Maintenance policy comparison

Within the Royal Netherlands Navy

MSc Thesis

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Maintenance policy comparison

Within the Royal Netherlands Navy

by

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During the preparation of this work the author used ChatGPT in order to rewrite non-confidential texts. This program is not used to withdraw any information. After using this program, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Preface

Dear reader,

Over the past months, I've had the opportunity to immerse myself in one of the more practical, yet surprisingly layered, challenges in naval engineering: maintenance. It's a topic that doesn't often attract attention outside engineering circles: no dramatic visuals, no grand innovations on display. Yet its impact on operational readiness, cost control, system longevity, and even crew morale, is profound. Especially within the Royal Netherlands Navy, where vessels are increasingly complex, budgets are under pressure, and the stakes (mission success or failure) are too high to rely on routine or habit.

This thesis has been a journey through that complexity. It allowed me to combine theory, real-world data, and input from professionals with decades of experience. The result is a decision support model that enables a structured comparison between Corrective Maintenance, Time-Driven Scheduled Maintenance, and Condition-Based Maintenance across different vessel types. What started as a straightforward comparison evolved into a deeper understanding of the trade-offs: the tension between availability and efficiency, the hidden impact of man-hours, and the challenge of translating ideal maintenance concepts into workable policy. Especially when you're dealing with hundreds of thousands of maintenance hours and multi-million-euro investments across a vessel's life-cycle.

This process was not something I could or would have wanted to do alone. I've been fortunate to work with people who not only supported this project but truly elevated it.

I would like to sincerely thank Dr. Ir. J.J. le Poole for his supervision on behalf of COMMIT. Joan has been, without exaggeration, one of the most engaged and constructive supervisors I could have hoped for. He was always available for questions, thought along with me in moments of conceptual or practical deadlock, and provided clear, grounded feedback throughout. Beyond that, he managed to strike the perfect balance between professional distance and personal accessibility. His guidance shaped the quality of this thesis, but also made the work behind it more enjoyable.

I also wish to thank Dr. A.A. Kana from TU Delft for his academic oversight. Austin helped keep the work anchored in academic rigor, while still allowing space for practical intuition and iteration. His feedback was always thoughtful and sharp, and I truly appreciate the freedom he gave me to perform this research, even when it sometimes meant reshuffling parts of the structure.

Thanks also go out to the many people within the maintenance departments of the Royal Netherlands Navy. Despite full schedules, many were willing to sit down with me and share their insights, frustrations, and practical experience. Their input ensured that this research never drifted into abstraction. Instead, it remained grounded in the reality of the work being done every day on board and ashore. Whether it was help in interpreting SAP data, insights into BSMI structuring, or thoughts on CBM implementation, their contributions were invaluable. I hope they'll recognize some of their perspectives in these pages.

Lastly, I want to thank my friends and family, for keeping me grounded during the peaks and valleys of this journey. Specifically, I would like to thank Casper, Harm, Loek, Sil, Tijn, Tjeerd and Tycho for reading my work, providing feedback, and for being a generally supporting factor during my time at the TU Delft.

I hope this work contributes to more structured decision-making in naval maintenance planning, and above all, encourages future research that bridges technical insight with practical usability.

Enjoy reading.

Lars van Geffen
Delft, July 2025

Summary

In an era where fleet readiness is critical and defense budgets are under careful examination, inefficiencies in maintenance routines can have significant strategic and economic implications. Historically, the Royal Netherlands Navy (RNLN) has relied on standard scheduled maintenance practices designed to prevent unexpected breakdowns. However, as ships have grown increasingly complex, these conventional strategies have begun to show their limitations: fixed maintenance intervals often result in either redundant work or unanticipated failures. The risks of unscheduled repairs, unexpected downtimes, and the rising costs associated with emergency repairs have pushed the desire for more adaptive approaches. In response to these challenges, a new maintenance method has emerged that promises to align maintenance actions with the real operating conditions of systems onboard.

This research is motivated by the need to develop a decision support tool that systematically compares maintenance strategies so that the RNLN can optimize long-term cost and workforce efficiency. At its core, the study addresses how to apportion maintenance activities among three distinct methods: Corrective Maintenance (CM), Time-Driven Scheduled Maintenance (TDSM), and Condition-Based Maintenance (CBM).

The model is built upon data obtained from the RNLN's SAP system and furthermore on expert opinion. By categorizing ship installations according to their codes, the model aggregates maintenance costs and man-hours from related groups such as command systems, nautical systems, HVAC, and hull structure. This grouping enables a level of analysis that is specific enough to capture system-specific profiles while remaining applicable across different vessel types.

Scenarios are generated by altering the maintenance mix in predetermined increments through varying the proportional contributions of CM, TDSM, and CBM in steps of 10%. In each scenario the model projects the required lifetime maintenance costs and required man-hours by linearly, and at times non-linearly, extrapolating data from an eight-year period to the entire service life of a vessel.

A sensitivity analysis forms an integral part of the research. The tests following from this analysis reveal that for high-criticality system groups (i.e., command systems and power generation systems), the model's preferred maintenance mix remains stable even when CBM parameters experience significant fluctuations. In contrast, for groups where the balance between CM and CBM is more subtly balanced, shifts of 10% to 20% in the output maintenance mix are observed with moderate changes in input values.

The analysis of model outputs is conducted on an installation group and vessel type basis. For instance, in groups containing high-criticality installations, scenarios that incorporate a higher share of CBM (typically ranging between 20% and 40%) tend to generate lower overall costs despite their initial investment. Here the long-term savings stem not only from reduced emergency repair costs but also from a smoother distribution over time.

Furthermore, when the model outputs are examined from the perspective of required man-hours, a slightly different picture emerges. Although cost-efficient strategies generally advocate for increased CBM usage in mission-critical groups, the model shows that man-hour efficiencies might favor a modest increase in CM. This divergence can be attributed to how labor hours are recorded in SAP; for certain maintenance actions, especially mission-critical repairs, the recorded man-hours capture only the immediate "hands-on" work, neglecting preparation and logistical support. As a result, scenarios with higher CM might appear more efficient in terms of labor even though they might conceal hidden downtime costs.

Overall, this research shows that an optimized mix of CM, TDSM, and CBM can improve cost-efficiency and can lead to reductions in man-hours and downtime.

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Nomenclature

Abbreviations

Abbreviation	Definition
AM	Assisted Maintenance (scheduled maintenance period)
BO	Benoemd Onderhoud (Scheduled Maintenance Period)
BSMI	Beheersstructuur Materieel Instandhouding (Maintenance Management Structure)
CapEx	Capital Expenditure
CBM	Condition-Based Maintenance
CM	Corrective Maintenance
CPA	Condition and Performance Assessment
CSS	Combat Support Ship
EPV	Empirical Performance Validity
ESV	Empirical Structural Validity
FTE	Full Time Employee
JSS	Joint Logistic Support Ship
LCC	Life Cycle Cost
LCF	Air Defence and Command Frigate
LPD	Landing Platform Dock
M2	Maintenance call within SAP
M2*	Corrected number of M2 calls
MF	Multipurpose Frigate
MRC	Material Replacement Costs
MTBF	Mean Time Between Failures
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
OpEx	Operational Expenditure
OPV	Offshore Patrol Vessel
PdM	Predictive Maintenance
PM	Preventive Maintenance
RNLN	Royal Netherlands Navy
SAP	ERP system used by the RNLN
TCO	Total Cost of Ownership
TDSM	Time-Driven Scheduled Maintenance
TPM	Total Productive Maintenance
TPV	Theoretical Performance Validity
TSV	Theoretical Structural Validity
WACC	Weighted Average Cost of Capital
WP	Work Package Call, a maintenance call within SAP

1

Introduction

This chapter introduces the background, focus, and structure of the thesis. Section 1.1 defines the central problem motivating this research. Section 1.2 outlines the boundaries and focus areas of the study. The research approach is explained in Section 1.3, followed by the main research question and supporting sub-questions in Section 1.4. Section 1.5 discusses the societal and scientific relevance of the research. Finally, Section 1.6 provides an overview of the structure of the thesis.

1.1. Problem definition

The Royal Netherlands Navy (RNLN) is encountering growing complexity in the maintenance of its fleet, driven by advances in technology, evolving operational requirements, and a greater emphasis on cost-efficiency (Tinga, 2013; Mooij, 2023; Simion et al., 2021). Traditional preventive maintenance strategies, which operate on fixed schedules rather than real-time system conditions, are increasingly challenged in efficient resource use (Tinga, 2013; Mooij, 2023). At the same time, the potential advantages of Condition-Based Maintenance (CBM), aimed at optimizing maintenance timing through system data, are not yet fully realized due to technical, organizational, and cultural factors (Mooij, 2023; Tinga, 2013; Simion et al., 2021; Karatuğ, Arslanoğlu, and Soares, 2023).

Another consideration is the structure of the Dutch naval maintenance market, where a limited number of external providers are involved in major maintenance activities. This can pose challenges in terms of maintaining transparency, controlling costs, and ensuring timely execution (Interview 1, 2024; Ford, Housel, and Mun, 2012). Furthermore, the practice of bundling large volumes of Preventive Maintenance into single periods can contribute to peaks in workload, which may affect efficiency and increase the likelihood of delays (McDevitt, Zabarouskas, and Crook, 2003; Interview 1, 2024; Mooij, 2023).

In this context, the absence of a structured approach for determining the most appropriate maintenance strategy for each system presents a further challenge (Goossens and Basten, 2015; Ibazebo et al., 2023; Emovon, 2016). Current practices do not yet differentiate systems based on their operational criticality, reliability impact, or suitability for CBM application. As a result, the allocation of maintenance resources may not always be optimal, with implications for both required man-hours, downtime and cost management.

With maintenance resources under increasing pressure and high fleet availability remaining a priority, enhancing the selectivity and efficiency of maintenance planning is essential. A model that provides a systematic evaluation of maintenance strategies per system can support better-informed decision-making, helping to ensure that financial and human resources are employed effectively.

1.2. Scope

This thesis focuses on developing a model to support the RNLN in selecting the most suitable maintenance strategy: Corrective Maintenance (CM), Time-Driven Scheduled Maintenance (TDSM), or CBM, for individual ship systems. The model is designed to systematically compare these maintenance strategies based on cost-efficiency and man-hour efficiency.

The research will concentrate on three of the major surface combatants in the RNLN fleet and will use historical maintenance data to perform the analysis. The model evaluates cost and man-hour components but does not integrate real-time monitoring data, nor does it address the technical design of sensors or the detailed failure mechanisms of systems.

1.3. Approach

This thesis adopts a model-based approach to support maintenance decision-making within the RNLN. The model systematically compares maintenance strategies CM, TDSM, and CBM, on a per-system basis, evaluating each based on two performance indicators: total maintenance costs and required man-hours, including downtime, derived from historical records and expert input. The research begins with an analysis of current maintenance challenges through literature review and interviews with RNLN subject-matter experts. Next, historical data from the RNLN's maintenance management system is structured and cleaned to ensure the reliability of cost and man-hour estimates used in the model. Maintenance scenarios are generated by systematically varying the shares of CM, TDSM, and CBM in 10% increments, creating a set of mixed strategies. Finally, the model is applied to a selection of representative ship types and installation groups to demonstrate its practical value. A sensitivity analysis is conducted to assess the robustness of results under uncertainty in key inputs.

1.4. Research Questions

During the thesis the following main research question will be answered:

MQ: How to provide insights into the cost-effectiveness and vessel availability of different maintenance methods for the Royal Netherlands Navy?

To answer this main question, the following sub-questions will be answered:

1. What are the general challenges surrounding RNLN ship maintenance? [Chapter 2]
2. Which maintenance methods are currently used within the Royal Netherlands Navy, and outside the navy organization, and which are relevant to include in the cost determination? [Chapter 3]
3. How to provide insights into the maintenance costs and required man-hours per relevant maintenance method for the Royal Netherlands Navy? [Chapter 4 and 6]
4. How can the model be verified and applied by the Royal Netherlands Navy? [Chapter 5 and 8]
5. How can the model help the Royal Netherlands Navy in their maintenance decision-making? [Chapter 6 and 7]

1.5. Societal and scientific relevance

Every research project carries practical, scientific, and societal implications. This section discusses the implications of developed model.

1.5.1. Practical Implications

By systematically comparing maintenance strategies per system, the developed model enables the RNLN to allocate resources more effectively, resulting in lower maintenance costs, man-hours and downtime. This supports the RNLN in meeting national defense and international mission commitments with a leaner maintenance effort. The structured approach may also be adapted by other naval fleets or government organizations facing similar maintenance challenges.

1.5.2. Scientific Implications

This research advances the scientific discourse on maintenance strategy optimization, addressing a gap in naval applications where empirical studies are limited. While sectors like aviation and energy have embraced data-driven maintenance, naval systems lag behind. By combining historical data analysis with scenario modeling and sensitivity testing, this thesis offers a framework adaptable to other complex, data-constrained technical systems, bridging theory and practical application.

1.5.3. Societal Implications

Optimizing maintenance reduces resource consumption, minimizes waste, and extends the lifespan of assets, aligning with sustainability objectives. Moreover, better maintenance planning supports the safety of naval personnel by ensuring that systems are more reliable and less prone to unexpected failures. In a broader sense, enhancing the efficiency of defense spending allows governments to better balance defense budgets with other societal needs, contributing to both national security and the responsible use of public funds.

1.6. Structure of thesis

This thesis is structured as follows. Chapter 2 outlines the general challenges in Dutch naval ship maintenance. Chapter 3 reviews the main maintenance strategies. Chapter 4 describes the development of the model and its methodology. Chapter 5 covers the model's implementation and validation. Chapter 6 applies the model to selected ship systems. Chapter 7 presents a sensitivity analysis to test the model's robustness. Chapter 8 presents a validation. Finally, Chapter 9 concludes with findings and provides recommendations for future research.

2

General challenges surrounding Dutch naval ship maintenance

The maintenance of navy ships is a complex and essential task that ensures the operational capacity and safety of the RNLN. The challenges faced by the RNLN are numerous and range from organizational complications and logistical difficulties to technical and strategic issues. This chapter describes the major challenges in the maintenance of Dutch navy ships, with particular attention to the relationship with external parties, the application of a certain type of maintenance policy, called CBM, and the logistical complications of maintenance intervals. The chapter aims at providing an answer to the first subquestion of this research, namely SQ1: *"What are the general challenges surrounding Dutch naval ship maintenance?"*

2.1. External Parties for the Maintenance of Dutch Navy Ships

An important consideration in the maintenance of Dutch navy ships is the current market structure within the Dutch naval ship maintenance industry. At present, the RNLN primarily works with a single external party for most of its major maintenance and repair projects for vessels larger than frigates (Interview 1, 2024). This concentrated market can sometimes pose challenges in terms of maintaining the desired level of control, transparency, cost management, and operational efficiency.

2.1.1. Limited Control and Transparency

Because expertise is concentrated in a single external party, the RNLN has somewhat less direct oversight over the planning and execution of its maintenance work. This sometimes results in reduced flexibility and transparency, which can make it more challenging for the RNLN to adjust plans or intervene promptly when issues occur (Interview 1, 2024). In addition, installation managers who supervise maintenance activities report that ensuring advanced and highly specialized systems are maintained to the desired standard can be demanding. With new or complex technologies evolving rapidly, additional time and resources may sometimes be needed to carry out thorough inspections and confirm that all work is performed as intended (Interview 1, 2024).

2.1.2. High Costs

The limited competition in the Dutch naval ship maintenance market can lead to elevated base prices for maintenance projects, as is in line with the general knowledge on monopoly and oligopoly economics (Toppr, n.d.). The limited competition creates budgetary challenges for the RNLN. In addition to higher base costs, unforeseen additional work often incurs extra charges, which may not be accounted for in the initial financial plans (Interview 1, 2024). Strict interpretations of contracts and specifications can further complicate budget management, leading to cost overruns in maintenance projects.

2.1.3. Operational Inefficiencies

The working relationship between the Ministry of Defense and its external maintenance providers occasionally presents operational challenges that can influence the overall effectiveness and timeliness of maintenance projects. Some delays may be partially attributed to the inherent complexity of the tasks involved and the level of coordination required for large-scale maintenance efforts (Interview 1, 2024). Furthermore, while the inspection and approval processes are essential for ensuring quality, they can be time-consuming and extend the duration of operations. Communication and coordination between the RNLN and its external providers, although crucial, sometimes encounter difficulties that may further affect project timelines and resource allocation (Interview 1, 2024).

2.1.4. Challenges of Foreign Outsourcing

There has been consideration of outsourcing maintenance to foreign parties, But, apart from the fact that there is a Dutch public preference for keeping naval engineering knowledge in their own country and stimulating their own country's economy, this option presents logistical and operational challenges. The cost of transport and the complexities of coordinating work over long distances can increase the logistical burden. Additionally, cultural and language barriers pose risks of miscommunication, which can reduce the overall effectiveness of maintenance efforts and delay project completion (Interview 1, 2024).

The relatively limited competition in the Dutch naval ship maintenance industry can present challenges in maintaining tight control, managing costs effectively, and optimizing operational efficiency. These factors, in turn, complicate maintenance project planning and contribute to occasional delays and higher expenditures.

2.2. Problems with Condition Based Maintenance

CBM is a maintenance method that uses prediction of failure of a system with system-data, like usage and load based data, which will be further explained in the next chapter. Although CBM involves relatively high investment costs, this maintenance method offers significant potential for improving the efficiency and effectiveness of maintenance processes, since it is 'predicted' when a failure occurs (Ali and Abdelhadi, 2022; Mooij, 2023; Su et al., 2015; Simion et al., 2021). But, it also presents considerable challenges for the RNLN. One of the biggest issues is the enormous variability in the use of systems on board navy ships. These ships operate under very diverse conditions, making it difficult to collect and interpret reliable data (Interview 2, 2024; Interview 1, 2024; Tinga, 2013).

2.2.1. Variable Operating Conditions

The variable conditions under which ships operate, such as varying speeds, see state and weapon usage, make it difficult to define consistent baselines for data analysis (Interview 2, 2024; Interview 1, 2024; Ellis, 2009; Nunes, Santos, and Rocha, 2023; Su et al., 2015). The intensity of system usage varies greatly. During operations, some systems are used intensively, while others are less burdened, complicating CBM. As noted by Interview 1 (2024): "These ships are either in port, or they sail, or they sail at 10%, or they sail at 100%, or they are stationary, or they have headwinds. So many variables. I worry about whether we can do predictions based on data at all."

2.2.2. Limited Data Availability

Although there is one Combat Support Ship that collects data, collection of data by this single vessel alone will not be enough to identify data patterns that apply for multiple ships in the fleet. More usage data of systems is needed to identify patterns and norms (Interview 1, 2024; Interview 2, 2024; Ford, Housel, and Mun, 2012; Mooij, 2023; Tinga, 2013; Nunes, Santos, and Rocha, 2023). Most existing Dutch naval ships do not yet collect extensive operational data (Interview 1, 2024; Interview 2, 2024), meaning it could take years to gather sufficient data to make CBM effective. In the automotive industry, CBM is much more developed due to continuous and consistent data collection. For example, Tesla vehicles constantly collect data and send it to the manufacturer for analysis (James, 2023;Wang, 2023). This is possible because cars operate under more predictable and uniform conditions than navy ships (apart from the fact that the size of cars is much smaller).

2.2.3. Lack of Comprehensive Data Packages

A potential solution to a part of the data problem would be for suppliers of onboard systems, to provide data packages with their systems. This way, baselines for data analysis could be defined more quickly (Interview 1, 2024; Nunes, Santos, and Rocha, 2023). However, no supplier currently includes comprehensive data packages with their products (Interview 1, 2024), limiting the possibilities for CBM. Without the necessary data packages, the Ministry of Defense cannot get a complete picture of the status of these systems, and essential information for CBM is missing (Interview 1, 2024;Nunes, Santos, and Rocha, 2023).

2.2.4. Infrastructure for Data Analysis

While more data is being collected, there is no comprehensive infrastructure for data analysis (Interview 1, 2024;Interview 2, 2024;Karatuğ, Arslanoğlu, and Soares, 2023;Mooij, 2023). Within the RNLN, there is a lack of necessary algorithms and software to process and use the data effectively for CBM. No standard methods have yet been developed to analyze and use the collected data for CBM, delaying its implementation (Interview 1, 2024;Interview 2, 2024;Mooij, 2023).

Also it is unknown which systems are really suitable for application for CBM. To make a start with CBM, the RNLN decided to put sensors on different systems within the vessel HNLMS Den Helder. However, they have not been sure yet which systems are suitable to apply CBM to. It could be possible that for some systems, application of CBM doesn't yield a benefit in terms of costs and less downtime of vessels (Interview 1, 2024).

All together, CBM offers potential benefits, but is hampered by variable operating conditions, limited data availability, lack of comprehensive data packages from suppliers, and lack of knowledge which systems are suitable for application of CBM. This lack of advancement in CBM within the RNLN is reflected by Mooij (2023). Who uses the CBM maturity model, made by van de Kerkhof, Akkermans, and Noorderhaven (2019) to compare the CBM maturity within the RNLN with other industries. This CBM maturity model describes the CBM development stages on a scale from 1 to 5, as described below

1. No CBM: Assets are not maintained or monitored at all.
2. Reactive CBM: Monitoring is not done regularly, but CBM can be used to identify problems when they occur.
3. Scheduled CBM: CBM is used to boost maintenance efficiency, relying on simple, easy-to-use tools and techniques.
4. Proactive CBM: The approach is aimed at enhancing the reliability and performance of key assets.
5. Top-tier CBM: The goal is to extract maximum value from the entire asset base through advanced CBM methods.

According to Mooij (2023) the CBM maturity within the RNLN is only 2.4, compared to an average CBM development of 3.7 for other industries.

2.3. Cultural challenges

One observed challenge is the adoption of new maintenance methods. Many workers tend to favor traditional approaches, such as performing maintenance on a fixed schedule (i.e., once every five years), rather than adopting predictive maintenance strategies (Interview 2, 2024; Mooij, 2023). This preference may stem from a limited familiarity or comfort level with new CBM technologies. Additionally, transitioning to CBM requires that workers acquire skills in data analysis and the use of new maintenance tools. In some cases, there appears to be a need for more motivation, training, and educational support among the maintenance staff, which could help facilitate a smoother and more effective use of CBM (Interview 1, 2024; Interview 2, 2024; Mooij, 2023).

Good application of CBM requires smoother communication between different levels of the organization (Interview 1, 2024;Interview 2, 2024;Mooij, 2023). Interview 1 (2024), Interview 2 (2024) and Mooij (2023) note that there are communication gaps, especially between the ship crew and maintenance engineers on land. This gap causes misunderstandings and inefficiencies in the maintenance process.

Not all maintenance workers consistently log data or fully implement new procedures (Mooij (2023); Interview 2 (2024)). This appears to be partly due to a natural tendency to rely on familiar routines. Accurate data entry is essential for effective CBM, and as Ford, Housel, and Mun (2012) and Mooij (2023) note, there are occasions when the data recorded in the RNLN's maintenance registration system is incomplete or contains errors. Addressing these challenges could help improve the reliability of the data used for CBM (Ford, Housel, and Mun, 2012; Mooij, 2023).

2.4. Challenges of Overloading Maintenance Schedules: Impact on Efficiency and Error Rates

Another major challenge in the RNLN naval ship maintenance is the current model of Preventive Maintenance. Preventive Maintenance means that maintenance is scheduled every couple of months and years. For example, frigates undergo a maintenance period after four operational years, during which a year is dedicated to comprehensive maintenance. During this four-year period, assistant maintenance periods are also scheduled, lasting approximately four to eight weeks, during which all necessary maintenance is planned and performed (Interview 1, 2024;Interview 2, 2024;Mooij, 2023). A characteristic of Preventive Maintenance is that systems are replaced, regardless of the actual condition of the system. It is possible that the system could still function for years. This can result in increased expenditures and inefficient allocation of labor.

With Preventive Maintenance many tasks are scheduled to be performed simultaneously (Interview 1, 2024)(Ford, Housel, and Mun, 2012). Carrying out a large number of maintenance tasks in a single period is organizationally complex and logistically challenging. Concentrating a large number of maintenance tasks within a single period can lead to significant peaks in the demand for resources and personnel. This increase in workload raises the likelihood of errors and can slow down the entire maintenance process (Interview 1, 2024; Ghamlouch, Fouladirad, and Grall, 2019;McDevitt, Zabarouskas, and Crook, 2003; Vintr and Valis, 2006). McDevitt, Zabarouskas, and Crook (2003) highlight this issue, showing that factors like worker fatigue, infrastructure strain, and imbalances in the labor-to-infrastructure ratio directly affect productivity and error rates. When the workload becomes too high compared to the available resources, these inefficiencies lead to delays, increased maintenance costs, and a prolonged time for navy vessels to return to operation.

Figure 2.1 presents a visual of how productivity decreases as various factors (such as workforce fatigue, infrastructure limitations, and workforce-to-infrastructure imbalances) increase. The **X-axis** in these graphs represents the degree of fatigue, workforce ratio, or experience level, while the **Y-axis** shows the corresponding effect on productivity, where values below 1 indicate a reduction in productivity.

1. Fatigue's Impact on Productivity: As worker fatigue grows, the productivity multiplier declines, meaning the more exhausted workers are, the less efficient they become.
2. Infrastructure Fatigue's Role: As infrastructure fatigue increases, productivity decreases non-linearly. Beyond a certain point, the infrastructure becomes inefficient at supporting the workforce, reducing overall productivity.
3. Labor-to-Infrastructure Ratio: When the workforce outgrows the infrastructure's capacity, productivity is further reduced. For example, if too many workers are using limited tools and spaces, overcrowding and competition for resources slow down the work, reflecting a decrease in efficiency.
4. Worker Experience: Conversely, productivity rises as worker experience increases. Experienced workers are more adept at handling tasks efficiently, leading to fewer mistakes and quicker task completion. With maintenance peaks, the number of experienced workers relatively reduces.

Figure 2.2 elaborates on this by illustrating how various factors affect error rates in ship repair. The **X-axis** here represents variables such as worker fatigue, the workload-to-labor ratio, and experience, while the **Y-axis** displays the error rate multiplier, where values above 1 indicate an increase in errors.

1. Fatigue and Errors: As workers become fatigued, the error rate climbs non-linearly. Tired workers

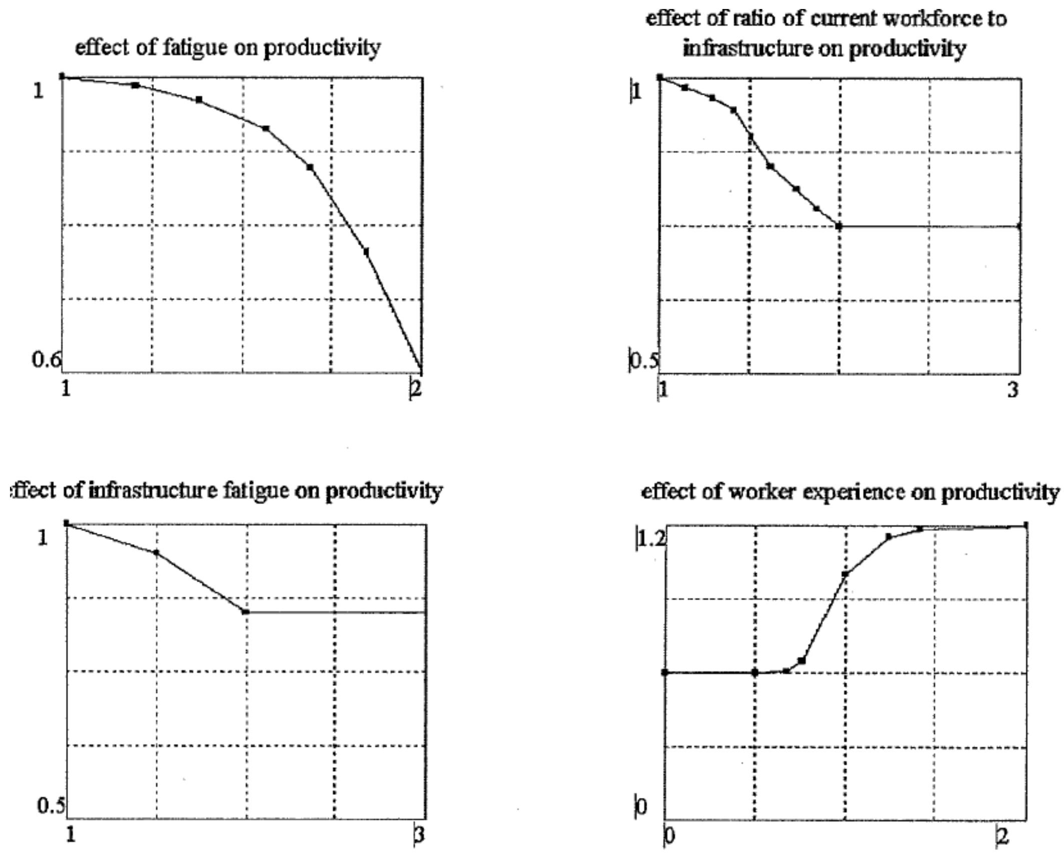

Figure 2.1: Impact of various factors on shipyard productivity. (McDevitt, Zabarouskas, and Crook, 2003)

are more prone to making mistakes, which increases the need for rework and extends maintenance time.

2. Workload-to-Labor Ratio: When the workload exceeds the available labor force, errors increase. This often happens when shipyards are overburdened with too many maintenance tasks at once, leading workers to rush and make more errors.
3. Labor-to-Infrastructure Imbalances: Similarly, when there is a mismatch between the size of the workforce and the available infrastructure, error rates rise. Overloaded infrastructure results in insufficient support for workers, causing more mistakes during repairs.
4. Worker Experience Reducing Errors: More experienced workers make fewer errors, as shown in the graphs. This is a linear relationship, where increasing experience directly leads to a lower error rate. Experienced workers are better at avoiding mistakes, leading to faster and more accurate repairs.

Together, these findings emphasize that overloading the maintenance schedule leads to more errors and delays, and thus higher costs and less vessel availability. By managing workloads and ensuring a proper balance between labor and infrastructure, shipyards can minimize errors, optimize expenditures, and shorten repair times (McDevitt, Zabarouskas, and Crook, 2003; Interview 1, 2024).

Also, the current model of Preventive Maintenance offers little room for adjustments based on the actual condition of the systems (Interview 1, 2024;Barlow et al., 2021;Vintr and Valis, 2006). This means that some maintenance tasks are performed unnecessarily early (leading to higher expenditures and inefficent use of labor), while others may be postponed to the next maintenance period, potentially reducing the reliability of the ships.

All together, the current Preventive Maintenance model, which bundles many tasks into a single period, leads to organizational complexity, increased costs, and potential reductions in ship reliability due to

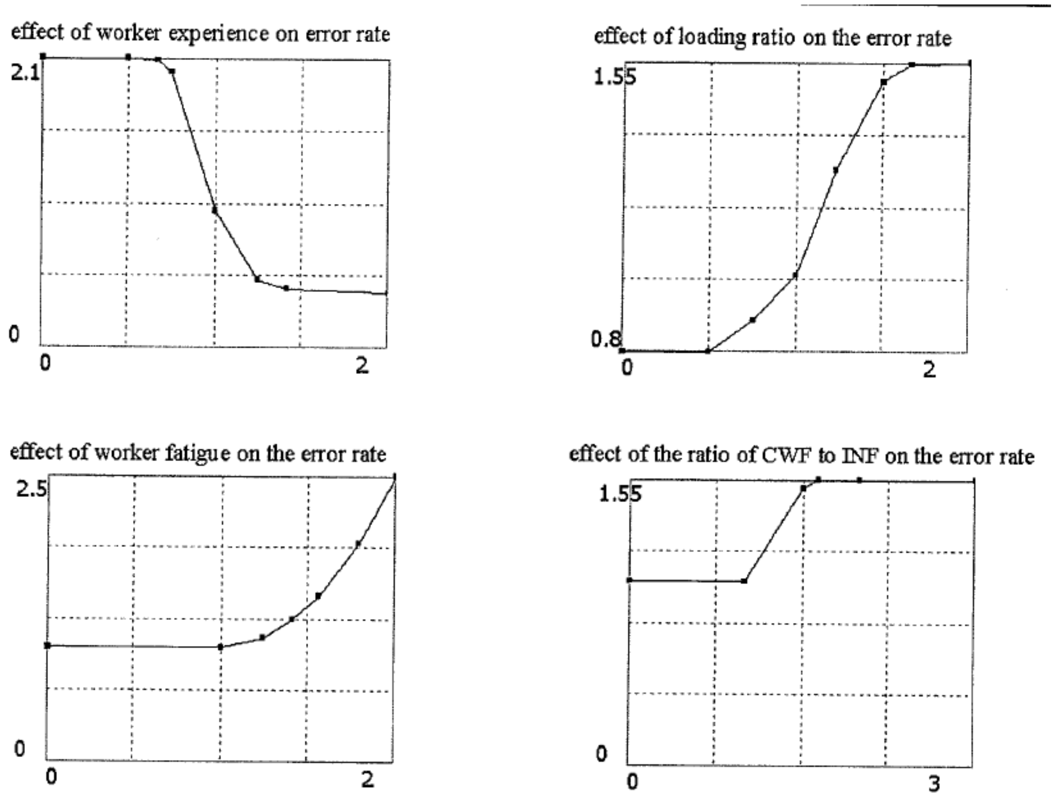

Figure 2.2: Impact of various factors on error rates in ship repair. (McDevitt, Zabarouskas, and Crook, 2003)

the inflexibility of maintenance scheduling. An absence of CBM leads to a increase in the number of workload peaks and the height of workload peaks (Interview 1, 2024;Bengtsson et al., 2004;Ghamlouch, Fouladirad, and Grall, 2019).

2.5. Need for Prioritization in Maintenance

To make a start with CBM, the RNLN installed sensors on several systems, but without knowing which systems are most relevant for CBM. This is logical, because one way of finding out whether CBM works, is by trying. However, this approach leads to a lot of potentially unnecessary costs and does not consider the varying importance of different systems (Interview 1, 2024). Not every system is critical enough to warrant CBM. As Abels mentioned, “We have put sensors on all systems, and now we are looking to see what will happen. This approach brings many extra costs, and not every system is relevant to apply CBM to.” Tinga, 2013 describes how one of the most critical steps in the process is determining which systems are suitable for CBM. This involves overcoming several key challenges to ensure the selected systems benefit from CBM and justify the investment. This way, the least amount of the limited resources the RNLN has (like data sensors, data engineers and data algorithms), would be spilled (Interview 1, 2024;Alhouli, 2011;Interview 2, 2024;Mooij, 2023;Tinga, 2013;Pieterman et al., 2011).The following sections outline these challenges in detail.

One of the primary challenges in implementing CBM is choosing the right parameters to monitor (Mooij, 2023;Tinga, 2013). These parameters must accurately reflect the system’s health and performance, providing early warnings of potential failures. Selecting incorrect parameters can lead to unnecessary maintenance or missed opportunities to prevent failures, which undermines the effectiveness of CBM.

Another significant challenge is ensuring sensor availability and proper placement (Mooij, 2023;Tinga, 2013). CBM relies on sensors to gather accurate data, but placing these sensors in optimal locations can be difficult. Sensors must be suitable for the environment they operate in and must provide reliable data without being affected by interference or damage. This often involves dealing with physical constraints and ensuring that sensors can withstand harsh operating conditions.

Economic feasibility is another critical factor that must be considered. It's essential to assess whether implementing CBM is economically viable (Interview 1, 2024;Alhouli, 2011;Mooij, 2023;Tinga, 2013;Pieterman et al., 2011). This involves determining if the benefits of CBM, such as reduced maintenance costs and improved system availability, outweigh the initial investment costs. These costs include purchasing and installing sensors, hardware network to gather the data, developing data processing systems, and creating failure prediction models. The goal is to ensure that the long-term savings and benefits justify the upfront expenses.

Figure 2.3, shows the challenges that come with choosing which systems are suitable for CBM (Tinga, 2013). It outlines a process for picking the right parameters, placing sensors correctly, building physical failure models, and checking if CBM is more cost-effective than traditional maintenance methods. Although formulating these questions is simple, trying to come up with an answer to these questions can be challenging. Especially the question on "A4)does application of CBM yield financial or safety benefit?". This question remains unanswered within the RNLN.

All together, the Navy's approach of installing sensors on all systems without prioritization leads to unnecessary costs and inefficiencies. The challenge is in determining which systems are relevant for CBM.

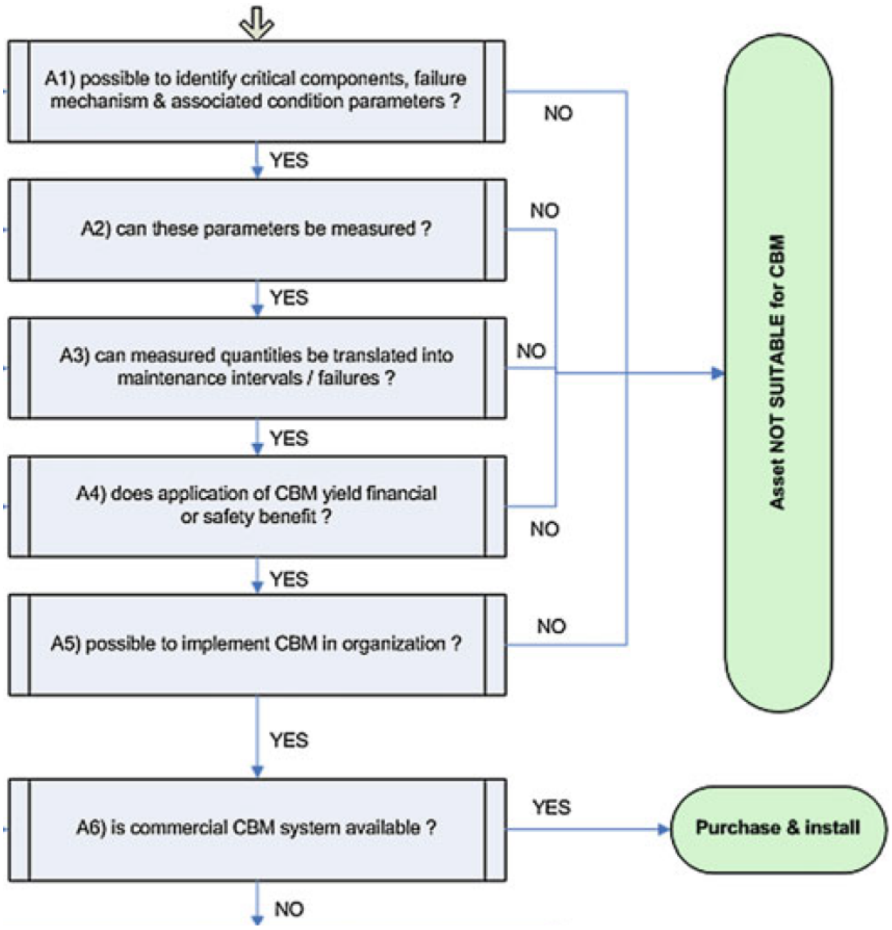

Figure 2.3: A scheme to determine whether a system is suitable for CBM, created by Tinga (2013).

2.6. Conclusion

This chapter aimed to address the first sub-question of this research, SQ1: "What are the general challenges surrounding Dutch naval ship maintenance?".

The maintenance of Dutch navy ships is confronted with a range of intricate challenges that span organizational and technical dimensions. Key issues include the reliance on an external partner, the implementation of CBM, and the complexities associated with maintenance scheduling. The relationship with external companies, characterized by a monopoly that limits control and transparency, increases costs and operational inefficiencies. Meanwhile, the adoption of CBM, though promising, is hindered by variable operating conditions, insufficient data, missing knowledge on CBM-suitable installations and inadequate infrastructure. Planning wise, challenges further complicate maintenance, particularly when large volumes of tasks are scheduled simultaneously, leading to inefficiencies and potential reductions in ship reliability. To cope with these challenges, it is important to understand which maintenance methods will yield the best financial benefit and least downtime of systems. This way the least amount of the limited resources the RNLN has would be spilled. Meanwhile, the high maintenance peaks could potentially be shaved.

Although the RNLN faces significant challenges in balancing maintenance costs with operational readiness, especially in the context CBM, existing research and practical frameworks provide limited guidance on how to select the most effective maintenance strategy at the system level. Most current approaches either generalize maintenance planning across vessel types or focus narrowly on technological implementation without evaluating trade-offs between different maintenance methods. As a result, there is a lack of decision-support models that enable comparison of maintenance strategies across different shipboard systems in terms of both cost and downtime. This gap makes it difficult for decision-makers to allocate limited resources efficiently and optimize maintenance schedules. Therefore, further research is needed to develop a model that allows for systematic comparison of maintenance approaches per system and vessel type to support evidence-based decision-making in naval fleet maintenance.

3
Currently used maintenance methods

To identify which maintenance methods are yielding least downtime of vessels and least costs, first needs to be determined which maintenance policies are relevant to compare. Therefore the second sub question, SQ2: *"Which maintenance methods are currently used within the Royal Netherlands Navy, and outside the navy organization, and which are relevant to include in the cost determination?"* will be answered. This is done by providing an overview of the various maintenance strategies currently employed by RNLN, as well as those used in other industries. It also examines how these strategies are applied within the RNLN. Additionally, the chapter addresses common misconceptions about maintenance terminology, specifically the differences between Preventive Maintenance, Time-Driven Scheduled Maintenance, and Condition-Based Maintenance, to ensure a clear understanding of the terms used in this report.

3.1. General maintenance methods

Across multiple industries, maintenance strategies can be divided into reactive, proactive, and aggressive maintenance policies, each with specific methods and goals (Tinga, 2013;Alhouli, 2011;Goossens and Basten, 2015;Emovon, 2016). An overview and classification of the different maintenance policies can be seen in Figure 3.1.

3.1.1. Reactive maintenance policies

Reactive maintenance policies focus on fixing problems only after they happen. Corrective Maintenance is a key part of Reactive Maintenance and involves repairing or replacing parts after they fail. While this approach makes full use of the parts, it can lead to unexpected downtime and higher costs due to the unplanned nature of the repairs. Detective Maintenance, another form of Reactive Maintenance, is used for hidden problems, particularly in protective devices like sensors (i.e., fire alarms). Maintenance is only done when tests reveal a failure, which may have occurred long before it was detected, potentially leading to safety risks.

3.1.2. Proactive maintenance policies

Proactive maintenance policies aim to prevent problems before they happen by monitoring or predicting the condition of equipment. Preventive Maintenance is the most traditional form of Proactive Maintenance and involves regularly scheduled activities such as inspections, part replacements, and routine services to avoid unexpected breakdowns. CBM and Predictive Maintenance are key components of Preventive Maintenance. CBM relies on real-time monitoring to decide when maintenance is needed based on the actual condition of the equipment, while Predictive Maintenance uses historical data and usage patterns to predict the best times for maintenance, reducing unnecessary work. An important part of Predictive Maintenance is Time-Driven Scheduled Maintenance. This approach involves performing maintenance tasks at predetermined intervals, based on elapsed time or operating hours, regardless of the current condition of the equipment. The primary goal is to prevent failures by replacing parts or servicing equipment before it is likely to fail. For example, the RNLN has a policy for ves-

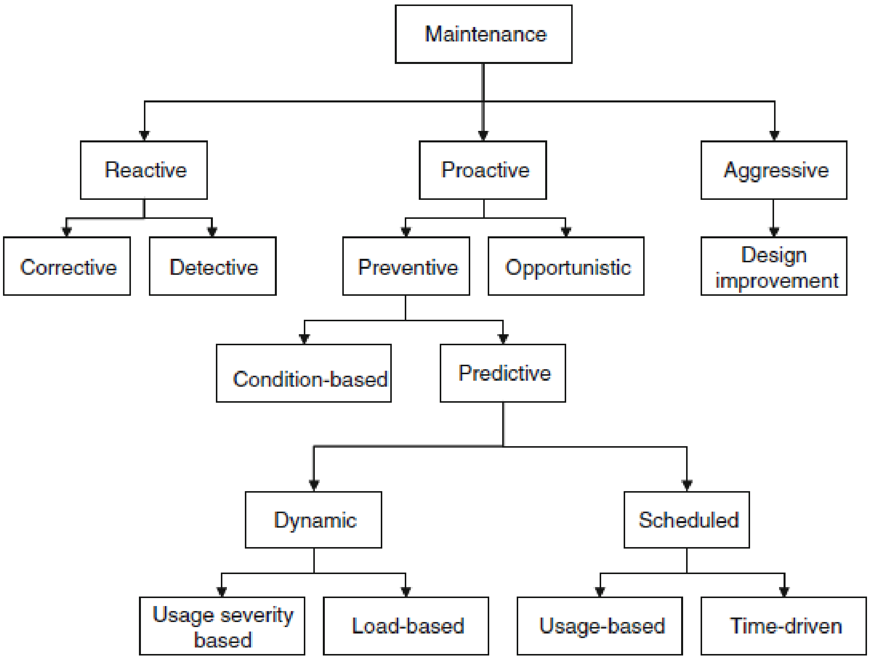

Figure 3.1: Overview and classification of the different maintenance policies (Tinga, 2013).

sels that are larger than frigates to undergo a major maintenance period called ”Benoemd Onderhoud” (BO) after five operational years, with a year dedicated to maintenance (Interview 1, 2024;Interview 2, 2024;Mooij, 2023). Frigates undergo a BO after four operational years, during which a year is dedicated to comprehensive maintenance. During this maintenance period, assistant maintenance periods are also scheduled, lasting approximately four to eight weeks, during which all necessary maintenance is planned and performed (Interview 1, 2024;Mooij, 2023). While this method helps avoid unexpected breakdowns, it can also result in the replacement of parts that still have useful life left, leading to higher maintenance costs and can lead to inefficient use of labor.

Opportunistic Maintenance

Opportunistic Maintenance is a strategy that is part of the Proactive Maintenance policy. The strategy involves doing maintenance on a specific part when other work is being done on the same part, even if the maintenance is not urgently needed (Tinga, 2013;Ibazebo et al., 2023) This saves time and money by reducing repeated preparation tasks.

Condition Based Maintenance

Condition Based Maintenance (CBM) is a way of doing maintenance that uses the actual condition of equipment to decide when maintenance should be done. This approach aims to perform maintenance only when necessary, based on real-time data collected from the equipment.

CBM involves several key steps (Tinga, 2013).

1. First, data collection is done using sensors and monitoring devices that gather information on things like vibration, temperature, pressure, and other signs of equipment health. This data is collected continuously or at regular times to keep track of the equipment’s condition.
2. The next step is condition monitoring, where the collected data is collected to see the current state of the equipment. Techniques like vibration analysis, thermography, and oil analysis are commonly used to spot signs of wear and tear or possible failure.
3. Data analysis and interpretation come next. Here, the data is examined using statistical and computer models to find unusual patterns and trends that show potential failures. Advanced

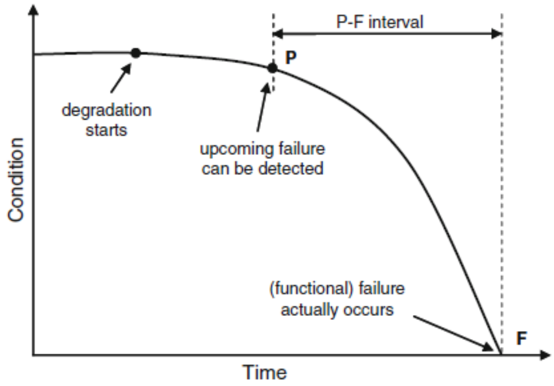

Figure 3.2: P-F interval. (Tinga, 2013)

software tools help interpret the data accurately.

4. Based on the analysis, decisions are made about the timing and type of maintenance actions needed. The goal is to do maintenance only when necessary, reducing unnecessary maintenance and preventing unexpected failures.

Figure 3.2 explains the idea of the PF interval, which is a crucial part of the CBM process. The PF interval is the time period between noticing a potential failure (P) and the point where a functional failure (F) happens. Where P is the point at which a problem or anomaly is first noticed through condition monitoring. At this stage, the equipment is still working, but there are signs that a failure is likely to happen soon. F is the point at which the equipment stops performing its intended function. Functional failure leads to downtime and usually requires immediate repair.

The importance of the PF interval is that it allows for early detection of potential failures, enabling maintenance actions to be scheduled before the failure becomes serious. By understanding the length of the PF interval, maintenance can be done at the best time, maximizing equipment uptime and minimizing disruptions. Additionally, knowing the PF interval helps in better planning and allocation of maintenance resources, ensuring that parts and personnel are available when needed.

While CBM can help minimize the misallocation of resources by predicting when an installation is likely to fail, it does require a relatively high upfront investment, due to investment in IT infrastructure, sensor allocation and sensor installation.

3.1.3. Aggressive maintenance policies

Aggressive maintenance policies take things a step further by focusing on improving the system design to reduce the number of problems. Total Productive Maintenance (TPM)is an example of this approach, emphasizing the involvement of all employees in maintenance activities with the goal of achieving zero breakdowns and defects through continuous system improvements (Alhouli, 2011;Tinga, 2013).

3.2. Maintenance Practices within the RNLN

The RNLN follows a structured approach to maintenance, with a strong focus on preventive measures. Within the RNLN, a distinction is made between Preventive Maintenance, Corrective Maintenance, and CBM (Interview 1, 2024;Interview 2, 2024;Mooij, 2023). Also in other naval industries, a distinction is made between those three maintenance methods (Alhouli, 2011;Tinga, 2013). However, CBM is considered a subset of Preventive Maintenance, as demonstrated by the theoretical models outlined by Tinga, Alhouli, and Goossens in section 3.1. In the RNLN, Preventive Maintenance is commonly referred to as Time-Driven Scheduled Maintenance.

3.2.1. Preventive Maintenance

Preventive Maintenance is the most traditional and widely practiced strategy within the RNLN (Interview 1, 2024;Mooij, 2023). It is characterized by the planning and scheduling of maintenance activities

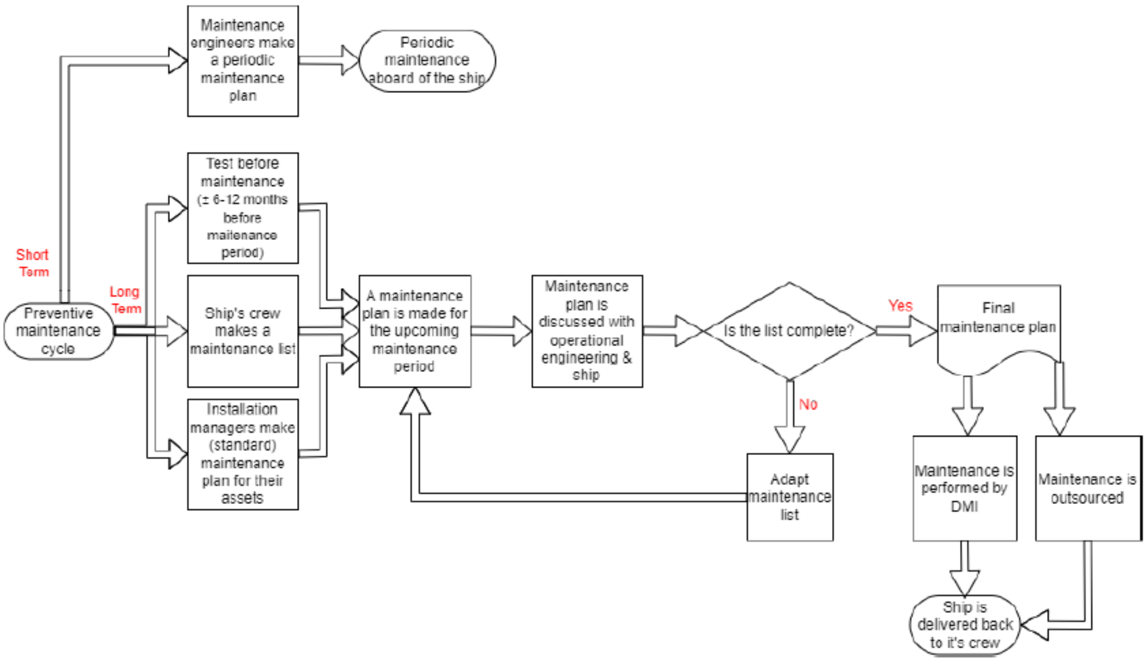

Figure 3.3: Preventive Maintenance cycle of the RNLN (Mooij, 2023).

based on time intervals rather than the actual condition of the equipment. The RNLN has a policy for vessels larger than frigates to undergo a major maintenance period (BO period) after five operational years, with a year dedicated to maintenance. Frigates undergo a BO period after four operational years, during which a year is dedicated to comprehensive maintenance. Apart from this significant overhaul every couple of years, there are also two other maintenance periods: short-term maintenance tasks performed aboard the ship and long-term maintenance every three monthsm, also called assisted maintenance, lasting approximately four to eight weeks (Interview 1, 2024;Interview 2, 2024;Mooij, 2023). Preventive maintenance accounts for about 80% of the RNLN's maintenance activities (Interview 1, 2024; Interview 2, 2024; Interview 3, 2024; Interview 6, 2024; Mooij, 2023), reflecting its key role in keeping the fleet ready for action.

Figure 3.3 demonstrates how the preventive maintenance process is structured, involving both short-term and long-term cycles. The diagram highlights the interaction between various stakeholders, such as maintenance engineers, ship crews, and installation managers. The flow diagram begins and ends with oval-shaped symbols, representing the start and end of the process. Square shapes indicate processes or actions, while diamond shapes represent decision points. Arrows illustrate the flow of the maintenance process. The graph also shows how the maintenance plan is adapted based on the crew's feedback, leading to a final maintenance plan.

3.2.2. Corrective Maintenance

Corrective Maintenance is done when equipment fails unexpectedly (Interview 1, 2024;Mooij, 2023;Ibazebo et al., 2023;Wahid et al., 2018). This type of maintenance is important for fixing problems that preventive measures might have missed. When a system on board a ship fails, operational engineers are first called in. They determine the cause of the problem and what is needed to fix it. If they cannot resolve the issue, a specialist is brought in. If the problem cannot be solved on-site, the ship is brought to a maintenance facility, or an external company is involved to carry out the repair (Interview 1, 2024). Corrective maintenance makes up about 15% of the RNLN's maintenance activities (Interview 1, 2024; Interview 2, 2024; Interview 3, 2024; Interview 6, 2024; Mooij, 2023).

Figure 3.4 shows the Corrective Maintenance cycle used by the RNLN, focusing on how breakdowns are managed. The flow diagram begins with an oval-shaped start symbol and ends with an oval-shaped end symbol, with various steps in between. Squares represent processes or actions, while diamonds

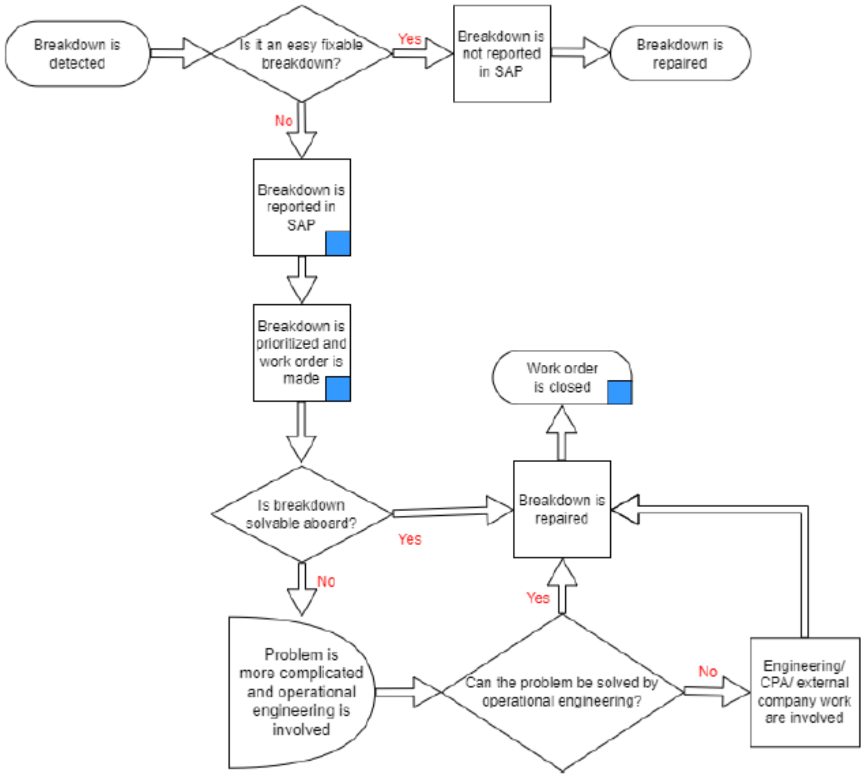

Figure 3.4: Corrective Maintenance cycle at the RNLN (Mooij, 2023).

indicate decision points. Arrows show the flow of the maintenance process, with blue squares indicating actions within the maintenance registration system. The Corrective Maintenance process begins with the detection of a breakdown, which is reported to the head of technical services and registered in the maintenance registration system. The breakdown is then prioritized, and repairs are conducted by shipboard mechanics, the RNLN maintenance department, or outsourced to external companies (Mooij, 2023).

3.2.3. Condition-Based Maintenance

Condition Based Maintenance (CBM) is a newer approach within the RNLN, focusing on maintenance based on the actual condition of the equipment (Interview 1, 2024;Mooij, 2023;Ibazebo et al., 2023;Wahid et al., 2018. CBM involves regular monitoring using techniques like vibration analysis and fluid inspections. These measurements are taken approximately every four months and analyzed by the Condition and Performance Assessment (CPA) department to provide maintenance recommendations based on the current state of the equipment (Interview 1, 2024;Mooij, 2023). CBM is a newer practice and accounts for about 5% of the RNLN's maintenance efforts (Interview 1, 2024; Interview 2, 2024; Email communication 1, 2024; Mooij, 2023). A relatively new ship, the HNLMS Den Helder, is equipped with more sensors that collect data on the systems on board (Interview 1, 2024). Though data is being collected, interpreting and using it for predictive maintenance is still under development. Drawing conclusions from the acquired data requires enough data and software that can analyze the data and provide meaningful insights.

Figure 3.5 shows the CBM cycle within the RNLN. The flow diagram begins with an oval-shaped start symbol and ends with an oval-shaped end symbol, with various steps in between. Squares represent processes or actions, while diamonds indicate decision points. Arrows show the flow of the maintenance process, with blue squares indicating actions within the maintenance registration system. The CBM process begins with condition monitoring, where data is collected through vibration and liquid analyses conducted by the CPA department approximately every four months. The gathered data is then analyzed, and maintenance recommendations are made. The ship's crew receives this information

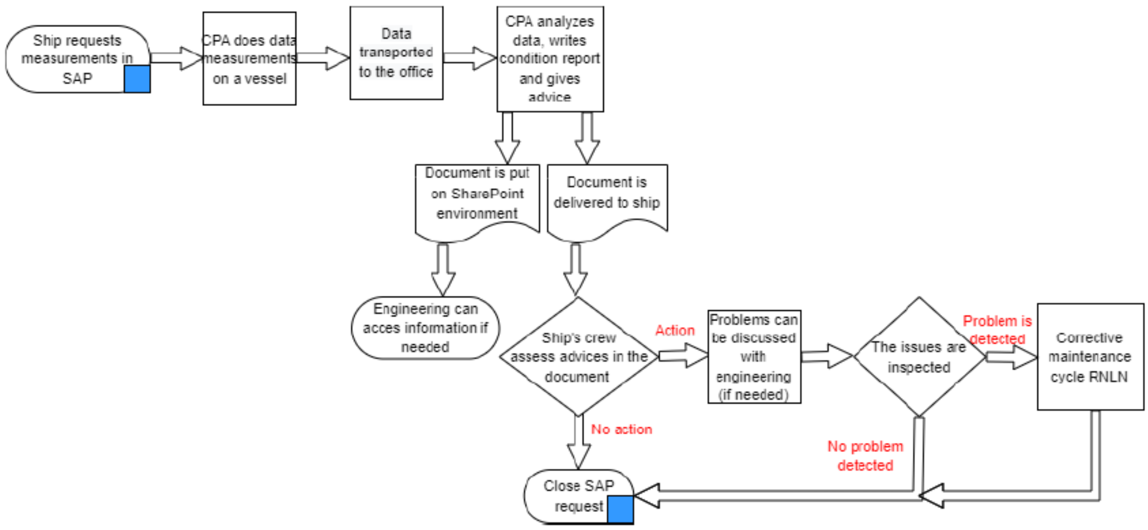

Figure 3.5: CBM process at the RNLN (Mooij, 2023).

and decides whether to act on it (Mooij, 2023).

3.3. Misconceptions in Maintenance Terminology

As can be concluded from Sections 3.1 and 3.2, Alhouli (2011), Tinga (2013) and Goossens and Basten (2015) use different terms for Preventive Maintenance than the RNLN. In everyday language within the RNLN, Preventive Maintenance is often understood as Time-Driven Scheduled Maintenance which misses the fact that true Preventive Maintenance includes both Time-Driven Scheduled Maintenance ánd Condition-Based Maintenance, as described by Alhouli (2011), Tinga (2013) and Goossens and Basten (2015).

In this report, there will be made distinct according to Alhouli (2011), Tinga (2013) and Goossens and Basten (2015), as described in section 3.1. In other words, a distinction will be made between Corrective Maintenance, Time-Driven Scheduled Maintenance and Condition Based Maintenance.

3.4. Conclusion

This chapter aimed to address the sub-question SQ2: *"Which maintenance methods are currently used within the Royal Netherlands Navy, and outside the navy organization, and which are relevant to include in the cost determination?"*

To answer this question, various maintenance strategies employed both within RNLN and in other industries were explored. These strategies are broadly categorized into reactive, proactive, and aggressive maintenance policies. In the broader ship industry, these categories encompass methods such as Corrective Maintenance, Time-Driven Scheduled Maintenance, and CBM. The RNLN predominantly uses these three approaches: Corrective Maintenance to address unexpected failures, Time-Driven Scheduled Maintenance as part of its preventive maintenance strategy, and CBM, which is still being developed and implemented more widely.

Additionally, this chapter highlighted a common confusion within the RNLN regarding maintenance terminology, specifically the difference between Preventive Maintenance and CBM. For clarity in this report, the definitions provided by Alhouli (2011), Tinga (2013) and Goossens and Basten (2015) are followed, where Preventive Maintenance encompasses both Time-Driven Scheduled Maintenance and CBM.

Since the maintenance methods currently used within the RNLN are Corrective Maintenance, Time-Driven Scheduled Maintenance, and CBM, all these methods are relevant to include in the cost and reliability comparison, as they each play a critical role in ensuring the reliability and readiness of naval assets. An overview of the (dis)advantages of each method is given in Table 3.1.

It is now known which maintenance methods will be compared on costs and vessel reliability. The next step is to identify how these maintenance methods can be compared on financial benefits (least costs) and vessel reliability (least downtime). This will be explained in Chapter 4.

Table 3.1: Description of each method

Maintenance method	**Resource-related description**
Corrective Maintenance	No scheduled expenditure on work or materials until an installation fails. This approach can be very economical, but an unexpected breakdown during a mission may lead to significant, unpredictable expenses and substantial downtime.
Time-Driven Scheduled Maintenance	Maintenance is performed at predetermined intervals. While this strategy avoids unexpected failures, it may result in workload surges and the premature replacement of installations, which can lead to inefficient resource utilization.
Condition-Based Maintenance	Maintenance is scheduled based on real-time condition monitoring, enabling peak workload shaving and more efficient resource use by avoiding unnecessary replacements. However, it demands higher initial investments in IT infrastructure, specialized personnel, and sensors.

4
Theoretical basis of model

Chapter 2 outlined the main challenges in Dutch naval ship maintenance and the research gap. Chapter 3 identified the relevant maintenance methods to include in this research. This chapter describes the theoretical foundation of a model that enables such a comparison. The model is designed to evaluate the total costs and man-hours, including downtime, associated with different maintenance distributions over the lifespan of a naval vessel.

This chapter starts with an explanation of the structure of the model and its in-depthness, in Section 4.1. Section 4.2 describes how raw maintenance data and expert input is transformed into cost and man-hour projections for different distributions of CM, TDSM, and CBM.

4.1. Model Development

Following on the research gap identified in Chapter 2, the following model requirements were derived:

1. Applicability Across Different Ships
   The model needs to work for all major ships in the RNLN fleet, including OPVs, M-Frigates, LCFs, LPDs, JSS, and the CSS. If the installation breakdown is too detailed, it might only work for certain ships, making it less useful.
2. Model complexity
   The model should not be too complex. Focusing too much on individual parts of installations could lead to a “Christmas tree effect”, where too much detail makes it hard to manage and understand the results.
3. Providing Useful Insights
   The model should enable clear conclusions about the optimal maintenance strategy for different onboard systems.

To develop the model, twelve interviews were held with fourteen experts from RNLN’s maintenance department, DMI. The interviewees included, among others, weapon system managers, data analysts, engineers, and maintenance planners. An oversight of the interviews and other personal communication is given in Appendix D. These conversations helped to understand how maintenance is done and what factors affect the costs and man-hours needed for maintenance. From these interviews, it was found that the RNLN’s maintenance activities can be divided into three levels:

1. Macro Level:
   Macro level is about maintenance planning for the whole fleet, focusing on using financial and labour resources efficiently across different ships (Interview 3, 2024; Interview 7, 2024).
2. Meso Level:
   Meso level looks at maintenance for individual ships. (Interview 3, 2024; Interview 6, 2024; Email communication 5, 2024).

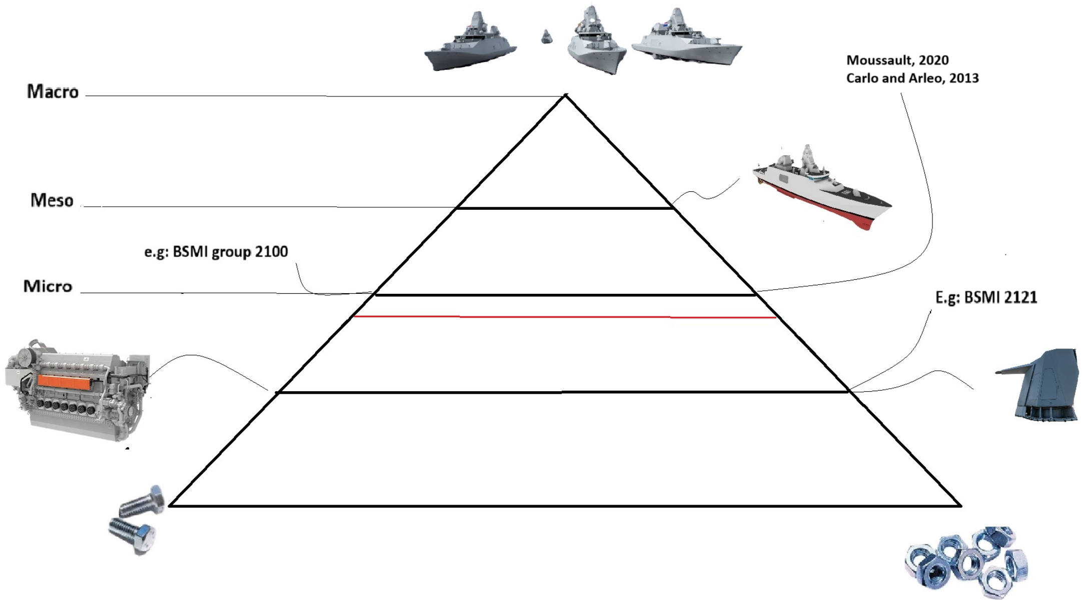

Figure 4.1: System pyramid within the RNLN.

3. Micro Level:
   Micro level is the most detailed level, focusing on maintenance of specific systems and parts onboard. It covers everything from large groups of systems like sensors and weapons to small parts like engines, cannons, and even screws and bolts. (Interview 1, 2024; Interview 3, 2024; Interview 4, 2024; Interview 5, 2024; Interview 6, 2024; Email communication 2, 2024)

A view of these maintenance levels is shown in Figure 4.1. The studies of Moussault (2020) and Carlo and Arleo (2013) can also be seen. These studies did calculations on the involved costs of maintenance as well. And these studies were performed by looking at the top of micro-level maintenance.

Since macro and meso levels focus on fleet-wide and ship-wide planning, respectively, these levels were not considered in this research. Instead, this study focuses on costs, man-hours and downtime at micro level, where individual and groups of installations can be analyzed.

All onboard systems were categorized using BSMI codes. Each system on board has its own BSMI code, such as 2121 for the SONAR system on an LCF. Through usage of these codes, systems were grouped into broad categories, such as propulsion (1200), sensors (2100), and weapons (2200), as summarized in Table 4.2.

The model focuses primarily on the first two digits of each BSMI code. These digits are consistent across all major RNLN vessel types (including OPVs, M-Frigates, LCFs, LPDs, the JSS, and the CSS) ensuring broad applicability. A focus on the full four-digit codes would make the model too specific and reduce its value as a fleet-wide decision-making tool. In some cases, such as the 1100 (Hull), 1300 (Power Systems), and 1600 (Piping and Electrical Systems) categories, A/B subdivisions were introduced only when clear functional differences existed and without reducing cross-vessel applicability.

This level of detail is visualized by the red line in Figure 4.1. The model zooms in just below the top of the micro level, avoiding very detailed component-level modeling (like individual engines or cannons), but still offering specific enough insights to differentiate between major onboard systems.

This design directly addresses the model requirements set in Section 4.1:

- Limited complexity is maintained by grouping systems at a high enough level to prevent overcomplication.
- Applicability across vessel types is ensured by using consistent BSMI code groupings common to all major ships.

- Usefulness for decision-making is achieved by enabling system-level analysis of cost and man-hours, including downtime, without getting lost in unnecessary detail.

In conclusion, by using BSMI-based system groupings and focusing on the first two digits, the model strikes the intended balance between detail and simplicity. This makes it broadly usable across the RNLN fleet, while still supporting relevant maintenance insights.

BSMI	Description of Installation and Components	BSMI Specification
110A	Hull (e.g., structure with bulkheads and decks, hull plating, deck-houses, bridge, etc.)	BSMI 1100 to 1169 + 1190 to 1199
110B	Paint System (mainly Chemical)	BSMI 1170 to 1189
1200	Propulsion (e.g., diesel engines, gas turbines, electric motors, PODs, converters, propellers, shafts, gearboxes, etc., including pipelines mounted on these main components)	BSMI 1200 to 1299
130A	Power Generation (mechanical, rotating parts) such as diesel generators, including some construction (foundations)	BSMI 1300 to 1329
130B	Power Distribution (mainly electrical parts) such as switchboards and distribution panels, including some electronics and construction (cable ducts, panel foundations)	BSMI 1330 to 1399
1400	HVAC (e.g., ventilation, air treatment, fans, AC units, ducts, filters, valves, tanks, foundations, pumps, motors, etc.)	BSMI 1400 to 1499
1500	Fluid Piping Systems for liquids, including compressors, centrifuges, motors, and control/monitoring systems	BSMI 1500 to 1599
160A	Gas and Workshop Piping Systems, including mechanical and construction elements (workshop equipment and lifting tools)	BSMI 1600 to 1619 + 1630 to 1639 + 1680 to 1699
160B	Lighting, Control, Monitoring, and Signaling (e.g., lighting installations, switches, cables, and electronic components like sensors and display units)	BSMI 1620 to 1629 + 1640 to 1679
2100	Sensor Systems (e.g., radars, optical, NBC) with mechanical, electrical (motors and power cables), and electronic components	BSMI 2100 to 2199
2200	Weapon Systems (e.g., EOV weapon systems, guided weapon systems, underwater defense systems)	BSMI 2200 to 2299
2300	Command Systems (e.g., information processing systems, communication systems like UHF/VHF, CCTV, video conferencing)	BSMI 2300 to 2399
2400	Nautical and Hydrographic Systems (e.g., compass, log, meteorological equipment, satellite navigation, wind measurement instruments, barometers)	BSMI 2400 to 2499

Table 4.2: BSMI Breakdown

Based on discussions Interview 4 (2024), installation manager for sonar systems and with Interview 5 (2024), head of the maintenance production department, an understanding of the repair process when a critical system on board fails during a mission was obtained. In these situations, quick repairs are required to ensure that the mission can continue. The repair process involves several steps:

- Preparing for the repair and assembling a maintenance team.
- Sending the maintenance team to the ship.
- Transporting the necessary equipment to the ship.
- Performing the repair work on board.
- Additional port time required for the vessel.
- Dockyard time for further repairs, if necessary.

Each of these factors contributes to the overall repair costs. However, according to Interview 4 (2024) and Interview 5 (2024), the exact values of these factors vary significantly from one situation to another. It all depends on the specific failure and circumstances. This variability makes it difficult to create a fixed mathematical model that accurately predicts the costs and man-hours required for CM.

Moreover, this variability is not unique to sonar systems; it applies to other types of installations as well (Interview 5, 2024; Interview 6, 2024). The unpredictable nature of CM makes it challenging to apply a standardized cost calculation method.

As a result, developing a comparison model solely based on expert interviews is not feasible. While expert input provides valuable qualitative insights, a structured mathematical approach requires additional data sources, such as maintenance records and cost breakdowns. This is why the model also incorporates historical data. The data source comes from SAP. SAP is the enterprise resource planning (ERP) software used for the central administration of maintenance by the RNLN. For administration of these maintenance tasks, the SAP system divides maintenance tasks into different call types, each representing a different kind of maintenance (Interview 3, 2024; Interview 6, 2024; Email communication 1, 2024; Interview 12, 2025; Email communication 7, 2025; Email communication 8, 2024; Email communication 9, 2024; Personal Communication 1, 2025; Personal Communication 2, 2025).

- M1 Calls:
  For systems that fail during missions but can be fixed later during scheduled maintenance.
- M2 Calls:
  For mission-critical systems that must be fixed immediately during a mission.
- M4 calls:
  Are manually created by maintenance personnel. They typically concern maintenance tasks based on usage or time, such as engine checks after a certain number of operating hours or starts, or replacing fire extinguishers based on expiration dates.
- M8 Calls:
  Are generated automatically by SAP. These immediately triggers a maintenance order, without requiring a separate notification step. The trigger is also usage-based (i.e., a cannon after a certain number of shots or an engine after a number of starts). Compared to the M4 process, the main advantage of the M8 process is that it enables maintenance staff to track which specific objects have been checked, repaired, or approved. Without this feature, individual maintenance notifications would have to be created for each object separately.
- Work Package (WP) calls Administrative activations of planned maintenance tasks based on time intervals. Tied to BO or AM periods.

Each maintenance call in SAP is broken down into four components: material costs, salary costs, external party hiring costs, and the required man-hours. M5 calls were excluded from this research because they refer to non-BSMI-specific work. Additionally, M6, M7, and M9 calls focus on design changes rather than regular maintenance and were therefore not considered in this analysis. For a full explanation of all SAP call types, see Appendix B.

How these maintenance calls are applied for CM and TDSM is explained in Sections 4.2.1 and 4.2.2, respectively. For CBM, it is different, since it is a relatively new method for the RNLN and, as explained in Section 3.2.3, not applied for more than five percent of the total maintenance. Therefore, there is not enough data in SAP to model it properly. To fill this gap, the model uses estimates for CBM based on studies and expert opinions. All together, this model is based on a combination of data from SAP and components identified through experts their experience.

4.2. Configuration of the model

Figure 4.2 gives a view of how the model works. The model consists of three main steps.

1. Input Determination:
   In the first step, maintenance data from SAP for the years 2017 to 2024 is used. This eight-year period was chosen because it is only since 2017 that the RNLN started to gather data per

maintenance call in SAP for each vessel (Email communication 1, 2024; Email communication 7, 2025). The input includes the costs and man-hours needed for each type of maintenance.

2. Baseline Calculation:
   In the second step, the eight-year data is used to estimate the total costs and man-hours for the entire life of a vessel. This is done through a linear calculation that scales the eight-years of available data up to represent the entire expected lifetime of the vessel.
   Within this second step, the costs over the entire lifetime of the vessel are calculated for a specific amount of maintenance that is being applied. In case of CM, this is 15%. Since, 15% of the entire maintenance within the RNLN is done through CM, as was explained in Section 3.2.2 In case of TDSM, this would be 80%. Since 80% of the total maintenance within the RNLN is applied through TDSM, as was explained in Section 3.2.1. For CBM, this is different. Currently there is not enough CBM applied within the RNLN to use corresponding data. Therefore assumptions need to be made where different amounts of CBM are applied. That explains the X% in step 2 of CBM.
3. Optimization:
   The last step in the process involves going from costs and man-hours over the entire lifetime of the vessel for a specific amount of maintenance, to a different amount of maintenance of CM(Y1%), TDSM(Y2%), and CBM(Y3%). This step also incorporates downtime.

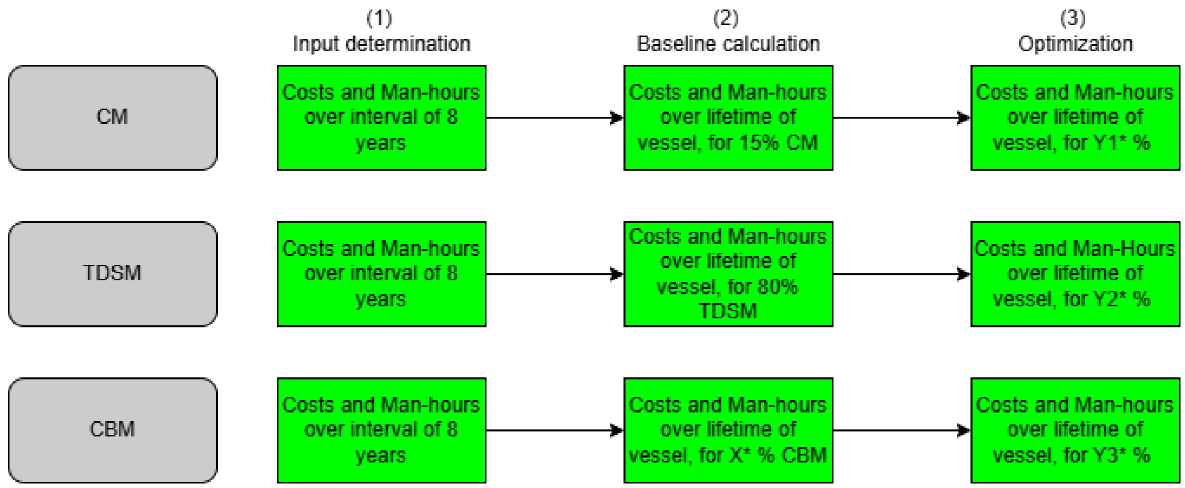

Figure 4.2: Representation of the model

In Sections 4.2.1, 4.2.2 and 4.2.3, each maintenance method will be discussed in more detail.

4.2.1. Model Explanation: Corrective maintenance

The entire costs and required man-hours for CM can be defined by the sum of M1 and M2 calls from SAP. In Figure 4.3, the step-by-step structure of the CM model is visualized, illustrating how costs and man-hours are calculated. It follows the same steps as explained the previous paragraph (Section 4.2). While SAP also breaks down call types into salary costs, external party costs, and material costs, things are simplified by not showing these details.

- For M1 calls, the model incorporates the impact of productivity changes when scaling CM levels (when going from step 2 to step 3). Since M1 maintenance tasks are scheduled during BO and AM periods, variations in CM levels affect workload distribution. Increasing CM leads to higher maintenance demands during these periods, which in turn reduces productivity due to workforce fatigue and resource constraints. Conversely, reducing CM reduces workload pressure and improves productivity. This productivity effect is discussed in detail in Section 4.2.2. Because of these productivity dynamics, the transition from Step 2 to Step 3 follows a nonlinear pattern, as represented in Figure 4.3.
- For M2 calls, the model assumes that costs and man-hours follow an exponential growth pattern.

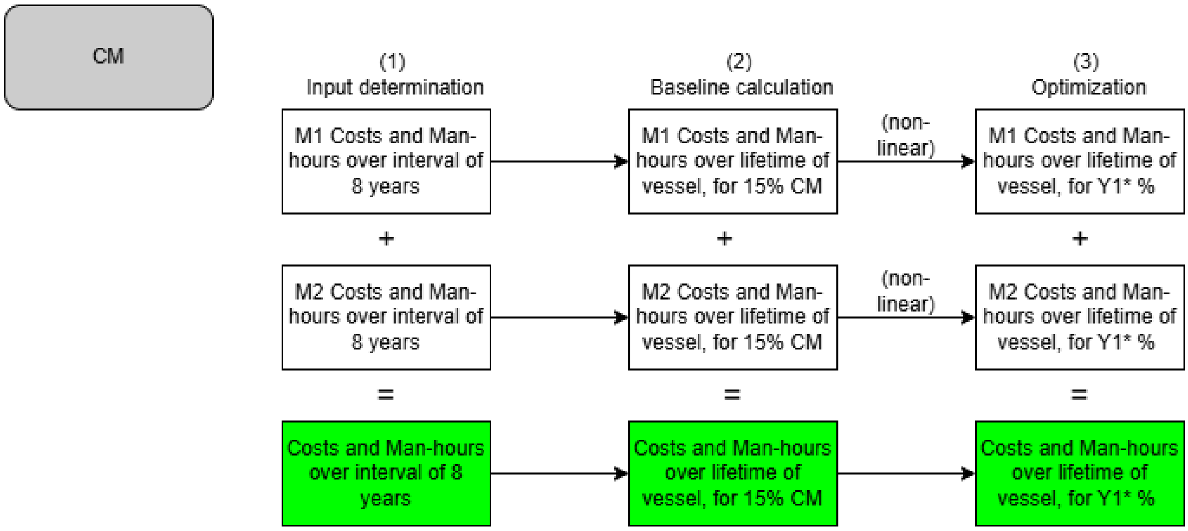

Figure 4.3: Representation of the CM-part of the model

Urgent mission-critical repairs require immediate action, leading to significantly higher expenses associated with emergency labor, transportation of personnel and materials, and unscheduled port calls (Interview 5, 2024; Interview 4, 2024; Email communication 1, 2024; Interview 9, 2025; Interview 10, 2025). The exponential nature of M2 development is why Figure 4.3 visually represents a nonlinear transition from Step 2 to Step 3.

When analyzing M2 related man-hour data from SAP, several significant limitations must be acknowledged. The registration of M2 man-hours only accounts for the actual repair time performed on board the vessel. This excludes a substantial portion of the total workload. As highlighted by Interview 4 (2024), Interview 9 (2025), Interview 10 (2025), and Interview 11 (2025), a considerable number of hours are spent on preparation activities prior to boarding the vessel, such as troubleshooting, team coordination, and logistical planning. This preparation phase demands more man-hours than the repair itself (Personal Communication 1, 2025; Interview 11, 2025; Interview 9, 2025).

Additionally, SAP does not register travel time to and from the vessel as working hours, even though engineers do consider this time part of their working schedule. As a result, a key component of their workload is structurally underrepresented. Interview 9 (2025) further points out that in practice, multiple engineers may be dispatched to a mission-critical repair, while only the hours of one engineer are logged in SAP. Moreover, hours spent on transporting specialized tools or components to the vessel are also omitted from the database.

In summary, while SAP maintains consistent records, it systematically excludes major segments of the actual maintenance effort for M2 tasks. This leads to an underestimation of total man-hours (and thus costs) and, without adjustments, the SAP data is unreliable for modeling CM.

To address this, the model applies a multiplication factor of 10 to the man-hours and salary costs reported under M2 calls. This estimate is based on the understanding that SAP captures only active 'hands-on' time, whereas the full workload also includes travel time (often involving multiple engineers), preparation efforts, and logistical handling of materials. This adjustment is substantiated by expert input from Interview 4 (2024), Interview 9 (2025), Interview 10 (2025), and Interview 11 (2025). Although this factor is admittedly a coarse approximation, it reflects a more realistic picture of the true labor investment associated with mission-critical repairs. It remains impossible to precisely quantify M2 maintenance due to the case-specific nature of such interventions (Interview 4, 2024; Interview 11, 2025; Interview 5, 2024; Interview 9, 2025; Interview 10, 2025). Nonetheless, applying this correction enhances the model's reliability when estimating the cost and workload implications of CM.

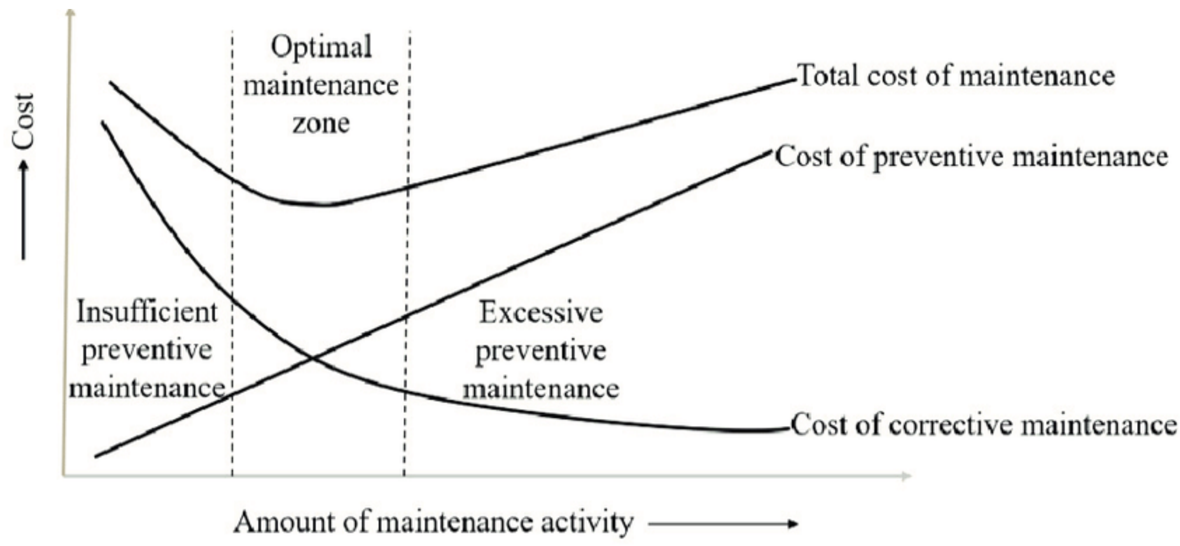

Figure 4.4: Maintenance cost development for Preventive Maintenance and Corrective Maintenance (Le et al., 2018).

M2 cost development

A question arises how the M2 costs develop over the amount of applied CM. To answer this question, Figure 4.4 illustrates that there is an optimal balance between Corrective Maintenance and Preventive Maintenance (PM), where PM includes TDSM. The optimal balance differs per sector. According to Hamasha et al. (2023), the ideal percentage of CM varies between 15% and 30%, depending on the industry:

- Transportation Sector: 25% CM and 75% PM
- Oil and Gas Sector: 20% CM and 80% PM
- Manufacturing Sector: 30% CM and 70% PM
- Power Generation: 35% CM and 65% PM
- Healthcare Sector: 15% CM and 85% PM

Additionally, other sources such as Legát et al. (2017) and Smith and Mobley (2008) indicate that the optimal maintenance strategy is around 20% CM and 80% PM.

Further research by Stenström et al. (2016) highlights that any increase in CM beyond the optimal level has a significant impact on total maintenance costs. Specifically, every 1% rise in CM above the optimal level results in a cost multiplication factor of 3.3.

Also, Interview 4 (2024) and Interview 5 (2024) revealed that certain cost components associated with corrective maintenance (such as port calls, dockyard work, urgent transportation of replacement parts and the deployment of personnel to the vessel's location) tend to be significantly more expensive compared to scheduled maintenance costs. The urgent nature of CM, especially for M2 tasks, requires rapid mobilization of resources, leading to higher expenses.

Combining these different factors: the cost-growth pattern combined with the understanding that the optimal CM-to-PM ratio generally lies between 15% and 30% , along with qualitative insights from expert interviews, provides the basis for defining the cost development curve for M2 maintenance. It is shown in Figure 4.5. The figure illustrates how costs escalate as CM increases. At 15% CM, the associated costs remain at the baseline level (100%). However, at 30% CM, costs increase significantly to approximately 330% of the baseline, and at 60% CM, the cost multiplier reaches nearly 1000%. The steep rise in costs highlights the exponential nature of cost increases as more CM is applied.

That the curve increases exponentially is in line with the expectations. Relying solely on corrective maintenance would lead to excessively high costs to keep vessels operational. The lack of preventive

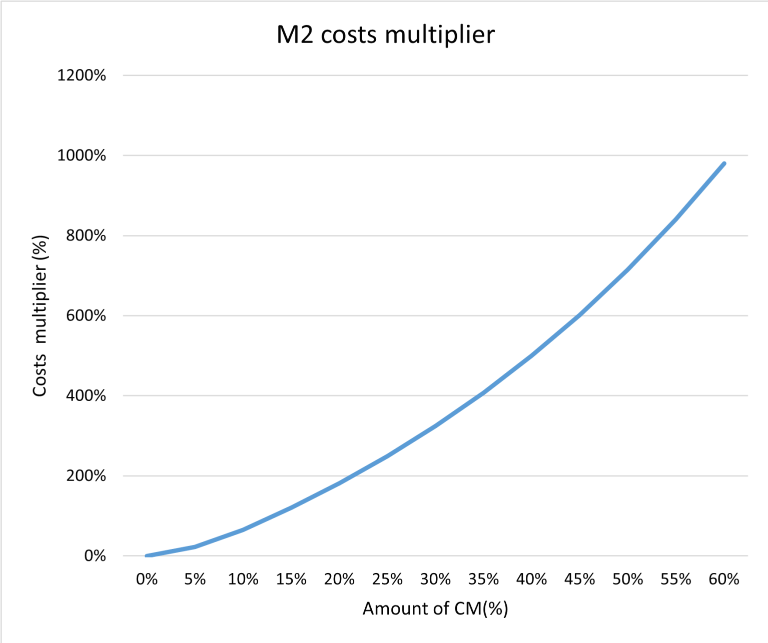

Figure 4.5: M2 cost growth curve.

measures would result in frequent unexpected failures, each requiring costly emergency repairs and logistical efforts.

Based on the optimal maintenance point along with the absence of literature about the cost development of corrective maintenance beyond this optimal range, it was determined that scenarios exceeding 60% CM are not relevant for further analysis. This decision is supported by the practical limitations of corrective maintenance. Applying more than 60% CM would lead to an unsustainable maintenance strategy, as the operational and financial impact of frequent unplanned repairs would become unmanageable. The lack of preventive measures at such high levels of CM would likely result in excessive failures, requiring an impractical allocation of resources to emergency repairs.

M2 man-hour development

So far, the discussion has primarily focused on the cost multiplier associated with M2 tasks. However, another equally critical factor is the man-hour component.

In addition to the direct financial costs of corrective maintenance, sudden repair activities also demand significant labor time. Tasks such as port calls, dockyard work, urgent transportation of replacement parts, and the deployment of personnel to the vessel all consume substantial man-hours. Furthermore, as the share of corrective maintenance increases, vessel downtime rises accordingly, further amplifying the labor burden.

To estimate the total man-hours, including those tied to downtime, a correction factor is required. Several sources in the topic of Reliability Engineering like Birolini (2017), Woo (2020) and Blanchard (1995) explain the relation between downtime and CM. However, for CM application above 30%, this is difficult to quantify. Therefore, the multiplier effect is assumed to be as follows:

- 20% CM:
  Represents the current CM level within the RNLN. Sudden repairs occur occasionally, but these can still be absorbed within existing planning structures.
- 30% CM:
  Unplanned maintenance begins to impact planning stability. Resource allocation becomes less efficient, and downtime during missions starts to emerge as a visible operational risk. This results in four to five times higher man-hours compared to 20% CM.
- 40% CM:

CM becomes a dominant factor in the maintenance workload. Emergency repairs increasingly disrupt scheduled tasks, reduce vessel availability, and strain logistics and personnel coordination. This results in six to seven times higher man-hours, compared to 20% CM.

- 50%+ CM:
  High reliance on reactive repairs leads to significant operational instability. Cumulative downtime, crew saturation, and overstretched support systems result in severe efficiency loss. At this point, vessel availability trends toward zero. The man-hours of CM are eight to 10 times higher, compared to 20% CM. Scenarios above 60% CM are considered operationally infeasible.

These multiplier effects are incorporated into the model to construct the M2 man-hour growth curve, shown in Figure 4.6. The curve visually reflects how required man-hours escalate as the proportion of CM increases, especially due to the indirect labor caused by logistical complexity and operational disruption.

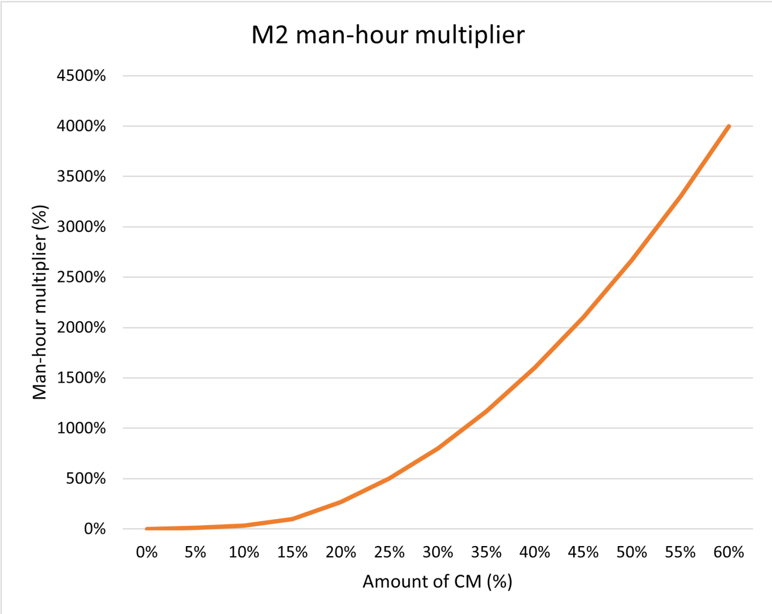

Figure 4.6: M2 man-hour growth curve.

In conclusion, the exponential increase in man-hours associated with rising CM is a crucial part of the model. It highlights how even small shifts toward more corrective maintenance can trigger a disproportionate rise in total workload and cost, underscoring the operational risks of relying too heavily on unplanned maintenance.

4.2.2. Model Explanation: Time-driven scheduled maintenance

Figure 4.7 shows how the model works for TDSM. TDSM can be calculated entirely by taking the sum of the following components.

- M4 Calls
- WP Calls
- M8 Calls
- BO and AM preparation: The scheduled maintenance periods BO and AM are being prepared by a maintenance planner. Based on experts this preparation is taking 1.5 year of 2 Full Time Employee (FTE) (Email communication 4, 2024; Email communication 5, 2024).

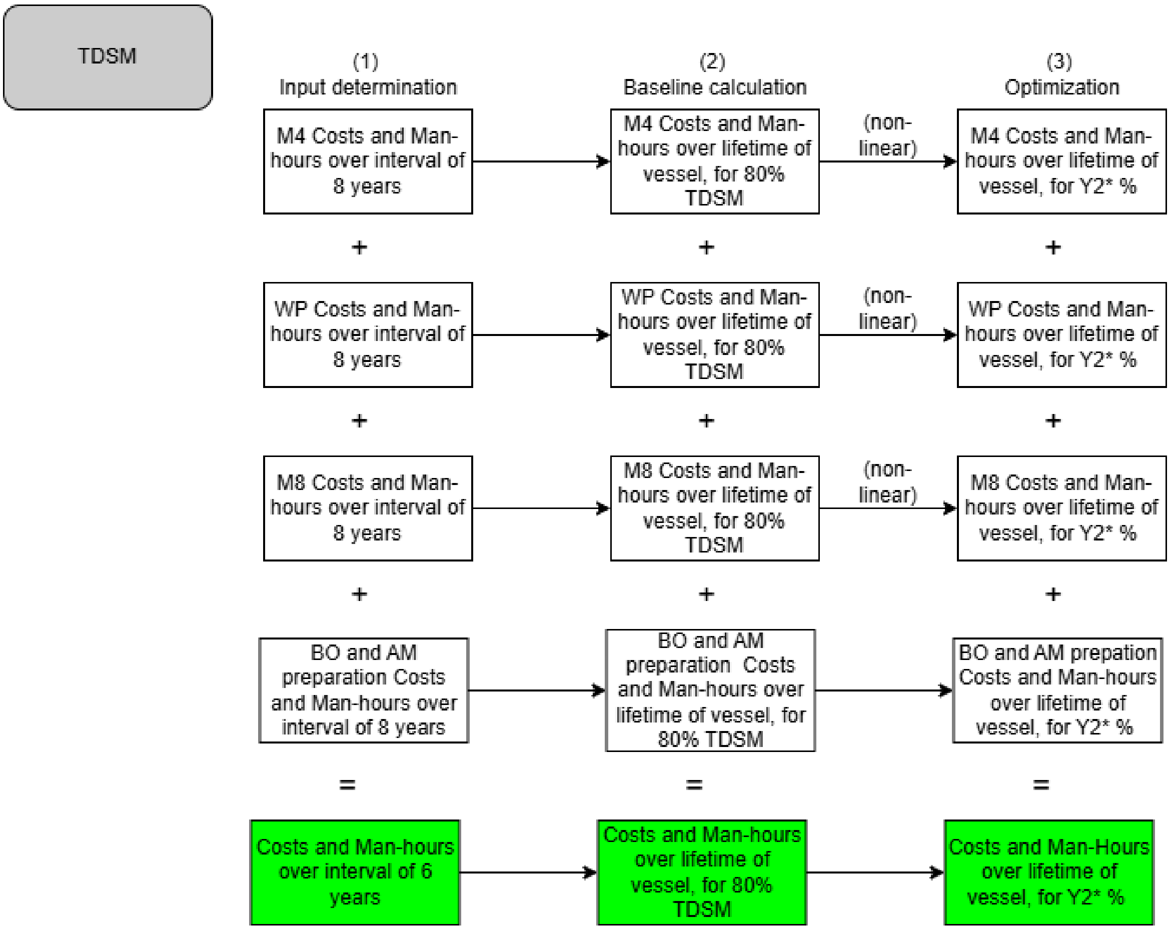

Figure 4.7: Representation of TDSM-part of the model

In accordance with what was described in Section 4.2, the following steps are taken:

- Step 1:
  The model first compiles the total costs and required man-hours associated with M4 calls, WP calls, M8 Calls and preparation tasks over a eight-year period.
- Step 2:
  A straight-line estimation is applied to project the total costs and man-hours over the vessel's entire lifespan, assuming a maintenance strategy with 80% TDSM. This assumption aligns with the current maintenance distribution within the RNLN, where 80% of all maintenance is scheduled-based.
- Step 3:
  The model evaluates different levels of TDSM application and their impact on costs and man-hours.
  - For BO and AM preparation, the transition from Step 2 to Step 3 follows a linear relationship. This means that adjusting TDSM levels from 80% to any other percentage results in a proportional increase or decrease in BO and AM preparation time. Given that TDSM consists primarily of scheduled maintenance actions, early-life and end-of-life equipment failures are not considered, making a linear extrapolation appropriate.
  - However, for M4 calls WP and M8 calls, the transition from Step 2 to Step 3 is nonlinear due to productivity effects, which will be further explained in this section. Changes in TDSM influence workforce fatigue, infrastructure efficiency, and overall operational effectiveness, making the relationship between TDSM levels and maintenance costs more complex. This

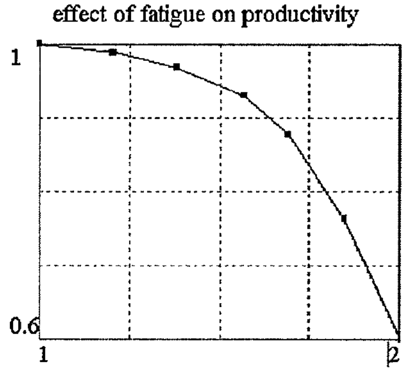

Figure 4.8: Effect of productivity of employees on shipyard productivity (McDevitt, Zabarouskas, and Crook, 2003).

is why Figure 4.7 shows a nonlinear effect when transitioning from Step 2 to Step 3 for M4, WP and M8 maintenance.

The impact of TDSM on productivity plays a role in the model. As mentioned in Section 2.4, TDSM is directly linked to productivity levels. This is because the maintenance tasks from these calls are planned within BO and AM periods. When the workload during these periods increases, productivity decreases due to higher pressure on resources and personnel. On the other hand, reducing the workload in BO and AM periods leads to improved productivity, as maintenance teams can work more efficiently with fewer bottlenecks. It is assumed that productivity is directly connected to both costs and required man-hours. As a result, the model adjusts costs and man-hours in proportion to productivity changes. This approach makes sense since productivity measures how much output is achieved for a given amount of input (costs and man-hours). By scaling productivity up or down based on workload, the model provides a more realistic estimation of maintenance efficiency under different TDSM levels.

Impact of Fatigue on Productivity

One of the main factors leading to reduced productivity at high levels of TDSM is fatigue (Panuwatwanich, Mohamed, and Abualqumboz, 2013; Mahmud and Ahmad, 2011; McDevitt, Zabarouskas, and Crook, 2003). Fatigue refers to both physical and mental exhaustion, which directly impacts the quantity and quality of work performed by employees. Figure 4.8 illustrates the relationship between fatigue and productivity as described by McDevitt, Zabarouskas, and Crook (2003). On the vertical axis, the productivity factor can be seen. Ranging from 0.6 to 1. On the horizontal axis, the workload factor can be seen, ranging from 1 to 2. The reduction in productivity aligns with the findings of Herdiana and Sary (2023), reinforcing that increased workload can lead to decreased efficiency. This effect is incorporated into the model to account for the impact of fatigue on productivity.

In the model, it is assumed that applying 80% TDSM corresponds to a workload factor of 1.5 in Figure 4.8. This assumption allows for a slight increase in productivity if TDSM decreases, aligning with expectations that reducing scheduled maintenance can lessen fatigue and improve efficiency. However, beyond a certain point, the productivity gains stabilize, as there is only so much flexibility in adjusting work shifts.

Similarly, an increase in TDSM results in lower productivity, as higher maintenance workload leads to greater fatigue and reduced efficiency. This pattern is consistent with real-world scenarios, where excessive scheduled maintenance can place increased strain on personnel. A clearer visualization of productivity changes due to variations in TDSM application is presented in Figure 4.9, which represents Figure 4.8, with the assumption that 80% TDSM corresponds to a workload factor of 1.5. This relationship is integrated into the model to account for the effects of changing TDSM levels on productivity. As with other productivity factors, the model assumes that productivity directly influences costs and required man-hours, meaning that an increase or decrease in productivity is proportionally reflected in overall maintenance efficiency.

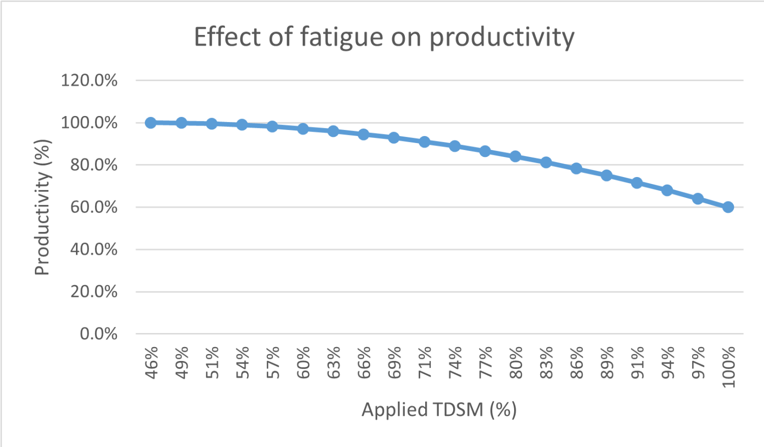

Figure 4.9: Derived relationship between productivity and the amount of TDSM.

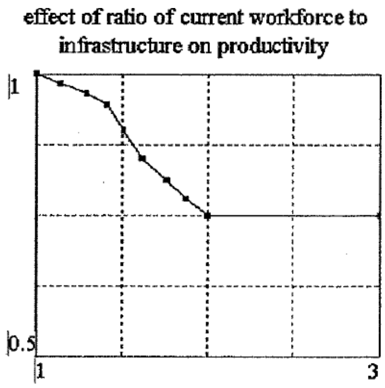

Figure 4.10: The effect of workforce to infrastructure ratio on productivity. (McDevitt, Zabarouskas, and Crook, 2003)

Effect of Workforce to Infrastructure Ratio on Productivity

The ratio of the current workforce to the available infrastructure also influences productivity (Hasan et al., 2018; Duggal, Saltzman, and Klein, 1999; McDevitt, Zabarouskas, and Crook, 2003). This refers to the balance between the number of workers and the resources (like equipment, workspaces, and support systems) available to them. If the workforce is too large for the available infrastructure, it leads to:

- Overloading: More workers sharing the same resources causes delays.
- Coordination Problems: Too many workers can lead to inefficiencies in task planning and workflow management.
- Higher Error Rates: Limited resources can make it harder to maintain quality checks and supervision.

In Figure 4.10 the effect of workforce to Infrastructure Ratio on productivity, according to McDevitt, Zabarouskas, and Crook (2003) can be seen. On the vertical axis, the productivity factor can be seen. Ranging from 0.5 to 1. On the horizontal axis, the workload factor can be seen, ranging from 1 to 3. The effect is used in the model to accommodate the productivity effect of workforce to infrastructure ratio.

In the model, it is assumed that a workload factor of 1.5 corresponds to an 80% application of TDSM. This assumption allows for an increase in productivity when TDSM decreases, as well as a decline in productivity when TDSM increases. This pattern aligns with real-world expectations, as a reduction in TDSM frees up resources, reduces coordination issues, and lowers the likelihood of errors, all of which contribute to improved productivity. Conversely, an increase in TDSM leads to greater strain on resources, more coordination challenges, and higher error rates, ultimately reducing productivity.

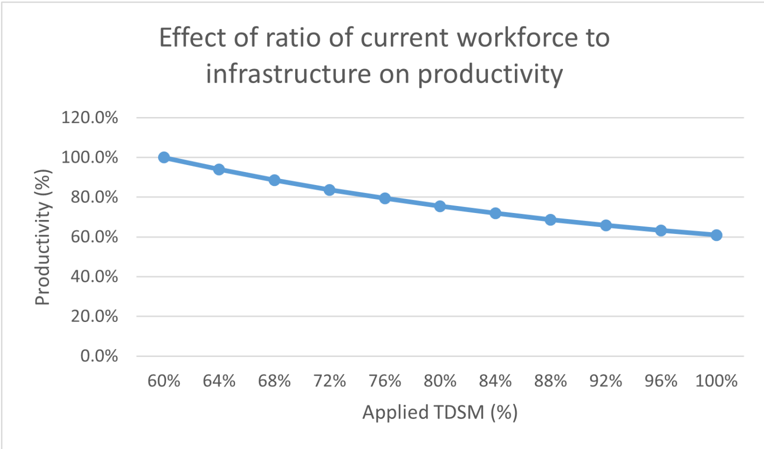

Figure 4.11: Derived relationship between productivity and the amount of TDSM.

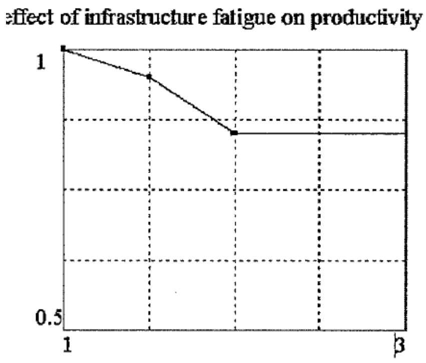

Figure 4.12: Effect of infrastructure fatigue on productivity. (McDevitt, Zabarouskas, and Crook, 2003).

By integrating this effect into the model, the relationship between workforce distribution, infrastructure availability, and TDSM application is captured, ensuring that maintenance planning reflects realistic operational constraints and efficiency trends.

Based on the assumption that a workload factor of 1.5 corresponds to an 80% application of TDSM, ta relationship between productivity and the amount of TDSM is established. This is visually represented in Figure 4.11.

Impact of Infrastructure Fatigue on Productivity

Another factor is infrastructure fatigue, which refers to the loss of efficiency when machines, workspaces, and other support systems are overused or not properly maintained (Hasan et al., 2018; Duggal, Saltzman, and Klein, 1999; McDevitt, Zabarouskas, and Crook, 2003). When infrastructure becomes worn out, several problems arise:

- Slower Processes: Equipment works less efficiently, making tasks take longer.
- More Breakdowns: Worn-out machines fail more often, causing work stoppages.
- Safety Risks: Old or damaged infrastructure can lead to accidents or unsafe working conditions.
- Lower Productivity: Workers cannot perform at their best when they have to deal with faulty equipment.

Figure 4.12 illustrates the influence of infrastructure fatigue on productivity, as described by McDevitt, Zabarouskas, and Crook (2003). The vertical axis represents the productivity factor, ranging from 0.5 to 1, while the horizontal axis represents the workload factor, ranging from 1 to 3. This relationship is incorporated into the model to account for the impact of infrastructure wear and degradation on overall maintenance efficiency.

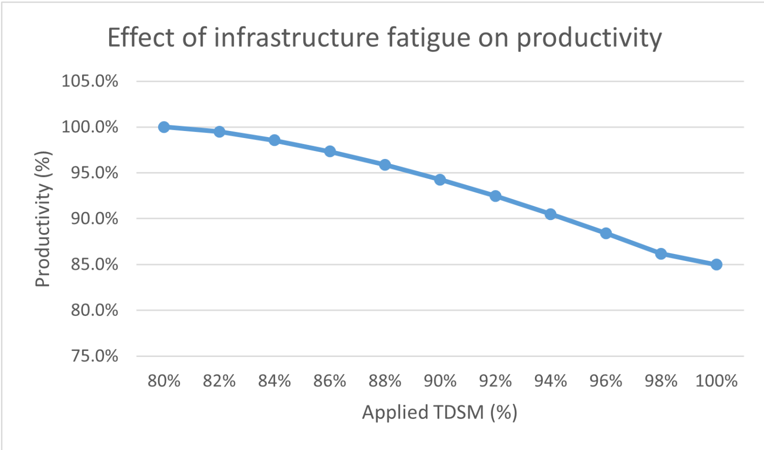

Figure 4.13: Derived relationship between infrastructure fatigue and productivity decline due to increasing TDSM levels.

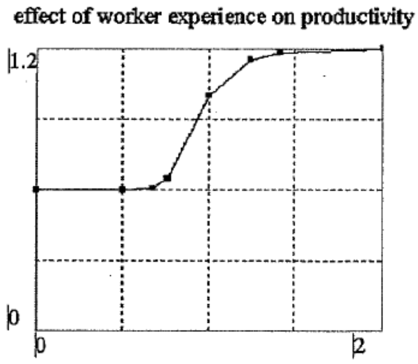

Figure 4.14: Effect of worker experience on productivity (McDevitt, Zabarouskas, and Crook, 2003).

In the model, it is assumed that a workload factor of 1 corresponds to an 80% application of TDSM. This assumption is based on the fact that infrastructure and equipment are currently optimized for this maintenance level. When TDSM increases beyond 80%, productivity declines due to increased infrastructure strain, more frequent maintenance activities, and a higher likelihood of inefficiencies caused by overuse of equipment and resources.

To represent this relationship more clearly, Figure 4.13 has been developed, showing how productivity decreases as TDSM increases.

Impact of Worker Experience on Productivity

The experience levels of workers also play a role in productivity (Hasan et al., 2018; Duggal, Saltzman, and Klein, 1999; McDevitt, Zabarouskas, and Crook, 2003). More experienced workers can work faster, make fewer mistakes and solve problems more quickly. On the other hand, a less experienced workforce leads to lower productivity, more mistakes and efficiency loss during rapid expansion.

Figure 4.14 illustrates the impact of worker experience on productivity, as described by McDevitt, Zabarouskas, and Crook (2003). The vertical axis represents the productivity factor, ranging from 0 to 1.2, while the horizontal axis represents the workload factor, ranging from 1 to 2. This relationship is incorporated into the model to account for how varying levels of experience influence efficiency and overall maintenance performance.

In the model, it is assumed that a workload factor of 1 corresponds to an 80% application of TDSM. Based on this assumption, the relationship between TDSM and productivity is further refined. As shown in Figure 4.15, reducing TDSM to approximately 62.5% could increase productivity to 120%. However, this growth is limited, as productivity gains diminish beyond a certain point. Conversely, if TDSM is increased to 100%, productivity declines to around 60%.

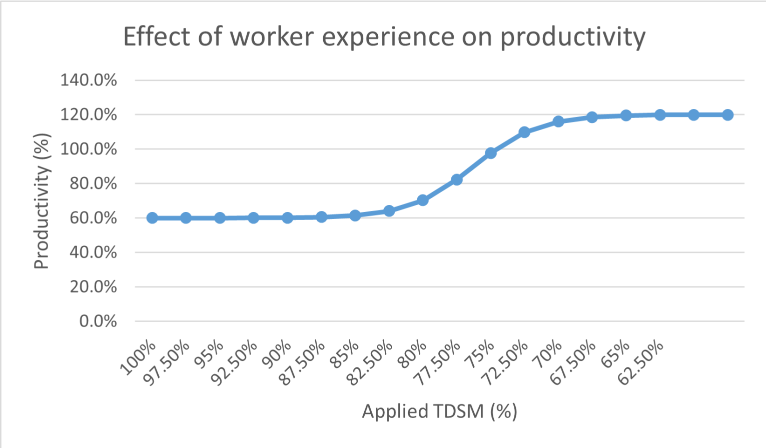

Figure 4.15: Derived relationship between worker experience and productivity.

This pattern aligns with real-world expectations, where a more experienced workforce enhances productivity by improving efficiency, reducing errors, and optimizing task execution. However, excessive maintenance demands can still lead to resource overload, personnel fatigue, and diminishing efficiency.

To visually represent this trend, Figure 4.15 has been developed, showing how productivity changes as TDSM levels vary. This relationship is integrated into the model to ensure that the effects of worker experience on productivity are accurately reflected in maintenance cost and efficiency estimations.

Summary

In summary, the impact of TDSM on productivity is influenced by fatigue (both workers and infrastructure), work force to infrastructure-ratio and worker experience.

Each of these factors affects productivity in different ways and is accounted for within the model. It is assumed that productivity changes directly influence both costs and required man-hours, ensuring that variations in TDSM application are reflected in the model's calculations.

4.2.3. Model Explanation: Condition-Based Maintenance

Unlike CM and TDSM, there is limited data available for CBM within SAP. As explained in Section 3.2.3, only 5% of maintenance activities are classified as CBM (Interview 1, 2024; Email communication 2, 2024; Email communication 1, 2024). Because historical data on CBM is scarce, the model relies on expert interviews to define the key cost and man-hour components.

Model Structure for CBM

Figure 4.16 provides a visual representation of the CBM model.

- Step 1:
  Summing up costs and man-hours over 8 years of data.
- Step 2:
  Projecting these costs and man-hours over the vessel's lifetime, using a linear approach for most components but treating one-time costs (i.e., sensor infrastructure) separately.
- Step 3:
  Testing different levels of CBM.

Cost Components and Assumptions

Unlike CM and TDSM, CBM cannot rely on historical data from SAP in the same way. This is because only around 5% of the current maintenance is done through CBM, which results in too few data points to build a reliable baseline.

As a result, Step 2 of the model (the baseline projection over the vessel's lifetime) does not use a fixed reference point like 15% CM or 80% TDSM. Instead, each CBM-related cost or man-hour component

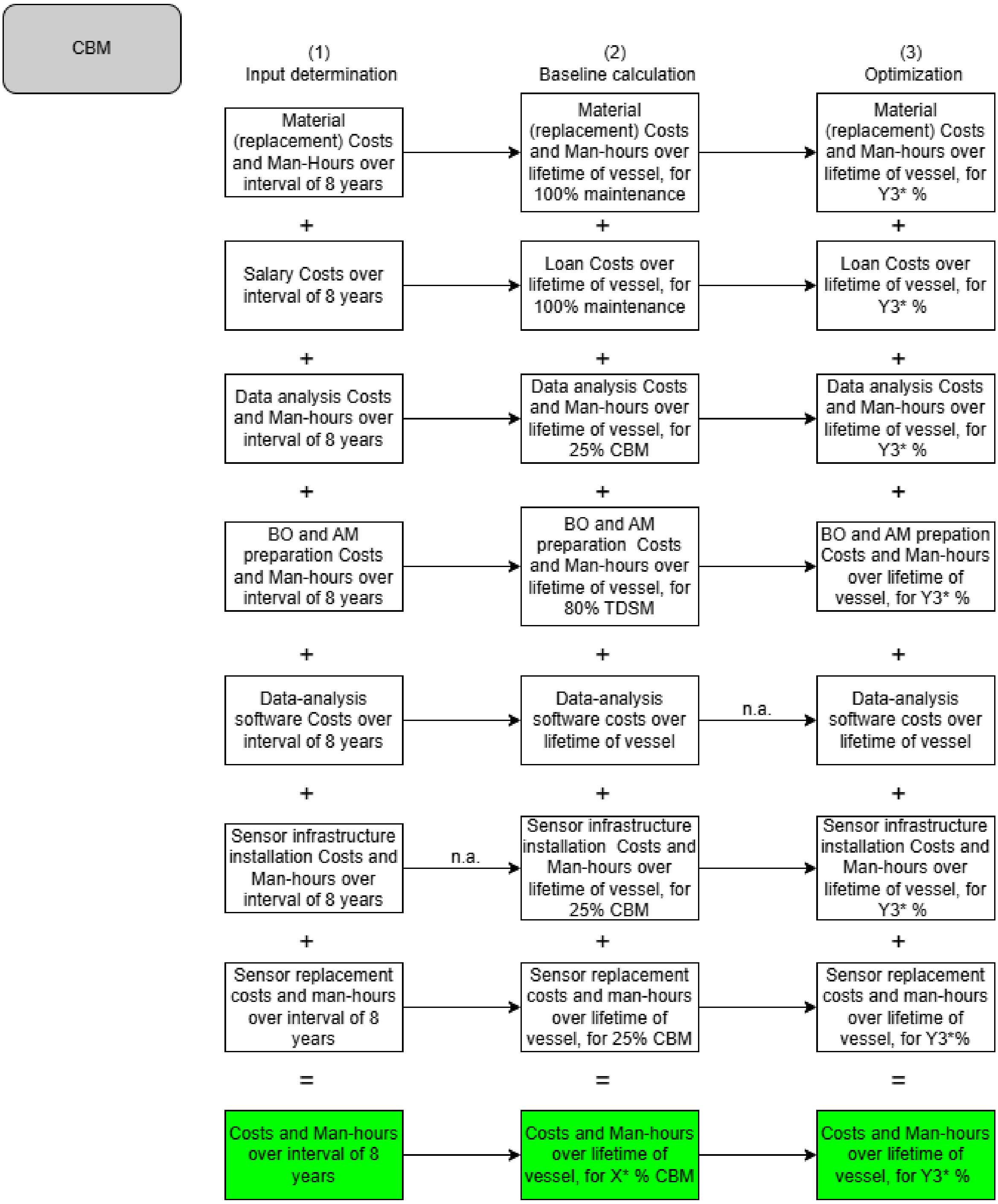

Figure 4.16: Representation of the CBM- part of the model.

is handled differently, depending on how much data or insight is available for that specific component. This explains the usage of X*% in the green part (step 2) of Figure 4.16.

This tailored approach allows the model to still represent CBM realistically, even without a consistent baseline percentage like in the other methods. The following cost and man-hour components have been identified and estimated:

- Material Replacement Costs (MRC):
  These costs account for replacing parts based on sensor data predictions. To determine a reference value for MRC, an assumption is made that 100% CBM application would mean CBM covers the full scope of material replacement costs. This means:

  $$100\%CBM_{MRC} = 100\%MRC = M1_{MRC} + M2_{MRC} + M4_{MRC} + M8_{MRC} + WP_{MRC} \quad (4.1)$$

  This assumption is justified by the fact that M3 and M5 calls are not installation-specific,and M6, M7, and M9 calls deal with modifications rather than maintenance.

  Model Steps for MRC:

  - In Step 1, the total MRC over eight years is determined.
  - In Step 2, this value is projected over the vessel's entire lifetime for a scenario where 100% of maintenance is CBM.
  - In Step 3, the MRC is linearly scaled to different CBM levels (i.e., 80% CBM corresponds to 80% MRC).
- Salary Costs:
  Similar to material replacement costs, salary costs for CBM are assumed to follow the same scaling approach.

  This linear scaling approach is also applied to man-hours.
- Data Analysis Hours and Costs:
  These hours and costs relate to the analysis of sensor data to predict failures. Based on expert input:

  1. One full-time equivalent (FTE) is required for every 100 installations. This estimate is verified by Email communication 2 (2024) and Email communication 3 (2024). Initially, this 1 FTE is needed to set up the data software and develop efficient analysis methods.
  2. According to Email communication 3 (2024), in the future, AI and automated software will reduce the need for manual data analysis. For now, this model assumed that the entire data-analysis will take a tenth of a single FTE.
  3. It is assumed that 100 installations represent approximately 25% of total maintenance requirements, as there are around 400 installations per vessel (Email communication 2, 2024; Email communication 3, 2024).
  4. The number of required data analysts scales directly with CBM application (i.e., 25% CBM = 1 FTE, 50% CBM = 2 FTE).
- Scheduled Maintenance Preparation Hours and Costs:
  Since maintenance tasks predicted by CBM are often scheduled during planned maintenance periods, there are additional preparation man-hours and costs. (Email communication 4, 2024; Email communication 5, 2024). The following assumptions are made:

  1. Scheduled maintenance preparation currently accounts for 80% of total maintenance, in line with RNLN's current maintenance distribution.
  2. The preparation costs scale linearly with CBM application. If 100% of scheduled maintenance preparation equals 80% of maintenance, then 50% scheduled maintenance preparation corresponds to 40% maintenance.
- Software Costs for Data Analysis:
  CBM-related software is assumed to cost €100,000 per year, regardless of the level of CBM applied (Email communication 2, 2024; Email communication 3, 2024). Because this cost remains

constant regardless of CBM application, Figure 4.16 marks this component as 'not applicable' (n.a.) when transitioning from Step 2 to Step 3 in the CBM model.

- Sensor Installation Hours and Costs:
  Sensor installation consist of two parts:
  1. Initial Infrastructure Installation:
     This includes sensors, data cables, and supporting infrastructure (Email communication 2, 2024; Email communication 3, 2024). These costs represent a one-time investment, meaning they do not scale over the vessel's lifetime. Consequently, Figure 4.16 marks this component as 'not applicable' (n.a.) when transitioning from Step 1 to Step 2 in the CBM model.
  2. Sensor Replacement Costs:
     Sensors must be replaced approximately every six years according to Redi-Sensor (2022). These replacements involve both material costs and the required man-hours for sensor installation and removal.

  For modeling purposes, it is assumed that installing sensors on 100 installations covers 25% of total maintenance requirements. In other words, 100 installations = 25% CBM.

Productivity effects with application of CBM

A question that may arise is why productivity effects are not considered within the CBM part of the model. The reason is that CBM is assumed to contribute to a more evenly distributed workload. In other words, the application of CBM is expected to lead to peak-shaving, reducing sudden peaks in maintenance workload and ensuring a more balanced distribution of tasks over time (Interview 1, 2024; Bengtsson et al., 2004; Ghamlouch, Fouladirad, and Grall, 2019).

Since the effects of TDSM on productivity (both increases and decreases) are already incorporated into the model, including productivity adjustments for CBM would be redundant.

Summary

The CBM model is built on expert insights rather than historical SAP data. This is because CBM is still in the early stages of implementation within the RNLN, meaning there is currently not enough recorded data in SAP to support a reliable analysis. By defining and estimating the key cost components through expert interviews, the model still allows for an assessment of CBM's impact on total maintenance costs and system availability. A sensitivity study in Chapter 7 will show whether the assumptions are robust.

As CBM adoption within the RNLN increases and more data becomes available, the assumptions can be gradually replaced with real operational data, enhancing the model's accuracy and reliability over time.

4.3. Conclusion

In Chapter 2, the need for a structured approach to compare different maintenance methods for different installations on board different navy vessels was established. In response to this, the current chapter introduces a mathematical model designed to estimate maintenance costs and required man-hours, including downtime, across different maintenance strategies used within the RNLN. While this model lays the groundwork for answering the following research question, the actual insights will be derived in chapters 5 and 6 through practical application and testing.

3. How to provide insights into the maintenance costs and required man-hours per relevant maintenance method for the Royal Netherlands Navy?

The model integrates historical SAP maintenance data and expert input to define financial and labor components for CM, TDSM and CBM. It projects these elements over the lifetime of a vessel and includes factors such as the productivity impact of TDSM and the exponential growth associated with M2 maintenance. For CBM, due to limited available data, expert-derived assumptions were used to estimate relevant drivers such as sensor installation, data analysis, and material replacement.

With the theoretical basis now established, Chapter 5 will proceed with the implementation and verification of the model, followed by the application of the model (Chapter 6) to generate insights to directly answer Sub-Question 3.

5
Application of the model

This chapter describes the practical implementation, input-output structure, interpretation, and verification of the model. It therefore tries to further answer Research Question 3 and 4:

- 3: *How to provide insights into the maintenance costs and required man-hours per relevant maintenance method for the Royal Netherlands Navy?*
- 4: *How can the model be verified and applied by the Royal Netherlands Navy?*

Section 5.1 begins with a description of the software selection. The structure of the model is then outlined, from the scenario generator to the analysis. Section 5.2 details how the model has been tested step by step to confirm that it calculates and behaves as expected under different inputs and assumptions.

5.1. Usage of the model

In this section, the choice of software is discussed first. This is followed by an explanation of the model's inputs and outputs.

5.1.1. Software choice

The model must be accessible to a broad and diverse group of professionals. Intended users include personnel from the cost-analysis team within COMMIT, maintenance engineers within DMI, vessel managers, and members of the data and maintenance analysis departments at DMI. Given this diversity in background, technical expertise, and daily responsibilities, and considering that advanced numerical computing tools are not always readily available within (some of these) departments, it was decided to develop the model using Microsoft Excel. This ensures broad accessibility, ease of use, and compatibility with existing workflows. The use of Python as software choice was considered. But since not many professionals within DMI are familiar with Python, it was decided to use Excel.

5.1.2. Overview and scenario setup

Figure 5.1 shows the complete setup of how different maintenance methods are compared. On the left of Figure 5.1, "(1) Scenario Generator" is displayed. To make sure that all possible combinations are considered, a wide range of scenarios was created. Each scenario represents a different ratio of CM, TDSM, and CBM, increasing in steps of 10%. The total percentage always adds up to 100%. For example, one scenario could consist of 30% CM, 50% TDSM, and 20% CBM. This approach allows the model to calculate the outcome for every realistic maintenance mix. However, scenarios with more than 60% CM were excluded, as was explained in Section 4.2.1. A sample of the scenarios can be seen in Table 5.1.

Ship + BSMI	M1 Salary costs	M1 External party costs	M1 Material costs	...	M8 External party costs	M8 Material costs
OPV 110A	€ 1,564	€ 445	€ 8,133	...	€ 34,455	€ 3,242
OPV 110B	€ 22,328	€ 1,091	€ 252,257	...	€ 28,302	€ 19,840
OPV 1200	€ 8,258	€ 186	€ 180,960	...	€ 22,880	€ 36,657
...	...	...	...	...	...	...
JSS 160A	€ 8,534	€ 1,423	€ 217,882	...	€ 31,316	€ 114,154
JSS 160B	€ 4,927	€ 1,324	€ 248,603	...	€ 47,257	€ 33,477
JSS 2100	€ 16,058	€ 210	€ 66,393	...	€ 17,480	€ 56,418
...	...	...	...	...	...	...
MF 2200	€ 25,950	€ 708	€ 178,775	...	€ 50,487	€ 20,817
MF 2300	€ 1,225	€ 1,324	€ 12,498	...	€ 29,170	€ 71,180
MF 2400	€ 3,370	€ 641	€ 232,866	...	€ 28,129	€ 101,229

Figure 5.2: A sample of costs database (vessel types and numbers are randomized).

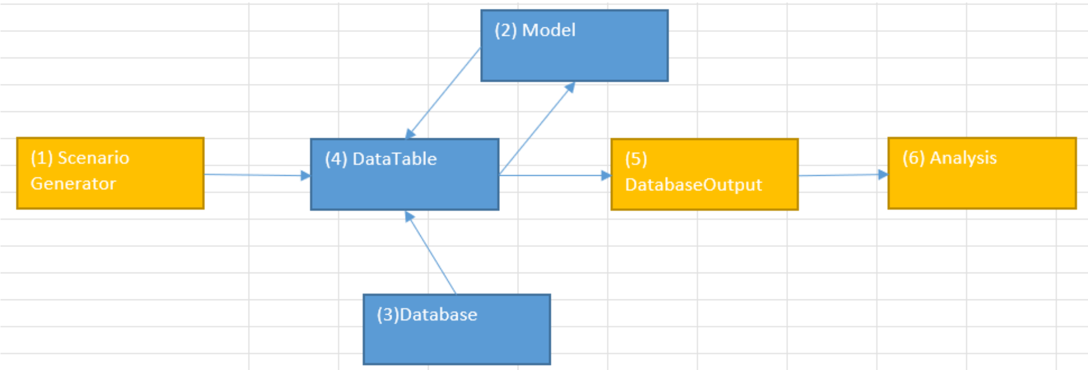

Figure 5.1: Setup

Table 5.1: A subset of the possible combinations of CM, TDSM and CBM.

Scenario	CM	TDSM	CBM
1	0%	0%	100%
2	0%	10%	90%
3	0%	20%	80%
4	0%	30%	70%
5	0%	40%	60%
...	...	...	...
51	60%	0%	40%
52	60%	10%	30%
53	60%	20%	20%
54	60%	30%	10%
55	60%	40%	0%

At the top of the figure, “(2) Model” is shown. This is the model as described in Section 4.2. Next, at the bottom of Figure 5.1, “(3) Database” is shown. This database contains all the cost and man-hour data that is retrieved via SAP. Every maintenance call, for each ship type and every BSMI group, is included. In Figure 5.2, a sample of the costs database can be seen.

In addition to data, the model uses several fixed input values. These include the expected lifespan of each ship type and the standard hourly wage for maintenance work. When the input database and model calculations are combined, the results are stored in “(4) Data Table.” This table contains all calculated data for every ship type, and BSMI group. From this table, combined with the scenario generator, an output dataset is created in “(5) DatabaseOutput”. This output set contains all data for every scenario, ship-type and BSMI group. A sample of the database-output is shown in Figure 5.3.

Scenario	Schip+BSMI	...	AM and BO prep	Material costs	...	New-sensor costs	Sensor replacement costs
1	OPV 110A	...	€ 7,370	€ 1,704,351	...	€ 2,474,037	€ 1,476,684
2	OPV 110A	...	€ 517	€ 1,432,925	...	€ 2,435,474	€ 1,525,182
3	OPV 110A	...	€ 15,634	€ 1,332,426	...	€ 2,508,238	€ 1,908,939
...	...	...	...	...	...	...	...
47	OPV 2200	...	€ 14,156	€ 1,477,409	...	€ 2,529,910	€ 370,812
48	OPV 2200	...	€ 13,136	€ 899,271	...	€ 1,542,591	€ 1,468,289
49	OPV 2200	...	€ 14,055	€ 290,480	...	€ 1,263,125	€ 226,240
...	...	...	...	...	...	...	...
37	JSS 130A	...	€ 435	€ 548,959	...	€ 213,638	€ 799,976
38	JSS 130A	...	€ 14,990	€ 668,821	...	€ 1,996,384	€ 1,354,702
39	JSS 130A	...	€ 7,161	€ 887,202	...	€ 607,380	€ 301,915
...	...	...	...	...	...	...	...
11	JSS 2400	...	€ 657	€ 804,856	...	€ 1,329,068	€ 1,201,819
12	JSS 2400	...	€ 9,877	€ 1,270,671	...	€ 2,247,423	€ 1,561,309
13	JSS 2400	...	€ 15,932	€ 1,057,199	...	€ 181,244	€ 764,521
...	...	...	...	...	...	...	...
23	MF 1200	...	€ 6,010	€ 89,229	...	€ 926,814	€ 1,436,006
24	MF 1200	...	€ 11,620	€ 167,240	...	€ 109,774	€ 325,304
25	MF 1200	...	€ 8,170	€ 979,555	...	€ 1,886,052	€ 1,717,997
...	...	...	...	...	...	...	...
33	MF 1500	...	€ 5,087	€ 1,353,856	...	€ 2,513,880	€ 1,596,241
34	MF 1500	...	€ 14,674	€ 1,143,769	...	€ 1,863,863	€ 1,312,792
35	MF 1500	...	€ 9,268	€ 1,249,712	...	€ 2,099,134	€ 205,921

Figure 5.3: A sample of the costs database-output (vessel types and numbers are randomized).

Finally, the output is passed to "(6) Analysis". This section transforms the output-data into insights. One of those insights is which maintenance strategy leads to the lowest costs or fewest required man-hours. An example of such a result can be seen in Figure 5.4. The figure shows the costs (y-axis) of CM, TDSM, CBM and their total per scenario (x-axis) for vessel type OPV and BSMI group 1200. From this figure can be concluded that scenario 9 (80% TDSM and 20% CBM) is the most cost-efficient strategy. Due to confidentiality requirements, the values shown are normalized. The actual costs are divided by the combined total of CM, TDSM, CBM, and overall costs. This preserves the relative proportions between cost categories. Additionally, for confidentiality reasons, these figures are not presented in Chapter 6 or anywhere else in this report.

Another capability of the model lies in its ability to compare different vessel types across BSMI groups within a single maintenance scenario. This allows for an understanding of how various ship types perform relative to each other under identical maintenance strategies. An example of such a comparison is shown in Figure 5.5, which visualizes the cost distribution (y-axis) across BSMI groups (x-axis) for three different vessel types. Due to confidentiality requirements, all values have been randomized. For the same reason, these types of figures are not included elsewhere in the report.

In addition, the model supports comparison between different maintenance scenarios for a single vessel type. This shows how resource demands across BSMI groups change in different scenarios. An example is shown in Figure 5.6, which illustrates man-hour requirements (y-axis) for the OPV across different BSMI groups (x-axis) under various scenarios. Again, all values are randomized to preserve confidentiality and are not intended to reflect actual distributions. These types of visual analyses further demonstrate the flexibility and comparative insight that the model offers.

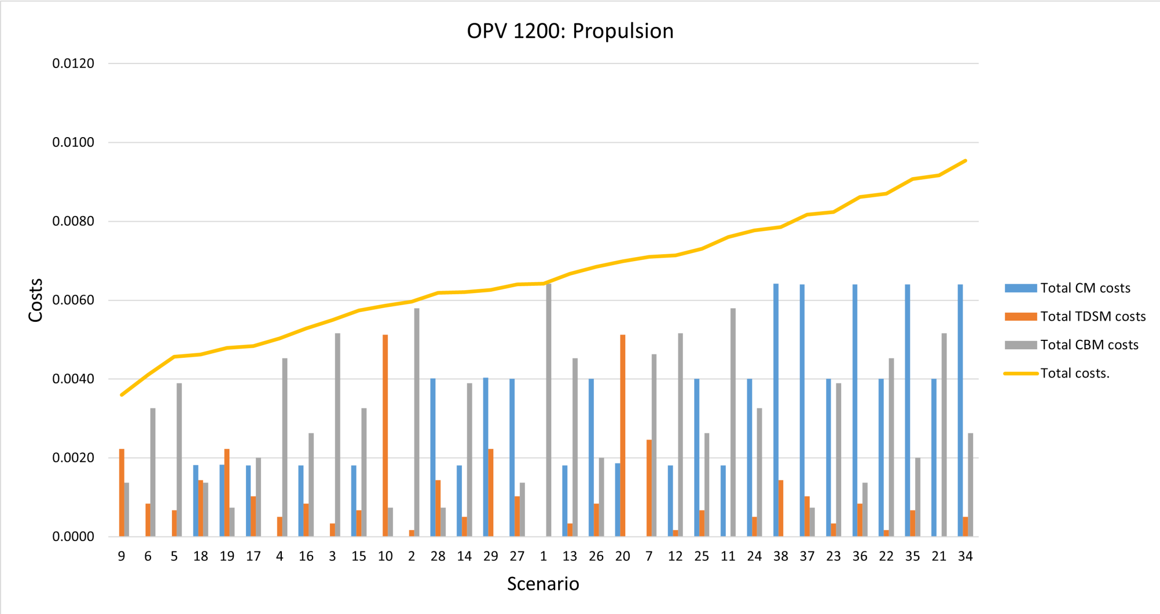

Figure 5.4: The results for vessel type OPV and BSMI group 1200.

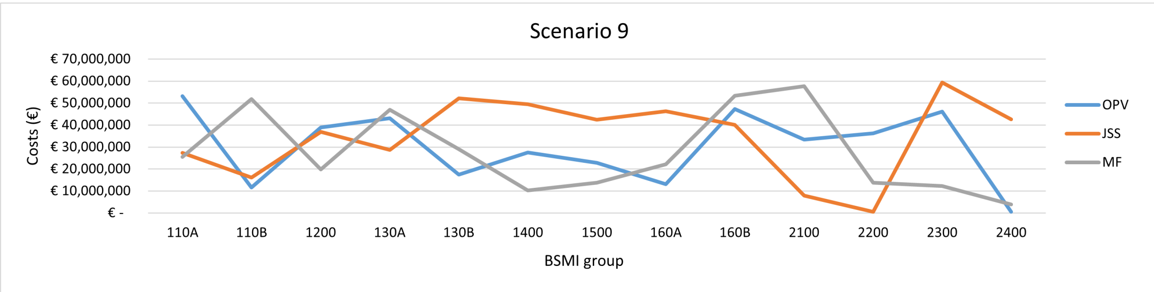

Figure 5.5: Vessel type comparison

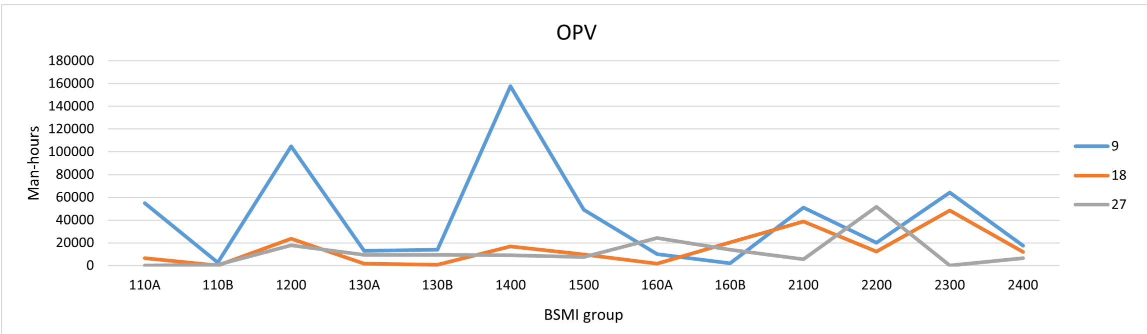

Figure 5.6: Scenario comparison

5.2. Verification

A verification was conducted. The process, including the predicted and actual results, is detailed in Table 5.2.

#	Action	Hypothesis	Outcome	Verified?
1	Set all costs and man-hours to 0	Total cost and man-hours = 0	Total cost and man-hours became 0	✓
2	Set salary costs to 0	Total cost decrease	Salary costs removed, total cost decreased	✓
3	Set material cost to 0	Total cost decrease	Material costs removed, total cost decreased	✓
4	Set external party cost to 0	Total cost decrease	External party costs removed, total cost decreased	✓
5	Set wage- and external party components at 0	TDSM costs and man-hours increase linearly	Result matched	✓
6	Increase External Party Costs	Total costs for M1, M2, M4, WP increase	Costs increased accordingly	✓
7	Increase hourly wage by 50%	All wage-based costs increase	Observed	✓
8	Set M8 material costs to 0	CBM costs decrease with decrease in M8 material costs	Result matched	✓
9	Set WP and M4 cost to 0	Only BO-prep remains for TDSM	Result matched	✓
10	Remove BO-prep (FTE) costs	Linear reduction in TDSM costs	Linear drop confirmed	✓

Table 5.2: Verification Steps 1–10

Table 5.2 shows only part of the verification steps to keep things clear and easy to read. The full list of all 60 checks for costs as well as man-hours is included in Appendix A. With the verification actions performed and verified, it can be said that the model works as intended.

5.3. Conclusion

In this chapter, the model developed to compare different maintenance strategies (CM, TDSM, and CBM) was implemented and tested. Microsoft Excel was selected as the platform due to its availability, usability, and compatibility with existing workflows within the RNLN. The model structure includes a scenario generator (covering all realistic maintenance mixes), a cost and man-hour input database sourced from SAP, and a calculation engine that produces outputs for each scenario, ship type, and BSMI group. These outputs are then analyzed to provide insight into which maintenance strategy yields the lowest cost or fewest man-hours.

Verification of the model was performed by testing each part, as shown in Table 5.2 and detailed further in Appendix A. These tests confirmed that the model reacts logically to changes in inputs, such as costs and component selections.

Sub-question 4 *How can the model be verified and applied by the Royal Netherlands Navy?* is largely addressed in this chapter. While full validation being done in Chapter 8, the model has been verified through scenario testing and input manipulation. It has been structured to be accessible to stakeholders across the RNLN, including engineering personnel, analysts, and maintenance planners.

6 Application of the model for the RNLN

This chapter applies the model to the operational context of the RNLN. The goal is to assess how the model can inform decisions about maintenance distribution across vessel types and system groups.

The chapter is structured into two main sections. First, Section 6.1 presents findings for several BSMI groups. Although this model is applicable to all major vessels within the fleet (JSS, MF, LPD, LCF and OPV), the results are shown for three different vessel types within the RNLN, showing both expected and unexpected trends. Unfortunately, for reasons of confidentiality, the specifics of the vessel types can not be shared. Next, the chapter assesses cost- and man-hour reduction potential by comparing the current (baseline) maintenance strategy with optimized scenarios in Section 6.2.

This chapter serves a dual purpose. It not only answers sub-question 5: *How can the model help the Royal Netherlands Navy in their maintenance decision-making?*, but also validates the model's behavior against known system characteristics.

6.1. Findings per installation group

This section presents the model outcomes for several BSMI groups. The analysis is conducted per system group and per vessel type, enabling a comparison of maintenance strategies across vessel types. Each subsection begins with a description of the criticality of the systems involved in the group, followed by the expected outcomes. The actual model results are then presented and evaluated against these expectations. Where discrepancies occur, possible explanations (often related to SAP data quality) are provided.

It was chosen to start this section with the BSMI groups that are expected to show results that have a contrast with the current applied level of maintenance within the RNLN. The increasing group ID (A to N) corresponds to a decreasing order of criticality, reflecting the prioritization of systems based on their operational impact. For reasons of confidentiality, the specifics of each BSMI group have not been shared. Neither are the absolute numbers for costs and man-hours in the data shared. Instead, the costs and man-hour data are normalized by dividing each single value by the sum of all values of each SAP component. The values within each SAP component consist of the value for each BSMI group, for each vessel type. An example of this normalization is given in Figure C.1. It shows the different BSMI groups for each vessel type and the corresponding normalized value for the M1 component. This normalization makes it possible to compare internal distributions without revealing absolute figures.

Normally, results from the model are displayed in a graph showing all 60 maintenance scenarios. An example is shown in Figure 5.4. However, due to confidentiality reasons, these graphs are not included. Instead the five most efficient scenarios are visualized in a table. These represent the strategies with the lowest total costs or man-hours (with downtime included), offering a view on the most relevant outcomes.

In terms of expectations on what the results will look like per installation group, the hypothesis is based on the relationship between system criticality and the preferred maintenance approach. For groups with a high number of mission-critical systems, such as sensors or weapon systems, it is expected that strategies with a higher application of CBM will prove most efficient. This is because failures in these systems during missions can lead to disproportionally high CM costs and man-hours. CBM, despite requiring additional investments, can prevent such failures and spreads maintenance effort more evenly over time. This is in contrast to TDSM, which tends to create concentrated workload peaks.

In contrast, BSMI groups composed of systems that are less critical, such as lighting, paint, or distribution panels, are more suited to CM-heavy strategies. Failures in these systems are less disruptive and can be resolved at lower cost and with fewer man-hours at a later time. In these cases, CBM adds limited value and is not expected to feature prominently among the most efficient maintenance approaches.

The following hypotheses are formulated to assess how system criticality and repairability influence the efficiency of maintenance strategies across vessel types and BSMI groups:

- H1:
  For BSMI groups with a high share of mission-critical systems, targeted use of CBM (20-50%) is expected to reduce both resource expenditures and downtime because proactive condition monitoring prevents the costly and disruptive effects of unexpected failures.
- H2:
  For BSMI groups with low-criticality systems, a higher reliance on CM (20-60%) is anticipated to lower overall expenses and labor requirements since these systems can be repaired cheaply and their failure does not critically disrupt operations.
- H3:
  For BSMI groups where systems are of moderate to high criticality yet easily repairable onboard, an elevated use of CM (20-60%) is likely efficient because the inherent low repair complexity offsets operational expenditures associated with reactive maintenance.
- H4:
  The most man-hour efficient strategies are expected to employ a higher proportion of CM (10%-30%) than the most cost-efficient strategies (0%-20%) because, in the model, CM incurs a lower labor burden compared to TDSM and CBM when it comes to man-hours.

6.1.1. BSMI group A

Among all groups, BSMI Group A contains one of the highest concentrations of mission-critical systems on board. Therefore, the results are expected to match H1.

For all three vessel types, both the most cost- and man-hour efficient scenario's including its breakdown are presented in Table 6.1. All five scenarios for costs (in the blue part of the table) feature CBM application levels between 10% and 50%. These results align well with H1 and suggest that CBM contributes to optimal maintenance strategies for this high-criticality group. Next, the five most man-hour efficient scenarios for Vessel Type 1 and 3 are similar, with CBM applications ranging between 20% to 40%, and therefore in line with H1. On the contrary, the man-hour efficient scenario's for Vessel Type 2 show CBM application ranging between 0 and 20%, while CM ranges from 20% to 40%. This is not in line with H1. The reason for this difference can be explained through the man-hour data. Figure 6.1 shows man-hours in the dataset for all different data components. The registered M2 data for Vessel Type 2 is noticeably lower than for the other vessel types. Since M2 man-hours are low, the multiplier curve has less effect and thus total required man-hours (including downtime) for CM remains low. This explains the higher preference for CM. However, it remains uncertain whether these results, showing a high application of CM, are fully realistic. It is plausible that M2 man-hours for Vessel Type 2 are significantly underreported, and the model may not fully correct for this underregistration, which would reduce the calculated burden of CM and distort the model outcomes. Additionally, it is possible that downtime effects are not sufficiently captured in the current version of the model. A 40% CM application level could, in practice, result in considerably more downtime than the model currently reflects. Due to the absence of both literature and empirical data on the required man-hours and downtime associated with higher CM applications (above 30%), the model cannot be further refined to correct for these potential inconsistencies.

Table 6.1: The 5 most efficient scenarios (top to bottom, #) per vessel type, for both costs (blue) and man-hours (orange), for BSMI Group A

Type	#Costs	CM%	TDSM%	CBM%	#Man-hours	CM%	TDSM%	CBM%
Vessel Type 1	9	0%	80%	20%	17	10%	60%	30%
	10	0%	90%	10%	18	10%	70%	20%
	8	0%	70%	30%	27	20%	60%	20%
	7	0%	60%	40%	16	10%	50%	40%
	6	0%	50%	50%	7	0%	60%	40%
Vessel Type 2	9	0%	80%	20%	38	30%	70%	0%
	8	0%	70%	30%	37	30%	60%	10%
	7	0%	60%	40%	28	20%	70%	10%
	18	10%	70%	20%	47	40%	60%	0%
	6	0%	50%	50%	27	20%	60%	20%
Vessel Type 3	8	0%	70%	30%	27	20%	60%	20%
	7	0%	60%	40%	28	20%	70%	10%
	9	0%	80%	20%	17	10%	60%	30%
	18	10%	70%	20%	18	10%	70%	20%
	17	10%	60%	30%	26	20%	50%	30%

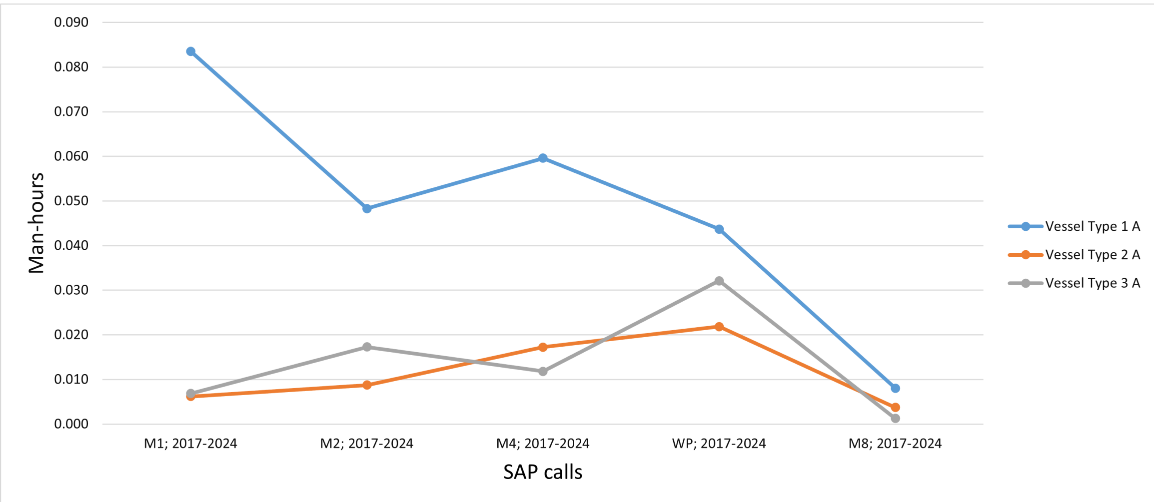

Figure 6.1: SAP man-hour component comparison for BSMI Group A across vessel types.

6.1.2. BSMI group I

BSMI Group I contains no mission-critical installations. Therefore, it is expected that H2 will be confirmed. The rationale is as follows: repair for installations within this group is relatively inexpensive, and failures do not jeopardize operational capabilities. As such, scenarios that favor CM applications of 30% and higher are likely to be among the most efficient scenario's.

The most efficient scenarios can be seen in Table 6.2. The scenarios all share a common structure: CM percentages range from 10% to 60%, while TDSM varies from 50% to 90%. Notably, none of these top-performing strategies include CBM, which confirms H2.

This consistency across vessel types is notable but must be interpreted with caution. One important detail stands out: for Vessel Type 2 and 3, the model records no CM costs nor man-hours for BSMI Group I. This is due to the absence of any M1 or M2 maintenance calls in the SAP data for these vessels. As a result, the model assumes CM costs to be zero. Consequently, scenario 65, which applies the highest level of CM, emerges as the most cost-efficient simply because the model interprets CM as a cost-free option. In reality, this is misleading, since higher application of CM would not increase CM costs. While the model results provide a useful comparison, they must be weighed against operational

Table 6.2: The 5 most efficient scenarios (top to bottom, #) per vessel type, for both costs (blue) and man-hours (orange), for BSMI Group I

Type	#Costs	CM%	TDSM%	CBM%	#Man-hours	CM%	TDSM%	CBM%
Vessel Type 1	29	20%	80%	0%	65	60%	40%	0%
	38	30%	70%	0%	56	50%	50%	0%
	47	40%	60%	0%	47	40%	60%	0%
	20	10%	90%	0%	38	30%	70%	0%
	56	50%	50%	0%	29	20%	80%	0%
Vessel Type 2	64	60%	30%	10%	65	60%	40%	0%
	56	50%	50%	0%	56	50%	50%	0%
	47	40%	60%	0%	47	40%	60%	0%
	38	30%	70%	0%	38	30%	70%	0%
	29	20%	80%	0%	29	20%	80%	0%
Vessel Type 3	65	60%	40%	0%	65	60%	40%	0%
	56	50%	50%	0%	56	50%	50%	0%
	47	40%	60%	0%	47	40%	60%	0%
	37	30%	60%	10%	38	30%	70%	0%
	29	20%	80%	0%	29	20%	80%	0%

experience and data limitations. In reality, a scenario that reflects the current maintenance strategy for BSMI Group I specifically would be more realistic.

6.1.3. BSMI group B

Given the critical importance of installations within BSMI Group B, maintenance expectations for this group closely align with those for BSMI Group A: it is expected that H1 will be confirmed.

During the analysis of BSMI Group B, it was found that some of the most cost-efficient scenarios showed negative values for TDSM. This caused scenarios with high levels of TDSM to appear more cost-efficient, simply because increasing TDSM would lower the total cost in the model. Of course, negative maintenance costs are not realistic.

After investigating the data in SAP, the cause of this issue was identified. For each vessel, the WP material costs are negative. This raised the question: how can there be negative costs in SAP?

The answer is shown in Figure 6.2. In the example, a certain installation is removed from the ship to undergo maintenance. At the time of removal (step 1), it is registered in SAP with a negative value, which is standard procedure in the RNLN to reflect the system leaving the vessel. After removal, the system is sent to the maintenance hall (step 2), where maintenance is carried out. According to policy, the system should then be returned and re-registered in SAP with a positive value (step 3), just before being reinstalled on board (step 4). However, this final registration step is often skipped due to time pressure or administrative oversight (Interview 11, 2025; Interview 10, 2025; Interview 9, 2025). This skipped step is marked in the figure with a red line. Because the return is not recorded, the maintenance costs stay negative in SAP. This registration issue mostly affects M4, WP and M8 maintenance types, which are usually done during BO or AM maintenance periods. Since systems within BSMI Group B are often physically removed for this kind of maintenance, this group is especially vulnerable to this type of data error.

Further review of the dataset showed that the negative WP costs for all three vessel types were caused by the same installation. Due to reasons of confidentiality, the exact installation can not be further explained. Since the negative values corresponding to this specific installation are not realistic, and clearly the result of a data entry issue, it was decided to adjust the negative values in the dataset with the height of the costs of the installation. This is in line with the process described through Figure 6.2 and improves the reliability of the model results. Also, other negative entries for other BSMI groups were adjusted based on the height of the negative costs for certain installations.

The updated outcomes are included in Table 6.3. After correcting the data, the cost results show what was originally expected: all three vessel types now favor maintenance scenarios with a relatively high application of CBM (10% to 50%) and a low application of CM (0% to 10%). Therefore, H1 is confirmed.

While the conclusions for cost-efficiency are clear, they do not apply in the same way to man-hour efficiency. The results for man-hours are also shown in Table 6.3. It can be seen that the most man-hour efficient scenarios generally have 10% to 40% CM and CBM application between 10% and 30%. In addition, the preferred man-hour strategies differ across vessel types. The underlying reasons for these differences can be traced to the man-hour composition of the data. As shown in Figure 6.3 M1 and M2 man-hours for Vessel Type 2 are lower than for the other vessels. This explains why Vessel Type 2 favors a relatively high application of CM (30% to 50%), while Vessel Type 1 and Vessel Type 3 lean more towards lower CM percentages. Between these two, Vessel Type 1 tends to favor 10% to 30% CM, whereas Vessel Type 3 prefers an even lower range of 0% to 10%. This is also supported by the data: Figure 6.3 shows that Vessel Type 1 has up to four times higher costs for M4, WP and M8 maintenance compared to Vessel Type 3. These findings highlight how optimal scenarios vary not only per BSMI group, but also between cost and man-hour perspectives, and between different vessel types.

All together, the most efficient costs-scenarios confirm H1, but the man-hours do not. Instead, the man-hours confirm H4.

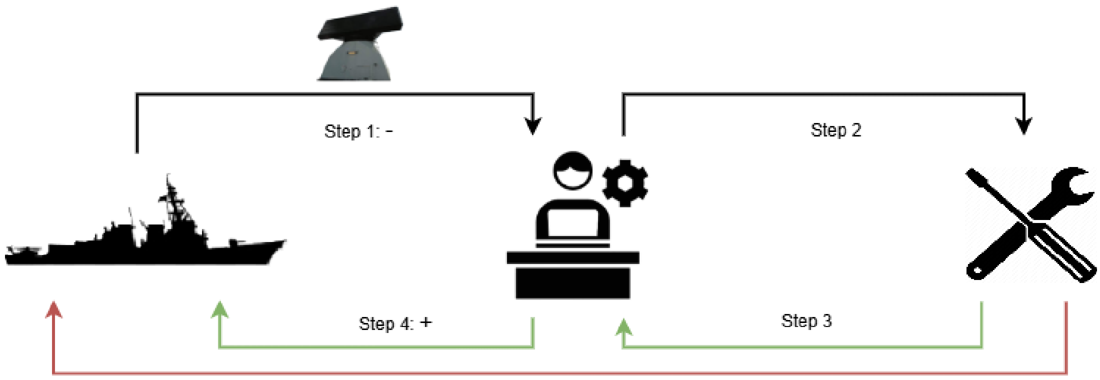

Figure 6.2: Maintenance registration process for on board installations.

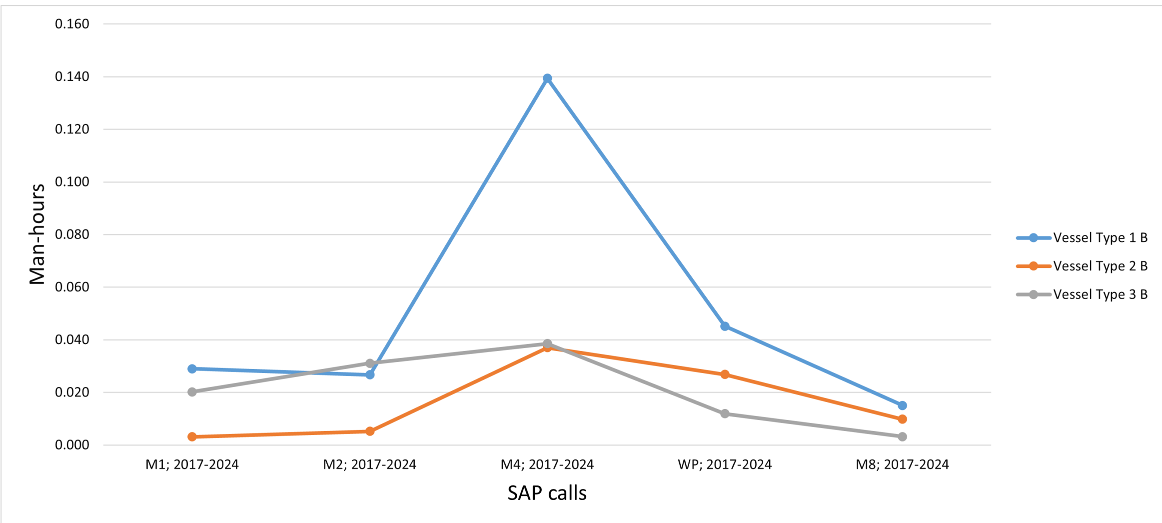

Figure 6.3: SAP man-hour component comparison for BSMI Group B across vessel types

6.1.4. BSMI group H

While some systems in BSMI Group H are mission-critical, they are generally straightforward to repair. Most of the equipment can be fixed quickly on board without the need for support from external

Table 6.3: The 5 most efficient scenarios (top to bottom, #) per vessel type, for both costs (blue) and man-hours (orange), for BSMI Group B

Type	#Costs	CM%	TDSM%	CBM%	#Man-hours	CM%	TDSM%	CBM%
Vessel Type 1	8	0%	70%	30%	27	20%	60%	20%
	7	0%	60%	40%	37	30%	60%	10%
	9	0%	80%	20%	17	10%	60%	30%
	6	0%	50%	50%	26	20%	50%	30%
	18	10%	70%	20%	28	20%	70%	10%
Vessel Type 2	8	0%	70%	30%	47	40%	60%	0%
	18	10%	70%	20%	56	50%	50%	0%
	9	0%	80%	20%	37	30%	60%	10%
	7	0%	60%	40%	46	40%	50%	10%
	19	10%	80%	10%	38	30%	70%	0%
Vessel Type 3	9	0%	80%	20%	17	10%	60%	30%
	8	0%	70%	30%	18	10%	70%	20%
	7	0%	60%	40%	16	10%	50%	40%
	10	0%	90%	10%	7	0%	60%	40%
	6	0%	50%	50%	8	0%	70%	30%

Table 6.4: The 5 most efficient scenarios (top to bottom, #) per vessel type, for both costs (blue) and man-hours (orange), for BSMI Group H

Type	#Costs	CM%	TDSM%	CBM%	#Man-hours	CM%	TDSM%	CBM%
Vessel Type 1	29	20%	80%	0%	38	30%	70%	0%
	38	30%	70%	0%	47	40%	60%	0%
	47	40%	60%	0%	28	20%	70%	10%
	56	50%	50%	0%	37	30%	60%	10%
	20	10%	90%	0%	29	20%	80%	0%
Vessel Type 2	47	40%	60%	0%	65	60%	40%	0%
	55	50%	40%	10%	56	50%	50%	0%
	65	60%	40%	0%	47	40%	60%	0%
	37	30%	60%	10%	38	30%	70%	0%
	29	20%	80%	0%	29	20%	80%	0%
Vessel Type 3	29	20%	80%	0%	20	10%	90%	0%
	20	10%	90%	0%	19	10%	80%	10%
	38	30%	70%	0%	10	0%	90%	10%
	47	40%	60%	0%	29	20%	80%	0%
	19	10%	80%	10%	9	0%	80%	20%

maintenance teams (Interview 9, 2025). Therefore H3 would be expected to be confirmed.

The five most efficient scenarios per vessel type are listed in Table 6.4. It can be concluded that all these top-performing scenarios are characterized by high CM application (ranging from 10% to 50%) and low CBM application (between 0% and 20%). This outcome confirms H3.

6.1.5. BSMI Group E

BSMI Group E contains installations that are considered mission-critical due to their role in essential onboard processes. Therefore, H1 would be expected to be confirmed.

The breakdown for the five most efficient scenarios per vessel type is listed in Table 6.5. It can be concluded that Vessel Type 1 and Vessel Type 3 follow similar patterns in their most cost-efficient scenarios, with CM ranging between 0% and 10%, and CBM ranging from 10% to 40%. Thereby confirming H1. In contrast, Vessel Type 2 leans more heavily on CM, with application levels between 20% and 50%, while CBM remains limited to 0% to 10%, disconfirming H1.

This difference in maintenance strategy can be directly linked to the cost data from SAP, as illustrated in Figure 6.4. The figure shows that M1 and M2 costs for Vessel Type 2 are three to five times lower than those for Vessel Type 1 and Vessel Type 3. Since M1 and M2 are the primary cost drivers for CM, this lower baseline makes CM-heavy strategies more attractive for Vessel Type 2. Meanwhile, Vessel Type 1's M1 costs are elevated due to multiple installations making high-CM scenarios less favorable.

A similar trend is visible in the man-hour data. The results confirm H1 for Vessel Type 1 and Vessel Type 3, while it disconfirms H1 for Vessel Type 2. Vessel Type 2 results lean more towards confirmation of H2. Figure 6.5 shows that M2 man-hours for Vessel Type 2 are roughly four times lower than for Vessel Type 1 and up to eighteen times lower than for Vessel Type 3. This substantial difference in labor effort explains why the most man-hour efficient strategies for Vessel Type 2 also lean toward higher CM usage.

It is possible that Vessel Type 2 genuinely benefits more from CM due to its operational characteristics. However, it is plausible that the relatively high application of CM observed in the model results is influenced by data limitations. Specifically, the registration of M2 maintenance actions (both costs and man-hours) for Vessel Type 2 is significantly lower than for the other vessel types. This aligns with findings from (Email communication 5, 2024), who argues that Vessel Type 2 is equipped with less advanced systems and therefore exhibits lower failure sensitivity. As a result, less reactive maintenance is needed, which may explain the reduced volume of CM-related data. This lower registration of CM calls, especially under M2, leads to a reduced multiplier effect in the model, keeping the total estimated costs and labor for CM low. Consequently, scenarios with high CM application (above 30%) appear more efficient than they may be in practice. It is important to recognize that such results could be unrealistic, as the model does not currently compensate enough for potential underregistration of CM data. Additionally, it is uncertain whether the model accurately captures the full impact of downtime at these high CM levels. A more realistic maintenance strategy for Vessel Type 2 may involve increased application of TDSM. If so, the current output could represent a model limitation that warrants further examination. Chapter 7 and Chapter 8 will further explore these concerns through sensitivity analysis and validation.

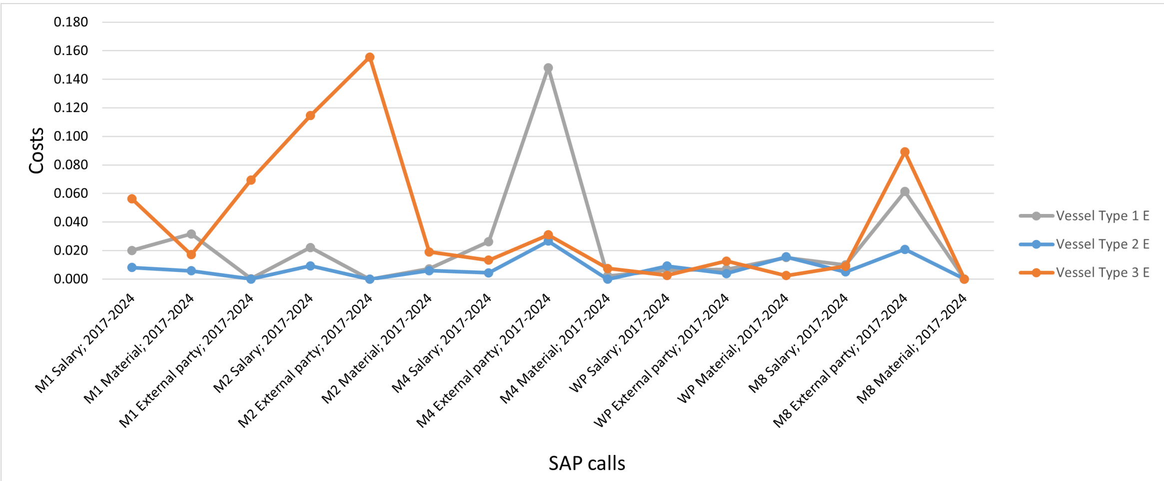

Figure 6.4: SAP cost component comparison for BSMI Group E across vessel types

Table 6.5: The 5 most efficient scenarios (top to bottom, #) per vessel type, for both costs (blue) and man-hours (orange), for BSMI Group E

Type	#Costs	CM%	TDSM%	CBM%	#Man-hours	CM%	TDSM%	CBM%
Vessel Type 1	9	0%	80%	20%	27	20%	60%	20%
	8	0%	70%	30%	28	20%	70%	10%
	7	0%	60%	40%	18	10%	70%	20%
	19	10%	80%	10%	17	10%	60%	30%
	18	10%	70%	20%	26	20%	50%	30%
Vessel Type 2	38	30%	70%	0%	38	30%	70%	0%
	29	20%	80%	0%	28	20%	70%	10%
	47	40%	60%	0%	37	30%	60%	10%
	28	20%	70%	10%	47	40%	60%	0%
	55	50%	40%	10%	29	20%	80%	0%
Vessel Type 3	8	0%	70%	30%	8	0%	70%	30%
	9	0%	80%	20%	7	0%	60%	40%
	7	0%	60%	40%	18	10%	70%	20%
	18	10%	70%	20%	17	10%	60%	30%
	19	10%	80%	10%	6	0%	50%	50%

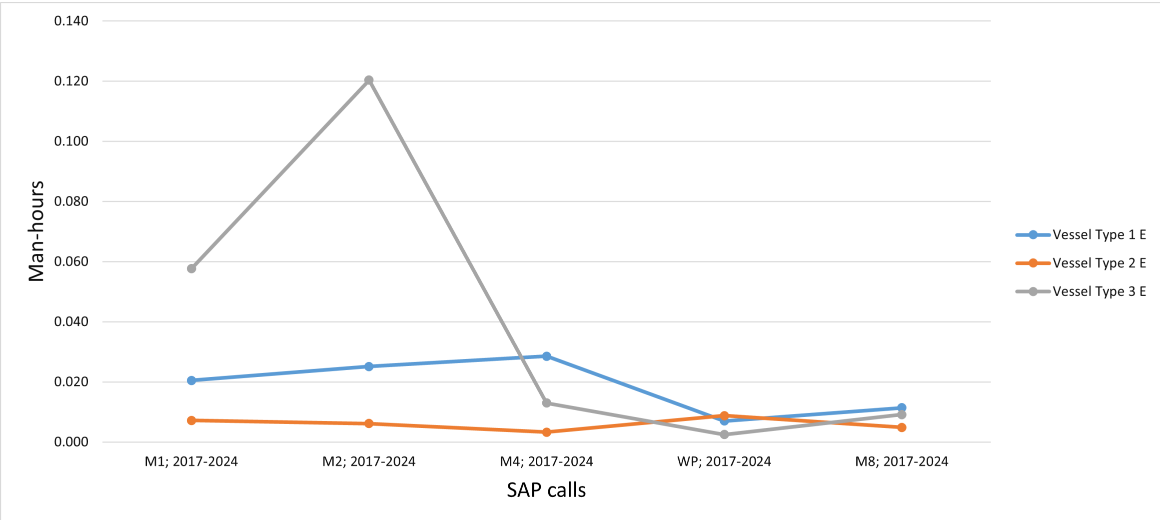

Figure 6.5: SAP man-hour component comparison for BSMI Group E across vessel types

6.1.6. BSMI group G

BSMI group G consists of systems that are critical to ship operations. Meanwhile, they typically have onboard spare parts and can often be repaired by the crew without external support. For this reason, it is expected that H3 will be confirmed.

The maintenance distributions for the most efficient scenarios per vessel type are presented in Table 6.6. It can be seen that the most cost-efficient scenarios for Vessel Type 1 involve low CM application (0% to 10%) and moderate to high CBM application (20% to 50%). In contrast, Vessel Type 2 and Vessel Type 3 show a preference for higher CM levels (10% to 40%) and lower CBM levels (0% to 20%). This difference is explained by the SAP data presented in Figure 6.6, which breaks down the total maintenance costs by component. It becomes clear that M2 cost, which is the main contributor to CM in the model, is at least two times higher for Vessel Type 1 compared to Vessel Type 2 and Vessel Type 3. As a result, high-CM scenarios are less attractive for Vessel Type 1, pushing the model toward CBM-heavy strategies.

When looking at man-hours, Table 6.6 shows that both Vessel Type 1 and Vessel Type 3 favor low CM application (0% to 10%), whereas Vessel Type 2 shows a preference for CM levels between 10% and

30%. This difference is supported by the SAP man-hour data in Figure 6.7, which shows that Vessel Type 2 has at least three times fewer M2 man-hours compared to Vessel Type 1 and Vessel Type 3. The same figure also shows that Vessel Type 1 has more than eight times the number of M4, WP and M8 man-hours compared to Vessel Type 3. This helps explain the relatively low use of TDSM in Vessel Type 1 scenarios (40% to 70%), whereas Vessel Type 3 favors much higher levels (70% to 90%).

Once again, these variations across vessel types underline a key point: the optimal maintenance strategy is not uniform, but depends strongly on the vessel type specific cost and man-hour data. With regards to Vessel Type 2 (both costs and man-hours) and Vessel Type 3 (costs), H3 is confirmed. On the contrary, for Vessel Type 1 (both costs and man-hours) and Vessel Type 3 (man-hours), the results tend to confirm H1.

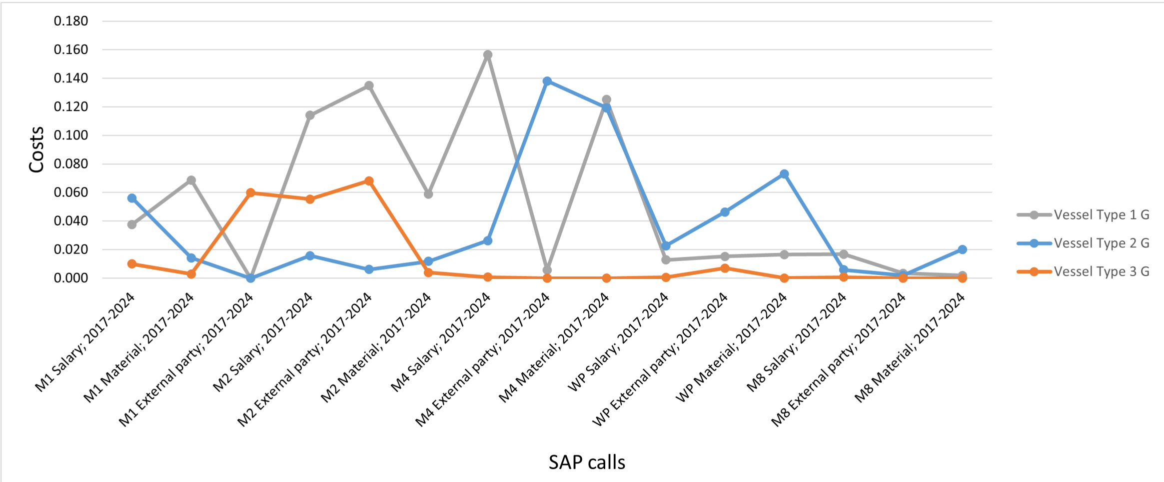

Figure 6.6: SAP cost component comparison for BSMI Group G across vessel types

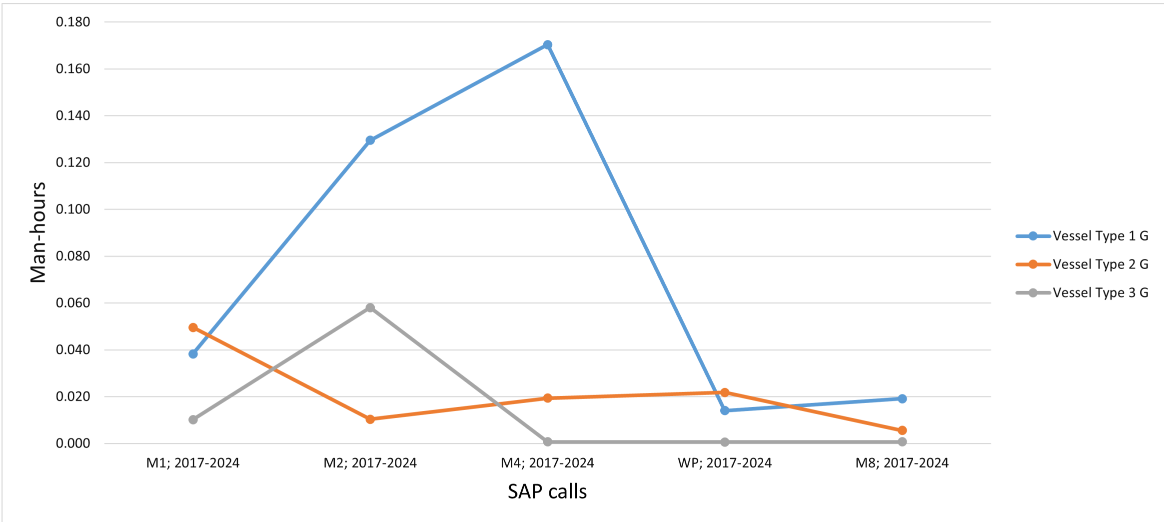

Figure 6.7: SAP man-hour component comparison for BSMI Group G across vessel types

6.1.7. BSMI Group C

Installations within BSMI Group C are considered highly critical to mission success and operational coordination. As such, H1 is expected to be confirmed.

Table 6.7 lists the five most efficient scenarios for each vessel type. A comparison of the cost results reveals that Vessel Type 1 and Vessel Type 3 show similar behavior, aligning with the expected pattern: scenarios with minimal CM (0 to 20%) and high CBM application (20% to 50%) dominate the top

Table 6.6: The 5 most efficient scenarios (top to bottom, #) per vessel type, for both costs (blue) and man-hours (orange), for BSMI Group G

Type	#Costs	CM%	TDSM%	CBM%	#Man-hours	CM%	TDSM%	CBM%
Vessel Type 1	8	0%	70%	30%	17	10%	60%	30%
	9	0%	80%	20%	16	10%	50%	40%
	7	0%	60%	40%	18	10%	70%	20%
	6	0%	50%	50%	7	0%	60%	40%
	18	10%	70%	20%	15	10%	40%	50%
Vessel Type 2	38	30%	70%	0%	27	20%	60%	20%
	47	40%	60%	0%	28	20%	70%	10%
	28	20%	70%	10%	37	30%	60%	10%
	18	10%	70%	20%	38	30%	70%	0%
	27	20%	60%	20%	18	10%	70%	20%
Vessel Type 3	29	20%	80%	0%	19	10%	80%	10%
	20	10%	90%	0%	9	0%	80%	20%
	19	10%	80%	10%	10	0%	90%	10%
	38	30%	70%	0%	20	10%	90%	0%
	9	0%	80%	20%	18	10%	70%	20%

positions. Thereby confirming H1. In contrast, Vessel Type 2 displays a deviation from this trend. Its most cost-efficient scenarios are characterized by relatively high CM levels (10–30%) and lower CBM usage (0–20%).

This deviation can be explained by examining the SAP cost data shown in Figure 6.8. As illustrated, Vessel Type 2 exhibits a significant spike in WP material costs, approximately seven times higher than those of Vessel Type 1 and more than twice as high as those of Vessel Type 3. This peak is caused by maintenance on a specific installation within Group E that causes 65% of the total costs in this SAP component. Since WP costs are included in both TDSM and CBM, this anomaly leads to inflated cost estimates for these methods on Vessel Type 2. Consequently, the model favors maintenance scenarios with a heavier reliance on CM, as they appear more cost-efficient due to elevated CBM and TDSM costs.

Regarding man-hours, the results show a different pattern. For both Vessel Type 1 and Vessel Type 2, CM is applied at a moderate level, typically between 10% and 30%. CBM also falls within a similar moderate range of 10% to 30%. Thereby disconfirming H1 and showing more balance between CM and CBM, therefore confirming H4. In contrast, Vessel Type 3 exhibits a low application of CM (0 to 10%) and a relatively high application of CBM (20% to 50%). Therefore confirming H1 again.

This difference can be explained by examining the man-hour data in Figure 6.9. Vessel Type 3 shows a more prominent peak at M2, compared to Vessel Type 1 and Vessel Type 2. As explained in Section 4.2.1, the multiplier effect of M2 significantly increases total man-hours when CM is heavily applied. Consequently, to avoid this spike, scenarios for Vessel Type 3 tend to maintain a low level of CM application.

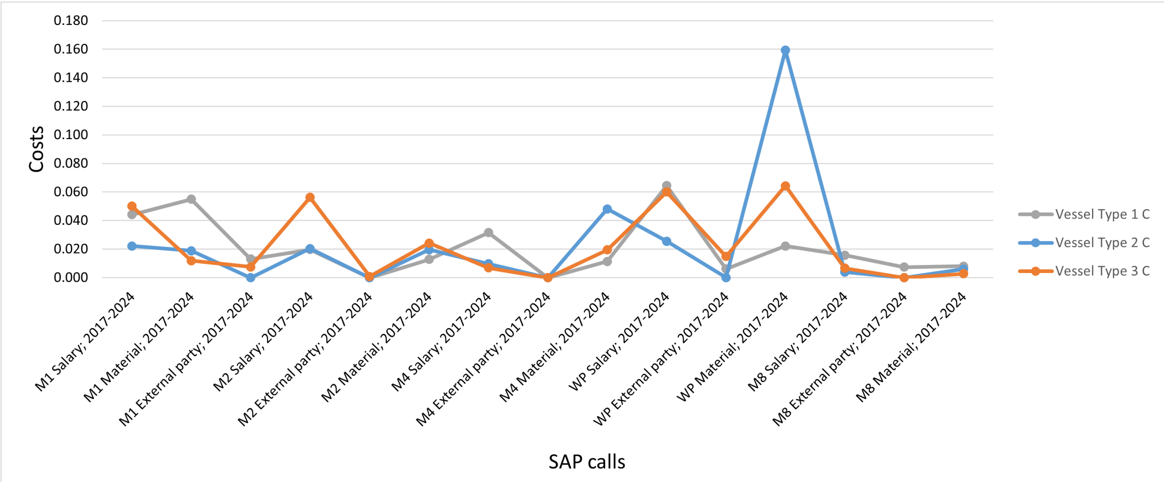

Figure 6.8: SAP cost component comparison for BSMI Group C, across vessel types

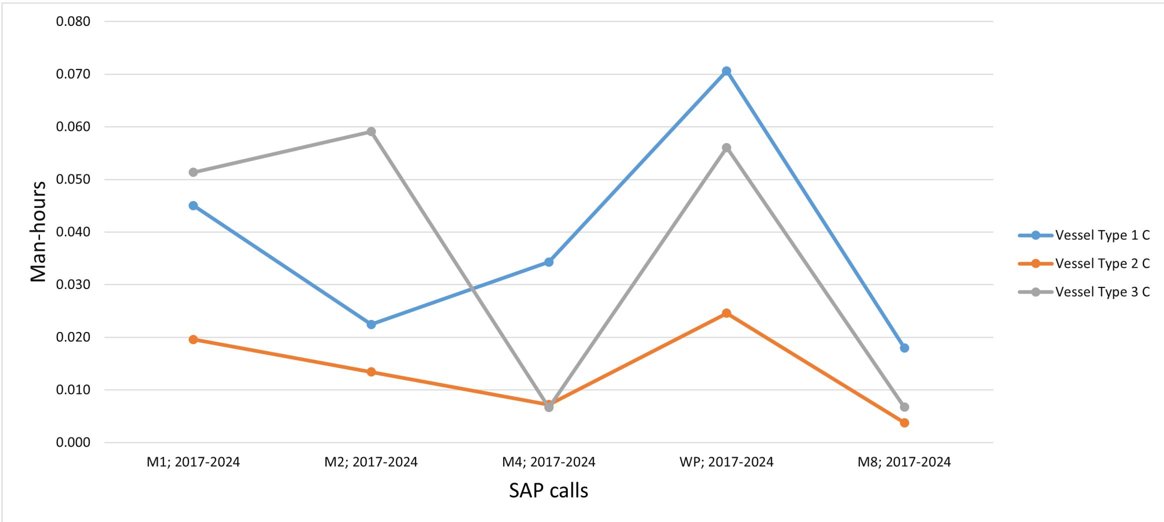

Figure 6.9: SAP man-hour component comparison for BSMI Group C, across vessel types

6.1.8. Summary

The application of the model across various BSMI groups has provided insight into the costs and labour of different maintenance strategies for different vessel types within the RNLN. The results show a correlation between the criticality of systems and the preferred maintenance approach. As expected, groups with a high share of mission-critical systems, such as BSMI groups A and B tend to favor strategies with higher CBM application compared to minimal reliance on CM. In contrast, groups with lower operational risk, such as BSMI groups H and J are more cost-efficient when CM plays a bigger role ranging from 10% to even 50%. However, results showing a high application of CM should be interpreted with caution, as they may stem from under registration of M2 costs or man-hours. This highlights a limitation in the model: when the dataset contains little to no M2 data, the multiplier curve described in Section 4.2.1 has limited effect. As a result, even at CM applications of 40–60%, CM remains relatively inexpensive compared to TDSM and CBM. This can lead to unrealistic outcomes with CM being the most preferred maintenance method with application of 30% and higher.

A noteworthy trend is the deviation observed in Vessel Type 2 results compared to those of Vessel Type 1 and Vessel Type 3. Across multiple BSMI groups, Vessel Type 2 consistently shows a higher reliance on CM. This can be traced to lower M1 and M2 registration in the SAP data, which reduces the modeled cost and labor impact of CM. This aligns with the fact that Vessel Type 2 has less advanced

Table 6.7: The 5 most efficient scenarios (top to bottom, #) per vessel type, for both costs (blue) and man-hours (orange), for BSMI Group C

Type	#Costs	CM%	TDSM%	CBM%	#Man-hours	CM%	TDSM%	CBM%
Vessel Type 1	8	0%	70%	30%	27	20%	60%	20%
	7	0%	60%	40%	37	30%	60%	10%
	9	0%	80%	20%	26	20%	50%	30%
	6	0%	50%	50%	17	10%	60%	30%
	18	10%	70%	20%	36	30%	50%	20%
Vessel Type 2	29	20%	80%	0%	28	20%	70%	10%
	38	30%	70%	0%	27	20%	60%	20%
	28	20%	70%	10%	38	30%	70%	0%
	18	10%	70%	20%	37	30%	60%	10%
	19	10%	80%	10%	18	10%	70%	20%
Vessel Type 3	17	10%	60%	30%	17	10%	60%	30%
	7	0%	60%	40%	16	10%	50%	40%
	18	10%	70%	20%	18	10%	70%	20%
	27	20%	60%	20%	7	0%	60%	40%
	8	0%	70%	30%	15	10%	40%	50%

systems and thus lower failure sensitivity, resulting in fewer reactive maintenance actions. However, this reduced data input weakens the multiplier effect and may lead the model to overstate the efficiency of CM-heavy strategies (above 30%). As a result, such outcomes may not fully reflect operational reality, especially as downtime effects may be underrepresented.

During the data review, some entries with negative values were identified, prompting further investigation into the SAP system. It was determined that these negative values stemmed from registration errors. To address this, the dataset was adjusted by offsetting the negative costs of installations against the original entries.

The man-hour results show a relatively higher application of CM compared to the cost-driven outcomes. This could potentially reflect reality, as CM might require fewer man-hours than preventive methods. However, it can also be influenced by the quality of the SAP man-hour data. Despite the applied corrections the dataset may still underestimate the actual labor effort required for CM. Especially the consequences of downtime. Therefore, the observed trend should be interpreted with caution, as it may result from residual data limitations.

6.2. Total comparison for different scenarios

In addition to identifying the most efficient scenarios per BSMI group, it is also insightful to assess how total maintenance costs and man-hours may be reduced when shifting from the current maintenance strategy (referred to here as the baseline) to the most efficient scenario. The baseline costs were calculated by summing all maintenance costs recorded in SAP, supplemented with the costs for AM and BO preparations, which are not included in SAP. A breakdown of these scenarios is presented in Table 6.8.

6.2.1. Costs

The results of the cost-part of the analysis are shown in Table 6.9. While cost savings are observed across multiple BSMI groups, some outcomes warrant careful interpretation.

Reviewing Table 6.9, BSMI groups I, J and L exhibit cost reductions exceeding 45%. These savings stem from the near-absence of corrective costs in the baseline, which causes CM-heavy scenarios (47 and 65) to appear unrealistically efficient. As discussed in Section 6.1, such inflated benefits require cautious interpretation. By contrast, more moderate cost reductions, ranging from 3% to 29% (averaging 18%), are achieved in groups A, B, C, D, E and F, driven by CBM application intensities of 10%–30%.

Table 6.8: Overview of several cost-efficient scenarios.

Scenario	%CM	%TDSM	%CBM
7	0%	60%	40%
8	0%	70%	30%
9	0%	80%	20%
17	10%	60%	30%
18	10%	70%	20%
20	10%	90%	0%
29	20%	80%	0%
38	30%	70%	0%
47	40%	60%	0%
65	60%	40%	0%

Table 6.9: Cost savings per BSMI group and vessel type when comparing the baseline to the most cost-efficient scenario.

Ship + BSMI	Scenario #1	Reduction(%)
Vessel Type 1 A	9	60%
Vessel Type 1 B	9	25%
Vessel Type 1 C	8	10%
Vessel Type 1 D	9	23%
Vessel Type 1 E	9	11%
Vessel Type 1 F	9	3%
Vessel Type 1 G	9	29%
Vessel Type 1 H	Baseline	-
Vessel Type 1 I	Baseline	-
Vessel Type 1 J	47	52%
Vessel Type 1 K	Baseline	-
Vessel Type 1 L	20	21%
Vessel Type 1 M	Baseline	-
Vessel Type 2 A	9	25%
Vessel Type 2 B	8	6%
Vessel Type 2 C	Baseline	-
Vessel Type 2 D	47	17%
Vessel Type 2 E	Baseline	-
Vessel Type 2 F	Baseline	-
Vessel Type 2 G	38	1%
Vessel Type 2 H	47	13%
Vessel Type 2 I	65	54%
Vessel Type 2 J	65	99%
Vessel Type 2 K	47	11%
Vessel Type 2 L	Baseline	-
Vessel Type 2 M	Baseline	-
Vessel Type 3 A	8	12%
Vessel Type 3 B	9	47%
Vessel Type 3 C	17	4%
Vessel Type 3 D	7	13%
Vessel Type 3 E	9	27%
Vessel Type 3 F	7	2%
Vessel Type 3 G	Baseline	-
Vessel Type 3 H	20	1%
Vessel Type 3 I	65	51%
Vessel Type 3 J	65	61%
Vessel Type 3 K	Baseline	-
Vessel Type 3 L	29	60%
Vessel Type 3 M	Baseline	-

6.2.2. Man-hours

The results of the man-hour analysis are shown in Table 6.10. While man-hour reductions are observed across various groups, some outcomes require careful interpretation.

Looking at Table 6.10, BSMI groups H, I, J and M display reductions exceeding 45%. This is caused by the near absence or complete lack of registered M2 man-hours in SAP for these groups. As a result, scenarios with high CM application (20% to 60%) appear most efficient. As discussed in Section 6.1, this limitation inflates the apparent benefit of CM-heavy scenarios and calls for caution when interpreting these reductions. By contrast, more moderate man-hour reductions, ranging from 1% to 45% (averaging 22%), are observed in groups A, B, C, D, F and G, driven by CBM application intensities of 10%–30%.

Table 6.10: Man-hour (including downtime) savings per BSMI group and vessel type when comparing the baseline to the most man-hour efficient scenario.

Ship + BSMI	Scenario #1	Reduction (%)
Vessel Type 1 A	17	5%
Vessel Type 1 B	27	0%
Vessel Type 1 C	27	2%
Vessel Type 1 D	37	5%
Vessel Type 1 E	27	2%
Vessel Type 1 F	18	2%
Vessel Type 1 G	17	19%
Vessel Type 1 H	38	8%
Vessel Type 1 I	65	90%
Vessel Type 1 J	65	58%
Vessel Type 1 K	Baseline	-
Vessel Type 1 L	47	14%
Vessel Type 1 M	38	10%
Vessel Type 2 A	38	2%
Vessel Type 2 B	47	23%
Vessel Type 2 C	Baseline	-
Vessel Type 2 D	Baseline	-
Vessel Type 2 E	38	9%
Vessel Type 2 F	Baseline	-
Vessel Type 2 G	27	1%
Vessel Type 2 H	65	91%
Vessel Type 2 I	65	92%
Vessel Type 2 J	65	59%
Vessel Type 2 K	38	8%
Vessel Type 2 L	29	41%
Vessel Type 2 M	29	24%
Vessel Type 3 A	27	5%
Vessel Type 3 B	17	5%
Vessel Type 3 C	17	10%
Vessel Type 3 D	17	19%
Vessel Type 3 E	8	39%
Vessel Type 3 F	19	64%
Vessel Type 3 G	65	45%
Vessel Type 3 H	20	44%
Vessel Type 3 I	65	98%
Vessel Type 3 J	65	45%
Vessel Type 3 K	29	6%
Vessel Type 3 L	37	1%
Vessel Type 3 M	56	54%

6.3. Conclusion

This chapter demonstrated the model's application within the RNLN, providing insights into costs and labour across seven BSMI groups and three vessel types for various maintenance strategies (CM, TDSM, CBM).

The findings confirm that system criticality plays a role in shaping optimal maintenance approaches. For high-criticality groups like A and B, CBM consistently emerges as the most effective strategy. In contrast, less critical groups such as H and J are more suited to CM-heavy strategies, confirming the formulated hypotheses. This model shows reductions in costs ranging between 1-99%, with 28% on average. For man-hours, the model shows reductions from 1% to 98%, with 31% on average. Meanwhile, for results showing high application of CM, these results should be interpreted with caution. Since, these results can be a consequence of low administration of M2 data. As a consequence, the multiplier curve as described in Section 4.2.1 does have limited effect and therefore high application of CM (ranging between 30-60%) becomes the most preferable outcome. Therefore, it could be possible that these kind of results do not reflect reality.

A consistent observation is Vessel Type 2's higher reliance on CM across BSMI groups. This is primarily driven by significantly lower registration of M2 costs and man-hours in SAP, which reduces the modeled impact of CM. While this may partially reflect the vessel's simpler systems and lower failure sensitivity, it also weakens the multiplier effect in the model and may cause CM-heavy strategies (above 30%) to appear more efficient than they are in practice. As such, these outcomes must be interpreted with caution, as they may not fully represent operational reality.

Cost-driven and man-hour-driven strategies diverge as well: man-hour efficient scenarios favor CM more often than the cost part. This suggests CM appears less labor-intensive, though limitations in SAP's man-hour data, despite corrections like M2, may still affect accuracy, regardless of the applied correction.

Chapter 4 began addressing Sub-Question 3 on providing maintenance cost and man-hour insights. This chapter completes it by showing how the model quantifies the impact of CM, TDSM, and CBM strategies by system group and vessel type, confirming its value for maintenance planning.

Sub-Question 4: *How can the model be verified and applied by the Royal Netherlands Navy?* was partially addressed in Chapter 5. This chapter further answers this sub question by showing the model's practical use in identifying optimal strategies and data issues. The rest of the sub qeustion will be fully answered in Chapter 8.

In addition, this chapter offers a first answer to Sub-Question 5: *How can the model help the Royal Netherlands Navy in their maintenance decision-making?*. The results show the model's practical value by identifying optimal maintenance mixes, revealing cost and man-hour saving opportunities, and exposing inconsistencies in the underlying data. These insights contribute to more transparent, data-driven maintenance planning. A full exploration of this question will follow in Chapter 7.

Overall, the findings presented here show that the model is ready to support decision-making. Its accuracy, however, is strongly dependent on the quality of input data. Chapter 7 will further test the reliability of certain results through sensitivity analysis, evaluating how robust the conclusions remain under input variations.

7 Analysis of maintenance comparison

This chapter presents a sensitivity analysis to evaluate how uncertainty in key inputs affects the model outcomes. It examines how variations in cost and man-hour component for both CBM and CM influence the most efficient maintenance scenarios. A sensitivity factor, ranging from 0.0 to 2.0 in steps of 0.2, is applied to each component, proportionally scaling its original value while keeping other inputs constant.

To clarify some of the parameters used in this sensitivity analysis, Figure 7.1 is used as an example. As shown in this figure, the values on the y-axis are normalized. For confidentiality reasons, all values are normalized. This means that for each vessel type and corresponding BSMI group, the value is expressed as the quotient of the scenario's value and the sum of all scenario values within that same vessel type and BSMI group.

In addition, all graphs in this chapter include error bars that represent a 10% deviation from the most efficient scenario. This 10% margin is applied to assess whether scenarios fall within close proximity of each other. If multiple scenarios remain within this range, it cannot be determined which one is most efficient. The 10% threshold is chosen to account for general model uncertainty.

Besides checking whether scenarios fall within this 10% range, this analysis also investigates the presence of critical tipping points, where small changes in input lead to significant shifts in the preferred scenario.

7.1. Sensitivity of CBM components

In the model, CBM components are assumed to behave linearly and independently. Therefore, by varying one representative component while keeping the others constant, its impact can be extrapolated to similar CBM components. This allows the analysis to focus on a single cost and a single man-hour component. Since CBM relies more on expert judgment and limited data compared to TDSM and CM, testing its robustness is especially important. Since CBM variation will have the biggest influence on scenarios where CBM application is relatively high (30-50%), the sensitivity analysis focuses on installation groups within that range.

7.1.1. CBM cost component

The CBM component 'Material costs' is selected, as it represents 40–60% of total CBM costs in every scenario involving CBM, making it a key contributor to the CBM cost structure.

The first case concerns Vessel Type 3, BSMI group A. Figure 7.1 shows the five most efficient scenarios for this group. As stated earlier in this chapter, the values are normalized by taking the quotient of each scenario's value and the sum of all values for this vessel type within the same BSMI group.

From the figure, it can be observed that Scenario 8 (0% CM and 30% CBM) remains the most efficient scenario across the entire sensitivity factor range. In addition, Scenarios 7 (0% CM and 40% CBM), 9 (0% CM and 20% CBM), and 18 (10% CM and 20% CBM) all stay within the 10% margin from the most efficient scenario. Since these scenarios lie within this margin, it is not possible to determine which one

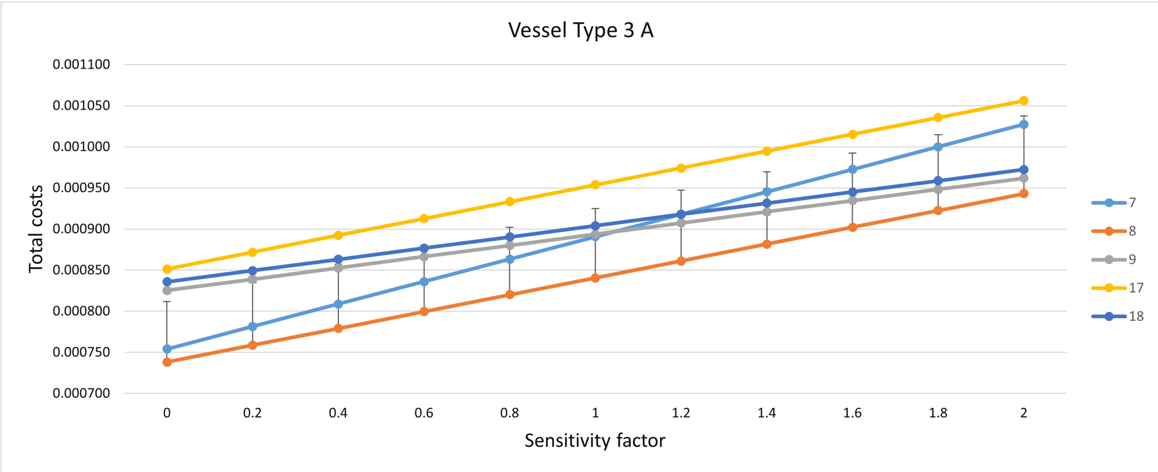

Figure 7.1: CBM cost sensitivity of Vessel Type 3 A.

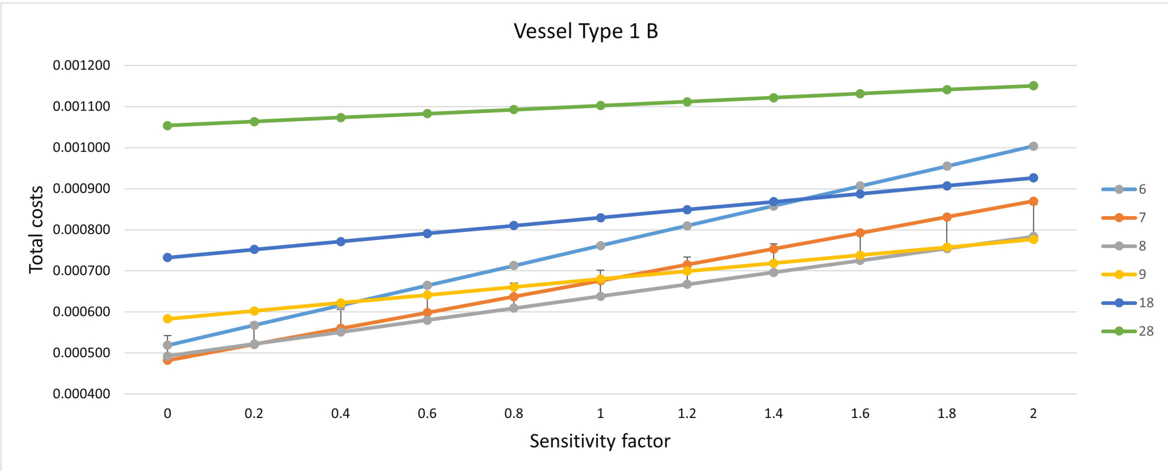

Figure 7.2: CBM cost sensitivity of Vessel Type 1 B.

is truly the most efficient. However, since all of these scenarios involve at least 20% CBM, it can be concluded that a minimum CBM application of 20% is preferred for this BSMI group.

This conclusion is further supported by the fact that Scenario 19 (10% CM and 10% CBM), the first scenario with less than 20% CBM, consistently deviates by at least 14% from the most efficient scenario across the full range of the sensitivity factor.

The second case involves Vessel Type 1, BSMI group B. Figure 7.2 displays the five most efficient scenarios for this group, along with Scenario 28 (20% CM and 10% CBM) for comparison. Based on the error bars shown in the figure, it can be concluded that Scenarios 6 (0% CM and 50% CBM), 7 (0% CM and 40% CBM), 8 (0% CM and 30% CBM), and 9 (0% CM and 20% CBM) all fall within the 10% uncertainty margin. Therefore, no definitive conclusion can be made about which of these is the most efficient.

However, since all four of these scenarios include at least 20% CBM, it can be confidently stated that a minimum application of 20% CBM is preferred for this BSMI group. This conclusion is reinforced by the performance of Scenario 28 (20% CM and 10% CBM), which is the first scenario containing less than 20% CBM. It consistently shows a deviation of at least 49% from the most efficient scenario across the full sensitivity factor range.

The final case concerns Vessel Type 1, BSMI group C. Figure 7.3 presents the five most efficient scenarios for this group, along with Scenario 19 (10% CM and 10% CBM) for reference. According to the error bars shown, Scenarios 7 (0% CM and 40% CBM), 8 (0% CM and 30% CBM), and 9 (0%

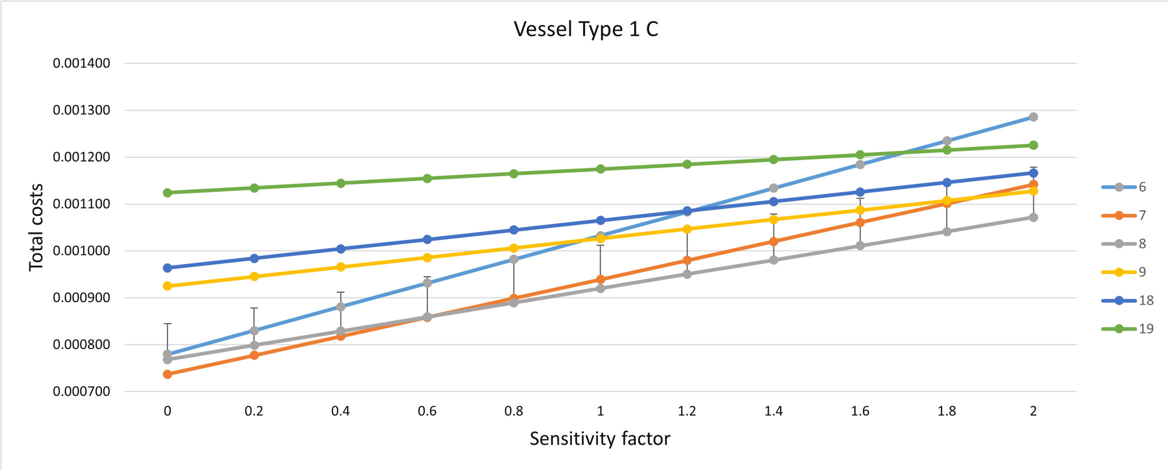

Figure 7.3: CBM cost sensitivity of Vessel Type 1 C.

CM and 20% CBM) all lie within the 10% uncertainty margin. As a result, no conclusion can be drawn about which of these is the most efficient.

However, since all three of these scenarios share at least 20% CBM, it can be confidently concluded that a minimum CBM application of 20% is favourable for this BSMI group. This conclusion is reinforced by the performance of Scenario 19 (10% CM and 10% CBM), which is the first scenario containing less than 20% CBM. It consistently deviates by at least 18% from the most efficient scenario across the full sensitivity factor range.

In all three cases, the most efficient scenarios consistently include at least 20% CBM across the full sensitivity factor range. This indicates that for installation groups with relatively high CBM application, the model outcomes are robust against uncertainty in CBM cost estimates. No critical tipping points were observed within the tested cost range.

Since these groups are the most sensitive to CBM cost variation, it follows logically that installation groups with little or no CBM are even less affected. In those cases, the preferred scenario remains unchanged even when CBM material costs vary between 0 and 200% of their estimated values. This confirms that the model is generally insensitive to CBM cost uncertainty and maintains stable outcomes.

Therefore, results showing a high preference for CBM (typically 20-50%) can be considered reliable.

7.1.2. CBM man-hour component

The CBM component 'Man-hours for replacement / repair of installations' is selected for this purpose. These costs make up between 40-60% of the total CBM man-hours in every scenario that includes CBM, making them one of the most significant contributors to the CBM man-hour structure.

The first case is Vessel Type 1, installation group G. Figure 7.4 shows the five most efficient scenarios for this group, along with Scenario 28 (20% CM and 10% CBM). Scenario 17 (10% CM and 30% CBM) includes upward-reaching error bars representing a 10% deviation. From the figure, it is clear that Scenarios 7 (0% CM and 40% CBM), 16 (10% CM and 40% CBM), and 17 (10% CM and 30% CBM) all remain within a 10% margin of each other across the entire sensitivity range. Therefore, it cannot be concluded which of these is the most efficient.

However, Scenario 28 (20% CM and 10% CBM), which is the first scenario with less than 20% CBM, only comes within the 10% margin at a sensitivity factor of 1.9. Its influence is negligible across the full range. This supports the conclusion that an application of at least 20% CBM is preferred for this BSMI group.

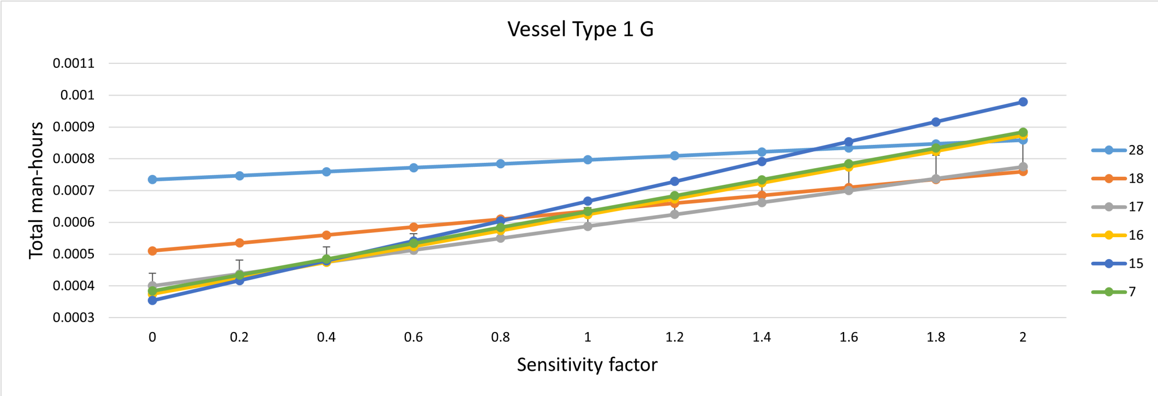

Figure 7.4: CBM man-hour sensitivity of Vessel Type 1 G.

five most efficient scenarios for this group, along with Scenario 28 (20% CM and 10% CBM), which is the first scenario containing less than 20% CBM. Scenarios 7 (0% CM and 40% CBM), 8 (0% CM and 30% CBM), 17 (10% CM and 30% CBM), and 18 (10% CM and 20% CBM) all remain within a 10% margin of each other over the full sensitivity range. Therefore, it cannot be determined which of these is the most efficient.

However, since Scenario 28 (20% CM and 10% CBM) never falls within this 10% range, it can be concluded with confidence that an application of at least 20% CBM is favourable for this BSMI group.

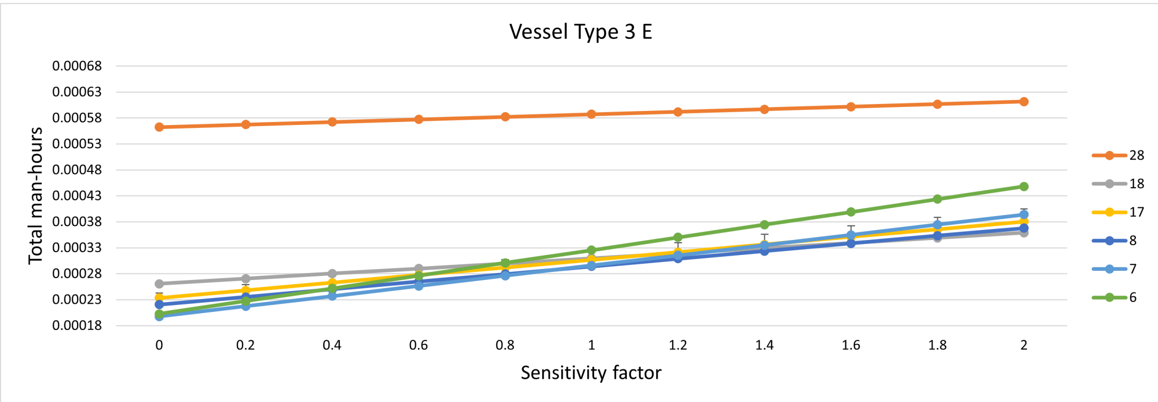

Figure 7.5: CBM man-hour sensitivity of Vessel Type 3 E.

The third and final case is Vessel Type 3, installation group C. Figure 7.6 displays the five most efficient scenarios for this group, along with Scenario 19 (10% CM and 10% CBM), which is the first scenario containing less than 20% CBM. From the figure, it can be seen that Scenarios 7 (0% CM and 40% CBM), 16 (10% CM and 40% CBM), and 17 (10% CM and 30% CBM) consistently lie within a 10% margin of each other. Therefore, it cannot be concluded which of these is the most favourable scenario.

However, Scenario 19 (10% CM and 10% CBM) remains outside the 10% range across the entire sensitivity domain. This leads to the conclusion that, for this BSMI group, an application of at least 20% CBM is certainly favourable.

The sensitivity analysis of the CBM man-hour component shows that, as is the same with the CBM cost part, for BSMI groups containing top five scenario's all having 20% application of CBM or higher are stable. It can not be concluded which of the top five scenario's is most favourable. As they often are within a 10% range of each other. However, it can be said for certain that at least 20% application of CBM is favourable and remains stable.

The sensitivity analysis of the CBM man-hour component shows a similar pattern to that of the CBM cost component. For BSMI groups where the top five scenarios all include at least 20% CBM, the

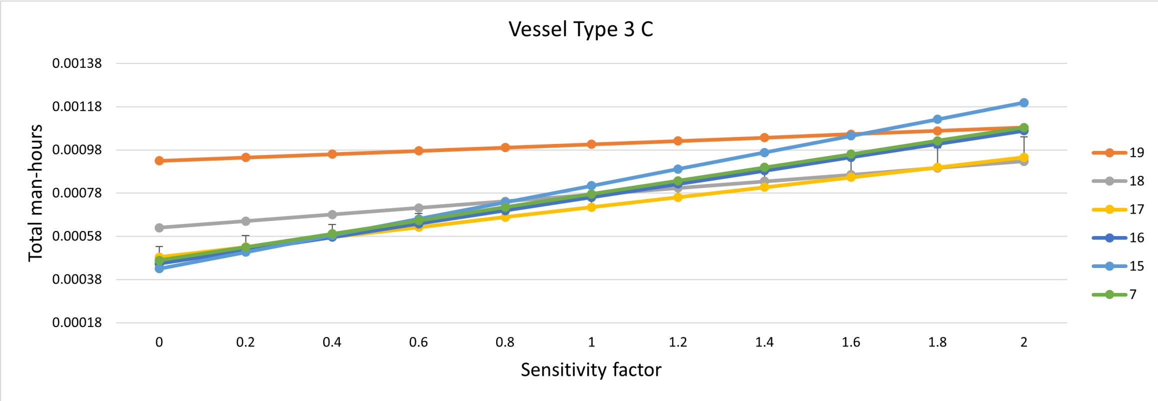

Figure 7.6: CBM man-hour sensitivity of Vessel Type 3 C

results remain stable across the full sensitivity range. Although it cannot be determined which specific scenario is the most favourable, since they consistently fall within a 10% margin of each other, it can be concluded with certainty that an application of at least 20% CBM is favourable and robust against variations in man-hour estimates.

7.2. Sensitivity of CM components

This section examines how uncertainty in M2 costs and man-hours affects model outcomes. As discussed in Section 4.2.1, M2 data, both costs and man-hours, is limited in reliability. The analysis therefore focuses on how variations in M2 inputs influence scenario results.

Scenarios with high CM application (30–60%) and those with high CBM application (30–50%) are excluded from the analysis. For these installation groups, either M2 data is unreliable (in the case of high CM), or the influence of CM is limited (in the case of high CBM). The analysis therefore targets installation groups where the most efficient scenarios fall within moderate CM application (0–20%) and moderate CBM application (0–20%).

7.2.1. CM M2 costs

The first case concerns Vessel Type 2, installation group G. Figure 7.7 shows the five most efficient scenarios for this group. Error bars of 10% (both upward and downward) are applied to the line representing Scenario 28 (20% CM and 10% CBM). When the sensitivity factor reaches 0.8, all five scenarios fall within a 10% range of each other. Therefore, no definitive conclusion can be drawn about which scenario is the most efficient within that range.

The outermost scenarios in this group—Scenario 8 (0% CM and 30% CBM) and Scenario 38 (30% CM and 0% CBM), demonstrate that the results are highly sensitive to changes in the M2 cost input. However, outside the 0.8–1.2 sensitivity factor range, the most efficient scenarios become clearer. Below a factor of 0.8, Scenario 38 (30% CM and 0% CBM) emerges as the most efficient. Beyond a factor of 1.2, Scenarios 8 (0% CM and 30% CBM), 17 (10% CM and 30% CBM), and 18 (10% CM and 20% CBM) become the most efficient options.

A similar pattern is observed for Vessel Type 3, installation group G. Figure 7.8 shows the five most efficient scenarios. Within the sensitivity factor range of 0.8 to 1.2, all scenarios remain within a 10% margin of each other. As a result, it is not possible to determine which scenario is the most efficient in that interval.

This reflects high sensitivity, as the outermost scenarios in this top five include Scenario 9 (0% CM and 20% CBM) and Scenario 29 (20% CM and 0% CBM). Outside the 0.8–1.2 range, clearer trends emerge. For sensitivity factors below 0.8, Scenario 29 (20% CM and 0% CBM) is the most efficient. For values above 1.2, Scenarios 9 (0% CM and 20% CBM) and 10 (0% CM and 10% CBM) gradually become the most favourable options.

The final case is Vessel Type 2, BSMI group C. Figure 7.9 presents the five most efficient scenarios for

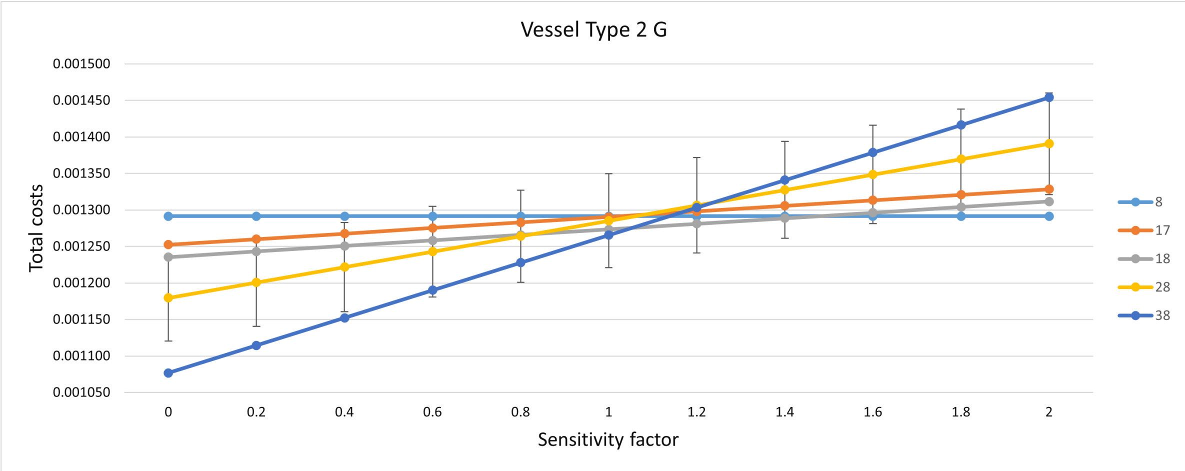

Figure 7.7: M2 cost sensitivity of Vessel Type 2 G.

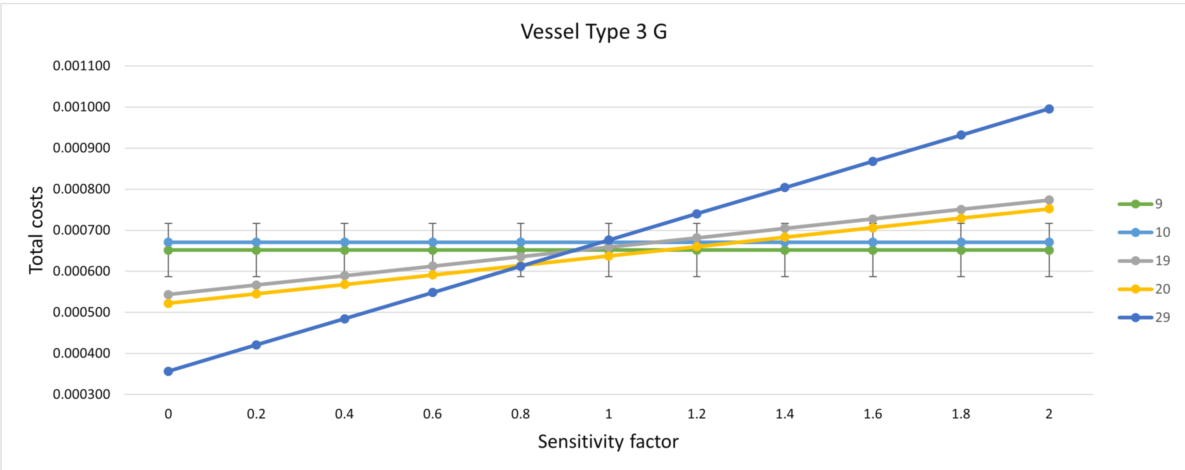

Figure 7.8: M2 cost sensitivity of Vessel Type 3 G.

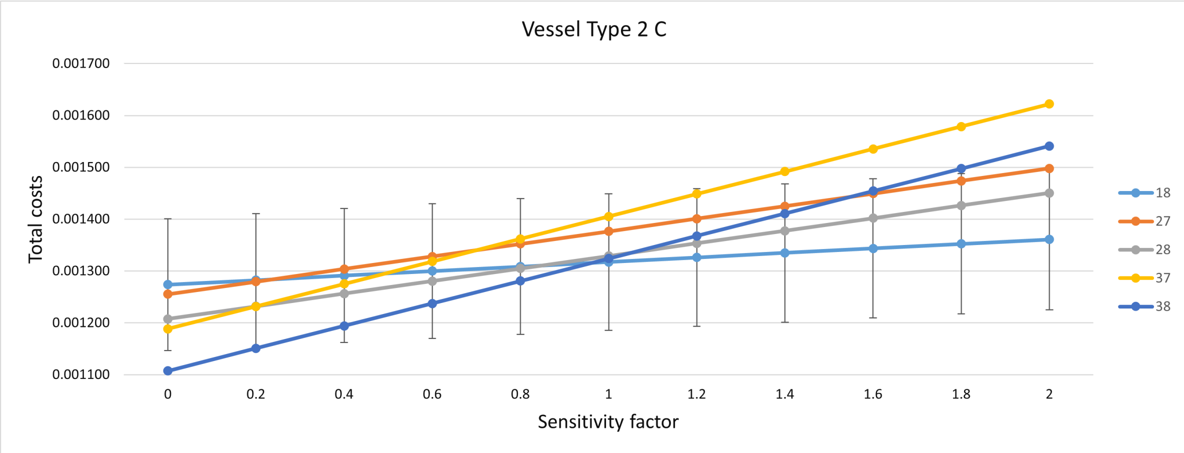

Figure 7.9: M2 cost sensitivity of Vessel Type 2 C.

this group. Within the sensitivity factor range of 0.6 to 1.4, all scenarios remain within a 10% margin of each other. Therefore, it is not possible to determine which scenario is the most efficient within this range.

Notably, the outermost scenarios in this group—Scenario 18 (10% CM and 20% CBM), with the lowest CM and highest CBM, and Scenario 38 (30% CM and 0% CBM), with the highest CM and no CBM, are both plausible candidates. This further illustrates the model's sensitivity in this zone. Outside the 0.6–1.4 range, however, the results become more distinct, with Scenario 18 and Scenario 38 separating and becoming more clearly favourable in different parts of the domain.

Overall, it can be concluded that when the model indicates moderate levels of both CM (0–20%) and CBM (0–20%), it is not possible to determine which of the top five scenarios is the most efficient. The most efficient options often differ by up to 20% in their CM or CBM application, highlighting sensitivity in this range. This also means that it becomes difficult to draw firm conclusions about whether the application of CBM in these cases reflects realistic or reliable results.

When M2 costs decrease, scenarios with higher CM application tend to become more favourable. Conversely, as M2 costs increase, scenarios with greater CBM application become more clearly preferred.

7.2.2. CM M2 man-hours

The first example is Vessel Type 2, installation group G. Figure 7.10 shows the five most efficient scenarios for this group. Error bars representing 10% deviations in both directions are applied to Scenario 27 (20% CM and 20% CBM). Around a sensitivity factor of 1.0, all scenarios lie within a 10% range of each other. Therefore, no clear conclusion can be drawn about which scenario is the most efficient in that range.

This indicates a high level of sensitivity, especially considering that the outermost scenarios in this group are Scenario 18 (10% CM and 20% CBM) and Scenario 38 (30% CM and 0% CBM). As the sensitivity factor moves toward the outer bounds of the tested range, the most efficient scenarios become more distinct.

A similar pattern is observed in Vessel Type 2, installation group F. Figure 7.11 presents the five most efficient scenarios. Around a sensitivity factor of 1.0, all scenarios, except for Scenario 29 (20% CM and 0% CBM), fall within a 10% margin of each other.

The outermost scenarios in this group are Scenario 28 (20% CM and 10% CBM) and Scenario 17 (10% CM and 30% CBM). This again reflects a variation of up to 20% in CM or CBM application among the most efficient scenarios, underlining the sensitivity of the results in this range.

Comparable sensitivity behavior is observed in Vessel Type 1, installation groups E and K. In both cases, the top five scenarios show that around a sensitivity factor of 1.0, the results differ by less than 10%. However, within this narrow range, the scenarios still vary by up to 20% in their CM or CBM

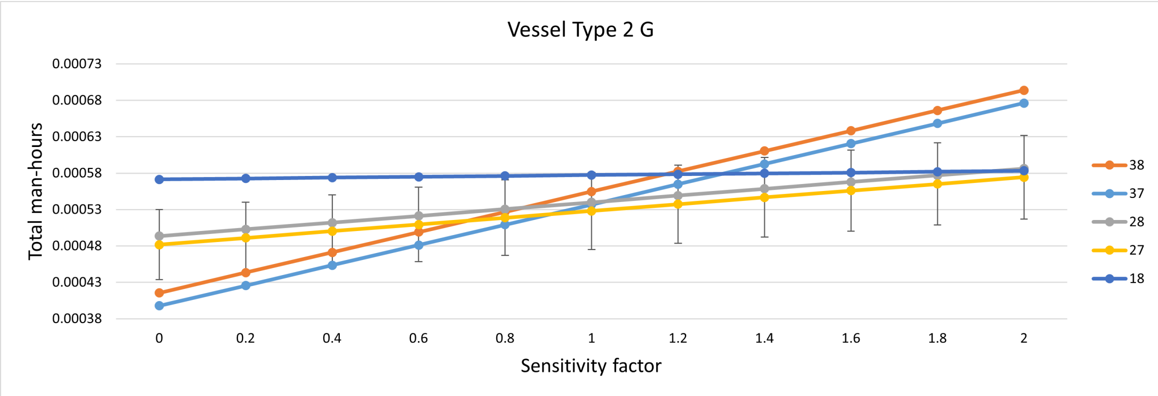

Figure 7.10: M2 man-hour sensitivity of Vessel Type 2 G.

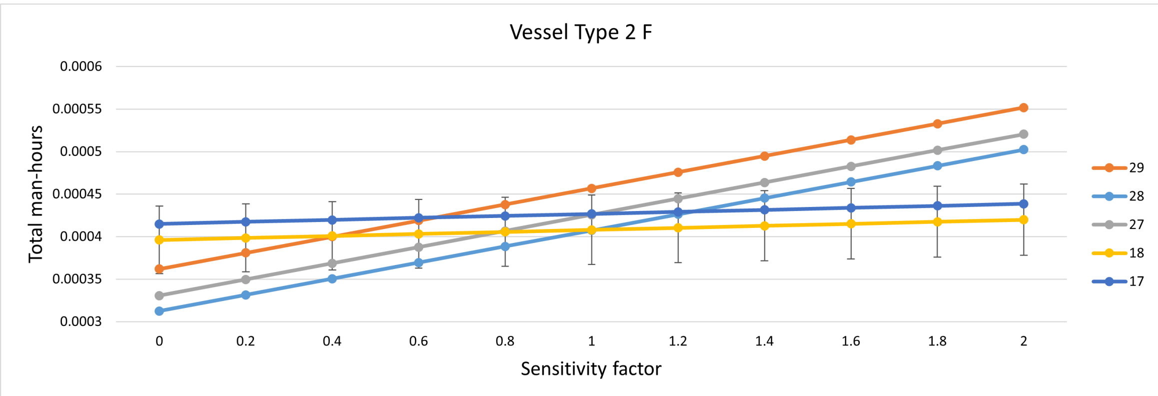

Figure 7.11: M2 man-hour sensitivity of Vessel Type 2 F

application. This again highlights sensitivity. As a result, no definitive conclusions can be drawn about whether the application of CBM is actually more efficient for these installation groups.

7.3. Conclusion

To further answer RQ5, a sensitivity analysis was conducted.

RQ 5: *How can the model help the Royal Netherlands Navy in their maintenance decision-making?*

This chapter tested the robustness of the model's recommendations under uncertainty by varying four key input components: the cost and man-hour components for both CBM and CM. These components were selected because they are the largest contributors to total maintenance effort and cost, and because underlying data for especially CBM and M2 is limited in precision. A sensitivity factor between 0.0 and 2.0 was applied to each component individually, to assess whether changes in these inputs affect which maintenance scenario is considered most efficient.

The analysis evaluated each scenario on its normalized total value, where results were interpreted using a 10% deviation margin to account for model uncertainty. Scenarios falling within this 10% band are considered indistinguishably efficient.

For installation groups with high CBM application (30–50%), the outcomes remained consistent across the full sensitivity range. Scenarios with at least 20% CBM remained among the most efficient, regardless of variations in CBM-related cost or man-hour components. No tipping points were observed. This confirms the reliability of model recommendations favouring 20–50% CBM in these cases.

In contrast, installation groups with moderate CM and CBM levels (0–20%) showed significantly more variation. Even small changes in input led to shifts in the most efficient scenario, often by as much as 20% in CBM or CM allocation. This higher sensitivity indicates that recommendations for these groups should be interpreted with more caution, and cannot be considered robust.

Table 7.1 summarizes these findings.

Table 7.1: Table showing the conclusions from the sensitivity analysis

Strategy	**Reliability of results**
CM 0-20% and CBM 0-20%	Results show variability of 0-20% in application of CM and CBM
CBM 20-50%	Results consistently indicate that applying at least 20% CBM remains favourable across the full sensitivity range.

8

Validation of the developed model

This chapter presents an assessment of the validity of the methodology developed in this thesis, following the framework proposed by Pedersen et al. (2000), known as the "validation square". This approach is designed to evaluate both the internal consistency and practical relevance of the model, aiming to determine its overall usefulness for its intended application.

Usefulness here means not only that the methodology works as intended (effectiveness), but also that it provides relevant results (efficiency). The validation square offers a structured process for assessing both, using both qualitative and quantitative criteria.

The validation is organized into four main types, as can be seen in Figure 8.1. Theoretical Structural Validity (TSV) examines the soundness of individual elements and the consistency with which they are integrated, based on the strength of the underlying sources and logical connections. Empirical Structural Validity (ESV) tests whether these elements, once theoretically validated, perform as expected when applied to known example problems. Empirical Performance Validity (EPV) addresses the practical usefulness of the methodology in meeting its objectives, focusing on how well the model and its parts contribute to achieving its intended results in real or case-based scenarios. Theoretical Performance Validity (TPV) considers the extent to which the methodology's usefulness can be generalized, looking at whether its principles and outcomes hold beyond just isolated cases.

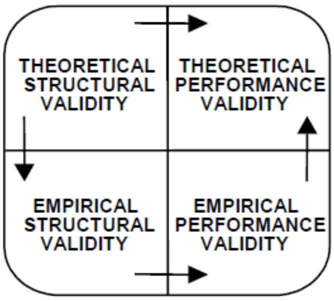

Figure 8.1: Validation square by Pedersen et al. (2000)

8.1. Theoretical Structural Validity

Key elements like data inputs, CBM, TDSM, CM modeling, and cost and man-hour calculations were built using multiple sources and verified by expert input.

CBM parameters and efficiency effects were cross-checked with several experts and based on both recent and older literature (i.e., (McDevitt, Zabarouskas, and Crook, 2003); (Hasan et al., 2018)). SAP maintenance call meanings were only included after consensus from at least three sources. The BSMI breakdown was constructed from classification sheets and refined through review by RNLN experts.

The M2 multiplier was developed from literature and expert opinion. While its core is well-founded, its behavior after 30% CM is assumed and can not be validated, therefore this is the only part of the model that does not contain TSV. Throughout, flowcharts (see Figure 4.2 to Figure 4.16) ensured internal consistency in all calculation steps.

8.2. Empirical Structural Validity

In this thesis, ESV is primarily assessed through two elements: the applied effects in the M2 multiplier and the use of external models on efficiency loss.

Figure 8.2 shows the difference in modeled efficiency between the productivity loss curve by (McDevitt, Zabarouskas, and Crook, 2003) and the workload ratio model by (Chang and Sullivan, 2006). Both were used to underpin the assumptions in this thesis. In the operational range of TDSM application, from 49% to 94%, the discrepancy in predicted efficiency remains within 10%, indicating consistent behavior across sources. At the outer ends (97% and 100% TDSM), deviations rise to 12.8% and 17.6% respectively, suggesting increasing model sensitivity near the limits of full scheduling.

As described in Section 4.2.1, the M2 multiplier models the exponential growth in cost and man-hours as CM increases beyond the optimal range. With regards to the costs-part of the model, literature sources (i.e., (Hamasha et al., 2023); (Le et al., 2018)) identify this optimal CM-to-PM ratio between 15% and 30%, while Stenström et al. (2016) quantifies cost growth with a multiplier of 3.3 for every 1% CM beyond that point.

Figure 4.5 illustrates this steep rise, which reflects the urgent and resource-intensive nature of M2 tasks. The curve is capped at 60% CM due to practical infeasibility and limited supporting data. While the central range is well-founded, outcomes beyond 30% CM remain theoretical and should be interpreted with caution.

In addition to cost, the model also assumes that required man-hours for M2 tasks grow exponentially as CM increases. This assumption is based on expert input showing that SAP data does not fully reflect the actual workload. While SAP registers the time spent on repairs on board, it leaves out important tasks like troubleshooting, coordination, travel, and logistics. To correct for this, the model applies a multiplication factor of 10 to the reported M2 man-hours. This estimate is supported by multiple RNLN experts and based on repeated observations in practice (Interview 4, 2024; Interview 9, 2025; Interview 10, 2025; Interview 11, 2025).

Although the factor of 10 is a simplification, it helps the model give a more realistic view of the full workload linked to M2 tasks. It does not aim to be exact, but it tends to show the trend. In the middle range of the curve, the results are supported by data and expert opinion. Beyond 30% CM, the outcomes become more uncertain and should be seen as indicative, not precise.

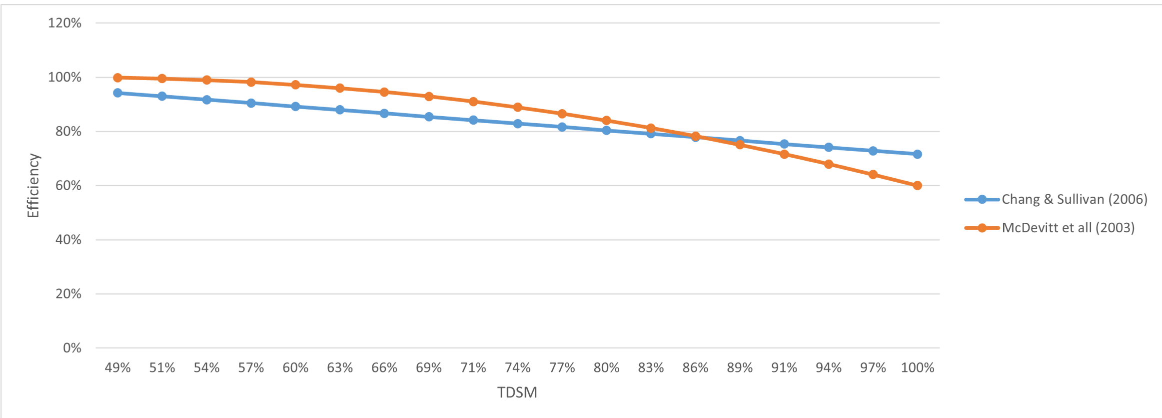

Figure 8.2: Efficiency loss comparison between (McDevitt, Zabarouskas, and Crook, 2003) and (Chang and Sullivan, 2006) across varying levels of TDSM application.

8.3. Empirical Performance Validity (EPV)

EPV assesses the practical usefulness of the model in solving the specific problem it was designed for, as well as its value in real-world application (Pedersen et al., 2000). In this thesis, usefulness is interpreted as the degree to which the model enables the identification and evaluation of cost- and man-hour efficient maintenance strategies for different system groups within the RNLN fleet.

Throughout this research, it is demonstrated that the effectiveness of a maintenance approach is highly dependent on the interplay between system criticality, maintainability, and the underlying SAP cost data. At the outset, it was uncertain whether the model would consistently capture these nuanced relationships or simply reflect dominant cost drivers in the SAP data. The systematic analysis of each BSMI group showed, however, that the model is capable of distinguishing between cases where CBM, TDSM, or CM provide the greatest benefit. For example, groups containing mission-critical systems consistently showed that increased CBM application led to more cost-efficient outcomes, as anticipated. In contrast, non-critical groups (i.e., paint or lighting systems) revealed that a reactive, CM-heavy strategy is often preferable.

Moreover, the model facilitated scenario-based comparisons that go beyond simply reproducing historical costs and man-hours, providing insight into the potential reductions achievable through targeted changes in maintenance strategy. Chapter 6 illustrates how the model's outputs, validated against expectations and operational experience, support informed decision-making for resource allocation and maintenance planning.

Importantly, the model's outputs also highlighted the influence of data quality, such as registration errors in SAP, which can affect perceived cost-efficiency. These findings reinforce the necessity of robust data practices for reliable model application and interpretation.

Overall, the model proved empirically useful for the RNLN context. It not only identified cost-effective maintenance strategies per system group and vessel type, but also revealed where further improvements in data quality and maintenance registration are required. This supports both the specific goal of optimizing RNLN maintenance and the broader purpose of advancing practical knowledge in maintenance strategy comparison for complex naval systems.

8.4. Theoretical Performance Validity (TPV)

Theoretical Performance Validity (TPV) concerns the extent to which the methodology and its results can be generalized beyond the specific cases or datasets analyzed (Pedersen et al., 2000).

In this research, the model was designed with flexibility in mind, enabling systematic comparison of maintenance strategies (CM, TDSM, CBM) across a wide variety of system groups and all major vessel types within the RNLN. The core principles, which relates maintenance cost and man-hour impacts to system criticality, maintainability, and historical cost data, are not limited to a single installation group or platform. Instead, the model structure allows for adaptation to other vessels in the fleet, as well as to other organizations with comparable data.

However, there are also boundaries to the generalization. The model's effectiveness is dependent on the availability and reliability of detailed maintenance and cost data, as well as a clear distinction between maintenance types in the source data (CM, TDSM, CBM). Additionally, the current implementation treats each BSMI group as a homogeneous unit, which may obscure sub-group differences in risk or repairability. While the methodology could in principle be refined to include further granularity or even applied outside the RNLN, this would require careful recalibration and validation against local data and operational realities.

Despite these limitations, the model's underlying approach, using cost and availability impacts to guide maintenance policy selection, can be adapted to support decision, making for other naval organizations, or even for different industries where similar maintenance challenges exist.

8.5. Conclusion

This chapter assessed the validity of the developed comparison model using the framework of the validation square. By evaluating four types of validity (TSV, ESV, EPV, and TPV), both the internal consistency and practical relevance of the model have been examined. This provides confidence in the model's capability to compare maintenance strategies based on cost and man-hour efficiency across different system groups and vessel types. This provides the last piece of the answer to sub-question 5:

RQ5: How can the model be verified and applied by the Royal Netherlands Navy?

9
Conclusion

Growing pressure on maintenance budgets and the ongoing need for high fleet readiness make it essential for the Royal Netherlands Navy to improve maintenance efficiency. Traditional approaches such as TDSM are not always sufficient for increasingly complex systems, while CBM is still under development. This context formed the motivation for this research, which investigates how different maintenance strategies can be systematically compared.

This chapter summarizes the key outcomes of the research. Section 9.1 addresses the principal limitations encountered during the study. In Section 9.2, the main conclusions are presented. Section 9.3 details the scientific contributions made by this work. Finally, Section 9.4 offers suggestions for future research directions.

9.1. Limitations

While the developed model offers valuable insights into maintenance strategy optimization, several limitations must be acknowledged.

First, the model's accuracy is highly dependent on the quality and completeness of the input data sourced from the RNLN SAP system. Instances of missing, inconsistent, or outdated cost, man-hour and downtime registrations, particularly in the recording of M2, have affected the reliability of the outputs for certain BSMI groups. For example, in cases where no M2 records were available, the model defaulted to scenarios with very high CM shares, which are unlikely to represent realistic maintenance strategies. For this reason, cost reductions due to CM application above 30% should always be interpreted with caution and are deemed unreliable.

Second, the assumed maintenance strategy mixes do not always reflect realistic operational scenarios. While useful for theoretical exploration, pure strategies (for example, 100% TDSM or 0% CM) are rarely feasible in practice. This highlights the need for a more nuanced interpretation of the model's outcomes: extreme values in maintenance allocation should be approached with caution. For instance, if the model suggests an optimal scenario of 100% TDSM, a more realistic configuration might be closer to 5% CM, 90% TDSM, and 5% CBM.

Third, the grouping of systems into broad BSMI categories, while practical for analysis, may mask variations in risk profiles and maintenance demands within groups. A more granular approach might yield deeper insights but would make applicability of the model for the entire fleet impossible.

Moreover, it is uncertain whether the model's treatment of M2 maintenance does fully capture the operational downtime caused by corrective maintenance. As a result, scenarios with high CM application may incorrectly appear more favorable in terms of man-hour efficiency. This risks underestimating the operational consequences of high CM reliance. Therefore, again, results showing CM application above 30% should always be interpreted with caution.

An important limitation lies in the divergence between cost-optimal and man-hour-optimal strategies.

The model shows that the scenarios which minimize total maintenance costs do not always correspond with those that minimize required man-hours. This highlights an inherent trade-off between financial efficiency and labor efficiency. As such, the model does not offer a one-size-fits-all recommendation for each BSMI group.

This trade-off implies that decision-making must consider the Navy's current priorities. In periods where reducing man-hours and minimizing downtime are more critical (for example, during staffing shortages or heightened operational readiness), strategies with slightly higher costs but lower labor demands may be preferable. Conversely, in times of budgetary pressure, the Navy might choose to prioritize cost savings even if that results in increased man-hour demands. The model does not resolve this tension but instead provides insights to support these strategic decisions.

Lastly, the model does not explicitly incorporate system availability or operational readiness metrics, focusing instead on costs, man-hours and downtime. While lower maintenance hours generally contribute to better availability, this relationship is indirect and could lead to suboptimal decisions when using this model for drawing conclusions on vessel availability.

9.2. Conclusion

The thesis aims to provide an answer to the main research question:

MQ: How to provide insights into the cost-effectiveness and vessel availability of different maintenance methods for the Royal Netherlands Navy?

Throughout the chapters of this thesis, the main research question is answered with several sub-questions. First, this thesis addresses the first sub-question:

SQ1: What are the general challenges surrounding RNLN ship maintenance?

The RNLN primarily collaborates with a single external partner for major vessel maintenance, fostering continuity but limiting competition and flexibility. This dependence can challenge cost management and lead to occasional scheduling delays.

In addition, several challenges specific to CM were identified. CM is by nature reactive and typically involves unplanned interventions after failures occur. This can lead to long downtimes, logistical inefficiencies, and higher operational disruption.

While CBM has potential for optimizing maintenance through predictive data, adoption is hindered by operational variability, unavailability of supplier data, and an underdeveloped data analysis infrastructure. Uncertainty about which systems are most suited for CBM further slows progress.

Additionally, the current reliance on TDSM leads to periods of organizational overload, decreasing productivity and vessel availability while increasing costs.

With maintenance resources under increasing pressure and high fleet availability remaining a priority, enhancing the selectivity and efficiency of maintenance planning is essential.

Building on these findings, the next sub-question explores the maintenance methods that need to be taken into account in order to enhance selectivity and efficiency in maintenance:

SQ2: Which maintenance methods are currently used within the Royal Netherlands Navy, and outside the navy organization, and which are relevant to include in the cost determination?

Maintenance strategies can be broadly classified as reactive, proactive, and aggressive. In the RNLN, three methods are used:

- CM addresses failures after they occur, and while essential for unforeseen breakdowns, it can cause higher downtime and expenses (≈15% of activities).
- TDSM uses fixed intervals irrespective of condition to prevent failures, though it may lead to premature replacement of components (≈80% of activities).
- CBM relies on real-time data to trigger maintenance only when needed, potentially reducing unnecessary actions, though it is still under development and involves higher investment costs (≈5% of activities).

Following these insights, Sub-Question 3 addresses how a model can be developed that compares the three identified maintenance methods to enhance selectivity and efficiency in maintenance:

SQ3: How to provide insights into the maintenance costs and required man-hours per relevant maintenance method for the Royal Netherlands Navy?

A model was developed that allocates maintenance data and metrics defined through expert opinions across the three maintenance methods. The model systematically applies varying combinations of CM, TDSM, and CBM strategies across each BSMI group and vessel type, enabling the evaluation of different maintenance scenarios in terms of cost and man-hour efficiency. System criticality is identified as a key driver for the preferred maintenance method. High-criticality systems are more cost efficient under CBM-heavy strategies. For man-hours the results showed higher reliance on CM, which could be a consequence of underestimation of CM man-hours and downtime in this model.

Results show promising cost reductions especially for BSMI groups A, B, D and E with costs reductions between 13-60% and 25% on average.

Building on these findings, the next sub-question explores the verification, application and validation of the developed model.

SQ4: How can the model be verified and applied by the Royal Netherlands Navy?

To ensure practical use within the RNLN, the model was built in Microsoft Excel for broad accessibility. It combines a scenario generator, database, and an analysis engine to evaluate CM, TDSM, and CBM mixes.

Verification through systematic input testing confirmed consistent, logical behavior. Validation using Pedersen's framework showed the model is structurally sound, performs reliably on historical data, and effectively identifies cost-efficient strategies. While tailored to the RNLN, the approach is adaptable to similar contexts with comparable data. However, uncertainties remain regarding the registration of M2 which could influence the reliability of results showing applications of CM ranging between 20-60%.

Building on these findings, the last sub-question answers:

SQ5: How can the model help the Royal Netherlands Navy in their maintenance decision-making?

The model provides the Royal Netherlands Navy with a systematic approach to assess maintenance strategies across vessel types and system groups based on costs and required man-hours.

It shows that, with regards to costs, high-criticality systems are best maintained through CBM-heavy approaches.

Sensitivity analyses confirm that for systems with high CBM application (30-50%), the model's recommendations remain robust under varying input assumptions. Systems with both moderate CM and CBM application (0–20%) show that the five most efficient scenarios often fall within a 10% deviation range from each other. However, the variation between these scenarios can be as large as 20% in terms of CM and CBM allocation. This indicates a relatively high level of sensitivity in this application range. As a result, it becomes more difficult to determine with confidence which maintenance strategy is truly the most efficient or realistic. Therefore, conclusions in these cases should be drawn with caution.

Moreover, the model highlights areas for improvement in data registration. Inconsistencies in SAP records, such as occasional negative values, typographical errors, and variations in the registration of M2 hours, can influence the results. By bringing these aspects to light, the model not only supports the optimization of maintenance strategies but also provides insights that can help enhance data quality and registration practices within the RNLN.

With the sub-questions individually addressed, the main research question is revisited:

MQ: How to provide insights into the cost-effectiveness and vessel availability of different maintenance methods for the Royal Netherlands Navy?

The objective of this research was to develop a model that provides the RNLN with improved insights into maintenance costs and vessel-availability across maintenance strategies, consisting of CM, TDSM and CBM, for different vessel types and system groups.

The developed model showed potential improvements both for costs and also reductions in man-hours. With potential cost reductions for BSMI groups ranging between 1-99%, with an average of 28%. And potential man-hour reductions of 1-98%, with an average of 41%. However, not all results are always reliable, depending on the advised maintenance strategy. A summary of the reliability of results following from the model can be seen in Table 9.1.

With regard to vessel availability, an initial attempt was made to assess this by analyzing man-hours combined with downtime, under the assumption that a reduction could indicate improved availability. However, because the combination of man-hours and downtime does not directly reflect vessel availability, and given the limitations in the quality of the downtime data, this research cannot provide definitive conclusions regarding vessel availability.

Table 9.1: Reliability of model results

Strategy	Reliability assessment
CM $> 30\%$	Results are considered unreliable due to low registration of M2.
CM 0–20% and/or CBM 0–20%	Sensitivity analysis shows variability of 0-20% in application of CM and CBM; results should be interpreted with caution.
CBM 30-50%	Results consistently indicate that applying at least 20% CBM is favourable.

9.3. Scientific contributions

This study has resulted in several scientific contributions, summarized as follows:

- Development of a decision-support model for naval maintenance strategy optimization:
  A model was developed that systematically compares maintenance strategies for different vessel installations for different vessel types, enabling cost and man-hour, combined with downtime, evaluation per system group and vessel type within the RNLN.
- Integration of real-world SAP data with maintenance modeling:
  The model integrates historical SAP data with expert-validated cost and man-hour factors, enabling evaluation of maintenance strategies.
- Identification of system criticality as a driver for maintenance strategy selection:
  The analysis confirmed that system criticality significantly influences the optimal maintenance mix, with high-criticality systems benefiting from CBM-heavy strategies, or favoring less application of CM.
- Contribution to maintenance modeling for naval fleets:
  By combining practical data and expert input, the study advances the methodology for maintenance strategy assessment in military contexts. The model's structure also offers potential for adaptation to other fleets or industries with similar maintenance challenges.

9.4. Recommendations

Based on the findings of this research, the following recommendations are proposed for the RNLN:

- Early integration of CBM for new vessels:
  For vessels entering the fleet, it is recommended to integrate CBM capabilities during the design and construction phase. This ensures that condition-monitoring infrastructure is built into the ship from the outset, avoiding costly retrofitting later. Priority should be given to implementing CBM for system groups A, B, D and E which the model identifies as the most promising candidates for cost reductions through CBM application.
- Scaling up CBM and data collection for future readiness:
  As the model calculates over the full service life of a ship and does not assess immediate cost benefits, it is recommended to begin comprehensive data collection for all existing onboard installations within BSMI groups A, B, D and E being highest priority. Followed by BSMI groups C, F and K This will build the foundation for effective CBM application for future vessels.

- Improve M2 data registration practices:
  While SAP data quality is relatively good, the recording of M2 man-hours is currently not realistic as a standalone factor. Moreover, repair processes where weapon systems are temporarily removed and reinstalled without proper administration lead to negative maintenance entries. It is recommended to avoid these inaccuracies.
- Improve downtime registration:
  Currently, downtime caused by mission-critical system failures is registered in SAP, but not accurately. Although the start date of a downtime event is often recorded, the end date is frequently missing or incorrectly logged. This results in unrealistically long downtime durations, sometimes spanning several years, making the current downtime data unreliable and unusable for analysis. It is therefore recommended to improve the registration process by accurately logging both the start and end times of downtime events caused by maintenance-related mission interruptions. A more reliable downtime record would allow better integration of availability metrics into future models and provide deeper insights into the operational impact of system failures.
- Expand the model to include availability metrics:
  Although the current model focuses on cost and man-hour (combined with downtime) reductions, ship availability is a critical metric for naval operations. Future research should extend the model to incorporate availability calculations by integrating downtime effects.
- Adopt more granular system groupings:
  Introducing more detailed classifications could provide sharper insights into which specific systems are truly mission-critical and drive maintenance costs or man-hours. Although this would make the model inapplicable for fleet-wide analysis, it would offer deeper, system-specific recommendations.
- Introduce a new SAP maintenance call type (e.g., M10) for CBM:
  To better capture maintenance actions arising from CBM, it is recommended to introduce a new maintenance call type in SAP, for instance, M10. Unlike M8, which is triggered based on hours of operation, number of rounds fired, or time-based lifespans, M10 would specifically represent predictive maintenance based on deviations in monitored parameters from their expected baselines. For example, abnormal vibration levels in a mechanical system could trigger an M10 maintenance event. This distinction will improve data quality and support more accurate future analysis of CBM effectiveness.

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A

Verification steps

Table A.1: Verification steps for validating the cost model across CM, TDSM, and CBM.

#	Action	Hypothesis	Outcome	Verified?
1	Set all costs to 0	Total cost = 0	Total cost became 0	✓
2	Set wage cost to 0	Total cost decrease	Wage costs removed, total cost decreased	✓
3	Set material cost to 0	Total cost decrease	Material costs removed, total cost decreased	✓
4	Set external party cost to 0	Total cost decrease	External party costs removed, total cost decreased	✓
5	Set wage- and external party components at 0	TDSM costs and man-hours increase linearly	Result matched	✓
6	Increase External Party Costs	Total costs for M1, M2, M4, WP increase	Costs increased accordingly	✓
7	Increase hourly wage by 50%	All wage-based cost increases	Observed	✓
8	Set M8 material costs to 0	CBM costs decrease with decrease in M8 material costs	Result matched	✓
9	Set WP and M4 cost to 0	Only BO-prep remains for TDSM	Result matched	✓
10	Remove BO-prep (FTE) costs	Linear reduction in TDSM costs	Linear drop confirmed	✓
11	Set M2 costs and man-hours to 0	Only lineair increase in costs and Man-hours for CM	Results matched	✓
12	Set sensor installation to 0	Initial CBM cost drops	Matched	✓
13	Turn off sensor replacement	CBM cost decreases with reduction in sensor replacement costs	Result matched	✓
14	Remove data analysis costs for CBM	CBM total cost decreases by the amount associated with FTEs for data analytics; no change in other methods	Output correctly shifted	✓

#	Action	Hypothesis	Outcome	Verified?
15	Change share of CBM to 0%	CBM costs and man-hours = 0	CBM output = 0	✓
16	Change share of CM to 0%	CM costs and man-hours = 0	CM output = 0	✓
17	Change share of TDSM to 0%	TDSM costs and man-hours = 0	TDSM output = 0	✓
18	Set TDSM = 100%, CM = 0%, CBM = 0%	Only M4, WP, and BO-prep show results	Only those components showed results	✓
19	Apply base values: 15% CM, 80% TDSM, 5% CBM	Model shows baseline values for CM and TDSM	Baseline behavior observed	✓
20	Set CBM to 100%	CBM costs become dominant	CBM costs > all others	✓
21	Change share of CM to 60%	M2 cost grows exponentially	M2 cost increase observed	✓
22	Change share of TDSM to 100%	Total costs of TDSM increase non-linearly	Result matched	✓
23	Set productivity factor to 1.0	No nonlinear man-hour changes; linear effect	Linear behavior confirmed	✓
24	Set ship lifetime to 1 year	Long-term costs drop significantly	Costs dropped	✓
25	Set ship lifetime to 50 years	Long-term costs increase	Costs increased	✓
26	Increase recurring CBM software cost	Total CBM cost increase with increase of software costs	Increase observed	✓
27	Increase number of sensor-covered installations from 100 to 200	CBM costs (sensor installation, analysis, replacements) roughly double due to proportional scaling.	Results matched	✓
28	Set number of installations groups to 0	No results will be produced	There are no results produced	✓
29	Set number of scenario's to 0	no results are produced	No results were produced	✓
30	Increase sensor lifetime from 6 to 10 years	Fewer replacements; cost and man-hours decrease	Correct	✓

Table A.2: Verification steps for validating the man-hour model across CM, TDSM, and CBM.

#	Action	Hypothesis	Outcome	Verified?
1	Set all man-hour values to 0	Total man-hours = 0	Output showed 0 man-hours	✓
2	Set only M1 man-hours to 0	Drop in CM man-hours, rest unchanged	Only CM man-hours dropped	✓
3	Set only M2 man-hours to 0	CM man-hours reduce significantly	CM dropped, others unchanged	✓
4	Set BO and AM prep man-hours to 0	TDSM man-hours decrease	TDSM output dropped	✓
5	Set WP, M4, M8 man-hours to 0	All scheduled maintenance effort gone	TDSM man-hours near zero	✓
6	Set M8 man-hours to 0	CBM man-hours related to usage drop	CBM man-hours dropped	✓

#	Action	Hypothesis	Outcome	Verified?
7	Set sensor installation man-hours to 0	CBM start-up man-hours disappear	One-time CBM drop observed	✓
8	Set sensor replacement man-hours to 0	CBM man-hours decrease for recurring intervals	Reduction matched	✓
9	Set data analysis man-hours to 0	CBM effort decreases slightly	Small reduction confirmed	✓
10	Set all CBM man-hours to 0	CBM total = 0, others unaffected	Output matched	✓
11	Increase M2 share to 30%	Total CM man-hours increase exponentially	Exponential growth confirmed	✓
12	Increase M2 share to 50%	Man-hour multiplier effect results in 8–10× increase	Man-hour growth aligned with exponential curve and multiplier	✓
13	Apply 10× factor to M2 man-hours	Total CM man-hours grow sharply	Confirmed steep rise	✓
14	Set productivity factor to 1.0	TDSM man-hours scale linearly	Linear output confirmed	✓
15	Increase productivity to 1.2	TDSM man-hours decrease	Higher productivity led to fewer hours	✓
16	Decrease productivity to 0.6	TDSM man-hours increase	Output grew as expected	✓
17	Set TDSM = 100%	All man-hours allocated to TDSM components	Confirmed TDSM dominance	✓
18	Set TDSM = 0%	No M4, WP, M8 or BO/AM work	TDSM man-hours dropped to 0	✓
19	Set CM = 0%	No M1 or M2 man-hours	CM output dropped	✓
20	Set CBM = 100%	All man-hours tied to sensors, analysis	CBM output increased	✓
21	Set sensor-covered installations = 200	CBM installation and replacement man-hours double	Confirmed doubling	✓
22	Set installations = 0	No CBM hours required	Output confirmed	✓
23	Remove data analysis effort	Drop in recurring CBM man-hours	Observed expected drop	✓
24	Add 2 FTE for data analysis	CBM man-hours rise proportionally	Linear increase observed	✓
25	Set CBM = 0%	All CBM man-hours = 0	Output matched	✓
26	Set CBM to 50%, TDSM to 50%, CM to 0%	Only CBM and TDSM man-hour components remain active	CM disappeared, CBM and TDSM active	✓
27	Remove productivity effects	TDSM man-hours become linear	Output changed accordingly	✓
28	Disable infrastructure fatigue multiplier	Slight TDSM productivity gain	Minor man-hour reduction seen	✓
29	Increase TDSM from 80% to 100%	All productivity factors apply negatively, leading to max man-hour inefficiency	Sharp man-hour increase confirmed	✓
30	Disable all amplifying effects	Model becomes fully linear	Smooth and proportional changes observed	✓

B

Overview of all different relevant maintenance calls in SAP

Notification	Purpose / Description
M1	Failures during missions that can be fixed later during scheduled maintenance. Falls under CM.
M2	Mission-critical failures requiring immediate resolution during the mission. Falls under CM.
M3	Quick fix without tools, lasting less than 2 hours. Not administratively processed. Falls under CM.
M4	Manually created by maintenance staff. Falls under TDSM. Examples include scheduled inspections, routine checks, or servicing every 250 operating hours.
M5	Engineering preparation for a modification (e.g., cannon replacement planning). Out of scope.
M6	Other maintenance for non-BSMI systems. Out of scope.
M7	Execution of a Navy-initiated modification (follows M5). Out of scope.
M8	Automatically generated by SAP. Directly creates a maintenance order. Falls under TDSM. Examples include: fire extinguisher replacement after expiry, engine checks, or cannon maintenance after specific usage.
M9	Execution of a modification from an external request (e.g., government). Out of scope.
WP	Administrative conversion from Primavera to SAP for BO. Contains hours and costs. Falls under TDSM.

Table B.1: Overview and classification of SAP maintenance notification types relevant to the Royal Netherlands Navy, highlighting their function and scope within the research.

C

Data normalization example

Ship + BSMI	M1; 2017 t/m 2024
Vessel Type 1 A	0.016
Vessel Type 1 B	0.000
Vessel Type 1 C	0.038
Vessel Type 1 D	0.076
Vessel Type 1 E	0.033
Vessel Type 1 F	0.083
Vessel Type 1 G	0.020
Vessel Type 1 H	0.022
Vessel Type 1 I	0.012
Vessel Type 1 J	0.084
Vessel Type 1 K	0.029
Vessel Type 1 L	0.045
Vessel Type 1 M	0.008
Vessel Type 1 N	0.063
Vessel Type 2 A	0.000
Vessel Type 2 B	0.000
Vessel Type 2 C	0.050
Vessel Type 2 D	0.005
Vessel Type 2 E	0.000
Vessel Type 2 F	0.019
Vessel Type 2 G	0.007
Vessel Type 2 H	0.001
Vessel Type 2 I	0.001
Vessel Type 2 J	0.006
Vessel Type 2 K	0.003
Vessel Type 2 L	0.020
Vessel Type 2 M	0.003
Vessel Type 2 N	0.035
Vessel Type 3 A	0.010
Vessel Type 3 B	0.000
Vessel Type 3 C	0.010
Vessel Type 3 D	0.061
Vessel Type 3 E	0.007
Vessel Type 3 F	0.054
Vessel Type 3 G	0.058
Vessel Type 3 H	0.009
Vessel Type 3 I	0.010
Vessel Type 3 J	0.007
Vessel Type 3 K	0.020
Vessel Type 3 L	0.051
Vessel Type 3 M	0.003
Vessel Type 3 N	0.021

Figure C.1: Data normalization example

D
Overview of interviews

Table D.1: Interview and communication sources

Reference	Function / Role	Topic
Interview 1	(2p) Weapon System Manager CSS / Johan de Witt and the Weapon System Manager of the M-Frigates	Maintenance methods in the RNLN
Interview 2	(2p) Engineer within the department 'Data for Maintenance'(RNLN) and Condition monitoring advisor within the same department.	Data templates and conversion to optimisation models
Interview 3	Weapon System Manager Small Navy Vessels	Maintenance planning and CBM integration
Interview 4	Installation Manager SONAR	SONAR maintenance and onboard repair process
Interview 5	Head of DMI Production Department	Team deployment and CM-related cost components
Interview 6	Head of Engineering, Small Navy Vessels	SAP system use and maintenance planning
Interview 7	Navy Portfolio Manager	Macro-level maintenance and resource coordination
Interview 8	Owner, Copernicos / WSM Dynamics	Development of WSM Dynamics maintenance model
Interview 9	Submarine Fleet Work Planner	Interpretation of model results, M2 data quality
Interview 10	Head of Engineering, Small Navy Vessels	Validation of M2 man-hour underregistration
Interview 11	Data Analyst, RNLN	SAP man-hour registration reliability (M2 focus)
Interview 12	Operational Engineer, Bureau PO FF&OPV	M4 and M8 SAP notification workflows
Phone communication 1	Installation Manager SONAR	WP notification structure and interpretation
Phone communication 2	Head of DMI Production	BO/AM WP notification clarification
Email communication 1	Data Analyst	Explanation of SAP component structure
Email communication 2	Data Advisor	CBM cost and man-hour drivers

Reference	Function / Role	Topic
Email communication 3	Weapon System Manager CSS	CBM assumptions and scope discussion
Email communication 4	Project Planner, DMI	Duration and cost factors of AM maintenance
Email communication 5	Weapon System Manager M-frigates	Planning and budgeting of AM tasks
Email communication 6	Owner, Copernicos	A/B classification logic in BSMI groups
Email communication 7	Weapon System Engineer, Submarines	SAP M1, M4, WP notification clarification
Email communication 8	Operational Management Officer, FF & OPV	Incident type linkage to WP categories
Email communication 9	BO Coordinator, FF & OPV	WP report classification and practice
Email communication 10	Data Analyst, RNLN	Explanation of cost anomaly in BSMI 1156 and SAP analysis method for identifying incorrect labor entries