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Reliability Methods in Maintenance and Failure Analysis of Marine Systems

Damir BUDIMIR[1], Ivan GRGUREVIĆ[2], Jasna LEDER HORINA[3]

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[1] Corresponding author, dbudimir@fpz.unizg.hr, University of Zagreb, Faculty of Transport and Traffic Sciences
[2] igrgurevic@fpz.unizg.hr, University of Zagreb, Faculty of Transport and Traffic Sciences
[3] jleder@fpz.unizg.hr, University of Zagreb, Faculty of Transport and Traffic Sciences

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ABSTRACT

This paper explores the application of advanced analytical methods and predictive maintenance technologies to optimise maintenance strategies for complex technical systems, with a specific focus on marine engines and high-pressure fuel pumps. Weibull analysis facilitated the identification of failure patterns and precise planning of maintenance intervals, while hidden Markov models (HMM) provided deeper insights into the dynamics of state transitions, such as degradation and failure. The results demonstrate that combining reliability theory with cost analysis ensures an optimal balance between maintenance costs and system reliability. HMM revealed how changes in pump performance directly impact engine functionality, whereas failure data alone often fail to provide a clear understanding of system conditions. Integrating HMM enabled better comprehension of underlying processes, which is crucial for aligning pump maintenance with reduced failure rates and improved operational efficiency. The application of these methods and technologies reduces maintenance costs, extends equipment lifespan and enhances overall efficiency. System safety is ensured, and the risk of unexpected failures is minimised, contributing to the stability and economic sustainability of complex technical systems. This integrated approach offers a framework for future maintenance strategies, uniting technical and financial aspects into a comprehensive solution for long-term reliability and effectiveness.

KEYWORDS

Weibull analysis; hidden Markov models (HMM); preventive maintenance; predictive maintenance; system reliability; technical logistics.

1. INTRODUCTION

Reliability theory is often applied to analyse the safety and maintenance of complex systems, including maritime systems [1].

According to research by Dominguez-Péry, Tassabehji and Corset (2023), maritime incidents caused by ship system failures, such as fires and collisions, significantly threaten safety and emphasise the need for implementing advanced risk assessment methods [2]. These findings highlight the critical importance of integrating reliability and risk analysis methods to identify critical failure points and reduce the risk of future incidents.

Analyses of maritime accidents, including collisions, loss of control and fires, emphasise the need for innovative approaches to risk prevention and maintenance optimisation. Recent studies, such as the work of Yang (2023), stress the importance of advanced reliability models and control frameworks for ensuring operational safety, particularly in autonomous marine systems. Methods like Bayesian networks and scenario analysis are employed to assess the safety and reliability of these systems, aiding in the early identification of failure risks. This approach aligns with the broader field of reliability theory, which plays a key role in optimising preventive maintenance and improving the predictability of system performance. Through data-driven risk assessments, such research contributes to reducing incidents, improving operational safety and lowering costs in maritime transportation [3].

Methods such as the component criticality analysis proposed by Daya and Lazakis (2023) enable not only accurate assessment of current risks but also improved prioritisation of maintenance needs. Their work focuses on the preventive maintenance of ship engines, emphasising that a lack of understanding and application of reliable analytical methods, such as fault detection and criticality analysis, often contributes to maritime accidents. They propose enhancing the overall reliability of ship systems as a crucial factor in preventing unexpected failures and optimising maintenance planning [4].

Reliability and maintenance of complex technical systems, such as ship engines, are critical factors for the safety and efficiency of maritime transport. The main ship engine serves as the primary source of power and propulsion, with its functionality relying on the performance of critical components, notably high-pressure fuel pumps. Failures of these pumps significantly impact engine operation, causing bottlenecks in supply chains, high corrective maintenance costs and delays in maritime operations [5].

Studies show that high-pressure pump failures are often linked to sudden performance drops, necessitating adaptive maintenance strategies to reduce costs and enhance system reliability [6, 7]. Long-standing discussions in academic and technical circles emphasise the advantages of preventive over corrective maintenance. Research by Bukša (2005) and Mihanović (2015) highlights the economic justification of reliability-based maintenance (RCM) systems. Bukša's doctoral thesis introduces Weibull distribution modelling for ship propulsion systems, offering guidelines for optimising the maintenance of critical components like main diesel engines [5]. Similarly, Mihanović's work confirms the effectiveness of Weibull analysis in assessing failures of high-speed radial engines [6].

Advanced mathematical models, such as the Weibull distribution, have proven useful across industries. For instance, Kunar et al. (2013) applied this model to analyse diesel locomotive failures, identifying causes and proposing strategies to mitigate logistical losses [7]. These findings underscore the importance of reliability models for understanding degradation processes and planning more effective maintenance.

This study is based on data collected from the technical services of container ships over a one-year period (2022/23), encompassing real-world operating conditions and insights into pump and engine failures. Particular attention is given to the reliability analysis of pumps using the discussed models, which reveal hidden factors contributing to failures and support the development of effective maintenance strategies. Condition-based maintenance (CBM) strategies also represent a significant advancement in technical system management. Karatuğ et al. (2024) applied neural networks to predict failures in ship systems, improving equipment reliability, reducing operating costs and enhancing operational safety [8]. These findings highlight the potential of artificial intelligence for maritime industry applications, particularly in maintenance optimisation.

Moreover, the study emphasises the importance of RCM implementation, which not only reduces the number of sudden failures but also optimises resources, including spare parts and human resources [9]. By leveraging reliability-based maintenance, both technical and economic efficiency are enhanced, making it an indispensable part of modern maintenance strategies. These models provide deeper insights into the underlying failure processes and suggest optimal maintenance intervals, reducing unexpected breakdowns and improving overall system performance. Notably, fuel pump failures can indirectly contribute to these events, emphasising the need for maintenance optimisation [10] and the modernisation of diagnostic systems.

This research focuses on improving the reliability and safety of ship propulsion systems, with a particular emphasis on the impact of pump failures on operational performance. It contributes to a better understanding of maritime maintenance challenges and offers practical guidelines for further research and optimisation of data-driven maintenance processes.

2. BACKGROUND

2.1 The role of container ships in the global supply chain

Container ships are a vital segment of the global transportation system due to their adaptability, capacity and efficiency. Their classification is based on various criteria, including operational profiles, size, generation and cargo handling methods. *Figure 1* illustrates the developmental generations of container ships. Starting from the first-generation vessels with a capacity of up to 1,000 TEU, advancements have led to modern Megamax-

24 ships with capacities exceeding 20,000 TEU. This progression reflects the growing demands of global trade and continuous technological innovations, enabling greater economic and operational efficiency.

Each generation of ships introduces improvements in capacity, stability and adaptability to meet infrastructural requirements, making them indispensable to effective maritime logistics. In the context of the reliability of ship pumps, this classification provides insights into specific maintenance challenges associated with different generations of vessels.

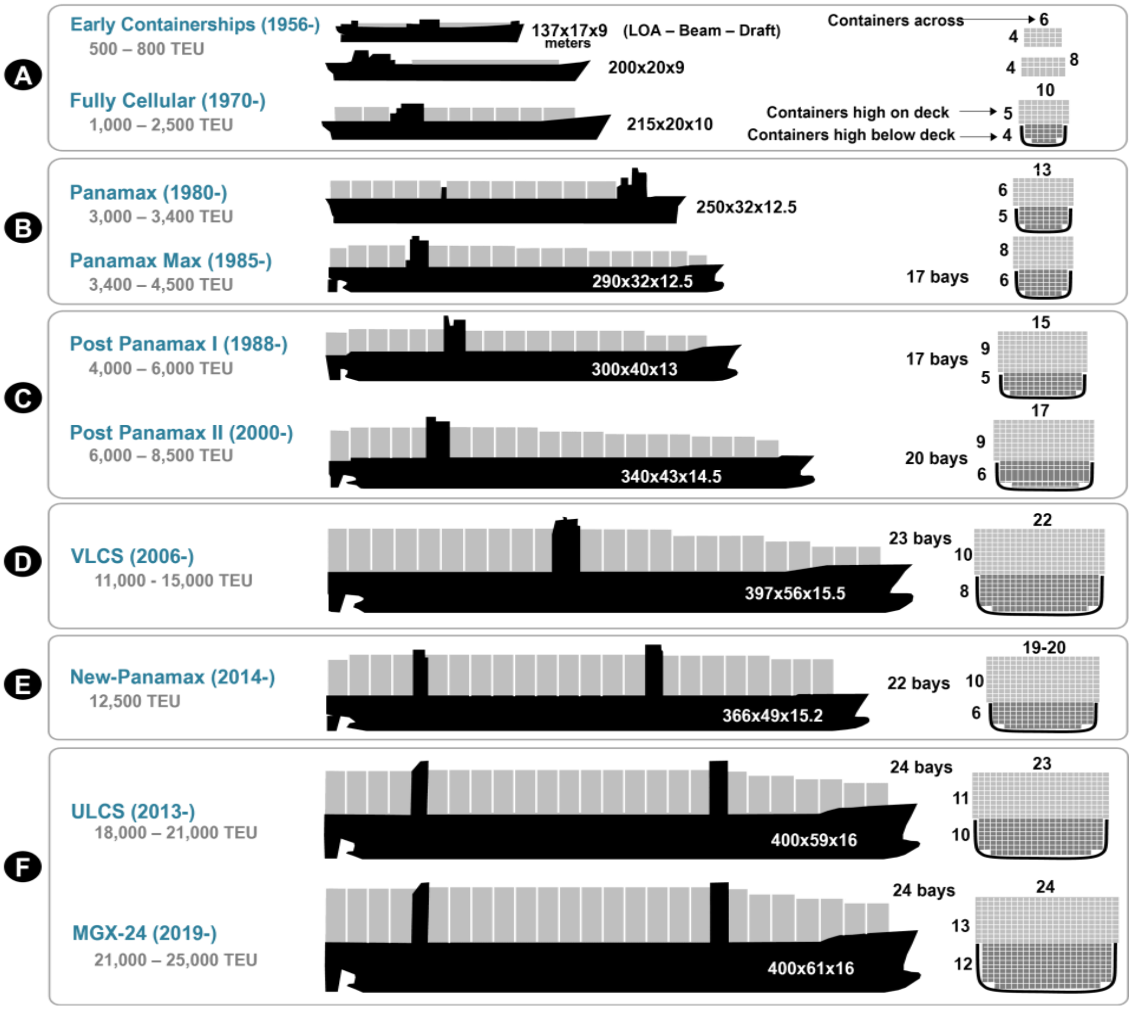

Figure 1 – Developmental generations of container ships [11]

2.2 International maritime trade

Maritime transport handles approximately 80% of global trade, serving as a vital connection between international markets. Despite economic crises causing occasional declines, the sector has grown annually by 2.6% since 2005, reaching 11 billion tons of cargo in 2021. This resilience underscores its pivotal role in the global economy.

Container freight rates peaked in 2021, yielding historically high profits, but stabilised by 2023, albeit above 2019 levels. This trend reflects the sensitivity of maritime trade to macroeconomic shifts and its adaptability to challenges.

Reliability analysis of ship pumps plays a critical role in boosting operational efficiency and minimising engine failure risks. Understanding the interaction between market changes, technical requirements and maintenance strategies is essential for enhancing global supply chain management [12].

2.3 Leading global market leaders in container maritime transport

Container shipping plays a crucial role in global maritime trade, with top companies like MSC and Maersk controlling 86% of the world's container fleet in 2022, creating near-monopolistic market dominance. Maersk managed a fleet capacity of 4.4 million TEU, while MSC took the lead in 2023 with a fleet of 643 owned and 292 chartered vessels.

Despite pandemic-related challenges in 2020, container ship orders surged in 2021 and 2022, reflecting their importance in maritime transport. Container ships made up 13.34% of the global fleet, ranking third after bulk carriers and tankers, but showed the highest growth rate of 4.11% during this time.

The global expansion of container fleets strengthens supply chains by enhancing efficiency and transport capacity. At the same time, maintaining technical systems like ship pumps is essential for reliability. Applying reliability theory to these systems optimises operations, reduces costs and prevents disruptions in global supply chains [13].

2.4 Technical failures and main engine downtime

Main engines, vital to container ship operations, increasingly focus on energy efficiency, emission reduction and reliability throughout their 25-year service life. Maintenance costs, including routine servicing and unplanned failures, constitute 25% of operational expenses, with failures imposing significantly higher costs [14].

From 2012 to 2022, reported engine failures rose from 700 to 1,500, driven by the complexity of new engines, alternative fuels and digitalisation. Main engine failures account for 80% of maritime incidents, such as collisions and fires, emphasising the need for proactive maintenance to reduce risks and operational disruptions [14, 15].

A notable case in 2022 involved an MSC vessel's engine explosion caused by inadequate pump maintenance, resulting in crew injuries and delays. This highlights the importance of comprehensive maintenance practices to enhance reliability and safety [15].

2.5 Future projections

Global maritime trade exceeded 11 billion tons in 2023, growing at a slower annual rate of 2.1% for 2023–2027 compared to 3.3% over the past three decades. Increased container ship orders have expanded capacity but also intensified challenges such as port congestion. New IMO regulations, including EEXI and CII standards introduced in 2023, mandate fleet modernisation, emission reductions and slower sailing speeds, reducing operational capacity. Rising inflation and living costs further threaten trade growth. Failures of main engines and fuel pumps disrupt supply chains and incur significant economic costs, highlighting the need for enhanced maintenance control and spare parts management to improve reliability and operational efficiency [16].

2.6 The importance of maintenance in reducing overall costs

The maintenance of ship systems is a critical factor in reducing the number of accidents [17]. Regular upkeep of main and auxiliary systems ensures their functionality, extends their service life and minimises unexpected failures. With maintenance costs comprising up to 25% of operational expenses, implementing strategies like reliability-centred maintenance (RCM) becomes essential.

In addition to lowering corrective action costs, regular maintenance contributes to navigation safety and facilitates the timely replacement of key components, such as fuel pumps, preventing critical incidents like engine explosions [18]. Effective maintenance strategies enhance crew safety, reduce the risk of severe accidents and improve the operational reliability of ship systems.

3. AVAILABLE OPERATIONAL DATA AND PROBLEM DEFINITION

The maintenance of ship engines is crucial to ensure their reliability and longevity. High-pressure fuel pumps, as critical components, frequently fail due to fuel quality and viscosity issues, resulting in operational disruptions, increased costs and jeopardising the maritime supply chain.

Collected data on 12- and 8-cylinder engines provide insights into the operational duration of key components, such as pistons and stuffing boxes, before maintenance is required. *Figure 2* illustrates the operating hours logged before the last maintenance, enabling failure analysis and forecasting future maintenance needs.

	MAN B&W 12K98 MC-C7				MAN B&W 12K98 ME7	
COMPONENT	RUN. HOURS LAST MAINTEN.	PERIOD	RUN. HOURS LAST MAINTEN.	PERIOD	RUN. HOURS LAST MAINTEN.	PERIOD
Fuel Pump N°1	41200	28000	45844	28000	26664	24000
Fuel Pump N°2	41200	28000	48202	28000	25464	24000
Fuel Pump N°3	24049	28000	49148	28000	25992	24000
Fuel Pump N°4	44230	28000	49317	28000	34490	24000
Fuel Pump N°5	24049	28000	59072	28000	34693	24000
Fuel Pump N°6	24049	28000	67270	28000	34821	24000
Fuel Pump N°7	24049	28000	60212	28000	17545	24000
Fuel Pump N°8	24042	28000	52668	28000	27545	24000
Fuel Pump N°9	24049	28000	52773	28000	26744	24000
Fuel Pump N°10	24049	28000	56645	28000	26772	24000
Fuel Pump N°11	23296	28000	50782	28000	26894	24000
Fuel Pump N°12	44317	28000	51492	28000	26894	24000

Figure 2 – Overview of collected data on high-pressure fuel distributor pumps

One of the main goals of this research is to identify critical system points using Weibull analysis, which will determine the mean time to failure (MTTF) and the optimal timing for preventive maintenance. Special attention will be given to high-pressure fuel pumps, which, according to previous observations, are the predominant cause of failures due to poor fuel quality and viscosity. This assertion will be supported by mathematical modelling of the failure intensity function ($\lambda(t)$), describing the current failure rate of the system under the assumption that it has not failed until that point, and the use of the failure equation for analysing cause-and-effect relationships between operational conditions and failures.

The failure equation will be employed for discrete analysis of real-time data across specific intervals, demonstrating improved results in condition-based maintenance supported by various sensor technologies [16]. Additionally, data consolidation and analysis through Markov chains will uncover relationships between system failures and the frequency of corrective maintenance. Combining Weibull analysis with Markov models, the study aims to deliver a comprehensive understanding of system reliability, optimise maintenance schedules and recommend sensor technologies to enhance condition-based maintenance for ship pumps. This integrated approach seeks to improve the reliability of high-pressure fuel pumps, reduce maintenance costs and enhance the safety of technical systems by mitigating failure risks and providing actionable insights for operational efficiency.

The study utilises data from six container ships with varying specifications and main engine types. These vessels, belonging to the VLCS and ULCS generations, feature carrying capacities of 12,000–21,000 TEU, widths of 48–53 metres, drafts of 9–15.5 metres, speeds of 18–22 knots and operational ages of six to thirteen years. Data from two-stroke diesel engines, aged five to ten years, were collected from technical logs and databases maintained by technical services. These records include operational hours, maintenance intervals, failure reports and repair activities. Notably, high-pressure fuel pumps were identified as critical components, with failures occurring before the manufacturer-recommended service interval of 18,000 operating hours, emphasising the need for improved maintenance strategies.

3.1 Description of data for marine engine system analysis

The engine log is an official record of the operational performance of ship machinery, maintained daily during voyages. This document plays a crucial role in monitoring the operation and condition of the system and is essential for the maintenance, safety and efficiency of the ship [17]. The entries recorded in the engine log include data related to the main engine, such as:

— Components of the main engine
— The last maintenance date
— Operating hours since the last maintenance for each component
— Current operating hours
— Maintenance interval (overhaul) prescribed by the manufacturer
— Cause of failure
— Remarks

Data on failures and operating hours form the basis for the reliability analysis of components using the two-parameter Weibull distribution. These data facilitate modelling reliability functions, failure density and failure intensity, enabling the prediction of failures and optimisation of preventive maintenance intervals [19].

Furthermore, the insights derived from this analysis contribute significantly to the integrated logistics support of ship systems.

3.2 Problem definition

Preventive maintenance, based on operational data analysis, is critical for ensuring the reliability and efficiency of marine engines, particularly in the context of container ships. Regular monitoring and recording of operating hours, failures and maintenance of main engine components enable technical departments to identify potential issues before critical failures occur [15].

Collected data on the operation of key components, such as pistons, exhaust valves and high-pressure fuel supply pumps, serve as a foundation for analytical models, including the two-parameter Weibull distribution.

Special attention is given to high-pressure fuel supply pumps, identified as critical components due to their frequent failures before the recommended service intervals. By identifying failure patterns, including vibrations, poor fuel quality and substandard materials, maintenance strategies can be improved. This includes replacing parts with higher-specification alternatives or adjusting service protocols to enhance the reliability of these systems [17].

4. BASIC ASSUMPTIONS AND CONCEPTUAL DEVELOPMENT

The successful integration of reliability theory into the maintenance of complex technical systems, such as marine engines, requires clearly defined assumptions and a well-structured conceptual framework. A key challenge lies in understanding the interplay between technical parameters and operational conditions that influence system reliability. Additionally, developing models based on real-world data creates opportunities for maintenance optimisation and failure prediction.

This section explores the fundamental assumptions required for the development of analytical reliability methods and their application to preventive maintenance. Emphasis is placed on integrating data analysis and reliability theory to enhance the safety, efficiency and operational performance of maritime systems. The conceptual frameworks developed support the implementation of advanced failure analysis methods and the optimisation of maintenance strategies, thereby increasing the functionality of critical systems and reducing operational risks.

4.1 Integration of reliability and data analysis

The complexity of marine engines necessitates an integrated approach combining reliability and operational data analysis. Preventive maintenance, informed by real-world data and analytical models like failure intensity functions, facilitates early issue detection, reducing critical failure risks, extending mean time to failure (MTTF) and sustaining vessel performance. Diagnostic systems, such as vibration analysis and simulation models, enhance failure prediction accuracy and optimise maintenance intervals, addressing technical, operational and economic dimensions to ensure safety and efficiency in maritime transport.

4.2 Application of Weibull analysis in failure intensity and density analysis

Weibull analysis, one of the most widely used models for reliability estimation, enables the determination of the mean time to failure (MTTF) and the prediction of the behaviour of critical components. Based on collected operational data from fuel pumps, Weibull distribution is applied to:

- Identify key reliability parameters, including the shape parameter (β), which indicates failure frequency across different operational phases.
- Determine optimal maintenance intervals to minimise the risk of sudden failures.
- Analyse the impact of operational conditions, such as fuel quality and viscosity, on pump performance.

This method identifies failure patterns and defines timely preventive maintenance measures. As one of the most versatile methods in reliability analysis, the Weibull distribution uses two key parameters: shape (β) and scale (α). These parameters provide flexibility in describing various failure scenarios, allowing detailed assessments of system reliability and failure intensity [20, 21].

For the Weibull distribution, the failure density function is expressed as:

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} \cdot e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \quad (1)$$

and the failure intensity function is:

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\alpha} \cdot \left(\frac{t}{\alpha}\right)^{\beta-1} \tag{2}$$

This function facilitates the analysis of failure dynamics throughout different life cycle phases of components. Based on empirical data from 56 high-pressure fuel pumps and 6 engines collected during operation, failure density (1) and intensity functions (2) were calculated. These functions enable the optimisation of maintenance strategies and the reduction of unplanned downtimes, ensuring continuous operational efficiency of ship systems. Further application of these results focuses on developing preventive measures to enhance the long-term reliability of pumps, engines and related components.

4.3 Hypothesis

Preventive maintenance is essential for ensuring the reliability and efficiency of complex technical systems, such as marine engines. Due to the interdependence of components and exposure to diverse operating conditions, regular monitoring and analysis of real data enable early identification of potential issues and informed decision-making regarding maintenance [21].

The application of advanced analytical methods, such as Weibull distribution and hidden Markov models, facilitates precise analysis of failure intensity functions and links the maintenance of high-pressure fuel pumps to the operating parameters of main engines. These models optimise maintenance intervals, reduce the risk of critical failures and enhance the safety of maritime transport [17].

It is hypothesised that the application of preventive maintenance based on the analysis of operational data significantly increases the reliability of marine engines and reduces the failure frequency of their critical components, such as high-pressure fuel pumps, thereby optimising the operability and safety of the marine system.

This hypothesis emphasises the importance of integrating preventive maintenance and real data analysis to reduce failure frequency and optimise maintenance intervals, contributing to technical reliability, supply chain stability and maritime traffic safety.

5. PROCESSING AND MODELLING OF COLLECTED DATA FOR MAINTENANCE OPTIMISATION

5.1 Application of Weibull analysis in the evaluation of collected data

Following the analysis of the collected data, the parameters of the Weibull distribution were estimated, resulting in the generation of *Figure 3* and *Figure 4* (Weibull PDF diagrams). These diagrams provide a detailed representation of failure distribution over various time periods, offering critical insights for more accurate risk modelling. The estimated shape and scale parameters are used to analyse the temporal behaviour of failures and predict optimal maintenance intervals.

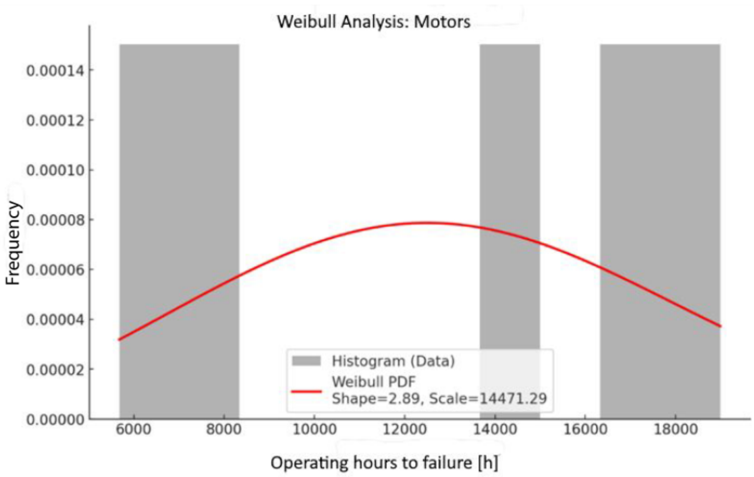

Figure 3 – Histogram of operating hours until failure and the corresponding Weibull distribution for ship engines

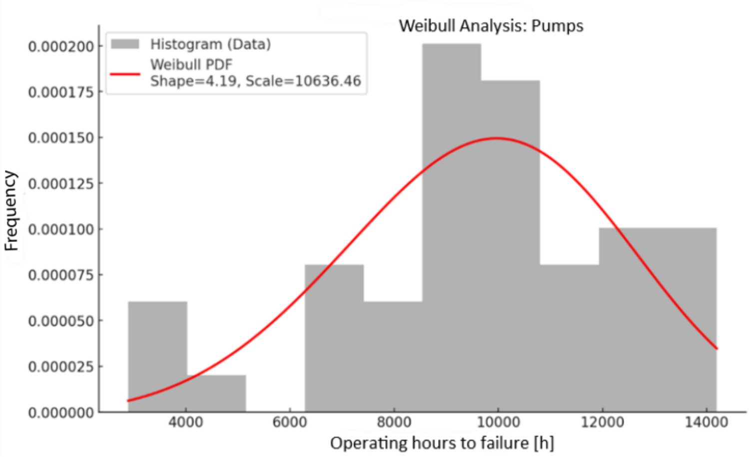

Figure 4 – Displays the histogram of operating hours until failure and the corresponding Weibull distribution for pumps

The presented graphs highlight probable failure times, aiding maintenance planning and risk minimisation. Key parameters identified include engines with a shape parameter (β) of 2.89 and scale parameter (α) of 14,471.29 hours and pumps with a shape parameter (β) of 4.19 and scale parameter (α) of 10,636.46 hours.

The mean time to failure (MTTF) (3):

$$MTTF = \alpha \cdot \boldsymbol{\Gamma}\left(\frac{1}{\beta} + 1\right) \tag{3}$$

was calculated as approximately 12,900 hours for engines and 9,670 hours for pumps, providing valuable insights for maintenance scheduling and resource optimisation. The Weibull parameters highlight the differences in failure behaviour between engines and pumps, enabling tailored maintenance strategies for each component type. These analyses collectively enhance the overall reliability of the ship system.

The following section analyses the cumulative failure probability (CDF): Weibull probability plot: Engines.

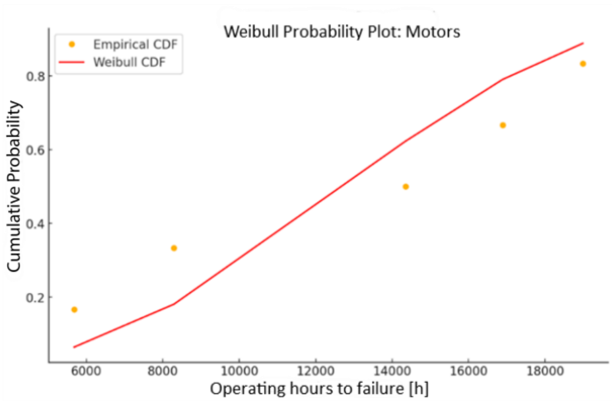

Figure 5 – Displays the Weibull CDF function, based on the calculated parameters

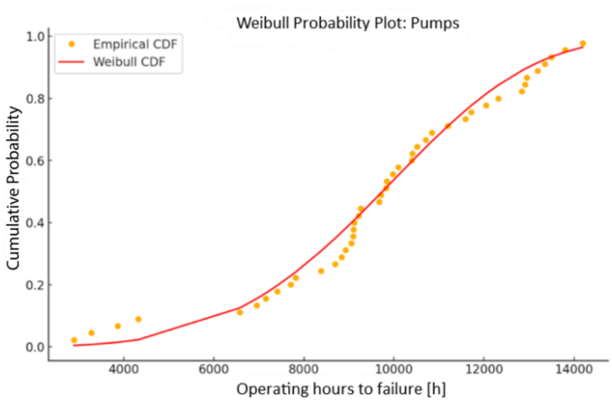

Figure 6 – Displays the Weibull CDF function for pump failures

Figures 5 and *6* provide a comparison of empirical data with the theoretical Weibull distribution, enabling visualisation of the model's fit.

The reliability analysis of engines and pumps using the Weibull distribution provided insights into failure prediction and maintenance optimisation. By estimating failure probabilities within specific intervals, this method supports proactive maintenance planning, reducing unexpected breakdowns and improving system reliability. The analysis identified optimal preventive maintenance intervals, enhancing efficiency and lowering costs.

A comparison of Weibull parameters revealed higher failure risks for pumps, with a relative risk ratio (engines/pumps) of 0.69, emphasising the need for tailored maintenance strategies. Visual analyses, such as the probability density function (PDF), highlight key Weibull parameters, aiding in maintenance decision-making. These visuals demonstrate a progressive rise in failure probability, with a 10% threshold for preventive maintenance and recommended intervals for minimising risks.

This approach enhances system reliability and operational efficiency while reducing failure risks. The cumulative failure function quantifies failure rates over time, supporting precise monitoring and effective maintenance strategies to improve overall system performance.

5.2 Application of HMM in analysing collected data

In the previous analysis, the Weibull reliability model proved to be an effective tool for estimating the mean time to failure (MTTF) and failure intensity of pumps in ship engine systems. To further understand the impact of pump conditions on engine performance, an HMM was applied to model transitions between various system states. Key parameters such as flow rate and pressure are critical for pump operation, with volumetric flow being particularly essential as it governs energy and material balances and process productivity. Cavitation, occurring when fluid pressure in the pump falls below the vapor saturation pressure, leads to bubble formation that collapses at higher pressures, causing hydraulic shocks and damage to pump walls. This phenomenon reduces pump efficiency, causes noise, vibrations and decreases delivery height and flow rate. Preventing cavitation requires maintaining suction conditions where pressure remains above the fluid's vapor saturation pressure.

The application of HMM facilitates the analysis of the relationship between hidden pump states (e.g. degradation) and engine performance. By integrating operational data and Weibull analysis results, HMM identifies system behaviour patterns. Hidden states represent the operational conditions of the pumps, while observed system states reflect engine performance, offering insights into system reliability and critical failures.

Hidden states representing pump conditions:

- Normal operation: The pump operates within optimal parameters.
- Cavitation: Occurrence of cavitation that may cause pump damage and reduced efficiency.
- Overload: The pump operates beyond its capacity, leading to decreased efficiency and higher failure risks.

Observational states reflecting engine performance:

- Engine efficiency: Measured as a percentage of available power utilised.
- Fuel consumption: The amount of fuel consumed by the engine over a specific time period.
- Vibrations: The level of vibrations indicating potential pump degradation or issues.

Key components for system analysis using HMM include:

- States of pumps: Defined as "functional", "degraded" and "failed," allowing the modelling of various operational phases and reliability.
- Observations: Measurable parameters linking pump conditions to engine performance.
- Transition probabilities: Define system dynamics and determine the likelihood of transitioning between states:
  - *Normal → Degraded*: Indicates gradual system deterioration.
  - *Degraded → Failed*: Represents the risk of complete dysfunction.
  - *Failed → Normal:* Depicts recovery to operational status following corrective maintenance.

The transition matrix quantifies the probabilities of transitions between system states. For example, the transition matrix P_A, represented as shown in (4), can be expressed as:

$$P_A = \begin{bmatrix} 0.8 & 0.1 & 0.1 \\ 0.3 & 0.4 & 0.3 \\ 0.2 & 0.5 & 0.3 \end{bmatrix} \tag{4}$$

This matrix enables precise modelling of system dynamics and analysis of transitions between the hidden states of pumps and observations of engine performance. By employing an HMM, patterns in system behaviour can be identified, facilitating informed decision-making regarding preventive maintenance and failure prediction.

For each hidden state of the pumps, an observation distribution can be defined, describing the probability of specific outcomes related to engine performance:

Normal operation:
- Engine efficiency: 90% high, 10% medium.
- Fuel consumption: 80% optimal, 20% high.

Cavitation:
- Engine efficiency: 30% high, 70% low.
- Fuel consumption: 10% optimal, 90% high.

Overload:
- Engine efficiency: 40% high, 60% low.
- Fuel consumption: 20% optimal, 80% high.

These distributions enable the analysis of system performance under various conditions. The observation distribution provides critical insights into how hidden states of the pumps (e.g. cavitation or overload) affect engine parameters such as efficiency and fuel consumption.

Operational probabilities (B) quantify the likelihood of specific observations for each hidden state. The operational probability matrix (B) can be represented as (5):

$$\mathrm{B} = \begin{bmatrix} \mathrm{P(Low\ fuel\ consumption|Normal)} & \mathrm{P(High\ fuel\ consumption|Normal)} \\ \mathrm{P(Low\ fuel\ consumption|Degraded)} & \mathrm{P(High\ fuel\ consumption|Degraded)} \\ \mathrm{P(Low\ fuel\ consumption|Failure)} & \mathrm{P(High\ fuel\ consumption|Failure)} \end{bmatrix} \quad (5)$$

For example, the specific probabilities in the operational matrix (P_B) are expressed as:

$$P_B = \begin{bmatrix} 0.9 & 0.1 \\ 0.8 & 0.2 \\ 0.4 & 0.6 \end{bmatrix} \quad (6)$$

The matrix B (5) establishes the relationship between observations, such as fuel consumption and hidden states of the system (e.g. normal, degraded or failed). Using the specific probabilities in P_B (6), it becomes possible to model these relationships in detail, forming the foundation for HMM applications in performance analysis and failure prediction. By combining observation distributions (B) and transition probabilities (P_A), a comprehensive model for monitoring and optimising the operation of pumps and engines is achieved.

Such an HMM model provides a sophisticated tool for analysing the dynamics of ship system states, quantifying the impact of degradation and optimising maintenance. The model begins with defining the initial state probabilities (π) (7):

$$\pi = [\mathrm{P(Normal), P(Degraded), P(Failure)}] \quad (7)$$

In addition to the initial probabilities, transition matrices (A) and operational probabilities (P_B) are employed, enabling a better understanding of transitions between normal operation, degradation and failure states.

6. OPTIMISING MAINTENANCE INTERVALS THROUGH TOTAL COST PREDICTION

The primary objective of this research is to analyse and optimise the maintenance costs of ship engines and pumps by utilising available data on preventive maintenance (PM) and corrective maintenance (CM) costs, as well as Weibull reliability parameters. The methodology involves:
- Assessing the costs of the current maintenance strategy.
- Comparing the current strategy with extended maintenance intervals.
- Identifying the optimal maintenance strategy that minimises total costs while maximising system reliability.

This research demonstrates an optimisation approach for preventive maintenance (PM) and corrective maintenance (CM) of ship engines and pumps by leveraging advanced analytical methods and comprehensive datasets on costs, operational intervals and reliability metrics. The data modelling and simulations were conducted using robust libraries like *NumPy*, *SciPy* and *pandas*, ensuring precision in statistical analysis, while *Matplotlib* and *Seaborn* facilitated effective visualisation of key findings.

SciPy and *NumPy* played a pivotal role in estimating Weibull parameters accurately, offering insights into component reliability and failure trends. Meanwhile, *pandas* streamlined data manipulation and processing, and *Matplotlib* provided a clear graphical representation of Weibull distributions, illustrating critical failure intervals. The optimisation of maintenance schedules was achieved through analytical functions and cost-minimisation techniques implemented using *SciPy optimise*, offering actionable insights for balancing operational efficiency and maintenance costs.

The application of an optimisation approach reduced overall maintenance costs by minimising expensive corrective interventions and improving the operational efficiency of the system. For ship engines, extending maintenance intervals by 5,000 hours decreased the frequency of preventive maintenance (PM) from 0.45 to 0.34 times annually but simultaneously increased the frequency of corrective maintenance (CM) to 0.75 times annually. As an optimal solution, preventive maintenance every 3,000 hours was proposed to balance costs and reliability.

For pumps, extending maintenance intervals by 1,500 hours resulted in an increase in CM frequency to 1.05 times annually. As a compromise, preventive maintenance every 1,000 hours was recommended to minimise risks and ensure system stability. Improvements were achieved through maintenance optimisation, where for engines, a reduced number of preventive interventions lowered total PM costs, while the increase in corrective costs remained within limits that did not outweigh the savings from PM. For pumps, more frequent preventive maintenance prevented costly failures, reducing the frequency of preventive maintenance for the overall system contributed to maintaining stable total maintenance costs and ensured system operation continuity.

6.1 Integration model for reliability analysis and financial impact of maintenance

The development of a model integrating reliability analysis with the financial impacts of maintenance represents a key step in optimising complex technical systems, such as ship engines and pumps. This model enables informed decision-making based on analytical assessments of reliability and costs, providing clear guidelines for balancing preventive and corrective maintenance. By leveraging the Weibull distribution to assess failure intensity and HMM to simulate the dynamics of system states, it becomes possible to accurately predict the failure frequency of critical components and quantify maintenance costs.

By integrating analytical methods, the model identifies optimal maintenance intervals that minimise costs while adapting strategies to system-specific needs. The use of HMM ensures dynamic updates based on real performance data, enhancing accuracy and flexibility in maintenance planning. This approach reduces operational costs, improves reliability and minimises sudden failures, contributing to long-term stability and economic sustainability. Maintenance cost evaluation, combining Weibull analysis and HMM, provides insights into failure and preventive maintenance expenses. Weibull distribution predicts failure frequencies, enabling cost calculations for part replacements, labour and downtime. For instance, in a system with 100 pumps and a 5,000-hour projection (10% annual failure rate), failure costs reach 75,000 EUR annually, while preventive measures reducing failures by 50% significantly lower these costs. Furthermore, macroeconomic trends, such as trade growth and fluctuating energy prices, emphasise the importance of preventive maintenance to reduce downtime and failure expenses. Strategies include identifying optimal replacement intervals, prioritising preventive measures, aligning budgets with global trends and leveraging HMM to predict critical failures. This comprehensive approach ensures resource optimisation, operational safety, financial efficiency and enhanced system performance over the long term.

6.2 Optimal preventive maintenance points and their relationship with maintenance activity intensity

Weibull analysis and HMM form the foundational basis for applying the MA-CAD (maintenance adjustment for cost analysis and design) decision-making method, enabling precise reliability assessment, identification of failure patterns and modelling transitions between various system states. Weibull analysis provides insights into failure intensity and MTTF, while HMM facilitates dynamic tracking of hidden degradation processes and predicts transitions between states such as "operational", "degraded" and "failed". The combination of these methods ensures informed decisions for maintenance optimisation, aiming to reduce costs and improve system reliability. *Figure 7* illustrates how a preventive maintenance cost analysis helps identify optimal maintenance points that minimise overall costs without compromising safety and reliability.

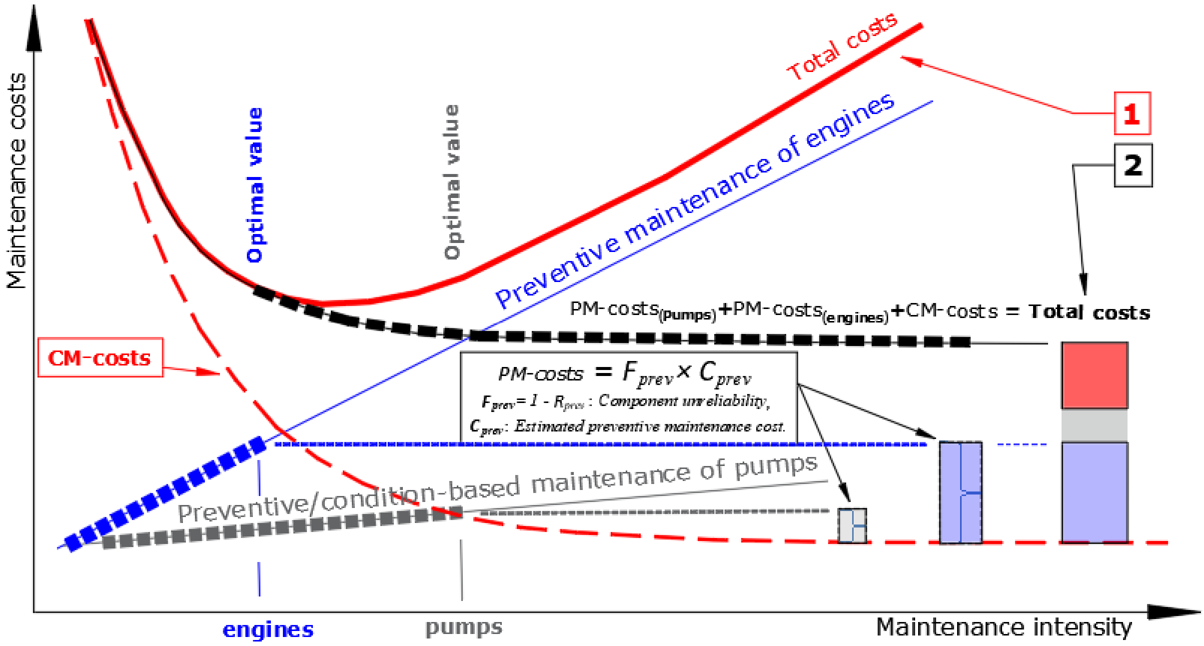

Figure 7 – Maintenance costs based on preventive maintenance (PM) intensity for system components

The total maintenance costs can be expressed as:

$$Total\ costs = PM\text{-}costs_{(pumps)} + PM\text{-}costs_{(engines)} + CM\text{-}costs \quad (8)$$

where:

PM-costs$_{(pumps)}$: Preventive maintenance costs for pumps.
M-costs$_{(engines)}$: Preventive maintenance costs for engines.
CM-costs: Total corrective maintenance costs.

Curve 1 illustrates the total maintenance costs under conditions of excessive preventive maintenance for system components, highlighting inefficiencies that increase overall costs. In contrast, *Curve 2* represents the total costs (8) when applying optimal predictive maintenance. This organised approach, where scheduled pump repairs are aligned with predictive strategies, significantly enhances the operational capacity of ship engines. By employing the MA-CAD method, *Curve 2* demonstrates the benefits of tailoring preventive maintenance to optimal intensities, confirming the research hypothesis and providing a robust framework for optimising maintenance strategies for complex systems. Through the application of reliability theory, redundant activities that do not significantly reduce failure risks are identified, enabling more efficient maintenance planning and overall cost reduction.

An example from the study further illustrates the effectiveness of this method: Weibull analysis of high-pressure pumps revealed a significant increase in failures after 10,000 operating hours, while HMM indicated a 20% probability of transitioning from the "functional" to the "degraded" state and a 15% probability of transitioning from the "degraded" to the "failed" state. Using these data, the MA-CAD method recommended intensifying preventive maintenance after 8,000 operating hours, which reduced corrective interventions by 30% and achieved annual savings of 50,000 EUR while maintaining a high level of system reliability. This example demonstrates how the synergy of Weibull analysis, HMM and the MA-CAD method enables precise, cost-effective and sustainable maintenance decisions.

7. DISCUSSION

This study emphasises the need for investments in advanced technologies that integrate reliability theory with preventive maintenance models, laying the groundwork for improving operational safety and reducing costs. Analysing maritime accidents reinforces this necessity, with high-pressure fuel pumps identified as critical components requiring optimisation of maintenance strategies due to frequent failures.

The Weibull model offers a reliable framework for estimating failure probabilities and planning strategic maintenance through the cumulative distribution function (CDF). An aging trend ($\beta > 1$ for engines and pumps) indicates increasing failure intensity, necessitating more frequent maintenance. With an MTTF of 11,062.21 hours providing a basis for maintenance intervals, integrating HMM analysis enables dynamic monitoring and adaptation of strategies, reducing costs and improving efficiency.

Maintenance cost optimisation and system efficiency improvements have been achieved through the application of reliability-centred maintenance (RCM), significantly reducing costs and increasing operational reliability. The key benefits of RCM include:

1) Reduction of unplanned downtimes: Preventing potential failures reduces costs associated with production losses and emergency repairs.
2) Extension of equipment lifespan: Regular maintenance extends the working life of critical components, lowering replacement costs.
3) Optimisation of preventive maintenance: Focusing on critical components minimises unnecessary interventions and reduces costs.
4) Precise spare parts management: Accurate predictions reduce storage costs and ensure availability.
5) Increased technical efficiency: Enhanced operational efficiency lowers long-term maintenance costs.

The application of HMM further optimises preventive maintenance by analysing transitions between states such as "functional" "degraded" and "failed". Based on transition probabilities (e.g. 15% for transitioning to a degraded state), the model predicts hidden system states linked to observable performance metrics such as operating hours and failure intensity. Implementation in Python, leveraging advanced libraries such as NumPy, SciPy and hmmlearn, enabled precise analysis of hidden state impacts on system performance, facilitating strategic maintenance decisions.

The combination of Weibull analysis, HMM and MA-CAD methods offers a comprehensive approach to optimising maintenance strategies for complex technical systems. While Weibull analysis provides insights into failure patterns, HMM enables monitoring of hidden degradation processes, and MA-CAD optimises preventive maintenance by identifying redundant activities. This integrated approach ensures reduced maintenance costs, enhanced system reliability, and offers guidance for future applications in maintaining complex technical systems.

For modernising maintenance systems, the implementation of predictive maintenance technologies is recommended, including IoT sensors for continuous system monitoring, big data analytics for data processing and artificial intelligence for failure prediction. Additionally, system simulation in virtual environments enables scenario testing and the development of optimal maintenance strategies. This approach reduces costs, extends equipment lifespan and enhances system safety, significantly contributing to the efficiency and reliability of technical operations.

8. CONCLUSION

The application of advanced analytical methods, such as Weibull analysis and HMM, facilitates precise planning and optimisation of maintenance strategies for complex technical systems. These approaches identify failure patterns, support informed decision-making for preventive and corrective interventions, reduce overall maintenance costs, enhance system reliability and ensure safety in the maritime industry.

The implementation of predictive maintenance technologies, including IoT sensors, big data analytics and artificial intelligence, further enhances maintenance management by enabling continuous monitoring and analysis of system conditions. The integration of these technologies facilitates the timely identification of potential failures, reduces unplanned downtime and improves operational efficiency. Additionally, system simulation using digital twins ensures scenario testing and the prediction of optimal maintenance strategies.

A combination of preventive and corrective maintenance, supported by methods such as MA-CAD, ensures a balance between costs and system reliability. By introducing an optimal ratio of preventive to corrective maintenance (PM/CM), it is possible to reduce lifecycle costs, extend equipment lifespan and improve personnel efficiency while meeting high safety standards.

Future advancements in predictive maintenance require the integration of real operational data from planned maintenance systems (PMS), such as Bassnet and AMOS. These systems contain structured records of failure history, service activities and component conditions, providing a valuable foundation for real-time analytical modelling. Through the interpretation of technical logs using natural language processing (NLP) technology, automated data flows and advanced dashboards, maintenance strategies can be dynamically updated to make maintenance decisions more efficient, precisely targeted and financially optimised.

The maritime industry is increasingly moving towards data-driven maintenance as the new standard. Expected benefits include reduced overall fleet maintenance costs and increased ship availability due to fewer breakdowns. Achieving these goals will require coordinated collaboration between shipping companies, standardisation of data exchange protocols and active involvement of technology providers. Open-source tools, crew training and interoperable system design will play a crucial role in enabling the maritime sector to align with the Industry 4.0 paradigm.

REFERENCES

[1] Čovo P, Baričević H, Vukušić A. Reliability of technological parameters in road infrastructure maintenance. *Promet - Traffic & Transportation*. 2009;21(3). DOI: 10.7307/ptt.v21i3.226.

[2] Dominguez-Péry C, Tassabehji R, Corset F. A holistic view of maritime navigation accidents and risk indicators: examining IMO reports from 2011 to 2021. *Journal of Marine Safety and Risk Management*. 2023. DOI: 10.1186/s41072-023-00135-y.

[3] Yang R. Methods and models for analyzing and controlling the safety in operations of autonomous marine systems. *Ocean Engineering*. 2023. DOI: 10.1016/j.oceaneng.2022.111100.

[4] Daya AA, Lazakis I. Component criticality analysis for improved ship machinery reliability. *Machines*. 2023;11(7):737. DOI: 10.3390/machines11070737.

[5] Bukša A. *Modeliranje održavanja brodskog porivnog sustava* [PhD thesis]. Rijeka, Croatia: Pomorski fakultet Sveučilišta u Rijeci; 2005.

[6] Mihanović L. *Istraživanje eksploatacijske pouzdanosti i pogodnosti održavanja brzookretnih brodskih motora* [PhD thesis]. Rijeka, Croatia: Pomorski fakultet Sveučilišta u Rijeci; 2015.

[7] Kunar S, et al. Measurement and evaluation of reliability, availability, and maintainability of a diesel locomotive engine. *Journal of Mechanical and Civil Engineering*. 2013;8:31–46.

[8] Karatuğ Ç, Arslanoğlu Y. A hybrid predictive maintenance approach for ship machinery systems: a case of main engine bearings. *International Journal of Maritime Engineering*. 2024. DOI: 10.1080/20464177.2024.2393484.

[9] Pilatis AN, et al. A statistical analysis of ship accidents (1990–2020) focusing on collision, grounding, hull failure, and resulting hull damage. *Journal of Marine Science and Engineering*. 2024. DOI: 10.3390/jmse12010122.

[10] Martin J, Martin S, Pettit S. Container ship size and the implications on port call workload. *International Journal of Shipping and Transport Logistics*. 2015. DOI: 10.1504/IJSTL.2015.072016.

[11] Rodrigue J-P. *The geography of transport systems*. 5th ed. New York, USA: Routledge; 2020. DOI: 10.4324/9780429346323.

[12] Yue Z, Mangan J. A framework for understanding reliability in container shipping networks. *Maritime Economics & Logistics*. 2024;26(3):523–544. DOI: 10.1057/s41278-023-00269-7.

[13] Notteboom T, Pallis A, Rodrigue JP. *Ports and container shipping*. In: Port Economics, Management and Policy. 2022. DOI: 10.1057/s41278-019-00136-4.

[14] Junaidi A, Yudo H, Abdul Samat H. Identify the trends on maritime safety management system studies: A review. *TransNav: The International Journal on Marine Navigation and Safety of Sea Transportation*. 2024;18(4):775–784. DOI: 10.12716/1001.18.04.03.

[15] Islam R, et al. Determination of human error probabilities for the maintenance operations of marine engines. *Journal of Ship Production and Design*. 2016;32(1):1–9. DOI: 10.5957/JSPD.32.1.150034.

[16] Ugoji KU, Isaac OE, Nkoi B. Improving the operational output of marine vessel main engine system through cost reduction using reliability. *IIARD International Journal of Mechanical Engineering*. 2022;8(2).

[17] Pšihistal T. *Procjena stanja brodskih sustava i planiranje održavanja* [Master's thesis]. Rijeka, Croatia: Pomorski fakultet Sveučilišta u Rijeci; 2024. Available from: URN:HR:187:845205.

[18] Bosanac M. *Sustavi za dijagnostiku kvarova na električnim strojevima* [Master's thesis]. Rijeka, Croatia: Pomorski fakultet Sveučilišta u Rijeci; 2024. Available from: URN:HR:187:295521.

[19] Weibull W. A statistical distribution function of wide applicability. *Journal of Applied Mechanics*. 1951;18(3):293–297.

[20] Shahriari M, Shahrasbi H. Reliability analysis of lifetime systems based on Weibull distribution. *International Journal of Nonlinear Analysis and Applications*. 2024;15(1):321–329. DOI: 10.22075/ijnaa.2024.31309.4609.

[21] Šegulja I, Bukša A, Tomas V. Maintenance interval adjustment of significant ship propulsion components. *Promet - Traffic & Transportation*. 2009;21(3):175–182. DOI: 10.7307/ptt.v21i3.223.

Damir BUDIMIR, Ivan GRGUREVIĆ, Jasna LEDER HORINA

Metode pouzdanosti u funkciji održavanja i analize kvarova pomorskih sustava

Sažetak

Ovaj rad istražuje primjenu naprednih analitičkih metoda i tehnologija prediktivnog održavanja u svrhu optimizacije strategija održavanja složenih tehničkih sustava, s posebnim naglaskom na brodske motore i visokotlačne pumpe goriva. Weibullova analiza omogućila je identifikaciju obrazaca kvarova i precizno planiranje intervala održavanja, dok su skriveni Markovljevi modeli (HMM) pružili dublji uvid u dinamiku prijelaza stanja, poput degradacije i otkaza. Rezultati pokazuju da kombinacija teorije pouzdanosti i analize troškova osigurava optimalnu ravnotežu između troškova održavanja i pouzdanosti sustava. HMM je otkrio kako promjene u radu pumpi izravno utječu na funkcionalnost motora, dok sami podaci o kvarovima često ne pružaju dovoljno jasan uvid u stanje sustava. Integracijom HMM modela omogućeno je bolje razumijevanje temeljnih procesa, što je ključno za usklađivanje održavanja pumpi s ciljem smanjenja broja kvarova i povećanja operativne učinkovitosti. Primjena ovih metoda i tehnologija smanjuje troškove održavanja, produljuje vijek trajanja opreme i poboljšava ukupnu učinkovitost. Time se osigurava sigurnost sustava i smanjuje rizik od neočekivanih kvarova, čime se doprinosi stabilnosti i ekonomskoj održivosti složenih tehničkih sustava. Ovakav integrirani pristup nudi okvir za buduće strategije održavanja, objedinjujući tehničke i financijske aspekte u sveobuhvatno rješenje za dugoročnu pouzdanost i učinkovitost.

Ključne riječi

Weibullova analiza; skriveni Markovljevi modeli (HMM); preventivno održavanje; prediktivno održavanje; pouzdanost sustava; Tehnička logistika