultation with Naval Base Command V cost accountants confirming reasonableness of cost assumptions; and benchmarking of reliability improvements against published case studies in maritime maintenance showing comparable or superior results.

Quality assurance measures included documentation of all data transformations and analysis steps in audit trails; retention of raw data files, intermediate calculations, and final outputs for independent verification; use of version-controlled spreadsheets for optimization models with change logging; and peer review of FMECA questionnaires, analysis protocols, and findings interpretation by two independent reliability engineers with maritime experience.

The combination of these validation and quality assurance measures provides confidence that research findings accurately represent system behavior and that conclusions are supported by rigorous, transparent analysis. Limitations are explicitly acknowledged in findings interpretation, and recommendations are appropriately qualified based on the scope and constraints of the investigation.

4. Results And Discussion.

4.1. Compressed Air System Configuration and Operational Characteristics.

The compressed air system aboard PKR-Class vessels employs a dual-compressor configuration designed to provide redundancy and ensure continuous compressed air availability for mission-critical functions. The system architecture consists of two Sauer WP65L reciprocating air compressors rated at 40 bar maximum working pressure and 65 m^3/hour free air delivery capacity. Compressor placement follows a distributed approach with one unit located in the main engine room and the second in the diesel generator room, minimizing the risk of common-cause failures from localized damage or environmental hazards.

Each compressor operates through a two-stage compression process. The first-stage cylinder compresses ambient air from atmospheric pressure to approximately 10 bar, with interstage cooling provided by water-cooled heat exchangers to enhance compression efficiency and reduce thermal stress on components. The second-stage cylinder further compresses the air from 10 bar to the final delivery pressure of 40 bar. This staged compression approach improves thermodynamic efficiency compared to single-stage compression and distributes mechanical loading across multiple cylinder assemblies, extending component service life.

Compressed air is stored in a network of high-pressure receivers with total capacity of 2000 liters, strategically distributed throughout the vessel to minimize pressure drop and ensure rapid response to demand transients. The storage capacity provides sufficient air volume for multiple main engine start attempts without compressor operation, a critical safety feature enabling engine restart following compressor failure. Distribution piping is manufactured from seamless steel tubing rated for 60 bar working pressure, incorporating 1.5× safety factor above system operating pressure.

Operational data extracted from ship logbooks and Planned Maintenance System (PMS) databases reveals concerning reliability patterns. Over the 36-month observation period, the compressed air system experienced 247 documented failure events across the PKR-Class fleet, translating to an average failure rate of 2.06 failures per 100 operating hours. Component-level failure analysis indicates that 62% of failures occur in valve assemblies (solenoid valves, safety valves, lamellar valves, non-return valves), 23% in piston and cylinder assemblies, 8% in electrical control components, and 7% in filtration and moisture separator systems. This failure distribution pattern is consistent with maritime compressed air system experience reported by Júnior and Pereira (2023) and Ceylan (2023), who identified valve failures as the predominant reliability concern in shipboard pneumatic systems.

4.2. Multi-Expert FMECA Results and Critical Component Identification.

The systematic FMECA process evaluated 14 component-failure mode combinations across the compressed air system, assessing each through four independent expert evaluators representing diverse organizational perspectives and technical backgrounds. The multi - expert approach employed in this study addresses a critical limitation of conventional single - expert FMECA applications, where subjective bias and limited perspective can skew criticality rankings (Gupta et al., 2021; Kalathil et al., 2020).

Table 2 presents the comprehensive FMECA assessment results, showing individual expert ratings for Severity (S), Occurrence (O), and Detection (D), along with calculated Risk Priority Numbers (RPN) for each expert-component combination. The geometric mean RPN formulation, RPN = (S × O × D)∧(1/3), provides more balanced risk quantification compared to traditional arithmetic multiplication, which can be dominated by extreme values in any single dimension (Carpitella et al., 2018). Average RPN values were calculated across the four-expert panel to produce final criticality rankings.

Table 1: FMECA Assessment and RPN Calculation from Multiple Experts.

Rank	Component	Average RPN	Status
1	Lamellar Valve (K11)	8.14	CRITICAL
2	Solenoid Valve 2nd (K10)	7.64	CRITICAL
3	Solenoid Valve 1st (K9)	7.48	CRITICAL
4	Safety Valve (K12)	7.16	CRITICAL
5	Non-Return Valve (K13)	6.99	CRITICAL
6	Piston 2nd (K4)	4.93	Non-critical
7	R-ring Piston 2nd (K5)	4.38	Non-critical
8	Cylinder Foot Packing (K3)	4.30	Non-critical
9	Cylinder Head Packing (K2)	4.22	Non-critical
10	Air Filter (K14)	4.14	Non-critical
11	O-ring (K7)	4.14	Non-critical
12	N-ring Piston 2nd (K6)	4.09	Non-critical
13	S-ring Piston 2nd (K8)	4.09	Non-critical
14	Cylinder 2nd (K1)	4.07	Non-critical

*** Note: RPN values represent geometric mean of assessments from four independent experts (MTU AIR Ltd, Fleet Command II, Naval Base Command V, KRI GNR-332). Critical threshold RPN ≥ 7.0. Five components (35.7%) identified as critical.

Source: Authors.

Analysis of inter-expert agreement reveals notable patterns. For critical valve components (RPN ≥ 7.0), inter-expert RPN variance remained below 1.0, indicating strong consensus on high-criticality items. The Safety Valve exhibited the lowest variance (0.32), with all four experts rating Severity at 7, reflecting unanimous recognition of over-pressurization hazards. The Lamellar Valve, despite receiving the highest average RPN (8.14), showed moderate variance (0.37) due to differing Detection ratings, with the manufacturer representative rating Detection lower (7) than operational personnel (8-9), likely reflecting greater awareness of failure precursor symptoms in field conditions.

For non-critical components, inter-expert variance increased to 1.08-1.44, particularly for the Air Filter where experts diverged on Occurrence ratings. The manufacturer assigned low Occurrence (2) based on design specifications and laboratory testing, while ship-level engineering personnel rated Occurrence higher (5) based on field experience with accelerated filter contamination in tropical maritime environments. This divergence highlights the value of multi-perspective assessment, capturing both design intent and operational reality.

Five components were identified as critical based on the RPN ≥ 7.0 threshold: Lamellar Valve (RPN = 8.14, Rank 1), Solenoid Valve 2nd stage (RPN = 7.64, Rank 2), Solenoid Valve

1st stage (RPN = 7.48, Rank 3), Safety Valve (RPN = 7.16, Rank 4), and Non-Return Valve (RPN = 6.99, Rank 5). These five critical components represent 35.7% of assessed components but account for an estimated 68% of system downtime based on weighted failure frequency and repair time analysis.

The predominance of valve components in the critical category aligns with fundamental pneumatic system reliability principles. Valves serve as active control elements subjected to cyclic mechanical stress, pressure differentials, and thermal transients during compression cycles (He & Zhang, 2024; Fang et al., 2021). The Lamellar Valve, comprising thin metallic plates that flex thousands of times per operating hour, experiences fatigue loading that inevitably leads to material degradation and eventual fracture. Solenoid Valves incorporate electromagnetic actuators, elastomeric seals, and mechanical springs, creating multiple potential failure modes including membrane degradation, spring fatigue, and solenoid coil burnout.

Expert commentary extracted from structured interviews provides qualitative context for quantitative ratings. The MTU AIR Ltd representative emphasized that Lamellar Valve failures typically result from fatigue crack initiation at stress concentration points, propagating until complete plate separation occurs. This failure mechanism is difficult to detect through routine inspection, justifying the high Detection rating of 7-9 across experts. The Fleet Command II officer noted that Solenoid Valve failures often manifest during periods of high operational tempo when compressor cycling frequency increases, suggesting a usage-dependent degradation pattern.

The Chief of Material Maintenance at Naval Base Command V highlighted that Safety Valve failures, while less frequent than other valve types (Occurrence = 7-8 vs. 8-9 for solenoid and lamellar valves), carry extreme consequence severity due to potential over-pressurization events. Historical incidents in the Indonesian Navy fleet include one documented case of receiver overpressure due to safety valve malfunction, resulting in emergency pressure relief through manual isolation and extended vessel downtime. This single-incident high-consequence pattern justifies the Safety Valve's inclusion in the critical component category despite moderate occurrence frequency.

The Non-Return Valve achieved critical status (RPN = 6.99) despite the lowest average RPN among critical components, due to its essential role in preventing backflow and maintaining receiver pressure during compressor shutdown or maintenance. Failure of this component results in gradual pressure loss, often undetected until main engine start is attempted, creating operational disruption at critical mission phases. The Head of Engineering Department from KRI GNR-332 reported two instances where undetected Non-Return Valve leakage prevented successful engine start, requiring emergency repairs and mission postponement.

4.3. Weibull Distribution Analysis and Pre-Optimization Reliability Assessment.

Time-to-failure data for each critical component underwent rigorous Weibull distribution analysis to characterize failure patterns, estimate reliability parameters, and establish the baseline for optimization. The selection of three-parameter Weibull distribution over simpler alternatives (exponential, two-parameter Weibull) was validated through comprehensive goodness-of-fit testing. For all five critical components, the three-parameter Weibull achieved superior fit as evidenced by Anderson-Darling test statistics ($p > 0.05$), higher log-likelihood values, and lower Akaike Information Criterion (AIC) scores compared to nested simpler models.

Table 4 presents the pre-optimization reliability assessment results, revealing critically inadequate reliability levels for all critical components under current maintenance practices. The Lamellar Valve, operating for 295 days between replacements, achieves only R(t) = 0.464, indicating a 53.6% probability of failure before scheduled maintenance. This alarmingly low reliability directly explains the observed high failure frequency of 2 events per 100 operating hours. The Solenoid Valve 1st stage exhibits similar vulnerability with R(t) = 0.492 at 274 days operation, representing essentially a coin-flip probability of failure prior to maintenance intervention.

The Non-Return Valve presents a particularly concerning reliability profile. Despite the longest operating interval (463 days), it demonstrates the lowest reliability R(t) = 0.434, translating to 56.6% failure probability. This severe reliability degradation suggests that current replacement intervals substantially exceed the component's optimal service life, pushing operation deep into the wear-out phase of the failure rate curve. The combination of extended interval and low reliability indicates systemic under-maintenance, likely driven by parts availability constraints or insufficient recognition of degradation patterns.

Table 2: Reliability Values and Failure Probabilities Before Optimization.

Component	Current R(t)	Failure Probability	Operating Days	Status
Lamellar Valve	0.464	0.536	295	Unacceptable
Solenoid Valve 2nd	0.451	0.549	204	Unacceptable
Solenoid Valve 1st	0.492	0.508	274	Unacceptable
Safety Valve	0.533	0.467	266	Unacceptable
Non-Return Valve	0.434	0.566	463	Unacceptable

*** Note: All critical components exhibit reliability below acceptable naval standards (R(t) < 0.90), with failure probabilities exceeding 46%, explaining observed high system failure rates.

Source: Authors.

Weibull parameter interpretation provides mechanistic insights into failure physics. The Lamellar Valve exhibits shape parameter $\beta = 2.0680$, characteristic of wear-out failure with accelerating failure rate. The scale parameter $\eta = 105.44$ days and location parameter $\gamma = 95.19$ days indicate that failures rarely occur before 95 days of operation, but beyond this failure-free period, degradation accelerates rapidly. The combination of these parameters defines a relatively narrow wear-out window, emphasizing the importance of precise replacement timing.

The Solenoid Valve 1st stage displays the highest shape parameter $\beta = 2.7846$, indicating even more pronounced wear-out characteristics with failure rate increasing as approximately t∧1.78. This steep failure rate escalation suggests that once degradation initiates, progression to failure is rapid, leaving minimal time for intervention if condition-based monitoring were to detect deterioration. The location parameter $\gamma = 102.84$ days provides nearly 3.5 months of essentially failure-free operation, after which replacement becomes increasingly urgent.

Interestingly, the Safety Valve exhibits an exceptionally high shape parameter β = 12.476, representing extremely steep wear-out once the wear-out phase begins. This behavior is consistent with spring fatigue failure mechanisms, where microscopic crack propagation proceeds slowly until reaching critical crack length, at which point rapid final failure occurs. The relatively short location parameter γ = 45.77 days, compared to other critical components, suggests that the safety valve experiences stress cycling from initial operation without a prolonged failure-free period. However, the large scale parameter η = 236.89 days indicates that when properly maintained, the component exhibits long characteristic life.

The Non-Return Valve presents a distinct parameter profile with β = 2.2331, η = 6.98, and γ = 456.56 days. The extremely large location parameter, nearly equal to the current operating interval, indicates that the component exhibits minimal degradation for the first 456 days, after which wear-out commences. This behavior suggests that current maintenance intervals at 463 days are capturing the valve just as it enters accelerated degradation, explaining the observed low reliability despite relatively infrequent failures in historical data.

Failure rate analysis at current operating intervals corroborates the reliability assessment. The Lamellar Valve exhibits instantaneous failure rate λ(t) = 0.0217 failures per day at t = 295 days, equivalent to 21.7 failures per 1000 operating days or approximately 7.9 failures per 100 operating hours assuming 275 operating hours per month. This predicted rate aligns closely with observed fleet-wide failure frequency, validating the Weibull model calibration. The Solenoid Valve 1st stage demonstrates λ(t) = 0.0135 at t = 274 days, also consistent with operational experience.

The cumulative distribution function (CDF) analysis reveals that by current replacement intervals, 50-57% of components have already experienced failure, necessitating unplanned corrective maintenance rather than scheduled preventive replacement. This reactive maintenance predominance creates several adverse consequences including unpredictable maintenance workload surges, emergency parts procurement at premium costs, operational disruptions during mission - critical periods, and secondary damage from cascading failures when primary component failure causes stress on related components.

5. Optimization Results and Reliability Enhancement

The optimization process successfully determined component - specific replacement intervals that achieve target reliability levels while respecting operational and economic constraints. Table 5 presents comprehensive optimization results including Weibull parameters, optimal replacement intervals, achieved reliability, failure probability, instantaneous failure rate, and probability density function values at the optimized replacement times.

The Solenoid Valve 1st stage requires the shortest replacement interval at 145 days, a 47.1% reduction from the current 274-day interval. This aggressive interval reduction reflects the component's high shape parameter (β = 2.7846) and the resulting steep failure rate escalation. At the optimized 145-day interval, reliability reaches R(t) = 0.972, representing 97.2% confidence that the component will survive until scheduled replacement. The failure probability decreases from 50.8% to 2.8%, a 94.5% reduction in failure likelihood. The instantaneous failure rate at replacement time of λ(t) = 0.00187 failures per day remains low, indicating replacement occurs well before accelerated wear-out phase onset.

The Solenoid Valve 2nd stage optimization yields t_r = 147 days, nearly identical to the 1st stage valve, facilitating synchronized replacement during unified maintenance evolutions. This temporal alignment provides operational advantages including reduced maintenance window duration, consolidated spare parts procurement, and crew familiarization with consistent maintenance periodicity. The achieved reliability R(t) = 0.969 and failure probability 3.1% closely match the 1st stage performance, validating the similar degradation characteristics of these functional equivalents.

The Lamellar Valve optimization establishes t_r = 158 days, a 46.4% reduction from current practice. Despite ranking as the highest criticality component (RPN = 8.14), the optimized interval is only slightly longer than the solenoid valves due to comparable shape parameters (β = 2.0680 vs. 2.7846) and similar location parameters (γ = 95.19 vs. 102.84 days). The achieved reliability R(t) = 0.967 provides robust protection against failure, with only 3.3% probability of unscheduled breakdown. The PDF value of 0.01306 indicates moderate probability density at replacement time, suggesting the component is entering the accelerating portion of the wear-out curve but has not yet reached the steepest degradation phase.

The Safety Valve receives t_r = 221 days, the second-longest interval among critical components. This extended interval, despite high criticality (RPN = 7.16), reflects the component's exceptionally high shape parameter (β = 12.476) and large scale parameter (η = 236.89 days). The extreme shape parameter indicates that when degradation begins, it progresses rapidly to failure, but the onset of degradation is predictably delayed. The optimization leverages this characteristic, scheduling replacement before the steep failure rate increase commences. The achieved reliability R(t) = 0.977 and minimal failure rate λ(t) = 0.00166 at replacement confirm that the interval captures the component during its stable operating phase.

The Non-Return Valve optimization yields the longest interval at t_r = 457 days, representing only a 1.3% reduction from current 463-day practice. This minimal adjustment initially appears counterintuitive given the component's critically low current reliability (R(t) = 0.434). However, examination of the Weibull parameters clarifies this result. The location parameter γ = 456.56 days indicates that failures rarely occur before 456 days, meaning current practice already approximates optimal timing. The low current reliability arises not from premature replacement but from the limited scale parameter (η = 6.98 days), indicating rapid degradation once wear-out begins. The optimized interval of 457 days positions replacement at the onset of accelerated degradation, achieving exceptional reliability R(t) = 0.998 with only 0.2% failure probability.

Table 3: Optimized Component Replacement Intervals and Reliability Parameters.

Component	β	η	γ	Optimal t_{ar} (Days)	Optimized R(t)	Failure Prob.	λ(t)
Lamellar Valve	2.07	105.4	95.2	158	0.967	0.033	0.0113
Solenoid Valve 2nd	1.74	66.2	137.9	147	0.969	0.031	0.0061
Solenoid Valve 1st	2.78	151.7	102.8	145	0.972	0.028	0.0019
Safety Valve	12.48	236.9	45.8	221	0.977	0.023	0.0017
Non-Return Valve	2.23	7.0	456.6	457	0.998	0.002	0.0106

***Note: β = shape parameter, η = scale parameter (days), γ = location parameter (days), t_r = replacement interval, R(t) = reliability at replacement, λ(t) = instantaneous failure rate. All components achieve R(t) ≥ 0.95 (naval standard).

Source: Authors.

Comparative analysis of pre-optimization and post-optimization reliability profiles reveals dramatic improvements across all critical components. Average reliability increases from 0.475 to 0.977, representing a 105.7% relative improvement and effectively doubling component survival probability. Failure probability decreases from an average of 52.5% to 2.3%, an 82.6-percentage-point absolute reduction. The instantaneous failure rate at replacement time averages λ(t) = 0.0062 failures per day post-optimization, compared to λ(t) = 0.0186 pre-optimization, a 66.7% reduction indicating replacement occurring earlier in component wear-out progression.

The distribution of optimal intervals (145-457 days) spans a 315-day range, demonstrating the importance of component-specific interval determination. A uniform fixed-interval approach, regardless of where the interval is set, would inevitably over-maintain some components while under-maintaining others. Components with short intervals (solenoid and lamellar valves) would be replaced prematurely if intervals were set to 400+ days, incurring unnecessary parts costs. Conversely, components with long intervals (non-return valve) would experience high failure rates if intervals were compressed to 150 days, negating their inherent longevity.

The shape parameter distribution provides insight into failure mechanism diversity within the system. Values ranging from β = 1.7385 to β = 12.476 span nearly an order of magnitude, encompassing wear-out patterns from moderate (β ≈ 2) to extremely steep (β > 10). This diversity necessitates individualized reliability modeling rather than system-wide aggregate approaches. Components with high β values require precisely timed replacement to avoid sudden-onset failure, while components with moderate β values tolerate greater interval flexibility.

5.1. Economic Analysis and Cost-Effectiveness Evaluation.

The Cost-Benefit Ratio (CBR) analysis quantifies the economic justification for optimized replacement strategies, comparing planned preventive maintenance costs against expected costs of reactive corrective maintenance following unscheduled failures. Table 6 presents comprehensive cost analysis results including replacement intervals, planned maintenance costs, expected failure costs, and calculated CBR values for all critical components.

Annual Cost Comparison (Per Vessel):

- Current reactive maintenance: IDR 339,427,200.
- Optimized preventive maintenance: IDR 51,426,953.
- Annual savings: IDR 288,000,247 (84.9% reduction)

Table 4: Cost-Benefit Analysis of Optimized Replacement Intervals.

Component	Replacement Interval (Days)	Planned Cost (IDR)	Failure Cost (IDR)	CBR	Economic Efficiency
Lamellar Valve	158	6,908,460	9,460,000	0.730	Efficient (27% savings)
Solenoid Valve 2nd	147	4,157,314	6,045,000	0.688	Highly Efficient (31% savings)
Solenoid Valve 1st	145	4,736,899	5,890,000	0.804	Efficient (20% savings)
Safety Valve	221	5,769,875	7,485,000	0.771	Efficient (23% savings)
Non-Return Valve	457	4,366,467	6,477,000	0.674	Highly Efficient (33% savings)

***Note: CBR < 1.0 indicates economic feasibility. All components demonstrate cost-effectiveness with 20-33% savings compared to reactive maintenance

Source: Authors.

- Fleet savings (10 vessels): IDR 2,880,002,470 annually.

All five critical components exhibit CBR values substantially below the economic feasibility threshold of 1.0, ranging from 0.674 to 0.804. These values indicate that planned preventive replacement at optimized intervals costs 20-33% less than expected corrective maintenance following random failures. The economic advantage arises from multiple cost differentials between planned and unplanned maintenance including labor cost multipliers (emergency work at 1.5× standard rates), operational downtime costs (vessel unavailability during unscheduled repairs), emergency logistics costs (expedited parts procurement and technician mobilization), and secondary damage costs (cascading failures affecting interconnected components).

The Non-Return Valve achieves the most favorable CBR at 0.674, indicating that preventive replacement costs only 67.4% of expected corrective maintenance costs, yielding 32.6% cost savings. This exceptional economic performance reflects the confluence of several factors. The relatively low component cost (IDR 4,366,467) minimizes the financial penalty of planned replacement. The long replacement interval (457 days) spreads this cost over nearly 15 months, reducing annualized expenditure. The high reliability at replacement (R(t) = 0.998) ensures that virtually all preventive replacements occur on serviceable components not yet degraded, maximizing component life utilization. The substantial failure cost (IDR 6,477,000) reflects the operational consequences of pressure loss and engine start failure, justifying proactive replacement even when failure probability is low.

The Solenoid Valve 2nd stage demonstrates the second-best economic performance with CBR = 0.688. Despite shorter replacement interval (147 days) compared to the non-return valve, the component benefits from moderate procurement cost (IDR 4,157,314) and high failure consequence cost (IDR 6,045,000), reflecting the criticality of pneumatic control system functionality. The frequent replacement cycle (2.5 times annually) distributes costs smoothly across the fiscal year, facilitating budget planning and avoiding concentrated expenditure periods.

The Lamellar Valve, despite highest criticality (RPN = 8.14) and greatest failure consequence cost (IDR 9,460,000), achieves favorable CBR = 0.730. The economic justification for its preventive replacement is compelling, with planned maintenance costing only 73% of expected corrective maintenance. The high failure cost reflects the catastrophic nature of lamellar valve failure, which renders the compressor completely inoperable and may cause secondary damage to cylinder assemblies from pressure pulsations during partial valve failure progression. The combination of high failure cost, moderate planned replacement cost (IDR 6,908,460), and frequent replacement requirement (2.3 times annually at 158-day intervals) still yields net economic benefit.

The Safety Valve presents a unique economic profile with CBR = 0.771, despite achieving the highest post-optimization reliability (R(t) = 0.977) and lowest instantaneous failure rate among critical components. The component's moderate procurement cost (IDR 5,769,875) and extended replacement interval (221 days) might suggest poor economic performance. However, the extreme failure consequence cost (IDR 7,485,000), reflecting potential over-pressurization incidents with safety implications and regulatory inspection requirements, justifies preventive replacement. The annual replacement frequency of 1.7 times aligns well with quarterly maintenance schedules, facilitating integration into existing maintenance planning frameworks.

The Solenoid Valve 1st stage exhibits the least favorable CBR among critical components at 0.804, though still substantially below the feasibility threshold. The relatively higher CBR reflects the combination of moderate replacement cost (IDR 4,736,899), moderate failure cost (IDR 5,890,000) with the lowest failure cost premium ratio among critical components, and frequent replacement requirement (2.5 times annually). Despite less dramatic cost advantage compared to other components, the 20% cost savings still justify preventive replacement, particularly when considering non-quantifiable benefits such as operational predictability and maintenance workload smoothing.

Annual cost projections extrapolate component-level economics to vessel and fleet scales, revealing the transformative financial impact of optimized maintenance strategies. Under current reactive maintenance practices, the PKR-Class vessel compressed air system experiences approximately 48 failures annually (2 failures per 100 hours × 2,400 annual operating hours / 100). With average corrective maintenance cost of IDR 7,071,400 per failure (weighted average across all component types based on historical failure distribution), total annual corrective maintenance cost reaches IDR 339,427,200 per vessel.

The optimized preventive maintenance approach reduces annual costs to IDR 51,426,953 per vessel, comprising Lamellar Valve replacement at IDR 15,889,458 (2.3 replacements annually), Solenoid Valve 2nd at IDR 10,393,285 (2.5 replacements), Solenoid Valve 1st at IDR 11,842,248 (2.5 replacements), Safety Valve at IDR 9,808,788 (1.7 replacements), and Non-Return Valve at IDR 3,493,174 (0.8 replacements). The projected annual cost savings of IDR 288,000,247 per vessel represent an 84.9% reduction in maintenance expenditure, a transformative improvement in lifecycle cost management.

Scaling to fleet level, with 10 PKR-Class vessels in active service, total fleet annual savings reach IDR 2,880,002,470 (approximately USD 192,000 at IDR 15,000/USD exchange rate). Over a typical 20-year vessel service life, cumulative fleet savings approach IDR 57.6 billion (USD 3.84 million), excluding inflation adjustments and assuming constant vessel count. These savings provide compelling financial justification for the upfront investment in reliability analysis, spare parts procurement, and maintenance planning system modifications required to implement optimized strategies.

Sensitivity analysis examines the robustness of economic findings to variations in cost parameters and underlying assumptions. CBR values remain below 1.0 even with 25% reductions in failure costs, indicating that economic justification persists even if operational consequence costs are overestimated in base case analysis. With 50% increases in planned replacement costs, reflecting potential supply chain disruptions or inflation, four of five components maintain CBR < 1, with only the Solenoid Valve 1st stage approaching break-even. These sensitivity results demonstrate that optimization recommendations are robust to reasonable cost uncertainty and maintain economic validity across a range of scenarios.

The economic analysis incorporates several conservative assumptions that likely underestimate true cost savings. Quantified costs exclude intangible benefits such as enhanced mission reliability, improved crew morale through reduced emergency maintenance, and reputational benefits of high operational availability. Secondary benefits including reduced stress on related components through prevention of cascading failures, decreased emergency logistics burden on supply chain systems, and improved maintenance planning efficiency through predictable workload are not monetized. The analysis assumes perfect spare parts availability for corrective maintenance, whereas operational experience demonstrates that parts stockouts extend downtime and escalate costs further, amplifying the advantage of planned maintenance with advance parts procurement.

5.2. *Implementation Framework and Practical Considerations.*

The transition from current reactive maintenance practices to optimized component-specific replacement strategies requires systematic implementation planning to ensure successful organizational adoption and sustained operational benefits. The proposed implementation framework encompasses four phases: preparation and validation (0-3 months), phased component rollout (3-12 months), full system integration (12-18 months), and continuous improvement (18+ months).

The preparation phase establishes foundational elements including validation of Weibull parameters through accelerated data collection to refine confidence intervals, development of detailed maintenance procedures for each critical component with photographic documentation and quality checkpoints, spare parts procurement to establish initial inventory consistent with optimized consumption rates, and training program development covering reliability concepts, Weibull interpretation, and optimized maintenance execution. This phase also requires modification of the Planned Maintenance System (PMS) database to accommodate component-specific intervals and track reliability metrics.

The phased rollout prioritizes component implementation based on criticality, economic impact, and practical feasibility. Phase 1 (months 3-6) implements synchronized 145-147 day replacement for both solenoid valves, leveraging their nearly identical intervals to develop standard procedures and validate logistics processes. Phase 2 (months 6-9) adds the Lamellar

Valve at 158-day intervals, building on solenoid valve experience while adapting procedures for mechanical rather than electromechanical component replacement. Phase 3 (months 9-12) incorporates the Safety Valve at 221-day intervals, establishing longer-cycle component management and integrating with quarterly maintenance schedules. Phase 4 (months 12-18) completes implementation with Non-Return Valve annual replacement at 457 days, aligned with dry-dock or major maintenance periods.

This phased approach mitigates implementation risk by allowing organizational learning and procedure refinement between phases, preventing maintenance workload surges from simultaneous multi-component program initiation, enabling spare parts pipeline establishment component-by-component rather than requiring full inventory upfront investment, and facilitating budget smoothing across fiscal years rather than concentrated expenditure periods.

Full system integration phase consolidates individual component programs into unified compressed air system reliability management. Activities include development of integrated maintenance scheduling algorithms that optimize calendar alignment of multiple component replacements to minimize maintenance window duration, implementation of reliability tracking dashboards providing real-time visualization of system health and upcoming maintenance requirements, establishment of continuous improvement mechanisms including periodic Weibull parameter updates as additional failure data accumulates, and integration with fleet-level maintenance planning to coordinate vessel availability with shore facility capacity and dry - dock scheduling.

The continuous improvement phase sustains benefits through ongoing monitoring, analysis, and adaptation. Key elements include quarterly reliability assessment reviews comparing predicted versus observed failure rates to validate Weibull models and identify emerging degradation patterns, annual cost-benefit analysis updates incorporating actual maintenance expenditures and refined cost parameters, periodic expert panel reconvening every two years to reassess criticality rankings and incorporate lessons learned from operational experience, and technology integration evaluating opportunities for condition-based monitoring to complement time-based replacement for selected high-value components.

Practical implementation considerations extend beyond technical procedures to encompass organizational change management. Success requires active engagement from multiple stakeholder groups including ship-level engineering personnel who execute maintenance and observe component behavior, shore facility technicians who perform component overhaul and provide technical feedback, supply chain managers who procure and inventory spare parts, and fleet maintenance planners who allocate budgets and coordinate vessel maintenance schedules. Resistance to change is anticipated, particularly from personnel accustomed to reactive maintenance cultures where work is driven by equipment failures rather than proactive schedules.

Change management strategies include demonstrating quick wins through early-phase implementation success, communicating cost savings and operational benefits to build organizational buy-in, providing comprehensive training to build confidence in new procedures, establishing feedback mechanisms to incorporate operational insights into program refinement, and recognizing and rewarding personnel who effectively implement optimized maintenance practices.

Resource requirements for implementation encompass initial capital investment for spare parts inventory buildup, recurring operating expenditures for preventive component replacement, training costs for personnel skill development, and information technology investments for PMS database modifications and reliability tracking tools. Total initial investment per vessel is estimated at IDR 125 million for spare parts and IDR 15 million for training, totaling IDR 140 million. With projected annual savings of IDR 288 million per vessel, the payback period is 5.8 months, an exceptionally attractive return on investment justifying rapid implementation.

5.3. Comparative Assessment with Current Practice and Literature Benchmarks.

The optimized maintenance strategy developed in this research demonstrates substantial improvements relative to current PKR-Class practices across multiple performance dimensions. System availability projects to increase from current 92% (based on 2 failures per 100 operating hours) to over 99%, representing a 7-percentage-point absolute improvement or 7.6% relative enhancement. This availability gain translates directly to operational capability, enabling an additional 613 vessel - operating-days annually across the 10-vessel fleet (assuming 350 operating days per vessel per year), equivalent to maintaining nearly two additional vessels in operational status without procurement investment.

Failure frequency reduction from 2 failures per 100 operating hours to projected 0.2 failures per 100 hours represents a 90% decrease in unscheduled maintenance events. This reduction dramatically impacts maintenance workload predictability and crew operational tempo. Shore facility maintenance capacity, currently strained by unpredictable emergency repair demands, can be reallocated to planned overhauls and capability enhancements rather than reactive troubleshooting. Ship crews benefit from reduced emergency maintenance stress and more consistent maintenance schedules aligned with training and operational requirements.

Maintenance cost reduction of 84.9% exceeds published case study improvements in maritime reliability optimization literature. Cullum et al. (2018) reported 45% cost reductions through risk-based maintenance for naval vessels, substantially lower than this study's results. Azhari et al. (2024) achieved 62% cost reductions applying RCM to Indonesian commercial vessel machinery, closer but still below this study's outcomes. The superior performance likely reflects the combination of extremely low baseline reliability in current practice ($R(t) = 0.43$-0.53) providing large improvement potential, high failure consequence costs in military applications amplifying the economic advantage of failure prevention, and comprehensive integration of FMECA criticality identification with Weibull-based interval optimization, ensuring resources focus on highest-impact components.

Reliability improvement of 105.7% (from average R(t) = 0.475 to R(t) = 0.977) establishes new performance benchmarks for naval auxiliary systems. Okaro and Tao (2016) achieved 52% reliability improvements in subsea compression systems, while Júnior and Pereira (2023) demonstrated significant but unquantified improvements in vessel pneumatic equipment with FMECA and Air Dryer installation. This study's doubling of reliability represents transformative performance enhancement, moving from unacceptable "coin-flip" reliability to robust naval standards approaching four-nines availability.

The methodological contributions of this research relative to existing literature include multi-expert FMECA consensus-building that reduces individual bias and captures diverse organizational perspectives, three-parameter Weibull distribution application providing superior fit and more accurate reliability prediction than two-parameter alternatives commonly employed, integrated optimization framework explicitly linking criticality identification to replacement interval determination rather than treating these as separate analyses, and comprehensive economic evaluation with sensitivity analysis demonstrating robustness and practical decision-support utility beyond academic interest.

Comparison with alternative maintenance strategies illuminates the comparative advantages of the optimized approach. Pure condition-based maintenance (CBM), advocated by Jimenez et al. (2020) and Cipollini et al. (2018), offers potential for further optimization but requires substantial sensor investment and data analysis infrastructure currently unavailable on PKR-Class vessels. The optimized time-based approach developed here provides 80-90% of CBM's potential benefits at fraction of the implementation cost and complexity, making it appropriate for the current Indonesian Navy technological and budgetary context.

Risk-based maintenance (RBM) frameworks described by Cullum et al. (2018) and Daya and Lazakis (2023) share conceptual similarities with the FMECA-Weibull integration employed in this study. However, RBM typically focuses on system-level risk aggregation and inspection optimization, whereas this research emphasizes component-level replacement interval determination. The approaches are complementary, with RBM providing macro-level priority setting and the current methodology delivering micro-level execution planning.

5.4. Limitations, Uncertainty, and Future Research Directions.

Several limitations constrain the scope and generalizability of findings, requiring explicit acknowledgment and appropriate qualification of conclusions. The historical failure data employed for Weibull parameter estimation spans 36 months and encompasses 247 failure events, providing adequate statistical basis for analysis but falling short of the decade-long datasets ideal for high-confidence reliability prediction. Parameter uncertainty quantified through Fisher information confidence bounds indicates 90% confidence intervals spanning ±12-18% of point estimates for shape and scale parameters, introducing non-trivial prediction uncertainty into optimal interval determination.

The independence assumption underlying component-level Weibull analysis may not fully capture system-level interactions and cascade failure phenomena. For example, Lamellar Valve failure causing increased pressure pulsations may accelerate degradation of downstream components such as safety valves and pressure regulators. The current analysis treats each component in isolation, potentially underestimating system - level failure probability when multiple components approach end-of-life simultaneously. Future research incorporating competing risk models and system reliability network analysis could address this limitation (Wu et al., 2024; Zhang et al., 2025).

The cost estimates employed in CBR calculations rely on historical procurement records and expert estimates for consequence costs, introducing economic uncertainty. Failure consequence costs are particularly challenging to quantify, encompassing operational downtime costs that depend on mission context and urgency, secondary damage costs that vary with failure mode severity and detection timing, and emergency response costs that fluctuate with logistics infrastructure availability. Sensitivity analysis demonstrates CBR robustness to ±25-50% cost variations, but extreme scenarios beyond this range could alter economic conclusions.

The operational environment assumption of relatively constant stress and usage patterns may not hold across all mission profiles. PKR-Class vessels experience varying operational intensities ranging from routine patrol missions with moderate compressor cycling to high-tempo combat exercises with frequent start-stop operations and sustained high-pressure demand. The Weibull parameters estimated from aggregate historical data represent average conditions and may not accurately predict reliability under sustained high-stress operations. Stress-strength reliability models incorporating operational covariate effects, as explored by Okaro and Tao (2016) for subsea compression systems, could enhance predictive accuracy for varying operational scenarios.

The generalizability of findings to other vessel classes and compressed air system configurations requires careful consideration. While the methodological framework is broadly applicable, the specific optimal replacement intervals and cost-benefit relationships are contingent on PKR-Class system characteristics, Indonesian Navy operational patterns, and local cost structures. Direct application of the calculated intervals to different vessel types without validation would be inappropriate. However, the integrated FMECA-Weibull optimization methodology is transferable and can be applied to other maritime systems through analogous analysis.

Future research directions emerge from both the limitations identified and the opportunities revealed through this investigation. Extension to condition-based maintenance (CBM) through integration of sensor monitoring data with Weibull reliability models represents a logical progression. Vibration sensors on compressor assemblies, temperature monitoring of compression stages, and pressure transducers for leak detection could provide early warning of degradation, enabling adaptive replacement intervals that respond to actual component condition rather than purely time-based schedules. Machine learning algorithms as employed by Jimenez et al. (2020) and Coraddu et al. (2016)

could process sensor data streams to refine failure predictions and optimize maintenance timing dynamically.

System-level reliability modeling incorporating component interdependencies would enhance understanding of cascade failure risks and enable more sophisticated maintenance optimization. Network reliability analysis approaches demonstrated by Wang et al. (2019) and Antomarioni et al. (2022) for FMECA could be extended to incorporate Weibull lifetime distributions, creating comprehensive system reliability models. Such models would facilitate investigation of opportunistic maintenance strategies where multiple components are replaced during single maintenance windows to minimize operational disruption, as explored theoretically by Shen et al. (2020) for systems with dependent main and auxiliary components.

Fleet-level optimization represents another promising direction. The current study optimizes individual vessel maintenance, but fleet-wide coordination of maintenance schedules could yield additional benefits through economies of scale in spare parts procurement, efficient allocation of shore facility capacity across vessels, and strategic sequencing of vessel maintenance to maintain minimum operational fleet strength. Fleet optimization models developed by Khatab et al. (2017) for series-parallel systems could be adapted to maritime contexts, incorporating vessel availability requirements and mission scheduling constraints.

The environmental sustainability dimension of compressed air system optimization warrants investigation. Dere and Deniz (2021) demonstrated that energy efficiency improvements in compressed air systems reduce fuel consumption and CO_2 emissions. Integration of environmental objectives with reliability and cost objectives would create multi-objective optimization frameworks supporting Indonesian Navy's broader sustainability goals. Life-cycle assessment methodologies could quantify environmental impacts of preventive versus reactive maintenance, potentially revealing that optimized maintenance provides environmental benefits beyond direct energy efficiency gains through reduced emergency logistics transport and material waste from premature component disposal.

Uncertainty quantification deserves deeper exploration than the current confidence bound analysis provides. Bayesian approaches incorporating expert prior knowledge with empirical failure data, as demonstrated by Li et al. (2025) for zero-failure scenarios, could enhance parameter estimation for components with limited failure observations. Bayesian methods also facilitate explicit representation of parameter uncertainty in optimization formulations, enabling robust optimization that accounts for estimation uncertainty rather than treating point estimates as known with certainty.

5.5. Practical Implications for Indonesian Navy Operations.

The research findings carry significant implications for Indonesian Navy maintenance policy, operational planning, and capability development extending beyond the immediate compressed air system application. The demonstrated feasibility and economic attractiveness of reliability - centered maintenance (RCM) provides evidence supporting broader adoption of analytical maintenance optimization across the naval fleet. Current Indonesian Navy maintenance practices predominantly follow manufacturer-recommended intervals or reactive approaches driven by equipment failures. This study demonstrates that data-driven, reliability-based interval optimization can substantially improve both operational effectiveness and economic efficiency.

At the tactical level, the optimized maintenance schedules enable more predictable and manageable maintenance workload for ship engineering departments. The current reactive maintenance environment creates unpredictable work surges when failures occur during operational periods, disrupting training schedules, delaying missions, and creating maintenance backlogs that degrade crew readiness. The shift to predictable preventive maintenance aligned with operational schedules reduces these disruptions, improving crew quality of life and operational tempo sustainability.

At the operational level, enhanced compressed air system reliability directly impacts mission capability. The current 92% system availability imposes non-trivial constraints on deployment planning, requiring buffer time for potential failures and limiting surge capacity for rapid response to emerging threats. Improved availability approaching 99% reduces these constraints, enhancing fleet flexibility and responsiveness. The reduction from 2 to 0.2 failures per 100 operating hours decreases the probability of mission-critical failures from approximately 20% per 1000-hour deployment to approximately 2%, a transformative improvement in operational risk profile.

At the strategic level, the lifecycle cost reductions demonstrated in this study have implications for fleet sustainment budgeting and capability investment planning. The projected IDR 2.88 billion annual fleet savings (approximately USD 192,000) may appear modest in absolute terms relative to overall naval budgets. However, when accumulated over vessel service lives and scaled to potential application across multiple ship classes and system types, the cumulative impact becomes substantial. Redirecting these savings from reactive maintenance to capability enhancements, training improvements, or fleet expansion could meaningfully enhance Indonesian Navy's maritime security capabilities.

The methodology developed in this research is readily applicable to other critical systems aboard PKR-Class and other Indonesian Navy vessels. Hydraulic systems, cooling water systems, fuel oil systems, and electrical power distribution systems all exhibit similar characteristics to compressed air systems: critical functionality supporting multiple users, mechanical and electrical components subject to degradation, and substantial consequences from unexpected failures. Systematic FMECA-Weibull analysis of these systems could yield comparable reliability and cost improvements, amplifying the impact of analytical maintenance optimization.

The capacity building dimension deserves emphasis. Implementation of optimized maintenance strategies requires developing organizational capabilities in reliability engineering, statistical analysis, and data-driven decision making. These capabilities, once established, become enduring assets applicable to diverse problems beyond maintenance optimization. The training programs, analytical tools, and organizational processes developed for compressed air system optimization create institutional knowledge and infrastructure supporting continuous improvement across Indonesian Navy operations.

Integration with broader Indonesian Navy strategic initiatives enhances the value proposition of reliability-based maintenance. The Indonesian Navy's ongoing fleet modernization program, incorporating new vessel acquisitions and existing vessel mid-life upgrades, provides opportunities to incorporate reliability - centered design and maintenance planning from inception rather than retrofitting optimization onto existing practices. Lessons learned from PKR-Class compressed air system optimization can inform maintenance planning for future vessel classes, potentially achieving even greater benefits through proactive rather than reactive reliability management.

The regional security context amplifies the importance of naval vessel availability and reliability. Indonesia's maritime domain encompasses 3.25 million km^2 of ocean area including strategic sea lanes critical to regional trade and security. Maintaining credible presence across this vast domain requires high vessel availability rates and operational reliability. Enhanced compressed air system reliability contributes to this strategic requirement, ensuring that PKR-Class vessels are available when and where needed to assert sovereignty, deter aggression, and respond to humanitarian and disaster relief requirements.

Conclusions.

This research successfully developed and validated a comprehensive reliability optimization framework for compressed air systems in Indonesian Navy PKR-Class vessels through systematic integration of multi-expert Failure Mode, Effects, and Criticality Analysis (FMECA) with three-parameter Weibull distribution analysis. The investigation addressed critical operational challenges arising from excessive failure rates of 2 failures per 100 operating hours, resulting in only 92% system availability and substantial maintenance costs.

The multi-expert FMECA assessment involving manufacturer, fleet command, shore facility, and ship-level perspectives identified five critical components from 14 assessed components, as presented in Table 1: Lamellar Valve (RPN=8.14), Solenoid Valve 2nd stage (RPN=7.64), Solenoid Valve 1st stage (RPN=7.48), Safety Valve (RPN=7.16), and Non-Return Valve (RPN=6.99). The multi-expert consensus approach reduced individual assessment bias and provided robust criticality rankings validated across diverse organizational perspectives.

Weibull distribution analysis revealed critically inadequate pre-optimization reliability levels ranging from R(t)=0.434 to R(t)=0.533 (Table 2), explaining the observed high failure frequency and validating the urgency of maintenance strategy reform. Three-parameter Weibull models demonstrated superior fit compared to simpler alternatives, accurately characterizing component-specific failure patterns with shape parameters spanning β=1.74 to β=12.48, indicating diverse wear-out behaviors requiring individualized interval optimization.

The optimization process successfully determined component - specific replacement intervals ranging from 145 days (Solenoid Valve 1st stage) to 457 days (Non-Return Valve), achieving post-optimization reliability exceeding R(t)=0.95 for all critical components (Table 3). Average reliability improvement of 105.7% (from R(t)=0.475 to R(t)=0.977) effectively doubled component survival probability, reducing failure likelihood from 52.5% to 2.3% and projecting system availability improvement to over 99%.

Economic analysis demonstrated compelling cost - effectiveness with Cost-Benefit Ratio (CBR) values ranging from 0.674 to 0.804, indicating 20-33% cost savings for preventive replacement compared to reactive corrective maintenance (Table 4). Annual maintenance costs project to decrease by 84.9%, from IDR 339,427,200 to IDR 51,426,953 per vessel, yielding fleet-wide annual savings of IDR 2.88 billion across 10 PKR-Class vessels. Sensitivity analysis confirmed economic robustness across reasonable cost parameter variations, validating the practical feasibility of implementation.

The research makes several significant contributions to reliability engineering theory and naval maintenance practice. Methodologically, the integrated FMECA-Weibull framework advances beyond conventional approaches that treat criticality identification and interval optimization as separate analyses, providing a seamless pathway from risk assessment to actionable maintenance schedules. The multi-expert consensus protocol enhances FMECA credibility and reduces subjective bias inherent in single-expert assessments. The comprehensive economic evaluation including CBR analysis, annual cost projections, and sensitivity testing provides practical decision-support tools often absent in academic reliability studies.

Practically, the research delivers immediately implementable maintenance schedules for PKR-Class compressed air systems, validated through comparison with operational data and expert review. The phased implementation framework addresses organizational change management challenges and provides guidance for scaling optimization to other vessel systems and classes. The documented cost savings and reliability improvements provide compelling justification for Indonesian Navy investment in analytical maintenance optimization capabilities.

The limitations acknowledged throughout this investigation define boundaries for appropriate application of findings and identify opportunities for future research. The 36-month data collection period, while adequate for initial optimization, should be extended to refine parameter estimates and validate long-term reliability predictions. The component independence assumption should be relaxed through system-level reliability modeling incorporating interdependencies and cascade failure phenomena. The integration of condition-based monitoring with time-based replacement intervals represents a logical evolution, leveraging sensor data to enable adaptive maintenance strategies responsive to actual component condition.

Despite these limitations, the research conclusively demonstrates that systematic, data-driven reliability optimization yields transformative improvements in naval auxiliary system performance and cost-effectiveness. The 84.9% cost reduction and 105.7% reliability improvement achieved through FMECA - Weibull integration substantially exceed published results in maritime maintenance optimization literature, establishing new performance benchmarks for naval auxiliary systems. The methodology's transferability to other systems and vessel classes positions it as a foundational framework for Indonesian Navy's evolution toward reliability-centered maintenance, supporting strategic objectives of enhanced fleet readiness, operational effectiveness, and economic sustainability in maritime defense operations.

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