The impact of data-driven maintenance on the Royal Netherlands Navy's maintenance planning and execution

Redel, W.H.

Award date:
2022

Department of Industrial Engineering & Innovation Sciences
Operations, Planning, Accounting & Control

The impact of data-driven maintenance on the Royal Netherlands Navy's maintenance planning and execution

W.H. Redel

0909373

Supervisors Eindhoven University of Technology:
dr.ir. R.J.I. Basten
dr. C. Fecarotti
dr. A.E. Akçay

Supervisor Royal Netherlands Navy:
dr. W.W. Tiddens

Eindhoven, May 5th, 2022

Eindhoven University of Technology
School of Industrial Engineering
Series Master Theses
Operations Management and Logistics
2021-2022

Keywords: Data-driven Maintenance, Decision Table, Preventive Maintenance, Failure Diagnostics, Predictive Maintenance, Impact Of Data-driven Maintenance Support, Analysis of Maintenance Plannings, Improving Maintenance Plannings, Organizational Structure, Implementation of Data-Driven Maintenance Support, Royal Netherlands Navy

Abstract

Increasing attention is paid to data-driven maintenance support in various industries. In line with this trend, the Royal Netherlands Navy (RNLN) shifted focus towards data-driven maintenance support. Introducing these new techniques must contribute to a well-maintained and deployable fleet, against reasonable costs. Data-driven maintenance support is expected to reduce costs and maintenance resource utilization. This research shows how organizations can start with using data for maintenance purposes, and shed light on the associated impact on maintenance planning and execution. This is done by using a combination of conducting twenty interviews at the RNLN and scientific literature. The current maintenance policy at the RNLN is explained in detail by outlining the maintenance tasks, stakeholders, and planning procedures. We identified a three-level maintenance structure (OLM, ILM, DLM) that is currently used, which separates maintenance tasks by their frequency, departments involved, and required facilities. Data-driven maintenance support is required, since six main factors cause that maintenance periods have a longer duration than originally foreseen. We identify potential methods of data-driven maintenance, and indicate the two most important methods: failure diagnostics is applicable for all three maintenance levels and predictive maintenance mainly for ILM and DLM tasks. These two methods contribute to cost and capacity usage reduction, which we express in six objectives for the RNLN. To express the impact of data-driven maintenance support on maintenance planning, we outline methodologies for analyzing maintenance plannings. Furthermore, we suggest improvements for the maintenance planning quality, such as introducing critical path planning. We conclude this research by proposing a decision table that supports the maintainer, improvement parties, and the design authority in linking the input requirements, system characteristics and objectives to the type of data-driven maintenance support. Moreover, the decision table distinguishes three levels of maintenance. Three case studies show the applicability of our decision table and how data-driven maintenance support impacts the maintenance planning and execution at the RNLN. This research shows how data-driven maintenance support can be implemented in organizations' maintenance operations for multiple purposes, and how it impacts maintenance planning and execution. Furthermore, this study uncovers points of attention to ensure successful implementation of data-driven maintenance support in the organization.

Executive Summary

The Royal Netherlands Navy (RNLN) provides security at sea and from the sea. Currently, the RNLN's preventive ship maintenance is based on time-based and usage-based maintenance policies. These maintenance policies contribute to a well-maintained fleet that is ready for deployment against reasonable costs. For many years, the RNLN faces financial and maintenance capacity shortages. By introducing data-driven maintenance support, costs and workload of maintenance departments and facilities must be reduced. This research focuses on the impact of introducing data-driven maintenance support tools on maintenance execution and maintenance planning at the RNLN. The main question that is answered is:

What is the impact of introducing various types of data-driven maintenance support on the maintenance planning and maintenance execution of the Royal Netherlands Navy?

The main question is answered in four steps, each formulated by a research question, see Figure 1. First, the current maintenance execution and planning processes at the RNLN are identified. Additionally, the stakeholders and their relations to the maintenance processes are examined. Interviews are conducted in order to obtain information from multiple perspectives within the RNLN. Second, the potential data-driven maintenance support techniques are identified by using a combination of interviews and a literature study. Third, we explore methods to analyze and improve maintenance plannings. Such methods are required to determine the impact of data-driven maintenance support on maintenance planning and execution. Again, a literature search and interviews are used. Fourth, the impact of data-driven maintenance support tools is identified. The information from interviews and scientific literature are combined to reflect upon the impact on finances and the utilization of maintenance resources.

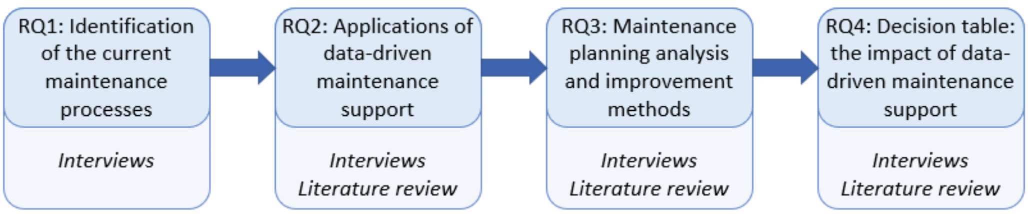

Figure 1: Research design

We conducted twenty interviews and found a triangular structure of stakeholders: the user, the maintainer and the design authority. Most attention in this research is paid to the maintainer. Maritime Sustainment groups manage the maintenance execution and planning processes of a specific ship class. By hiring specialists from Maritime Technology groups, Intermediate Level Maintenance (ILM) and Depot Level Maintenance (DLM) tasks are executed. Together with Organic Level Maintenance (OLM) that is performed by the crew on board, a three-level maintenance policy is applied. All three levels of maintenance are described in the ship's maintenance policy, developed by the design authority, which also describes the strategic spare parts inventory on board and ashore. OLM is the lowest level of maintenance, with mostly small preventive maintenance tasks such as oil change and small replacements. These tasks are mostly time-based and usage-based. The crew on board is equipped with the required tooling and are trained for OLM tasks. The OLM tasks can be performed during the operations, after consulting the commander's operational planning.

ILM and DLM tasks require more detailed planning. MT specialists perform maintenance on a specific type of system, such as diesel engines, but on multiple ship classes. Therefore, a complex planning is required to align maintenance tasks for the specialists, but also schedule ILM and DLM periods for each ship. ILM tasks are performed every four months, and have a duration of three to six weeks. DLM periods can take over a year and are performed every four to five years. In ILM and DLM maintenance periods, a total repair list needs to be completed, which is a combination of a maintenance policy's standard repair list, corrective tasks, and the postponed tasks from a lower maintenance level. ILM tasks are performed at the maintenance facilities in Den Helder, but not necessarily in the docks. Docking is essential for specific DLM tasks. Furthermore, visual inspections are an important part of DLM periods, which is needed to check systems' health, but inspections can also be required for certification. During the ILM and DLM periods in Den Helder, the Condition and Performance Analysis department is able to perform fluid and vibration measurements that are used for condition monitoring.

Data-driven maintenance support is required, since the maintenance periods have a longer duration than originally foreseen. The conducted interviews show six factors that cause that the original planning duration is exceeded: (i) due to the high complexity caused by the number of tasks and parties involved, a limited degree of insight into the work to be performed is available; (ii) the large number of planning disruptions (also caused by other ships' maintenance periods) which are not included in the maintenance planning; (iii) the capacity restrictions on personnel and maintenance facilities; (iv) not all UGDs correspond with the overall maintenance planning due to continuous changes; (v) insufficient information on the availability of resources, such as spare part lead times, personnel, and facilities; and (vi) insufficient educational level of work planners.

Therefore, the RNLN strives to implement data-driven maintenance in order to reduce the capacity usage of maintenance facilities and costs. We explain the RNLN's motivation for implementing data-driven maintenance support by six objectives: (i) costs reduction, (ii) corrective maintenance reduction, (iii) spare parts lead time reduction, (iv) inspection time reduction, (v) preventive maintenance time reduction and (vi) insight in system use. Failure diagnostics and predictive maintenance are the two main data-driven maintenance support techniques that contribute to these objectives, by reducing costs and maintenance resource utilization. Failure diagnostics support the maintainer by indicating which component failed for all three maintenance levels, and predictive maintenance informs the maintainer that a component is about to fail for ILM and OLM tasks mainly. These techniques can be applied to systems individually, but also in parallel. The interviews also shed light on additional applications of data, such as for educational, on board video assistance, and facility maintenance purposes. Altogether, the implementation of the suggested data-driven maintenance support techniques require considerable effort for the organizational implementation. The organizational culture on the field of innovations, the current software, and the structure of financial budgeting and investments are point of concern among the interviewees.

In order to examine the impact of data-driven maintenance support on maintenance plannings, methods must be applied to analyse the quality of maintenance output and maintenance execution. We found a set of indicators, such as the absolute and relative delay of a planning, the quality of SAP maintenance messages, and the number of unplanned maintenance tasks. Furthermore, critical path planning is a method that identifies the bottleneck tasks that need attention in order to avoid or mitigate delays. This technique can help the RNLN's planning department to improve the maintenance planning. Maintenance tasks can also be classified by their impact on the operational criticality and seaworthiness. The conducted interviews show three factors that prevent that data-driven maintenance support can be implemented to analyse the duration, criticality and quality of maintenance tasks within the RNLN: (i) the absence of (registration of) maintenance event data, (ii) the software design, and (iii) the limited alignment of the current software architecture with the current maintenance processes. The interviews show that previous software implementation projects did not always result in uniformity of the software design and insufficient attention was paid to guarantee adherence to the usage instructions. Therefore, the implementation of data-driven maintenance support requires considerable effort in order to realize a uniform adoption throughout the organization.

To guide the adoption of data-driven maintenance support, this research proposes a decision table, which links input requirements, system criteria and objectives to failure diagnostics and predictive maintenance for the three maintenance levels. The decision table supports maintenance engineers in selecting the right data-driven maintenance support technique, and can be used as a systematic approach to identify the needs for a new data-driven maintenance support projects. Furthermore, improvement parties can identify objectives that can be achieved by the available data. Also the design authority can use the decision table to identify the requirements for data-driven maintenance support, in order to equip new ships with correct hardware. Altogether, the decision table gives a structured approach for organizations that start with data-driven maintenance support. As a consequence, the objectives in the decision table contribute to the overall objective to have a deployable fleet, while reducing costs and resource utilization. Three case studies show the relevance and applicability of our decision table, and how stakeholders can implement data-driven maintenance support. The first two case studies show how the maintainer is able to identify the needs and data-driven method that contribute to the maintainer's objective. The third case study shows how a developer is able to terminate a new project in an early stage that turned out to be infeasible. Furthermore, a step-by-step approach is included in this research for all three user types.

Concluding, we identified the maintenance planning and execution tasks, as well as the stakeholders involved that are part of the RNLN's current maintenance policy. The interviews shed light on the organizational hurdles to be taken. Our decision table links the two main data-driven maintenance support techniques, failure diagnostics and predictive maintenance, to the required inputs and the maintainer's objectives for each maintenance level. The objectives show the impact of data-driven maintenance support: more system-state information that result in a reduction of costs and resource utilization at the RNLN.

Acknowledgments

This master thesis completes my time at the Eindhoven University of Technology. I started with the bachelor Industrial Engineering, fulfilled a board year at Industria and this master thesis completes my master Operations Management and Logistics. This thesis marks the end of my student career, and thus I would like to take the opportunity to thank a number of people.

First of all, I would like to thank my first supervisor of the Eindhoven University of Technology, Rob Basten. Already during bachelor courses, I appreciated your style of communication and the enthusiasm to support students to excel. I enjoyed our meetings, in which you provided me with constructive feedback and challenged me in discussions, alternated with informal talks. Furthermore, I want to thank Claudia Fecarotti, my second supervisor. You showed great enthusiasm and the willingness to contribute to a great result with helpful suggestions.

Although it was a challenging start, I received a warm welcome at the RNLN, and DVO in particular. A special thanks to my RNLN supervisor, Wieger Tiddens, for all his guidance in the very interesting environment. Our frequent calls, meetings and little chats helped me tremendously in understanding the operations of the RNLN and finding my way in the organization. I am also grateful for the enthusiasm and support of all other colleagues of DVO, especially Bart Pollmann and Dennis Curvers. Furthermore, I would like to thank all interviewees for their cooperation and useful input.

Last but not least, I would like to thank my friends and family. I had a great time in Eindhoven during my time as a student. I enjoyed the informal chats, unforgettable events and challenging study moments. Therefore, a big thanks to my fellow students. In particular, a big thanks to my fellow Industria board members. I had an amazing year with you, with a still enduring friendship. A special thank you to Nina Rovers for your enthusiasm, support, patience, and endless listening to my graduation struggles. Moreover, thanks a lot to my friends in Eindhoven and Westland for amazing moments and full support. I would like to end by thanking my family. I am grateful for the guidance that i got from my parents, and that I was in the position to go to university. Together with my sisters, you gave me endless support! Thanks all four of you!

I am proud of the result of this master thesis. It has been a project with ups and downs, but it was an incredible learning curve. I hope you will enjoy reading my master thesis. Cheers!

Ward Redel

Eindhoven, May 2022

Contents

List of Figures

List of Tables

List of Abbreviations

AM	Assisted Maintenance
BO	Benoemd Onderhoud (English: Assigned Maintenance)
BVO	Beproevingen Voor Onderhoud (English: Teste Before Maintenance)
CPA	Conditie- en Prestatie Analyse (English: Condition- and Performance Analysis)
DLM	Depot Level Maintenance
DMI	Directie Materiële Instandhouding
DMO	Defensie Materieel Organisatie
DvO	Data voor Onderhoud (English: Data for Maintenance)
HTD	Hoofd Technische Dienst (English: Head Technical Services)
ILM	Intermediate Level Maintenance
MI	Maritieme Instandhouding (English: Maritime Sustainment
MLU	Mid-Life Update
MT	Maritieme Techniek (English: Maritime Technology)
NATO	North Atlantic Treaty Organization
OJP	Operationeel Jaarplan (English: Operational Annual Plan)
OLM	Organic Level Maintenance
OPV	Ocean-going Patrol Vessel
RNLN	Royal Netherlands Navy
TG	Techniekgroep (English: Technology Group)
UGD	Uiterste Gereedheids Datum (English: Final Deadline)
VAM	Vraag- en Aanbod Management (English: Demand and Supply Management)
WSM	Wapensysteemmanager (English: Weapon System Manager)

Chapter 1

Introduction

The introduction aims to provide background information on the research topic. First, we introduce the general and organization background in Section 1.1. Second, in Section 1.2, the department where this research is conducted is described. After these introductions, the problem that is addressed by this research is defined, see Section 1.3. The design of the research is stated in Section 1.4, which includes the introduction of the main question, the research questions, and the methodology. In Section 1.4.3, attention is payed to the setup of the interviews, and the in-text alphanumeric references to the interviewees, such as DV1, are explained. Lastly, the outline of this research is described briefly in Section 1.5.

1.1. General and organization introduction

Every person and every organization has to deal with maintenance. Cars, buildings, machinery and dikes: all need a form of maintenance. Over its lifetime, an object degrades due to usage and/or age, and ultimately it fails (Ben-Daya et al., 2016). Timely maintenance is essential to prevent an object from loosing the ability to perform its function. The type of maintenance differs for every situation. The practical and financial impact of failures and maintenance costs are important factors that determine organizations' maintenance strategy (Wu et al., 2021). Furthermore, situational factors play an important role, such as geographical positions of the object and repair facilities.

The Royal Netherlands Navy (RNLN) operates worldwide to ensure security at sea and from the sea (Royal Netherlands Navy, 2021b) by conducting crisis management and defense operations, protecting shipping routes, and carrying out patrols against drugs transports. Also, the RNLN provides humanitarian assistance and transports relief supplies. The RNLN is responsible for the maritime services of the Dutch defence organisation, and cooperates with the Army, Air Force, Marechaussee, and international allies. For the Dutch defence organisation, there are three pillars that enable participation in military missions: readiness of material, readiness of personnel, and proficiency (Dutch Ministry of Defence, 2020). The deployability of the fleet and the crew are essential to the operations (Royal Netherlands Navy, 2021a), which require frequent training and a maintained fleet. Contrary to private companies that approach operations from a profit-making perspective, the RNLN focuses on fleet deployability.

The RNLN is part of the Dutch Ministry of Defence. This ministry has an umbrella function for the four services of the Dutch armed forces. From this central organ of the Dutch government, decisions about finances, equipment, human resources, and military missions are taken. With a total budget of 11.628 billion euros in 2021, the Ministry of Defence has to allocate budgets to the four services (Ministerie van Financiën, 2021). Moreover, the ministry determines how the budgets need to be spend within each department, and which military missions will be participated in. For this research, the RNLN's fleet maintenance and fleet replacement budgets are important. As in many countries, the Dutch defence organization is confronted with financial shortages. This forces the RNLN to make strategic decisions for the allocation of (maintenance) budgets.

1.2. Department description

This research is conducted at the Data for Maintenance department of the Royal Netherlands Navy. The Data for Maintenance department (DvO, in Dutch: Data voor Onderhoud), established roughly three years ago, strives to support the crew on board and ashore to perform data-driven maintenance. Data-driven maintenance support can be described as the provision of system-state and failure information that follow from sensor data to the user or maintainer, which assists maintenance departments during different stages in the maintenance planning and execution processes. This support should improve the quality of the maintenance processes, and avoid impactful and expensive failures. Ultimately, this should lead to a maintained fleet that is ready for military missions, against reasonable costs. Furthermore, DvO uses its knowledge for other data-related topics, such as reducing the fleet's carbon footprint. By processing data from previous missions into clear visualisations, DvO contributes to this social issue. The multi-disciplinary team includes a combination of operational, IT and industrial knowledge. The core team is expanded by employees from other departments, students and external individuals with domain-specific knowledge.

Currently, DvO faces new challenges. DvO wants to explore in what way information can be gathered from available data sources, and how this can support maintenance planning and execution. Furthermore, it is desired to have insight in the impact of data-driven maintenance support on the execution and planning of maintenance operations.

1.3. Problem definition

The maintenance strategy of the RNLN can be summarized as follows: (preventive) maintenance should contribute to a reliable and deployable fleet (DV1). In order to achieve this objective, data-driven maintenance support is one of the new contributors. DvO succeeded in earlier steps to clear the way for data-driven maintenance support. For the implementation of data-driven maintenance support, the practical consequences need to be discovered. One of the challenges is to analyze the impact of the data-driven maintenance support tools, and in particular on the planning and execution of maintenance. It is valuable for the organization to support the right processes with data-driven support tools. To identify which processes DvO needs to focus on (first), the impact of the data-driven maintenance support must be considered.

Data-driven maintenance support is expected to influence multiple phases of the maintenance processes. DvO expects that the duration of maintenance tasks and the planning of maintenance tasks will be affected most. Planning maintenance is a complex task that depends on many factors. Obviously, the capacity of facilities and employees and the availability of the fleet are important to take into account. Currently, the planning is based on the maintenance policy of each ship, established by DMO, see Section 2.1. Given the available capacities, a basic planning is created. However, information from inspections and (self-announcing) breakdowns force the RNLN to deviate from the original maintenance planning where necessary. This often causes problems due to the limited capacity. These planning deviations are undesired. With the introduction of data-driven maintenance support, a new information source is added to the maintenance planning processes. This new type of information can cause extra changes to the original planning.

To illustrate, when it follows from the data that a component needs to be maintained earlier or later than at the originally scheduled moment, the RNLN will probably adjust the original planning. Furthermore, when a failed system needs to be repaired, engineers spend time on finding the cause of the failure. Time might be saved if a support tool specifies the cause of the failure. At the end, the duration of maintenance tasks can be shortened by the use of data-driven support tools. For the RNLN, the impact of such deviations that follow from ship data, is not identified yet. This is the main focus of this research. To summarize: it is unclear how data-driven maintenance support can be used, and for which processes in particular. The RNLN wants to identify the impact of data-driven maintenance support on the planning and execution phases of the maintenance processes. These insights must help the RNLN and DvO to identify the processes for which data-driven maintenance support adds value.

1.4. Research design

In this section, the research design is presented. First, the main question is introduced. The main question is answered throughout the research. To maintain a structured approach, the main question is broken down into four research questions: RQ1-RQ4, which are answered in Chapter 2-5, respectively. The research design is also depicted in Figure 1.1, which describes the steps taken and the core methodologies used. Furthermore, this section provides an overview of the methodologies used for all research questions.

1.4.1. Main question

The goal of this research is, as mentioned in Section 1.3, to identify the impact of data-driven maintenance support on the execution and planning processes of maintenance interventions. Altogether, the main question is stated as follows:

What is the impact of introducing various types of data-driven maintenance support on the maintenance planning and maintenance execution of the Royal Netherlands Navy?

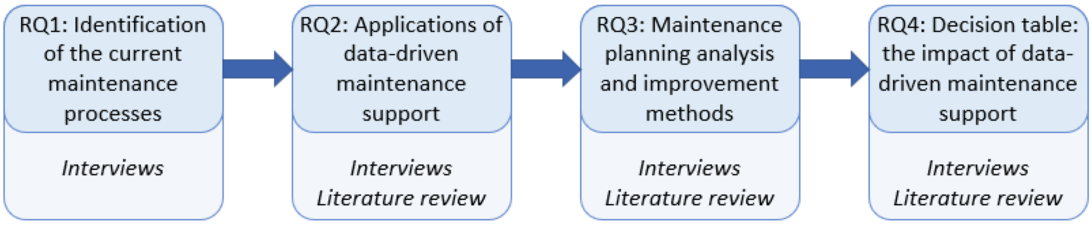

Figure 1.1: Research design

1.4.2. Research questions and methodology

It is essential to fully understand the current situation with respect to maintenance operations and planning at the Royal Netherlands Navy, before considering improvements. The focus is on the maintenance planning on both ship and fleet level, and the actual execution of the different maintenance levels, described in Section 2.2. This also involves the identification of departments that are involved, and their relation to the maintenance operations and planning. Furthermore, it is important to identify the systems that force a ship to participate in a certain maintenance intervention, and understand the reasoning behind the current planning methods of maintenance interventions. Therefore, the first research question is:

RQ1: What are the current maintenance operations and how are these maintenance operations planned and executed at the Royal Netherlands Navy?

RQ1 is answered by providing an overview and description of the three maintenance levels. Through interviews with staff members of departments involved, important aspects of maintenance at the RNLN are examined. For each level we describe which type of components need to be maintained, and what actions need to be taken. Furthermore, the answer to this research question provides insight in the planning of the three maintenance levels. For each maintenance action it is explained why it is part of a certain maintenance level, and we outline the characteristics for the planning process. The departments that are responsible for each of these tasks are related to these maintenance tasks. The organizational structure is relevant for the type of data-driven maintenance support contributing to the current operations, their users and their dependencies. This organizational information is mainly obtained from interviews, but internal documents from the RNLN contribute to answering this research question as well. The setup of the interviews is explained in Section 1.4.3.

Once there is a clear overview of the current situation with respect to maintenance execution and planning at the RNLN, our next step is to identify improvements and the associated impacts. As mentioned in Section 1.3, the objective of DvO is to improve the maintenance processes by implementing data-driven maintenance support. However, it is not yet determined in which form data-driven maintenance can be implemented best. The opportunities of data-driven maintenance are identified, before considering the impact. Next to identifying the possibilities, the added value of each method is also considered. Therefore, the second research question is:

RQ2: Which forms of data-driven maintenance can support the maintenance planning and maintenance execution at the RNLN?

In order to answer RQ2, a part of the fleet is examined. The maintenance program of a set of systems is observed. These systems are selected by their impact on the maintenance planning. A general description of applicable data-driven maintenance support methods are given. The methods are gathered via interviews and literature research. The outcomes of both information sources resulted in a list of potential methods of data-driven maintenance support. The outcomes are discussed within the RNLN. These discussions serve as a form of validation of the collected methods, and as verification of the potential added value of each method.

The answers to RQ1 and RQ2 give insight in the current maintenance execution and planning processes, and expose the potential of data-driven maintenance support. This is done by comparing the current and proposed situation. This comparison can only be made if the quality of a planning and the maintenance execution can be quantified. The next step in this research is the identification of key performance indicators that adequately express the quality of the maintenance planning and execution processes. This leads to the following research question:

RQ3: How can the maintenance planning and execution at the RNLN be analyzed and improved?

In order to answer RQ3, the previously mentioned interviews are used for RQ3 as information source. The interviewees are the employees that work with the planning, or have another stake within the maintenance process. Therefore, the interviewees are able to highlight the important aspects of the RNLN's maintenance planning. Furthermore, scientific literature provides other studies that address this problem. These studies are used directly and indirectly. With the direct form, their outcomes are used as an example for the type of key performance indicators or frameworks that were found. Next to that, the indirect use of these studies is useful to adopt their research methods. Not only for the content of the interviews, but also for possible other information sources. The advantage of the combination of interviews and literature research is that on the one hand, the experience of interviewees is used for this research, which clearly describes the current situation at the RNLN. On the other hand, the subjectivity of interviewees' responses is mitigated by the use of scientific literature. By including the approaches from other studies, a tunnel vision focused purely on the outcomes of the interviews is avoided.

After identifying the potential methods of data-driven maintenance support, the corresponding impact must be mapped. This is done separately for every maintenance level, since the processes in each maintenance level differ significantly from each other. The last step in this research identifies the processes and systems in the maintenance program, which can be supported by data analysis. Extending the current processes with data must result in an improvement of the current process. Furthermore, the type of data-driven maintenance support tool needs to be determined per system type. The fourth research question that needs to be answered is:

RQ4: How does data-driven maintenance support affect the maintenance planning and maintenance execution of each observed system, for each maintenance level?

This research question brings the answers to the three previous research questions together, and finally answers the overall main question of this research. RQ4 is answered by a description of how the data-driven methods, found in the answer to RQ2, influence the execution and planning of tasks for Organic-, Intermediate-, and Depot Level Maintenance interventions. A decision table is constructed that informs the user about the required inputs, selection criteria, and the different objectives that can be achieved by data-driven maintenance support and the method that needs to be used. These four parts of the decision table are explained in detail. Furthermore, the practical implications for the maintenance execution and planning processes are described. The practical implications are linked to the fleet availability and deployability. The decision table is based on the interviews conducted for this research and outcomes from other studies that address related topics. An iterative approach resulted in a decision table that suits the situation at the RNLN and thus can be used in practise, and served as a validation procedure. Moreover, the support from other studies increases the decision table's correctness.

It is expected that the new insights in the current state of systems and the failure predictions, the RNLN decides to postpone or bring forward certain maintenance processes. Obviously, the predictions must be sufficiently reliable in order to make this decision. The set of quality criteria, that must be met by data-driven maintenance support tools, are examined and explained. With case descriptions the expected effects of introducing data-driven maintenance support tools on the planning of maintenance interventions are examined and explained. Furthermore, the addition of system-state information, such as failure diagnostics, reduces the duration of maintenance tasks. This also affects the planning, and is part of the answer to RQ4.

1.4.3. Interviews

The input from the RNLN is mainly obtained via interviews. For this research, we use a semi-structured interview design. The wide range of interviewees' backgrounds make the semi-structured a useful setup. The topics that need to addressed by the interviews are covered by a set of standard questions, see Appendix A. On the basis of the interviewee's background or answers to the standard questions, we were able to ask more detailed questions for specific topics. These follow-up questions allowed us to make more use of the interviewee's expertise. Furthermore, this structure enabled us to add questions to subsequent interviews, when a new topic arose in a previous interview. Thus, the semi-structured approach resulted in addressing all general topics during the interviews, and provided flexibility for in-depth questions.

For the interviews, we selected interviewees with a variety of backgrounds. This resulted in different perspectives on the topics discussed. Although in-text references to interviews are not common, we regard it as valuable to give the reader an understanding of the background of the interviewees. Therefore, anonymous references are included, by alpha-numeric abbreviations, which can be found in Table 1.1. In order to keep a cohesive group of interviewees, we only interviewed employees that are involved in the maintenance processes of the OPV class. This is best observable for the Maritime Sustainment group: Frigates and OPVs. Other Maritime Sustainment groups are not part of this research's scope. More arguments for the selection of the OPV class can be found in Section 1.4.4.

There are things that must be taken into account for the interviews. Most crucial is the correctness of the answers to our questions and the statements made. When interviewing multiple individuals, the chance of receiving contradictory answers exist. We applied the rule-of-thumb that at least two-third of the answers to a specific standard question must be similar for the interviewees, in order to use the answer in this research. When a question is answered in a fifty-fifty proportion, we do not consider either of the answers reliable. Also, in semi-structured and unstructured interview designs, there is space for the interviewee's individual input. We experienced that interviewees occasionally introduced topics, deficiencies to the current maintenance policy and personal statements that do not necessarily match reality. For these situations, in which the interviewee gave an answer that is not part of the standard questions, we included the answer only if this could be validated by at least three other interviewees afterwards.

In-text abbreviation	Division/department	Function
CP1	Condition and Performance Analysis	Senior engineer
CP2	Condition and Performance Analysis	Engineer
CP3	Condition and Performance Analysis	Officer
DM1	Defensie Materieel Organisatie	Senior consultant
DV1	Data for Maintenance	Manager
DV2	Data for Maintenance	Manager
HT1	OPV on board	Officer
LO1	Logistics	Manager
MS1	Maritime Sustainment	Manager
MS2	Maritime Sustainment	Manager
MT1	Maritime Technology	Senior engineer
MT2	Maritime Technology	Senior engineer
MT3	Maritime Technology	Manager
MT5	Maritime Technology	Senior engineer
MT6	Maritime Technology	Manager
MT7	Maritime Technology	Manager
MT8	Maritime Technology	Senior engineer
TF1	Technology Group Facility Maintenance	Manager
TF2	Technology Group Facility Maintenance	Manager
WP1	Weapon System Manager	Manager

Table 1.1: Interviewees (unclassified version)

1.4.4. Scope

The objective of this research is to gain insight in the impact of data-driven maintenance support. To retain an understandable and manageable project, not the full organization and fleet are observed. However, we recognise the strength of observing multiple units of the fleet in order to draw conclusions that are generalizable to the entire fleet. Therefore, in this research we focus on the Ocean-Going Patrol Vessels (OPV), also called the 'Holland class'. The RNLN has four ships of this type, which is above average compared to other ship types. The advantage is that in this way the planning of multiple ships is observed, with a reasonable complexity level. Related to this, is the number of OPV crews. Because the RNLN has multiple OPVs, there are multiple crews that can be interviewed, and the probability of an interviewee's absence is minimized. Furthermore, DvO already collaborates closely with the crew of the OPVs for other projects. This is beneficial to reach out to relevant stakeholders to retrieve information during the process. Furthermore, OPVs' age is below the fleet's average. This relatively modern ship is equipped with more sensors than other ship types. One of the OPVs is even further equipped with sensors, in order to gain experience with data-driven techniques.

Military ships contain many systems, which would result in a complex project (Nguyen et al., 2015). Therefore, in the early stages of the project a selection of systems is made. Systems are selected by their impact on the planning. The impact of a system can be defined by the duration or prioritization of the maintenance tasks for that system. When a task needs to be executed at another moment than the originally scheduled moment, the impact on the total maintenance planning is higher for prioritized or time-consuming tasks.

The systems that are selected to be observed, are maintained by the Maritime Technology (MT) group Platform. This department is chosen because it has a diverse range of systems, and is relatively accessible for interviews. Other maintenance groups, such as radar and weapon groups, have to deal with a higher degree of confidentiality, but Platform has lower security restrictions. Furthermore, the expectation was that MT group Platform would come into view for this research, because of their crucial systems. This department is also able to provide DvO with failure data, which is extracted from SAP, the RNLN's enterprise resource planning tool. Other types of data, such as high-frequency data from the periodic inspections, are not be part of this research. Contrary to the data, outcomes of the periodic inspections are reported by the Condition and Performance Analysis (CPA) department are useful for this research. The input from CPA is obtained via interviews. CPA's tasks are a form of data-driven maintenance, albeit in a periodic manner.

The current maintenance planning is the starting position for this research. This means that the maintenance strategy with periodic maintenance interventions is used for all three maintenance levels. The interval between two consecutive maintenance intervals remains unchanged. Earlier projects of the RNLN focused on optimizing the length of the intervals between two consecutive maintenance periods, but this is not part of this research. Despite the focus on all three maintenance levels, ILM and DLM received most attention. The OLM tasks do not need a detailed planning, see Section 2.2.1 and Section 2.3, but still can be improved by data-driven maintenance support. The identification of the maintenance execution process is done for all three levels, as well as the search for tasks that can be supported by using data. However, due to the absence of a detailed planning for OLM tasks, the impact on the maintenance planning is only investigated for ILM and DLM.

Related to the characteristics of maintenance tasks, this research focuses on the maintenance tasks that are executed internally. The RNLN has many and diverse maintenance facilities, but some tasks are outsourced. The outsourced tasks are not ignored in the planning, but it is assumed that there are no capacity restrictions. Furthermore, the data-driven maintenance support during the maintenance intervention are not part of this research for outsourced tasks.

1.5. Outline

The structure of this research follows the order of the research questions. Chapter 2 describes the current maintenance strategy used at the RNLN. This chapter dives into maintenance planning and maintenance execution. Moreover, the stakeholders from these processes are described, together with their interrelations. In order to come to a valid review of potential data-driven maintenance support methods, Chapter 3 shows an exploration of the potential techniques in scientific literature and interviews. The most promising techniques, failure diagnostics and predictive maintenance, are explained in more detail, as well as the organizational transition barriers.

Chapter 4 outlines the assessment of planning processes. Both literature review as well as interviews are used to identify relevant measures that can be used to express maintenance plannings and execution of maintenance plannings. In Chapter 5 a decision table is presented. The decision table links the required input data, system characteristics and objectives to appropriate data-driven maintenance support methods. Furthermore, the chapter outlines in what ways data-driven maintenance support tools impact the maintenance planning and execution of the RNLN.

Chapter 2

Current maintenance policy at the RNLN

The RNLN's fleet needs many forms of maintenance. Chapter 2 describes the processes and stakeholders that are involved in order to answer RQ1: What are the current maintenance operations and how are these maintenance operations planned and executed at the Royal Netherlands Navy? In Section 2.1, the maintenance policy and the maintenance levels are described. Second, the stakeholders are mentioned, and their relation to the processes. Last, the planning process for all maintenance levels are explained. Interviews are the main information source for this chapter. We refer with alphanumeric abbreviations, such as CP1, to the background of the interviewee, which can be found in Table 1.1. In Section 1.4.3, the setup of these references is described in more detail.

2.1. Stakeholders of the maintenance processes at the RNLN

The overall goal of the maintenance divisions is to have a maintained fleet that is employable to serve the Dutch Defense organization (DV1). Many departments are involved to reach this goal, even from outside the RNLN. There are three umbrella stakeholders: the user, the maintainer, and the design authority. These three cooperate in a triangle structure, see Figure 2.1 (CP3,WS1). Each of them has its own responsibilities, but decisions have to be made in collaboration with one or more stakeholders. These three stakeholders are described in detail, including all involved departments, and summary is presented in Table 2.1.

Centered between these three stakeholders is the weapon system manager (WSM). The WSM functions as the linchpin, and manages the operational deployability, the configuration and reliability of a ship class (WS1). Furthermore, the WSM is responsible for the ship budgets and for the modifications. By consulting all parties involved, the WSM makes informed decisions for the state of the ships in the class.

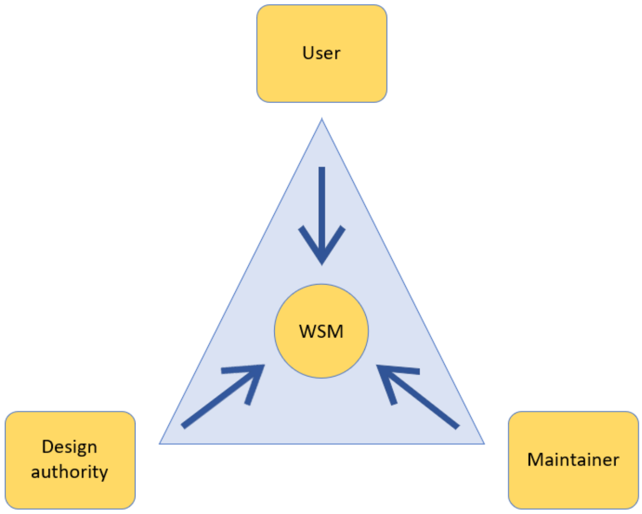

Figure 2.1: Triangular structure

2.1.1. User

One stakeholder that is obvious is the user, which includes all levels of crew on board. Formally, the user is the RNLN, represented by the board of operations (WS1, MT3). It is commonly known that the RNLN heavily relies on a hierarchical structure, which helps smooth operations during missions. When one refers to the user, often the commander of the ship is meant. The commander is responsible for all operations on board and for the condition of the ship. The commander decides when a ship needs to undergo maintenance or when it is ready for deployment (WS1). However, from a maintenance perspective, the technical service on board is another key player. More specifically, the head of the technical services (HTD) who reports to the commander. The HTD manages staff members who are assigned to one or multiple systems, depending on the size of the ship. The technical staff performs maintenance tasks within the OLM category. Furthermore, it is their responsibility to evaluate the systems and complete prescribed checks. Although it sounds contradictory, not the maintainer, but the user is responsible for small daily maintenance and inspection tasks. When a maintenance task pops up from the SAP software or after an inspection, the HTD decides, in alignment with the commander's operational plan, when to complete this task (HT1). When it is decided to complete a maintenance task, the right tooling and spare parts need to be available. Additionally, the crew must have the right knowledge and certification for the execution of the task. When one of these elements misses, the task must be postponed until the next ILM period.

One of the challenges is that the RNLN copes with staff shortages. Furthermore, the trend moves towards crews exchange between identical ships. This leads to a decrease of ship-specific knowledge (MT6). Reporting maintenance tasks and failures becomes increasingly important, in order to transfer the information to the other crew. Using data might contribute to the retention of knowledge, and compensate for the work load of smaller crews.

Stakeholder	Description
User	The RNLN as a whole is the user, represented by the board of operations.
Maintainer	Umbrella term for MI groups that manage the maintenance execution and planning processes for a particular ship class, and MT groups with specialized technicians for a specific type of system.
Design authority	Division of the Dutch Defense Organization, that manages the procurement of new ships and MLU modifications, and establishes maintenance policies.

Table 2.1: Three main stakeholders

2.1.2. Maintainer

The term 'maintainer' represents a complex network of departments. The Directie Materiele Instandhouding (DMI)is the umbrella maintenance organization of the RNLN (CP3). In general, all departments can be structured into two main divisions: Maritime Technology and Maritime Sustainment. Maritime Technology (MT) covers all departments that have specialized knowledge on a specific system level. One could think of systems such as propulsion-, power supply-, and radar systems. For every system, or group of systems, there is a technology group. MT groups maintain a specific type of system, but for all types of ships. Maritime Sustainment (MI) is responsible for one or more classes of ships, for example the MI group for frigates and OPVs. The group manages the maintenance tasks for that class of ship, and thus for all systems. Note that the MI group does not maintain the class itself, but manages the maintenance process by hiring specialized groups from MT.

2.1.2.1. Maritime Sustainment

As mentioned in Section 2.1.2, the MI division is focused on managing maintenance for a ship class in a broad context, see the orange cross-hatched row in Figure 2.2 (MS1). In total, there are four MI groups. Close collaborations with WSMs, MI, users and the design authority result in the maintenance plan for a ship. MI manages the maintenance in terms of planning and process management, process analysis, assigning tasks to maintenance periods, logistics support and functions as an information source for crews on board with respect to maintenance (MS2). For ILM and DLM maintenance periods, a list of tasks must be completed. During the preparation phase of such maintenance periods, a project team is formed, headed by the project leader, who is part of the MI division. More about the plannings phase can be found in Section 2.3.

2.1.2.2. Maritime Technology

Since there are many systems that require maintenance from specialized engineers, there is a large number of specialized departments for all types of systems within the MI division. These departments are structured by their type of specialism. MI is divided into five technology groups (TG): Platform, C4I (Command, Control, Communication, Computers, Intelligence), Sewaco (SEnsors, WeApons, COmmand systems), Facility Maintenance, and Defense Special Products.

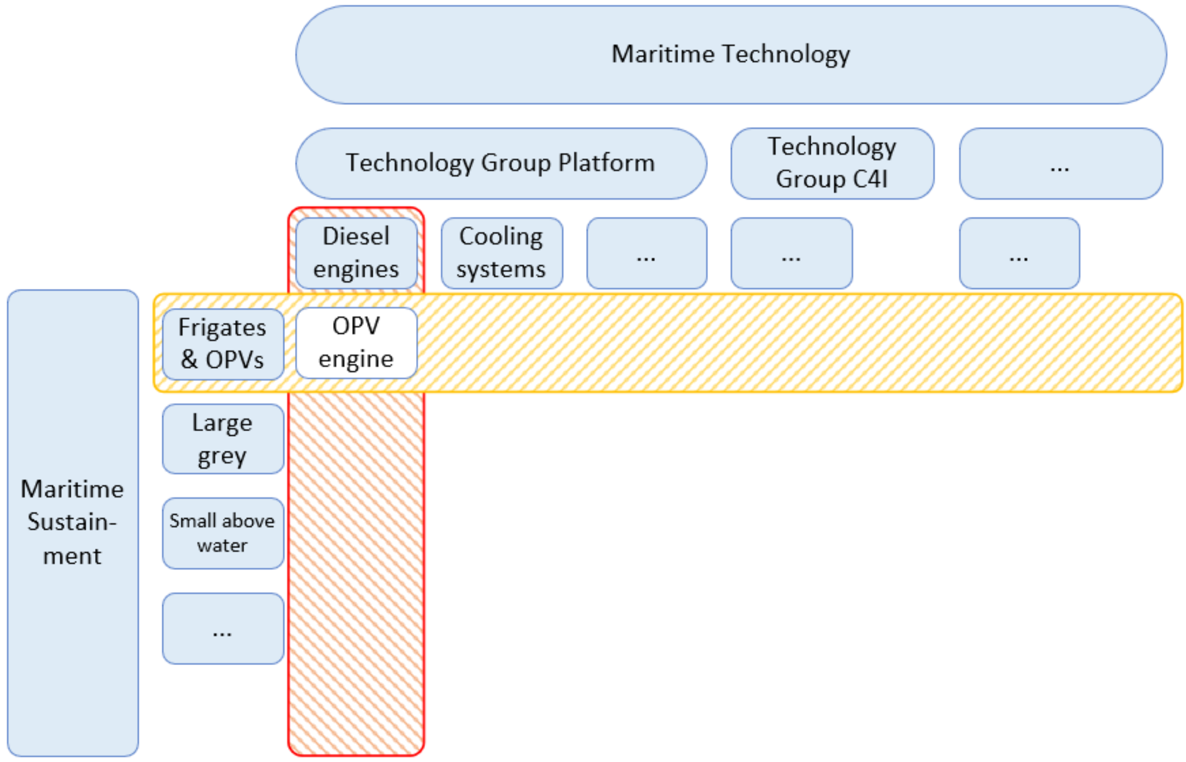

Figure 2.2: Matrix structure MI and MT

The TGs are even further divided into single departments that focus on one specialism. Examples of specialisms within TG Platform are diesel engines, ventilation and cooling systems. An example illustration can be found in Figure 2.2, which shows that the diesel engine department of TG Platform performs maintenance to various types of ships (red cross-hatched column), that belong to different MIs. Each installation is managed by a system manager, who leads the team of technicians and functions as an intermediate between management staff, technicians and MI divisions (MT5). Once the planning on system level for a certain maintenance period is finalized, the work preparation responsible, the work planners, can start the preparations (MT6). This employee is responsible for the operational planning for a specialized group of system technicians.

2.1.3. Design authority

The last division of the triangular structure described in Figure 2.1 is the design authority. This division is not part of the RNLN, but of the entire Dutch Defense Organization. This division is responsible for procurement and requirements that must be set for the entire fleet, weapon systems and other equipment of the Dutch Defense Organization (DV1, DM1). As mentioned before, this division is called Defensie Materieel Organisatie (Defense Material Organization, DMO). Procurement processes start with identifying the needs of the future user. This is not only in terms of user requirements, but also with respect to the maintainability of the equipment. The next step is to find a supplier via a tendering process, as this is a governmental purchase. However, there are exceptions for product categories that are purchased without public tendering due to confidentiality. Furthermore, the decision to replace old units or to add new ship types to the fleet, is a political decision, made by the Dutch Minister of Defense and the Dutch parliament.

Once new ships are purchased and built, the maintenance divisions also need to prepare for the new units in the fleet. Therefore, DMO establishes a maintenance policy for every fleet unit (WS1). This document prescribes which tasks need to be executed and the according frequency, and the moment of the MLU, described in Section 2.2.3. Moreover, for all systems there is a list of requirements that must be met. Once a system's performance or condition does not meet these requirements, maintenance must be performed. The impact of systems that do not respect their requirements differs. In the maintenance policy, there is special attention for critical systems for which hold that failures cause immediate deployability disruptions or safety risks. A list of critical systems and the related requirements form the checklist for the seaworthiness of a unit (DM1). Ships that do not meet all of the requirements are not allowed to participate in missions or any other operation. Maintenance must be performed to restore the seaworthiness adequately. Allowing of dispensation is possible (WS1, LO1). In that case, a ship must take action to guarantee safety, or operational restrictions can be imposed. For the procurement process and the construction of the maintenance policy hold that there are three main information sources: specifications from the manufacturer, user experience and research that is conducted internally within the Dutch Ministry of Defense.

2.1.4. Support departments

Maintenance tasks that are executed by the RNLN's technicians are preceded by many preparation tasks. Core tasks that are performed by MI and MT divisions are mentioned in Section 2.1.2, but other divisions also contribute to the execution of maintenance tasks. For this research, there are two support divisions that are highlighted, because of the potential contribution of data for their operations.

The first support task is the maintenance of facilities, performed by TG Facility Maintenance (FO). This TG focuses on maintaining objects such as the maintenance facilities, docks and buildings. TF1 and TF2 mention their core focus as: 'everything that needs maintenance, but is not a weapon system.' A set of tasks is performed internally, but other tasks are outsourced to external parties. Generally, outsourcing is the case for tooling and other movable objects. The work of TG FO is essential to the availability of the maintenance facilities for the operational departments within the MT division. TF1 and TF2 stress that political budget cuts influence the performance of TG FO increasingly. Maintenance of weapon systems are given higher priority than maintenance of facilities. Due to a long period of financial shortages, the availability of facilities deteriorates. As a consequences, this may harm the maintenance of weapon systems, and thus the execution of the OJP. In the recent years, procedures for the maintenance tasks of maintenance facilities are updated and structured. TG FO operates relatively independently, as they take the role of maintainer and design authority for facilities. In this case, the MI groups are the user, that complements the triangular structure for maintenance facilities.

The logistics department is the second support division that is mentioned in this research. This division covers a wide range of tasks within the RNLN. Most important for this research, are the logistical operations for spare parts management. As mentioned in Section 2.1.3, the inventory strategy for spare parts is determined by DMO. The execution of this strategy is done by logistical departments (LO1). One can think of the procurement of spare parts, repair of defective parts, inventory management and supplier relationship management. Altogether, the logistic division manages an assortment of 350,000 parts and systems. A part of this assortment is not for the RNLN specifically, but concerns general products that are used by multiple armed services. Inventory management stands or falls with the correctness of data in SAP. This is an important challenge, and many improvement steps are needed on this topic. LO1 mentioned three important reasons for the current situation. First, the RNLN copes with incomplete product data for large numbers of components. This results in incorrect lead times or supplier information. Second, due to security measures, not all data can be shared with external parties. This hinders the RNLN to allow suppliers to observe the RNLN's inventory levels, and send supply orders when needed. For other industries, this is a common phenomenon. Third, related to this topic is the overall connection to the industry. Suppliers have a monopoly position which does not urge them to innovate and introduce data-driven techniques.

2.2. Current maintenance policy at the RNLN

The maintenance policy of the RNLN consists of many preventive maintenance tasks. These should together contribute to a maintained fleet that is ready for deployment. Due to the large number of systems and components, it is necessary to structure all preventive maintenance tasks for every unit in the RNLN's fleet. However, not all failures can be foreseen. There is always a risk that unplanned maintenance must be performed after an unforeseen failure of a system. This can be caused by multiple reasons. Some items fail at random moments, and items can fail due to external factors such as weather circumstances, undersea volcanoes and collisions. These tasks cannot be planned, which leads to undesired disruptions in the maintenance planning and operational schedules. Missions must be interrupted, and the failure needs to be repaired. It is a challenge to get the unit back in operational strength within limited time. This is due to the availability constraints of spare parts, facilities and maintenance technicians (LO1, MT6). There are cases in which the RNLN is even not able or allowed to repair certain systems at its own maintenance yards. To illustrate, this can be due to regulations from the supplier or for tasks that are performed rarely, but need certified technicians (MT1). This is solved by outsourcing such tasks to external parties. Furthermore, outsourcing might be useful in case of capacity problems (MT7). But not only deployability and capacity constraints force the RNLN to avoid unplanned maintenance. Financial stimuli urge the RNLN to avoid unplanned maintenance as well, since it is typically more expensive than planned, preventive maintenance. This is especially for the cases in which failures cause secondary damage to other systems or components (MT1, MT2, MT6).

For most systems, there is expert knowledge about the physical failure behaviour, which can be used in the maintenance policy. This knowledge leads to lists of tasks for systems that undergo planned maintenance, to avoid breakdowns of the systems. Each task is characterized by the required tooling, facilities, materials, and knowledge. These factors, in combination with the frequency and the duration of the task, determine when it needs to be performed. Logically, the maintenance impact to the operations of the RNLN must be reasonable. Therefore, all tasks are structured into three maintenance levels: Organic Level Maintenance (OLM), Intermediate Level Maintenance (ILM) and Depot Level Maintenance (DLM), which is a common policy (Blanchard et al., 1995). For every unit in the fleet, an operational annual plan is designed (OJP) (HT1). Not only the missions are included in this document, but also the maintenance intervals for the ILM and DLM levels. A brief overview of the core differences between the three maintenance levels is listed in Table 2.2.

2.2.1. Organic Level Maintenance

The OLM classification includes all maintenance tasks that can be performed by the crew on board a ship. In the ship's maintenance policy, established by DMO, is described which tasks are categorized as OLM tasks. The SAP software on board tracks the usage and age of components (HT1). When the usage or age of a component exceeds the pre-determined threshold value, the SAP software communicates a task to the user. The tasks of the OLM level can be executed on board, because of the level of the required system knowledge and the availability of tooling and materials. Furthermore, the spare parts need to be available. The selection of spare parts that a ship carries during missions, follows from a strategical decision that is officially taken by DMO, as the design authority (LO1). However, the spare part list and the maintenance policy are a joint conclusion with the user and maintainer. Since OLM tasks can be performed by the crew on board, the ship does not have to be docked in a harbour and OLM tasks can be performed during the missions. To plan these tasks, one should only take the operational day planning of the ship into account. Tasks such as oil change and small replacements fall within this lowest maintenance level (MT8).

Level	Description	Interval	Duration
OLM	Small maintenance tasks performed by crew on board	continuous	task-dependent
ILM	Intermediate maintenance tasks performed by specialized engineers	4 months	3-6 weeks
DLM	Largest form of maintenance performed by specialized engineers	4-5 years	> 1 year

Table 2.2: Maintenance levels

2.2.2. Intermediate Level Maintenance

DMO's maintenance policy informs the user and maintainer which tasks are part of this maintenance level. This second level maintenance, ILM, covers all tasks for which the crew of a ship needs support from specialized technicians and/or for which the equipment and spare parts on board lack. Within the RNLN, this maintenance level is also called 'Assisted Maintenance' (AM), which highlights the support of engineers ashore (WS1). ILM periods are typically planned thrice a year. In a period of three to six weeks, specialized technicians work, when possible, simultaneously on multiple systems. Ships have to be in the harbour in Den Helder, but not necessarily in the docks. This depends on the required tooling and materials, and the type of maintenance task. The tasks come forward in two ways. First, the messages from the SAP software about tasks that are part of the OLM task, may be postponed until the next ILM maintenance period. This can be the case when the required spare parts are not available, or when the task does not fit in the operational schedule of a ship. In rare cases, the crew on board is not allowed by the system supplier to work on a system, or with certain repair tooling. In those cases, the OLM task is forwarded to the next ILM period (MT2, MT6). Second, there is a standardized repair list of tasks. These tasks are not communicated to the crew on board, but to the technicians ashore. These two types of task arrival together form the basis for the maintenance planning for the ILM category. In Section 2.3, the maintenance planning is described in detail.

2.2.3. Depot Level Maintenance

Lastly, DLM tasks are categorized as the highest level of maintenance. During this maintenance period, all systems have to be checked, and large forms of maintenance is executed. Internally, this maintenance level is referred to as 'Benoemd Onderhoud' (Appointed Maintenance, BO). Moreover, halfway the ship's expected lifetime a mid-life update (MLU) is combined with the DLM tasks (MT2, WS1). In general, a ship is expected to serve the RNLN 25-30 years. A MLU covers updating or replacing systems, to improve the ship's employability and introduce modern techniques. The MLU is part of the maintenance policy of DMO. After introducing new or updated systems, the maintenance policy is updated as well. During the DLM period, many inspections are performed. This informs the maintainer about the state of the system, and forms the basis to repair or replace components. However, there is a second reason for inspections. In order to be allowed to join the operations and NATO missions, certificates are needed. These inspections are part of the class and NATO-certification procedures (MS2).

DLM is planned on intervals of approximately four to five years. For this type of maintenance, the pre-determined repair list is of greater influence than for ILM periods (MT6). Again, tasks of lower maintenance levels that are postponed can be part of the DLM period. Unique for this maintenance level is the set of tests that have to be executed before the start of the DLM period. The 'Beproevingen Voor Onderhoud' (Tests Before Maintenance, BVO) require special knowledge of systems (MT1). Engineers that usually work ashore, join the crew on board to complete the set of tests for designated systems. The test results are evaluated afterwards, and may face the maintainer with new defects or the need for further inspections. The standard repair list, postponed tasks from lower maintenance levels, and BVO results lead to a complete repair list that is used as input for the maintenance planning, described in Section 2.3.

As the name of this maintenance level suggests, these tasks require ships to be docked at the specialized maintenance yard, and for some tasks even in a dry dock. The great number of tasks, which can exceed 2200, make this form of maintenance to have a duration of longer than a year (MT7). This automatically holds that this form of maintenance has a high impact on the capacity usage of the RNLN's maintenance facilities. For both ILM and DLM holds that the DLM tasks can be (partly) outsourced if the capacity restrictions urge the RNLN to do so. Furthermore, for this highest maintenance level, it is not uncommon to hire specialist from outside the organization to fulfill maintenance tasks. Other reasons to rely on external parties are the certification of engineers, the certification of repaired components and financial stimuli.

2.2.4. Condition monitoring

Within the RNLN, there are various methods to support the execution of the maintenance policy. One of them is to monitor the systems of a ship with inspections by the crew on board and specialized technicians ashore. But the RNLN also has a specialized department that periodically examines the condition of systems (CP1, CP2). This department, Condition and Performance Analysis (CPA), uses vibration and fluid analysis methods to determine the condition and performance of a system, and as a check-up after maintenance execution (CP1, CP2). The measurements are executed by trained employees of the department, and translated into useful condition information in a later stage. This report is sent to the commander of a ship, who is responsible for the state of a ship. However, in practise, important outcomes of this report that are relevant for the maintainer, are sent to the specialized technician group and WSM as well (CP1). The maintainer comes into view for ILM and DLM tasks, which means that the results of CPA's measurements are mainly applicable for these two maintenance levels. Lessons can be learned from this implementation process, in order to realize successful and uniform adoption of data-driven maintenance support. Furthermore, DvO focuses on continuous condition monitoring as a future perspective. This must partly replace the periodic measurements, but will mostly be an addition to the current condition monitoring. More information about DvO and their goals can be found in Chapter 1.

2.3. Current maintenance planning procedures at the RNLN

The three maintenance levels that are described in Section 2.2 all contain another set of tasks, summarized in Table 2.3, and require different departments to be involved. This has consequences for the planning process of the three maintenance levels. OLM tasks are performed on a daily basis. On board a ship, maintenance messages pop up during the missions. These tasks will be performed at a suitable moment, when the operations allow. For this maintenance level, there is not a planning for the maintenance execution. Spare parts are part of the standard inventory on board, and also do not require extra planning. However, in case of a long period of missions, a ship can be resupplied in foreign harbors (MT1). A NATO-wide (North Atlantic Treaty Organization) classification of spare parts, such as engine oil, is used to facilitate this process.

ILM and DLM periods have to be planned in advance, since numerous departments, facilities, and materials have to be available. For both maintenance levels, a planning is created. However, this process differs for both levels. Section 2.2.2 describes the ways in which the set of tasks are determined for ILM periods. The maintenance tasks that are automatically indicated by SAP and manually generated SAP maintenance tickets both arrive at the VAM-counter (demand and supply counter) of the MI groups (MT6). A work coordinator at the VAM-counter informs the relevant technician groups about the maintenance tasks that need to be executed. The work coordinator creates a planning for the ILM period, after which work planners can prepare the tasks itself.

For DLM periods, a more extensive planning needs to be created. This process starts with the project mandate. This is the management approval of the DMI board to start a DLM project for a ship (MT6). The next step is the designation of a project team. This team collects all maintenance tasks, from the various sources that are described in Section 2.2.3. Due to the large number of maintenance tasks and DLM's duration, the planning process starts months before the start of the maintenance execution. However, at the start of the planning process, not all tasks can be identified. This is especially the case for the BVO outcomes, that is performed just weeks before the start of a DLM period. This may have consequences for the DLM planning. Pending on the findings of the BVO, a project team already starts with the preliminary repair list. The team creates a planning that suits the various technology groups and corresponds with the availability of the facilities. Often, availability of facilities is a bottleneck for the maintenance planners (MT6). This becomes a larger problem when urgent failures arise at other ships, that need to be repaired with higher priority. Often, this comes at the expense of DLM tasks, and thus results in planning disruptions. A DLM planning process starts with a high-level draft. After an iterative process, all stakeholders need to approve the broad outline. The next step is that work planners start preparing all individual tasks (MT6). A detailed planning is created for all specialisms, and spare parts need to be ordered. Again, new tasks can be added to the planning and other factors might cause disruptions. This is one of the reasons that plannings start on a high level, and become more detailed towards the execution period. Also in rare cases, unplanned maintenance can cause elimination of tasks. If a system fails before the moment of planned maintenance, corrective tasks must be performed. In such situations, it might be unnecessary to perform the task again at the originally scheduled moment.

The disruptions have to be processed in the planning of maintenance. First, the extra work needs to be identified in order to determine the impact to other tasks. The specialized engineers involved propose a solution to the project leader. This proposal consists of the indication of extra work, and which other tasks need to be rescheduled or even postponed until a next maintenance period (MT6). As mentioned earlier, ILM tasks can be postponed to the next ILM period, but also to the next DLM period. For postponement of DLM tasks, however, this has a higher impact. Not all maintenance tasks can be postponed for about five years. Because of the impact on the reliability of systems, this is observed as the undesired last resort.

The capacity restrictions on personnel and facilities are a recurring issue for the RNLN. During the interviews with MT1 and MT2, it was mentioned independently of each other that both face capacity shortages on a weekly basis, especially due to unplanned maintenance tasks. MT3 confirms this wisdom: 'We have capacity shortages on staffing level, both in terms of quantity and quality (education level).'

MT2 showed the planning tools that are used for the planning process. Due to confidentiality, these cannot be described or depicted in detail. Generally, for every maintenance task a duration estimation is determined. This estimation is based on expert knowledge, and partly on historical information from SAP. All task estimations together result in an overview of the total maintenance duration for each specialism. SAP automatically determines for every specialism the remaining capacity per week, or eventually the capacity shortage. Furthermore, plannings are constructed by using deadlines (UGD) for every individual task. However, reality shows that all staff members are authorized in SAP to adjust the UGD without justification (TF1). Moreover, even without these adjustments, it appears that not all UGDs correspond with the overall planning, due to continuous changes (MT6). When reviewing the maintenance plannings, we could not find a critical path. This was confirmed by MT7. Focusing on a critical path would not be valuable, because of the low accuracy of task time estimations. There is no feedback loop for the duration of previously executed tasks, that would adjust the time estimations. Also other forms of automated feedback and updates are lacking. Only via expert knowledge, time estimations can be updated.

Level	**Planning procedure**
OLM	Tasks are notified by SAP software on board. No detailed maintenance planning is required, but must be aligned with daily ship operations.
ILM	Repair list is based on automated SAP notifications, maintenance tickets from the crew on board and postponed OLM tasks. The VAM-counter transfers the maintenance requests to MT groups, after which work coordinators creates a planning.
DLM	A total repair list is created, which consists of standard tasks, automated SAP notifications, maintenance tickets from the crew on board an postponed ILM tasks. A project team creates the planning.

Table 2.3: Maintenance planning characteristics per maintenance level

2.4. Findings on the RNLN's current maintenance policy

This chapter describes the current maintenance policy at the RNLN, which answers RQ1. The interviews show that the current maintenance processes are structured in three levels: organic, intermediate, and depot level maintenance. The tasks and standards for all three maintenance levels are described in the maintenance policy that is designed by DMO, the design authority of the Dutch Defense Organization. A ship's maintenance policy also prescribes a spare part inventory policy, which is executed by logistic departments. The collaboration of all departments involved can be described best by the triangular structure depicted in Figure 2.1 and summarized in Table 2.1. The maintenance processes are managed per ship class by MI groups that hire the specialist from MT groups for the execution of maintenance tasks ashore, visualized in Figure 2.2.

The planning process for ILM and DLM periods is the responsibility of MI groups, but are the result of close collaboration with different TGs. OLM periods do not require detailed planning, since these tasks can be performed on board, without assistance of technicians and equipment ashore. Interviewees unanimously mentioned the frequent maintenance delays. The conducted interviews show six factors that cause that the original planning duration is exceeded:

(i) due to the high complexity caused by the number of tasks and parties involved, a limited degree of insight into the work to be performed is available; (ii) the large number of planning disruptions (also caused by other ships' maintenance periods) which are not included in the maintenance planning; (iii) the capacity restrictions on personnel and maintenance facilities; (iv) not all UGDs correspond with the overall maintenance planning due to continuous changes; (v) insufficient information on the availability of resources, such as spare part lead times, personnel, and facilities; and (vi) insufficient educational level of work planners.

Chapter 3

Applications of data-driven maintenance support

This chapter outlines how data can be applied in the maintenance processes of the RNLN, and answers RQ2: Which forms of data-driven maintenance can support the maintenance planning and maintenance execution at the RNLN? The chapter explains the objectives of data usage at the RNLN in Section 3.1. In Section 3.2 and Section 3.3 the two main potential applications of data that are mentioned in the interviews, are described. These two main methods are validated by MT1, HT1, DV1, and MT3 after conduction all interviews at the RNLN. In Section 3.4, a description of other data-driven methods are described. These do not purely contribute to the maintenance execution and planning processes, but are considered to be valuable for the RNLN by the interviewees. The chapter ends with Section 3.5, which highlights organizational challenges that need attention in the run-up to data-driven maintenance support.

3.1. Objectives of data usage

This research is focused on the impact of data on the execution and planning processes of maintenance at the RNLN. The RNLN focuses on a maintained fleet against reasonable costs. Maintenance execution is costly and has direct influences on the availability and deployability of the fleet. The RNLN faces capacity and financial shortages. The use of data is one of the solutions that must decrease costs and capacity usage. There are multiple ways in which the use of data can be beneficial to the RNLN. Using data is not an objective, but a means to reach the overall objective. In order to find suitable candidate methods for data usage, specific objectives must be determined first. During the interviews, special attention is paid to the six objectives that are described below. The six objectives contain overlap, which can be explained by their relation. For example, maintenance resource usage reduction, without increasing the number of corrective maintenance tasks, often goes hand in hand with reducing costs. Although, both reducing resource usage and costs reduction can be a goal for the RNLN in itself.

- **Cost reduction:** When the RNLN has better insight in the state of components and systems, a decrease of costs is foreseen (Al-Najjar, 2007)(Sharma et al., 2018). When the maintainer is informed that preventive maintenance can be postponed, because of the healthy state of a component, this automatically results in lower costs. Furthermore, when data indicates that a component needs maintenance urgently, secondary damage can be avoided. Multiple interviewees mentioned secondary damage as an important cost driver. The impact of this objective overlaps with other objectives of introducing data-driven maintenance support. However, reducing costs is an objective in itself and thus is this objective mentioned separately.

- **Corrective maintenance reduction:** When failures can be prevented by using data, it results in less corrective maintenance. Corrective maintenance is not only costly, but also causes extra downtime. Furthermore, corrective maintenance must usually be executed at unknown moments. Because failures are not included in the maintenance and operations schedules, it highly impacts other maintenance plannings throughout the fleet. Furthermore, corrective maintenance hinders ships in their operations, which is detrimental for the execution of the RNLN's core tasks.

- **Spare parts lead time reduction:** When upcoming failures can be recognized in advance, it enables the RNLN to act on this information with respect to spare parts (Yuan et al., 2013). The DMO's spare parts strategies prescribe the spare part strategy for each set of component on board and ashore. In any case, the logistics department can fulfill the demand of a component by taking it from the shelf, or by purchasing it from a (predetermined) supplier. When accurate failure information or failure predictions reach the RNLN at an earlier moment in time, the spare part process can be started immediately, instead of waiting until technicians' manual inspections are completed. To illustrate, when failures can be diagnosed or predicted by using data, the failure information can be communicated to technicians ashore. The spare parts can therefore be ordered from suppliers immediately, even when the ship is still at sea. Currently, failures are diagnosed by manual inspections in Den Helder. Only after the manual inspections the ordering process of spare parts starts. The use of data results in an earlier start of the spare parts ordering process, and thus an earlier completion of the maintenance execution processes. This contributes to an earlier deployability and less downtime for ships.

- **Inspection time reduction:** For a set of systems and components, sensors inform the maintainer about the physical condition. When a system fails, technicians have to search for the cause of the failure, which can be a time-consuming task. Data can be used in certain situations to identify the cause or even warn the maintainer before the failure occurs, which makes a time-consuming inspection of the entire system redundant (Yuan et al., 2013). Both methods contribute to less downtime of a ship, and less capacity usage of facilities and personnel.

- **Preventive maintenance time reduction:** Less maintenance time results in lower capacity usage at the maintenance facilities of the RNLN, which is often a hindrance in the maintenance execution and planning. When data informs the user that preventive maintenance is not yet needed, the task can be postponed, the remaining useful life of a component can be used more efficiently (Yuan et al., 2013)(Jain et al., 2019). Over a longer time horizon, the specific preventive maintenance task can be performed less frequently, which decreases the capacity usage for that specific maintenance period and the required time for the total maintenance planning. Furthermore, when preventive maintenance needs to be executed less frequently, this results in a decrease of costs and downtime.

- **Insight in system use:** This objective is not directly focused on maintenance, but must indirectly decrease the demanded maintenance capacity. Operational tasks on board always have priority, which can result in rough usage of systems. Furthermore, interviewees mentioned that a lack of knowledge and usage insight result in deterioration of systems and higher fuel consumption. An often mentioned problem is the usage of diesel engines. Diesel engines function more efficient and deal with less internal contamination when used at higher power levels. Using two identical diesel engines simultaneously at a 25% power level means higher fuel consumption and more contamination, when compared with using a single engine at a 50% power level. Furthermore, in the latter case, only for one engine the running hours increase, which is beneficial for postponing usage-based maintenance. For such reasons, data-driven maintenance support helps to inform the user with system usage insights.

This list outlines the direct benefits from data usage mentioned by the interviewees and in scientific literature. The six objectives contribute to cost and capacity usage reductions. However, there are also indirect effects that contribute to a better maintenance execution. When more system information is known beforehand, the planning can be created on a better basis. This is a consequence of a reduction of unplanned maintenance, but also because more specific component information informs technicians and planners which components need maintenance.

Another indirect effect that can result from data usage contributes to a better planning quality. Currently, the expected duration of ILM and DLM tasks used in the planning phase is based on a fixed estimation. These estimations are not subject to updates. The implementation of feedback loops that update these duration estimations is expected to improve the accuracy of maintenance plannings. Currently, planning deviations and planning delays result in cancellation and postponement of preventive ILM and DLM tasks. A better planning quality results in fewer preventive maintenance tasks cancellations, which lead result in fewer failures. Ultimately, a reduction of failures reduces the number of unplanned corrective maintenance tasks, and thus to fewer planning deviations. Since this objective is purely focused on the maintenance planning and in impacts the maintenance processes indirectly, we do not include this in the list of the six main objectives in this section. Furthermore, this objective is not part of the decision table that is introduced in Chapter 5. Moreover, whereas we elaborate in detail on the two main data-driven maintenance support methods,failure diagnostics and predictive maintenance, this is not the case for this data-driven method.

3.2. Failure diagnostics

The interviews with interviewees with a variety of backgrounds, resulted in two main topics of potential data usage methods. The first is using data for diagnosing failures. Generally, sensors collect data about the physical condition of a component. Mostly, wear can be recognized by physical measurements, such as vibrations, oil monitoring and condition monitoring (Xu et al., 2020). Furthermore, performance measurements can identify failures in the system. At the RNLN, this is the case for water pressure and yield measurements. This data can be used for a variety of maintenance models. Xu et al. (2020) stress that the diagnosis is mostly based on statistical, mathematical-physical and intelligent algorithms. Each of these three methods has its own advantages, but the introduction of machine learning models resulted in cost savings, increased sensitivity and more efficient methods for failure diagnostics. Moreover, complicated nonlinear relations can be identified more easily. Data can be used to identify if a system failed, but failure diagnostics models also inform the user which component failed. Interviewees mentioned that this is a useful data-driven maintenance technique for the three maintenance levels in different ways.

For OLM tasks on board ships, it is expected that this type of data-driven maintenance support can save time for the crew. Daily during missions, multiple rounds of inspection need to be completed in order to verify whether systems are functioning correctly (HT1). This is time consuming and subject to human errors. Furthermore, this manual method is less applicable for finding the exact cause of certain failures. Also, when data from sensors informs the user about the failure of a component, it also saves time in the identification process of corrective maintenance tasks on board. This is the case when from the data follows which component needs to be replaced at this moment, but it suffice to postpone the preventive replacement of related components. Obviously, less maintenance contributes to the availability of ship systems and a reduction of costs. This latter is the case due to a better usage of the component's remaining useful life.

ILM tasks are also expected to benefit from data-driven failure diagnoses. As mentioned in Section 2.2.2, the repair list for this maintenance level is partly based on manual SAP messages from the crew on board. A common issue for specialized technicians ashore is the poor quality of SAP messages from the crew on board. This makes the identification of a component that needs corrective maintenance more difficult. Automated failure diagnostics from data is objective and specific, and it is expected that the inspection time decreases (HT1, MT1, MT2). The outcomes from the diagnoses can be sent to the shore immediately. Furthermore, when a failure is identified correctly, the correct spare parts and maintenance facilities can be scheduled accurately and at an earlier stage.

For DLM, similar applications of the principle of failure diagnostics are expected as for ILM. For the decrease of inspection time, even greater reductions are expected. In the standard repair list tasks numerous inspections are included. These may be replaced by monitoring via sensors. This must be technically feasible, and result in at least equally reliable results. Furthermore, it must be examined whether this is financially advantageous, since DLM maintenance periods only take place every five years. When a large investment is needed for a particular sensor and the construction of the corresponding algorithms, it must be outweighed by the inspection costs and time savings. Lastly, there are inspections that are required for certification of systems for the RNLN and the NATO. Therefore, replacing manual inspections by (the absence of) failure diagnosis, must also be legally permitted.

3.3. Predictive maintenance

The principle of predictive maintenance is well expressed by Xu et al. (2019, p.103): 'Predictive Maintenance (PdM) is a maintenance strategy which predicts equipment failures before they occur and then performs maintenance in advance to avoid the occurrence of failures. A PdM system generally consists of four main components: data acquisition and preprocessing, fault diagnostics, fault prognostics and maintenance decision-making.' Predicting failures before occurrence brings the RNLN major benefits, which follows from the interviews and scientific literature (Cheliotis et al., 2020). Similar as for the principal of failure diagnostics, described in Section 3.2, applying predictive maintenance differs for the three levels of maintenance. Furthermore, the reason to use predictive maintenance differs for every company (Baidya and Ghosh, 2015). The managerial criteria vary per company. Therefore, the input from interviews and scientific literature together strengthen the assessment of predictive maintenance applications.

During the interviews, our initial expectations were confirmed that most of the interviewees see limited added value for adding predictions to the OLM tasks. Most of these tasks are preventive, and have a limited execution duration. Furthermore, for this level of maintenance there is no schedule, as mentioned in Section 2.2.1. Also the nature of these tasks are not focused on avoiding immediate breakdowns of the systems. Predictions would therefore not contribute to the essence of predictive maintenance: 'predicts failures before they occur.' This view is shared among most interviewees. However, WS1 mentioned that predictions can be used for spare parts purposes. Ships that are about to participate in a long-term mission or spend multiple months in The Caribbean need to be equipped with extra spare parts. Currently, a rough indication of expected spare part volumes is constructed, based on the time- and usage-based OLM tasks. When the RNLN moves away from purely time- and usage-based maintenance for the set of systems, predictions are needed for this purpose. In the study of Tiddens et al. (2018), the claim is made that for selecting systems for predictive maintenance, the added value and suitability of predictions must be identified. Triggers such as time, costs and operational consequences urge the user or maintainer to apply predictive maintenance. In the case of OLM tasks, it is considered that all three triggers will be minimally improved by applying predictive maintenance. From a managerial perspective, it might also be an excessive method for this level of tasks. Pintelon and Van Puyvelde (2006)'s cost-benefit approach summarizes this perspective. The interviewees expect little advantages, but considerable effort and investments are needed to incorporate predictive maintenance in the OLM operations.

The interviewees showed greater confidence in the contributions of predictive maintenance for ILM operations. For ILM periods, facility capacity reservations and the presence of specialized technicians is of major importance. Furthermore, the required spare parts must be present at the right time. Accurate indications of tasks that need to be performed increase the quality of a planning and the execution of maintenance. Especially because of the high utilisation of facilities and technicians, unplanned maintenance tasks highly impact the maintenance processes. In other words, the benefits, described by Pintelon and Van Puyvelde (2006), of applying predictive maintenance can be considered to be significant. Whether this outweighs the costs, must be examined for every system or component.

Also for maintenance on depot level, it is expected that the benefits are significant, both in terms of time and finances. This level contains many inspection tasks, which are time-consuming. If data can be used to accurately predict the reliability or the remaining useful life, these inspections may become obsolete. The predictions' accuracy for this level of tasks must be high (MT1). The time between two consecutive DLM periods is five years, which urges the maintainer to be convinced that this period can be bridged. If the failure arises before the next scheduled DLM period, a major impact on the operations might be the result. Next to that, facility capacity, spare parts and technicians are not easily available at unplanned moments, which causes planning disruptions and delays. Furthermore, the interviewees mentioned that the type of components that are inspected during DLM periods, are not always part of the strategic stock. Unexpected demand for these components have on average a large lead time.

3.4. Additional applications of data

Besides the data application for failure diagnostics and predictive maintenance, data and digital support systems can be used for other purposes as well. During the interviews, other forms of data usage were mentioned. First, the application of Virtual Reality (VR) glasses was mentioned by HT1. Recently, application of VR glasses was introduced at the RNLN for educational purposes. The VR glasses enable the instructors to train a new crew, without having a physical ship present. The VR environment is expected to show a digital copy of technical rooms. In other industries, VR glasses are used for maintenance execution as well (TF2). One can inspect the systems virtually, because the VR environment is fed with real-time system data. Technicians can therefore inspect more frequently, even without being on board. Furthermore, TF1 mentioned the advantages of tablets and smart glasses. During inspection rounds, real-time system information can be presented to the technician via the tablet or the glasses. This saves time and contributes to better informed decision making. Lastly, TF1 stressed that for some systems, this results in earlier fault detection.

HT1 also foresees a more important role for digital support on board. The trend at the RNLN shows that ships are equipped with smaller crews. From the shore, crews on board can be supported with respect to maintenance. Currently, this is partly implemented in the operations. The RNLN is focused on the security of information flows, which hinders digital initiatives. On board, there is a secured satellite connection to the shore, albeit limited. A video connection for maintenance assistance from the shore consumes a lot of capacity, and cannot be used if other systems need bandwidth simultaneously. When the bandwidth can be extended, live digital support can be given greater influence.

The third application of data came from TF1 and TF2. Their focus is on the maintenance of all maintenance facilities that are not a weapon system itself. Obviously, data can support their activities as well. Especially, because of the high utilization of the facilities, downtime has a great impact on the execution of maintenance and the planning of subsequent maintenance tasks. Similarly as for the data-driven maintenance support for weapon systems, facilities can be equipped with and monitored via sensors. Also the type of data-driven maintenance support, predictive maintenance or failure diagnostics, can be selected in a similar way as for the weapon systems. TF1 and TF2 expect an increase of the availability of facilities, a reduction of costs and a reduction of maintenance time. When facilities are out of order, tasks are postponed or outsourced to external private maintenance yards, which is very costly compared to the internal facilities' usage costs (MT7). When availability increases and unexpected downtime decreases, TF1 and TF2 expect that the number of outsourced tasks decreases, and thus the costs.

3.5. Organizational transition

This chapter describes the potential of data usage for maintenance purposes. However, there are factors that hinder the RNLN to implement data-driven maintenance support. The interviews were used to answer the research questions for this research. Nevertheless, due to the semi-open structure the interviewees came up with other topics and insights as well. One of the most important findings is the attitude of individuals towards software implementation projects. All interviewees responded to this topic, and all shared a form of resistance towards data implementation. We regard this essential to include in this research, because the human acceptance of data-driven maintenance is essential for a successful transition.

The introduction of data-driven maintenance support is not only pushed towards the RNLN by the industry through innovations, but also pulled by the RNLN itself. Data is desired to be one of the contributors to solve current challenges. As for many nations, the Dutch Navy has faced the recent years budget cuts and understaffing. Data might help to increase efficiency of operations and add new information to the organization. This is in line with the trend that ships carry smaller staffs, which increases the potential for data. On the one hand, this is because of modern technologies that make human support redundant. On the other hand, the RNLN copes with difficulties in recruiting new personnel. Moreover, from the interviews followed that the educational level of the new staff is considered to be insufficient. These factors together show the importance to introduce new technologies, and focus on the support by data.

One of the innovations is to enable shore support from a maintenance control tower. Experts ashore are available to assist crews on board with maintenance tasks that need to be performed. Support can be implemented in various ways. Currently, shore support is realized on a limited basis. The crew can request assistance via video connections. This is not fully implemented yet, since this connection consumes a large part of the bandwidth (HT1). This capacity will be expanded for new ships, and during current ships' MLUs. However, it is expected to be beneficial that system parameters can be exchanged to the shore without the video connections. The experts can assess the system's performance and condition, and initiate maintenance tasks to repair systems when needed.

Another focus point of the RNLN is the method of financial budgeting. Currently, there are many budgets for individual departments. Interviewees acknowledge that this is the correct method for the majority of situations. However, it has a counter-efficient outcome in a number of situations. The interviews showed that this is a sub-optimal procedure for the process of purchasing new fleet units (MT3, HT1). The budget of the purchasing phase is owned by DMO, whereas DMI manages the financial consequences of maintenance during a ship's lifetime. Practise showed that financial savings in the procurement phase lead to inferior materials, systems and even elimination of certain systems during construction of the ship (MT3). After years of deployment, DMI is faced with high maintenance costs, that could have been avoided. Taking this together, results in a broad-based need to focus on life-cycle costs. In large organizations, such as the RNLN, it is difficult to fully implement this principle. But a start can be made by relaxing the budget constraints of the purchasing phase, that have a negative impact on the maintenance and life-clycles costs. Related to this, is the strategy that is used for the strategical spare parts inventory management. Again, budget cuts urge responsibles to lower the volume of spare parts. Multiple interviewees mentioned that this negatively impacts the life-cycle costs and increases the duration of (unplanned) maintenance. It must be noted here that the reduction of spare parts is not only the consequence of budget cuts, but also because of the lower capabilities of the crew on board. Staff must be trained to perform the maintenance task, otherwise the presence of the particular spare part is redundant.

From the interviews followed that SAP is not used according to the procedures, and that the design of this software does not suit to the operations (MT3). This results in limited reports of failures, and limited insight in the maintenance processes. The interviewees mentioned two main topics for this problem. First, the implementation of SAP into the processes of Dutch Ministry of Defense was time-consuming and exceeded the budgets. A political decision stopped the project before all functionalities were designed. Users of SAP describe the consequences of this limited technical design, which make it unattractive to work with. This results in low-quality failure reports and contaminated data. Currently, a project is running to introduce a new version of SAP, which must (partly) solve these problems. Second, the attitude towards this software is mostly negative. This is partly because of the incompleteness of the software, as mentioned above. However, multiple interviewees also described an organizational culture that is not focused on using software correctly.

Within the RNLN, the focus on human interaction and acceptance of software tools grows. Moreover, within the DvO department, a study has been conducted to the hindrances of data implementation (Brus, 2022). The study uses the model of Venkatesh et al. (2003) that expresses the user acceptance of information technology by four determinants: performance expectancy, effort expectancy, social influences and facilitating conditions. Furthermore, Brus (2022) concludes that in general, the attitude towards predictive maintenance has to be improved. Scepticism, a lack of awareness, and a variety of expectations are among the findings. This is in line with the findings of this research. Most responses that describe potential hindrances can be grouped by the overall organizational culture that is not ready, or is perceived not to be ready, for such data-driven transitions. An often heard response was that the current processes are satisfying, and improvement is unnecessary. Employees also perceive the implementation of information systems as a negative impact on their autonomy (MT5). Lastly, managers described the need of sufficient communication and resources to facilitate successful implementation (MT3, MS1). The organizational transition can be summarized in two main topics. First, the operational processes and the software must have a better alignment. Second, the human factor needs to be taken into account in order to make sure that employees are open to digital innovations.

In conclusion, the organizational transition of RNLN requires considerable effort in order to successfully introduce data-driven maintenance support. The interviews showed scepticism towards data-driven maintenance support among the interviewees, but also towards the organizational culture. Educational level, the structure of financial budgeting and investments, and the human acceptance of technology are organizational factors that must be improved. On the technical level of implementation of data-driven maintenance support, interviewees showed concerns about the poor design of SAP, the limited band with on board, and the inferior systems' quality.

3.6. Findings on the applications of data-driven maintenance support techniques

RQ2 is answered in this chapter. Data can be used to reach the overall goal of the RNLN, which is to have a deployable, maintained fleet against reasonable costs. Cost reductions and lower capacity usage of maintenance facilities and personnel can be achieved by the six objectives mentioned in Section 3.1: cost reduction, corrective maintenance reduction, spare parts lead time reduction, inspection time reduction, preventive maintenance reduction, and insight in system use. These objectives can be achieved by using two data-driven maintenance support methods: failure diagnostics for all maintenance levels and predictive maintenance mainly for ILM and DLM tasks. These techniques can be applied to systems individually, but also in parallel. Failure diagnostics help the maintainer to diagnose failures without time-consuming inspections, even when the ship is not back at the maintenance yard. Predictive maintenance prevents systems from failing, which avoids consequential damage and time-consuming, expensive corrective maintenance. Data can also be used to support other processes, such as visual inspections on board, maintenance of facilities and educational purposes. For all applications of data, the RNLN needs to pay attention to the transition phase, since the organization is not expected to be fully ready yet.

Chapter 4

Analysis and improvement of maintenance plannings

This chapter describes methods to analyze and improve maintenance plannings at the RNLN and in other industries, in order to answer RQ3: How can the maintenance planning and execution at the RNLN be analyzed and improved? The outcomes of the interviews and scientific literature, see Section 4.1 and Section 4.2, respectively, are used to describe the quality of plannings, and the extend to which the original planning is executed accurately. In Section 4.3 presents a brief discussion on the comparisons and differences between our findings from interviews and scientific literature.

4.1. Planning analysis and improvement at the RNLN

The interview outcomes on current planning measurements at the RNLN can be summarized unanimously: planning quality is not analyzed at all at the RNLN. MT3 phrased it as: 'We do not fulfill our plannings at all.' All interviewees recognized the situation that maintenance execution is delayed most of the times, especially for DLM periods. Furthermore, none of the interviewees had a clear view on how the quality of maintenance plannings can be analyzed. Due to the semi-structured interview approach, the follow-up questions and interactions shed new light on this topic. An important finding is that the objective of measuring maintenance plannings needs to be defined before considering measuring methods. However, there is a consensus among the interviewees that planning quality lacks, and that maintenance execution needs to adhere to its planning. The main reasons that were put forward are capacity shortages and high number of unplanned and corrective maintenance tasks. Despite the fact that the interviewees identify consequences of poor planning quality, there is currently no focus on planning improvements within the RNLN. Introducing key performance indicators that express the quality of maintenance planning, and map the main causes for planning deviations, result in desired performance feedback loops. These loops help the RNLN to improve the maintenance planning quality (MS1).

Currently, for each planning the capacity usage for every specialized department is measured, and the capacity usage per maintenance task. However, this is only used as support tool for the planning process, but not for reflection purposes afterwards. Furthermore, the current reflection on the execution of maintenance tasks is done manually. MT7 mentioned that the manager intervenes when the execution diverts too much from the original planning. During the interviews, multiple main factors were mentioned that can be improved. We list the most important key performance indicators:

1) Input quality: First of all, the input quality of the SAP messages from the crew on board can be measured. Multiple interviewees mentioned the time consuming consequences of incomplete or incorrect SAP messages that arrive at the VAM-counter. However, their view on poor message quality cannot be supported quantitatively, since the quality is not measured. The input quality can be measured by registering the correct and incorrect messages. Improved quality of messages in SAP contributes to a better input for planning, and it is expected that the execution will follow the planning more accurately when the input quality improves.

2) Maintenance delay: A second quantitative measure that is proposed, is the delay of maintenance execution when compared to the original planning. This can be measured in multiple ways. Not only the absolute maintenance delay in days or weeks, but also relative as a percentage. Absolute measures give the stakeholders a clear overview of the duration of the delay, whereas relative measures relate the delay to the overall planned duration of maintenance periods. To illustrate, a delay of one week is for an ILM period in relative terms more substantial than for a DLM period. Even further on a detailed level, the number of tasks that exceed the planned duration or its scheduled due date can be identified. When reviewing the planning afterwards, one can see whether the total delay is caused by a few major delays, or many slight delays. An addition to the insights in the delay duration is the cause of the delay. Delay due to complicated repairs cannot be merged into a single measure with a delay caused by long spare part lead times.

3) The number of unplanned maintenance tasks: The third factor that can be measured is the number of unplanned maintenance tasks that interrupt plannings at the maintenance departments of the RNLN. Unplanned maintenance is considered as an important disruptance factor, but the number of occurrences cannot be expressed. This measure is not focused on a planned maintenance project of one fleet unit, but over a time horizon for all concurrent maintenance projects. As mentioned in Section 2.3, projects are frequently interrupted by unplanned maintenance tasks of other fleet units. Disruptions due to unplanned maintenance is undesired, and the objective of the RNLN is to minimize the number of unplanned maintenance tasks. Clarification of the current situation, with respect to unplanned maintenance, is essential in order to initiate improvements.

4) Critical path planning: The fourth important factor is focused on the critical path of the maintenance planning. In contrast to the previous three factors, this is not a performance measure, but a planning technique. The critical path method identifies the sequence of tasks that determine the minimum length of the planning for large and complex plannings. By clarifying this set of tasks, one can understand whether planning disruptions impact the overall duration of a maintenance period, and how the planning must be modified eventually (Atli and Kahraman, 2012). Modifications can be considered necessary for tasks that are part of the critical path, since delays of these tasks result in a delay of the entire maintenance period. Tasks that are not on the critical path do not necessarily cause projects delays. Currently, the phenomenon of the critical path is not used at the RNLN. Many interviewees see the potential, but acknowledge that the implementation will be difficult for the large number of tasks for DLM periods. Improvements on input data such as the task duration estimations, lead time duration, and tasks interrelations, must be made before critical path planning can be implemented.

5) Distinction of tasks: A fifth general topic that was highlighted is the distinction between the different types of maintenance tasks. The total repair list for a maintenance period is a combination of corrective tasks, preventive standard repair list tasks, seaworthiness tasks, and inspection tasks. Not all tasks require equal urgency for repair. When time constraints urge the maintainer to postpone or cancel tasks, this insight will be valuable. In general, corrective and seaworthiness tasks have higher priority than inspection tasks of non-critical systems. When performance of a maintenance project is reviewed afterwards, the distinction between the different types of tasks can be made. The distinction informs the user about the impact of the postponed or eliminated tasks or about the resulting delay.

These five factors follow from the interviews, and show measurement and planning technique suggestions. Interviewees also show a critical attitude towards the feasibility of such maintenance planning measures. The main concern is about the practical consequences. Not all interviewees are confident that this new flow of information will be adopted in the processes. The information must be stored correctly and the processes must be adjusted in order to use the feedback of historical maintenance periods (MS1). Furthermore, the high capacity utilization results in time pressure for the departments involved. Therefore, multiple interviewees foresee practical problems due to the limited available time. And again, the experiences with SAP implementations also forms an obstacle in the perspective of the interviewees. The software is not sufficiently equipped to measure maintenance planning performance indicators. Also, the presentation of key performance indicators is not possible. No clear examples could be given, but at least it is perceived as insufficient by the interviewees.

4.2. Planning measurement in scientific literature

The performance of (maintenance) plannings is a small field of research. Our search often resulted in findings that link maintenance to operations, and how this combination can be implemented best. Measuring the quality of a planning is not a straightforward concept. Moreover, the interviewees of our research showed difficulties in finding terms to express the correctness of a planning. In literature, we find more focus on the output quality as a measure of planning quality, but other factors can also be measured and implemented in order to improve the maintenance planning quality. We describe six factors from literature:

1) Input and output measures: In the case of the RNLN, one should identify the output of the maintenance execution processes, which is not easily unambiguously expressible. For production processes, output performance measures are clearer to define. In the study of Ashayeri et al. (1996), the planning of production and preventive maintenance jobs are taken into account, whilst minimizing costs. The total costs are the summation of production, backorder, preventive and corrective maintenance costs.

Studies such as the one from Ashayeri et al. (1996) introduce a model that combines operational schedules with preventive maintenance. Their key performance indicators are also mostly focused on the output of the process, which is a production volume in this case. This is not fully applicable to the RNLN, especially not, since this research states that the time between two consecutive planned maintenance intervention periods remains unchanged.

Concentrating on the output solely is not recommendable, according to Johnson et al. (1995). The framework described in their research aims to measure success of services. It is claimed that input, process and output together contribute to quality with impact scores of 39%, 45% and 16%, respectively. Maintenance execution can also be interpreted as a service. In the case of the RNLN, input can be defined as the resources, time, training, and costs. The process can be defined as the maintenance execution itself and the output is a combination of the maintenance result and reliability of the fleet. Again, these factors cannot be unambiguously defined, but this research stresses that purely focusing on the output is not correct.

2) Multi-project KPIs: Another research in the field of project management comes from Sandru et al. (2014). Instead of focusing on a single project, this study addresses the situation of multiple projects with shared goals. The objective of their research is to set up performance measures on project and portfolio level. This can be used for the situation of the RNLN, in which multiple maintenance projects take place in the form of multiple ships. Furthermore, unplanned and corrective maintenance interrupts the planned projects, but contribute to the overall objective of the RNLN to have a deployable fleet. The study constructs a framework to create key performance indicators. Furthermore, it provides working procedures that contribute to reaching project and portfolio goals. The RNLN can therefore use such frameworks for managing the maintenance projects. It helps in analyzing the maintenance execution processes, but also support management decision making with respect to maintenance planning throughout the fleet.

3) Maintenance tasks distinction and equipment availability: Pujadas and Chen (1996) support that identification of maintenance output is a difficult concept. In their work, Reliability-Centered Maintenance (RCM) is combined with Failure Mode Effect and Criticality Analysis (FMECA). The study targets higher equipment availability and effectiveness by planning tasks that most prominently determine equipment's availability. For the RNLN this means that one should identify the most important maintenance tasks with respect to the availability and reliability of the fleet. These should be given priority over other tasks when constructing maintenance plannings. This distinction forms a measure of the output quality of maintenance execution. Furthermore, Pujadas and Chen (1996) stress that failure modes are not the only target, but human safety and environmental impact must be taken into account as well. This is also in line with the overall objective of the RNLN's maintenance strategy. The fleet must be deployable in technical, safety, and environmental terms.

4) Critical path planning: In Section 4.1 we described the principle of a critical path in maintenance plannings from the perspective of the interviewees, and thus from the RNLN. In scientific literature, critical path is widely described. Already decades ago, Kelley Jr and Walker (1959) described in what ways critical path planning are beneficial to organizations that need to coordinate many diverse tasks. In their study, it is concluded that four key management tasks must be completed in order to create accurate plannings: forming a basis for prediction and planning, evaluating alternative plans to achieve the objective, checking progress against current plans and objectives, and forming the basis for decision making based on facts. These four principles need to be taken into account for the RNLN as well, in order to succeed in implementing critical path planning. A few years later, Kelley Jr (1961) went a step further by focusing on the mathematical aspects of critical path planning. Time, sequence and costs of individual tasks are among the most important parameters of the mathematical expressions. From the interviews we know that these parameters lack accuracy at the RNLN.

5) Critical path identification: The study of Yang and Miller (1988) focuses more on the performance of a planning. With their Program Analysis Graph (PAG) technique, they identify the critical path. PAGs can be made by measuring all paths throughout a planning. The longest path is the critical path, which means that the bottlenecks that need attention lie on that specific path. In their study, multiple algorithms are tested, that all select the longest path. However, in their conclusion it is mentioned that their technique exposes bottlenecks, but performance measures other than the duration are not mentioned.

6) The relation of stakeholders' perspectives and project success: The analysis of production and maintenance plannings can be observed in a wide perspective. The study of Dvir et al. (2003) is focused on the relation between project plannings and project successes at the Israeli ministry of Defense. The methodology of their concept is applicable to the maintenance situation of the RNLN. In the study, three planning aspects and three stakeholder perspectives form the basis of reviewing project successes. The perspective of end-users, the project manager and the contracting office (ministry of Defense) are taken into account when determining the overall success. The planning aspects are described in terms of functional and technical specifications, and project management processes. Observing 110 research and development projects by the use of questionnaires resulted in success measures per stakeholder. A combination of measures for the three stakeholders and overall success measures are compared with the input effort for the three mentioned aspects. Their conclusion is that the success of a project is related to all three aspects. In practise, this means that all stakeholders' perspectives must be taken into account from an early phase in project planning. This is in line with the findings from the interviews, described in Section 4.1, that the objective of planning measurements must be described first.

4.3. Discussion on the RNLN situation and literature

This chapter combines input from the RNLN via interviews and other views from scientific literature. These information sources show similarities and contradictions, which are briefly described in this section. The relevance of an objective for measuring the planning performance is supported by both sources, as well as it is agreed to be difficult and ambiguous. Output can be defined in multiple ways, and differs for each perspective. The RNLN should identify the stakeholders and the impact of (in)complete maintenance execution, as well as the consequences of delays. Furthermore, the interviews did not shed light on the performance measures for the entire fleet. Most interviewees immediately focused on a single maintenance planning for one fleet unit instead.

The importance of priorities for different maintenance tasks is recognised by both the RNLN as well as other studies. Postponing or cancelling tasks cannot be expressed with one, uniform impact. A classification system must be constructed to distinguish the impact for different tasks. Frameworks that we found in literature can be used to establish such classifications, but also to determine the overall success of maintenance execution and maintenance planning. Frameworks are also expected to help the RNLN in introducing feedback loops in order to improve the maintenance planning of future maintenance periods.

4.4. Findings on maintenance planning analysis and improvement

The interviewees mentioned unanimously that no planning measures are implemented in the current processes. Therefore, we studied the impact of data-driven maintenance support on maintenance plannings in this chapter, which answers RQ3. The interviews show that input quality, the absolute and relative delay, and the number of unplanned maintenance tasks are expected to be applicable planning measures. Other studies support these three measures, but also indicate the usefulness of multi-project KPIs. Measures for multiple projects are very applicable for the RNLN, since the maintenance departments work on multiple ships simultaneously. In order to improve maintenance planning, from the interviews and scientific literature we conclude that critical path planning and a distinction of tasks with respect to their criticality and seaworthiness are relevant improvement methods. The literature study also indicated that the relation of stakeholder's perspectives and project success. Interviewees also suggested to implement measures for corrective maintenance tasks and planning delays. Therefore, we can conclude that there are useful methods to analyze and improve maintenance plannings, but that the RNLN currently is not ready for the implementation of such methods. The maintenance event data and software design needed for this implementation must to be improved first. Furthermore, the software must be better aligned with the maintenance processes, and vice versa. However, the implementation of data-driven maintenance support based on failure diagnostics and predictive maintenance is not hindered by the absence of such measures. But the downside of implementing failure diagnostics and predictive maintenance without maintenance planning analysis methods, is that the effect of the implementation of data-driven maintenance support cannot be clearly measured. A lesson that can be learned follows from the focus of these analysis and improvement methods, namely the duration, operation criticality, and input and output quality. When data-driven maintenance support affects these three factors positively, it is expected that introduction of data-driven maintenance support improves maintenance planning and execution.

Chapter 5

Impact of data-driven maintenance support

By introducing a decision table, we answer RQ4: How does data-driven maintenance support affect the maintenance planning and maintenance execution of each observed system, for each maintenance level? Interviews and scientific literature form the input for the decision table. An iterative approach is used to update and improve the decision table, which is done in follow-up meetings with interviewees. Section 5.2 describes the essential input elements. Next, in Section 5.3 the system characteristics of the decision table are explained. For the explanation of the objectives of the decision table, we refer to Section 3.1. In Section 5.4 the actual decision table is depicted, together with an explanation of the content and a description of the impact per objective for both types of data-driven maintenance support. The two types of data-driven maintenance support techniques in the decision table follow from Section 3.2 and Section 3.3. This chapter ends with three case studies in Section 5.6 that show the relevance and applicability of the decision table.

5.1. Introduction on the decision table

The impact of data-driven maintenance on the RNLN's maintenance planning and execution needs is identified, and needs to be communicated to the stakeholders. Three main stakeholders that can be guided at the start of data-driven maintenance support projects are identified, which is explained in Section 5.5. Interviews showed that it is often unclear what benefits can be achieved, and which steps need to be taken to identify the applicability of data-driven maintenance support. Communication of these steps can be done in multiple ways. For this research, multiple methods are explored: purely textual explanation, a scoring system, a mathematical approach, a decision tree and a decision table. Purely textual descriptions are regarded as too vague, and scoring systems require an extensive validation procedure to avoid subjectivity (Carnero, 2005), which could not be done at the RNLN. The mathematical approach did not result in a satisfying description of the impact. Currently, the quality and presence of historical maintenance data is insufficient. The maintenance departments could not provide a maintenance planning and the according time logs of the execution of the maintenance planning. Therefore, it is impossible to express the impact of maintenance planning deviations quantitatively.

Therefore, a quantitative approach turned out to be the best approach for the current situation. We examined the usefulness of quantitative techniques that help the stakeholders to obtain insight in the impact of data-driven maintenance support, and link the required input to the stakeholders' objectives. Two main methods are found to be promising: a decision tree and a decision table. It is decided to use the decision table, because of the large number of elements that must be visualized: input requirements, system characteristics, objectives, maintenance levels, and failure diagnostics and predictive maintenance. Furthermore, the study of Huysmans et al. (2011) shows that decision tables perform better in terms of accuracy, response time, answer confidence, and ease of use. The use of a decision tree would result in a large figure, whereas the decision table is relatively compressed. Furthermore, multiple decision trees are needed to include all factors. For each maintenance level, an individual decision tree is needed. Furthermore, combining the six objectives in a single decision tree is not expected to give the clear overview that we strive for, in order to present all steps in a structured way. A clear advantage of a decision tree is the ranking of requirements and decision steps (Shamim et al., 2010), but that is not relevant for this case. Furthermore, the decision table can be easily adjusted by organizations, if necessary. Taking all these arguments into account, it is decided to create a decision table, because of the information density, the clear overview, and the adjustability in later stages. Furthermore, a decision tree is more self-explaining than a decision table. this is solved by giving a clear description of all elements in the decision table, and a description of the application in practise in Section 5.5. The choice for the decision table is validated by consulting five interviewees. Moreover, the content and applicability of the decision table is validated by these five interviewees. In addition, case studies are used as a validation procedure. Three of the cases are described in Section 5.6.

5.2. Decision table input

Input factors describe the types of data that need to be available in order to apply data-driven maintenance techniques. The input factors describe measurements of sensors, but also event data and component standards. Input factors can be described as the technical conditions that enable data-driven maintenance support, independent of the system characteristics.

Event data: This type of data covers a wide range of data types. All relevant moments, with respect to failures and maintenance fall within this category. One can think of the moments of maintenance tasks that are executed. Furthermore, failure moments and descriptions of the failure can be used as data for future data-driven maintenance support (Jardine et al., 2006). Also the moment of installation of systems and components, as well as the moment that modifications are made are registered. Event data plays an important role in identifying the performance of a system. In other words, when observing sensor data, one should know when the system was in a new or good state, and when the system failed. Often, this type of data needs manual entry.

Sensor data: Sensor data must be transformed into useful information. For the some diagnostics or predictions the data of multiple senors is needed, as they all contain partial information. In that case, a multisensor data fusion approach is needed to come to accurate diagnostics or predictions (Jardine et al., 2006). Sensor data can be of multiple types. Within the RNLN there are multiple types of system measurements: vibration, oil, fluid, temperature, pressure, flow, current, etc. Furthermore, the RNLN has ship routing and performance data: course direction, time stamps, engine power and sea conditions. Failures can only be detected if the right type of data is available. Therefore, it must be physically possible to measure directly or indirectly the state or performance of a system. Furthermore, the sensors must be correctly installed, data must be stored in the right way and the data must be transferred to the shore in case the algorithms do not run on board the ship.

Component standards: Components and systems are all described in DMO's ship maintenance policy. The health of a component can be observed by its performance, but also by its state. Therefore, minimum standards for components' state and performance are part of DMO's maintenance policy (WS1). Systems can be taken out of service if the measurements exceed the standards set by DMO. Taking ships out of service can be the consequence of technical reasons, warranty reasons, but also for safety purposes. Sensor data can be continuously compared with the system standards in order to monitor the components' performance and/or condition.

5.3. Decision table characteristics

Whereas the input factors focus on the technical aspects of data-driven maintenance support, the characteristics described in this section cover system characteristics in a broad perspective. Technical, financial, operational and maintenance aspects that can be linked to systems and components fall within this category. The presence of these characteristics cannot all be identified on beforehand, such as the presence of detectable failure patterns described by 'technical feasibility'. Furthermore, the characteristics form a guidance function, since not all characteristics need to be met in order to complete a data-driven maintenance support project. In Section 5.4 the optional characteristics per objective are described in more detail.

Operational critical: Systems can be categorized on their criticality to the operations (Tinga et al., 2017). For example, the propulsion systems are critical to the operations of a ship. However, there are systems that do not immediately cause down time when a failure occurs, such as a water pump in a parallel system with redundancy. Critical systems generally receive more attention because of the operational risks. When applying data-driven maintenance support that is focused on a ship's deployability, operational critical systems are usually given higher priority. In scientific literature, multiple criticality identification techniques exist (Tiddens et al., 2018).

Technical feasible: The success of data support depends on a number of essential factors. Of course, sensor data must be available, which is an input requirement of the decision table. However, there must be a form of failure behavior or failure pattern be observable for predictive maintenance. This cannot always be ensured before the start of data-driven maintenance support project for a system. The failure mode must be identified, ans well as the cause of the failure. When it is known that historical failures occurred at random moments or due to external factors, difficulties in finding a failure pattern are expected. Moreover, the failure pattern must be identifiable in technical terms (Tiddens et al., 2018). The available techniques for data-driven maintenance support must be capable of diagnosing or predicting the failures.

Investment: Data-driven maintenance support needs managerial support in multiple ways. The most important motivation for introducing data-driven maintenance support for the RNLN is increased deployability of the fleet. However, investments are needed to introduce this new concept. The benefits, both in terms of deployability as well as finances, must exceed the costs. Financial and capacity investments must be made to establish this new working method. (Mobley, 2002, p.33) phrased it as: 'Preventive maintenance is an investment. Like anything in which we invest money and resources, we expect to receive benfits from preventive maintenance that are greater than our investment.' To illustrate, the result of predictions probably alter the moment of preventive replacements, which might cause an increase in preventive maintenance costs. The objective is to reduce the workload and corrective maintenance costs and increase the deployability. The relation of preventive and corrective maintenance costs can even be described in a ratio (Fajardo and Ortiz, 2011). The management must decide upon this trade off, thus to what extent the decrease of corrective maintenance costs can be compensated by the increase of preventive maintenance costs.

Consequential damage: An often heard complication of failures is that it results in damage to subsequent systems. This can be illustrated by an example. In case of damage or wear of a water pump's impeller, the loose particles of the impeller flow further into the system. These particles can cause damage to pipes and systems downstream the water pump, such as the cooling system. We call this consequential damage (Besnard et al., 2010). This regularly results in longer maintenance time, longer inspection time and higher maintenance and spare parts costs.

Significant inspection time: This criterion is difficult to express in a uniform threshold value. But a request for the start of a new data-driven maintenance project comes from the user or maintainer (DV2). In general, the perception of the user or maintainer needs to be that the inspection time delays the overall process of maintenance execution, and that a significant amount of valuable time and capacity can be saved by reducing inspection time. On board, this can be the case for inspection tasks that need to be performed regularly and consume a few hours per week. Ashore, long inspection tasks that sometimes have a duration of multiple days can be replaced by the use of data-driven maintenance support. Also without a uniform expression, this is a valuable characteristic to consider.

Significant spare parts lead time: In the current situation, visual inspections identify failures or approve the health of a component. When an inspection results in the diagnosis of a failure, spare parts are taken from the shelve or ordered at suppliers at that moment. Parts with significant lead times can delay the overall maintenance execution process. Data-driven maintenance support identifies failures at an earlier stage, sometimes even before the actual occurrence of the failure, and before the ship is back at the maintenance facilities. It is expected that this saves significant time for the overall maintenance execution processes.

5.4. Decision table

The proposed decision table links the objectives (red, bottom row) to the required input data (yellow, left column) and characteristics (blue, left column), see Figure 5.1. Furthermore, every objective is separated for each of the three maintenance levels (grey, top row). The red and green squares and circles in the cells are explained in the legend: a square represents essential elements, whereas the circles represent optional elements. Furthermore, green squares and circles represent the failure diagnostics method of data-driven maintenance support, and the red squares and circles represent the predictive maintenance form of data-driven maintenance support. We explain the content of the decision table and impact per objective:

Cost reduction:

- **Input:** The cost reduction objective can be achieved via both types of data-driven maintenance support methods. Both require sensor data that can be translated into system condition and health monitoring, and eventually in failure predictions. Furthermore, in order to establish predictive algorithms, it is needed to have access to event data about historical maintenance tasks and historical failures. Furthermore, component standards must be used to reflect upon the health of components and systems. Event data is not needed for failure diagnostics for ILM and DLM tasks, since the sensor data is compared with the component standards. Event data is typically used for the construction of predictive algorithms.

- **Characteristics:** The diverse opportunities for cost reductions result in multiple types of characteristics that can be used for the two data-driven maintenance support methods. For all objectives, it is beneficial if technical feasibility can be confirmed before the start of a project. However, practise shows that at the start of developing data-driven maintenance support tools one cannot always guarantee the technical ability to transform sensor data into useable information. Sometimes, the technical abilities are insufficient for diagnosing or predicting failures. Furthermore, it cannot always be confirmed on beforehand that benefits will be achieved in terms of costs and effort. The positive result of the investments appears afterwards. However, a positive prospect helps in supporting the project. Lastly, optional characteristics such as consequential damage that can be avoided and a significant inspection time that can be reduced are factors that can be identified in early stages of the development phase. However, these are depicted as optional characteristics, as they depend on the type of costs that will be reduced, and not for all types of costs. Operational critical and significant spare part lead time characteristics are not depicted for this objective. Spare part lead time reduction and the operational criticality do not necessarily lead to lower costs.

Input / Characteristics	Cost reduction OLM	Cost reduction ILM	Cost reduction DLM	Corrective maintenance reduction OLM	Corrective maintenance reduction ILM	Corrective maintenance reduction DLM
Event data	green ■	red ■	red ■	red ■	red ■	red ■
Sensor data	green ■	green ■, red ■	green ■, red ■	red ■	red ■	red ■
Component standards	green ■	green ■, red ■	green ■, red ■	red ■	red ■	red ■
Operation critical				red ●	red ●	red ●
Technical feasible	green ●	green ●, red ●	green ●, red ●	red ●	red ●	red ●
Investment	green ●	green ●, red ●	green ●, red ●			
Consequential damage	green ●	green ●, red ●	green ●, red ●	red ●	red ●	red ●
Significant inspection time	green ●	green ●, red ●	green ●, red ●			
Significant spare parts lead time						

Input / Characteristics	Spare parts lead time reduction OLM	Spare parts lead time reduction ILM	Spare parts lead time reduction DLM	Inspection time reduction OLM	Inspection time reduction ILM	Inspection time reduction DLM
Event data		green ●, red ■	green ●, red ■	green ●	green ●, red ■	green ●, red ■
Sensor data		green ■, red ■	green ■, red ■	green ■	green ■, red ■	green ■, red ■
Component standards		green ■, red ■	green ■, red ■	green ■	green ■, red ■	green ■, red ■
Operation critical				green ●	green ●, red ●	green ●, red ●
Technical feasible		green ●, red ●	green ●, red ●	green ●	green ●, red ●	green ●, red ●
Investment		green ●, red ●	green ●, red ●			
Consequential damage						
Significant inspection time				green ●	green ●, red ●	green ●, red ●
Significant spare parts lead time		green ●, red ●	green ●, red ●			

Input / Characteristics	Preventive maintenance time reduction OLM	Preventive maintenance time reduction ILM	Preventive maintenance time reduction DLM	Insight in system use OLM	Insight in system use ILM	Insight in system use DLM
Event data		red ■	red ■	green ●	green ●	green ●
Sensor data		red ■	red ■	green ■	green ■	green ■
Component standards		red ■	red ■			
Operation critical						
Technical feasible		red ●	red ●	green ●	green ●	green ●
Investment				green ●	green ●	green ●
Consequential damage						
Significant inspection time						
Significant spare parts lead time						

	Diagnostics	Predictions
Essential	green ■	red ■
Optional	green ●	red ●

Figure 5.1: Data-driven maintenance support decision table

- **Impact:** OLM tasks are expected to benefit only from failure diagnostics methods, according to the interviewees. Corrective maintenance tasks that avoid immediate system and operational downs are not part of the OLM classification. Corrective OLM tasks are only performed for systems with a low impact on the deployability, and the crew on board concentrates mostly on preventive maintenance tasks. Therefore, the main benefits for the crew on board are less preventive maintenance tasks and less inspection tasks. When the crew on board can rely on data-driven failure diagnostics, less time needs to be spent on root-cause analysis. Furthermore, the system condition can be determined by the use of data, which can result in postponing preventive maintenance tasks. Both consequences lower the workload on board. This is in line with the trend of decreasing crew sizes and the reduction of labor costs. Furthermore, better usage of the remaining useful life of components result in lower spare parts costs. For ILM and DLM, the similar impacts can be achieved as for OLM by applying data-driven diagnostics, such as workload reduction due to lower inspection time and postponing preventive maintenance. Especially for DLM tasks, inspections can take a significant amount of time, even longer than a week. Furthermore, for ILM and DLM data-driven maintenance support can reduce costs by avoiding failures by applying predictive maintenance techniques. Corrective maintenance is typically costly because of the required spare parts and the higher capacity usage of labor and facilities. As mentioned in Section 3.1, this objective overlaps with other objectives in our list, but reducing costs is an objective in itself as well. Concluding, for maintenance tasks ashore and on board holds that a reduction of resource utilization leads to costs reductions. Furthermore, cost savings can be achieved by a reduction of required spare parts.

Corrective maintenance reduction:

- **Input:** Predictive maintenance typically needs three forms of data: sensor data, event data and component standards. Sensor data can be translated into system state information, and event data is needed to construct a model that recognizes failures and maintenance execution. Component standards can be used to identify the new-state conditions and to set minimum and maximum standards that must be met by the system.

- **Characteristics:** For this objective, three characteristics are of importance. Similar as for the cost reduction objective, is the technical feasibility. For predictive models, it is advantageous to recognize in early stages of the development process whether technical abilities are sufficient to recognize and predict failures, and whether failure patterns are expected to be identifiable. Furthermore, operational criticality gives priority to systems to be supported by data. Failures of non-critical systems are undesired, but do not result in immediate interruption of the operations. But for operational-critical systems, mission stoppage are the result of failures. Therefore, operation-critical systems are more likely to be involved in predictive data-driven maintenance support projects. Also the possibility of occurrence of consequential damage is a factor that prioritizes systems in predictive maintenance projects. Consequential damage results in more corrective maintenance tasks, since other components are damaged as well. Their impact in terms of costs and maintenance time are relatively large, thus the benefits of failure avoidance are large as well.

- **Impact:** The method used for achieving this objective must be capable of avoiding failures. Diagnosing failures does not lead to avoidance of the failure, but to mitigating the consequences for maintenance execution. Therefore, only predictive maintenance is considered as an adequate method for this objective. For all three maintenance levels, it is considered as a valuable method, albeit to a limited extend for OLM. Avoiding failures result in less unplanned maintenance tasks, and less operation stoppages. Furthermore, less unplanned maintenance for a specific ship also contributes to less planning disruptions for other ships. The unplanned tasks do not have to interfere other ships' maintenance executions. Furthermore, avoiding unplanned maintenance is expected to reduce spare parts costs and labor costs significantly. Furthermore, when preventive maintenance can be applied instead of corrective maintenance, the capacity usage of maintenance facilities is typically lower. Lastly, related to the previous objective is the expected reduction of costs. A clear example is described in Section 5.6.

Spare parts lead time reduction:

- **Input:** In order to reach this objective, failure diagnostics and predictive maintenance can be used. The input is similar for both methodologies. As for all combinations of objectives and methodologies, sensor data is required for ILM and DLM. Furthermore, component standards are needed to assess the measured sensor data. Furthermore, event data is needed to establish predictive maintenance models. Event data is also useful for the failure diagnostics method to identify the moments of maintenance execution and the moments in which the component was in new-state.

- **Characteristics:** Similar as for the previous objectives, it is beneficial to have an understanding about the technical feasibility of both methods of data-driven maintenance support. Furthermore, insight in the cost-benefit analyses helps to support the development process in early stages. When it appears that great efforts and financial investments are not outweighed by the attained benefits, the development project might be ceased. Furthermore, 'significant spare parts lead time' is depicted as a characteristic for failure diagnostics and predictive maintenance. There is not a unique measure, but the problem owner must have the perception that the lead time of spare parts forms a bottleneck for the progress of the maintenance execution process. The spare part lead time is a typical characteristic of a component, but on beforehand cannot be assured that the significant lead time can be reduced by earlier ordering of spare parts at suppliers.

- **Impact:** In the decision table can be observed that OLM is not represented. Spare parts on board ships are the result of DMO's strategic inventory levels. The absence of spare parts on board can only be compensated by spare part supplies ashore. Failure diagnoses and predictions are not expected to contribute to earlier completion of OLM tasks. Most components for OLM tasks are on stock on board or at the maintenance facilities of the RNLN. Reduction of spare part lead time from suppliers will not have a result for OLM task durations. For ILM and DLM, it is expected that for situations in which spare parts are not on stock, earlier order placement results in lower duration of maintenance execution. This is only the case when maintenance tasks are delayed due to the absence of the spare parts. In order to be able to place orders at suppliers earlier, the failure must be diagnosed earlier or predicted on beforehand. The result for the RNLN is earlier ship deployability after maintenance execution, and thus a higher overall deployability for ships.

Inspection time reduction:

- **Input:** There are two types of data-driven maintenance support for this objective. Sensor data is essential for all levels and both forms of data-driven maintenance support. The sensor data needs to be compared with component standards in order to diagnose failures, or develop predictive models. Therefore, component standards need to be available as well. The event data is a key input for predictive models. The historical new-states, failures and maintenance periods can be recognized in order to develop the model. Furthermore, event data can be beneficial to failure diagnostics methods to identify historical failure states of the components.
- **Characteristics:** System characteristics that are convenient in the development phase are partly comparable with other objectives. Again, technical feasibility helps model developers in early phases of the process. Furthermore, operation criticality might be an incentive for the construction of such models. When the inspection task of an operation critical component forms the bottleneck of the maintenance execution process, the ship cannot be deployed at an earlier moment. Replacing the manual and visual inspections by data-driven inspections decreases the impact of this bottleneck task. Inspections that form a bottleneck can be replaced by the use of data, but also the reduction of workload for maintenance personnel can be a reason for the implementation of such methods. Furthermore, the problem owner must have the perception that the inspection time can be reduced significantly by data-driven maintenance support. This cannot always be claimed before developing data-driven maintenance support tools, which makes it an optional characteristic.
- **Impact:** Inspections are essential tasks for all three maintenance levels. Crews on board perform inspections on a regular basis throughout the operations, and focus most on identifying failures. For ILM and DLM tasks, technicians do not only search for failures, but also assess the condition of systems and components in order to determine whether preventive maintenance is needed. Failure diagnostics can replace the manual inspections in the search of failures, or the cause of failures. Predictive maintenance typically makes condition assessments obsolete. Predictions help the maintainer in determining the right moment for preventive maintenance, which makes the manual and visual inspections redundant. A reduction of inspection time mostly influences the capacity usage and thus

the workload for maintenance crews. It is expected that the maintenance plannings of ships can be shortened, and the capacity usage at the maintenance yards decrease. Furthermore, the workload on board decreases, which contributes to the trend of decreasing crew sizes.

Preventive maintenance time reduction:

- **Input:** For the application of predictive maintenance for ILM and DLM, similar input is required as described in input description of the objective 'corrective maintenance reduction.'
- **Characteristics:** The system characteristics for this objective are relatively limited, and show similarities with the objective 'corrective maintenance reduction.' As for other objectives, the technical feasibility contributes to successful development of data-driven maintenance support. Operation-critical components are eligible for predictive maintenance, but this is not a strict requirement. One can also consider to apply predictive maintenance for components that require time-consuming corrective maintenance after failures. Furthermore, the characteristic of consequential damage is not depicted, since this would fit to situations that are mostly focused on the objective 'corrective maintenance reduction.'
- **Impact:** This objective sounds overlapping with other objectives. The objective is focused on better usage of remaining useful life of components. Data helps the maintainer to identify the latest moment before a failure to preventively maintain or replace the component. Failure predictions ideally give an accurate expected remaining useful life, which can be used in planning preventive maintenance tasks. For ILM and DLM it is expected to improve the maintenance planning. When preventive maintenance can be postponed, over a longer time horizon, the preventive maintenance task can be executed less often. The elimination of tasks result in lower capacity usage and less preventive maintenance time that is needed. Failure diagnostics are not expected to contribute to this objective, since it identifies failures after incurring. Corrective maintenance is still needed, and does not reduce the number of preventive maintenance tasks.

Insight in system use:

- **Input:** The required input for this objective differs from the other five objectives. This is due to the nature of the objective, which has an informative function to the user. Use insights must indirectly decrease the maintenance demand, as described in Section 3.1. The sensor data does not need to be compared with component standards in order to assess the health of the component. Furthermore, event data is not an essential input. For certain system use insights it is valuable to identify maintenance moments or the type of operation that is executed, which both can be retrieved from event data. However, for other systems the events are not essential to describe the use. One can think of the fuel consumption, which does not need to be linked to the events.

- **Characteristics:** There are two characteristics for this objective. The technical feasibility is the link between the types of sensor data that form an accurate representation of the type of usage. In other words, use patterns are preferred to be identifiable in the available data, such as the engine rotations per minute that are translated into the used engine configuration. The investment characteristic stresses the benefits that must be attained by data-driven maintenance support for this objective. As described in Section 3.1, the benefits cover a wide range, such as fuel reduction, less operating hours for systems and improvement of the system use. Before the start of a project that must gain insight in the system use, there must be a reason what the insight brings to the organization.

- **Impact:** The impact of this objective cannot be expressed by a single description. Insight in system use can be applied to a variety of operational improvement projects, for all levels of operations and maintenance. Most of the insights inform the user and can be used to improve the working procedures for systems. At the end, this must contribute to a better condition of the system and less maintenance that must be performed. The background of this objective requires a diagnosis of the type of use, in the form op performance measures or usage dashboards. Predictions do not form an adequate answer to the question of the user about usage patterns, which makes that there are no red prediction elements in the decision table for this objective. The earlier used example in Section 3.1 of the insights in the use of main diesel engines demonstrates the results clearly. When fewer main diesel engines are used, but at a higher power level, the deactivated main diesel engine does not increase its operation hours. For time-based inspection tasks and maintenance tasks, this means that over a certain time horizon, the tasks can be performed less frequently. Furthermore, higher power levels result in less internal engine contamination which is beneficial to the condition of the diesel engine. This also might result in less maintenance tasks that need to be executed. Taking both consequences together, we identify a lower demand of maintenance tasks and thus a decrease in the demanded capacity of the maintenance facilities.

5.5. Decision table application in practise

The decision table can be used for multiple reasons and by multiple stakeholders. We describe the three main stakeholders that can use the decision table: the maintainer, the developer and the design authority. All three can use the decision table for different reasons, and in a different way. For all three stakeholders, the usefulness and a step-by-step approach is explained, and visualized in Figure 5.2. As mentioned in Section 3.6, systems can be equipped with failure diagnostics techniques, predictive maintenance techniques, or both techniques. Both types of data-driven maintenance support result in other types of information, and thus can be used in parallel. The approach visualized in Figure 5.2 can be followed twice in a row for both techniques.

One option to start new data-driven maintenance support projects, is by the maintenance engineer's requests at the developers, such as DvO. The maintenance engineer's request follows from a business problem, which is represented by one of the six objectives in the decision table. The maintenance engineer also determines for which maintenance level a request is done. In order to let the project succeed, essential input requirements that belong to the objective need to be met. The maintenance engineer can assess the presence of these input requirements, such as sensor and event data. The next step is to verify the system characteristics. Although these are not all crucial, it helps to identify obstacles and verifies the appropriateness of data-driven maintenance support for specific systems. At the end, the decision table depicts the appropriate data-driven maintenance technique that belongs to the maintenance engineer's request. When all essential input and system characteristics are present for the specific objective, the data-driven maintenance support project can start and is expected to succeed.

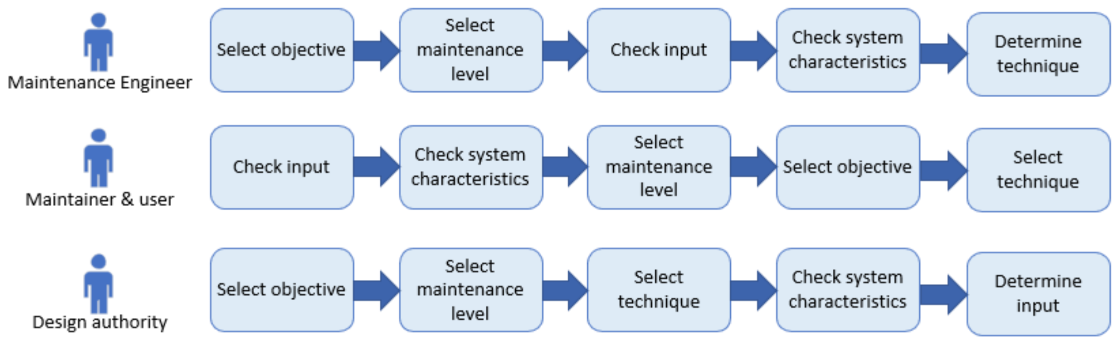

Figure 5.2: Stakeholders of the decision table

From an improvement perspective, the decision table can be used to identify new data-driven maintenance support projects. In practise, these improvement parties, such as DvO or consultants, represent both the maintainer and user. Improvement parties that possess data of a particular system, can identify objectives that can be achieved using our decision table. First, the essential input requirements can be assessed on their presence in the data. The improvement party can conclude which objectives can be met, based on this first selection criterion. Second, the system characteristics can be observed. Again, these do not always form hard criteria, but at least give an indication on the appropriateness of data-driven maintenance support for the particular system. When the system characteristics are observed, the developer can identify the maintenance level for which improvements can be achieved. This also determines the project's stakeholders, such as technicians ashore or the crew on board. Based on these selection criteria, the improvement party can select an objective that can be met by the available data. The last step is to select the data-driven maintenance technique from the decision table.

The third stakeholder, the design authority, can also use the decision table. In the design phase of a new ship or for the design of a MLU, the decision table can inform the design authority about the requirements for data-driven maintenance support. Increasing data-driven maintenance support is part of the maintenance strategy of the RNLN. Systems must be equipped with sensors, which can be done in the building phase for new ships, but also during MLUs. The design authority can use the decision table by selecting an objective first. This objective must suit the case that is tackled, such as reducing labor costs by focusing on data-driven inspections instead of visual inspections. Second, the maintenance level of the case must be selected. Third, the applicable maintenance data-driven maintenance technique must be selected. The fourth step serves as a validation. The system characteristics can be checked in order to verify if the technique suits the kind of system that is observed. Last, the design authority can observe in the table which input is essential for the success of the data-driven maintenance support implementation. From this, the ship can be correctly equipped with sensors and other hardware.

5.6. Case studies

The use of the proposed decision table in Section 5.4 and the associated impact can be described best by case studies from the RNLN. Furthermore, these three case study served as a part of the validation procedure of the decision table. We describe two cases in which data-driven maintenance support is beneficial, and one case in which data-driven maintenance support did not succeed. For all three cases an introduction on the case is mentioned, the applicability of the decision table is described, and the impact of data-driven maintenance is explained.

5.6.1. Case study I: main diesel engine bearings

Each OPV features two identical main diesel engines. Bearings in the main diesel engine are so-called journal bearings, which support the crankshaft without physical contact. An oil film is created, which is the result of rotation and oil pressure (Heek, 2021). The oil temperature is measured by sensors, for each of the seven bearings. When damage to the bearings occurs, the temperature of the return oil increases. The individual measurements per bearing enable the RNLN to identify the defective bearing. Cavitation is not only detrimental to the bearing itself, but it also damages the other bearings, other parts in the oil pressure system and the crankshaft. The original maintenance policy for this component was a time-based visual inspection, which was executed by specialized technicians. This is a time-consuming task, and cavitation is not necessarily a type of wear that follows a linear pattern. Therefore, time-based inspection and preventive maintenance are not the optimal policy.

The decision table can be used to tackle this problem. First, the objective needs to be identified by the maintainer, which clearly is the reduction of corrective maintenance. Second, the correct maintenance level needs to be identified. In this case, this is ILM. Third, the availability required input must be checked. The RNLN possesses relevant sensor data about the return oil temperature, event data about historical failures and maintenance actions, and component standards for this type of bearing. All relevant input requirements are met. Fourth, the system characteristics need to be observed. In the decision table, three characteristics are listed: operation critical, technical feasible and consequential damage. Correct functioning of the main diesel engine is essential to the operations, thus this component suits this characteristic. Furthermore, the failure follows from cavitation, which can be described as a typical failure behavior. Therefore, this problem is also technical feasible. Lastly, consequential damage is indeed a result of bearing damage. We can conclude that for this problem, predictive maintenance is a suitable data-driven maintenance support technique that can be applied in order to reduce corrective maintenance.

Bearing cavitation caused financial, capacity and operational issues in the recent years. Therefore, the study of Heek (2021) was conducted at the DvO department, in close collaboration with technicians of TG Platform. A regression model is established that identifies cavitation by return oil temperature measurements. Failures of individual bearings can be recognized in advance. The algorithm informs the maintainer approximately 200 hours in advance, which is incorporated in the renewed working procedures. The introduction of predictive maintenance is expected to prevent the bearings from failing unexpectedly. The most recent failure had a significant financial impact, and the corrective maintenance tasks were time-consuming. The cavitation caused consequential damage to other bearings, the oil pressure system and the crankshaft. Corrective maintenance costs of a bearing are more than ten times higher than the preventive maintenance costs. Furthermore, the preventive replacement of the bearings can be scheduled in an ILM period, and has a duration of a day. In contrast, the corrective replacement took months and was at an unplanned moment during deployment. The duration of preventive maintenance consists of the maintenance execution itself, but also the lead time of spare parts. Crankshafts are not part of the regular spare parts strategic inventory of the RNLN, which resulted in a significant lead time for the spare crankshaft. Also, the corrective task interrupted the maintenance planning of other fleet units. All together, the introduction of this form of data-driven maintenance support impacts the number of corrective maintenance tasks, the financial consequences and the duration of the maintenance intervention of the main diesel bearings, which are all three part of the objectives of the decision table.

In this case, the RNLN decided to apply predictive maintenance to this system. The organization could also decide to focus on data-driven failure diagnostics. For this situation, failure diagnostics would improve the maintenance execution as well. When from the data followed that the original bearing failure caused consequential damage to the crankshaft as well, the spare parts order could be placed at an earlier moment. At the moment of the failure, the OPV was several thousand kilometers away from the maintenance facilities of the RNLN. The weeks of the return trip could have been used for the ordering process of a new crankshaft. In other words, data-driven failure diagnostics could reduce the spare parts lead time by several weeks for this example. Furthermore, when the system could be diagnosed at an earlier moment in time, the crew on board would have been commanded to not use that main diesel engine until maintenance was performed. However, the particular main diesel engine was started once more, which caused additional damage (MT1).

5.6.2. Case study II: ventilation system filters

The second case study is focused on the filters in the ventilation system of the OPVs. Ventilation systems are critical, since they provide fresh air throughout the entire ship. Furthermore, this system also manages the temperature on board by heating and cooling air. The filters need to be inspected periodically, and replaced when it is clogged. This is a manual process, and time-consuming. The crew needs to open shutters in the ceiling, and inspect each filter. Since this is a task that is performed during the operations of the ship, it is classified as an OLM task. Because of the smaller crews on board, it is valuable to automate this inspection process. The ventilation system already has a set of sensors, but this set does not fulfill the needs of data-driven maintenance support. During the interviews, it was mentioned that extra air pressure sensors per air filter throughout the ventilation system are needed. These must be placed in specific places, in order to be able to determine which air filter needs to be replaced. If the pressure upstream the air filter is normal, but downstream the air filter low, it indicates that the filter is clogged. From the support tool, the crew is informed which filter needs to be replaced.

The situation with additional pressure sensors is considered for this case. The decision table can be used to assess the appropriateness of data-driven maintenance support. First, the reduction of inspection time can be selected as the objective. Second, the maintenance level must be determined. In this case, that is OLM. Third, the input requirements must be checked. When the additional sensors are installed, the required sensor data is available. Also maintenance action data is logged as event date, but this is not necessarily needed. The component standards follow from the maintenance policy, which describes the pressure difference caused by the clogged air filter. Therefore, all required input is available. Fourth, system characteristics must be considered. For the air filter replacement, operation critical, technical feasible and significant inspection time are relevant characteristics. As explained in the previous paragraph, ventilation is operation critical. Furthermore, this problem is technical feasible, because clogged air filters can be recognized by measuring the difference in air pressure upstream and downstream the air filter. The crew on board mentions that inspection of air filters take significant time, which is in line with the last characteristic of the decision table. The decision table shows that for this case, failure diagnostics is an appropriate data-driven maintenance support technique that contributes to achieving inspection time reduction.The duration of such inspection tasks are not registered in SAP, and thus can the impact not be quantified. However, DV2, MT5, and HT1 emphasize the relevance of this type of data-driven maintenance support.

5.6.3. Case study III: diesel generators

Diesel generators on board ships are needed for the electricity supply. Electricity is essential for various types of systems on board, as well as for electric propulsion of the OPVs. Within the RNLN, a data-driven maintenance support project was started, because of the criticality of diesel generators to the operation. Therefore, failures must be avoided.

First, the objective needs to be determined. The reduction of corrective maintenance was the objective for the diesel generators. Second, the maintenance level needs to be selected, which is DLM for this case. Maintenance to the diesel generators is currently executed according to a usage-based maintenance policy. Due to confidentiality, we cannot mention the threshold value of the operating hours. Third, the required input must be checked. Sensor data that describes the performance of diesel generators is available. However, when the event data is checked, one could discover that there is no failure data available for this system. Diesel generators appear to be very reliable and require little maintenance. Therefore, this data-driven maintenance support project can be terminated in an early stage. However, in practise, it took a long time before this shortcoming was discovered. The structural approach of this decision table would have saved time to draw the same conclusion.

5.7. Findings on the impact of data-driven maintenance support tools

This chapter concludes this research with an answer to RQ4. We introduced a decision table that supports the maintainer, user, and design authority by linking the three input factors, six system characteristics and six objectives to two data-driven maintenance support techniques for each of the three maintenance levels. For each objective, described in Section 3.1, the associated impact on costs, maintenance execution and maintenance planning is outlined. We identified three main users of the decision table: the maintenance engineer, the improvement party, and the design authority. Three cases studies show the practical applicability and the potential of data-driven maintenance support on the overall goals of the RNLN. The formulated objectives that are implemented in the decision table show how failure diagnostics and predictive maintenance techniques lower the number of corrective maintenance tasks, the duration of manual inspections, and the duration of maintenance execution. As a consequence, these techniques reduce maintenance costs and capacity usage, and improve the fleet's deployability at the RNLN. Moreover, the decision table can be used by the design authority to identify the requirements and applicability of data-driven maintenance support during the design phase of new ships and MLUs.

Chapter 6

Conclusion, Discussion, Recommendations & Future Research

In this chapter, we present this research' conclusion in Section 6.1, and the discussion on this research in Section 6.2. In Section 6.3 we outline four main recommendations to the RNLN that follow from this research. Lastly, in Section 6.4 the limitations and suggestions for further research are described.

6.1. Conclusion

For answering the research questions, the step-wise approach of the four research questions enables us to conclude upon the main question: *What is the impact of introducing various types of data-driven maintenance support on the maintenance planning and maintenance execution of the Royal Netherlands Navy?*

In this research twenty interviews are conducted that shed a light on the maintenance planning and execution processes within the RNLN. The combination of interviews and literature review shows that data-driven maintenance support is perceived to impact the maintenance execution and planning in terms of resource utilization and costs. This contributes to the maintainer's objective: deployability of the fleet, against reasonable costs. Data-driven maintenance support is required, since the maintenance periods have a longer duration than originally foreseen. The conducted interviews show six factors that cause that the original planning duration is exceeded: (i) due to the high complexity caused by the number of tasks and parties involved, a limited degree of insight into the work to be performed is available; (ii) the large number of planning disruptions (also caused by other ships' maintenance periods) which are not included in the maintenance planning; (iii) the capacity restrictions on personnel and maintenance facilities; (iv) not all UGDs correspond with the overall maintenance planning due to continuous changes; (v) insufficient information on the availability of resources, such as spare part lead times, personnel, and facilities; and (vi) insufficient educational level of work planners.

In the RNLN's three-level maintenance structure (OLM, ILM, DLM), the application of failure diagnostics is relevant for all three maintenance levels and predictive maintenance techniques mainly for ILM and DLM tasks. The introduction of failure diagnostics and predictive maintenance is expected to benefit the RNLN in costs reduction, corrective maintenance reduction, spare parts lead time reduction, inspection time reduction, preventive maintenance time reduction and insight in system use, which are termed as the six objectives of data-driven maintenance in this study. Fewer maintenance tasks and shorter maintenance duration reduce the required capacity of resources. Furthermore, the reduction of corrective maintenance tasks leads to less unplanned maintenance, and thus to less planning disruptions. Maintenance plannings are not only interrupted less often, but can also be based on accurate system failure information that follows from the failure diagnostics and predictions. It is expected that tasks, and their duration, can be planned better by using this new information. Also indirectly, data can be used to impact the maintenance planning. Providing the crew on board with insights in system usage contributes to better system handling, which leads to lower demand for maintenance.

Our study identified methods that can be used to analyze and improve maintenance plannings. The conducted interviews show three factors that prevent that data-driven maintenance support can be implemented to analyze the duration, criticality and quality of maintenance tasks within the RNLN: (i) the absence of (registration of) maintenance event data, (ii) the software design, and (iii) the limited alignment of the current software architecture with the current maintenance processes. The interviews show that previous software implementation projects did not always result in uniformity of the software design and insufficient attention was paid to guarantee adherence to the usage instructions. Therefore, the implementation of data-driven maintenance support requires considerable effort in order to realize a uniform adoption throughout the organization.

To guide the adoption of data-driven maintenance support, this research proposes a decision table that links the input factors (required data), system characteristics, the three maintenance levels (OLM, ILM, DLM), and the two data-driven maintenance techniques (failure diagnostics and predictive maintenance) to the six objectives of data-driven maintenance. Three main users are identified that can use the decision table for different purposes: the maintenance engineer, improvement parties, and the design authority. The decision table clearly informs each user how data can be used to achieve one of the objectives and vice versa. Furthermore, the decision table can be used to identify the requirements and applicability of data-driven maintenance support during the design phase of new ships and MLUs. A step-by-step approach is introduced for all three stakeholders, in order to identify their input requirements or data-driven maintenance objectives and techniques.

6.2. Discussion

In this section, we discuss the results of this research and the applicability for the RNLN. RQ1 is answered in Chapter 2 by describing the current maintenance policy of the RNLN. Such description is not new to the RNLN, as it describes its own processes and stakeholders. The added value to the RNLN is therefore limited. Still, the RNLN can use this detailed description of maintenance procedures to inform individuals in different stages of the organization. For others, the insights in the complex maintenance policy and cohesion of departments might be valuable. Especially, the matrix structure of MI and MT can be adopted by other organizations and other industries. Despite the aim to obtain objective descriptions of the current maintenance policy and the role of each stakeholder, we discovered differences between answers of interviewees. Differences with respect to expectations or one's personal view are understandable and sometimes even valuable to the research. Different perspectives strengthen the exploration on innovative topics, such as data-driven maintenance support. On the other hand, unanimity is expected for current procedures or collaboration descriptions. In case of contradicting answers, the rule-of-thumb is used, as described in Section 1.4.3. Contradicting responses did not result in problems, and incorrect answers could be filtered out easily. A clear example is the diversity of responses about the planning phase of ILM and DLM periods. We are convinced that the large number of interviews, more emphasis on experts involved, and the different perspectives filtered out imperfections. However, it cannot be fully guaranteed that all subjectivity is avoided. The absence of unanimity shows that standardization of procedures does not necessarily result in unanimous and correct answers. This must be taken into account for the implementation of standardized procedures for data-driven maintenance support as well. Introducing standard procedures does not automatically result in standardized adoption and execution of these procedures. In the current situation, we saw this for the standardized procedures of the CPA reports that result from fluid and vibration measures. Officially, the report must be sent to the ship's commander, but practise showed that the report is not used correctly. Therefore, CPA sends the report also to the maintainer, in order to create more awareness for certain failures. This is also a valuable insight for the RNLN, with respect to change management. For the introduction of new SAP software, already more attention is paid to change management. From the interviews, we conclude that sufficient financial and personnel resources must be available for successful adoption of innovations. This was the main hurdle in the previous SAP introduction.

The potential applications of data are described in Chapter 3, in order to answer RQ2. We first described the objectives of data-driven maintenance support, in order to emphasize the relevance of these techniques. The split of the RNLN's overall goal into six objectives enabled us to be more specific in the explanation why one would apply data-driven maintenance support in practise. The separation gives clear insight in the steps that can be taken by the maintainer and improvement party. A disadvantage is the switch from aggregation level: from the perspective of the entire RNLN to the perspective of the maintainer and user. We solved this textually, because the overall objective of the RNLN, which is to have a well-maintained fleet, is too general to be linked to data-driven maintenance support in daily operations.

From all candidates among the data-driven maintenance techniques, failure diagnostics and predictive maintenance turned out to be most promising, as expected at the start of this research. The current application of both methods in other industries strengthen our findings. The literature search and interviews, especially with interviewees that gained experience at other organizations, show uniformity with respect to the applicability of these two methods. However, we must mention the difference with other industries. Airlines and oil refineries are often used in scientific literature (Antomarioni et al., 2018). Such industries are on a higher level with regards to the implementation process of data-driven maintenance support in their maintenance policy. Furthermore, we recognise that the relatively old fleet of the RNLN and the organizational culture do not allow fast adoption of data-driven maintenance support. In general, we expect that failure diagnostics techniques can be implemented more easily than predictive maintenance, due to the lower technical complexity. We also outlined other types of data-usage, but these do not immediately contribute to the six objectives described in this chapter.

In Chapter 4, we examine potential methods to analyze and improve maintenance plannings. The interviews showed the difficulty of expressing planning quality. Also in scientific literature we only found limited information. The chapter outlines possible methods, and reflects upon the applicability of these methods for the RNLN. However, no strong conclusions can be drawn. Due to the absence of historical maintenance planning data and the according maintenance execution data of the same maintenance intervention period, we were unable to test these methods. The information from the interviews and the descriptions in scientific literature show us that the methods are mostly applicable, but quantification of these results would strengthen our claim. The next step for the maintainer is to complete the data logs for the maintenance processes on board and ashore. Currently, this is partly not the case due to the design of SAP, but also because procedures are not followed correctly. The RNLN must stress the relevance of data logs for maintenance purposes, because an often heard response was that individuals do not understand the need of this task.

A strong claim that we can make, is the implementation of a classification in the analysis method. Not all maintenance tasks are equally relevant. This follows from the interviews, but also in the current maintenance execution processes, incidental prioritization is applied. When only limited time or capacity is available, tasks with the highest impact on operations or seaworthiness are prioritized. Using such distinctions in measurements is therefore a logical step. We also foresee this as a starting position for the implementation of measurement techniques. Current working procedures and software are not designed for such measures. Furthermore, the organizational culture is not expected to be ready for such disruptive transition. A more gradual implementation suits this organization better, and enables the RNLN to gain experience by starting with a subset of the entire maintenance execution process. What can be learned from the answer to RQ3, is about the fundamentals of the analysis techniques. Most methods focus on time, criticality, and input and output quality. These factors cover most of our decision table's system characteristics. The objective of data-driven maintenance support is to affect these factors, which shows the correctness of the system characteristics in the decision table.

In Chapter 5, we answer RQ4. We visualize the input requirements, system characteristics and objectives for each of the three maintenance levels in a structured manner. Furthermore, we link these elements to the failure diagnostics and predictive maintenance. The setup of this decision table makes it accessible for multiple departments within the RNLN and outside the organization. Furthermore, it can be implemented without large organizational transitions, which makes the use very accessible. The main advantage of the table is that it can be used by multiple key players, of which we described the three most important ones.

In the validation of the decision table, we used an iterative approach, and discussed the content and structure with multiple interviewees with different backgrounds. Furthermore, the decision table is presented to people outside the organization without prior knowledge. This did not only improve the quality and correctness of the final version of the decision table, but also showed the usefulness. The responses showed that we managed to include much information within one table, which can be used for multiple purposes. This is at the same time a point of attention, since the high information density can hinder correct use.

A side-effect of our decision table is that certain patterns are visualized, which were unclear on beforehand. The decision clearly shows that predictive maintenance is valuable for ILM and DLM tasks, but not for OLM tasks. Furthermore, the definition of the six objectives showed overlap, which initially was not the intention. However, discussions convinced us that objectives do not need to be fully separated, especially because of the relation of capacity usage and costs. A third thing that becomes clear from the decision table, is the unusability of diagnosis techniques for two of our objectives. These are examples of side-effects that follow from our structured visualization, but more can be found.

6.3. Recommendations

This research focused on the impact of the introduction of data-driven maintenance support on the maintenance execution and maintenance planning. During the execution of this research, we discovered improvement steps within and outside the scope of this research. Especially due to the research design with semi-structured interviews, many topics have been discussed. We mention a number of recommendations to the RNLN that are regarded as valuable. Furthermore, we stress that more data and higher data quality are relevant for different stages of this topic. The interviews and conversations with DvO employees show that sensor data sometimes lacks quality, or is not even available. Next to that, maintenance event data is not logged in a structured and usable way. Also the data transfer from ships to servers ashore is a manual process that is not always executed correctly. Next to that, the origin of certain data is unclear, because of the absence of senor description lists. Improving the safe availability and correctness of data is essential for data-driven maintenance support. Currently, DvO already focuses on improving data quality, data transfer, and the procedural transition. We recommend to continue on these topics. However, besides the data improvements, we focus on five main recommendations.

First, we consider the implementation of the results of this research as an important addition to the current processes. This research shows that data-driven maintenance support positively impacts maintenance planning and execution. Integrating the decision table in the organization is beneficial for multiple stakeholders. DvO is one of these stakeholders, but we also advise them to take the lead in the roll-out of the decision table in other parts of the organization. This can be implemented in the overall roll-out of data-driven maintenance throughout the organization. The decision table helps to give an understanding of the objectives and the steps to be taken.

Furthermore, DvO can use the decision table within the department to identify new data-driven maintenance support projects that can be executed by employees and students.

Second, we recommend the RNLN to incorporate unplanned maintenance tasks in the weekly plannings. Currently, the maintenance planning of individual ships and the week planning of the MT groups do not reserve time slots for unplanned maintenance tasks from other ships. We agree that it sounds counter-intuitive to schedule time for tasks that are unplanned and that are not known at the moment of the planning process. However, during the interviews almost all interviewees mentioned the problem of unplanned maintenance tasks that interrupt the maintenance plannings and maintenance execution. One unplanned task can lead to delay or cancellation of tasks at multiple ships that undergo planned maintenance. Unplanned maintenance occurs frequently, albeit in varying quantities for different specialisms. The frequency of these unplanned tasks is of such a high level, that it is almost deterministic for certain specialisms that multiple hours per week need to be spent on unplanned maintenance. We encourage to implement slack time or reserve time slots for the unplanned tasks. By doing so, maintenance plannings and maintenance execution of planned maintenance projects face fewer planning disruptions, and thus fewer delays and cancellations of planned maintenance tasks. An often heard reaction during the interviews was that the actual capacity usage and the planned capacity usage do not allow time slot reservations for unplanned maintenance. However, due to the weekly frequency for certain specialisms it is beneficial to include spare time in the weekly planning to avoid delays and false project expectations.

The third recommendation is about the correctness of maintenance planning input. Currently, the maintenance tasks are planned by using time approximations per maintenance tasks. However, these approximations are fixed and not subject to updates. Furthermore, the tasks do not always distinguish lead time and pure maintenance execution time. This makes the approximation unreliable. A feedback loop improves the correctness of the approximations. The actual time needed for previous executions of identical tasks, strengthen the planning for future maintenance periods. Furthermore, a feedback loop enables the maintainer to compare the actual execution of a maintenance period with the original planning. Without feedback, systematic inadequacies may be missed and lessons cannot be learned. For the RNLN it may be a good step to start with this feedback loop slowly, thus with only measuring actual maintenance execution durations only. Further implementation can be completed at later stages.

Also for data-driven maintenance support, the input must be correct. When the RNLN decides to rely more on data-driven maintenance support, the organization must ensure that the retrieved data is correct. Sensors and other hardware are needed to support the concept of data-driven maintenance support. However, these are also systems themselves that need maintenance. A maintenance plan must be established for all hardware that is introduced on board, thus also for the hardware that enable data-driven maintenance support. Furthermore, sensors need to be calibrated on a regular basis. This must also be part of the maintenance policy for this type of hardware. Even a step further is maintenance to the software. Algorithms must be checked on a regular basis, in order to guarantee the maintainer that the outcomes of the algorithms are correct. The maintenance policies for hardware and software must also contribute to a uniform approach throughout the entire fleet.

The last recommendation follows from the interviews with managers. It became clear that managers are informed to a limited extend on the progress of data-driven maintenance support, and the progress and objectives of DvO in particular. Not only did they express their preference to be informed more often on the steps made with respect to data-driven maintenance support, but also the desire to receive support on the implementation of data-driven maintenance support. Most of the interviewees know the basics of data-driven maintenance support, but the interviews also showed that some interviewees have an incorrect perception. Therefore, we recommend to promote the status and objectives of data-driven maintenance support more frequently. Furthermore, the managers' demand of support in the implementation process is regarded as valuable. They did not show high levels of resistance, but a lack of knowledge on the topic. Moreover, when the implementation support comes from a single source in the organization, for example from DvO, it is expected that the implementation throughout different departments and levels of the RNLN can be completed more uniformly. DvO currently collaborates more intensively with certain specialized departments and technicians. From this collaborations, the best practises can be used in the change management process for the other departments.

6.4. Limitations and future research

This research shows how data impacts maintenance execution and planning at the RNLN. Despite a thorough research design, there are some limitations. Furthermore, outside the scope of this research there are opportunities for further research.

First, we want to mention the qualitative background of this research design. The interviews and scientific literature give insight in the expected impact of data-driven maintenance support, but this is not quantified in this research. Although three case studies and expert knowledge from different perspectives are part of the research, it is valuable to quantify the impact of introducing data-driven maintenance support tools. Future research can be conducted with a more quantitative perspective, or a simulation of (a part of) the maintenance processes can be constructed. Especially the impact on the costs and capacity usage of maintenance facilities and personnel are relevant to observe. A start can be made with observing the effects of data-driven maintenance support of a handful of systems on which data-driven maintenance is applied, such as in the study of Heek (2021). Combining multiple systems give an indication of the impact on ship and organizational level.

Related to the first limitation is the measurability of maintenance plannings for this research. During the start-up phase, we expected to find useful data. The research design aimed at a quantitative support by comparing an original maintenance planning and the actual execution of the planning. The goal was to map the delays of the planning execution. However, we concluded in Chapter 4 how maintenance plannings can be analyzed and improved. Future research can examine the cause and impact of delays, by making use of our maintenance planning analysis techniques.

While executing this research, the maintenance structure with scheduled maintenance periods on a fixed interval were a recurring topic during the interviews. For the scope of this research, we assume the fixed interval. It is questionable whether this structure needs to be preserved when data-driven maintenance support gains more influence. Research can be conducted to completely releasing fixed maintenance intervals, or to the optimal time between two consecutive maintenance interventions. Because altering the time between two consecutive identical maintenance tasks are not part of this research, we did not focus on the impact on this interval.

The focus of this research is on ships in the OPV class, which have a below average age when compared to the rest of the fleet, as mentioned in Section 1.4.4. These ships are equipped with more sensors than older ship types. Another advantage of OPVs is the opportunity to send data to support departments ashore. However, not all ships are equipped sufficiently, or cannot send data due to operational restrictions. One can think of the limited communication possibilities of submarines. Therefore, further research to the technical applicability must be performed. Also the applicability of the decision model is not tested in practise. After implementation of the decision table in the maintenance processes, the applicability can be assessed and adjustments can be made to improve the useability.

References

Al-Najjar, B. (2007). The lack of maintenance and not maintenance which costs: A model to describe and quantify the impact of vibration-based maintenance on company's business. *International Journal of Production Economics*, 107(1):260–273. 23

Antomarioni, S., Bevilacqua, M., Potena, D., and Diamantini, C. (2018). Defining a data-driven maintenance policy: an application to an oil refinery plant. *International Journal of Quality & Reliability Management*, 36(1):77–97. 57

Ashayeri, J., Teelen, A., and Selenj, W. (1996). A production and maintenance planning model for the process industry. *International journal of production research*, 34(12):3311–3326. 34

Atli, O. and Kahraman, C. (2012). Aircraft maintenance planning using fuzzy critical path analysis. *International Journal of Computational Intelligence Systems*, 5(3):553–567. 33

Baidya, R. and Ghosh, S. K. (2015). Model for a predictive maintenance system effectiveness using the analytical hierarchy process as analytical tool. *IFAC-PapersOnLine*, 48(3):1463–1468. 26

Ben-Daya, M., Kumar, U., and Murthy, D. P. (2016). *Introduction to maintenance engineering: modelling, optimization and management*. John Wiley & Sons. 1

Besnard, F., Nilsson, J., and Bertling, L. (2010). On the economic benefits of using condition monitoring systems for maintenance management of wind power systems. In *2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems*, pages 160–165. IEEE. 41

Blanchard, B. S., Verma, D. C., and Peterson, E. L. (1995). *Maintainability: a key to effective serviceability and maintenance management*, volume 13. John Wiley & Sons. 16

Brus, D. (2022). The social impact of implementing predictive maintenance at the royal netherlands navy. *Bachelor thesis Eindhoven University of Technology*. 29

Carnero, M. C. (2005). Selection of diagnostic techniques and instrumentation in a predictive maintenance program. a case study. *Decision support systems*, 38(4):539–555. 38

Cheliotis, M., Lazakis, I., and Theotokatos, G. (2020). Machine learning and data-driven fault detection for ship systems operations. *Ocean Engineering*, 216:107968. 26

Dutch Ministry of Defence (2020). Personeelsrapportage defensie midden 2020, https://www.defensie.nl/binaries/defensie/documenten/rapporten/2020/09/15/personeelsrapportage-midden-2020/personeelsrapportage+defensie+midden+2020.pdf , date visited: 2022-03-21. 1

Dvir, D., Raz, T., and Shenhar, A. J. (2003). An empirical analysis of the relationship between project planning and project success. *International journal of project management*, 21(2):89–95. 35

Fajardo, M. and Ortiz, L. V. (2011). Analysis of the preventive/corrective maintenance ratio for ddg class ships. Technical report, Naval Postgraduate School Monterey CA. 41

Heek, D. (2021). A data-driven condition monitoring approach for the main bearings of a marine diesel engine. *Master thesis Eindhoven University of Technology*. 50, 51, 60

Huysmans, J., Dejaeger, K., Mues, C., Vanthienen, J., and Baesens, B. (2011). An empirical evaluation of the comprehensibility of decision table, tree and rule based predictive models. *Decision Support Systems*, 51(1):141–154. 39

Jain, P., Pistikopoulos, E. N., and Mannan, M. S. (2019). Process resilience analysis based data-driven maintenance optimization: Application to cooling tower operations. *Computers & Chemical Engineering*, 121:27–45. 24

Jardine, A. K., Lin, D., and Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, 20(7):1483–1510. 39, 40

Johnson, R. L., Tsiros, M., and Lancioni, R. A. (1995). Measuring service quality: a systems approach. *Journal of Services Marketing*, 9(5):6–19. 34

Kelley Jr, J. E. (1961). Critical-path planning and scheduling: Mathematical basis. *Operations research*, 9(3):296–320. 35

Kelley Jr, J. E. and Walker, M. R. (1959). Critical-path planning and scheduling. In *Papers presented at the December 1-3, 1959, eastern joint IRE-AIEE-ACM computer conference*, IRE-AIEE-ACM '59 (Eastern), pages 160–173. Association for Computing Machinery. 35

Ministerie van Financiën (2021). Ministerie van financiën defensie jaarbegroting, https://www.rijksfinancien.nl/visuals/2021/begroting/uitgaven/x , date visited: 2021-09-07. 2

Mobley, R. K. (2002). *An introduction to predictive maintenance*. Elsevier. 41

Nguyen, K.-A., Do, P., and Grall, A. (2015). Multi-level predictive maintenance for multi-component systems. *Reliability engineering & system safety*, 144:83–94. 8

Pintelon, L. and Van Puyvelde, F. (2006). *Maintenance decision making*. Acco. 26, 27

Pujadas, W. and Chen, F. F. (1996). A reliability centered maintenance strategy for a discrete part manufacturing facility. *Computers & industrial engineering*, 31(1-2):241–244. 34

Royal Netherlands Navy (2021a). Royal netherlands navy fleet, https://www.defensie.nl/organisatie/marine/eenheden/schepen, date visited: 2021-09-05. 1

Royal Netherlands Navy (2021b). Royal netherlands navy task description, https://english.defensie.nl/organisation/navy/tasks, date visited: 2021-09-05. 1

Sandru, M., Olaru, M., Pirnea, I. C., and Weber, G. (2014). Multi project management kpis. In *European Conference on Management, Leadership & Governance*, page 522. Academic Conferences International Limited. 34

Shamim, A., Hussain, H., and Shaikh, M. U. (2010). A framework for generation of rules from decision tree and decision table. In *2010 International Conference on Information and Emerging Technologies*, pages 1–6. IEEE. 39

Sharma, S., Cui, Y., He, Q., Mohammadi, R., and Li, Z. (2018). Data-driven optimization of railway maintenance for track geometry. *Transportation Research Part C: Emerging Technologies*, 90:34–58. 23

Tiddens, W. W., Braaksma, A. J. J., and Tinga, T. (2018). Selecting suitable candidates for predictive maintenance. *International Journal of Prognostics and Health Management*, 9(1):1–14. 26, 40, 41

Tinga, T., Tiddens, W., Amoiralis, F., and Politis, M. (2017). Predictive maintenance of maritime systems: models and challenges. In *European Safety and Reliability Conference (ESREL)*. 40

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 27(3):425–478. 29

Wu, C., Wu, P., Wang, J., Jiang, R., Chen, M., and Wang, X. (2021). Critical review of data-driven decision-making in bridge operation and maintenance. *Structure and Infrastructure Engineering*, 18(1):47–70. 1

Xu, G., Liu, M., Wang, J., Ma, Y., Wang, J., Li, F., and Shen, W. (2019). Data-driven fault diagnostics and prognostics for predictive maintenance: A brief overview. In *2019 IEEE 15th International Conference on Automation Science and Engineering (CASE)*, pages 103–108. IEEE. 26

Xu, X., Zhao, Z., Xu, X., Yang, J., Chang, L., Yan, X., and Wang, G. (2020). Machine learning-based wear fault diagnosis for marine diesel engine by fusing multiple data-driven models. *Knowledge-Based Systems*, 190:105324. 25

Yang, C.-Q. and Miller, B. P. (1988). Critical path analysis for the execution of parallel and distributed programs. In *The 8th International Conference on Distributed*, pages 366–367. IEEE Computer Society. 35

Yuan, Y., Jiang, X., and Liu, X. (2013). Predictive maintenance of shield tunnels. *Tunnelling and Underground Space Technology*, 38:69–86. 23, 24

Appendices

Appendix A

Interview questions

This appendix provides the interview questions that are used for this research. Due to the semi-structured approach of the interviews, these questions form the basis of the interviews. Follow-up questions were formulated, based on the interviewee's answers and role.

- What is the relation of your current (and previous) functions to the entire maintenance process, and with which departments do you collaborate most?
- What is the role of your department in the entire maintenance planning and/or maintenance execution process?
- From your perspective, where can data add most value for maintenance planning and maintenance execution?
- Which forms of data-driven maintenance support do you regard valuable?
- For which systems can data-driven maintenance support add value to the current maintenance execution operations?
- Which systems have a high impact on the maintenance planning in terms of duration and planning difficulties? And which systems have a high impact on the maintenance planning due to unplanned tasks?
- How are the maintenance tasks planned?
- How can the quality of the maintenance planning be measured?
- How can the maintenance planning be improved?
- How would you describe the current maintenance planning quality?
- What makes the maintenance planning process complex?
- How frequent do maintenance planning deviations occur?
- What are key processes in the current maintenance policy that should not change at all?