# Smart Maintenance for Modern Naval Ships

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**Synopsis**

The Royal Netherlands Navy (RNLN) aims to bring into service new platforms across its force structure, including a combat support ship, anti-submarine warfare frigates, submarines, and various auxiliary vessels. A constant pressure on reducing ships' crews and an increasing complexity of systems aboard naval ships creates pressure on the maintenance of these future naval ships.

The increase in the number of sensors on board and the emergence of learning algorithms offer an opportunity to identify failures at an earlier stage, better plan maintenance and reduce the (corrective) workload aboard ships with the help of data analysis. The RNLN therefore works on a transition from planned periodic maintenance towards condition-based maintenance and predictive maintenance based on advanced condition monitoring and data analysis techniques, which necessitates the development of improved shore support.

The RNLN developed the smart maintenance roadmap to guide this transition towards a data driven maintenance organisation. This roadmap covers the process of collecting raw operational ship data to the change in the RNLN's asset management process and consists of five strategy lines: data acquisition, data infrastructure, data governance, data analysis and asset management. The activities described in this paper have been developed in close collaboration with academic partners and industry. This paper presents the smart maintenance roadmap and gives practical examples of developments and challenges within each of the five strategy lines. This paper concludes with future directions that are envisioned for the development of smart maintenance within the RNLN and reflects on the social aspects of implementing smart maintenance within the maintenance organisation of the RNLN.

Keywords: Smart Maintenance; Predictive Maintenance; Condition Based Maintenance; Organisational transition; Royal Netherlands Navy.

**Author's Biography**

**dr. Wieger Tiddens** has extensive experience and knowledge on the implementation and development of predictive maintenance. His passion is to achieve the maintenance of tomorrow. Within the Royal Netherlands Navy's Data for Maintenance group, he works on data driven asset management and Predictive Maintenance for the current and future fleet.

**Cdr. (ME) ret. Bart Pollmann** has fulfilled a lifetime military career in various marine engineering jobs, both at sea and in support and policy roles. From a maintenance perspective, his passion is to develop and implement solutions to improve the maintainability of future navy ships, allowing for trends of increased system complexity and reduced crew sizes.

**Dennis Curvers BSc** is an experienced Information Management Professional with a background in Chemistry and Quality Management. Complemented with keen analytical skills and a practical approach, he finds his way in getting reliable information to the right people at the right time. Within the Royal Netherlands Navy's Data for Maintenance group, he puts his experience into practice with a focus on Data Acquisition, -Infrastructure and -Governance for the current and future fleet.

**Maaike Teunisse BSc** is a data scientist within the Royal Netherlands Navy's Data for Maintenance group. She has a background in applied mathematics and is studying for a master's degree in Business Analytics. She works on various data projects for the maintenance engineers as well as for the crew of the fleet.

**Shadia Shaneh Saz MSc** is a Senior Consultant Reliability & Maintenance with ADSE B.V. In all her past projects, optimizing the maintenance has been a key focus, from the aerospace and rail industries, now towards the maritime domain. She is currently placed at the Defence Materiel Organisation as the technical coordinator Smart Maintenance and is responsible for coordinating the pilot projects within the Data for Maintenance roadmap and translating the lessons learned towards the specifications in the acquisition projects of future ships.

**LtCdr. Jan Zegers** made, after an operational career, the switch to IT and data science. He is involved in the Royal Netherlands Navy's Data for Maintenance Group from the beginning, as part of developing and implementing the use of data science and AI within the navy, resulting in a Maritime Data Science Capability. In the group he works on the IT solutions and Data Governance.

## 1. Modern maintenance for the current and future fleet

The Royal Netherlands Navy (RNLN) aims to bring into service new platforms across its force structure, including a combat support ship (CSS), anti-submarine warfare frigates (ASWF), submarines and various auxiliary vessels. A constant pressure on reducing ships' crews and an increasing complexity of systems aboard naval ships creates pressure on the maintenance of these future naval ships.

Modern ships are increasingly equipped with sensors. The emergence of learning algorithms offers an opportunity to identify failures at an earlier stage, better plan maintenance and reduce the (corrective) workload aboard ships with the help of data analysis. The RNLN therefore works on a transition from planned periodic maintenance towards condition-based maintenance (CBM) and predictive maintenance (PdM) based on advanced condition monitoring and data analysis techniques, which necessitates the development of improved shore support.

These developments towards, so called, Smart Maintenance trigger the RNLN to collect and store more and more data from its ships. Data has traditionally been stored on-board for only days or weeks. Nowadays, the value of long term (onshore) storage is recognized, as it enables reconstructing long usage histories of specific systems or even complete ships (Rijsdijk *et al.*, 2020). The Defence Vision 2035 (Netherlands Ministry of Defence, 2020) recognizes this and indicates that efforts should be made to prevent the risk of drowning in a sea of information. The defence organisation has to modernise. This, however, should be achieved from a base that has suffered from years of cutbacks combined with a shortage of personnel for the way the NLMOD is currently set up. Change is therefore needed, both in the maintenance of the RNLN's ships which is carried out by the Directorate of Materiel Sustainment (DMI) of the RNLN as well as in the procurement of new naval ships, which is carried out by the Defence Materiel Organisation (DMO).

The RNLN's Sail Plan (Royal Netherlands Navy, 2018) guides the RNLN for the road to 2030. The materiel track in this plan ensures that all new ships and weapon systems meet the RNLN's requirements and aims for a balance between deployment and maintenance. To this end, the RNLN orchestrates maintenance, new construction projects and maintenance knowledge within the military-maritime domain. Adequate maintenance and cooperation with civil partners should guarantee the continuity of maritime maintenance. It is therefore crucial that DMO as designer and the RNLN as user and maintainer work closely together.

The DMI's vision document for 2030 (Directorate of Materiel Sustainment, 2017) adds to this with aiming for a more directorial role on the maintenance process together with industry and international partners, more focus on innovation and focus on a smooth introduction of new ships.

The three vision documents of the NLMOD, the RNLN and the DMI therefore pave the way for the introduction of the smart maintenance roadmap. Following the three vision documents, five strategic goals guide the smart maintenance roadmap: autonomous operation (ships should be able to operate with limited shore support); optimal availability (finding an optimal balance between ship's availability and costs); unburdening the ship's crew (ensuring that tasks are automized where possible to make sure that ships can be sailed with fewer personnel); a directorial role at the DMI (creating sufficient expertise to become a smart maintainer); and relevant during the whole life cycle (applied technologies should still be relevant in ten to twenty years of time).

Smart maintenance offers the opportunities to radically change the view on the RNLN's maintenance process. The application of these approaches of smart maintenance is however rather limited in the maritime industry (Tiddens *et al.*, 2022). Many organisations have a high ambition to accurately predict failures of individual systems in their fleet, but this ambition does not match with the low quality and amount of (failure) data. This also holds for the RNLN.

The 'Data for Maintenance' (in Dutch: 'Data voor Onderhoud', abbreviated as DvO) initiative therefore set out in 2019 to develop a structured programme to introduce data driven maintenance within the RNLN. Setting up such a structured programme is required since it takes time to identify the technology's potential performance with targeted experiments, to integrate the technology into the existing hardware and processes, and to further improve the quality of analyses via processes of learning-by-doing (van de Kerkhof, 2020).

The basic idea for this programme has been around since 1992, but budget cuts and limited computing possibilities of the time prevented its development and the idea disappeared in a drawer. Nowadays, a strive for data driven operations as promoted in the defence vision combined with modern computer technology makes this an opportune time.

The Holland-class ocean-going patrol vessel (OPV) HNLMS Groningen (Figure 1) has been the 'DvO fieldlab' from day one. The OPVs are equipped with an Integrated Platform Management System (IPMS) which provides the remote monitoring and control services of the ship's platform by means of computerized equipment. The system measures lots of parameters (thousands), for example the rotational speed of the shaft. Many of these sensors are not intended for diagnosing a system or even predicting its failures, as also concluded by (Rijsdijk *et al.*, 2020), but for monitoring and controlling the ship. The HNLMS Groningen has therefore been equipped with additional sensors such as high-frequency current and vibration measurements of sea water cooling pumps and cylinder-pressure measurements on its main diesel engines.

Figure 1: HNLMS Groningen (Netherlands Ministry of Defence, 2022)

This paper presents the RNLN's smart maintenance roadmap (Section 2) and gives practical examples of developments and challenges within each of the five strategy lines (Section 3). This paper concludes with future directions that are envisioned for the development of smart maintenance within the RNLN and reflects on the social aspects of implementing smart maintenance within the maintenance organisation of the RNLN.

## 2. Introducing the Smart Maintenance Roadmap

The smart maintenance roadmap, shown in Figure 2, forms the backbone of the DvO initiative. The diagonal arrow in the centre shows the development stages of the programme. These go together with the introduction of new ships and work toward realising the goals stated in the vision documents of the NLMOD, the RNLN and the DMI. The foreseen end state is an optimally data driven maintenance organisation in 2035. Four intermediate phases are defined.

Currently, the programme is in the concept development phase. The goal of this is to experiment with a multitude of small pilot projects divided over the five strategy lines. These strategy lines must be developed in conjunction. This is best achieved by concentrating the development, as much as possible, on one pilot ship: HNLMS Groningen. The second phase follows the introduction of the Combat Support Ship (CSS) in 2024. This ship will already be equipped with many additional sensors, e.g., vibration. Additionally, all data from electric switches will be extracted using industrial internet of things concepts.

The DvO programme must be realized in the third phase when the anti-submarine warfare frigates (ASWF) will be introduced. Finally, concept optimisation will take place during the final stage, which goes together with the replacement of the submarines. The DvO initiative is centered around these major milestones. Many smaller projects (i.e., introduction of new ships) will take place between these major milestones. Where possible, these will be included in the programme.

Developments within the programme are split into five strategy lines: data acquisition, data infrastructure, data governance, data analysis and asset management.

Technicians on board and at the DMI are tasked with solving incidental and structural technical problems in addition to carrying out preventive maintenance. There is often a need for data that makes clear what causes a system to malfunction. It also helps to make connections with similar problems in other systems, to arrive at structural solutions. Data for this is often not available, or not in a structured way. The first strategy line therefore focuses on (additional) data collection from sensors as well as hand-held devices. This is shown in the left lower corner of the roadmap and further detailed in section 3.1. The collected data needs to be structured aboard the ship and transported from ship to shore, preferably using existing (e.g., SatCom or broadband) connections. From this, the data needs to be pre-processed before it is stored in a data warehouse and complemented with additional data sources (e.g., hindcast weather data or failure data from an ERP system). The design and development of the required infrastructure are discussed in section 3.2.

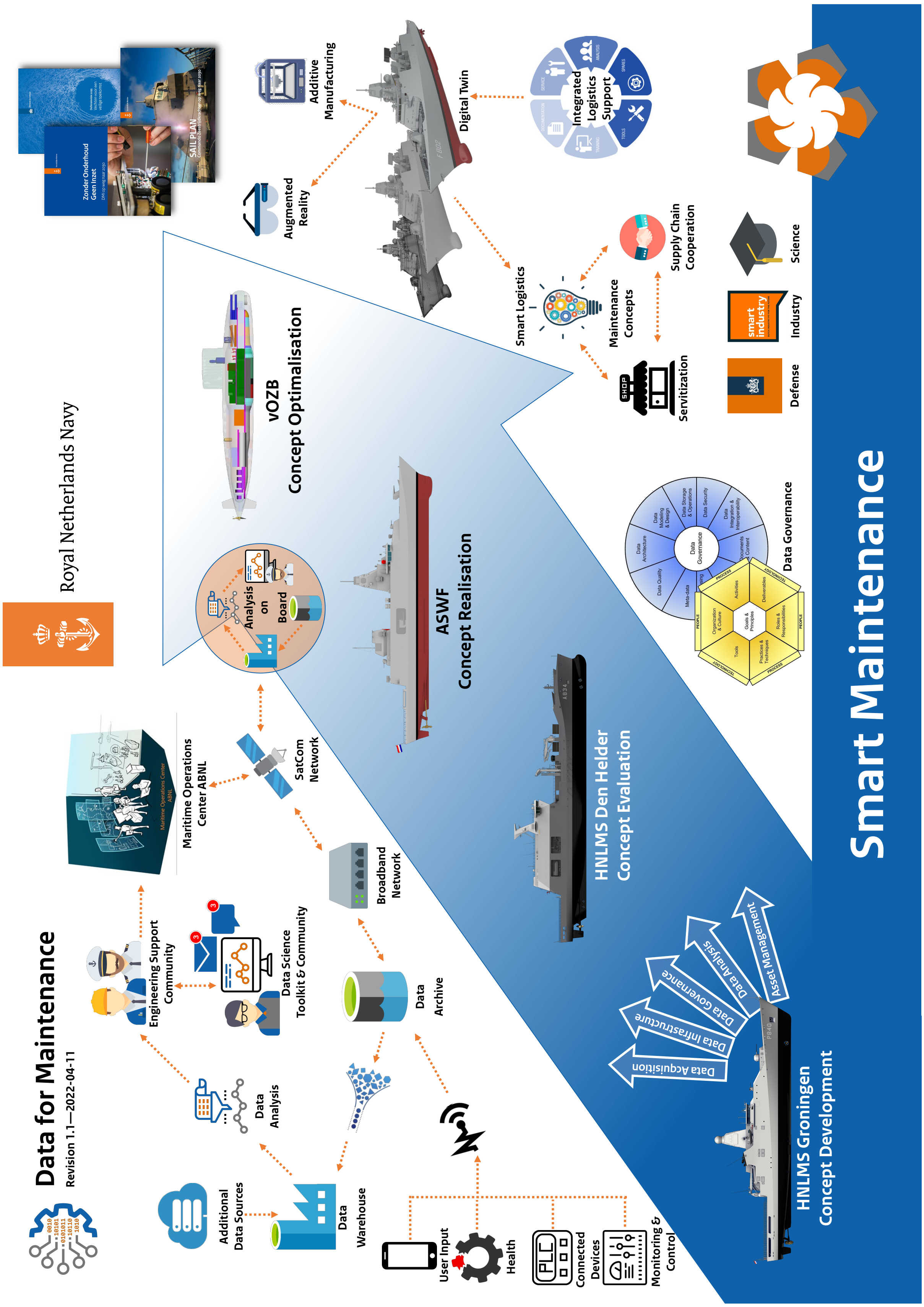


Figure 2: The RNLN’s Smart Maintenance roadmap

Data scientists can then design, in collaboration with an engineering support community, algorithms that automatically detect the development of defects and give an alarm to a maintenance engineer in the event of deviations. The focus of maintenance thus shifts from periodic to predictive. In the event of urgent alarms, the ship's crew is immediately notified, and if defects develop slowly, this is reported to a DMI engineer. This person then could plan for solving the defect so that he/she can unburden the crew. The development of the data analyses (see section 3.4) heavily relies on the trustworthiness and quality of the data and related information. Therefore, a data governance plan is set up is (see section 3.3) that manages the security and usability of the data.

The roadmap smart maintenance depicts the technical developments that are required to use the data and developed algorithms. Next to such technological developments, the introduction of smart maintenance requires an organisational transition (van de Kerkhof, 2020; Tiddens *et al.*, 2022). The strategy line asset management focusses on this organisational transition towards smart maintenance, further detailed in section 3.5. Cooperation is key for the success of this programme. This roadmap is therefore a cooperation between defence, industry, and science.

In the above manner, DvO works on solutions to unlock and interpret data. The programme contributes to the modernisation of maintenance for the new generation of ships. The developed solutions, together with additive manufacturing (3D printing) and extended reality, among others, ensure that technical users on board and within the DMI are guided towards a data driven future.

## 3. Narrowing it down in five strategy lines

The roadmap smart maintenance composes of five separate strategy lines. The challenges, activities, and opportunities within these five separate lines will be discussed in this section.

### *3.1. Data acquisition*

Focus on the data acquisition strategy-line lies on collecting data from pre-installed sensors, installing (additional) sensors where needed and enriching the data (for example with data of (maintenance) events). One of the important steps towards data driven maintenance is to determine for which systems condition monitoring will be most beneficial, since Predictive Maintenance (PdM) is only suitable for a limited number of systems (Tiddens *et al.*, 2018). For this purpose, the condition monitoring scoping method is created, consisting of two steps.

The first step in this method (the left downward side of Figure 3) is to determine which ship systems are most critical in terms of availability killers and cost drivers. This has been determined based on maintenance data from the enterprise resource planning (ERP) system and from interviews with maintenance engineers. This has led to a top-40 ranking of ship systems. For the top 5 of these systems, an FMECA is conducted, where per component is evaluated how it fails, what the effects are and how critical the failures are. Then per failure mode is analysed whether there is a failure indication, i.e., if there is any change in certain parameters that will make the failure evident. If so, this parameter can then be monitored and thus be placed on the condition monitoring list. A distinction is made between logging process parameters that are already standard part of the system, for example temperature or pressure, and the placement of additional sensors, for example vibration monitoring.

Once the condition monitoring list is created, the impact of logging these process parameters or placing those additional sensors can be evaluated (the right upward side of Figure 3). This is done by first evaluating the impact on the maintenance tasks, which can be both on corrective and preventive maintenance tasks. For the corrective tasks, can we look back at the current fleet and determine which failures could have been prevented if these parameters were monitored? And for the preventive maintenance, are there any calendar-based or running hours-based tasks that can be replaced by condition-based tasks? If so, the availability of the component will be increased, and that can in its turn lead to a higher availability of the system and of the entire ship. Another consequence would be a decrease in the maintenance costs. In this manner a business case for investing in additional sensors is made and for the RNLN’s future ships a condition monitoring scope is determined which will lead to higher availability and lower costs.

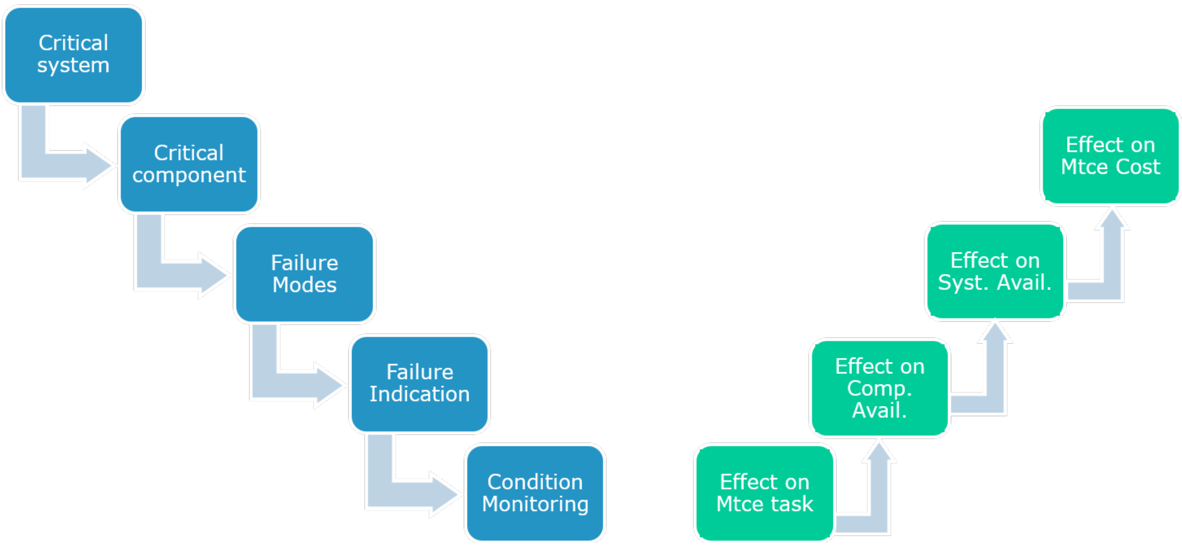


Figure 3: Scoping method to select required additional sensors

### 3.2. *Data infrastructure*

One of the challenges is the IT infrastructure needed to transfer the data from the ships to shore and building the infrastructure to be able to analyse the data. The initial approach has been to develop a basic end-to-end data pipeline, covering all steps: acquire, organize, analyse, and deliver (Gartner, 2017). Next steps are to move the organisation of data closer towards the data creation and develop a common on-board structured data storage and analysis platform that is reliable, scalable and fits both existing and future vessels. The maritime military environment brings additional challenges, such as the limited bandwidth available, the classification and security of data and a fragmented IT architecture. Before the programme started, the ship's platform data was only stored aboard the ships for a period varying from a couple of weeks to a couple of months. The first step was to periodically collect this data and archive it ashore.

The following step, shown in Figure 4, has been realised recently for four ships: data is pre-processed on board and transferred via existing networks from ship to shore daily. As can be seen in Figure 4, multiple airgaps exist in this data pipeline. This is partly due to the separation of networks aboard the ships, requiring human action. This is not in line with the goals of the programme, as stated in the introduction. Future projects will therefore be undertaken to break down this barrier and ensure that this feature will be included in the requirements of future naval ships. The realisation of the semi-automatic data pipeline has enabled that operators aboard ships, who in the past were only able to visualise one-dimensional parameters over a limited period, can currently easily visualise these over an extended period of time from the browser.

Meanwhile, the NLMOD is extensively revising its IT infrastructure. This infrastructure will include a common data science environment for lower classified data as well as a federated architecture for higher classified data. As part of this federated network, the RNLN is planning to build a maritime data environment with artificial intelligence and data science components. DvO will be one of the launching customers.

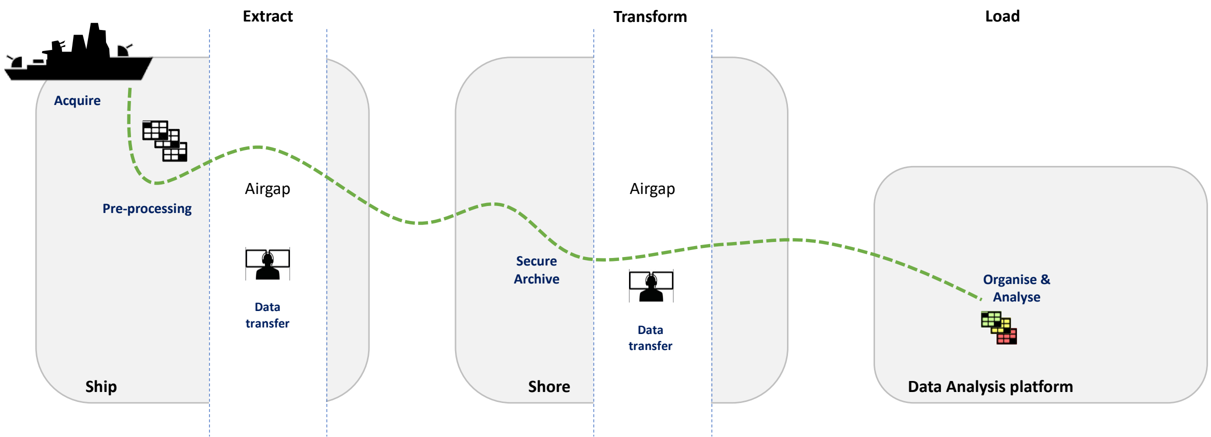


Figure 4: The data infrastructure pipeline from ship to shore

### *3.3. Data governance*

Data governance (DG) is the process of managing the availability, usability, integrity, and security of data in enterprise systems throughout its lifecycle and is based on (internal) data standards and policies that also control data usage (Stedman and Vaughan, 2022). Budget cuts resulted in limited resources for coping with everyday developments in society, including the ever-growing importance of data as an enterprise asset. DG maturity overall exists on a very basic level within the RNLN.

Only recently, the NLMOD formally recognized the importance of data management by appointing a chief information officer (CIO) and chief data officer (CDO). Both offices have begun working on a data strategy and general guidance on the topic, including a standards framework for algorithms that promotes explainable AI and responsible data use. Current developments include a hub-spoke CIO organisation that will address the specific needs for the RNLN.

A low DG maturity at this point poses a challenge for the DvO initiative as products (such as analyses and algorithms) delivered need to be reliable to be accepted by the user community. Furthermore, all data handling exercises still need to be compliant to existing standards and policies that have not been updated to address 'big data' issues. Pending top-down guidance from the CIO and CDO, DvO has started bottom-up DG initiatives for example by organizing workshops on the subject as part of a DvO course for engineers within the DMI organisation, but also by documenting its processes, installing a quality assurance program, and addressing any security compliance issues.

Given the overall ambition of the DvO initiative and by specifically incorporating DG as part of its strategy, it is expected the initiative will contribute to an increase in DG maturity within the DMI and RNLN over time.

### *3.4. Data analysis*

Transferring data into actionable information is done in the data analysis strategy-line where big data analysis and machine learning are being studied to extract value from the data. To gain trust within the organisation, the programme starts with visualising basic insights. The next step, before developing prognostic algorithms, is to help engineers and the technical crew aboard ships with diagnostic analyses.

Showing the actual use of machinery aboard vessels is one of these basic insights. These prove to be even more relevant to ship's crews and maintenance engineers than foreseen at the start of the DvO programme. Also, these insights often form the start of the conversation on data driven maintenance with engineers and crews and support the required social transition within the organisation.

Based on Figure 5 for example, low load operation of diesel engines can be detected. The crew can then be advised to use electrical propulsion, even though this can be less efficient than mechanical propulsion (Vasilikis *et al.*, 2022). Insights are also related to the fuel consumption of ships given certain operational modes (both sailing and in harbour). Thus, these analyses are not only required from a maintenance perspective, but they also shed a light on the environmental perspective. (Vasilikis *et al.*, 2022) showed that decisions made by the crew of one of the RNLN's OPV's, such as the selection of operational mode and the selection of vessel speed, have a similar impact on overall energy performance as design decisions. Attention is therefore paid within DvO to supporting the development of sailing assistants: advising the crew on the optimal route (e.g., fastest, shortest, or most eco-friendly) and giving the crew eco-related insights, such as optimal loading of machinery or trim settings (van der Bos, 2021). These advises are embedded in a serious game; a socially integrated $CO_2$ challenge for seagoing vessels (OceansX, 2022). Finally, data driven models are developed to evaluate the biofouling state and its effects on vessels' hull and propeller performance, thereby impacting performance, financial and environmental aspects (Valchev *et al.*, 2022).

Together with researchers from academia, steps are made towards developing diagnostic and prognostic models. DvO fulfils a hub function where research at universities is translated into production-worthy applications that can be deployed within the RNLN. Also, DvO's aim is not only to develop accurate algorithms to detect, diagnose or predict failures of systems and components, but also to learn the capabilities of these models. This enables the RNLN to become a smart customer in buying systems that are equipped with prognostic capabilities and specifying requirements for future systems.

Prognostic models have been developed to detect crankshaft bearing failures in main diesel engines using regression models combined with statistical process control (SPC) methods (Heek, 2021; Stijns, 2021). Also, explainable black-box models are used to detect anomalies in the behaviour of diesel engines (Teunisse, 2021). These models can indicate when engine parameters (such as temperatures) are behaving out-of-control. It is however not yet clear when a maintenance engineer should act and conduct maintenance (i.e., inspect or repair a system). A limited amount of failure data (caused by a limited number of failures but also poor failure registrations) makes it hard to perform accurate remaining useful life analyses. Therefore, others work on developing hybrid prognostic models that combine physics-of-failure methods with a data driven approach, as done in (Keizers *et al.*, 2021), and apply these to diesel engine data sets.

The combat support ship (CSS), the first major milestone within the project, will be equipped with a large amount of vibration sensors, installed on equipment like pumps, fans, motors and gearboxes. The RNLN's ambition is that these sensors' data can be automatically processed when this vessel comes into service. Preliminary work indicates that machine learning techniques, that use features based on physical knowledge, can classify the state of components and that pre-processing steps can be applied to significantly reduce the amount of data, which ensures that this data can be transferred using the pipeline shown in Figure 4 (van der Heijden, 2022).

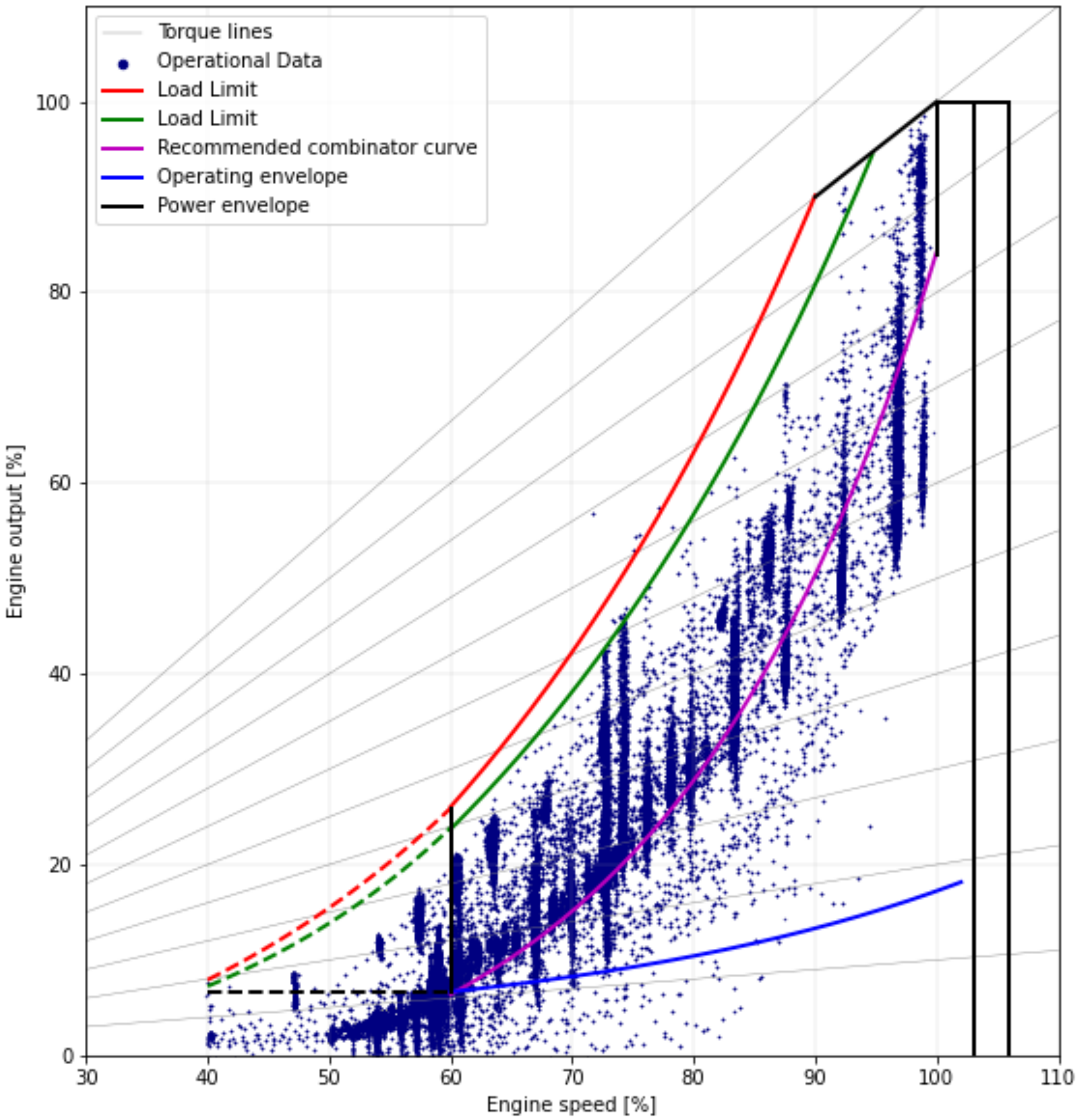


Figure 5: Basic data insights that show the use of a main diesel engine over a specific period in its engine envelope are now available in an online app for engineers and the technical crew aboard vessels

### *3.5. Asset management*

It all comes together in the final strategy line. Asset management entails the translation of the technological and social advancements into the business process of conducting predictive or condition-based maintenance on the RNLN's ships. This transition and implementation of the new technologies developed within the DvO programme requires understanding of the innovation process and its outcomes – such as the usage of tools developed in the programme. Thus, adapting the organisation collectively and over time and reinventing the technology to the context of the organisation (van de Kerkhof, 2020).

Within the programme, this is also seen as the most important success factor: the organisational change process needed for acceptance of the new technology. New developments need to be fitted in a modernized version of the organisation and its service supply chain in a way that feels comfortable for all (supply chain) partners. This includes cooperation with original equipment manufacturers and service providers outside the defence organisation and, even more important, embedding the new technology within the maintenance organisation.

Timing of the introduction of the DvO initiative is crucial. As the DvO initiative is still in a pilot phase with only a small number of ships sending limited data sets to the shore, it would be unrealistic to expect all engineers to immediately jump on the developments: most of the engineers would not have access to relevant data for the problems they are working on. On the other hand, it is necessary to involve engineers who do have the opportunity to use the available data.

Therefore, one (maintenance) engineer per engineering department of the DMI, who has an affinity with 'data' and has a supportive nature, has been appointed as a so called 'data ambassador' by the DMI's engineering management group. The DvO course has been developed and given for this group of 10+ engineers to educate them with the principles of data driven maintenance. These frontrunners of the DvO initiative form the bridge to the larger community of maintenance engineers. The frontrunners assist in amending work processes to fit the increased availability of data to support engineering advice and tweaking the programme and its outcomes (i.e., apps, analyses, and algorithms) to the needs of the (maintenance) engineering community. After educating the initial group, the course will be expanded gradually to an increasing number of engineers and technical crews aboard ships until the technology is fully introduced in all work processes.

The introduction of data driven maintenance also requires cooperation with industry to work on topics that require knowledge and/or data to optimize the supply chain. Traditionally, data is often stored in separate systems behind passwords whilst the value of data can be best explored in cohesion with contextual data in other network domains. The challenge is to overcome limitations to share data and/or algorithms within the supply chain to combine relevant data to correlate parameters that indicate abnormal system behaviour. Experiments with sharing algorithms instead of data have been conducted using federated learning (Vriend, 2022), Furthermore, it is in the interest of both the RNLN and industry to work together: industry gets access to knowledge that allows them to focus their R&D on the most relevant topics and to design features that can be marketed in products for other customers whilst the RNLN will ultimately benefit from systems with increased maintainability. Doing so, together with main suppliers from the maritime sector, we contribute to a modern maintenance ecosystem.

## 4. Conclusions and further directions

The current paper presented the foundation that has been laid down for the smart maintenance programme within the RNLN. Several challenges are foreseen in growing from a start-up to a scale-up.

Expansion of the DvO programme will be sought in two areas: (i) only data of a limited number of ships is available, the programme aims to expand and roll-out to other ships within the fleet, and (ii) the current focus primarily lies on analysing platform data of sensor-rich systems (e.g., propulsion and energy), the aim is to expand to all relevant systems, including weapon control and command systems.

Attention will be paid to further automate the data pipeline workflow from ship to shore (Figure 4) to unburden the crew, one of the main goals of the programme. For this, the use of data filters and data diodes will be studied. Next, as an ever-increasing amount of data will be generated, attention will be paid to finding ways to reduce the amount of data that has to be transferred to shore on a daily base, using on-board analytics, pre-processing (e.g., filtering), compression and reduction.

To achieve these goals, a joint effort is needed from the NLMOD, industry and science. Partnerships will therefore be sought to accelerate developments, find workable solutions in the field of securtity and governance and cooperate on developing practically applicable algorithms for PdM.

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